

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

S. Oraei Zare¹, B. Saghafian ¹, A. Shamsai ² and S. Nazif ³

[1] Department of Technical and Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

[1] Department of Technical and Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

[2] Department of Civil Engineering, Sharif University of Technology, Tehran, Iran

[3] Department of Civil Engineering, Univ. of Tehran, Tehran, Iran

Correspondence to: S. Oraei Zare (sadegh.oraei@gmail.com)

Abstract

Urban development affects the quantity and quality of urban runoff. In recent years, a concept called best management practices (BMPs) 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 is still under research. In this paper, three objective functions related to the minimization of the quality and quantity of runoff, as well as low construction costs are

considered. The Biological Oxygen Demand (BOD5) and total Total Suspended Solid (TSS) parameters are employed as measures of urban runoff quality. Furthermore, the runoff volumes produced at each sub-basin are representative of runoff quantity. The construction and maintenance cost of the BMPs are also estimated based on the local price standards. Urban runoff quantity and quality in the case study watershed is simulated with SWMM model. MOPSO (Multi-Objective Particle Swarm Optimization) and NSGA-II (Non-Dominate Solution Genetic Algorithms) optimization techniques are applied to derive the optimal trade off curve between various objectives. In the proposed structure for NSGAI algorithm, a continuous structure and intermediate crossover are used because they perform better as far as the optimization efficiency is concerned. To compare the performance of the two optimization techniques, a number of statistical indicators (standard diffusion, mean, frequency and normal distribution curve) are computed for the last generation of solutions. The results indicated that the NSGAI pareto solution was more optimal than that of the MOPSO. For example, standard deviation of solutions in the last generation showed differences between MOPSO and NSGAI techniques. Finally flood management scenarios were presented based on the optimal trade-off curve using k-means method.

Keywords: BMPs, Optimization, Runoff, Quality, Quantity, SWMM, NSGA-II, MOPSO

1- Introduction

Financial risks and health threats attributed to urban floods has always been a challenge 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 measures aimed at prevention and/or crisis management during and after the floods are part of flood management. In recent years, a new 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 techniques that was coupled with a watershed model, i.e. the Agricultural Nonpoint Source Pollution model (AnnAGNPS), to minimize pollution cost under various combinations of BMPs. They used the AnnAGNPS model to assess

long-term reservoir performance subject to deposition of sediments. Moreover, using the scatter search algorithm, they selected the best locations for storage reservoirs.

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 a 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 pond in multiple parallel catchment using dynamic programming. Graupensperger and Stroschein (2003) emphasized the use of 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 storm-water systems by the aggregation of economic-financial indicators with performance indicators. Based on their methodology, a decision aid tool (AvDren) was created to allow the choice of convenient projects 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 -NSGAI algorithm to optimize both the flood volume and cost of implementing three types of BMPs. They found their methodology as an efficient algorithm in management 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 best management practices 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, requiring an optimization approach. A Pareto frontier describing the trade-off between the numbers of BMPs, representing project cost, and watershed flooding was developed.

Rodriguez et al. (2011) showed that the BMPs (combinations of pasture management, buffer zones, and poultry litter application practices) were effective in controlling water. Also They used NSGA-II to select and locate BMPs that minimize nutrients pollution cost effectively by providing trade-off curves between pollutant reduction and total net cost increase. Their optimization model generated a number of near-optimal solutions by selecting from 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 in 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 flood quantity and quality control measures are simulated using SWMM model in a case study urban watershed in Iran. In an optimization framework, three objective functions are developed for optimum flood quantity and quality control. The aerial coverage level of each BMP in each sub-basins is considered as a decision variable. Optimal decision variables are determined using MOPSO and NSGAI evolutionary optimization algorithms. The results of the proposed model are extracted in the form of the optimal trade-off curves. Each point on this curve represents a flood 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. In at least a number of times per year, Tehran residents must cope with excessive runoff impeding the traffic and causing damage to the 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 south of the city where they are used for irrigation. Thus, implementation of integrated flood management to deal with quantity and quality issues is a necessity.

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 to 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 meters above mean sea level, while the lowest is 1264 meters. The urban area of about 670.2 hectare is divided into 32 sub-basins (Figure 1). A typical rainfall temporal pattern derived from observations with a 5-year return is shown in Figure 2

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. Furthermore, specific urban flood management scenario can emerge from the analysis. Now, the procedure of conducting details of the methodology is described below.

3.1 Data Needs

Three types of data used in the study include: 1. Physiographic and hydrological data such as land use, rainfall statistics and the sub-basin characteristics; 2. Hydraulic data such as channel network and dimensions, roughness coefficient and required elevations; 3. Quality data for build up and wash off model simulation.

3.2 Hydraulic, hydrologic and quality modelling using SWMM

In this study, Storm Water Management Model (SWMM) was employed to simulate quantity /quality hydrologic and hydraulic routing of urban runoff. SWMM has been 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 handling both water quantity and quality routing aspects. Typical urban settings such as manholes, underground pipes, storage units, dividers, orifices, weirs, and open channels can be represented 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. The CN method was adopted since the runoff depth may be expressed in terms of readily available land use and hydrologic soil groups maps. The CN method has been embedded into various watershed models for hydrologic, flood analysis, water quality and quantity modelling and land use optimization (Yeo and Guldman, 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).

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

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 via surface runoff (Hossain and Imteaz, 2009). Storm-water 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

In SWMM, a pollutant model has been developed and integrated with the runoff model. The model will first estimate the pollutants build-up from a catchments during the antecedent dry days (the days without rain) and then simulates 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 catchments surfaces is a function the number of preceding dry weather days. Pollutant build up 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. Generally, mass is expressed with two units such as pounds in US units and kilograms in SI units. In this

study, kilogram is used for mass parameter. The amount of build up is a function of the number of preceding dry weather days (Rossman, 2010; Egodawatta et al., 2009) as follows

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

where B is the pollutant build-up (mass per unit area or curb length, kg/100-m), C_1 is the maximum build-up possible (mass per unit area or curb length, kg/100-m), C_2 is the build-up rate constant (kg/day*100-m), t is the number of preceding dry weather days and C_3 is the time exponent.

- **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 follows.

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

where is the wash-off load (W) in units of mass per hour (kg/hour), B_1 is the wash-off coefficient (dimensionless), B_2 is the wash-off exponent (dimensionless), q is the runoff rate per unit area (mm/hour), and M is the pollutant build-up in mass units (kg). The build up here is the total mass (not per area or per curb length). Both build-up and wash-off mass units are the same as used to express the pollutant's concentration (milligrams, micrograms, or counts).

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

3.3 Selection of BMPs

There are varieties of BMPs that can be used on a site. Not all BMPs techniques 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 the appropriate BMP are land use characteristics, site characteristics, catchments characteristics, quantity and quality performance requirements, amenity and environmental requirements. The selected BMPs applied in this research consist of rain barrel, porous pavement, and bio-retention. Due to great need for

expanding the green space in Tehran area to meet the standards, bio-retention was selected. Porous pavement is a feasible BMPs in areas such as parking, courtyard houses and sidewalks. Rain barrels are suited to urban buildings and can supply a portion of non-potable water.

- **Porous pavements**

Porous pavements are sustainable drainage systems (SUDS) 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 infiltrating into the ground, reuse, or discharge to a watercourse or other drainage systems. Pavements with aggregate sub-bases can provide good water quality treatment. The three principal system types are described in Figure 3 to Figure 5.

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).

- **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 from 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 convey water in excess of the design volumes to appropriate receiving drainage systems safely (Figure 6).

- **Rain barrel**

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.

3.4- Structure of the proposed multi-objective model

- **Decision variables**

Decision variables for each sub-basin include BMP type 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-basins 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 feasibility in the study area.

- **Objective Functions**

Three objective functions were considered in this study: minimization of the total damages caused by floods, reducing the amount of TSS and BOD quality parameters up to the standard level and minimizing the total runoff. The mathematical structure of the objective functions and constraints are presented below.

