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Optimal Operation of Dam Reservoir Using Gray Wolf Optimizer Algorithm (Case Study: Urmia Shaharchay Dam in Iran)

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ABSTRACT

Reservoir storage prediction is so crucial for water resources planning and managing water resources, drought risk management and flood predicting throughout the world. In this study, Gray Wolf Optimizer algorithm (GWO) was applied to predict Shaharchay dam reservoir storage of located in the Urmia Lake basin, northwest of Iran. The results of the GWO algorithm have been compared with the continuous genetic algorithm (CGA). The predicted values from the GWO algorithm matched the measured values very well. According to the results, the error is not significant (2.11%) in the implementation of the GWO and the correlation coefficient between the predicted and measured values is 0.92. In addition, the statistical criteria of RMSE, MAE and NSE for GWO algorithm were estimated to be 0.03, 0.41 and 0.74, respectively, indicated a satisfactory performance. Excessive value of correlation coefficient expresses that the GWO algorithm pretty suit the variables and may finally be used for predicting of reservoir storage for operational overall performance. Comparison of results showed that the GWO algorithm with average best objective function value of 121, 112 and 83.10 with a number of further evaluations of the objective function to achieve higher capacity is the optimum answer.

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1. Introduction

To population increase, growing water needs, constrained available water, and unequal distribution, control plans are more critical for predicting and controlling destiny water use. Those problems lead to excessive operational losses and miss-fit of water shipping with water needs. The use of analytical and optimization strategies may want to address a number of those difficulties. Making use of optimization techniques for reservoir operation isn't always a new idea [1]. Various strategies have been implemented in try to improve the efficiency of reservoirs operation [2].

The aim is to optimize the reservoir volume (this is storage) for abstracting enough quantity of water from the dam reservoir. The principle data series is the monthly reservoir flow. It's miles perfect to have an information document length so long as viable. For example, to the monthly inflows, the monthly evaporation losses, monthly irrigation release and monthly downstream irrigation need are every other primary statistic [2].

Many researchers have applied Evolutionary algorithms (EAs) to model different complex hydrological processes. The EAs methods have good generalization efficiency and are commonly used in practical hydrologic projects. GWO algorithm is a kind of EAs mimics the leadership hierarchy and looking mechanism of gray wolves in nature. In prediction of the reservoir storage, Kumar and Reddy in 2007 [3] supplied an elitist-mutated particle swarm optimization algorithm to derive reservoir operation rules for multipurpose reservoir structures. Afshar et al. in 2007 [4] proposed the honeybee mating optimization (HBMO) set of rulalgorithm to resolve the unmarried reservoir operation optimization issues. Bozorg- Haddad et al. (2008) carried out the HBMO algorithm to extract linear monthly operation policies for each irrigation and hydropower reservoirs.

Ahmadian et al. in 2013 [5] investigated the multi-objective optimization (maximizing power generation and flood control) of Pir-Taghi Dam reservoir in Qezel-Ozan Basin using the Imperialist Competitive algorithm. Considering a one-year planning horizon and monthly periods, the Imperialist Competitive algorithm has been implemented. The results showed that the proceeds from the hydropower energy sale in the summer months, due to more electricity consumption and an increase in electricity prices were more than other months, and also in flood months, the reservoir, due to the flood control, has a lower elevation and produces less hydropower energy in comparison with other months, which was clearly observed from February to May.

Karamouz et al. in 2014 [6] proposed a model for the optimal operation of Karkheh Dam reservoir, considering the factors such as benefits and authority of the stakeholders of water resources. This model was formulated using Conflict Resolution theory and AHP. Imperialist Competitive and particle swarm optimization algorithms were used to derive optimized reservoir releases in each period. The criteria such as reliability, Resiliency, and vulnerability were used to evaluate the functionality of proposed algorithms, which recommended the greater performance of ICA in comparison with PSO.

Izadbakhsh and Javadikia in 2015 [7] evaluated utility of hybrid FFNN-Genetic algorithm for predicting evaporation in dam reservoir storage. Daily meteorological data during the period

1994-2009 were used as model inputs. Results showed the satisfactory structure had simplest one hidden layer with 14 neurons and it had MSE=0.021 with correlation coefficient of 0.977. The determination coefficient for this model was 0.9. Abdulkadir et al (2015), used ANN model for predicting reservoir storage for hydropower dam operation in Nigeria. Results confirmed the trained models with 95% & 97% of goodness match respectively for training and testing at Jebba, 69% &75% at Kainji and 98% & 97% at Shiroro. additionally, the correlation coefficients among expect and measured reservoir storage of 0.64, 0.79 and 0.84 have been acquired for Jebba, Kainji and Shiroro reservoirs, respectively.

Adeyemo and Stretch in 2018 [8] carried out an evaluate of hybrid evolutionary algorithms for optimizing a reservoir. They stated that researchers need to develop greater hybrid algorithms from the prevailing ones so that it will locate stepped forward answers to reservoir operation and different water resources management issues.

Parlikar et al in 2017 [9] evaluated reservoir releases using Genetic algorithm. The sensitivity analysis of GA model carried out to this particular reservoir system suggested most desirable length of population of 60 and opportunity of crossover of 0.64, to locate best releases.

