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Application of PSO algorithm in short-term optimization of reservoir operation

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Abstract The optimization of the operation of existing water systems such as dams is very important for water resource planning and management especially in arid and semi-arid lands. Due to budget and operational water resource limitations and environmental problems, the operation optimization is gradually replaced by new systems. The operation optimization of water systems is a complex, nonlinear, multi-constraint, and multidimensional problem that needs robust techniques. In this article, the practical swarm optimization (PSO) was adopted for solving the operation problem of multipurpose Mahabad reservoir dam in the northwest of Iran. The desired result or target function is to minimize the difference between downstream monthly demand and release. The method was applied with considering the reduction probabilities of inflow for the four scenarios of normal and drought conditions. The results showed that in most of the scenarios for normal and drought conditions, released water obtained by the PSO model was equal to downstream demand and also, the reservoir volume was reducing for the probabilities of inflow. The PSO model revealed a good performance to minimize the reservoir water loss, and this operation policy can be an appropriate policy in the drought condition for the reservoir.

Keywords Reservoir operation · Particle swarm optimization · Mahabad dam · Iran · PSO model

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Introduction

The occurrence of drought in watersheds creates many problems in the water resource management systems. As the drought conditions continue and intensify, the reservoir volume decreases to a critical level that can create irrecoverable damages in the future. Recently, as a result of drought in Iran (especially surface waters), water resource management becomes a very important case for many researchers. Hence, paying more attention to resource management and offering the most efficiency operation policy is required for preventing water loss (Moradi-Jalal et al. 2007). The most important issue in the operation of dams is when there is a water resource shortage, which necessitates preparing a target function and special planning for dam operation. Since reservoir management and operations are so complex (Simonovic and Savic 1989), they need careful planning and management strategies. Continuous changes in inflow, variation in periodical water requirement, and trade-offs between wide ranges of conflicting objective are major reasons (Rani and Moreira 2010). The consideration of

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management policies is a sustainable and correct use of reservoir water to respond requirements. Reservoir optimization management is a multiconstraint (in objectives) and multidimensional optimization problem. To solve this complex problem, powerful optimization methods are required. The meta-heuristic methods have been developed as powerful methods to optimize operation policies. The meta-heuristic methods are very flexible to formulate target functions and constraints. Also, they have easy performance, and significant knowledge of optimization models is not needed (Schardong and Simonovic 2011).

The practical swarm optimization (PSO) is one of the meta-heuristic methods that are widely used in water resource management. The main advantage of PSO is that it provides near-optimal solutions with rational computational cost. It also has high convergence speed and entrapment difficulty in a local optimum (Montalvo et al. 2008). Studies show that PSO model has better efficiency for achieving an optimal solution with spending less time than other collective models, e.g., genetic algorithm (GA) (Kumar and Reddy (2007); Montalvo et al. (2008)). Although it cannot be claimed that the heuristic methods are unable to find an absolute optimum and as the iterations are tended to infinite, the convergence is proved. However, in many issues especially in the optimization of reservoir operation, the optimum is not always considered, and the main goal is to find a satisfactory answer with consuming reasonable time and cost. The concept of high fitness member (elitist selection) in PSO is not used, and unlike GA, the selection is not based on fitness function. So, particles with low fitness can also remain in optimization process and can move everywhere in search space. The removal of low fitness members in every generation in the GA model can reduce the efficiency of the algorithm with increasing the number of generations in target function optimization. Furthermore, the number of parameters in PSO model is less than GA that represents its simplicity and higher speed to reach the best answer.

