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# Optimal reservoir operation using Nash bargaining solution and evolutionary algorithms

Salman Sharifazari [a], Mahmood Sadat-Noori [a,*], Habibeh Rahimi [b], Danial Khojasteh [a], William Glamore [a]

[a] *Water Research Laboratory, School of Civil and Environmental Engineering, University of New South Wales, Sydney, NSW 2052, Australia*
[b] *Department of Watershed Management, University of Zabol, Zabol 35856-98613, Iran*

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**Abstract**

Optimizing reservoir operation is critical to ongoing sustainable water resources management. However, different stakeholders in reservoir management often have different interests and resource competition may provoke conflicts. Resource competition warrants the use of bargaining solution approaches to develop an optimal operational scheme. In this study, the Nash bargaining solution method was used to formulate an objective function for water allocation in a reservoir. Additionally, the genetic and ant colony optimization algorithms were used to achieve optimal solutions of the objective function. The Mahabad Dam in West Azerbaijan, Iran, was used as a case study site due to its complex water allocation requirements for multiple stakeholders, including agricultural, domestic, industrial, and environmental sectors. The relative weights of different sectors in the objective function were determined using a discrete kernel based on the priorities stipulated by the government (the Lake Urmia National Restoration Program). According to the policies for the agricultural sector, water allocation optimization for different sectors was carried out using three scenarios: (1) the current situation, (2) optimization of the cultivation pattern, and (3) changes to the irrigation system. The results showed that the objective function and the Nash bargaining solution method led to a water utility for all stakeholders of 98%. Furthermore, the two optimization algorithms were used to achieve the global optimal solution of the objective function, and reduced the failure of the domestic sector by 10% while meeting the required objective in water-limited periods. As the conflicts among stakeholders may become more common with a changing climate and an increase in water demand, these results have implications for reservoir operation and associated policies.


*Keywords:* *Mahabad dam*; *Lake urmia*; *Genetic algorithm*; *Ant colony algorithm*; *Nash bargaining method*

## 1. Introduction

As water demand increases globally, competition between water users can intensify, increasing the need for improved water resources allocation and management (Yan et al., 2018). In many cases, reservoir supplies are expected to meet water needs of multiple sectors. To efficiently manage and optimize reservoir operations, water usage should be prioritized, and an optimal allocation scheme for different sectors should be developed (Golfam et al., 2019). Therefore, an initial step in optimizing water usage is to identify the water resources system requirements and associated stakeholders. The environmental sector is one of the beneficiaries of water resources systems but is usually overlooked in management systems (especially in developing countries), thereby causing irreparable damage to the environment for current and future generations (Tavassoli et al., 2014).

Stakeholders often have different interests that can cause conflict and competition in common-pool resources (Ratner et al., 2018). One method to address this issue is to use

* Corresponding author.
*E-mail address:* m.sadat-noori@unsw.edu.au (Mahmood Sadat-Noori).
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conflict resolution models (Karamouz et al., 2014). Currently, conflict resolution models, which ensure that different viewpoints of decision-makers are incorporated into a system, are gradually replacing multi-criteria decision-making models (Safari et al., 2014). The ordinal games and the Nash bargaining theory are among the best methods that consider disagreements and the degree of desirability of each stakeholder to seek an optimal solution in the decision-making process (Gudmundsson et al., 2018; Karamouz et al., 2003; Nafarzadegan et al., 2018; Safari et al., 2014; Varouchakis et al., 2017).

The achievement of a near-optimal solution in complex water allocation problems can be aided by the use of evolutionary optimization algorithms (Nanda and Panda, 2014). The successful application of a variety of nature-inspired methods, such as the ant colony optimization algorithm (ACO), genetic algorithm (GA), and artificial neural networks, has been previously shown in complex engineering problems (Aly and Peralta, 1999; Kuo et al., 2006; Nicklow et al., 2010; Foong et al., 2008; Szemis et al., 2013, 2014; Zecchin et al., 2012). As such, nature-based management optimization systems have been accepted as an important source of modeling ideas and have been used to develop various artificial modeling algorithms (Maier et al., 2014). Among these algorithms, the GA method has been widely used in the exploitation and optimization of water resources systems due to its high efficiency (Ahmed and Sarma, 2005; Assaf et al., 2008; Kumar et al., 2006; Nicklow et al., 2010; Sadat-Noori et al., 2020). Additionally, ACO for a continuous domain, which is an expansion of the discrete ant community algorithm for continuous space optimization, has shown to be an efficient method in optimizing the operation of water resources systems (Socha and Dorigo, 2008; Madadgar and Afshar, 2009).

