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Application of Meta-Heuristic Algorithms in Reservoir Supply Optimization, Case Study: Mahabad Dam in Iran

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ABSTRACT

In arid and semi-arid areas, optimization and strategic planning of water delivery through an optimal and intelligently designed reservoir supply system is a primary task for water resources management. In this regard, the election algorithm (EA) is presented to estimate the optimal storage capacity of the Mahabad dam located in northwest Iran. EA is an intelligent iterative population-based algorithm that has recently been introduced for dealing with different optimization purposes. The capability of EA to address issues of local minimums in the feature search space is employed to yield a globally optimal explanation of the present issue. The data used in this study comprise 7-year (2008-2015) evaporation, rainfall, reservoir storage, reservoir inflows, and outflow. The results obtained from the EA approach are approximated with the continuous genetic algorithm (CGA). Based on the estimated results in the testing phase, an average relatively error (5.65%) is attained in the last implementation of the algorithm. The high efficacy of EA relative to the benchmark models in terms of the NSE and RMSE, MAE is found to be approximately 0.037, 0.41, and 0.74, respectively, which are less than the values of these criteria for the CGA. These error measures, i.e. NSE, MAE, and RMSE, for the CGA were calculated to be 0.66, 0.56, and 0.042, respectively. The obtained accurate results show the high performance of the EA model in estimating the optimal reservoir capacity and its efficiency in water resources management.

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1. Introduction

One of the most efficient infrastructure components in integrated water management is reservoirs. Reservoirs are an essential prerequisite for water supply in local water management. Adequately estimating the storage capacity for the assessed consumption is a major task in planning a dam. The more accurately the reservoir capacity is estimated, the less water loss and water supply inconsistency. Therefore, management plans to predict and control water usage will become increasingly important in the future. Analysis and optimization methods can be used to solve some of these problems. Optimization techniques have great advantages in finding optimal solutions in complex situations. Several techniques have been developed to solve various optimization problems [1], [2]. Two different methods, the classical method and the evolutionary algorithm (EA), have already been applied to solve the reservoir operational optimization problem. Linear programming (LP), dynamic programming (DP), stochastic dynamic programming (SDP), and nonlinear programming (NLP) are classified as classical methods [3]. EA is widely used in various areas of water resources, such as reservoir prediction and optimization. Many researchers have applied (EA) to model a variety of complex hydrological processes. EA has high overall efficiency and is widely used in water resource management. The Election Algorithm (EA) first presented by Emami and Derakhshan, is one of the EAs with a difference inspired by presidential elections [4]. Several studies have been conducted to predict and optimize reservoir storage. Franchini et al. [5] used genetic algorithms combined with sequential quadratic programming to tune a conceptual rain runoff model. Karamouz et al. [6], presented an optimal operating model for the Karkheh dam reservoir in Iran using the imperialist competition algorithm (ICA) and the particle swarm optimization algorithm (PSO). The results showed that the ICA algorithm outperforms the PSO algorithm. Haddad et al. [7], used the water cycle algorithm (WCA) algorithm to determine the optimal operation of Karoun 4's reservoir policy considering four consecutive reservoir systems. Results showed the efficiency of the model in optimizing the continuous reservoir. Stretch and Adeyemo [8], reviewed hybrid evolutionary algorithms in reservoir optimization, allowing researchers to build on existing ones to find improved solutions to reservoir operations and other water resource management problems.

Emami and Parsa [9], used ICA to predict reservoirs of the Shaharchay dam in the Lake Urmia basin and concluded that the ICA algorithm has excellent ability to predict reservoirs. Issa et al. [10], evaluated several experimental and semi-experimental approaches for predicting reservoir storage curves. Results showed that the modified method achieved reasonable agreement. Fatih [11], Estimated variability of reservoirs using the adaptive neural fuzzy inference system ANFIS. The results showed that the ANFIS model works well for estimating dam water storage. Bertone et al. [12], used hybrid regression and stochastic models to predict medium-term storage volumes for optimal reservoir management. Results showed the success of the hybrid model in optimal deposit management. Naderpour et al. [13] predicted the compressive strength of environmentally friendly concrete using artificial neural networks. The results showed that ANN is an efficient model to use as a tool to predict the compressive strength of RAC. Emami et al. [14], evaluated the efficiency of the gray wolf optimizer algorithm (GWO) in predicting the reservoir storage capacity of the Shaharchay dam in the Lake Urmia basin. The results showed the superiority of GWO algorithm in achieving the optimal response, with objective functions of 121, 112, and averages of 83.10. Unes et al. [11], used generalized regression neural networks (GRNN), support vector machines (SVM), and M5-tree (M5) models to model the storage capacity of the Estonia Brook dam in the United States. The results showed that the SVM model works well in predicting the reservoir level of dams. Moeini and Babaei [15], optimized a dam reservoir using the PSO-SVM method. The results showed that the PSO-SVM method was highly accurate in predicting optimal drainage levels. Naderpour et al. [16] estimated the moment capacity of ferrocement members using the group method of data management (GMDH). The results showed that the GMDH model is significantly better than some previous models. Ghanizadeh et al. [17] developed models for predicting collapse settlement and stress release coefficient of sand-gravel soil through evolutionary polynomial regression. The results showed that the developed models are consistent with the results of previous studies. Rezazadeh Eidgahee et al. [18] evaluated the prediction models based on machine learning, including artificial neural networks (ANN), genetic programming (GP) and data management combined GMDH method to predict asphalt mixtures dynamic modulus. ANN model with R^2 of 0.98 has high accuracy compared to GMDH (R^2=0.95) and GP (R^2=0.94).