In recent years, different studies about PSO application and comparison of its performance with other optimization models have been done that some of them are mentioned as follows. Chau (2004) applied the PSO method in forecasting real-time runoffs. The PSO was also adopted to train ANNs in prediction of water levels, and the satisfactory results were obtained (Chau 2006). Kumar and Reddy (2007) developed a PSO model by incorporating a new strategic mechanism called elitist-mutation (EMPSO) for the optimization operation of multipurpose reservoir systems. The comparison of the EMPSO results with standard PSO and GA models showed better performance of EMPSO compared with the other two methods. Montalvo et al. (2008) compared PSO with ant colony algorithm (ACO) and GA techniques in designing of water supply system. The results revealed that PSO method has given possible and better solutions compared to ACO and GA techniques for the water supply problems. Izquierdo et al. (2008) studied optimization of wastewater collection networks design by PSO method. The obtained results were compared with those given by using dynamic programming to solve the same problem under the same conditions. The results showed that PSO model was better for finding an optimal solution. Baltar and Fontane (2008) used multiobjective particle swarm optimization (MOPSO) for multipurpose reservoir operation issues. Chu and Chang (2009) employed PSO method to parameter estimation of the nonlinear Muskingum. Simulation results indicated that the proposed model can improve the accuracy of the Muskingum model for flood routing. Mathur and Nikam (2009) applied GA to optimize the operation of the multipurpose reservoir and to gain reservoir operating rules for optimal reservoir operations. The target function used was minimizing the squared deviation of monthly irrigation demand along with the squared deviation in the mass balance equation. Their results indicated that even during the low flow condition, the GA model applied to the Upper Wardha reservoir can satisfy downstream irrigation demand. Monem and Nouri (2010) developed PSO model to optimize water delivery in irrigation networks. They compared the outcomes with simulated annealing model and concluded that PSO model was better for designing of optimal irrigation networks. Asfaw and Saiedi (2011) performed an optimal operation of a cascade hydro-electricity reservoir system using GA and excel optimization solver. They revealed that the release policy of GA was better than the excel optimization solver. Cyriac and Rastogi (2013) investigated the basic concepts and successful application of PSO algorithm in water resource optimization. Some studies have also been performed on the application of different methods for operation optimization under in drought conditions. Taghian et al. (2014) presented a hybrid model of MOPSO and fuzzy logic to optimization of reservoir operation and to minimize drought effects. The results showed that the developed model had a good performance on reservoir operation in drought and normal conditions. Khanjari Sadati et al. (2014) used GA to develop optimal reservoir water allocation policies for Doroudzan dam in the south of Iran and to present the optimal cropping pattern. They defined four weather conditions by combining different probability levels of evapotranspiration, rainfall, and inflow. They defined two irrigation approaches, deficit and full irrigation under these four conditions. The results showed that under deficit irrigation conditions, the total farm income and the total cropped areas were larger compared with the full irrigation. Ahmadianfar et al. (2016) proposed optimal reservoir operation policies for the Zohreh multiobjective and multireservoir system in southern Iran. For this purpose, a conventional hedging rule was incorporated with a simple fuzzy logic concept to prevent water reservoir shortage in drought condition. In order to optimize hedging rule parameters, the MOPSO was applied. They showed that the performance of the system in short and long term is improved in contrast with conventional hedging. The hedging system can find an appropriate hedging rule for the multipurpose and multireservoir system in drought periods. Other researches on optimal reservoir operation in drought conditions include Shih and Revelle (1994, 1995), Dariane (1999, 2003), Felfelani et al. (2013), and Hu et al. (2016).

In the present study, the PSO algorithm is adopted for the optimal operation of the multipurpose Mahabad dam reservoir. This model is employed with a purpose of reduction probability of inflow for the four scenarios of normal and drought conditions.

Materials and methods

Case study

The case study considered in this paper is the Mahabad watershed which is located in the northwest region of Iran between the geographical coordinates 45° 25′ to 45° 46′ E longitudes and 36° 26′ to 36° 46′ N latitudes. The Mahabad dam site covers an area of 807 km^2 with 142 km perimeter. The dam is a multiobjective rockfill dam with clay core which was designed, e.g., to store drinking water, prepare agricultural water, control seasonal floods, and generate electricity (Table 1). The Coter and Bytas rivers originated from the southern heights of the Jandaran and Siahghol Mountains are the two most important rivers of the basin that finally drain into the Mahabad dam reservoir (Fig. 1).

