Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 8 (22): 4186-4191, 2008
ISSN 1812-5654

Stochastic Multi-Purpose Reservoir Operation Planning by Scenario Optimization and Differential Evolutionary Algorithm

[1]M.A. Soltani, [2]A. Karimi, [2]M.R. Bazargan-Lari and [3]E. Shirangi
[1]Department of Civil Engineering, School of Engineering,
University of Tehran, Tehran, Iran
[2]Department of Civil Engineering, School of Engineering, Islamic Azad University,
East Tehran Branch, Tehran, Iran
[3]Department of Civil Engineering, School of Engineering, Islamic Azad University,
Karaj Branch, Karaj, Iran

Abstract: Indices usually considered to measure uncertainty of parameters and optimality of reservoir operation rules are expected value or variance of the slacks in supplying water demands. However, indices like reliability range to average ratio of supplied water as well as the average ratio of allowed river flow to released water for planning horizon will lead to a better description of uncertainty measurement. Considering this index within the objective function will lead to a problem with discrete non-linear objective function that minimizing it will show a better improvement in reservoir operation planning which is the least sensitive to the uncertainty of inflows. In this research, this problem is formulated as optimized-simulation, while considering stochasticity of inflows by scenarios, which is optimized by differential evolutionary algorithm, combined with scenario optimization. Inflow scenarios show the uncertainty band of inputs which is narrowed in outputs, like, demand supplying through optimal reservoir operation planning and assessed by the coefficient of variation index defined above. Application of this problem formulation and solution in a real world case Zayandehrud Dam in Isfahan, Iran, shows the robustness and reliability of the operation rules in comparison with actual operation within the years 1975 to 1994.

Key words: Reliability, scenario optimization, coefficient of variation, stochastic programming, stochastic inflows, Zayandehrud reservoir

INTRODUCTION

Reservoirs are structural measurements which help regulating and redistributing watershed water resources temporal and spatial availability. Obtaining optimal reservoir operation rules entails formulating it as a mathematical program and optimizing it according to an objective function which represent operator and/or some other user's utility functions. Problem formulation, while considering most of the operational considerations, may lead to a linear or nonlinear mathematical representation. Solution of such problems that includes discrete non-smooth variables and functions are better handled by evolutionary algorithms (Hota *et al*., 1999). Karamouz *et al*. (2002) formulated an optimization model for Zayandehrud reservoir operation rules by formulation and solved that by genetic algorithm. Another important aspect of reservoir operation rules optimization would be uncertainty of inflows to reservoir, which affects operational rules in long term planning. Rules obtained from a long term planning will have more reliability in comparison with rules obtained from a mid or short term planning. However, in long term planning uncertainty of inflows affects optimality of rules. Considering these uncertainties will improve reliability of operation rules application. Most applied approach to uncertainty consideration in reservoir operation planning is stochastic programming by Stochastic Dynamic Programming (SDP), Stochastic Linear Programming (SLP) and chance constrained formulation. Any of the approaches mentioned has limitations such as computational burden or curse of dimensionality for SDP and SLP approaches. Chanced constrained approach forces the problem to be solved within a very small portion of feasible region, which eliminates possibility of a better solution in excluded feasible region. Therefore, it is a very

Corresponding Author: Mohammad Reza Bazargan-Lari, Department of Civil Engineering, School of Engineering, Islamic Azad University, East-Tehran Branch, P.O. Box 33955-163, Tehran, Iran
Fax: +98(21) 335 80 330

conservative and non-economic approach to uncertainty consideration. On the other hand, Monte Carlo sampling approach to stochastic programming will lead to a more reasonable method of solving a problem under uncertainty from computational burden and precision point of view (Dembo, 1991). Scenario based optimization as a Monte Carlo sampling approach to stochastic programming has been used by many researchers in solving reservoir operation planning (Dembo, 1991; Shapiro, 2007). Scenario Optimization as a scenario based approach is much simpler and computationally lighter and faster approach to stochastic programming. However, in all mentioned approaches indices like expected value or variance of some objective function is optimized. These indices do not represent uncertainty in a measurable manner. However, an index like coefficient of variation shows uncertainty in a more meaningful way. Formulation of reservoir operation problem considering such indices will make a non-linear discrete non-convex problem which is difficult to solve by gradient based algorithms. On the other hand, evolutionary algorithms can cope with this problem which its combination with stochastic programming will ensure high reliability of obtained operation rules. In this research, reservoir operation rules optimization under uncertainty of inflows in a long term horizon would be done by scenario optimization and differential evolutionary algorithm. This type of problem formulation and solving is applied to a real world case study, Zayandehrud reservoir in Isfahan, Iran.

