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Multi-objective optimization using evolutionary algorithms for qualitative and quantitative control of urban runoff

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Abstract

Urban development and affects the quantity and quality of urban floods. Generally, flood management include planning and management activities to reduce the harmful effects of floods on people, environment and economy is in a region. In recent years, a concept called Best Management Practices (BMPs) has been widely used for urban flood control from both quality and quantity aspects. In this paper, three objective functions relating to the quality of runoff (including BOD_5 and TSS parameters), the quantity of runoff (including runoff volume produced at each sub-basin) and expenses (including construction and maintenance costs of BMPs) were employed in the optimization algorithm aimed at finding optimal solution MOPSO and NSGAII optimization methods were coupled with the SWMM urban runoff simulation model.

In the proposed structure for NSGAII algorithm, a continuous structure and intermediate crossover was used because they perform better for improving the optimization model efficiency. To compare the performance of the two optimization algorithms, a number of statistical indicators were computed for the last generation of solutions. Comparing the pareto solution resulted from each of the optimization algorithms indicated that the NSGAII solutions was more optimal. Moreover, the standard deviation of solutions in the last generation had no significant differences in comparison with MOPSO.

1 Introduction

Financial risks and health threats due to urban flood is always a challenge in flood management plans of large cities. Urban runoff is often studied in terms of runoff control, flood damage and costs flood control measures. All activities aimed at prevention and crisis management during and after the floods are known as flood management. In recent years a new concept called Best Management Practices(BMPs) has been proposed in order to control the quality and quantity of urban floodwaters.

Different models have been used to simulate BMPs effect on run off and BMPs selection, for example Zhen et al. (2004) used scatter search method for considering the optimal size and location the BMPs and developed the cost-reduction of infection curve and a gradient-based search procedure in a simplified mathematical model(Elliot, 1998). Some researchers have studied on the effects of urban development and reduction of permeable areas (Moglen and Mejia, 2009). They also demonstrated the effects of water quantity and quality using a numerical modeling. The Institute of International Science and Technology of India conducted a research to optimize the costs of storage tanks which control the pollution and urban runoff quantity (Rathnam et al., 2004). Graupensperger and Stroschein (2003) emphasized the use of GIS for the 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. Lee et al. (2005) discussed methods to reduce pollution and runoff volumes with regard to economic indicator. The study aimed 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. He applied ε-NSGAII algorithm to optimize both the flood volume and cost of implementing three types of BMPs. Perez-Pedini et al. (2005) used genetic algorithm to minimize the peak discharge of surface runoff and costs of BMPs implementation in the urban areas using infiltration-based localizing in different sub-catchments.

Post studies have not performed multiobjective optimization of urban runoff control considering features 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 the target single objective optimization in the previous researches. Also assumptions used in the simulation of BMPs are not fully reflected all the characteristics and types of BMPs. For instance, defining the separate subcatchment and permeability coefficient, the infiltration trench is simulated. In reality, however more parameters are required to characterize this BMP.

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Briefly, in this research a number of urban flood quantity and quality control BMPs methods are applied to simulate their effects on flood characteristics in a case study. Using MOPSO and NSGAII evolutionary optimization algorithms and by defining the cost, quality and quantity objective functions, the optimization model is made to minimize functions simultaneously. Moreover, the results for application of each optimization method are discussed and the superior algorithm is proposed. Furthermore, in methodology section, the structure of optimization models is discussed.

2 Case study

In recent years, Tehran, the capital of Iran, has been rapidly developing without proper 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. Lack of a systematic approach to runoff management in Tehran has led to frequent overflow of channels and some environmental hazard problems in rainy seasons. In this paper, the northwest part of Tehran is nominated for the case study. This area is located in the downstream of Kan and Vardij rivers. It is confined to Alborz mountains in north, Kan River in east, Tehran-Karaj highway in south and Vardavard forest in west. The highest elevation is 1459 meters above sea level and the lowest is 1264 meters. The urban area is about 670.2 hectares. The study area is divided into 32 sub-basins are assigned to the study area.

3 Methodology

The purpose of this study is to optimize BMPs solutions to control the quantitative and qualitative adverse effects of floods in the part of city of Tehran. The methodology flow chart is given in Fig. 2.

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3.1 Data collection

Three types of data are used in the study: (1) the basin hydrological data such as land use, rainfall statistics and the sub-catchment characteristics. (2) The hydraulic data such as channel dimensions, roughness coefficient and the required elevations. (3) Quality data for build up and wash off model simulation.

3.2 The hydraulic, hydrological and urban runoff quality modeling using SWMM

In this study the hydrological and hydraulic simulation of urban runoff quality is made using SWMM (Storm Water Management Model), Developed by 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 making both water quantity and quality predictions. Typical urban settings such as manholes, underground pipes, storage units, dividers, orifices, weirs, and open channels can be represented within SWMM (Huber and Stouder, 2006).

3.2.1 Hydraulic and hydrological simulation

In SWMM model, the hydrological modeling is initiated by the definition of sub-basins as well as rainfall and pollution properties. Sub-basins are simulated as nonlinear reservoirs and the resulted hydrograph is routed based on the kinematic(KW) or dynamic wave(DYW) approaches within the water conveyance system.

In this study, the SCS curve number (CN) method is used to calculate infiltration. This method has been chosen, because the relationship between land use and peak runoff is expressed in terms of hydrologic soil groups and land use/cover conditions (Bingner and Theurer, 2001) and the CN method has been embedded into various watershed models for hydrology, flood analysis, water quality and quantity modeling and land use optimization modeling (Yeo and Guldmann, 2010; Soulis and Valiantzas, 2011). There have been continuous efforts to modify the CN values under different physiographic and climatic conditions (Arnold et al., 1998).

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The antecedent soil moisture condition is considered by using the default estimation of the SCS method. In this paper, flood routing is performed using the kinematic wave method. Kinematic wave uses the normal flow assumption for routing flows through the conveyance system.

3.2.2 Quality simulation

Pollutant loads from catchments vary depending on the characteristics of the catchment surfaces. From the catchment surface the pollutants will travel to the waterways and water bodies by the surface runoff (Hossain and Imteaz, 2009). Stormwater pollutant models are viewed as two stage processes:

- gradual increase in dry air pollutants in land with various uses
- washing pollutants from the ground during rainfall

Keeping in mind the stages, a pollutant model has been developed and integrated with the runoff model. The model will first estimate the pollutants build-up from a catchment during the antecedent dry days (the days without rain) and then the transport of the pollutants to the waterways and receiving water bodies during surface runoff (Hossain et al., 2010).