Prasanchum and Kangrang in 2017 [10] used GA to link with a reservoir simulation model to search most reliable reservoir rule curves for Lampao dam located inside the northeast of Thailand. The results confirmed that the new rule curves have been improved via the GA connected simulation model and may mitigate the frequency of water scarcity situations and the releases of excess water during inflow changes within the future. Kangrang et al. 2018 [11] presented future rule curves for multipurpose reservoir operation the use of conditional Genetic and Tabu search algorithms in Ubolrat reservoir located within the northeast of Thailand. The results confirmed that the most excellent rule curves from CGA and CTSA connected with the simulation model can mitigate drought and flood situations than the present rule curves. The premier future rule curves have been better than the other rule curves.

Anand et al. in 2018 [12] optimized of multipurpose reservoir operation by coupling SWAT and Genetic algorithm for optimal operating policy in Ganga river basin. The objective function was set to minimize the annual sum of squared deviation form desired irrigation release and desired storage volume. Result showed, this research has been successfully able to exhibit the efficiency and effectiveness of multi-objective GA algorithm for varying multi-objective reservoir operation strategies.

Cuvelier et al. in 2018 [13] in comparison robust and stochastic optimization for long-time period reservoir control below uncertainty. They suggest a methodology to derive minimum bounds even as offering formal ensures about the fine of the received answers.

Olukanni et al. in 2018 [14] optimized-primarily based reliability of a multipurpose reservoir with the aid of GA Algorithm in Jebba hydropower dam, Nigeria. The particular goals are to have a look at the reservoir operation rule; model the reservoir parameters which include inflow, elevation, turbine release, producing head, electricity generation, tailrace water level and plant coefficient. to be had statistics for 27-year duration (1984–2011) turned into acquired from the dam station for statistical evaluation. consequences confirmed the software of GA will result in a more practical and dependable optimal value for the development of hydroelectric power era and flood management, which might manual decision makers inside the hydropower quarter.

Rabiei et al. 2018 [15] reservoir operation optimization using CBO, ECBO and VPS algorithms. To evaluate the performance of these three recent population-based meta-heuristic algorithms, they were applied to one of the most complex and challenging issues related to water resource management, called reservoir operation optimization troubles.

A significant point in past research is that despite the use of hybrid optimization techniques in and other methods such as ANN, Genetic, PSO, Cuckoo search algorithms and etc., have paid less attention to the prediction problem of dam reservoir storage in relation to water resources management.

It could be visible within the literature that many heuristic techniques had been used for optimizing the reservoir-operating and reservoir storage machine. Therefore, we use a new evolutionary algorithm that is stimulated by GWO algorithm, as a new evolutionary method and also adaptation of this algorithm to a smaller number of parameters for optimizing and prediction the reservoir storage system. We apply the GWO algorithm in predicting reservoir storage to show that it is able to provide a valid solution for reservoir storage prediction [16].

2. Material and method

The investigation of the developed GWO algorithm has been carried out through applying to the Shaharchay river basin. Shaharchay river basin is placed in the north-western of Iran. The basin overall place is about 369 Km^2. There are 1 reservoir operated in the basin; Shaharchay reservoir dam. The Supply framework worked for three primary purpose, Water system, drinking water supplies and industry. Figure 1 illustrates basin location of the studied area in Iran and the schematic reservoir on the Shaharchay river basin.

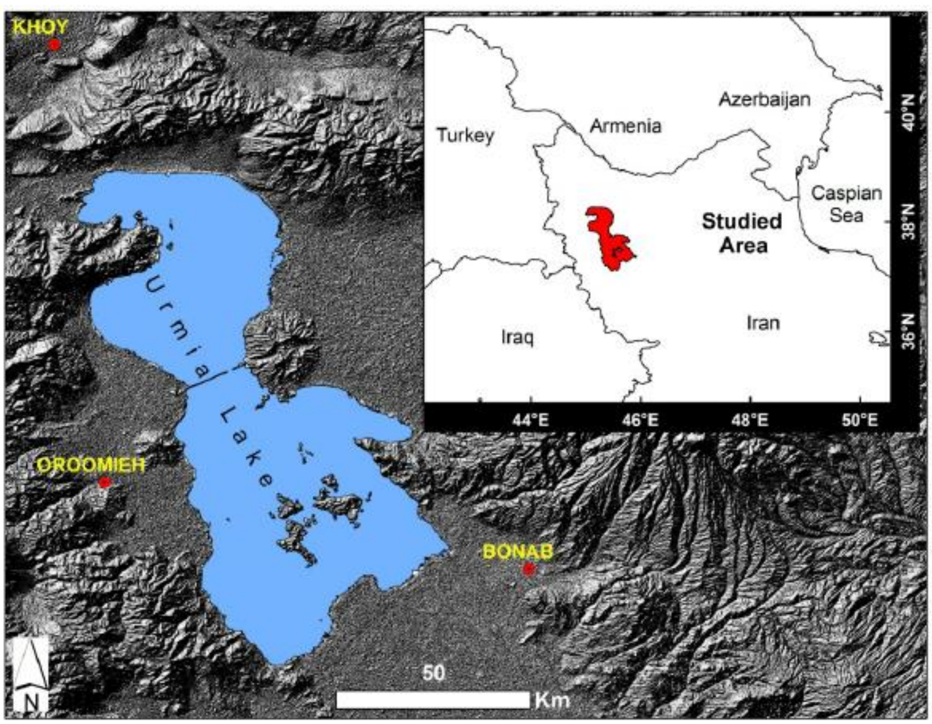

Fig. 1. Basin location in Iran.

The Shaharchay dam is built on Shaharchay river at 35 km north-west of Urmia city in Iran. The dam location is found at the height of 1519 m from sea-level, at 44.904/ E-longitude and 37.447/ N-latitude. The capacity volume of this dam supply at ordinary pool level is 213 mm^3. This capacity volume can supply water system water for 13000 hectares of arrive. The least capacity volume of store rises to 7 mm^3. The normal stream rate of Shaharchay river at the dam location is 168 m^3/sec [17].