PROBLEM FORMULATION

Operational considerations of the reservoir, uncertainty of inflows to the reservoir in future and performance criteria for reservoir operation are important aspects that consideration of them makes the operation rules reliable with least unfavorable effects. Considering these aspects will formulate a nonlinear stochastic problem with non-continuous non-convex objective function. Solving this problem will entail combination of two efficient solution algorithms in a manner that their combination is still effective. These two algorithms are Scenario optimization and Differential evolutionary algorithm. In this research problem is formulated to be solved in an optimized-simulation algorithm. Reservoir operation is done according to scenario optimization, say; releases are allocated as target releases until upper and lower limit of storage values are met. Rule curves are generated, simulated and optimized within a combined algorithm made up of differential evolutionary algorithm and Scenario optimization. Main equation of the system is:

$$S_t + QI_t - Rl_t = S_{t+1} \tag{1}$$

where, S_t shows reservoir water volume, QI_t represents the inflow to reservoir and Rl_t is the release decision variable. This equation is corrected for evaporation losses if some conditions are met:

$$Rl_t \leq \mathrm{Min}\left(a + b \cdot S_t^C, \mathrm{Target}_t\right) \tag{2}$$

In this non-equation $a + b \cdot S_t^C$ is the reservoir outflow rating curve and Target is the amount determined in rule curves. If according to the release determined above S_{t+1} is higher than maximum storage capacity then spillage exists and S_{t+1} is set to maximum storage capacity. On the other hand, if S_{t+1} is less than minimum storage capacity then S_{t+1} is set to minimum storage capacity and release is set to:

$$Rl_t = S_t + QI_t - \mathrm{Stmin}_t \tag{3}$$

Objective function of this problem consists of reliablity range to the mean ratio in supplying water demands. Objective function of the reservoir operation problem is shown below, which is minimized.

$$Z = \mathrm{Max}\left(\frac{\mathrm{Relrange}}{\mathrm{Relmean}}\right)^r \tag{4}$$

where, Relrange and Relmean stand for reliability range and mean, respectively. The r is the importance factor.

It is clear that the problem formulation is nonlinear, discontinuous and non-convex though it represents a better uncertainty measurement index. In the problem to be solved QI's are indeterministic and have an uncertainty band, which in optimum operation planning it should be dissipated as much as possible in reservoir operation performance index defined earlier.

SCENARIO OPTIMIZATION

When problem conditions become stochastic, decision making needs more considerations so that the failure probability of decisions applications reaches the least possible value. While, decisions are deterministic anyway, conditions are uncertain at present or in future. Scenario optimization formulates this problem in a way that deterministic decisions with least deviation from the optimum of each scenario are obtained. In mathematical formulation a problem with some uncertain parameters could be expressed as below (Dembo, 1991):

$$\begin{aligned}&\text{Min. } Z = F^U(X)\\ &\text{s.t.}\\ &\quad g_i^U(X) = b_i^U\\ &\quad h_j^D(X) = e_j^D\end{aligned} \tag{5}$$

where, X's, e_j and h_j (X) are deterministic decision variable vector, right hand side and constraints, respectively. However, b_i, g_i (X) and Z are uncertain parameters, constraints and function, respectively. This problem is solved in a discretized deterministic form, b_i^S is described by independent scenarios b_i^S. For each scenario S, a deterministic problem is formulated, which is called sub-problem:

$$\begin{aligned}&\text{Min. } Z = F^S(X^S)\\ &\text{s.t.}\\ &\quad g_i^S(X^S) = b_i^S\\ &\quad h_j^D(X^S) = e_j^D\end{aligned} \tag{6}$$

