COMPARISON ABILITY OF GA AND DP METHODS FOR OPTIMIZATION OF RELEASED WATER FROM RESERVOIR DAM BASED ON PRODUCED DIFFERENT SCENARIOS BY MARKOV CHAIN METHOD

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ABSTRACT

Planning for supply water demands (drinkable and irrigation water demands) is a necessary problem. For this purpose, three subjects must be considered (optimization of water supply systems such as volume of reservoir dams, optimization of released water from reservoir and prediction of next droughts). For optimization of volume of reservoir dams, yield model is applied. Reliability of yield model is more than perfect model and cost of solution of this model is less than other methods. For optimization of released water from reservoir dams, different methods can be applied. In this research, dynamic programming method (a discrete method for optimization) and genetic algorithm (a searcher method for optimization) are considered for optimization of released water from the Karaj reservoir dam. The Karaj dam locates in west of Tehran. This research shows that reliability and resiliency of GA method is more than DP method and vulnerability of GA method is less than DP method. For improving of results of GA method, mutation rate of GA method is considered from 0.005 to 0.3 for different generations. For prediction extreme droughts in future, the Markov chain method is used. Based on generated data by Markov chain method, optimum volume of reservoir dam is determined by yield model. Then optimum released water from reservoir dam is determined by DP and GA methods for different scenarios that produced by Markov chain method. The Markov chain and yield model show that volume of reservoir Karaj dam should increase 123 MCM for overcoming to next droughts.

Keywords: genetic algorithm method; dynamic programming method; markov chain method; the Karaj dam; mutation rate.

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1. INTRODUCTION

Supply water demands such as drinkable water demand, irrigation water demand, industrial water demand and etc is a principle necessary for development of societies. At recent years by global warming of earth, melting of polar ices and rising of sea water level, extreme droughts occurred in Middle East countries. These droughts produced many economic, politic and social problems. In these conditions, correct planning and programming for water resources management is very important. Water resources management has different aspects. An aspect of water resources management is optimization of water resources and supply water demands. For optimization of water resources and supply water demands, two stages must be accomplished (optimization and simulation). By these stages, reliability, resiliency and vulnerability of system are determined.

Xu et al. [1] utilized MACP (Markov Auto- Correlation Plus) method for prediction of daily, monthly and annual stream flow of the Wupper River in Germany. They studied about spatial correlation between two adjacent stations. Also Xu et al. [2] used of MCCP (Markov Cross- Correlation Plus) method for forecasting of daily stream flow of the Wupper River in Germany. They determined wet and dry periods. Aksoy [3] utilized two states and three states Markov chain method for prediction of daily stream flow. He determined wet and dry days in different watersheds. Szilagyi et al. [4] used of hybrid Markov chain method for forecasting daily stream flow of the Tisza River and its top branches (Szamos, Bodrog and Kraszna) in Hungary. They utilized observed data from 1951 to 2000 and considered two states wet and dry and transfer probability between them (dry to dry, wet to dry, dry to wet and wet to wet). Sarlak et al. [5] predicted annual stream flow of the Goksu River in Turkey based on oscillation of sea water level in North Atlantic Ocean.

Marino and Mohammadi [6] used of combination of LP and DP for optimization of volume of parallel multi objective reservoirs. Their case study was Shasta and Folsom dams in California Valley project. Also Becker et al. [7] combined LP and DP methods for solving a system with 22 decision variables. They utilized small time steps (hourly and daily) in central valley project. Bogle and O'sullivan [8] applied DP method for determination of the value of water demand at future. Kumar and Baliarsingh [9] developed folded dynamic programming (FDP) method. This method is applied for optimization of multi reservoirs systems. This method does not need to primary path for finding of global optimum. Therefore this method does not converge to local optimums. Also the number of iteration of this method is less than the number of iteration of dynamic programming for reaching to global optimum. Bhaskar and Whitlatch [10] extracted monthly optimization scenarios for Hoover reservoir in central Ohayo. They used of dynamic- regression programming and LP with chance restriction. The results of operation scenarios of two methods were compared by simulation methods. Mean yearly damage of operative scenarios of LP with chance restriction was less than mean yearly damage of operative scenarios of dynamic- regression programming. Also Karamouz et al. [11] used of DP for optimization of multi objective reservoirs. Teixeira and Marino [12] applied a forward dynamic programming (FDP) model for optimization of reservoir operation and irrigation scheduling. They considered two reservoirs and three irrigation districts and forecasted crop transpiration, reservoir evaporation and inflows to reservoirs.

Kuo et al. [13] applied GA method for maximization of economic profit an irrigation

project in Wilson channel of Delta, Utah of USA. They determined projected profit, projected water demand and area percentages of crops. Vasan and Raju [14] applied SA, SQ and GA methods for maximization of the annual net benefits of different irrigation projects in Mahi Bajaj Sagar Project, India. They showed that GA method can maximize annual net benefits more than other methods. Momtahen and Dariane [15] utilized direct search approach to determine optimal reservoir operating policies. They applied a real coded genetic algorithm (GA) for this purpose. In this research, different reservoir release rules or forms, such as linear, piecewise linear, fuzzy rule base and neural network are applied to a single reservoir system. They compared GA with conventional models such as stochastic dynamic programming and dynamic programming and regression and showed that GA method is superior method. Dariane and Momtahen [16] used of this method for 3, 7 and 16 reservoirs systems in the Karun River, Iran. They confirmed advantages of GA for optimization of multi reservoirs system too. Also Hakimi-Asiabar et al. [17, 18] utilized GA method for multi objective reservoir systems. Also Chang et al. [19], Elferchichi et al. [20] and Azamathulla et al. [21] applied GA for optimization of reservoir systems.

   In this research, the volume of reservoir dam is optimized by yield model for generated different scenarios by Markov chain method. Three states are considered for this purpose (generated the driest series by Markov chain method, generated the wettest series by Markov chain method, mean of generated all series by Markov chain method). Then released water from reservoir is optimized by DP and GA methods for four states (real volume of reservoir dam, volume of reservoir dam for the driest series, the wettest series and mean all series that are generated by Markov chain method). For optimization of released water from reservoir, water demands such as irrigation and drinkable water demands can be considered. Also for optimization of released water from reservoir by GA methods, two states are considered (GA with constant mutation rate and GA with variable mutation rate for different generations). At the end the best optimized method is distinguished. This method has the least vulnerability and the most reliability and resiliency.