The above studies demonstrate the importance of reservoirs and their operational policies in the context of water management. Optimization algorithms and their performance in water resource management, especially reservoir management, require close attention. An important point of previous work is that despite the recent use of hybrid optimization techniques and the use of algorithms such as fuzzy, GA, PSO and EWCA, this work was rather the first application dealing with water. about it. Resource issues are less relevant to reservoir performance. Although it can be seen in the literature that many heuristic methods have been used to optimize reservoir operations and reservoir systems, there are no studies on the application of EA algorithms, but they have the advantage of being computationally efficient and non-trapping. Therefore, in this study, we propose an EA algorithm for optimizing the reservoir system for the example reservoir (Mahabad dam). The purpose of this study is to compare the EA algorithm and the continuous genetic algorithm (CGA) in estimating the dam for a given month of operation. This study also describes how to implement EA to optimize and estimate dam storage. Moreover, we compared the performance of EA with CGA. After the introduction, the rest of this study is organized as follows: Section 1 describes previous research, followed by case studies, Section 2 presents the process of EA and CGA algorithms, Section 3, the problem (optimization and estimation of dam storage) is solved by EA and CGA algorithms. Finally, Section 4 presents conclusions.

2. Methods

2.1. Case study

EA and CGA algorithms were evaluated for dam storage optimization and forecasting. Mahabad dam is located on the Mahabad river. Figures 1 and 2 show the schematic of the water system of Mahabad dam. On average, the total annual water inflow to the dam is 339.304 MCM. Water from the dam reservoir is used to irrigate about 20,000 hectares (49,000 acres). This dam also has a hydroelectric power plant (Table 1). Construction began in 1968 and the dam was completed in 1970.

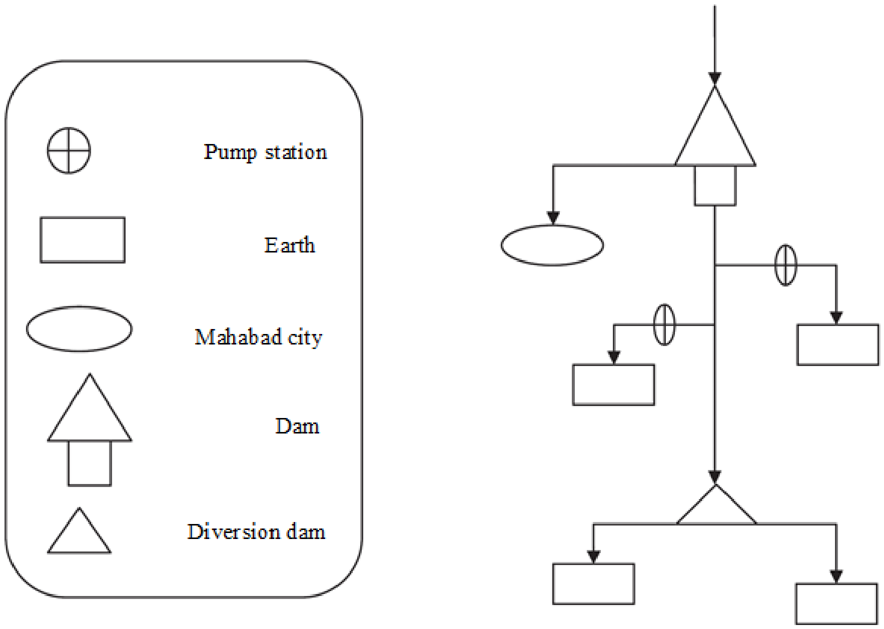

Fig. 1. Schematic of Mahabad dam water system.

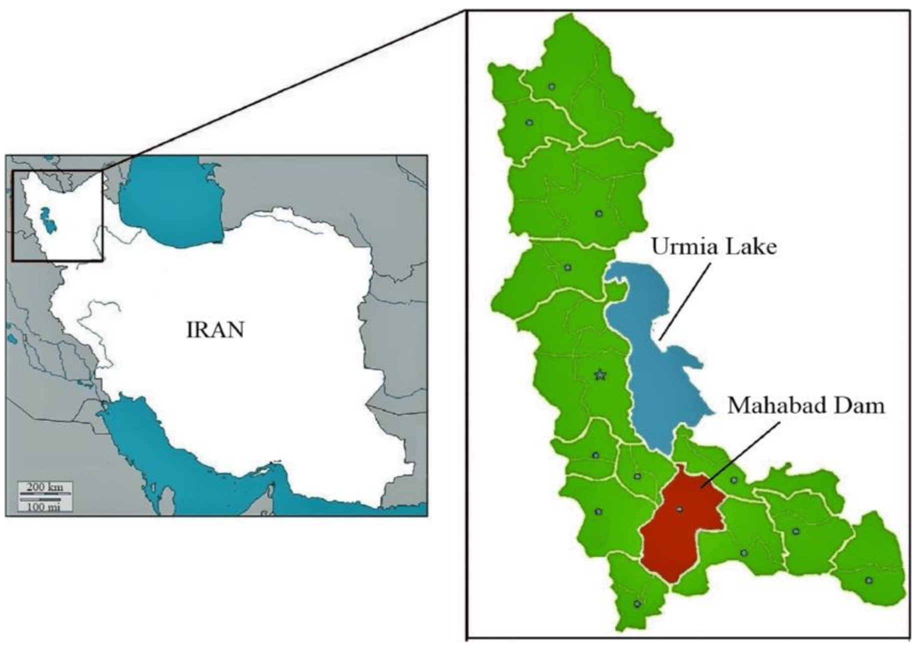

Fig. 2. Basin location in Iran [19].