In this study, the Nash bargaining solution was used in a system where water allocation conflicts exist among different end users, including agriculture, domestic users, industry, and the environment, to satisfy the water requirement of all sectors. Although different evolutionary algorithms have been used to solve conflict resolution models, their performances have rarely been compared with one other. Thus, GA and continuous ACO were used as the optimization methods, and their performances were compared. Additionally, a discrete kernel was used to assign weights to the water utility of various sectors in the conflict resolution model based on the priorities for water allocation regulated by the Lake Urmia National Restoration Committee in Iran. The approach was applied to the Mahabad Dam in Iran to demonstrate the feasibility of the proposed methodology. Furthermore, the regional management policies on the restoration of Lake Urmia (the largest salt lake in Iran, which dried out from 2012 to 2017) through water conservation in the regional agricultural sector were considered in order to satisfy the water demand of the environmental sector. Three water scenarios were developed, and the regional specifications, resources, water usages, and environmental needs to determine the water demand of the Mahabad region of Iran are presented and discussed below.

## 2. Study area

The Mahabad River Basin is located south of Lake Urmia in West Azerbaijan Province, Iran, and lies in the latitude band of 36°23′N−37°02′N and the longitude band of 45°25′E−45°55′E, with an area of 829 $km^2$. The Mahabad Dam is 700 m long and 46 m high, and the lake behind this reservoir is 360 $hm^2$ (Nazari-Sharabian et al., 2019). The dead storage volume of the reservoir is $25.3 \times 10^6$ $m^3$, and its volume at the maximum level is $196.7 \times 10^6$ $m^3$. The Mahabad River Basin has 60 000 $hm^2$ of agricultural land, 12 000 $hm^2$ of which lie on the Mahabad Plain and are irrigated through 450-km irrigation canals. Other water uses in the study area include the domestic water demand of Mahabad City, with a population of approximately 150 000 inhabitants, and the water demand of the petrochemical industry, according to the statistics from the Iranian Ministry of Agriculture. Fig. 1 shows a map of the study area.

Annually, an average of approximately 0.1 $km^3$ of water is released from the Mahabad Dam for agricultural purposes. As the irrigation season of wheat and cereals ends, the water discharge declines gradually. The Mahabad Dam is also used for potable water supply, with about $19.8 \times 10^6$ $m^3$ of water stored in the reservoir and released for 150 000 people. Water consumption in the industrial sector is largely related to the newly established Mahabad petrochemical industry. Currently, 350 $m^3$/h of water is allocated to the petrochemical industry. Furthermore, when floods occur, water is discharged from the dam to meet the environmental needs of wetlands in this region and Lake Urmia, which are important seasonal habitats for many species of migratory birds. The ecosystem of Lake Urmia has been facing various threats, such as desertification, salt dust storms, and disappearance of migratory birds due to declined water levels resulting from limited water allocated to the environment (Abbaspour and Nazaridoust, 2007).

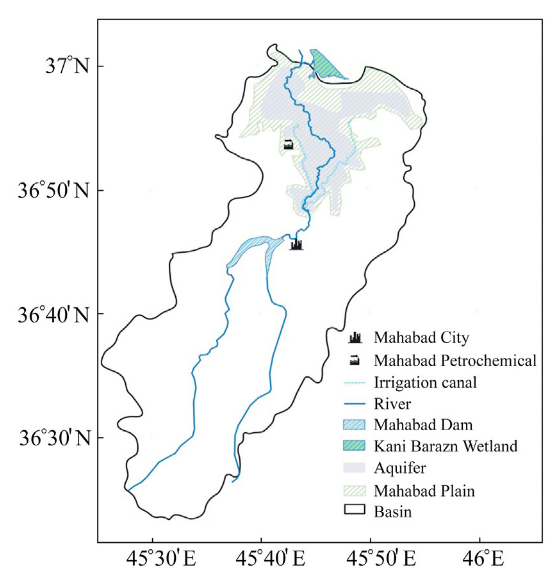


Fig. 1. Map of study area.

## 3. Methodology

In this section, evolutionary algorithms and the Nash bargaining method for conflict resolution are presented. The described methodology was used to model the interactions among water users and the reservoir operator for optimum water allocation.

### 3.1. Optimization algorithms

GA is a search algorithm derived from natural selection processes. The approach is based on Darwin's theory that the most stable organisms will survive in a changing environment (Holland, 1975). The algorithm starts with a set of initial random solutions, called populations. Each population consists of a set of chromosomes, each of which is a solution to the problem. Each chromosome is a set of genes that form the decision variables of the problem. Generally, in a GA cycle, an initial population of individuals is randomly selected regardless of any specific criterion. For all chromosomes in the zero generation, a fit value that describes what is considered fit is determined according to the objective function. Afterwards, based on selection operations, individuals are selected and form a new population/generation. The mating and mutation operators are then carried out on the selected population, depending on the problem. The fit value of the population is compared with that of the zero generation. It is expected that the evolving generations are more competent as they have gone through the GA algorithm, and the population with the highest fit value will survive. For a complete description of this method, refer to Nicklow et al. (2010).

