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RESEARCH PAPER

Performance Improved Multi-Objective Optimization in Applying Low-Impact Development Strategies to Control Urban Runoff

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ABSTRACT: Best Management Practices (BMPs) can play a vital role to control natural disasters like floods. In this paper, retention pond and vegetative swale are considered to restrain urban runoff. Storm water management modeling (SWMM) is used for runoff modeling. A piece of code is developed based on Non-dominated Sorting Genetic Algorithm (NSGA-II) in MATLAB to optimize the BMPs application. The aim is comparing the effect of roulette wheel, tournament and random selection operators to obtain the optimal location and area of BMPs. Minimizing the runoff volume and pollution in sub-catchments and the construction cost of the BMPs are three objective functions. Rafsanjan city located in southeast of Iran is selected as an appropriate case study. Estimating the best pressure of selection operator in roulette wheel and the best selection size in tournament operator and simultaneous quantitative and qualitative optimization using two BMPs are the innovations of this study. The results indicate that the pressure of the selection operator in roulette wheel which leads to the optimal answer is three and nine while the best size of selection in the tournament operator is nine. Optimum location, type, area and volume for each BMP are obtained after running the code.

Keywords: Best Management Practices, Roulette Wheel, Selection Operators, SWMM, Tournament.

1. Introduction

Recently, due to climate change, the amount of rainfall and its intensity has been affected. This phenomenon has caused a sharp increase in the quantitative characteristics of runoff in some areas which in turn reduces its quality. Quantitative and qualitative control of urban runoff in order to reduce human, environmental, health and financial losses is of interest to different communities. To reduce the risk of flooding, Best Management Practices (BMPs), known as Low-Impact Developments (LIDs), have been developed. These new flood

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management methods are hydrological controllers that use two processes of storage and absorption at different scales to manage the quantity and quality of runoff. Some of these LIDs are retention pond, green roof, rain barrel, absorption well, vegetative swale, permeable pavement and infiltration trench. To achieve a suitable control program, it is necessary to identify the goals and use optimization methods. For this purpose, several algorithms called Multi-Objective Evolutionary Algorithms (MOEAs) have been developed in recent decades. Mathematical models (analytical, numerical and optimization) are employed in many fields including planning, engineering and water resources management. Particle Swarm Optimization algorithm (PSO) and Non-dominated Sorting Genetic Algorithm (NSGA-II) are two of them. These algorithms try to find the best values of the objective functions on the Pareto front while satisfying the existing constraints. In the structure of genetic algorithms, selection operators are used to determine the ability of a particular strand to participate in the reproduction process. These operators play an important role in selecting the most appropriate population in the algorithm. Thus, they are also called reproduction operators. Selection scheme is also an important issue in Genetic Algorithm (GA). A chromosome from the current generation would be selected to enter the next population (Kumar et al., 2016). Selection of operator pressure is important in the degree of convergence of GA. Therefore, determining the appropriate pressure of the selection operator or the appropriate size of the populations participating in the crossover operation can play an important role in the optimal performance of the selected algorithm and achieving better results.

Siriwardene and Perera (2006) selected appropriate operators in GA to optimize parameters of urban drainage model. The sensitivity of these operators was analyzed by repeated simulation through numerical experiments considering one GA operator at a time, by consolidation urban drainage modeling software and GA. In that study the tested GA operators were population size, number of generations, number of model parameter sets that should be considered from the previous generation to settle the optimum set, selection type, crossover and mutation rates. Results showed that models of urban drainage with a small number of parameters (two or less) could be optimized with any of the tested GA operator sets. Therefore, proper selection of operators in GA is essential to reach the optimum parameters in urban drainage models with large number of parameters (five or more). The performance of roulette wheel, elitism and tournament was compared as parents selection operators in Travelling Salesman problem (Chudasama et al., 2011). The results showed that elitism is the best compared to other methods. Sharma et al. (2014) delivered some selection strategies in GA for solving optimization problems and compared their performance. Roulette wheel, rank, tournament and elitism were four types of selection operators in the study. Best result achieved by applying roulette wheel and tournament selection with two points and one point crossover, respectively.

In a study two optimization algorithms, PSO and Global Gradient Algorithm (GGA) were used for hydraulic analysis of water distribution systems. The results showed that GGA and PSO perform better in convex and non-convex problems, respectively. However, by increasing the coefficient of the penalty function, the accuracy of the answers obtained from the two algorithms increased significantly (Moosavian and Jaefarzadeh, 2015).

Rathnayake (2015) improved the GA algorithm in such a way that it could control the storm migration. Optimal control of urban sewer networks was the main aim of the study. Solutions were acquired from the multi-objective optimization. Results showed the effective role of on-line storage tanks in controlling urban sewer flow. A method was presented by Martínez-Solano et al. (2016) that limits the searching domain of solutions in GA in order to rehabilitate drainage networks. In this method, an iterative process was used which gradually reduced the search area that contains the optimal solution. The results showed the effectiveness of the procedure in reducing the search space for solutions to face the problem of matching the results of the algorithm with what happens. Modern Optimization Methods (MOMs) were used for planning, engineering and management of water resources (Tayfur, 2017) . The comparative analysis between seven types of GA-based algorithms showed that choosing the appropriate population size is necessary to verify the efficiency. It revealed the importance of selection operator. A study was conducted by Dastorani et al. (2018) in the Zayande Rood dam basin of Iran with the aim of predicting runoff volume caused by rainfall using data mining and machine learning methods. They concluded that Support Vector Machines (SVM), CART algorithm, model tree and artificial neural network methods have the highest accuracy in estimating runoff volume, respectively. A method was presented to improve Urban Drainage Systems (UDS) based on Model Predictive Control (MPC) (Abou Rjeily et al., 2018). Using EPA-SWMM and GA led to optimization of the time-scale schedules for actuators of UDS. The results indicated the high efficiency of the MPC method in improving the use of retention elements capacity in Lille university campus. Wang et al. (2018) compared MOEAs, MATLAB global optimization toolbox (MLOT), newly developed hybrid MOEA called GALAXY and NSGA-II in better adaptation to urban drainage system in China. GALAXY was the most powerful and the simplest tool among the three MOEAs because of its mechanism to significantly reduce parameterization issues. Non-dominated sorting genetic algorithm-III (NSGA-III) was used to calibrate storm water management model (SWMM) parameters (Swathi et al., 2019) . By comparing simulated and observed peak flow data, the efficiency of the calibration was evaluated. Results indicated that calibrated parameters related to a rainfall event are applicable for sequential runoff modeling. In a study, the reduction of Total Nitrogen (TN) and Total Phosphorus (TP) under the effect of two BMPs, namely, Fertilizer and Irrigation Reduction (FIR) and Vegetated Filter Strips (VFS) in the agricultural lands of Zrebar lake basin were investigated (Jamshidi et al., 2020). Soil and Water Assessment Tool (SWAT) was used for modeling and calibration of the basin. The results showed that the combination of these two BMPs reduced the concentration of TN and TP by up to 60 percent over eight years. A study was conducted to identify flow properties through grassed canal in Egypt during one year (Gad et al., 2020). Manning coefficient and specific energy were determined. The results were compared to those gathered from last studies in both grassed and ungrassed canals. Gene Expression Programming (GEP) and Statistical Package for the Social Sciences (SPSS) were used to derive formulas which relates Manning coefficient into specific energy of flow. Hai (2020) used the optimal design of permeable pavements, green roofs and tree boxes as LIDs to increase urban runoff quality. To reach the aim, NSGA-II was used to minimize the total relative cost of LIDs and maximize runoff quality. Rainfalls with a two year return period showed more effective results than the others in the Cau Bay river basin in Vietnam. Ochoa-Barragán et al. (2021) proposed a mathematical model that merge fair distribution schemes to design water allocation systems in the context of water scarcity in the city of Morelia in Mexico. The results provided optimal solutions for the equitable distribution of water supply resources in the scarcity scenario for the public consumptions. Alaneme et al. (2021) studied the fuzzy analytical hierarchical procedure to evaluate inefficiency of flexible pavement drainage system. The research was done for a highway in Nigeria. It was proposed to redesign the flexible pavement of the highway, to evaluate the intensity of rainfall and to survey the topography along with the rehabilitation of the worn road using standard materials. In other research Huang et al. (2021) used GA to optimize LIDs distribution with concept of flood peak reduction. The reduction in LID performance was noticeable for return periods of more than ten years. The research results can afford general instruction for urban planning in order to design LIDs in urban areas. Xiong et al. (2021) optimized the service frequency and route network for shuttles by a solution that includes three components. The third component was GA procedure which consists of selection and mutation operators and multiple crossovers. This led to generate feasible solutions. Taban et al. (2021) used Multi-Variable Regression (MVR) and GA in order to select 3 out of 6 parameters that have the greatest influence on obtaining the Q-value in the Q-system (a technique used to determine the support system of a tunnel in rock). Subsequently, a fitness function was used to obtain optimal values in the GA.

