# Assessment of Evolutionary Algorithm for Reservoir Operation

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**Abstract:** The complexity of water resources management problems, especially for multipurpose reservoirs, increases the motivation to find a robust method to overcome this challenge. Evolutionary optimization algorithms are used widely to handle reservoir management problems. In this research, one of the competitive methods of optimization named Borg MOEA was used to achieve reservoir operation control. A case study from the literature was used to test the algorithm's performance on this type of problems. The objective was to reduce the difference between reservoir releases and water demands and also to maintain a suitable amount of storage in the reservoir. The adopted method produced competitive solutions by improving the objective function value significantly when compared with the result in the literature. In addition, the quantity of water stored in the reservoir was increased.

**Keywords:** Evolutionary optimization algorithm, Borg MOEA, reservoir operation, multipurpose reservoir system.

## 1. INTRODUCTION

In recent decades, significant demands on water exploitation were observed. This raises the difficulties to manage and allocate water in a sustainable way. Reservoirs are essential for water resources management in a river basin which needs a powerful method for optimum operation strategies (Jothiprakash and Shanthi 2006).

Multipurpose reservoirs are widely used to serve many demands for domestic, industrial, irrigation, environment, hydropower production and flood control to satisfy the mentioned demands and maximize the economic benefits. These types of problems are complex because of nonlinear storage-inflow relationship, conflicting objectives, dynamic properties, constraints, etc. (Haimes and Hall 1977). Many methods for optimization were found to solve complex problem such as linear programming, non-linear programming, and dynamic programming. But these methods are generally not suitable for multipurpose reservoirs as Yeh (1985) observed.

To solve these types of problems, a new approach has been found based on evolutionary algorithms (EAs). EAs use a set of solutions as population, rather than one solution in every iteration (Deb, 2001). Many researchers adopted EAs to solve complex problems in different fields of science and engineering (Coello *et al.* 2007). In the field of water management, Javadi *et al.* (2015) used non-dominated sorting genetic algorithm (NSGA-II) to optimize seawater intrusion in coastal aquifer. Seyoum *et al.* (2016) used a penalty-free approach in water distribution network design. Sidiropoulos *et al.* (2016) used simulation-optimization for groundwater management. Additionally, Oxley and Mays (2016) applied a genetic algorithm (GA) for long-term planning and sustainable water resources management. Tigkas *et al.* (2016) investigated the efficiency of evolutionary algorithms for the calibration of a conceptual hydrologic model. In the area of integrated urban wastewater management, Rathnayake and Tanyimboh (2015) developed a methodology to control combined sewer overflows that combined a multi-objective algorithm and the storm water management model (SWMM 5.0) (US Environmental Protection Agency) (Rossman, 2009).

For reservoir operation and management, Ahmad *et al.* (2014) reviewed common optimization algorithms used in this field. In addition, Choong and El-Shafie (2015) compared different optimization algorithms used in reservoir management. Noori *et al.* (2013) used a GA to solve a multi-reservoir problem to maximize both hydropower production and flood protection. Chenari *et al.* (2014) also used a GA to assess the operation of a reservoir. Pianosi *et al.* (2011) combined an artificial neural network and a multi-objective GA (MOGA) for reservoir management. Zou and Wu (2012) applied MOGA to maximize both power generation and irrigation benefits. Scola *et al.* (2014) used NSGA-II, Hosseini-Moghari *et al.* (2015) applied two optimization algorithms, and Tayebiyan *et al.* (2016) applied a GA to optimize hydropower generation. Azizipour *et al.* (2016), implemented a weed optimization algorithm for hydropower production. Furthermore, Qi *et al.*

(2016) proposed a multi-objective immune optimization algorithm for flood control. Chen *et al.* (2016) proposed a parallel strategy for NSGA-II to optimize reservoir operation.

In this study, a recently introduced algorithm, Borg MOEA, was selected to solve a reservoir operation problem. The aim of the current study was to test the performance of the above-mentioned algorithm on a real-word reservoir operation problem, based on a case study from the literature.

Hadka and Reed (2013) introduced Borg MOEA for many-objective and multimodal optimization problems. Some of the features in Borg MOEA include (a) diversity preservation; (b) tracking of the optimization progress and stagnation; and (c) restart to move away from any local optima. The algorithm uses six recombination operators to improve the search process.