ACO uses a discrete structure to determine the solution to a complex problem. It discretizes decision variables and creates a set of solution components for each variable. A solution is constructed through the choice of one component of each discretized decision variable. Each solution component has a probability of selection that will be updated by the pheromone model at each step. The pheromone model resembles the behavior of real ants. Ants deposit pheromones on the ground during their return trip when they have discovered a food source. Thus, a discrete probability distribution is defined for each decision variable. Instead of this discrete distribution, a continuous probability density function (Gaussian function) can be used to extend the domain and develop the ant colony optimization for continuous domains (ACOR). For a detailed description including the mathematical structure of ACOR, refer to Socha and Dorigo (2008).

### 3.2. Conflict resolution method

In the Nash bargaining theory, the goal is to find a point in the decision domain that has the greatest concurrent distance from the point of disagreement. The objective function of the Nash bargaining model was developed for the Mahabad Dam reservoir considering the agricultural, industrial, domestic, and environmental sectors as the stakeholders. This objective function is a non-symmetric Nash product, obtained by multiplying the differences between the utility function and the point value of disagreement for all sectors:

$$\begin{cases} \max U = \prod_{x=1}^{N} [f_x(Z_x) - d_x]^{w_x} \\ f_x(Z_x) = \dfrac{1}{T}\sqrt{T^2 - Z_x^2} \\ Z_x = \sum_{t=1}^{T} \dfrac{D_{xt} - R_{xt}}{D_{xt}} \end{cases} \tag{1}$$

$$\text{s. t.} \begin{cases} R_{xt} \le D_{xt} \\ R_t = \sum_{x=1}^{N} R_{xt} \\ S_{t+1} = S_t + I_t - R_t - L_t \\ S_{\min} \le S_t \le S_{\max} \\ S_1 = S_T \end{cases} \tag{2}$$

where $U$ is the objective function; $N$ is the number of sectors; $x$ is the index of sectors, with 1, 2, 3, and 4 denoting the agricultural, industrial, domestic, and environmental sectors, respectively; $f_x$, $Z_x$, $d_x$, and $w_x$ are the utility function, deficit value, disagreement value, and relative weight for sector $x$, respectively; $D_{xt}$ is the water demand of sector $x$ in month $t$; $R_{xt}$ is the allocated water for the water demand for sector $x$ in month $t$; $R_t$ is the total amount of water released from the reservoir; $I_t$ is the amount of water entering the reservoir; $T$ is the total number of months of reservoir operation; $S_1$, $S_t$, $S_{t+1}$, and $S_T$ are the storage volumes of the reservoir in the first month of operation and in months $t$, $t+1$, and $T$, respectively; $L_t$ is the amount of reservoir losses in month $t$; $S_{\min}$ and $S_{\max}$ are the minimum and maximum storage volumes of the reservoir, respectively. The third constraint condition in Eq. (2) is the water balance equation for the reservoir, which links the storage at the end of each month with the reservoir storage and water cycle components at the beginning of next month.

A higher value of $Z_x$ or deficit in sector $x$ indicates a lower utility value. Also, the relative weights for different sectors were calculated according to the Lake Urmia National Restoration Committee priorities (Salimi et al., 2019), using a discrete probability distribution function:

$$w_x = 1 \Big/ \left[ i \sum_{i=1}^{N} (1/i) \right] \tag{3}$$

where $w_x$ is the relative weight of sector $x$ with priority $i$. The priority levels and relative weights for different sectors are presented in Table 1.

Evaluating the operational policies is the last and most important step in using simulation and optimization models for reservoir operation problems (Karamouz et al., 2003). To optimize the utilization of the Mahabad Dam, the reliability in meeting the water demand of different sectors, volumetric reliability, and vulnerability measures were used:

$$\alpha_{\mathrm{n}} = 100 \times \left(1 - \frac{1}{T}\sum_{t=1}^{T}\eta_t\right) \tag{4}$$

$$\alpha_{\mathrm{v}} = \frac{100}{T}\sum_{t=1}^{T}\frac{R_{xt}}{D_{xt}} \tag{5}$$

$$\lambda = \max\frac{D_{xt} - R_{xt}}{D_{xt}} \tag{6}$$

where $\alpha_{\mathrm{n}}$ is the time-based reliability in meeting the water demand of sector $x$; $\eta_t$ is the failure of sector $x$ in month $t$, where if $R_{xt} \geq D_{xt}$, $\eta_t = 1$, and otherwise $\eta_t = 0$; $\alpha_{\mathrm{v}}$ is the volumetric reliability; and $\lambda$ is the system vulnerability in meeting the water demand of sector $x$. The values of these criteria range from 0 to 1. In terms of time and volume, a higher value of reliability represents a greater reliability, while a smaller vulnerability value indicates a better performance of the system.