Pollutant Build-up Model

Pollutants accumulation on catchment surfaces is a function of the number of preceding dry weather days. The maximum accumulation of pollutants depends on the climatic and other site specific factors. Pollutant buildup that accumulates within a land use category is described (or "normalized") by either a mass per unit of sub-basin area or per unit of curb length. Mass is expressed in pounds for US units and kilograms for metric units. The amount of buildup is a function of the number of preceding dry weather days (Rossman, 2010; Egodawatta et al., 2009).

$$B = \mathrm{Min}(C_1, C_2 * t^{C_3}) \quad (1)$$

where C_1 = maximum buildup possible (mass per unit of area or curb length), C_2 = buildup rate constant, and C_3 = time exponent.

Pollutant Wash-off Model

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

$$W = B_1 * q^{B_2} * M \quad (2)$$

where B_1 = wash-off coefficient, B_2 = wash-off exponent, q = runoff rate per unit area ($\mathrm{mm\,h^{-1}}$), and M = pollutant buildup in mass units. The buildup here is the total mass (not per area or per curb length) and both buildup and wash-off mass units are the same as used to express the pollutant's concentration (milligrams, micrograms or counts).

The proposal coefficients values in Eqs. (1) and (2) are presented by Tajrishi in Tehran area (Table 1). In this study BOD_5 and TSS quality indicators are included.

3.3 Selection BMPs

There are variety of BMPs that can be used on a site. Not all BMP techniques are suitable for all sites and therefore it is important that the possibility and constraints are identified at an early stage in the design process. The restrictions in choosing the appropriate BMP include: land use characteristics, site characteristics, catchment characteristics, quantity and quality performance requirements, amenity and environmental requirements. The selected BMPs applied in this research consist of rain barrel, porous pavement, bio retention.

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3.3.1 Pervious pavements

Pervious pavements provide a pavement suitable for pedestrian and/or vehicular traffic, while allowing rainwater to infiltrate through the surface and into the underlying layers. The water is temporarily stored before infiltration to the ground, reuse, or discharge to a watercourse or other drainage system.

3.3.2 Bioretention

Bioretention areas are shallow landscaped depressions which are typically under-drained and rely on engineered soils and enhanced vegetation and filtration to remove pollution and reduce runoff downstream.

3.3.3 Rain barrel

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

3.4 Definition of decision variables and objective functions

3.4.1 Decision variables

Decision variables for each of sub-catchment include: BMPs types consisting of rain barrel, porous pavement, bio retention and different land uses consisting of industrial, high density residential and low density residential.

Since there are 32 sub-basin within the study area, The optimization problem has 192 decision variables. It should be emphasized that these BMPs were chosen on the basis of their function on constraints of the study area.

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3.4.2 Objective functions

The values of objective functions must be calculated after getting the values of Decision variables in each generation.

Achieving this goal and based on objective functions and their relevant variables we perform the following steps in hydraulic and hydrologic modeling in SWMM.

– *Step 1:* The runoff coefficient is generated for each sub-basin based on the average level of runoff production coefficients for different parts in the basin. Accordingly, the runoff coefficient in each sub-basin is calculated as follows:

$$\overline{C} = \frac{\sum_{i=1}^{4} C_i \times \text{Area}_i}{\text{Area}} \tag{3}$$

where Area_i is area of ith land use and C_i is the impermeability in ith land use then, the weighted average of curve number in each sub-basin is calculated as follows: Based on this, the curve number in each sub-basin is calculated as follows:

$$\overline{Cn} = \frac{\sum_{i=1}^{4} Cn_i \times \text{Area}_i}{\text{Area}} \tag{4}$$

where Area_i is area of ith land use and Cn_i is the curve number in ith land use.

– *Step 2:* The next step is making an input file for the SWMM software. The decision variables are listed in this file.

$$f1(x) = \min\left(\sum_{i=1}^{32}\left[\left\{\sum_{j=1}^{3}\text{COST(Imp.)}_{\text{BMPs}_{ij}} + \sum_{k=1}^{4}\text{COST(Const.)}_{\text{Land use}_{ik}}\right\} + \text{COST(Damage)}_i\right]\right) \tag{5}$$

$$f2(x) = \text{Min}\left(\sum_{i=1}^{32}\text{Quality(BOD}_5\text{\&TSS)}_i\right) \tag{6}$$

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$$f3(x) = \text{Min}\left(\sum_{i=1}^{32} \text{Volume(runoff)}_i\right) \quad (7)$$

$$0 \le \sum_{j=1}^{3} (\text{Area percentage without BMPs} + \text{BMPs}_j) \le 100 \quad (8)$$

$$0 \le \sum_{k=1}^{4} (\text{Area percentage in Land use}_k) \le 100 \quad (9)$$

$$\forall i, \forall j, \forall k$$

i = Sub-Basin No., j = BMPs No., k = Land Use No.
$\text{COST(Damage)}_i = (d(x).\ \text{house value})_i$
COST(Damage)_i = Damage cost in ith sub-basins
$\text{COST(Imp.)}_{\text{BMPs}_{ij}}$ = Implementation cost of jth BMP in ith sub-basins
$\text{COST(Const.)}_{\text{Land use}_{ik}}$ = Construction cost of kth land uses in ith sub-basin:
Volume (runoff)_i = Volume of runoff in ith sub-basin
$\text{Quality (BOD}_5\ \&\ \text{TSS)}_i$ = Amount of quality parameter in ith sub-basin

The damage percentage ($d(x)$) in the ith sub-basin is calculated by Tajrishi and MalekMohammadi in 2009:

$$d(X) = 3.28X^3 + 22.9X^2 + 51.2X + 2 \quad (10)$$

where X is flood level.

The runoff objective function is determined through adding runoff depth at all sub-catchment. Maintenance and operation costs and land values are equal to ten percent of the implementing cost of BMPs. The total cost is calculated by adding the expenses for all sub-basins.

3.5 Multi-Objective Evolutionary Optimization Algorithms

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

NSGA-II is based on Darwin's theory proposed by Holland in 1975. It has been used by engineers to find optimal solutions for more than three decades. In this study, the NSGA-II algorithm is used as was developed in 2000 by Deb et al.

In NSGAII, a solution is ranked according to the number of solutions that dominate it. Two-step crowded binary tournament selection is then carried out based on the fitness value of each solution. During the process, the solution with a lower rank is always preferred. When two solutions have the same rank, the one with a larger crowding distance is selected. By doing this NSGAII ensures a more distributed set of solutions along the final Pareto front (Kollat and Reed, 2005).

3.5.2 The proposed structure in NSGAII

- *Continuous genetic algorithms*
  The initial genetic algorithm proposed by Holland was in binary coded. This algorithm is highly consistent with the structure of chromosomes in nature and the genetic algorithm operators such as crossover and mutation are easy. But this algorithm has many limitations. One of the problems in binary genetic algorithms with continuous decision variables is that movement from point to point in space requires a large number of bits which decreases the search efficiency in the decision environment. Moreover, this method enters coding and un-coding in the decision variables in each step.

