Advances in Environmental Research, *Vol. 7, No. 2 (2018) 87-107*
DOI: https://doi.org/10.12989/aer.2018.7.2.087

Optimization of water quality monitoring stations using genetic algorithm, a case study, Sefid-Rud River, Iran

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(Received November 6, 2017, Revised February 18, 2018, Accepted May 3, 2018)

Abstract. Water quality monitoring network needs periodic evaluations based on environmental demands and financial constraints. We used a genetic algorithm to optimize the existing water quality monitoring stations on the Sefid-Rud River, which is located in the North of Iran. Our objective was to optimize the existing stations for drinking and irrigation purposes, separately. The technique includes two stages called data preparation and the optimization. On the data preparation stage, first the basin was divided into four sections and each section was consisted of some stations. Then, the score of each station was computed using the data provided by the water Research Institute of the Ministry of energy. After that, we applied a weighting method by providing questionnaires to ask the experts to define the significance of each parameter. In the next step, according to the scores, stations were prioritized cumulatively. Finally, the genetic algorithm was applied to identify the best combination. The results indicated that out of 21 existing monitoring stations, 14 stations should remain in the network for both irrigation and drinking purposes. The results also had a good compliance with the previous studies which used dynamic programming as the optimization technique.

Keywords: genetic algorithm; network design; optimization, sampling site; water quality monitoring

1. Introduction

A water quality monitoring network needs periodic evaluations based on environmental demands and financial limitations. Therefore, a suitable procedure is necessary to reduce the number of water quality monitoring stations.

In addition, water quality data collection is a costly method which requires considerable investments. Even in developed countries, the system of data collection should be carried out with limited financial resources, facilities, equipment for sampling and analysis, and human resource.

Several methods are available to assess the monitoring stations such as Sanders method, multi-criteria decision making (MCDM), dynamic programming method (DP) and genetic algorithm

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http://www.techno-press.org/?journal=aer&subpage=7 ISSN: 2234-1722 (Print), 2234-1730 (Online)

(GA).

Genetic algorithms are multi-purpose search strategies based on natural selection and natural genetics (Mitchel 1979, Goldberg 1989). The GA has recently been applied in water resources and environmental engineering. Lettenmaier *et al.* (1984) used optimization models in the design of monitoring systems for water quality monitoring stations. They reduced the number of monitoring stations from 81 to 41 and this reduction resulted in preventing the depreciation of equipment and saving indirect costs up to $ 33,000. Harmancioglu *et al.* (1992) investigated a statistical method based on the entropy principle to network performance and its cost-effectiveness. Karpouzos *et al.* (2001) used the genetic algorithm method to achieve water quality reliability. Park *et al.* (2006) designed water quality monitoring network for the Nakdong river by applying geographical information system (GIS) and also combination of water quality monitoring network with the genetic algorithm. Karamouz *et al.* (2009) designed water quality monitoring network of the dam on the Karun River down to the Persian Gulf in the south of Iran. In this regard, an optimization model based on genetic algorithm and combination of Keriging method and developed analytic hierarchy process (AHP) was applied. Asadollahfardi *et al.* (2011) applied multiple criteria decision-making (MCDM) method to evaluate and prioritize Karun river water quality monitoring stations located in the south west of Iran, due to its kind of water consumption. Asadollahardi *et al.* (2014) optimized the number of water quality monitoring stations on Sefid-Rud River by applying the DP method.

Based on environmental requirements and financial constraints, the monitoring system should be evaluated periodically, which we also attempted to reduce the number of monitoring stations based on the amount of pollutants present and their importance in terms of drinking and agriculture consumption. To reach a minimum cost, we can only monitor water quality stations which have a more critical situation in terms of accumulation of pollutants. Reduction of monitoring station cause to decline budget and resource for water quality management.

The objective of our study was the optimization of existing water quality monitoring stations on the Sheffield-Red River, North of Iran, for irrigation and drinking propose, using a genetic algorithm optimization.

Fig. 1 The study area, Sefid-Rud River

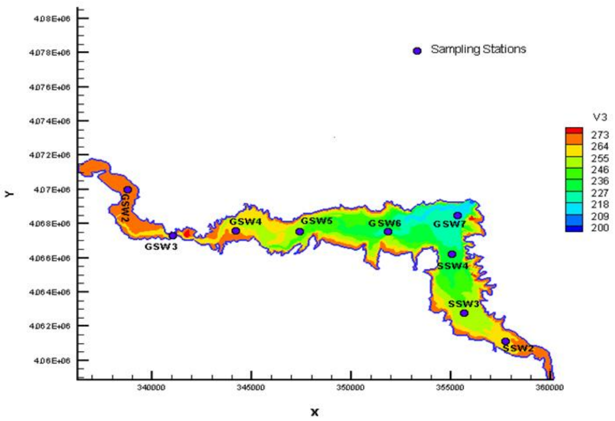

Fig. 2 Water quality monitoring stations on the Sefid-Rud Dam (upstream of the river)

Fig. 3 The water quality monitoring stations on the Sefīd̄ -Rūd River (downstream of the river)

1.1 The study area

Qezel-Owzan, and Shah-Rūd Rivers are the major origins of Sefīd-Rūd river. Sefīd-Rūd Dam was constructed on the Sefid-Rud River at the confluence of its two branches, Qezel-Owzan and Shah-Rūd for different purposes such as flood control, providing the drinking water and the agricultural water needed for plains of Gilan and also for power generation. Qezel-Owzan River is originated from the mountains of Kurdistan and Azerbaijan and its minimum and maximum flow rate is 4 and 2000 m^3/s and after traveling a distance of 500 km reaching to the dam. The Shah-Rūd River is originated from the mountains of Alamut and Taleghan and its minimum and maximum flow rate is 6 and 800 m^3/s and after traveling a distance of 180 km reaches the dam. Sefid-Rud is located at 200 km northwest of Tehran and 100 km from the Caspian Sea near the Manjil at the confluence of Qezel-Owzan, and Shah-Rūd rivers. The study area (Figs. 1-3) consists of Qezel-Owzan and Shah-Rūd branches at the upstream of the dam and Sefid-Rud River on the downstream of the dam. Tables 1 and 2 provide the information about location and name of sampling stations at downstream and upstream of Sefid-Rud dam.

