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An Evolutionary Model for Operation of Hydropower Reservoirs

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Abstract

In this study, an optimization model is developed for monthly operation of a multi-purpose hydropower reservoirs using genetic algorithm. The real value encoding approach is used considering alternative representation, selection, crossover, and mutation schemes. The constraints are handled using the Multiplicative Penalty Method (MPM) function, in order to evaluate the objective function in deferent conditions. The reliability of water allocation to different demands and hydropower generation are evaluated using an economic objective function which has been calculated based on the actual value of water and energy of Karoon-I Reservoir in southwestern part of Iran. The results of this study have shown the importance of selecting a suitable mutation operator for reducing the computational run time of the optimization model. The robustness and efficiency of genetic algorithm in developing the operation policies for a multi-purpose hydropower reservoir is discussed in the paper.

Introduction

Application of GAs in river-reservoir systems operation has been limited comparing with the other optimization techniques. Esat and Hall (1994) developed a GA based optimization model for operation of a reservoir system where the hydropower generation and water allocation to agricultural water demands are maximized. Fahmy et al. (1994) compared the efficiency of GAs and dynamic programming models in reservoir operation. They also showed the potential of genetic algorithms in optimization of large river basin systems. Oliveira and Loucks (1997) proposed a GA based optimization model to derive the multi-reservoir operation policies. The real valued vectors containing information needed to define both system releases and individual reservoir storage volume targets are presented in their model. Wardlaw and Sharif (1999) proposed several GA based formulations for deterministic modeling of a four-reservoir system. Chang and Chang (2001) used an intelligent control model, which applies GA to first search for the optimal reservoir operation and then an Adaptive Network-based Fuzzy Interface System (ANFIS) is built to estimate the optimal release based on the current reservoir volume and inflow. Karamouz et al. (2002) developed a GA model for multi-purpose reservoir operation. They showed that their proposed model can improve the result of the demand driven stochastic dynamic programming (DDSP) model develop by Vasiliadis and Karamouz (1994).

In this study, the monthly linear policies of hydropower reservoirs are developed using the proposed GA based optimization model. The optimization model provides the optimal coefficients of the linear policies, which has used in many reservoir operation models such as

DPR (Dynamic Programming and Regression Model), which was developed by Karamouz and Houck (1982). The results of the proposed model are compared with the results of DPR model. In DPR model, increasing in the number of discretizations can effectively improve the results of the optimization process, but the results of the simulation model based on the rules derived in regression process might be unsatisfactory, because of variability of release, storage, and inflow to the reservoir in the historical period of operation. The proposed model can help to achieve more efficient operation policies with less reservoir storage discretization.

Formulation of the Optimization Model

Water and power are not one to one commodities. In other words, losses of shortage in allocating water to different users such as agriculture can not be replaced by the power generation benefits. In this study, for simultaneous optimization of water supply and power generation, two approaches have been considered to formulate the objective function of the optimization model:

1- The relative cost function is used to estimate the cost associated with the deviation from target values of water and energy supply
2- Economic cost function is developed based on the economic value of water allocated to different demands and is used in the GA model.

These two approaches are briefly explained in the following sections:

1. Relative Cost Function

The relative cost function is defined in order to minimize the deviation from target values of water and energy supply as follows:

$$Loss_t = LossWater_t + LossPower_t \tag{1}$$

Where:

$Loss_t$: Reservoir operation cost in month t
$LossWater_t$: Water supply cost in month t
$LosPower_t$: Cost of shortage in supplying energy demands in month t

The cost associated with the water release from reservoir (water supply cost) is assumed to be estimated as follows:

$$LossWater_t = \begin{cases} 3.88\times 10^{5} \times \left[exp\left(0.8 - \dfrac{R_t}{D_m} \right) - 1 \right] & if \quad R_t \le 0.8D_m \\ 0 & if \quad 0.8D_m \langle R_t \langle 1.2D_m \\ 1.58\times 10^{6} \times \left[exp\left(\dfrac{R_t}{D_m} - 1.2 \right) + 1 \right] & if \quad R_t \ge 1.2D_m \end{cases} \tag{2}$$

Where:

R_t: Release from the reservoir is month t (t=1, …, T)
T: Planning time horizon
D_m: Water demand in month m (m=1, …, 12)

As it can be seen in Equation (2), in order to incorporate the variations in water demands, a safe range is identified, in which the cost associated with the releases greater than $0.8D_m$ and less than $1.2D_m$ is zero. For the high rate of deviation from the safe range, the cost is progressively increased in order to incorporate the losses associated with sever shortages and flooding damages in high flow seasons.

