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An Optimizing Operational Model for Multiobjective Serial Reservoirs (Case Study of Aras River Basin, Northwestern Iran)

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Abstract: Using Genetic Algorithm (GA) for the practical multiple reservoir release problem in which various water utilizations are considered is important goal of this research. The investigation of developed GA technique was carried out through application to the Aras River Basin. In order to evaluate the efficacy and applicability of the present model in optimization of the operation of serial reservoir systems, the Aras River Basin in northwestern Iran was studied using this model. The area of this river basin is about 100,220 square kilometers. This technique is an optimization approach based on the mechanics of natural selection, derived from the theory of natural evolution. The fitness function used to minimize the squared deviation of monthly irrigation demand along with the squared deviation in mass balance equation, the penalty functions are included if the downstream demands did not satisfied. A real world multiple reservoir release problem was solved satisfactorily using the GA approach. The results of the GA were compared with those of Standard Operation Policy (SOP)'s simulation models. The GA derived operating curves bring the higher benefits, in terms of irrigation production and electricity production in the study area.

Key words: Optimizing · Reservoir · Genetic Algorithm · Aras River Basin

INTRODUCTION

Mathematical models are often used to make decision. When they are used to select the best alternative out of a large number of possibilities, they are called optimization models. This research introduces a new optimization technique to the multiple reservoir operation instead of using traditional simulation techniques.

Genetic Algorithm which is based on Darwin's principle of evolution was first proposed by Holland in 1960 and developed by him and his students and colleagues during 1960 to 1970, Goldberg and Deb [1].However complete introduction to GA was given by Goldberg[2].Oliveira and Loucks[3] reported that GA can be used to identify effective operation policies. Sharif and Wardlaw [4] used GA in water resource development and compared it with dynamic programming; they concluded that both results were comparable. Ahmed and Sarma [5]. Applied a piecewise-linear operating rule approach and a GA to single-reservoir optimization in India. They used 4, 6, 7 and 11 segmented piecewise-linear operating rules and generated synthetic monthly inflow data over 100 years using an artificial neural network (ANN). Last decade, Genetic Algorithms (GAs) has been applied to search optimal rule curves of the reservoir system [6-9]. The best part of GAs is that they can handle any type of objective function. Furthermore, the proposed model can handle any condition of reservoir simulation such as initial reservoir capacity and the period of inflow record. The accepted objective functions are a shortage index, frequency of water shortage, average water shortage and magnitude of water deficit. However, the appropriate objective function for searching the curves is average water shortage. Also, a smoothing function constraint is required to include into the proposed GAs for fitting the rule curves[10]. Raju and Nagesh Kumar [11] applied a GA for evolving an optimum cropping pattern utilizing surface

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water resources in the command area of a multipurpose reservoir system. Morshed and Kaluarachchi [12] employed three GA enhancement methods to a nonlinear groundwater problem for minimizing the costs of pumping for meeting a specific demand. Yandamuri *et al.* [13] and Dorn and Ranjithan [14], among others, couple MOGAs with water quality simulation models in order to find trade-offs between required contamination levels in river networks, treatment costs and land use alternatives. The preferred algorithm in most of the aforementioned studies is NSGA-II. According to Dorn and Ranjithan [14], NSGA-II outperforms the Pareto-Archived Evolution Strategy (PAES) and the Strength Pareto Evolutionary Algorithm (SPEA) in terms of computational efficiency and achieving a better spread along the final Pareto frontier. Nevertheless, NSGA-II failed to approximate a ''true'' Pareto frontier obtained with a single-objective GA and the e-constraint method . The main purpose of this research is to apply a GA to the practical multiple reservoir release problem in which many utilization of the multipurpose reservoirs are considered. The specific objectives are as follows:

- Applying a GA to the multiple reservoir operation in the Aras River Basin.
- Optimizing the operating curves for reservoir system in the Aras River Basin.
- Evaluating GA performance against that of conventional approach in multiple reservoir release problem.

MATERIALS AND METHODS

Genetic Algorithm: The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. We can apply the genetic algorithm to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear. The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

- *Selection rules* select the individuals, called *parents*, that contribute to the population at the next generation.
- *Crossover rules* combine two parents to form children for the next generation.
- *Mutation rules* apply random changes to individual parents to form children.

The genetic algorithm differs from a classical, derivative-based, optimization algorithm in two main ways, as summarized in the following Table 1.

