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Multi-objective optimization for combined quality–quantity urban runoff control

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Abstract. Urban development affects the quantity and quality of urban surface runoff. In recent years, the best management practices (BMPs) concept has been widely promoted for control of both quality and quantity of urban floods. However, means to optimize the BMPs in a conjunctive quantity/quality framework are still under research. In this paper, three objective functions were considered: (1) minimization of the total flood damages, cost of BMP implementation and cost of land-use development; (2) reducing the amount of TSS (total suspended solid) and BOD5 (biological oxygen demand), representing the pollution characteristics, to below the threshold level; and (3) minimizing the total runoff volume. The biological oxygen demand and total suspended solid values were employed as two measures of urban runoff quality. The total surface runoff volume produced by subbasins was representative of the runoff quantity. The construction and maintenance costs of the BMPs were also estimated based on the local price standards. Urban runoff quantity and quality in the case study watershed were simulated with the Storm Water Management Model (SWMM). The NSGA-II (Non-dominated Sorting Genetic Algorithm II) optimization technique was applied to derive the optimal trade off curve between various objectives. In the proposed structure for the NSGA-II algorithm, a continuous structure and intermediate crossover were used because they perform better as far as the optimization efficiency is concerned. Finally, urban runoff management scenarios were presented based on the optimal trade-off curve using the k-means method. Subsequently, a specific runoff control scenario was proposed to the urban managers.

1 Introduction

Financial risks and health threats attributed to urban floods have always been challenging issues in urban planning of large cities. Urban runoff is often studied for planning purposes involved in runoff quality control, flood damage estimates and flood control management. Most of the measures aimed at prevention and/or crisis management during and after the floods are parts of flood management. In recent years, a concept called BMPs, or alternatively known as the low impact development (LID), has been promoted in order to control the quality and quantity of urban floodwaters.

Zhen et al. (2004) used a heuristic optimization technique that was coupled with a watershed model, i.e. the Annualized Agricultural Nonpoint Source Pollution model (AnnAGNPS), to minimize pollution cost under various combinations of BMPs. They used the AnnAGNPS model to assess the long-term reservoir performance subject to sediment deposition. Moreover, using the scatter search algorithm, the best locations for storage reservoirs were selected.

Mejia and Moglen (2009) studied the effects of urban development and reduction of permeable areas by simulating water quantity and quality using a numerical model. They concluded that the resulting optimized landscapes provided a helpful understanding of the important role played by the spatial form of the urban pattern when trying to minimize impacts to water resources.

The Institute of International Science and Technology of India conducted research to optimize the costs of storage tanks in order to control the pollution and quantity of urban runoff (Rathnam et al., 2004). They developed an optimization model for storm-water detention ponds in multiple parallel catchments using dynamic programming. Graupensperger and Stroschein (2003) emphasized the use of a geographic information system (GIS) for site selection of structural and non-structural BMPs, including a combination of wetlands, ponds and natural channels. Baptista et al. (2007) investigated the use of BMPs with regard to production cost, environmental impact and quantity control of floods. They described several steps of a decision making tool development, based on a multi-criteria procedure allowing a priori evaluation of the storm-water systems by aggregation of economic–financial–performance indicators. Based on their methodology, a decision aid tool was created to allow the choice of convenient project alternatives.

Lee et al. (2005) discussed methods to reduce pollution and runoff volumes in terms of some economic indicators. The study went further to evaluate and optimize the effects of wetlands in urban runoff quality control. Zhang et al. (2006) investigated the application of BMPs in urban runoff quantity control. They applied ε-NSGA-II algorithm to minimize the flood volume and cost of implementing three types of BMPs. They found their methodology as an efficient algorithm in decision making. Perez-Pedini et al. (2005) developed a distributed hydrologic model of an urban watershed in the northeast United States and combined it with a genetic algorithm to determine the optimal location of infiltration-based BMPs for storm-water management. The results indicated that the optimal location and the number of BMPs was a complex function of watershed network connectivity, flow travel time, land use, distance to channel, and contributing area, thus requiring an optimization approach. A Pareto frontier describing the trade-off between the number of BMPs (representing the project cost) and watershed flooding was developed.

Rodriguez et al. (2011) showed that the BMPs (combination of pasture management, buffer zones, and poultry litter application practices) were effective in controlling water. They used the NSGA-II to select and locate BMPs that effectively minimize nutrients pollution control cost by providing trade-off curves between the pollutant reduction and total net cost increase. Their optimization model generated a number of near-optimal solutions by selecting among 35 BMPs. For instance, total phosphorous (TP) could be reduced by at least 76 % while increasing the cost by less than 2 % in the entire watershed.

To our knowledge, previous studies have not reported multi-objective optimization of urban runoff control considering coupled quality and quantity control. Flood quantity, cost of flood control, flood damages, capacity of sewerage systems in transmitting the floods or quality issues have been considered as single objectives in optimization frameworks of previous studies. Furthermore, assumptions used in the simulation of BMPs do not take all BMP characteristics into account. In reality, however, more parameters are required to properly characterize the BMPs. In this research, the effect of implementation of a number of urban runoff quantity and quality control measures are simulated using the Storm Water Management Model (SWMM) in a case study of a urban watershed in Tehran. In an optimization framework, three objective functions are developed for optimum runoff quantity and quality control. The aerial coverage of each BMP in each sub-basin is considered as a decision variable. Optimal decision variables are determined using the NSGA-II evolutionary optimization algorithm. The results of the proposed model are extracted in the form of the optimal trade-off curves. Each point on this curve represents a runoff management scenario.