Objective Functions:

$$F_1 = \min \left(\sum_{i=1}^{32} \left(\sum_{j=1}^3 (\cos tI_{ij}) + \sum_{j=1}^4 (C_j^L A_j^L) + 10.13 \left(A_i^T - \sum_{j=1}^3 A_j^L \right)^{0.7} \right) + \cos tD \right) \quad (3)$$

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

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

where:

$$\text{cost}I_{ij} = 10.13A_{ij1}^{0.7} + 1.6A_{ij2} + 587.3A_{ij3} - 432 \quad (6)$$

$$\text{cost}D = \sum_{f=1}^{nflood} (3.28 \times h_f^3 - 22.9 \times h_f^2 + 51.2 \times h_f + 2) \quad (7)$$

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

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

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

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

$$\nabla_f = f \left(SWMM \left(\left[\sum_{j=1}^3 A_{ij1} + \left(A_i^T - \sum_{j=1}^3 A_j^L \right), \sum_{j=1}^3 A_{ij2}, \sum_{j=1}^3 A_{ij3} \right], C_i, C_i^n \right) \right) \quad (12)$$

$$Con_p^{ave} = \frac{\sum_{i=1}^{32} (Ct_i^p \times A_i^T)}{\sum_{i=1}^{32} A_i^T} \quad (13)$$

The above relationships are subject to the following constraints:

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

$$A_{ij1} = A_i^T - \sum_{j=1}^3 A_j^L, \quad i = 1, 2, \dots, 32, \quad j = 4 \quad (15)$$

$$0 \leq \sum_{k=1}^3 A_{ij2} \leq 0.6 \times \sum_{j=1}^3 A_j^L, \quad i = 1, 2, \dots, 32 \quad (16)$$

$$0 \leq \sum_{k=1}^3 A_{ij3} \leq A_i^T - 0.6 \times \sum_{j=1}^3 A_j^L, \quad i = 1, 2, \dots, 32 \quad (17)$$

All variables are defined as follows:

i : refers to sub-basin

j : refers to land use type

k : refers to BMP type

C_j^L : cost of developing j -th land use (Table 2)

$\cos tI_{ij}$: BMP construction cost over the j -th land use type in the i -th sub-basin (Details of the costs are according to Table 3)

A_j^L : Total area of j -th land use (m^2)

A_i^T : Total area of i -th sub-basin (m^2)

$\cos tD$: 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)

$nflood$: 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 from height at the f -th flooding node

\forall_f : Runoff volume at the f -th flooding node (m^3)

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^r : Curve number attributed to the j -th land use (Table 4)

C_i : Average curve number of the i -th sub-basin

c_j^n : Runoff coefficient attributed to the j -th land use (Table 5)

C_i^n : Runoff coefficient of the i -th sub-basin

$f(SWMM(\))$: SWMM simulation model

Con_p^{ave} : Average value of pollutant p over the entire basin (mg/l)

Con_p^{st} : Standard value of pollutant p (mg/l)

np : Number of pollutants involved in the simulation

Ct_i^p : Concentration of the pollutant p over the i -th sub-basin (mg/l)

R_i : Runoff volume in the i -th sub-basin (m^3)

Non-dominated Sorting Genetic Algorithm (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) optimization techniques were employed to handle the multi-objective optimization task. For this purpose, required data as well as the characteristics of the BMPs are inputted to the SWMM. Then, for various values of decision variables, the SWMM simulation model is run and flooded areas are identified in each sub-basin. The cost of flood damage is determined using Eq. (7). The cost of implementing BMP in any sub-basin is also considered. Accordingly, land use construction cost in each sub-basin may be calculated via Eq. (6). Based on quality simulation results, TSS and BOD₅ values at each node is determined and compared with the standard values. If the simulated values exceed the standards, then the loss function is determined based on Eq. (13). The total volume of runoff produced in all flooded nodes constitutes the total amount of runoff as in Eq. (5). A trade-off curve among the objectives is then extracted that contains various control scenarios.

Figure 7 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, kilogram and cubic meters, respectively. It should be noted that according to equation 4, the value of 2nd term in second objective function is dimensionless. This term is associated with the penalty function.

3.5 Multi-objective evolutionary optimization algorithms

- **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 non-dominated sorting genetic algorithm (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 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. The major difference between 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 holds three new innovation 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: 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 m objectives.

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.

The pseudo code of the NSGA-II is shown in Table 7 (Deb et al., 2000). In addition, Figure 8 shows the flow diagram that illustrates the way that NSGA-II works in which P_t is the

parent population and Qt is the offspring population at generation t , $F1$ is the best solution from the combined populations (parents and offspring) and $F2$ are the second best solutions and so on.

- **Particle swarm optimization algorithm (PSO)**

PSO is a social search algorithm based on the social behaviour of bird bands. PSO algorithm, first described by Kennedy and Eberhart (1995), 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. This may be mathematically expressed by:

$$V_i^{i+1} = \chi(wV_i^i + c_1 \text{rand}(0,1)(pbest_i - X_i^i) + c_2 \text{rand}(0,1)(gbest_i - X_i^i)) \quad (18)$$

$$X_i^{i+1} = X_i^i + V_i^{i+1} \quad (19)$$

where V_i^{i+1} is the velocity of particle i in the new repetition, V_i^i is the velocity of particle i in the current repetition, X_i^i is the current position of the particle, $pbest_i$ is the best position for the i particle, X_i^{i+1} is the particle position in the new repetition, $gbest_i$ is the best position of particle i and $\text{rand}(0,1)$ is a random number between 0 and 1. The 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 neighbours. Both are normally defined as constants.

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 χ is the constriction factor which can restrict the velocity as well as the w parameter (Table 6).

In order to apply multi-objective PSO for the current problem, the original scheme has to be modified. In a multi-objective optimization framework, we aim to find not one, but a set of different solutions (the so-called Pareto optimal set). In general, the main goal is 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. So, 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 MOPSO apply some sort 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, 2011).

4. Results and Discussion

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 assigned. For this purpose, the proposed values in the Tehran master plan were used as the base while the lower and upper ranges were 10% less than and greater than the base values, respectively.

Based on Figure 9 and Figure 10, rain barrel and porous pavement have similar performance to reduce the quantity and quality of flood. 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 barrel would have a stronger effect on improving the quality and quantity (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 BMPs' 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 cost) versus BMPs' coverage area is illustrated in Figure 11. As it is observed, the costs of bio-retention and porous pavement change slightly compared to the rain barrel.

4.2- Sensitivity analysis to combined selection of decision variables

Different combination of variables were studied in the sensitivity analysis of optimization results based on three objective functions. The combinations were: (A) BMPs & land use areas; (B)

land uses areas; and (C) BMPs. The aim of sensitivity analysis was to determine the change in values of objective functions in the Pareto front end. As shown in Table 8, combination A showed the best capability for reducing the quality and quantity of runoff. Regarding the expenses, reduction of the second and third objective functions under combination A was more than B and C combinations. Thus, only combination A was further studied in the following. Figure 12 shows the results of the last generation of Pareto front corresponding to the three combinations.

4.3- Comparison of MOPSO and NSGAII Algorithms

To determine the optimal trade-off between the objective functions, maximum number of iterations must be specified. The two optimization algorithms were run for different number of iterations. The results of NSGA-II algorithm is shown in Figure 13 for 40 to 200 iterations. According to this figure, 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 NSGA-II algorithm. A similar process was repeated for the MOPSO algorithm. Accordingly, the appropriate number of iterations was found to be 150 for MOPSO algorithm.

As far as convergence to the trade-off curves, the criterion proposed by Chen et al. (2007) was adopted. In this criterion, the distribution of production solution set and 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 can be presented as follows:

$$DM = \frac{d_b + d_e + \sum_{i=1}^{n-1} |d_i - \bar{d}|}{d_b + d_e + (n-1)\bar{d}} \quad (20)$$

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

The NSGA-II algorithm convergence condition is met when the criterion value is as close to zero as possible. The criterion for NSGA-II and MOPSO algorithms were calculated at 0.4 and 0.65,

respectively. These values generally indicate suitability of the number of iteration for the two algorithms.

Based on the optimal trade-off curve obtained with the two algorithms, a range of variation objective functions may be identified (Figure 14). According to this figure, the rate of variation in MOPSO algorithm is higher than that of the NSGA-II algorithm.

Variation of objective functions in the two algorithms in terms of the average and standard deviation of the solution set are presented in

Table 9. According to this table that we can get the standard deviation of objectives in MOPSO algorithm is less than NSGA-II algorithm. Drawing the frequency and normal distribution associated optimal trade-off curve that produced by NSGA-II and MOPSO tools for objective functions, can be well found due to low standard deviation in MOPSO algorithm (Figure 15 to Figure 20).

As it can be seen in the table, NSGAII algorithm (in the Pareto front solutions) is better at providing results according to the indicators. Although the variation rang in MOPSO algorithm is higher than that of the NSGA-II algorithm (Figure 14), the answers in NSGA-II algorithm have adequate dispersion. . Since the selection of parameters has a significant impact on the acceptability of the optimal solution Other algorithm parameters were chosen based on recommendations about the selection of relevant parameters based on available literature (Eberhart and Kennedy, 1995; Parsopoulos and Vrahatis, 2002; Carlisle and Dozier, 2001).Then, the effects of the parameters' variation on the solution were assessed and suitable parameters were selected.

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 k centroids, one for each cluster. These centroids should be placed in a cunning way because different location produces 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 recalculate 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. A loop is generated. As a result of this loop, 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:

$$J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2 \quad (21)$$

where $\|x_i^{(j)} - c_j\|^2$ 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 flood management scenarios were reduced based on the optimal trade-off curve using 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 10 shows the range of the objective functions of each class representative. Based on the selected classes, range of variation of decision variables were determined. For example, Figure 21 to Figure 23 show the variation range of decision variables associated with classes 1, 5 and 10. According to these figures, due to very small changes in the decision variables it may be

concluded that the number of classes is a suitable choice. Thus, the number of scenarios can be reduced from 200 to 10 and decision makers may opt for one of these 10 scenarios for flood control management.