- *Selection operator*
  In this study advanced tournament selection operator is used for choosing parental chromosomes. The advantage of this method compared to as natural selection is that it does not need to sort the entire chromosome or defining the threshold. Here, the number of competition members is set to two.

- *Crossover operator*
  Up to now, variety of methods for Crossover operator in the binary and continuous genetic algorithm are introduced. In this research, the intermediate crossover method is used where the produced children are average weight of two parents:

$$\text{child}_1 = \text{parent}_1 + \text{rand} * \text{ratio} * (\text{parent}_2 - \text{parent}_1) \tag{11}$$

$$\text{child}_2 = \text{parent}_2 + \text{rand} * \text{ratio} * (\text{parent}_2 - \text{parent}_1) \tag{12}$$

  In this study, the ratio is assumed 1.2 and the crossover rate is considered 0.8.

- *Mutation operator*
  Gaussian mutation method is used in this study. This formulation is as follows:

$$\text{Child} = \text{Parent} + S * \text{random} * (\text{ub} - \text{lb}) \tag{13}$$

$$S = \text{scale} * (1 - \text{shrink} * k / \text{Max Gen}) \tag{14}$$

  where S is the deviation from the standard normal distribution, scale parameter is set to 0.1 and shrink parameter is set to 0.5. K represents the current generation.

3.5.3 Using particle swarm optimization algorithm (PSO) to solve the problem

PSO algorithm is a social search algorithm based on the social behaviour of bird bands. PSO algorithm was first described in 1975 by James Kennedy and Russell C. Eberhart.

The PSO is based on the principle that each particle in each moment sets up its location with respect to the best place so far in the group and the best location in its neighbourhood.

$$V_i^{i+1} = x(wV_i^i + c_1\text{rand}(0,1)(p\text{best}_i - X_i^i) + c_2\text{rand}(0,1)(g\text{best}_i - X_i^i)) \tag{15}$$

$$X_i^{i+1} = X_i^i = v_i^{i+1} \tag{16}$$

Where V_i^{i+1} is the velocity of particle i in new repetition, V_i^i is the velocity of particle i in current repetition, X_i^i is the current position of the particle, $p\text{best}_i$ is the best position for the i particle, X_i^{i+1} is the particle position in new repetition, $g\text{best}_i$ is the best position of particle and rand(0,1) is a random number between 0 and 1.

C_1, which is the cognitive learning factor, represents the attraction that a particle has toward its own success while C_2, which is the social learning factor, represents the attraction that a particle has towards the success of its neighbors. Both are normally defined as constants.

Also the inertial weight (denoted by w) is adopted to control the impact of the previous history of velocities on the current velocity of a given particle. Moreover, parameter is the constriction factor which can restrict the velocity as well as the w parameter.

3.5.4 Particle Swarm Optimization for Multi-Objective Problems

In order to apply the PSO (Particle Swarm Optimization) strategy for solving MOPs (Multi-Objective Problems), it is obvious that the original scheme has to be modified. in multi-objective optimization, we aim to find not one, but a set of different solutions (the so- called Pareto optimal set). In general, when solving a MOPs, the main goals are to converge to the true Pareto front of the problem (i.e. to the solutions that are globally non-dominated) and to have such solutions as well-distributed as possible along the Pareto front.

Figure 7 shows the way in which a general MOPSO works. First, the swarm is initialized. Then, a set of leaders is initialized with the non-dominated particles from the swarm. The set of leaders is usually stored in an external archive. Later on, some sort of quality measure is calculated for all the leaders in order to select (usually) one leader for each particle of the swarm. At each generation, for each particle, a leader is selected and the flight is performed. Most of the existing MOPSOs apply some sort

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of mutation operator after performing the flight. Then, the particle is evaluated and its corresponding pbest is updated. A new particle replaces its pbest particle usually when this particle is dominated or if both are incomparable (i.e. they are both non-dominated with respect to each other). After all the particles have been updated, the set of leaders is updated, too. Finally, the quality measure of the set of leaders is re-calculated. This process is repeated for a certain (usually fixed) number of iterations (Coello Coello C. A., 2011).

4 Results and discussion

4.1 Effect of BMPS in control quality and quantity runoff

In this section the effects of variation of the designated area for each BMPs on the pollution and runoff volume objective functions are investigated. For this purpose, the percentage of area BMPs is varied from −10 %–+10 %. Based on Figs. 8 and 9, rain barrel and porous pavement have similar performance to reduce the quantity and quality of flood. However, bio retention is more suitable for pollution reduction and runoff volume than two other BMPs.

The variation of cost function versus area is illustrated in Fig. 10. As it is observed, increasing the area for Bio retention and Porous Pavement will decrease the cost function while rain barrel it will cause to increase the cost function. This is because of the higher influence of Implementation cost for rain barrel.

4.2 Sensitivity analysis to combined selection of decision variables:

To select the optimal combination of decision variables, NSGAII optimization model with 3 combinations of BMPs & Land Uses, BMPs, Land Uses was performed.

According to Table 7, the change in land use has deeply influences the quality objective function since the build up and wash off parameters are dependent on land use.

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Comparing the results for combination of "BMPs and land uses" shows that, in the case of "BMPs and land uses" the amount for pollution quantity has decreased significantly while the cost and runoff objective functions have increased slightly in "Land Uses" and "BMPs" cases.

4.3 Comparison of results from particle swarm algorithm (MOPSO) and Genetic algorithm (NSGAII)

As illustrated in Figs. 12 and 13 and Table 8, although MOPSO is faster, has fewer parameters and is a simpler procedure than NSGAII but it will converge at higher generations. Moreover, standard deviation in MOPSO is not much of a difference rather than NSGAII.

On continue, some of chromosomes based on the values of the objective functions are illustrated.

In Figs. 14 to 15, some aspects of BMPs features in quantity and quality of runoff are presented.

5 Conclusions

Decision-making in stormwater control always involves maximizing the improvements in stormwater runoff quantity and quality while minimizing the total control cost. Thus a Pareto-front that depicts the trade-off between the total cost and the improvements in runoff conditions is crucial to defendable stormwater control decision-making. Previous studies either rely on traditional gradient-based methods to carry out the optimization (Elliot, 2009; Lee et al., 2005) or focus on optimizing a single type of BMPs, such as detention basins (Harrell and Ranjithan, 2003; Zhen et al., 2004). In this study the hydrological and hydraulic simulation of urban runoff quality is made using SWMM. In Hydrological processes, infiltration was modeled through SCS Curve Number method. In Flow routing, user decides on the simplification level of the equations such as the

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kinematic wave routing. Also in Water quality simulation, Runoff pollutant loads (TSS and BOD_5 parameters) was modeled using build-up and wash-off equations (Power function selected for build-up and Exponential function for wash-off).

