A new multi-criteria framework to identify optimal detention ponds in urban drainage systems

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A new multi-criteria framework to identify optimal detention ponds in urban drainage systems

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Abstract

Urban development broadly impacts the hydrological cycle, leading to increased peak flow and flooding. Surface water detention ponds are among the most efficient measures for attenuating peak flow and returning it from development to pre-development conditions. However, the major challenge is identifying optimal locations and cost-effective designs for these ponds. This paper presents a new framework for identifying the best strategies for using detention ponds to control floods in urban drainage systems (UDS). The framework comprises a portfolio of simulation tools coupled with evolutionary optimisation and multi-criteria decision analysis models. Hydraulic simulation of UDS is first modelled using SWMM and GIS tools. A multi-objective optimisation model was used to find the optimal location and design for detention ponds. The compromise programming (CP) multi-criteria decision-making method was then used to prioritise potential best management solutions for detention ponds based on several sustainability criteria comprising economic, environmental, physiographic and social factors. The results identified the key features of potential detention ponds appearing in all multi-objective optimal solutions that are useful for decision-makers/designers when planning/designing for new detention ponds. The selected optimal pond strategies can significantly improve the UDS performance by decreasing flood damage between 66% and 90% at the cost of between \$50,000 and \$160,000.

KEYWORDS

compromise programming, detention ponds, flood control, GIS, multi-objective optimisation

1 | INTRODUCTION

Expanding impervious surfaces in response to urbanisation leads to increased surface runoff and the risk of urban flooding. Flood control in cities is traditionally managed using a network of channels to transfer floodwater away from urban areas in the shortest possible time. This approach may also require sewer infrastructure with a significant conveyance and storage capacity to cope with the extra surface runoff during flood events while mainly remaining unused during dry weather. This is more important in arid and semi-arid climates with predominantly dry weather where the efficiency and cost-effectiveness of an adequate sewer system cannot be easily justified.

In recent decades, attention has been paid to more sustainable solutions, such as detention ponds as part of Sustainable Drainage Systems (SuDS), Low Impact Development (LID) or Blue-Green infrastructure solutions, to attenuate the peak flow of floods and significantly alleviate the problems related to large capital investments in urban flood infrastructure (Tansar et al., 2022). The main goal of flood control pond systems is to reduce the flood peak within the return period of the desired design to either achieve pre-development conditions or keep the flow within the maximum capacity of the existing drainage network (Soleymani et al., 2015). Other benefits of detention ponds are their multi-functionality including enhanced liveability, sustainability and value of development areas. These facilities also provide recreation activities and opportunities for residents to engage with the natural environment. Detention ponds can lessen the erosion of downstream channels during flood events (Ravazzani et al., 2014). These ponds can also prevent the backflow of water and surges of floodwater in the existing systems (Ting et al., 2020). Several studies show that detention ponds are among the most effective best management practices (BMP) for LID/SuDS for surface runoff attenuation and flood control (Sohn et al., 2019; Young et al., 2011), especially during short-term storms (Hoss et al., 2016; Liu et al., 2014). Basically, the detention ponds are mainly used to control the flood peak while the water quality in UDS can be effectively improved through a combination of ponds with other BMP methods (Damodaram & Zechman, 2013; Hopkins et al., 2017; Loperfido et al., 2014).

Optimal detention basins in urban stormwater management can be found using optimisation models developed in recent years (Zhao et al., 2021). The common objectives used in similar studies in the recent decade include minimisation of flood volume (Hosseinzadeh et al., 2022), maximisation of water quality of surface runoff (Li et al., 2019) and minimisation of the flood risk (Karami et al., 2022). Most of these models considered optimisation for some design parameters, such as site location, dimensions of detention ponds, and water quality control. Some of these typical studies are outlines here. Duan et al. (2016) coupled the SWMM simulation model with a modified particle swarm optimiser to determine the optimal design of detention ponds by minimising both flooding risks and construction costs of the ponds and LID devices under the specific local design criteria. Yu et al. (2015) specified the optimal location and dimensions of five detention ponds for different storm events using a non-dominated genetic algorithm by minimising flood damages and investment costs. Nazif et al. (2010) developed a three-objective optimisation model for management solutions to identify the optimal size of existing/new runoff ponds and sewer conduits, and the permeability of new channels and sub-basin by minimising the total capital cost of building and rehabilitation of BMPs/sewer systems, minimising flood damage, and maximising system reliability. Yazdi (2019) proposed a solution to manage the capacity of in-line storage tanks during flood periods by combining SWMM with an evolutionary algorithm known as Differential Evolution. Saadatpour et al. (2020) developed a multi-objective multi-circuit Electimize optimisation algorithm that was embedded into the SWMM simulation model based on economic and environmental aspects to determine the size and spatial allocation of the combination of ponds and LIDs in UDS. Some studies showed NSGA-II as one of the most popular and widely used evolutionary algorithms for industry and scientific works in water communities (Reed et al., 2013).

Finding the location of potential ponds in a catchment is a major challenge due to limited access to many sites in urban areas. This can lead to an increased risk of project failure without an integrated decision structure. Hence, it is crucial to properly find potential locations for ponds within the study catchment to ensure flood control management. Different approaches have been carried out to find potential locations for flood detention basins. GIS can be an efficient tool used for this purpose that provides an environment for capturing, storing, analysing, and managing spatially referenced data (Rızvanoğlu et al., 2020). There are several GIS-based techniques for selecting the location of flood detention ponds based on data layers such as land use, slope, or geomorphology. This analysis can be combined with Multi-Criteria Decision-Making (MCDM) methods within an integrated framework to solve complex problems affected by various indicators of sustainability in UDS.

Once potential detention pond solutions are identified by either experts or optimisation models, they can be ranked by several well-known MCDA techniques such as AHP (Analytical Hierarchy Process), TOPSIS (The Technique for Order of Preference by Similarity to Ideal Solution), and CP (Compromise Programming) (Karami et al., 2022). For example, Ahmadisharaf et al. (2016) developed a spatial MCDM framework for the site selection of detention basins based on TOPSIS for flood hazard performance indicators and five other criteria including permeability and topographic slope land acquisition, distance to channels, and social hotspots. Fedorov et al. (2016) proposed a GIS-based method to determine the location and height of flood dams and detention basins, focussing on lessening the impact on the environment. Saragih et al. (2020) found optimal locations for retention ponds in the form of a suitability map, using a GIS-based MCDM technique to analyse seven factors (rainfall, runoff, slope, aquifer, distance to channels, distance to river, land use/land cost) and constraints (well, road, utilities, railway, land use). The CP technique can be used to rank alternative options in a variety of applications in urban water systems, for example, long-term planning and integrated management of urban water resources based on a variety of assessment quantitative and qualitative criteria, including weighting factors from experts and decision makers (Behzadian et al., 2014; Karami et al., 2022; Morley et al., 2016).

According to the above literature review and to the best of the authors' knowledge, none of the previous research works presented an integrated framework for identifying detention ponds in UDS based on the combination of simulation, optimisation, and geo-environmental (geo-spatial) models coupled with MCDM techniques. This is mainly due to the challenges of coupling these simulation and optimisation models that hinder developing an integrated model for taking concurrent advantage of these capabilities. This study aims to present an integration of these three methods simultaneously within an integrated framework to identify several optimal solutions that meet spatial and design parameters, enhancing each method's effectiveness. Furthermore, compared to conventional methods, this approach can better provide solutions for decision makers based on the known criteria, including minimum cost, minimum flooding, and optimal location under the development circumstance. This paper aims to develop a holistic framework that integrates a geo-environmental model with simulation and optimisation models to obtain the optimal number, location and design parameters, including the dimensions of detention ponds that minimise flood damage and cost for a specific return period and maintain physiographic factors and social issues to produce the best solution for flood management. This framework is based on an integrated modelling approach that combines selected contemporary methods, including a multi-objective evolutionary optimisation model, SWMM simulation model, GIS environment, and multi-criteria decision-making method. The rest of this paper is organised as follows. Section 2 describes the study area and data used. Section 3 describes the methods used. Section 4 presents the results. Section 5 provides the conclusions and future research recommendations.

2 | CASE STUDY AND DATA USED

The study area selected for this study is the city of Karaj, in the Province of Alborz, Iran (Figure 1). This city is on the southern slopes of the Alborz Mountains between Latitudes 35°67′–36°14′ N, Longitudes 50°56′–51°42′ E. The elevation above sea level is 1341 m and the drainage basin area is 162 km^2. The difference between the highest and lowest points of the study area is 27.2 m. The general direction of the slope in the study area extends from the northern part to the southern part and hence, urban surface runoff follows the same direction. The average slope of the city is variable and estimated to be between 0.5% and 10%. The annual average temperature, rainfall, and wind speed of this city are around 14–15°C, 244 mm and 1.79 m/s, respectively. Surface runoff resulting from rainfalls is collected through open channels in the UDS. Figure 1 shows the catchment area and the relevant SWMM model.