5- Conclusions

Decision-making in urban storm-water control always involves maximizing the improvements in the runoff quantity and quality while minimizing the total control costs. Thus a Pareto-front that depicts 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 BMPs, such as detention basins (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 SWMM model. The results provided optimal scenario for urban flood management. Infiltration was modelled based on the SCS Curve Number method while flow routing was performed using kinematic wave method. In water quality simulation, runoff pollutant loads (TSS and BOD5) were modelled using build-up and wash-off equations.

Three different BMPs were considered based on the features and limitations involved in the urban runoff quantity and quality control. The selected BMPs consisted of rain barrel, porous pavement, and bio-retention. The area coverage of BMPs in each sub-basin were identified as the decision variables. Based on the proposed management model, the optimal trade-off curves were determined using two optimization algorithms, namely MOPSO and NSGA-II.

To compare the performance of the two optimization techniques, a number of statistical indicators (including standard diffusion, mean, frequency and normal distribution curve) were computed for the last generation of solutions. According to Table 9, it is implied that the mean values in NSGA-II are less than that of the MOPSO while it is the reverse in the standard deviation parameter. This demonstrates that NSGA-II is more efficient. Moreover, the NSGA-II is a more capable optimization algorithm due to features such as crowd distance and better speed. However, the MOPSO operates more easily since it has less parameter.

The results also showed that the rain barrel and porous pavement had similar performances to reduce the quantity and quality of flood. Also, the increased level of coverage continuously improved the objective functions despite increased construction and operation costs.

k-means clustering method was also employed to reduce flood 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 range of decision variables were determined. Thus, the number of applicable scenarios may be reduced from 200 to 10, enabling the decision makers to deal with only 10 flood management scenarios.

6- References

- Arnold, J.G., Srinivasan, R., Muttiah, R.S., and Williams, J.R.: Large Area Hydrologic Modeling and assessment – Part I: Model Development, *J. Am. Water Resour. As.*, 34(1), 73–89, 1998.
- ASCE.: Design and Construction of Sanitary Storm Sewers, American Society of Civil Engineers, Manuals and Reports on Engineering Practice No. 37, New York, NY, 1970.
- Baptista, M., and Nascimento, N., and Castro, L.M.A., and Fernandes, W.: Multicriteria evaluation for urban storm drainage, Proceedings of the first switch Scientific Meeting University of Birmingham, Birmingham, UK, 1-8, 2007.
- Bingner, R.L. and Theurer, F.D.: AnnAGNPS Technical Processes (Version 2), Available at: www.ars.usda.gov, 2001.
- Carlisle, A. and Dozier, G.: An off-the-shelf PSO, paper presented at the Particle Swarm Optimization Workshop, Purdue Sch. of Eng. And Technol., Indianapolis, Indiana, 2001.
- Chang, L.C.; Chang, F.J.: Multi-objective evolutionary algorithm for operating parallel reservoir system, *Journal of Hydrology*, 377(1-2), 12–20, 2009.
- Chen, L., McPhee, J., and Yeh, W.W.-G.: A diversified multiobjective GA for optimizing reservoir rule curves, *Advances in Water Resources*, 30(5), 1082–1093, 2007
- Cheng, J.Y.C.: Modification of Kinematic Wave cascading model for low impact watershed development, Ph.D. theses , University of Colorado at Denver, 242 pp., 2011.

- Coello, C.C.A.: An Introduction to Multi-Objective Particle Swarm Optimizers, Springer, 2011.
- Deb, K. and Samir, A. and Amrit, P. and Meyarivan ,T.: Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II, Indian Institute of Technology Kanpur, India, 11 pp., 2000.
- Egodawatta, P. :Translation of small-plot scale pollutant build-up and wash-off measurements to urban catchment scales, phd thesis, Faculty of Built Environment and Engineering, Queensland University of Technology, 334 pp., 2007.
- Egodawatta, P. and Thomas, E. and Gonnetilleke, A.: Understanding the physical processes of pollutant build-up and wash-off on roof surfaces, Science of Total Environment, 407, 1834-1841, 2009.
- Elliot, A.H.: Model for preliminary catchment scale planning of urban storm water quality controls, Journal of Environmental Management, 52(3), 273-288, 2009.
- Graupensperger, T.A. and Stroschein, T.A.: Storm water BMPs water quality maintenance and protection, Proceedings of the 2003 Pennsylvania Storm water Management Symposium Held at Villanova University, 1-10, 2003.
- Guo, J.C.Y. and Urbonas, B.: Conversion of Natural Watershed to Kinematic Wave Cascading Plane, J. Hydrol Eng, 14(8), 839-846, 2009.
- Harrell, L. J. and Ranjithan, S. R.: Detention pond design and land use planning for watershed management, Journal of Water Resources Planning and Management, 129(2), 98-106, 2003.
- Hossain, I. and Imteaz, M.A. and Gato, T.S. and Shanableh, A.: Development of a Catchment Water Quality Model for Continuous Simulations of Pollutants Build-up and Wash-off, International Journal of Civil and Environmental Engineering, 2(4), 210-217, 2010.
- Hossain, I. and Imteaz, M.A.: Development of a deterministic catchment water quality model, Proceedings of the 32nd Hydrology and Water Resources Symposium, 48-53, 2009.
- Huber, W. C. and Stouder, M.: BMP Modeling Concepts and Simulation, Open File EPA/600/R-06/033, U.S. Environmental Protection Agency (EPA), Cincinnati, OH., United State, 189 pp, 2006.
- Kennedy, J. and Eberhart, R.: Article Swarm Optimization, Proceeding of International Conference on Neural Networks, Perth, Australia, Nov. 27 - Dec. 1, 1942-1948, 1995.

- Lee, J.G. and Heaney, J.P. and Lai, F.: Optimization of integrated urban wet-weather control strategies, *Journal of Water Resources Planning and Management*, 131(4), 307-315, 2005.
- MacQueen, J.B., Some Methods for classification and Analysis of Multivariate Observations, *Proceedings of 5-th Berkeley Symposium on Mathematical Statistics and Probability*", Berkeley, University of California Press, 1:281-297, 1967.
- Mejia, A.I. and Moglen, G.E.: Spatial patterns of urban development from optimization of flood peaks and imperviousness-based measures, *Journal of hydrologic engineering*, 14(4), 416-424, 2009.
- Parsopoulos, K.E. and Vrahatis, M.N.: Particle Swarm Optimization Method in Multiobjective Problems, *Proceedings of the ACM 2002 Symposium on Applied Computing (SAC'2002)*, pp. 603-607, 2002.
- Perez-Pedini, C. and Limbrunner, J. F. and Vogel, R. M.: Optimal Location of Infiltration-Based Best Management Practices for Storm Water Management, *Journal of Water Resources Planning and Management*, 131(6), 441-448, 2005.
- Rathnam, E. V. and Cheeralaiiah, N. and Jayakumar, K. V.: Dynamic programming model for optimization of storm-water retention pond in multiple catchment system. *Proceedings of the International Conference on Hydrology: Science & Practice For The 21ST Century*, Imperial College, London, England, 12-16 July 2004, 326-330, 2004.
- Rodriguez, H. G. and Popp, J. and Maringanti, C. and Indrajeet Chaubey, I: Selection and placement of best management practices used to reduce water quality degradation in Lincoln Lake watershed, *Water Resources Research*, 47(1-13), W01507, doi:10.1029/2009WR008549, 2011.
- Rodriguez, H.G. and Popp, J. and Maringanti, C. and Indrajeet C. I.: Selection and Placement of Best Management Practices Used to Reduce Water Quality Degradation in Lincoln Lake watershed, *Water Resour. Res.*, 47,1-13, W01507, doi:10.1029/2009WR008549, 2011.
- Rossman, L. A.: SWMM (Storm-water Management Model) version 5.02 user's manual. EPA (Environmental Protection Agency), Open File Manual. EPA/600/R-05/040,295 pp., Washington D.C., United States, 2010.

- Soulis, K. X. and Valiantzas, J. D.: SCS-CN parameter determination using rainfall-runoff data in heterogeneous watersheds: The two-CN system approach, *Hydrol. Earth Syst. Sci. Discuss.*, 8, 8963–9004, 2011.
- Srinivas, N.; Deb, K.: Multi-objective optimization using non-dominated sorting in genetic algorithms, *Evolutionary Computation*, 2 (3), 221–248, 1994.
- Tajrishi, M. and Malekmohammadi, B.: Suitable method to accomplish flood insurance program for crisis management in flood condition of urban areas, *Proceedings of the 2nd international conference on integrated national disaster management*, Tehran, Iran, 12-13 February, 1-18, 2009.
- Woods-Ballard, B. and Kellagher, R. And Martin, P. and Jefferies, C. and Bray, R. and Shaffer, P.: *The SUDS manual*, Published by CIRIA, London, 2007.
- Yeo, I. Y. and Guldman, J. M.: Global spatial optimization with hydrological systems simulation: application to land-use allocation and peak runoff minimization. *Hydrol. Earth Syst. Sci.*, 14, 325–338, 2010.
- Zhang, G. and Hamlett, M.J. and Reed, P.: Multi-Objective Optimization of Low Impact Development Scenarios in an Urbanizing Watershed. *Proceedings of the AWRA Annual Conference*, Baltimore, Usa, 1-7, 2006.
- Zhen, X. and Yu, S.L. and Lin, J.: Optimal location and sizing of storm water basins at watershed scale, *Journal of Water Resources Planning and Management*, 130(4), 339–347, 2004.

