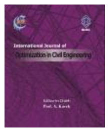
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2016; 6(1):27-42



DETERMINATION OF OPTIMAL HEDGING RULE USING FUZZY SET THEORY FOR MULTI-RESERVOIR OPERATION

I. Ahmadianfar[1* †], A. Adib[1] and M. Taghian[2]
[1]*Civil Engineering Department, Engineering Faculty, Shahid Chamran University, Ahvaz, Iran*
[2]*Water Engineering Department, Ramin University of Agriculture and Natural Resources, Ahvaz, Iran*

ABSTRACT

To deal with severe drought when water supply is insufficient hedging rule, based on hedging rule curve, is proposed. In general, in discrete hedging rules, the rationing factors have changed from a zone to another zone at once. Accordingly, this paper is an attempt to improve the conventional hedging rule to control the changes of rationing factors. In this regard, the simulation model has employed a fuzzy approach, and this causes rationing factor changing during a long term simulation gradually. To optimize different parameters of the purposed hedging a Multi-objective Particle Swarm Optimization (MOPSO) algorithm has been considered. The minimum of two objectives Modified Shortage Index (MSI) involving water supply of minimum flow and agriculture demands can be taken as the optimization objectives. The results of the proposed hedging rule indicate long term and annual MSI values have considerably improved compared to the conventional hedging rule. This determines that the proposed method is promising and efficient to mitigate the water shortage problem.

Keywords: fuzzy sets; hedging rule; MOPSO; multi-reservoir.

Received: 12 April 2015; Accepted: 20 September 2015

1. INTRODUCTION

Inadequate water supplies are frequently induced by prolonged and severe droughts that are inevitable and unpredictable. A common measure adopted to mitigate such adverse impacts is water rationing, which reduces water supplies in advance and conserves more water for

[*]Corresponding author: Civil Engineering Department, Engineering Faculty, Shahid Chamran University, Ahvaz, Iran
[†]E-mail address: im.ahmadian@gmail.com (I. Ahmadianfar)

future use [1, 2]. In order to, hedging rules in reservoir operation have been employed to save some of the available water in current period to reduce severe future deficits [3]. Hedging rules have been categorized into two group continuous and discrete approaches. Shih and Revelle [4, 5] were the first to introduce a systematic hedging rule. The application of hedging rules has been investigated in many other studies including Bayazit and Unal [1]; Shih and ReVelle [2]; Srinivasan and Philipose [3]; Shiau and Lee [4]; Shiau [6] for the continues rule, and Shih and ReVelle [5]; Neelakantan and Pundarikanthan [7,8]; Tu et al. 2003, 2008; and Barros et al. 2008 for the discrete (zone based) hedging rule [5, 7-10]. In the latter method, which is more appropriate for practical applications and is the focus of this work, using a set of rule curves the total storage space is divided into a number of zones. In fact, rule curves are the function of the current storage level to trigger hedging. In hedging rule introduced by Tu et al. [9, 10], the model optimized rule curves and rationing factor simultaneously; however, that was a one year model without considering the possibility of multi-year droughts. Taghian et al. [11] improved the introduced hedging rule by Tu et al. [10] using a hybrid model to optimize both the conventional rule curve and the hedging rule simultaneously. The authors considered a constant rationing factor for each zone. Commonly, the rule curve operations divide the reservoir volume into several operation zones and water supply reduction ratio (rationing factor) for different water use sectors is specified for each zone. A review on previous studies demonstrates the rationing factors change from a zone to another suddenly and have a constant value for each zone. Accordingly, this literature review indicates that there is a need to develop an appropriate method to control sudden changes in rationing factors. In this regard, an alternative approach is the application of fuzzy set theory and fuzzy logic. The fuzzy set theory proposed by Zadeh [12] allows various degrees of membership functions compared to classical set theory that has only two values of logic either zero or one. In the last decade, a large number of papers have been allocated to the solution of reservoir management problems based on fuzzy set theory. Many successful applications of fuzzy systems were reported in the field of reservoir management problems. For example, Russell and Campbell [13] developed reservoir operating rules with fuzzy programming and found that it is a promising area but suffers from a “curse of dimensionality”. Comparing fuzzy and non-fuzzy optimal reservoir operating policies have been presented by Tilmant et al. [14]. Akter and Simonovic [15] also, combined fuzzy sets and GA to deal with the uncertainties in short-term reservoir operation. Other applications of Fuzzy set theory to reservoir operations problem can be found in [16-20].

In the real world, there are many problems involving multiple objectives, which should be optimized simultaneously and are often conflicting and incommensurable. Many methods have been formulated for multi-objective analysis. Particle swarm optimization (PSO) is one of the newest techniques within the family of evolutionary optimization algorithms [21]. Recently few proposals on extension of PSO technique to multi-objective optimization have been reported. Coello and Lechuga [22] and Coello et al. [23] used an external repository to store non-dominated solutions, an adaptive grid approach to select the global best, and a mutation operator for further promote diversity. This operator ensures the search efficiency and increase diversity of population to achieve the optimum solution. Some successful applications of the MOPSO algorithms in the water resource management and planning have been performed: Baltar & Fontane (2008) applied the proposed MOPSO algorithm by

Coello and Lechuga [22, 24] in single-reservoir operation to find non-dominated solutions. Also, Reddy and Kumar [25] proposed a multi-objective optimization algorithm based on swarm intelligence using a mutation strategy called Elitist Mutation (EM). After achieving satisfactory performance in the test problems, EM-MOPSO was then applied to a single reservoir operation with conflicting objectives. Following the previous work, Reddy and Kumar [26] used the EM-MOPSO algorithm for water management and compared results of the proposed method with those of NSGA-II, showing the EM-MOPSO approach as having more ability to find the optimal Pareto front. Recently, Fallah-Mehdipour et al. [27] adopted a new technique in multi-objective optimization, called warm-up, based on the PSO algorithm is applied to improve the quality of the Pareto front by single-objective search. The proposed method applied as an optimization tool in real multi-objective problems in multi-reservoir system operations. Afshar et al. [28] also presented a multi-objective particle swarm optimization (MOPSO) solver to generate Pareto optimal solutions for calibration of any complex water quality model with up to two conflicting objectives. Ahmadianfar et al. [29] presented a Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D) for the optimal operation of a complex multipurpose and multi-reservoir system. They compared the algorithm with Non-dominated Sorting Genetic Algorithm (NSGA-II) using a set of common test problems and the real-world Zohre reservoir system in southern Iran. The Experimental results demonstrated that MOEA/D can improve system performance to reduce the effect of drought compared with NSGA-II superiority.