To preserve diversity, the objective space is divided into hyper-boxes whose dimensions are equal to $\epsilon$; the value of $\epsilon$ is specified by the user. The $\epsilon$-index vector is used for dominance evaluation instead of the objective function values. The algorithm calculates this index by dividing the objective function value by $\epsilon$, and the result is taken as the next integer number. If two or more solutions are in the same $\epsilon$-box, the dominant solution among these is the one which is nearest to the lower-left corner of the $\epsilon$-box in the case of a minimization problem.

To detect stagnation, Hadka and Reed (2013) employed $\epsilon$-progress, which measures progress while searching for new solutions. If the algorithm finds new solutions in a new previously unoccupied $\epsilon$-box, it means that there is progress and the algorithm is allowed to continue. On the other hand, if there is no improvement found based on $\epsilon$-progress for a certain number of function evaluations, a revive procedure occurs, to search for additional solutions and escape from the local optima. The details of the revive procedure are available in Hadka and Reed (2013).

Finally, the algorithm depends on six recombination operators to produce offspring. In fact, in Borg MOEA, the selection of the recombination operators is competitive, and evolves depending on the environment of the problem. These operators are: Simulated Binary Crossover (SBX) (Deb and Agrawal 1994), Differential Evolution (DE) (Storn and Price 1997), Parent-Centric Crossover (PCX) (Deb *et al.* 2002), Unimodal Normal Distribution Crossover (UNDX) (Kita *et al.* 1999), Simplex Crossover (SPX) (Tsutsui *et al.* 1999) and Uniform Mutation (UM) (Michalewicz *et al.* 1994). Furthermore, the Polynomial Mutation (PM) operator (Deb and Agrawal 1999) is applied to the offspring produced by all operators except for UM.

## 2. RESERVOIR OPTIMIZATION MODEL

Usually, multipurpose reservoirs serve many goals, like hydropower generation, domestic water supply, agricultural water supply, flood protection and other environmental management issues. In this study, the reservoir system consists of a single multipurpose dam constructed to control water discharge in the river for irrigation, domestic water supply, flood control and hydropower generation purposes. This type of dams has many economic benefits.

In the proposed model, three types of constraints were adopted for the operation and control of the reservoir system as follows.

The volume of storage in the reservoir is limited between the dead storage and the maximum capacity of the reservoir and can be expressed as

$$S_{min} \leq S_t \leq S_{max};\ t = 1, \ldots, 12 \tag{1}$$

where $S_t$ is the initial storage at the beginning of month $t$, $t = 1 \ldots 12$; $S_{min}$ is the dead storage of the reservoir; and $S_{max}$ is the maximum storage of the reservoir.

The releases from the reservoir should be between the minimum and maximum values, i.e.

$$R_{min} \leq R_t \leq R_{max};\ t = 1, \ldots, 12 \tag{2}$$

where $R_t$ is the mean monthly water release for the month $t$; $R_{max}$ is the maximum release of the reservoir; and $R_{min}$ is the minimum releases of the reservoir.

To ensure reservoir storage sustainability, another constraint was adopted in this study, which ensures that the amount of storage in the first month of the next year will be equal to or greater than the initial storage. This constraint can be expressed as

$$S_{13} \geq S_1 \tag{3}$$

where $S_1$ is the initial storage at the start of the first month and $S_{13}$ is the reservoir storage in the first month of the next year.

A drought condition was considered, to test the algorithm's ability to find near-optimal solutions in such critical conditions. To simulate this condition, 50% of the standard deviation of the monthly average inflow for many years was subtracted from the origin inflow as follows.

$$I_t = I'_t - \frac{SD_t}{2}; \quad t = 1, \ldots, 12 \tag{4}$$

where, for month $t$, $I_t$ is the reduced reservoir inflow; $I'_t$ is the original reservoir inflow; and $SD_t$ is the standard deviation of the reservoir inflow for month $t$.

The fitness function, that is to be minimized, for the reservoir operation can be expressed as

$$Minimize\ f = \left[\sum_{t=1}^{12}(R_t - D_t)^2 + \sum_{t=1}^{12}(S_t + I_t - S_{t+1} - R_t - E_t)^2\right](1 + C) \tag{5}$$

$D_t$ is the mean monthly downstream water demand for the month $t$. $S_t$ is the initial storage, i.e. the storage at the beginning of month $t$, where $t$ = 1, …, 12, while $S_{t+1}$ is the final storage at the end of month $t$. $E_t$ is the mean monthly evaporation from the reservoir during the month $t$ and $C$ is a penalty for constraint violations. The first term in the (square) brackets in Equation 5 represents the sum of the squares of the differences between the reservoir releases and the demands. The second term in the (square) brackets represents the sum of the squares of the errors in the flow continuity equation; this term should be zero, to satisfy the principle of conservation of mass.