Three different BMPs are proposed due to the features and limitations in urban runoff quantity and quality controlling: Pervious pavements, Bio Retention, Rain Barrel. Moreover, since the studied area is a developing area the influence of various land uses is also investigated in quality and quantity control of flood. The MOPSO and NSGAII are selected as the optimization model according to vast usages of genetic algorithm in water resource management. Based on the capabilities of continuous genetic algorithm rather than binary algorithm, we have applied it in production of NSGAII optimization model. The experiences show that decimal display for variables is faster than binary algorithm and also increases the accuracy of optimized results in the vast search area. Moreover, due to selection of intermediate crossover, it should be mentioned that its advantage to other methods relies on the fact that in this model the amount of genes for produced chromosomes is different to its parents. However, in other methods the amount is the same as parents. Standard deviation and mean value of results are applied for comparison of last generation results in both algorithms. According to Table 8 and the made comparison it is proved that the mean value of results is less in NSGAII rather than MOPSO, however the standard deviation is not seriously different for both. This demonstrates that NSGAII has more efficiency. Moreover, The NSGAII is more appropriate since using capabilities such as crowd distance and better speed in optimization algorithm. However, the MOPSO operates more easily since it has less involved parameters.

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Table 1. Build-Up and Wash-Off parameters (Tajrishi and malekmohammadi, 2009).

Land Use								Parameters	Equation of Pollution
Other.		Industrial		High Density		Low Density			
C_2	C_1	C_2	C_1	C_2	C_1	C_2^*	C_1^*		
1.9817	59.6	9.1635	193.7	3.0694	74.5	0.9834	2.98	TSS	BUILD-UP
0.00596	1.639	0.02682	3.725	0.01034	2.235	0.00517	1.49	BOD5	
B_2	B_1	B_2	B_1	B_2	B_1	B_2^{**}	B_1^{**}		
1.7	0.1	2.5	0.3	2.2	0.7	0.2	0.4	TSS	WASH-OFF
0.05	0.01	0.7	0.1	0.4	0.09	0.2	0.02	BOD5	

* C_1: kg/100-m & C_2: kg/day/100-m.
** B_1 & B_2: dimensionless.

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Table 2. Impermeability (%) in different local areas (ASCE.1970).

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

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Table 3. Characteristic curve number (Cn) in different land uses.

Land use	Cn
Low density residential	0.87
High density residential	0.92
Industrial	0.81
Other (play ground, park, ...)	0.7

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Table 4. Implementation cost of BMPs.

BMPs	COST
Rain barrel	$C = 2936^{*}V - 432$
Bio retention	$C = 0.25^{*}\ V^{0.7}$
Porous pavement	$C = 65000^{*}A$

* V is volume of BMPs in cubic meter and A is the area of BMPs in acres.

Table 5. Construction cost of different land uses.

Land use	Cost value of one square meter (USD)
Low density residential	4000
High density residential	8000
Industrial	2000
Other (Play ground, Park, ...)	500

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Table 6. Parameters used in the MOPSO algorithm.

Parameter Name	Global Learning Coefficient c_2	Personal Learning Coefficient c_1	Inertia Weight ω	Grid Inflation Parameter α	Constriction Factor χ
Amount	1.43	1.43	0.7	0.1	1

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Table 7. Sensitivity analysis in variable selection after 200 generation in genetic algorithm.

Variables	Mean			Standard Deviation		
	Cost ($) $*10^9$	Runoff (Lit)$*10^6$	Pollution Kg	Cost	Runoff	Pollution
BMPs & Land Uses	19.61	3	1.65	4.94	1.7	1.05
Land Uses	0.39	10.65	5.32	0.25	0.10	0.15
BMPs	8.79	10.65	390.36	0.22	0.10	101.40

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Table 8. Comparison of optimization results after 200 generations.

Algorithm	Mean			Standard Deviation		
	Cost ($) $*10^9$	Runoff (Lit)$*10^6$	Pollution (kg)	Cost	Runoff	Pollution
NSGA-II	19.61	3	1.65	4.94	1.7	1.05
MOPSO	24.53	3.25	2.15	5.28	1.76	1.55

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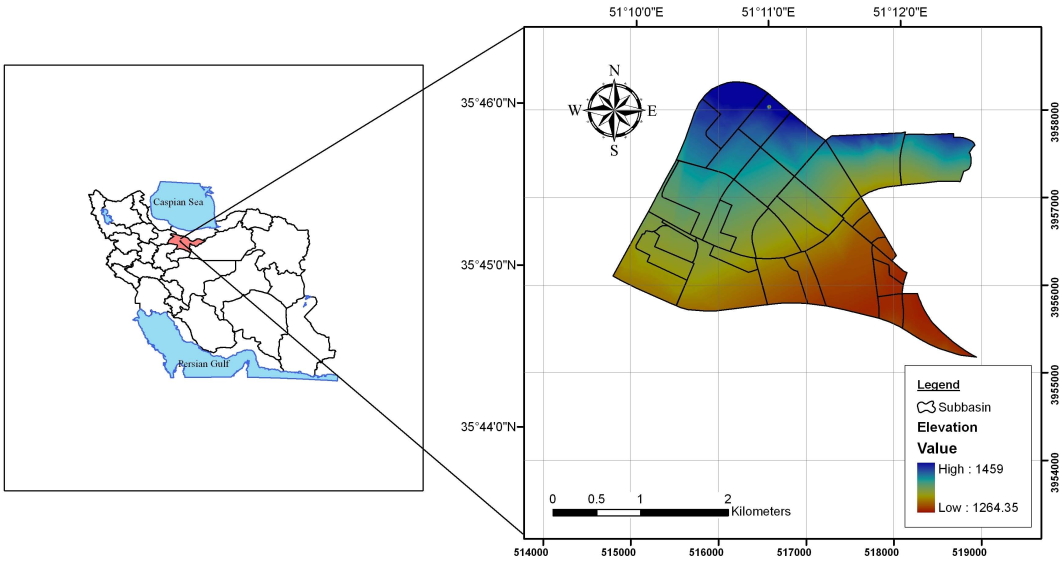

Fig. 1. The location of the study area.