The purpose of this paper is to develop an operation policy to solve a multi-reservoir system optimization by combining the conventional hedging rule with fuzzy logic concept to avoid severe water shortage. In fact, fuzzy logic is applied to increase the flexibility of the rationing factors. The proposed method was applied to the Zohre multi-reservoir system located in southern Iran as a case study. To solve the problem, a multi-objective optimization algorithm based on swarm intelligence (MOPSO) is coupled to the proposed simulation. The combined model obtained a trade-off between minimum flow and agriculture deficits. In the following sections the proposed methodology is explained in details.

2. SIMULATION METHOD

In this section, a new monthly operation simulation model based on fuzzy set theory is introduced. The developed simulation model is stated as follows;

Commonly the rule curves identify the storage zones associated with a certain operational behavior. In the hedging policy, the rule curves divide reservoir storage into several zones corresponding to several rationing factors. Thus, the zone-based hedging rules were characterized by two parameters: the monthly initial storage level and the rationing factors. In the study, two rule curves (upper and lower curve) are considered for each reservoir; thus, there are three zones. For the single reservoir with two kinds of water demands, details of the hedging rule curves used in this paper and its corresponding water-supply operation rule are illustrated in Fig. 1. In the hedging rule the reservoir releases at any time of the year is the function of existing storage volumes and water demands. The equations (1), (2), and (3) represent the function relationship:

$$if\ \ S_t \in zone1,\quad then\ R_{1t} = \alpha_1 D_{1t},\quad R_{2t} = \alpha'_1 D_{2t} \tag{1}$$

$$if\ \ S_t \in zone2,\quad then\ R_{1t} = \alpha_2 D_{1t},\quad R_{2t} = \alpha'_2 D_{2t} \tag{2}$$

$$if\ \ S_t \in zone3,\quad then\ R_{1t} = D_{1t},\quad R_{2t} = D_{2t} \tag{3}$$

Where S_t is beginning the reservoir storage at period t; D_{1t} and D_{2t} are planned minimum flow and agriculture water demands; R_t is reservoir release,α_1, α_2, $\alpha_1{}'$, $\alpha_2{}'$ are rationing factors, and $0 \le \alpha_1 \le \alpha_2 \le 1$, $0 \le \alpha'_1 \le \alpha'_2 \le 1$. The value of rationing factors can be obtained either by optimization.

As it was mentioned above, in the conventional hedging rule, considered only a constant rationing factor for each zone, the rationing factor changed from one zone to another suddenly. This makes instability in reservoir storage potential for water supply. To overcome this limitation, the fuzzy logic is employed to apply transition zones around the rule curves. Thus, when the reservoir level is moving from a zone to another, the rationing factor will be increased or decreased gradually (Fig.1). In the following, the developed model is briefly explained.

In Fig. 1, there are two rule curves (upper and lower rule curve) and four transition rule curves. In this figure, suppose that the initial reservoir storage is located in zone 2. So, the developed hedging rule can be described as following:

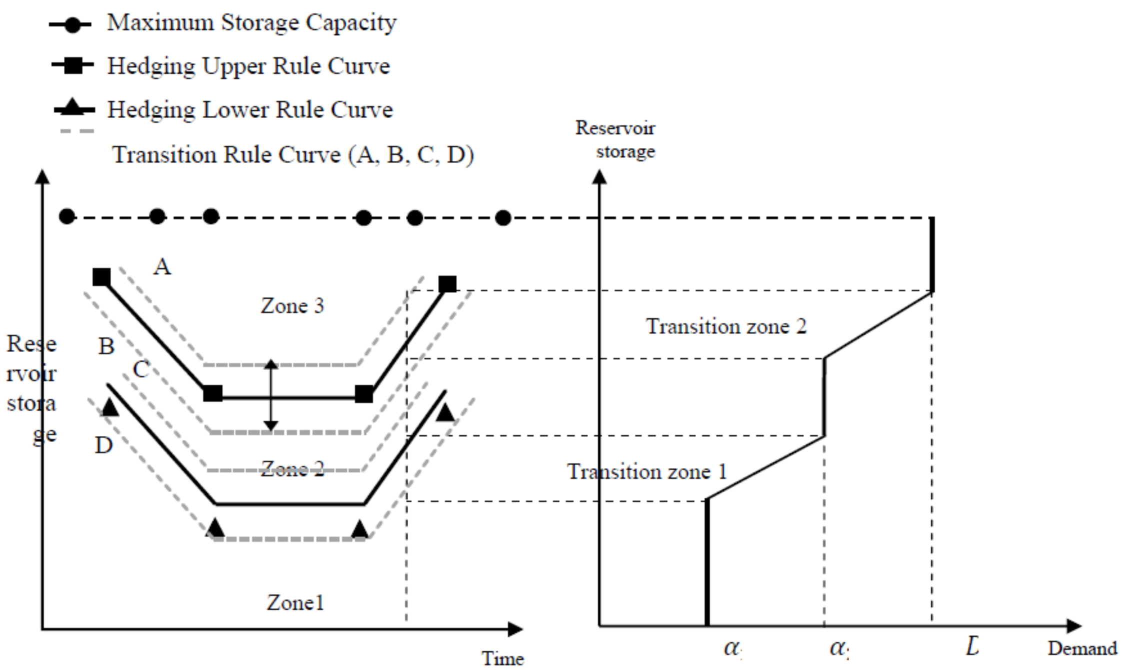
1) When the beginning reservoir storage is located in zone 2 (between transition rule curves B and C), the reservoir releases water to meet the α_2 level of the original target demand.

2) When the beginning reservoir storage is placed between transition rule curve B and upper rule curve and it is approaching to upper rule curve, the rationing factor is between α_2 and 1. Therefore, the rationing factor is more thanα_2.