### 3.3. Water allocation scenarios

Based on preliminary assessments of water use and available resources in the Mahabad River Basin, three scenarios were considered in this study to better plan and utilize water resources in this region. The water demands of the environmental, industrial, and domestic sectors were assumed constant across all scenarios. The water requirement of the environmental sector was calculated with the Tennant method (Tennant, 1976). Discharge data for the period of 1994−2018 at the Kutar and Beytas hydrometric stations upstream of the Mahabad Dam were used. The water demand for domestic and sanitation purposes in Mahabad City was extracted according to the water use per capita in different months reported by the West Azerbaijan Municipal Water and Wastewater Organization (Gholizadeh et al., 2017).

Table 1
Priority levels and relative weights of agricultural, industrial, domestic, and environmental sectors for Mahabad Dam.

| Sector | Priority | Relative weight |
| --- | --- | --- |
| Agricultural | 3 | 0.117 |
| Industrial | 2 | 0.176 |
| Domestic | 1 | 0.353 |
| Environmental | 1 | 0.353 |

#### 3.3.1. Scenario 1: present-day condition

In the first scenario, reservoir operation optimization was carried out using the existing conditions in the study area. The cultivation pattern in the Mahabad Plain was extracted according to data reported by the Iranian Ministry of Agriculture. The cultivation pattern in the Mahabad Plain consists of 5 200 $\mathrm{hm}^2$ of horticulture and 7 920 $\mathrm{hm}^2$ of cropland. The dominant orchard products include apples, pears, grapes, apricots, peaches, plums, tomatoes, cherries, walnuts, and almonds, and the dominant crops include wheat, barley, sugar beet, alfalfa, corn, and vegetables. The total irrigation efficiency in this region was considered less than 40% (Nasri et al., 2015). Accordingly, the water demand of the agricultural sector was calculated over a water year with the CropWat 8.0 software package. The water demands of all sectors are presented in Table 2.

#### 3.3.2. Scenario 2: modified cultivation pattern

An effective method of determining the optimal cropping pattern is to use a linear programming model (Singh et al., 2001). Therefore, in the second scenario, the optimal cultivation pattern in the study area was determined with a linear programming method for crops with low water requirements. To this end, common and regionally compatible products (e.g., wheat, barley, sugar beet, alfalfa, and corn) were selected. The water demands of these products were calculated with the CropWat 8.0 software package (Najafi, 2007). The objective function of the linear programming model was adjusted to minimize the regional water demand. It was assumed that the total cultivated area for garden products and the gross agricultural revenue remained unchanged in this region. The formulated linear programming model can be presented as follows:

$$\min V = \sum_{j=1}^{n}\left(a_j NIR_j\right) \tag{7}$$

$$\text{s. t.}\begin{cases}\sum\limits_{j=1}^{n}\left(a_j GI_j\right) \geq GI \\ a_j \geq a_{j\min} \\ \sum\limits_{j=1}^{n} a_j = A\end{cases} \tag{8}$$

where $V$ is the water demand volume for cultivation, $n$ is the total number of crop types, $a_j$ is the cultivation area of the $j$th crop, $NIR_j$ is the water requirement for net irrigation for the $j$th

Table 2
Monthly water demand for different sectors.

| Sector | Monthly water demand ($10^6$ $\mathrm{m}^3$) | | | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | January | February | March | April | May | June | July | August | September | October | November | December |
| Environmental | 1.46 | 1.88 | 5.54 | 24.41 | 14.61 | 2.94 | 0.79 | 0.26 | 0.23 | 0.18 | 0.35 | 1.25 |
| Domestic | 1.50 | 1.55 | 1.61 | 1.61 | 1.61 | 1.84 | 1.61 | 1.62 | 1.76 | 1.76 | 1.76 | 1.58 |
| Industrial | 0.25 | 0.25 | 0.24 | 0.26 | 0.26 | 0.26 | 0.26 | 0.26 | 0.26 | 0.25 | 0.25 | 0.25 |
| Agricultural | 0.21 | 0.72 | 1.55 | 6.96 | 15.73 | 38.56 | 37.76 | 33.81 | 21.11 | 7.05 | 0.41 | 0 |