2. MATERIALS AND METHODS

2.1 The Karaj dam

The Karaj dam was constructed on the Karaj River in 1961. The area of its watershed is 764 Km^2. The average of annual discharge of inflow to its reservoir is 444 MCM. This dam locates is 63 Km west north of Tehran and 23 Km north of Karaj city. This dam supplies a part of drinkable water demand of Tehran (340 MCM/year) and irrigation water demand of 50000 hectares of farms near to Karaj city (130 MCM/year). Also its hydropower plant can produce 150000 MW-hour electrical energies in a year. This dam is a two arches concrete dam. The height of dam from bottom, the length of crest of dam, the width of crest of dam and width of foundation of dam are 180m, 390m, 8m and 38m respectively. The total volume of reservoir dam is 205 MCM. The bottom elevation of reservoir and normal water surface elevation of reservoir are 1545m and 1610 m respectively. The volumes of useful and dead storage of reservoir dam are equal to 191.6 and 13.4 MCM respectively. The position of the Karaj dam in Iran and its watershed are shown in Fig. 1.
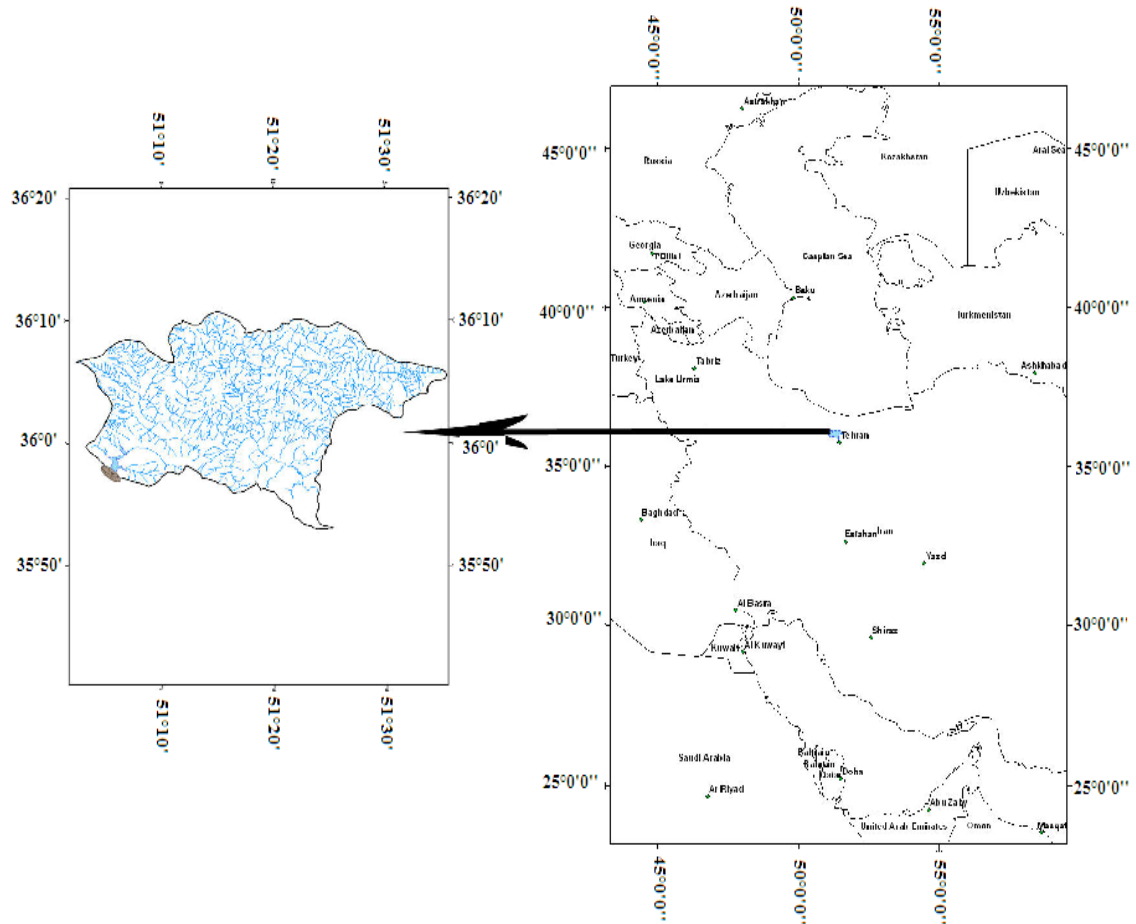
Figure 1. The position of the Karaj dam in Iran and its watershed

The volume- area relation of the Karaj dam is shown by bellow equation.

$$A=0.681+0.016S \qquad (1)$$

where A is the area of reservoir (Km^2), S is the volume of reservoir (MCM)

The volume of drinkable water demand and irrigation water demand are illustrated in Table 1.

Table 1: The volume of drinkable water demand and irrigation water demand

Month	January	February	March	April	May	June
Drinkable water demand(MCM)	16.897	17.037	18.001	18.266	19.802	23.919
Irrigation water demand(MCM)	5.448	4.714	3.228	5.18	20.17	24.715
Month	July	August	September	October	November	December

Drinkable water demand(MCM)	25.92	25.875	24.788	23.857	19.497	17.818
Irrigation water demand(MCM)	20.377	15.796	15.764	11.02	8.556	7.03

The height of monthly evaporation in reservoir of the Karaj dam is illustrated in Table 2.

Table 2: The height of monthly evaporation in reservoir of the Karaj dam

Month	January	February	March	April	May	June
The height of monthly evaporation (m)	0.076	0.073	0.07	0.166	0.371	0.554
month	July	August	September	October	November	December
The height of monthly evaporation (m)	0.68	0.654	0.514	0.296	0.082	0.079

The mean volume of inflow to reservoir of the Karaj dam is illustrated in Table 3.