The monthly inflow data were collected from the Mahabad Water Organization for a 32-year period 1975–2006. As shown in Table 2, the months of May, June, July, August, and September have the highest drinking and agricultural demands and these demands are more than the average inflow to the reservoir during this period (May–September). The maximum inflow occurs when demands are minimum. The annual average inflow of the dam is 280 million cubic meters (MCM), with a standard deviation ranging from 43.28 to 0.92 MCM. As expected, the maximum monthly net evaporation is observed in the summer season. The maximum release of the reservoir is 51.84 MCM in the first half of the hydrological year and 53.57 MCM in the second half based on the release of the reservoir and its powerhouse inflow conditions for hydroelectric power generation (as shown in the last column in Table 2). It should be noted that the agriculture planning for water demand was performed based on the guideline of Jahad-e-Keshavazi Organization that is the governmental official strategist for agriculture division in the Mahabad plain. The monthly municipal water demand was also determined based on regional water affair reports.

PSO algorithm

PSO is a meta-heuristic computation method and has been inspired by the social behavior of animals like bird flocking, fish schooling, and insect swarming (Kennedy and Eberhart 1995). This model is computationally inexpensive with a very simple theoretical structure and easy coding and performance. Recently, PSO has been applied in many research fields, particularly in unconstrained continuous optimization issues (Kennedy et al.

Table 1 Characteristics of Mahabad reservoir dam

Parameters	Quantities
Crest length	700 m
Crest width	8 m
Lake length of dam	12 Km
Lake area of dam	11 Km^2
Live storage capacity	180 Mm^3
Dead storage capacity	40 Mm^3