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

Equation of Pollution	parameter	Land Use							
		Low Density		High Density		Industrial		Other	
		C1*	C2*	C1	C2	C1	C2	C1	C2
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
WASH-OFF	parameter	B1**	B2**	B1	B2	B1	B2	B1	B2
	TSS	0.4	0.2	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

C₁: kg/100-m (100-m related to length curb) & C₂: kg/day /100-m

B₁ & B₂: dimensionless

Table 2- 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

Table 3- Implementation cost of BMPs

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

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

Table 4- Characteristic curve number (CN) in different land uses

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

Table 5- Run off Coefficient in different local areas (%) (ASCE, 1970)

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

Table 6- Parameters used in the MOPSO algorithm

	Global	Personal	Inertia	Grid	constriction
Parameter	Learning	Learning	Weight	Inflation	factor
name	Coefficient	Coefficient		Parameter	
	c_2	c_1	ω	α	χ
Values	1.43	1.43	0.7	0.1	1

Table 7- The procedure of NSGA-II algorithm

1:	procedure NSGA-II (N' , g , $fk(xk)$)	$\triangleright N'$ members evolved g generations to solve $fk(x)$
2:	Initialize Population P'	
3:	Generate random population - size N'	
4:	Evaluate Objective Values	
5:	Assign Rank (level) Based on Pareto dominance - <i>sort</i>	
6:	Generate Child Population	
7:	Binary Tournament Selection	
8:	Recombination and Mutation	
9:	for $i = 1$ to g do	
10:	for each Parent and Child in Population do	
11:	Assign Rank (level) based on Pareto - <i>sort</i>	
12:	Generate sets of no dominated vectors along PF <i>known</i>	
13:	Loop (inside) by adding solutions to next generation starting from the <i>first</i> front until	
	N'	
	individuals found determine crowding distance between points on each front	
14:	end for	
15:	Select points (elitist) on the lower front (with lower rank) and are outside a crowding distance	
16:	Create next generation	
17:	Binary Tournament Selection	
18:	Recombination and Mutation	
19:	end for	
20:	end procedure	

Table 8- Sensitivity analysis in variable selection after 200 generations in NSGA-II

Variable	Mean			Standard deviation		
	Cost	Runoff	Pollution	Cost	Runoff	Pollution
	(\$)*10 ⁹	(m ³)	(kg)	(\$)*10 ⁹	(m ³)	(kg)
BMPs & Land Uses	19.61	3000	1.65	4.94	1700	1.05
Land Uses	8.78	10653	4.83	0.25	97.2	0.154
BMPs	0.39	3320	172.85	0.22	1362	101.40

Table 9- Comparison of optimization results after 200 generations

Algorithm	Mean			Standard Deviation		
	Cost	Runoff	Pollution	Cost	Runoff	Pollution
	(\$)*10 ⁹	(m ³)	(kg)	(\$)*10 ⁹	(m ³)	(kg)
NSGA-II	19.61	3000	1.65	4.94	1700	1.05
MOPSO	27.79	3695	2.47	1.53	1608.7	1.51

Table 10- Range of variation of objective functions representative of each class

No. Class	Objective Function 1 (\$)*1e+9		Objective Function 2 kg		Objective Function 3 (Cubic Meter)	
	Min	Min	Min	Min	Min	Min
1	19.39	20.02	0.45	0.77	1500	1860
2	24.93	27.44	0.55	0.77	1300	1490
3	27.56	29.66	0.12	0.55	610	1530
4	17.31	17.90	1.49	1.94	2550	2940
5	17.98	18.57	1.07	1.58	2120	2800
6	14.82	15.65	2.74	3.26	4230	5550
7	15.69	16.68	2.37	2.83	3430	4030
8	13.95	14.74	2.87	4.12	5570	7200
9	18.58	19.26	0.71	1.23	1890	2250
10	16.77	17.26	1.87	2.42	2970	3400

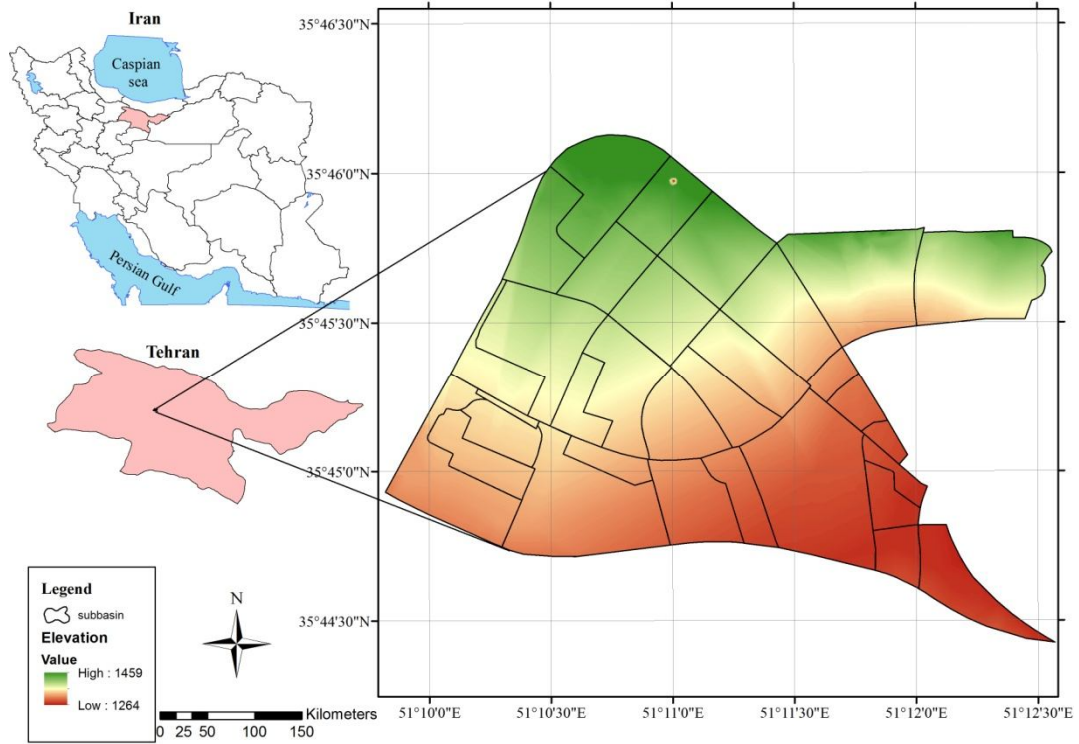


Figure 1- Location of the study area in the country and within the Tehran province

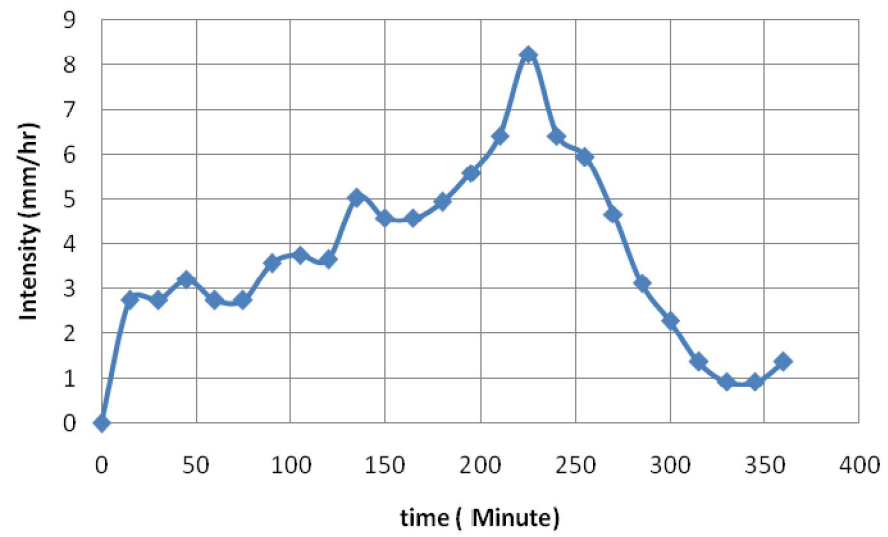


Figure 2- Rainfall design with 5 years return period

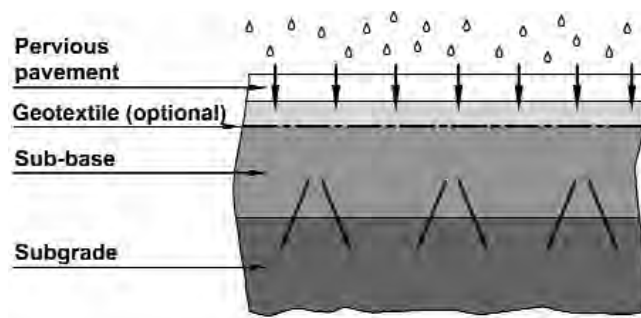


Figure 3- Porous pavement system types: Type A – Total Infiltration (Source: the SUDS manual)