The cost associated with shortages in supplying energy demands is estimated as follows:

$$LossPower_t = \alpha[PTarg(m) - PGen(m)]^2 \qquad (3)$$

Where:

$PTarg(m)$: Energy demand in month m
$PGen(m)$: Power generated in month m
: Parameter estimated based on sensitivity analysis of the tradeoff between water and energy supply

2. Economic Cost Function

In this study, a more realistic cost function is also used to reflect marginal cost of water shortages as well as marginal benefits of power generation. This cost function is based on the rate of the capital recovery. For this purpose the present value of monthly cost of reservoir operation is estimated as follows:

a. Present value of initial investment estimated based on the age of the dam and its appurtenant facilities, historical series of an indicator showing the discount rate (cumulative discount index) for concrete dams in Iran, and the rate of depreciation.
b. The present value is then distributed over the expected remaining life of the dam on a monthly basis
c. The cost of maintenance and operation is also added to the monthly cost
d. The total cost is then estimated as the summation of uniformly distributed present value of initial investment and the cost of maintenance and operation.

The cost associated with the unit volume of water release in each month ($Losswater_t$) is then estimated as the ratio of the total cost and the volume of water released in each month. In order to estimate the economic value of power generation in the hydropower plant ($Benefitpower_t$), the cost of supplying equivalent amount of energy by thermal plants is considered as the economic benefit of power generation in hydropower plant. The total cost of operation can then be estimated as:

$$Loss_t = \sum_{t=1}^{T}(Costwater(t) - Benefitpower(t)) \qquad (4)$$

3. Constraints

The main constraints included in the model can be summarized as:

- Water balance in the reservoir:

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

  Where, R_t, S_t, and I_t are the release, storage, and inflow to the reservoir during month *t,* respectively.
- Minimum and maximum water storage in the reservoir
- Power generation as a function of net head and turbine release
- Maximum allowable release based on the hydraulic capacity of turbines

Genetic Algorithm

GAs use random search techniques that evolve potential solution at a system in each step using genetic operators. Generation of initial population, representation and encoding, selection, crossover, and mutation are the main steps in GA based optimization models. The main characteristics of the GA operators are presented in the following sections.

1. Representation and Encoding

The binary encoding is the most common method in several proposed encoding approaches. In this method, discretization of state variables is required. If state variables are too long, the length of each chromosome and therefore the convergence time will be long. Another alternative method is real value encoding that is suitable in meeting optimal solution in large and complex problems (Wardlaw & Sharif 1999). Discretization of state variables and decoding process is not required in this method and thus it will provide the optimal solutions with more precision in lower computational time. Considering the advantages of real value encoding, it has been used in this study.

2. Selection Operator

The main objective of selecting process is to select the parents with higher fitness for generation of next population. Several approaches have been proposed for selection operator such as Roulette Wheel and Tournament methods. The selection operator can affect convergence and run time of the method and maintaining the diversity of the population in each generation. In this study, the Roulette Wheel selection method is used. To prevent premature convergence the value of objective functions are scaled.

In some cases, the difference between fitness values of the chromosomes is very low and it is possible that the best solution is not selected as a parent for generation of the next population. In Elitism approach that has been used in this study, the best chromosome in each population is directly selected as one of the parents for generation of next population.

3. Crossover and Mutation

Crossover operators randomly take one pair that performs well from the mating pool and by exchanging important building block between two strings, a new pair is obtained. Crossover occurs between two selected strings with a specific probability (P_c). One point crossover, which has been selected for this study, randomly chooses a position in the string and new chromosomes are obtained by swapping all genes after the position. Mutation is an important process that can provide diversity and new genetic information to the population and prevent premature convergence to local optimal solutions. The mutation operator changes randomly the bit value with a probability of P_{mut} and considering the range of variation of each bit in mutation process (D_{mut}), which is usually considered as a percent of the maximum range.

The characteristics of Proposed GA model

The proposed GA based model optimizes the coefficients of the linear monthly release policies, proposed by Karamouz et al. (1982) as follows:

$$\hat{R}_t = a \times I_t + b \times \hat{S}_t + c \tag{6}$$

Where, $\hat{R}_t$ and $\hat{S}_t$ the optimal release and storage in the reservoir during month *t,* respectively. As it can be seen in Equation 6, three coefficients should be estimated for each month and therefore, the total number of coefficients in each year is equal to 36.