Table 1 The location of water quality monitoring stations on the Sefīd̄ -Rūd River (UTM) (downstream of the River)

Location name	Stations	X	Y
Steel bridge of Sefid-Rūd dam	ST 1	356995	4070150
Steel bridge of Roudbar	ST 2	358369	4074507
Distance between Roudbar And Ganjeh	ST 2.1	360445	4077602
Steel bridge of Ganjeh	ST 3	363785	4079220
Steel bridge of Tonekabon (Rostam Abad)	ST 4	368121	4084094
Distance between bridge of Ganjeh and dam of Tarik	ST 4.1	369639	4089288
After dam of Tarik	ST 5	372492	4094826
Bridge of Emam Zadeh Hashem	ST 6	378319	4098546
Sangar-kouchEsfahan	ST 7	388849	4113660
kouchEsfahan to Astane Ashrafie	ST 8	391706	4121211
Bridge of Astane Ashrafie	ST 9	391690	4121212
Dehsar (Kamachal)	ST 10	406433	4133596
Bridge of Kiashar to Bandar Anzali	ST 11	403525	4141796

Table 2 The location of Water quality monitoring stations on the Sefīd̄ -Rūd Dam (UTM) (upstream of the river)

River	Stations	X	Y
Qezel-Owzan	GSW2	338765	4069980
	GSW3	341025	4067315
	GSW4	344185	4067605
	GSW5	347390	4067560
	GSW6	351820	4067545
	GSW7	355310	4068470
Sefid-Rud	SSW2	357760	4061110
	SSW3	355670	4062795
	SSW4	355065	4066195

2. Materials and methods

The Sefid-Rud basin is divided into four sections, each section includes several stations. The score of each station was computed using water quality criteria such as the weighting based on Asadollahfardi (2000) study. These stations were prioritized cumulatively according to their scores and we applied genetic algorithm to define which stations can remain in force.

Water quality sampling of Sefid-Rud River was carried out by the Water Research Institute, the Ministry of Energy, during 2005 to 2007. Water quality parameters included the temperature, dissolved oxygen (DO), ammonia (NH3), chemical oxygen demand (COD), biochemical oxygen demand (BOD), phosphate, nitrate, pH, total dissolved solids (TDS), total suspended solids (TSS), electrical conductivity (EC), Turbidity and heavy metals.

It is true that all water quality parameters should be measured according to the water quality standard range. However, considering a pollution index for determining water quality at each monitoring station are sum of linear or nonlinear weighting of the value of water quality parameters. The importance of water quality parameters or pollutants was based on the its importance for drinking or agriculture consumption and some parameters are more important for drinking than agriculture consumption.

2.1 Normalization and standardization procedure

To compare different parameters with different scales, data must be dimensionless. To create dimensionless data, they should be normalized. We applied Box-Cox normality method for this purpose (Eq. (1)). In Box-Cox technique, estimation of a value for λ is necessary.

$$y_i = \frac{X_i^{\lambda} - 1}{\lambda} \text{ , for } \lambda \neq 0 \tag{1}$$

where y_i = normalized data, X_i = original data and λ = a value which by its substitution in Eq. (1), the standard deviation of obtained y_i will be equal to zero. We used the S-Plus 8 (2007) software within the framework of Box-Cox method for the water quality parameters of the river to make them normalized and uniform. The parameter values were in the range of 0 and 1.

2.2 Weighting method

We applied a weighting method for parameters which was carried out based on sending questionnaires to ask the experts to define the significance of parameters for both irrigation and drinking usages. The parameters were BOD_5, COD, NO_3^- ,NH_3, PO_4^{-3} , EC - TDS-TSS-pH-Temperature-Turbidity, DO-Pb-Zn-Cd-Ni-Cu- Cr-Fe-As. We allocated grade 1 to the highest significance and grade 5 to the lowest significance. Sum of them was equal to 30. Then, we evaluated mean of all significances, temporary weights and eventually final weights (wi) (Asadollahfardi 2000).

2.3 Mathematic methods

In this study, $SU_{j(i)Kl}$ is considered as the normal and uniform form of the l th data for the station i and sub catchment K. For each value of TR_N (the number of remaining required stations), defining the number of selected stations in each primary catchment area (K) is necessary. Therefore, the selected stations are those stations that sum of their normalized data, i.e., $SU_{j(i)KI}$ is maximized. Sum of normalized data of $SU_{j(i)KI}$ for each station in each primary catchment area K, is indicated as $TS_{j(i)K}$ (Eq. (2)).

$$\mathrm{TS}_{\mathrm{j(i)k}} = \sum_{\mathrm{l=1}}^{\mathrm{l_N}} \mathrm{SU}_{\mathrm{j(i)kl}} \tag{2}$$

where I_N is the number of parameters in the station i and sub catchment area K.

If the significance of parameters is different, we use the relative weights due to the objectives of monitoring expectations. Eq. (2) is converted to Eq. (3).

$$\mathrm{TS}_{\mathrm{j(i)k}} = \sum_{\mathrm{l=1}}^{\mathrm{l_N}} W_I \times \mathrm{SU}_{\mathrm{j(i)kl}} \tag{3}$$

where W_I is the relative weight for parameter i for weighting of effective water quality parameters for irrigation and drinking purposes

Eq. (2) yields the total value of parameters in sub-basin K and station I.

In each primary catchment area K, due to the number of selected stations (R_K), the value of $TS_{j(i)K}$ is different while those combinations of selected stations that yield the maximum value of $TS_{j(i)K}$ are preferable ones (Eq. (4)).

By designation of TR_N , selection switch of R_K are which their $\mathrm{MTS}_{\mathrm{j(i)k}}$ value is maximized (Eq. (5)).

$$\mathrm{SMTS} = \mathrm{Max} \sum_{\mathrm{k=1}}^{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{R_K}} \mathrm{MTS}_{\mathrm{j(i)k}} \tag{4}$$

where SMTS = the maximum value for TR_N, N= the number of primary basins, R_k = the number of stations to be retained in primary basin k, and $MTS_{j(i)k}$ =maximum uniformized total attribute value of j(i)th station combination in primary basin k.

Eq. (4) has two dimensions. We applied genetic algorithm to solve it and used MATLAB 2011 a.