2 Characteristics of the case study

In recent years, Tehran, the capital of Iran, has been rapidly developing without due consideration of the adverse impacts on the environment and the water cycle. This has resulted in a wide range of challenges and obstacles in water supply and sanitation infrastructures. Integrated runoff quality and quantity management is a necessity as the city grows. At least a number of times each year, Tehran residents must cope with excessive runoff impeding the traffic and causing damage to properties. The last deluge came in April 2012, causing tremendous traffic as well as breaking some flood wall protections. The urban flood waters with degraded quality also end up in the southern part of the city where they are used for irrigation. Thus, implementation of integrated flood management to deal with quantity and quality issues is vital.

In this paper, a relatively small part of the northwest of Tehran is selected for the case study. This area is located downstream of Kan and Vardij Rivers, limited by Alborz Mountains in the north, Kan River in the east, Tehran–Karaj highway in the south and Vardavard Forest in the west. The highest elevation is 1459 m above mean sea level, while the lowest is 1264 m. This urban subarea of about 670.2 hectare was divided into 32 sub-basins (Fig. 1). The 5-yr design rainfall subject to an observation-based temporal pattern is used in this research.

3 Methodology

As stated before, the main objective of this study is optimization of urban runoff control considering coupled quality and quantity aspects. Specifically, the expected output of the proposed approach will be the optimal level and layout of the land allocated to each studied BMP. The procedure is described below.

3.1 Data requirement

Three types of data are used in this study that include: (1) physiographic and hydro-meteorological data such as land use, rainfall statistics and sub-basin characteristics; (2) hydraulic data such as channel network and dimensions, roughness coefficient and required elevations; and (3) quality data for build-up and wash-off model simulations.

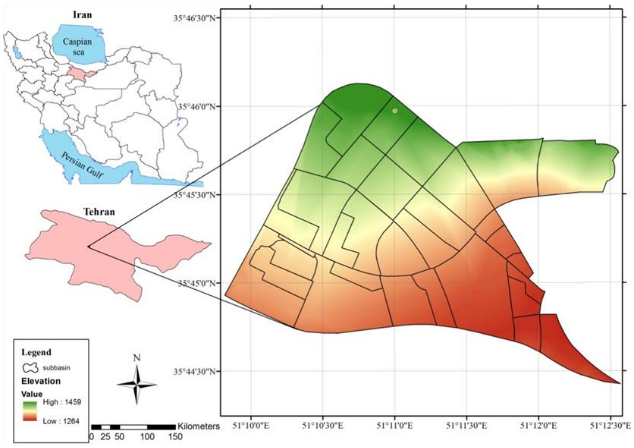

Fig. 1. Location of the study area in the country and within the Tehran province.

3.2 Hydraulic, hydrologic and quality modelling using SWMM

In this study, SWMM was employed to simulate quantity/quality hydrologic and hydraulic routing of urban runoff. SWMM has been developed by the USEPA (United State Environmental Protection Agency). SWMM (version 5.0.021) is a distributed on-site model primarily developed for urban areas. The model is capable of handling both water quantity and quality routing. Typical urban drainage network components such as manholes, underground pipes, storage units, dividers, orifices, weirs, and open channels may be introduced within the SWMM (Huber and Stouder, 2006). In SWMM, hydrologic modelling is initiated by the definition of sub-basin characteristics as well as rainfall and pollution properties. Sub-basins are simulated as nonlinear reservoirs while the output hydrograph is routed via kinematics wave (KW) or dynamic wave (DYW) approaches within the water conveyance system.

In this study, the SCS curve number (CN) method was selected to determine infiltration losses. The CN method was adopted since the runoff depth may be expressed in terms of readily available land-use and hydrologic soil group maps. The CN method has been embedded into various watershed models for flood analysis, water quality and quantity modelling and land-use optimization (e.g. Yeo and Guldmann, 2010; Soulis and Valiantzas, 2012). There have been continuous efforts to modify the CN values under different physiographic and climatic conditions (Arnold et al., 1998).

Furthermore, flood routing was performed using the kinematics wave method (Guo and Urbonas, 2009; Cheng, 2011). The kinematics wave method uses the normal flow assumption for routing flows through the conveyance system.

Pollutant loads vary depending on the characteristics of the catchment surfaces. From the surface, the pollutants will travel to the waterways and water bodies via surface runoff (Hossain and Imteaz, 2009). Storm-water pollutant models are viewed as two stage processes: (1) gradual increase in dry air pollutants over the land with various uses, and (2) washing of the pollutants from the ground during rainfall. In SWMM, a pollutant model has been developed and integrated with the runoff model. The model will first estimate the pollutant build-up during the antecedent dry days (the days without rain) and then simulates the transport of the pollutants to the waterways and receiving water bodies by the surface runoff (Hossain et al., 2010).

3.2.1 Pollutant build-up model

Pollutant accumulation on catchment surfaces is a function of the number of preceding dry weather days. Pollutant build-up that accumulates over a land-use category is described (or "normalized") by either a mass per unit of sub-basin area or per unit of curb length. The amount of build-up is a function of the number of preceding dry weather days (Rossman, 2010; Egodawatta et al., 2009) as follows:

$$B = \min\left(C_1, C_2, t^{C_3}\right), \tag{1}$$

where B is the pollutant build-up ($\mathrm{kg\,m^{-1}}$) (mass per length curb), C_1 is the maximum build-up possible ($\mathrm{kg\,m^{-1}}$) (mass per length curb), C_2 is the build-up rate constant $\left(\frac{\mathrm{kg}}{\mathrm{mday}^{C_3}}\right)$, t is the number of preceding dry weather days, and C_3 is the time exponent (dimensionless). In this research, the curb length is 100 m. The values of build-up coefficients (C_2 and C_3) were determined based on the relationship between build-up amounts with antecedent dry weather days for different land uses and different quality indicators on the experimental data (Egodawatta, 2007).