As synthetic design storms are typically used for designing the UDS and using actual historic rainfall requires a long-term rainfall record (e.g., 30–50 years) with high time resolution (e.g., 5–10 min) which was not available for the case study, the Intensity-Duration Frequency (IDF) curves of the rainfall of the nearest weather station (i.e., Mehrabad station, located in the east, 8 km away from the pilot study, on the west side of Tehran City) were selected for rainfall data in the SWMM model. Each IDF curve depicts the relationship between the duration and intensity of the rainfall for a certain frequency (inverse of return period). Analysis of the IDF curves in the case study revealed that rainfall with a 6-h duration represented the most critical precipitation among the station curves (Karami et al., 2015). Hence, an average rainfall intensity of 3.042 mm/h with a 10-year return period and 6-hour duration was selected from the available IDF curve of the Mehrabad station. Note that a 10-year return period was acceptable by local authorities for the design of the detention ponds. However, other return periods of storms can be tested based on the available standards and codes.

3 | METHODOLOGY

The analytical framework of this study is structured based on the four steps shown in Figure 2. The first step comprises the data collection and gathering of required information for the current infrastructure and conditions to develop a simulation model for the SWMM software. This step entails identifying potential ponds throughout the UDS that improve system performance for urban flood attenuation. The second step develops a multi-

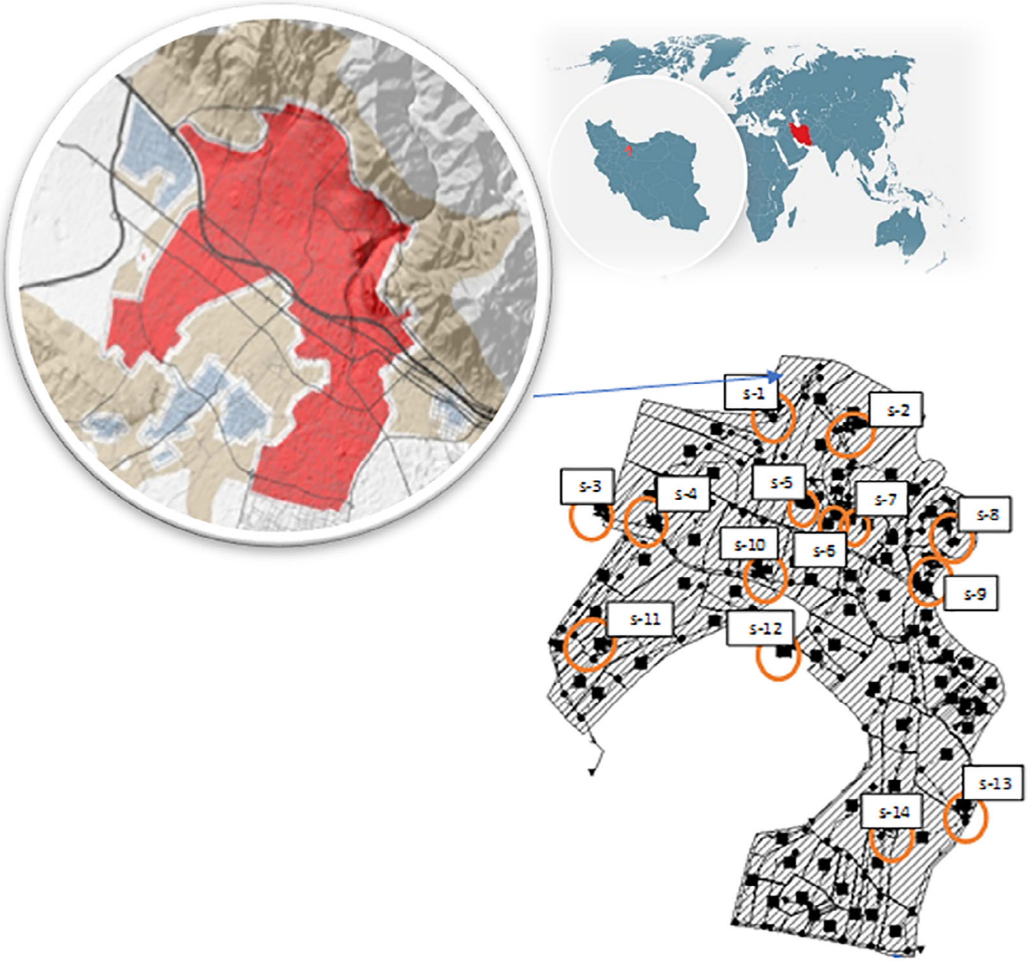

FIGURE 1 The Satellite map of the case study and simulated model in SWMM.

objective optimisation model based on economic factors and flood volume as a surrogate for flood damage. The optimisation model adopted in this study uses an evolutionary algorithm with an iterative loop of the model simulation. In each iteration of the optimisation algorithm, the key performance indicators of the UDS are calculated through the model simulation and considered as the objective functions of the optimisation model and evaluated for a number of potential solutions, comprising a specified number of detention ponds and their design parameters defined as decision variables. The evolutionary algorithm gradually generates new sets of solutions with better objective functions by evolving the decision variables and the algorithm operators iteratively within a pre-specified number of iterations to achieve a Pareto optimal front which comprises several non-dominated optimal solutions. The third step deals with two factors of location of detention ponds, including physiographic and land-use elements, using spatial analysis tools in ArcGIS software and the potential ponds are then scored. The final stage combines the results of the optimal solutions obtained in the second step with the scores relevant to the pond location for each solution. Then, a multi-criteria decision tool based on the CP technique is used to rank the solutions based on nearest distance to the ideal point (Nazari et al., 2014). The efficiency of each pond, flood damage and construction costs are further analysed and discussed.

3.1 | Urban stormwater runoff simulation

This study applies the stormwater management model (SWMM, V. 5) for model dynamic simulation of surface runoff in the UDS. The SWMM model is a rainfall-runoff model for urban basins developed by EPA in 1971 (EPA US 2004). SWMM defines the physical properties of UDS, including sub-catchments, conduits, junctions and other relevant components, and analyses the performance of UDS based on specific rainfall/contamination data and water loss methods. The hydraulic simulation in the UDS

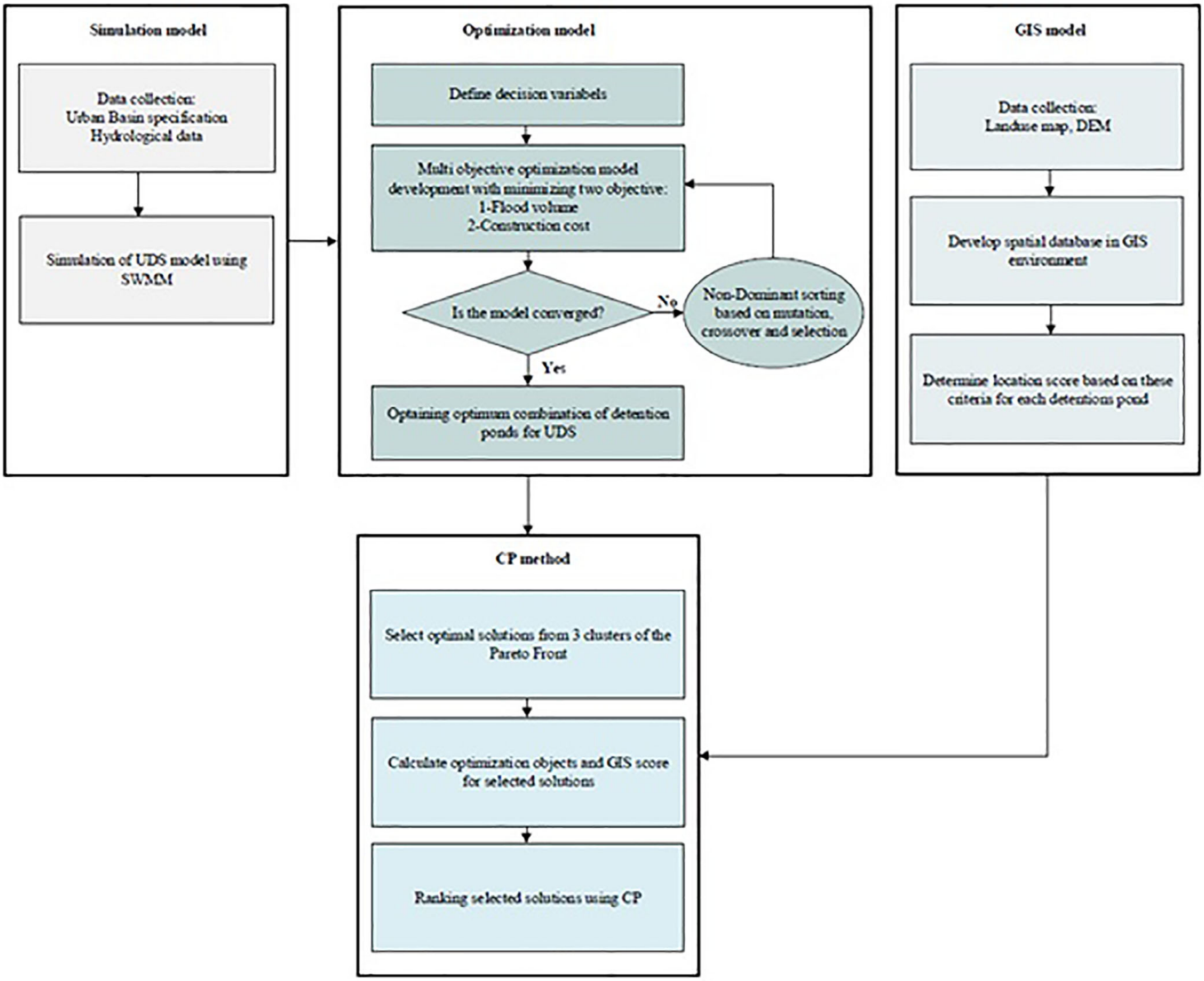

FIGURE 2 The proposed methodology for identifying detention ponds in UDS.

