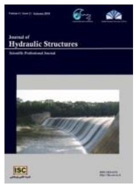
Journal of Hydraulic Structures
J. Hydraul. Struct., 2024;11(1):1-19
DOI: 10.22055/jhs.2024.47664.1317



OPEN ACCESS

Optimizing the urban runoff collecting network using Harris Hawks single-objective optimization algorithm (a case study of the flood network in West Tehran)

Seyed Masoud Majidi [1]
Hamed Reza Zarif Sanayei [*1]
Ali Raeisi Isa-Abadi [2]

Abstract

Today, optimization is very important and necessary in engineering works and it seems necessary in the field of urban runoff and flood management. In this research, a case study of Darakeh River in Tehran as an important links in flood management and runoff conveying is used to reduce the costs of constructing flood conveying routs and water leakage. In the next step, rainfall values are obtained in return periods of 20, 25, 35, 50, 75 and 100 years by using hydrological relationships. Then, the output runoff is extracted by modeling the network in numerical software and the output hydrographs of the created model are entered into SWMM software. In order to present the output results of the SWMM model in a better format, the SWMM results are entered into SSA software. The SSA results are linked into the Harris Hawks Optimization (HHO) algorithm and finally, the construction cost and water leakage functions are optimized. Eventually, the results of HHO are compared with the Particle Swarm Optimization (PSO) algorithm to check the accuracy of HHO. The value of changes for width and height in bridges and channels are compared in two algorithms. As a result, the HHO algorithm reduces the volume of flood and water leakage in different return periods by presenting less cost as compared to the PSO algorithm.

Keywords: Harris Hawks Optimization, Rainfall, Surface Water, Runoff Collecting Network, Flood Management.

Received: 04 October 2024; Accepted: 07 September 2024

[*] E-mail: Zarif@sku.ac.ir
[1] Department of Civil Engineering, Shahrekord University, Shahrekord, Iran.
[2] Department of Water Engineering, Shahrekord University, Shahrekord, Iran.

1. Introduction

The conveying of runoff and its collection is one of main problems of engineering community. Surface runoff collection networks are always expensive projects in every area. Therefore, reducing the construction cost of these projects is very important in the urban management. In other words, the lower construction cost of surface runoff collection projects will be created the better economic justification for implementation at the urban management level. Consequently, using new optimization methods for the optimal design of these networks with lower construction costs can be a very suitable idea. Many researches have been done on the simulation and modeling of the urban runoff collection network which are based on models such as MIKE 21, SWMM, SSA and etc. Researches on optimization issue of the urban runoff collection network are very limited in the literature.

Reddy and Kumar [1] presented multi-objective type of differential evolution (DE) algorithm. This method was called multi-objective differential evolution (MODE) and performed on a study model of a reservoir system. The results showed that the MODE algorithm provided better performance in optimizing the reservoir system compared to nondominated sorting genetic algorithm (NSGA).

Pan and Cao [2] used a combination of genetic algorithm and quadratic programming in the MATLAB software to optimize the cost function for a flood harvesting system. They compared the results of their work with the done previous works on the flood collection system and concluded that there is suitable alternative to the proposed previous works. Moghaddam et al. [3] worked on the optimal design of water distribution network using simple modified particle swarm optimization (SMPSO) algorithm. In their work, SMPSO algorithm was connected with EPANET 2.0 software. Their researches compared with the results of past studies including genetic algorithm (GA), simulated annealing (SA), shuffled frog leaping algorithm (SFLA), harmony search (HS) and scatter search algorithm (SS). The results showed that the SMPSO algorithm could be found the best solution in the shortest time compared to other algorithms. Azari and Tabesh [4] investigated studies on the optimal design of flood collection networks with considering hydraulic performance and best management practices (BMP). In their research, genetic multi-objective optimization algorithm (NSGA) was used. The results presented that using NSGA can be increased the system reliability up to 100% and the costs due to damages can be reduced to a surprising value. Abdy Sayyed et al. [5] investigated research with combined flow and pressure deficit in genetic algorithm for optimal design of water distribution network. Their study was on minimizing the cost function of constructing a water distribution network with sufficient pressure constraints at all points. They proposed a self-organizing penalty based on pressure heads to increase the effectiveness of numerical calculations and observe better solutions. In this research, it was observed that the modified penalty method was 4.2% cheaper than other researches in literature. Tanyimboh and Seyoum [6] presented an optimal design of water distribution network using multi-objective genetic algorithm without penalty function based on pressure simulation. They performed their studies on a real world study model with hundreds of variables. It was observed that the highest speed occurs at a distance of one meter from the water distribution network connections. Also, the cost function in this algorithm was reduced to 48.3% compared to previous algorithms. Ezzeldin and Djebedjian [7] worked on the optimal design of the water distribution network using the whale optimization algorithm (WOA). They used this new algorithm to optimize the cost function of pipe networks. This algorithm was implemented for 3 pipe networks and its results were compared with implemented previous algorithms on these networks. The results showed that the whale optimization algorithm (WOA) has the lowest design cost of the water distribution network compared to other tested optimization algorithms on this network such as genetic algorithm, frog jump and etc. Heydari Mofrad and Yazdi [8] studied on a multi-objective evolutionary algorithm for the reconstruction of urban drainage systems. They found a hybrid simulation-optimization model in the area of Tehran's main drainage network. Also, they used a combination of an EPA SWMM and a new improved evolutionary algorithm called Non-Dominated Enhanced Differential Evolution (NSDE) to optimize the walls of dams and detention basins. The optimized strategies reduced the retrofitting cost and network flooding up to 61.7% and 37.5%, respectively. Diao et al. [9] applied the improved particle swarm optimization (SAPSO) algorithm to optimize the flood control in the cascade reservoirs. By using the SAPSO algorithm, the maximum outputs of Tianzhuang and Bashan reservoirs were reduced up to 8.6% and 18.5%, respectively.

