

## Development of Reservoir Operation Policies Using Integrated Optimization-Simulation Approach

B. Zahraie<sup>1</sup>, and S. M. Hosseini<sup>2\*</sup>

### ABSTRACT

This study is focused on developing an integrated optimization-simulation based genetic algorithm model (IOSGA) to develop the operational policies for a multi-purpose reservoir system. The objective function of the optimization model is considered to be a linear function of Reliability (Rel), Resiliency (Res), and Vulnerability (Vul) of the river-reservoir system. Genetic Algorithm (GA) is employed to solve the optimization model in which the coefficients of reservoir operation policy equations are considered as decision variables. These coefficients are formulated in the form of fuzzy numbers to be able to capture the variations in releases and in water demands. Due to significant variations of agricultural water demands during different months and years, a water demand time series is considered as one of the inputs of the optimization model. Zayandeh-Rud River-reservoir system, in central part of Iran, is considered the case study. The results of the proposed approach are compared with those of the classic three cyclic algorithm in which the reservoir releases are the decision variables of the optimization model and the IOSGA model in which the coefficients of reservoir operation policies are considered to be classic (non-fuzzy) numbers. The results of the study indicated that the developed algorithm can significantly reduce the time and costs of modeling efforts and the run-time of the GA model, while it has also improved the overall performance of the system in terms of *Rel*, *Res*, and maximum Vulnerability ( $Vul_{Max}$ ) and the coefficient of efficiency (*CE*) and standard error (*SE*).

**Keywords:** Genetic algorithm, Reliability, Reservoir operation optimization, Resiliency, Vulnerability, Zayandeh-rud Reservoir.

### INTRODUCTION

Development of optimization and simulation models for defining reservoir operation policies has been the focus of attention of researchers for many years. Simonovic *et al.* (1992) and Labadie (2004) reviewed the state of the art in the field of reservoir operation optimization. Among different optimization methods, genetic algorithms (GAs) represented efficient and robust search methods for non-linear optimization problems and have been quite successfully applied to a number of reservoir operation optimization problems (East and

Hall, 1994; Wardlaw and Sharif, 1999; Chang *et al.*, 1998; Chang *et al.*, 2005). Oliveira and Loucks (1997) proposed a GA optimization model to derive multi-reservoir operation policies, taking into account the information needed to define both system releases and individual reservoir storage targets.

In most of the previous studies, a three-cycle algorithm has been employed for the development of reservoir operation policies. This algorithm cycles through a deterministic or stochastic optimization model, a multiple regression analysis, and a hydrological simulation. In this process, the optimal releases, obtained from the

<sup>1</sup> Department of Civil Engineering, University of Tehran, Tehran, Islamic Republic of Iran.

<sup>2</sup> Department of Irrigation and Reclamation Engineering, University of Tehran, Karaj, Islamic Republic of Iran.

\* Corresponding author; e-mail: smhosseini@ut.ac.ir



optimization model which determines the optimal reservoir release time series, are regressed to determine the monthly operating rules as a function of actual or forecasted inflows to the reservoir and the extent of water storage in the reservoir. In this approach, reservoir releases or storages are usually the decision variables of the optimization model.

Many research workers applied multi-cycle algorithms to find the optimal operation policies for river-reservoir systems. Young (1967) derived operation rules using simple and multiple linear regressions in which reservoir releases were estimated as based on inflow and reservoir storage. Bhaskar and Whitlatch (1980) considered a quadratic loss function and derived monthly releases through regression analysis by finding the relationship between optimal releases as input, and response variable to specified state variables of a system as predictors. Karamouz and Houck (1982) developed reservoir operation rules by deterministic optimization, using the DPR model which had an algorithm based on deterministic dynamic programming with a regression analysis. They employed a hydrological simulation model to assess the performance of the system. Karamouz *et al.* (1992) defined operation rules by coupling the regression analysis and real-time simulation with the optimization routine.

The major shortcoming with the three-cycle algorithms is that the optimization loop does not get any feedback from final results of hydrological simulation which shows the actual performance of a system using reservoir operating rules. Therefore, however the optimized series of releases and reservoir storages might show a good performance of a system, improper form of the operation policies might result in low efficiency of the overall modeling efforts. Another problem with using such search-based methods as GA in this type of optimization problem is the run-time and convergence speed. Selection of monthly releases or reservoir storages as the decision variables increases the population size and

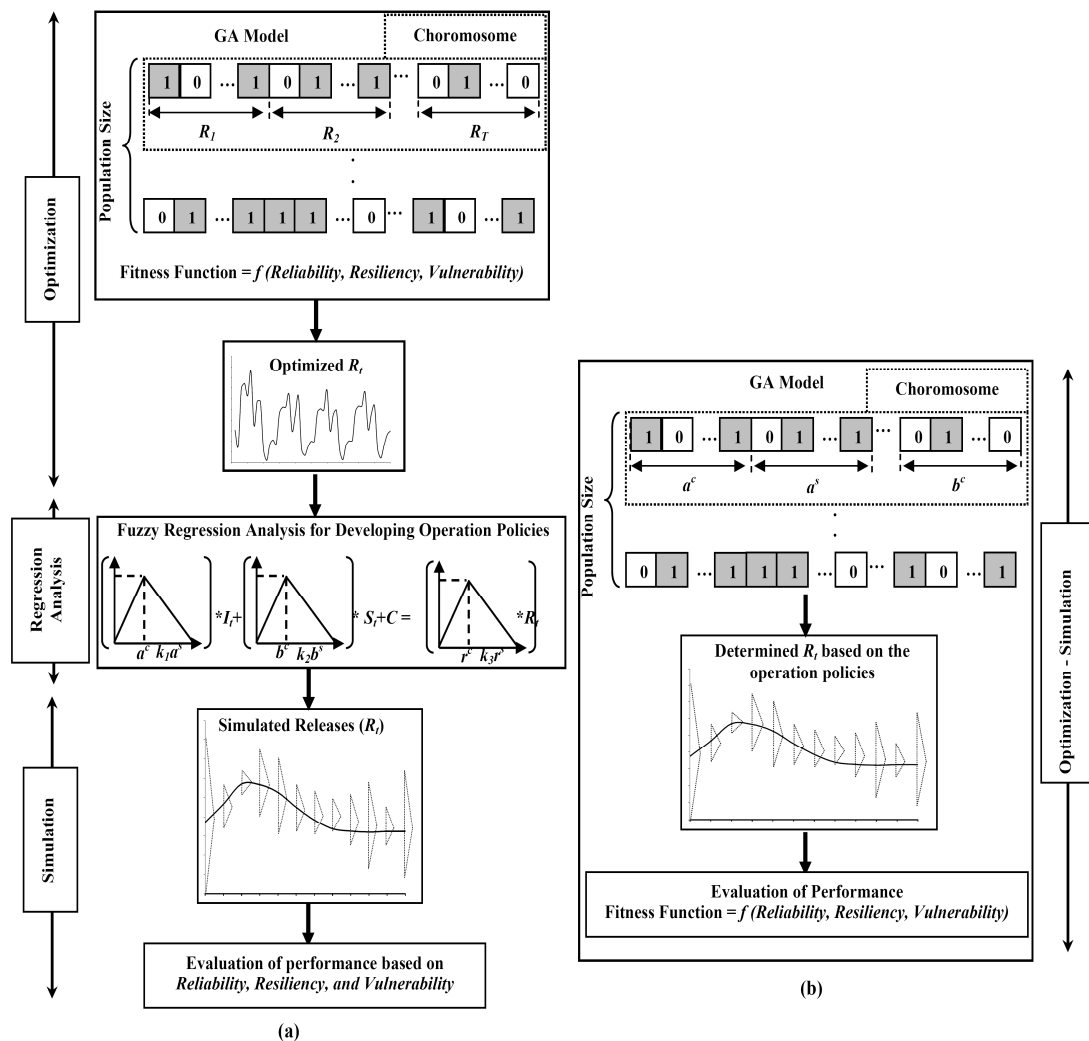
run-time of the model significantly and in many practical studies, it becomes needed to start with a proper initial solution, which is not easy to find either.