crop, $GI$ is the annual gross revenue of crops in the present state, $GI_j$ is the gross income obtained from the $j$th crop based on average yield at an average price, $A$ is the total cultivation area, and $a_{j\min}$ is the minimum cultivation area allocated to the $j$th crop. The optimization of the linear programming model was performed using the Linear Interactive Global Optimizer software (Srivastava and Singh, 2015). As the total cultivated area remained unchanged for garden products, only agricultural products were optimized. The irrigation method was assumed to be the same as the one already adopted in this area. Tables 3 and 4 demonstrate the optimal cultivation area for crops in this region using the above-mentioned linear model and the regional water demand for agricultural purposes, respectively. Through optimization of the regional crop pattern, the annual gross water demand of the agricultural sector decreased by 7.7% from $164.2 \times 10^6$ m$^3$ to $151.6 \times 10^6$ m$^3$ per year.

#### *3.3.3. Scenario 3: modified irrigation method*

The third scenario was designed according to the regional development plan and the need to shift from traditional to mechanized irrigation methods following the restoration plans for Lake Urmia. Therefore, the water demand of the agricultural sector was recalculated to consider sprinkler irrigation for agricultural crops and drip irrigation for horticultural crops. These pressurized irrigation systems increase irrigation efficiency and improve agricultural water management (Valipour, 2016, 2017). In this case, the efficiencies of sprinkler and drip irrigations were assumed to be 65% and 80%, respectively. Most these scenarios focused on reducing the water demand of the agricultural sector, the largest water consumer in this region. Accordingly, the water demand of the agricultural sector was modified and is presented in Table 4. The change of the irrigation method resulted in a reduction of 47% in the water requirement.

Table 3
Optimal cultivation area for crops in Mahabad Plain.

| Crop type | Optimal area (hm$^2$) | Crop type | Optimal area (hm$^2$) |
|---|---|---|---|
| Wheat | 4 142.6 | Onion | 0 |
| Barely | 462.5 | Potato | 0 |
| Sugar beet | 200.0 | Sunflower | 0 |
| Alfalfa | 70.0 | Tomato | 22.0 |
| Corn | 3 022.5 | Seed | 0 |
| Forage corn | 0 | | |

## 4. Results and discussion

### *4.1. Scenario 1*

To extract the operating criteria using the optimization methods considered in this study, the adopted optimization methods were first calibrated and sensitized based on effective parameters. The parameters of the GA method include population size, crossover fraction, elitism rate, and the selection method that influences the convergence process and the optimal solution. For the continuous ACOR, the size of the solution archive, the number of ants, the locality of the search process ($q$), and the speed of convergence ($\xi$) play important roles in the convergence and the optimal solution. These two algorithms were used to analyze the sensitivity and optimally determine the parameters with a trial-and-error method. In each case and for each combination of the parameters, each algorithm was run at least ten times until the convergence condition was reached. The obtained results for Scenario 1 are summarized in Tables 5 and 6. Fig. 2 demonstrates the objective function values versus time over a 3-h run for the GA and ACOR algorithms and compares the convergence process of these two algorithms. As shown in Fig. 2, the convergence speeds of the two algorithms were similar, but GA was slightly faster than ACOR. Meanwhile, the final value of the objective function from GA was preferable to that from ACOR.

Fig. 3 shows the amount of water released to different sectors against the corresponding water requirement. As shown in this figure, the agricultural sector, the largest water consumer in the study area, suffers from severe failures in periods of water scarcity. The two allocation models performed quite similarly for the agricultural and environmental sectors. However, for the domestic and industrial sectors, with fewer water demands, the output optimized by GA outweighed that of ACOR. The water release volumes from these models met the water demands of all sectors throughout the entire reservoir operation period, except for a few months. This minor failure was due to the conflict resolution approach implemented in the models, because the models tried to simultaneously increase the utility of the stakeholders in this region. An overview of the diagrams for Scenario 1 (Fig. 3) shows that the agricultural sector confronted a severe water shortage.

