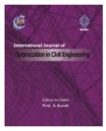
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2015; 5(2):167-187



A MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM USING DECOMPOSITION (MOEA/D) AND ITS APPLICATION IN MULTIPURPOSE MULTI-RESERVOIR OPERATIONS

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ABSTRACT

This paper presents a Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) for the optimal operation of a complex multipurpose and multi-reservoir system. Firstly, MOEA/D decomposes a multi-objective optimization problem into a number of scalar optimization sub-problems and optimizes them simultaneously. It uses information of its several neighboring sub-problems for optimizing each sub-problem. This simple procedure makes MOEA/D have lower computational complexity compared with non-dominated sorting genetic algorithm II (NSGA-II). The algorithm (MOEA/D) is compared with the Genetic Algorithm (NSGA-II) using a set of common test problems and the real-world Zohre reservoir system in southern Iran. The objectives of the case study include water supply of minimum flow and agriculture demands over a long-term simulation period. Experimental results have demonstrated that MOEA/D can improve system performance to reduce the effect of drought compared with NSGA-II superiority. Therefore, MOEA/D is highly competitive and recommended to solve multi-objective optimization problems for water resources planning and management.

Received: 20 December 2014; Accepted: 12 March 2015

KEY WORDS: multi-objective optimization; decomposition; multi-reservoir

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1. INTRODUCTION

Operation policies for reservoir management in drought periods are important for mitigating drought-related impacts. During the drought season, system managers would rather incur a sequence of smaller water supply shortages than one potential catastrophic shortage [14]. Reservoir operators must decide on how much quantity of water to release and what to store. In this regard, several types of reservoir operating rules have been previously suggested. Revelle et al. [18] first introduced the linear decision rule, which assumes releases linearly related to storage and decision parameters. Shih and Revelle [20, 21] developed a multiphase hedging rule with a discrete curtailment ratio which corresponds to the available water calculated from the current storage and projected inflow. Later, Neelakantan and Pundarikanthan [15] employed a simulation-optimization methodology using neural network and multiple hedging rules to improve reservoir operation performance for a drinking water reservoir system. A few years later, Tu et al [25, 26] developed the discrete hedging rule presented by Shih and Revelle [21]. They considered a set of rule curves that is the function of the current storage level to trigger hedging for a multi-purpose multi-reservoir system. Recently, several papers have developed the hedging rule presented by Tu et al [25] such as Guo et al [6] employed an operating rule for multi-reservoir by combining parametric rule with the hedging rule to avoid catastrophic water shortage during droughts. Taghian et al [24] also, employed a hybrid model to optimize both conventional rule curve and the hedging rule simultaneously. Ngoc et al [16] designed a reservoir operation model with interactive balancing of water releases and water storage including environmental base flow requirements and flood control storage. They used a genetic algorithm with a penalty strategy for optimizing reservoir operation rule curves for multi-use water resources management.

Many real-world optimization water resources management problems involve several conflicting objectives. For optimizing these problems to come into existence two types of methods, classical optimization methods and evolutionary algorithms. Some of the classical optimizing methods are linear programming (LP), non-linear programming (NLP) and dynamic programing (DP) [27, 12, 22 and 23]. Traditionally, all listed methods considered multiple objective functions using the weighting method or the ε-constraint method without considering all the objectives simultaneously [1]. Recently, there is an increasing interest in using of biologically based evolutionary algorithms (EAs) for optimizing complex systems with either a single or multiple objectives. Multi-objective evolutionary algorithms present a set of non-dominated solutions/Pareto Fronts (PF) for multi-objective problems, which give a decision maker more flexibility in the selection of a suitable alternative. Almost all well-known Multi-objective optimization evolutionary algorithms (MOEAs) such as NSGA-II and SPEA [29] use the Pareto dominance relation together with a crowding measure for the fitness evaluation of each individual. Pareto dominance-based algorithms work generally well to approximate PF in two or three objectives. However, their search ability is severely deteriorated by increasing the number of objectives, because almost all the solutions are non-dominated by each other under many objectives. To overcome this problem, recently, a new MOEA framework, multi-objective evolutionary algorithm based on decomposition (MOEA/D) [28, 13], has been proposed. It decomposes a multi-objective problem (MOP) into a set of scalar optimization sub-problems with neighborhood relations. Also, in the first version of MOEA/D employed simulated binary crossover (SBX) [3] and polynomial mutation [5] as the search engines [28].

The main characteristic of MOEA/D is that a multi-objective problem is handled as a collection of a large number of single-objective problems.

This study introduces a new multi-objective optimization algorithm based on decomposition (MOEA/D) as a new and capable multi-objective algorithm to obtain hedging rule parameters in a multiple reservoir system. Explicitly, MOEA/D decomposes the MOP into scalar optimization sub-problems. It simultaneously optimizes a number of single objective optimization sub-problems. In the following, to demonstrate the ability of purpose algorithm it has analyzed general MOEA/D algorithm in solving three benchmark functions, then it has compared the efficiency of the algorithm in solving benchmark functions with NSGA-II algorithm. After that, MOEA/D is used for obtaining the Pareto optimal rule curves for a multi-objective reservoir system management problem that considers minimum flow and agriculture demands as objective functions of Zohre reservoir system in southern Iran. In the following, a discussion is presented about the finding of this work.

2. MULTI-OBJECTIVE OPTIMIZATION

A multi-objective optimization problem (MOP) can be stated as follows:

$$\begin{gathered} \textit{Minimize } F(x) = (f_1(x),\dots,f_m(x))^T \\ \textit{Subject to } x \in \Omega \end{gathered} \tag{1}$$

where Ω is the decision (variable) space, F: $\Omega \to R^m$ consists of m real-valued objective functions, and R^m is called the objective space. The attainable set is defined as the set $\{F(x),\ x \in \Omega\}$. An x solution is said to dominate solution y if and only if $f_i(x) \le f_i(y)$ for every $i \in \{1,\dots,m\}$ and $f_i(x) < f_i(y)$ for at least one index $j \in \{1,\dots,m\}$. A point $x^* \in \Omega$ is Pareto optimal to (1) if there is no point $x \in \Omega$ such that $f(x)$ dominates $f(x^*)$. $f(x^*)$ is Pareto-optimal objective vector. The set of all the Pareto-optimal points is called the Pareto Set (PS).

3. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM BASED ON DECOMPOSITION (MOEA/D)

In this section, firstly, several scalarizing function-based algorithms are introduced and then the basic settings of MOEA/D are defined.