To tackle these shortcomings, in this paper, an integrated approach has been developed in which the coefficients of the operation policies are taken as the decision variables of the optimization model. For this purpose, a model is developed which is capable of carrying out all the three cycles of the previous approaches namely: reservoir operation optimization; regression analysis, and hydrological simulation. This model which is abbreviated as IOSGA in this paper has helped in significantly reducing the needed runtime of the modeling efforts and improving the overall performance of the operation policies. Figure 1 shows the general frameworks of the three-cycle algorithm and the IOSGA model.

### Overview of the Three Cyclic Algorithm and IOSGA Model

As can be seen in Figure 1-a, the three cyclic algorithm which is considered as a base for evaluating the performance of the IOSGA model, entails the following three major steps:

1. Optimization, in which a GA model is used to find the optimal series of reservoir releases. Equation (1) is here considered as the objective function while Equations (5), (6), and (7) include the constraints of the model.
2. Fuzzy regression analysis, in which the optimized values of monthly releases are considered as the dependent variable and monthly inflow series and optimized values of reservoir storage along the monthly demands are considered as independent variables of the regression equations. The cross validation technique has been employed and 12 policy equations are determined for different months of the year. A linear programming model has been developed to determine the fuzzy coefficients of the regression equations. In this step, the

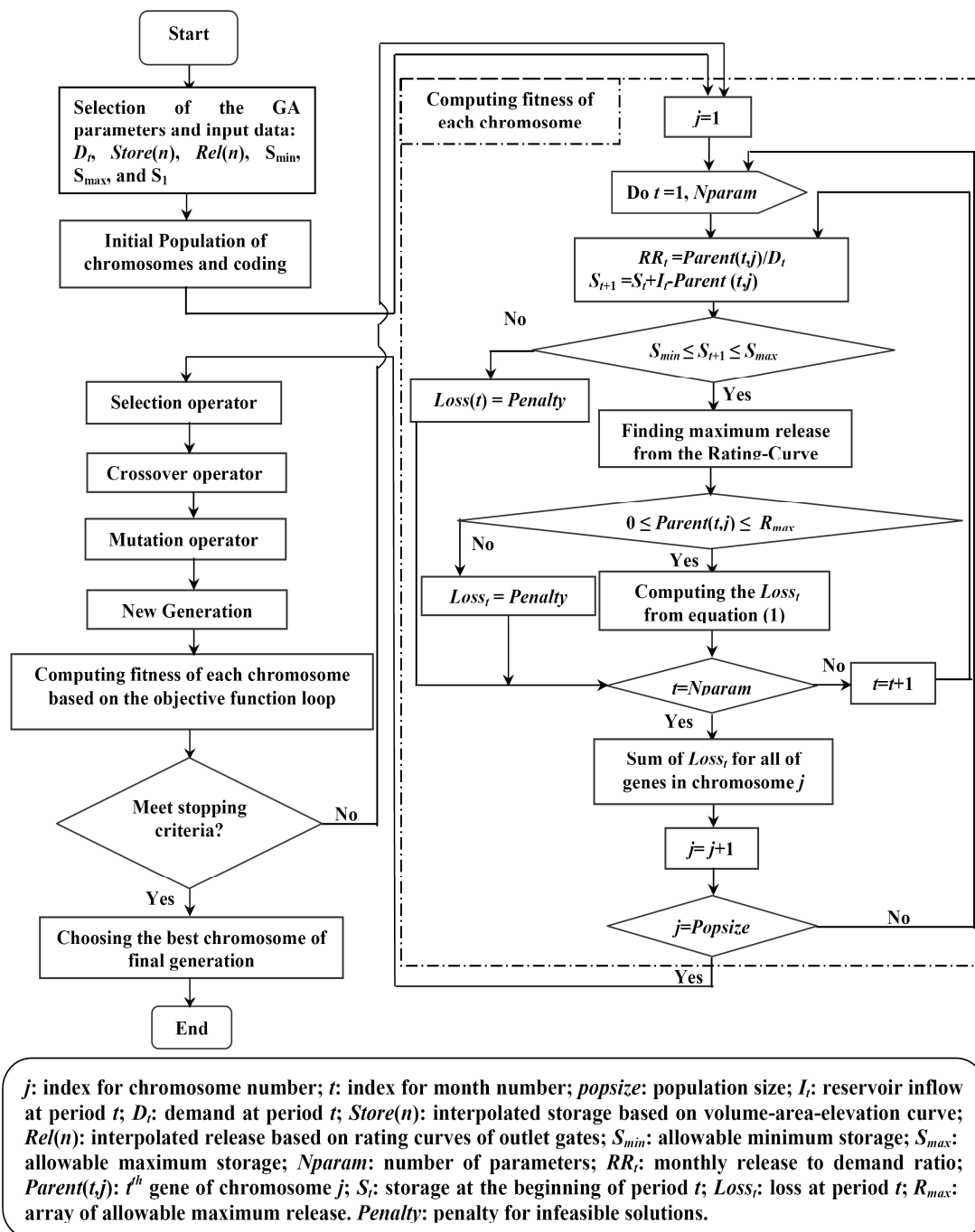


**Figure 1.** General framework of (a) The three-cycle algorithm and (b) The IOSGA model ( $R_t$ : Release in month  $t$ ;  $S_t$ : Storage in month  $t$ ;  $I_t$ : Inflow in month  $t$ ;  $a^c, b^c, c^c, r^c, a^s, b^s, c^s, r^s$ , and  $k_1, k_2, k_3$ : Fuzzy coefficients of the operation policies).

