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Optimal Operation of Hydropower Reservoir Systems Using Weed Optimization Algorithm

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Abstract The optimal hydropower operation of reservoir systems is known as a complex nonlinear nonconvex optimization problem. This paper presents the application of invasive weed optimization (IWO) algorithm, which is a novel evolutionary algorithm inspired from colonizing weeds, for optimal operation of hydropower reservoir systems. The IWO algorithm is used to optimally solve the hydropower operation problems for both cases of single reservoir and multi reservoir systems, over short, medium and long term operation periods, and the results are compared with the existing results obtained by the two most commonly used evolutionary algorithms, namely, particle swam optimization (PSO) and genetic algorithm (GA). The results show that the IWO is more efficient and effective than PSO and GA for both single reservoir and multi reservoir hydropower operation problems.

Keywords Hydropower operation · Invasive weed optimization · Genetic algorithm · Particle swarm optimization

1 Introduction

In the last decades, optimal use of water resources has become extremely important because of water and energy shortages, especially in arid and semi-arid regions in which uncertain watershed responds to various headwater management practices and variable climate conditions could impact on availability of water in the surface reservoir systems (York et al. 2015). Efficient management of reservoirs, as one of the most important existing surface water

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resources, is, therefore, of paramount importance. The main challenge of managing surface reservoir calls for extraction of optimal policies to operate surface reservoirs under extreme climate conditions (Karamouz et al. 2013). On the other hand, the complexity of the water resources management problems, including reservoir operation, is increasing due to continuous increasing of water and energy demand.

In recent years, hydropower has become one the most important sources for supplying electricity demand because of advantages of being clean and renewable. Therefore, more robust and reliable operation policies should be developed to operate hydropower plants such that reduce the vulnerability in the system (Goharian et al. 2015). For this, many optimization techniques have been used for optimal hydropower operation of reservoirs, with the main objective of the benefit maximization of hydropower generation.

Classic optimization algorithms such as linear programming (LP) (Ellis and ReVelle 1988; Yoo 2009; Wu et al. 2009), non-linear programming (NLP) (Arnold et al. 1994; Zambelli et al. 2009; Moosavian et al. 2010) and dynamic programming (DP) (Allen and Bridgeman 1986; Zhao et al. 2012; Li et al. 2014) have been extensively used for solving hydropower reservoir operation problems in different forms. However, classic optimization methods have some limitations such as trapping in local optima and curse of dimensionality.

To overcome the shortcomings of classic optimization methods for solving water resources management problems, many researchers used evolutionary and metaheuristic algorithms to solve the problems. Although these algorithms need long processing time to converge to a solution, they converge to a near-global optima for many types of problems. Genetic algorithms (GAs), as the heading of evolutionary optimization techniques, have been widely applied in various aspects of reservoir operation problems (Esat and Hall 1994; Oliveira and Loucks 1997; Jothiprakash and Shanthi 2006; Louati et al. 2011). Furthermore, other evolutionary and metaheuristic methods such as particle swarm optimization (PSO) (Afshar 2012, 2013a; Zhang et al. 2013), ant colony algorithm (ACO) (Afshar et al. 2006, 2015), simulated annealing (SA) (Teegavarapu and Simonovic 2002; Tospornsampan et al. 2005; Kangrang et al. 2010), honey bee mating optimization algorithm (Bozorg-Haddad et al. 2006, 2011), bio-geography based optimization algorithm (Bozorg-Haddad et al. 2016), genetic programming (Fallah-Mehdipour et al. 2013; Akbari-Alashti et al. 2014, 2015), bat algorithm (Bozorg-Haddad et al. 2015a), water cycle algorithm (Bozorg-Haddad et al. 2015b), and firefly algorithm (Garousi-Nejad et al. 2016a, b) employed for optimal operation of reservoirs with different objectives.

Since the optimal reservoir operation will contribute to getting better and more reliable operation rules, which will further increase the social and economic benefits in context of water and energy shortages, therefore, it is important to look for new algorithms with great potential to solve complex reservoir operation problems (Ming et al. 2015).