3) When the beginning reservoir storage is placed between transition rule curve C and lower rule curve and it is approaching to lower rule curve, the rationing factor is between α_2 and α_1. Therefore, the rationing factor is less thanα_2.

Similarly, the other zones have the same procedure, too. As a result of the presented explanations when the reservoir storage level is located in the transition zone the operator can release water more or less than the current status.

To determine the transition zone the trapezoidal membership functions are used. These transition zones are assigned by four coefficients (β_1,β_2 andβ_3 ,β_4). In Fig. 2 have been shown membership functions and in equations (4) - (7) have been presented the parameters of the each of the membership functions. Also during each time period t, the relationship between the rule curves, the employed hedging rules and its corresponding water-supply operation rule are illustrated in equation (8).



(a) Rule Curves (b) Rationing Factors

Figure 1. The proposed hedging rules for a multipurpose reservoir

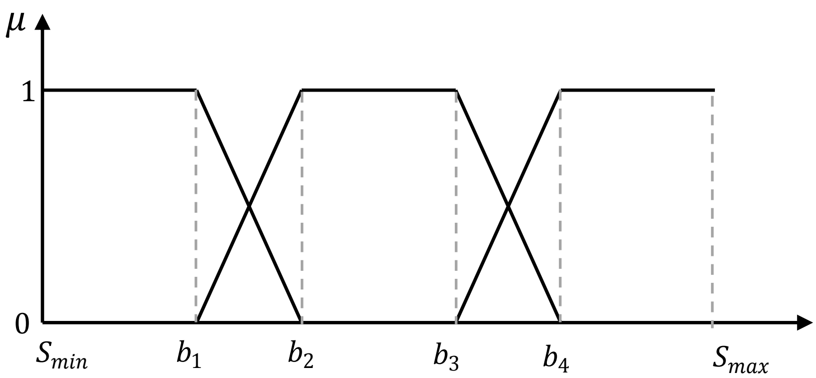


Figure 2. Trapezoidal membership functions for rationing factors

$$b_1 = S_{\min} + (RC_{1\tau} - S_{\min}) \times \beta_1 \tag{4}$$

$$b_2 = RC_{1\tau} + (RC_{2\tau} - RC_{1\tau}) \times \beta_2 \tag{5}$$

$$b_3 = b_2 + (RC_{2\tau} - b_2) \times \beta_3 \tag{6}$$

$$b_4 = RC_{2\tau} + (S_{\max} - RC_{2\tau}) \times \beta_4 \tag{7}$$

$$R_t = \begin{cases} D_t & if \quad S_t \in zone3 \\ (\mu_3 \alpha_2 + \mu_4) D_t & if \quad S_t \in transition\ zone2 \\ \alpha_2 D_t & if \quad S_t \in zone2 \\ (\mu_1 \alpha_1 + \mu_2 \alpha_2) D_t & if \quad S_t \in transition\ zone1 \\ \alpha_1 D_t & f \quad S_t \in zone1 \end{cases} \tag{8}$$

Where S_t is beginning reservoir storage at period t; D_t is planned water demand; R_t is reservoir release; μ is the degree of "belongingness" to a fuzzy set; $\alpha_1$and α_2 are rationing factors; S_{min} is the minimum water storage of reservoir; S_{max} is the maximum water storage of reservoir; $RC_{1\tau}$, $RC_{2\tau}$ are lower and upper rule curves, respectively (τ = 1,…, 12); and $0 \leq \alpha_1 < \alpha_2 \leq 1$.

In this study, the water demands are divided into three categories, such as agriculture, public and minimum flow requirements for environmental purposes. Also, the public demand has the highest priority compared to the other demands. In this regard, the public demands are full supplied as possible.

Multi-objective particle swarm optimization (MOPSO)

Particle swarm optimization introduced by Kennedy and Eberhart (1995), is based on the social behavior of birds [21]. There are many alternatives of the single objective PSO, but in most of them the movement of the swarm particles toward the optimum is governed according to the following equations:

$$x_{i+1}(t) = x_i(t) + rand \times c_1 \times (P_i - x_i(t)) + rand \times c_2 \times (P_g - x_i(t)) \tag{9}$$

$$V_{i+1}(t) = wV_i(t) + x_{i+1}(t) \tag{10}$$

Where w is an inertia coefficient that has an important role to control particles; P_i best position vector of particle i so far (personal best); Pg best position vector of all particles so far (global best); c_1 and c_2 are constants that indicate the attraction from P_i and Pg respectively; $x_i(t)$ is the current position vector of particle i; and $V_i(t)$ is the current velocity of particle i.

In this paper, a multi-objective particle swarm optimization (MOPSO) is presented which allows the PSO algorithm to be able to deal with multi-objective optimization problems. The optimization algorithm has been considered here is similar to the introduced algorithm by Coello Coello et al. [23] in which they used an external archive or repository which stores non-dominated solutions. The external repository consists of two main parts: archive controller and grid. The aim of the archive controller is to decide whether a certain solution should be added to the archive or not. The decision-making process uses the concept of dominating. To produce well-distributed Pareto fronts it used a variation of the adaptive grid proposed in Knowles and Corne [30].

The main difference between PSO and MOPSO is on the determination of both the personal best (P_i) and global best (Pg) (Equation (9)). In MOPSO, both P_i and R_h from equation (11) are used instead of P_i and Pg, respectively. Consequently, these two parameters need to be determined repetitively during PSO. The particles' positions will be subsequently updated as follows [24]:

$$x_{i+1}(t) = x_i(t) + rand \times c_1 \times (P_i - x_i(t)) + rand \times c_2 \times (R_h - x_i(t)) \tag{11}$$

Where R_h represents a selected solution from the external repository in each iteration t, and P_i represents the best position vector of particle i. Then, the particles' velocities updated are carried out using equation (10). The flowchart of the MOPSO algorithm is presented in Fig. 3.