The penalty function used is

$$C = \sum_{t=1}^{12}\sum_{j=1}^{NC} g_{tj}(S_t) \tag{6}$$

where $NC = 4$ is the number of constraint functions. The function $g_{tj}$, with $j$ = 1 to 4 and $t$ = 1 to 12, is defined for the various reservoir conditions as follows.

$$g_{t1}(S_t) = (S_{min} - S_t) \times 100, \text{ for } S_t < S_{min};\ t = 1, \ldots, 12 \tag{7}$$

$$g_{t2}(S_t) = (S_t - S_{max}) \times 100, \text{ for } S_t > S_{max};\ t = 1, \ldots, 12 \tag{8}$$

$$g_{t3}(S_t) = (S_1 - S_{13}) \times 100, \text{ for } S_{13} < S_1 \tag{9}$$

$$g_{t4}(S_t) = 0, \text{ for } S_{min} \leq S_t \leq S_{max};\ t = 1, \ldots, 12 \tag{10}$$

The penalty function method has some disadvantages regarding the convergence of evolutionary algorithms. The convergence rate is directly affected by the penalty function values. In general, the user specifies the penalty function after performing some trials. In addition, the performance of the penalty function may differ from a problem to another. Therefore, this function must be chosen

carefully for each problem (Siew and Tanyimboh 2010).

The mathematical model developed has some limitations. For example, very briefly, the period of operation considered is one year and seepage from the reservoir and other operational losses are neglected, as in Chenari *et al.* (2014).

## 3. RESULTS AND DISCUSSIONS

A case study based on a real-world reservoir system in the literature (Chenari *et al.* 2014) was considered. Chenari *et al.* (2014) employed a Genetic Algorithm (GA) to optimize the reservoir operation for Mahabad dam in Iran. The aim was to minimize the deficits in the monthly water releases. The dam is located in the northwest of Iran and has an approximate watershed area of 807 $km^2$. It is a cold semi-arid area with average annual rainfall of 542.58 mm. There is rainfall during the three months from February to April. The live storage and dead storage are 180 million $m^3$ and 40 million $m^3$ respectively. The minimum release was taken as zero, while the maximum release was 51.48 million $m^3$ per month for the first six months of the year and 53.57 million $m^3$ per month for the second six months of the year. Data for 32 years, from 1975 to 2006, were used in Chenari *et al.* (2014) to obtain the average monthly inflows to the reservoir. More details about the study area and the data can be found in Chenari *et al.* (2014).

We wrote a computer program in the C language to solve the optimization problem in Equations 1 through 10. The algorithm has many coefficients and parameters as summarised in Table 1 (Hadka and Reed 2013).

*Table 1. Default parameter values used in Borg MOEA*

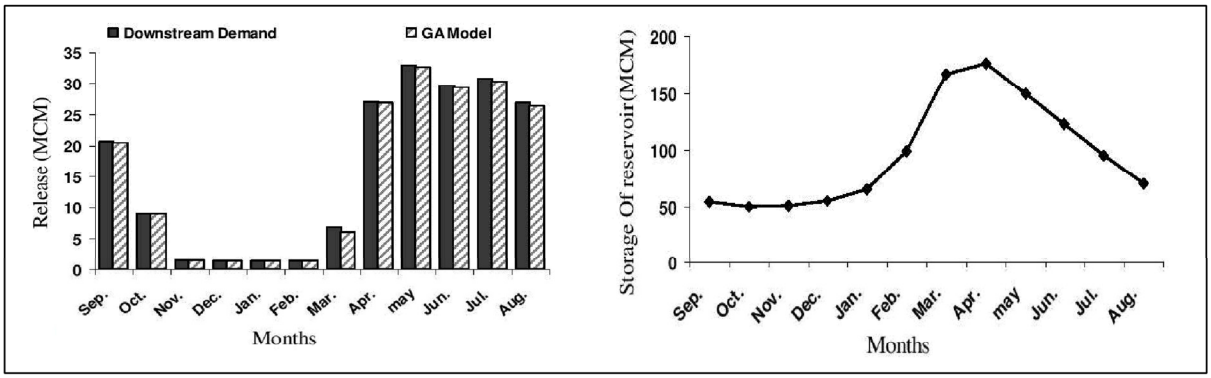
| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Initial population size | 100 | SPX parents | 10 |
| Tournament selection size | 2 | SPX offspring | 2 |
| Epsilon, $\epsilon$ | 0.01 | SPX epsilon | 2.0 |
| SBX crossover rate | 1.0 | UNDX parents | 10 |
| SBX distribution index | 15.0 | UNDX offspring | 2 |
| DE crossover rate | 1.0 | UNDX $\sigma_\xi$ | 0.5 |
| DE step size | 3.0 | UNDX $\sigma_\eta$ | $0.35/\sqrt{L}$ |
| PCX parents | 10 | UM mutation rate | $1/L$ |
| PCX offspring | 2 | PM mutation rate | $1/L$ |
| PCX $\sigma_\eta$ | 0.1 | PM distribution index | 20 |
| PCX $\sigma_\zeta$ | 0.1 | | |

