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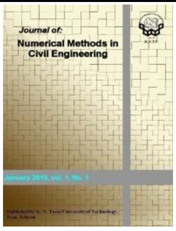

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Investigation of the Effect of Climate Change on the Optimization of Dam reservoir operation using Dolphin Echolocation and Gravitational Search Algorithms (Case study: Lar Dam Basin)

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Abstract:

Considering the recent human activities and the resulting climate change in optimizing the operation of the dam reservoir, the effects of climate change should be noticed. In this research, in order to extract command curves by dolphin echolocation and gravitational search algorithms, the monthly inflow of the reservoir, the reservoir storage volume, and the downstream demand of the reservoir in case of climate change were calculated .The optimal output values of the reservoir of Lar Dam (located in Larijan, Amol City) were determined by the approach of minimizing the total square of the monthly relative deficiencies in supply demand and climate change conditions based on the river flow According to the research, by using HADCM3 and scenarios RCP2.6, RCP4.5, and RCP 8.5, climate change has increased the maximum temperature by 5%, 5.2%, and 6.2%, respectively. It has increased the minimum temperature by 3.5%, 5.6%, 5.17%, and increased precipitation by 8.5%, 9.5%, and 13%, respectively. In addition, the runoff from the intermediate scenarios indicates an increase of 3.3% compared to the base period. Moreover, to examine the water allocation policies required downstream, two future and basic conditions are considered. In this study, reservoir efficiency indices in the conditions of (future) climate change and their corresponding values in the base period were compared. The execution results of each of the algorithms show that the execution speed of the DE algorithm is much higher than the GSA algorithm, as well as, in the conditions of climate change, the reliability index in the dolphin echolocation and gravity search algorithms has increased. 9.73 and 12.46% Vulnerability has decreased by 21.4% and 26.51%, respectively, and reversibility has increased by 18.27% and 17.64%, respectively. The execution results of each of the algorithms show that the execution speed of the DE algorithm is much higher than the GSA algorithm. Furthermore, in the conditions of climate change, the reliability index in the dolphin echolocation and gravity search algorithms has increased 9.73 and 12.46% Vulnerability has decreased by 21.4% and 26.51%, respectively, and reversibility has increased by 18.27% and 17.64%, respectively.

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1. Introduction

Due to more human activity, greenhouse gas emissions and vegetation loss will increase in the future, which will exacerbate climate-dependent variables on the planet. The consequences of these changes in the future can have different effects on different systems, including water resources, drinking water, agriculture, and the environment. Due to the important role of reservoirs in meeting water needs in different consumption sectors, the optimal operation of these systems in the context of climate change is significant. According to the optimal command curve, the best level of water released from the reservoir can be obtained in the conditions of climate change. Evolutionary algorithms and artificial intelligence methods in recent years have been introduced by researchers as suitable tools to solve these problems. Evolutionary algorithms include genetic algorithms (GA), ant community (ACO), firefly algorithm (FA), etc. Researchers have also used many of these command curves. For example, Karamooz and Houck (1982) [6] considered the decision rule that applied to release tank volume as a function of tank volume and inlet flow. Nakhaei et al. (2014) [17] have used the genetic algorithm to manage the optimal exploitation of the coastal plain aquifer of Urmia and determine the optimal pumping rate of exploitation wells. Grossinejad et al. have used the the firefly algorithm for the optimal operation of the reservoir for agricultural purposes and electricity generation (Garousi-nejad et al., 2016).[4]

In the article presented in 2022, Afkhamifar and Saraf [11] showed that the performance of machine learning and artificial neural network models, as well as their combination with the wavelet transfer algorithm, which is a hybrid model, performs better than other models, and also in training and The test works faster than other models.(Donyaii et al(2021)[19].

The Multi-Objective Grey Wolf Optimization (MOGWO) algorithm was developed to obtain the optimum rules on the operation of Golestan Dam in Golestan province, Iran, under climate change conditions. Their results showed that the river flow would decline by 0.17 percent of the baseline period under climate change conditions, in addition to increasing the temperature by 20 % as well as decreasing the rainfall by 21.1%. (Donyaii et al., 2020a) [14] In the article by Mr. Dunyaei, Saraf, and Ahmadi, the results showed that the multi-objective gray wolf optimization algorithm for calculating the optimal operation rules in the Golestan dam located in Golestan province in case of climate change in the river flow in the conditions of climate change decreased by 0.17% compared to the baseline. Also, temperature increases by 20%, and rainfall decreases by 21.1% (Donyaii et al., 2020) [14].

In another study in 2022, they showed that the multi-objective agricultural land fertility optimization algorithm, used to derive optimal rules for operating the Golestan dam in the context of climate change, increased the release rate for climate change conditions compared to baseline conditions, and the efficiency of dams in Climate change is more (Donyaii et al., 2020b) [13].

In the present study, the use of dolphin echolocation and gravitational search algorithms is proposed as optimization tools. Also, the rules of optimal operation of the Lar Dam reservoir system located in the north of Tehran province in basic (1991-2005) and future (2022-2036) conditions were determined with the help of dolphin echolocation and gravitational search algorithms with the aim of the sum of the squares of the relative monthly deficits in meeting the demands and in the conditions of climate change according to the river flow.

In order to use the command curves extracted from dolphin echolocation and gravitational search algorithms in climate change conditions, the amount of inlet flow to the reservoir and downstream demand volume in climate change conditions must first be calculated. Then, the relation should be considered based on the inflow, storage volume, and water demand downstream of the reservoir in the context of climate change at the beginning of each period. Therefore, downstream demand in the context of climate change is one of the independent and necessary variables. In this research, the optimal values of single reservoir dam system in the coming years (2022-2036) with the approach of minimizing the total squares of monthly relative deficiencies by dolphin echolocation algorithms and gravitational search in downstream water allocation in climate change conditions and based on the volume of inlet water of the reservoir in the corresponding condition is determined, and the efficiency indicators in the conditions of optimization of the reservoir in the condition of climate change and its corresponding condition in the base period (1991-2005) are compared.

2. Materials and Methods

Study area with coordinates:

35°53′17″ North 52°′36″ East / 35.88806 °N 52.01000 °East

Lar Dam is an earthen dam with a clay core located at the foot of Mount Damavand in Amol City, Mazandaran, Iran. The main purpose of this dam is to supply drinking water of Tehran City and required water for agricultural irrigation in nearby areas. The dam is 100 km of Amol City and 75 km northeast of Tehran. The construction studies of the dam began in 1951 and finally it was opened in 1982. The catchment area of the dam is 675 km^2 and has an average annual water flow of 481 million m^3.

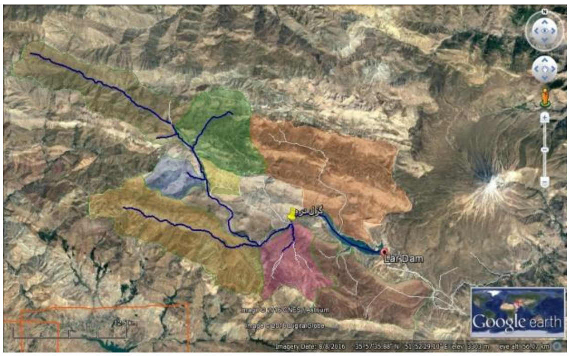


Fig. 1: Location of the study area

The required methods in this research include estimating climatic parameters (precipitation, minimum temperature and maximum temperature), simulating the runoff precipitation process, discharge volume to Lar dam reservoir, calculating the volume of demand in baseline, climate change, and finally, a comparison of these two modes in terms of reservoir performance criteria and reservoir efficiency indicators.