Table 3: The mean volume of inflow to reservoir of the Karaj dam

Month	January	February	March	April	May	June
The mean volume of inflow to reservoir (MCM)	12.954	14.674	29.843	74.444	107.585	82.481
month	July	August	September	October	November	December
The mean volume of inflow to reservoir (MCM)	44.714	21.185	13.437	12.061	15.708	14.821

2.2 The research methodology

This research has four steps.

1. Generation of synthetic data by the Markov Chain method:

Model that generates synthetic data must reserve characteristics of main data. Main data have serial correlation. Serial correlation is shown by $r(k)$ (k is time step). Data of each month have serial correlation with data of last month and data of next month. The equation between two dependent data is:

$$Y=a+bX \tag{2}$$

If $r^2=1$, the value of observed data (Y_0) will become equal to calculated value of data by Eq. (2) (Y).

r^2: Correlation coefficient between Y_0 and X

Because of $r^2<1$, Y cannot become equal to Y_0. Difference between Y and Y_0 is shown by e.

$$Y_0=Y+e=a+bX+e \tag{3}$$

The mean of e is equal to zero. The value of e is determined by Chow formula.

$$e = \bar{e} + K_T S_e \tag{4}$$

where S_e is standard deviation of e

Because of $\bar{e} = 0$, $e = K_T S_e$.

By attention to $r^2 < 1$ the Eq. (3) has two parts. These parts are deterministic part $(a+bX)$ and stochastic part (e). By assumption $t = K_T$, Eq. (3) converts to Eq. (5).

$$Y_0 = a + bX + tS_e \tag{5}$$

Because Y_o is summation of e and a constant value, governing stochastic distribution on it is similar governing stochastic distribution on e. Also t depends on governing stochastic distribution on e. The values of a and S_e are determined by Eqs. (6) and (7).

$$a = \bar{Y}_0 - b\bar{X} \tag{6}$$

$$S_e = S_{Y0}\left(1 - r^2\right)^{1/2} \tag{7}$$

where $\bar{Y}_0$ is the mean values of Y_0, $\bar{X}$ is the mean values of X, S_{Y0} is the standard deviation values of Y_0

By attention to Eqs. (6) and (7), Eq. (3) converts to:

$$Y_0 = \bar{Y}_0 + b(X - \bar{X}) + tS_{y0}\left(1 - r^2\right)^{1/2} \tag{8}$$

The value of b is calculated by Eq. (9):

$$b = r\frac{S_{y0}}{S_X} \tag{9}$$

In this research, a seasonal Markov chain method is applied with time step one month. The equation of this method is:

$$X_{i,j+1} = \bar{X}_{j+1} + b_j(X_{i,j} - \bar{X}_j) + t_{i,j+1}S_{X_{j+1}}\left(1 - r_j^2\right)^{1/2} \tag{10}$$

where i is Index of year, j is index of season or month or week or day, r_j is correlation coefficient between data of month j and data of month $j+1$, b_j is Regression coefficient that is calculated by Eq. (11).

$$b_j = r_j\frac{S_{j+1}}{S_j} \qquad j = 1,\ldots,\omega \tag{11}$$

ω : The number of months

If $j = \omega \rightarrow$ j+1 =1 , X$_{i,j+1}$=X$_{i+1,1}$, t$_{i,j+1}$=t$_{i+1,1}$, $b_j = r_j \dfrac{S_{X1}}{S_{X\omega}}$ and $b_\omega = r_\omega \dfrac{S_{X1}}{S_{X\omega}}$.

The value of $t_{i,j+1}$ is calculated by governing stochastic distribution on data. If governing stochastic distribution is normal distribution or log normal distribution, the value of $t_{i,j+1}$ will become equal to the value of parameter z of normal distribution. But if governing stochastic distribution is Pearson III distribution or log Pearson III distribution, $t_{i,j+1}$ will be calculated by Eqs. (12) and (13).

$$Cs_{e_j} = \left(Cs_{Xj} - r_{j-1}^3 Cs_{Xj-1}\right) \Big/ \left(1 - r_j^2\right)^{1.5} \tag{12}$$

$$t_{i,j+1} = \frac{2}{C_{se_{j+1}}} \left[1 + \frac{C_{sej+1} k_{i,j+1}}{6} - \frac{C_{sej+1}}{36}\right]^3 - \frac{2}{C_{sej+1}} \tag{13}$$

where C_{Sej} is skew ness coefficient of the values of e in month j, $K_{i,j+1}$ is equal to the value of parameter z of normal distribution.

2. Optimization of volume of reservoir of the Karaj dam by yield model:

Yield model considers critical year for optimization of volume of reservoir. The volume of inflow to reservoir in critical year is less than volume of inflow to reservoir in the other years. Therefore results of yield model are confident for design and planning. The determined volume of reservoir by yield model can often supply water demands of downstream of dam. While determined volume of reservoir by other models may not supply water demands of downstream of dam. In the other hand yield model considers only a year while a perfect model must consider total years of time series. This subject decreases the number of decision variables and restrictions considerably. Yield model assumes that summation of annual volume of inflow to reservoir at each year is equal to summation of annual volume of inflow to reservoir in critical year (Y_f). Also yield model assumes that monthly distribution of volume of inflow to reservoir in each year is similar to monthly distribution of volume of inflow to reservoir in critical year. Monthly distribution of volume of inflow to reservoir in critical year is shown by β_j.

$$\sum \beta_j = 1 \tag{14}$$

$$\sum \beta_j Y_f = Y_f \tag{15}$$

Continuous equation for critical year is shown by Eq. (16).

$$S_j + \beta_j Y_f - Y_{fj} = S_{j+1} \qquad \forall_j \tag{16}$$

where S_j is storage of reservoir in the start of month j, S_{j+1} is storage of reservoir in the end

of month j, $\beta_j Y_f$ is the volume of inflow to reservoir in month j, Y_{fj} is water demand in month j.

For determination of β_j, mean monthly distribution of volume of inflow to reservoir in critical year and the fifth critical year are applied.

$$\beta_j = \frac{q_{j_c}}{Q_c} \tag{17}$$

where q_{jc} is the volume of inflow to reservoir in month j of critical year, Q_c is the volume of inflow to reservoir in critical year.