2.1. The proposed algorithm

The GWO algorithm mirrors the authority progression and chasing component of grey wolves in nature proposed by Mirjalili et al. in 2014. Four sorts of dim wolves such as alpha, beta, delta, and omega are utilized for reproducing the specialist chain of command. In expansion, three primary steps of chasing, looking for prey, encompassing prey, and assaulting prey, are actualized to perform optimization. table 2 appears the pseudo code of the GWO (This pseudo code clarifies the essential GWO that was proposed by Mirjalili et al., 2014 [18–20].

Table 1
GWO algorithm pseudo-code.

Step 1: Initialize the guide outline grey wolf populace Xi (i = 1, 2... n), counting the pending information. Step 2: Initialize a, A, and C and trade the genuine time information in CFP period. Step 3: Calculate the wellness of each look operator (arrange the information) $X\alpha$ =the best look operator $X\beta$ =the moment best look operator $X\delta$ =the third best look operator Step 4: whereas (t < Max number of cycles) For each look specialist (esteem) overhaul the position of the current look operator (check the genuine time information position). Step 5: Upgrade α , $A\ and\ C$, and Calculate the wellness esteem for all look and begin CAP Step 6: Upgrade $X\alpha$, $X\beta$,$X\delta$, $make\ t = t + 1$;

2.1.1. Encompassing prey

Gray wolves encompass the prey amid the chase. The numerical demonstrate of the encompassing behavior is given underneath.

$$D = \left| C, X_p(t) - A, X(t) \right. \quad (1)$$

$$X(t+1) = X_p(t) - A, D \quad (2)$$

Where ‘t’ is the current emphasis, A and C are coefficient vectors, X_p is the position vector of the prey, and X demonstrates the position vector of a gray wolf.

2.1.2. Hunting

Chasing of prey is ordinarily guided by α and β , and δ will take an interest every so often. The leading candidate arrangements, α , β , and δ , have superior data around the potential area of prey. The other look specialists (ω) upgrade their positions concurring to the position of three best look specialists.

2.1.3. Assaulting prey

In arrange to scientifically demonstrate for drawing closer the prey, we diminish the esteem of $\vec{a}$. The Variance run of $\vec{A}$ is additionally diminished by $\vec{a}$. $\vec{A}$ could be an arbitrary esteem within the interim $[-a, a]$ where a is diminished straightly from 2 to over the course of emphases. When arbitrary values of $\vec{A}$ are in $[-1, 1]$, the another position of a look specialist can be in any position between it current position and the position of the prey. The esteem $|A| < 1$ powers the wolves to assault the prey. After the assault once more they hunt for the prey within the another emphasis, wherein they once more discover the another best arrangement α among all wolves. This prepare rehashes till the end measure is satisfied (figure 2).

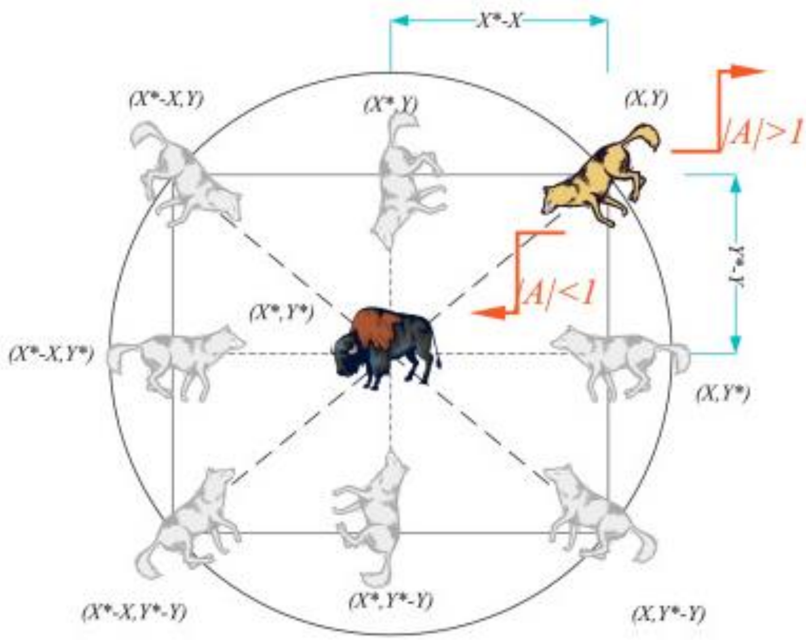

Fig. 2. Schematic of GWO algorithm performance.

2.1.4. Usage of CGA algorithm

To actualize the continuous genetic algorithm procedure (CGA), the taking after parameters have to be selected.

1. The number of initial countries usually 30–200.
2. The number of initial colonists
3. The number of colonies (Difference between 1, 2 steps).

The CGA algorithm procedure involves the following steps.