Table 1
Specification of Mahabad dam.

Type of dam	**Embankment, earth and rock-fill**
Height	47.5 m
Length	700 m
Volume	1.5 MCM
Foundation height	47.5 m
Total capacity	197 million cubic meters
Elevation	1358.5 m

2.2. Election algorithm (EA)

The EA starts the search and optimization process from the solution population [4]. Figure 3 shows the flowchart of the election algorithm. Each individual in the population is called an individual and can be either a candidate or a voter. By organizing multiple parties in the solution space, people can join the party of their choice. These parties then launch advertising campaigns. Advertising campaigns form the basis of this algorithm, causing people to converge on the global optimum of the solution space. During promotion, popular candidates use various techniques to attract more voters. As a result, the unpopular may lose supporters and step out of the voting arena. Advertisements make people converge towards the global optimum of the solution space. On election day, voters cast their ballots and the candidate who received the most votes was declared the winner [4].

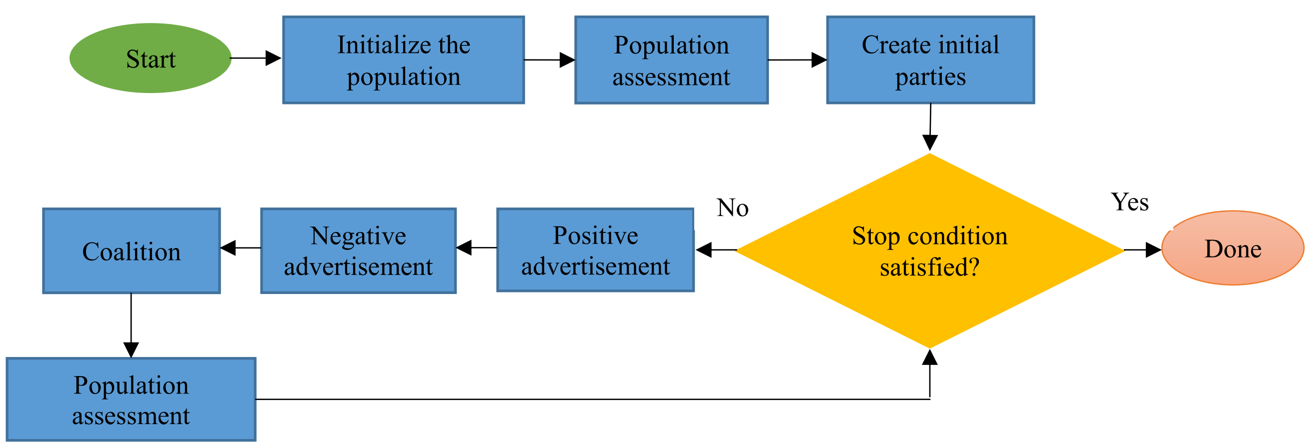

Fig. 3. Flowchart of EA algorithm.

2.3. Continuous genetic algorithm (CGA)

In CGA, a population of candidate solutions to an optimization issue (individuals, organisms, or phenotypes) develops to a better answer [20]. Each candidate answer has a collection of effects (chromosomal or genotype) that can be mutated or altered. Traditionally, solutions are represented in binary as strings of 0's and 1's, but other encodings are feasible. Evolution usually starts with randomly generated populations and is an iterative process through populations, with each iteration called a generation. At each generation, the fitness of each individual in the population is evaluated. Fitness is usually defined as the value of the objective function of the optimization problem being solved. Better-fit individuals are determined stochastically from the current population, and the genome of each individual is altered (recombined, possibly randomly mutated) to assemble a new generation [21]. The next iteration of the algorithm uses a further generation of candidate solutions. The algorithm usually concludes when the maximum number of generations has been generated [22]. Figure 4 shows a flowchart of the CGA algorithm.

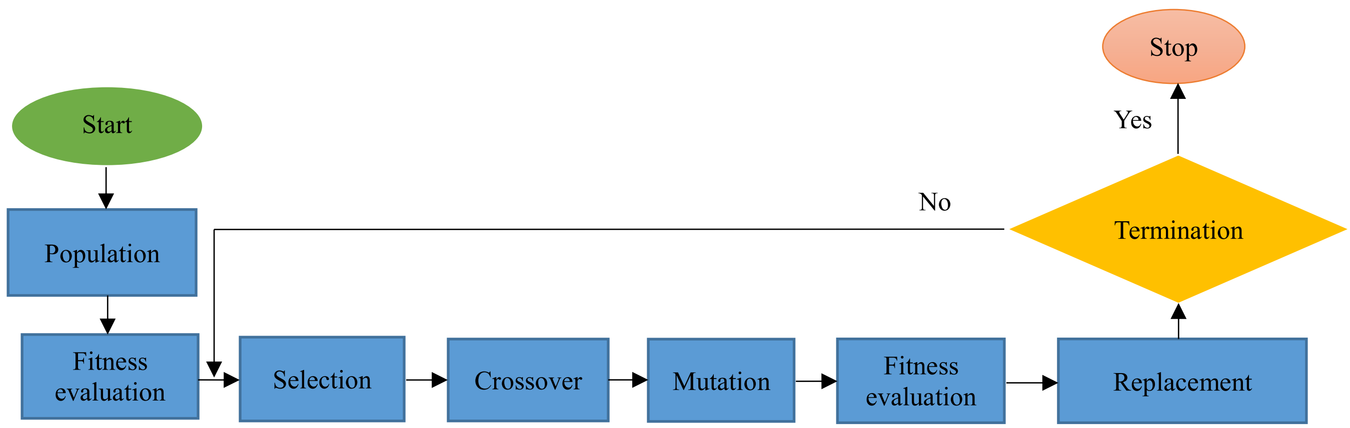

Fig. 4. Flowchart of CGA algorithm.