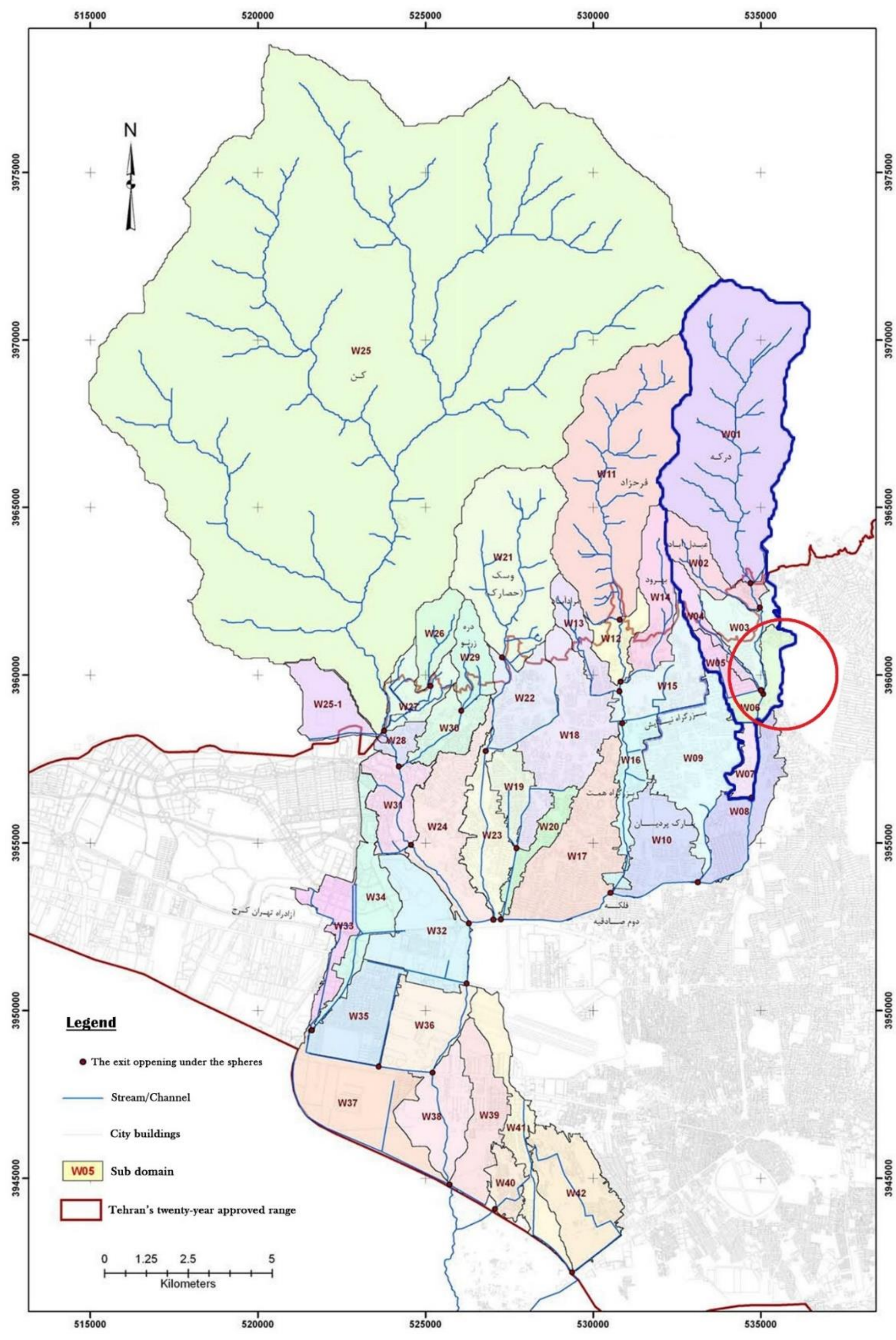
Cemiloglu et al. [10] worked on the enhancement of the urban surface runoff conveyance system through optimization using non-dominated cases of the meta-heuristic algorithm of sorting differential evolution (NSDE). They followed an innovative approach by combining NSDE meta-heuristic algorithm with SWMM software. In their research, the objective functions were minimizing costs and reducing water leakage from the network. Results showed that the water leakage was decreased up to 95.26% by using this algorithm. It should be noted that other studies have been performed in the field of the optimal design for Surface runoff collection networks and water distribution networks over the years [11-15].

The Harris Hawks Optimization (HHO) algorithm is a meta-heuristic algorithm that has been published by Heidari et al. [16] focusing on the mass hunting strategy of Harris hawks. This algorithm has been seriously considered in recent years to solve various problems. For example, Abbasi et al. [17] worked on the performance of the HHO algorithm on the design of microchannel heat sinks. The results showed that the HHO algorithm has an excellent performance in reducing the entropy generation of the microchannel. Elgamal et al. [18] also studied the simulation of annealing with the improved algorithm of Harris Hawks to select features in the medical field. They proved the superiority of CHHO algorithm by comparing the results of HHO algorithm with algorithms such as GOA, BOA, PSO and ALO. As another research, Wang et al. [19] used the HHO algorithm to solve industrial engineering optimization problems. They proposed a combination of two algorithms, AO and HHO, along with a non-linear escape energy parameter and a learning strategy based on random opposition, i.e. IHAOHHO, to improve the search process. They evaluated that the results were satisfactory by confirming the performance of this algorithm on 23 benchmarks. In another research, Nematollahi and Zarif Sanayei [20] presented an optimal model for predicting the exploitation of groundwater based on the HHO algorithm for the simultaneous use of the surface and groundwater resources. They performed a numerical simulation of the Mahabad aquifer at first step and then, investigated the optimization model using the HHO algorithm for a period of 20 years. In the following, they created seven scenarios to predict the optimized groundwater exploitation (OGE) by using the results of HHO data and combining with artificial neural network (ANN). The results showed the superior performance of the ANN-HHO model when it includes all the input variables.

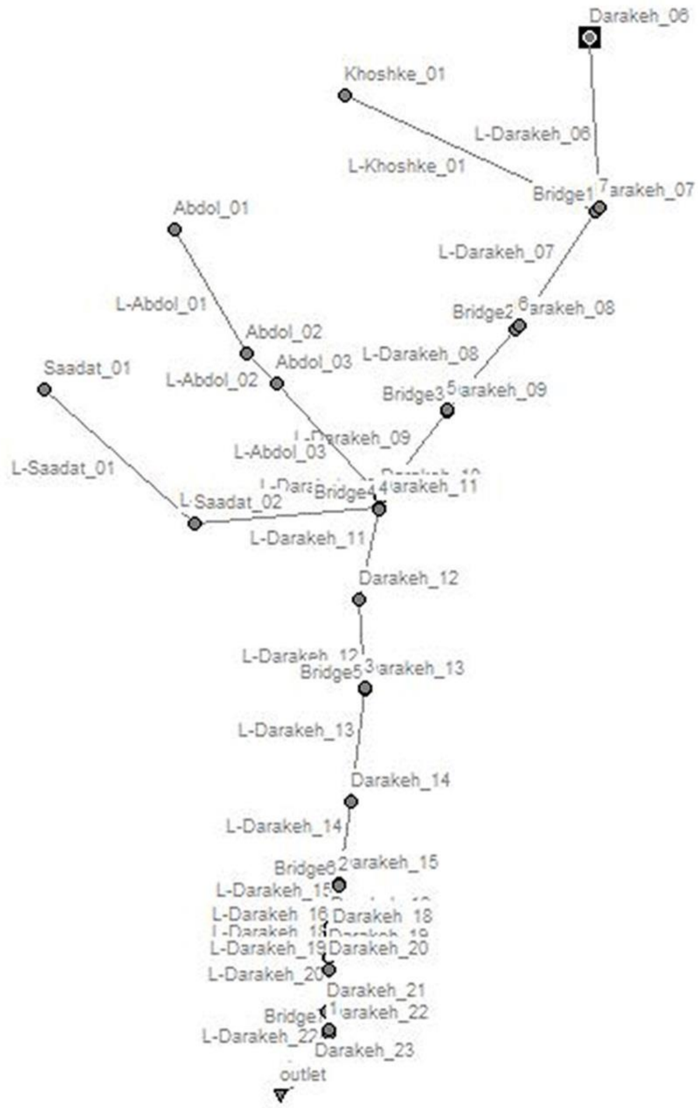
The HHO method has not been used seriously in the literature to optimize the design and construction costs of the surface runoff collection networks. In this research, the HHO method is used for optimal designing of these networks. In the current research, the rainfall of 20, 25, 35, 50, 75, 100 years of the West Tehran flood network is obtained in a number of sub-catchment. Then, the output runoff hydrograph is obtained from modeling the network in the HEC-HMS model. Next, the network flood is extracted by entering the runoff hydrograph into the SWMM and SSA models. Finally, by coupling these results with the HHO algorithm, the cost optimization of the construction of the runoff collection network and the optimization of water seepage are done. The main assumptions for optimal design of surface runoff collection network are using the Manning equation as resistance equation and the Saint-Venant equations as one-dimensional flow equations for routing flow in the open channel.

2. Study area

Darakeh River is located in the area with coordinates 35°49'05.35"N 51°23'01.87"E in the coordinate system N39_Zone_UTM_1984_W (Figure 1). This river is one of Tehran's rivers, which originates from the southern slope of Tochal peak and flows into the main river with six branches. This river provides access to the southern slopes of Alborz in the northwest of Tehran. It should be noted that this river is not seasonal and flows throughout the year. In some of these sections of the studied channel, there is a lack of capacity to pass the incoming flood for the return period of 20, 25, 35, 50, 75, 100 years. Therefore, due to the basic and important conditions of this river, investigating the flooding of this channel is important and sensitive. West Tehran network includes 23 channels and 7 bridges, and according to the conducted studies in the water comprehensive plan for Tehran development, the rainfall time for this area is considered to 6 hours [21].