The objective was to find a combination of stations to have the maximum $\mathrm{MTS}_{\mathrm{j(i)k}}$ corresponding to a certain TR_N. Eq. (5) indicates the fitness function of this study.

$$\mathrm{V} = \mathrm{Max} \sum_{\mathrm{k=1}}^{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{R_K}} \mathrm{MTS}_{\mathrm{j(i)k}} \tag{5}$$

The constraints of the parameters are as follows

$$\begin{gathered} \sum_{\mathrm{K=1}}^{\mathrm{N}} \mathrm{R_K} = TR_N \\ 0 \le \mathrm{R_K} \le \mathrm{TR_N} \\ 0 \le \mathrm{j(i)} \le \mathrm{P_K} \\ \mathrm{j(i)} \ne \mathrm{j(h)}\ ,\ \mathrm{i} \ne \mathrm{h} \end{gathered} \tag{6}$$

where V = the objective function, N= the total number of primary catchment area, R_K = the number of stations which are retained in the primary catchment area, i = an index of the station in the K primary station, j(i) = the number of indices of the stations i in the K primary station, and P_K = the number of pre-existing stations in the K primary station (Asadollahfardi *et al.* 2014).

2.4 Genetic algorithm (GA)

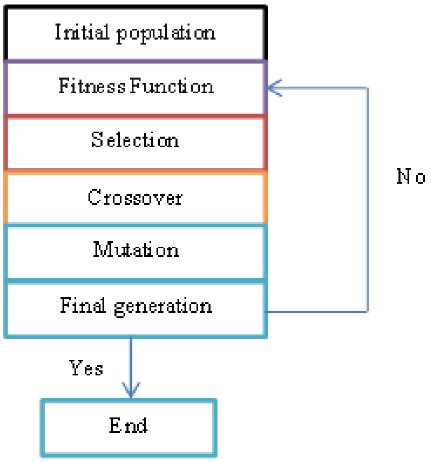

Fig. 4 Steps of the GA

Table 3 A schematic of single chromosome with 4 genes (n=4)

K^*_1	K_2	$K_{3...}$	K^*_n
a_1	a_2	a_3	a_n

K^*_1= First sub-basin

K^*_n= last sub-basin

a_i= the number of stations in each sub catchment K. $1 \leq i \leq n$

In this method, the characteristics of a numerical optimization problem are defined by their biological analogues. Each chromosome is a solution to a problem in the nature; all living cells possess the same set of one or more chromosomes that are called a string (DNA). In GA, a chromosome is encoded as a single bit or a bit stream and every bit is called a gene.

The bit values of genes can be either taken as 0 or 1, or other integer numerical strings (Osyczka 2002). The GA method can be explained in five steps (Osyczka 2002, Mitchel 1998) (Fig. 4).

First of all, we need to define individuals as the population. Here is a chromosome containing genes which illustrate the stations in each sub catchment K. Table 3 indicates a chromosome with 4 genes schematically.

1. Initial population: Initial population is a set of chromosomes that are randomly generated.

2. Initial population is randomly generated so that in each iteration, the best individuals are selected and the worst ones are replaced with new ones which were randomly generated before.

(Researchers usually argue that a “small” population size can guide the algorithm to poor solution and a “large” population size can make the algorithm expend more computation time in finding a solution.)

Therefore, here we are facing a trade-off that needs to be approximated feeding the algorithm with “enough” chromosomes to receive “good” solutions. Here “Enough” is directly related to instances in the search space and its diversity (Diaz-Gomez 2007).

3. Fitness function: our objective function which has the duty of maximization is called Fitness function. It is a function that receives chromosomes as inputs and calculates their value. The most crucial part of GA method is to define the fitness function.

4. Selection: (Selection determines which individuals are chosen for mating and how many offspring each selected individual produces. The first step is fitness assignment. Each individual in the selection pool receives a reproduction probability depending on its own objective value and the objective value of all other individuals in the selection pool).

Some methods for selecting parents such as Roulette Wheel, Tournament, Stochastic universal sampling, Local selection, Truncation selection, and Rank-based selection are available. We described the rank-based selection and applied it in our study.

In rank-based fitness assignment, the population is sorted according to objective values. The fitness assigned to each individual depends only on its ranking and not on an actual objective value. Rank-based fitness assignment overcomes the scaling problems of the proportional fitness assignment. The reproductive range is limited, so that the number of offspring for each individual is not excessive. Ranking introduces a uniform scaling across the population and provides a simple and effective way of controlling selective pressure.

Rank-based fitness assignment is a more robust procedure than proportional fitness assignment.

(Rank-based fitness assignment behaves in a more robust manner in comparison with proportional fitness assignment.) Here is linear ranking method:

Consider Nind is the number of individuals in the population; Pos is the position of an individual in this population (least fit individual has Pos=1, the fittest individual Pos=Nind) and SP is the selective pressure which is the probability of the best individual being selected compared to the average probability of selection of individuals. The fitness value for an individual is computed according to Eq. (8) (Simonovic 2008).

$$Fitness(Pos) or\ Scaled\ Rank = 2 - SP + 2 \times (SP - 1) \times \frac{Pos - 1}{Nind - 1} \tag{7}$$

Linear ranking allows values of selective pressure in [1.0, 2.0].

In Eq. (8), SP is a variable of interest which is selected to be in (1, 2). Linear ranking assigns the probability of an individual getting selected to be linearly, depending on the position of that individual in population sorted by rank. As SP approaches 1, all individuals have equal chance to be selected for crossover. On the other hand, a selective pressure value of 2 constitutes the probability of selecting the fit individuals being two times greater than that of selecting an individual with median fitness value. In this case, the probability of selecting the worst individual is zero (Sokolov 2005).

5. Crossover or recombination: crossover produces new individuals by combining the information contained in two or more parents. Depending on the representation of the variables, different methods must be used (Simonovic 2008).

Several methods are available to carry out crossover such as single point crossover, two-point crossover, uniform crossover, arithmetic crossover, discrete recombination, intermediate recombination, line recombination, and extended line recombination. We described the discrete recombination method. This method can be applied to all variable representations. Discrete recombination performs an exchange of variable values between the individuals. For each position the parent who contributes its variable to the offspring is selected randomly with equal probability.

$$\begin{gathered} Var_i^o = Var_i^{p_1} \times \alpha_i + Var_i^{p_2} \times (1 - \alpha_i) \qquad i \in (1,2,\dots,Nvar) \\ \alpha_i \in \{0,1\} \ \text{ uniform at random}, \alpha_i \text{ for each i new defind} \end{gathered} \tag{8}$$

where *o* is an abbreviation of offspring p_i is an abbreviation of parent *i*, *Nvar* is the number of variables.