3.2.2 Pollutant wash-off model

Pollutant wash-off is significantly influenced by the available pollutants on the catchment surfaces. Pollutant wash-off from a given land-use category occurs during wet weather periods (Egodawatta, 2007), as expressed by

$$W = B_1 q^{B_2} M, \tag{2}$$

where W is the wash-off load in units of mass per hour ($\mathrm{kg\,h^{-1}}$), B_1 is the wash-off coefficient $\left(\left(\frac{\mathrm{mm}}{\mathrm{h}}\right)^{-B_2}\left(\mathrm{h^{-1}}\right)\right)$, B_2 is the wash-off exponent (dimensionless), q is the runoff rate ($\mathrm{mm\,h^{-1}}$), and M is the pollutant build-up in mass unit (kg) (Gironás et al., 2009).

In Eq. (2), B_1 and B_2 were determined based on the relationship between wash-off load and pollutant build-up $\left(\frac{W}{M}\right)$ and q on experimental data (Egodawatta, 2007; Hossain et al., 2010).

It should be emphasized that Eqs. (1) and (2) and their parameters were estimated based on the experimental data and have been used in many research projects (e.g. Hossain et al., 2010).

Table 1. Build-up and wash-off parameters (Tajrishi and Malekmohammadi, 2009).

Equation of pollution	Parameter	Land use							
		Low density		High Density		Industrial		Other	
	Parameter	C_1	C_2	C_1	C_2	C_1	C_2	C_1	C_2
Build-up	TSS	2.98	0.9834	74.5	3.0694	193.7	9.1635	59.6	1.9817
	BOD5	1.49	0.00517	2.235	0.01034	3.725	0.02682	1.639	0.00596
	Parameter	B_1	B_2	B_1	B_2	B_1	B_2	B_1	B_2
Wash-off	TSS	0.4	2	0.7	2.2	0.3	2.5	0.1	1.7
	BOD5	0.02	0.2	0.09	0.4	0.1	0.7	0.01	0.05

In this research, the coefficients in Eqs. (1) and (2) are presented by Tajrishi and Malekmohammadi (2009) for the city of Tehran (Table 1), and BOD5 and TSS quality indicators are of primary concern.

3.3 Selection of the BMPs

There are several varieties of BMPs that can be used on a site. However, not all BMPs are suitable for all conditions. Therefore, it is important that the feasibility and constraints are identified at an early stage in the design process. The restrictions in choosing appropriate BMPs are land-use characteristics, site characteristics, catchment characteristics, quantity and quality performance requirements, amenity and environmental requirements. The selected BMPs applied in this paper consist of rain barrels, porous pavement, and bio-retention. First, bio-retention was selected due to the great need for expanding the green space in the city of Tehran. Second, porous pavement is a feasible BMP for parking, courtyard houses and sidewalk areas. Third, rain barrels are suited to urban buildings and can supply a portion of non-potable water.

3.3.1 Porous pavements

Porous pavements are sustainable drainage systems (SUDS) for pedestrian and/or vehicular traffic, allowing rainwater to infiltrate through the surface and into the underlying layers. The water is temporarily stored before infiltration into the ground, reuse, or discharge to a watercourse or other drainage system. Pavements with aggregate sub-bases can provide good water quality treatment. The three principal system types are described in Fig. 2.

Type A reflects a system where all the rainfall passes through the sub-structure into the soils beneath. In a Type B system, a series of perforated pipes at formation level will convey the portion of the rainfall that exceeds the infiltration capacity of the sub-soils to the receiving drainage system. There is no infiltration in a Type C system, and the system is generally wrapped in an impermeable, flexible membrane placed above the sub-grade. Once the water has filtered through the sub-base, it is conveyed to the outfall via perforated pipes or fine drains (Woods-Ballard et al., 2007).

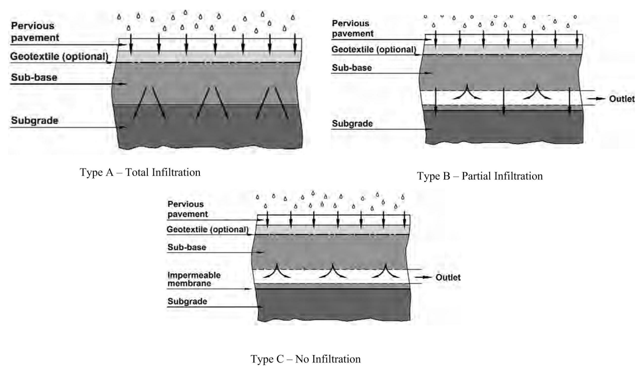

Fig. 2. Porous pavement system (Woods-Ballard et al., 2007).

3.3.2 Bio-retention

Bio-retention areas, also referred to as bio-retention filters or rain gardens, are structural storm-water controls that capture and treat storm-water runoff caused by more frequent rainfall events. Excess runoff from extreme events is passed forward to other drainage facilities. The water volume is treated using soils and vegetation in shallow basins or landscaped areas to remove pollutants. The filtered runoff is then both collected and returned to the conveyance system or, if site conditions allow, infiltrated into the surrounding soil. Part of the runoff volume will be removed through evaporation and plant transpiration. Suitable flow routes or overflows are required to safely convey water in excess of the design volumes to appropriate receiving drainage systems (Fig. 3).

3.3.3 Rain barrels

A rain barrel is placed at a downspout and collects and stores storm-water runoff from rooftops. The collected rainwater can be reused for irrigation of planting areas (or potted plants) around the property.