Since none of the scenarios may happen in reality, optimum X will have some slacks in satisfying uncertain constraint $g_i^S(X^S) = b_i^S$. Therefore problem of finding optimum X when occurrence of scenarios is uncertain and X in presence of uncertain parameters could be re-formulated as follow:

$$\begin{aligned}&\text{Min. } Z = F^S(X_{opt})\\ &\text{s.t.}\\ &\quad g_i^S(X_{opt}) \neq b_i^S\\ &\quad h_j^D(X_{opt}) = e_j^D\end{aligned} \tag{7}$$

Another representation of the problem for X_{opt} could be:

$$\begin{aligned}&\text{Min. } \sum_S P_S \times \left(\left(F^S(X_{opt}) - Z^S\right)^n + \left(\sum_i \left(g_i^S(X_{opt}) - b_i^S\right)^m\right)\right)\\ &\text{s.t.}\\ &\quad h_j^D(X_{opt}) = e_j^D\end{aligned} \tag{8}$$

The above problem which is solved after optimizing the sub-problems is called tracking model. In the above formulation, P_s is the probability of each scenario occurance. By solving the tracking model X_{opt} is determined, so that deviation form scenarios constraints and the optimum objective function is minimized. Optmization problem defined by Eq. (8) is solved after optmizating the sub-problems in Eq. (7). By this two stage solution method a stochastic problem is shown in a single iteration for deterministic decision.

Differential Evolutionary Algorithm (DEA): Problem formulation is not suitable for solution by gradient-based algorithms because of discontinuity and non-linearity of the problem. Therefore, an evolutionary algorithm or dynamic programming approach must be selected to solve the problem. From these two algorithms the one with least amount of computational burden should be selected. Differential evolutionary algorithm has proved to solve the complexity of this problem more efficiently than DP. This algorithm has the least computational burden and robust in solving complex engineering problems (Deb, 2001). Based on differential evolutionary algorithm, a random population of feasible target releases is generated as follow:

$$\text{Target}_{t,chr}^{Gen=1} = Rl_{lower,t} + \text{Ran} \cdot \left(Rl_{up,t} - Rl_{lower,t}\right) \tag{9}$$

Problem objective function, Eq. (4), is used for target release chromosome assessment, mutation and cross-over after their application in reservoir operation simulation. Next generation is produced by mutation and/or cross over while keeping the elites. Mutation occurs with probability Mutprob as follows:

$$\text{Target}_{t,chr}^{gen+1} = \text{Target}_{t,chr}^{gen} \begin{cases} +\Delta \times (Rl_t^u - \text{Target}_{t,chr}^{gen}) & \text{if} \rightarrow \text{Ran} > \text{prob} \\ -\Delta \times (\text{Target}_{t,chr}^{gen} - Rl_t^1) & \text{if} \rightarrow \text{Ran} < \text{prob} \end{cases} \tag{10}$$

Δ is a random parameter in above equations. Cross-over takes place with probability (1-Mutprob) as simple average:

$$\text{Target}_{t,chr}^{gen+1} = \frac{\text{Target}_{t,chr}^{gen} + \text{Target}_{t,chr'}^{gen}}{2} \tag{11}$$

Aside from mutation and cross over, elitism helps to keep the best of each generations through evolution. Reliability is computed for total demand supply as:

