A multi-objective approach towards urban drainage development prioritization and project definition structure

Iman Zahedi Rad and Abdollah Ardeshir

ABSTRACT

In developing countries, policy-makers at all levels are confronted with the problem of prioritizing different projects which needs to be done in a systematic method for the optimal allocation of funds. The current study is focused in addressing the above-mentioned problem for urban storm water drainage networks, and it aims to address two key questions: 'Which drainage projects should be tackled first?' and 'Does the project definition structure influence the prioritized projects?' The north-eastern part of Tehran is selected as the case study and the first question is addressed through a prioritization method based on particle swarm optimization (PSO) algorithm. Three different criteria including investment costs, flood damage costs, and exposure costs are considered. It is concluded that the multi-objective approach can better handle the problem in hand. To deal with the second question, two levels of project definition are investigated. The results reveal that the project definition structure has a clear impact on the objectives and its enhancement can lead to better system performance in terms of objective functions. This finding implies that despite the current trend in the city of Tehran, project definition structure should receive appropriate attention before the results are evaluated in a subsequent prioritizing framework.

Key words | multi-objective, prioritization, project definition structure, PSO, urban storm water drainage

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NOTATION

$Area_z$	z^{th} flooded area
C_1	learning factors for balancing exploration features of the search algorithm
C_2	learning factors for balancing exploitation features of the search algorithm
$Cost_{BU}$	cost of flooding related to location
$Cost_{dam}$	flooding cost
$Cost_i$	cost of each project
$Cost_{imp}$	total cost of implemented projects
$Cost_{pop}$	cost of flooding related to population per unit of area z
$f(\theta)$	error function
$Gbest_j$	optimal solution in iteration j
K	counter

K_1	maximum values of the first objective function
K_2	maximum values of the second objective function
M	number of non-dominated solutions
N_f	number of flooded regions
N_{obj}	number of objective functions
N_p	total number of projects
$Pbest_{ij}(t)$	the individual solution with best fitness in each iteration t
PR_{pop}	relative priority numbers for flooded regions based on population
PR_{BU}	relative priority numbers for flooded regions based on location
$Rand$	random number
U_i	the number of different sections in project i

W_e	inertia weight factor
X_i	binary vector
f_{dam}	flood damage function
f_{dam}^{max}	maximum flooding damage costs
f_{exp}	exposure damage costs in the flooded area
f_{exp}^{max}	maximum exposure flooding costs
f_k^{max}	maximum values of objective functions
f_k^{min}	minimum values of objective functions
f_{inv}	investment objective function
i	count
j	counter
t	iteration number
$sig(V_{ij}(t))$	sigmoid function
u	counter
u_k^i	linear membership function
u^p	normalized membership function
$v_{ij}(t)$	particle's velocity
$v'_{ij}(t)$	normalized velocity
$x_{ij}(t)$	particle's position
z	counter
θ	vector on the feasible parameter space which defines whether a project should be implemented or not
σ	optimization parameter calculated in sigma method

INTRODUCTION

Developing infrastructures for urban storm water drainage systems includes a vast range of activities that deal with safety and well-being of cities' inhabitants. Implementation of such projects is both costly and time-consuming, so the process is always constrained by budget limitation especially in developing countries. Therefore, decision-makers need to have a systematic way of project prioritization, so that the absorbed funds produce the maximum benefit. In recent years, prioritization has been the subject of many studies of management problems, e.g., pavement rehabilitation and maintenance (Moazami et al. 2011), sanitary sewers (Wright et al. 2006; Hagarty 2008; Rashid & Hayes 2011a, b; Tagherouit et al. 2011), and highway projects (Kulkarni et al. 2004).

Prioritization is a process in which different drivers need to be taken into account. The problem is basically an optimization process for which the objective is finding a better scheme for staging. This makes optimization an integral part of prioritization studies. Optimization is discussed as a single objective (Dandy et al. 1996; Abebe & Solomatine 1998; Dandy & Engelhardt 2001; Sebti et al. 2013) as well as multi-objective approach. Single objective optimization is an easier and a more straightforward approach so it is still an option if it can produce satisfactory results (e.g., Sebti et al. 2013). However, in real world problems with the existence of different criteria, a multi-objective approach allows the simultaneous evaluation of several objectives and also a better understanding of possible conflicts which finally leads to the best solution to a particular problem (Baptista et al. 2007). Such an approach is inevitable in many applications such as water resource management (Reddy & Kumar 2009; Fallah-Mehdipour et al. 2010), water distribution systems (Prasad & Park 2004; Farmani et al. 2006; Kapelan et al. 2006; Sun et al. 2011; McClymont et al. 2013), finding appropriate sewerage rehabilitation strategy (Yang & Su 2007), risk–cost optimization of hydraulic structures (Rasekh et al. 2010), highway projects' prioritization (Mak & Jones 1976; Kulkarni et al. 2004; Selih et al. 2008), and project time–cost trade-off problems (Leu et al. 2001; Akkan et al. 2005; Eshtehardian et al. 2009; Ammar 2011; Xu et al. 2012).

In the context of urban storm water asset management, Vojinovic et al. (2014) acknowledged three groups of activities, namely: (1) 'creation of assets' (planning, prioritizing, and acquiring); (2) 'operation of assets' (including their maintenance and rehabilitation); and (3) 'asset rationalization' (including their potential reuse, decommissioning, and disposal). The same scheme is also used in this paper to categorize the current studies of relevant subjects for the first two groups and to show the existing gap in the research which also shows the novelty of the present study. Apparently, the third group is not related to the subject of the present study so its relevant literature is not discussed herein.

Falling in the planning subgroup of 'creation of assets', Yeh & Labadiez (1997) studied a watershed-level planning of storm water detention systems using successive reaching dynamic programming (SRDP) to minimize detention costs and a

multi-objective genetic algorithm (MOGA) for generating non-dominated solutions for system cost and detention effect for a watershed-level detention system. Later, Delelegn et al. (2011) developed a 1D2D coupled model in conjunction with NSGA II optimization algorithm to solve almost the same problem of detention placement. Owing to the computational limitations, their method is still limited to modeling detention ponds to control the number of variables in the optimization problem. Their case study also suggests that the model is not yet applicable to sizable urban watersheds due to considerable computational demands. Baptista et al. (2007) developed a decision aid tool allowing a priori evaluation of storm water systems by the aggregation of economic–financial indicators with performance indicators. Oraei Zare et al. (2012) have used NSGA II to optimize best management practices using a combined quality–quantity urban run-off control. Deng et al. (2013) proposed a framework to value investment in urban water management systems under uncertainty. They use flexibility to deal with uncertainty pro-actively and propose a four-step procedure to design and evaluate flexible urban water management systems.

Falling in the rehabilitation subgroup of 'operation of assets', Barreto et al. (2010) proposed a multi-objective evolutionary approach to evaluate rehabilitation scenarios. They used NSGA II algorithm in the optimization process and compared it with ε-MOEA. Vojinovic et al. (2014) studied the rehabilitation problem under uncertainties that are inherent in the input data of the hydraulic models. Their study aims at providing a framework to make the systems more adaptable, reliable, and operable in a changing environment. Many other studies have also focused on the rehabilitation of urban drainage systems (UDS), such as those of Vojinovic et al. (2006), Barreto et al. (2008), Solomatine & Vojinovic (2008), Ammar (2011), and Sebti et al. (2013), to name a few.