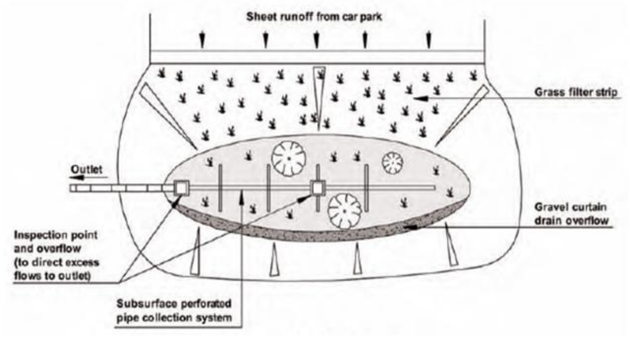

Fig. 3. Plan schematics of a typical on-line bio-retention area (Woods-Ballard et al., 2007).

3.4 Structure of the multi-objective optimization model

3.4.1 Decision variables

Decision variables for each sub-basin consist of rain barrel area (BMP1), porous pavement area (BMP2), bio-retention area (BMP3) and different land-use areas including industrial (land use 1), high density residential (land use 2) and low density residential (land use 3). Since there are 32 sub-basins within the study area, the optimization problem has a total of 192 decision variables (Fig. 4). Miscellaneous land-use area representing parks and green areas (land use4) is not considered as a decision variable; it is simply determined by subtracting the total areas of land use 1 to 3 from the sub-basin area.

3.4.2 Objective functions

Three objective functions were considered in this study: (1) minimization of the total flood damages, cost of BMP implementation and cost of land-use development; (2) reducing the amount of TSS and BOD5, representing the pollution characteristics, to below the threshold level; and (3) minimizing the total runoff volume. The objective functions may be expressed as follows:

$$F_1 = \min\left(\sum_{i=1}^{32}\left(\sum_{j=1}^{3}\left(\mathrm{cost}I_{ij}\right) + \sum_{j=1}^{4}\left(C_j^L A_j^L\right) + 10.13 A_{ij3}^{0.7}\right) + \mathrm{cost}D\right) \quad (3)$$

$$F_2 = \min\left(\sum_{p=1}^{n_\mathrm{p}}\left(\sum_{i=1}^{32} Ct_i^\mathrm{p} + \max\left(\frac{\mathrm{Con}_\mathrm{p}^\mathrm{ave}}{\mathrm{Con}_\mathrm{p}^\mathrm{st}} - 1, 0\right) \times 10^{10}\right)\right) \quad (4)$$

$$F_3 = \min\left(\sum_{i=1}^{32} R_i\right), \quad (5)$$

where

$$\mathrm{cost}I_{ij} = 20722.3 A_{ij1} + 16.055 A_{ij2} - 432 \quad (6)$$

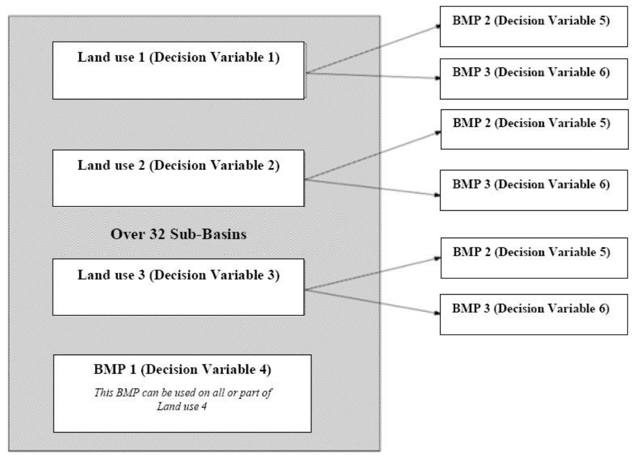

Fig. 4. The schematic of decision variables in each chromosome.

$$\mathrm{cost}D = \sum_{f=1}^{n_\mathrm{flood}}\left(3.28 \times h_f^3 - 22.9 \times h_f^2 + 51.2 \times h_f + 2\right) \quad (7)$$

$$h_f = \beta_f \sqrt{\forall_f} \quad (8)$$

$$\beta_f = \sqrt{\frac{S_f}{2B_f}} \quad (9)$$

$$C_i = \left[\sum_{j=1}^{3}\left(c_j^r A_j^L\right) + c_4^r\left(A_i^T - \sum_{j=1}^{3} A_j^L\right)\right] \Big/ A_i^T \quad (10)$$

$$C_i^n = \left[\sum_{j=1}^{3}\left(c_j^n A_j^L\right) + c_4^n\left(A_i^T - \sum_{j=1}^{3} A_j^L\right)\right] \Big/ A_i^T \quad (11)$$

$$\forall_f = f\left\{\mathrm{SWMM}\left(\left[A_{ij1}\right]_{j=1}^{3},\ \left[A_{ij2}\right]_{j=1}^{3},\ \left[A_{ij3}\right]_{j=4},\ \left[A_j^L\right]_{j=1}^{4},\ C_i,\ C_i^n\right)_{i=1}^{32}\right\} \quad (12)$$

and

$$\mathrm{Con}_\mathrm{p}^\mathrm{ave} = \frac{\sum_{i=1}^{32}\left(Ct_i^\mathrm{p} \times A_i^T\right)}{\sum_{i=1}^{32} A_i^T}. \quad (13)$$

The objective functions are subject to the following constraints:

$$\sum_{k=1}^{2} A_j^L = A_j^L\ ,\ \ i = 1, 2, ..., 32\ ,\ \ j = 1, 2, 3 \quad (14)$$

$$0 \leq A_{ija} \leq A_i^T - \sum_{j=1}^{3} A_j^L\ ,\ \ i = 1, 2, ..., 32\ ,\ \ j = 4 \quad (15)$$

Table 2. Construction cost of different land uses.

Land use	Cost value per one square meter (USD)
Low density residential	4000
High density residential	8000
Industrial	2000
Other (playground, park, ...)	500

Table 3. Implementation cost of BMPs.