Generally, in the previous studies, no steps have been taken to optimize the selection operator parameters in NSGA-II regarding the placement of BMPs in urban runoff control. This practice is performed for the first time in this study as the first innovation. In this paper, it is considered to reach the optimal location of BMPs, their types and area. Separate comparison of the different results of each scenario was the decision guide. The comparison of the results obtained from the use of different selection operators in the optimization algorithm illustrates the efficiency of each one. In the present study, two types of BMPs are used simultaneously in a multi-objective optimization to minimize runoff quantity and pollution. They should be assigned by a sub-catchment number that would be defined automatically. BMPs type selection is also done by the self-acting code to reach the optimal solution. The operator would be asked to determine the number of BMPs according to the organization budget at the beginning of running optimization program; also the range of land use percent for BMPs construction could be varied, both of which are other innovations of this study. Simultaneous qualitative and quantitative improvement of runoff, the type of BMPs, study region, the ability of user participation to determine the best solution compared to the real situation and proprietary optimization code using the NSGA-II algorithm which can be used for all other regions by defining the SWMM input file are the other distinctions compared to previous studies. Popular selection operators are roulette wheel, tournament, rank, stochastic universal sampling and Boltzmann (Katoch et al., 2021) as shown in Figure 1. Other operators used in GA are crossover, mutation and encoding.

Two selection operators have been used to compare with random selection of population in this research. First one is roulette wheel and the second is tournament. In the roulette wheel technique, all the chromosomes in the population are placed on a spinning wheel based on their fitness as shown in Figure 2. Genes that have a higher value based on the fitness function, play a larger role on this wheel and are used more frequently to produce offspring.

The tournament selection mechanism for selecting individuals is such that smaller populations are selected from the initial population. Genes selected from each population are used in the mating pool to produce the next generation (Shukla et al., 2015). The resulting offspring form the basis of the next generation as shown in Figure 3.

2. Methodology

The step-by-step procedure of the modeling and optimization is shown in Figure 4.

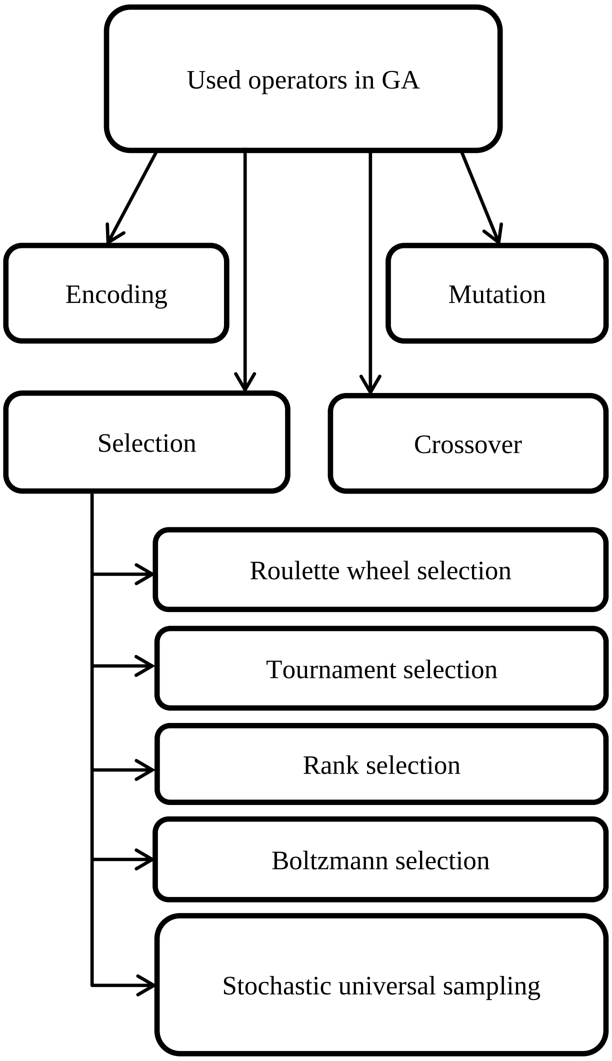

Fig. 1. Popular selection operators in Genetic Algorithm

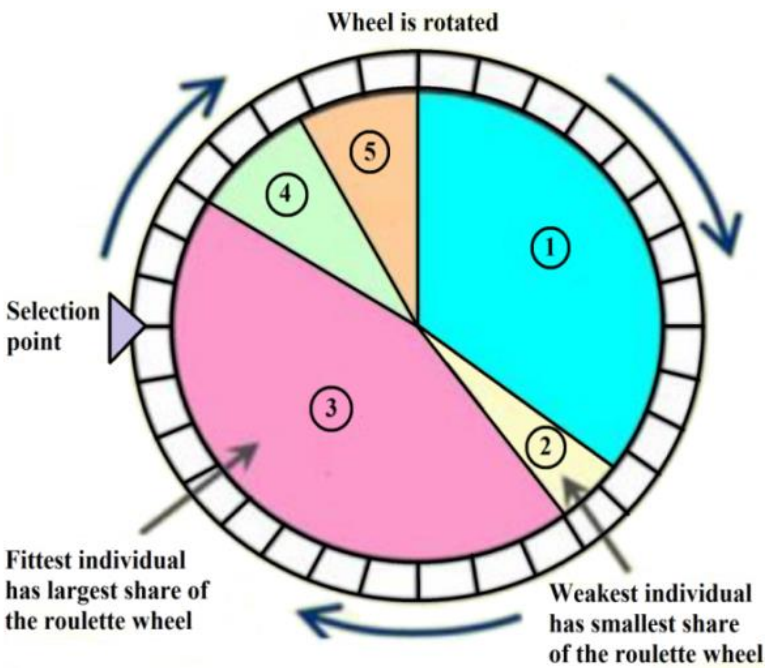

Fig. 2. Visual description of roulette wheel selection (Xavier et al., 2013)