Having a designed system in hand for development of an urban drainage system drives the need to have an efficient tool for prioritizing the implementation of system elements when it comes to budget limitation. From a management perspective, there should be a difference between designing a UDS and defining projects. The design phase normally produces a set of different development lines for a system. However, in large-scale projects, these development lines may not be built at the same time due to the lack of financial and executional resources. Top management needs to know which parts of the designed lines should be constructed taking into account these limitations and other variables. This is the gap in the research that this paper is trying to fill, in other words, presenting a systematic approach for budget allocation to urban drainage systems in large developing cities that have grown with inappropriate infrastructure. This subject falls in the prioritizing subgroup of 'creation of assets' in urban drainage systems and it has not received enough attention so far. In this regard, the concept of 'project definition structure' is used to discriminate between the designed UDS and the scheme projects are scrutinized for execution. In this regard, depending on the size of designed lines, they are subdivided into different projects. Each of these different schemes is considered to have a different project definition structure and the impact of these 'project definition structures' on the final outcome of the prioritized projects is studied. Thus, based on the presented extensive review of the previous studies, the novelties of the present work are: (a) providing a systematic means of prioritizing urban storm water development projects in developing cities in the context of limited budget; and (b) providing a new insight into the concept of project definition structure. For this purpose, this paper attempts to fill the current literature gaps through integrating the concept of budget allocation to different alternatives with providing a proper scheme for defining the projects.

The aim of this paper is to apply a systematic approach to prioritize urban drainage projects under different schemes for defining the structure of projects and also under different levels of budget limitation. Tehran, as the capital city of Iran, has been selected as the study area. The city is highly populated with the number of inhabitants above 10,000,000 and is rapidly developing. The rapid development in the city has not been accompanied with proportional infrastructure development. Lack of systematic approach for constructing runoff drainage systems has led to the frequent overflows of channels in rainy seasons (Jahani & Reyhani 2006), despite heavy investment by the public sector. The Tehran storm water master plan (2004, 2011) has investigated the city and recommended different alternatives to be implemented to safeguard the city against flood. Such a system includes over 80 km of main channels' development. This would cost the city more than 100 million US dollars. However, implementation of all these projects faces

the problem of budget limitation. This necessitates a proper strategy for project implementation. In order to tackle the above-mentioned subject, an extended version of the Storm Water Management Model (SWMM) as a comprehensive drainage simulator is linked with the particle swarm optimization (PSO) algorithm to assess the area in single and multi-objective approaches and with different levels of project definition.

METHODOLOGY AND FRAMEWORK DESCRIPTION

Description of the proposed framework

In the present study, several modules are combined to form a framework for the problem in hand. Figure 1 shows a schematic representation of the sequence and connection of these modules. The concepts and methods that are used in these modules are also described in the following sections.

Depending on the number of selected criteria (from three objectives that are defined here), the single objective optimization approach (SOPSO) or multi-objective optimization approach (MOPSO) is chosen. The optimization algorithm requires evaluation of the criteria. The hydraulic model assesses the hydraulic performance of the system to calculate the objective functions.

In the single objective approach, only one particle from N_p is selected as the *Pbest* and *Gbest*, while in the multi-objective approach, a set of non-dominated particles is considered as the *Gbest* particle. In SOPSO, the *Gbest* that is obtained from the last iteration is considered as the best solution, while in MOPSO the best compromise solution is selected from the *Gbest* archive.

Storm water management model

The SWMM 5.0 developed by the Environmental Protection Agency is a dynamic rainfall–runoff simulation model that is
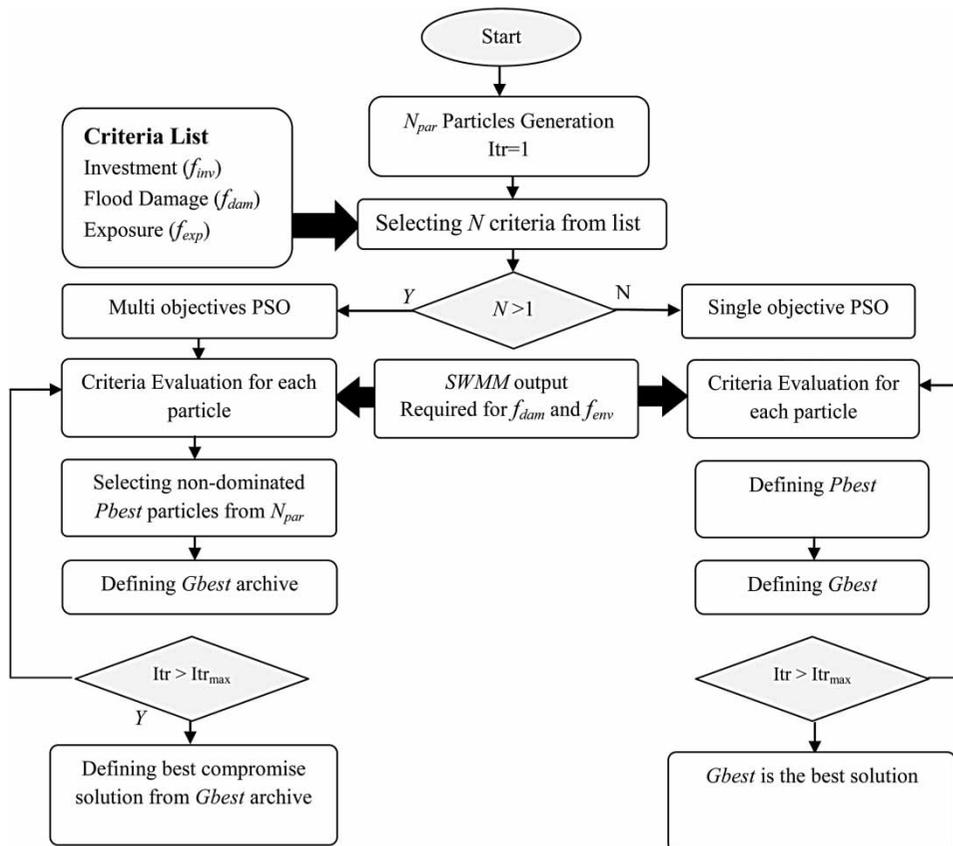

Figure 1 | Schematic representation of links between different modules in optimization approach for project prioritization.

used for single-event or long-term simulation of runoff quantity and quality from primarily urban areas (USEPA 2009). The model is divided into four conceptual compartments including atmosphere, land surface, groundwater, and transport. The runoff component of SWMM operates on a series of sub-catchment areas that receive precipitation and generate runoff. The routing portion of SWMM transports this runoff through a system of pipes, channels, and storage treatment devices. SWMM tracks the runoff generated within each sub-catchment, along with the flow rate, flow depth, quality and quantity of water in each pipe or channel through the simulation period. In this study, the role of SWMM is to identify flooded nodes in case some of the proposed projects are not implemented due to budget limitation.