Study Area: The investigation of developed GA technique has been carried out through application to the Aras River Basin. Aras River Basin is located in the north-western region of Iran. The basin total area is about 100,220 square kilometers. There are 2 reservoirs operated in the basin; Aras Reservoir and Khodaafrin Reservoir. The reservoir system is operated for two main purposes, irrigation, hydropower generation. Figure 1 and 2 illustrates basin location of study area in Iran and the schematic of reservoirs on the Aras River Basin. The Aras dam is built on Aras river at 50 kilometers north-east of Jolfa city in Iran. The dam site is located at the elevation of 749 m from sea-level, at 45.07 / E-longitude and 39.35/ N-latitude. The storage volume of this dam reservoir at normal pool level is 1500 million cubic meters. This storage volume can supply irrigation water for 140000 hectares of land. The minimum storage volume of reservoir equals to 200 million cubic meters .The average flow rate of Aras river at the dam-site is 183 m^3/sec. The Khodaafrin dam is built on Aras river at 50 kilometers north-east of Parsabad city in Iran. The dam site is located at the elevation of 250m from sea-level, at 47.40 / E-longitude and 39.42/ N-latitude. The storage volume of this dam reservoir at normal pool level is 1400 million

Table 1: Summary of Classical Algorithm and Genetic Algorithm

Classical Algorithm	Genetic Algorithm
Generates a single point at each iteration. The sequence of points approaches an optimal solution.	Generates a population of points at each iteration. The best point in the population approaches an optimal solution.
Selects the next point in the sequence by a deterministic computation.	Selects the next population by computation which uses random number generators.