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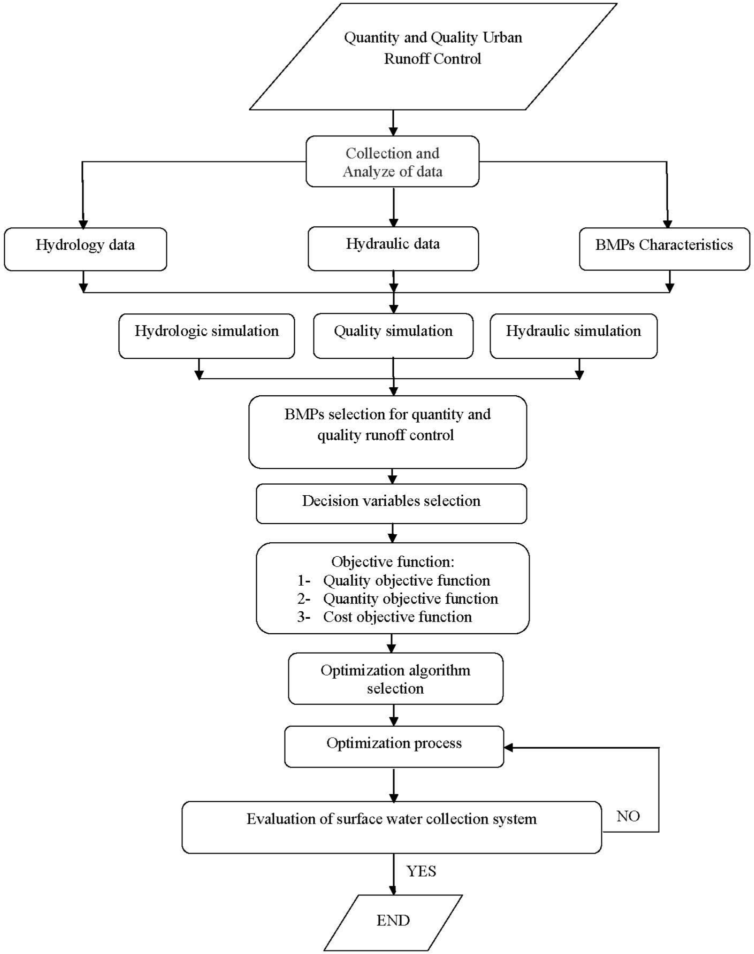

Fig. 2. The overall view of the methodology.

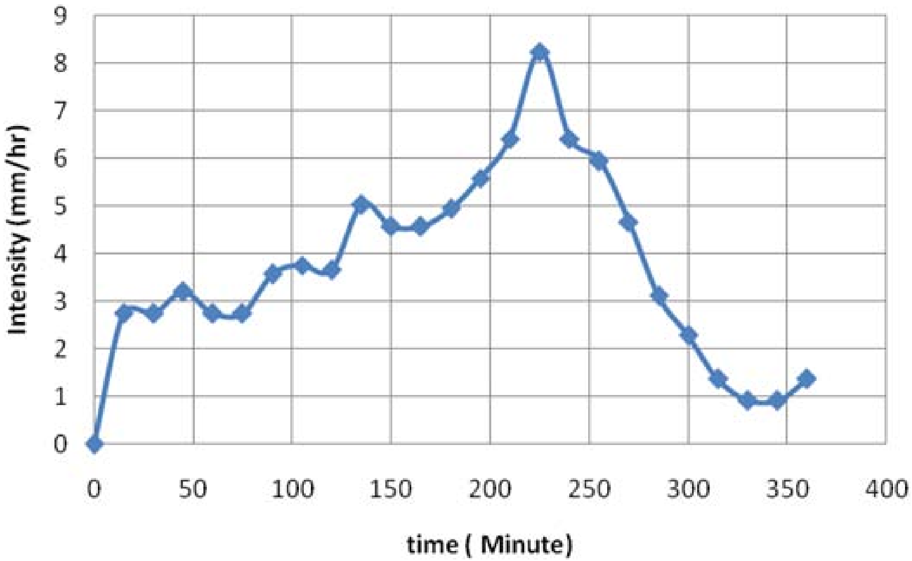

Fig. 3. Rainfall design with 5 yr return period.

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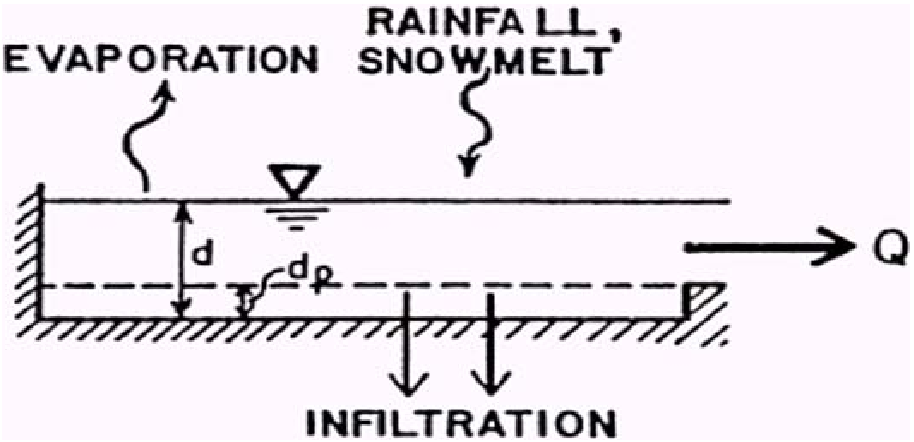

Fig. 4. Non-linear Reservoir Representation of a sub-catchment (Rossman, 2010).

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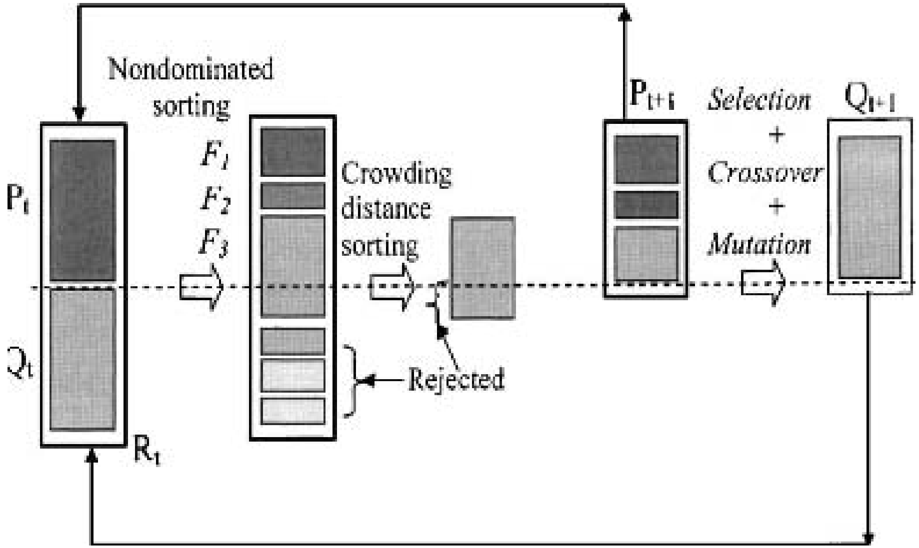

Fig. 5. Schematic of NSGA-II algorithm.

