Development of Fuzzy Reservoir Operation Policies Using Genetic Algorithm

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Abstract: This study is focused on developing an integrated optimization-simulation model to develop the operation policies for a multi-purpose reservoir. Objective function of the optimization model is considered to be a linear function of reliability, resiliency, and vulnerability of river-reservoir systems. Genetic Algorithm (GA) is used to solve the optimization model in which the coefficients of the reservoir operation policy equations are considered as the decision variables. These coefficients are formulated in the form of fuzzy numbers to better capture the variations in releases and water demands. Due to significant variations of agricultural water demands in 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 as the case study. Results of this study have shown that the developed algorithm can significantly reduce the time and costs of modeling efforts and also the run-time of the GA model, while it has also improved the overall performance of the system.

Key-Words: Reliability, Resiliency, Vulnerability, Genetic Algorithm, Zayandeh-rud Reservoir, Fuzzy Regression.

1- Introduction

Development of optimization and simulation models to define the reservoir operation policies has been the focus of many researchers for many years. Labadie (2004) discussed the state-of-the-art review for reservoir operation management. Simonovic et al. (1992) presented a review of mathematical models for reservoir operation management.

Among different optimization methods, the genetic algorithm (GA) represents an efficient and robust search method for non-linear optimization problems and has been quite successfully applied to a number of reservoir operation optimization problems [2, 3, 4, 10].

In most of the previous studies, a three-cycle algorithm has been used for development of reservoir operation policies. This algorithm cycles through a deterministic or stochastic optimization model, a multiple regression analysis, and a hydrologic simulation. In this process, the optimal releases, obtained from the optimization model, are regressed to determine the monthly operating rules as a function of actual or forecasted inflows to the reservoir and the amount of water storage in the reservoir. In this approach, usually reservoir releases or storages are the decision variables of the optimization models.

Many researchers have 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 release was estimated based on inflow and reservoir storage. Bhaskar and Whitlatch (1980) considered a quadratic loss function and derived monthly releases by regressing optimal set of releases on the input and state variables of system [1]. Karamouz and Houck (1982) developed reservoir operation rules by deterministic optimization using the DPR model. The DPR model had an algorithm based on deterministic dynamic programming with a regression analysis and next, to asses the performance of system a simulation model is applied [5]. Karamouz et al. (1992) defined operation rules by coupling the regression analysis and real-time simulation with the optimization routine [6].

The major shortcoming with this three-cycle algorithm is that the optimization loop does not get any feedback from the final results of simulation of the performance of the system using reservoir operating rules. Therefore, however the optimized series of releases and reservoir storages might show a good performance of the system, improper form of the operation policies might result in low efficiency of the overall modeling efforts. Another problem with using search-based methods such 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 will be needed to start with a proper initial solution, which is not also easy to find.

To tackle these short-comings, in this paper, an integrated approach has been developed in which the coefficients of the operation policies are considered as the decision variables of the optimization model. This model is called Integrated Optimization Simulation GA (IOSGA) model. This algorithm has helped in significantly reducing the runtime and the modeling efforts needed in the three cycle approach and also improving the overall performance of the modeling efforts. Fig. 1 shows the general frameworks of the three-cycle algorithm and the IOSGA model, which is developed in this study.

2- Model Formulation

The objective function of the IOSGA model is formulated as a linear function of the reliability (*Rel*), resiliency (*Res*), and vulnerability (*Vul*) of the system as follows [8]:

$$\text{Max} \quad Z = w_1(1-Rel) + w_2(1-Res) + w_3\, Vul \quad \left(\sum_{i=1}^{3} w_i = 1\right) \tag{1}$$

The weights of w_1, w_2, and w_3 reflect the conflict between system stability and system failure mode and show the relative importance of the above mentioned criteria used for assessing the performance of the system. In this study, these weights are considered to be equal ($w_1 = w_2 = w_3 = 1/3$). The maximum acceptable and feasible space of the risk criteria for a specific scenario has been defined for minimizing failure in water supply (1-*Rel*), water shortage intensity (*Vul*), and non-recovery speed from failure mode (1-*Res*).