The choice of objective functions

For the sake of optimization, a search algorithm (SOPSO and MOPSO as explained earlier) is run over the binary vector of project combinations. This algorithm tries to minimize three objective functions, separately or in connection with each other, taking into account different important aspects of the problem, namely investment deployment, flood damage, and exposure impacts with three performance criteria, f_{inv}, f_{dam} and f_{exp}, respectively. The f_{inv} (investment deployment criteria) attempts to select a budgetary feasible combination of projects based on the available budget and is defined as:

$$f_{inv} = \frac{Budget_{available} - \sum_{i=1}^{N_p} Cost_i \times X_i}{Budget_{available}} \qquad (1)$$

where $Budget_{available}$ indicates the current budget that is provided by the government. The main motivation behind this study is that the available budget is not enough to implement all the projects. Thus, clearly, $Budget_{available}$ is smaller than the total budget required to completely safeguard the study area against flooding. X_i is a binary vector indicating a combination of projects which takes value 1 if the project i is constructed or 0 if not. N_p is the total number of projects required to completely safeguard the study area against flooding. $Cost_i$ is the cost of each project and is estimated

based on the length and price of pipes with certain diameter and is calculated as:

$$Cost_i = \sum_{u=1}^{U_i} Length_{pipe_u} \times Price_{pipe_u} \qquad (2)$$

where U_i is the number of different sections in project i. Since it is easier to work with normalized costs, the cost values are evaluated as a ratio of the construction cost for maximum pipe size. In other words, the costs are calculated as a ratio of a constant value. We consider two situations of budget limitation. In the first approach, we assume that the available fund is 75% of the required budget. We investigate higher levels of limitation on budget through considering the available fund as 50% of the required budget. The f_{inv} should have values between 0 and 1. It takes value 0 when the set of chosen projects costs exactly equal to the available budget and 1 when none of the projects is implemented. We eliminated the sets of projects that impose higher costs than available budgets through assigning a penalty of 10,000 as shown in Equations (3) and (4). The normal range of our objective functions is [0,1] so a penalty of 10,000 would assure us that financially infeasible solutions will be eliminated in the optimization process.

f_{dam} reflects the cost of flooding if some of the projects are not implemented due to budget limitation, i.e., binary is 0. The function estimates the damage cost based on the flooding depth and the respective areal coverage as:

$$f_{dam} = \begin{cases} \dfrac{\sum_{z=1}^{N_f} Cost_{dam,z} * Area_z}{f_{dam}^{max}} & if \quad f_{inv} \geq 0 \\ 10,000 & if \quad f_{inv} < 0 \end{cases} \qquad (3)$$

where N_f is the number of flooded nodes in the SWMM model. $Cost_{dam,z}$ is the flooding cost per unit of area for region z. The cost for each region is defined based on the depth of flooded storm water extracted from hydraulic model SWMM. Three levels of damage costs (30, 60, and 100 percentile of maximum depth) are defined based on the flooding depth where the maximum cost 1 is assigned to 100 percentile flooding depth and 0.3 to flooding depth 30% percentile. The $Area_z$ is the respective flooded area for each node. We here would like to point out the

SWMM model cannot directly estimate the flooded area. However, we obtained the representative values for each node from hydrologic modeling of the study area performed by the Tehran storm water master plan (2004, 2011).

f_{dam}^{max} reflects the maximum flooding cost for the case where no project is implemented. However, this value will not always be the maximum possible flooding cost because a project might exist where its implementation increases the damage costs more than the 'do nothing' scenario, i.e., in some cases, due to dependence of projects, there are spots where construction of a drainage system without constructing another project in the downstream may impose more damage costs.

The f_{exp} (exposure impact function) aims to picture the flooding impact on the population through incorporating two concepts, namely, population density and relative importance of surrounding neighborhoods to minimize the exposure damage in the flooded area. As a result, f_{exp} is formulated as:

$$f_{\text{exp}} = \begin{cases} \dfrac{\sum_{z=1}^{N_f} Area_z \times \left[(Cost_{pop,z} \times PR_{pop,z}) + (Cost_{BU,z} \times PR_{BU,z})\right]}{f_{\text{exp}}^{max}} & if \quad f_{inv} \geq 0 \\ 10,000 & if \quad f_{inv} < 0 \end{cases} \tag{4}$$

where $Cost_{pop}$ and $Cost_{BU}$ are the costs of flooding related to population and location per unit of area. PR_{pop}, PR_{BU} are relative priority numbers for flooded region z related to population and location, respectively. PR_{pop} will take values 1, 2, and 3 for low, medium, and high population densities, respectively. The same scales apply to low, medium, and high importance locations for parameters PR_{BU}. For this process, a higher priority is given to regions where schools, monuments and administrative buildings are located. Also, considering transportation as an important infrastructure, the next higher priorities are given to highway areas. Similarly, f_{exp}^{max} reflects the maximum exposure cost for the case where no project is implemented.

It is recommended that the objectives are normalized into a uniform, dimensionless scale (Deb & Miettinen 2008). Thus all three objectives are normalized according to their respective maximum values. This will also help to easily compare different criteria.

Optimization algorithm

The general framework of minimal optimization with N_{obj} objective functions and a vector of feasible solution X (here, X is a binary vector that defines whether a project should be implemented or not) is expressed as:

$$\min \quad f(X) = \{f_1(X), f_2(X), \ldots, f_{N_{obj}}(X)\} \tag{5}$$

In multi-objective decision-making, the methods for extracting decision-makers' preference are divided into three categories: (1) the methods based on a priori articulation of preferences; (2) the methods based on a progressive articulation of preferences; and (3) the methods based on a posteriori articulation of preferences (Hwang & Masud 1979).

Pareto (non-dominated or non-inferior) optimality concept, introduced by Edgeworth (1881) and later generalized by Pareto (1896), is adopted when the preference structure of decision-makers is not specified. The concept would give rise to a set of acceptable solutions for decision-makers in which it is not possible to improve one objective function unless worsening at least another one (Osyczka 1985). The Pareto optimality conditions may be defined as:

$$\forall \ k = 1, \ldots, N_{obj}: \quad f_k(X_i) \leq f_k(X_j) \tag{6}$$

$$\exists \ k = 1, \ldots, N_{obj}: \quad f_k(X_i) < f_k(X_j) \tag{7}$$

The first expression divides the feasible parameter space into two sets of efficient (Pareto) and inefficient (inferior) solutions. The second expression states that in the absence of additional information, it is not possible to distinguish

any efficient solution as being objectively better than another one. This process discusses several layers of objectives for each cell defining the spatial distribution of the urban area. In this way, decision-makers and stakeholders are able to derive a suitable set of solutions that is essentially optimal and allows safe negotiation. We implement the particle swarm optimization (PSO) algorithm which can be adapted for both single objective and multi-objective optimization approaches.

Single and multi-objective particle swarm optimization

The PSO is a population-based optimization technique introduced by Eberhart & Kennedy (1995), motivated by collective and social behavior of bird flocking or fish schooling (Parsopoulos & Vrahatis 2002). The PSO algorithm is initialized with a population (swarm) of random solutions (X). In each iteration t, the individuals with best fitness are called *Pbest*, so it keeps a record of previous best performances for each particle. Conversely, *Gbest* is the value of best performance so far in the neighborhood (swarm).

$$v_{ij}(t+1) = [W_e \times v_{ij}(t)] + [C_1 \times rand \times (Pbest_{ij}(t) - x_{ij}(t))] + [C_2 \times rand \times (Gbest_j - x_{ij}(t))] \quad (8)$$

$$X_{ij}(t+1) = X_{ij}(t) + v_{ij}(t) \quad (9)$$

where i shows the particle's number in a swarm, j is the particle's dimension. W_e is the inertia weight which shows the effect of previous velocity on the new velocity and C_1 and C_2 are learning factors for balancing exploration and exploitation features of the search algorithm.