3.1. Scalarizing Functions

The search ability of Pareto dominance-based algorithms is severely deteriorated by increasing the number of objective functions [11, 17, 7 and 8]. This is because when all individuals in a population are non-dominated, and the fitness evaluation of each individual is based on only a crowding measure in each Pareto dominance-based algorithm. Thus, their search ability is severely deteriorated. This leads to poor search ability of these algorithms for many-objective problems. Recently, it has been reported that better results can be obtained for many-objective problems by the use of scalarizing functions [9, 10]. The scalarizing functions have advantages such as the scalability to many-objective problems and need much less computation load than Pareto dominance-based one, especially for many-objective problems. In order to, MOEA/D is introduced as a multi-objective algorithm. This algorithm is based on a decomposition approach to convert the PF approximation into a number of single objective optimization problems. There are several approaches to convert the problem of the PF approximation into a number of scalar optimization problems. In the following, two approaches, which are used in our experimental studies, are introduced.

1) Weighted Sum Approach

Several approaches have been considered for converting a MOP into a number of single-objective optimization sub problems. In the following, two most commonly used approaches are introduced. Let $\lambda = (\lambda_1, \ldots, \lambda_m)$ be a weight vector, i.e., $\sum_{i=1}^{m} \lambda_i = 1 \;\; \lambda_i \geq 0$ for all $I = 1, \ldots m$. Then, the optimal solutions to the following single optimization problems:

$$\begin{gathered} Minimize\ g^{ws}(x \mid \lambda) = \sum_{i=1}^{m} \lambda_i f_i(x) \\ Subject\ to\ x \in \Omega \end{gathered} \tag{2}$$

are Pareto optimal to (1) if the PF of (1) is convex, where $g^{ws}(x \mid \lambda)$ is used to emphasize that λ is a coefficient vector in this objective function, while x is the variable to be optimized. Where $g^{ws}(x \mid \lambda)$ is used to emphasize that λ is a weight vector in this objective function, while x is the variable to be optimized. However, when the PF is not convex, the weighted sum approach may not be able to find some Pareto-optimal solutions.

2) Tchebycheff Approach

The single-objective functions to be minimized are in the following form:

$$g^{te}(x \mid \lambda) = \min_{1 \leq i \leq m} \{\lambda_i (f_i(x) - z_i^*)\} \tag{3}$$

(3)

where $z^* = (z_1^*, \ldots, z_m^*)$ is the reference point, i.e.,

$$z^{*} = \min_{x \in \Omega} f_{i}(x) \tag{4}$$

For each i=1,…,m, $z_i^{*} = \max\{f_i(x), x \in \Omega\}$. Under some mild condition, for each Pareto-optimal point x^{*}, there exists a weight vector λ such that x^{*} is the optimal solution of (3), and each optimal solution of (3) is Pareto-optimal to (1). Therefore, one is able to obtain different Pareto optimal solutions by altering the weight vector.

At each generation, MOEA/D with the Tchebycheff approach maintains:

1) A population of N points $x^{1},...,x^{N} \in \Omega$ where x^i is the current solution to the *i*th sub-problem is;

2) $FV^{1},...,FV^{N}$, where FV^{i} is the F-value ofx^i, i.e., $FV^{i} = F(x^{i})$ for each i=1… N;

3) $z = (z_1,...,z_m)^T$, where z_i is the best value found so far for objectivef_i;

An external population (EP), which is used to store non-dominated solutions found during the search [28]. The flowchart of the MOEA/D algorithm is presented in Fig 1.

3.2 Basic Setting:

Setting of N and $\lambda^{1},...,\lambda^{N}$ **:** This is controlled by parameter H. More precisely, $\lambda^{1},...,\lambda^{N}$ are all the weight vectors in which each individual weight takes a value from

$$\left\{\frac{0}{H}, \frac{1}{H}, ..., \frac{H}{H}\right\}$$

Therefore, the number of such vectors is

$$N = C_{H+m-1}^{m-1} \tag{5}$$

Setting of Neighborhood: The Euclidean distance is used to compute the distance between any two weight vectors.

Decomposition Approach: Tchebycheff approach is used in this paper. In the Tchebycheff approach, the reference point z^{*} is substituted by $z = (z_1,...,z_m)$, where $z_i$is the best value of function f_i found so far.