515000
520000
525000
530000
535000
3975000
3970000
3965000
3960000
3955000
3950000
3945000
N
W25
W25-1
W01
W02
W03
W04
W05
W06
W07
W08
W09
W10
W11
W12
W13
W14
W15
W16
W17
W18
W19
W20
W21
W22
W23
W24
W26
W27
W28
W29
W30
W31
W32
W33
W34
W35
W36
W37
W38
W39
W40
W41
W42
Legend
The exit oppening under the spheres
Stream/Channel
City buildings
W05 Sub domain
Tehran's twenty-year approved range
0 1.25 2.5 5
Kilometers

(a)



(b)

Figure 1. (a) Study area (red circle); (b) The created network model in SWMM for red circle

3. Methodology

A flowchart of the performed method in this research is presented in Figure 2. First, the required data for simulation and optimization are prepared. These data include the geometric properties of the study area, weather properties such as rainfall value, properties and materials for the construction of channels and bridges. In the second stage, after determining the intensity of rainfall in different sub-catchments, the created runoff from rainfall in different sub-catchment and in different return periods is obtained by using HEC-HMS software. In the third step, the output hydrographs from HEC-HMS software are entered as time series input data to simulate runoff using SWMM and SSA models. In the fourth step, after running the done simulation in

SWMM, the channels outflow of the node location is determined.

In the fifth step, HHO and PSO algorithms are implemented in MATLAB software and the output flood from SWMM software is linked with MATLAB. In the sixth step, after implementing PSO and HHO algorithms in MATLAB software with the objective functions of reducing the cost and water leakage independently, the results are analyzed with comparison of PSO and HHO algorithms. In the seventh step, the results of HHO and PSO are evaluated.

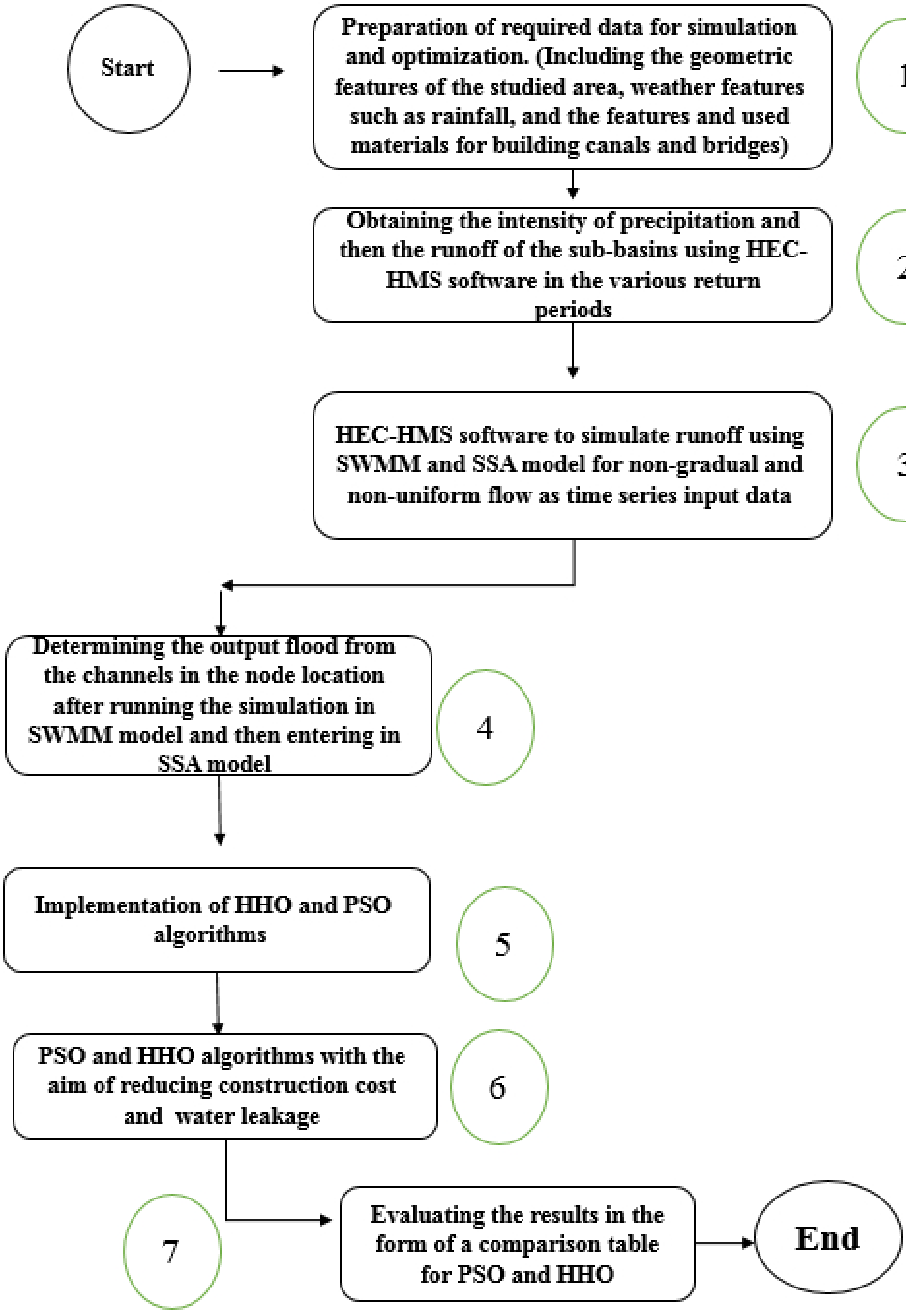


Figure 2. A flowchart of this research

4. Network simulation in HEC-HMS model

HEC-HMS model is used to obtain runoff from rainfall in the network. This software was presented in 1990 by the US Army Hydrologic Engineer Center under the name of HEC-1 model. In order to use this software, at first, the precipitation in all sub-basins including W01, W02,…., W07 should be obtained. To obtain the intensity of precipitation, the following relationships is used [22]:

$$i = C_{Alt.RP} D^{-0.645} \tag{1}$$

Where i is the intensity of rainfall (mm/hour), D is the duration of rainfall (minutes) and $C_{Alt,Rp}$ is a coefficient proportional to the design return period and the average height of basin. In addition, the temporal pattern of precipitation should be designed with the method of alternating blocks [23].

To enter other data into the HEC-HMS software for obtaining the rainfall-runoff hydrographs, the parameters of storage amount (S), initial abstraction (IA) and Lag time (LT) are entered and the SCS method is used [24]. Figure 3 shows the simulated network in the HEC-HMS. Also, the hydrographs of the output flood in the different return periods is shown in Figure 4. The negative flow values in the hydrographs of Figure 4 are the warm up time values for numerical methods in the initial times.