In a CGA, a populace of candidate arrangements (called people, animals, or phenotypes) to an optimization issue is advanced toward way better arrangements. Each candidate arrangement incorporates a set of properties (its chromosomes or genotype) which can be changed and modified; customarily, arrangements are spoken to in parallel as strings of 0s and 1s, but other encodings are moreover conceivable [21]. The advancement more often than not begins from a populace of haphazardly created people, and is an iterative handle, with the populace in each emphasis called a era. In each era, the wellness of each person within the populace is evaluated; the wellness is as a rule the esteem of the objective work within the optimization issue being fathomed. The more fit people are stochastically selected from the current populace, and each individual's genome is adjusted (recombined and conceivably randomly mutated) to create a modern era. The unused era of candidate arrangements is at that point utilized within the following iteratio

1. A hereditary representation of the arrangement domain.
2. A wellness work to assess the arrangement domain.

A standard representation of each candidate arrangement is as a cluster of bits. Clusters of other sorts and structures can be utilized in essentially the same way. The most property that creates these hereditary representations helpful is that their parts are effectively adjusted due to their settled measure, which encourages basic hybrid operations. Variable length representations may moreover be utilized, but hybrid execution is more complex in this case. Tree-like representations are investigated in hereditary programming and graph-form representations are investigated in developmental programming; a blend of both straight chromosomes and trees is investigated in quality expression programming. Once the hereditary representation and the fitness function are characterized, a CGA continues to initialize a populace of arrangements and after that to make strides it through dreary application of the change, hybrid, reversal and determination administrators [21].

2.2. Statistical criteria

A number of lists are required to compare the results of the calculations and the measured values as well as their assessment, which can judge the work of the demonstrate within the entirety set of information in comparison with the test comes about. To this conclusion, Mean Absolute Magnitude Error (MAE), Root Mean Square Error (RMSE) and Nash-Sutcliffe (NSE) were utilized. The conditions are as takes after [22]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|x_i - y_i\right|}{n} \tag{4}$$

$$NSE = \frac{\sum_{i=1}^{n}(y_i - \overline{x})^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{5}$$

In these equations, Y_i is observation data, X_i is predicted data. Also, results showed RMSE, MAE and NSE were 0.03, 0.41 and 0.74, respectively, which are in a great range of satisfaction.

3. Results and discussion

After the introduction of the objective function and perform sensitivity analysis to discover the ideal values of the successful parameters of the algorithm and the execution of the show, the decision variables of the problem, were calculated which includes 24 variables was calculated.

Too, GWO and CGA algorithms parameters, displayed in table 2 and 3.

Table 2
Parameters utilized for running GWO.

Parameter	Value
The number of wolves	12
Low range	30
Upper range	-30
Maximum repeat	300

Table 3
Parameters used for running CGA.

Parameter	Value
The number of initial population	100
% Of generation	60
Percent jump	10
To convey to the next generation	30
The way parents	Cost weighting

Figure 3 shows Relationship between water level and reservoir surface area.

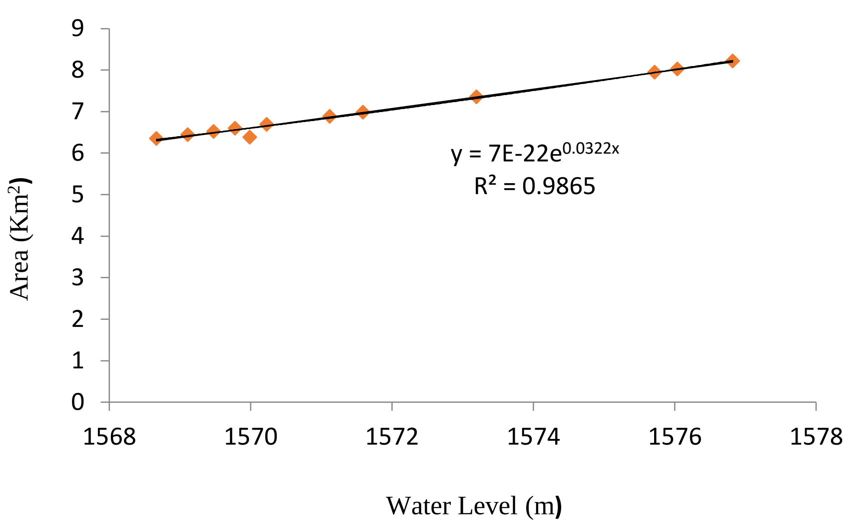

Fig. 3. Relationship between water level and reservoir surface area.

Variable number 1 to 12 is the output value of dam and the variables number 13 to 24 are related to the stored volume in the same month. In Figure 9 water volume stored in Urmia Shaharchay dam is predicted in different months of the year by using GWO. The Input data were inflow (I_t), evaporation (E_t), rainfall (R_t), reservoir storage (S_t) and outflow (O_t). The best convergence after more than 1000 trials was achieved for the combination of inflow (I_t), inflow (I_{t-1}), inflow (I_{t-2}), evaporation (E_t), reservoir storage (S_t), rainfall (R_t), outflow (O_{t-1}) and value for each variable is presented in figure 6. GWO function performance concluded 24 variables calculation. Variable number 1 to 12 is the output value of dam and the factors number 13 to 24 are related to the stored volume within the same month. Capacity in Urmia Shaharchay dam is anticipated in several months of the year by utilizing GWO in figure 4.

Figure 4 shows the amount of storage in the months leading up to the summer, such as May and June, which is the highest water demand in the Azerbaijani region during this season. Also, the lowest flood risk is predicting in November and December.

Figure 5 shows the amount of storage applied to implement the GWO algorithm which is very close to the measured value dam storage compared with CGA algorithm, and it proves the convergence, effectiveness and efficiency of the GWO algorithm rivalry in water resources systems.

In Table 4, the results of the CGA and GWO algorithm of Urmia Shaharchay dam has been determined, in different months of the year.