Discrete recombination can be used with any kind of variables (binary, real or symbols) (Simonovic 2008).

The number of offspring is obtained from the Eq. (9)

$$nc = 2 \times round(pc \times \frac{popsize}{2}) \quad (9)$$

where, round function will perform rounding to the nearest integer number, pop_{size}= the size of the population or the number of chromosomes, $p_{c\,=}$ crossover percentage

Mutation: Individuals are randomly altered by mutation. The role of mutation in the genetic algorithm is to restore missing genes within the population. The advantage of mutation is giving us access to all the search space. In this study mutation is carried out to replace some genes by other genes. The number of mutants is obtained from the Eq. (11)

$$nm = 2 \times round(pm \times popsize) \quad (10)$$

where round function will perform rounding to the nearest integer number.

6. Reinsertion: Once the offspring is produced by selection, recombination and mutation of individuals from the old population, the fitness of the offspring may be determined. If less offspring is produced than the size of the original population, then to maintain the size of the original population, the offspring have to be reinserted into the older population. Similarly, if not all offspring is used in each generation or if more offspring are generated than the size of the older population, then a reinsertion scheme must be used to determine which individuals are to exist in the new population.(Simonovic 2008).

2.5 Finding optimized number of stations

The goal of optimization here was to find an optimum number of stations to be retained in the network, instead of predicting a fixed number of stations which was carried out by Asadollahfardi *et al.* (2014). To determine the optimum number of stations, we applied a method which is approximately similar to the method of Cetinkaya *et al.* (2012). First of all, we computed the total MaxSMTS values for selecting 4 to 21 stations. Then, we analyzed the ΔMaxSMTS as indicated in Eq. (11).

$$\Delta\text{MaxSMTS} = MaxSMST_{i+1} \quad - MaxSMST_{i} \quad (11)$$

where *MaxSMTS* = the maximum value or the final score for TR_N, i = an index of the station in K primary

We plotted Δ*MaxSMTS* against TR_N. Then we considered the contribution of each new station after adding the number of stations to the system one by one. If the Δ*MaxSMTS* value of the system is very small and may be negligible after a specific number of stations, that station should be the optimum number of stations.

3. Results and discussion

Table 5 indicates the normalized and uniform data. The parameter’s values were between 0 and 1.

Tables 6 and 7 indicate the weight parameters based on drinking and agricultural consumption, respectively, and the values of both of these tables were used to obtain drinking and agricultural pollution indices. The importance of water quality parameters or pollutants are based on its importance for drinking or agriculture consumption and some parameters are more important for drinking than agriculture consumption. However, we had limitation to water quality data.

Tables 6 and 7 indicate the opinion of 30 water quality experts related to several water quality parameters considering water consumption for drinking and irrigation purposes.

The catchment area was divided into four sub-basins (Figs. 2 and 3). The 4 Sub basin has the common characteristics in area, economics, agriculture, and population aspects. The number of sub-basins should satisfy the condition which at least one monitoring station can be selected from each sub-basin. Therefore, we had at least 4 stations retained in monitoring network and the first and second sub-basin were the Shah-Rud branch and Qezel-Owzan branch on the reservoir of the Sefīd-Rūd Dam, which included stations SSW2, SSW3, SSW4, GSW3, GSW4, GSW5, GSW6 and GSW7 . The third and fourth sub-basins were included stations ST1, ST2, ST2-1, ST3, ST4, ST4-1, ST5, ST6, ST7, ST8, ST9, ST10 and ST11on the river. The Shah-Rud and Qezel-Owzan branches included at least one monitoring station and the other sub-basins which were longer in length included at least two monitoring stations. Tables 6 to 9 present sum of the weighted water quality parameters multiplied normalized data for irrigation and drinking water purposes. The amounts in the Tables 8-11 were considered as a score of each station.

Table 5 Normalized and uniform water quality parameters of the Sefīd -Rūd River using S-Plus software

Location	BOD5	COD	NO3	NH3	PO4-3	EC	TDS	TSS	pH	Temp.
SSW2	0.1803	0.1877	0.2377	0.1998	0.5222	0.2009	0.208	0.0254	0.2109	0.2046
SSW3	0.2102	0.2106	0.2297	0.2305	0.1131	0.2172	0.2188	0.0317	0.2217	0.204
SSW4	0.1813	0.1883	0.213	0.2605	0.1654	0.2312	0.2243	0.044	0.2182	0.2067
GSW3	0.2999	0.2671	0.2377	0.145	0.1654	0.2645	0.2512	0.2159	0.1974	0.2245
GSW4	0.2392	0.2322	0.2305	0.2529	0.1741	0.2382	0.2317	0.0523	0.2152	0.2107
GSW5	0.1747	0.1934	0.221	0.2072	0.1828	0.2547	0.2344	0.0562	0.2147	0.2011
GSW6	0.164	0.1804	0.2149	0.2246	0.2698	0.2452	0.2292	0.0719	0.2171	0.2017
GSW7	0.1836	0.1931	0.2175	0.2331	0.2524	0.2352	0.2261	0.0321	0.2149	0.208
ST-01	0.1564	0.1887	0.2183	0.2021	0.4265	0.2605	0.2329	0.0617	0.2206	0.2124
ST-02	0.1824	0.2038	0.2233	0.2094	0.2698	0.2535	0.2322	0.1451	0.2222	0.2122
ST-2.1	0.209	0.2182	0.2233	0.1741	0.148	0.2527	0.2516	0.1222	0.2222	0.2139
ST-03	0.1747	0.1994	0.2377	0.1842	0.1828	0.2107	0.2151	0.3596	0.2225	0.2158
ST-04	0.1547	0.1877	0.2267	0.2219	0.0783	0.191	0.2006	0.5276	0.223	0.2194
ST-4.1	0.2297	0.2287	0.2249	0.2633	0.1131	0.1927	0.2071	0.5195	0.2225	0.221
ST-05	0.2506	0.2389	0.2297	0.205	0.0783	0.1909	0.2013	0.2022	0.2222	0.2183
ST-06	0.2363	0.232	0.233	0.2094	0.1306	0.1882	0.2	0.1472	0.223	0.2226
ST-07	0.2867	0.2555	0.1939	0.2279	0.148	0.1856	0.1985	0.2193	0.2182	0.2348
ST-08	0.2513	0.2392	0.1936	0.1976	0.1915	0.1879	0.1958	0.1719	0.2179	0.237
ST-09	0.2384	0.233	0.2043	0.2815	0.087	0.1738	0.2249	0.1421	0.2193	0.2338
ST-10	0.2407	0.2341	0.1818	0.1976	0.148	0.179	0.1908	0.1628	0.2182	0.2363
ST-11	0.2544	0.2407	0.1753	0.2094	0.1393	0.1847	0.1925	0.1827	0.2193	0.237