needs the input data listed below: 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. The main elements for selecting SuDS include local land use, catchment features, environmental conditions, and catchment slope. Furthermore, due to its simplicity, the basic hyetograph proposed by Yen and Chow (1980) was employed in this study to construct the temporal distribution of rainfall. This hyetograph is a triangle shape with the peak intensity approximated as a function of total rainfall depth, duration, and peak intensity, with the time to peak intensity being roughly 0.375 times rainfall duration. A digital elevation map of the case study at a scale of 1:2000 was produced, and sub-catchments were made based on topography, street slope, runoff movement pathways, UDS arrangement, and outlets for surface runoff. Sub-catchments are hydrologic units that route surface runoff to a single discharge (outlet) point, which might be either other sub-catchments or nodes of the drainage system. The Manning coefficients are selected based on the recommended value in the SWMM software for the land use and coverage of the case study. Hence, it is 0.1 for the porous surfaces of sub-basins and 0.014 for their impervious surfaces and concrete channels. The hydraulic conductivity of saturated soil at the closest point to the study area is 10.58 m/day (approximately equal to 44 mm/h) for the Tehran region, with an area of 600 km^2 (Hafizi and Pashakhanloo, 2006). The Horton method used for modelling hydraulic conductivity assumes coefficients of maximum and minimum penetration velocities equal to 75 and 44 mm/h, respectively. The kinematic wave approach is used in the dynamic model to simulate the hydrological conversion of rainfall-runoff in the UDS catchments. The dynamic wave and one-dimensional Saint-Venant equation were selected for the flow routing to obtain high accuracy of the model simulation. In the simulated model, 14 potential ponds were analysed at different points of the UDS based on professional judgement and experts' recommendations in the case study (s-1-14, Figure 1). The results can be presented as runoff volume/flow in nodes and conduits. The volume and runoff rate directly depend on its temporal and spatial distribution over the basin. Accurate estimation of the surface runoff directly affects the design parameters of conduits and other relevant hydraulic structures and the percentage of catchments used for BMPs in the UDS.

3.2 | Development of optimisation model

A two-objective optimisation model was developed to find the optimal design of ponds based on minimisation of two objectives: (1) the construction cost of ponds and (2) flood damage costs. These costs are analysed below in further details.

3.2.1 | Cost-planning for construction

Cost estimation is essential for the cost-effective evaluation of surface water control systems for real-world applications. The cost of runoff control structures includes design, construction, and possible operation and maintenance costs. It is also assumed that public land will be used for ponds and hence the relevant cost is excluded in the total costs. Therefore, the total costs comprise capital costs, estimated as a function of the pond volume (V_s), and operation and maintenance costs, estimated as a percentage of the construction cost using the formula given by USEPA, as shown in Table 1 (Zhen et al., 2004). Note that in the current cost formulas taken from the literature, there are no inflation/interest rates to calculate the present value of detention ponds. However, the cost can be adjusted by including these rates if these formulas are used for practical applications. Having said this, neglecting this factor can have a minor impact on the optimisation results as all solutions are obtained on the same basis. Due to the lack of reliable and precise construction data, a variety of construction sites, and the variability between urban and regional environments, the projection of cost of detention ponds is challenging during the design stage. It is also common to include all costs related to design, construction, operation and maintenance over the structure's lifetime.

TABLE 1 Cost functions of construction and maintenance of concrete lined ponds.

Best management practice	Construction cost ($) as a function of V_s (m^3)	Annual maintenance cost as % of construction cost
Dry ponds	$C = 0.22 \times V_S^{0.78}$	<1

3.2.2 | Flood damage costs

The flooding depth at nodes in the UDS is used here based on the results of SWMM. Since there is no data available on flood damage in the pilot area, the flood depth-damage cost plot developed by Nascimento et al. (2006), as shown in Figure 3, is adopted in this study. This plot was originally developed for Itajubá City in Brazil, which has the same key features as the pilot area in this study. The similarity between the two cases includes the main land use (i.e., residential area), the soil type and density of housing. It should be noted that the cost of flood damage in the formula only considers direct damages and neglects intangible (indirect) damage in the inundation zones, which is the economic value of indirect physical damages, for example, job loss and health issues such as widespread of diseases and other impacts. Also note that the flood depth-damage cost was later on used by Karamouz and Nazif (2013) in which the currency unit was updated to $ that is also used in this study.

Flooding nodes are first identified in the SWMM, and the proportional area for high-risk nodes is then calculated. Finally, based on the flood volume, the water depth is calculated at each basin point which is the discharge outlet point of each sub-catchment, and the corresponding damage cost is calculated. Depth of flooding can be estimated from flood volume, estimated as SWMM divided by the catchment area, and the direct relationship between damage and flood depth described as:

$$D = 130.9 + 56.3\ln(y)$$

D: damage per unit area ($ per m^2) and Y: flooding depth (m).

3.2.3 | Decision variables

Decision variables comprise the location of detention ponds and their design parameters related to their volume and outlet structures. The first decision variable is

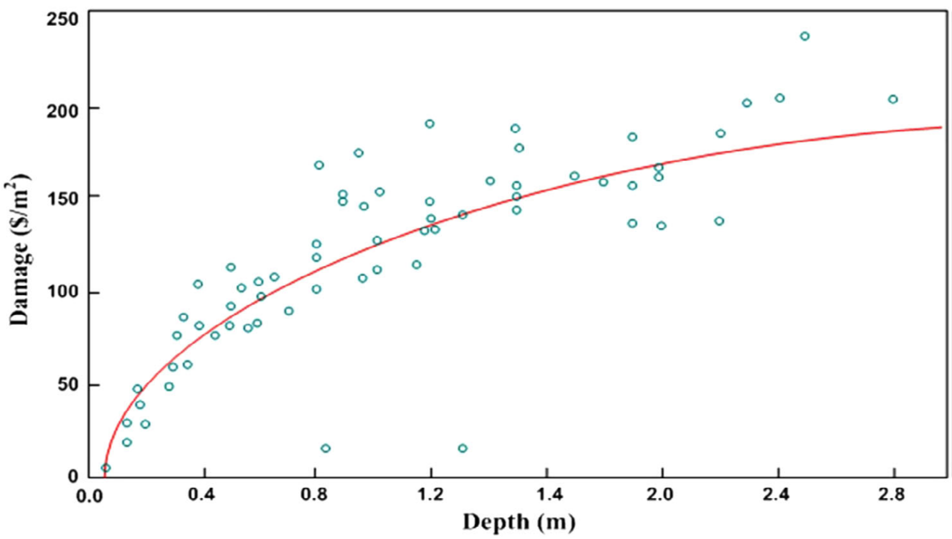

FIGURE 3 Damage-cost curve (originally from Nascimento et al., 2006 and replicated by Karamouz & Nazif, 2013).