The original PSO was developed for continuous valued spaces. We used the discrete binary version of the algorithm introduced by Kennedy & Eberhart (1997) which is compatible with binary valued space of the problem in hand. In a binary space, a particle may be seen to move to nearer and farther corners of the hypercube by flipping various numbers of bits; thus, velocity of the particle overall may be described by the number of bits changed per iteration. Thus the velocities of parameters are defined in terms of probabilities that a bit will change to 1. This restricts velocity within the range [0, 1]. The sigmoid normalization function used is defined as:

$$v'_{ij}(t) = sig(v_{ij}(t)) = \frac{1}{1 + e^{-v_{ij}(t)}} \quad (10)$$

Accordingly, the new position of the particle can be defined as:

$$X_{ij}(t+1) = \begin{cases} 1 & if\ rand < sig(V_{ij}(t+1)) \\ 0 & otherwise \end{cases} \quad (11)$$

where *rand* is a uniform random number in the range [0, 1]. Owing to the major issues and concerns about binary PSO (discussed by Engelbrecht (2005)), many improved versions of the algorithm are developed from which this paper uses the novel binary particle swarm optimization introduced by Khanesar *et al.* (2007) with the new interpretation of velocity. More description on equations of this technique is presented by Khanesar *et al.* (2007).

In single objective PSO (SOPSO), *Gbest* is determined easily by selecting the particle which has the best function value. However, in multi-objective PSO (MOPSO), *Gbest* is a set of Pareto optimal solutions saved in an archive. Several methods are proposed for finding the best local guides. In this study, we tested 'roulette wheel' selection method and Sigma method (Mostaghim & Teich 2003). The results showed that Sigma method provided better Pareto fronts where 'roulette wheel' selection did not yield the optimal front for our case and in most cases, only 1 single point from the Pareto front was identified. Other studies have also shown the outperformance of the Sigma method (Kamali *et al.* 2013). In this method for a case of two objective functions, each particle takes a Sigma value as:

$$\sigma = \frac{(K_2.f_1)^2 - (K_1.f_2)^2}{(K_2.f_1)^2 + (K_1.f_2)^2} \quad (12)$$

where K_1 and K_2 are maximum values of the first and the second objective functions. The particles then select the archive member which has closer Sigma value to its own value. Figure 2 shows a schematic representation on how the particles are directed. More description on implementation of the method for three objective functions is presented by Mostaghim & Teich (2003).
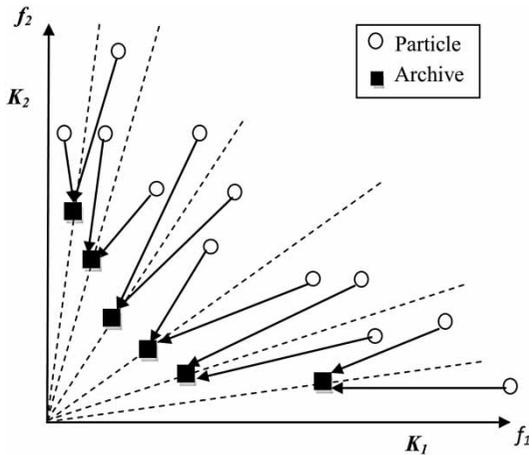
Figure 2 │ Finding the best local guide for each particle of the population using Sigma method (Mostaghim & Teich 2003).

Best compromise solution for MOPSO

The challenge in Pareto-based MOPSO is to select the best suitable solution, from M non-dominated solutions, when the preference structure of decision-makers is not specified. Abido (2006) proposed a fuzzy-based best compromise solution method in which a linear membership function is defined as:

$$
u_k = \begin{cases} 1 & f_k \leq f_k^{\min} \\ \dfrac{f_k^{\max} - f_k}{f_k^{\max} - f_k^{\min}} & f_k^{\min} < f_k < f_k^{\max} \\ 0 & f_k \geq f_k^{\max} \end{cases} \tag{13}
$$

where $f_k^{\max}$ and $f_k^{\min}$ are, respectively, the maximum and minimum values of objective functions. The membership function represents the degree of achievement for k^{th} objective function as a value between $u_k = 0$ (completely unsatisfactory) and $u_k = 1$ (completely satisfactory). For each non-dominated solution i, the normalized membership function u^p is calculated as:

$$
u^p = \frac{\displaystyle\sum_{k=1}^{N_{obj}} u_k^i}{\displaystyle\sum_{p=1}^{M} \sum_{k=1}^{N_{obj}} u_k^i} \tag{14}
$$

The function u^p represents a fuzzy cardinal priority ranking of the non-dominated solutions where the best

compromise solution is the solution with a maximum membership value.

Study area and model set-up

Tehran, the capital of Iran (Figure 3(a)), has rapidly developed and become highly populated in recent years. The Tehran storm water master plan (2004, 2011) has investigated the city and recommended alternatives to be implemented to completely safeguard the city against flood. However, with a limited budget, prioritizing these recommendations is of current concern for the decision-makers. The mountainous area in the north-eastern part of Tehran has been selected as the case study in this paper (Figure 3(a)–3(c)). The area includes four major channels, namely, the Velenjak channel, Tajrish channel (or Zargandeh), Jamshidieh channel, and Darabad channel, with many experiences of considerable flood damage. The area is approximately 150 square kilometers with around two million inhabitants. The area consists of mainly dense urban areas with heavy traffic so in the case of flooding everything becomes jammed in the streets and even a small flood can mean more than a million lost hours for people in the streets on top of other damage. Figure 4 demonstrates the relative priority of different regions in the study area taking into account the population and the importance of the surrounding buildings. The discharge of all four channels is finally directed to a downstream suburb through the EDC channel (Figure 3(c)) at the lower parts of the study area. Implementation of all designed channels in the study area would cost about 38 million dollars which is not affordable for the city.

Having modeled the current drainage system of the area in SWMM based on discharge values with a 50-year return period and 6 hours of rainfall, we identified 10 flood spots (Figure 3(c)). Therefore, to fully safeguard the system against flood, we need to implement modification in the conduits located in these regions. This is compatible with the findings of the Tehran storm water master plan. We designed the necessary conduits to eliminate the flooding considering the capacity of the available conduits in the system. These candidate projects are also shown in Figure 3(c) with their codes according to Table 1.