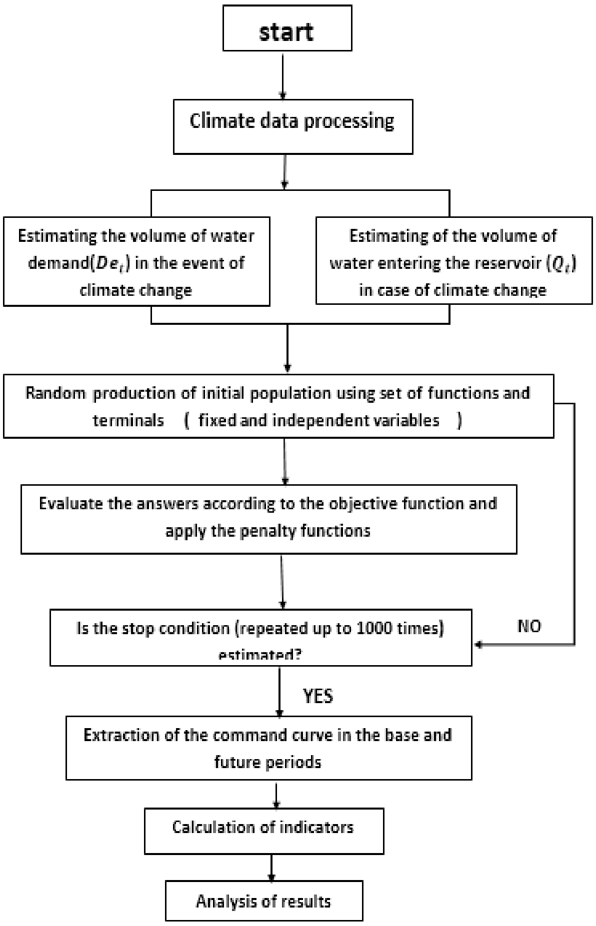


Fig. 2: Research steps flowchart

In this study, the CANESM2 climate model was applied using SDSM software under scenarios of RCP2.6, RCP4.5, and RCP8.5 to estimate climatic parameters. In the study area, the results of this model show a 5.2% increase in temperature, and a 9.5% increase in precipitation.In addition, Runoff volume was calculated using the HEC-HMS model.

3. Development of optimization model

Reservoir simulation is to determine the volume of reservoir storage in each period based on the inflow to the reservoir, release, and losses that occur according to the climatic and geological conditions of the site. Reservoir simulation is performed based on the connection relation, as follows:

$$S_t+1=S_t+Q_t-Re_t-Loss_t-S_P \qquad (1)$$

Where t is the number of the desired time period, S_t and S_t+1, respectively, are the storage volume of the reservoir at the beginning and end of the time period t, Q_t is the volume of river flow to the reservoir during the time period t, Re_t is the volume of release from the reservoir during the time period t, and $Loss_t$ is the amount of evaporation losses during the time period t [16].
In order to calculate the evaporation losses of the reservoir, Equation [2] is used. The free water level of the lake in each time period is considered a function of the storage volume in the same period, which is obtained from the surface-volume curve of the reservoir. In this study, the surface-volume relation is expressed as a quadratic power function, which is as follows:

$$Loss_t=A_t\times(Ev_t-R_t) \qquad (2)$$

$$\text{At}=a+b\times S_t+c\times S_{t2} \qquad (3)$$

Where Ev_t is the evaporation height of the lake behind the dam in the period t, R_t is the height of precipitation on the lake behind the dam in the period t; a, b, and c are the coefficients of the volume-surface relation of the dam reservoir. The overflow volume constraint is applied as follows:

$$Spt=\begin{cases} S_t - S_{max} + S_{min} & if\ S_t > (S_{max} - S_{min}) \\ 0 & if\ S_t \le (S_{max} - S_{min}) \end{cases} \qquad (4)$$

Where Spt is the volume of overflow from the reservoir during time period t, also, S_{min} and S_{max} are the minimum and maximum volume of the reservoir, respectively. Other constraints presented as follows:

$$De_{min_t}\le Re_t\le De_{max_t} \qquad (5)$$

$S_{max} \leq S_t \leq S_{min}x$ (6)

$Re_{min_t} \leq Re_t \leq Re_{max_t}$
(7)

Where Re_{min_t} and Re_{max_t} are the minimum and maximum release volumes of the reservoir in time period t , respectively; De_{min_t} and De_{max_t} are the minimum requirements and the maximum reservoirs in period t, respectively. Most reservoirs are constructed to meet various water needs, which are presented in the reservoir operation calculations, depending on the objectives under consideration, different objective functions, and other additional constraints in addition to the above constraints
To optimize the reservoir system, it is necessary to define an objective function in addition to the modeling relations. This objective function is differs according to the purpose of operating the reservoir system. In reservoir issues, the usual objective function for definitive optimization of a multi-reservoir system can be expressed as follows:

Max or (Min) F=$\sum_{t=1}^{T}\sum_{i=1}^{N} h_{i_t}, t(S_{i_t}, Re_{i_t}, De_{i_t})$ (8)

Where F is the target to be maximized or minimized, h_{i_t} is a function dependent on several parameters, and De_{i_t} is the downstream need of reservoir i during period t (Labadie, 2004) [2].

3.1 Tank performance indicators

Reliability is a category that is widely used in the evaluation of water resources systems during the operation period. It is sometimes referred to as a risk supplement (Reliability-Risk) Reliability can be defined as both temporal and volumetric. Temporal reliability refers to the percentage of periods, in which the system fully meets existing needs and does not fail. The value of this parameter is calculated from Equation [9].

α_t=($\mathbf{1}$–$\frac{NDe_f}{T}$)×$\mathbf{100}$ ، NDe_f= Number ($\boldsymbol{\alpha}$ ×De_t>Re_t) (9)

Where NDe_f *is* the total number of failures ,which occurred during the operation period, De_t is the required amount in the t period, Re_t is the output value of the t period, α is the supply requirement, and α_t is the system reliability during the operation period. The higher value of this parameter, the greater the temporal reliability of the system.
Another type of reliability is volumetric reliability, which is the amount of water released in the whole period relative to the total amount of tank required. Equation [10] is used to calculate this index (Hashimoto et al., 1982)[1].

α_v=$\frac{Ret}{Det}$ × 100 (10)

3.2 Vulnerability

This indicator indicates the magnitude of system failures. To calculate the vulnerability, Hashimoto et al. (1982) [1] presented the following equation:

ɳ = max {$\frac{(Dei-Rei)}{Dei}$} , i=1, 2,...., t (11)

Where ɳ is the magnitude of failure, Dei is the required value in period I, Re_t is the output value in period i, and t is the total number of operating periods [15].
3.3. Reversibility index
This indicator indicates the probability of the system returning to the suitable state (SA) after the failure state (FA). System reversibility in the planning horizon is defined as the following:

β= P{X_{i+1} □Sa|X_t□Fa} (12)

3.3 Operation Rule curves

In this research, the decision rule for exploiting the single reservoir system of Lar Dam to minimize the sum of the squares of relative monthly deficiencies in supply-demand is extracted using dolphin echolocation and gravitational search algorithms according to the following equations.

$\forall t$=1, 2 ,…,T Rebt=g1(Qbt, Sbt, Dbt) (13)

$\forall t$=1, 2 ,…,T Reft=g2(Qft, Sft, Dft) (14)

The first option is the results of algorithms in basic conditions with index b, and the second option is for climate change conditions with index f.

4. Dolphin echolocation algorithm (DEA)

Dolphins estimate shape, size and distance by sending sound waves to underwater objects and receiving their reflection. In this method, a dolphin that finds its prey using its voice reflection is elected as its leader and then informs the other dolphins of the its position (Kaveh and Farhoudi, 2013) [5].
For dolphins, the usual method of hunting is that a group of dolphins circle around the fish, gather them in a ball-shaped corner, bring them closer to the surface of the water, and then attack them (prey ball) and hunt the bewildered fish (Figure 3). In this method, dolphins spin circle around a group of fish and scare them to accumulate on the surface of the water. At this moment, the dolphins approach the gathering, one by one, and easily separate their prey from among them. The dolphin that has hunted changes its place with one of the other dolphins that have

caught the fish by spinning around them so that everyone can benefit from the meal (Kaveh and Farhoudi, 2013) [5].
To simulate the hunting process in this algorithm, the dolphins move toward the leader of the group, and the leader is a dolphin that has the best position in the current situation It is assumed that the leader finds the optimal point and the other members move toward it. Therefore, in this algorithm, by moving toward the leader, each dolphin corrects its position based on the position of the other members of the group. In group hunting, if the prey leaves the ring, the dolphins reorganize around the ring. In this algorithm, dolphins are given the ability to search outside the ring. The steps of the algorithm are as follows (Hamidzadeh et al. 2014): [12]
Before starting the optimization, the search space should be sorted using the following rule:
Search space order: For each variable to be optimized during the process, sort alternatives of the search space in an ascending or descending order. If alternatives include more than one characteristic, perform ordering according to the most important one. Using this method, for variable j, vector Aj of length LAj is created, which contains all possible alternatives for the jth variable. Putting these vectors next to each other as the columns of a matrix, the Matrix Alternatives$_{MA*NV}$ is created, in which MA is max($LA_{j=1:NV;}$) with NV being the number of variables. Moreover, a curve according to which the convergence factor should change during the optimization process should be assigned. Here, the change of CF is considered to be according to the following curve:

$$\mathrm{PP}(Loop_i)=PP_1+(1-PP_1)\,\frac{Loop_i^{Power}{}_{-1}}{(LoopsNumber^{Power})_{-1}} \quad (15)$$