BMP	Cost (in USD)
Rain barrel	$C = 2936 \times V - 432$
Bio-retention	$C = 18.5 \times V^{0.7}$
Porous pavement	$C = 65\,000 \times A$

V is the volume of the BMP in cubic feet and A is the area of the BMP in acres.

$$0 \le \sum_{k=1}^{3} A_{ij1} \le 0.6 \times \sum_{j=1}^{3} A_j^L\ , \quad i = 1, 2, ..., 32\ , \quad j = 1, 2, 3 \quad (16)$$

$$0 \le \sum_{k=1}^{3} A_{ij2} \le 0.4 \times \sum_{j=1}^{3} A_j^L\ , \quad i = 1, 2, ..., 32\ , \quad j = 1, 2, 3 \quad (17)$$

where

- i: refers to sub-basin number;
- j: refers to land-use type;
- k: refers to BMP type;
- A_j^L: total area of j-th land use (m^2);
- C_j^L: cost of developing j-th land use (Table 2);
- costI_{ij}: BMP implementation cost over the j-th land-use type in the i-th sub-basin (details of the costs are given in Table 3);
- A_i^T: total area of the i-th sub-basin (m^2);
- cost$D$: the cost of flood damage (in \$);
- A_{ijk}: area of the k-th BMP over the j-th land use in the i-th sub-basin (m^2);
- n_{flood}: total number of flood nodes;
- f: refers to the flooding nodes in each sub-basin;
- h_f: water level at the f-th flooding node (m);
- β_f: a coefficient to determine volume given the height at the f-th flooding node;
- $\forall_f$: runoff volume at the f-th flooding node (m^3);

Table 4. Curve number (CN) of different land uses.

Land use	CN
Low density residential	87
High density residential	92
Industrial	81
Other (playground, park, ...)	70

Table 5. Runoff coefficient of different land uses (ASCE, 1970).

Land use	C (%)
Low density residential	50
High density residential	60
Industrial	70
Other (playground, park, ...)	20

- S_f: sub-basin slope at the f-th flooding node (%);
- B_f: sub-basin width at the f-th flooding node (m);
- c_j^n: curve number attributed to the j-th land use (Table 4);
- C_i^n: average curve number of the i-th sub-basin;
- c_j^r: runoff coefficient attributed to the j-th land use (Table 5);
- C_i: runoff coefficient of the i-th sub-basin;
- f (SWMM ()): SWMM simulation model;
- $\text{Con}_\text{p}^\text{ave}$: average concentration value of pollutant "p" over the entire basin (mg l^{-1});
- $\text{Con}_\text{p}^\text{st}$: threshold (standard) concentration value of pollutant "p" (mg l^{-1});
- n_p: number of pollutants involved in the simulation;
- Ct_i^p: concentration of the pollutant "p" over the i-th sub-basin (mg l^{-1}); and
- R_i: runoff volume in the i-th sub-basin (m^3).

The Non-dominated Sorting Genetic Algorithm (NSGA-II) technique was employed to handle the multi-objective optimization task. For this purpose, required data as well as the characteristics of the BMPs were inputted to the SWMM. Then, for various values of decision variables, the SWMM simulation model was run and flooded areas were identified in each sub-basin. The cost of implementing BMP1 and BMP2 in any sub-basin was also considered in Eq. (6). The implementation cost for BMP3 was determined based on the third term in Eq. (1). Moreover, the cost of implementing different land uses was determined based on the second term

Fig. 5. The process leading to the optimal trade-off curve.

in Eq. (1). The cost of flood damage was determined using Eq. (7). Based on the quality simulation results, TSS and BOD5 values at each node were determined and compared with the threshold values. If the simulated values exceeded the thresholds, the loss function was determined based on the second term in Eq. (4). The total volume of runoff produced in all flooded nodes constitutes the total amount of runoff, as in Eq. (5).

According to Eq. (16), the covered area of BMP1 over land use 1, 2 and 3 in each sub-basin should be less than 60 % of the total sub-basin area. According to Eq. (17), total BMP2 covered area over land use 1, 2, and 3 in each sub-basin should be less than 40 % of the total sub-basin area.

A trade-off curve among the objectives was then extracted that contains various control scenarios. Figure 5 shows the process to arrive at the optimal trade-off curve. It should be noted that the values of the first, second and third objective functions are in dollars, kilograms and cubic meters, respectively. According to Eq. (4), the value of the second term in the second objective function is dimensionless. This term is associated with the penalty function.

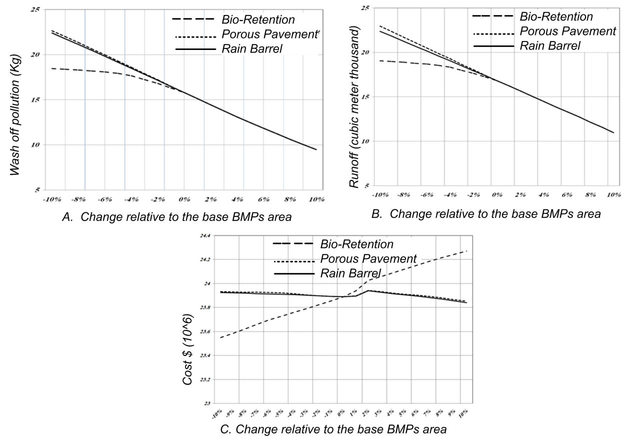

Fig. 6. BMP efficiencies: **(A)** in terms of runoff quantity control, **(B)** in terms of runoff quality control, and **(C)** on the damage cost.