To show the effect of project structure definition on prioritized projects, two levels of project definition are
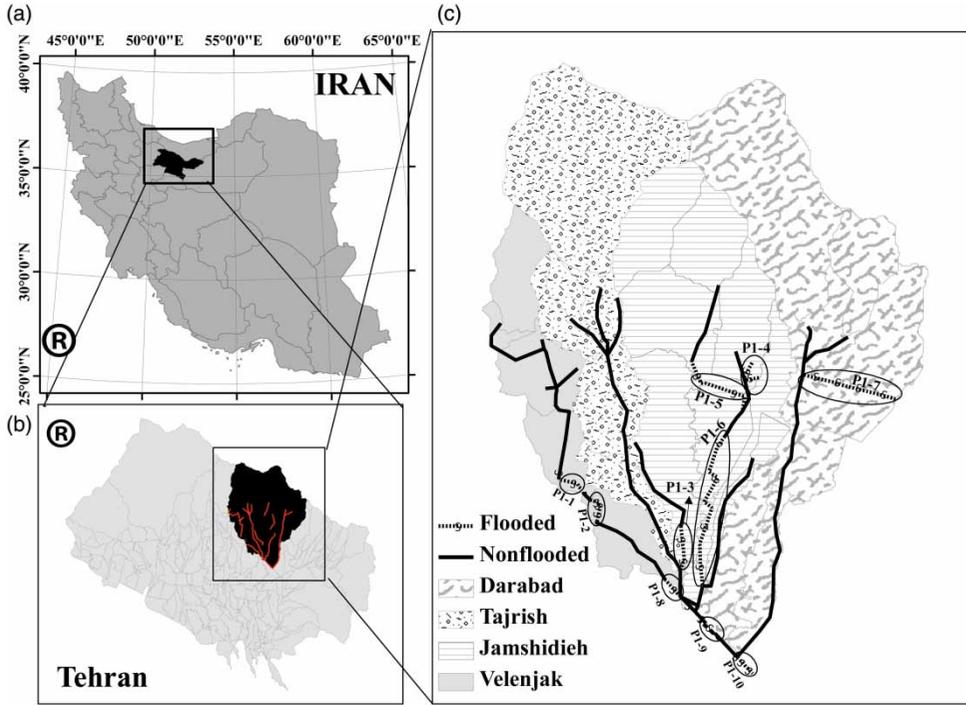
Figure 3 │ Overall view of the study area on Tehran and Iran maps; the locations of flooded and non-flooded channels in four major regions.
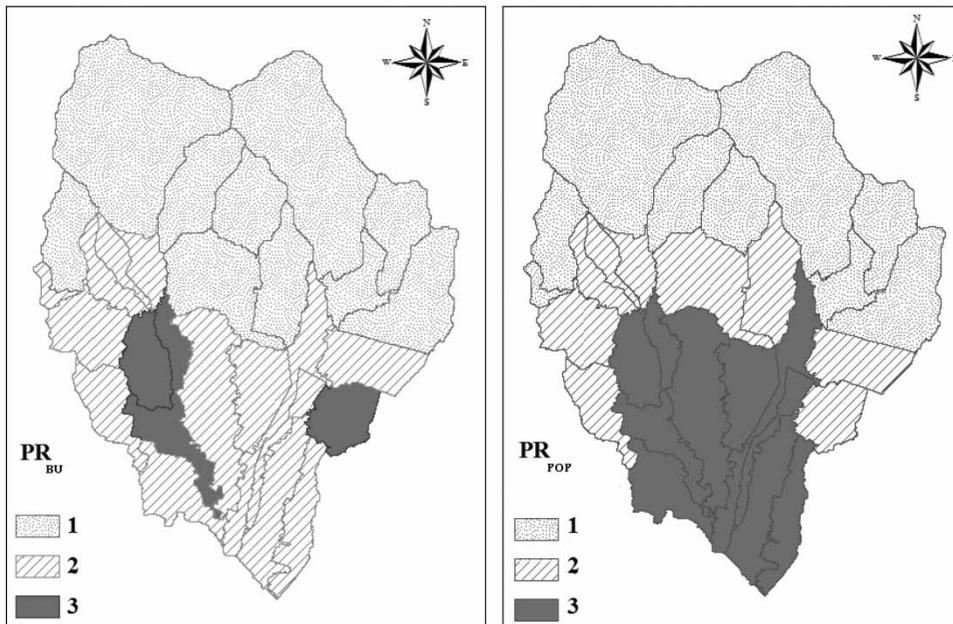

Figure 4 │ The priority number (PR_{pop}, PR_{BU}) allocated for population density and regions.

investigated, as shown in Table 1; coarse (Level-1) and discrete (Level-2). Level-1 is according to the Tehran storm water master plan for project definition which is, in fact, project definition based on designed lines in which the projects are defined based on 10 flooded locations. In Level-2, finer levels of project structure are defined. For example,

Project-6 in Level-1 (P1–6) is divided into four projects (P2–13, P2–14, P2–15, and P2–16). Therefore, the total number of projects has increased to 26. Table 1 also presents and compares the quantitative information of projects in both levels.

RESULTS

Single objective optimization approach

To highlight the importance of multi-objective optimization as well as having a benchmark, Table 2 represents the results of SOPSO for projects defined in Level-1 of the case study.

For the purpose of this table, each of the three criteria (f_{inv}; f_{dam}; f_{exp}) is used individually as the objective function, and the values of the other objective functions are calculated for the final selected combination of projects. As seen in Table 2, with the pursuit of one objective function, others become dramatically bad, e.g., for 75% budget, f_{dam} as the objective function gives (f_{inv}; f_{dam}; f_{exp}) = (0.037, 0.086, 0.49) and f_{exp} as the objective function gives (f_{inv}; f_{dam}; f_{exp}) = (0.102, 0.87, 0.047). This shows a noticeable deterioration of f_{exp} with the improvement of f_{dam} and vice versa. As the decision-makers are concerned with all objective functions at the same time, these findings suggest that a multi-criteria approach is needed to deal with the objective functions simultaneously. However, such an

Table 1 │ General characteristics of projects required to protect the whole area against flood in two coarse and discrete levels of project definition

| Channel name | Level-1 | | | Level-2 | | |
	Project name	Channel length (meters)	Channel diameter (meters)	Project name	Channel length (meters)	Channel diameter (meters)
Velenjak upstream	P1–1	1,400	2	P2–1	700	2
				P2–2	700	2
Velenjak downstream	P1–2	1,000	2.2	P2–3	500	2.2
				P2–4	500	2.2
Dolabi	P1–3	1,600	2	P2–5	800	2
				P2–6	800	2
Kashank	P1–4	300	2	P2–7	300	2
		500	2.5	P2–8	500	2.5
Giasvand upstream	P1–5	2,930	3	P2–9	730	3
				P2–10	730	3
				P2–11	730	3
				P2–12	730	3
Giasvand downstream	P1–6	2,200	3	P2–13	1,100	3
				P2–14	1,100	3
		2,200	3.5	P2–15	1,100	3.5
				P2–16	1,100	3.5
Ozgol	P1–7	3,000	2	P2–17	750	2
				P2–18	750	2
				P2–19	750	2
				P2–20	750	2
EDC and Zarrin	P1–8	400	3	P2–21	400	3
		1,200	4.5		200	4.5
			4.5	P2–22	1,000	4.5
EDC-part 2	P1–9	350	5.5	P2–23	350	5.5
					80	6
		1,480	6	P2–24	600	6
				P2–25	800	6
EDC-END	P1–10	650	5.5	P2–26	650	5.5

Table 2 │ Prioritized projects with different criteria in single objective optimization for 10 projects defined in Level-1

Criteria in PSO algorithm	Percent of provided budget	Prioritized projects	f_{inv}	f_{dam}	f_{exp}
f_{inv}	75	P1–2, P1–3, P1–4, P1–6, P1–8, P1–9, P1–10	1×10^{-3}	0.109	0.48
f_{dam}	75	P1–1, P1–3, P1–6, P1–8, P1–9, P1–10	0.037	0.086	0.49
f_{exp}	75	P1–1, P1–3, P1–4, P1–5, P1–6, P1–7, P1–8	0.102	0.87	0.047
f_{inv}	50	P1–3, P1–4, P1–6, P1–7, P1–8	1×10^{-4}	0.98	0.27
f_{dam}	50	P1–3, P1–8, P1–9, P1–10	0.042	0.23	0.70
f_{exp}	50	P1–1, P1–3, P1–4, P1–5, P1–6, P1–7	0.068	0.94	0.21

overview of results from SOPSO allows comparison of multi-objective and single objective approaches.