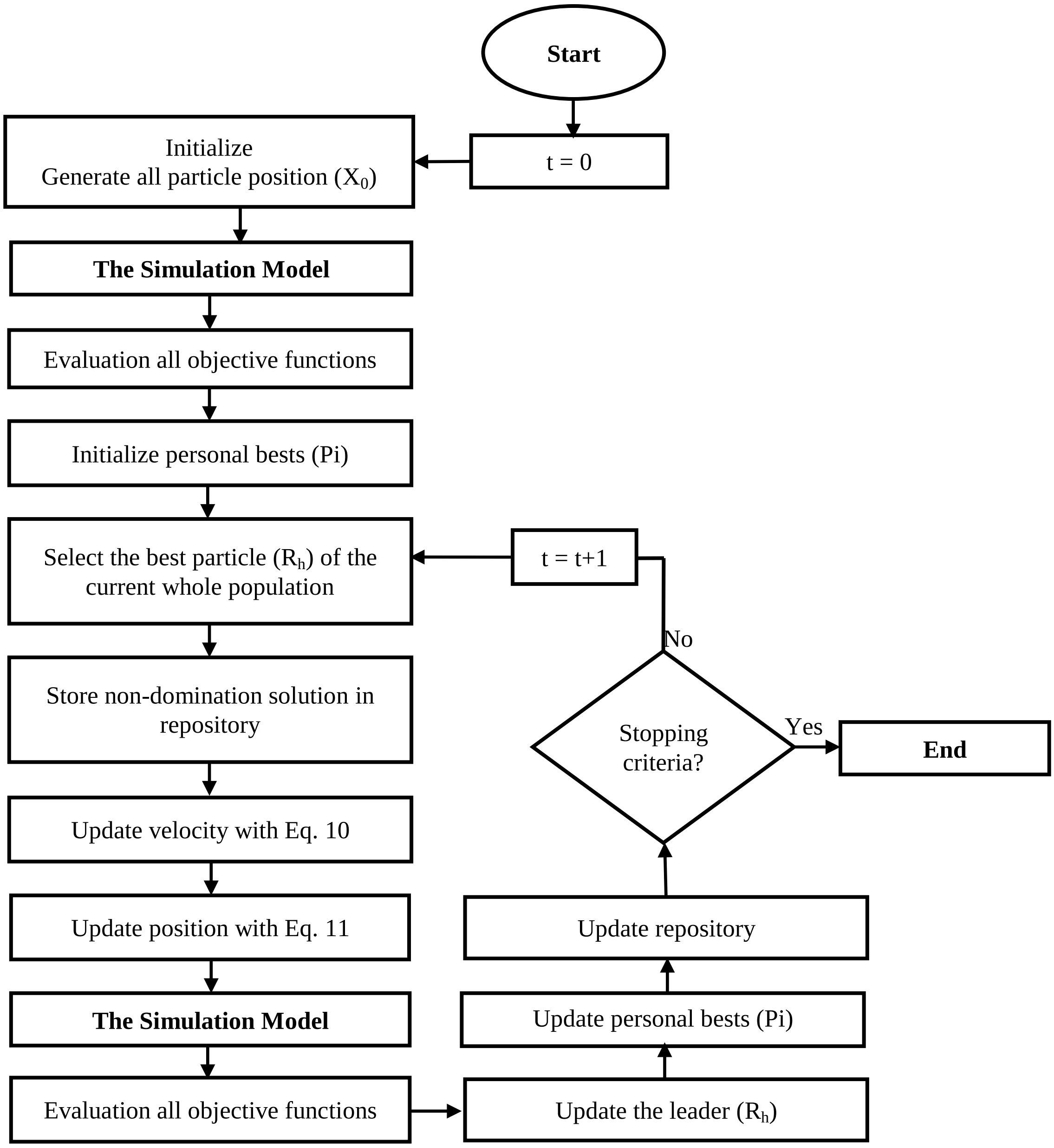


Figure 3. Flowchart of MOPSO applied to the proposed and simple hedging rule

3. CASE STUDY

The reservoir system chosen for the test of the proposed rule is Zohre multi-reservoir system, which is located in Sothern Iran. This river basin covers an area of 16,000 km^2. The schematic configuration was shown in Fig. 4. The system is comprised of 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 include Kosar, Chamshir, and Kheirabad, 418, 1576 and 104 million cubic meter, respectively.

4. FORMULATION OF THE OPTIMIZATION-SIMULATION MODEL

In this paper, a hybrid of MOPSO is connected to the simulation model to optimize the rule curves, rationing factors and the coefficients that determine the transition zones in Zohre multi-reservoir system simultaneously. In the compound model the modified shortage index (MSI) of Hsu and Cheng (2002) can be taken as the optimization objective [31]. Also, two objective functions are considered: (1) satisfaction of the minimum flow requirement; and (2) minimization of MSI for agricultural demands.

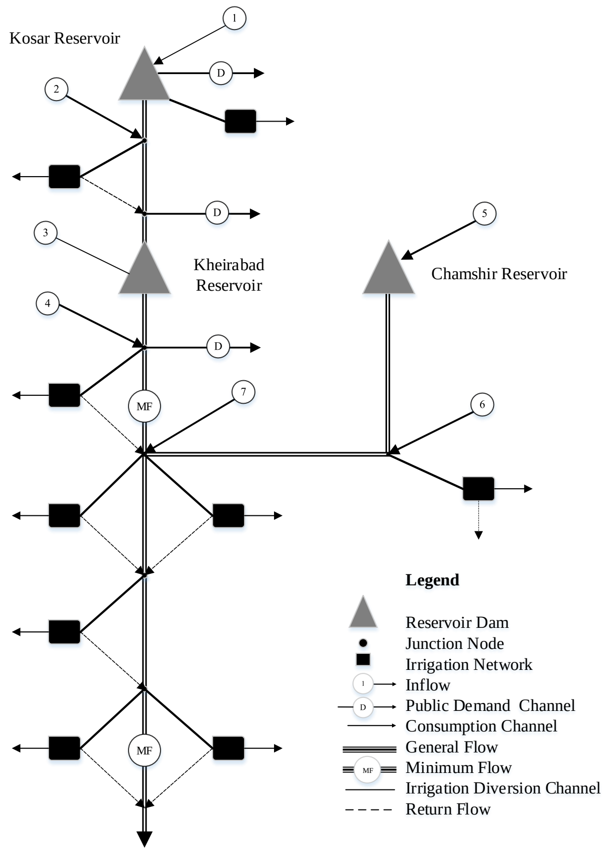


Figure 4. Schematic configuration of the water supply system

$$\text{f}_1: \quad MSI_m = \frac{100}{T}\sum_{t=1}^{T}\left(\frac{TS_t}{TD_t}\right)^2 \tag{12}$$

$$\text{f}_2: \quad MSI_\alpha = \frac{100}{T}\sum_{t=1}^{T}\left(\frac{TS_t}{TD_t}\right)^2 \tag{13}$$

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 MOPSO.