- variations of water demands in the planning time horizon are taken into account while the uncertainty of governing variables in the system (monthly inputs, demands, and storages) are also incorporated by adding fuzziness to the coefficients of regression. Because of the importance of this step in formulating the best form of the operating policies, three different equations namely Equations (8), (9), and (10) are taken into consideration.
- The results of step 2 are employed in a hydrological simulation model for evaluating the performance of the developed policies in achieving the

reservoir operation optimization objectives.

In the IOSGA model, as demonstrated in Figure 1-b, the three abovementioned steps have been summarized in one. For this purpose, the GA optimization model is formulated to find the optimal coefficients of the reservoir operation policies. As mentioned before, in the three cyclic algorithm, the optimization model does not receive any feedback from the long-term simulation of the system which is carried out based on the developed operation policies. Therefore, however the optimization results might be satisfactory in terms of different



**Figure 2.** Flowchart of the GA model in the three cyclic algorithm.

evaluation criteria, inefficiency of the operation policies might result in poor performance of the system. But, the IOSGA model incorporates the efficiency of the operation policies in the optimization process, and therefore it is expected that the

IOSGA model improves the value of objective function for the long-term simulation of the system. More details of the optimization model, operation policy formulations as well as results are presented in the forthcoming sections of the paper.

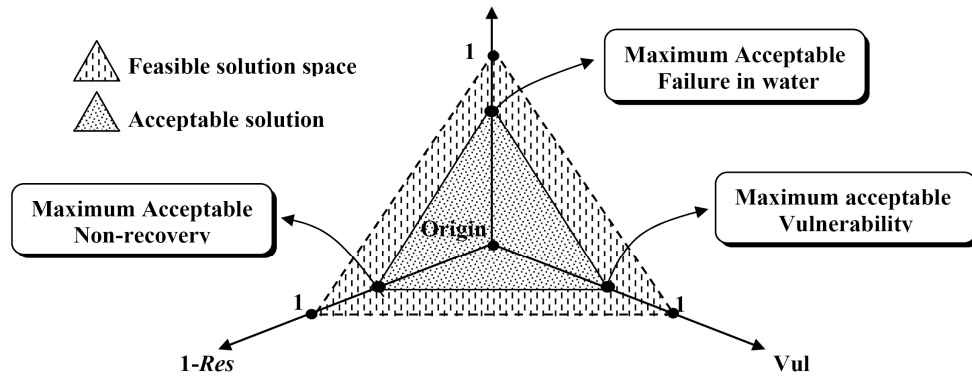


Figure 3. Three-dimensional feasible and acceptable risk space (Merabtene *et al.*, 2002).

### IOSGA Model Formulation

The IOSGA model is developed using binary genetic algorithm (BGA) code in Fortran Language. The objective function of the IOSGA model ( $Z$ ) is formulated as a linear function of the normalized values of Reliability ( $Rel$ ), Resiliency ( $Res$ ), and Vulnerability ( $Vul$ ) of the system (Merabtene *et al.*, 2002), as follows:

$$\begin{aligned} \text{Min } Z = & w_1 (1-Rel) + w_2 (1-Res) + w_3 Vul \\ (\sum_{i=1}^3 w_i = 1) \end{aligned} \quad (1)$$

where:

Reliability ( $Rel$ ) is defined as the ratio of the Number of months with Satisfactory performance ( $NS$ ) to the total number of operational time periods ( $T$ ):

$$Rel = \frac{NS}{T} \quad (2)$$

Throughout the study, satisfactory performance is achieved when a reservoir is capable of meeting all the demands, whenever a shortage encountered, it will be considered as a failure. Resiliency ( $Res$ ) is used to define the ability of a water supply system to recover to an "acceptable state", following a failure:

$$Res = Prob(R_{t+1} > D_{t+1} | R_t < D_t) \quad (3)$$

where  $D_t$  and  $R_t$  are water demand and release volumes in month  $t$ , respectively. Vulnerability ( $Vul$ ) criterion is introduced as

the ratio of the total water deficit to the total demand during the planning horizon ( $T$ ).

$$Vul = \frac{\sum_{t=1}^T (D_t - R_t)}{\sum_{t=1}^T D_t} \quad \text{when } R_t < D_t \quad (4)$$