One might argue that f_{inv} is not an objective function by itself, but in urban management sometimes it is. This is due to the fact that budgets are allocated to each sector and their consumption level is an important performance criterion for managers. As a result, they tend to consume the allocated budget regardless of other objectives. Rows 1 and 4 in Table 2 show that this approach might be misguiding in some cases such as in $(f_{inv}; f_{dam}; f_{exp}) = (0.001, 0.109, 0.48)$ for 75% budget allocation and especially in $((f_{inv}; f_{dam}; f_{exp}) = (0.001, 0.98, 0.27))$ for smaller budget allocation (50% of required budget). One can easily see that almost 50% of budget reduced only 2% of damage costs which is literally a waste of resources.

Multi-objective optimization approaches

The multi-objective problem is investigated in three bi-objective scenarios $((f_{inv}, f_{dam}); (f_{inv}, f_{exp}); (f_{dam}, f_{exp}))$ as well as one tri-objective $(f_{inv}; f_{dam}; f_{exp})$ scenario with the set of 10 projects defined in Level-1. The above-mentioned choices of criteria combinations are aimed at addressing different perspectives of the decision-makers towards the project selection and their objectives. In other words, it is not meant to select a better combination of the criteria, as it is not possible to select two or more criteria as the best. However, these different combinations would help to examine how the final result would change in each scenario based on the decision-makers' preferences and also compared to the single objective approach.

Figures 5(a)–5(f) and 6(a) and 6(b) show the Pareto fronts for bi- and tri-objective scenarios, respectively. It is clearly observed that different combinations of objective

functions lead to different sets of non-dominated solutions on Pareto fronts, for which, improving one objective function causes deterioration of the other functions. As a result, these Pareto fronts enable the decision-makers to choose a suitable solution based on their preference structure of the objective functions.

Another interesting observation in the above-mentioned figures is the fact that f_{dam} can, indeed, take values greater than 1 for some feasible points. In other words, there are cases where implementing improper selection of projects imposes even more damage costs to the system than the 'does nothing' scenario. For example, implementing a project in upper regions without appropriate collection in the downstream might direct huge amounts of storm water to that area, imposing more damage costs compared to the original state.

From this point on, different methods can be found in the literature to aggregate the results into one final solution or a ranking of solutions, among which, the fuzzy best compromise solution (BCS) is utilized in this paper. This method is normally used when the preference structure of the decision-makers is not clear. In applying this method, similar priority for all three criteria is presumed. However, in general, it is possible to have different weights for the objectives. As shown in Equation (13), BCS would need f_k^{max} and f_k^{min}, which would be extracted from the best and worst values of the functions for the feasible solutions considered in optimization. The values of objective functions corresponding to the BCS chosen solutions for 75% of budget allocation in Level-1 for different combinations of objective functions can be found in the top four rows of Table 3.

A comparison of the objective functions values with those of Table 2 shows that the use of MOPSO has altered the final solutions. As an example in SOPSO, when the
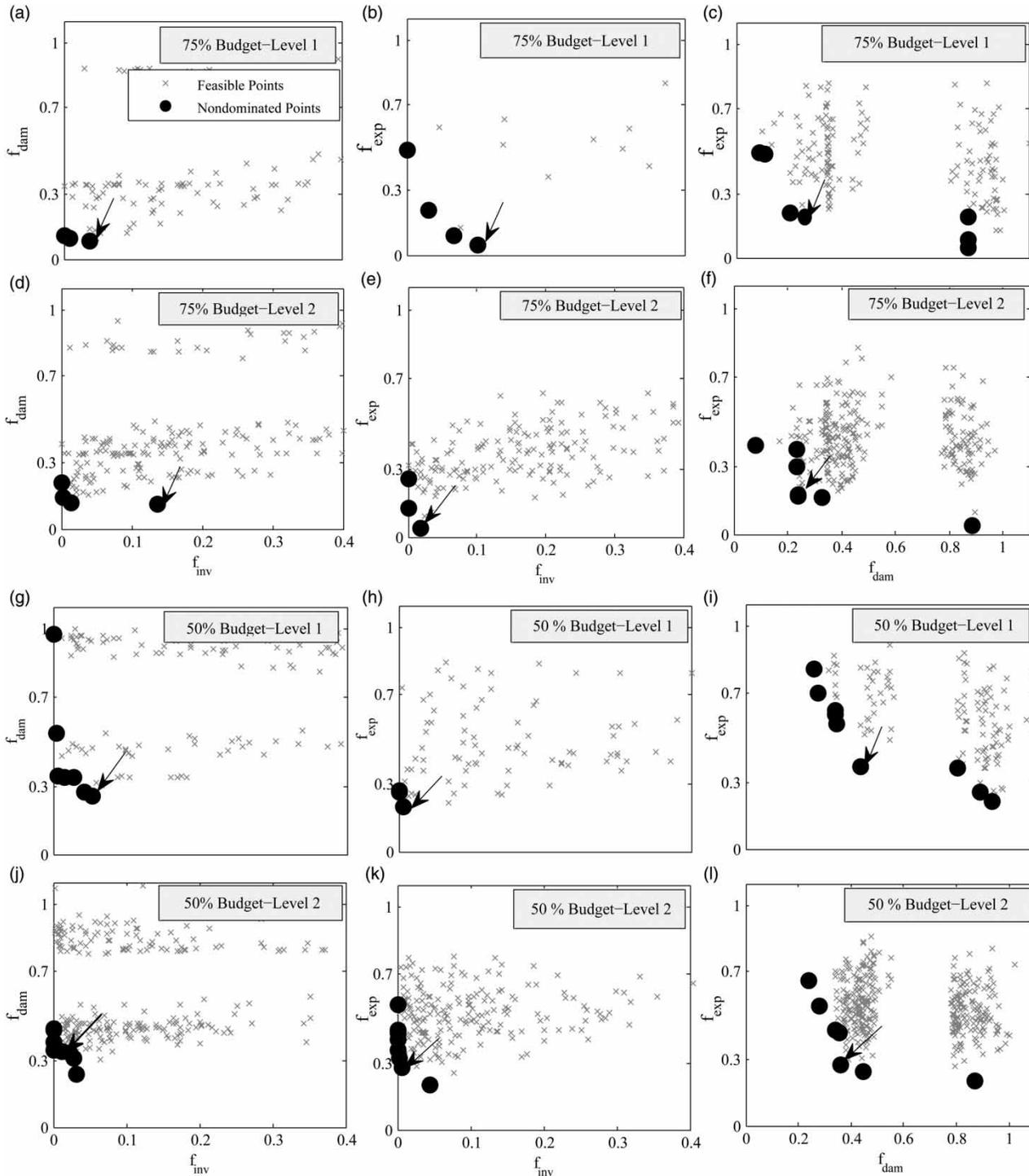
Figure 5 | Pareto front in bi-objective optimization with different combinations of objectives.

best value of $f_{dam} = 0.086$ is obtained, the value of f_{exp} increases to 0.49 and when the best values of $f_{exp} = 0.047$ is obtained, the value of f_{dam} increases as high as 0.87.