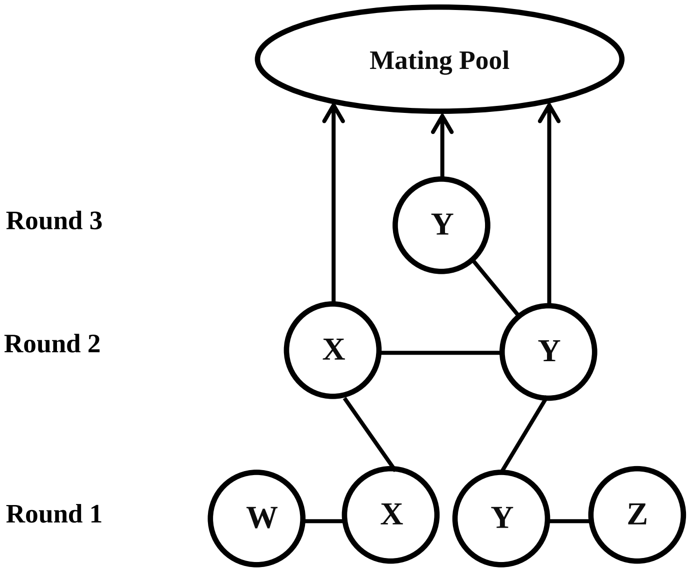

Fig. 3. Schematic concept of tournament selection (Höschel and Lakshminarayanan, 2019)

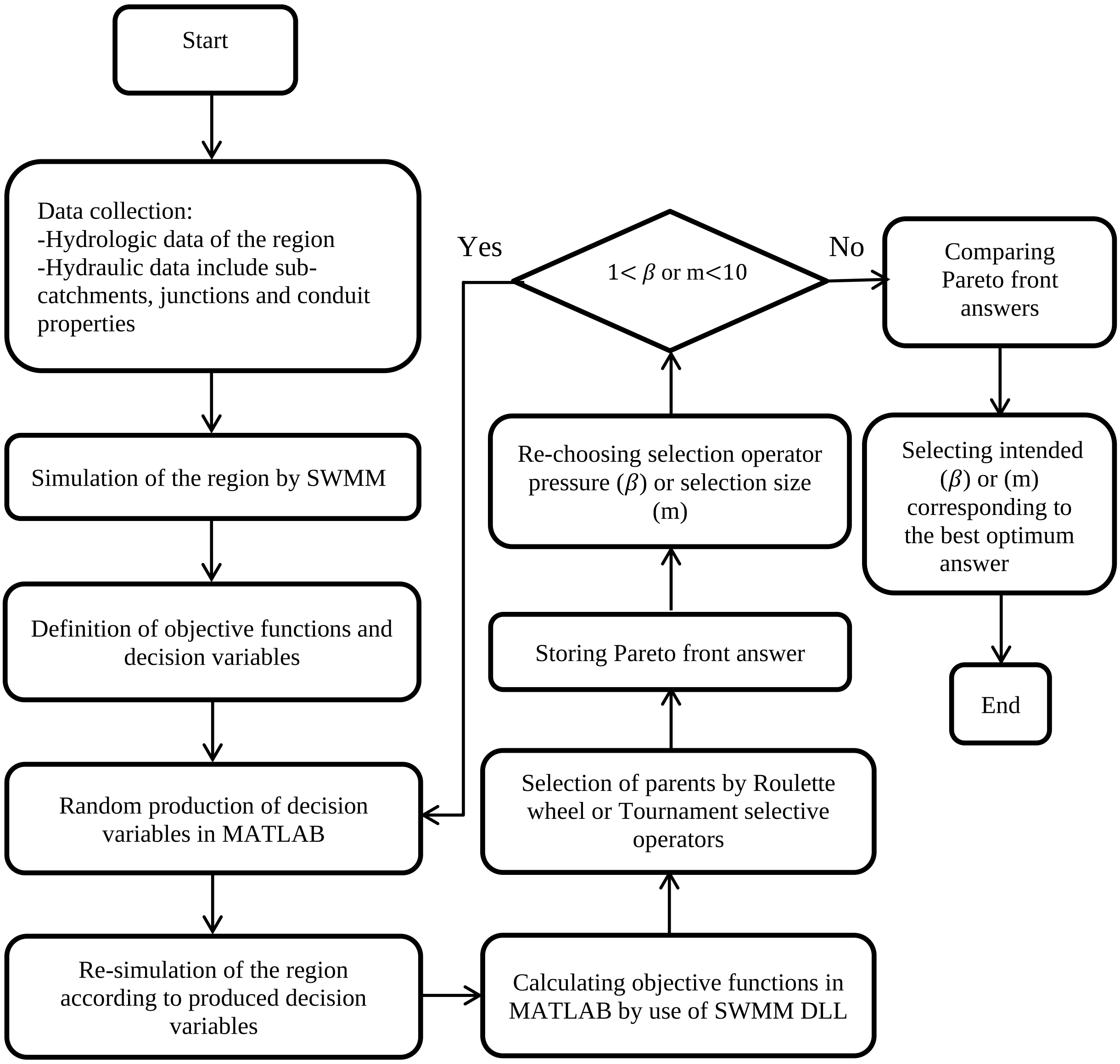

Fig. 4. Procedure of the modeling and optimization using selection operator pressure and selection size

2.1. Modeling in SWMM

In this study, first, the desired area is modeled using SWMM by employing two types of hydraulic and hydrological data. Hydraulic properties include physical characteristics of the area, such as topography, slope and permeability of each sub-catchment, land use and initial coefficients of build-up and wash-off. Other characteristics such as the area and outlet of each sub-catchment, the specifications and coordinates of conduits, outfalls and rain gage are defined as hydraulic data in the model. In addition to being divided into 127 sub-catchments, this region has 227 junctions and 19 outfalls. The total number of data entered into SWMM for modeling sub-catchments, junctions and conduits is 3940. Five types of land uses are considered which include residual (high, medium, low), commercial-industrial and green space. 635 input data have been used to define land uses and each sub-catchment includes five types of land uses. Finally, the percentage of each land use in each sub-catchment would be determined. The SWMM represents unsteady non-uniform flow by using differential equations of mass and momentum conservation known as the St. Venant equations. Volume conservation at each node, along with solving the St. Venant equations for each conduit simultaneously, provides information on temporal and spatial variation of discharge rates and water levels through the network. St. Venant flow equations would be solved by dynamic wave analysis and accurate theoretical answers would be obtained. Dynamic wave analysis account for backwater effects, flow reversal, channel storage, culvert flow and pressurized flow (Rossman , 2017). For unsteady free surface flow through a pipe or channel, the mass and momentum conservation are known as the St. Venant equations that can be expressed in terms of Eqs. (1) and (2).

$$\frac{\partial A}{\partial t}+\frac{\partial Q}{\partial x}=0 \tag{1}$$

$$\frac{\partial Q}{\partial t}+\frac{\partial (Q^2/A)}{\partial x}+gA\frac{\partial H}{\partial x}+gAS_f=0 \tag{2}$$

where x: is distance, t: is time, A and Q: are flow cross-sectional area and flow rate, respectively. H: is hydraulic head of water in the conduit ($Z+Y$). Z, Y and S_f: represent conduit invert elevation, conduit water depth and friction slope (head loss per unit length), respectively, and g: denotes acceleration of gravity.

The hydrological data of the region also include cumulative precipitation data with different return periods (Binesh et al., 2019). These data are obtained specifically for different regions of Iran by modifying the coefficients in the Bell method (Bell and Moore, 2000) (Figure 5). Precipitation data with a return period of two and five years is used in this paper. Selection of these two return periods is due to the fact that the recorded precipitation of the region is most similar to the precipitation height of the two and five years return period according to Figure 5. The calibrated runoff and Total Suspended Solid (TSS) related to the selected precipitation are compared with initial calculated results obtained by SWMM in Table 1.

As shown in Table 1, the greatest effect of SWMM parameters calibration is on rainfall results with a two-year return period and the initial and calibration results are very similar. Therefore, rainfall with a two-year return period was chosen to continue the study due to the high accuracy of its results.