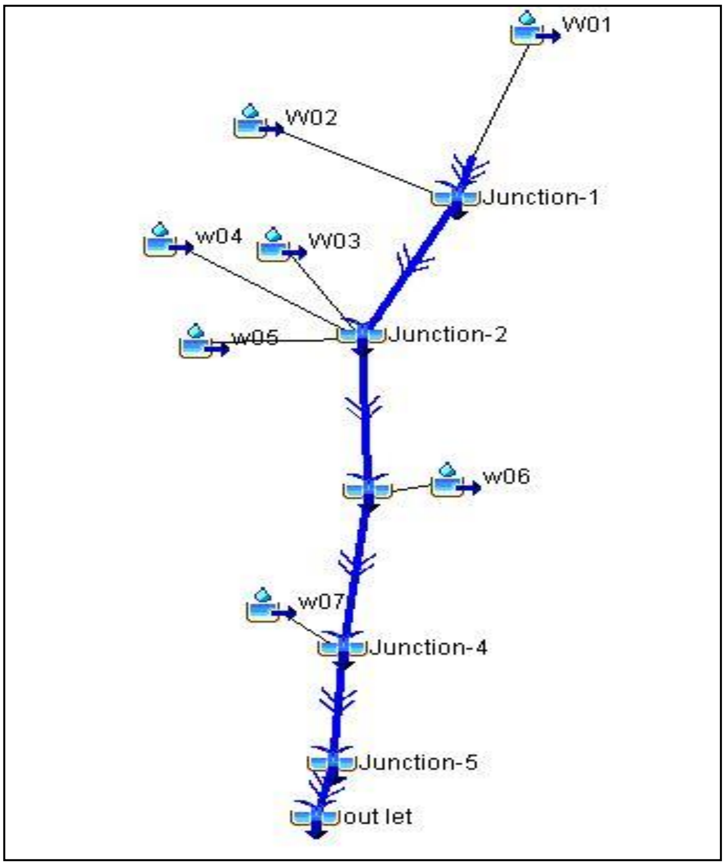


Figure 3. The simulated network in HEC-HMS.

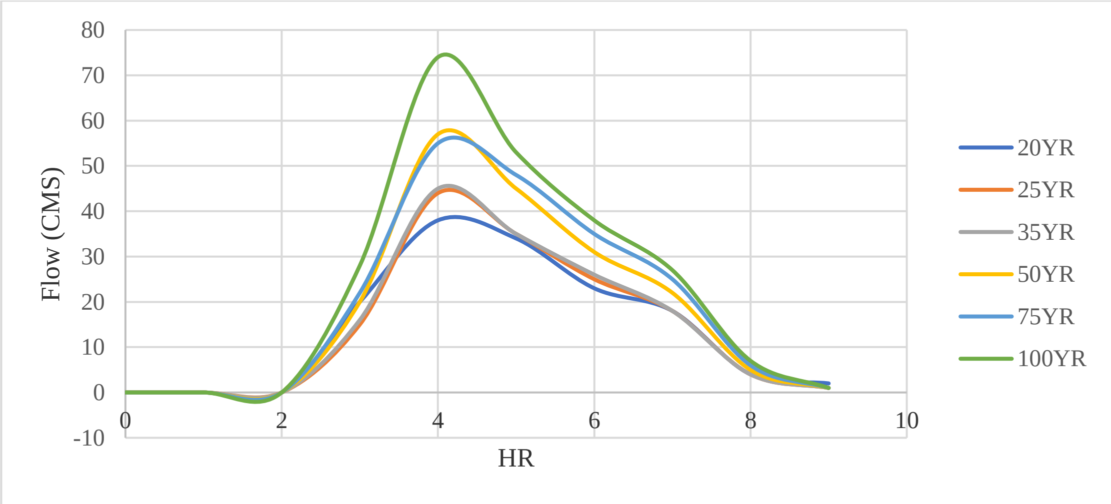


Figure 4. The hydrographs of the different return periods

5. Simulation with using SWMM and SSA

Hydrodynamic simulation in this research is performed with SWMM model. It was developed by the US Environmental Protection Agency (EPA). SWMM acts as a powerful hydrological simulation tool for analyzing and simulating storm runoff and drainage systems and their effects on urban systems [25]. SSA model is also a powerful hydrological simulation software developed by Autodesk and used for analyzing and simulating runoff and drainage systems with higher graphics than SWMM. Output hydrographs in HECHMS model is used to input time series data in SWMM model.

6. Using the optimizer model for network

6. 1. The objective functions

With the value of constant investment for flood management, it is possible to reduce the value of water leakage from the system with an optimal design. The water leakage is volume of runoff exceeding the capacity of channels and bridges. Consequently, further reduction requires an increase in the amount of investment in the project. Therefore, in this study, reducing the cost of building channels and bridges, as well as reducing network flood damage (the water leakage) are two independent functions. The objective functions are considered for the return periods of 20, 25, 35, 50, 75 and 100 years. Therefore, the objective functions are [26-28]:

Function F1= Min $\mathrm{Cost}_t = \sum_{i=1}^{n} Cost_i^B + \sum_{j=1}^{n} Cost_j^W = \sum_{i=1}^{n} f_1\left(H_i^B\right) + \sum_{j=1}^{m} f_2\left(H_j^W\right)$ (2)

Function F2= Min $\sum_{j=1}^{m}\left(V_{F,j}\right)$ (3)

Therefore, F1 is a function of reducing the costs of building channels and bridges, and F2 is a function of reducing water leakage from the system. In functions, Cost_i^B is the cost of building and repairing channels and bridges, Cost_j^W is the cost of increasing the height of channels walls or bridges in the interval j, H_i^B is the height of channels, H_j^W is the height of the channel wall in the interval j, W_j^W is the bottom width of the channels, W_i^B is the width of bridges, m is the number of flood flow channel and n is the number of critical bottlenecks and $V_{F,j}$ is the network flood and network water leakage volumes in the interval j. Considering the single objective, Harris Hawks algorithm is optimized by using the weighting method of both objective functions. The final objective function is presented in the following equation:

$$Z=0.5F1+0.5F2 \quad (4)$$

6.2. Constraints

The constraints in this optimization problem are equations 5, 6, 7 and 8 which are as follows:

$$V_{u} \leq V_{max} \quad (4)$$

$$H_i^B \epsilon \{H_1^B, H_2^B, \quad H_3^B, \dots, H_P^B\} \quad (5)$$

$$H_i^W \epsilon \{H_1^W, H_2^W, \quad H_3^W, \dots, H_q^W\} \quad (6)$$

$$\frac{\partial \boldsymbol{Q}}{\partial \boldsymbol{x}} + \frac{\partial \boldsymbol{A}}{\partial \boldsymbol{t}} = \boldsymbol{q} \quad (7)$$

$$S_f = S_0 - \frac{\partial \upsilon}{\partial x} - \frac{\upsilon}{g}\frac{\partial y}{\partial x} - \frac{1}{g}\frac{\partial \upsilon}{\partial t} \quad (8)$$

where V_z is the flood velocity in the channels and bridge and V_{max} is the maximum flood velocity in the channels and bridges which is assumed to be equal to 6 m/s based on Iranian standards. *e* is the number of considered discrete values for the height and width of different bridges, r is number of considered discrete values for the height and width of channels, Q is the channel discharge, A is the area of the channel, S_f is the energy slope; S_0 is the bed slope, v is the channel velocity, y is the water depth and g is the acceleration of gravity. Saint-Venant's equations include the continuity equation (7) and the motion equation (8) as the hydraulic constraints of the problem, which are implicitly solved by implementing the SWMM model.

6.3. Harris Hawks optimization (HHO)

In this paper, a new algorithm called Harris Hawks Algorithm (HHO) is used to optimize the cost function in the construction of the runoff collection network and also minimize the water leakage of system. Heidari et al. [16], for the first time, presented the HHO algorithm. They proposed a nature-based population inspired model. The main idea of the Harris hawk algorithm is the collective behavior and hunting style of the Harris hawk in nature, which is known as surprise attack.