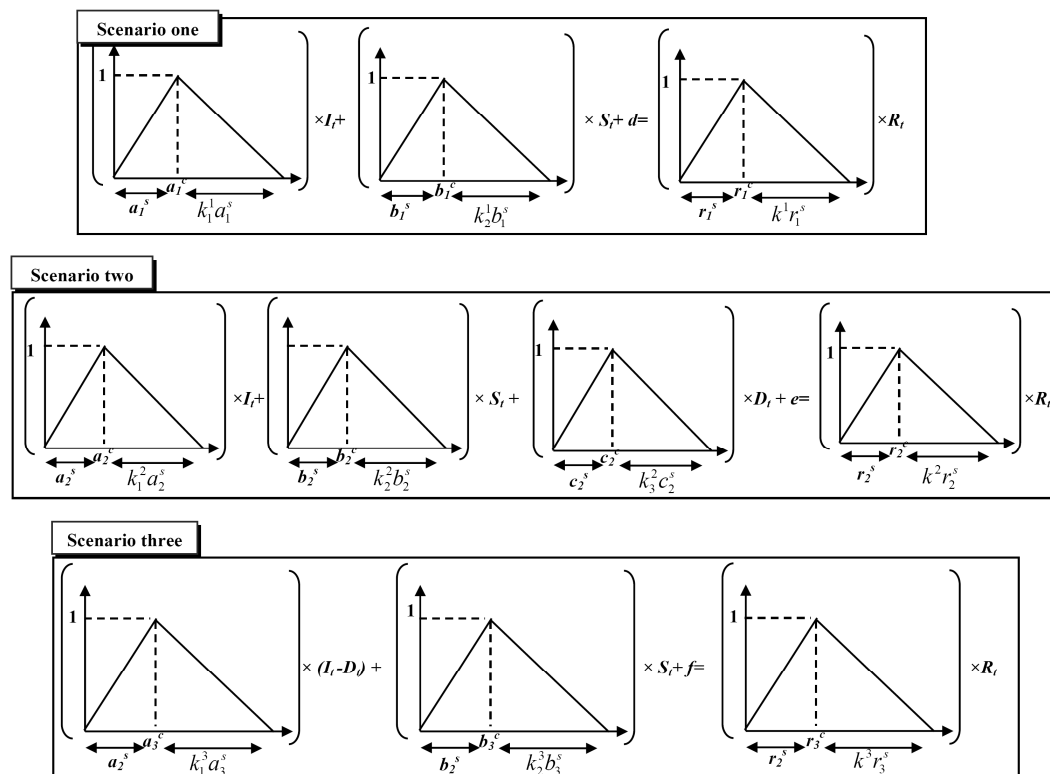
The weights  $w_1$ ,  $w_2$ , and  $w_3$  are to represent the conflict between system stability and system failure mode indicating the relative importance of the above mentioned criteria used for assessing the performance of the system. Throughout the study, it is assumed that the three criteria ( $Rel$ ,  $Res$ , and  $Vul$ ) are of the same importance and therefore, the weights are considered to be equal ( $w_1 = w_2 = w_3 = 1/3$ ). Figure 3 schematically indicates that the objective function can model simple performance failures (space near the origin) to major catastrophes (space near the dash-lines). In Figure 3, the maximum acceptable and feasible space of the risk criteria for a specific operation policy which has been defined for minimizing failure in water supply ( $1-Rel$ ), water shortage intensity ( $Vul$ ), and non-recovery speed from failure mode ( $1-Res$ ) is schematically indicated.

The constraints of IOSGA and the three cyclic algorithm models are defined as follows:

1). Mass balance equation for reservoir storage:

$$S_{t+1} = S_t + I_t - R_t \quad t = 1, \dots, T \quad (5)$$

where:



**Figure 4.** Fuzzy membership functions and relationships between regression coefficients in the three operation policies.

$R_t$ : Reservoir release in time  $t$ ,

$I_t$ : Reservoir inflow in time  $t$ ,

$S_t$ : Reservoir storage at the beginning of time  $t$ , and

$T$ : Planning horizon.

It should be mentioned that the reservoir inflows which are used in this study are the net values of inflows including monthly reservoir infiltration, evaporation losses, as well as precipitation over the reservoir.

2). Reservoir storage and release boundary conditions:

$$S_{\min} \leq S_t \leq S_{\max} \quad t = 1, \dots, T \quad (6)$$

$$0 \leq R_t \leq R_{t,\max} \quad t = 1, \dots, T \quad (7)$$

where:

$S_{\min}$ : Minimum reservoir storage,

$S_{\max}$ : Maximum reservoir storage, and

$R_{t,\max}$ : Maximum release capacity of the reservoir outlet gates in time  $t$  which is a function of reservoir storage.

### Operation Policy Equations

In the IOSGA model, three different forms

of operation policies in the forms of fuzzy linear regression are considered as follows:

Operation policy 1):  $(r_1^c, k_1^1 r_1^s)$ .  $R_t = (a_1^c, k_1^1 a_1^s) \cdot I_t + (b_1^c, k_2^1 b_1^s) \cdot S_t + d$  (8)

Operation policy 2):  $(r_2^c, k_2^2 r_2^s)$ .  $R_t = (a_2^c, k_2^2 a_2^s) \cdot I_t + (b_2^c, k_2^2 b_2^s) \cdot S_t + (c_2^c, k_3^2 c_2^s) \cdot D_t + e$  (9)

Operation policy 3):  $(r_3^c, k_3^3 r_3^s)$ .  $R_t = (a_3^c, k_3^3 a_3^s) \cdot [I_t - D_t] + (b_3^c, k_2^3 b_3^s) \cdot S_t + f$  (10)

where:

$D_t$ : Water demand in time period  $t$ ,

$r_i^c, a_i^c, b_i^c, c_i^c$ : The center of the fuzzy coefficients of monthly release, inflow, storage, and demand variables, respectively,

$r_i^s, a_i^s, b_i^s, c_i^s$ : The spread of the fuzzy coefficients of monthly release, inflow, storage, and demand variables, respectively,