However, the bi-objective optimization which considers both criteria (f_{dam}, f_{exp}) at the same time leads to compromised solutions of $f_{dam} = 0.35$ and $f_{exp} = 0.27$.
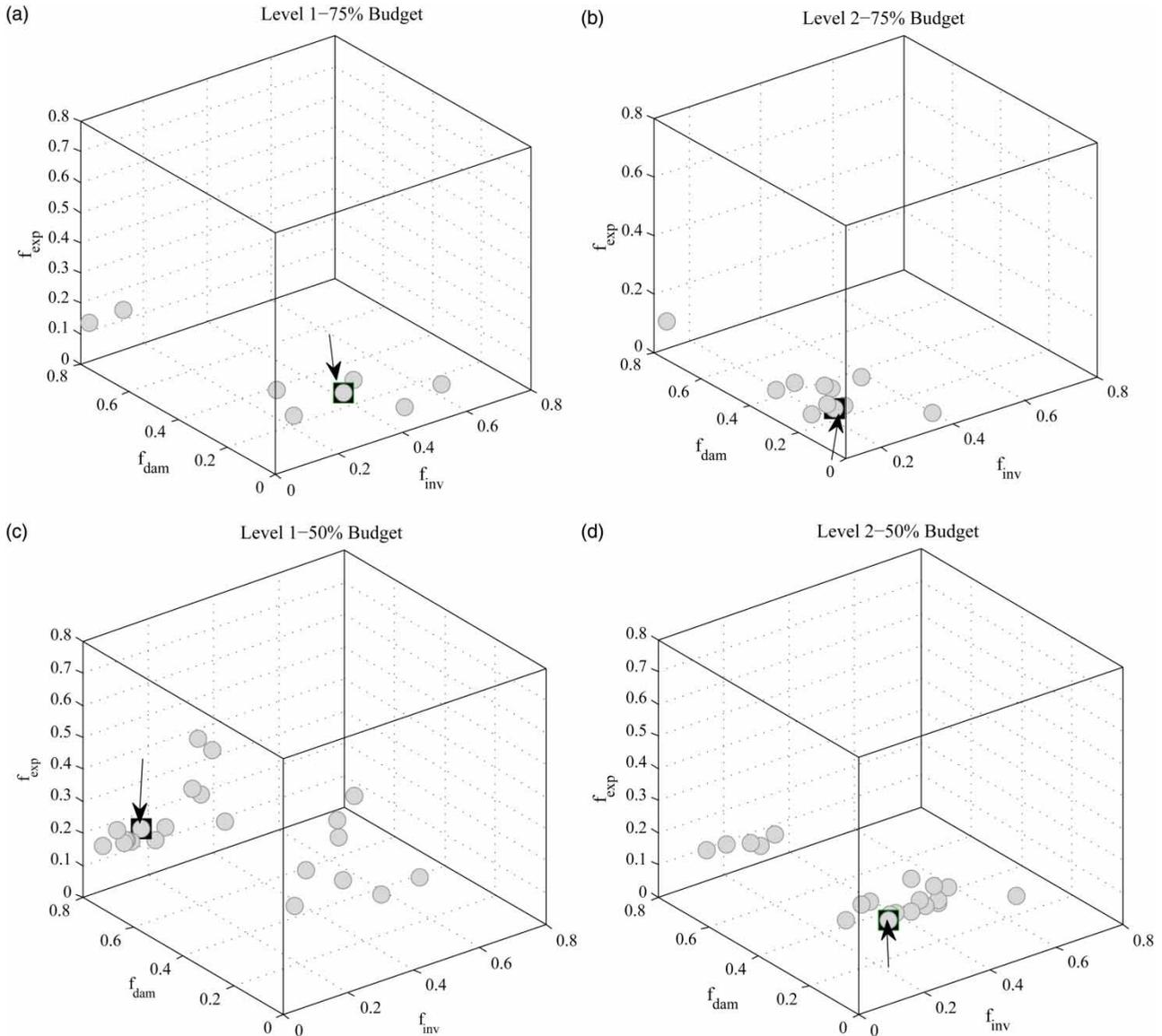
Figure 6 │ Pareto front in tri-objective optimization.

Conversely, with the current rate of budget allocation to the Tehran storm water network development, a 75% budget allocation seems too optimistic. Thus, a budget allocation of 50% is also considered (Figures 5(g)–5(l) and 6(c) and 6(d)) to examine the application of the approach for more limitation on the available budget, a case which corresponds more with the real situation. Table 3 also presents the final selected solutions using BCS in this case and they can be compared with those of 75% budget allocation. As expected, the objective functions get worse for smaller

budget allocations. A comparison between the tri-objective solution and the three individual solutions of SOPSO shows that the tri-objective optimization has led to a set of projects with better overall performance compared to the case when each function worked independently.

As mentioned above, less budget allocation leads to deterioration of objective functions. It thus becomes a matter of concern to be able to improve the objective functions, which needs better management policies, even with lower budget allocations. This strengthens the need to

Table 3 │ Prioritized projects with two levels of different criteria in multi-objective objective optimization for 26 projects defined in Level-1 and Level-2

Objective function	Percent of provided budget	Level-1			Level-2		
		f_{inv}	f_{dam}	f_{exp}	f_{inv}	f_{dam}	f_{exp}
f_{inv}, f_{dam}	75	0.008	0.096	0.59	0.01	0.12	0.34
f_{inv}, f_{exp}	75	0.069	0.88	0.09	0.01	0.45	0.03
f_{dam}, f_{exp}	75	0.025	0.35	0.27	0.02	0.23	0.16
f_{inv}, f_{dam}, f_{exp}	75	0.05	0.26	0.38	0.01	0.23	0.22
f_{inv}, f_{dam}	50	0.051	0.26	0.70	0.027	0.31	0.66
f_{inv}, f_{exp}	50	0.0065	0.98	0.35	0.006	0.78	0.28
f_{dam}, f_{exp}	50	0.011	0.44	0.37	0.02	0.35	0.37
f_{inv}, f_{dam}, f_{exp}	50	0.011	0.44	0.37	0.004	0.36	0.36

resolve the problem of not having good enough solutions for lower budget allocations. Further consideration of the search algorithm and final selected sets of projects reveals that the main reason is related to the approach used for project definition. Up to this point, projects in Level-1 are defined based on the conventional definition of the projects extracted from the Tehran storm water master plan, which defines projects based on the channels designed for each flooded area in which huge projects (longer length, larger sizes, and costs) are compared with the smaller projects. Therefore, when the projects are big, their respective costs will be comparable with the allocated budget for lower budget allocations and the algorithm fails to produce satisfactory results.

For example, when 50% of required budget is allocated, the value of f_{dam} becomes as high as 0.44 for tri-objective optimization. However, it is still a solution derived using the BCS method and would have a better overall performance compared to the solution obtained from single objective optimization. Nevertheless, in the next step, the project definition structure is changed and the projects are redefined as shown in Table 1. The new project structure definition is called Level-2. In this case, 10 projects defined in Level-1 are divided into 26 projects for Level-2. It is worth mentioning that in this level, the projects are subdivided into smaller projects so that all projects have approximately the same dimension. It is, in general, possible to merge some projects too.

Figures 5(d)–5(f), 5(j)–5(l), and 6(b) and 6(d) present the Pareto fronts obtained for projects defined in this level.

As shown in these figures, the number of feasible solutions on the Pareto fronts increases when the projects are divided into smaller ones and better Pareto fronts are obtained. Table 3 also presents the results of multi-objective optimization for the projects defined in Level-2. A comparison between the values of objectives in both levels shows that in all optimizations, Level-2 project definition structure gives better results as all objective functions become less with this approach. The decrease in f_{inv} values shows that the model can find solutions that use the available budget more efficiently, in other words with less damage and exposure costs on the site. As an example of the tri-objective approach with 75% budget allocation, the values of (f_{inv}, f_{exp}, f_{exp}) = (0.05, 0.26, 0.38) are obtained in Level-1, while the results for Level-2 are (f_{inv}, f_{dam}, f_{exp}) = (0.01, 0.23, 0.22).