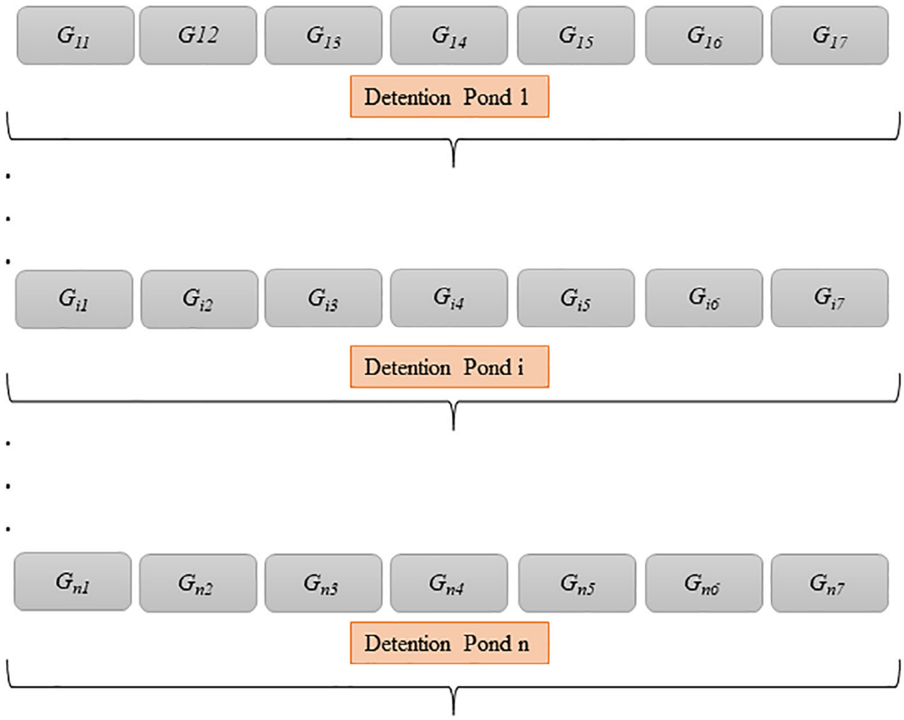

FIGURE 4 Decision variables for solutions in the optimisation model.

the presence of detention ponds at potential locations in the UDS. Other decision variables include (1) the area and depth of the pond which define the pond volume. (2) The cross-section of the bottom outlet and its distance from the floor. (3) The height and width of the weir. The designed ponds include a weir and an orifice. The structure of each solution (chromosome) is shown in Figure 4, with relevant decision variables for each pond, including pond height, weir height, bottom outlet height, and surface area. Figure 5 shows the schematic representation of a detention pond with its design parameters.

Based on *n* potential locations of detention ponds identified in the UDS, the structure of chromosomes is defined as below in the optimisation model:

- G_{i1} = the state of the presence of detention pond *i*.
- G_{i2} = height of detention pond *i*; G_{i3} = surface area of pond *i*.
- G_{i4}: orifice height of pond *i*; G_{i5}: distance from bottom of pond *i*.
- G_{i6}: weir width of pond *i*. G_{i7}: weir height of pond *i*.

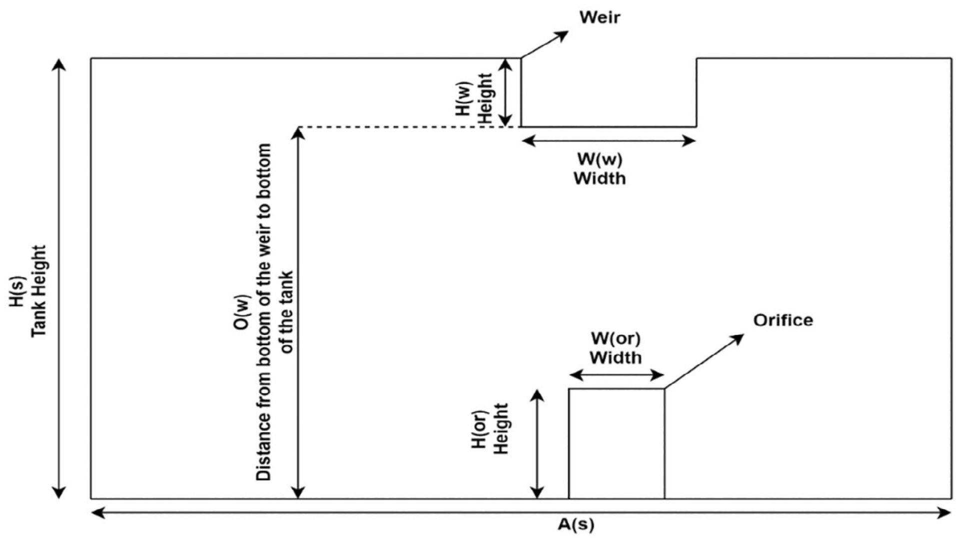

FIGURE 5 Schematic representation of design parameters (decision variables) of a detention pond.

3.2.4 | Optimisation method

A non-dominated sorting genetic algorithm II (NSGA-II) developed by Deb et al. (2000) is used here as the optimisation method to obtain non-inferior (known as Pareto optimal) solutions. This optimum method has been widely employed in urban water systems, particularly water supply systems and urban drainage systems, to solve multi-objective optimisation issues (Aminjavaheri & Nazif, 2018; Karamouz & Nazif, 2013). NSGA-II randomly generates solutions for the first iteration (population), and each solution is defined with a string (called chromosomes) that includes a number of genes, representing decision variables. The objective function of each chromosome is calculated as the chromosome fitness. New chromosomes are then selected and combined using crossover and mutation operators to form a new population for the next iteration. The population is ranked based on the ordering of subpopulation Pareto dominance. Each subgroup is evaluated and compared in terms of Pareto, and the resulting groups are used to develop a variety of non-dominated solutions.

3.3 | Spatial analysis in ArcGIS

The purpose of this section is to form a model based on GIS systems to determine the suitability of potential detention ponds, based on spatial criteria and slope factors for spatial analysis. This data is prepared in a shapefile in the ArcGIS environment. The slope criterion is considered as a critical factor for the technical requirements for the construction guide of these ponds, and for avoiding building on unstable slopes and slopes with a gradient of more than 15%. Public ownership over private ownership is an essential parameter for pond allocation. Thus, for the land acquisition criterion, green spaces and parks that are well suited to surface options are given first priority, and areas owned by the government and municipality that are suitable for underground options are given second priority. Residential areas and health care facilities are the least desirable land use areas and cannot be used due to city restrictions on urban encroachment (Ahmadisharaf & Tajrishy, 2015).

In the first stage, the required data was collected to achieve the optimal location and score for each point. To obtain the slope of the points and use it as one of the important factors in location choice, the digital elevation model (DEM) was obtained from elevation points in the 1:2000 topographic map of the area. The slope data in the ArcGIS area was produced using DEM. From an environmental and economic point of view, it is economically unsuitable for building ponds on sloping sites because of the increased excavation and embankment costs.

After importing these layers into the spatial information system, related spatial databases were designed. The UTM coordinate system is used in all layers. To perform calculations, a GIS layer was obtained for each criterion and then reclassified to integrate these layers. The reclassification was based on the following:

1. Compliance with slope regulations/recommendation: Detention ponds should not be located on unstable slopes or slopes greater than 15%, as outlined in Table 2 (County, 2008).
2. Economic and accessibility: The shorter the distance from access roads, the better for constructing these ponds. On the other hand, the construction of facilities which restricts the right of way is prohibited.
3. Land use: Ease of access to a construction area is considered an important environmental and social factor,

hence a score can be given to different land uses, as outlined in Table 3 (Ahmadisharaf & Tajrishy, 2015).

The analysis of this section is carried out using ArcGIS. The geodatabase is created in the Arc Catalog, and all data is stored in a spatial database (Marney, 2012). After the criteria have been established, all the necessary layers in the model are created. The final stage is to use GIS to create a spatial suitability map for the placement of detention basins. The reclassified raster layers are overlaid with equal weights to generate the main model, using the following equation:

$$F_i = \sum_{j=1}^{n} f_{ij}$$

where F_i is the total score of grid cell i, f_{ij} is the score of grid cell i with respect to criterion j, and n is the number of criteria. The output is a suitability map with grid cells indicating suitability for detention basin location.

3.4 | Ranking water management solutions

Once the multi-objective optimisation model generates a set of Pareto non-dominated optimal solutions, all non-dominated optimal solutions can be chosen as a selected solution based on the preference of the decision makers with respect to multiple criteria. These non-dominated solutions can also be clustered based on their key features by using some techniques such as K-means clustering (Karami et al., 2022). Hence, the multiple optimal solutions can be narrowed down to a small number of clusters and hence decision-makers can choose one optimal solution from each of those few K clusters. However, those chosen optimal solutions need to be ranked and prioritised that can be done by using the CP method. In other words, the CP is a method for combining the preferences of a group decision makers for multiple criteria together and converts them into one indicator called distance function used for ranking and prioritising the solutions. In this study, a set of optimal solutions is evaluated and compared to identify the best possible flood control measures. These solutions must achieve several goals including reducing flood damage, lowering construction costs, and considering location criteria.

Various solutions examined in this study need to be compared and ranked based on defined indicators. In this study, the Compromise Programming method (CP) is used as a multi-criteria decision analysis technique (MCDA), which is known to compare and calculate key performance indicators for different solutions (Behzadian & Kapelan, 2015). The CP method was initially introduced by Zeleny (1973). It calculates the distance function for any solution based on a subset of efficient solutions (called agreement sets) that are the 'closest' point to the 'ideal' in which all criteria are optimised.