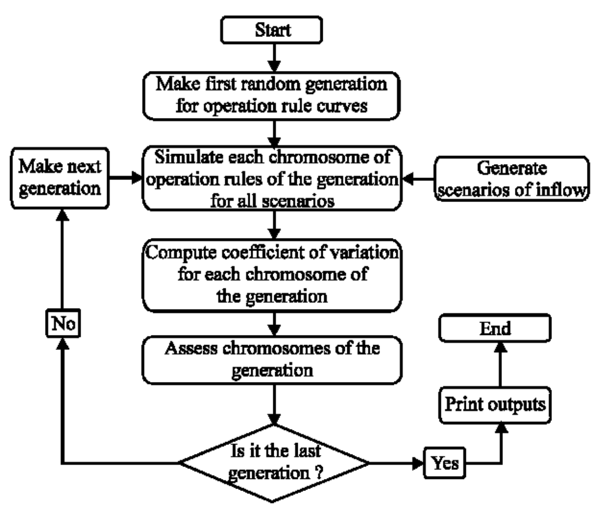

Fig. 1: Stochastic differential evolutionary algorithm

$$\text{Rel} = \frac{\sum_{t=1}^{TN} t}{TN} \quad \text{if} \left(\frac{Rl_t}{TDem_t} \right) \geq \text{Reliability factor} \tag{12}$$

This index is computed for each chromosome representing target release for reservoir operation within each generation over planning horizon. Next generations are produced using mutation and cross-over operators. Δ used in mutation operator resembles step-size in non-linear programming methods such as Newton-raphson (Coine *et al*., 1999; Deb, 2001).

Stochastic Differential Evolutionary Algorithm (SDEA): Each of the algorithms reviewed earlier are robust in solving stochastic or nonlinear non-convex discontinuous problems. However, the problem to be solved here entails use of both of them because of its nonlinearity and uncertainty. Combining both algorithms in a way not to affect their robustness will lead to another algorithm. This new algorithm makes use of scenarios within differential evolutionary algorithm. Reliability range to average ratio for each chromosome in the generation for all scenarios is computed and used for making the next generation. Scenarios are made with different methods which one of them is Indexed Sequential Modeling (ISM) (Labadie *et al*., 1987). ISM is a very simple method to model uncertainty when time series with long length is available and future trends are assumed to be like past trends. It is simply selecting a length equal to the planning horizon and shifting it according to the number of scenarios year by year for example. Combined algorithm for problem solving is shown in Fig. 1.

Reservoir operation rules optimization is formulated and solved by the combined algorithm SDEA.

CASE STUDY

Zayandehrud reservoir system at the upstream of Isfahan city in Iran is selected to be formulated and solved by the modeling approach introduced in this research. This reservoir plays an important role in the agriculture and economics of the downstream sub-basins. Reliability of supplying the downstream demands would be of great economic and social importance to the decision makers. Therefore, development of a long term reservoir operation model which considers stochasticity of inflows will help to obtain the most reliable reservoir operation rule. Reliability is taken as an objectiveto be maximized. It is stochastic therefore another index is used to measure stochasticity of reliability range to mean ratio. This index, that must be minimized to ensure the dissipation of uncertainty in decision making, makes the problem formulation nonlinear, discontinuous and non-convex. Therefore, Stochastic Differential Evolutionary Algorithm (SDEA) is used to solve this problem. Application of SDEA in this case could be compared to the actual operation for years 1975 to 1994. As said before inflows scenarios to Zayandehrud reservoir are made up with ISM method that some of them are shown in Fig. 2. Figure 2 and 3 show the scenarios considered according to ISM method to represent stochasticity of reservoir inflows. Actual inflow for years 1975 to 1994 do not mach any of scenarios and it is less than all. It means model has no pre-knowledge about actual inflows, so, its operation comparison to the actual operation becomes fair.

Figure 4 and 5, show evolution of objective function and its components by generation for 25 chromosomes. Evolution of reliability expected value (Fig. 5) has a jump in generation 2 which had a range that led the objective function to 0.015 value. In fact, though in generation 2 mean has increased suddenly but range to mean ratio has a larger value in comparison to next 3 to 17 generations. However, reliability mean has reached 1 and its range reach to 0.005 at optimum.