2.4. Objective function

The objective function is to minimize the square deviation of the monthly irrigation demand and the square deviation in the mass balance equation [10], [23]:

$$\text{Minimize } f = \sum_{t=1}^{12}(R_t - D_t)^2 + \sum_{t=1}^{12}(S_t + S_{t+1} + I_t - R_t - E_t)^2 \quad t+1 \le 12 \tag{1}$$

where R_t is monthly irrigation release for the month "t", D_t is monthly downstream irrigation demand for the month "t", S_t is initial storage at the beginning of month "t", S_{t+1} is final storage at the end of the month "t", I_t is monthly inflow during the period "t', E_t is monthly evaporation loss from the reservoir during the month "t".

The first part of Eq. 1 indicates the difference between irrigation release and downstream irrigation. The second part of this function includes a continuity equation that the input value (*It*) can be investigated for different probabilities. The structure of Eq. 1 is such that by calculating the output value of the dam, reservoir storage values can be estimated per month.

2.4.1. Release condition

The irrigation capacity of each month should be less than or equal to the irrigation requirement of that month. This limitation is defined as follows [10,24]:

$$R_t = D_t, \quad t = 1,2,3,\ldots.,12 \tag{2}$$

The 1-month storage should not exceed the capacity of the storage tank and should not be less than the dead storage. Mathematically, this constraint is defined as [10]:

$$S_{\min} = S_t \ \ and \ \ S_t = S_{\max}, \quad t = 1,2,3,\ldots.,12 \tag{3}$$

where S_{min} is the dead storage (MCM) of the reservoir and S_{max} is the maximum capacity (MCM) of the reservoir.

2.4.2. Over Flow Condition

If the storage at the end of the month exceeds the capacity of the reservoir, limits are given as follows [10,24]:

$$Q_t = S_{t+1} - S_{\max}, \quad t = 1,2,3,....,12 \tag{4}$$

and,

$$Q_t = 0, \quad t = 1,2,3,....,12 \tag{5}$$

where Q_t is the surplus from the reservoir for month "t".

In this paper, limitations are estimated into three categories:

1) Establishing the continuity equation: in all stages of the dam reservoir optimization, there must be a mass balance between the input and output values and reservoir storage capacity.

2) Reservoir storage capacity: in addition, in all stages of the optimization of the reservoir, the storage volume should be between the minimum and maximum values, another condition is to keep the water level in the reservoir constant, which according to that the initial and final volumes (in flood condition) should not differ by more than 10%.

3) Reservoir output: the optimized output value for each period should be between the maximum and minimum values [10,24].

$$S_{\min} \le S_t \le S_{\max} \tag{6}$$

$$R_{\min} \le R_t \le R_{\max} \tag{7}$$

The losses from the reservoirs evaporated were calculated according to the following equations [14]:

$$loss_t = E_{vt}, \overline{A_t} / 1000 \tag{8}$$

$$\overline{A_t} = (A_t + A_{t+1}) \tag{9}$$

$$A_t = a \times S_t + b \tag{10}$$

E_{vt} is the average of loss in the period t (mm), $\overline{A_t}$ is the average water level of the reservoir in the period t (km^2), A_t and A_{t+1} are the average water level of the reservoir at the beginning and end of the t period (km^2), a and b are the constant coefficients of the reservoir.

To properly utilize the reservoir, Eq. 11 was considered [14]:

$$S_1 = S_{t+1} \tag{11}$$

2.4.3. Effect of precipitation and evaporation

The effects of precipitation (P_r) and E_t on the value of the objective function depend on their amounts and differences [25], [26]. These amounts depend on the reservoir area and the geographic location. Pr and E_t can have a positive, negative, or no effect on the objective function. Based on the objective function, the expected effect of these two parameters is positive and negative. To identify the effects of E_t and Pr on reservoir behavior, their volumes measured by MCM were added to Eq. 1. Four. Unfortunately, due to the lack of available data, the amount of leaching was neglected (Eq. 12).

$$S_{t+1} = S_t + I_t - R_t - E_t + \mathrm{Pr}_t - SP_t \tag{12}$$

The output of the algorithms is a monthly outflow (m^3/s). These data were collected from the ministry of water resources –Iran. The data set has a record period of 7 years from 2008 to 2015.

The monthly evaporation height of the lake of the dam is presented according to the calibrated equations in Table 2.

Table 2
Hydrological variables determined at Mahabad dam.