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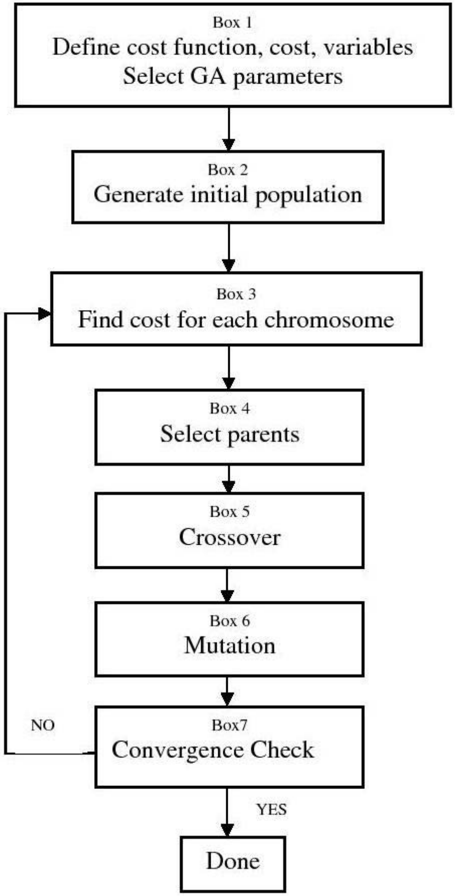

Fig. 6. Flowchart of a continuous GA (The proposed structure).