PP is the predefined probability, PP1 is the convergence factor of the first loop in which the answers are selected randomly, $Loop_i$ is the number of the current loop, and Power is the degree of the curve. As it can be seen, the curve in Equation [15] is of Power degree (Kaveh and Farhoudi, 2013) [5].
Loops Number: Number of loops in which the algorithm should reach the convergence point. This number should be chosen by the user according to the computational effort that can be afforded by the algorithm (Kaveh and Farhoudi, 2013) [5].

4.1 Parameters initialization and adjustment

Based on the number of dolphins, the group hunting matrix is filled with the generated random solution vector. Then, the maximum number of moves toward the leader is determined, and the dolphin's attention rate to the group that changes between 5 and 1 is determined. The value of the objective function is calculated, and the leader is determined based on it.

4.2 Moving toward the leader

At this stage, the new position of the dolphins (vector of the new solution) is generated by moving toward the leader based on the following relation. (Hamidzadeh et al., 2014) [12]

$$xi{*}=x_i+rand\times Mmax\times(x_i^l-x_i) \quad (16)$$

The new position of the dolphin, includes $xi{*}=x1{*}$, $2{*}$, $x3{*}$,…$xn{*}$,is the maximum number of moves toward the leader, so that the higher the value, the faster the algorithm converges, and it is in the range of 0 to 0.05.

$rand$ is a uniform random number between 0 and 1

x_i^l is the value of the leader position for the ivariable

For each dolphin, if the move to the leader is successful, the dolphin will be in a new position, otherwise, it will return to its previous position. (Donyaii and Sarraf 2021) [10]

4.3 Improving the position-cooperation between members

At this stage, cooperation between members is done to better guide the hunt. After moving towards the leader, the dolphin (based on the position of other dolphins and some random factors) chooses another position to find a better solution. Dolphins use the real value correction method to correct their position. (Hamidzadeh et al., 2014) [12]

4.4 Correcting the true value

In this method, the new position of the dolphin is produced based on attention to group hunting or position correction. Therefore, the ordering of variables is done based on the following relation (Hamidzadeh et al., 2014) [12].

$$x_i^{j*}\rightarrow\begin{cases} x_i^{j*} \in x_i^1, x_i^2, \ldots x_i^{DEA}\ If\ SDSP\ occures \\ x_i^{j*} = x_i^j \pm Rand \times R_a\ If\ (1-SDSP) occures \end{cases} \quad (17)$$

Where SDSP is the probability of selecting a quantity of dolphin group stored in each position, SDSP-1 is the probability of performing position correction; RAND is a uniform value between 5 and 1 , andR_a is the virtual distance radius for constructing a continuous variable that can be reduced during the optimization process. As shown in the following equation, after each evaluation of the objective function, the new position of the dolphin is checked. If the dolphin solution improves, it will move to a new position. Otherwise, like in the previous stage, it maintains its position (Hamidzadeh et al., 2014) (Donyaii and Sarraf, 2021) [12] [10].

$$R_a = R_{min}(max_{xi}\text{-}min_{xi})e^{\frac{ln(\frac{R_{min}}{R_{max}})\times i}{i_{max}}} \qquad (18)$$

Where i is the number of iterations, i_{max} is the maximum iteration in the optimization process, $max_{xi}$is the maximum , min_{xi} is the minimum value of the variable x_i, R_{min} is the minimum, and R_{max} is the maximum dolphin search radius.

Fig. 3: Hunting strategy of dolphins by circling around prey (Hamidzadeh et al., 2014) (Donyaii and Sarraf, 2021) [12] [10]

4.5 Reorganizing the dolphins

If the value of the objective function is less than the value specified by the leader and the worst dolphin in the group, and the algorithm termination criterion is not met, the dolphin group will be reorganized. This operation is such that the group leader maintains his position, and the other members change their position randomly using the following relation (Hamidzadeh et al., 2014): [12]

$$x_i^* = x_i^l\text{+rand} \times (max_{xi}\text{-}min_{xi})\times \alpha e^{-\beta\times EN} \qquad (19)$$

x_i^l is the value of the leader position of the i variable , and EN counts the number of times the group is trapped .However, β and α are positive real values that determine the final rate of global convergence of the algorithm. (Donyaii and Sarraf, 2021) [10]

4.6 Step to perform Optimization with algorithm (DEA)

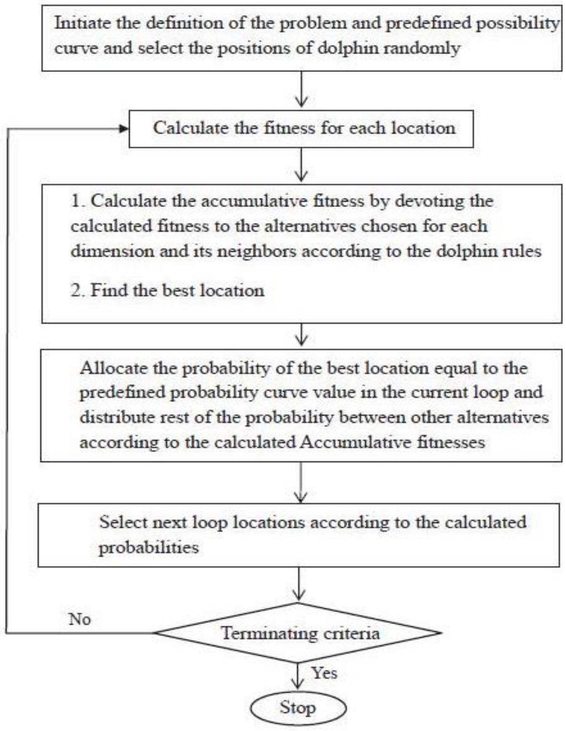


Fig. 4: The flowchart of the DE algorithm (Kaveh and Farhoudi, 2013) [5]

The flowchart of the algorithm is shown in Figure 4. The main steps of dolphin echolocation (DE) for discrete optimization are as follows:

1. Initiate NL locations for a dolphin randomly. This step contains creating an L_{NL*NV} matrix, in which NL is the number of locations, and NV is the number of variables (or dimension of each location). (Kaveh and Farhoudi, 2013) [5]

2. Calculate the PP of the loop using Equation [15].

3. Calculate the fitness of each location. Fitness should be defined in a manner in such a way that the better answers get higher values. In other words, the optimization goal should be to maximize the fitness. (Kaveh and Farhoudi, 2013) [5]

4. Calculate the accumulative fitness according to dolphin rules as follows:

(a)

for i = 1 to the number of locations

for j = 1 to the number of variables

find the position of L(i,j) in jth column of the

Alternatives matrix and name it A.

for k = -R_e to R_e

$$AF_{(A+K)j}=\frac{1}{R_e}*(R_e - |k|)Fitness(i) + AF_{(A+K)j}$$

end

end

end

where $AF_{(A+K)j}$ is the accumulative fitness of the (A + k)th alternative (numbering of the alternatives is identical to the ordering of the Alternative matrix) to be chosen for the jth variable; R_e is the effective radius, in which accumulative fitness of the alternative neighbors of A are affected from its fitness. This radius is recommended to be not more than 1/4 of the search space; Fitness (i) is the fitness of location i. (Kaveh and Farhoudi, 2013) [5]