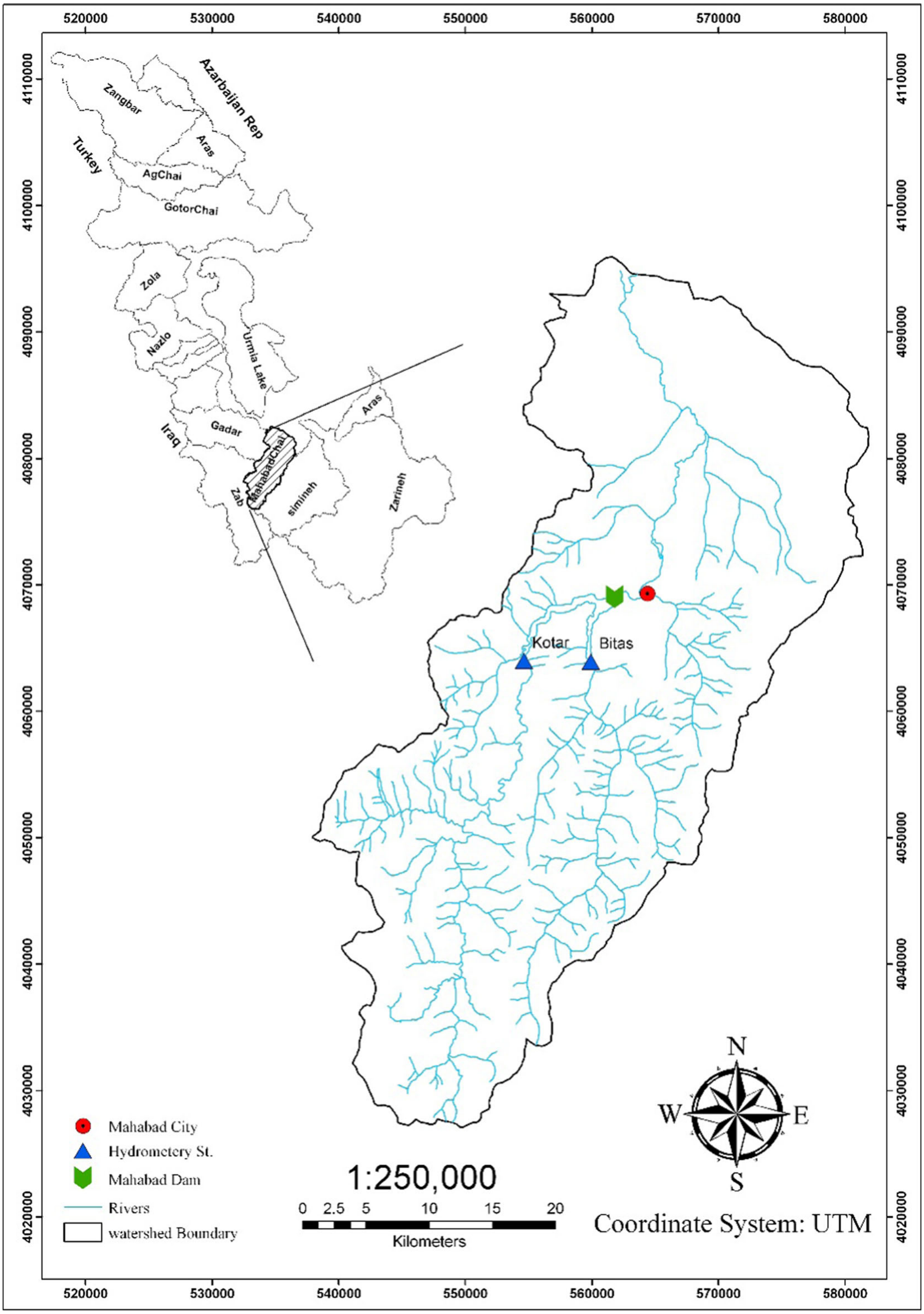

Fig. 1 Location of Mahabad dam

Table 2 Determined hydrological parameters at Mahabad dam site

Month	Average inflow (MCM)	Std. dev. (MCM)	Drinking & agricultural demand (MCM)[a]	Net evaporation (mm)	Maximum release of the reservoir (MCM)
September	1.34	1.45	20.67	120.5	51.84
October	7.85	11.86	9.11	40.77	51.84
November	11.03	11.33	1.53	–	51.84
December	16.28	15.3	1.43	–	51.84
January	20.98	14.36	1.4	–	51.84
February	54	33.26	1.44	–	51.84
March	97.13	43.28	6.92	50.88	53.57
April	55.88	37.7	27.04	156.39	53.57
May	10.9	10.8	33.01	274.91	53.57
June	2.47	1.87	29.64	321.52	53.57
July	1.14	0.94	30.74	314.3	53.57
August	0.9	0.92	26.8	242.5	53.57

[a] Jahad-e-Keshavazi Organization's guideline and Water & company, West Azarbaijan Province, Mahabad Town, Iran

2001). At first, this algorithm initializes with the population of individual particles, which is randomly located in the design space. Consequently, PSO simply regulates the trajectory of particles and provides the best solution for all the particles (gbest) and for each particle (pbest). However, each particle contains a velocity that is dynamically regulated based on flying experience of its own and other particles in the design space (He and Wang 2007). Suppose that the design space is D-dimensional, then, the ith particle of the population can be represented by a D-dimensional vector, $X_i = [x_{i,1}, x_2, \ldots, x_{i,d}]^T$. The velocity (position change) of this particle can be displayed by another D-dimensional vector, $V_i = [v_{i,1}, v_{i,2}, \ldots, v_{i,d}]^T$. The best prior gained position (*pbest*) of the ith particle is denoted as $P_i = [p_{i,1}, p_{i,2}, \ldots, p_{i,d}]^T$. The global best particle (*gbest*) is symbolized byP_g, which illustrates the best particle found so far in the whole population. The new velocity of each particle is calculated as follows:

$$v_{id}^{n+1} = wv_{id}^{n}(t) + c_1 r_{1,i,d}^{n}\left(p_{id}^{n} - x_{id}^{n}\right) + c_2 r_{2,i,d}^{n}\left(p_{gd}^{n} - x_{id}^{n}\right) \qquad (1)$$

Where, $d = 1, 2, \ldots D$, $i = 1, 2, \ldots N$with N being the size of the population, $c_1$and $c_2$are constants called acceleration coefficients, w is the inertia factor and $r_{1,i,d}$ and $r_{2,i,d}$ are the two independent random numbers uniformly distributed in the range of [0, 1]. Several studies on PSO showed different amounts of acceleration parameter: c_1 and c_2 are equal to 2 ($c_1 = c_2 = 2$) in theoretical study and equal to 0.5 ($c_1 = c_2 = 0.5$) in empirical study (Kennedy 1998). However, Carlisle and Dozier (2001) indicated that it is better to select a larger cognitive parameter, c_1, than a social parameter, c_2 with $c_1 + c_2 \leq 4$. We followed this suggestion and choose $c_1 + c_2 \leq 4$.