Month	Average Flow	Evaporation height	Downstream required	Maximum output
September	0.62	120.5	20.67	51.84
October	1.92	4077	9.11	51.84
November	5.27	-	1.53	51.84
December	8.63	-	1.43	51.84
January	13.8	-	1.4	51.84
February	37.37	-	1.44	53.57
March	75.49	50.88	6.92	53.57
April	27.03	156.39	27.04	53.57
May	5.5	274.91	33.01	53.57
June	1.47	321.52	29.64	53.57
July	0.76	314.3	30.47	53.57
August	0.41	242.5	26.8	53.57

Given the available data with different time intervals: (12 months) and during the 7-year survey period, 75% and 25% of data were used for model calibration and verification, respectively. Accordingly, for each period (12 months), the data were normalized as follows:

$$\begin{cases} Y_i = \dfrac{X_{oi}}{X_{o\max}}, & X_{oi} \geq 0 \\ Y_i = \dfrac{X_{oi}}{|X_{o\min}|}, & X_{oi} < 0 \end{cases} \tag{13}$$

where Y_i is standardized values, X_{oi} is observational values, X_{oimax} is maximum observational values, and $X_{oimin}$is minimum observational values.

2.5. Statistical criteria

Nash-Sutcliffe coefficient (NSE), correlation coefficient (R^2), mean squared error (RMSE) and mean absolute error (MAE) were used to evaluate the performance of the algorithm. Statistical criteria are presented in Table 3. These criteria are used to analyze the model's output data. These statistics are calculated using the following formulas [13,14,18,25,27,28].

Table 3
Statistical criteria.

Criteria	Definition
R^2	$R^2 = \left[\frac{\sum_{i=1}^{n} \left(c_i - \bar{c}\right)(d_i - \bar{d})}{\sum_{i=1}^{n} \sqrt{(c_i - \bar{c})^2} \sum_{i=1}^{n} \sqrt{(d_i - \bar{d})^2}} \right]^2$
RMSE	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (c_i - d_i)^2}$
MAE	$MAE = \frac{\sum \lvert c_i - d_i \rvert}{n}$
NSE	$NSE = \left[1 - \frac{\sum_{i=1}^{n} \left(c_i - d_i\right)^2}{\sum_{i=1}^{n} \left(c_i - \bar{d}\right)^2} \right]$

where c_i is measured data, d_i is estimated data, $\bar{c}$ and $\bar{d}$ are average measured and estimated data, and n is the total number of measured and estimated data.

2.6. Statistical analysis of flow data

Input flow data was examined to a 7 years old dam in terms of homogeneity and randomness. The double mass method is used to perform the data homogeneity test. The randomness of the flow data was obtained with a probability of 95%, which is presented in Table 4.

Table 4
The result of a randomized annual data test.

Type	Limits	Randomized data test
Mahabad dam	± 1.69	-1.22

3. Results and discussion

Population dispersion is one of the most important factors in the implementation of EA and CGA algorithms. If the dispersion of the population is too high or too low, the algorithm will not have a good function. Population dispersal control was carried out by adjusting the population's initialization option as well as determining the appropriate size for the population. In this paper, the initial range is considered from 0 to 10. To obtain the appropriate size of the population, various values were investigated. After conducting the sensitivity analysis, the appropriate value was estimated at 100, which achieved at least an objective function with this population. The results of sensitivity analysis to determine the optimal values of effective parameters of algorithms and decision variables are presented in Tables 5 and 6. Each of the 12 decision variables in the case study was represented by a substring that represented the 12 possible decisions.

Table 5
Parameters used for EA.

Parameter	Value
Initial population	100
Coalition rate	0.2
Selection rate	0.3
N_c	0.7

Table 6
Parameters used for CGA.

Parameter	Value
Initial population	100
Generation	60
Mutation	10
Select parents	Cost weighting

Another important option is to victories the objective function. As shown in Figure 5, the objective function significantly affected the speed of the algorithms.

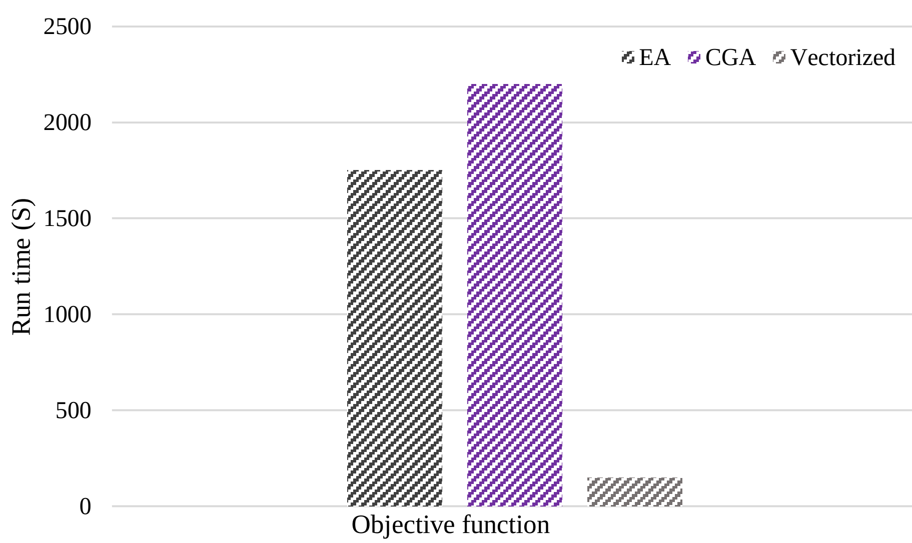

Fig. 5. Comparison of algorithms runtime.