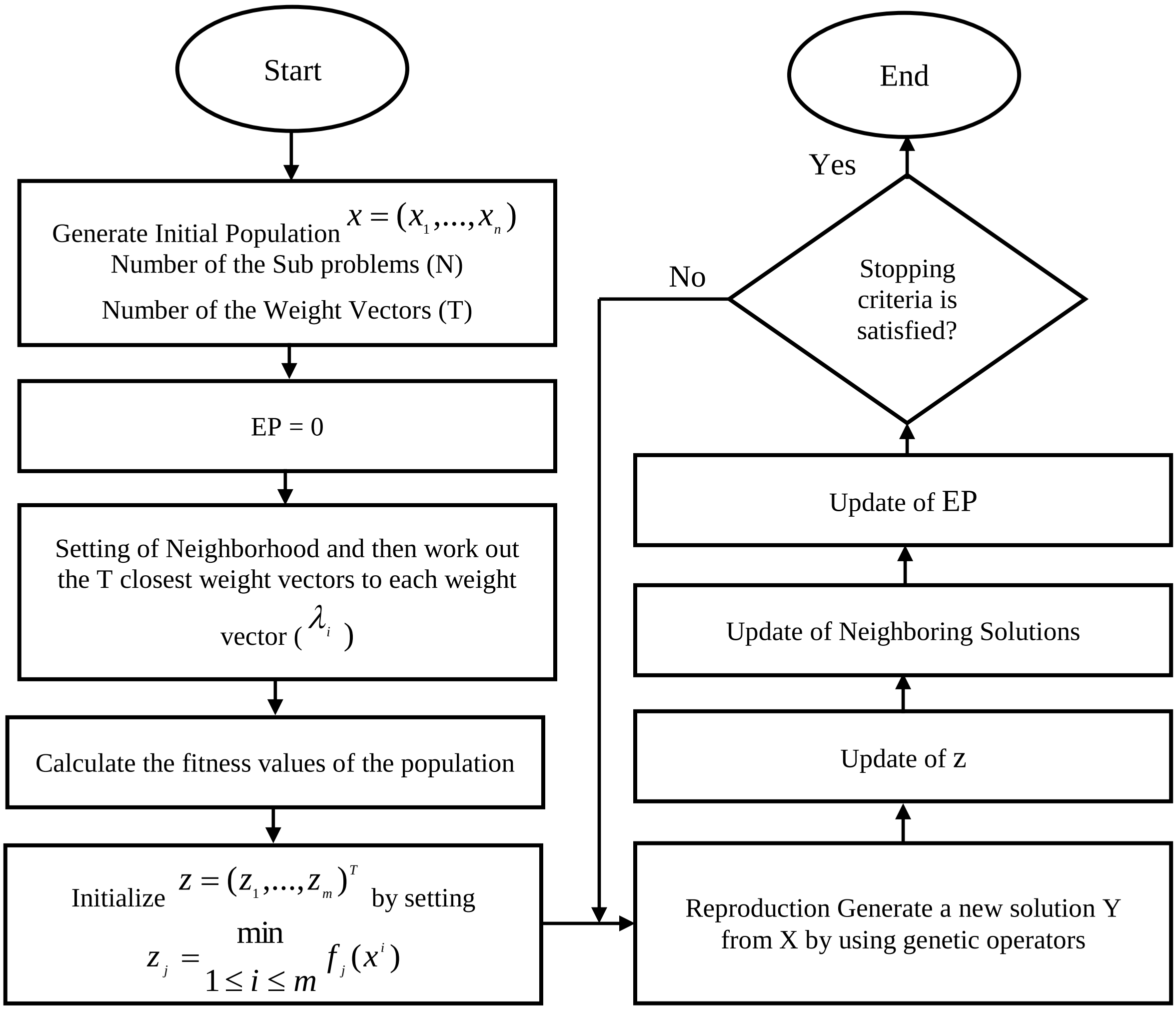


Figure 1. Flowchart of MOEA/D algorithm

4. NON-DOMINATED SORTING GENETIC ALGORITHM (NSGA-II)

Non-dominated Sorting Genetic Algorithm (NSGA-II) is a popular and efficient multi-objective evolutionary algorithm based on non-dominated sorting and elitist approach. The main difference between NSGA-II and other EAs is the method of operator selection. The NSGA-II employs the non-dominated sorting and ranking selection with the crowded comparison operator [4]. Three new innovations are described in the following:

1) **Fast non-dominated sorting:** The fast non-dominated sorting approach has been employed to reduce the computing time complexity to O (MN2) (N is population size and M is the number of objective function).

2) **Crowding Distance:** In the proposed NSGA-II, the crowding distance [2, 5] is used to get an estimate of the density of solutions surrounding a particular solution *i* in the population. For every chromosome in a Pareto front, a crowding distance is measured as the distance of the biggest cuboid contacting the two neighboring solutions. It adapts a suitable

automatic mechanics based on the crowding distance in order to guarantee the diversity and spread of solutions.

3) **Crowded Comparison Operator:** The crowded comparison operator guides the selection process at the various stages of the algorithm towards a good spread of the solutions in the optimum fronts. This operator apply between two solutions with differing non-domination ranks, it prefer the solution with better ranking. Otherwise, if both solutions belong to the same front, the solution which is located in a lesser crowded region is preferred [5].

5. PERFORMANCE METRIC

In order to allow a quantitative assessment of the performance of a multi-objective optimization algorithm, three performance metrics were calculated: the spacing metric (SP), the generational distance (GD), and the diversity metric (DM) [19].

The spacing metric is a measure of the distribution of the non-dominated solutions set found and is calculated as:

$$SP = \frac{1}{n-1}\sqrt{\sum(\bar{d} - d_i^2)} \tag{6}$$

Where, n= number of points on the non-dominated solution. $d_i = \min\left(\left|f_1^i(x) - f_1^j(x)\right| + \left|f_2^i(x) - f_2^j(x)\right|\right)$ $, i, j = 1,...,n$; and d: mean of all d_i.

Generational distance is a measure of the closeness of the non-dominated solutions set found to the true Pareto front, and it is calculated as:

$$GD = \sqrt{\frac{\sum_{i=2}^{n} d_i^2}{n}} \tag{7}$$

where, n = number of points on the non-dominated solution set; and d_i = Euclidian distance between each solution to the nearest point on the true Pareto front.

Application of the Methodology

The preceding two algorithms are applied to a set of test problems first and then to a real case study. These two applications are selected to investigate advantages and disadvantages of the MOEA/D algorithm compared with the NSGA-II algorithm.

Test Problem

In order to demonstrate the search performance of MOEA/D, three benchmark test functions are selected. Equations for and the optimal Pareto front of each test function are shown in Table 1. The parameter settings of both algorithms are given in Table 2.

Table 1: Test Problems

Problem	n	Objective function	Constrains
ZDT1	*30*	$f_1(x) = x_1$ $f_2(x) = g(x)[1-\sqrt{\frac{f_1(x)}{g(x)}}\,]$ $g(x) = 1+\frac{9}{n-1}(\sum_{i=2}^{n} x_i)$	$0 \le x \le 1$
FON	3	$f_1(x) = 1-\exp(-\sum_{i=1}^{3}(x_i - \frac{1}{\sqrt{3}})^2)$ $f_2(x) = 1-\exp(-\sum_{i=1}^{3}(x_i + \frac{1}{\sqrt{3}})^2)$	$-4 \le x \le 4$
SRN	2	$f_1(x) = (x_1\text{-}2)^2 + (x_2\text{-}1)^2 + 2$ $f_1(x) = 9\,x_1 - (x_2\text{-}1)^2$	$g_1(x) = x_1^2 + x_2^2 \le 225$ $g_2(x) = x_1 - 3\,x_2 \le -10$

Pareto fronts for the three test problems are presented in Fig. 2(a) for ZDT1 test, Fig. 2(b) for FON's test, and Fig 2(c) for SRN's test.

Table 2: The parameters of the algorithms

MOEA/D parameters		NSGA-II parameters	
Max iteration	500	Max iteration	500
Npop	100	Npop	100
Number of Archive	100	Crossover rate	0.8
Number of Neighbors	30	Mutation rate	0.3-0.01

The first function ZDT1 is perhaps the easiest of all of the ZDT problems, and the only difficulty of MOEA may face in this problem is that it has a large number of variables. Table 3 shows the quantitative results and Fig 2 shows qualitative results using the current algorithm.