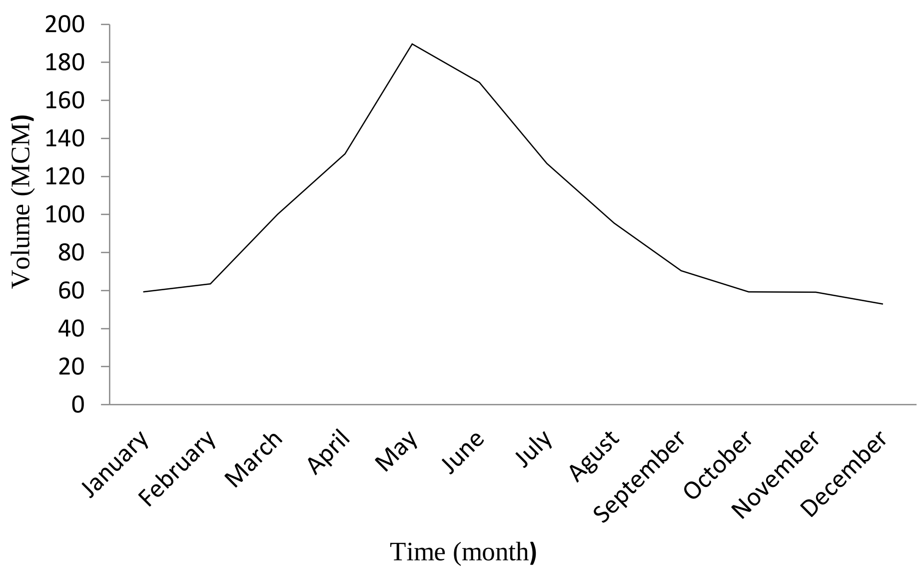

Fig. 4. Amount of dam storage volume per month.

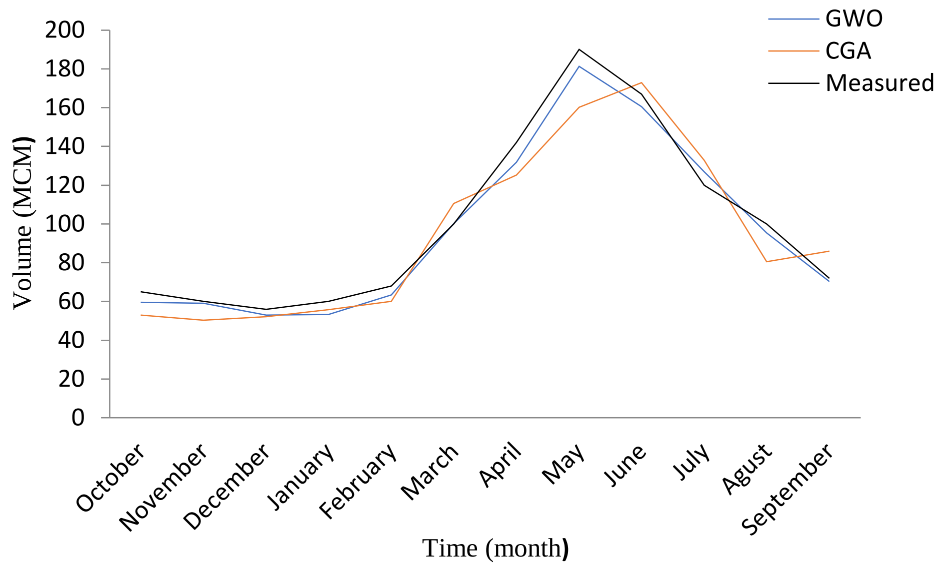

Fig. 5. Comparison of the amount of measured reservoir storage and calculated value by GWO and CGA algorithms.

Table 4
The results of the CGA and GWO algorithms for Urmia Shaharchay dam.

Optimum output volume of the model (GWO) (MCM)	Optimum output volume of the model (CGA) (MCM)	Optimized storage volume of the model (GWO) (MCM)	Optimized storage volume of the model (CGA) (MCM)	Month
14.3316	15.9038	59.531	56.5879	October
8.5820	9.7021	59.1144	55.2633	November
6.4916	6.1039	52.922	50.0000	December
7.6641	6.6323	59.331	56.2973	January
7.0330	6.3600	63.4209	59.2079	February
7.7041	7.7021	100.098	85.2735	March
9.4552	8.8232	131.875	124.9921	April
18.6577	18.2878	189.625	182.7490	May
20.5258	19.7081	169.509	154.7225	June
29.8412	29.1239	126.8962	121.1659	July
25.9913	25.6082	95.4145	89.4072	August
24.6658	23.5293	70.3536	65.4233	September

Figure 6 shows the convergence trend of GWO and CGA algorithms based on the best population obtained from the exploitation model. (Assuming the number of steps to implement: 1000 and initial population: 100). As can be seen, the loss rate of the operating program presented with GWO algorithm is significantly lower than that of CGA algorithm.