By confusing the prey during hunting, Hawks reduce the prey energy to escape and finally hunt it. The Harris Hawks algorithm has two main phases, discovery phase and exploitation phase. In the discovery phase of HHO, hawks are considered as candidate solutions and the best solution in each stage is considered as the target prey or an almost optimal solution. In HHO, hawks are randomly placed in different areas and waiting to identify a prey based on two strategies. The strategies are as follows:

$$X(t+1) = \begin{cases} X_{rand}\ (t) - r_1\left|X_{rand}(t) - 2r_2X_{(t)}\right| & q \geq 0.5 \\ \left(X_{rabbit}(t) - X_m(t)\right) - r_3\left(LB + r_4(UB - LB)\right) & q \leq 0.5 \end{cases} \quad (9)$$

where X(t+1) is the location of the hawks in different iterations, which in this study is the width and height of channels and bridges which are randomly selected. The position of rabbit

($X_{rabbit}(t)$) in the iteration t is the amount of width and height channels and bridges in the iteration t. $X_{(t)}$ is the previous position of the hawks in the iteration t, X_{rand} (t) is the random hawk position in the previous population, X_m is the average position of the hawks in the previous population. LB and UB respectively, are the lower and upper limits of variables that limits the amount of changes of width and height of channels and bridges. Rabbit energy in the HHO for this research is the building cost of channels and bridges for reducing flood. Also, E is the escape energy of the rabbit, which in this problem is the flood volume in the network in the iteration t. $\Delta X_{(t)}$ in the HHO algorithm in this research is the difference between the optimized widths and heights of the algorithm and random widths and heights. Also, Y and Z in this problem are the heights and widths of bridges and channels, which remain if they give a better answer, and otherwise the next iteration is done for comparison.

6.4. Optimized runoff exploration prediction

The effective parameters in the HHO and PSO algorithms such as the number of decision variables, the number of population and the number of iterations are listed in the Table 1:

Table 1. Number of input parameters for the HHO and PSO

Parameters	HHO	PSO
Number of decision variables	60	60
The number of repetitions	50	50
Number of populations	100	100

The maximum values of flooding in the network in the current state is shown in Table 2. This table shows how much flooding in the network will cause water leakage in different parts of the network in each return period.

Table 2. Maximum flood in the situation without network plan

Return period (year)	100	75	50	35	25	20
Flooding $m^3/_s$	596.4	479.01	367	179.8	173.8	126

7. Discussion and results

7.1. The simulation results of the network

According to the range of necessary changes for each variable, increasing the height and width of the dam walls of Darakeh river, the height of existing bridges in the desired urban network, making the walls and bridges wider should be optimized. The optimization process in the region is performed for return periods of 20, 25, 35, 50, 75, 100 years. By using hydraulic modeling outputs, it has been observed that in some cases, the dimensions and size of existing bridges and channels in the region are inadequate for conveying of flood. Consequently, the channels and bridges are blocked and the water does not pass completely through the channels which causes over flooding and increases the costs and damages caused by flood. After implementing the SWMM and SSA models, the overflooding is observed. In order to observe the results of the model implementation in the return periods of 20, 25 and 50 years, Figures 5, 6 and 7 are shown. As shown in Figure 5, water leakage occurs at 3 points. The value of flooding in these three nodes is shown in Table 3.

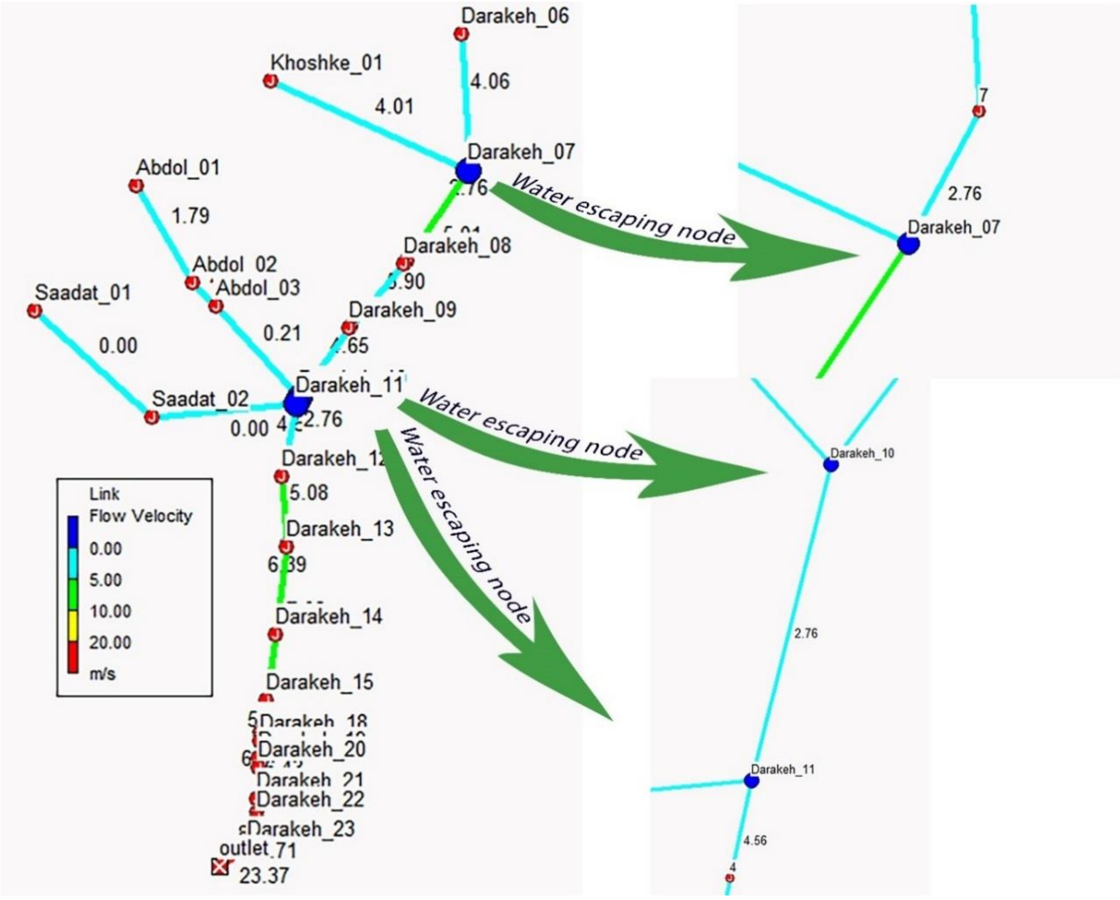


Figure 5. Network model in SSA in the return period 20 years

Table 3. Network flood volume for the return period of 20 years in the SSA and SWMM model

Node	Hours Flooded	Maximum Rate (CMS)	Day of Maximum Flooding	Hour of Maximum Flooding	Total Flood Volume (10^6 ltr)	Maximum Ponded Depth (m)
Darakeh_07	0.04	0.71	0	3:06	0.044	0.000
Darakeh_10	1.15	27.12	0	3:05	55.179	0.000
Darakeh_11	1.75	13.768	0	3:10	70.911	0.000

Figure 6 shows the points that experience water leakage during the return period of 25 years. Table 4 shows the flood volume at the location of these nodes.