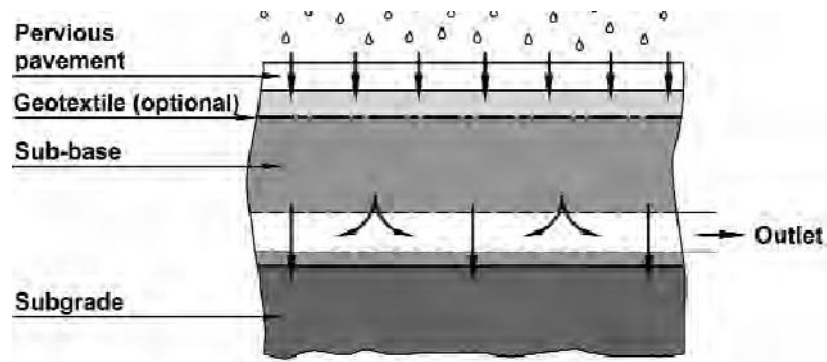


Figure 4 - Porous pavement system types: Type B – Partial Infiltration (Source: the SUDS manual)

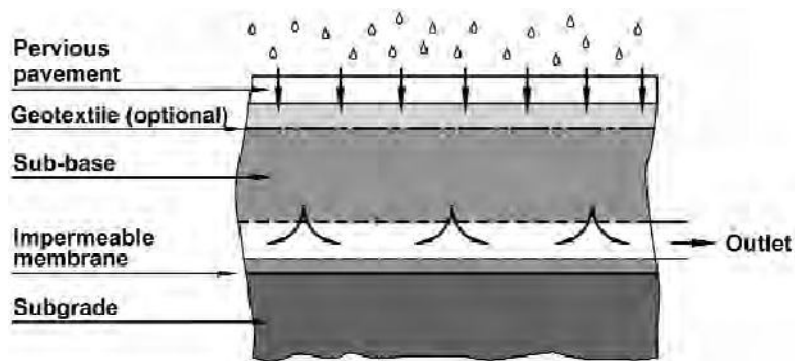


Figure 5 - Porous pavement system types: Type C – No Infiltration (Source: the SUDS manual)

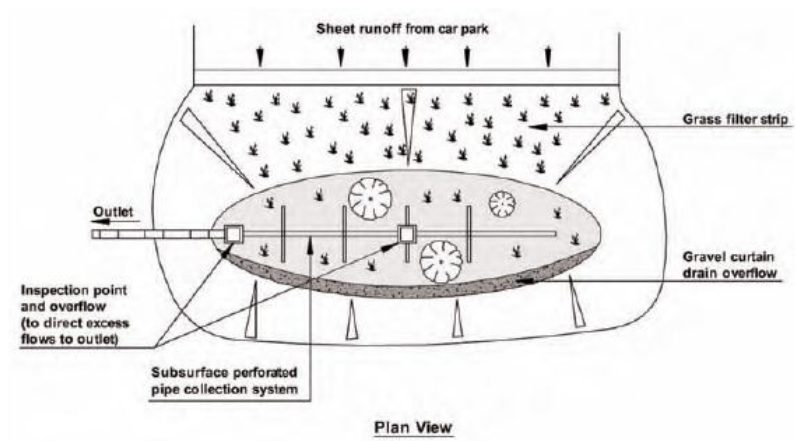


Figure 6- Plan schematics of a typical on-line bio-retention area (Source: the SUDS manual)

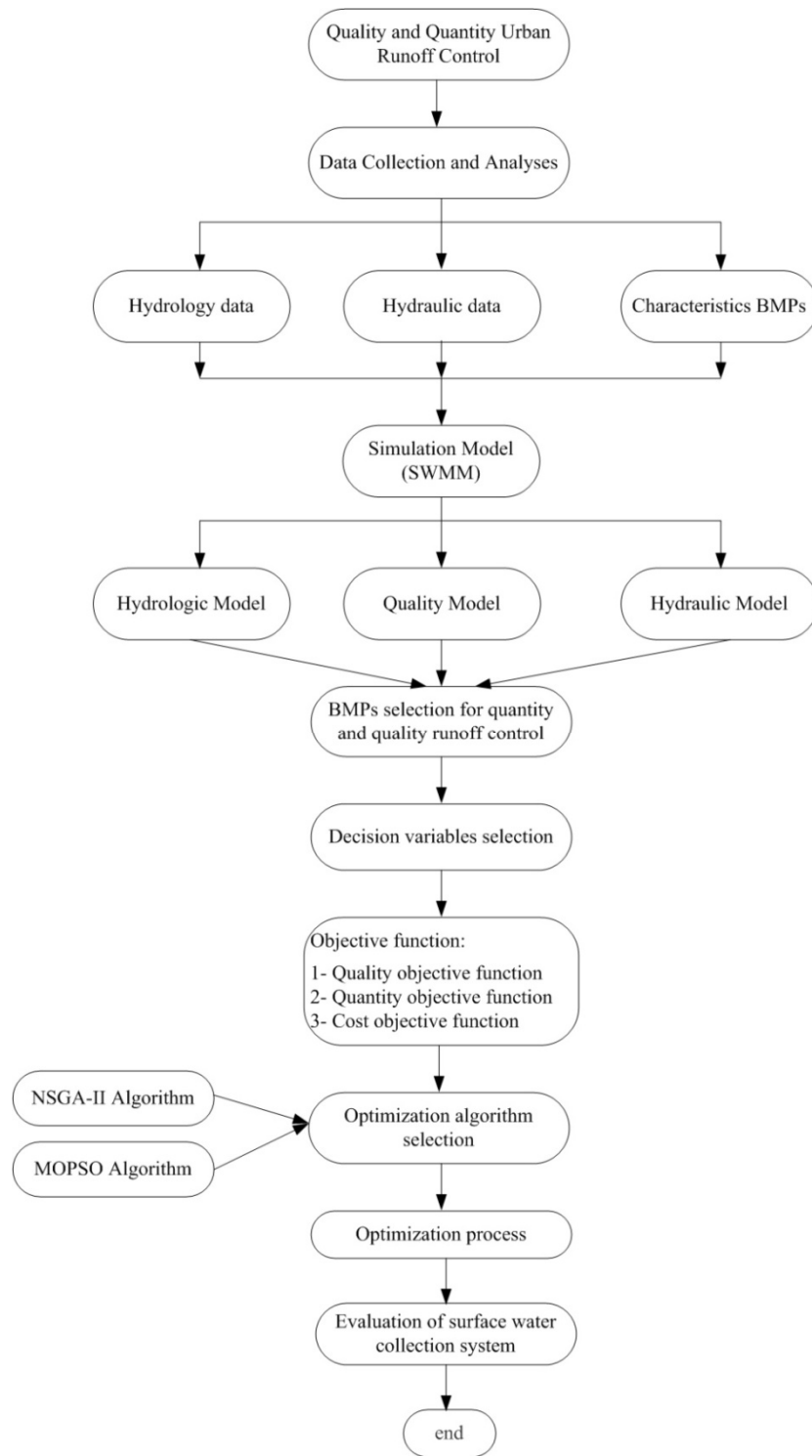


Figure 7- The process to achieve optimal trade-off curve

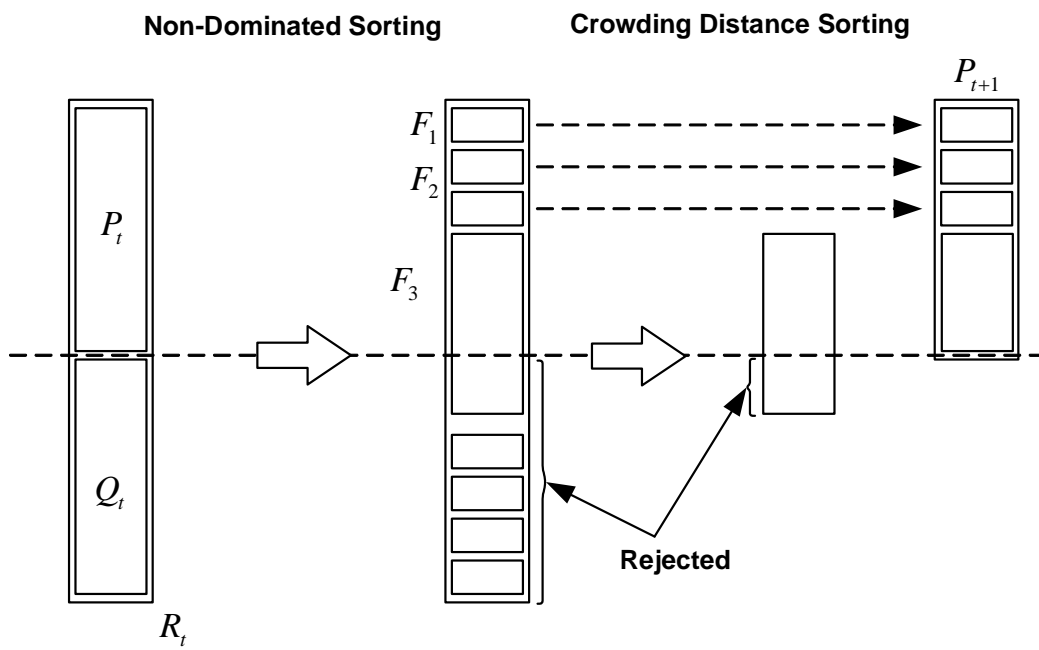


Figure 8- Flow diagram of how NSGA-II works (Source: Deb et al., 2000)