Table 3: Performance Metrics for Test Problems

Algorithm	Problem	ZDT1		FON		SRN	
	Statistic\metric	GD	SP	GD	SP	GD	SP
MOEA/D	Mean	**0.00091**	**0.00790**	**0.00096**	0.00957	**0.1819**	**1.4093**
	Worst	**0.00096**	**0.00868**	**0.00098**	0.01000	**0.1890**	1.5808
	Best	**0.00083**	**0.00618**	**0.00094**	0.00905	**0.1749**	**1.2124**
	SD	**0.00004**	**0.00094**	**0.00002**	**0.00034**	**0.0047**	**0.1193**
NSGA-II	Mean	0.00486	0.06609	0.00212	**0.00837**	0.4116	1.5850
	Worst	0.00493	0.06706	0.00216	**0.00918**	0.4320	**1.4601**

	Best	0.00469	0.06364	0.00209	**0.00764**	0.3966	1.7075
	SD	0.00009	0.00128	0.00003	0.00065	0.0152	0.1337

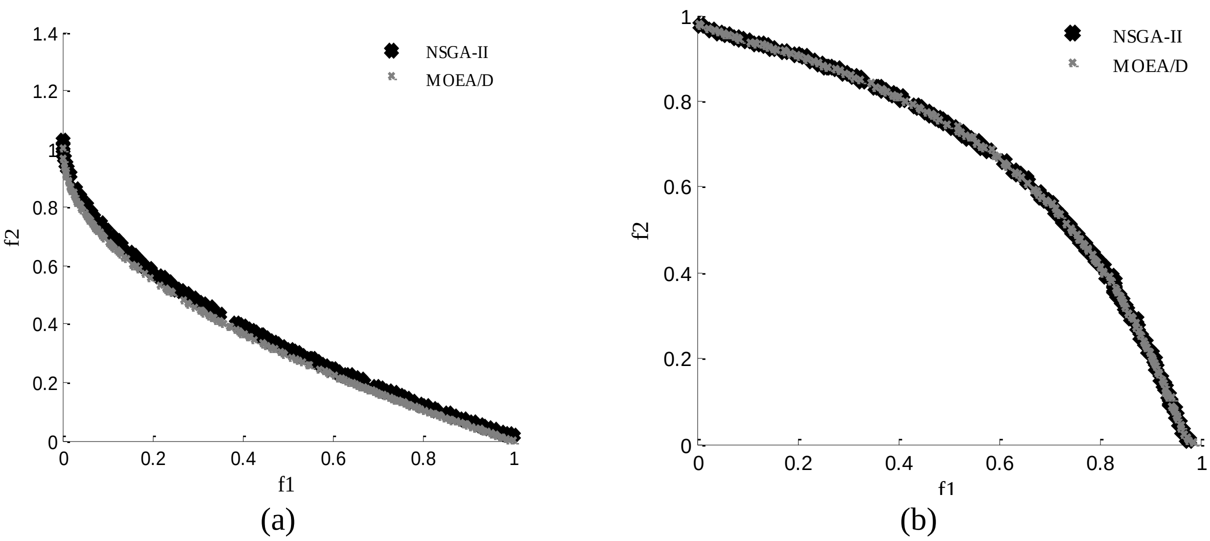
The second function, FON is the three-variable formulation of Fonseca and Fleming. Here, the objective function is scalable and the Pareto front is a single concave curve. From Fig. 2 it can be seen that the MOEA/D effectively finds diverse solutions along the optimal PF. Its good performance is also evident from Table 3.

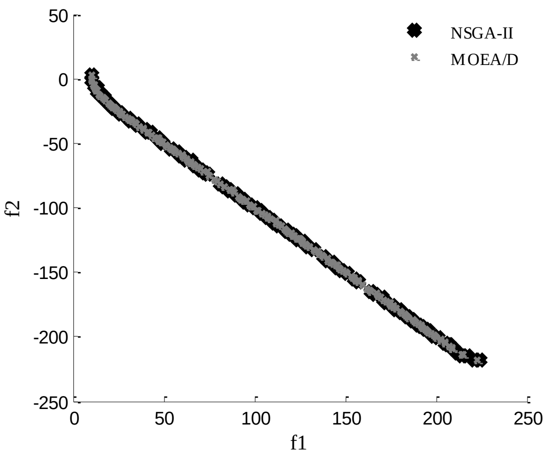
The third test problem, SRN is a MOOP with two objectives subject to two constraints. Here, the constrained Pareto optimal set is a subset of the unconstrained Pareto-optimal set, which gives difficulty in finding the true Pareto optimal region for the algorithm. From Table 3, it is clear that MOEA/D was able to attain the both goals. It can be seen clearly from figure 2 that the Pareto front is well predicted and a large number of optimal solutions spread out over the entire front are obtained.

The performance metrics results are presented in Table 3 for both MOEA/D and NSGA-II. The results have shown MOEA/D performance is better on GD metric in all test problems, whereas the NSGA-II performance is better on SP metric of FON test problem.

Multi-purpose and multi-reservoir operation problem

In this section, the MOEA/D algorithm is used to determine the optimal hedging rule curves of the Chamshir, Kosar, and Kheirabad reservoirs located in Zohre reservoir system in southern Iran. This system has an area of about 16,000 km^2. The schematic configuration is shown in Fig. 3. The future system comprises 3 reservoir dams, 7 input stream flows, 9 irrigation network, 3 public demand channels, 2 minimum flow channels, 9 junction nodes, and some general channels. The useful storage volumes for the reservoir dams including Kosar, Chamshir and Kheirabad are 418, 1576 and 104 million cubic meter, respectively.





(c)