Table 7 shows the system performance indicators for the four stakeholders. The GA algorithm performed better than the ACOR algorithm in optimizing water allocation. It also had

Table 4
Monthly water demand for agricultural sector in Scenarios 2 and 3.

| Scenario | Monthly water demand ($10^6$ m$^3$) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | January | February | March | April | May | June | July | August | September | October | November | December |
| 2 | 0.24 | 0.84 | 1.81 | 7.75 | 16.26 | 38.26 | 35.19 | 29.91 | 15.80 | 5.10 | 0.40 | 0 |
| 3 | 0.12 | 0.42 | 0.90 | 3.98 | 8.48 | 20.68 | 20.06 | 17.90 | 10.88 | 3.60 | 0.24 | 0 |

Table 5
Optimal parameter values of GA and objective function statistics for Scenarios 1, 2, and 3.

| Scenario | Parameter | | | | Objective function statistics | | |
|---|---|---|---|---|---|---|---|
| | Population size | Crossover fraction | Elitism rate | Selection method | Mean value | Standard deviation | Best value |
| 1 | 200 | 0.70 | 0.030 | Roulette wheel | 0.992 1 | 0.000 5 | 0.996 9 |
| 2 | 400 | 0.70 | 0.050 | Roulette wheel | 0.992 0 | 0.000 9 | 0.997 0 |
| 3 | 400 | 0.75 | 0.025 | Roulette wheel | 0.995 0 | 0.000 4 | 0.999 0 |

Table 6
Optimal parameter values of ACOR and objective function statistics for Scenarios 1, 2, and 3.

| Scenario | Parameter | | | | Objective function statistics | | |
|---|---|---|---|---|---|---|---|
| | Solution archive size | Number of ants | $\xi$ | $q$ | Mean value | Standard deviation | Best value |
| 1 | 30 | 80 | 0.50 | 0.35 | 0.983 3 | 0.000 6 | 0.986 8 |
| 2 | 25 | 80 | 0.45 | 0.40 | 0.982 0 | 0.000 9 | 0.987 0 |
| 3 | 30 | 80 | 0.50 | 0.50 | 0.995 0 | 0.000 5 | 0.998 0 |

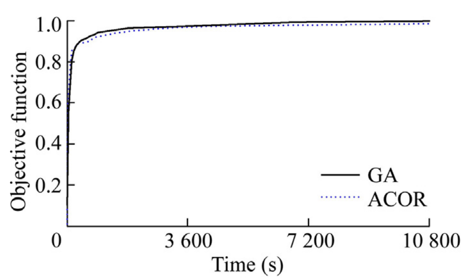


Fig. 2. Convergence of GA and ACOR algorithms to optimal solution in Scenario 1.

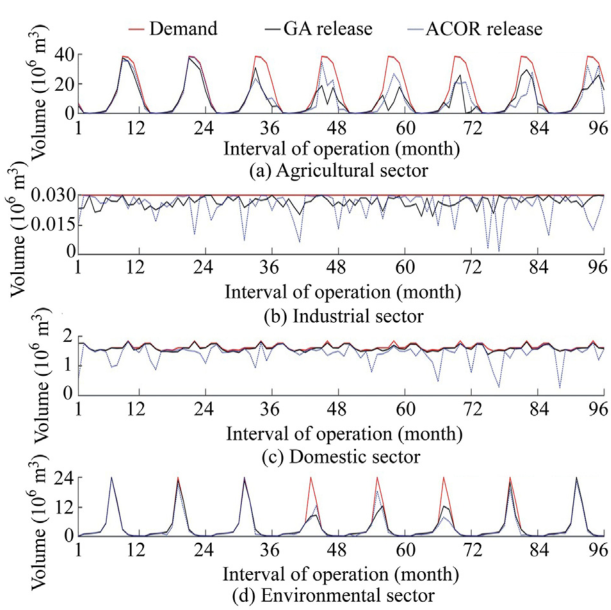


Fig. 3. Allocated release volumes for different sectors obtained by GA and ACOR algorithms with average demands in Scenario 1.

less vulnerability, indicating a better performance. Table 7 indicates an improper performance of the optimization algorithms for the agricultural sector, which can be attributed to the low priority given to the agricultural sector and its considerably higher water requirement than other sectors.

### 4.2. Scenario 2

In the second scenario, the water demand of the agricultural sector, the largest consumer in the study area, was reduced by optimizing the cultivation pattern. Therefore, the performance of the algorithms in water allocation was expected to improve. Tables 5 and 6 display the obtained optimal parameters and the objective function statistics of GA and ACOR in Scenario 2, respectively. Fig. 4 shows the convergence trends of the GA and ACOR algorithms. The convergence processes of the two algorithms were similar, although GA converged slightly faster than ACOR. The final value of the objective function obtained from GA was better than that of ACOR.

Fig. 5 shows the volumes of water allocated to various sectors in Scenario 2. Despite a decline in the water demand of the agricultural sector in this scenario, the water supply suffered severe failures in the water scarcity periods. Therefore, with a reduction of 7.7% in the water demand for the agricultural sector, the improvement in system performance was insignificant. As in Scenario 1, GA performed better than ACOR in meeting the needs of domestic and industrial sectors with lower water demands.