The constraints of IOSGA model are defined as follows:

1. Mass balance equation for reservoir storages:

$$S_{t+1} = S_t + I_t - R_t \qquad t = 1,\ldots, T \tag{2}$$

Where:
R_t: Reservoir release in time t;
I_t: Reservoir inflow in time t;
S_t: Reservoir storage at the beginning of time t;
T: Time horizon

2. Reservoir storage and release boundary conditions:

$$S_{min} \le S_t \le S_{max} \qquad t = 1,\ldots, T \tag{3}$$

$$0 \le R_t \le R_{t,max} \qquad t = 1,\ldots, T \tag{4}$$

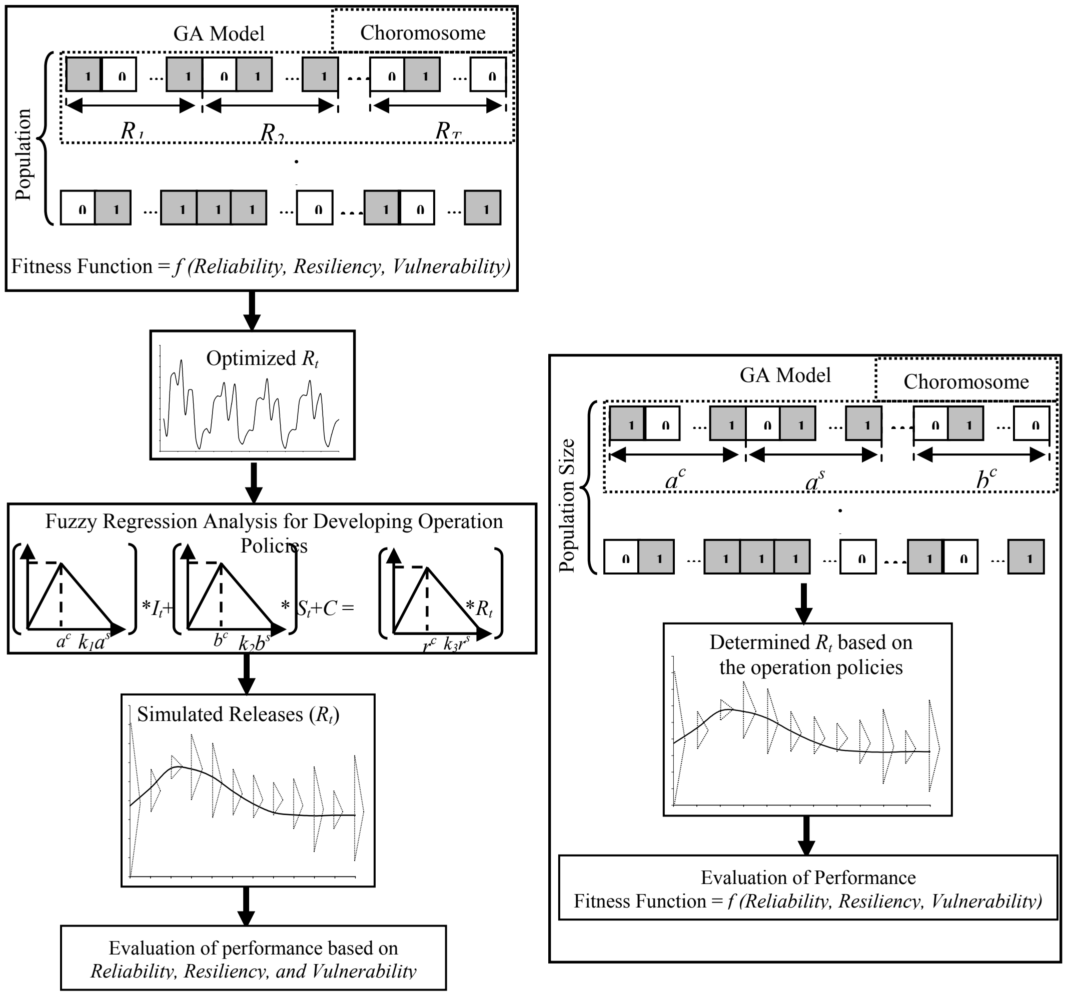
Where
S_{min}: minimum storage of reservoir;
S_{max}: maximum storage of reservoir;
$R_{t,max}$: maximum release capacity of the gates in time t, which is function of reservoir storage.