Figure 2. Results for test problems: (a) ZDT1; (b) FON; (c) SRN

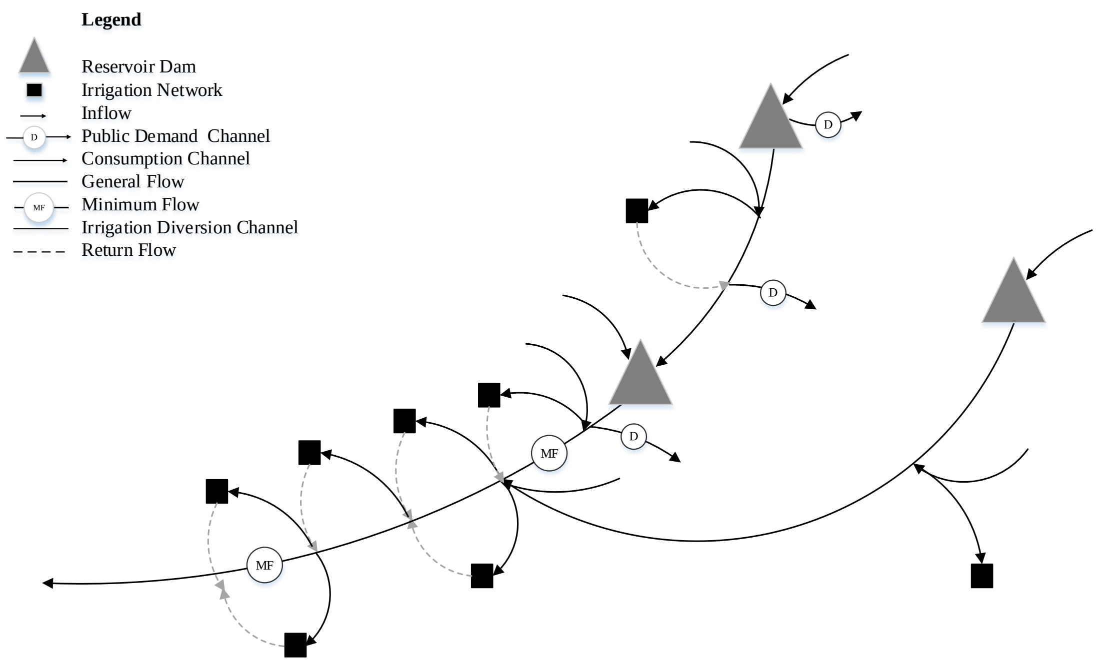


Figure 3. Schematic configuration of the water supply system

6. METHODOLOGY

6.1 Simulation method

This paper presents a monthly reservoir operation of the multi-purpose and multi-reservoir systems according to hedging rule curves. These rule curves are established at the planning stage to provide guidelines for operating the reservoir. In this simulation model, the total reservoir storage space is divided into a number of zones using a set of rule curves. In fact, rule curves show the current storage level to trigger hedging. Additionally, the amounts of the hedging rule are specified through the rationing factors as a percent of target demands for each zone [25, 26]. This study considered two rule curves (upper and lower curve), thus there are three zones of normal, drought, and severe drought conditions (Fig. 4). MOEA/D is applied to the simulation model for optimizing simultaneously the rule curves and rationing factors in the multi-purpose multi-reservoir system. The simulation model creates the operation rules based on hedging rule for the multi-reservoir system water supply. Decision variables in the proposed rule are given by the optimization model. How to apply simultaneously both the rule curves coupled with hedging rules is described next.

1) When the beginning reservoir storage is in zone 3 (Fig. 4), all target demands are met at the 100% level.

2) When the reservoir storage is in zone 2, the reservoir release for meeting the planned demand must be cut back for instance by 30%.

4) When the beginning reservoir storage is in zone 1, the reservoir release for meeting the planned demand must be cut back for instance by 60%.

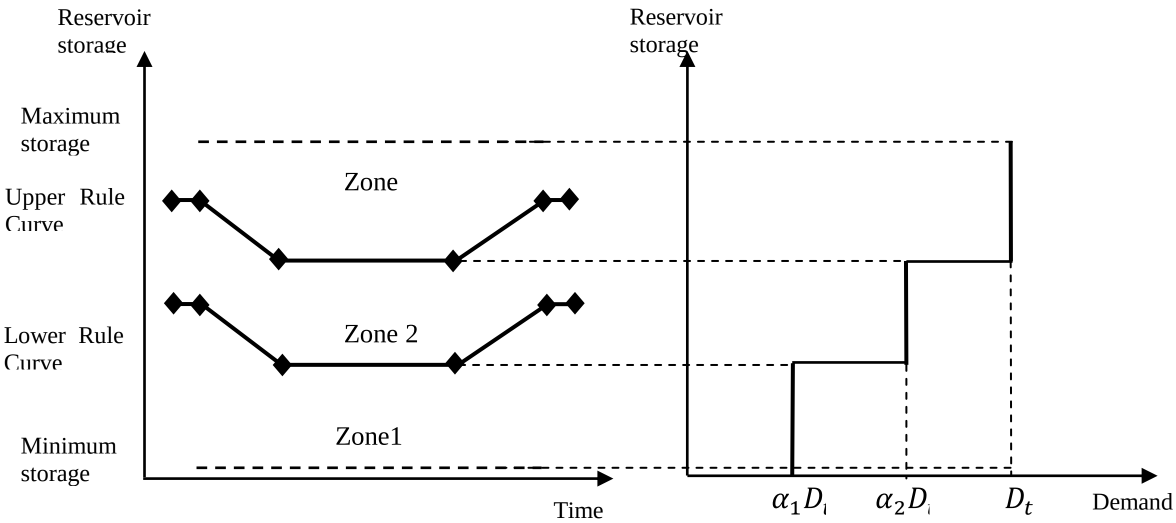
The equations (8), (9), and (10) represent the function relationship:

$$if\ S_t \in zone1, \quad then\ R_t = \alpha_1 D_t \tag{8}$$

$$if\ S_t \in zone2, \quad then\ R_t = \alpha_2 D_t \tag{9}$$

$$if\ S_t \in zone3, \quad then\ R_t = D_t \tag{10}$$

where S_t is beginning reservoir storage at period t; D_t is planned water demand; R_t is reservoir release, α_1 and α_2 are rationing factors, and $0 \le \alpha_1 \le \alpha_2 \le 1$. The value of rationing factors can be obtained either by optimization.



(a) Rule Curves (b) Rationing Factors

Figure 4. The new hedging rules for a multipurpose reservoir

In this research, the water demands are divided into three categories, such as agriculture, public and minimum flow requirements for environmental purposes. The public demands have the highest priority in comparison with the other demands. Thus, the public demands are full supplied as possible. Fig. 5 shows the flowchart of the proposed simulation method.

7. OBJECTIVE FUNCTION

The first objective of this study is the minimization of the minimum flow demand shortage and the second objective is to minimize the agriculture demand shortage. In this proposed, the modified shortage index (MSI) of Hsu and Cheng (2002) is used in the present study, that is:

$$\text{f}_1: \quad MSI_m = \frac{100}{T}\sum_{t=1}^{T}\left(\frac{TS_t}{TD_t}\right)^2 \tag{11-1}$$

$$\text{f}_2: \quad MSI_\alpha = \frac{100}{T}\sum_{t=1}^{T}\left(\frac{TS_t}{TD_t}\right)^2 \tag{11-2}$$

Where, TS_t is the total shortage in the t^{th} period (month); TD_t is the total demand; T is the total number of time periods. MSI_m and MSI_a are modified water shortage indexes for minimum flow and agriculture demands, respectively. These two competing system objectives are both considered and minimized. The complete multi-objective problem is solved based on MOEA/D. The next section illustrates the detailed description of system constraints.

System Constraints

In this paper, numbers of decision variables consist of 24 target levels (12 monthly levels for each rule curve of each reservoir) which refer to the position of hedging rule curves, 4 rationing factors for the agricultural demands, the minimum flow and 4 coefficients for determining the transition zone in rule curves. Thus, there are 80 decision variables.

The water balance of a reservoir system is considered as the system constraint, that is:

$$S_{t+1} = S_t + Q_t - R_t - Sp_t - E_t \tag{12}$$

In addition, minimum and maximum allowable values for the storage volume at each period:

$$S_{\min} \le S_t \le S_{\max} \tag{13}$$

Where, S_t is the reservoir storage at period t; Q_t is the water inflow to reservoir at period t; S_{min} is the minimum water storage of reservoir; S_{max} is the maximum water storage of reservoir. E_t is volume of evaporation during period t; and Sp_t is volume of spilled water from reservoir at period t.