Table 5 Continued

Location	Turbidity	DO	Pb	Zn	Cd	Ni	Cu	Cr	Fe	As
SSW2	0.0994	0.2296	0.2259	0.2494	0.1779	0.2429	0.0544	0.0891	0.0675	0.0726
SSW3	0.1726	0.227	0.2213	0.1425	0.5338	0.2429	0.1087	0.2673	0.2119	0.0979
SSW4	0.1441	0.2073	0.2259	0.2494	0.1423	0.0972	0.1087	0.1782	0.31	0.1397
GSW3	0.1619	0.2359	0.239	0.2494	0.3558	0.0729	0.1631	0.3563	0.2778	0.153
GSW4	0.1488	0.2434	0.2259	0.2494	0.1423	0.0972	0.1087	0.1782	0.1607	0.174
GSW5	0.1318	0.2401	0.2119	0.0356	0.1779	0.2429	0.0544	0.0891	0.2051	0.1956
GSW6	0.1367	0.2132	0.2213	0.285	0.1779	0.3158	0.1087	0.3563	0.1791	0.1965
GSW7	0.1441	0.2065	0.2167	0.2137	0.1423	0.2429	0.0544	0.1782	0.1378	0.1209
ST-01	0.1626	0.1871	0.239	0.2494	0.0712	0.0486	0.1087	0.0891	0.1166	0.3192
ST-02	0.1665	0.215	0.2474	0.1781	0.1423	0.2915	0.1631	0.1782	0.0972	0.2043
ST-2.1	0.1993	0.2439	0.1429	0.2137	0.3558	0.17	0.0544	0.2673	0.1791	0.1397
ST-03	0.2915	0.2141	0.2119	0.2494	0.1245	0.1457	0.1087	0.1782	0.2624	0.2541
ST-04	0.2477	0.2007	0.2304	0.1425	0.0712	0.17	0.1087	0.0891	0.2857	0.2369
ST-4.1	0.2737	0.2242	0.2213	0.285	0.1601	0.17	0.0544	0.3563	0.2119	0.2541
ST-05	0.2572	0.236	0.2167	0.2137	0.1779	0.1943	0.1087	0.1782	0.344	0.3192
ST-06	0.3922	0.2007	0.239	0.1781	0.1779	0.2429	0.1631	0.0.0891	0.149	0.272
ST-07	0.25	0.218	0.202	0.2494	0.1423	0.2672	0.0544	0.2673	0.1166	0.2043
ST-08	0.2356	0.218	0.1969	0.1425	0.1068	0.2186	0.1087	0.1782	0.1791	0.2454
ST-09	0.2506	0.2223	0.1969	0.2137	0.0712	0.2429	0.1087	0.3563	0.1984	0.272
ST-10	0.2468	0.1904	0.2167	0.2494	0.3558	0.2915	0.1631	0.0891	0.3018	0.1889
ST-11	0.2399	0.1958	0.2119	0.1781	0.089	0.2915	0.0544	0.0891	0.3018	0.2904

Table 6 The results of expert's opinion for different water quality parameters for drinking purposes

Parameter	1= The highest significance 5= The lowest significance					Sum of The vote	Mean of all significance *	Temporary weights **	Final weights (wi)
	1	2	3	4	5				
BOD_5	5	22	3	-	-	30	1.93	0.52	0.043
COD	3	20	7	-	-	30	2.13	0.47	0.039
NO_3	30	-	-	-	-	30	1.00	1.00	0.082
NH_3	28	2	-	-	-	30	1.07	0.94	0.077
PO_{4-3}	4	6	19	1	-	30	2.57	0.39	0.032
EC	21	7	2	-	-	30	1.37	0.73	0.060
TDS	23	4	3	-	-	30	1.33	0.75	0.062
TSS	-	-	10	18	2	30	3.73	0.27	0.022
pH	-	1	5	23	1	30	3.80	0.26	0.022
Temperature	-	-	-	4	26	30	4.87	0.21	0.017
Turbidity	18	9	3	-	-	30	1.50	0.67	0.055
DO	-	-	5	11	14	30	4.30	0.23	0.019

Table 6 Continued

Parameter	1= The highest significance 5= The lowest significance					Sum of The vote	Mean of all significance*	Temporary weights**	Final weights (wi)
	1	2	3	4	5				
Pb	21	7	2	-	-	30	1.37	0.73	0.060
Zn	23	5	2	-	-	30	1.30	0.77	0.063
Cd	22	4	3	1	-	30	1.43	0.70	0.057
Ni	26	3	1	-	-	30	1.17	0.86	0.071
Cu	5	19	6	-	-	30	2.03	0.49	0.040
Cr	22	8	-	-	-	30	1.27	0.79	0.065
Fe	7	21	2	-	-	30	1.83	0.55	0.045
As	25	4	1	-	-	30	1.20	0.83	0.069
								Σ=12.15	Σ=1

Note: There were thirty respondents in current research

To obtain this column, the weighted votes are divided by the number of votes

**Temporary weights were divided by dividing the mean height of all significant rating, returned by respondents, by the mean significance rating of each parameter.

Table 7 The results of expert's opinion for different water quality parameters for irrigation purposes

Parameter	1= The highest significance 5= The lowest significance					Sum of the vote	Mean of all significance*	Temporary weights**	Final weights (wi)
	1	2	3	4	5				
BOD_5	-	-	1	18	11	30	4.33	0.23	0.030
COD	-	-	-	20	10	30	4.33	0.23	0.030
NO_3	-	-	2	15	13	30	4.37	0.23	0.030
NH_3	-	-	4	19	7	30	4.10	0.24	0.032
PO_{4-3}	-	-	1	20	9	30	4.27	0.23	0.030
E.C.	30	-	-	-	-	30	1.00	1.00	0.129
TDS	29	1	-	-	-	30	1.03	0.97	0.125
TSS	-	19	9	2	-	30	2.43	0.41	0.053
pH	-	-	4	26	-	30	3.87	0.26	0.033
Temperature	-	-	-	4	26	30	4.87	0.21	0.027
Turbidity	-	-	7	22	1	30	3.80	0.26	0.034
DO	-	-	-	14	16	30	4.53	0.22	0.028
Pb	2	22	6	-	-	30	2.13	0.47	0.061
Zn	1	25	4	-	-	30	2.10	0.48	0.062
Cd	-	19	10	1	-	30	2.40	0.42	0.054
Ni	1	23	6	-	-	30	2.17	0.46	0.060
Cu	-	22	8	-	-	30	2.27	0.44	0.057
Cr	-	20	10	-	-	30	2.33	0.43	0.055