*$\epsilon$ is the dimension of the hyper-boxes in the objective space; $\sigma_\eta$, $\sigma_\zeta$ and $\sigma_\xi$ are parameters of variance; and L is the number of decision variables.*

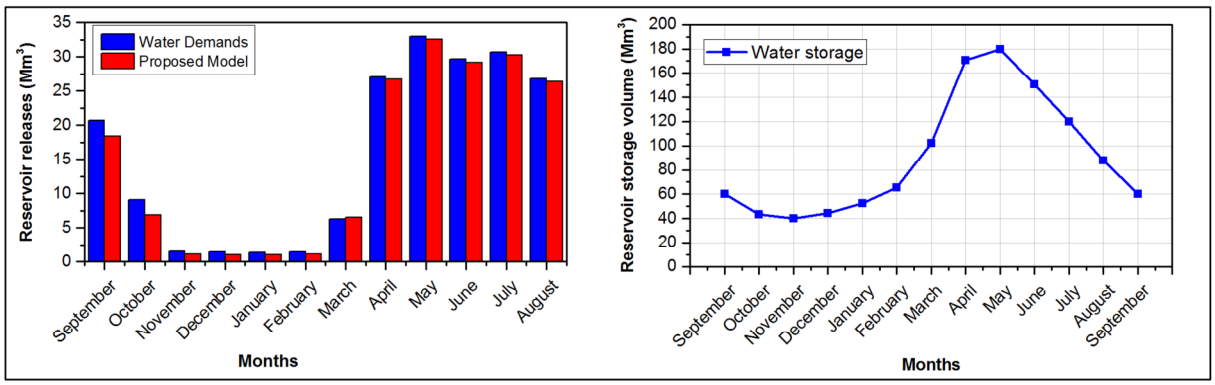
The algorithm was executed 10 times with 200,000 function evaluations in each run. Figure 1a shows the monthly reservoir releases and storage achieved by the GA in Chenari *et al.* (2014) while Figure 1b shows the results achieved by Borg MOEA. The value of the fitness function, Equation 5, using the GA was $185.3\times10^6$ $m^3$ (Chenari *et al.* 2014) and for Borg MOEA it was $23.0135\times10^6$ $m^3$.

There were some deficits in the monthly releases, especially in the first two months (September and October). Also, the effect of the sustainability constraint on the releases is observed especially in the last five months from April to August, which causes some deficits in the releases in order to satisfy the requirement.

For the algorithm itself, Figure 2 shows the convergence characteristics. It can be seen that the algorithm began to converge around 25,000 function evaluations. At 25,000 function evaluations, the value of fitness function was about $65\times10^6$ $m^3$, i.e. less than the best value found using the GA in Chenari *et al.* (2014). Then, after 40,000 function evaluations, the algorithm approached the best solution with a stable trend. The number of function evaluations for the GA (Chenari *et al.* 2014) was 525,000.