$k_i^j$ : The skew factors of membership functions for fuzzy coefficients of

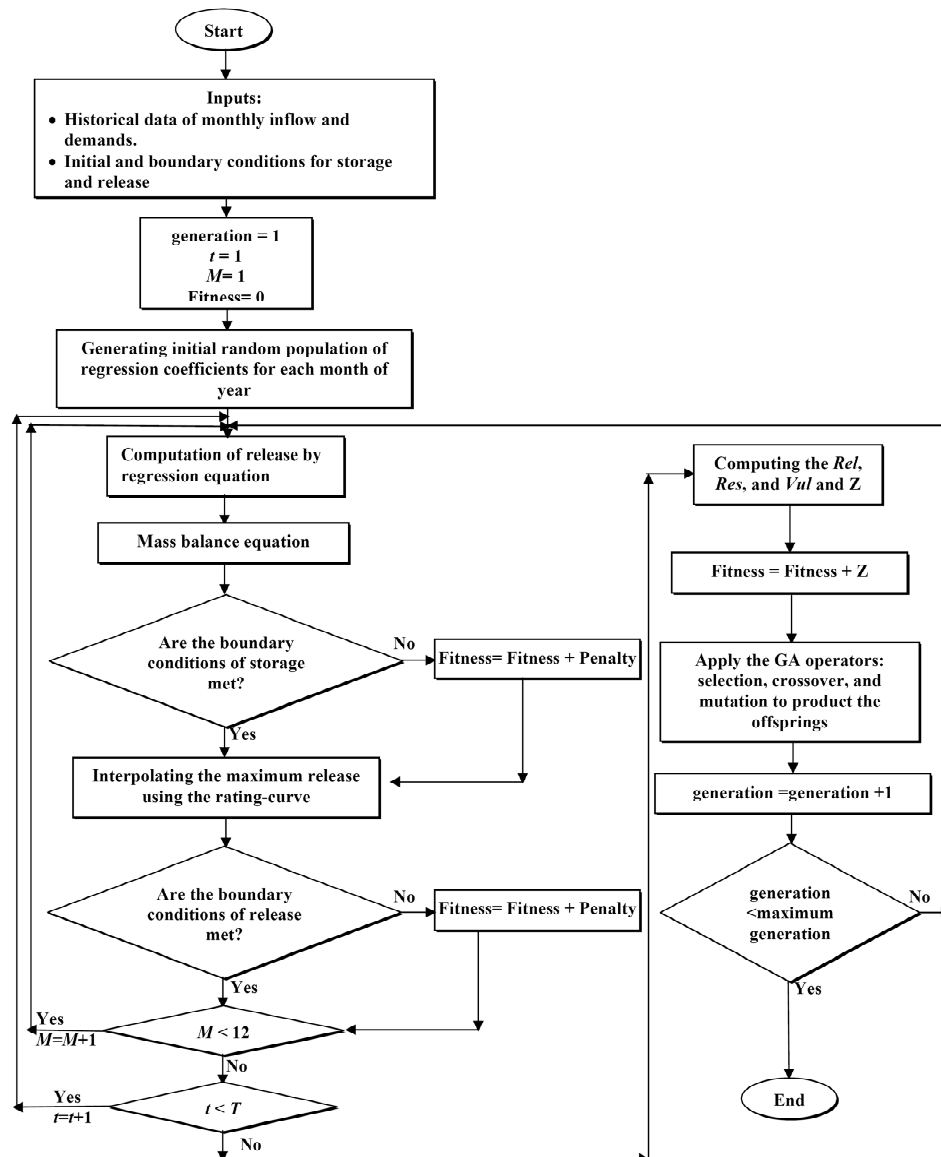


Figure 5. Flowchart of the IOSGA model.

independent variable  $i$  in the  $j^{\text{th}}$  operation policy, and

$d, e, f$ : Constants of the regression equations.

It should be noted that the Eqs. 8 to 10 are selected based on the previous studies by Karamouz et al. (1992) and Torabi (1996) in which they used classic linear regression as follows:

$$\begin{aligned} &\text{Operation policy 4)} \\ &R_t = a_1 \cdot I_t + b_1 \cdot S_t + d \end{aligned} \quad (11)$$

Operation policy 5)

$$R_t = a_2 \cdot I_t + b_2 \cdot S_t + c_2 \cdot D_t + e \quad (12)$$

Operation policy 6)

$$R_t = a_3 \cdot (I_t - D_t) + b_3 \cdot S_t + f \quad (13)$$

where:

$a_i, b_i, c_i, d, e, f$ : Coefficients of classic linear regression equations.

In this study, both operation policy Equations of (1) to (3) and (4) to (6) are used in the IOSGA model and the results are compared.

Figure 4 shows the membership functions and the relationships between the regression



variables in the operation policies in Equations (1) to (3), schematically. In IOSGA model, the optimal values of fuzzy coefficients parameters as well as constant values have been considered as decision variables, therefore the model can be used to find their optimal values.

The parameters of the operation policy equations namely:  $a_i^c, b_i^c, c_i^c$ ;  $a_i^s, b_i^s, c_i^s$ ; and  $d, e, f$ , during the twelve months of the year are selected as the decision variables of the IOSGA model and therefore the total number of decision variables (chromosome length) for the operation policies in Equations (1), (2) and (3) are amounted to  $7 \times 12 = 84$ ,  $10 \times 12 = 120$ , and  $7 \times 12 = 84$ .

The skew factors ( $k_j^i$ ) are also considered as the decision variables in the IOSGA model. The upper and lower limits of the coefficients are considered to be free, while the skew coefficients are limited to [0, 1]. The defuzzifier method, which has been used, is centroid defuzzifier. Figure 5 indicates schematically the flowchart of the optimization algorithm in IOSGA model.

The next step in using IOSGA Model is to assess the long-term performance of the system using the optimal operation policies developed by the model. For this purpose, system performance is simulated using leave-one-out-cross-validation technique (LOOCV).

In the LOOCV method, for each specific month, the data for the rest of months is used for calibrating the operation policies and the derived policy is employed for reservoir operation simulation in that specific month. This process is repeated for all the available historical data.

### The Formulation of Models in the Three Cyclic Algorithm

Figure 2 shows the algorithm of the GA model in the three cyclic algorithm. The model is developed using binary genetic algorithm (BGA) code in Fortran Language. The objective function and the constraints of the GA optimization model in the three cyclic algorithm is the same as in IOSGA model as shown in Equation (1) and Equations (5) to (7), respectively. The decision variables in this model are reservoir releases in different months of the planning horizon. Therefore, the total number of decision variables are equal to  $T \times 12$  in which  $T$  is the number of years in the planning horizon.

The next step, as shown in Figure 1-a, is the regression analysis to estimate the parameters in the operation policy equations. The operation policies shown in Equations (8) to (10) are employed. The following Linear Programming Problem (LPP) needs to be solved in order to find the fuzzy coefficient parameters based on the long-term optimal operation results.

Tanaka *et al.* (1982) formulated a LPP to determine the fuzzy number coefficients with asymmetric membership functions where data available is non-fuzzy. In the present study, LPP approach is employed to estimate the coefficients of the operation policies in the three operation policies shown in Equations (8) to (10). Based on Yen *et al.* (1999), the fuzzy linear regression with triangular membership function is capable of reflecting the uncertainty in regression coefficients. The LPP formulation for the second operation policy [Equation 10] is presented here as an example (Yen *et al.*, 1999) (Equations 14, 15):