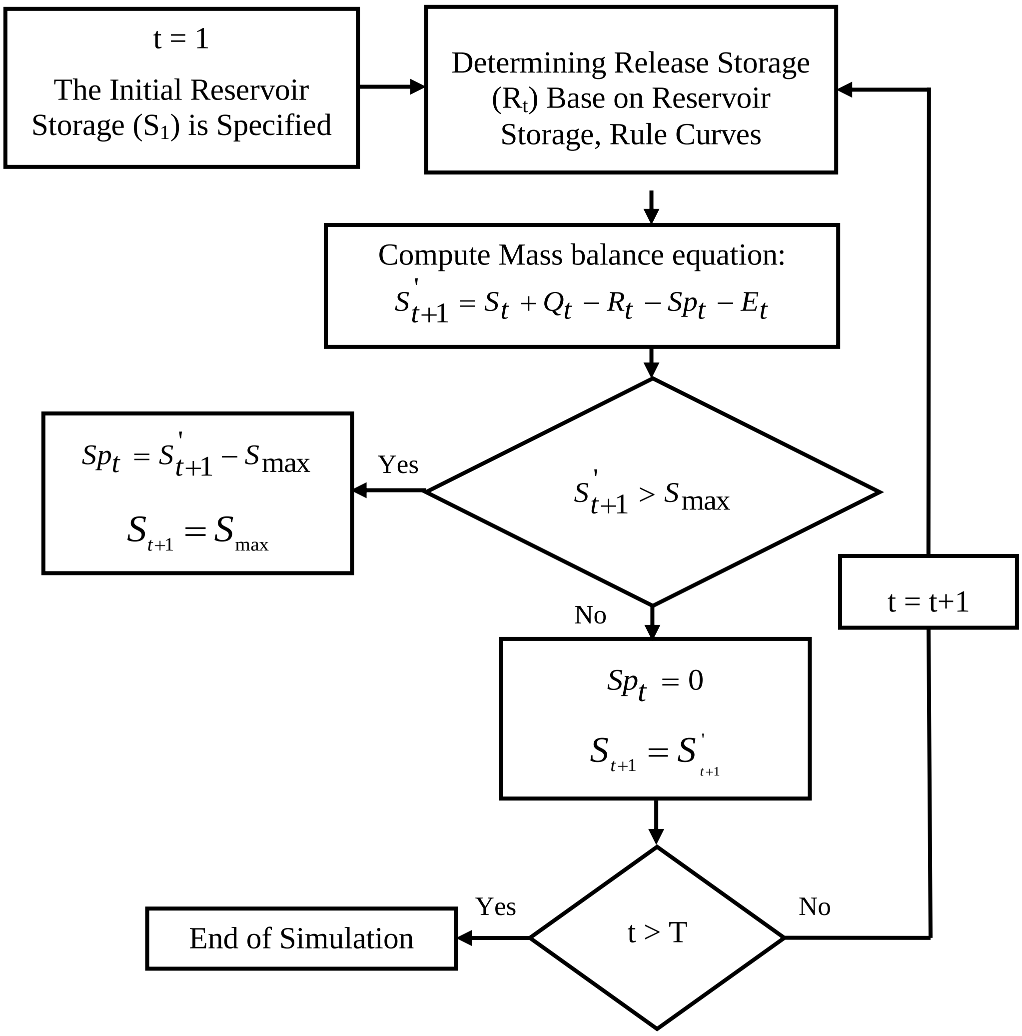


Figure 5. Flowchart of the simulation method

8. RESULTS AND DISCUSSION

This paper aims to investigate the utility of the hybrid of hedging policy with MOEA/D algorithm in reservoir operation. In the paper, the following two operational objectives are considered: (1) satisfaction of the minimum flow requirement; and (2) minimization of MSI for agricultural demands. To compare the performance between the conventional and new hedging rules, we considered the historical records spanning 48 years, from 1956 to 2003. The record includes severe drought periods particularly from 1958 to 1966 for nine successive years. Fig. 6 shows the monthly time series for the inflow and demand in the system. The MOEA/D is coupled with the reservoir simulation model to optimal operation of the multi-reservoir system for water supply.

To evaluate the obtained optimal Pareto set of MOEA/D, non-dominated sorting genetic algorithm (NSGA-II) has been considered during two scenarios, these scenarios has been described in the following:

1) A point of Pareto set has been selected that it's the agriculture MSI value is equal for two optimization methods.

2) A point of Pareto set has been selected that it's the minimum flow MSI value is equal for two optimization methods.

The parameter settings of both algorithms are given in Table 2. Considering the previous scenarios, the procedure simulation-optimization is solved then the Pareto set presented in Figs. 7 and 8.

The performance metrics results are presented in Table 4 for both MOEA/D and NSGA-II. The results show MOEA/D performance better on all statistic metric of GD and maximum and standard deviation of SP, whereas the NSGA-II results are slightly better on minimum and mean of SP.

With the same optimization objective and constraints, the rationing factors and the rule curves are optimized using the same algorithm of MOEA/D and get the similar values in Table 5 and Figs. 9, 10 and 11. In order to analyze the differences of the operation results derived from the hedging rule, the MSI and the maximum MSI of water supply were considered.

The hedging rule curves for minimum flow and agriculture divide the storage of reservoirs into three zones. When the reservoir storage stays in some zones during operation, the water supply decision for each water demand is made according to the Eqs. 8, 9 and 10.

Minimum flow usually requires better water supply than agriculture. Therefore, if the restriction of water supply has to be made, the water supply for agriculture should be reduced first instead of Minimum flow. In this paper, the proposed operating policy can deal with this problem.

As shown in Table 6, the long term minimum flow MSI value of the proposed algorithm is equal to 1.03, which is 40% better (less) than the NSGA-II value of 1.72. Also, the total MSI value equal to 4.18 in the proposed algorithm was slightly better than the NSGA-II value of 4.88. Also, Table 7 shows that the maximum of annual minimum flow MSI values given by the proposed algorithm are smaller than those of the NSGA-II. In Table 7, in all failure years it has been determined that the minimum flow MSI values of the proposed method is less than NSGA-II. It shows that the proposed algorithm is slightly superior to reduce the maximum and total MSI value in compared with NSGA-II.

In Tables 6 and 8, the results of the second scenario have been presented. In this case the long term minimum flow MSI value is equal for two optimization algorithms, and the long term agriculture MSI value improved 9 percent. Comparing these scenarios, it was indicated the method with lower the maximum and total MSI prevents critical shortages and spreads shortages across operational periods.

Finally, optimum rule curves coupling to hedging rules for Kosar, Kheirabad, and Chamshir reservoirs are shown in Figs. 9, 10, and 11. Note that according to the irrigation practices in Iran, the water year begins from October.

The following may be concluded from the presented results:

- Table. 3 clearly indicates that for all the test instances, the GD-metric obtained by MOEA/D is better than that obtained by NSGA-II.