The solutions are then ranked according to this distance. Without losing totality, and assuming that all criteria are maximised, the total distance function for the intervention strategy is evaluated with function (f_i), absolute maximum (ideal) (f_i^*), absolute minimum (non-ideal) (f_{i^*}), the weight of relative importance (W_i) for criterion i and a topological metric unit P calculated as follows:

$$\text{minimise}\, L_p \equiv \left[\sum_{i=1}^{n\ \text{Criteria}} \left(\frac{W_i\left(f_i^* - f_i\right)}{\left(f_i^* - f_{i^*}\right)^P}\right)\right]^{\frac{1}{p}} W_i > 0, 1 \le p \le \infty \quad (1)$$

The value of the parameter P is defined between 1 and infinity. This maximum deviation can reflect the decision makers' concerns. In Equation (1), the effect of a standard index based on its distance from the ideal point and the distance between the ideal and non-ideal refers to the overall performance of the function. Therefore, each indicator should be carefully selected based on the actual goal of the decision-makers. Due to the difference in

TABLE 2 Classification of topographic slope criteria for pond construction.

Class	Slope (%)	Description
1	0–2	Very suitable
2	2–9	Suitable
3	9–15	Partly suitable
4	>15	Unsuitable

TABLE 3 Land uses score according to their accessibility.

Land use	Green space	Sport land	Barren land	Official	Cultural	Health centres	Mountainous land	Residential	Religious places	Urban facilities
Score	9	9	9	7	7	3	3	1	7	7

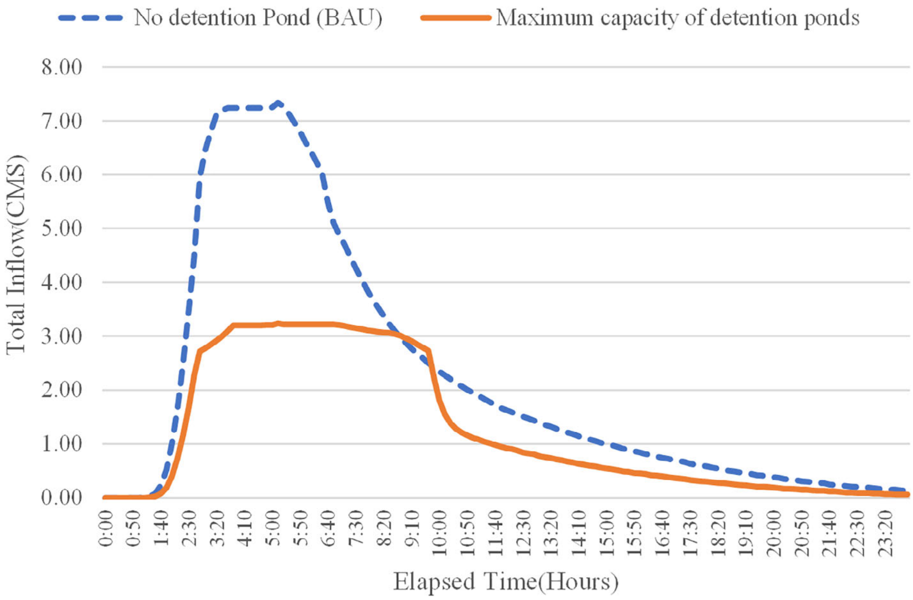

FIGURE 6 Total inflow of hydrograph at node M6 (near one of the outlets) for states without any detention ponds and maximum capacity of detention ponds.

performance between different intervention strategies, commission may be negligible for an indicator. However, the target point of that indicator has a great distance from the calculated performance.

4 | RESULTS AND DISCUSSION

Based on the pre-defined locations for detention ponds in this study, the UDS considers 14 potential sites for detention ponds at UDS junctions. Based on the seven decision variables for each pond in the model, the total number of decision variables for each solution are equal to $14 \times 7 = 98$. After several trials with randomly generated seeds, the NSGA-II settings were set to achieve the fastest convergence rate for optimal solutions. As a result, the best values for these parameters are a population size of 80, a probability of mutation of 0.03, and a probability of crossover of 0.85. The model was run numerous times after the optimisation parameters were adjusted, each time with a different seed value (i.e., initial generation) to ensure that the Pareto-optimal solutions were resilient. The following constraints were also considered for decision variables in the case study:

$$1\text{cm} < H_{\text{or}} < 60\text{cm} \quad 1\,\text{m} < H_s < 9\,\text{m}$$

$$1\,\text{m} < W_w \leq 8\,\text{m} \quad 50\,\text{m}^2 < A_s < 400\,\text{m}^2$$

where H_{or}, height of orifice from the pond bottom; H_s, the pond depth, w_w, the weir width, and A_s, the surface area of the pond. After running the optimisation model by using NSGA-II with the above settings, the non-dominated optimal front was obtained as shown in Figure 6. The results show that the total flooding in the existing operates of the UDS, that is, no pond is equal to $280 \times 10^3\,\text{m}^3$ while adding detention ponds can significantly reduce the total flooding. For example, when the maximum capacity of detention ponds is used, the flood peak of the hydrograph at node M6 would reduce by over 50% compared to the state with no detention pond in the UDS as shown in Figure 6.

Figure 7 shows the non-dominated optimal solutions for the trade-off between total volume of ponds and total flood volume in the final Pareto front, that is, a generation number of 2000. As it can be seen, the more total volume of detention ponds is considered in the UDS, the more flood volume is reduced in the UDS. Hence, the decision-maker can select any of these solutions to make a final decision on flood management solutions. Three solutions can be typically selected for the total volume of ponds, that is, the solution with the maximum volume of ponds (the most expensive one) corresponding with maximum reduction in flood volume (top left points), the solution with the minimum volume of ponds (the cheapest one) corresponding with maximum flood volume in UDS (bottom right points) and compromised solution between the above limits for total volume of ponds corresponding to reduced volume of flood between the above limits. The last solution can be selected based on the budget limit corresponding to specific total volume of ponds.

4.1 | Optimisation results

The non-dominated optimal solutions in the Pareto front show the interaction between the two objectives, minimising the total volume of flooding and the total volume of detention ponds, that led to 42 non-dominated

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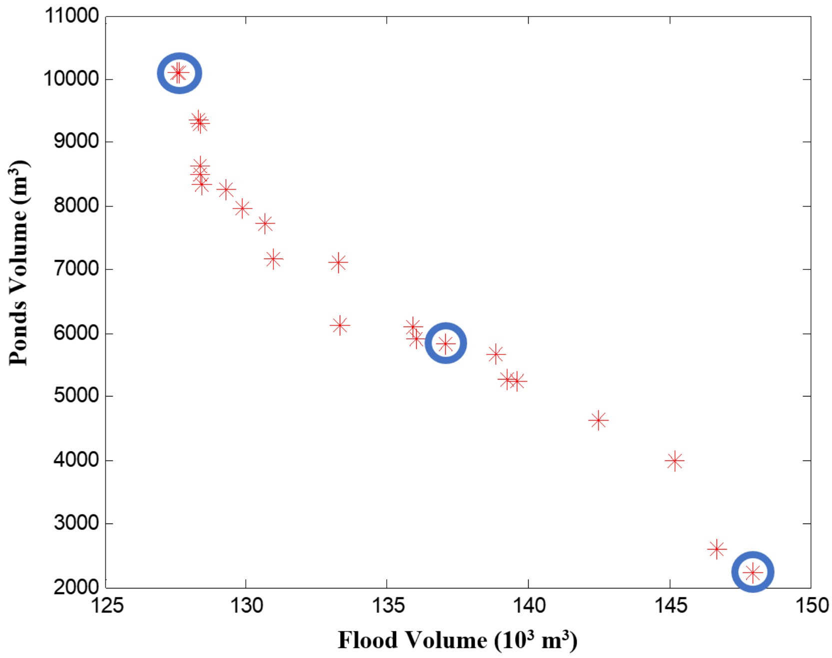

FIGURE 7 Pareto optimal solutions and different selection of solutions on the front.

solutions. It is evident that these objectives have an indirect relationship, that is, increase in the ponds volume would result in decreasing the flood volume. Furthermore, given the constant total volume of detention ponds, the flood volume can decrease further when the number of ponds is increased. This can be linked to the fact that flood magnitude and its impacts disperse and hence preventing inundation of one point and heavy damage.