Annual water demand has several components as drinkable water demand, irrigation water demand, hydropower plant water demand and etc. Drinkable water demand should be prepared ceaselessly. This component is named primary demand. But continuous preparation of other components is not necessary. These components are named secondary demands. Secondary demands are supplied occasionally. The probability of preparation of secondary demands is calculated by Eq. (18).

$$P = \frac{(n-f)}{n+1} = \frac{n_s}{n+1} \Rightarrow n_s = (n+1)P \tag{18}$$

where f is the number of deficits (the number of months that released water from reservoir in them is less than water demand in the downstream of dam.), n is the number of years, n_s is the number of successful years, P is the probability of preparation of secondary demands.

For determination of n_s, the one-zero programming must be applied. The one-zero programming is an integer programming. The coefficient of the one-zero programming is α ($\alpha = 1$ for successful years $\alpha = 0$ for deficits). Relation between α and n_s is shown by Eq. (19).

$$\sum_{i=1}^{n} \alpha_i = n_s \tag{19}$$

Monthly distribution of primary demands and secondary demands are shown by Eqs. (20) to (23).

$$y_{firmt} = \wp_{ft} * y_{firm} \tag{20}$$

$$y_{pt} = \wp_{pt} * y_p \tag{21}$$

$$\sum_{t=1}^{T} \wp_{ft} = 1 \tag{22}$$

$$\sum_{t=1}^{T} \wp_{pt} = 1 \tag{23}$$

where $\wp_{ft}$ is monthly distribution coefficient of primary demands, $\wp_{pt}$ is monthly distribution coefficient of secondary demands, Y_{firmt} is monthly primary demands, Y_{pt} is monthly secondary demands, Y_{firm} is annual primary demands, Y_p is annual secondary demands.

$$\textit{Objective function in yield model= min Ka} \tag{24}$$

Restrictions of yield model divide to two parts:
Yearly restrictions:
ST:

$$S_{i+1} \leq S_i + Q_i - Y_{firm} - E_i - \alpha_i y_P \quad \text{i=1 to n} \tag{25}$$

$$E_i = \left[a + b \left(S_i + \sum_{t=1}^{T} \frac{S_t + S_{t+1}}{2} * \wp_t \right) \right] * E_m \tag{26}$$

$$S_{n+1} = S_1 \tag{27}$$

$$S_i \leq K_a^0 \quad \forall_i = 1,...,n \tag{28}$$

where Ka is total storage of reservoir, S_i is storage of reservoir in the start of year i, S_{i+1} is storage of reservoir in the end of year i, Q_i is the volume of inflow to reservoir in year i, E_i is the volume of evaporation from reservoir in year i, a, b are constants that are calculated by volume- area curve of reservoir, $\wp_t$ is monthly distribution coefficient of evaporation, S_t is storage of reservoir in the start of month t, S_{t+1} is storage of reservoir in the end of month t, E_m is the annual height of evaporation from reservoir, K_a^0 is over-year storage of reservoir.

Monthly restrictions:
ST:

$$S_{t+1} \leq S_t + \beta_t \lfloor y_{firm} + y_P + E_i \rfloor - Y_{firmt} - e_t - y_{Pt} \tag{29}$$

$$e_t = \left[a + b \left(\frac{S_t + S_{t+1}}{2} \right) \right] e_{mt} \quad \forall_t = 1...T \tag{30}$$

$$S_{T+1} = S_1 \tag{31}$$

$$S_{\min} + K_a^0 + S_t \leq K_a \quad \forall_t = 1,...,T \tag{32}$$

where e_t is the volume of evaporation from reservoir in month t, e_{mt} is the height of evaporation from reservoir in month t, S_{min} is the dead storage of reservoir.

3. Optimization of released water from reservoir of the Karaj dam by DP method:
DP method converts a multi states- multi variables problem to several one state- one variable problems. Therefore this method reduces time of solution of problem considerably.

In this research, time is stage variable and state variable is storage of reservoir in the start of month t and decision variable is storage of reservoir in the end of month t. In this method storage of reservoir divides to several classes. In the other word, storage of reservoir converts to several discrete variables. The objective function is:

$$Objective\ function= min\ [loss] \tag{33}$$
$$Loss= ((R_t-D_t)/D_{max})^2 \tag{34}$$

where R_t is released water from reservoir in month t, D_t is water demand in month t, D_{max} is maximum monthly water demand.

Restrictions of DP methods are:

$$S_{min}<S<K_a \tag{35}$$

Released water from reservoir is calculated by bellow equation.

$$R_{klt} = S_{kt} + Q_t - S_{lt+1} - E_{klt} \tag{36}$$

where S_{kt} is storage of reservoir in the start of month t and k is index of class of this storage, S_{lt+1} is storage of reservoir in the end of month t and l is index of class of this storage, Q_t is the volume of inflow to reservoir in month t, R_{klt} is released water from reservoir in month t (k is index of class of storage in month t and l is index of class of storage in month $t+1$), E_{klt} is the volume of evaporation in month t.

If $R_t<D_t$ this month is a deficit. This research utilizes backward propagation method. In stage one and the last period ($t=T$), damage function is:

$$f_T^1(k) = Min\ [Loss_{klT}] \tag{37}$$

In stage two and $t=T-1$, damage function is:

$$f_{T-1}^2(k) = Min\ [Loss_{klT-1} + f_T^1(l)] \tag{38}$$

And in stage n and $t=h$, damage function is:

$$f_h^n(k) = Min[Loss_{klh} + f_{h+1}^{n-1}(l)] \tag{39}$$

If $f_t^n(k)-f_{t+1}^{n-1}(l)= f_{t+1}^{n-1}(k)- f_{t+2}^{n-2}(l)$, optimum storage of reservoir for different months will be determined. After determination of optimum storage for different months, released water from reservoir will be calculated by attention to inflows to reservoir and volume of evaporation from reservoir.

4. Optimization of released water from reservoir of the Karaj dam by GA method:

Restrictions convert to penalty function in GA method and GA solves a problem without restriction. Objective function of GA method is:

$$\min f = \sum_{t=1}^{12} ff_t + \sum_{t=1}^{12} pen_t \tag{40}$$

$$ff_t = ((R_t - D_t)/D\max)^2 \tag{41}$$

$$pen_t = n_t \times r_t \times \left(\frac{R_t}{D\max} - 1\right)^2 \tag{42}$$

where r_t is penalty coefficient is equal to 100000, n_t is a zero-one variable.