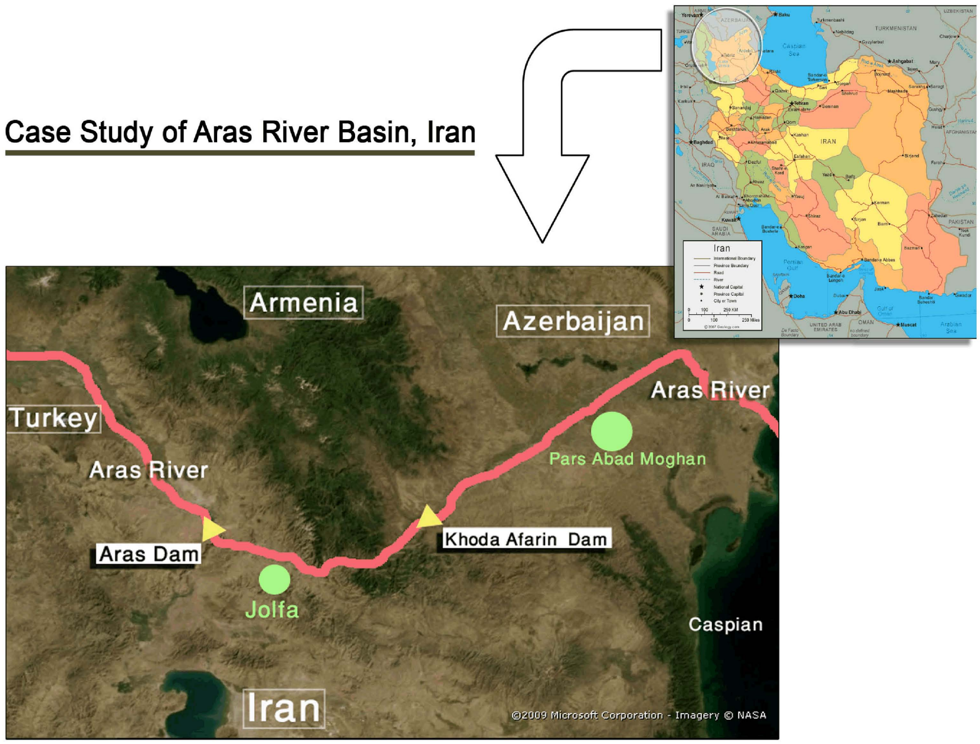


Fig. 1: Basin location in Iran

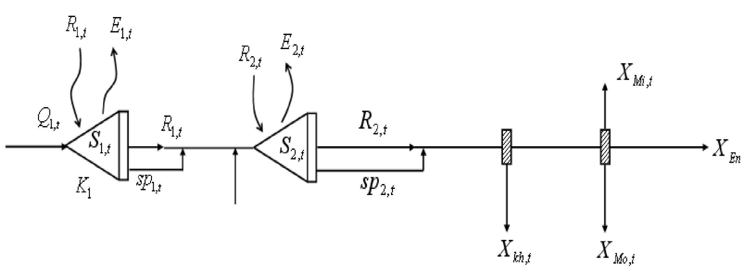


Fig. 2: Schematic of Aras River Basin

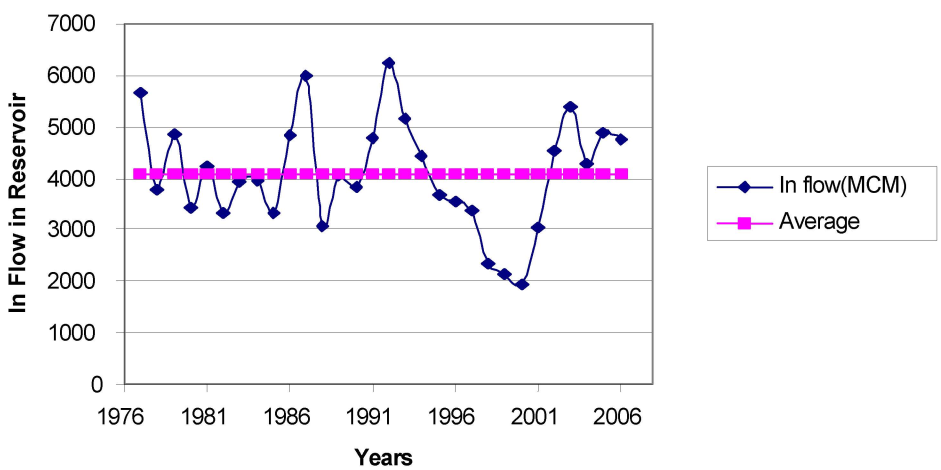


Fig. 3: Annual Reservoir inflows

cubic meters. This storage volume can supply irrigation water for 140000 hectares of land. The minimum storage volume of reservoir equals to 200 million cubic meters .The average flow rate of Aras river at the dam-site is 250 m3/sec. In this study, the volumes of 30-years monthly stream flow of the Aras River and Khodaafrin have been used. Figure 3 shows the plot of years against reservoir inflow and average annual inflow in MCM.

Objective Function: In the present study, the fitness function of the GA model is minimizing the squared deviation of monthly irrigation demand and squared deviation in mass balance equation:

$$MinimizeF = \sum_{k=1}^{m=2}\sum_{t=1}^{12}(R_t - D_t)^2 + \sum_{k=1}^{m=2}\sum_{t=1}^{12}(S_t - S_{t+1} + I_t - R_t - E_t)^2 \quad (1)$$

Where:

R_t is Monthly irrigation release for the month't', D_t is Monthly downstream irrigation demand for the month't', S_t is Initial storage in the beginning of month't', S_{t+1} is Final storage at the end of month't', I_t is Monthly inflow during the period 't' and E_t is Monthly evaporation loss from the reservoir during the month't'. The above fitness function of GA model is subjected to the following constraints and bounds.

Release Constraint: The irrigation release during any month should be less than or equal to the irrigation demand in that month and this constraint is given by

$$R_t = D_t, \quad t = 1, 2, 3, \ldots 12 \quad (2)$$

Storage Contraint: The reservoir storage in any month should not be more than the capacity of the reservoir and should not be less than the dead storage. Mathematically this constraint expressed as:

$$S_{min} = S_t$$

and

$$S_t = S_{max} \quad t = 1, 2, \ldots 12 \quad (3)$$

Where:

S_{min} is Dead Storage of the reservoir in MCM and S_{max} is Maximum capacity of the reservoir in MCM.

Over Flow Constraint: When the final storage in any month exceeds the capacity of the reservoir the constraint is given by:

$$O_t = S_{t+1} - S_{max} \quad t = 1, 2, \ldots 12 \quad (4)$$

and

$$O_t = 0 \quad t = 1, 2, \ldots 12 \quad (5)$$

Where:

O_t is Surplus from the reservoir during the month':'.

RESULTS

In this research for collecting operational model, we encode at MATLAB software for optimizing operational model for multiobjective serial reservoir on Aras river basin. The use of efficiency from GA formulation at optimizing operational model for multiobjective serial reservoirs by sensitivity analysis and the results extracted.

In the Aras river basin, we consider time steps in monthly . Thus, There are two storage reservoirs in this basin , It will have 48 discrete variables.

The evaluation function used by GA corresponds to the objective function given in previous part. Also, a penalty function based upon the constraints on storage are handled the degree of constraint violation.