Matlab software was used to develop EA and CGA optimization models. Input data were inflow (*It*), evaporation (E_t), precipitation (*Pr*), reservoir (S_t), and outflow (O_t). Figure 6 compares the estimated and measured storage values of the dam reservoir. The performance of the EA algorithm has completed the calculation of 24 variables. Variables 1-12 are dam output values, and variables 13-24 represent the storage volume for the same month. Torabi et al. [29] discussed a linear programming model for optimal operation of the Dorodzan dam. The results indicate that the use of linear programming models can be effective in the region of optimal reservoir operation, which is consistent with the results of this study.

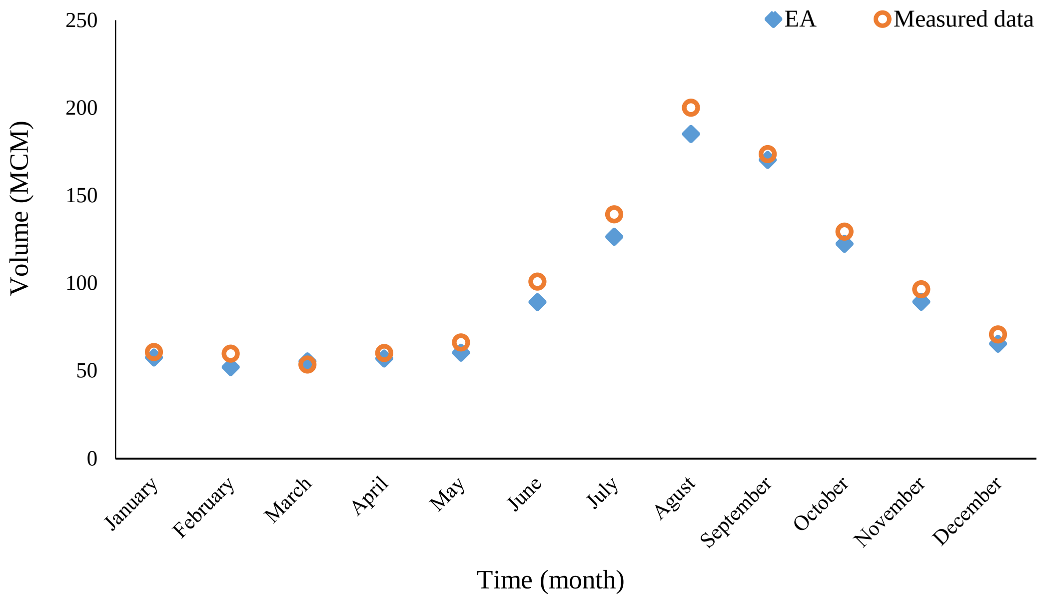

Fig. 6. Comparison of estimated and measured values of dam reservoir storage.

Mahabad reservoir storage levels in different months were compared using both CGA and EA algorithms and the measured storage per month, as shown in Figure 7.

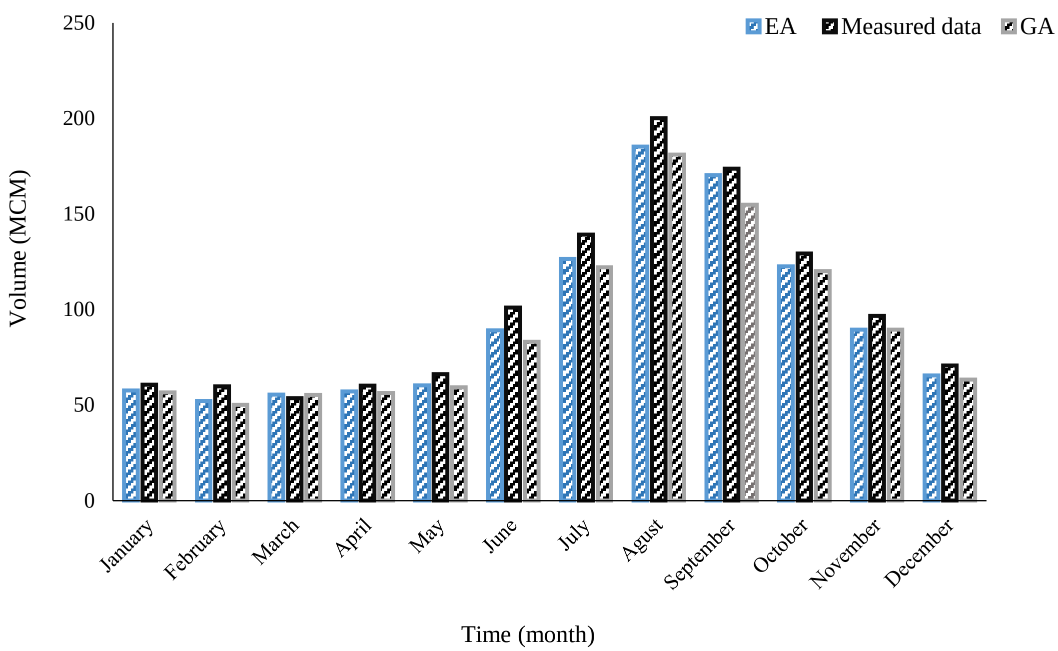

Fig. 7. Evaluation of reservoir storage values in different months.

The values of R^2, RMSE, MAE, and NSE for the EA algorithm were 0.90, 0.037, 0.41, and 0.74, respectively, and the values of these criteria for CGA were estimated to be 0.82, 0.042, 0.56 and 0.66, respectively. Emami and Parsa [9] in a similar study estimated the reservoir storage of Shaharchay dam and reported the ICA algorithm has a good ability to estimate reservoir storage. The results showed very high accuracy and convergence speed of EA algorithm.