If R_t is more than 1.01 D_t or less than 0.99 D_t, r_t will be equal to 1. r_t controls released water from reservoir.

After determination of optimum storage for different months, released water from reservoir will be calculated by attention to inflows to reservoir and volume of evaporation from reservoir by bellow equation.

$$R_t = S_t + Q_t - S_{t+1} - E_t \tag{43}$$

Characteristics of applied GA at this research are:

Rate of crossover = 0.8, Type of mutation= Uniform, Type of crossover = Heuristic, Selection method= Stochastic universal sampling, Number of generations = 3000, Population of each generation = 120

Two types of rate of mutation are considered at this research (constant and variable for different generations). Results of these types will be shown in results part.

3. RESULTS AND DISCUSSION

3.1 Results of the Markov chain method

Based on observed monthly inflows to reservoir of the Karaj dam (from 1961 to 2007), sixty series are generated for monthly inflows to reservoir by Markov chain method. These series are 50 years series. Governing stochastic distributions on observed monthly inflows to reservoir of the Karaj dam are illustrated in Table 4.

Table 4: Governing stochastic distributions on observed monthly inflows to reservoir of the Karaj dam

Month	January	February	March	April	May	June
Governing stochastic distribution on monthly inflow to reservoir	Log Person III	Log Person III	Person III	Lognormal 2 parameters	Lognormal 3 parameters	Lognormal 2 parameters
Month	July	August	September	October	November	December
Governing stochastic distribution on monthly inflow to reservoir	Lognormal 3 parameters	Lognormal 3 parameters	Lognormal 2 parameters	Lognormal 3 parameters	Person III	Person III

The mean of observed annual discharge of inflow to reservoir of the Karaj dam is 444 MCM. The mean of annual inflow to reservoir of the driest and the wettest series that are generated by Markov chain method is 390.84 and 542.64 MCM respectively.

3.2 Results of the yield model

In this research for application of yield model, three series of inflows data are used.
   1. Observed data
   2. Generated the driest series by Markov chain method
   3. Generated the wettest series by Markov chain method
   In this research, it is assumed that reservoir supply total drinkable water demand and 70% of irrigation water demand.
   Results of yield model for three series are illustrated in Table 5.

Table 5: Optimized volume of reservoir by yield model for different series

Series	With in-year storage (MCM)	Over-year storage (MCM)	Useful storage (MCM)
Observed data	130.7804	78.5979	209.3783
The driest series	131.1086	183.0521	314.1607
The wettest series	130.1023	0	130.1023

Real useful storage of reservoir of the Karaj dam is 191.6 MCM.

3.3 Results of DP and GA methods for optimization of released water from reservoir

The number of used classes in DP method for different volumes of reservoir is illustrated in Table 6.

Table 6: The number of used classes in DP method for different volumes of reservoir

Volume of reservoir (MCM)	Number of used classes
130.1	10
191.6	15
209.4	15
314.2	20

For application of GA method in this research, two types of mutation rate are used.
1. Constant mutation rate = 0.01
2. Variable mutation rate for different generations
In this method, mutation rates for different generations are:
Mutation rate=0.3 if (no of generation<700)
Mutation rate = $(-0.295/1300)*$(no of generation-700) +0.3 if (700<no of generation<2000).
Mutation rate=0.005 if (no of generation>2000)
The number of deficits and vulnerability of different methods are illustrated in Table 7. In this table, number of observed data is 552 (46 years) and number of generated data is 480 (40 years).

Table 7: The number of deficits and vulnerability of different methods

Volume of reservoir (MCM)	Type of data of inflow to reservoir	DP		GA with variable mutation		GA with constant mutation	
		Vulnerability	Number of deficits	Vulnerability	Number of deficits	Vulnerability	Number of deficits
130.1	Observed data	4890.9	348	2933.2	380	2009.2	264
	Generated data (the wettest series)	3981.3	309	2051.8	282	1338.3	201
	Generated data (the driest series)	5114	346	3223.3	335	2688.5	261
191.6	Observed data	3901.5	272	2047.8	208	2471	258
	Generated data (the wettest series)	3436.6	234	1290.7	151	1775.5	193
	Generated data (the driest series)	4545.5	281	2726.9	220	3116.7	260
209.4	Observed data	3100.1	241	1947.2	196	2948.2	351
	Generated data (the wettest series)	2932.6	220	1147.8	139	2256.8	258
	Generated data (the driest series)	3841.4	249	2605.1	204	3362.8	320
314.2	Observed data	2510.4	201	1993	180	2096.4	253
	Generated data (the wettest series)	2443	187	1190	131	1483.7	207
	Generated data (the driest series)	3257.4	212	2678	195	2816.7	283

Reliability and resiliency of DP and GA with variable mutation rate methods are illustrated in Table 8.

Table 8: Reliability and resiliency of different methods

| Volume of reservoir (MCM)	Type of data of inflow to reservoir	DP		GA with variable mutation	
		Reliability	Resiliency	Reliability	Resiliency
191.6	Observed data	0.507	0.2212	0.623	0.4595
	Generated data (the wettest series)	0.513	0.4286	0.685	0.6429
	Generated data (the driest series)	0.415	0.2178	0.542	0.2381
209.4	Observed data	0.563	0.3134	0.645	0.4737
	Generated data (the wettest series)	0.542	0.4862	0.710	0.6587
	Generated data (the driest series)	0.481	0.2308	0.575	0.2667