Figure 4 illustrates the plot of generation number versus Best fitness and Mean fitness of the population.

Figure 4 shows the GA run begins slowly but rises fast. As the GA run progresses , the unsuitable answers are omitted because the penalties assigned to them reduce their fitness ,thus making their chances slim for selection process in the next generation and some fine-tuning may improve them. At the end of the run , a large number of suitable and near optimal answers have been obtained.

Also, the analysis of sensitivity to evaluate the effect of crossover probability and mutation probability on the GA performance . A mutation probability of 0.125 , that related to 5 mutations per chromosome ,was used to analyze the sensitivity . The other parameters considered constant.

Figure 5 shows the crossover probability is from 0.55 till 0.95 fitness is expressed with the best crossover probability.

The best values were obtained for the crossover probability of 0.75 . Figure 5 illustrates that if too low values of crossover probabilities are used , the minimum performance was obtained with a crossover probability of 0.75 . The number of mutations per chromosome , are varied from 1 mutation to 10 mutations per chromosome.

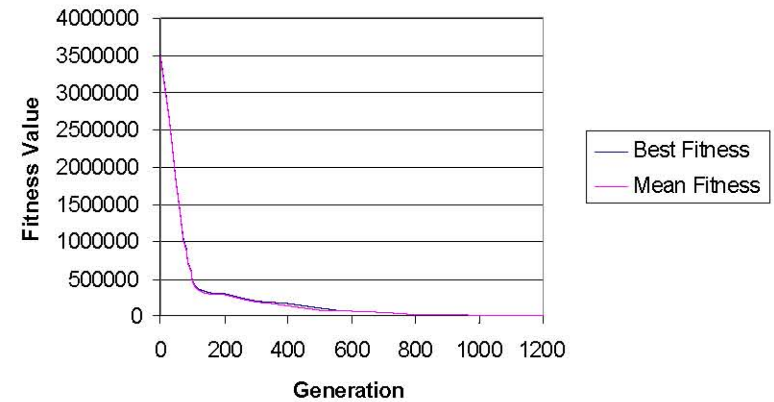


Fig. 4: Generation versus Best average fitness

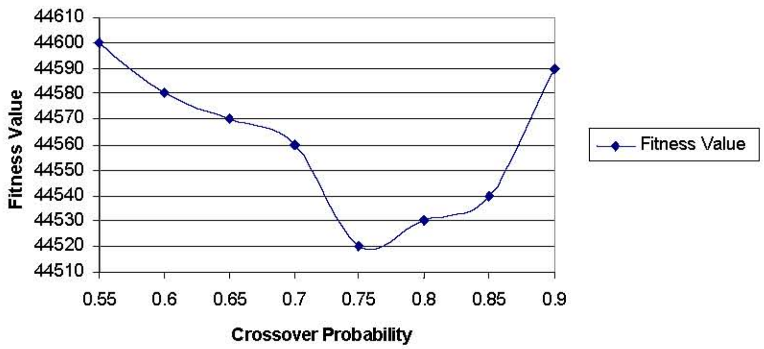


Fig. 5: Sensitivity to crossover probability

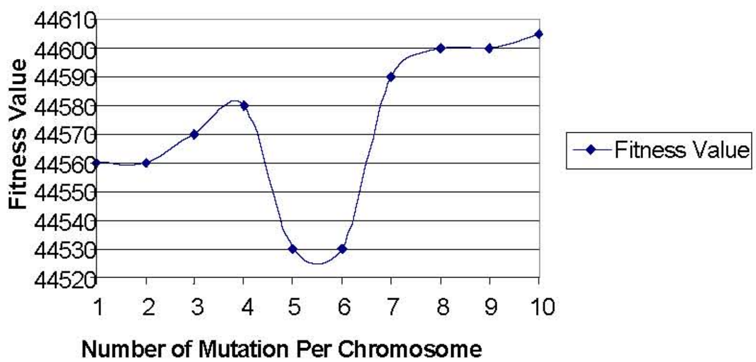


Fig. 6: Sensitivity to mutation probability

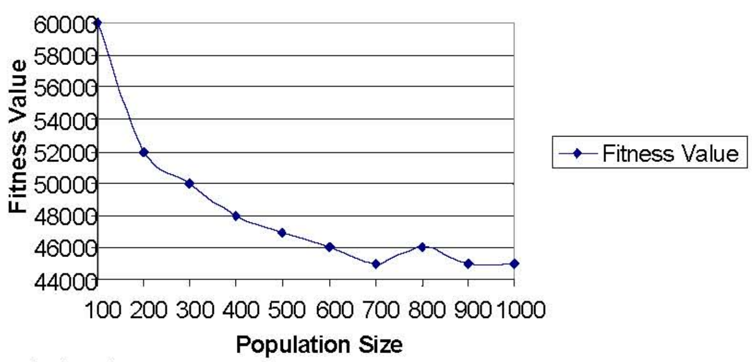


Fig. 7: Sensitivity to population size

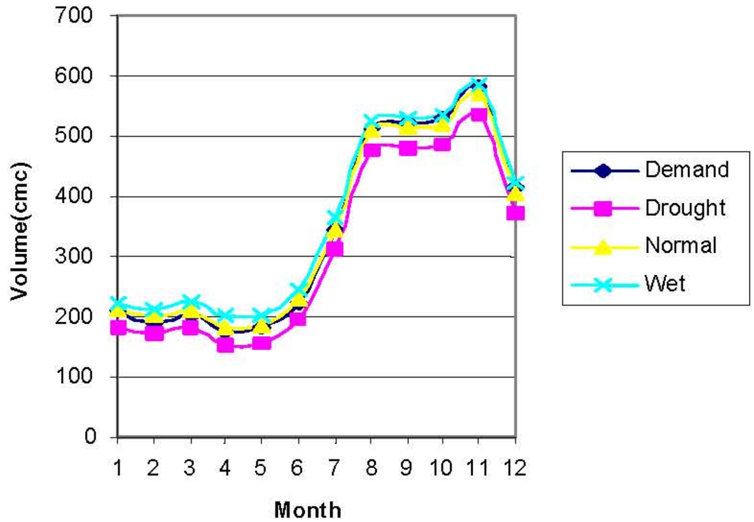
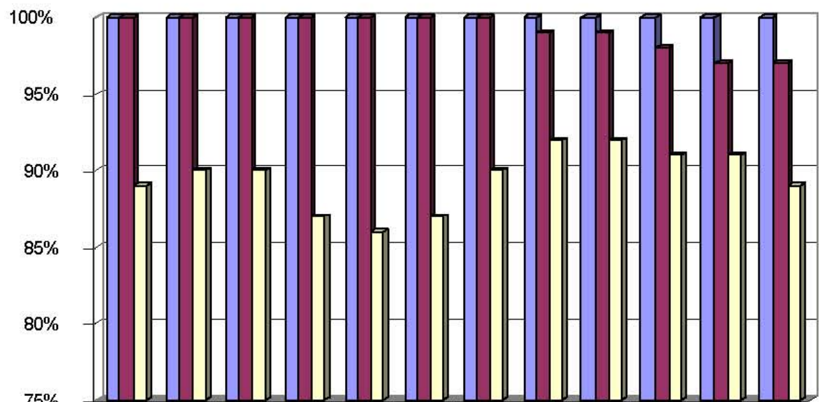