Table 8 shows the indicators of the performance of the system for the four stakeholders in Scenario 2. The utility of the water supply for the four stakeholders with the GA algorithm was superior to that with ACOR. With the decrease in the water demand of the agricultural sector in Scenario 2, the

Table 7
System performance indices of two algorithms for four stakeholders in scenario 1.

| Sector | Model | Time-based reliability | Volumetric reliability | Vulnerability | Utility |
|---|---|---|---|---|---|
| Environmental | GA | 85.42 | 95.25 | 0.66 | 0.999 |
| | ACOR | 44.79 | 82.22 | 0.97 | 0.984 |
| Domestic | GA | 65.63 | 98.14 | 0.12 | 0.999 |
| | ACOR | 28.13 | 87.13 | 0.83 | 0.992 |
| Industrial | GA | 52.01 | 88.63 | 0.36 | 0.993 |
| | ACOR | 56.25 | 83.43 | 0.94 | 0.986 |
| Agricultural | GA | 64.58 | 84.86 | 0.99 | 0.988 |
| | ACOR | 48.96 | 69.57 | 0.94 | 0.982 |

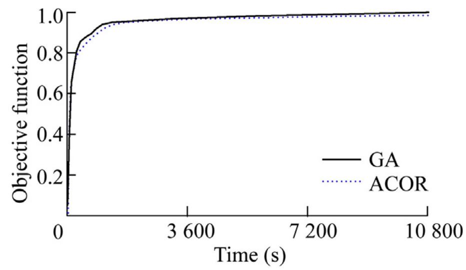


Fig. 4. Convergence of GA and ACOR algorithms to optimal solution in Scenario 2.

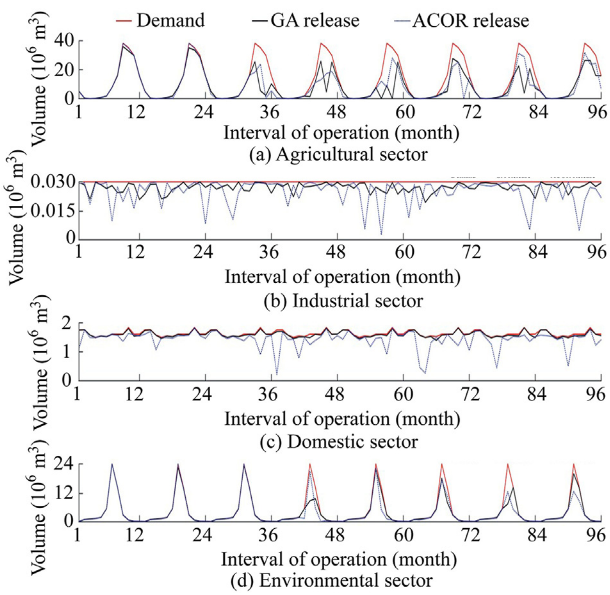


Fig. 5. Allocated release volumes for different sectors obtained by GA and ACOR algorithms with average demands in Scenario 2.

time-based and volumetric reliabilities of both algorithms for this sector were significantly improved compared to those in Scenario 1. This effect was less evident in other sectors. Therefore, GA performed better than ACOR.

### *4.3. Scenario 3*

To reduce the water demand of the agricultural sector in Scenario 3, it was assumed that irrigation in the Mahabad Plain would shift from traditional to modern approaches. Therefore, the water demand of this sector using the pressurized irrigation system was recalculated, and it was found that the water demand decreased significantly. As in the previous two scenarios, the parameters of the optimization algorithms in Scenario 3 were optimally determined. Tables 5 and 6 show the optimal values of these parameters. Fig. 6 demonstrates the convergence trends of the GA and ACOR algorithms in Scenario 3. This figure shows that despite the similar convergence pattern of two algorithms as in Scenarios 1 and 2, the ACOR algorithm converged faster than the GA algorithm. However, the final value of the objective function in the GA algorithm was better than that of the ACOR algorithm. Fig. 7 shows the water allocation to different sectors. It is evident that with a

Table 8
System performance indices of two algorithms for four stakeholders in scenario 2.

| Sector | Model | Time-based reliability | Volumetric reliability | Vulnerability | Utility |
|---|---|---|---|---|---|
| Environmental | GA | 88.54 | 95.80 | 0.69 | 0.999 |
| | ACOR | 46.87 | 86.08 | 0.95 | 0.990 |
| Domestic | GA | 66.67 | 98.43 | 0.08 | 0.999 |
| | ACOR | 18.75 | 87.74 | 0.87 | 0.992 |
| Industrial | GA | 63.54 | 90.59 | 0.36 | 0.996 |
| | ACOR | 58.33 | 82.71 | 0.91 | 0.985 |
| Agricultural | GA | 75.00 | 84.10 | 0.99 | 0.987 |
| | ACOR | 59.37 | 74.43 | 0.99 | 0.962 |

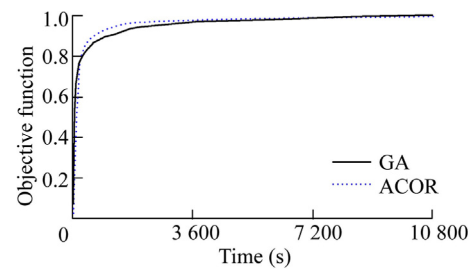


Fig. 6. Convergence of GA and ACOR algorithms to optimal solution in Scenario 3.