Comparison between calculated released water by DP and GA with variable mutation rate methods is illustrated in Figs. 2 and 3.
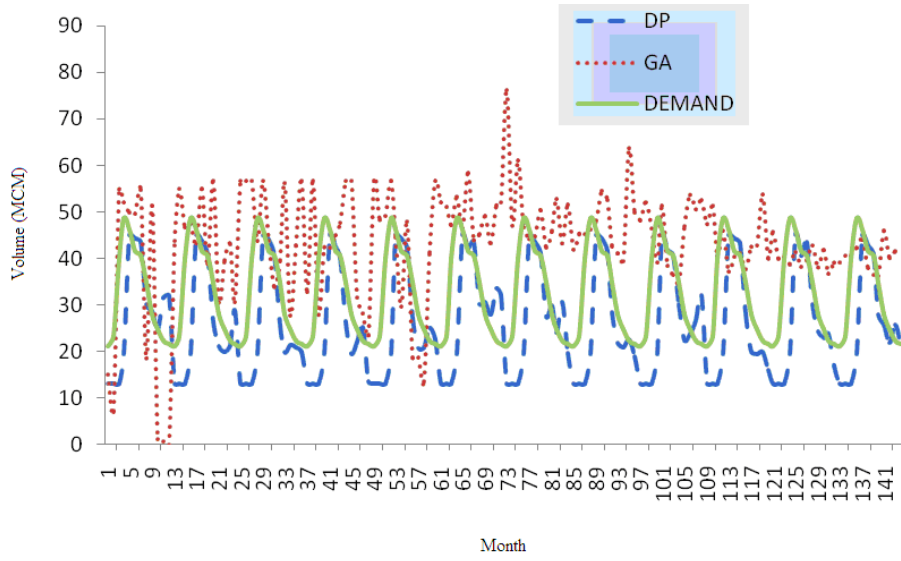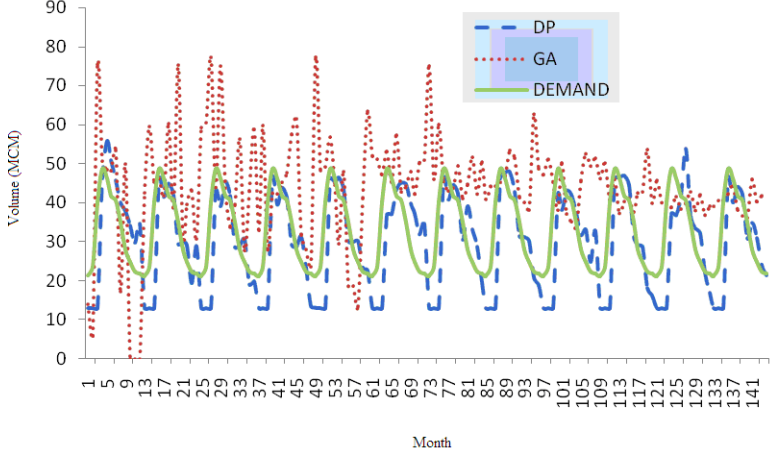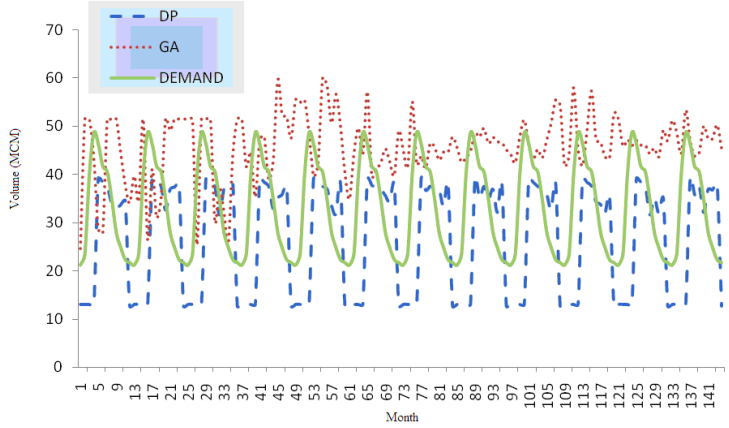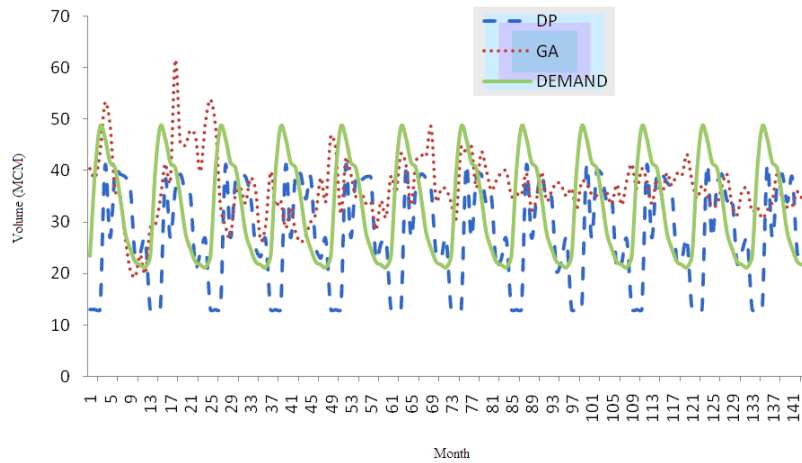