Fig. 8: Monthly Irrigation Demand and Releases as per GA model



	1	2	3	4	5	6	7	8	9	10	11	12
Wet	100	100	100	100	100	100	100	100	100	100	100	100
Normal	100	100	100	100	100	100	100	99%	99%	98%	97%	97%
Drought	89%	90%	90%	87%	86%	87%	90%	92%	92%	91%	91%	89%

Fig. 9: Monthly Irrigation Demand and Releases as per GA model

According the Figure 6, the best answers were obtained with 5 and 6 mutations per chromosome . the value of 5 mutation is suitable because it is lower. Since the chromosome for the Aras river basin was made up of 48 genes , the mutation probability relating per chromosome is 0.125 . It is used from the best parameters in GA.

The GA was run with different population sizes ranging from 350 to 900 . The sensitivity of obtained maximum fitness to population size is shown in Figure 7.

At optimizing methods , research starts from one point, whereas at Genetic Algorithm method research begins smaller population. Thu, It does not pay attention to the choice of population. In this research Genetic Algorithm runs with different sizes of population ranging 100 to 1000. Figure 6 shows fitness of sensitivity and minimum of objective function to population sizes . The acceptable results are produced with population over 300. The best is 700. A decrease in population size decrease the objective function. The number of objective function may not be obtained with smaller population. Thus , The choice of population size depend on the judgment and experience of the user.

To apply GA to the above formulated model, average annual inflows into the reservoirs have been used. The inflow scenarios represent, normal, drought and wet seasons in the region.