The results also show that only four active ponds in the UDS can significantly reduce the flood volume by 47%. With an addition of one further pond, that is, a total of 5 ponds, flooding can be reduced to 51% and ultimately, the maximum reduction of flood volume would be 62% when all 14 potential ponds are used in the UDS. A frequency analysis of potential ponds identified in the non-dominated Pareto optimal solutions can also reveal some key points that are analysed here. Considering a pre-specified number of active ponds (between 4 and 8 as assumed probably the most cost-effective investment in the construction of detention ponds by stakeholders), the relative frequency for each of the 14 potential ponds in the 42 optimal solutions is calculated as shown in Table 4 and Figure 8. For example, out of optimal solutions with 4 active ponds, all solutions would select S3, S4, S8 and S12. However, out of the solutions with 5 active ponds, only S3 and S12 are always selected (i.e., 100%) while S4 or S12 would appear in 50% of the solutions and S1 would only appear in 16% of the solutions. As can be seen, among all potential ponds in the UDS, S3 and S12 are selected in all sets of active ponds of the solutions, followed by S4 used in most of the solutions. Ponds S10, S11 and S13 are selected in the solutions with over 4 active ponds. On the other hand, three ponds (S5, S6 and S7) would be never selected in any optimal solution and S9 appear only in 50% of optimal solutions with a set of 8 active ponds. This analysis can be used to determine the potential places for further analysis of detention ponds in the next planning steps. For example, the focus of the potential sites should be on six ponds (i.e., S3, S4, S10, S11, S12 and S13) and four sites (i.e., S5, S6, S7 and S9) are unlikely to be considered for further analysis. Furthermore, the optimal size of each of these ponds can be determined based on the combination with other ponds in the selected optimal solution. Although the same analysis can be conducted for the range of optimal size in these ponds, no specific size can be determined individually for each of these ponds. Hence, the best combination of detention ponds with the optimum size is found in the optimal solution that satisfies both the requirements of reducing the flood volume and the budget limitations for the construction of detention ponds in the UDS as shown in Figure 7.

For further analysis and better cluster of the optimal solutions, it is assumed that Pareto optimal solutions for the two objectives of construction cost and flood volume can be divided into three groups (Figure 7). The first group of solutions has high flood volume reduction with high construction costs (around upper circle in Figure 7); the second group considers the solutions with low total costs but a high flood volume, causing high damage costs (around lower circle in Figure 7); the third group includes the solutions with flood volume and total cost between the first two groups (around middle circle in Figure 7).

TABLE 4 Relative frequency of selection of each pond in the non-dominated optimal solutions per given number of active ponds.

Pond #	4 active ponds	5 active ponds	6 active ponds	7 active ponds	8 active ponds
S1	0	0.16	0.33	0	0.5
S2	0	0	0.66	1	1
S3	1	1	1	1	1
S4	1	0.5	0.88	1	1
S5	0	0	0	0	0
S6	0	0	0	0	0
S7	0	0	0	0	0
S8	1	0.33	0.22	0	0
S9	0	0	0	0	0.5
S10	0	0.5	0.44	1	1
S11	0	0.66	0.77	1	1
S12	1	1	1	1	1
S13	0	0.83	0.66	1	1
S14	0	0	0	0	0

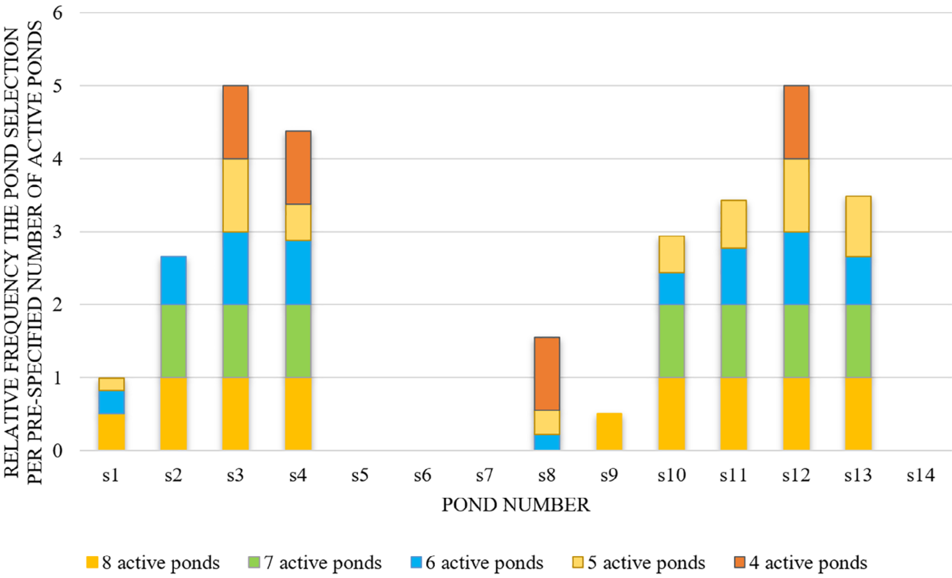

FIGURE 8 Contribution of each optimal pond in solution per the given number of active ponds.

4.2 | ArcGIS results

Further spatial analysis of the results is carried out in this study through the land use data in the ArcGIS environment. The slope map for each point was extracted using DEM and expressed in a percentage format as shown in Figure 9. According to the slope map, most of the catchments in the case study have a gentle slope of less than 3% in the south and southwest and mild and slightly steep slope of around 3%–10% in the north. These ranges of slope can be quite suitable for construction of detention ponds as per classes outlined in Table 2.

The land use map of different areas in the case study is shown in Figure 10. As can be seen, most of the catchment are residential areas as shown in red colour. Due to the private ownership of these lands, most of areas in the case study can be unavailable and undesirable for construction of a detention pond, and hence be given the lowest score among different uses according to Table 5.

The final suitability map for detention basin placement in the case study is presented in Figure 11. This map is the result of the paradigm described in Section 3.2 for detention basin site selection. The score of each pond is calculated using the polygon containing it and, in some cases, the average of intersecting polygons with the corresponding detention pond. The scores obtained for each pond are shown in Table 5.

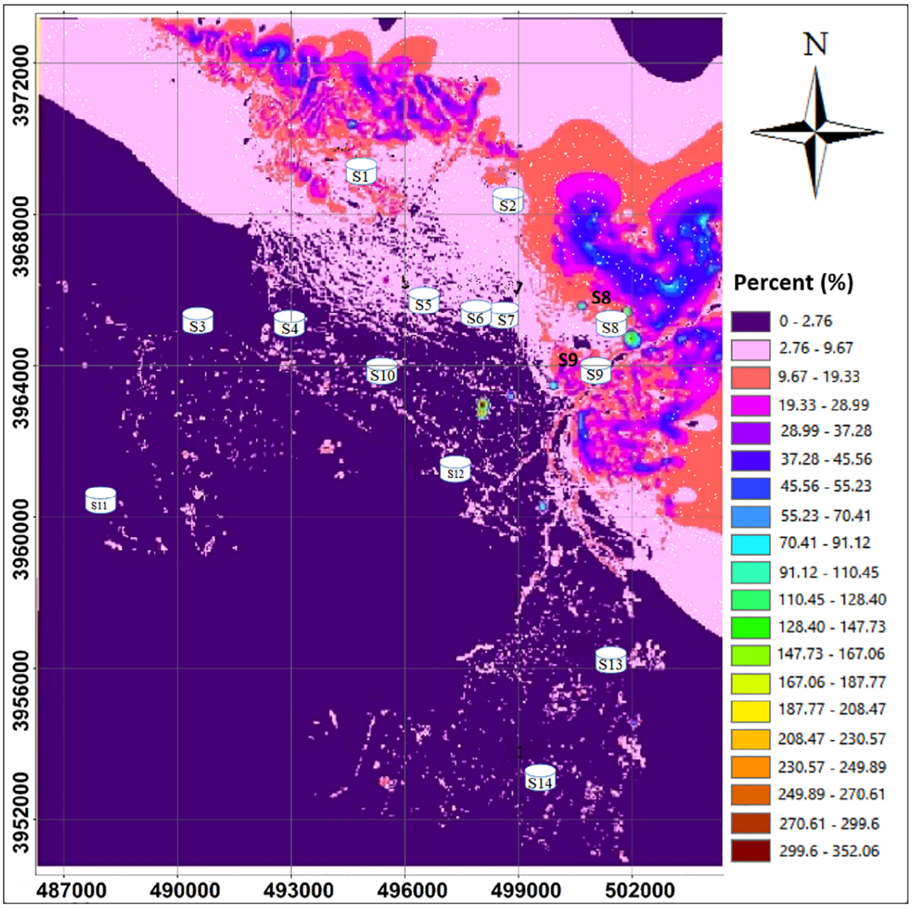

FIGURE 9 The slope map (%) of the UDS in ArcGIS.

More specifically, pond S3 with a score of 37 has the highest score as it is located on barren land, and pond S2 has the lowest which is the highest score among residential areas and the lowest score among land uses. Concerning distance from the main roads, S2 has the lowest score as it is located on a slope of around 5.5% and hence be given undesired score for slope.