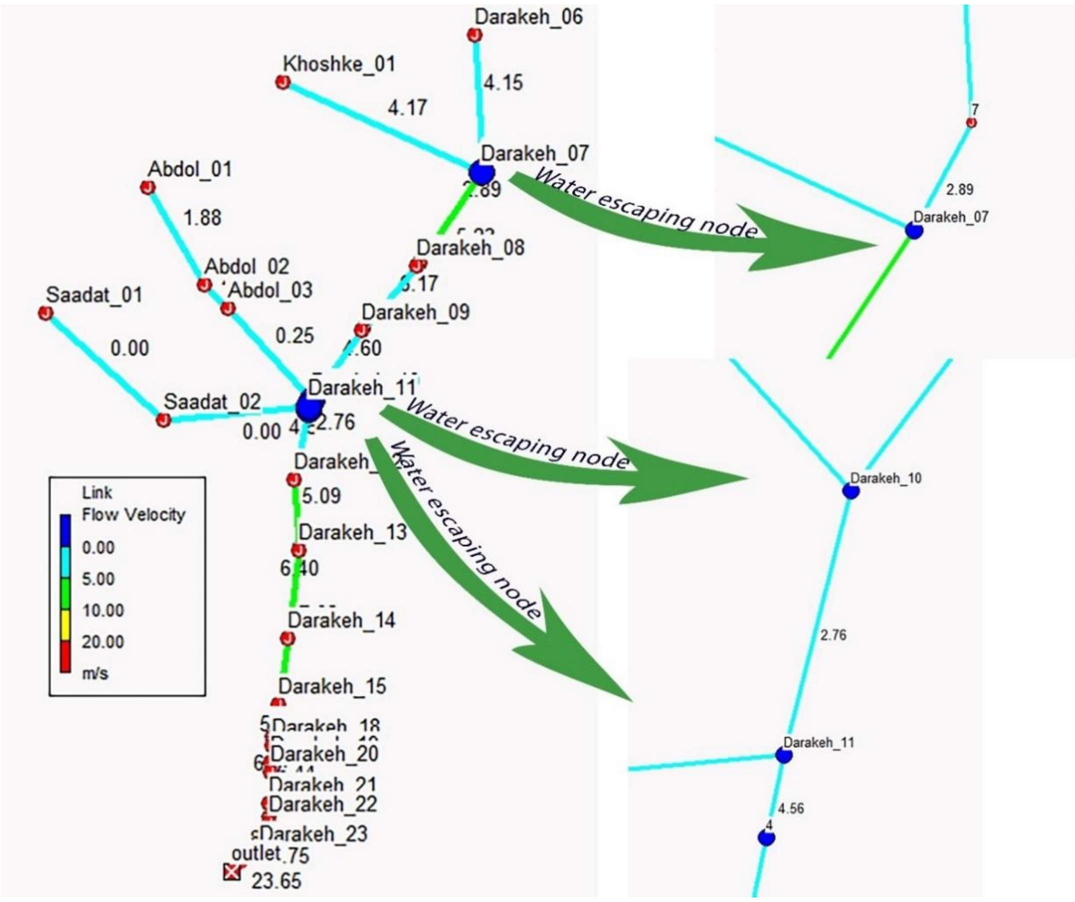


Figure 6. Network model in SSA in the return period of 25 years

Table 4. Network flood volume in the return period of 25year in the SSA and SWMM model

Node	Hours Flooded	Maximum Rate (CMS)	Day of Maximum Flooding	Hour of Maximum Flooding	Total Flood Volume (10^6 ltr)	Maximum Ponded Depth (m)
Darakeh_07	0.41	10.069	0	2:58	10.517	0.000
Darakeh_10	1.39	29.233	0	3:02	81.839	0.000
Darakeh_11	1.98	13.908	0	3:07	81.428	0.000

In the Figure 7 can be seen the points where water escape occurs during the return period of 50 years. Table 5 shows the flood values in each node.

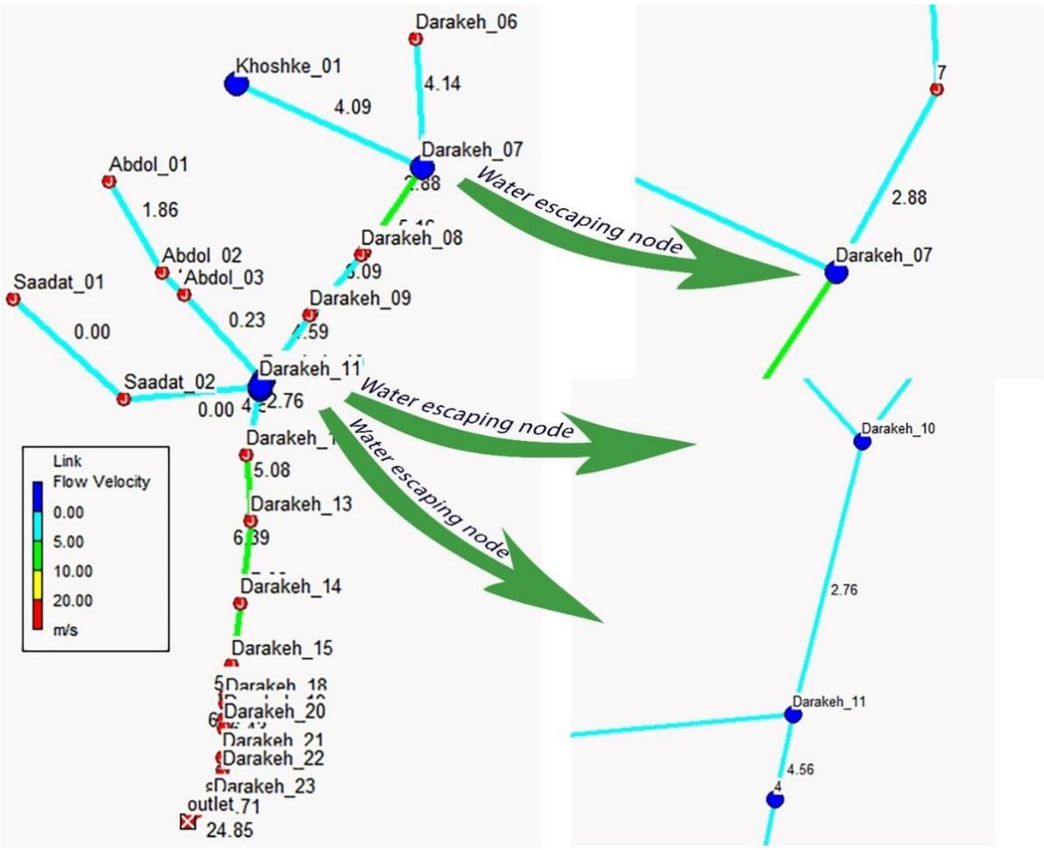


Figure 7. Network model in SSA in the return period of 50 years

Table 5. Network flood volume in the return period 50 years in the SSA and SWMM model

Node	Hours Flooded	Maximum Rate (CMS)	Day of Maximum Flooding	Hour of Maximum Flooding	Total Flood Volume (10^6 ltr)	Maximum Ponded Depth (m)
Darakeh_07	1.14	46.937	0	2:47	82.933	0.000
Darakeh_10	1.9	30.662	0	2:55	142.661	0.000
Darakeh_11	3.52	14.374	0	3:00	131.071	0.000
Khoshke_01	0.51	5.564	0	3:00	10.33	0.000

Figure 8 shows a comparison of the presented maximum rate values in tables 3, 4 and 5 for the return periods. As shown in this figure, as the return period increases, the maximum rate also increases.

According to the overflooding points in the simulation models in the SSA software, after implementing the optimization algorithms in the software, the results is checked in next section.