Therefore, the update of the position of individual particle in each generation is done by

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \qquad (2)$$

The inertia weight,w in Eq. 1 is used to control the influence of the preceding velocity history on the present one. Therefore, the inertia factor, w, regulates the mutual relationship between the global and personal discovery power of the population (Abraham et al. 2006). Empirical outcomes showed that to prevent global discovery power of the design space and gradually decrease it to achieve the best solution, it is suitable to put inertial factor on the large value (Shi and Eberhart 1998a, b, 1999). Thus, Shi and Eberhart (1998a, b, 1999) improved performance of the PSO model as a weighting function:

$$w = w_{\max} \frac{(w_{\max} - w_{\min}) \times n}{iTer_{\max}} \qquad (3)$$

where, $w_{\max}$is the initial weight, $w_{\min}$ is the final weight, $iTer_{\max}$ is the maximum iteration number, and n is the current iteration number. Flowchart of PSO is shown in Fig. 2 (Gholizadeh and Seyedpoor 2011).

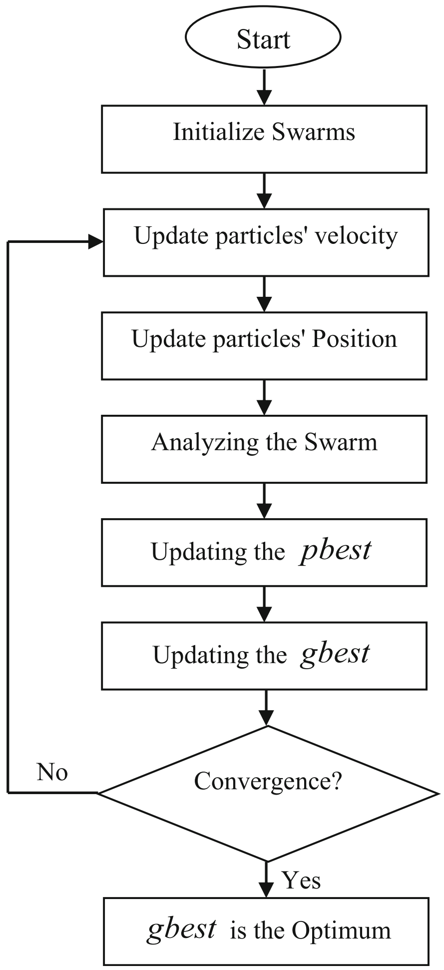

Fig. 2 The flowchart of PSO algorithm

Model development

The target function used in this study for the mathematical model of the operation optimization of the Mahabad dam reservoir minimizes the difference between monthly downstream demands and release (Mathur and Nikam 2009; Taghian et al. 2014):

$$\text{Minimize } F = \sum_{t=1}^{12} (R_t - D_t)^2 \tag{4}$$

where, R_t is monthly water release for the month t and D_t is the monthly downstream water demand for the month t.

The sum of agricultural and drinking demands is considered as downstream demand. There are 24 decision variables including 12 variables (one for each month) for the release and 12 variables for the storage volume of the reservoir.

Constraints of the system: To minimize the target function, three main constraints are considered in the current study:

I. Reservoir mass balance constraint

In this constraint, the final storage at the end of the month t is equal to the initial storage in the beginning of the month$t$plus monthly inflow during the period t mines monthly watery release for the month $t$and monthly evaporation loss from the reservoir during the month$t$. This equation is called mass balance (Becker and Yeh 1974; Yeh 1985; Wurbs 1993; Russell and Campbell 1996; Labadie 2004):

$$S_{t+1=}S_t + I_t - R_t - E_t \qquad t = 1, \ldots, 12 \tag{5}$$

Where, S_{t+1} is the final storage at the end of the month$t$, S_t is the initial storage at the beginning of the month$t$, I_t is the monthly inflow during the period t,R_t is the monthly water release for the month t, and E_t is the monthly evaporation loss from the reservoir during the month t.