As it was mentioned before, development of reservoir operation policies has been considered as part of the optimization loop. For this purpose, fuzzy linear regression is considered as follow:

$$(r^c, k_4 r^s).R_t = (a^c, k_1 a^s)\,.\, I_t + (b^c, k_2 b^s).\, S_t + (c^c, k_3 c^s).D_t + d \tag{5}$$

Where:
D_t: Water demand in time t;
r^c, a^c, b^c, c^c: the center of the fuzzy coefficients of monthly release, inflow, storage, and demand variables, respectively;
r^s, a^s, b^s, c^s: the spread of the fuzzy coefficients of monthly release, inflow, storage, and demand variables, respectively;
k_1, k_2, k_3, k_4: the skew factors of membership functions for fuzzy coefficients of inflow, storage, demand, and release coefficients, respectively;
d: constant of regression equations.

Fig. 2 shows the membership functions and the relationships between the regression variables in this scenario, schematically. In this study, the skew factors for the fuzzy coefficients are considered to be equal to 0.1 ($k_1 = k_2 = k_3 = 0.1$) (Yen et al., 1999). As it was mentioned before, in this study, development of operation policies is considered as part of the optimization loop. Therefore, the parameters of operation policy equations including a^c, b^c, c,; a^s, b^s, c^s, and d in twelve months of the year are selected as the decision variables of the optimization model. The upper and lower limits of the decision are considered to be free. The defuzzifier method, which has been used, is centroid deffuzzifier. Fig. 3 indicates schematically the flowchart of IOSGA model.



(a) (b)

Fig. 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^i, b^i, c^i, r^i, and k_j: Fuzzy coefficients of the operation policies)

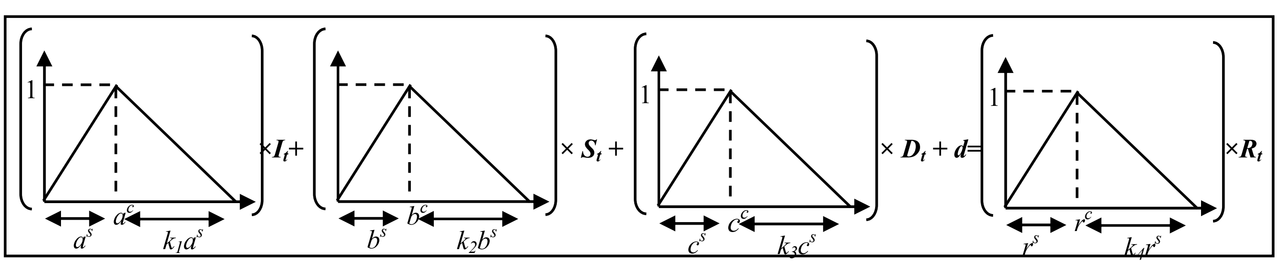


Fig.2. Membership functions and the relationships between the fuzzy regression variables

3- Case Study

The Zayandeh-rud Reservoir is located in a semi-arid region in central part of Iran and the area of its watershed is about 41500 km^2 (Fig. 4). This reservoir has been constructed for supplying agricultural, domestic, and industrial demands. The total capacity of the reservoir is about 1450 million cubic meters.

Monthly inflow and water demands in 29 years time horizon are used for evaluating the performance of the developed models in this study.