Figure (1) shows the flowchart of the proposed GA based reservoir operation optimization model. In this study, considering the reservoir volume, water demands and inflow rates, the range for the coefficients are considered as follows:

$$-5 \leq a \text{ and } b \leq +5 \tag{7}$$

$$-1000 \leq c \leq +1000 \tag{8}$$

Selection of initial population of feasible solutions can considerably reduce the convergence time of the model. The fitness values of the non-feasible solutions are penalized using the Multiplicative Penalty Method (MPM), which has a better performance relative to Additive Penalty Method (APM) (Chan Hilton & Culver 2000). The penalty value, allocated to the fitness of each gene, is calculated as follows:

1- When the release volume is more than the release capacity (R_{max}) in each month:

$$(R_t > R_{max}) \quad \Rightarrow \quad Penalty = (R_t - R_{max})^2 \tag{9}$$

2- When the storage volume is more than maximum (S_{max})or less than minimum storage volume (S_{min}):

$$(S_t \leq S_{min}) \quad \Rightarrow \quad Penalty = (S_{min} - S_t)^2 \tag{10}$$

$$(S_t \geq S_{max}) \quad \Rightarrow \quad Penalty = (S_{max} - S_t)^2 \tag{11}$$

3- When the monthly release is less than zero $(R < 0)$:

$$Penalty = R^2 \tag{12}$$

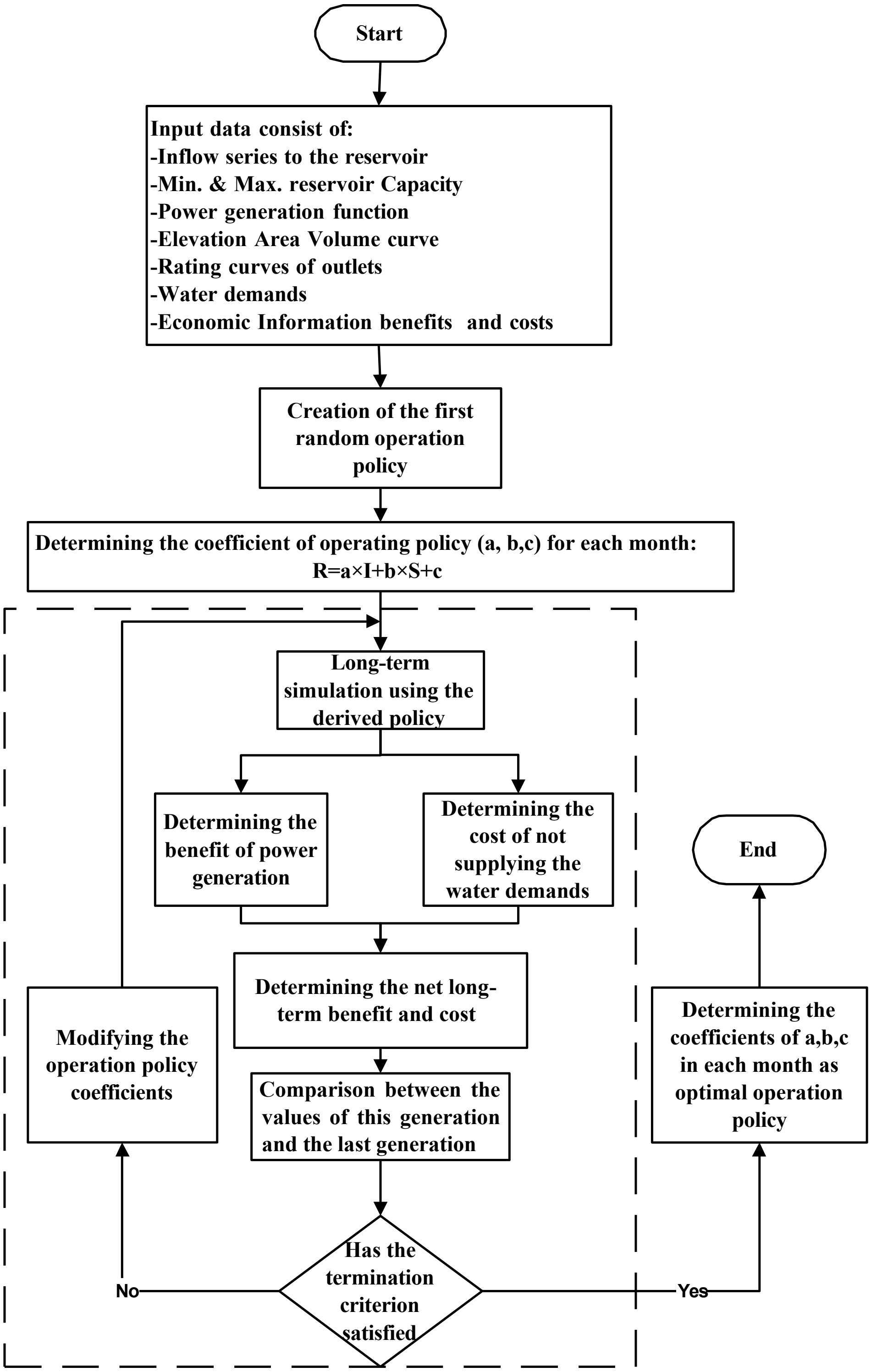

Figure 1. Flowchart of the proposed GA based optimization model

In this study the fitness function of each chromosome is calculated based on the costs and benefits associate with the meeting or not meeting the water and energy demands using one of the following equation:

$$Fitness = \sum_{t=1}^{T} (Costwater_t - Benefitpower_t) \times Penalty \qquad (12)$$

Where i is the time period, T is the length of the planning horizon (i=1,…, T). The optimal values of probability of crossover and mutation and population length have been estimated by trial and errors to provide the optimal or near optimal solution with lowest computational cost.

The Case Study

Karoon drainage basin is located in southwestern part of Iran and carry more than one fifth of the surface water supply of the country. The total area of this basin is about 67000 square kilometers of foothills and Khozestan Plain. Karoon-I reservoir, which is constructed on this river has a total storage capacity of 2900 million cubic meters. The Karoon River joins Dez River at a location called Band-e-Ghir some 40 Kilometers north of the city of Ahwaz (the capital of the strategic border province of Khozestan) and form the so-called “Great Karoon River”. This river passes Ahwaz and reaches the Persian Gulf some 120 Kilometers South of Ahwaz. Average annual streamflows to Karoon-I reservoir is 13.1 billion cubic meters. Power generation capacity of Karoon power plant is 1000 Megawatts.

The two rivers supply water for domestic, industrial and agro-industrial demands. Total irrigation networks downstream of Dez and Karoon dams are estimated as 250,000 hectares (1 hectare = 10000 square meters). The total water demand for the existing cropping mix is about 5260 million cubic meters. Low irrigation efficiency within the agricultural lands, large amount of water losses along the transfer channels, and high evaporation rate are the main reasons for the high agricultural water demand in this region.

Results and Discussion

GA parameters have been selected in this study based on sensitivity analysis in order to decrease the computational efforts needed for convergence of the results in different generations. Results of the sensitivity analysis have shown that the convergence time can be significantly reduced by using following parameters:

- Mutation Probability = 0.1
- Crossover Probability = 0.5
- Range of change in mutation process = ± 0.05, ± 0.05, and ± 100 for a, b, and c, respectively

Results of this part of the study also showed that for a specific number of generations, only mutation probability, P_{mut}, can significantly change the run-time needed for convergence. For example, Figure 2 shows the variations of the objective function of the model for different values of mutation probability as follows:

$$P_{mut} - \{0.005, 0.05, 0.1, 0.5\}$$

As it can be seen in this figure, for $P_{mut} = 0.1$, the results have converged to the optimal solution faster than the other values for this parameter.

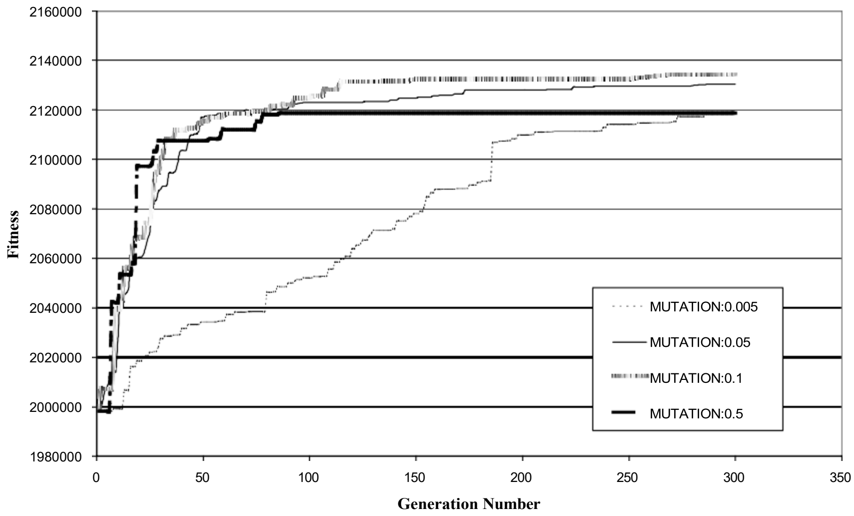

Figure 2. Results of the sensitivity analysis for different values of mutation probability

In order to investigate the performance of the GA model, three sets of models have been compared as follows:

- GA model using the relative cost function
- GA model using the economic cost function
- DPR model using the economic cost function

In this study, the planning horizon is 19 years or 228 months. Table 2 shows the average long-term reliability of water supply to agricultural lands and power generation base on the optimal policies of the above three models. As it can be seen, the reliability of water supply has been improved by using economic cost function. Comparison between the results of DPR and GA models (with economic cost function) in supplying water demands shows that the average reliability of water supply has not been significantly changed.