Recently, an efficient optimization technique, named invasive weed optimization (IWO) was introduced by Mehrabian and Lucas (2006). They employed the method for solving some problems and concluded that the method is superior to common evolutionary and metaheuristic methods, namely, GA, PSO and SA. Since the IWO is simple in structure, easy in application and effective in optimization, it has been widely used in various disciplines such as electromagnetics (Karimkashi and Kishk 2010), design of antenna arrays (Roy et al. 2011), automatic clustering (Chowdhury et al. 2011) unit commitment (Saravanan et al. 2014), power flow (Ghasemi et al. 2014) and large scale economic problems (Barisal and Prusty 2015).

The application of IWO to water resources management is, however, only recent. As a first application of the method to these problems of interests, Asgari et al. (2015) employed IWO for optimal water supply operation of reservoirs. They compared the results of IWO for reservoir operation problems with those obtained by LP, NLP and GA, and concluded that the method is efficient for solving water supply reservoir operation.

In this study, IWO is applied for optimal hydropower operation of reservoir systems. Hydropower reservoir operation problems are well known as nonlinear nonconvex optimization problems which are difficult to solve by classical optimization methods. Here, two cases of single reservoir and multi reservoir operation are considered over short, medium and long term operation periods so that the efficiency and effectiveness of the IWO algorithm are truly assessed through solving problems with different levels of complexity. In order to show the capabilities of the IWO algorithm to find the optimal solution, the problems are considered with existing results obtained by two well-known evolutionary algorithms, namely PSO and GA. For single reservoir case, hydropower operation of Dez reservoir in Iran is used as a case study, and a well-known benchmark four-reservoir problem is considered for multi-reservoir case. The results are compared with those obtained using two powerful evolutionary algorithms, PSO and GA, indicating that the proposed IWO for hydropower operation of reservoirs is superior to PSO and GA to solve optimal hydropower reservoir operation problems, in particular for the solution of large scale problems.

2 Invasive Weed Optimization (IWO) Algorithm

The IWO is a stochastic optimization algorithm which inspired from weed colonization. Weeds have shown to be very robust and can quickly adapt to any environment. Thus, capturing their properties lead to a powerful optimization algorithm (Mehrabian and Lucas 2006).

Weed colonization starts with invading a cropping system by means of dispersal. The weeds occupy unused spaces between crops and take the remained resources and grow to flowering weeds and produce new weeds. The weeds with better adaptation to environment have more chance to produce more seeds and consequently reproduce more new weeds which are randomly dispersed in the field. This process is repeated until the maximum number of weeds is reached, considering the fact that the weeds with better adaptation have more chance to survive.

Considering an N-variable optimization problem, the IWO mimics the weed colonization by defining an initial population such that the number of seeds are randomly spread over the field. In optimization problems, seeds and field represent randomly generated initial solutions and N-dimensional problem space, respectively. The fitness of each seed is calculated based on a predefined objective function of the problem. A seed of the colony is then allowed to reproduce new seeds depending on its own fitness value and the best fitness value in the colony. The number of seeds which be allowed to produce by a considered seed is calculated as

$$S_n = S_{min} + \frac{S_{max} - S_{min}}{F_b - F_w}\left(F_p - F_w\right) \quad (1)$$

Where S_n is the number of allowable reproduced seeds, S_{min} and S_{max} are the minimum and maximum number of seeds, respectively; F_b and F_w are the best and the worst fitness values, respectively; and F_p is the fitness of the considered seed.

The next step for implementing IWO, is dispreading the new produced seeds over the solution space, near the producing plants, by normally distributed random numbers with mean equal to zero and varying standard deviation. The standard deviation is started from a predefined initial value (σ_{initial}) and reduced to a final value (σ_{final}) and calculated based on

$$\sigma_{iter} = \left(1 - \frac{iter}{iter_{max}}\right)^{n} \left(\sigma_{initial} - \sigma_{final}\right) + \sigma_{final} \tag{2}$$

Here, σ_{iter} is the standard deviation of current iteration, $iter_{max}$ is the maximum number of iterations, and n is the predetermined nonlinear modulation index. Starting with a high standard deviation, the algorithm is allowed to be explored through the whole solution space. By increasing the number of iteration, the standard deviation is gradually decreased in order to exploitation.