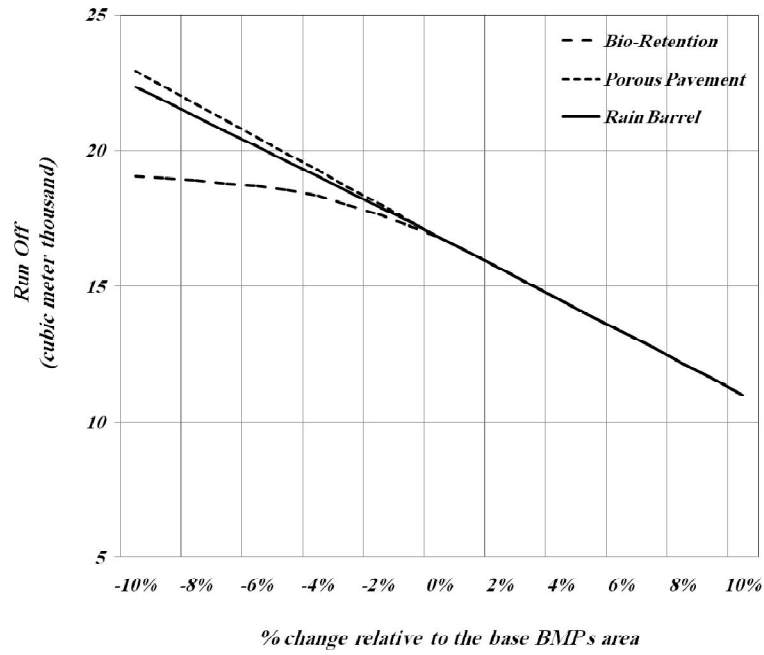


Figure 9- BMPs' efficiency in terms of runoff quantity control

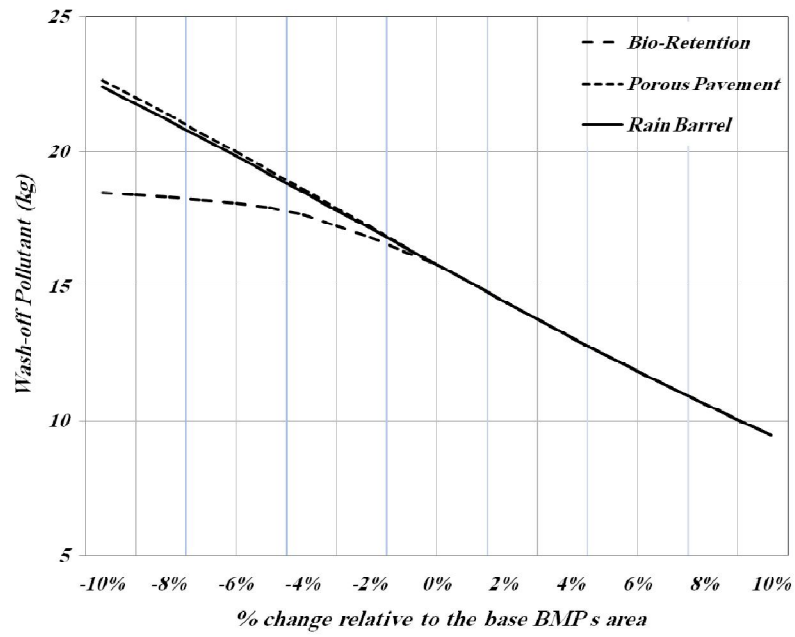


Figure 10- BMPs' efficiency in terms of runoff quality control

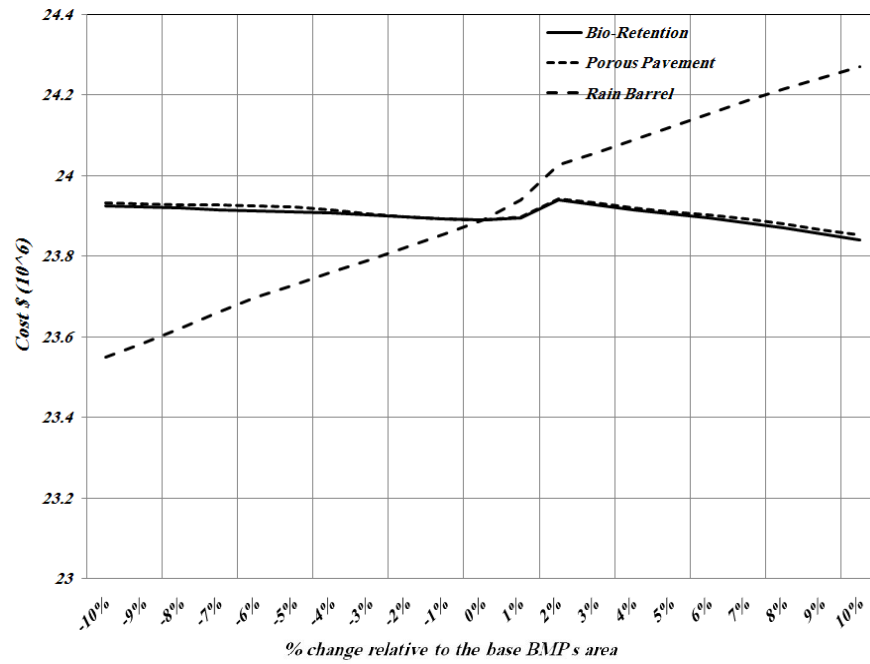


Figure 11- BMPs' effect on damage cost

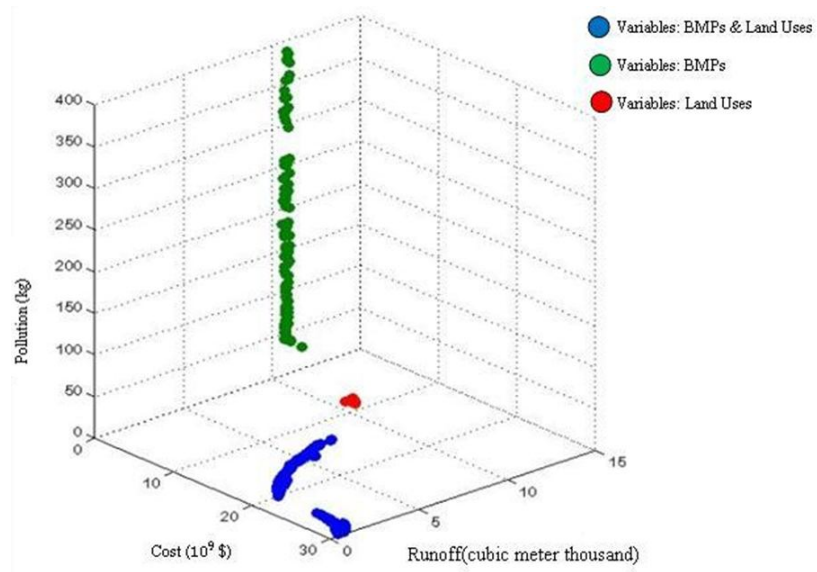


Figure 12- Results of the last generation in NSGA-II

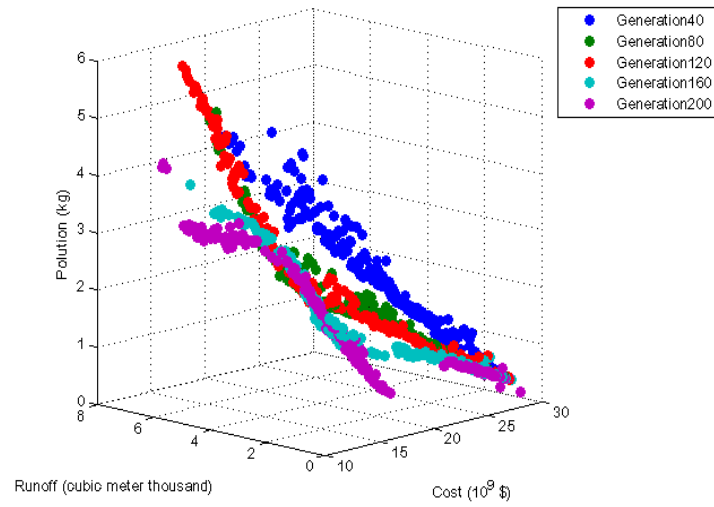


Figure 13- The convergence procedure in NSGA-II

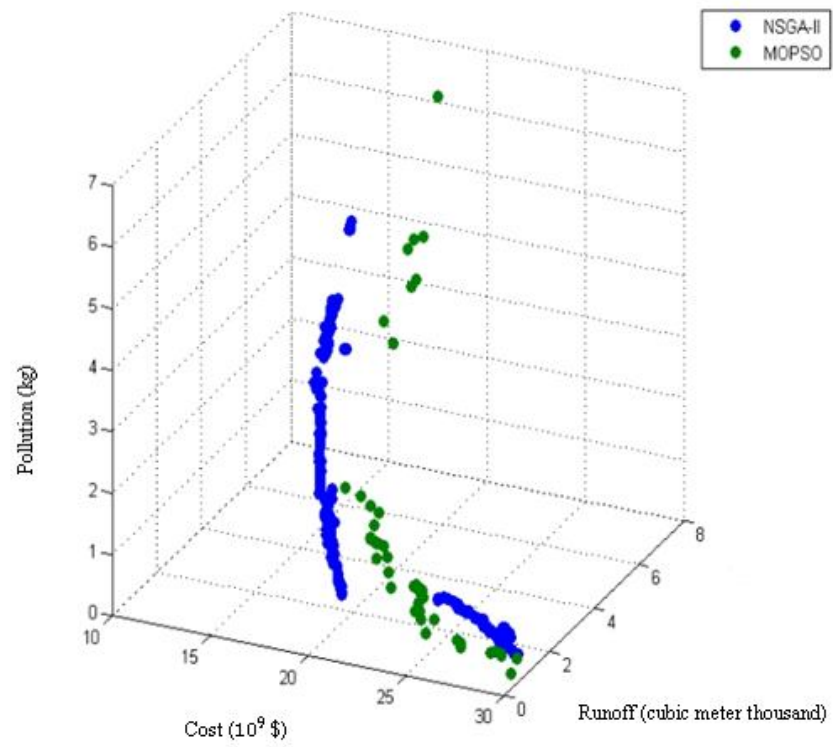


Figure 14- Comparison of the last generations in NSGA-II and MOPSO

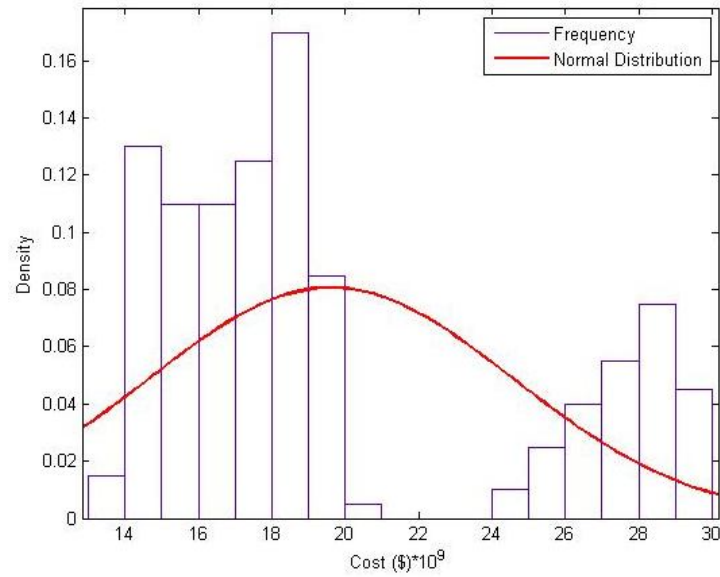