(a)
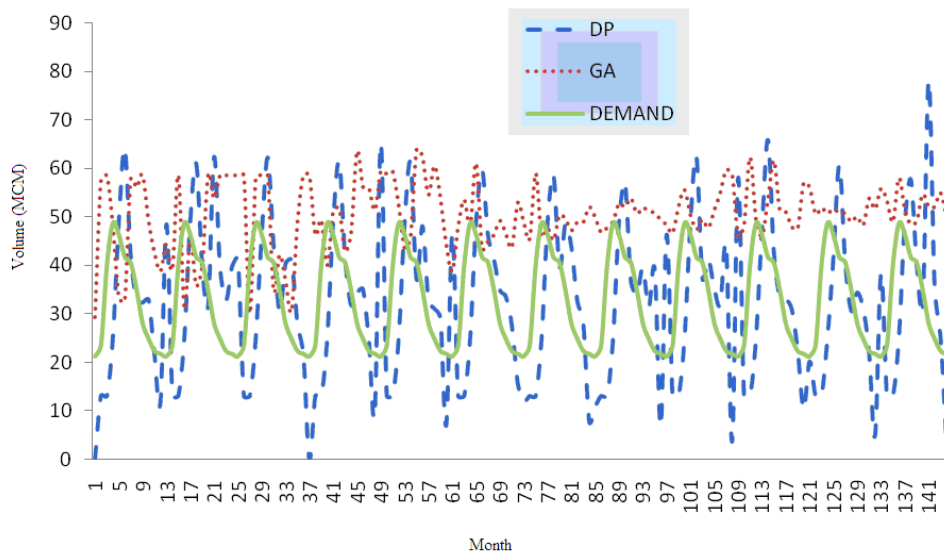
(b)
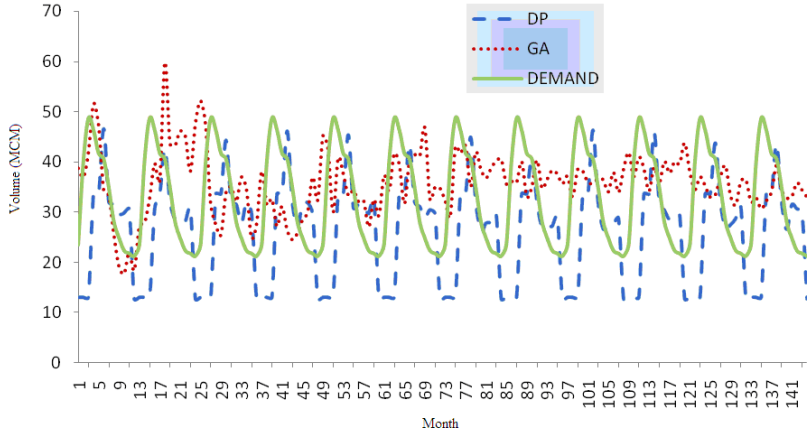
(c)

Figure 2. Comparison between calculated released water by DP and GA with variable mutation rate methods (volume of reservoir= 191.6 MCM) (a) Observed data (b) Generated data (the wettest series) (c) Generated data (the driest series)


(a)

(b)

(c)

Figure 3. Comparison between calculated released water by DP and GA with variable mutation rate methods (volume of reservoir= 209.4 MCM) (a) Observed data (b) Generated data (the wettest series) (c) Generated data (the driest series)

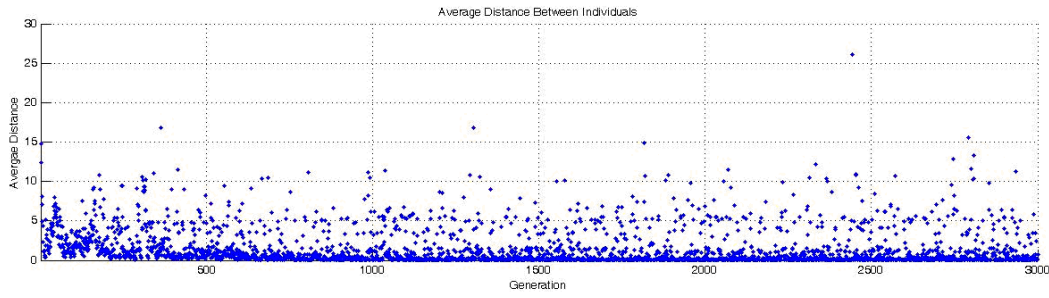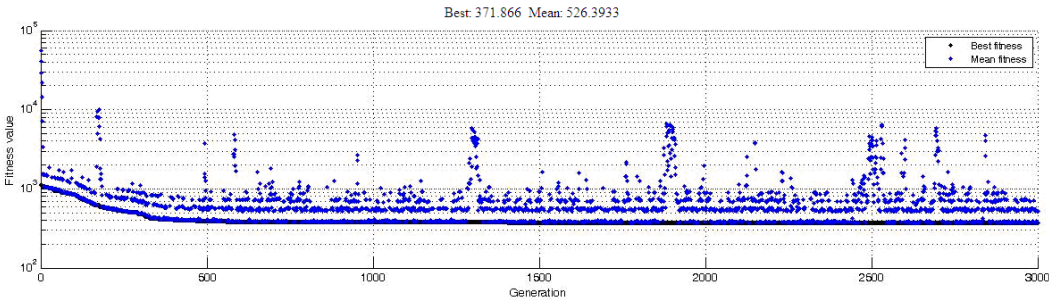## 3.4 Comparison between results of GAs with different mutation rates