Once all seeds found their positions and the new plants grew to the flowering plants, they are ranked together with their parents. Some of the existing plants is then removed based on a competitive process such that plants with better ranking are survived. It should be noted that the number of plants is to be survived is equal to the maximum number of plant in the colony, P_{max}, which is a constant parameter. This process is continued until the convergence criteria are met. A descriptive flowchart of IWO is presented in Fig. 1.

3 Hydropower Reservoir Operation Model

The hydropower reservoir operation problems can be either single-reservoir or multi-reservoir systems in which the system is operated such that maximize the benefit or energy production over operation period. In this study, both cases of single-reservoir and multi-reservoir hydropower operation are considered.

The objective function of single-reservoir hydropower operation can be mathematically defined as

$$Min\ OF_s = \sum_{t=1}^{NT} \left(1 - \frac{P_t}{Icap}\right) \tag{3}$$

Subject to following constraints

$$S_{t+1} = S_t + Q_t - R_t \tag{4}$$

$$S_t^{min} \le S_t \le S_t^{max} \qquad t = 1, \ldots., NT + 1 \tag{5}$$

$$R_t^{min} \le R_t \le R_t^{max} \qquad t = 1, \ldots., NT \tag{6}$$

$$P_t = \left(\frac{g \times \eta \times R_t \times h_t}{P_f \times time}\right) \tag{7}$$