3.5 Non-dominated Sorting Genetic Algorithm (NSGA-II)

A number of multi-objective evolutionary algorithms (MOEAs) have been proposed in the last two decades. The NSGA-II is one of the promising MOEAs and has been successfully applied in many engineering fields. The initial NSGA proposed by Srinivas and Deb (1994) could locate multiple Pareto-optimal solutions in one simulation run for multi-objective optimization problems. The NSGA-II is an improved version of the NSGA, developed to address issues of computational complexity as well as to provide an explicit mechanism for diversity preservation (Deb et al., 2000). The NSGA-II algorithm consists of five operators: initialization, fast non-dominated sorting, crossover, mutation and the elitist crowded comparison operator. A major difference between the NSGA-II and other EAs is the method of operator selection. The NSGA-II uses the non-dominated sorting and ranking selection with the crowded comparison operator (Deb et al., 2000). This model has three new innovative aspects (Chang and Chang, 2009):

1. Fast non-dominated sorting: The fast non-dominated sorting approach has a better book-keeping strategy to speed up the non-dominated sorting process and reduce the computation complexity.

2. Crowding distance calculation: The NSGA-II adopts a crowding distance to measure the density of individuals in the same front. The overall crowding distance is calculated as the sum of individual distance values corresponding to each objective. Besides the non-domination rank, the crowding distance of each individual is also calculated by the average Euclidean distance between the individual and those adjacent individuals in terms of each of the objectives.

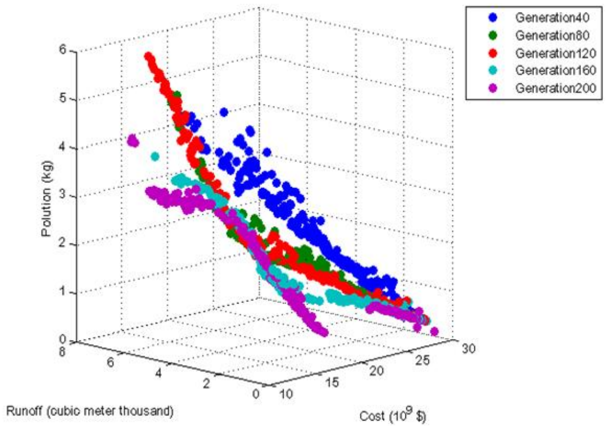

Fig. 7. Results of the last generation in the NSGA-II.

3. Crowded comparison operator: This operator guides the selection process at various stages towards a uniformly spread-out Pareto-optimal front. The crowding distance is applied to select one with a greater crowding distance from two individuals in the same front. The elitist crowded comparison operator combines offspring population members with parent population in the selection process that significantly speeds up to capture the previously found nice solutions.

4 Results and discussion

One criterion for selection of the appropriate BMP is the suitability of implementation in the selected land use and its effect on the runoff quantity and quality. In this section, the effect of each BMP on the runoff quantity and quality control is described first. Then, the superior scenario for runoff quantity and quality control by means of a multi-objective optimization algorithm will be discussed.

4.1 Effect of BMPs on runoff quality and quantity control

Suitable definition of objective functions in determining the optimal solution is quite critical. In this study, the sensitivity of each objective function was assessed. Since the decision variables are the level of coverage for each BMP, changes in the levels were enforced. For this purpose, the proposed values in the Tehran master plan were used as the base values while the lower and upper ranges were 10 % less than and greater than the base values, respectively.

Based on Figs. 6 to 8, rain barrels and porous pavement have similar performances in reducing the quantity and pollution of flood. An increased level of coverage is desirable in improving the runoff quality while reducing its quantity, despite increased construction and operation costs. According to these figures, porous pavement and rain barrels would have a stronger effect on improving the quality and quantity

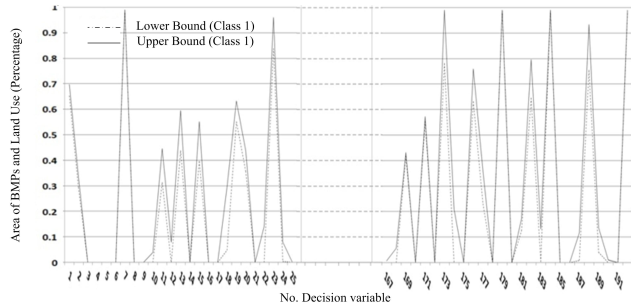

Fig. 8. Variation of decision variable in class 1 based on the k-means method.

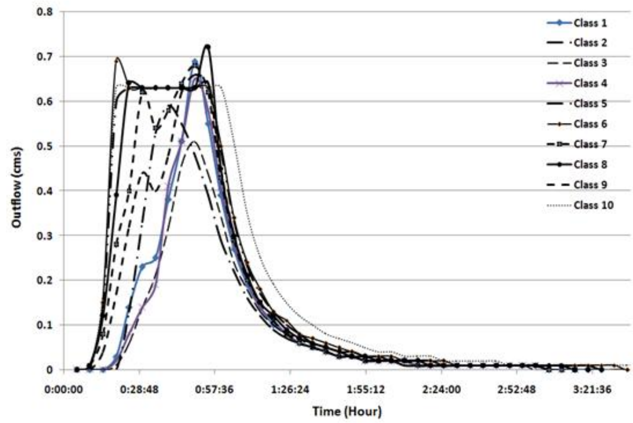

Fig. 9. Flood hydrographs at the outlet for each class.

(the second and third objective functions) of runoff compared with the bio-retention.

The degree of improvement on the second and third objective functions due to the increase in the BMP coverage levels is similar. However, bio-retention is more suitable for pollution and runoff volume reduction than the other two BMPs. The variation of the first objective function (construction and operation costs) versus BMP coverage area is illustrated in Fig. 6c. As it is observed, the costs of bio-retention and porous pavement change slightly compared to that of the rain barrels.