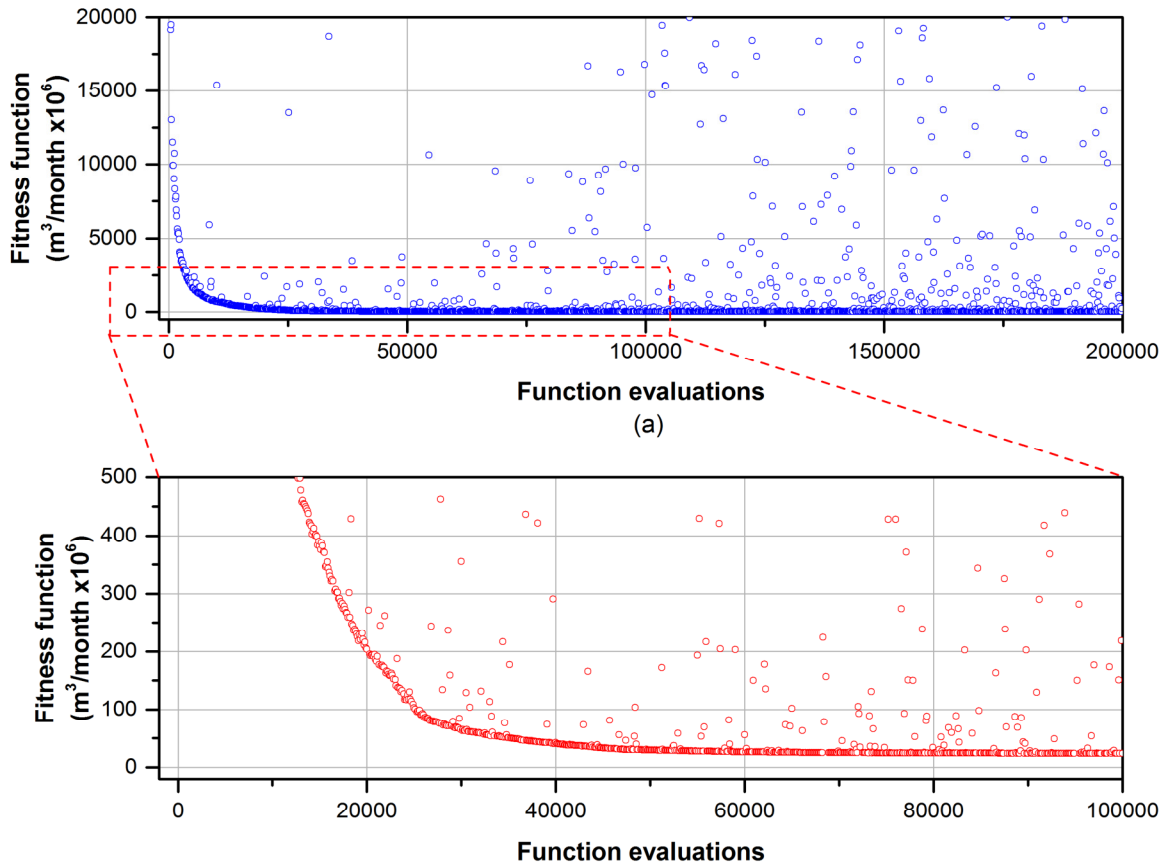



(a)




(b)

*Figure 1. Reservoir operation results (a) Chenari et al. (2014 ) (b) Present approach*




(a)

(b)

*Figure 2. Convergence characteristics of the fitness function using Borg MOEA*

Figure 2 also illustrates the effects of the penalty on the fitness function. It can be seen that the initial values were far away from the final solution. This observation seems to reflect the algorithm's ability to converge early in the environment provided by the dynamic penalty function in Equation 6. The execution of the algorithm took only a few seconds, i.e. fast outputs could be achieved repeatedly. The research outcomes could help the relevant planning authorities and decision makers to improve the economic benefits of reservoir projects. Furthermore, the results strengthen the motivation for future work to solve more complex water management problems in the real-world.

## 4. CONCLUSIONS

An evolutionary optimization algorithm was used in this study to solve a real-world scenario reservoir operation and management problem. The state-of-the-art Borg MOEA optimization algorithm was selected to solve a multipurpose reservoir operation problem. A case study based on a reservoir system in the literature was selected to test the algorithm's performance and reliability. The early results are encouraging. The fitness function was improved by 87.6%, from $185.3\times10^6$ $m^3$ to $23.0135\times10^6$ $m^3$. The convergence was relatively quick. Furthermore, the results strengthen the motivation for future work to solve more complex water management problems in the real-world.

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