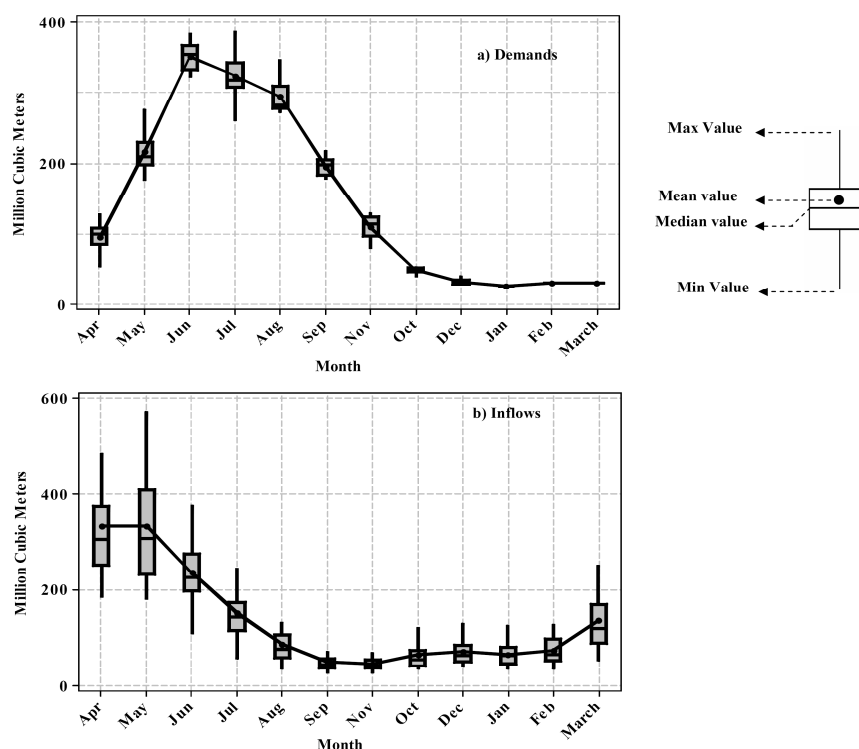
Minimize

$$Z = (1 + k_1) a_2^s \sum_{t=1}^N |I(t)| + (1 + k_2) b_2^s \sum_{t=1}^N |S(t)| + (1 + k_3) c_2^s \sum_{t=1}^N |D(t)| + d \quad (14)$$

Subject to:

$$\begin{cases} (1-h)I(t)a_2^s + (1-h)S(t)b_2^s + (1-h)D(t)c_2^s + d + I(t)a_2^c + S(t)b_2^c + D(t)c_2^c \geq R(t) \\ (1-h)k_1 I(t)a_2^s + (1-h)k_2 S(t)b_2^s + (1-h)k_3 D(t)c_2^s - d - I(t)a_2^c - S(t)b_2^c - D(t)c_2^c \geq -R(t) \end{cases} \quad (15)$$





**Figure 6.** The box-plot of the historical (a) Demands and b) Inflows to the Zayandeh-rud Reservoir.

where  $a_2^s, b_2^s, c_2^s$  refer to the spread of the fuzzy membership functions for the coefficients of the inflow, storage, and the water demands, respectively,  $h$  is the target level of belief (this term is considered as a measure of goodness of fit),  $a_2^c, b_2^c, c_2^c$  refer to the center of fuzzy membership functions for the coefficients of inflow, storage, and water demand, respectively, and  $k_i$  refers to skew factor of these variables.

The optimized values of skew factors for the fuzzy coefficients must be estimated through sensitivity analysis. In the present study, the optimal values of the skew factors estimated by the IOSGA model are employed as input values for these parameters in the three cyclic algorithm.

The next step in this process is the reservoir operation simulation for assessing the performance of the system using the optimal operation policies. The LOOCV method is also used for simulation of the system performance as explained in the previous section of the paper.

## Case Study

Zayandeh-rud Reservoir with a watershed area of about 41,500 Km<sup>2</sup> is located in a semi-arid region in central part of Iran. This reservoir has been constructed for supplying the agricultural, domestic, and industrial water demands. The total capacity of the reservoir is about 1,450 million cubic meters. Monthly inflows and water demands in a 29 year time horizon were employed for evaluating the performance of the models developed in this study (Figure 6).

The variations of water demands are estimated based on climatic variations recorded in the climatological stations in Zayandeh-rud basin. As can be seen in Figure 6, the highest ranges of variations in water demands have occurred in the months of May to July. It should be mentioned that in the three cyclic algorithm model, the number of decision variables is equal to  $29 \times 12 = 348$ , whereas for IOSGA model it

**Table 1.** The evaluation criteria for selecting the best form of policy equation in two approaches.

Model	Operation policy	Skew factors	Evaluation Criteria				
			<i>Rel</i> (%)			<i>Res</i> (-)	<i>Vul<sub>Max</sub></i> (MCM) <sup>a</sup>
			80	90	100		
Three cyclic algorithm (with FLR <sup>b</sup> )	One	$k_1^1 = 0.08 ; k_2^1 = 0.23$	88	80	75	0.33	160
	Two	$k_1^2 = 0.16 ; k_2^2 = 0.05 ; k_3^2 = 0.11$	93	83	79	0.55	139
	Three	$k_1^3 = 0.28 ; k_2^3 = 0.17$	92	81	73	0.49	165
IOSGA model (with CLR <sup>b</sup> )	Four	-	80	77	75	0.76	250
	Five	-	85	84	81	0.34	245
	Six	-	84	82	80	0.35	260
IOSGA model (with FLR <sup>b</sup> )	One	$k_1^1 = 0.08 ; k_2^1 = 0.23$	88	86	84	0.23	105
	Two	$k_1^2 = 0.16 ; k_2^2 = 0.05 ; k_3^2 = 0.11$	98	97	96	0.53	99
	Three	$k_1^3 = 0.28 ; k_2^3 = 0.17$	94	95	95	0.45	124

<sup>a</sup> Million cubic meters.<sup>b</sup> CLR and FLR refer to classic and fuzzy linear regression, respectively.

is varied depending on the formulation of operation policies as explained before.

## RESULTS AND DISCUSSION

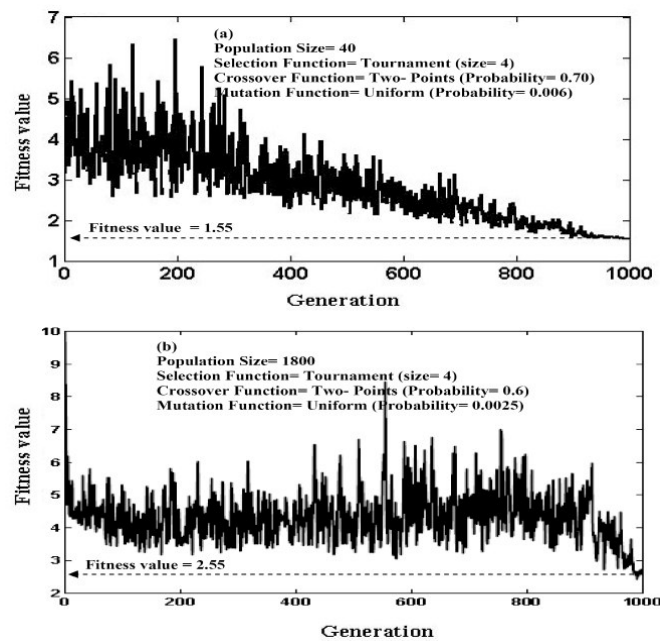
To select the best set of parameters of GA model, a sensitivity analysis has been carried out. The GA operators that were used in IOSG and the operation optimization models in the three cyclic algorithm include two-point crossover, tournament selection, and uniform mutation operators. The trend of GA convergence and the best set of parameters of the GA model in the two models, which were obtained by sensitivity analysis are shown in Figure 7.