-Table 3 also shows that the standard deviation of both GD-metric and SP-metric in MOEA/D is smaller than that in NSGA-II for all the instances, which implies that MOEA/D is more stable than NSGA-II.

-The proposed algorithm is much better to minimize the maximum of annual minimum flow MSI than that obtained by NSGA-II. This means Pareto distribution is better for the proposed algorithm. The proposed algorithm has better Pareto distribution.

- According to Table 5, it can be concluded that the proposed algorithm has a better ability to reduce the total MSI.

Table 4: Performance Metrics for Zohre Water resources System Problem

Statistic\metric	MOEA/D		NSGA-II	
	GD	SP	GD	SP
Max	**0.0067**	**0.0760**	0.0142	0.0806
Min	**0.0035**	0.0376	0.0070	**0.0285**
Mean	**0.0048**	0.0568	0.0094	**0.0485**
SD	**0.0012**	**0.0150**	0.0025	0.0191

Table 5: Rationing factors for different demands

Rationing Factor	Agriculture Demands	Minimum flow requirements
α_1	0.21	0.65
α_2	0.79	0.92

Table 6: Long-term system performance during period (1956-2003)

Hedging Rule	The first scenario			The second scenario		
	MSI For Different Demands			MSI For Different Demands		
	Min. Flow	Agriculture	Total	Min. Flow	Agriculture	Total
MOEA/D	1.03	3.16	4.18	1.19	3.02	4.21
NSGA-II	1.72	3.16	4.88	1.19	3.43	4.62

Table 7: Annual system performance during failure years (the first scenario (S_1))

Failure years	MOEA/D			NSGA-II		
	Objective Function Value			Objective Function Value		
	Min. Flow	Agriculture	Total	Min. Flow	Agriculture	Total
1959	0.70	1.91	2.61	1.52	4.20	5.72
1960	2.64	8.10	10.74	4.29	10.12	14.41
1961	5.40	21.78	27.19	9.22	18.68	27.90
1962	9.56	38.66	48.22	19.07	34.34	53.41

1963	**15.95**	45.32	61.28	**26.18**	41.85	68.03
1964	8.61	15.01	23.62	11.74	14.83	26.57
1965	2.29	7.29	9.58	3.25	7.2	10.45
1966	2.18	5.33	7.50	3.10	6.97	10.07
1967	0.76	1.36	2.13	0.85	1.91	2.76
1968	0	0.47	0.47	0	0	0
1970	0.47	1.50	1.97	0.63	2.6	3.23
1971	0	0.66	0.66	0.13	1.4	1.53
1984	0	0.25	0.25	0	0	0
2000	0.83	2.03	2.86	1.82	4.40	6.22
2001	0.24	1.25	1.50	0.93	3.04	3.97

Table 8: Annual system performance during failure years (the second scenario (S_2))

Failure years	MOEA/D			NSGA-II		
	Objective Function Value			Objective Function Value		
	Min. Flow	Agriculture	Total	Min. Flow	Agriculture	Total
1959	1.01	1.63	2.64	0.53	4.17	4.70
1960	3.45	7.81	11.26	2.04	11.17	13.20
1961	5.91	21.08	26.99	6.33	20.63	26.97
1962	11.40	37.35	48.75	15.37	39.65	55.01
1963	18.38	45.40	63.79	18.51	43.38	61.89
1964	8.50	14.27	22.77	8.09	14.78	22.87
1965	2.77	7.28	10.06	1.71	7.94	9.65
1966	2.37	4.09	6.46	2.69	8.57	11.26
1967	0.97	1.04	2.01	0.38	1.94	2.32
1968	0.12	0.36	0.47	0	0.37	0.37
1970	0.56	1.06	1.62	0.19	2.67	2.86
1971	0	0.48	0.48	0	1.57	1.57
2000	1.14	1.74	2.89	0.70	4.17	4.87
2001	0.55	1.27	1.81	0.54	3.50	4.04