Figure 7 also shows a schematic view of the location of the prioritized projects as well as their names based on tri-objective optimization. On the left side, the current state of the channels are shown. It is observed that with a different budget allocation, a totally different set of projects will be selected for implementation. Figure 7(a)–7(d) show the BCS chosen projects for 75% and 50% budget allocation in Level-1 and Level-2. As shown, for 75% budget allocation and in Level-1 (Figure 7(a)), the downstream section of the Ghiasvand (P1–6 with a length of 4,400 meters) is proposed to be implemented. Splitting this project into four smaller projects (P2–13 to P2–16) with the same budget allocation but in Level-2, it is observed that if only the upper parts of the project are implemented (P2–13 and P2–14), then less damage
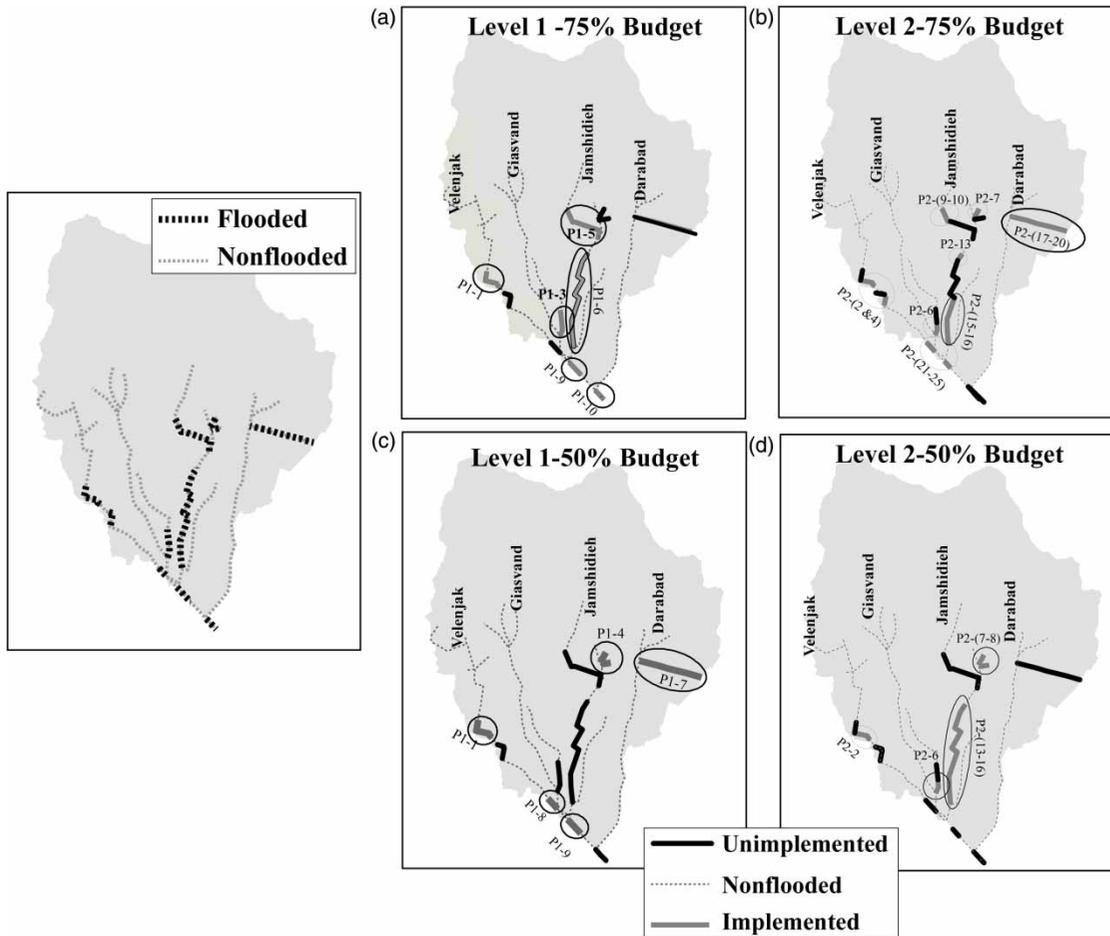
Figure 7 │ Comparative representation of selected projects in two levels of project definition and budget allocation based on tri-objective optimization.

and exposure costs will be imposed on the systems. The project definition in the Level-1 approach could not distinguish this point of view.

DISCUSSION AND CONCLUSIONS

The particle swarm optimization algorithm is used to prioritize and select the best combination of urban storm water drainage projects in the northern region of Tehran, Iran, under different budget limitations. Based on an extensive review of the current literature it is concluded that the present study fills some of the existing knowledge gaps in the subject. The chosen study area is a region where a large number of projects and major channels are required to be implemented to protect it against flood damage.

For the purpose of finding the best combination of projects under budget limitation, the PSO optimization algorithm in both single and multi-objective approaches is utilized to address the preferences of decision-makers with respect to different objectives. Three criteria and two levels of budget allocation, namely 75% and 50% of the total required budget, are considered for this purpose. The results of single objective optimization reveal that single optimization is not adequate to fulfill the objectives of the decision-makers. As the problem is inherently multi-criteria based, optimizing based on only one criterion neglects other objectives.

In the next step, multi-objective optimization is utilized and the Pareto fronts are established in bi- and tri-objective approaches. It is concluded that the multi-objective algorithm gives solutions that have better overall performance.

As well, the Pareto front obtained in each scenario provides the base for decision-makers to select among the non-dominated solutions based on changing the relative weights of different criteria. It is also concluded that using the allocated budget in a haphazard way might also lead to inadequate improvement of the objectives. The feasible solutions depicted in Figures 5 and 6 for f_{dam} criterion are good examples in this regard.

Comparing two budget allocation levels shows that when more limitation on budget is imposed upon decision-makers, the effect of project definition structure is important and needs to be investigated. Therefore, a more discrete structure of flooded channels consisting of 26 projects is defined. It is also shown that proper project definition has a positive impact on the objectives and so it should be duly addressed while prioritizing projects. Comparing the spatial variation of the final set of proposed projects in two levels highlights this necessity.

For the optimization process, the population size and number of iterations are chosen so as to obtain the optimal solutions while keeping the algorithm computationally efficient. For SOPSO, a population size of 8 with 35 iterations is used. However, for other cases, the number of iterations had to be increased to 50 to produce satisfactory results. For Level-1, a population size of 15 was found suitable for both bi- and tri-objective optimization whereas for Level-2 a population size of 20 and 25 is used, respectively.

It is worth mentioning that over-discretizing the projects into very small ones might lead to improvement of the objective functions, but conversely, to start implementing the projects based on an over-discretized scheme might lead to an unsystematic development and also might have adverse impacts on other aspects such as transportation and social acceptance. Therefore, project definition needs to be seriously investigated by stakeholders before the results are assessed in subsequent project prioritization. It is recommended that the impacts of project prioritization on other criteria such as transportation and urban construction should be assessed.

It is also important to note that BCS solutions selected from Pareto front are based on equal weight of the criteria, while the results will significantly change when these relative weights are changed. Therefore, it is mandatory that multi-criteria decision analysis is performed to select the criteria with higher influence and to define the relative importance of the criteria.

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