The best set of GA operators in the IOSGA model, include: Population size= 40; Tournament selection size= 4; two-points crossover probability= 0.70; uniform mutation probability= 0.006, and in three cyclic algorithms: population size=1800; tournament selection size= 4; two-points crossover probability= 0.60; uniform mutation probability= 0.0025. The number of function evaluations needed for convergence of the IOSGA model has been 920, which is about 56 percent less than the number of function evaluations needed for

the convergence of the optimization model in the three cyclic algorithm (2200). It should also be remembered that without considering a good initial solution (good initial population) in the three cyclic algorithm, the convergence of GA is nearly unattainable.

As indicated earlier, the skew factor values ( $k_i$ ) for each coefficient in the three operation policies have also been considered as decision variables in the IOSGA model. The optimal values of these parameters are shown in Table 1. These values are used in the three cyclic algorithm as well.

For selecting the best form of fuzzy linear regression in either one of the approaches, the efficiency of the system in water supply (*Rel*), the speed of system recovery (*Res*) following occurrence of a failure and the maximum vulnerability of the system (*Vul<sub>Max</sub>*) are also considered with the results shown in Table 1. As evident from this table, when comparing the IOSGA model with fuzzy operation policies and the three cyclic algorithm with the same group of operation policies, the IOSGA model is of a higher efficiency in terms of reliability in supplying demands, and of maximum vulnerability as compared with the three-cycle model. The speed of system recovery



**Figure 7.** Trend of GA convergence and optimum set of parameters of GA in (a) IOSGA model and (b) Three cyclic algorithm.

in the three cyclic model is higher than that in IOSGA model.

In the mean time, to investigate the effects of fuzzy linear regression on the results, IOSGA model has also been solved using the classic linear regression (CLR) (operation policies 4, 5, and 6). The results have been shown in Table 1. As can be seen from the table, the fuzzy operation policies show a better performance in terms of all the three criteria except for the resiliency criterion, when using the operation policy 4.

Table 2 shows the percentage of improvement of  $Rel$ ,  $Res$  and  $Vul_{max}$  of the results of IOSGA model applying operation policies 1 to 3 to the same model when using operation policies 4 to 6 and the three cyclic

algorithm. The results in Table 2 indicate a higher efficiency of IOSGA model in terms of reliability of supplying demands and maximum vulnerability while using fuzzy operation policies of Equations (8) to (10). Comparing the results of the IOSGA model using the fuzzy operation policies 1 to 3 also shows that the second operation policy [Equation (9)] outperforms the other two policies. As it can be seen in the above table, the operation policies have been improved by incorporating variable demands,  $D_t$ . Figure 8 shows the comparison between monthly water demands and the release fuzzy membership functions determined using the IOSGA model with the operation policy 2. As it can be observed, the spread of

**Table 2.** The improvement percentage of the results of IOSGA model with FLR compared with IOSGA with CLR and the three cyclic algorithm.

Model	Operation policy	Evaluation Criteria				
		$Rel$			$Res$	$Vul_{Max}$
		80	90	100		
Three cyclic algorithm	One	0	8	12	-30	34
	Two	5	17	22	-4	29
	Three	2	17	30	-8	25
IOSGA model (with CLR)	One	10	12	12	-70	58
	Two	15	15	19	56	60
	Three	12	16	19	29	52



fuzzy membership functions cover the variability of demands in different months. The conformity of optimized monthly releases (using the operation policy 2) of the three cyclic algorithm and the range of monthly releases fuzzy membership functions obtained from IOSGA model is investigated and shown in Figure 9. This figure indicates that the release's fuzzy membership function obtained from IOSGA model is capable of covering the range of monthly releases obtained from the three cyclic algorithm. During the last months of the year (October to December), the range of releases of the IOSGA model is lower than the releases obtained from the three cyclic algorithm which is more compatible with the low water demands during these months.

The population size, number of generations, and the number of parameters are playing their main roles in the run-time of GA models. The values of these parameters for both models are listed in Table 3. As seen in the table, by using the IOSGA model developed in this study, population size is decreased by about 98 percent (1,800 to 40) and number of decision variables is also reduced from 348 to 87.

To evaluate the suitability of the IOSGA and the three cyclic models for supplying demands, two criteria were chosen to analyze the degree of goodness of fit as follows:

- 1). The coefficient of efficiency ( $CE$ ):

$$CE = 1 - \frac{\sum_{t=1}^T [R_t - D_t]^2}{\sum_{t=1}^T [D_t - \bar{D}]^2} \quad (12)$$

where  $\bar{D}$  is average monthly demand (Nash and Sutcliffe 1970). Closer  $CE$  to one

indicates better fit.

- 2). Standard error ( $SE$ ):

$$SE = \frac{\sqrt{\frac{1}{T} \sum_{t=1}^T [R_t - D_t]^2}}{\bar{D}} \quad (13)$$

Closer  $SE$  to zero shows a better fit. The values of  $CE$  for IOSGA model and the three cyclic algorithm (with the operation policy 2) are estimated as 0.90 and 0.87, respectively. The second criterion figures for IOSGA model and the three cyclic algorithm are estimated as 0.26 and 0.29, respectively. The IOSGA model has a higher  $CE$  while a less  $SE$ , which shows a better consistency between the release and demand series.

## CONCLUSIONS

An integrated approach for development of reservoir operation policies is presented here in which the decision variables of the model are fuzzy coefficients of the reservoir operating rules. This setup for the optimization model helped in reducing the modeling efforts as compared with the three-cycle modeling approach (optimization, regression analysis for development of operation policies, hydrological simulation for assessing the performance of the system using the operation policies).