2.2. Study Area

Rafsanjan is known as a city with a relatively high risk of floods in the northwest of Kerman province in southeast of Iran as shown in Figure 6. Rapid development without considering the requirements of sustainability has caused problems in the sanitary infrastructures and water supply in the region. Qualitative and quantitative management and improvement of runoff is very important alongside urban development. The 2016 flood caused severe damage to the city residents and roads and disrupted traffic. The poor quality of the resulting runoff also affected the region's agriculture. Therefore, urban runoff control is becoming more important than before. In this research, the city of Rafsanjan has been considered as a suitable case according to the mentioned contents and the available topographic information. Two rivers named Shoor and Givdari pass through the city, which are the entrances of sub-catchments runoff in the region. The lowest elevation of the city is 1489 m while highest elevation is 1557 m above mean sea level. This region covers an area of 48.07 km^2 and is divided into 127 sub-catchments in SWMM according to Figure 7.

Table 1. Initial and calibrated parameters used in the simulations

Return period (year)	**2**		**5**	
Data type	**Initial**	**Calibrated**	**Initial**	**Calibrated**
Total runoff (m^3/s)	0.9	0.948	1.3	1.373
Total TSS (kg)	453.6	453.8	655.2	609.315

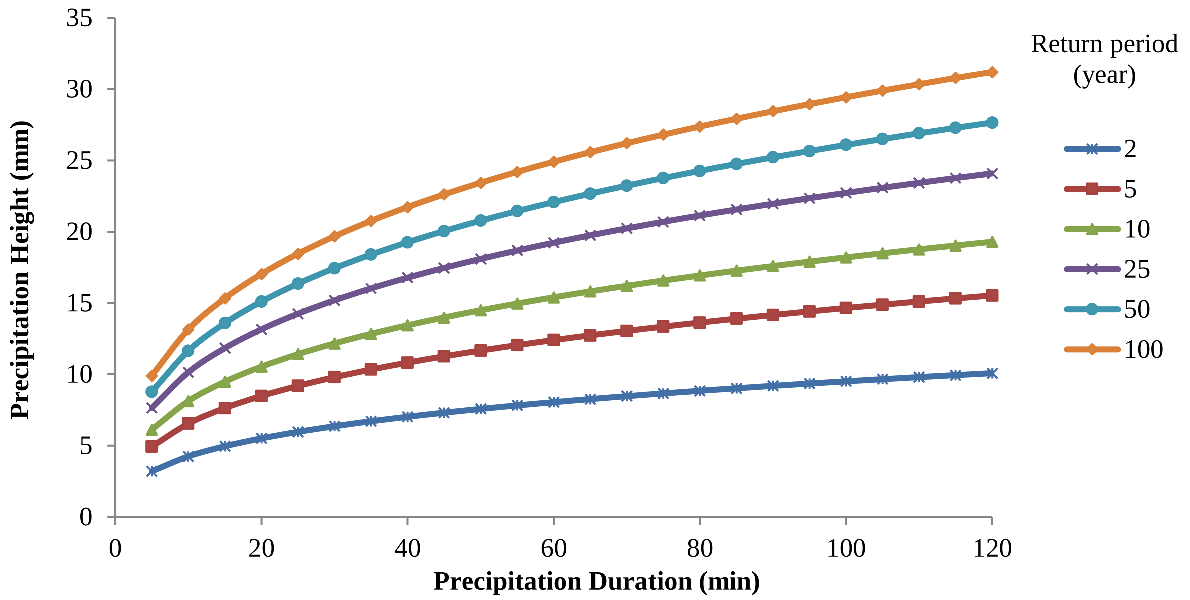

Fig. 5. Two-hour rainfall curves in different return periods for the study area (Binesh et al., 2019)

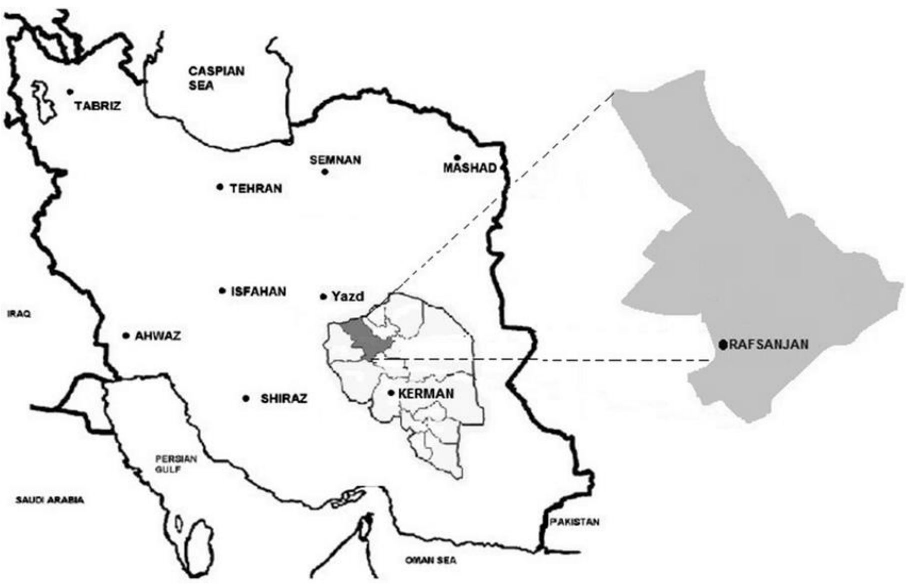

Fig. 6. Rafsanjan location in Iran, Kerman (Hakimi et al., 2021)

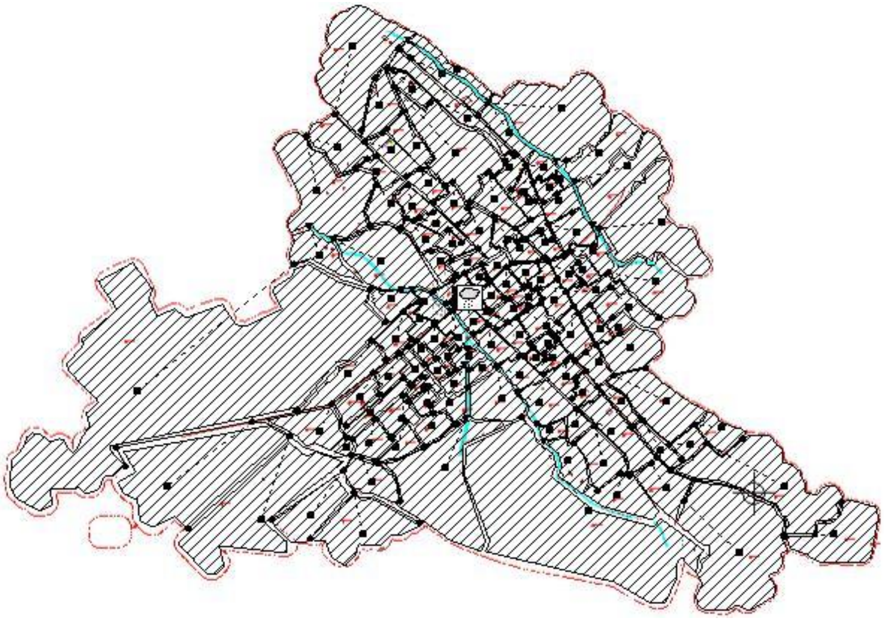

Fig. 7. Study area in SWMM including the plan of the region and separated sub-catchments

In this paper, locating the BMPs and determining the optimal area of each one has been done in order to achieve highest quality of urban runoff and the lowest flood volume for each sub-catchment. Two types of BMPs called retention ponds and vegetative swales indicated in Figures 8 and 9 have been recommended as the BMP for reducing Runoff Nonpoint Source (NPS) pollution (Li and Kuo, 2021). Minimizing the total cost of these BMPs is another goal that has to be met.