It should be added that for alternatives close to edges (where A + k is not valid; A + k < 0 or A + k > LA_j), the AF is calculated using a reflective characteristic. In this case, if the distance of an alternative to the edge is less than R_e, it is assumed that the same alternative exists where the picture of the mentioned alternative can be seen if a mirror is placed on the edge. (Kaveh and Farhoudi, 2013) [5]

(b) In order to distribute the possibility more evenly in the search space, a small value of ε is added to all the arrays as AF = AF +ε. Here, ε should be chosen according to the way that the fitness is defined. It is better to be less than the minimum value achieved for the fitness. (Kaveh and Farhoudi, 2013) [5]

(c) Find the best location of this loop and name it ‘‘The best location’’. Find the alternatives allocated to the variables of the best location, and let their AF be equal to zero. (Kaveh and Farhoudi, 2013) [5]

In other words:

for j = 1: Number of variables

for i = 1: Number of alternatives

if i = The best location(j)

AF_{ij} =0

end

end

end

5. for variable $j_{(\mathrm{j=1toNV})}$, calculate the probability of choosing alternative $i_{(\mathrm{i=1toALj})}$, according to the following relation:

$$P_{ij} = \frac{AF_{ij}}{\sum_{i=1}^{LAj} AF_{ij}} \tag{20}$$

6. Assign a probability equal to PP to all alternatives chosen for all variables of the best location, and devote the rest of the probability to the other alternatives according to the following formula:

for j = 1: Number of variables

for i = 1: Number of alternatives

if i = The best location(j)

P_{ij} =PP

else

$P_{ij} = (1 - PP)P_{ij}$

end

end

end

Calculate the next step locations according to the probabilities assigned to each alternative.

Repeat Steps 2–6 as many times as the Loops Number.

4.7 Parameters of algorithm

Input parameters for the algorithm are:

(a) Loops number

For an optimization algorithm, it is beneficial for the user to dictate the algorithm to work according to the affordable computational cost. The answers may obviously be dependent on the selected number of loops and will improve by an increase in the number of loops. However, the point is that one may not achieve results as bad as those of other optimization algorithms gained in fewer loops because, in this case, although the algorithm quit its job much sooner than expected, the answer is good because of convergence criteria being reached. The number of loops can be selected by sensitivity analysis when high accuracy is required, however, in structural optimization of normal buildings, the number of loops is recommended to be more than 50. (Kaveh and Farhoudi, 2013) [5]

(b) Convergence curve formula

This is another important parameter to be selected for the algorithm. The curve should reach the final point of 100% smoothly. If the curve satisfies the above-mentioned criteria, the algorithm will perform the job properly. Although, it is recommended to start with a linear curve and try the curves that spend more time (more loops) in high values of the PP. For example, if one is using the proposed curves of this research, it is recommended to start with Power =1 which usually gives good results, and it is better to try some cases of the Power < 1 to check if it improves the results. (Kaveh and Farhoudi, 2013) [5]

(c) Effective radius (R_e)

This parameter is better to be chosen according to the size of the search space. It is recommended to be selected less than 1/4 of the size of the search space. (Kaveh and Farhoudi, 2013) [5]

(d) ε

This parameter is better to be less than any possible fitness. (Kaveh and Farhoudi, 2013) [5]

(e) Number of locations (NL)

This parameter is the same as the population size in GA or the number of ants in ACO. It should be chosen in a reasonable way(Kaveh and Farhoudi, 2013) [5]

5. Gravitational search algorithm (GSA)

Rashedi, Nezamabadipour, and Saryazdi (2009) [3] created the GSA algorithm inspired by the laws of nature. In nature, there are a number of general laws, such as the law of gravity between all objects, electric and electromagnetic forces between electric charges, the laws of motion, the law of conservation of energy, and so on. The law of gravity inspires the gravitational optimization algorithm, and the gravitational force and its parameters are set intuitively. Search agents are a collection of objects that can be considered as planets in a system. The optimal region attracts the planets like a black hole. Information about the suitability of each object is stored in the form of gravitational and inertial masses. The exchange of information and the effect of objects on each other takes place under the gravitational force.

There are four main forces in nature: gravitational force, weak force, electromagnetic force, and strong force. Among these forces, the gravitational force is weaker than the others ; Although, due to the wide range of action and having the power of only absorption, it controls the fate of the universe. The force of gravity is very pervasive and covers the entire universe, while other forces are local. This force is the oldest, and in some ways, the newest force known to humankind, and some of its aspects are still unknown. Gravity is the dominant force anywhere on the Earth. The force pulls all objects together, holds the universe together, and determines the motion of objects. These properties distinguish the force of gravity from other forces of nature.

Newton stated that each body attracts the other body, and the amount of gravitational force between two objects with mass M_1 and M_2 and distance R, is proportional to the product of the mass of those two objects and the inverse of the square of the distance between them (Rashedi, Nezamabadipour, and Saryazdi, 2009) [3]

Newton obtained the relation (19) for the amount of force F, the absorption force between two objects, by calculating G in the Earthcalled the gravity constant.

$$F=G\,\frac{M_1 \times M_2}{R^2} \tag{21}$$

This relation shows that each object understands the location and mass of other objects due to gravity . Each object affects other objects in proportion to its mass and the distance it has from other objects, and exerts force on them.

Another of Newton's great works is Newton's laws, which are the basic laws of physics. According to Newton's first law, any object maintains its stillness or uniform motion on a straight line unless it is forced to change its position under the influence of force or forces. According to Newton's second law, when a force enters an object, it accelerates, which depends on the force and mass of the object. The greater the force, the greater the acceleration; and the greater the mass of the object, the lower the acceleration. Newton expressed the relationship between acceleration, force, and mass according to Equation [22] (Rashedi, Nezamabadipour, and Saryazdi, 2009) [3]

$$a =\frac{F}{M} \tag{22}$$

In this relation, acceleration with force with F, and mass with M are shown. Note that acceleration is equals the change in speed per unit of time, and the concept of speed is to travel certain distances at a given time. In a multi-object system, gravitational forces are applied to each object by other objects. As a result, the object accelerates toward the result of these forces, denoted by F_r (as shown in Figure 5)

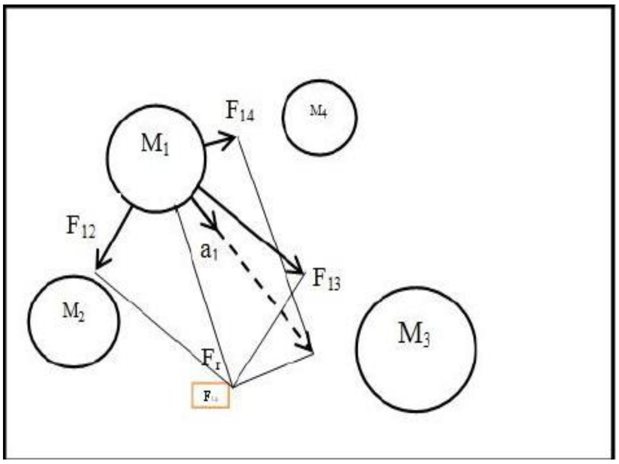


Fig. 5: The result of gravitational force on objects (Rashedi, Nezamabadipour, and Saryazdi, 2009) [3]

Equations (21) and (22) state that each object invites the other object to itself, however, the effect of the larger and closer object is greater. For example, an apple falling from a tree moves toward the ground. Considering the law of gravity, and the laws of motion, the amount and direction of motion of any object is an agreement between the effect of gravity on it, and the current velocity of the object. Another point is that, in physics, three types of mass can be defined for each object: active gravitational mass, passive gravitational mass, and inertial mass. In physics, the values of these three masses are equal to each other.