The results of application of the model to the Zayandeh-Rud River-reservoir system in central part of Iran using GA as the solution to the optimization model has shown that the run-time of the model has been significantly reduced while the performance of the system, with respect to the reliability of meeting of the demands as well as vulnerability, being improved. On the other hand, the statistical

**Table 3.** Evaluation of the long-term performance of the optimal operation policies through different models.

Model	GA parameters		
	No. of parameters	Population size	No. of function evaluation
Three-cycle modeling approach	348 <sup>a</sup>	1800	2200
IOSGA model	87 <sup>b</sup>	40	920

<sup>a</sup> According to the  $R_t$ ;  $t=1, \dots, 348$

<sup>b</sup> According to the regression coefficients of operation policy two (12×7) and their skew factors (3).

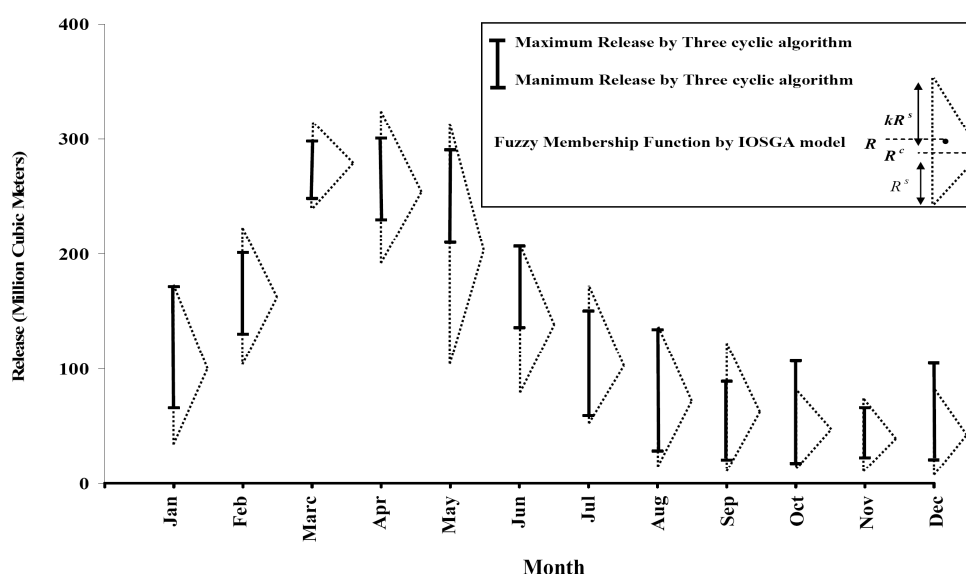


Figure 8. Optimized average monthly releases and the fuzzy membership functions

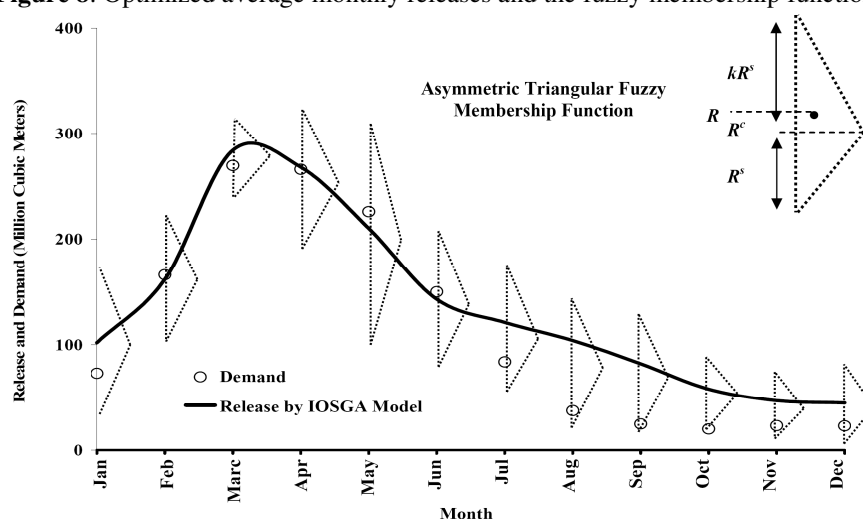


Figure 9. Conformity of the optimized release fuzzy membership function obtained from IOSGA model and the range of optimized releases by three cyclic algorithm using operation policy 2 in either model.

criteria for evaluating the model suitability indicate that the IOSGA model shows better performance than the three cyclic model in terms of supplying demands. The results also indicate that when the water demands, including the values of monthly demands in the operation policies are varied, it helps in improving the long-term efficiency of the system performance.

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## تدوین سیاست‌های بهره‌برداری از مخزن: یک رهیافت تلفیقی

ب. زهرایی و س. م. حسینی

### چکیده

هدف این تحقیق تدوین یک مدل شبیه‌سازی-بهینه‌سازی بهره‌برداری از مخزن با در نظر گرفتن تغییرات نیاز آبی می‌باشد. تابع هدف مدل بهینه‌سازی ترکیب خطی از اطمینان‌پذیری، برگشت‌پذیری و آسیب‌پذیری سیستم رودخانه-مخزن در نظر گرفته شده است. الگوریتم ژنتیک به منظور بهینه نمودن ضرایب معادله سیاست بهره‌برداری بکار گرفته شده است. به منظور در نظر گرفتن عدم قطعیت موجود در نیازهای آبی خصوصاً نیاز کشاورزی و همچنین مقادیر خروجی، این ضرایب در فرم اعداد فازی فرموله شدند. بواسطه تغییرات معنی‌دار نیاز آبی کشاورزی در ماه‌های مختلف و سال‌های مختلف، سری زمانی نیاز آبی پایین دست مخزن مورد استفاده قرار گرفت. سیستم رودخانه-مخزن زاینده‌رود در مرکز ایران به عنوان مطالعه موردی ارزیابی مدل پیشنهادی در نظر گرفته شد. به منظور بررسی کارایی مدل پیشنهادی، رهیافت سه سیکلی که کاربرد فراوان در بهره‌برداری از مخزن دارد، مورد استفاده قرار گرفت. نتایج این تحقیق نشان داد که رهیافت جدید در انتخاب متغیرهای تصمیم مسئله بهینه‌سازی و پارامترهای فازی مربوطه به‌طور قابل ملاحظه‌ای از زمان محاسبات می‌کاهد در حالی که عملکرد سیستم در ترم‌های اطمینان‌پذیری، برگشت‌پذیری و آسیب‌پذیری دارای مزیت می‌باشد.