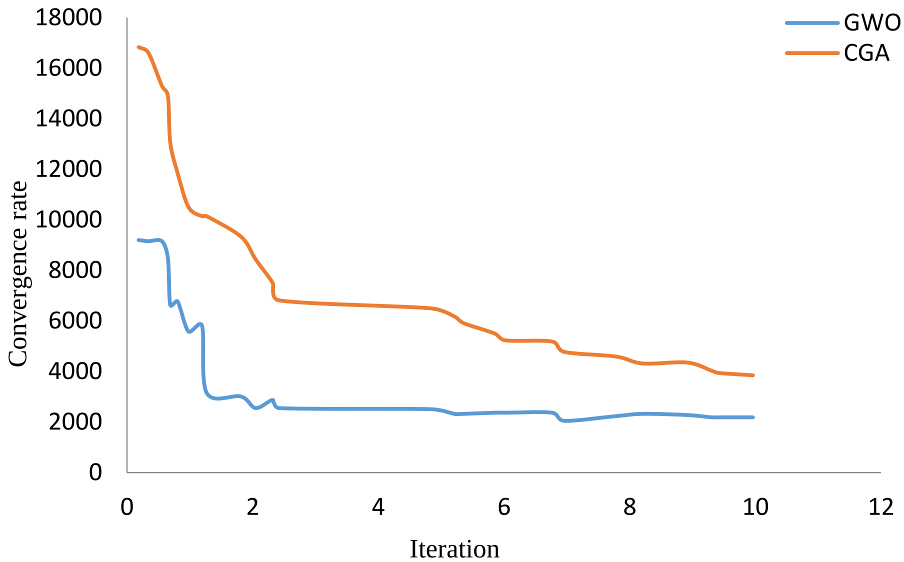

Fig. 6. Convergence trend of GWO and CGA algorithms.

The error percent between the measured data and the results of calculation for the implementation of CGA and GWO algorithms are shown in Table 5 and Figure 7. Error percent noticing to the performance of both model, would be figured out that the results of GWO is very satisfactory compared to CGA.

Table 5
Percentage error between the measured and calculated data.

CGA algorithm	GWO algorithm
6.65%	1.80%
7.42%	0.96%
6.51%	1.04%
6.28%	1.23%
10.45%	4.082
15.51%	0.82%
10.18%	5.23%
8.63%	5.19%
10.90%	2.07%
6.30%	1.87%
7.35%	1.13%
7.44%	0.47%

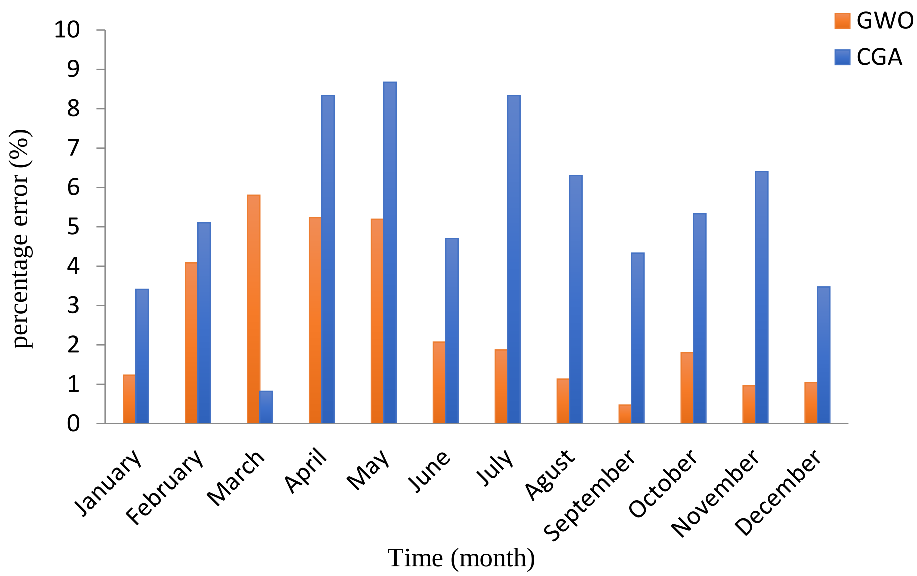

Fig. 7. Compare the percentage errors in different months.

The match rate for the entire 12 month periods, shows monthly output operation of the reservoir in figure 8, Both diagrams are Coincident perfectly with downstream irrigation demand.

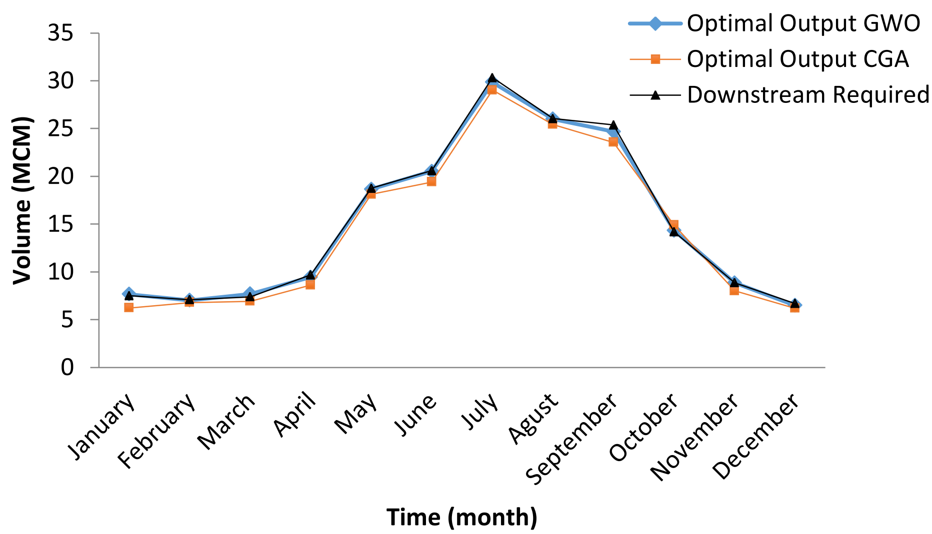

Fig. 8. The match rate for the entire 12-month period.