Table 7 shows the average relative error (ARE) of the measured and estimated data for the CGA and EA algorithm implementations [30]. A satisfactory advantage of errors utilized by most overview researchers ordinarily fails between 4% and 8% at the 95% certainty level. It is possessed by test measures, populace measures, and rates [31]. From the ARE, the importance of the absolute error can be determined. If the actual value is not available, the ARE can be calculated from the measured value of the quantity. ARE is dimensionless and unitless. The results show that the EA algorithm's results are very satisfying compared to the CGA algorithm.

Table 7
ARE of the measured and estimated data.

Time (month)	CGA (%)	EA (%)
October	15.12	5.65
November	11.42%	7.42%
December	10.2%	6.51%
January	9.18%	6.28%
February	20.01%	8.45%
March	13.36%	10.51%
April	13.19%	10.18%
May	12.21%	8.63%
June	12.82%	7.90%
July	7.43%	6.30%
August	9.78%	7.35%
September	11.32%	7.44%

Prasanchum and Kangrang [32] reported that the rule curves simulated by the improved GA algorithm can reduce the frequency of water scarcity situations and excess water release during future inflow changes. Adherence rates over 12 months are shown in Figure 8 for the monthly baseline operation. Both graphs are completely consistent with downstream irrigation demand. The results of the EA algorithm are satisfactory. First, the capacity of the reservoir is approximately determined. Second, downstream irrigation demand is met by a high percentage.

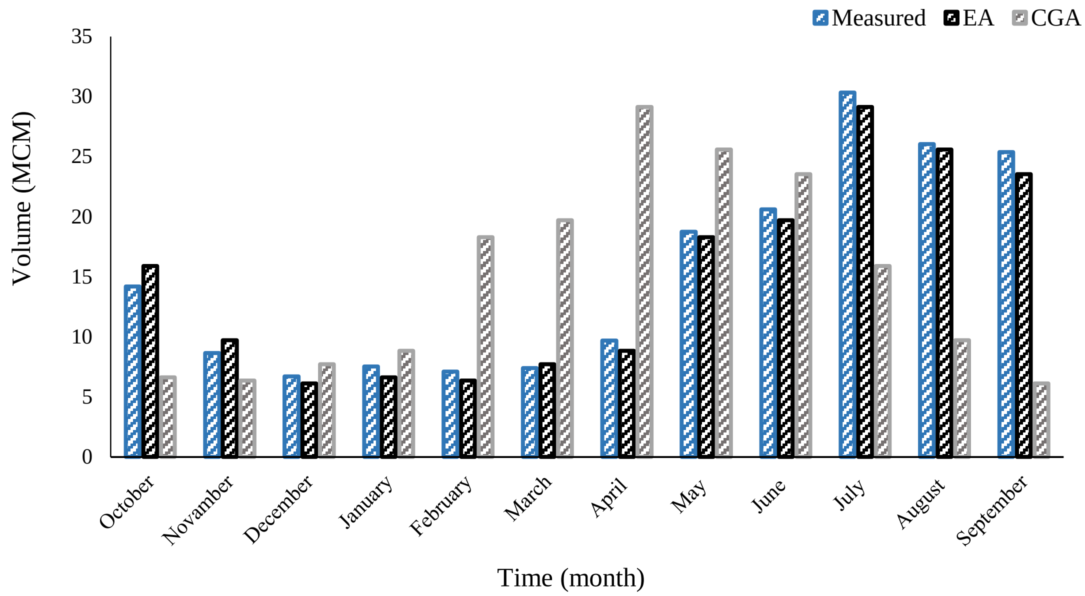

Fig. 8. Comparison of measured and estimated downstream irrigation demand.

Given that the input values of Mahabad dam follow the distribution of normal logs, the input was considered with a probability of 90%. In other words, the input value is 90% equal to or greater than the amount considered in the analysis of the present problem. In February, March, April, and May, the necessary space for flood control is well provided. Therefore, it is clear that the results of the EA algorithm are more satisfactory concerning the determination of the reservoir capacity between the limits and the supply of water required downstream with a high percentage. In a similar study, Emami et al. [14] obtained the same results.

Given the structure of the objective function, it's so easy to solve the problem for any input value with the probability percentage of 90 % (Eq. 14):

$$I_t = \overline{I}_t - 0.9(SD)_t \tag{14}$$

where $(SD)_t$ represents the standard deviation of the input flow in month t.

All outcomes of the input are estimated with 90% probability. The functionality of the EA algorithm can test different input choices as shown in Figure 9, so changing the input value as the output of the algorithm does not cause substantial differences. Scenarios include 50%, 60%, 70%, 80%, and 90% probability inputs.

The scenario results have shown that the output doesn't have any significant change since there is a variation in input value, that is, the changes that the algorithms apply to the amount of dam storage. Emami and Parsa [9] and Saberchenari et al. [33] obtained similar results that are consistent with the results of the present study. As shown in Figure 9, reservoir storage increases in summer, but there is no increase in the amount of dam storage in flood months like December. This is consistent with the findings of Mathur and Nikam [34], and Asfaw and Saiedi [35]. Azari and Arman [36], optimized the real-time utilization of water resources of the Gavoshan dam based on the NSGA-II algorithm and SVM method.