Table 7 Continued

Parameter	1= The highest significance 5= The lowest significance					Sum of the vote	Mean of all significance*	Temporary weights**	Final weights (wi)
	1	2	3	4	5				
Fe	-	-	2	24	4	30	4.07	0.25	0.032
As	-	1	20	9	-	30	3.27	0.31	0.040
								Σ=7.74	Σ=1

Table 8 The amount of the sum of weighted water quality parameters multiplied normalized data for irrigation and drinking water purposes for the first sub-basin K = 1, $P_1 = 3$

No.	Stations	Irrigation	Drinking
1	SSW2	18.23	18.28
2	SSW3	20.97	21.48
3	SSW4	18.87	19.07

Table 9 The amount of the sum of weighted water quality parameters multiplied normalized data for irrigation and drinking water purposes for the second sub-basin K = 2, $P_2 = 5$

No.	Stations	Irrigation	Drinking
1	GSW3	23.29	22.53
2	GSW4	19.24	19.37
3	GSW5	18.03	17.90
4	GSW6	21.85	22.08
5	GSW7	18.74	18.84

Table 10 The amount of the sum of weighted water quality parameters multiplied normalized data for irrigation and drinking water purposes of the third sub-basin K = 3, $P_3 = 7$

No.	Stations	Irrigation	Drinking
1	ST1	19.03	18.86
2	ST2	21.89	21.88
3	ST2-1	23.73	23.32
4	ST3	21.03	20.85
5	ST4	19.82	19.20
6	ST4-1	22.91	22.98
7	ST5	20.71	21.67

Table 11 The amount of the sum of weighted water quality parameters multiplied normalized data for irrigation and drinking water purposes for the fourth sub-basin K = 4, $P_4 = 6$

No.	Stations	Irrigation	Drinking
1	ST6	20.07	21.04
2	ST7	20.35	20.92
3	ST8	18.94	19.38

Table 11 Continued

No.	Stations	Irrigation	Drinking
4	ST9	20.49	20.81
5	ST10	21.01	21.51
6	ST11	19.14	19.94

Table 12 A schematic of single chromosome with 4 genes

K_1	K_2	K_3	K_4
a1	a2	a3	an

K_1= First sub-basin, K_2= Second sub-basin, K_3= Third sub-basin and K_4= Fourth sub-basin

3.1 Optimization procedures using GA and MATLAB 2011a

Step 1: First of all, we should define chromosomes with 4 genes which illustrate the stations in each sub catchment K. Table 12 schematically indicates the chromosomes with 4 genes.

Therefore, we can randomly encode the chromosomes in MATLAB. For example, if we consider 15 stations to be retained in the river for irrigation purpose, the arrangement of stations is similar to the following procedure

3 4 2 6 $\dashrightarrow$ (3+4+2+6=15)
2 5 6 2 $\dashrightarrow$ 15
1 1 7 6 $\dashrightarrow$ 15
3 3 4 5 $\dashrightarrow$ 15

The 15 in the right hand side indicates the number of total stations to be retained.

For example 3, 4, 2 and 6 means that we select three stations (SSW2, SSW3,SSW4) from first sub-basin K_1, four stations (GSW3,6,4,7) from the second sub-basin K_2 ,two stations (ST2-1,4-1) from the third sub-basin K_3 ,and six stations (ST10,6,7,8,9,11) from the fourth sub-basin K_4 for both irrigation and drinking purposes. Therefore, we totally selected 15 stations.

Therefore, we intended to have 100 chromosomes in this study for the initial population. Due to its random searching mechanism, GA can always find a better solution compared to the other solutions. Therefore, the initial population is chosen randomly by a trade-off.

Step 2: After we selected some chromosomes as initial population, the computer program (MATLAB 2011a) computed their fitness function.

The fitness function determines the sum of cumulative scores of all four sub-basins due to selected stations from each sub-basin. The resulted value is called the fitness number of that chromosome (Affenzeller 2009) (Tables 13-16).

The stations were prioritized according to the irrigation and drinking water quality indices (Tables 6-9) and the number of selected stations in each sub-basin, considering the irrigation and drinking water quality indices. Therefore, the station with the first highest score was selected while selecting only one station (R_K=1) and the first two stations with highest amount of score were selected while selecting two stations (R_K=2) and the same method was applied up to the end.

3 4 2 6 $\dashrightarrow$ (58.07+83.12+46.64+120.01 = 307.84)
2 5 6 2 $\dashrightarrow$ 311.95
1 1 7 6 $\dashrightarrow$ 313.40
3 3 4 5 $\dashrightarrow$ 313.09

Table 13 Stations monitoring prioritization in the first catchment, according to the number of selected stations for irrigation and drinking purposes K = 1, $P_1 = 3$

R_1	Stations for Irrigation	Irrigation score	Stations for drinking	Drinking score
1	SSW3	20.97	SSW3	21.48
2	SSW2, 3	39.20	SSW2,3	39.76
3	SSW2,3,4	58.07	SSW2,3,4	58.83

Table 14 Stations monitoring prioritization in the second catchment area ,according to the number of selected stations for irrigation and drinking purposes K = 2, $P_2 = 5$

R_2	Stations for Irrigation	Irrigation score	Stations for drinking	Drinking score
1	GSW3	23.29	GSW3	22.53
2	GSW3,6	44.61	GSW3,6	44.61
3	GSW3,6,4	64.38	GSW3,6,4	63.98
4	GSW3,6,4,7	83.12	GSW3,6,7,4	82.81
5	GSW3,6,5,7,4	101.15	GSW3,6,7,4,5	100.71

Table 15 stations monitoring prioritization in the third catchment area, according to the number of selected stations for irrigation and drinking purposes K = 3, $P_3 = 7$