As we can see, the results of the GWO algorithm are satisfactory. Because the diagrams fit together so well that both the downstream water needs are met and water loss is avoided. As mentioned above, the results for the input is predicted with probability 90%. The capabilities of GWO algorithm can examine various possibilities for input, as it can be seen in figure 9, that variation in the input value as the output of the algorithm would not provide significant changes, and it requires the same amount remains low and the algorithm will create a major change in the value will be stored. According to the storage value in the months leading up to summer, which is the maximum amount of downstream, demand increases.

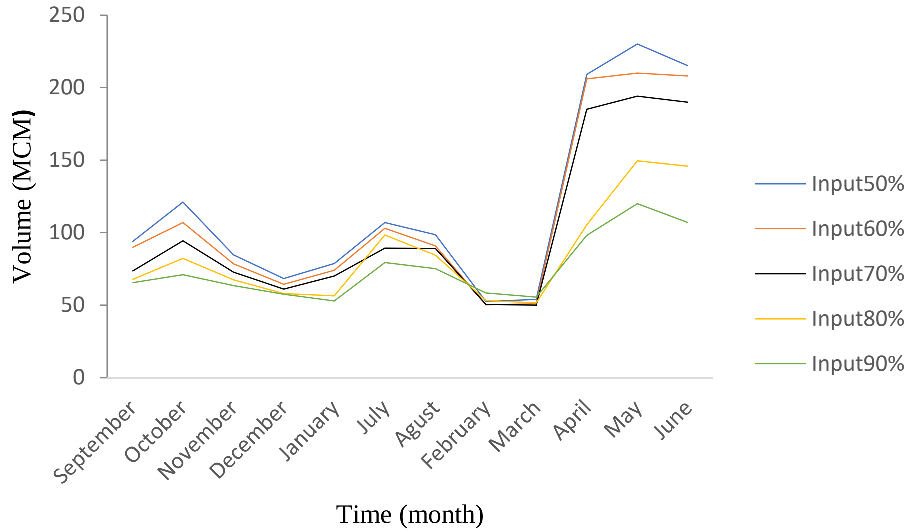

Fig. 9. Comparison of reservoir storage for the input of various possibilities.

The storage values in the reservoir have been predicted for three years 2018 to 2020, as shown in figure 10, and this shows the power, integration, high performance and efficiency GWO algorithm for solving the complex problems of water resource.

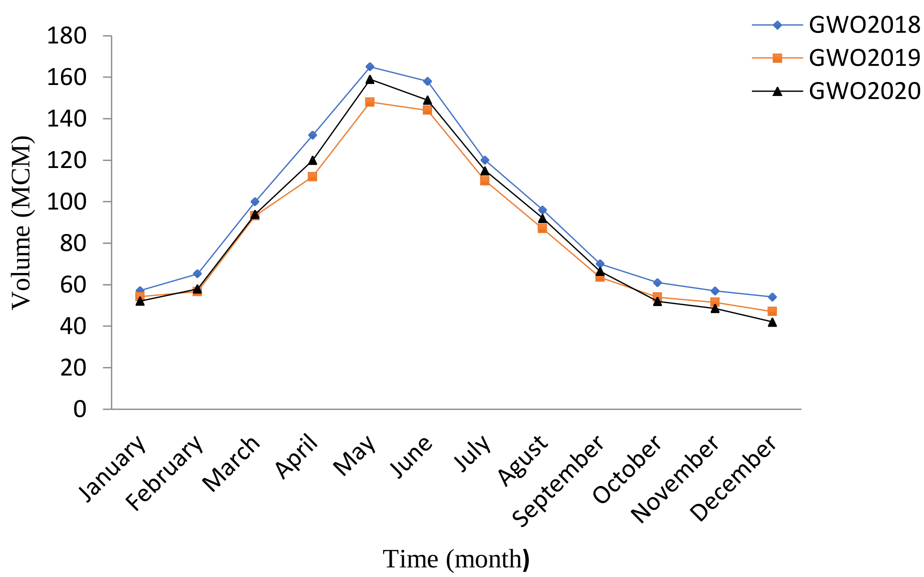

Fig. 10. The reservoir storage for three years 2018 to 2020.

3.1. Comparison of optimization methods in prediction dam reservoir storage

In this part, the efficiency of optimization algorithms is compared with the optimization of the dam reservoir. The wellness work of all models is minimizing the squared deviation of month to month water system request and squared deviation in mass adjust condition. In this study, the efficiency of the GWO model was compared with the results of the Chenari (2013) study [23], which optimized dam reservoir with PSO and Genetic (GA) models.

Comparison of GWO model with PSO and GA algorithms in population 100 showed that the GWO algorithm with average best objective function value of 168.30, 121 and 112.10 with a number of further evaluations of the objective function to achieve higher capacity is the optimum answer, while average best objective function value of PSO and GA algorithms is 181.1 and 181.79 respectively.

4. Conclusion and recommendations

In this study, a strategy for the application of the GWO algorithm to supply ideal operation has been displayed. This study is the first study in Iran to predict the reservoir storage used new and powerful method which is GWO algorithm. The result shows the optimal solutions with CGA algorithm convergence speed and high accuracy and the predict storage values in the reservoir that have been highly optimized for this model. The results obtained from the implementation of the proposed algorithm in Matlab software and showed the GWO supremacy to the other evolutionary algorithms such as CGA. The efficiency and the convergence rate of the new method is proved to predict dam reservoir storage. Also the results showed a 2.11% average error in the implementation of the GWO algorithm between the observed and predicted storages. Generally, according to the results of this research, the predominance of the GWO in terms of efficiency and high convergence rate in predicting the storage of dam reservoirs is proved. In generally, the GWO algorithm is effortlessly connected to nonlinear issues and to complex frameworks and can create a total set of elective arrangements near to the ideal, which gives selectivity to an administrator of a complex store framework.