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```
Begin
    Initialize swarm
    Initialize leader in an external archive
    Quality(leader)
    g=0
    While g<gmax
            For each particle
                Select leader
                Update Position (Flight)
                Mutation
                Evaluation
                Update pbest
            End for
            Update leader in external archive
            Quality(leader)
            g++
    End While
    Report results in the external archive
End
```

Fig. 7. Pseudocode of a general Multi-Objective Particle Swarm Optimization algorithm. (Coello Coello C. A., 2011).

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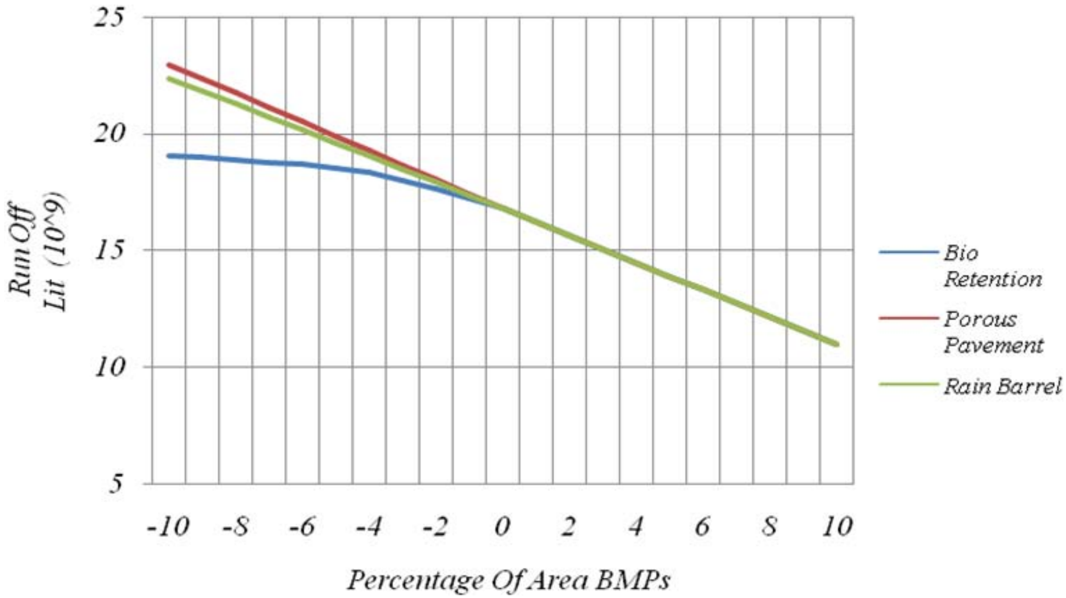

Fig. 8. BMPs efficiency in quantity control.

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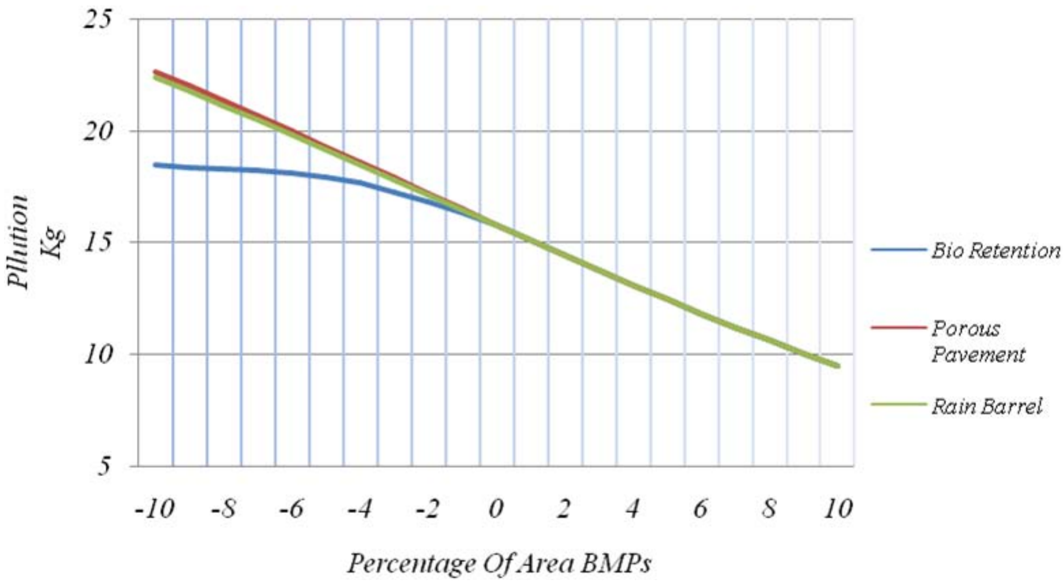

Fig. 9. BMPs efficiency in quality control.