2.2.1. Retention Pond

Retention ponds are storm water control structures that help to retain the water and treat contaminated storm runoff. Retention ponds remove pollutants and should be surrounded by natural vegetation to improve sustainability and the overall view of the basin. Water is sent to the pool using a network of underground pipes and released through outlets to maintain the desired water level. The biggest advantage of using a retention pond is the simplicity of placement, improving water quality and creating new habitats.

Fig. 8. Implemented retention pond (Wanielista and Academy, 2007)

2.2.2. Vegetative Swale

Vegetated swales are shallow, broad channels designed to reduce runoff volume, improve infiltration and filter contaminants and sediments during runoff flow. Vegetated swales are an excellent ecological alternative to conventional curb and stream conveyance systems, while supplying pretreated and semi- distributed flows. Swales are often densely vegetated and include a variety of early-maturing, resistant and native plants with great potential of pollution reduction. The mechanism of a swale for reducing the pollutant contains vegetative sedimentary filtering and subsoil matrix filtering or infiltration into the underlying soils (Pennsylvania Department of Environmental Protection, Bureau of Watershed Management, 2006).

With a two-year return period precipitation, the original model is run. The build-up and wash-off coefficients are improved by comparing measured TSS amount with SWMM obtained results. The build-up and wash-off coefficients are confirmed by area modeling with the help of precipitation data with a return period of five years. The results are shown in Table 2.

In Table 2, C_1: is the maximum possible build-up (mass per unit of area or curb length). c_2: is rate constant of build-up function (1/day) in exponential function and c: represents the wash-off pollutant concentration in mass per liter in event mean concentration function. A similar method is performed to modify the Manning coefficient using simulated runoff values and observational data. The results are shown in Table 3. Finally, the model calibrated by obtained coefficients.

Table 2. Initial and modified build-up and wash-off coefficients after model calibration

Return period (years)		**2**		**5**		**Average amount of calibration**
Data type	**Land use**	**Initial**	**Calibrated**	**Initial**	**Calibrated**	
C_1 for Build-up exponential function (kg/m curb)	High dense residual	0.003	0.003	0.003	0.003	0.003
	Medium dense residual	0.003	0.002	0.003	0.003	0.0025
	Low dense residual	0.003	0.001	0.003	0.003	0.002
	Commercial and industrial	0.015	0.034	0.015	0.05	0.042
	Green space	0.08	0.08	0.08	0.08	0.08
c_2 For Build-up exponential function (1/day)	Residual, commercial and industrial	0.8	0.8	0.8	0.8	0.8
	Green space	0.1	0.1	0.1	0.1	0.1
c For wash-off event mean concentration function (kg/m curb)	High dense residual	200	180	200	250	210
	Medium dense residual	200	180	200	250	210
	Low dense residual	200	180	200	250	210
	Commercial and industrial	300	250	300	300	275
	Green space	65	65	65	100	83

Table 3. Initial and modified manning's coefficients after model calibration

Return period (years)		**2**		**5**		**Average amount of calibration**
Parameter	**Member**	**Initial**	**Calibrated**	**Initial**	**Calibrated**	
Manning's coefficient	conduits	0.025	0.025	0.025	0.035	0.03

Fig. 9. Implemented vegetative swale (Pennsylvania Department of Environmental Protection Bureau of Watershed Management, 2006)

2.3. Application of Optimization Algorithm

The NSGA-II optimization algorithm is used to optimize the three objective functions according to Eqs. (3) to (5).

$$Ob_1 = min(\sum_{i=1}^{127} R_i) \quad (3)$$

$$Ob_2 = min(\sum_{i=1}^{127} \sum_{j=1}^{2} Co_{ij}) \quad (4)$$

$$Ob_3 = min(\sum_{i=1}^{127} Po_i) \quad (5)$$

where R_i: is the runoff volume in ith sub-catchment. i and j: are the number of sub-catchments and BMP's type, respectively. Co_{ij}: represents construction and maintenance cost of the jth BMP in the ith sub-catchment and Po_i: denotes concentration of pollution in ith sub-catchment.

Based on the experimental studies of Bayou Land RC&D and Louisiana Public Health Institute (2010), the cost of manufacturing and maintenance of BMPs has been estimated employing Eqs. (6) to (10).

$$Co = RC_c + RC_m + VC_c + VC_m \quad (6)$$

$$VC_c = (0.25 - 0.5)A_i \quad (7)$$

$$VC_m = (0.25 - 0.5)(0.05 - 0.07)A_i \quad (8)$$

$$RC_c = 307.76V^{0.71} \quad (9)$$

$$RC_m = 307.76(0.03 - 0.06)V^{0.71} \quad (10)$$

Where VC_c and VC_m: are the construction or investment cost of vegetative swale and cost of maintenance for vegetative swale in USD, respectively. RC_C and RC_m: describe construction or investment cost of retention pond and cost of maintenance for retention pond in USD, respectively. V: is the retention pond volume in m^3 and A_i: is the vegetative swale area in m^2.

MATLAB is employed for coding and communication between DLL of SWMM and the code containing optimizer algorithm. Subsequently, the number of sub-catchments in which BMPs should be constructed, the type and the optimal area of each one, are derived in the form of results. In the next step, according to the selection operators that are used in the algorithm (roulette wheel, tournament and random), the results of using each operator in selecting the population of each generation are compared with each other. Finally, the best selection operator is determined according to the calculated quantitative and qualitative runoff values. Also, the best pressure of the selection operator in the roulette wheel and the best size of the tournament selection operator are selected, which leads to the optimal solutions.

2.4. Decision Variables

The first variable is a binary variable which its upper limit is the number of sub-catchments that is 127 in this study. It determines the chance of a sub-catchment being selected as a BMP construction site. The second variable considers whether a BMP is randomly selected within the sub-catchment. This variable is in form of 0 and 1. The third variable specifies the allowable range of BMP area for construction, which is considered to be between one and five percent. This value is selected according to the conditions and restrictions of the region and can be changed in the code. The corresponding code is developed with three types of selection operators that allow the user to select one of them at the beginning of the program execution. These operators are roulette wheel, tournament and random selection that are used in the algorithm. In roulette wheel, population members are ranked based on their fitness function. Population members with larger fitness functions have a better chance of being selected as parents in the crossover and mutation phases. The fitness function is described in Eq. (10) (Chetan and Nitesh, 2021).The flowchart on how to apply the roulette wheel selection operator code in MATLAB is shown in Figure 10.

$$P(y_i) = \frac{p(y_i)}{\sum_{i=1}^{N} p(y_i)} \tag{11}$$

where N: is the number of population in the selection pool. y_i: is the population i. p(y_i): is the value of objective function for population i and P(y_i): represents the fitness value for population i .

In Figure 10, parameter β : is the selection operator pressure. This parameter must be selected in such a way that the best answer is obtained according to the objective functions. N_{pop}: is the number of population which is selected. $pop(y)$: is the yth member of the population and cost(1) is the value of objective function for first member of the population. Last equation in Figure 10 is described in Eq. (11). The flowchart of the tournament selection operator code is shown in Figure 11.