4.3 | Ranking strategies with the CP method

The compromise programming (CP) MCDA technique is used here to rank the selected solutions according to the criteria outlined here. This approach was adopted in this study as it can be simply applied for group decision-making when assessing a list of alternative solutions in urban water systems based on a variety of assessment criteria (Morley et al., 2016). For better comparison of the optimal solutions obtained from the Pareto front in Figure 6 with the UDS with no detention pond (i.e., business as usual), three optimal solutions (called here optimal strategies 1, 2 and 3) are selected from the three clusters defined in the optimisation results in Figure 6 and outlined in Table 6. The pond combination and configuration for three optimal strategies are also given in Tables 6–9. These strategies can be ranked by using the CP method based on the following three criteria: (1) total costs of the new ponds, including construction and operational costs; (2) total flood damage costs based on the flood volume and (3) pond location obtained in the ArcGIS analysis. The following are the flood damage cost, the construction and operational cost, and the average pond location score for the three strategies defined in Table 6.

As there are no specific preferences for the assessment criteria, the same weighting is applied here for the three criteria. Hence, the distance of each criterion and the overall distance of the CP method for each strategy can be calculated in Table 10 based on the overall distance calculated from Equation (1) and the data collected for the strategies in Table 6. As can be seen, strategy 2 as one of the optimal solutions is ranked first. Figure 12 also shows the comparison of these strategies based on normalised criteria (using the max technique for normalisation) and how these strategies function under different criteria (the minimum is the best for each of distances). The areas enclosed in this radar chart represent the strategies' performance for three criteria in three dimensions: cost construction, flood damage cost, and average

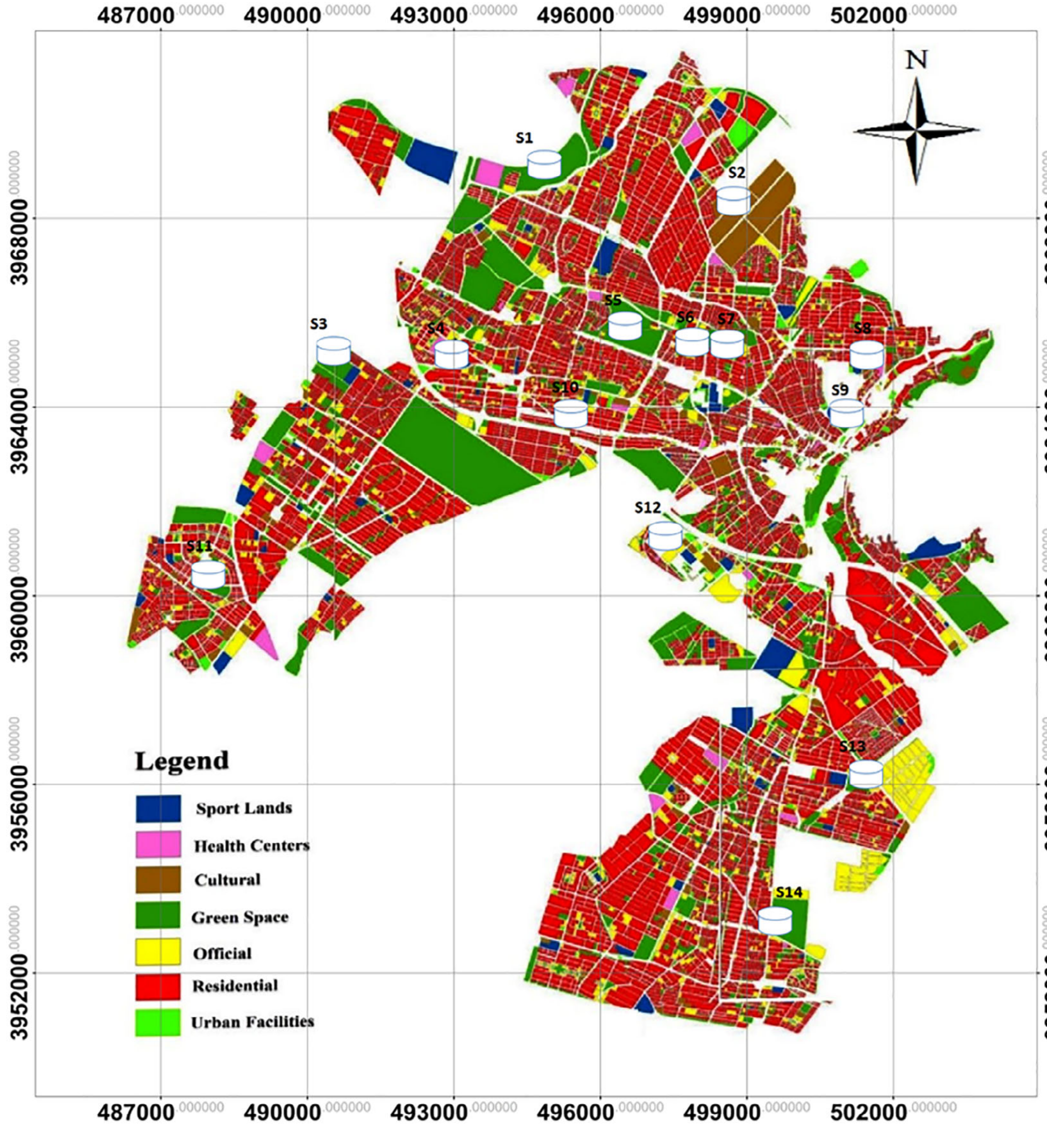

FIGURE 10 The land use map of the UDS in ArcGIS.

TABLE 5 Final score of locations for potential ponds.

Pond number	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14
Final scores	12	10	37	31	21	25	33	17	19	29	34	31	20	20

location score. The grey triangle indicates the second scenario outperformed other scenarios in all criteria while the red and yellow triangles (i.e., first and third strategies, respectively) have poor performance in both construction cost and flood damage cost, respectively.

Based on the ranking of the solutions obtained from the CP method, the following results can be inferred:

1. The compromised strategy (Strategy 2) is optimal as it can significantly reduce flood damage by 66% for $50,000. This strategy also has a high average pond location score (Table 6).
2. Although Strategy 1 reduced the flood volume by 90%, the total costs associated with ponds are three times larger than Strategy 2 and 1.5 times larger than Strategy 3. This strategy also has the worst (lowest) score among other strategies based on the GIS analysis.
3. The comparison between Strategies 2 and 3 shows that the flood volume in Strategy 3 one is only 7% less than Strategy 2, while the cost of Strategy 3 is 2.2 times larger Strategy 2.

By considering various local design criteria and conditions in the UDS based on additional field surveys and

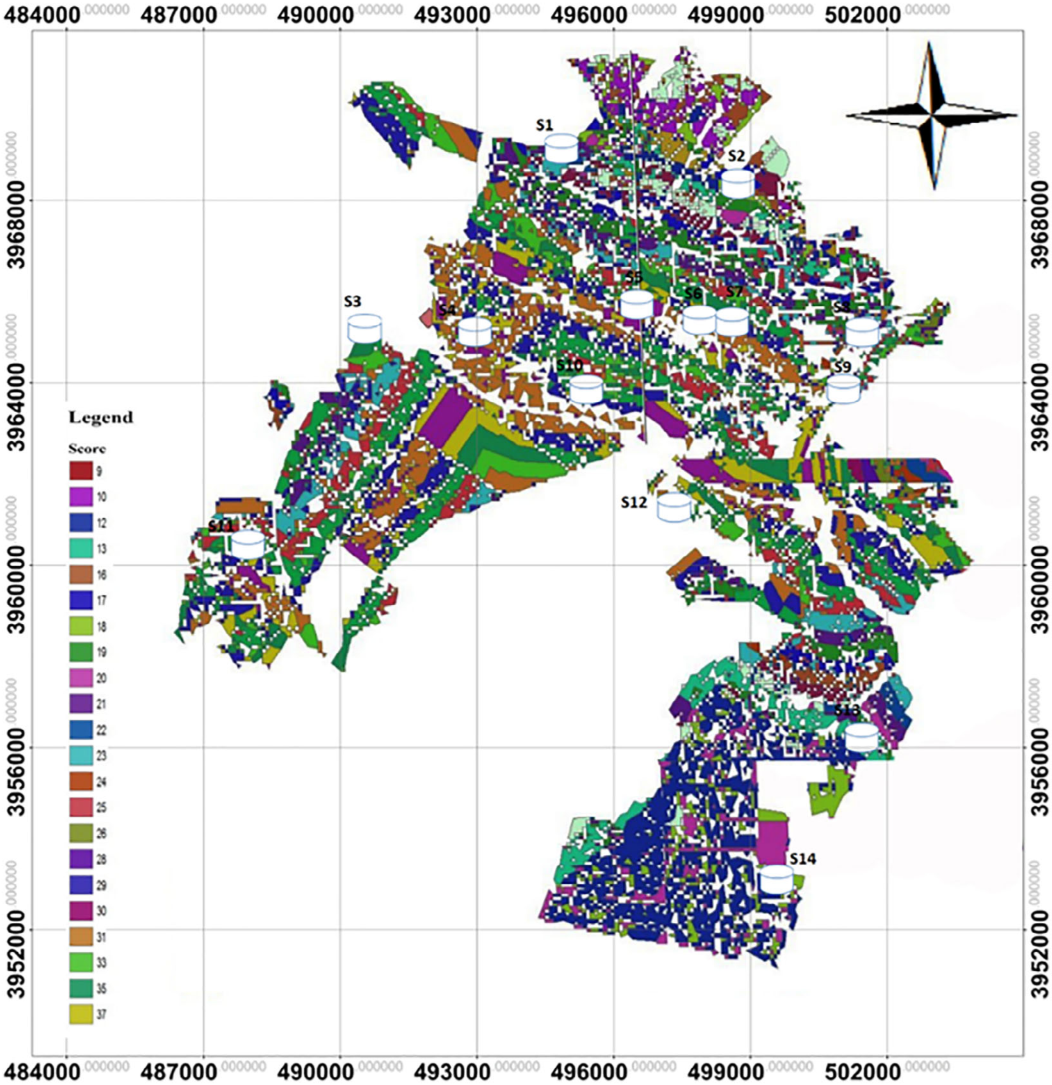

FIGURE 11 The final score of locations for each point of the case study.