5. SYSTEM CONSTRAINTS

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

The mathematical model of the reservoir system is represented to use the continuity Equation:

$$S_{t+1} = S_t + Q_t - R_t - Sp_t - E_t \tag{14}$$

The model's formulation is constrained by the following relation:

$$S_{\min} \le S_t \le S_{\max} \tag{15}$$

Where S_t is the reservoir storage at period t; Q_t is the water inflow to reservoir at period t. E_t is volume of evaporation during period t; Sp_t is volume of spilled water from reservoir at period t.

6. RESULTS AND DISCUSSION

This paper aims to show hybrid modeling efficiency of hedging policy with fuzzy approach. To optimize the parameters of the purposed hedging rule, the MOPSO algorithm is considered. Inflow data used for this study was obtained from historical records spanning 48 years, from 1956 to 2003. The record includes severe drought periods from 1958 to 1966 for nine successive years particularly. Fig. 5 shows the annual time series for the inflow and demand in the system. According to the developed hedging rule the multi-reservoir operation is simulated.

As it was mentioned earlier, MOPSO is coupled with the simulation model to optimize the parameters of the hedging rule; these parameters are consisted of a set of rule curves and fuzzy-rationing factors. The setting parameters of the algorithm are: Maximum iteration = 500, population size= 100, number of repository = 100, w = 0.7, c_1= 1.5, c_2 = 1.5, CR = 0.5, β= 20.

After model optimization, the optimal quadruplet coefficients to determine the transition zones are 0.76, 0.52, 0.70 and 0.50. The optimum rationing factors for agricultural and minimum flow demands are shown in Table 1. Also, the Pareto set presented according to Fig. 6 and 7.

To verify the developed hedging rule performance compared to the conventional hedging rule, two balanced optimal solutions are selected from the Pareto frontiers in Figs. 6 and 7.

Table 1: Rationing factors for different demands

Reservoir storage	Rationing factors for each demand	
	Agriculture Demands	Minimum flow requirements
Zone 1	$\alpha_1 = 0.31$	$\alpha'_1 = 0.70$
Zone 2	$\alpha_2 = 0.72$	$\alpha'_2 = 0.88$
Zone 3	1	1
Rationing factors	α_1, α_2	α'_1, α'_2

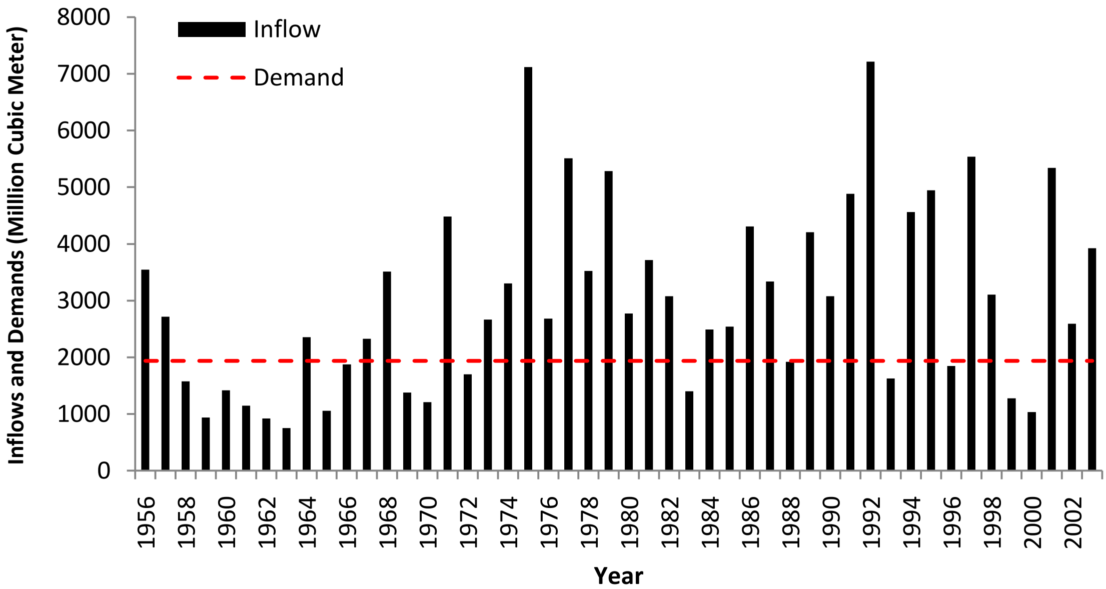


Figure 5. Total annual inflows and demands in the system

In the case study, the severe drought periods from 1958 to 1971 have been observed. According to the obtained results, the diagram of rationing factors of both hedging rules during the severe drought periods has been presented in Fig. 8. As it can be seen in this figure, the proposed and conventional hedging factors have changed gradually and suddenly. Also, some sharp dropping of the conventional hedging factors has been shown, while due to gradual changes of the proposed hedging factors have avoided the sharp dropping.