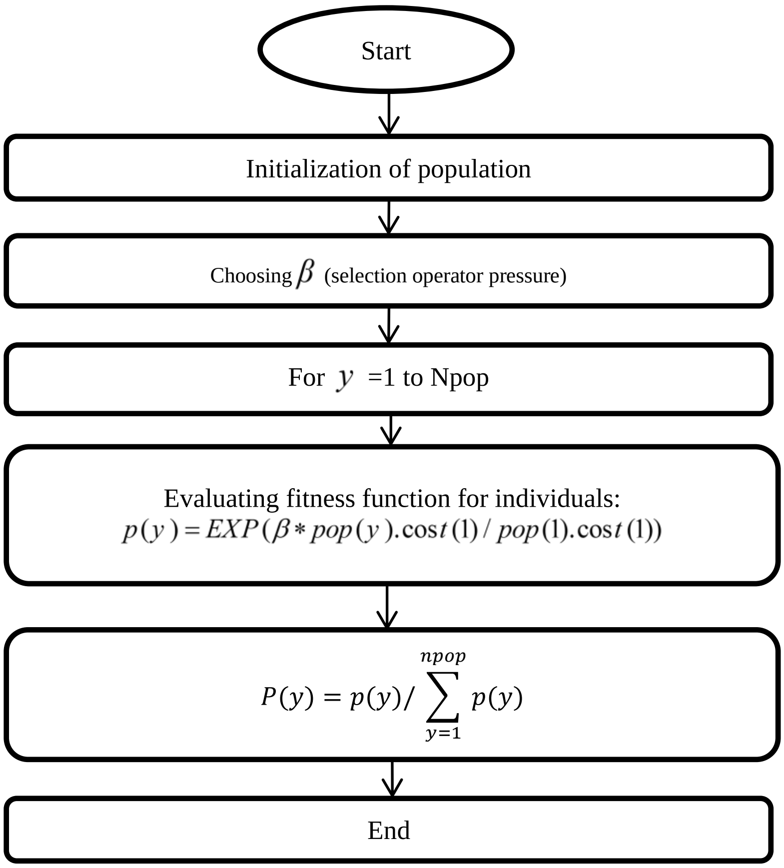

Fig. 10. Employing the roulette wheel selection operator

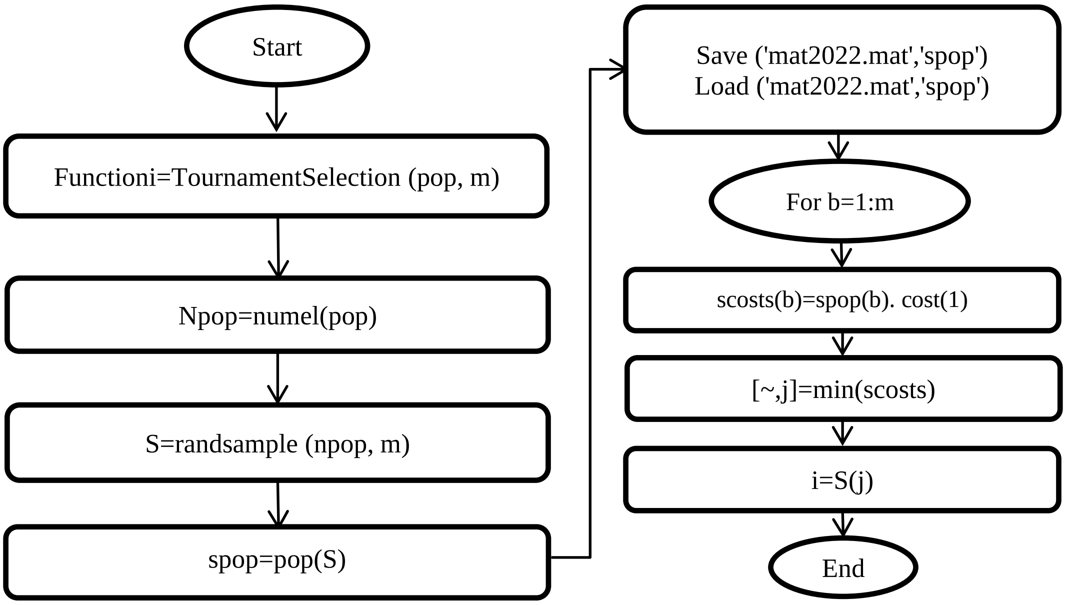

Fig. 11. Employing tournament selection operator

In Figure 11 for the tournament selection operator, m: is the tournament size. It should also be selected in such a way that the optimal solutions are determined according to the value of the objective functions. S: is a random selection of *m* from the selected population (npop). spop: is the population of the selected set S and 'mat2022.mat': represents the matrix related to the population S, which is first formed and then loaded to accommodate the members. In Figure 11, the optimal m produces the minimum value of 'scosts' and 'scosts(b)' is the product of each member of the matrix, 'spop(b)', multiplied by the value of the objective function for the first member of population (cost(1)). Finally, S(j): is the selected population of the tournament operator function. Ranking of answers is done by comparing the values of the objective functions in each iteration. The higher number of iterations and selected population leads to more accurate and convergent optimization results. In NSGA-II, the selection operator is used before using crossover and mutation operators (Deb et al., 2002). The selection operator is employed to determine the population of participants in the next steps, which are known as parents in the algorithm. The combination of simulation and optimization for the study area has been done using coding method in MATLAB and NSGA-II algorithm. The population size in the algorithm is 50 and the crossover percentage is 5. In order to obtain results to compare the performance of the selection operators, the maximum number of BMPs is considered as 6 and their maximum construction cost is considered 1.5 million USD in the code. Maximum area occupancy level of 5 percent for each sub-catchment is considered. In order to apply these restrictions, the optimization code works almost as a software and receives the mentioned information from the user as inputs at the beginning of the program execution. It is worth mentioning that this program has been prepared in such a way that it has the ability to call any type of INP file, which is the suffix of the urban runoff modeling file in SWMM and can be applied to any other areas. This is a significant innovation and advantage over other previous studies. Each of the input information (number of population, crossover percent, number of iteration, maximum number of LIDs that can be built, available budget and maximum percentage of allowable occupied area of each sub-catchment to construct BMPs) can be changed. This information can be adjusted depending on the urban architecture plan, municipal permissions, required accuracy and available budget. Subsequently, 'β' and 'm' are changed alternately, and the results of the NSGA-II performance are compared with each other in the form of the objective function values, and the best 'β' and 'm' are selected.

3. Results and Discussions

The selection operator pressure in the roulette wheel and the selection size in the tournament operator are changed from 1 to 10, and the results have been obtained. Tables 4 and 5 show the results of the objective functions obtained by changing the parameter 'β' in the roulette wheel operator and 'm' in the tournament operator, respectively. In order to show the efficiency of using the selection operators compared to the random selection of the population participating in the crossover, the program has been executed once using the random selection operator. The results are shown in Table 6. For each selection operator pressure change (1 to 10), the values of the objective functions have been calculated using a three-objective genetic optimization algorithm. Runoff volume, pollutant amount and BMPs construction and maintenance costs are three objective function values, which are calculated in each program execution. This study is a pioneer in obtaining the best operator pressure selection and tournament size in multi-objective optimization of urban runoff. The numerical range obtained for the runoff volume is between 14781.8 and 14868.9 m^3 using the roulette wheel selection operator. This value varies between 14839.2 and 14873.4 if the tournament selection operator is used. The pollution range is also obtained between 2271.1 and 2291.05 kg for using the roulette wheel selection operator While, this value is between 2263.57 and 2290.9 kg for using the tournament selection operator. Finally, BMPs construction and maintenance costs for each selection are derived, which is varied from 133207 and 1630000 USD for roulette wheel and 162807 and 1008260 USD for tournament operator application. In the random selection operator, the optimal values of runoff volume, pollution and total BMPs costs are 14839.2 m^3, 2274.99 kg and 287702 USD, respectively.