R_3	Stations for Irrigation	Irrigation score	Stations for drinking	Drinking score
1	ST2-1	23.73	ST2-1	23.32
2	ST2-1,4-1	46.64	ST2-1,4-1	46.29
3	ST2-1,4-1,2	68.53	ST2-1,4-1,2	68.18
4	ST2-1,2,3,4-1	89.57	ST2-1,5,2,4-1	89.84
5	ST2-1,2,3,4-1,5,	110.28	ST2-1,5,2,4-1,3	110.69
6	ST2-1,2,4,4-1,5,3	130.09	ST2-1,4,2,4-1,3,5	129.89
7	ST2-1,2,1,4-1,5,3,4	149.13	ST2-1,1,2,4-1,3,4	148.75

Table 16 Stations monitoring prioritization in the fourth catchment area according to the number of selected stations for irrigation and drinking purposes K = 4, $P_4 = 6$

R_4	Stations for Irrigation	Irrigation score	Stations for drinking	Drinking score
1	ST10	21.01	ST10	21.51
2	ST10,9	41.51	ST10,6	42.55
3	ST10,9,7	61.86	ST10,6,7	63.47
4	ST10,6,7,9	81.93	ST10,6,7,9	84.28
5	ST10,6,7,11,9	101.07	ST10,6,7,9,11	104.22
6	ST10,6,7,8,9,11	120.01	ST10,6,7,9,8,11	123.60

Steps 3, 4, 5:

Table 17 Discrete recombination for two individuals with assuming the variable's values

Individual 1	1	1	7	6

Table 17 Continued

Individual 2	3	3	4	5
Var^{O1} *	1(α=1)	1(α=1)	1(α=1)	2(α=0)
Var^{O2}	2(α=0)	2(α=0)	2(α=0)	1(α=1)
offspring 1	1	1	7	5
offspring 2	3	3	4	6

*Var^{Oi} = the varibales of individuals which are chosen for offspring

Table 18 selected stations for irrigation water monitoring

TRN	Selected stations	Final score
4	ST10 │ ST2-1 │ GSW3 │ SSW3	89.00
5	ST10 │ ST2-1, 4-1 │ GSW3 │ SSW3	111.92
6	ST10 │ ST2-1, 4-1, 2 │ GSW3 │ SSW3	133.81
7	ST10 │ ST2-1, 4-1, 2 │ GSW3, 6 │ SSW3	155.66
8	ST10 │ ST2-1, 4-1, 2,3 │ GSW3, 6 │ SSW3	176.69
9	ST10 │ ST2-1, 4-1, 2,3,5 │ GSW3, 6 │ SSW3	197.40
10	ST10,9 │ ST2-1, 4-1, 2,3,5 │ GSW3, 6 │ SSW3	217.90
11	ST10,9,7 │ ST2-1, 4-1, 2,3,5 │ GSW3, 6 │ SSW3	238.25
12	ST10,9,7,6 │ ST2-1, 4-1, 2,3,5 │ GSW3, 6 │ SSW3	258.32
13	ST10,9,7,6 │ ST2-1, 4-1, 2,3,5,4 │ GSW3, 6 │ SSW3	278.14
14	ST10,9,7,6 │ ST2-1, 4-1, 2,3,5,4 │ GSW3, 6,4 │ SSW3	297.37
15	ST10,9,7,6,11 │ ST2-1, 4-1, 2,3,5,4 │ GSW3, 6,4 │ SSW3	316.51
16	ST10,9,7,6,11 │ ST2-1, 4-1, 2,3,5,4,1 │ GSW3, 6,4 │ SSW3	335.54
17	ST10,9,7,6,11,8 │ ST2-1, 4-1, 2,3,5,4,1 │ GSW3, 6,4 │ SSW3	354.48
18	ST10,9,7,6,11,8 │ ST2-1, 4-1, 2,3,5,4,1 │ GSW3, 6,4,7 │ SSW3	373.23
19	ST10,9,7,6,11,8 │ ST2-1, 4-1, 2,3,5,4,1 │ GSW3, 6,4 │ SSW3,2,4	391.58
20	ST10,9,7,6,11,8 │ ST2-1, 4-1, 2,3,5,4,1 │ GSW3, 6,4,7 │ SSW3,2,4	410.33
21	ST10,9,7,6,11,8 │ ST2-1, 4-1, 2,3,5,4,1 │ GSW3, 6,4,7,5 │ SSW3,2,4	428.36

Table 19 Selected stations for drinking water monitoring

TRN	Selected stations	Final score
4	ST10 │ ST2-1 │ GSW3 │ SSW3	88.84
5	ST10 │ ST2-1, 4-1 │ GSW3 │ SSW3	111.81
6	ST10 │ ST2-1, 4-1 │ GSW3,6 │ SSW3	133.90
7	ST10 │ ST2-1, 4-1, 2 │ GSW3, 6 │ SSW3	155.78
8	ST10 │ ST2-1, 4-1, 2,3 │ GSW3, 6 │ SSW3	176.63
9	ST10,9 │ ST2-1, 4-1, 2,3 │ GSW3, 6 │ SSW3	197.44
10	ST10,9,7 │ ST2-1, 4-1, 2,3 │ GSW3, 6 │ SSW3	218.37
11	ST10,9,7 │ ST2-1, 4-1, 2,3,5 │ GSW3, 6 │ SSW3	240.03
12	ST10,9,7,6 │ ST2-1, 4-1, 2,3,5 │ GSW3, 6 │ SSW3	261.07
13	ST10,9,7,6,11 │ ST2-1, 4-1, 2,3,5 │ GSW3, 6 │ SSW3	281.01

Table 19 Continued

TRN	Selected stations	Final score
14	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5 | GSW3, 6 | SSW3	300.39
15	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5 | GSW3, 6,4 | SSW3	319.75
16	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5,4 | GSW3, 6,4 | SSW3	338.95
17	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5,4,1 | GSW3, 6,4 | SSW3	357.81
18	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5,4,1 | GSW3, 6,4,7 | SSW3	376.64
19	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5,4,1 | GSW3, 6,4 | SSW3,2,4	395.15
20	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5,4,1 | GSW3, 6,4,7 | SSW3,2,4	413.99
21	ST10,9,7,6,8,11 | ST2-1, 4-1, 2,3,5,4,1 | GSW3, 6,4,7,5 | SSW3,2,4	431.89

We allocated 0.8 to the pc that means 80 offspring are generated in crossover.

Mutation: The role of mutation in the genetic algorithm is to restore missing genes within the population. The advantage of mutation is the ability to access all search space.