Model operation by SDEA shows meaningful improvements in reservoir operation for validation years (Fig. 6). The SDEA needs relatively small amount of generations and chromosomes to evolve which reduces the computational burden. Besides, SDEA needs no ranking or fitness computation which reduces the

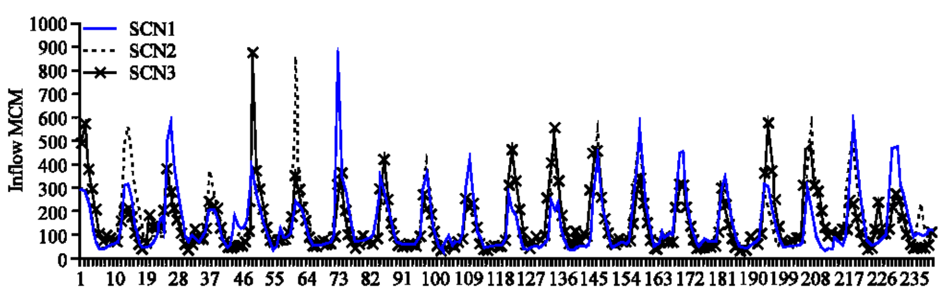

Fig. 2: Scenarios of inflow to reservoir for 20 years planning horizon

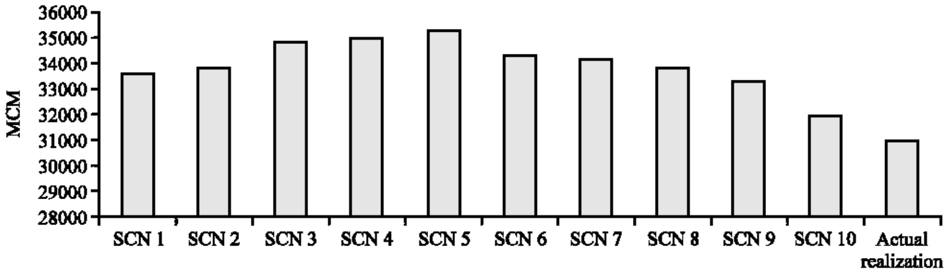

Fig. 3: Total Inflow volume of each scenario for 20 years and actual inflow

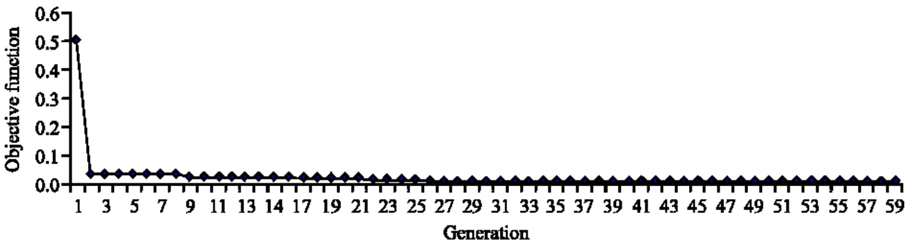

Fig. 4: Evolution of objective function (reliability range to mean ratio) for chromosome number 25

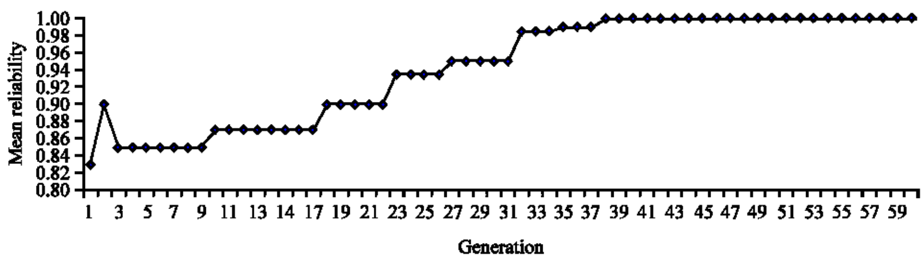

Fig. 5: Mean reliability evolution for 25 chromosomes in each generation (Reliability to supply 95% of demand or more)