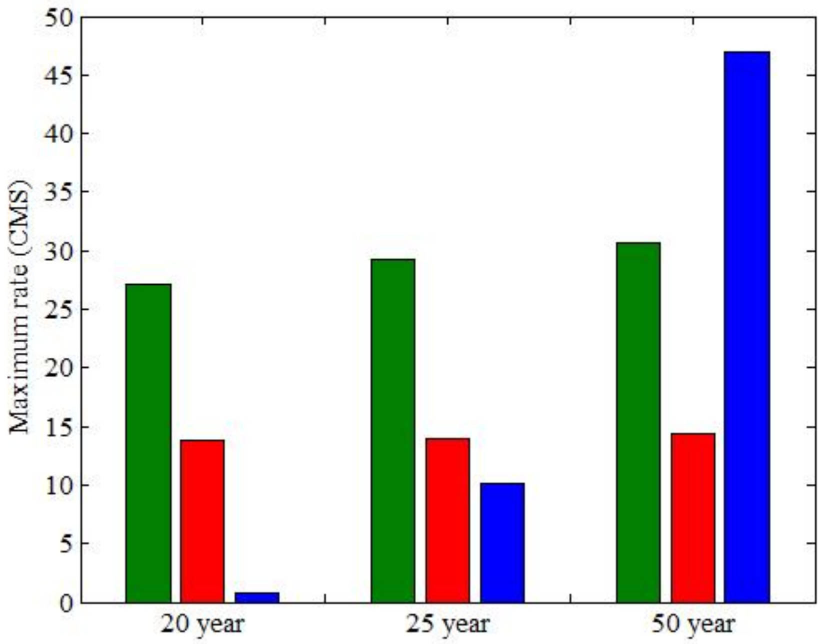


Figure 8. A comparison of the maximum rate values for different return periods (green: Darakeh_10; red: Darakeh_11; blue: Darakeh_7)

7.2. Results of HHO and PSO algorithms

Optimizer results for return periods of 20, 25, 35, 50, 75 and 100 years are obtained after implementing of single objective HHO algorithm. Also, this process is implemented with the PSO algorithm. The obtained results from these optimization models indicate the best solutions for different situations. At Table 6, the best answers of different return periods are given for comparison in HHO and PSO.

Table 6. The best solutions of optimal functions in different return periods for HHO and PSO

Optimizer	Function	Flood return periods					
		20 yr	25 yr	35 yr	50 yr	75 yr	100 yr
HHO	Cost (10^{10})	1.83	2.07	2.24	1.31	2.014	2.13
	Flooding (10^3 m^3)	0.002	0.002	0.002	0.779	0.786	0.107
PSO	Cost (10^{10})	3.96	2.74	2.55	2.48	2.63	2.71
	Flooding (10^3 m^3)	0.4	0.1	0.025	0.226	0.032	0.045

In the performed optimization model, the decision variables are defined in such a way that they have the ability to solve the objective functions of the studied problem. So that, the optimization model reduces the volume of flood output and the costs according to the implementation plan. Furthermore, the best optimal design for the channel dimensions is created with considering objective functions. It should be noted that the changes corresponding to each channel or bridge are in the simulator model according to the placement and definition of the channel and the bridge. These changes are completely specific for any bridge or channel. The position of channels and bridges are shown in Figure 9. As shown in the Table 7, it is not necessary to change the dimensions and size of all channels or bridges. Therefore, after solving the optimizer problem for each design, it has been shown that in some bridges or channels that are critical in the optimizer model, changes in their dimensions and sizes should be applied. In the table 7, H_i^B is the height of bridges, W_i^B is the width of bridges, W_j^W is the channels width and H_j^W is the channels height. According to Table 7, it is clear that in most places, HHO algorithm reduces the construction costs and flooding by obtaining the least possible changes in the heights and widths of the channels. These changes reduce flood in the urban network, with regard to the reduction of operational costs.

It should be noted that achieving such the optimized plan may be impossible without optimization programs, which shows the efficiency of these models to carry out the optimal design of the surface water collection network in are urban areas.

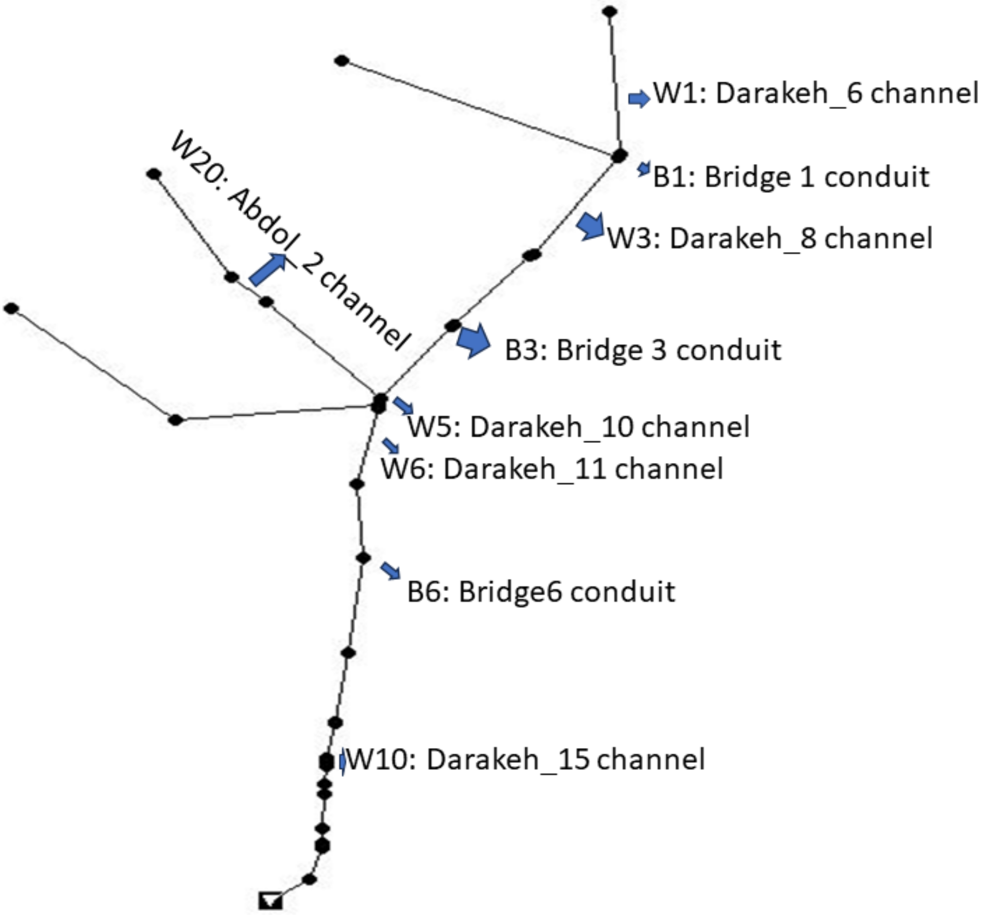


Figure 9. The location of some bridges and channels for comparison of HHO and PSO results

Table 7. Results and changes of some widths and heights of channels and bridges in HHO and PSO algorithms.

No	Variable	20	25	35	50	75	100	optmizer
1	H_3^B	0.04	0.2	1.5	0.64	4.53	0.4	HHO
		3.16	0.62	4.5	2.5	2.81	0.42	PSO
2	W_1^B	1.3	0.66	0.01	0	1.85	3.06	HHO
		2.78	1.33	2.1	2.14	5.44	3.29	PSO
3	H_3^W	0.32	0.45	0.67	0	1.53	0.02	HHO
		0	0.07	0.97	0.07	0	0.14	PSO
4	H_6^W	2.06	1.76	0.24	1.34	2.49	0.76	HHO
		1.29	0.59	1.76	1.57	0.06	0.82	PSO
5	H_{10}^W	0.04	1.31	2.31	1.34	0	0.15	HHO
		2.99	0.9	0.06	3.89	7.7	1.9	PSO
6	H_6^B	0.04	5.02	1.07	3.55	1.04	0.79	HHO
		6.99	3.3	6.16	7.44	2.77	0.78	PSO
7	W_5^W	1.41	1.93	3.83	7.54	5.97	9.99	HHO
		1.81	3.48	4.16	5.44	8.32	9.25	PSO
8	W_{10}^W	0.04	0.84	0.66	0	5.52	4.25	HHO
		0.8	7.36	0.75	2.58	9.36	1.62	PSO
9	W_{20}^W	0.46	2.33	1.34	1.12	1.57	5.25	HHO
		3.02	1.71	0.99	8.81	5.97	2.04	PSO

In this research, by comparing the best answers with PSO, the best design for the surface water collection network by HHO was selected. This research showed that the HHO algorithm has a better performance than the PSO algorithm in reducing costs. Also, with a better speed, the value of network flooding tends to zero.