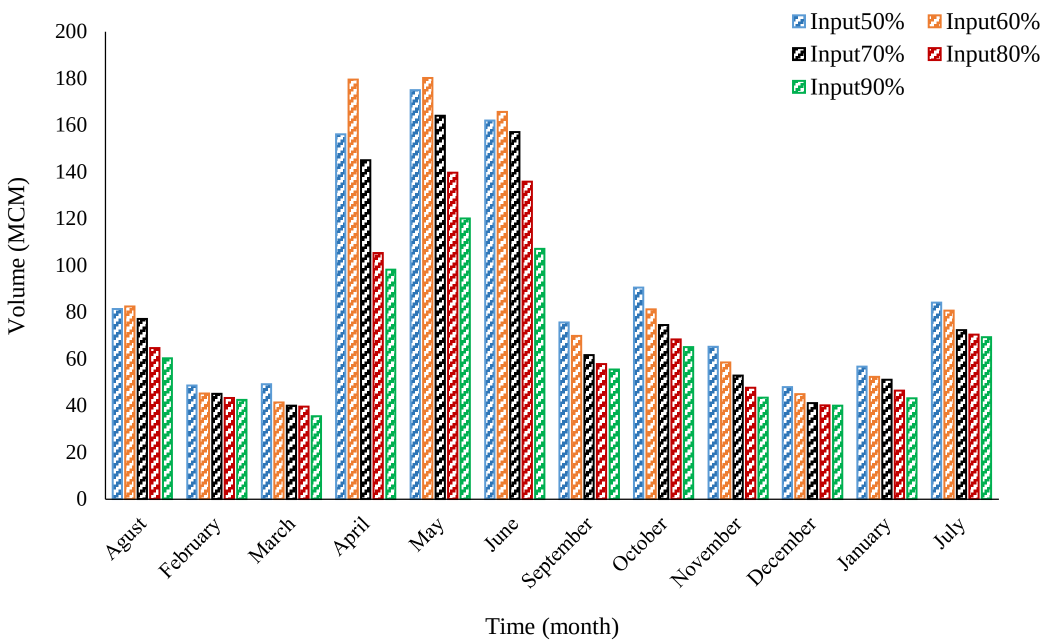

Fig. 9. Different scenarios for comparison of dam reservoir input.

3.1. Estimating reservoir storage equations on the Mahabad dam

To determine the reservoir storage equation on the Mahabad dam, linear and non-linear regressions were used. To obtain the best equation, different functions for S_t as the dependent variable about independent variables as (D_t, R_t, I_t), some equations were extracted for S_t. Based on the obtained fitting of the measured data and the resulted data by the EA algorithm, reservoir storage equation for Mahabad dam can be obtained as follows:

$$S_t = 14.4D_t - 18.6R_t + 0.5I_t + 151 \tag{15}$$

$$S_t = 0.39D_t * 0.97I_t (R_t)^{-0.97} \tag{16}$$

Above equations, with an R^2 value of 0.9, were presented as the best equation to estimate the reservoir storage over the Mahabad dam.

3.2. Comparison of optimization methods

In this section, we compare the efficiency of the optimization algorithm with reservoir optimization. The fitness function for all models minimizes the square of the monthly watering requirement and the square of the mass balance equation. The efficiency of the EA algorithm was compared with the results of Saberchenari [33], optimized dam reservoirs using the PSO algorithm and a GA model. Comparing the EA algorithm with the PSO and GA algorithms shows that the EA algorithm, which achieves higher capacity with an average optimal objective function value of 136.40, is the best answer. On the other hand, the average optimal objective function values for PSO and GA algorithms are 181.1 and 181.79 respectively. Chen et al. [37]

demonstrate the possibilities of adopting the operation tree (GAOT) method coupled with the GA algorithm to estimate the algae concentration of the Taiwan reservoir by Landsat sensor data. The result showed that GAOT used real number coding as an efficient and robust model. Emami and Parsa [9] estimated the Shaharchay dam reservoir storage using ICA and concluded that the ICA algorithm has a good ability to estimate reservoir storage, which is consistent with the results of the present study.

4. Conclusion

In this paper, we developed an optimization model for operating the Mahabad Dam using EA algorithms. The results show the optimal solution with the convergence speed and high accuracy of the EA algorithm and the estimated reservoir value of the reservoir highly optimized for this model. The results showed good agreement between measured and estimated values and concluded that the EA algorithm has a high potential in estimating reservoir storage compared with CGA. Comparison of EA results with results of CGA indicates a higher convergence rate and more suitable results of EA than CGA. Numerical results were obtained from both algorithms, considering that the error rate of EA is significantly lower than the CGA, therefore, the output program efficiency of EA is more than CGA. CGA has some weaknesses, such as the sensitivity of the model's performance to its execution parameters, such as population size and operator's probability, which reduces its efficiency compared with EA in optimization. An initial population size of 100, a coalition rate of 0.2, and a selection rate of 0.3 yielded the best results. The results of this study show that the EA algorithm is a suitable method for optimal exploitation of the dam reservoir. In general, EA algorithms can be easily applied to nonlinear problems and overly complex systems, and generate near-optimal class-wide alternative solutions to give operators selectivity in complex reservoir systems.

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Conflicts of Interest

The authors declare no conflict of interest.

Authors contribution statement

SE, HY: Conceptualization; SE, OJ: Data curation; SE, HE: Formal analysis; SE, HE, OJ: Investigation; HY, MA: Methodology; SA, HY: Project administration; HE, MA: Resources; SE, HE: Software; SE: Supervision; HE, OJ, MA: Validation; SE, HY, MA: Visualization; SE, MA, HE: Roles/Writing – original draft; SE, HY, OJ, HE, MA: Writing – review & editing.

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