4.2 Sensitivity analysis to combined selection of decision variables

Different combinations of variables were studied in the sensitivity analysis of optimization results based on the three objective functions. The combinations were: (a) BMPs and land-use areas, (b) land-use areas, and (c) BMPs. The aim of sensitivity analysis was to determine the change in objective function values in the Pareto front end. As shown in Table 6, combination A was more effective in reducing the pollution and quantity of runoff. Regarding the expenses, reduction of

Table 6. Sensitivity analysis in variable selection after 200 generations.

Variable	Mean			Standard deviation		
	Cost ($) × 10^9	Runoff (m^3)	Pollution (kg)	Cost ($) × 10^9	Runoff (m^3)	Pollution (kg)
BMPs & land uses	1.05	1700	4.94	1.65	3000	19.61
Land uses	0.154	97.2	0.25	4.83	10 653	8.78
BMPs	101.40	1362	0.22	172.85	3320	0.39

Table 7. Range of variation of objective functions in each class.

Class No.	Objective function 1 (1000 Million Dollar)		Objective function 2 (kg)		Objective function 3 (m^3)	
	Min	Max	Min	Max	Min	Max
1	19.39	20.02	1.50	1.86	452	773
2	15.69	16.99	3.18	4.03	2115	2831
3	26.93	28.33	1.15	1.53	442	606
4	24.93	26.64	1.38	1.49	603	766
5	28.38	29.66	0.61	1.47	117	545
6	14.65	15.65	4.23	5.60	2736	3263
7	17.98	18.51	2.14	2.80	1112	1581
8	17.03	17.90	2.55	3.14	1487	2081
9	18.51	19.26	1.89	2.29	714	1233
10	13.95	14.64	5.67	7.20	2874	4117

the second and third objective functions under combination A was more than those of the B and C combinations. Thus, only combination A was further studied.

4.3 Convergence criteria

To determine the optimal trade-off between the objective functions, the maximum number of iterations must be specified. The optimization algorithm was run for different numbers of iterations. The results are shown in Fig. 7 for 40 to 200 iterations. It is seen that the variation of the objective functions between 160 and 200 iterations is negligible. So, the number of iterations needed for arriving at optimal decision variables as well as optimal trade-off was set to 200.

For convergence of the trade-off curves, the criterion proposed by Chen et al. (2007) was adopted. In this criterion, the distribution of the production solution set and the maximum number of non-dominate solutions located on the trade-off curve are considered. Based on the cumulative distance values of each solution, convergence criterion may be presented as follows:

$$\mathrm{DM} = \frac{d_b = d_e = \sum_{i=1}^{n-1} |d_i - \overline{d}|}{d_b + d_e + (n-1)\overline{d}}, \tag{18}$$

where d_b and d_e are extreme values on the converged trade-off curves, d_i is the cumulative distance value of each solution on the trade-off curves, $\overline{d}$ is the average value of cumulative distance solutions, and n is the number of points on the converged trade-off curves.

Table 8. Number of flooded nodes in each class.

Class	Number of flooded nodes
1	4
2	4
3	0
4	4
5	0
6	5
7	4
8	4
9	4
10	16

The NSGA-II algorithm convergence condition is met when the criterion value is as close to zero as possible. The criterion for NSGA-II was determined as 0.4.

4.4 Classification of optimal trade-off curves

k-means (MacQueen, 1967) is one of the simplest unsupervised clustering algorithms. The procedure follows an easy way to classify a given data set to a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define

Table 9. Optimal level of coverage (km^2) associated with class 3.

No. of sub-basin	Bio-retention	Porous pavement	Rain barrel	Without BMPs	Low density residential	High density residential	Industrial	Other (playground, park, ...)
1	38 318	75 886	149 609	36 787	105 160	91 776	51 103	52 561
2	3008	29 496	100 213	79 083	83 383	52 220	60 687	15 510
3	18 502	55 552.8	83 329.2	14 416	61 028	54 191	23 663	32 918
4	58 082	28 495	88 653	1770	17 188	43 859	45 983	69 970
5	71	82 112	73 624	82 393	112 585	60 713	62 520	2382
6	63 883	81 232	103 257	22 428	60 482	40 838	101 760	67 720
7	44	51 908	49 384	62 264	60 639	29 037	72 288	1636
8	16157	75 950.4	27 137	97 256	74 053	31 570	84 253	26 624
9	23 318	101 656	65 589	114 636	69 851	51 032	133 258	51 059
10	790	175 496	136 935	130 380	200 834	86 140	151 766	4861
11	4463	158 178	122 540	132 120	181 258	35 206	178 980	21 856
12	1477	107 356	79 125	169 442	139 674	99 317	102 687	15 722
13	14 914	44 844	67 749	15 293	44 372	50 270	27 807	20 351
14	39	39 039	38 603	30 919	19 330	33 121	55 063	1086
15	84 970	89 820	83 005	2506	35 081	53 091	87 164	84 965
16	13 164	58 273	108 555	24 908	43 416	72 635	67 073	21 776
17	7407	7625	24 711	13 957	8613	8510	24 157	12 420
18	855	13 558	19 045	34 143	13 244	24 572	24 368	5417
19	1268	12 820.4	11 620	9992	7432	21 314	3305	3649
20	14 974	40 109.2	17 233	50 484	22 256	31 393	46 624	22 527
21	1807	54 922.8	39 437	49 733	37 352	54 909	45 046	8593
22	6455	86 537	151 197	82 911	106 653	106 035	90 837	23 575
23	2405	181 291	156 558	152 147	241 484	57 323	174 626	18 968
24	638	27 457	21 877	26 128	25 380	29 644	17 002	4074
25	14 739	71 593.2	19 895	113 273	65 438	27 769	85 776	40 517
26	1635	30 019	36 785	57 361	40 055	42 003	34 432	9310
27	141	127 272	207 083	266 604	219 914	134 900	240 226	6060
28	5114	17 933.6	12 757	17 897	28 927	3208	12 699	8867
29	32	17 656	35 651	33 860	42 923	24 577	18 668	1031
30	25	27 859	27 692	32 324	10 612	42 159	34 250	879
31	7612	60 121	89 653	42 014	35 826	60 592	84 032	18 950
32	4	3427	3567	9302	7105	3628	5397	170
Sum	406 309	2 035 495	2 252 068	2 008 731	2 221 548	1 557 552	2 247 500	676 004