- ✓ Active gravitational mass is a measure of the intensity of gravitational force around an object. The larger the active gravitational mass of an object, the more gravitational force it creates around it.
- ✓ Passive gravitational mass indicates the strength of the interaction in the gravitational field. The larger the mass of the body, the more gravitational force the body experiences.
- ✓ Inertial mass is a measure of an object's resistance to change in position and motion. An object with a lower inertia mass changes speed much faster.

$$F_{12} = G\ \frac{M_{a2} \times M_{p1}}{R_2} \tag{23}$$

In an isolated system with two objects 1 and 2, object 1, under the influence of the gravitational force of object 2, acquires acceleration equal to a_1, which is calculated by Equation (24). F_{12} is the amount of gravitational force exerted on body 1 by body 2 obtained from relation (23).

$$a_1 = \frac{F_{12}}{M_{i1}} \tag{24}$$

Where M_{p1} represents the inertial gravitational mass, M_{i1} represents the inertial mass of the first body, and M_{a2} represents the active gravitational mass of the second body. The coefficient G is the Newton gravitational constant. It has been shown in physics that the gravitational coefficient decreases very slowly with time (Mansouri et al., 1999) [18]

5.1 Step to perform Optimization with algorithm (GSA)

The different steps of the proposed algorithm

are the followings:

(a) Search space identification.

(b) Randomized initialization.

(c) Fitness evaluation of agents.

(d) Update G(t), best(t), worst(t) and Mi(t) for i = 1,2,. . ., N.

(e) Calculation of the total force in different directions.

(f) Calculation of acceleration and velocity.

(g) Updating agents' positions.

(h) Repeat steps c to g until the stop criteria is reached.

(i) End. Figure [6] (Rashedi, Nezamabadipour, and Saryazdi, 2009) [3]

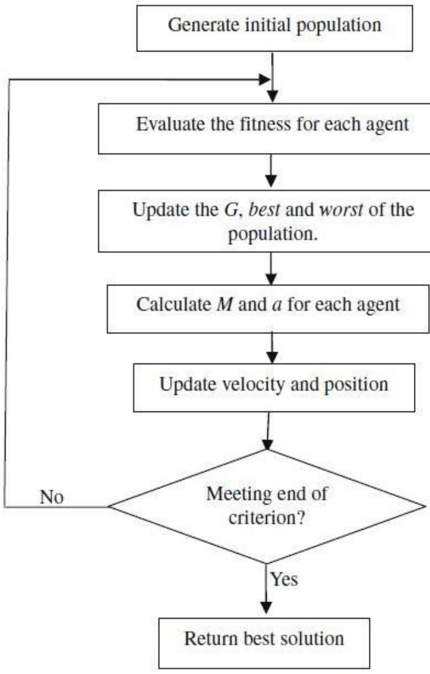


Fig. 6: General principle of GSA(Rashedi , Nezamabadipour, and Saryazdi, 2009) [3]

6. Case study and Used data

Table 1: Characteristics of the Basin and Reservoir

Characteristics	Area	$514km^2$
Basin	Annual irrigation of the river	$435mm^3$
	The length of the river	70km
	Average annual rainfall	553ml
Dam and reservoir	Maximum height	2509m
	Minimum height	2460m
	Height from the bottom of the lake	2431m
	Total capacity	$960mm^3$
	Useful reservoir capacity	$940mm^3$
	The Dead capacity of the reservoir	$23mm^3$
	Annually adjustable water	$340mm^3$
	Coefficient of evaporation	0.74956

The study area in this study is Lar Dam, located in Amol City, and due to data coverage in the years 1991 to 2005, this time period is considered as base years.
Runoff volume was calculated using the HEC-HMS model. The method of calculation in this software is that the climatic parameters and physiographic factors of the earth are entered in it. The amount of runoff is calculated in such a way that, first the basin is drawn, and the inputs and daily data (24-hours) are entered, then the model. It has been calibrated and verified, and the results obtained from the data are used. There are three main parts in this watershed simulation software. 1. Basin model 2. Meteorological model 3. Control characteristics. In this research, the scs unite hydrograph method is used to calculate rainfall and runoff. HEC-HMS software was evaluated in the calibration and validation periods, and the result showed that in the calibration period, the correlation coefficient R, and the given error criteria performed well compared to the observation period

Table 2: Statistical coefficient of HEC-HMS model in calibration and validation periods

Topic	R	RMSE	MAE	NSE
Calibration period	0.782	0.23	0.13	0.537
Validation period	0.791	0.27	0.15	0.502

According to the research of Benjamin and Schumacher (2005) [7] and Santi et al. (2001) [8], the result of modeling ,based on R coefficient, is satisfactory and acceptable more than 0.6 and Nash-Sutcliffe more than 0.5.
Simulated runoff due to climate change conditions and downstream demand in climate change conditions can be seen in Figure [7]

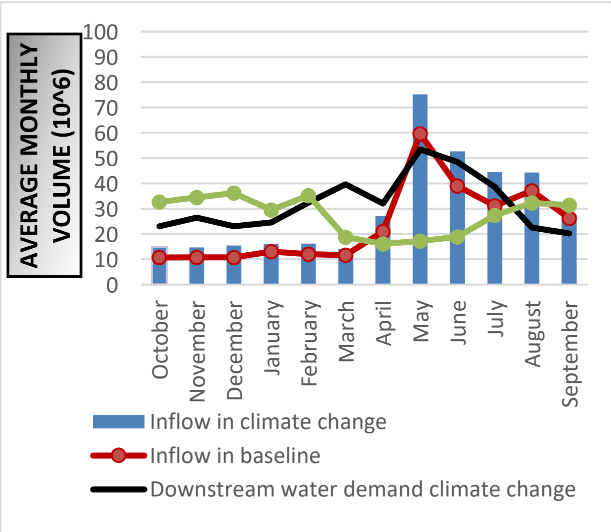
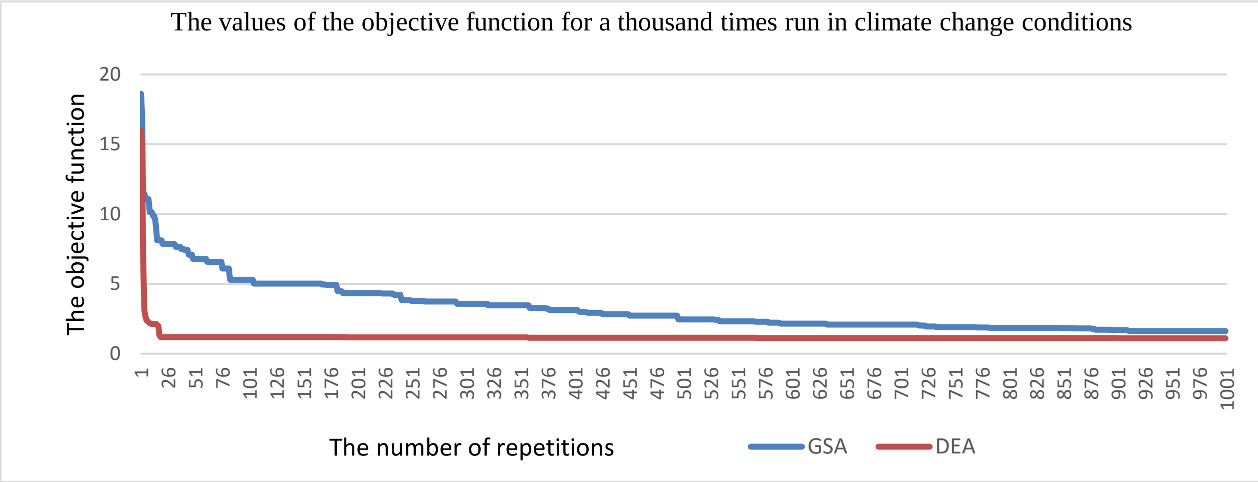


Fig. 7: Average monthly volume of reservoir discharge in baseline and climate change conditions, along with average monthly volume of water demand