II. Reservoir storage constraint

The constraint considered for reservoir storage implies that the storage in each month should not be more than the maximum capacity of the reservoir and less than the dead storage. The constraint is expressed as:

$$S_{\min} \le S_t \le S_{\max} \qquad t = 1......12 \tag{6}$$

where, S_t is the reservoir storage for the month $t$and $S_{\max}$ and $S_{\min}$ are the maximum capacity and dead storage of the reservoir in MCM, respectively.

III. Release constraint

Release from the reservoir for the month t (R_t) must be more than or equal to zero and smaller than or equal to the maximum release of the reservoir. This constraint is given by:

$$R_{\min} \le R_t \le R_{\max} \qquad t = 1......12 \tag{7}$$

where $R_{\max}$are $R_{\min}$ are the maximum and minimum releases of the reservoir in MCM, respectively.

In order to optimize the operation of the Mahabad dam, the inflow to the dam with reduction probability against mean monthly flow was considered. In fact, the optimization was performed in low inflow conditions in drought situations when the water system of the dam faces water shortage problems. The inflows to the dam with reduction probability are computed using the following equation:

$$I_t = \overline{I}_t + K.\mathrm{SD}_t \tag{8}$$

where I_t is the storage inflow for the month t, $\overline{I}_t$ andSD_t are the average and standard deviation of inflow for the month t, respectively.

In order to define different drought scenarios, different values of K ($K = -0.25$, $K = -0.5$, and $K = -0.75$) were used in Eq. 7. Eq. 7 for different drought scenarios can be written as follows:

$$I_t = \overline{I}_t + (-0.25)(\mathrm{SD})_t \tag{9}$$

$$I_t = \overline{I}_t + (-0.5)(\mathrm{SD})_t \tag{10}$$

$$I_t = \overline{I}_t + (-0.75)(\mathrm{SD})_t \tag{11}$$

In addition, $K = 0$ was applied to describe the normal scenario.

$$I_t = \overline{I}_t \tag{12}$$

In normal condition, the inflow is considered equal to the mean inflow. However, in drought condition, the inflow with a risk lower than normal condition (reduction probability) is considered. It means that the amount of inflow (I_t) decreases as the Kvalue decreases. In other words, the optimization is performed in various scenarios of drought conditions.

As PSO generally solves unconstrained problems, constrained problems should be converted to an unconstrained one. There are several methods to convert target function and constrains to an unconstrained function which is called pseudo target function. One of the most common methods is the exterior penalty function method, where target function and constrains are transformed into a pseudo target function as shown below (Ebrahinifarsangi 2002; Parsopoulos and Vrahatis 2002; hashemi et al. 2008):

$$\varphi = F + P \tag{13}$$

in which

$$P = R_P.\sum_{i=1}^{n_C}\left[\max\left(\frac{g_i}{\overline{g}_i}-1, 0\right)\right]^2 + R_p.\sum_{j=1}^{n_c}\left[\max\left(1-\frac{g_j}{\overline{g}_j}, 0\right)\right]^2 \tag{14}$$

where P is the penalty function, R_P is the penalty coefficient, $g_j, g_i, \overline{g}_J, \overline{g}_i$ are both side phrases of unequal constraints and F is the basic target function.

Results and discussion

In this research, the evaluation of decision variables to the present solution and borders was controlled. A penalty function was considered for the variables that are in violation of border. Since an accurate selection of parameters in the PSO model will affect the functioning and speed running of the PSO program, the sensitivity analysis of the PSO model was performed by consideration of various combinations of the parameters. After performing the sensitivity analysis, the parameters selected for the PSO model are demonstrated in Table 3. The sensitivity analysis of the population size is shown in Fig. 3. The initial value for the sensitivity analysis of population size increased from 50 to 300, and the target function value decreased from 217.09 to 181.04. Decline of the target function is significant until 150 populations but a significant change is not observed in the target function value with more population size increases. Therefore, the optimum size of the population is determined as 150 (Fig. 3). Afterwards, the PSO model was performed to obtain 24