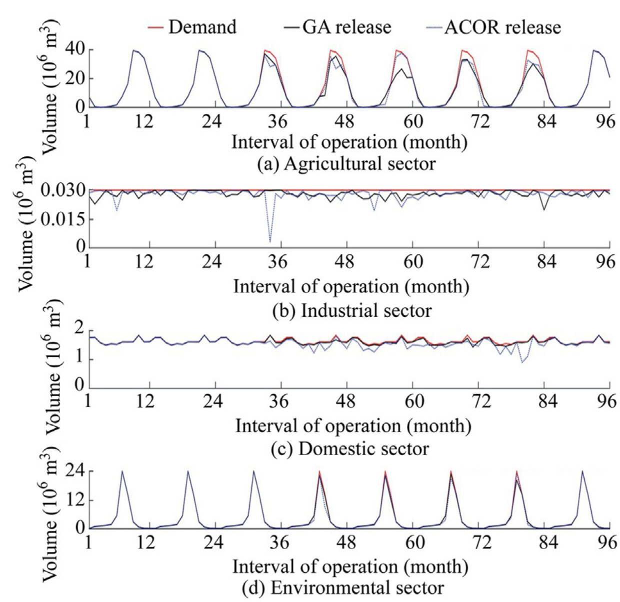


Fig. 7. Allocated release volumes for different sectors obtained by GA and ACOR algorithms with average demands in Scenario 3.

decrease in water demand in the agricultural sector, water allocated to all other sectors increased in Scenario 3 in comparison to the situation in Scenarios 1 and 2. Thus, water demands were fully met in most cases in Scenario 3.

As in Scenarios 1 and 2, the GA algorithm performed better for both industrial and domestic water sectors in Scenario 3, although it did not meet the water demand of the agricultural sector in most months. Table 9 shows the system performance

Table 9
System performance indices of two algorithms for four stakeholders in Scenario 3.

| Sector | Model | Time-based reliability | Volumetric reliability | Vulnerability | Utility |
|---|---|---|---|---|---|
| Environmental | GA | 91.67 | 98.46 | 0.15 | 0.999 |
| | ACOR | 72.92 | 94.76 | 0.41 | 0.999 |
| Domestic | GA | 80.21 | 98.75 | 0.11 | 0.999 |
| | ACOR | 57.29 | 95.15 | 0.44 | 0.999 |
| Industrial | GA | 77.08 | 93.31 | 0.35 | 0.998 |
| | ACOR | 80.21 | 93.07 | 0.89 | 0.998 |
| Agricultural | GA | 92.71 | 94.70 | 0.49 | 0.999 |
| | ACOR | 89.58 | 90.87 | 0.86 | 0.996 |

indicators in Scenario 3. The significant reduction of water demand in the agricultural sector increased the efficiency of the system by supplying water to all sectors. It was observed that the desirability of all sectors increased simultaneously as well. It can be concluded that the GA algorithm performed better than the ACOR algorithm because GA had a higher reliability and a lower vulnerability than ACOR.

## 5. Conclusions

In this study, a mathematical model of reservoir operation function for the Mahabad Dam was established and optimized with the non-symmetric Nash bargaining and evolutionary algorithms. This will help various stakeholders with different interests meet their water requirements as reasonably as possible. Two evolutionary algorithms were used in this work, and the optimum values of the effective parameters in the two algorithms were determined through a trial-and-error process. The Nash bargaining method resulted in a simultaneous increase of 98% in water utility for all stakeholders. The algorithms used to achieve the global optimal solution of the objective function reduced the failure of the domestic sector by 10% and met the required objective in water-limited periods. GA outperformed ACOR in all three scenarios with an increase of 20% in average time-based reliability, an increase of 8% in volumetric reliability, and a decrease of 40% in vulnerability.

The methodology presented in this work can be applied to any reservoirs with conflict in water demands, and the outcomes can be used to develop an optimal reservoir operating policy, which will help decision makers manage limited water resources efficiently.

## Declaration of competing interest

The authors declare no conflicts of interest.

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