We allocated 0.3 to the pm that means 30 mutants are generated in mutation.

We used MATLAB 2011a software for Mutation performance and some genes are exchanged between two chromosomes.

If the sum of gene values from each chromosome is not 15, by changing the value of one of the genes, the necessary condition is satisfied.

1 1 7 5 $\dashrightarrow$ 1 2 7 5

(The 1 is changed to 2)

3 3 4 6 $\dashrightarrow$ 3 2 4 6

(The 3 is changed to 2)

1 2 7 5 $\dashrightarrow$ 1 5 7 2

(The 5 and 2 are replaced by each other)

3 2 4 6 $\dashrightarrow$ 3 2 6 4

(The 6 and 3 are replaced by each other)

Then we calculated the new generation fitness

1 2 7 5 $\dashrightarrow$ 315.78
3 2 4 6 $\dashrightarrow$ 312.26
1 5 7 2 $\dashrightarrow$ 312.76
3 2 6 4 $\dashrightarrow$ 314.71

We mixed the new and pervious population and then we sorted them based on their fitness value. After that, we selected new population with P size (initial population or the number of initial chromosomes) with the highest fitness values. In this situation, we had a new generation with better fitness average than the previous generation. Then, we repeated this procedure with 30 iterations until reaching to the best generation.

The result of the GA was to find 4 to 21 optimized stations. Their scores are shown in tables 18 and 19 for irrigation and drinking purposes.

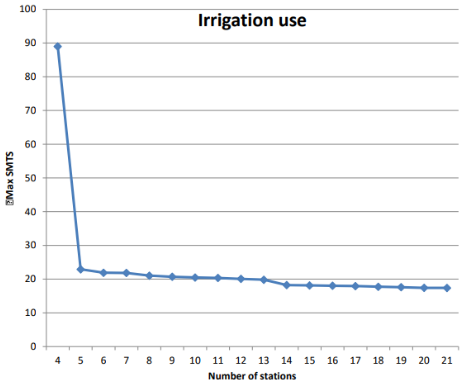

Fig. 5 The trend of the maximum sum of maximum total scores related to an increase number of stations for irrigation purpose

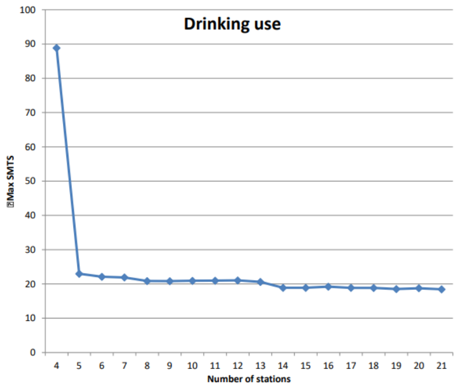

Fig. 6 The trend of the maximum sum of maximum total scores related to an increase number of stations for drinking purpose

3.2 Finding optimized number of stations

Figs. 5 and 6 indicate that the contribution of each new station after approximately 14 stations to the total MaxSMTS value of the water quality monitoring system. The contribution is very small and may be negligible. Therefore, the results indicate that a minimum of 14 stations should be operated.

Comparing the results of our study to Asadollahfardi *et al.* (2014)'s work which was carried out using DP method indicated our results are relatively similar to their results. Some differences between our study and Asadollahfardi *et al.* (2014) exist. We used weighing method to reach significance of parameters considering water usage. However, they used weighting method which was previously provided by Jafar Nejad (2005). In addition to the water quality parameters which they used in pervious study, we also considered turbidity. Comparing our study with Su-Young Park *et al.* (2006)'s work, they used GIS on Nakdong River but we did not apply GIS. In comparison with Icaga's study (2005) on the Gediz River in Turkey, quality observations were selected in different combinations for point pollutions (As, BOD_5, Cd, COD, Cr, Cu, DO, E-Coli, Fe, F-Strep, Mn, NH_3-N, NO_2-N, NO_3-N, Pb, pH, SS, T-Coli, Turbidity), and nonpoint pollutions (Ca, Cl, EC, K, Mg,Na, NH3-N, NO2-N, NO3-N, SO4, SS, TDS). According to these data, maximum total scores of water quality data representing point and nonpoint pollutions for station combination in the sub basins were calculated. However, due to the constraints we assessed the Irrigation and drinking consumptions and we did not separate pollutants as point or non-point pollutions.

The equality trend of decreasing the stations in Figs. 5 and 6 is a coincidence, and the number of stations can be different based on drinking and irrigation. In that case, the number of stations would be the minimum number of stations based on consuming drinking water. Because the importance of water quality for drinking is much higher than the importance of agricultural water quality.

Compared to Cetinkaya and Harmancioglu (2014)'s work, our results are relatively similar to their results with some differences. We used a weighing method to obtain significance of parameters considering water usage, but they preferred to avoid the dominance of any attributes over the others so that all weights were assigned with a value of 1, meaning that under the water quality management alternatives selected, each attribute was considered to be equally significant. In addition, they use Sanders *et al. (1983)* method to divide the basin and categorized the stations while we divided basin based on common characteristics in the area, economics, agriculture, and population aspects to categorize the stations. Therefore, our study has a few differences in comparison with other researches which it may be considered as the novel part of our work.

4 Conclusions

Considering the results of applying GA for the optimization of existing water quality stations in Sefid-Rud River, we summarized the following key results:

1. Using GA may reduce the number of unnecessary monitoring stations, and this reduction cause abatement of the financial cost of the monitoring station installation and operation.
2. From 21 existing monitoring stations, we can remove 7 stations for both drinking and irrigation purposes.
3. The results indicated that more stations were retained in upstream than downstream of the network. Upstream of the network may be more crucial than the downstream area, considering discharge of pollution to the river.
4. This method can determine the required number of stations, in case of a network reduction problem, instead of predicting a fixed number of stations to be retained in the network.
5. The result indicated that station attributes (criteria) and the weights to be assigned to the parameters must be delineated precisely. Essentially, these factors have to be determined by the decision maker or practicing professionals in charge of the Ministry of Energy.
6. In this study, we investigated the optimum number of stations instead of predicting a fixed number of stations at what was accomplished in prior studies. Hence, a method should be utilized to determine the optimum number of stations to be retained in the network. Therefore, most of the river's water quality monitoring in Iran should be reassessed time to time to replace an optimum number of stations instead of foreseeing a fixed number of stations.

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