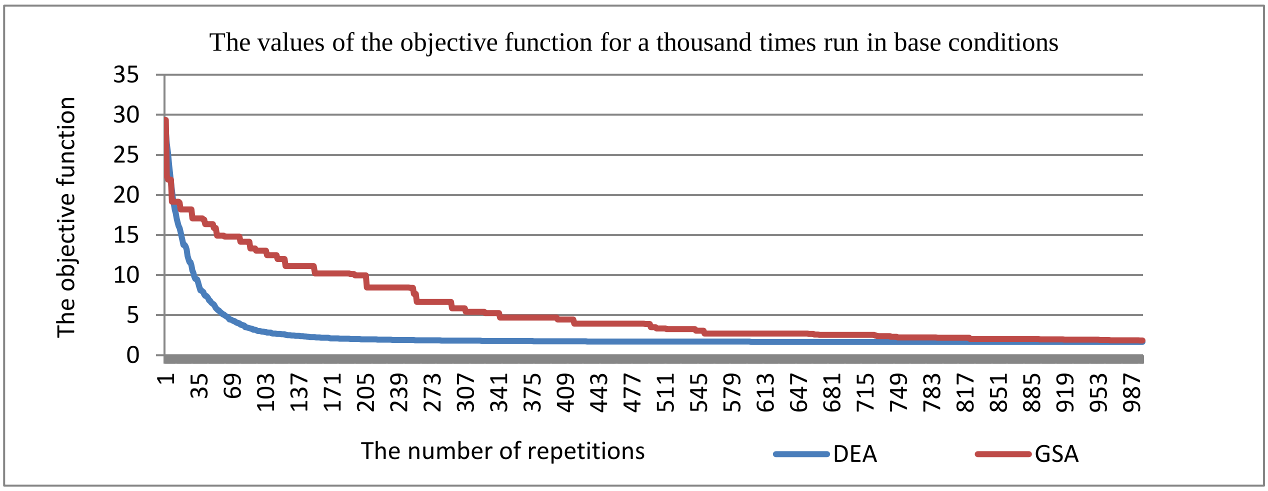
The results showed that the volume of discharge in the conditions of climate change has increased by 3.3%, which is caused by the increase in temperature and water due to melting snow and an increase in rainfall in the coming years. Also, the volume of demand has increased by 14.12% in the context of climate change. In this study, the study situations were performed in two modes of climate change and baseline. In the first case, the current rules are considered based on the volume of changes in the inflow to the reservoir and the volume of downstream water demand in baseline conditions and similarly in future conditions.

7. Findings and Discussion

In this section, the results of the command curve are examined in the Lar Large Reservoir Dam in the two basic and future periods. Figures (8) (a) and (b) show the downward trend of the values of the objective function for a thousand times in two periods with the optimal value of the objective function. As a result, dolphin echolocation and gravitational search algorithms converge, and the next two periods and the base values of the objective functions are 1.1031, 1.6242, 1.65, and 1.83, respectively.
In this study, in Figures (11), (12), (13) ,and (14) the changes in the volume of released water were investigated. In Figures (9) and (10), the amount of reservoir storage volume was examined with the rules of group hunting of dolphins and gravitational search in the future and basic periods. The results show that the volume of water released in the future period is higher, which is due to the increase in the volume of water demanded downstream and this period. For this reason, the model has increased the release volume in this period. And the amount of storage volume in the future period is less than the base period due to the increase in the volume of water demanded downstream, and finally, the increase in release volume.



(a)



(b)

Fig. 8: (a) The values of the objective function for a thousand times run in climate change conditions, (b) The values of the objective function for a thousand times run in base conditions

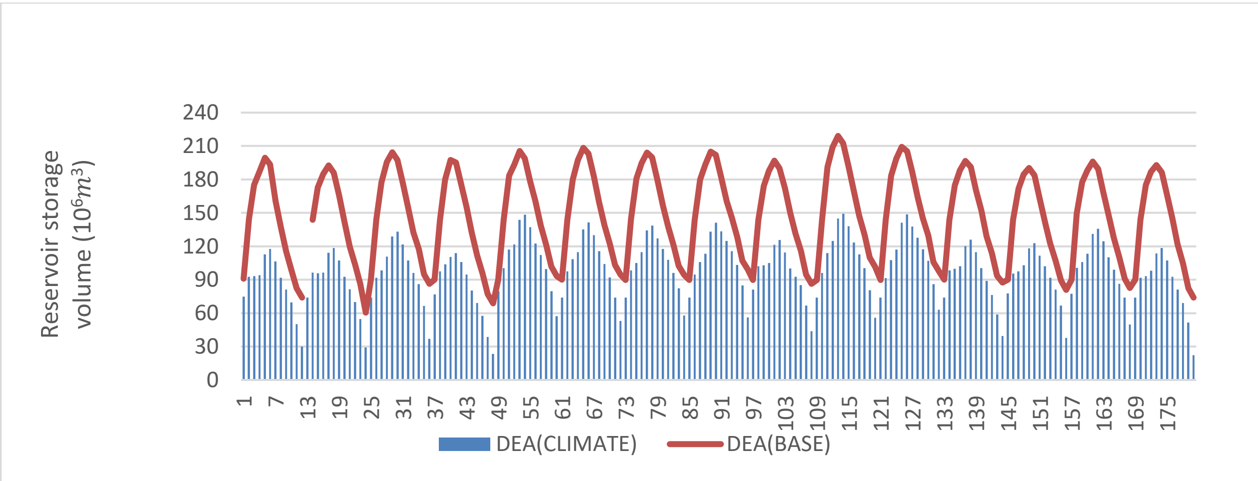


Fig. 9: Reservoir storage volume in base and climate change conditions with DEA algorithm

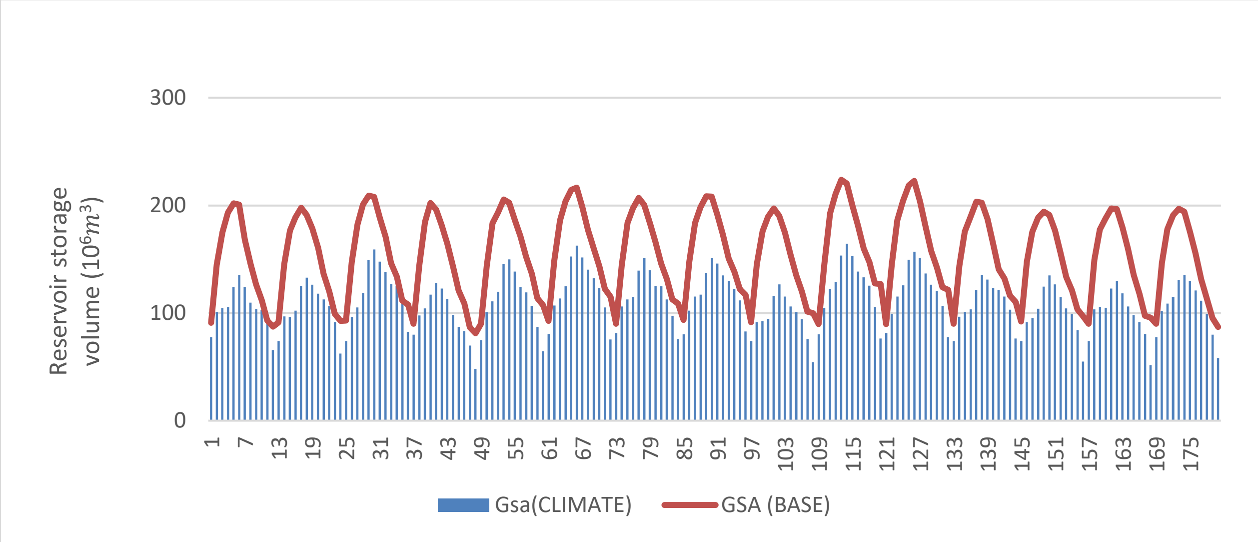


Fig. 10: Reservoir storage volume in base and climate change conditions with GSA algorithm