8. Conclusion

In this research, the single-objective Harris Hawks optimization (HHO) algorithm was used to solve the optimizer problem and the particle swarm optimization (PSO) algorithm was used for comparison. HEC-HMS model has been used to determine the rainfall-runoff model. The hydraulic model used in this research to discuss flood management and control by SWMM and SSA hydrodynamic models. Two objective functions were considered in this research. It was found that the functions are in the form of reducing costs and the outflow of water from the urban network in Darakeh River in Tehran city;

The optimization process for the urban network was performed for the return periods of 20, 25, 35, 50, 75 and 100 years. The results showed that the HHO algorithm has a better performance than the PSO algorithm and reduces the costs to a suitable extent. The results showed that the HHO algorithm has a better performance than the PSO algorithm and reduces the costs to a suitable extent. Also, the results presented the efficiency of the HHO algorithm to carry out the optimal design of the surface water collection network in are urban areas. The HHO method has not been used in past researches for optimizing the construction cost of the surface runoff collection network in the current form. The modeling form and linking the SWMM and SSA results with the HHO method in the current study can be a suitable idea for future researches.

References

1. Reddy M. J., Kumar D. N. (2007). Multiobjective differential evolution with application to reservoir system optimization. Journal of Computing in Civil Engineering, pp: 21(2):136–146.
2. Pan T, Kao J (2009). GA-QP model to optimize sewer system design. Journal of environmental engineering, pp: 135(1):17–24.
3. Moghaddamam A, Alizadeh A, Faridhosseini A, Ziaei A. N., Heravi D. F. (2018). Optimal design of water distribution networks using simple modified particle swarm optimization approach. Desalination and Water Treatment, pp: 104: 99–110.
4. Azari B, Tabesh B (2018). Optimal Design of Stormwater Collection Networks Considering Hydraulic Performance and BMPs. International Journal of Environmental Research, pp: 12: 585-596.
5. Abdy Sayyed M. A. H., Gupta R, Tanyimboh T (2021). Combined flow and pressure deficit-based penalty in GA for optimal design of water distribution network. ISH Journal of Hydraulic Engineering, pp: 27:146-156.
6. Tanyimboh T. T, Seyoum A. G. (2020). Design optimization of water distribution networks: real-world case study with penalty-free multi-objective genetic algorithm using pressure-driven simulation. Water SA. pp: 46:(3): 465–475.
7. Ezzeldin R. M., Djebedjian B (2020) Optimal design of water distribution networks using whale optimization algorithm. Urban Water Journal, pp: 17 (1):14-22.
8. Heydari Mofrad H., Yazdi J. (2022). An enhanced multi-objective evolutionary algorithm for the rehabilitation of urban drainage systems. Engineering Optimization, pp: 54 (2), 349-367.
9. Diao Y., Ma H., Wang H., Wang J., Li S., Li X., Pan J., Qiu Q. (2022). Optimal Flood-Control operation of cascade Reservoirs Using an Improved Particle Swarm Optimization Algorithm. Water, pp: 14(8): 1239.
10. Cemiloglu A., Zhu L., Chen B., Lu L., Nanehkaran Y. A. (2023). Enhancing Urbun Surface Runoff Conveying System Dimensions through Optimization Using the Non-Dominated Sorting Differential Evolution (NSDE) Metaheuristic Algorithm. Water, pp: 15(16): 2927.
11. Babonneau F., Gilbert D., Piller O., Vial J.P. (2024). Robust optimal design of a tree-based water distribution network with intermittent demand, European Journal of Operational Research, pp: 319 (3): 834-844.
12. Riyahi M. M., Bakhshipour A. E., Haghighi A. (2023). Probabilistic warm solutions-based multi-objective optimization algorithm, application in optimal design of water distribution networks, Sustainable Cities and Society, pp: 91: 104424.
13. Jenks B., Pecci F., Stoianov I. (2023). Optimal design-for-control of self-cleaning water distribution networks using a convex multi-start algorithm, Water Research, pp: 231: 119602.
14. Essamlali I., Nhaila H., El Khaili M. (2024). Optimizing runoff and pollution mitigation through strategic low-impact development (LID) integration in the Bouznika city development plan, Case Studies in Chemical and Environmental Engineering, pp: 10: 100838.
15. Liu Z., Han Z., Shi X., Liao X., Leng L., Jia H. (2023). Multi-objective optimization

methodology for green-gray coupled runoff control infrastructure adapting spatial heterogeneity of natural endowment and urban development, Water Research, pp: 233: 119759.
16. Heidari A. A., Mirjalili S, Faris H, Aljarah I, Mafarja M, Chen H. (2019) Harris hawks optimization: Algorithm and applications. Future Generation Computer Systems, pp: 97:849-872.
17. Abbasi A., Firouzi B., Sendur P. (2021). On the application of Harris hawks optimization (HHO) algorithm to the design of microchannel heat sinks. Engineering with Computers, pp: 37: 1409-1428.
18. Elgamal Z. M., Yasin N. B. M., Tubishat M., Alswaitti M., Mirjalili A. S. (2020). An Improved Harris Hawks Optimization Algorithm with simulated Annealing for Feature selection in the Medical field. IEEE Access, pp: 8: 186638-186652.
19. Wang S., Jia H., Abualigah L., Liu Q., Zheng R. (2021). An Improved Hybrid Aquila Optimizer and Harris Hawks Algorithm for solving industrial engineering optimization problems. Processes, pp: 9(9): 1551.
20. Nematollahi Z., Zarif Sanayei H. R., (2023). Developing an optimized groundwater exploitation prediction model based on the Harris hawks optimization algorithm for conjunctive use of surface water and groundwater resources, Environmental Science and Pollution Research, pp: 30: 16120-16139.
21. TDDTM. 2011a. Tehran Stormwater Management Master Plan, Vol 2, Part 3: Urban Food Hydrology & Sediment Load, December 2011. Tehran: Technical & Development Deputy of Tehran Municipality.
22. TDDTM. 2011b. Tehran Stormwater Management Master Plan, Vol 4: Existing Main Drainage Network, Part 2: Hydraulic Modeling and Capacity Assessment, December 2011. Tehran: Technical & Development Deputy of Tehran Municipality.
23. Na W., Yoo C., (2018). Evaluation of Rainfall Temporal Distribution Models with Annual Maximum Rainfall Events in Seoul, Korea. Water, pp: 10(10): 1468.
24. USACE. 2008. Hydrologic Modelling System HEC-HMS, Quick Start Guide, Version 4.0. Davis: Institute for Water Resources Hydrologic Engineering Center.
25. Jang S., Cho M., Yoon J, Yoon Y., Kim S., Kim G., Kim L., Aksoy H., (2007). Using SWMM as a tool for hydrologic impact assessment. Desalination, pp: 212 (1–3): 344-356.
26. Lord S. A., Ghasabsaraei M. H., Movahedinia M., Shahdany S. M. H., Roozbahani A. (2021). Redesign of stormwater collection canal based on flood exceedance probability using the ant colony optimization: study area of eastern Tehran metropolis. Water Science & Technology, pp: 84 (4): 820-839.
27. Yazdi, J. (2016). Decomposition Based Multi Objective Evolutionary Algorithms for Design of Large-Scale Water Distribution Networks. Water Resources Management, pp: 30 (8): 2749–2766.
28. Yazdi, J., A. Sadollah, E. H. Lee, D. G. Yoo, and J. H. Kim. (2017). Application of Multi-Objective Evolutionary Algorithms for the Rehabilitation of Storm Sewer Pipe Networks. Journal of Flood Risk Management, pp: 10 (3): 326–338.