Table 2. Long-term average reliability of supplying irrigation demands and power generation

Month	GA with Relative Cost Function		GA with Economic Cost Function		DPR with Economic Cost Function	
	Power Generation (MWh)	Water supply reliability (%)	Power Generation (MWh)	Water supply reliability (%)	Power Generation (MWh)	Water supply reliability (%)
April	507647	100	506903	100	435629	100
May	504180	100	475739	100	439601	100
June	316657	95	333407	99	297244.8	99
July	196527	56	233759	86	215925.5	88
August	231954	74	210090	80	210400.6	89
September	143754	50	168765	78	151456.9	87
October	174565	84	121381	83	108342.2	92
November	179676	100	143313	100	83672	82
December	190468	100	262001	100	196538.1	94
January	226099	100	256066	100	217846	100
February	358276	100	339714	100	314138.8	100
March	352644	98	390420	99	351645.5	99
Average Annual	**3382446**	**88**	**3441558**	**94**	**3022440**	**94**

As it can be seen, the GA model with relative and economic cost functions has been able to increase the power generation comparing with the results of DPR model. The average annual increase in power generation has been about 14% with economic cost function and 12% with relative cost function (comparing with the results of the DPR model). Figure 3 shows the comparison between monthly power generation based on the optimal policies of the models.

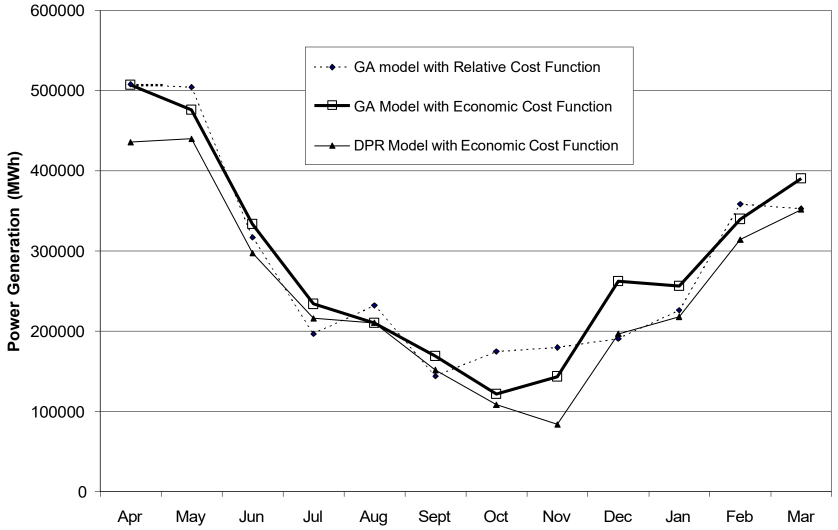

Figure 3. Long-term average power generation of Karoon–I power plant (MWh)

Summary and Conclusion

In this study, an optimization model is developed for monthly operation of a multi-purpose hydropower reservoir using genetic algorithm. The proposed GA model optimizes the coefficients of the linear monthly release policies. The constraints are handled using the Multiplicative Penalty Method (MPM) function, in order to evaluate the objective function in different forms. The reliabilities of water allocation to irrigation demands and hydropower generation are evaluated using an economic objective function, which has been calculated based on the actual value of water and energy of Karoon-I Reservoir in the southwestern part of Iran. The long-term results of the proposed GA model have been compared with DPR model, which is a deterministic dynamic programming model developed by Karamouz and Houck (1982).

In this study, the parameters of GA model including mutation and crossover probability and range of change in mutation process has been calibrated in order to reduce the computational efforts. Results of the sensitivity analysis have shown that the mutation probability has a significant effect on the convergence of the proposed GA model. Results of this study have shown that application of the economic cost function in GA mode has resulted in more benefits and increase in the long-term power generation of Karoon-I reservoir, while keeping the water supply reliability in an acceptable range.

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