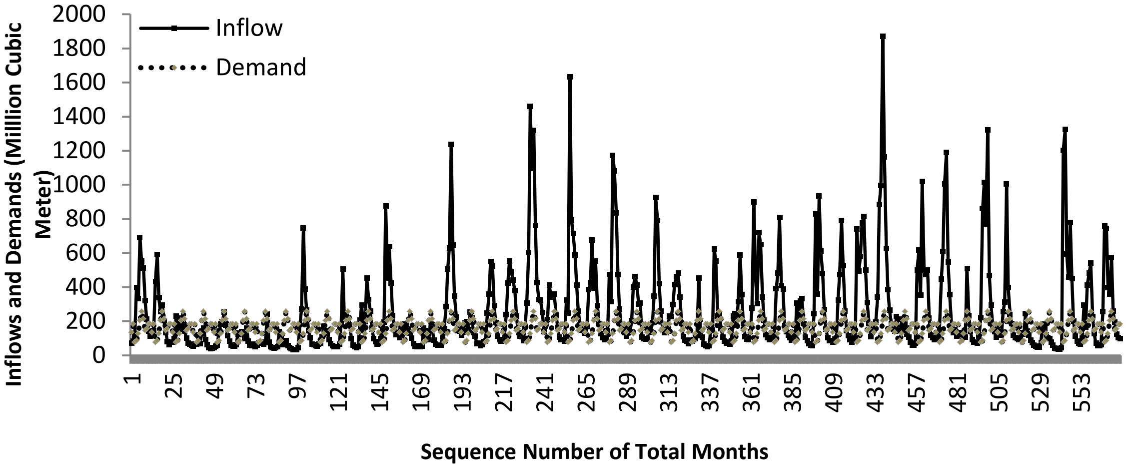


Figure 6. Total monthly inflows and demands in the system

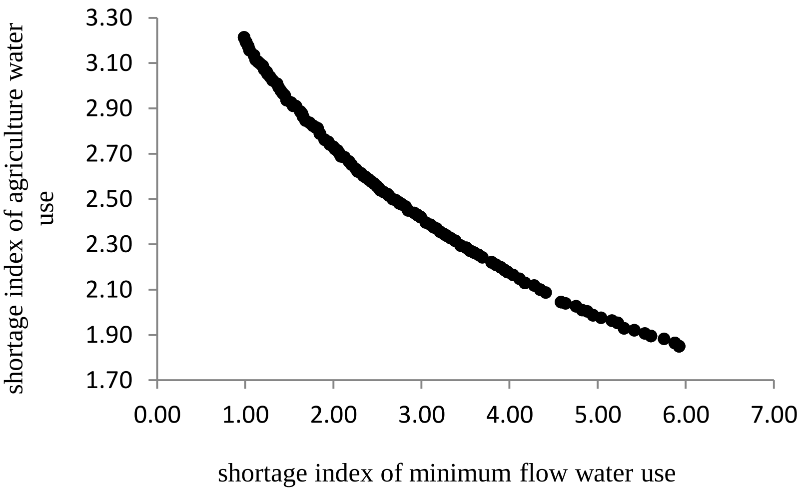


Figure 7. Non-domination solutions with MOEA/D

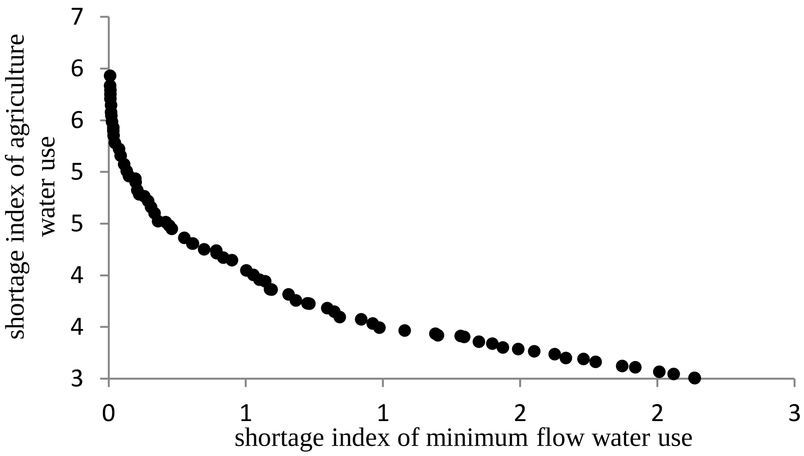


Figure 8. Non-domination solutions with NSGA-II

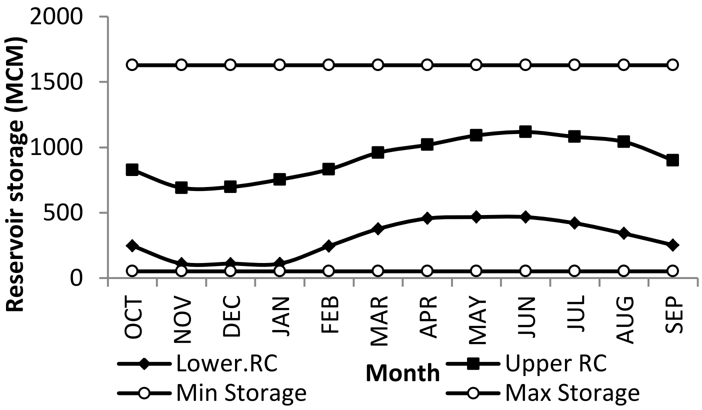


Figure 9. Rule curves of the new hedging rules for Chamshir reservoir

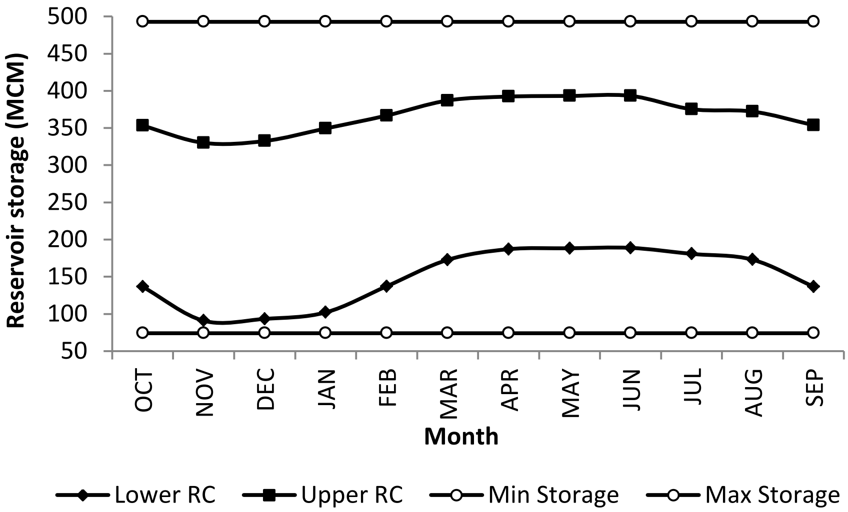


Figure 10. Rule curves of the new hedging rules for Kosar reservoir

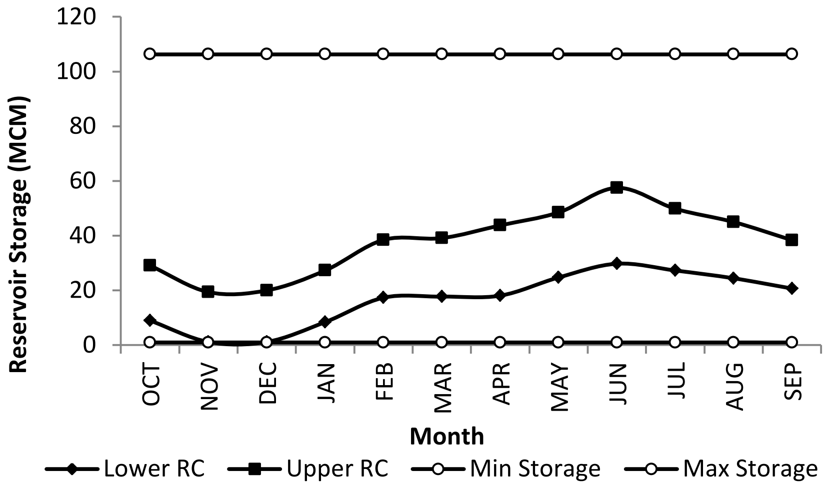


Figure 11. Rule curves of the new hedging rules for Kheirabad reservoir

9. CONCLUSIONS

This work has presented a simple and generic evolutionary multi-objective optimization algorithm based on decomposition; called MOEA/D. The MOEA/D first decomposes the MOP into a number of sub optimization problems. Then, these sub-problems are optimized by an EA. A neighborhood relationship among all the sub-problems is defined based on the distances of their weight vectors. To evaluate the algorithm performance, the MOEA/D has been applied to solve the three benchmark test functions. The experimental results indicate that MOEA/D could significantly outperform NSGA-II on these test instances. Also, the proposed algorithm has been successfully applied for optimization of a multi-objective and multi-reservoir system operation namely Zohre system in southern Iran. Considering the main objective of the paper that is reduction of minimum flow shortage, the results have shown the minimum flow MSI value improved considerably. It was shown that the proposed algorithm is successful in field of water resources management and reduction of severe drought periods. In real life, the optimal tradeoff surface (or Pareto front) is then presented to the decision makers who will select one solution based on their preferences. Therefore, the results show that the proposed algorithm is able to find improved hedging rules for a multiple reservoir system.

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