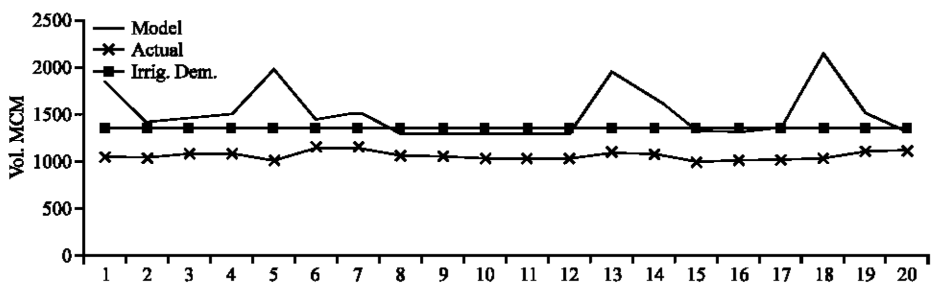

Fig. 6: Model vs. actual operation for years 1975 to 1994 (yearly sums)

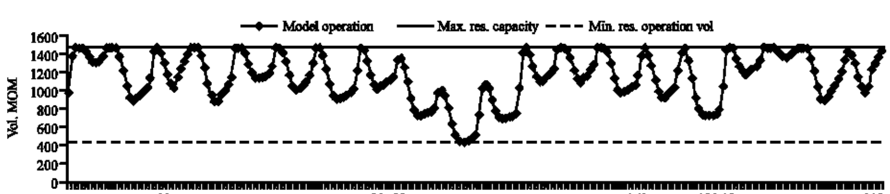

Fig. 7: Reservoir operation obtained from model application in Zayandehrud Reservoir

computational burden much. This problem with 240 real variables has reached optimum value at generation number 38 with 25 chromosomes. Number of scenarios is 10, as shown in Fig. 3. Reservoir operation according to SDEA solution of Zayandehrud reservoir operation model is represented in Fig. 7. Demands include agricultural, domestic and industrial, which domestic and industrial are 10 MCM per month for all periods. Domestic and industrial demands are fully met by model operation.

CONCLUSIONS

In this research stochastic programming is viewed from another point of view by considering reliability range to mean ratio for supplying water demands. It is more representative than expected value or standard deviation in measuring uncertainty, as objective function to be minimized. Minimizing the objective function tries to narrow the uncertainty of releases reliability and sensitivity to uncertainty of inflows (inputs) as much as possible. It will lead to a nonlinear, non-convex and discontinuous mathematical program that a suitable category of solution algorithms for it would be evolutionary algorithms. A new hybrid algorithm based on differential evolutionary algorithm and scenario optimization is set up and applied in a real world case, Zayandehrud reservoir in Iran. Application of model decisions shows substantial improvements in reservoir operation for a test period of 20 years. This improvement is mostly related to the problem formulation selected in this research which is much more representative of uncertainty in a system operation. Optimization procedure tries to make the decisions insensitive to problem input (inflows) uncertainty as much as possible. This approach will increase reliability of obtained decisions for application in real world cases.

ACKNOWLEDGMENTS

The technical contribution of Ms. Leyla Karimi and Mr. Yousef Bazargan-Lari is hereby acknowledged.

REFERENCES

Coine, D., M. Dorigo and F. Glover, 1999. New Ideas in Optimization. 1st Edn., McGraw-Hill Company, New York, USA., ISBN: 0-07-709506-5 .

Deb, K., 2001. Multi-Objective Optimization Uses Evolutionary Algorithms. 1st Edn., John Willy and Sons, New York, USA., ISSN: 047187339X .

Dembo, R.S., 1991. Scenario optimization. Ann. Operat. Res., 30: 63-80.

Hota, P.K., R. Chakrabarti and P.K. Chattopadhyay, 1999. Short_term hydrothermal scheduling through evolutionary programming technique. Elect. Power Syst. Res., 52: 189-196.

Karamouz, M., N. Khodatalab, S. Araghi-Nejad and R. Kerachian, 2002. Multi-purpose reservoir operation optimization: Application of genetic algorithm. Proceedings of ASCE EWRI Conference, Virginia, May 19-22.

Labadie, J.W., D.G. Fontane, G.Q. Tabios and N.F. Chou, 1987. Stochastic analysis of dependable hydropower capacity. ASCE J. Water Resourc. Plann. Manage., 113: 422-437.

Shapiro, A., 2007. Stochastic programming approach to optimization under uncertainty. Mathematical Programming: Series A and B, 112: 183-220.