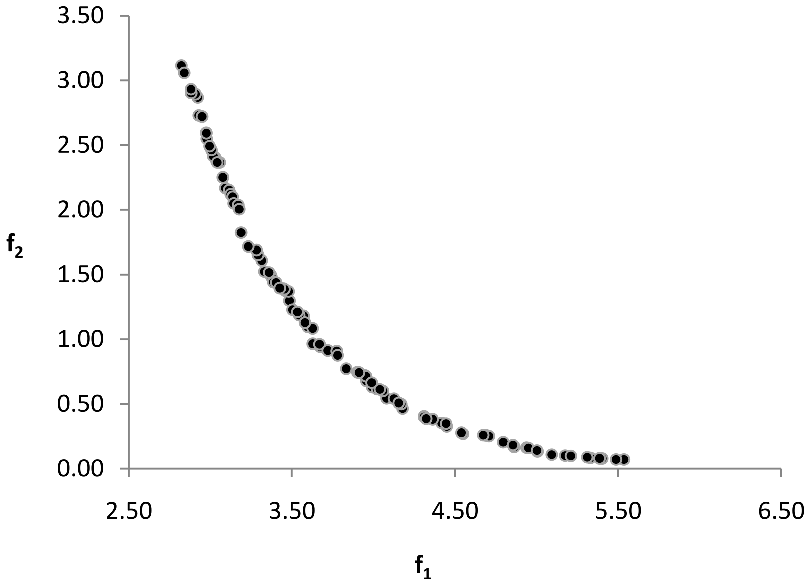


Figure 6. Non-domination solutions with MOPSO on the proposed hedging rule

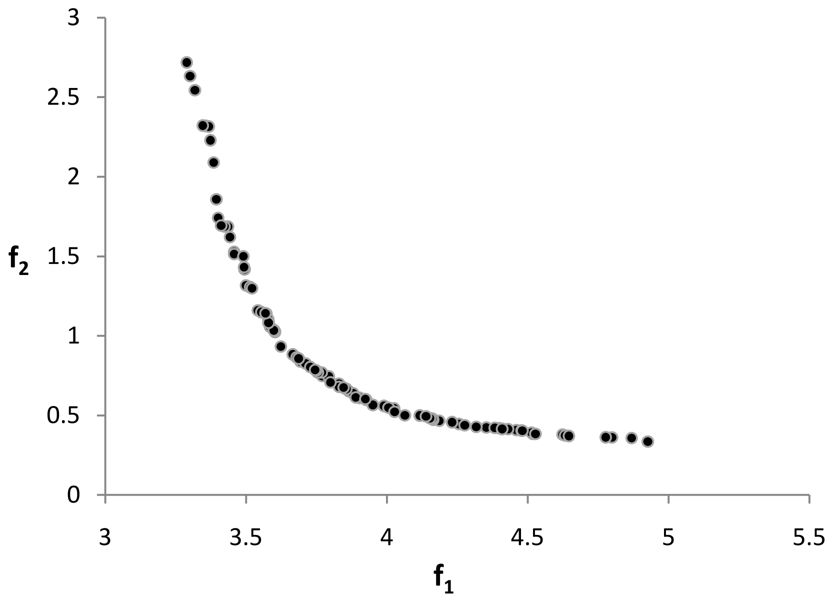


Figure 7. Non-domination solutions with MOPSO on the simple hedging rule

Following, the results of selected points of Pareto frontiers have been presented in Tables (2), (3) and (4). The long term MSI value of both hedging rules has been presented in Table (2). The maximum MSI value for minimum flow and agriculture demand of the proposed hedging has been improved 30% and 20% compared to the conventional hedging, respectively (Tables 3, 4). Also the maximum total MSI value of the proposed hedging has been improved 20% compared to the conventional hedging (Tables 3, 4). These results imply that the proposed hedging rule is able to distribute the shortage more evenly.

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

Table 2: Long-term system performance during period (1956-2003)

Hedging Rule	MSI For Different Demands		Objective Function Value
	Minimum Flow	Agriculture	
Simple	1.50	3.45	4.95
New	1.37	3.43	4.80

Table 3: Annual system performance of the conventional hedging during failure years

Failure years	Objective Function Value		
	Min. Flow	Agriculture	Total
1959	2.53	3.25	5.78
1960	7.39	10.83	18.22
1961	6.51	22.68	29.19
1962	**11.94**	**38.01**	**49.95**
1963	**18.18**	**49.24**	**67.42**
1964	9.17	17.52	26.69
1965	3.49	6.52	10.00
1966	2.88	4.02	6.90
1967	2.54	2.81	5.35
1968	0.45	0.65	1.09
1970	2.29	3.13	5.43
1971	0.32	0.86	1.17
1983	0.14	0.28	0.42
1999	0.50	0.23	0.73
2000	2.73	3.45	6.18
2001	0.86	2.05	2.92

Table 4. Annual system performance of the proposed hedging during failure years

Failure years	Objective Function Value		
	Min. Flow	Agriculture	Total
1959	3.18	6.05	9.23
1960	6.53	13.72	20.25
1961	8.04	23.38	31.43
1962	**9.93**	**30.84**	**40.77**
1963	**12.84**	**39.82**	**52.66**
1964	7.75	16.90	24.65
1965	5.14	10.11	15.26

1966	4.36	7.00	11.36
1967	1.56	1.96	3.52
1970	1.47	3.99	5.46
1971	0.42	1.29	1.71
1983	0.14	0.46	0.60
1999	0.16	0.59	0.75
2000	3.30	5.74	9.03
2001	1.10	2.74	3.84