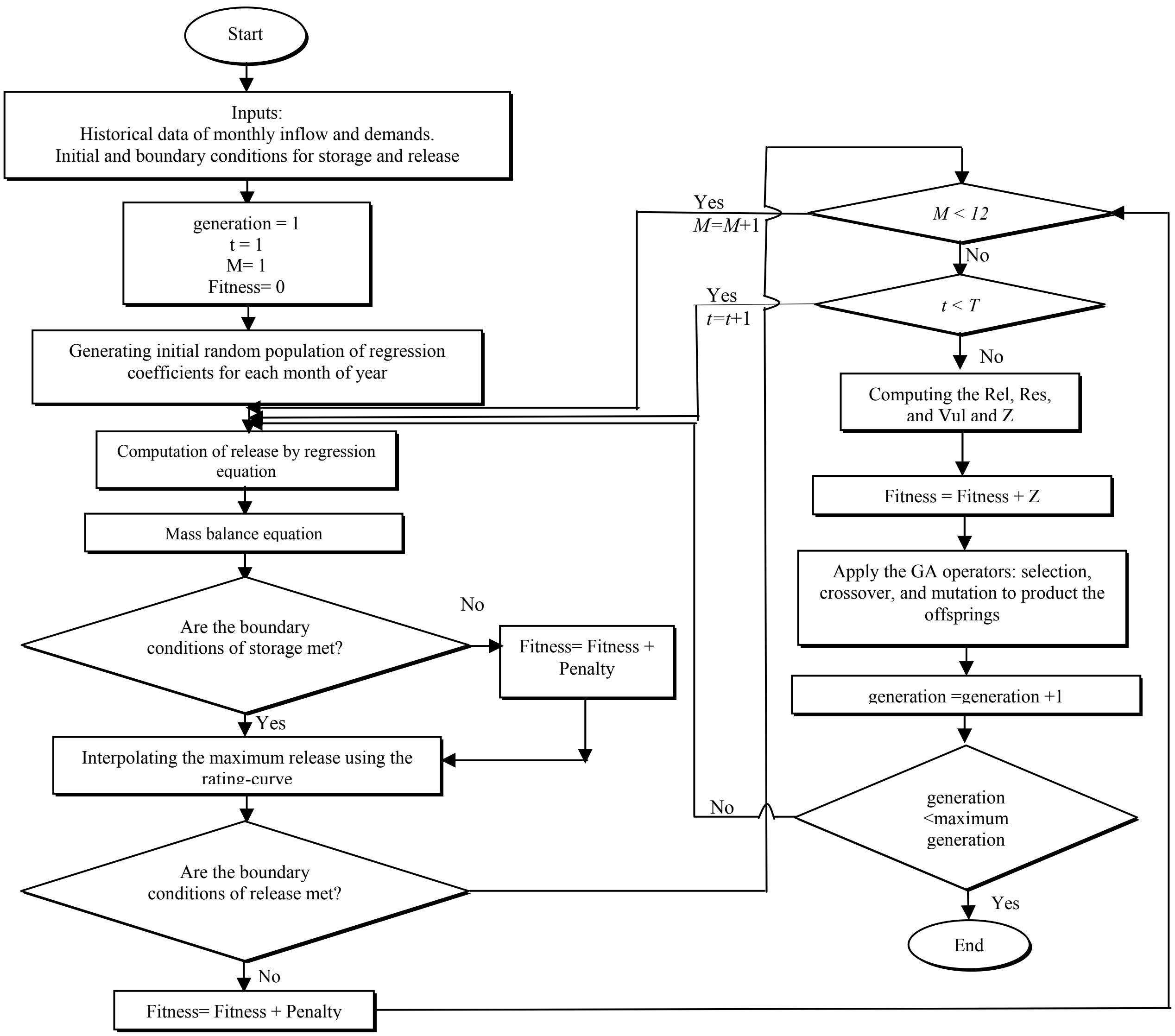


Fig. 3. Flowchart of the IOSGA model

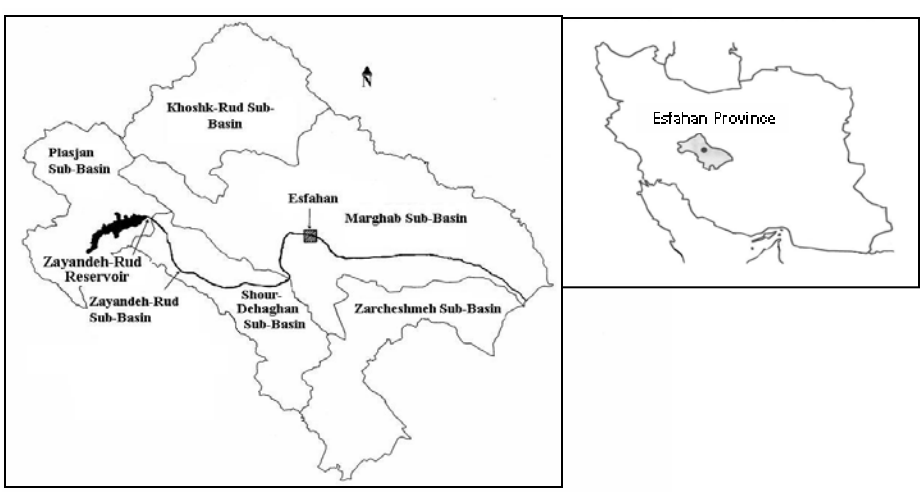


Fig. 4. Location of the Zayandeh-rud River-reservoir system and its sub-basins

4- Results and Discussion

To select the best set of parameters of GA model, sensitivity analysis has been carried out. The trend of GA convergence and best parameters of GA which obtained by sensitivity analysis in three cycle algorithm and IOSGA model are shown in Fig. 5(a,b). The number of generations needed for convergence of IOSGA model is 920 generations, which is about ten percent less than the number of generations needed in the three cycle algorithm. It should also be mentioned that without considering a good initial solution in three cycle algorithm, the convergence of GA is nearly unreachable.

The evaluation criteria *Rel*, *Res*, and *MaxVul* are computed to investigate the model performance in the planning horizon. Results of these criteria in Table 1 indicate that IOSGA model has higher efficiency in terms of reliability in supplying demands and less maximum vulnerability comparing with the three-cycle model. The speed of system recovery in three cycle model is higher than IOSGA model. Fig. 6 shows the monthly average releases and fuzzy membership functions.

The population size, number of generations, and number of parameters are playing main roles in run-time of GA model. The values of these parameters for both models are listed in Table 1. As it can be seen in this table, by using the IOSGA model developed in this study, population size is decreased about 98 percent (1800 to 40). Number of decision variables is also reduced from 348 to 84.