Table 3 Sensitivity analysis for PSO model parameters

Parameter	Population size	Maximum iteration	C_1	C_2	W_{max}	W_{min}
Value	150	1000	1.5	2	0.5	0.1

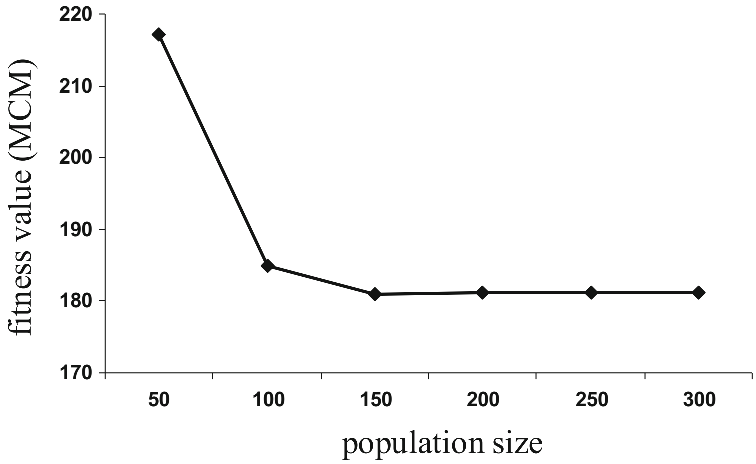

Fig. 3 Sensitivity analysis for population size

variables with function of constraint mentioned above. Twelve variables are related to the monthly release of water and the remaining variables are related to the storage volume of the reservoir. Figure 4 exhibits the amount of monthly released water for drinking and agriculture obtained from the PSO model. As shown, the months of May, June, July, and August have the highest releases.

Figure 5 shows the amount of released water obtained from the PSO model under the four scenarios and the amount of drinking and agricultural water demands in the downstream. In the normal conditions ($K = 0$) during all months, the amount of the released water estimated by the PSO can satisfactory provide the water demands of downstream. In fact, it prevents the water loss in all months except March, April, and May. These water losses are due to the high volume of inflow to the dam returned in March. In two drought scenarios ($K = -0.25, K = -0.5$), the amount of the released water calculated by the PSO can provide the drinking and agricultural water demands of downstream, especially during the first 6 months of the hydrological year which have high water demands. This prevents additional loss of consuming water in drought conditions. This is confirmed with the graphs of the downstream water requirements and the amount of the released water estimated by the model shown in Fig. 5. However, in a drought scenario ($K = -0.75$), there is not a suitable adaptation between the amount of the released water calculated by the model and the downstream water demands exception for September, October, March, May, June, July, and August months (Fig. 5).

The optimum storage of the water volume calculated for Mahabad reservoir dam in the four different scenarios is shown in Fig. 6. In all of the four studied scenarios, the maximum and minimum optimized storage volumes have been occurred in April and October, respectively. Generally, with decreasing K value from $K = 0$ to $K = -0.75$, the optimal volume of the reservoir obtained by the model decreases in different months. The optimal volume of the dam's