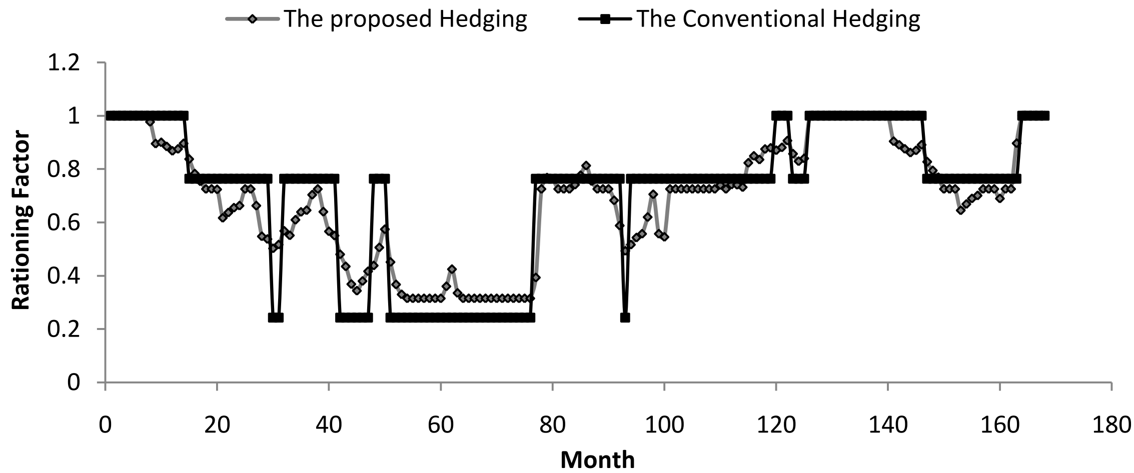
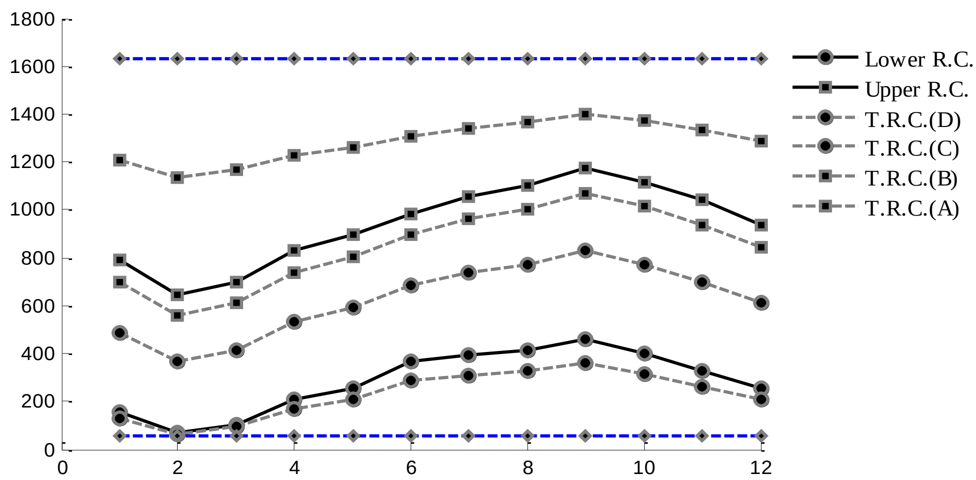
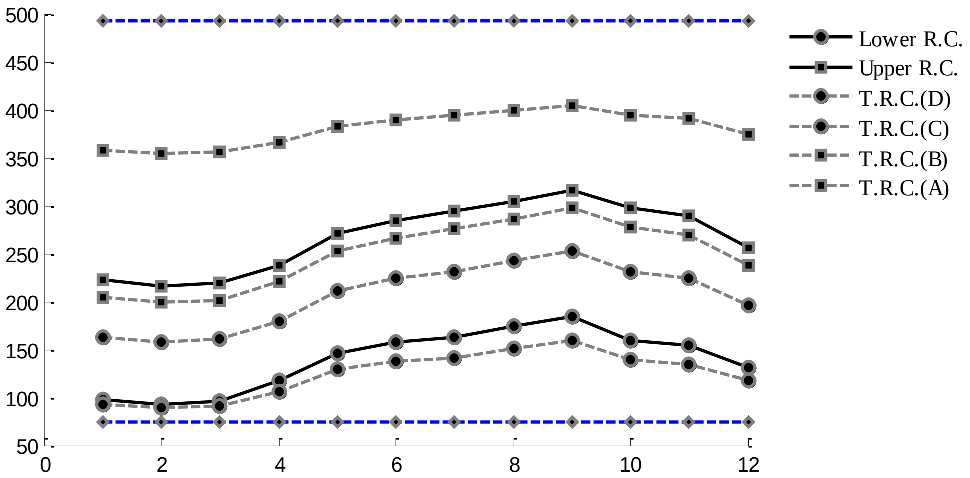


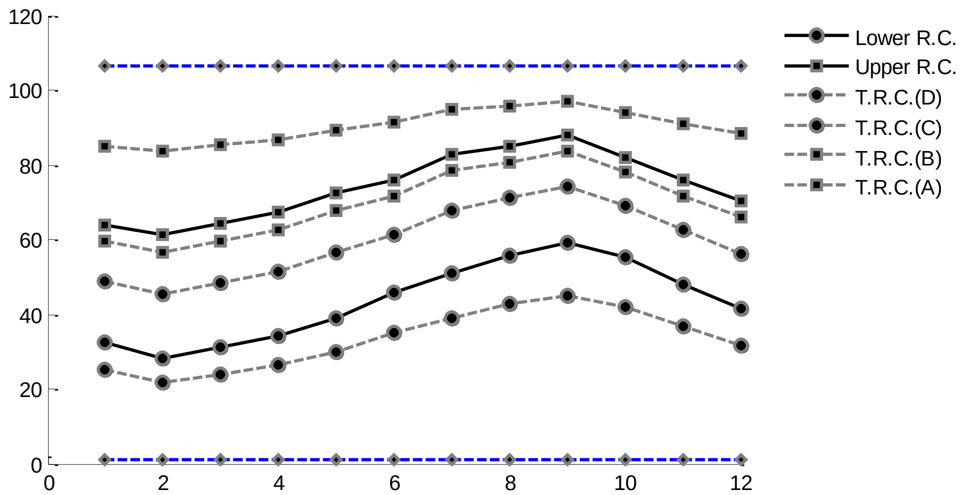
Figure 8. Diagram of Fuzzy and simple rationing factors changes



(a)



(b)



(C)

Figure 9. Rule curves of the proposed hedging rules for (a) Chamshir, (b) Kosarand (c) Kheirabad reservoirs

7. CONCLUDING REMARK

In this study, development of optimal reservoir operation policies for a multipurpose and multi-reservoir system, namely Zohre system was presented. In this regard, the combination of a simple fuzzy logic concept with the conventional hedging rule has been proposed to increase the rationing factors flexibility and improvement of the system operation during severe drought periods. To optimize the simulation model, it has been employed the MOPSO algorithm. The optimization objectives are consisted of the MSI of minimum flow and agricultural water supply. To demonstrate the compound model ability, that was compared to the conventional hedging rule. The results demonstrated the annual and the long term system performance improved compared to the conventional hedging considerably. In the paper the main objective was the minimum flow shortage reduction. The results have shown a very good performance of the model to achieve this aim. Therefore, the proposed hedging rule is able to find improved hedging rules for a multiple reservoir system during drought periods.