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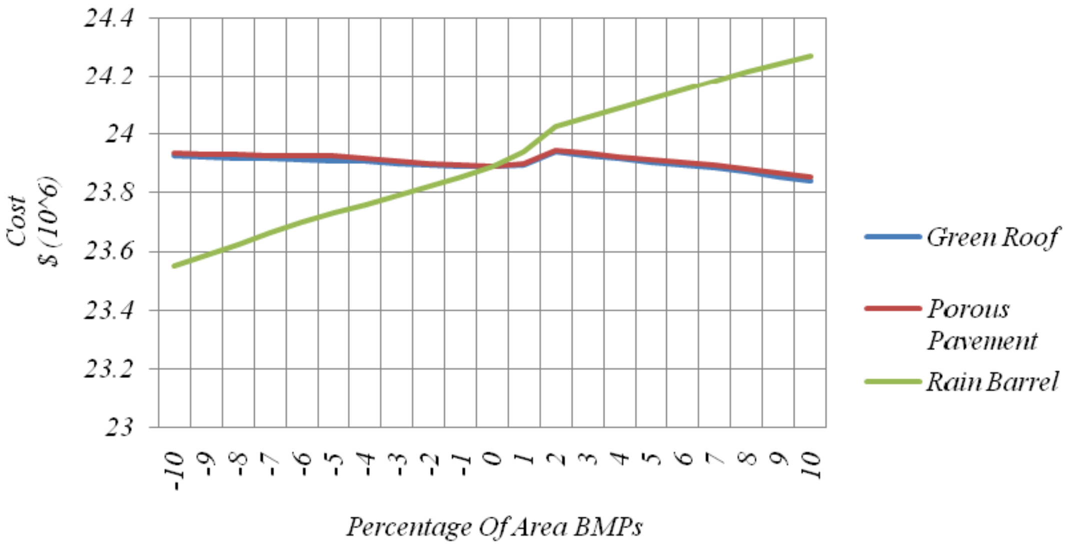

Fig. 10. BMPs efficiency in damage control.

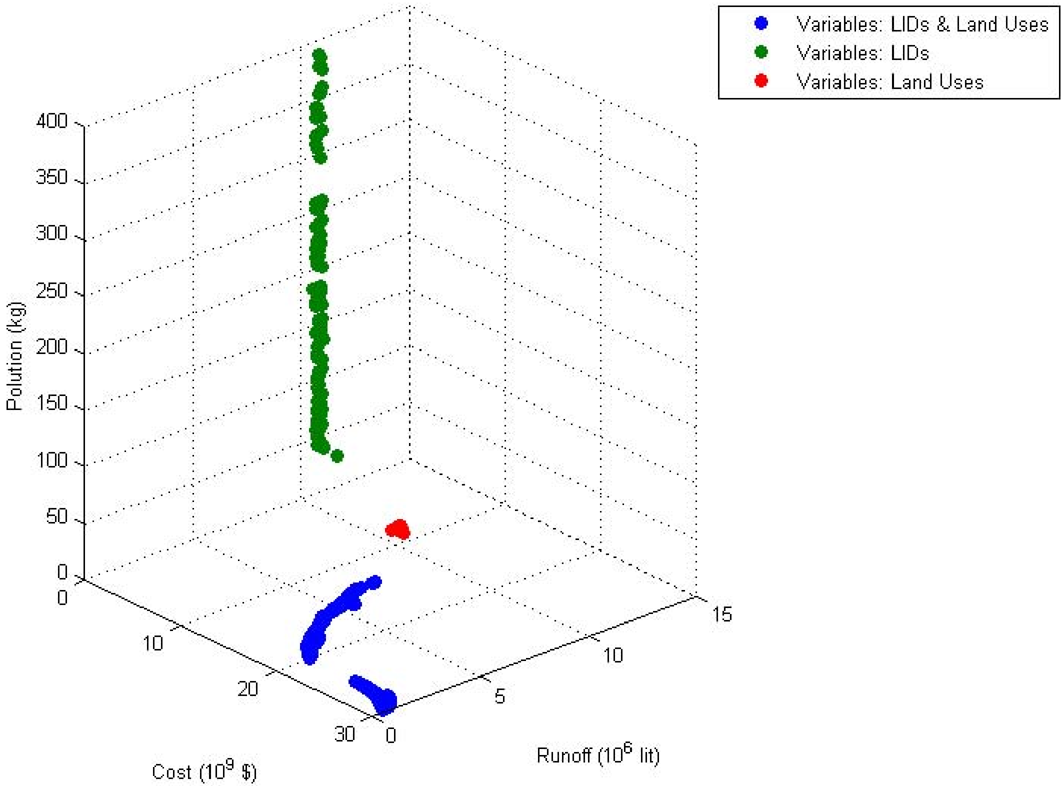

Fig. 11. Comparing the results of the last generation in NSGAII.

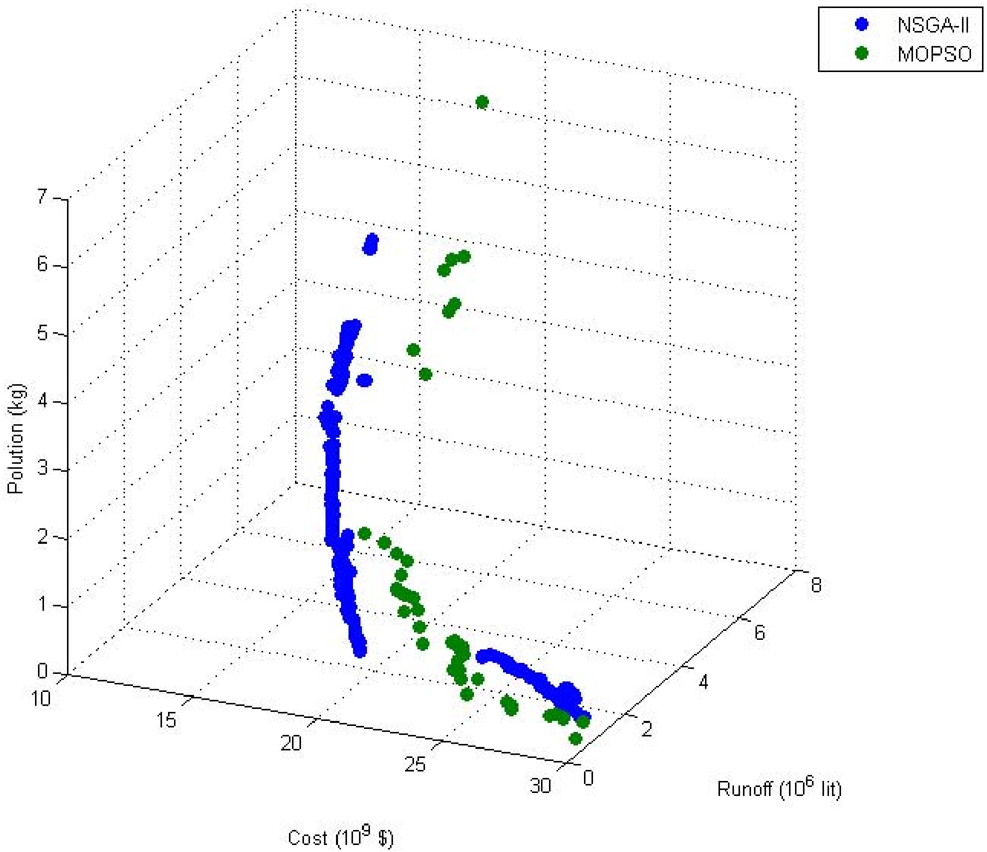

Fig. 12. Comparison of last generation in NSGAII with MOPSO.

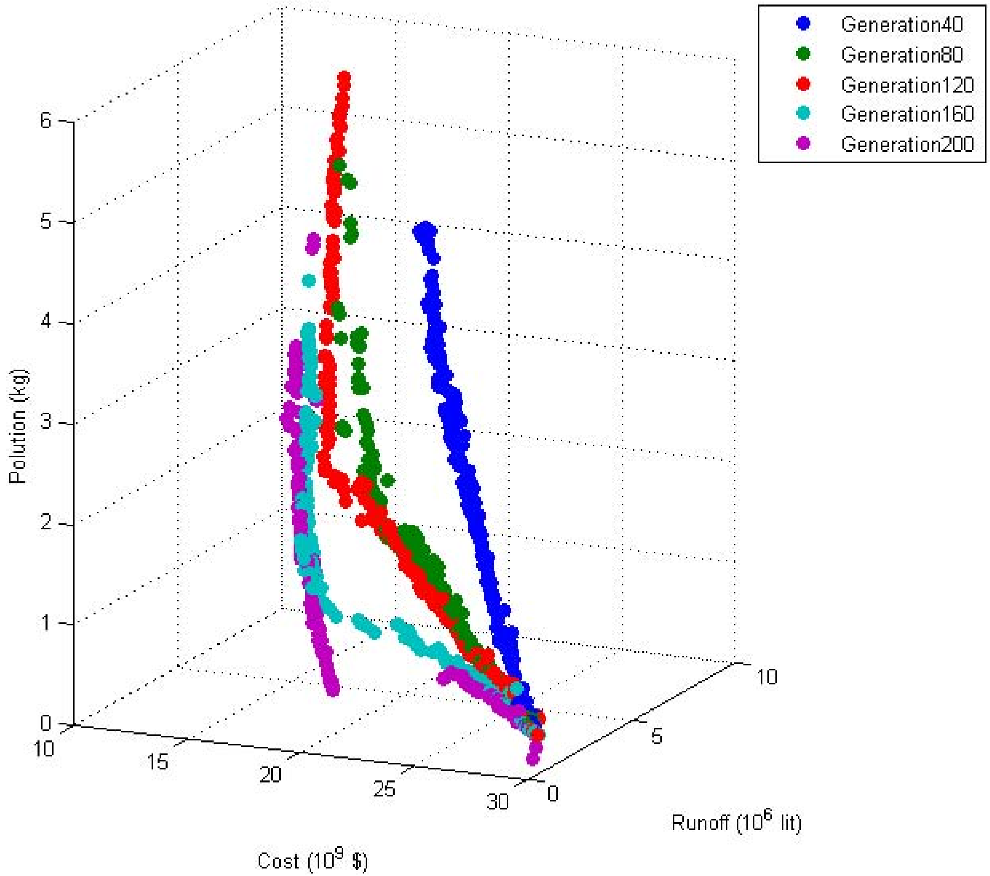

Fig. 13. The convergence procedure in NSGAII.

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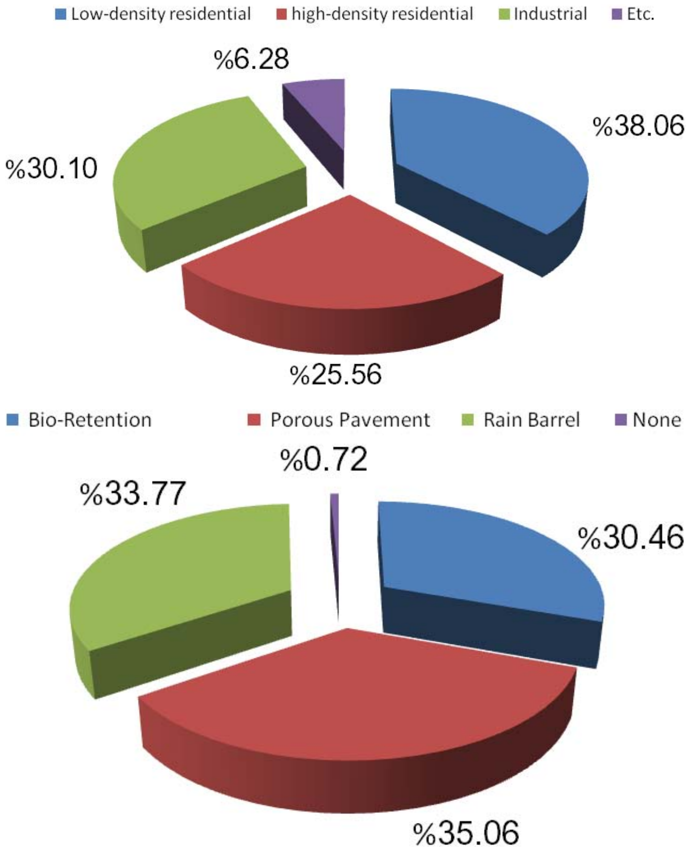

Fig. 14. Area percentage in corresponding chromosomes of the least amount in pollution and runoff objective function.

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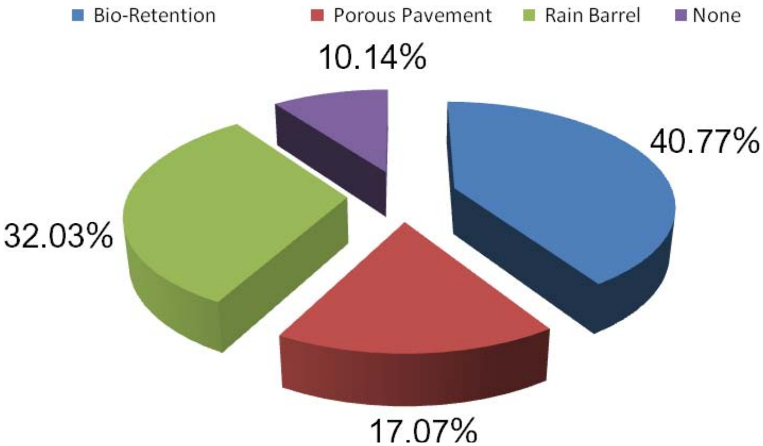

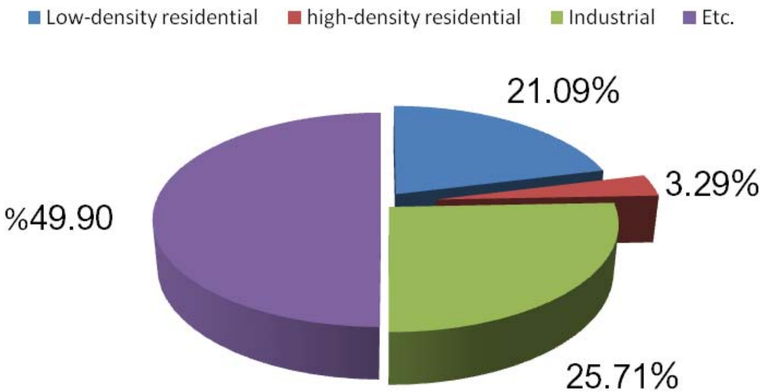

Fig. 15. Area percentage in corresponding chromosome with the lowest cost in the objective function.

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