k-centroids, one for each cluster. These centroids should be placed in a cunning way because different locations produce different results. A better choice is to place them as far away from each other as possible. The next step is to take each point belonging to a given data set and assign it to the nearest centroid. When no point is pending, the first step is completed and an early grouping is done. At this point, we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding between the same data set points and the nearest new centroid is performed in a loop. As a result, one may notice that the k centroids change their location step by step until centroids do not move any more. The clustering algorithm aims at minimizing the following objective function:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2, \tag{19}$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, and j is an indicator of the distance of n data points from their respective cluster centres.

At this stage, the runoff management scenarios were reduced based on the optimal trade-off curve using the k-means method. For this purpose, based on the objective function value associated with 200 points on the trade-off curve (corresponding to 200 chromosomes), 10 classes were selected. Table 7 shows the range of the objective functions for each

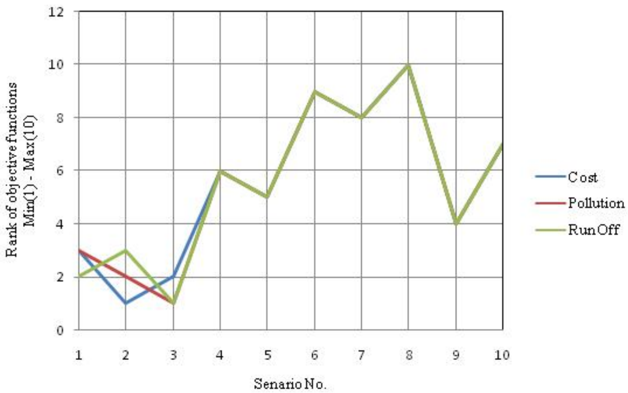

Fig. 10. Comparison of scenarios based on the rank of objective functions.

class representative. Based on the selected classes, the range of variation of decision variables was determined. For example, Fig. 8 shows the variation range of decision variables associated with class 1. According to this figure, it may be concluded that the number of classes is a suitable choice. Thus, the number of scenarios may be reduced from 200 to 10, and decision makers may opt for one of these 10 scenarios for runoff control management.

Based on Table 8, increased flood damage costs are proportional to the number of nodes that have flooded. Accordingly, class 10 with the lowest cost may be proposed. To evaluate the volume of runoff generated at the basin outlet, the runoff hydrographs corresponding to various classes were plotted in Fig. 9, which shows approximately similar flood peaks produced by all classes while the temporal distribution of the discharge varies.

Figure 10 may be used for selection of the best scenario. In this figure, scenarios have been ranked based on the value of objective functions from 1 to 10. Clearly, scenario No. 3 may be identified as the superior scenario. Optimal levels of coverage associated with class 3 are presented in Table 9. The levels of coverage in low density residential and industrial land uses must be 33 %, in high density residential 23 % and in other land uses 10 %. Such a combination is due to the lower cost of implementation in the low density residential and industrial land uses than in the high density residential land use. Moreover, the level of coverage of other land uses should be reduced.

5 Summary and conclusions

Decision-making in urban storm-water control involves maximizing the improvement of runoff quality while minimizing the runoff quantity as well as the total costs. Thus, a Pareto-front that incorporates the trade-off between the total cost and the improvements in runoff conditions is crucial. Previous studies either rely on traditional gradient-based methods to carry out the optimization (e.g. Elliot, 2009; Lee et al., 2005) or focus on optimizing a single type of BMP, such as detention basins (e.g. Harrell and Ranjithan, 2003; Zhen et al., 2004).

In this study, a multi-objective simulation–optimization scheme was proposed in which simulation of hydraulic, hydrologic and quality aspects were performed via the SWMM model. Infiltration was modelled based on the SCS curve number method while flow routing was performed using the kinematic wave method. In water quality simulation, runoff pollutant loads (TSS and BOD5) were modelled using build-up and wash-off relationships. Three different BMPs were considered based on the features and limitations involved in urban runoff quantity and quality control. The selected BMPs consisted of rain barrels, porous pavement, and bio-retention. The reason for selection of these BMPs was their relative ease of implementation in the study area. Decision variables for each sub-basin included BMP type (rain barrel, porous pavement, bio-retention) and different land uses (industrial, high density residential and low density residential). With 32 sub-basins in the study area, the optimization problem had a total of 192 decision variables. The three objective functions considered in this study were some measures of costs as well as the quality and quantity of runoff.

The results showed that the rain barrel and porous pavement had similar performances in reducing the quantity and pollution of runoff.

The k-means clustering method was employed to reduce the number of runoff management scenarios based on the optimal trade-off curve. For this purpose, the objective function values associated with 200 points on the trade-off curve were classified into 10 classes. Based on the selected classes, variation ranges of the decision variables were determined. Thus, the number of applicable scenarios was reduced from 200 to 10, enabling the decision makers to deal with only 10 runoff management scenarios. Scenarios were ranked from 1 to 10 based on the objective function values. Finally, scenario No. 3 that involves the least amount of pollution, runoff and cost function was selected as the superior scenario.

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