Table 4. Optimization results employing of roulette wheel selection

Selection operator pressure (β)	**Objective functions value** **Runoff volume (m^3)**	**Pollutant (kg)**	**Cost (USD)**
1	14867.1	2280.45	734200
2	14839.2	2274.99	287702
3	14868.9	2271.1	133207
4	14868.9	2279.73	1630000
5	14868.9	2290.66	1322425
6	14868.9	2281.28	1292460
7	14781.8	2284	1301470
8	14839.2	2274.99	287702
9	14868.9	2271.1	133207
10	14868.9	2291.05	269424

Table 5. Optimization results by use of tournament selection

Tournament size (m)	**Objective functions value** **Runoff volume (m^3)**	**Pollutant (kg)**	**Cost (dollar)**
1	14868.9	2270.47	835972
2	14873.4	2276.79	530899
3	14868.9	2273.82	261919
4	14868.9	2283.22	353534
5	14839.2	2274.99	287702
6	14868.9	2271.71	652823
7	14868.9	2263.57	1008260
8	14868.9	2290.9	170596
9	14868.9	2280.66	162807
10	14868.9	2263.57	1008260

Table 6. Optimization results by use of random selection

Objective functions value		
Runoff volume (m^3)	**Pollutant (kg)**	**Cost (USD)**
14839.2	2274.99	287702

According to the results obtained from the tables, runoff values versus the values of parameters 'β' and 'm' for both selection operators are shown simultaneously in Figure 12. The minimum runoff value created in all sub-catchments is obtained for the roulette wheel selection operator in the amount of 'β' equal to seven hence the lowest amount of surface runoff in the tournament selection operator is obtained in the amount of 'm' equal to five.

A similar procedure is followed to represent the TSS pollution values of runoff in exchange for the quantities of 'β 'and 'm'. The graph is indicated in Figure 13. Minimum value of TSS obtained from using the roulette wheel selection operator in 'β' equal to 3 and 9. For the tournament selection operator, this minimum is achieved at 'm' equal to 7 and 10.

Similarly, the minimum total costs of BMPs for each described parameters can be seen in Figures 14 and 15. Three and nine as selection operator pressures give the lowest construction and maintenance costs, while size nine in tournament selection presents the lowest costs.

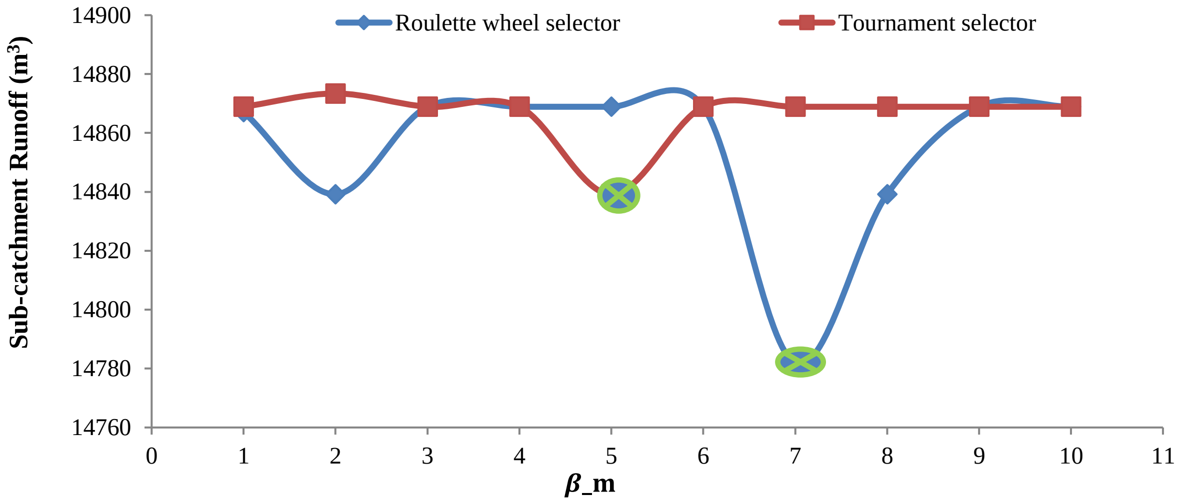

Fig. 12. Optimum runoff quantity derived by using different amounts of selection pressure and size in roulette wheel and tournament

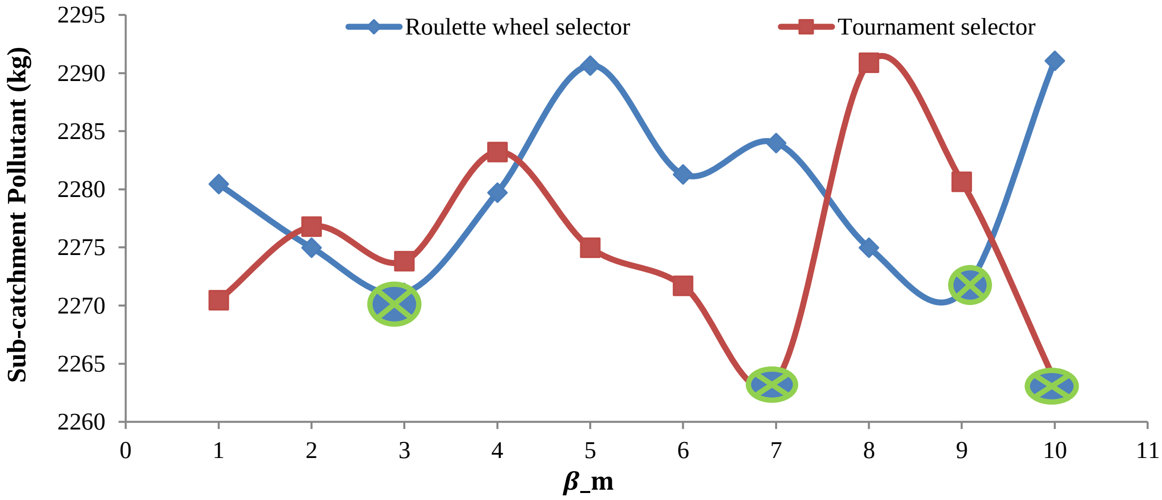

Fig. 13. Optimum pollution quantity derived by using different amounts of selection pressure and size in roulette wheel and tournament

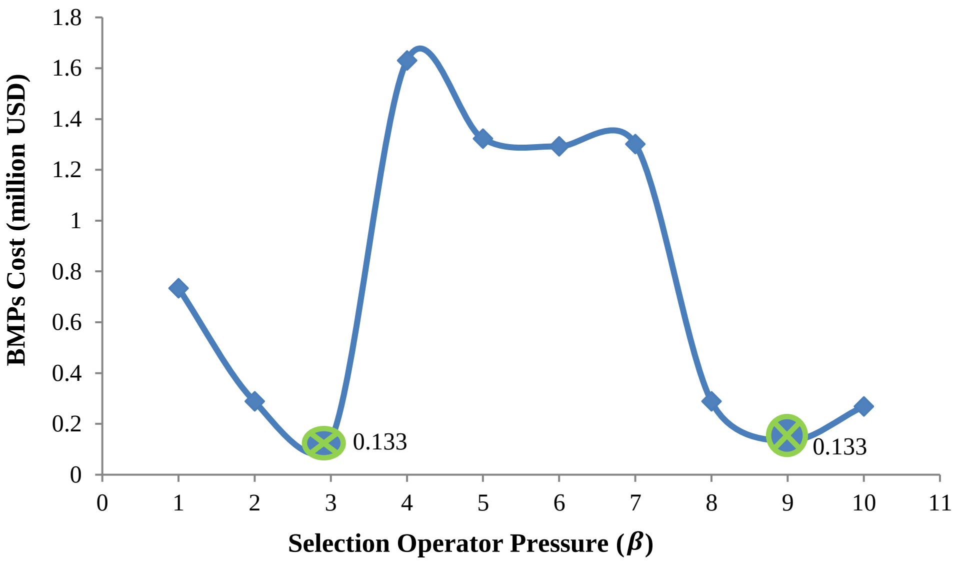

Fig. 14. Optimum cost of BMPs using different amounts of selection pressure in roulette wheel operator