TABLE 6 Damage and cost for different strategies.

Strategy number	Strategy description	Total flood damage costs ($)	The total cost of ponds ($)	The average pond location score
Business as usual	Business as usual	153,030,303	0	0
Strategy 1	Optimal solution with minimum flood damage	29,720,000	159,962	25.5
Strategy 2	Optimal solution with minimum construction cost	101,000,000	49,043	29
Strategy 3	Optimal solution with compromised objective functions	77,650,594	107,909	31

incorporating local policy, the approach in this study can still be a basis for incorporating those factors and the applicability and robustness of the methodology to specify the suitability of detention ponds (layout, size and other parameters). This methodology can also give a flexibility to decision-makers for improved planning and management of the UDS. The findings and approaches in this study can have significant effects and contributions

TABLE 7 Pond combination and configuration for optimal strategy 1.

Pond number	Weir height of the pond	Weir width of the pond	Distance from the bottom of the pond	Orifice height of the pond	The surface area of the pond	Height of detention pond
S1	3.36	3.8	0.027	0.180	260.00	5.60
S2	3.63	6.6	0.370	0.600	168.51	5.45
S3	3.73	6.6	0.300	0.180	121.19	5.62
S4	4.35	2.4	0.410	0.240	230.00	6.80
S10	5.37	3.8	0.420	0.060	170.00	8.60
S11	5.16	5.2	0.000	0.180	260.00	8.60
S12	1.48	5.7	0.340	0.500	110.00	7.40
S13	4.44	8.0	0.084	0.090	142.34	6.80

TABLE 8 Pond combination and configuration for optimal strategy 2.

Pond number	Weir height of the pond	Weir width of the pond	Distance from the bottom of the pond	Orifice height of the pond	The surface area of the pond	Height of detention pond
S3	1.56	6.6	0.146	0.24	50	2.6
S4	4.93	2.4	0.540	0.18	110	7.4
S8	2.64	5.2	0.250	0.06	260	4.4
S12	1.92	3.8	0.140	0.06	50	2.6

TABLE 9 Pond combination and configuration for optimal strategy 3.

Pond number	Weir height of the pond	Weir width of the pond	Distance from the bottom of the pond	Orifice height of the pond	The surface area of the pond	Height of detention pond
S3	1.76	3.8	0.22	0.18	140.00	4.4
S10	5.73	3.8	0.42	0.06	170.00	8.6
S11	5.16	5.2	0.8	0.18	260.00	8.6
S12	1.48	5.7	0.34	0.48	110.00	7.4
S13	4.44	8.0	0.08	0.09	142.34	6.8

TABLE 10 Final ranking of the alternatives using the CP method.

Procedures	Ranking	Distance from the ideal
Business as usual	4	0.471
Strategy 1	3	0.339
Strategy 2	1	0.153
Strategy 3	2	0.241

to the extension and development of the scientific decision-making framework for planning, design and construction of SuDS in the UDS in more realistic contexts.

The analysis performed in this study specified some important detention ponds with a significant effect on decreasing flood at various levels. For example, detention pond S3 is selected in all optimal solutions and has a high location score in the ArcGIS analysis that can be selected as a priority for practitioners in various planning for any urban flood control management. The result of this study showed the combination of detention ponds in sub-catchments is an effective approach for reducing flooding.

5 | CONCLUSIONS

This study aims to provide the best solutions for using detention ponds for flood control. The methodology was based on a multi-objective optimisation model that combined hydrological-hydraulic simulation modelling of detention ponds in SWMM, with a multi-objective

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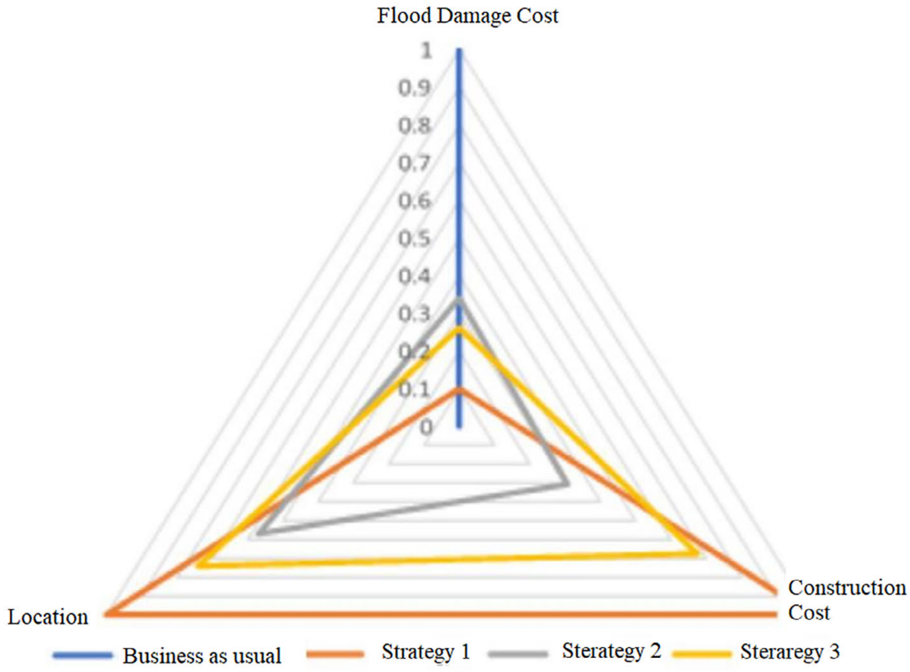
FIGURE 12 Comparison of three optimal solutions and business as usual.



optimisation model to reduce flood damage costs while reducing the total cost of building and managing detention ponds. GIS modelling was also employed to incorporate some additional characteristics that impacted location. Using the CP method, three ideal solutions from the three clusters were compared and ranked with the BAU. A real-world case study of the Karaj UDS in Iran was also used to demonstrate the methodology. The following results can be obtained from the application of the methodology in the case study:

- The framework proposed here, combining optimisation, simulation, GIS and MCDM methods, can provide cost-effective and practical solutions that reduce both the cost of flood damage in the UDS and the total cost of construction and operation of detention ponds.
- The optimal solutions in the Pareto front show that there are indirect correlations between non-dominated solutions that minimise flood volume (i.e., those minimising the flood damage cost have a high construction cost). This is due to solutions which mainly transport the flood downstream in addition to the pollution discharged into receiving water bodies.
- The ranking of the selected solutions using the CP method shows that all optimal solutions are ranked higher than business as usual. For example, the cost of flood damage is decreased significantly in all optimal solutions, by up to 55%, compared to the BAU.

A major limiting factor in this study is the uncertainty of some parameters that need to be calibrated within the UDS modelling process (e.g., the roughness coefficients of conduits and perviousness of sub-catchments). Examination of different design storms is also a major component of the planning and design process that should be incorporated in future studies with the actual historical data of long-term rainfall records that can provide more accurate and robust model simulation for the long-term water balance and hydrologic performance of alternative stormwater management options. It should also be noted that although hydrological modelling in data scarcity with missing data of rainfall or ungauged basins is challenging, future studies can consider data-driven models to estimate runoff in ungauged catchments or rainfall in catchments with missing data. Future works can also combine various types of SuDS with detention ponds based on the land use in the catchment area. It is also recommended using different types of SuDS in addition to detention ponds such as those analysed in Sattari et al. (2020) and Shamshirband et al. (2020). Decision makers can use the proposed approach for long-term planning of the most effective combination of detention ponds, optimising size and location, resulting in the best performance of the UDS and lower flood damage costs. While this is an effective method for lowering flood damage costs, the most reliable design for these optimal solutions should also use additional analysis to determine their robustness against other factors, such as pollution control and the sensitivity of their design parameters under external drivers in urban stormwater management such as urbanisation and increased frequency and intensity of rainfall events.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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