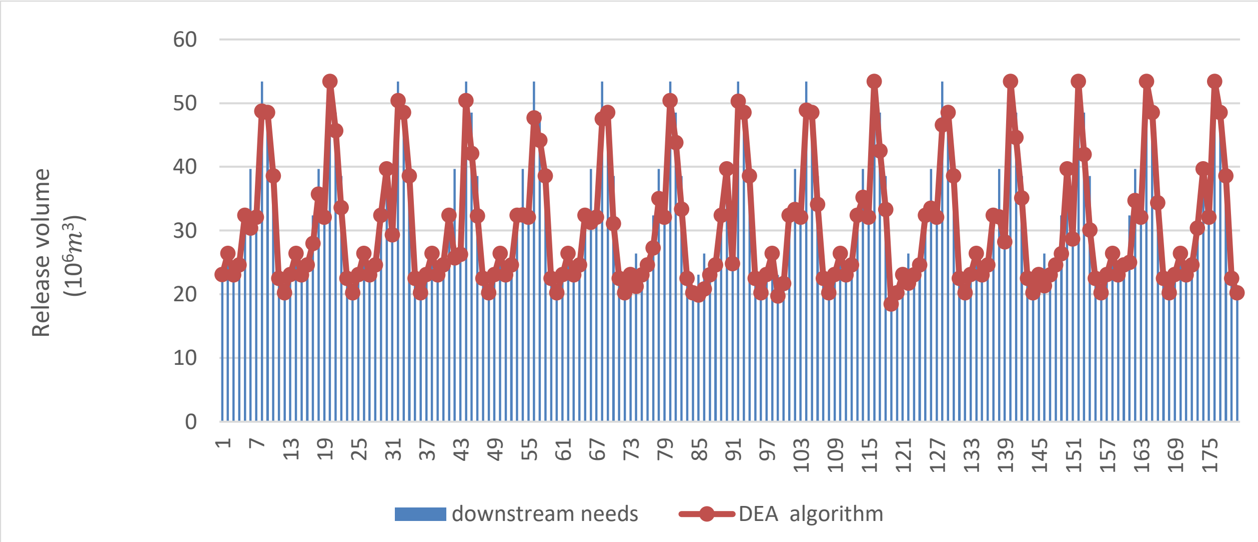


Fig. 11: Release volume in climate change conditions with the DEA algorithm

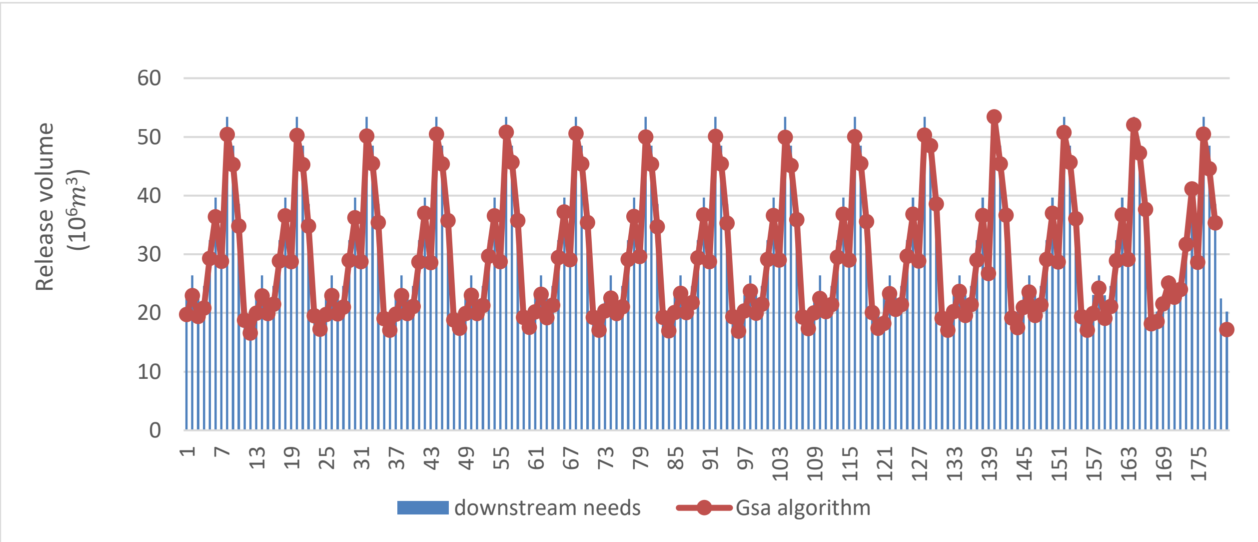


Fig. 12: Release volume in climate change conditions with the GSA algorithm

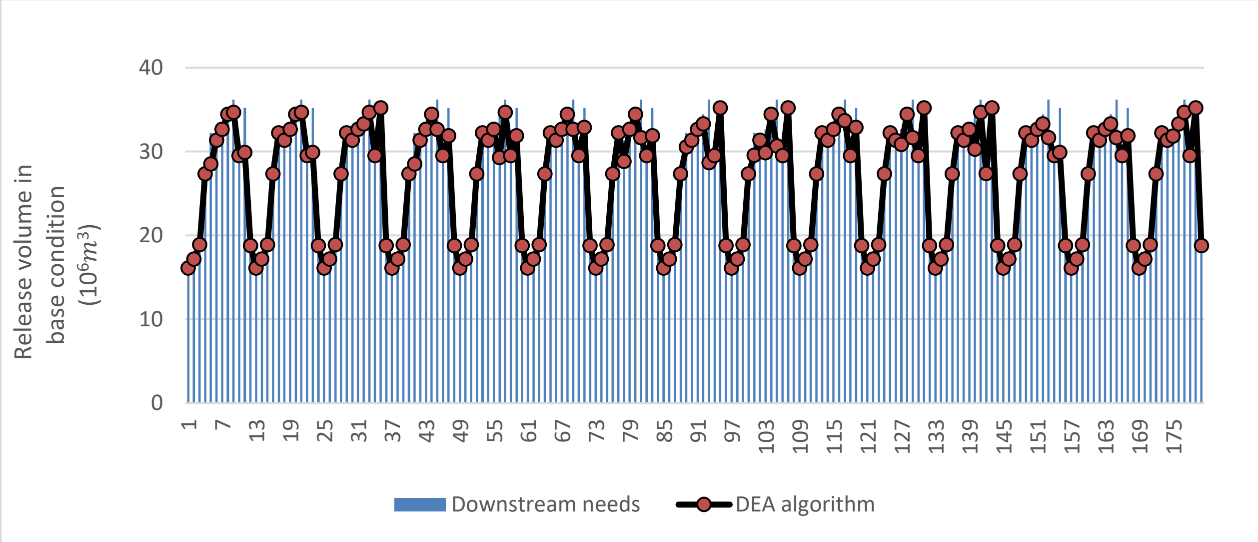


Fig. 13: Release volume in base conditions with DEA algorithm

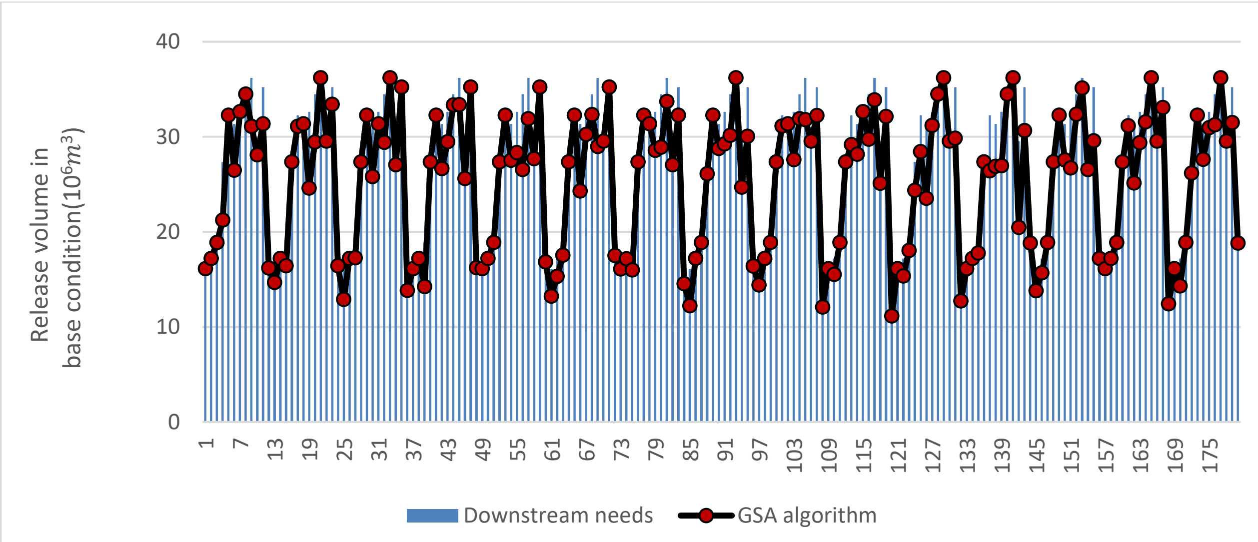


Fig. 14: Release volume in base conditions with GSA algorithm

As can be seen in Figures (15) and (16), the current rules with the basic conditions are not suitable for future conditions. To further investigate this issue, the squares criteria of error RMSE and mean absolute error (MAE) and (NSE) have been used (Ashofte et al.2013b) [9].