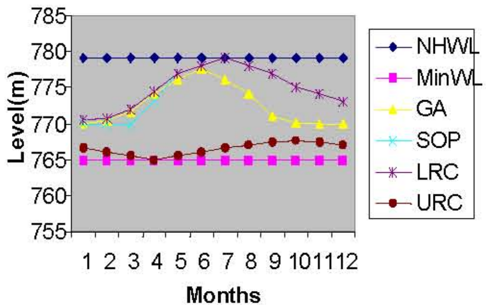


Fig. 10: Comparison in Aras Reservoir

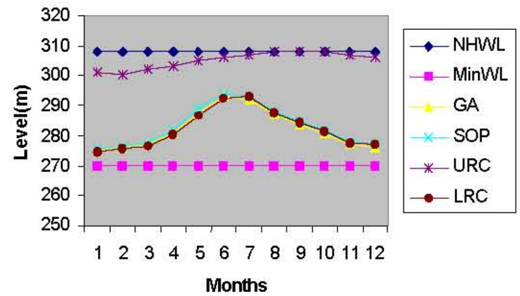


Fig. 11: Comparison in Khodaafrin Reservoir

Table 2: Summary of economic returns in million Rial|

	GA	SOP
Irrigation Production	153230	134670
Energy Benefits	47501	42421
Total	200731	177091

A comparative plot of actual demand and GA model release for an average inflow shown in Fig.7 shows that the demand is almost satisfied with the releases obtained through GA model. To derive rule curve the results obtained are plotted in Figure. 8.The parameters used in applying GA to reservoir operation model were those selected after a thorough sensitivity analysis by varying each of the parameters. A population size of 900 and crossover probability of 0.75 are chosen to run the model. Fig. 9 shows the amount of water released for irrigation for each month.

The comparisons of the operating curves achieved from GA and SOP are showed in figure 10 and figure 11 . The GA results are based on the best parameter set resulting from the analysis of sensitivity. The SOP is based on the operating curve simulated by using inflows data and water requirements data in consistent with the upper rule curve (URC) and the lower rule curve (LRC) . But both of them begin at the same level.

As It is shown in figure that operating curve for Aras reservoir matches to the SOP's operating curve for a few points only in the early period of the water year but not completely.

The operating curve is drawn between the existing upper rule curve (URC) and lower rule curve (LRC) in every period of the water year. Also, it is drawn between the normal high water level (NHWL) and minimum water level (MINWL) of reservoir . Thus the upper operating curve is the best. The operating curve from GA and SOP does not match even first time steps.

As the figure 8 show resulting curve from GA at some parts (section) match with lower rule curve but this is not completely. The GA curve in months of 7, 8, 9, 10, 11, 12 at year is lower than lower rule curve (LRC). The upper curves indicates that the operable space between the (LRC) and (URC) can not be efficient and the existing rule curves can not lead the optimized reservoir operation.

The response of the reservoir system to the operating curves produced by GA and the existing rule curves produced by SOP's simulation model was also evaluated. The economics returns that could be realized from the basin for the operating curves produced by GA and those produced by SOP's simulation model have been compared and are presented in Table 2.

Table 2 shows that the operating curves derived by GA produce significantly higher total returns than those obtained from the operating curves produced by SOP's simulation model. Operation by using SOP's rule curves returns lower benefits in case of energy benefits and irrigation production. The results demonstrate that the GAs can be used efficiently in identifying operation policies for multiple reservoir systems.

CONCLUSION

In this research GA was applied for a real multiple reservoir system in the Aras River Basin in northern of Iran. The results from simulation model conducted by SOP were used in the comparison with other optimization model using GAs.

For analyzing GA approach, a case study of Aras River Basin problem was carried out, satisfactorily. The best parameter set obtained from sensitivity analysis had 10 a crossover probability of 0.75, mutation probability of 0.125, which corresponds to 6 mutations per chromosome, for a population size over 900.

The results of the GA with SOP method were compared and the GA with SOP method were compared and the operation curve from GA indicates the higher benefits , in term of irrigation production and electricity production.

The comparison of operating curves with GA and SOP show that in Khoodaafrin reservoir , the space between upper rule curve (URC) and lower rule curve (LRC) of it doesn’t cover the best ruling level and that can not lead to the best utilization.

Thus we should revised the upper rule curve(URC) and the lower rule curve(LRC) of it is unavoidable. Because we should satisfy all demands as much as possible and lead up to the best utilization of water resources in the basin.

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