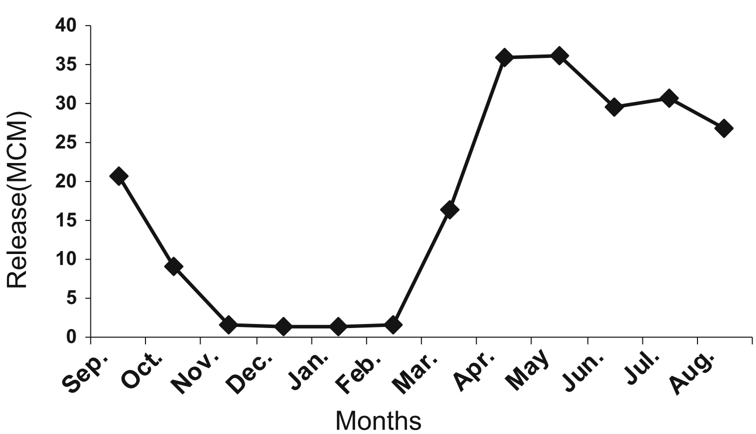

Fig. 4 Monthly release of reservoir

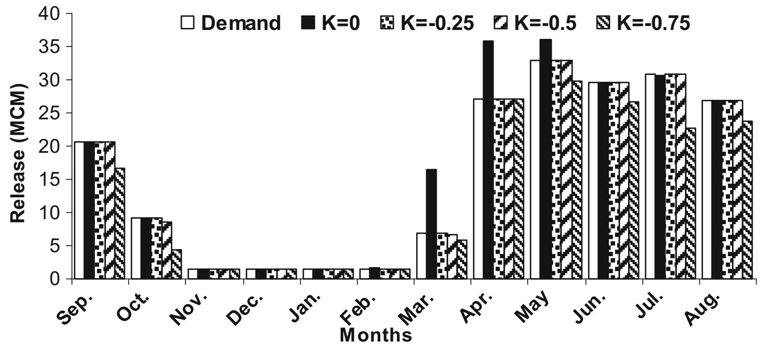

Fig. 5 Monthly demand and release obtained from the PSO model

reservoir has been defined for all the scenarios. In the first three scenarios, the reservoir has suitable storage for water supply of downstream, while in the last scenario ($K = -0.75$), according to the continuity rules, reservoir storage has decreased especially during the months with high water demands.

Conclusions

In this study, the PSO model was used for optimizing the operation of multipurpose Mahabad reservoir dam by considering the reduction of the probabilities of inflow. For the preparation of Mahabad reservoir system in critical conditions, inflows to the dam were considered with reducing the probabilities of monthly average inflows in four scenarios under normal and drought conditions. Generally, in most of the defined scenarios ($K = 0$, $K = -0.25$, and $K = -0.5$), the amounts of the released water obtained by the PSO model had a good agreement with the downstream water demands, and the storage dam had suitable reservoir to supply the water demands of the next months. Only in scenario $K = -0.75$, there is some problem in fully providing the drinking and agricultural water requirements of downstream in some months, because of the decreased dam's inflow and the amount of the released water and the optimum storage of reservoir calculated by the PSO. This research aimed to minimize the reservoir water loss and the PSO model showed a good performance to achieve this goal. Therefore, the operation policy can be used as an appropriate policy for the reservoir in drought conditions. In addition to the good performance of the PSO algorithm, the low sensitivity of the PSO model to the initial population and its high speed to achieve optimal response than other heuristic algorithm (e.g., genetic algorithm) make it a suitable option for optimal allocation of water under shortage and drought conditions. From the obtained results in this study, it can be concluded that PSO model has high ability to provide acceptable results for optimizing the operation of the reservoir in a short time. The developed model in this study can be used for better water resource management in the semi-arid study region. Water manager and policy makers with implementing an appropriate plan and the use of new optimization methods such as PSO can achieve optimum exploitation values for large water systems such as storage dams even in drought conditions.

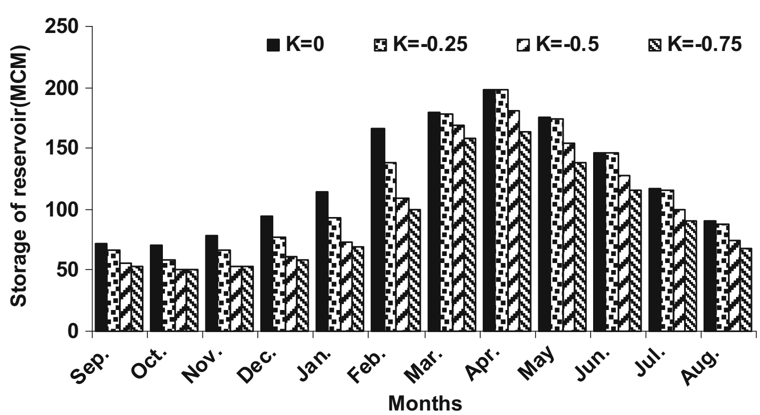

Fig. 6 Monthly reservoir storages

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Compliance with ethical standards This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest The authors declare that they have no conflict of interest.

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