Table 3: Comparison of performance in the two situations under consideration in meeting the downstream needs in the future period (long-term monthly average)

Condition	R (%)	RSME	MAE	NSE
Current Rules with Future Conditions (DEA)	0.81	10.32	5.73	-0.31
Future Rules with Future Conditions (DEA)	0.92	7.10	3.79	0.62
Current Rules with Future Conditions (GSA)	0.79	9.53	4.90	-0.28
Future Rules with Future Conditions (GSA)	0.88	6.86	3.10	0.53

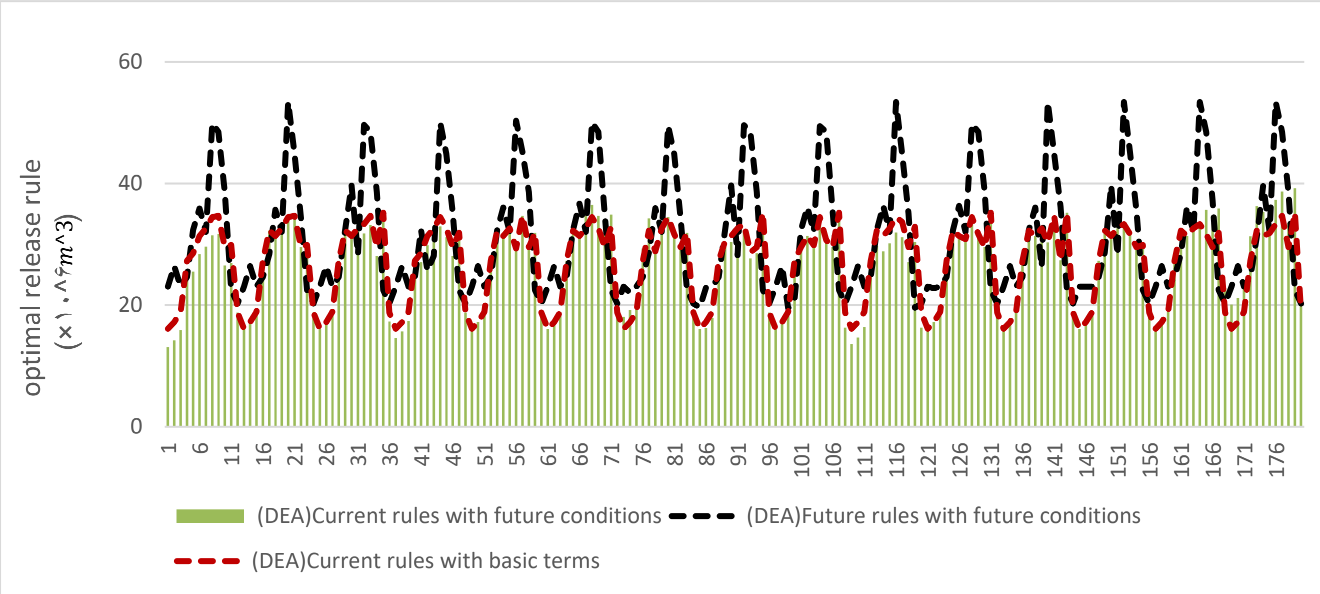


Fig. 15: Comparison of current release rules with future conditions and future rules with future conditions in the DEA algorithm

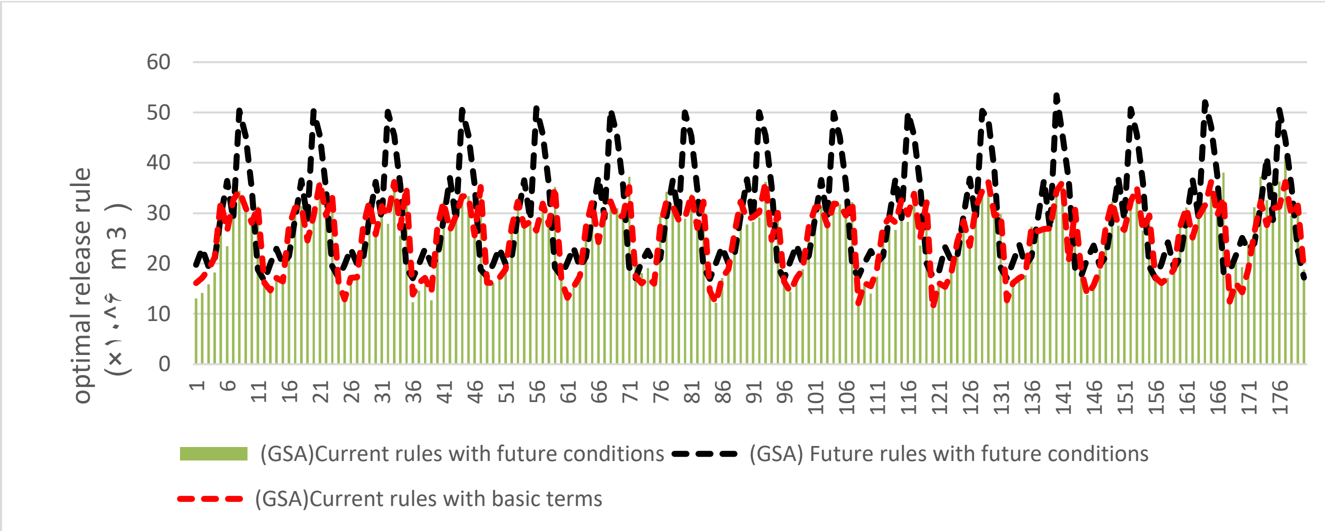


Fig. 16: Comparison of current release rules with future conditions and future rules with future conditions in the GSA algorithm

The results of Table (2) show a lower relative performance error in the status of current rules with future conditions than future rules with future conditions in supplying downstream water demand in the future period. Therefore, operating policies in future conditions should be changed and optimized.

In the next step, in order to evaluate the performance of the reservoir in delivering water demand based on the volume of river inflow, the values of efficiency criteria in the basic and future periods are compared, which are given in Table (2).

8. Conclusion

Reservoir efficiency criteria were compared to further evaluate the performance of the reservoir in delivering the requested water in the basic and future periods.

Table 4: Percentage values of tank performance criteria

Period	Reliability (%)	Vulnerability (%)	Reversibility (%)
Basic DEA	77.77	27.79	16
Future DEA	70.2	35.5	13
Basic GSA	44.44	40.82	17
Future GSA	38.9	55.55	14

The results of examining the execution time of each algorithm showed that the execution speed of the DE algorithm is much higher than the GSA algorithm; for example, in climate change, the GSA algorithm with a value of 176.7301 seconds is about three times the execution time of the DEA algorithm with a value of 56.967959 seconds also The results of Table 3 show that the reliability in the context of climate change is less than the base period, and according to the index in which the number of months with a deficit determines it, not its amount. As a result, due to the distribution of deficit volume in more months in terms of climate change than in the base period, this amount is higher in baseline conditions. Also, the difference in the reliability of the gravitational search algorithm compared to the dolphin echolocation algorithm indicates the distribution of deficiencies in more months in this algorithm. The Vulnerability index indicates that this index has increased in the conditions of climate change, and its conditions are worse, which is 14.7% due to the increase in water demand in the period of climate change. Meanwhile, the volume of reservoir inlet in the conditions of climate change has increased by about 3.3%, and the index of reversibility in the conditions of climate change has decreased compared to the base period. Considering that this index determines the number of months of supply and shortage, not their amount, therefore, this index depends on how there is a certain amount of supply after a certain amount of shortfall during the period within the months of that period.

The release rate in climate change conditions is higher than the baseline conditions due to the increase in demand in climate change conditions. Because of this increase, the storage volume of the dam reservoir is less than the base period.

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