Figure 15- Frequency and normal distribution associated optimal trade-off curve produced by
NSGA-II tools for first objective function

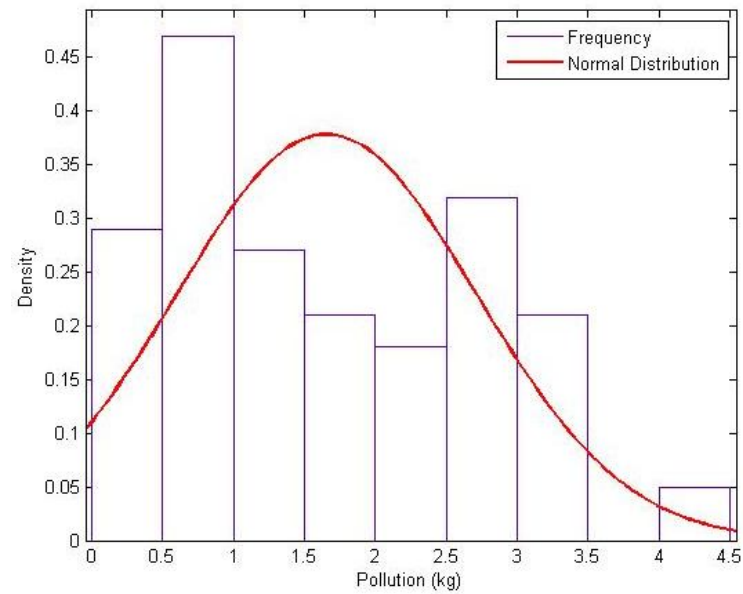


Figure 16- Frequency and normal distribution associated optimal trade-off curve produced by
NSGA-II tools for second objective function

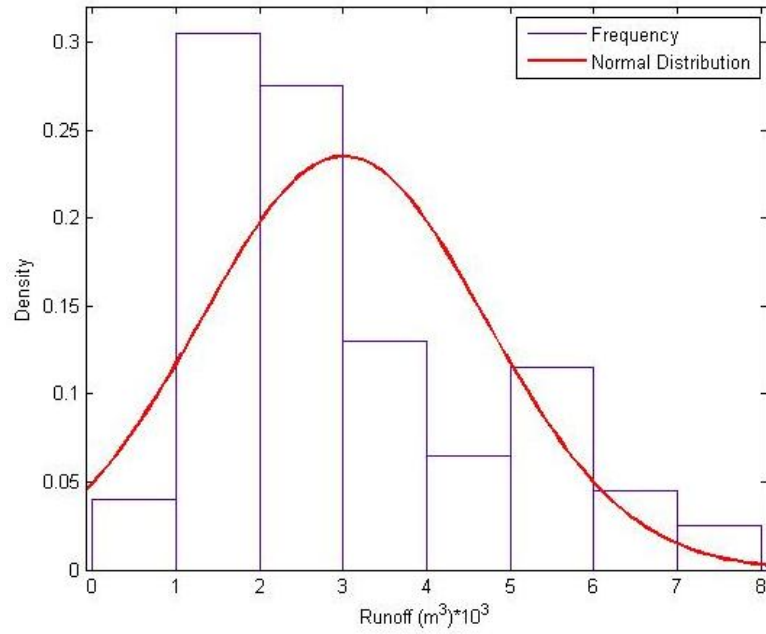


Figure 17- Frequency and normal distribution associated optimal trade-off curve produced by NSGA-II tools for third objective function

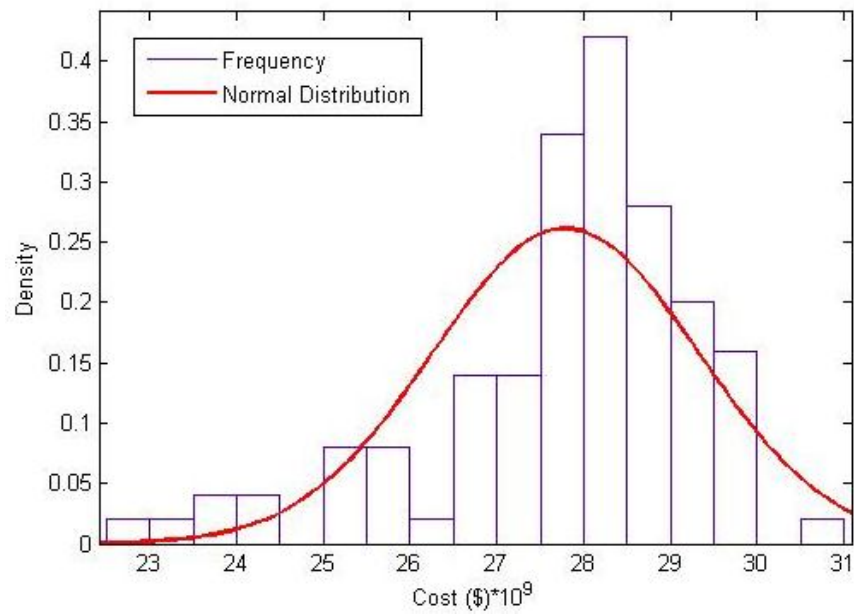


Figure 18- Frequency and normal distribution associated with the optimal trade-off curve produced by MOPSO for the first objective function