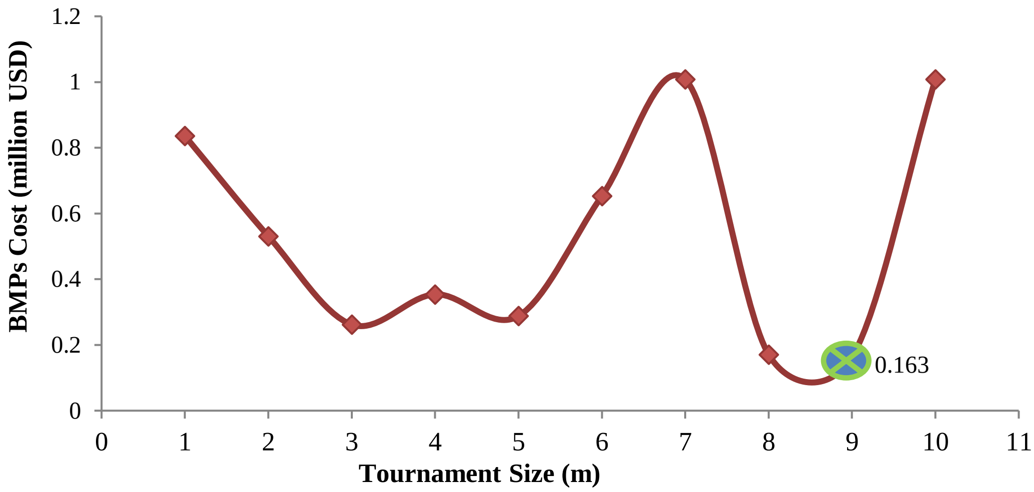

Fig. 15. Optimum cost of BMPs using different amounts of tournament size

According to the obtained results, it can be seen that the difference in the amount of runoff volume in the study area using the roulette wheel is 87.1 m^3 in the worst and best alternatives. This difference in runoff volume is 34.2 m^3 if the tournament selection operator is used. In a similar comparison, it can be seen that the difference between the maximum and minimum TSS pollution values using roulette wheel operator is approximately 20 kg, while this value is about 28 kg for the tournament operator. It is easy to see that these values are small and indicate that the selected options do not have much effect on the amount of runoff volume and pollution objective functions. But the difference in the values of the third objective function, which is the total cost of BMPs, is enormous. These values are 1496793 and 845453 USD, respectively, in case of using roulette wheel and tournament operators. Therefore, due to this large difference, the cost function can be the basis for making decision.

Due to the fact that the selection operator pressure with the value of three is the most effective choice in providing the optimal solution of the objective functions, multi-objective optimization in the study area is performed using this selection operator pressure (three). NSGA-II with roulette wheel operator is implemented in MATLAB to locate BMPs. Three sub-catchments are assumed to locate each type of BMPs as the maximum allowable number and since two types of BMPs are used in this research, six sub-catchments are totally considered as the maximum number that can be used to place all two types of BMPs at the same time. The population size is selected as 50 and number of iteration is 100 that according to required accuracy they can be varied. Finally, the program is executed by defined characteristics.

The result that submit Pareto front is shown in Table 7 where the first eight populations have been ranked. The values of three objective functions are indicated in the first column in Table 7. The optimal area of BMPs (A_1 to A_6) and volume of each BMP located in the selected sub-catchment are also presented in columns two and three, respectively. It should be mentioned that in each row, first three optimum areas in bracket, are related to retention ponds and the other three values are related to vegetative swales. Subsequently, the number of optimum volumes in column three is equal to the number of retention ponds. The number, that each population is dominated, is known as dominated count. Besides, the ranking of selected BMPs construction locations in satisfying the objective functions is determined in rank column. When the solutions have the same rank the greater crowding distance represents better solution which is shown in last column.

The best selection of sub-catchments which derives optimum objective functions in each rank according to the Table 7 is shown in Table 8. In Table 8, the best selected sub-catchments number, for constructing each type of BMPs have been shown. These data correspond to the areas obtained in the second column of Table 7.

Table 7. Optimum results of objective functions by running the code in the studied region (Rafsanjan)

Objective functions value			Optimum area for BMPs A_1 to $A_6 (m^2)$	Optimum retention ponds volume (m^3)	Dominated count	Rank	Crowding distance
Runoff (m^3)	Pollutant (kg)	Cost (USD)					
14869	2271	133207	[2090,1212,0,8453,7420,0]	[1463,848]	0	1	Inf
14794	2295	185361	[0,6521,0,0,19627,15436]	[4565]	0	1	9.5878×10^{-4}
14899	2309	161679	[0,0,5941,10726,0,0]	[4159]	0	1	5.4858×10^{-4}
14899	2313	188371	[7021,0,0,7198,16721,0]	[4915]	0	1	6.7807×10^{-5}
14899	2302	189706	[2521,0,3020,7169,0,8541]	[1765,2114]	0	1	8.2461×10^{-6}
14897	2313	199234	[0,4827,1524,0,6272,3668]	[3379,1067]	0	1	5.2536×10^{-6}
14897	2311	216266	[8125,0,0,21430,7940,10834]	[5688]	0	1	7.5736×10^{-7}
14899	2271	476545	[8050,12202,0,19751,16513, 6950]	[5635,8541]	0	1	0

Table 8. selected sub-catchments for optimum solutions

Sub-catchment number for locating BMPs					
Retention ponds			Vegetative swales		
88	124	-	11	62	-
-	123	-	-	127	86
-	-	112	66	-	-
88	-	-	11	62	-
103	-	92	96	-	86
-	20	12	-	41	19
113	-	-	119	41	127
61	56	-	108	56	9

The first row of results in Table 8 shows that two sub-catchments with numbers 88, 124 have been used for the construction of the retention ponds and sub-catchments 11, 62 have been used for the construction of the vegetative swales, respectively. These sub-catchments are the results of multi-objective optimization (NSGA-II), for locating BMPs. Comparing Tables 4 and 7, shows that the objective functions in the row corresponding to $\beta = 3$, in Table 4, is derived from the first row of Table 7, which is the best answer. This process is performed sequentially for each type of the selected operators ('β','m'), from 1 to 10 separately. The results are shown in Tables 4 and 5. The optimized areas of the selected BMPs are 2090, 1212, 8453 and 7420 m^2. The first two values belong to retention ponds and the other values relate to vegetative swales. The optimized volume of retention ponds are 1463 and 848 cubic meters. The wash-off, build-up and manning coefficients are calibrated but the physical characteristics of conduits like shape, max depth, length, roughness, inlet and outlet offset and invert elevation of the nodes are associated with some uncertainty in few parts of the city. Obviously the model is executed in SWMM by these input data. The other uncertainties incorporated in this study include curb length and sub-catchments specifications like permeability, slope and width.

4. Conclusions

The results of this paper indicated that the optimal choice of 'β'and 'm' in the roulette wheel and tournament selection operators had a significant effect on the construction costs of BMPs in the best selected alternatives. Therefore, construction cost can be used as a main decision criterion according to the values of the other two objective functions. However, it should be noted that in this study, due to show the ability of define limitations in the designed program, the budget and the maximum number of BMP types and the maximum occupancy of each sub-catchments were predefined and the population participating in the optimization algorithm process was determined. By increasing the values of each program inputs, the runoff volume and pollution could be reduced and the best sub-catchments for the construction of BMPs and their area could be obtained. Finally, according to the values of all three objective functions and the maximum effect of the selection operator pressure on each one, it can be concluded that the best 'β' in the roulette wheel operator is 3 or 9, which gives almost similar results. For the tournament operator, considering earlier given description, the best 'm' is 9. This study was conducted to design a program to be used in any desired region and any SWMM input file. The values of 'β' and 'm' are applicable for other similar studies in order to obtain optimal solutions. When optimal values of selection operator pressure and selection size are used, both roulette wheel and tournament selectors give better results than the random operator. The results of this study can be generalized to other similar studies that may be performed in the future.

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