REFERENCES

1. Shiau J, Lee H. Derivation of optimal hedging rules for a water-supply reservoir through compromise programming, *Water Resour Manage* 2005; **19**(2): 111-32.
2. Shiau JT. Optimization of reservoir hedging rules using multiobjective genetic algorithm, *J Water Resour Plan Manage* 2009; **135**(5): 355-63.
3. Bayazit M, Ünal N. Effects of hedging on reservoir performance, *Water Resour Manage* 1990; **26**(4): 713-9.
4. Shih J-S, ReVelle C. Water-supply operations during drought: Continuous hedging rule, *J Water Resour Plan Manage* 1994; **120**(5): 613-29.
5. Shih J-S, ReVelle C. Water supply operations during drought: A discrete hedging rule, *Europ J Oper Res* 1995; **82**(1): 163-75.
6. Srinivasan K, Philipose M. Effect of hedging on over-year reservoir performance, *Water Resour Manage* 1998; **12**(2): 95-120.
7. Neelakantan T, Pundarikanthan N. Hedging rule optimisation for water supply reservoirs system, *Water Resour Manage* 1999; **13**(6): 409-26.
8. Neelakantan T, Pundarikanthan N. Neural Network-Based Simulation-Optimization Model for Reservoir Operation, *J Water Resour Plan Manage* 2000; **126**(2): 57-64.
9. Tu M-Y, Hsu N-S, Tsai FT-C, Yeh WW-G .Optimization of hedging rules for reservoir operations, *J Water Resour Plan Manage* 2008; **134**(1): 3-13.
10. Tu M-Y, Hsu N-S, Yeh WW-G. Optimization of reservoir management and operation with hedging rules, *J Water Resour Plan Manage* 2003.
11. Taghian M, Rosbjerg D, Haghighi A, Madsen H. Optimization of conventional rule curves coupled with hedging rules for reservoir operation, *J Water Resour Plan Manage* 2013; **140**(5): 693-8.
12. Zadeh LA. Fuzzy sets, *Inform Control* 1965; **8**(3): 338-53.
13. Russell SO, Campbell PF. Reservoir operating rules with fuzzy programming, *J Water Resour Plan Manage* 1996; **122**(3): 165-70.
14. Tilmant A, Fortemps P, Vanclooster M. Effect of averaging operators in fuzzy optimization of reservoir operation, *Water Resour Manage* 2002; **16**(1): 1-22.
15. Akter T, Simonovic SP. Modelling uncertainties in short-term reservoir operation using fuzzy sets and a genetic algorithm/Modélisation d'incertitudes dans la gestion de barrage à court terme grâce à des ensembles flous et à un algorithme génétique, *Hydrol Sci J* 2004; **49**(6).
16. Choudhari S, Anand Raj P. Multiobjective Multireservoir Operation in Fuzzy Environment, *Water Resour Manage* 2010/08/01 2010; **24**(10): 2057-73.
17. Deka PC, Chandramouli V. Fuzzy neural network modeling of reservoir operation, *J Water Resour Plan Manage* 2009; **135**(1): 5-12.

18. Dubrovin T, Jolma A, Turunen E. Fuzzy model for real-time reservoir operation, *J Water Resour Plan Manage* 2002; **128**(1): 66-73.
19. Huang WC, Yuan LC. A drought early warning system on real-time multireservoir operations, *Water Resour Res* 2004; **40**(6).
20. Teegavarapu RS, Simonovic SP. Modeling uncertainty in reservoir loss functions using fuzzy sets, *Water Resour Res* 1999; **35**(9): 2815-23.
21. Eberhart RC, Kennedy J. A new optimizer using particle swarm theory. Paper presented at: Proceedings of the Sixth International Symposium on Micro Machine and Human Science, 1995.
22. Coello CAC, Lechuga MS. MOPSO: A proposal for multiple objective particle swarm optimization. Paper presented at: Evolutionary Computation, 2002. CEC'02. Proceedings of the 2002 Congress on, 2002.
23. Coello CAC, Pulido GT, Lechuga MS. Handling multiple objectives with particle swarm optimization, Trans *Evol Comput*, *IEEE* 2004; **8**(3): 256-79.
24. Baltar AM, Fontane DG. Use of multiobjective particle swarm optimization in water resources management, *J Water Resour Plan Manage* 2008.
25. Reddy MJ, Nagesh Kumar D. Multi-objective particle swarm optimization for generating optimal trade-offs in reservoir operation, *Hydrol Proc* 2007; **21**(21): 2897-2909.
26. Reddy M, Kumar D. Performance evaluation of elitist-mutated multi-objective particle swarm optimization for integrated water resources management, *J Hydroinform* 2009; **11**(1): 79-88.
27. Fallah-Mehdipour E, Haddad OB, Mariño M. MOPSO algorithm and its application in multipurpose multireservoir operations, *J Hydroinform* 2011; **13**(4): 794-811.
28. Afshar A, Shojaei N, Sagharjooghifarahani M. Multiobjective calibration of reservoir water quality modeling using Multiobjective Particle Swarm Optimization (MOPSO), *Water Resour Manage* 2013; **27**(7): 1931-47.
29. Ahmadianfar I, Adib A, Taghian M. A multi-objective evolutionary algorithm using decomposition (moea/d) and its application in multipurpose multi-reservoir operations, *International J Optim Civil Eng* 2015; **5**(2): 167-87.
30. Knowles J, Corne D. The pareto archived evolution strategy: A new baseline algorithm for pareto multiobjective optimization, Paper presented at:, 1999, CEC 99, Proceedings of the 1999 Congress on Evolutionary Computation, 1999.
31. Hsu NS, Cheng KW. Network flow optimization model for basin-scale water supply planning, *J Water Resour Plan Manage* 2002; **128**(2): 102-112.