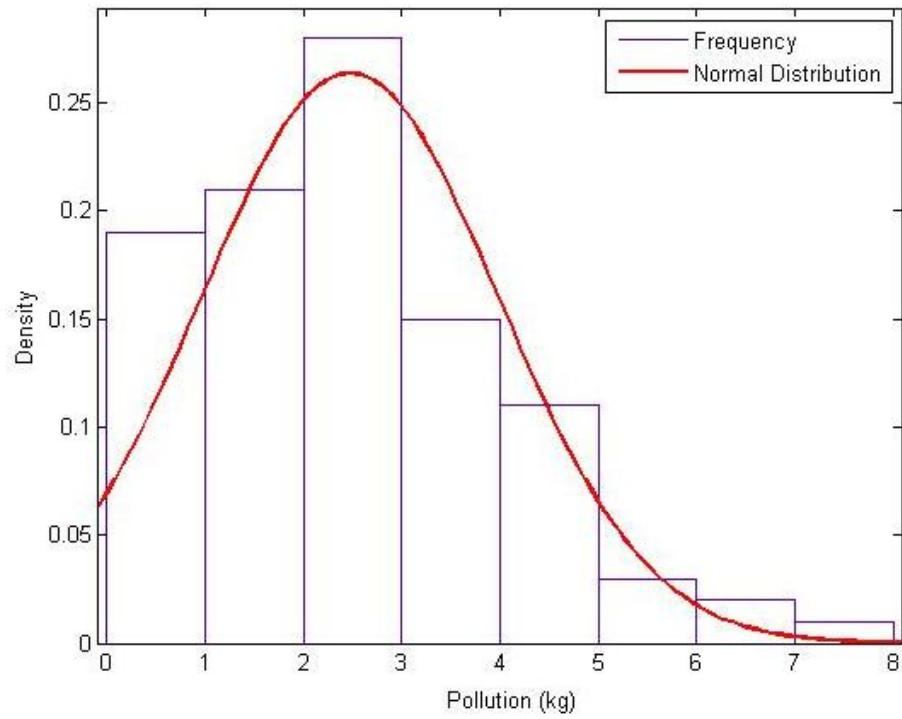


Figure 19- Frequency and normal distribution associated with the optimal trade-off curve produced by MOPSO algorithm for the second objective function

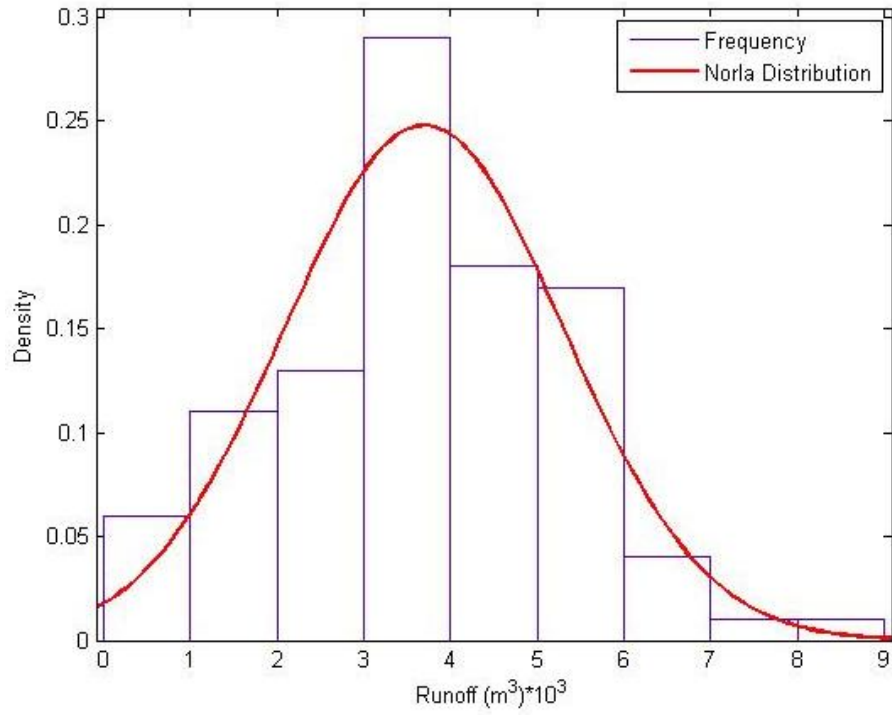


Figure 20- Frequency and normal distribution associated with the optimal trade-off curve produced by MOPSO algorithm for the third objective function

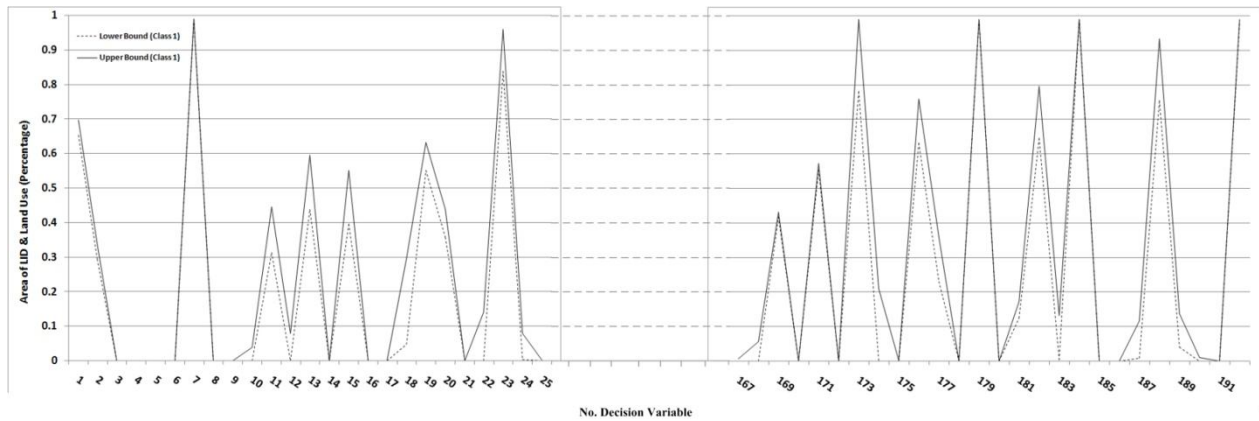


Figure 21- Variation of decision variable in class 1 based on k-mean method

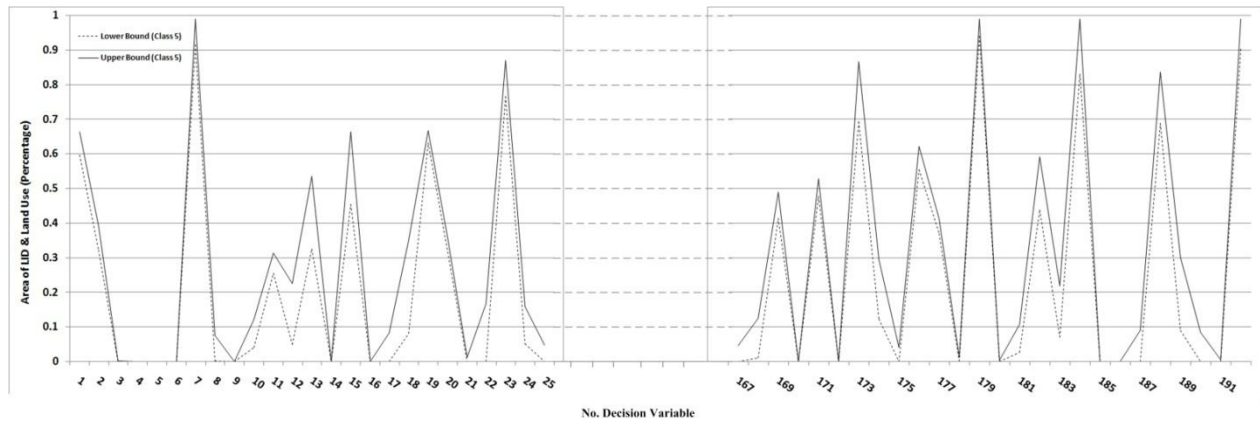


Figure 22- Variation of decision variable in class 5 based on k-mean method

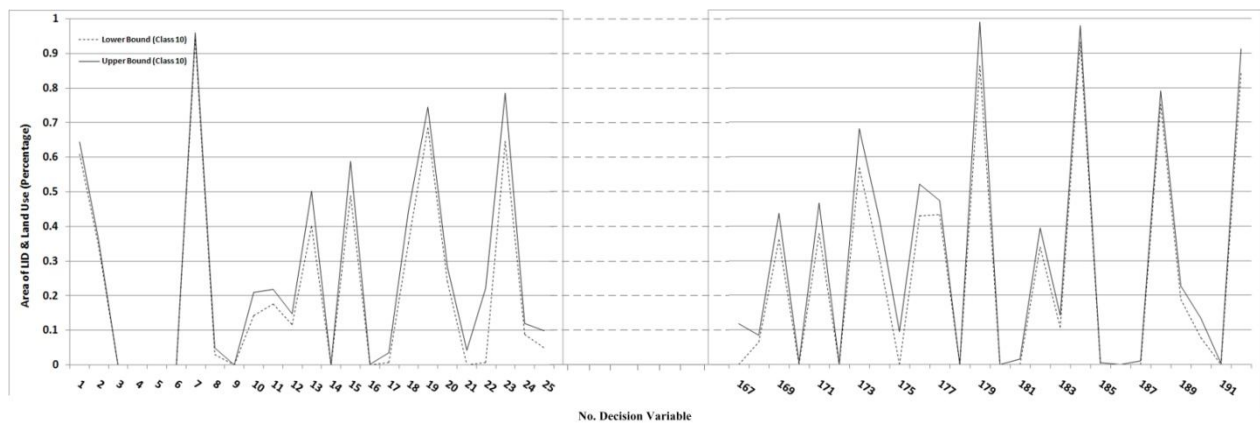


Figure 23- Variation of decision variable in class 10 based on k-mean method