Fitness values and average distance between individuals of each generation (genetic variation) are illustrated in Fig. 4 for different mutation rates.
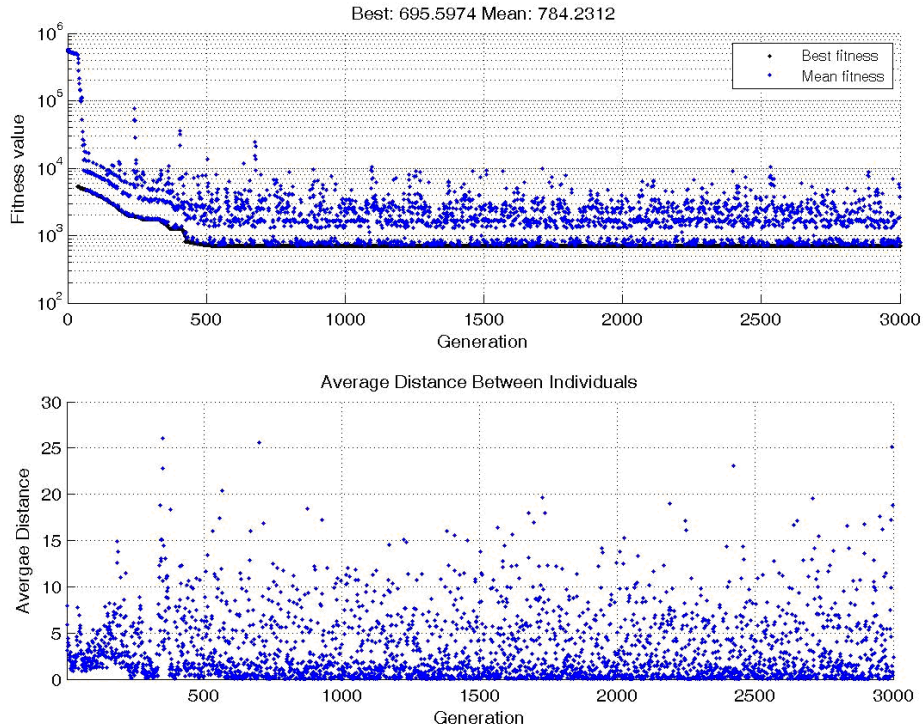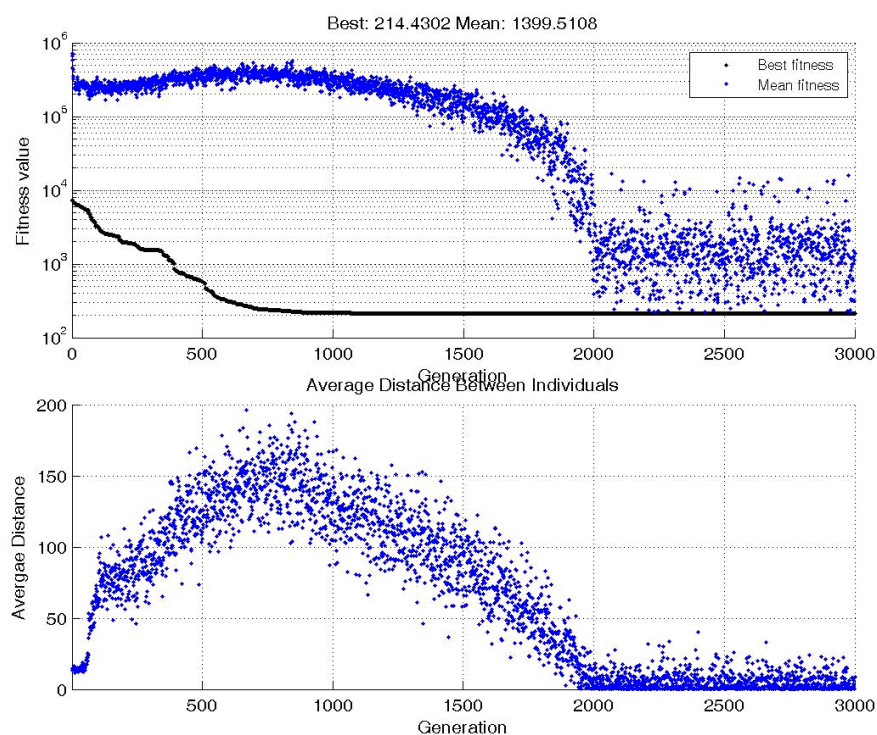

(a)
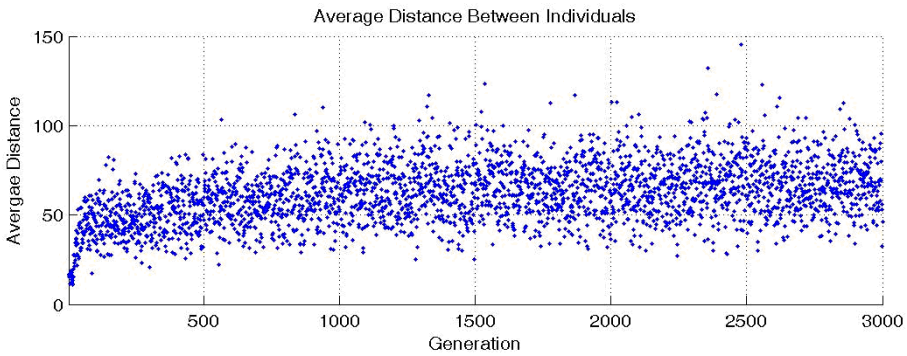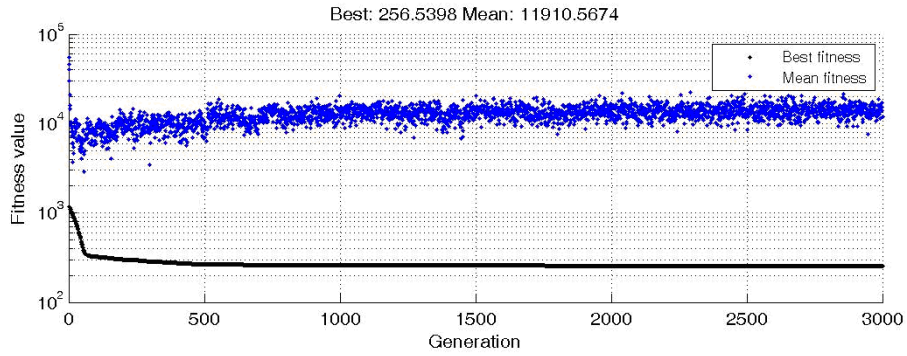
(b)

(c)

(d)

Figure 4. Fitness values and average distance between individuals of each generation (genetic variation) (a) Mutation rate=0.01 (b) Mutation rate=0.3 (c) Mutation rate=0.005 (d) Variable mutation rate from 0.005 to 0.3

4. CONCLUSION

GA method with variable mutation rate is the best method for increasing of reliability (number of success to number of data) and resiliency (number deficits that convert to success to number of deficits) and reduction of vulnerability (damage function). Fig. 4 showed that GA with variable mutation rate has the least fitness value (faster than other GAs reaches global optimum). While fitness value reduces by decreasing of mutation rate but genetic variation between individuals of each generation decreases too. Genetic variation should not become very low or very high. If average distance between individuals of each generation is very low or very high, suitable genetic variation must be found by error trial method (finding of global optimum become very difficult). By using of variable mutation rate, genetic variation will have a suitable range and finding of global optimum will become faster.

Also Figs. 2 and 3 showed that calculated water released by GA can supply water demands better than calculated water released by DP (GA method uses of penalty function in objective function). Nature of DP method is alternative because this method converts

problem to several one stage-one variable problems. Therefore DP method cannot supply water demands suitability. In the other hand DP cannot predict months that deficits occur in them correctly. DP that has alternative nature showed that deficits occur at entire months of year (from January to December) while GA showed that deficits occur from July to October. In these months, volume of inflow to reservoir is low while water demands are high.

Table 7 showed results of GA method were better than results of DP method. Also using of variable mutation rate reduced vulnerability and number of deficits at most of states. This subject states that GA with variable mutation rate can optimize released water from reservoir better than other methods. This method increased reliability and resiliency to 30% and reduced vulnerability to 50% than DP method.

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