References

[1] Kilinç I, Cigizoglu K. Reservoir management using artificial neural networks. Proc 14th Reg Dir DSI (State Hydraul Work Istanbul, Turkey 2005.

[2] Pilpayeh A, Sedghi H, Fahmi H, Jahromi HM. An optimizing operational model for multiobjective serial reservoirs (case study of Aras River Basin, Northwestern Iran). World Appl Sci J 2010;10:234–41.

[3] Nagesh Kumar D, Janga Reddy M. Multipurpose Reservoir Operation Using Particle Swarm Optimization. J Water Resour Plan Manag 2007;133:192–201. doi:10.1061/(ASCE)0733-9496(2007)133:3(192).

[4] Afshar A, Bozorg Haddad O, Mariño MA, Adams BJ. Honey-bee mating optimization (HBMO) algorithm for optimal reservoir operation. J Franklin Inst 2007;344:452–62. doi:10.1016/j.jfranklin.2006.06.001.

[5] Ahmadian MR, Farid-hosseini AR, Hojjati A. Multi-objective optimization using Imperialist Competitive algorithm. 5th Natl Water Resour Manag Conf Tehran, Iran Water Resour Sci Eng Soc ShahidBeheshti Univ, 2013.

[6] Karamouz M, Nazif S, Sherafat MA, Zahmatkesh Z. Development of an Optimal Reservoir Operation Scheme Using Extended Evolutionary Computing Algorithms Based on Conflict Resolution Approach: A Case Study. Water Resour Manag 2014;28:3539–54. doi:10.1007/s11269-014-0686-z.

[7] Izadbakhsh MA, Javadikia H. Application of hybrid FFNN-genetic algorithm for predicting evaporation in storage dam reservoirs. Agric Commun 2014;2:57–62.

[8] Adeyemo J, Stretch D. Review of hybrid evolutionary algorithms for optimizing a reservoir. South African J Chem Eng 2018;25:22–31. doi:10.1016/j.sajce.2017.11.004.

[9] Parlikar AS, Dahe PD, Vaidya M, Sharma K. Reservoir Releases using Genetic Algorithm. Int J Innov Adv Comput Sci 20127;6:363–6.

[10] Prasanchum H, Kangrang A. Optimal reservoir rule curves under climatic and land use changes for Lampao Dam using Genetic Algorithm. KSCE J Civ Eng 2018;22:351–64. doi:10.1007/s12205-017-0676-9.

[11] Kangrang A, Prasanchum H, Hormwichian R. Development of Future Rule Curves for Multipurpose Reservoir Operation Using Conditional Genetic and Tabu Search Algorithms. Adv Civ Eng 2018;2018:1–10. doi:10.1155/2018/6474870.

[12] Anand J, Gosain AK, Khosa R. Optimisation of multipurpose reservoir operation by coupling SWAT and genetic algorithm for optimal operating policy (case study: Ganga River basin) 2018.

[13] Cuvelier T, Archambeau P, Dewals B, Louveaux Q. Comparison Between Robust and Stochastic Optimisation for Long-term Reservoir Management Under Uncertainty. Water Resour Manag 2018;32:1599–614. doi:10.1007/s11269-017-1893-1.

[14] Olukanni DO, Adejumo TA, Salami AW, Adedeji AA. Optimization-based reliability of a multipurpose reservoir by Genetic Algorithms: Jebba Hydropower Dam, Nigeria. Cogent Eng 2018;5. doi:10.1080/23311916.2018.1438740.

[15] Rabiei MH, Aalami MT, Talatahari S. Reservoir operation optimization using CBO, ECBO and VPS algorithms. Int J Optim Civ Eng 2018;8:489–509.

[16] Kilinç I, Ciğizoğlu K. Reservoir management using artificial neural networks. 14th Reg Dir DSI (State Hydraul Work Istanbul, Turkey 2012.

[17] www.agrw.ir n.d.

[18] Mirjalili S, Mirjalili SM, Lewis A, Optimizer GW. Advances in engineering software. Renew Sustain Energy Rev 2014:46–61.

[19] Mech LD. Alpha status, dominance, and division of labor in wolf packs. Can J Zool 1999;77:1196–203. doi:10.1139/z99-099.

[20] Muro C, Escobedo R, Spector L, Coppinger RP. Wolf-pack (Canis lupus) hunting strategies emerge from simple rules in computational simulations. Behav Processes 2011;88:192–7. doi:10.1016/j.beproc.2011.09.006.

[21] Goldberg DE. GeneticA lgorithm in Search, Optim ization andM achineLearning. Read Addison2wes2 Ley 1989.

[22] Ghorbani MA, Shamshirband S, Zare Haghi D, Azani A, Bonakdari H, Ebtehaj I. Application of firefly algorithm-based support vector machines for prediction of field capacity and permanent wilting point. Soil Tillage Res 2017;172:32–8. doi:10.1016/j.still.2017.04.009.

[23] Saber Chenari K, Abghari H, Erfanian M, Ghaderi M, Salmani H, Asadi Nalivan O. Optimization Reservoir Operation Policy with Approach reduces probability of inflow Using Genetic Algorithm (The case study: Mahabad Reservoir Dam). Water Shed Manag Res 2016;29:34–43.