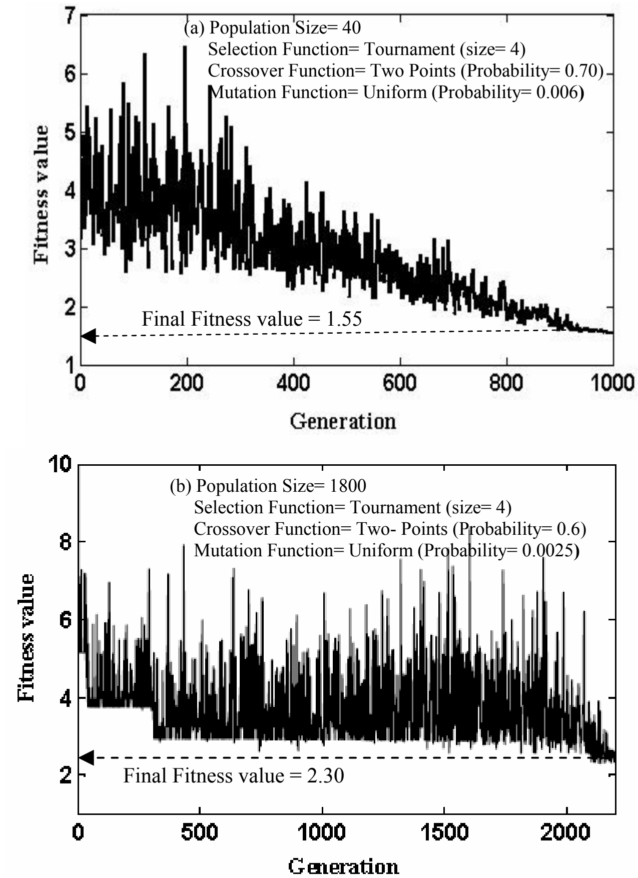


Fig. 5: Trend of GA converging and optimum parameters of GA in a) IOSGA model and b) three cycle algorithm

5- Conclusion

In this study, an integrated approach for development of reservoir operation policies is developed in which the decision variables of the model are fuzzy coefficients of the reservoir operating rules. This setup for the optimization model has helped in reducing the modeling efforts comparing with three-cycle modeling approaches (optimization, regression analysis for development of operation policies, simulation for assessing the performance of the system using the operation policies). Results of application of this model to the Zayandeh-rud River-reservoir system in central part of Iran using GA as the solver of the optimization model have shown that the run-time of the model has been reduced to more than 50% of the three cycle algorithm while the performance of the system with respect to reliability of supplying demands and vulnerability has also been improved.

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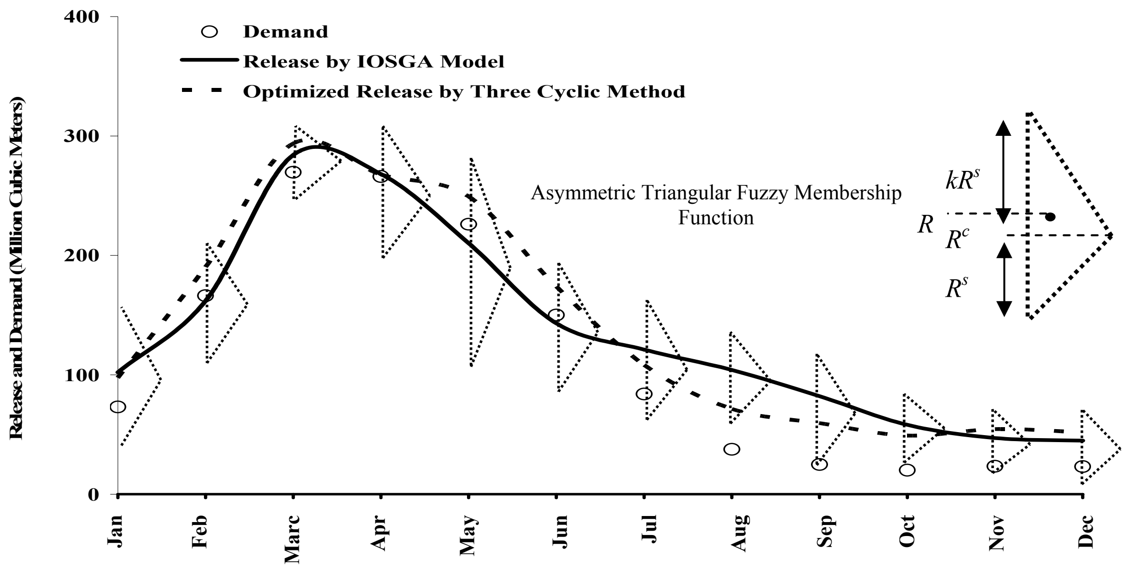

Fig 6. Optimized average monthly releases and the fuzzy membership functions

Table 1. Evaluation of the long-term performance of the optimal operation policies by IOSGA and the three cycle algorithm model

Model	GA parameters			Evaluation criteria		
	No. of parameters	Population size	No. of Generations to converge	*Rel* (percent)	*Res* (-)	*MaxVul* (MCM)*
Three-cycle algorithm	348	1800	More than 2000	94	0.54	159.6
IOSGA model	84	40	920	95	0.51	109.40

* Million Cubic Meters.

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