$$h_t = \left(\frac{H_t + H_{t+1}}{2}\right) - TWL \tag{8}$$

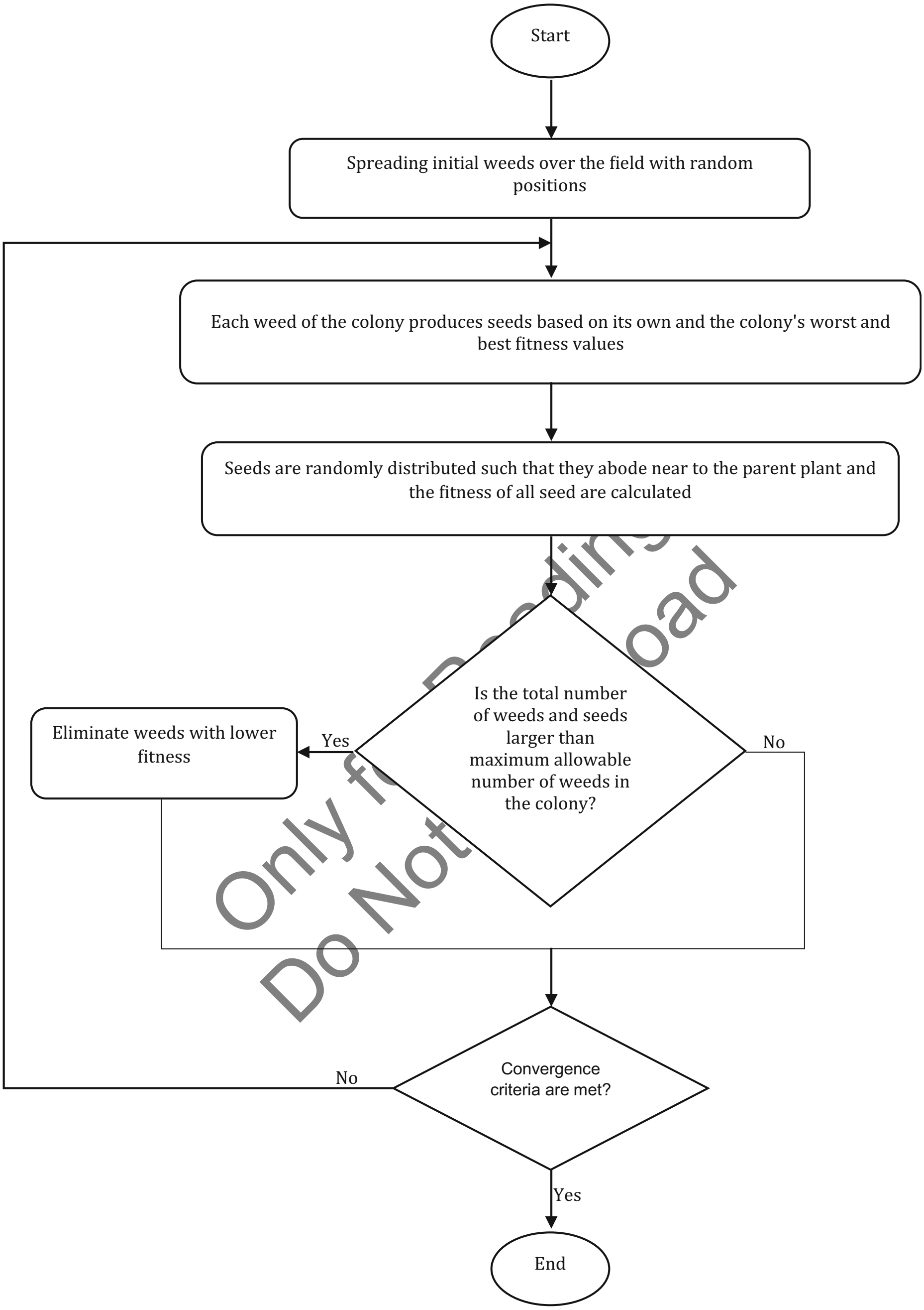


Fig. 1 Descriptive flowchart of IWO algorithm

$$H_t = a + b \times S_t + c \times S_t^2 + d \times S_t^3 \tag{9}$$

Here, OF_s is the objective function of single reservoir problem, NT is the number of periods, P_t is the power generated by the hydroelectric plant at period t (MW), $Icap$ is the installed capacity of hydroelectric plant (MW), g is gravity acceleration equal to 9.81 m^2/s; η is the efficiency of the hydroelectric plant, R_t is the released water at period t, P_f is the plant factor, $h_{t.}$ is the effective head of the hydroelectric plant, H_t is the elevation of water in reservoir at period t, TWL is the downstream elevation of the hydroelectric plant, S_t is the water storage of the reservoir at period t, Q_t is the water inflow in the reservoir at period t, S_t^{min} is the minimum water storage of the reservoir, S_t^{max} is the maximum water storage of the reservoir, R_t^{min} is the minimum water release of the reservoir, and R_t^{max} is the maximum water release of the reservoir. The volume-elevation curve of the reservoir is defined by Eq. (9) in which a, b, c and d are constant coefficients.

In multi-reservoir systems, the benefit based operation is considered in which the system is operated so that the net benefit of the operation is maximized over the operation horizon, with the optimization model in form of

$$Max\ OF_m = \sum_{k=1}^{K}\sum_{t=1}^{NT} B_{k,t} \times E_{k,t} \tag{10}$$

$$\boldsymbol{S}_{t+1} = \boldsymbol{S}_t + \boldsymbol{Q}_t - \boldsymbol{A}\boldsymbol{R}_t \tag{11}$$

$$S_{k,t}^{min} \le S_{k,t} \le S_{k,t}^{max} \qquad t = 1, .., NT + 1 \quad \text{and} \quad k = 1, .., K \tag{12}$$

$$R_{k,t}^{min} \le R_{k,t} \le R_{k,t}^{max} \qquad t = 1, .., NT \qquad \text{and} \quad k = 1, .., K \tag{13}$$

$$E_{k,t} = R_{k,t} \times h_{k,t} \tag{14}$$

$$h_{k,t} = \left(\frac{H_{k,t} + H_{k,t+1}}{2}\right) - TWL_{k,t} \tag{15}$$

$$H_{k,t} = a_k + b_k \times S_{k,t} + c_k \times S_{k,t}^2 + d_k \times S_{k,t}^3 \tag{16}$$

Where OF_m is objective function of multi-reservoir problem, K is number of reservoir in system, $B_{k,t}$ and $E_{k,t}$ are benefit and produced energy of reservoir k in period t, respectively; $\boldsymbol{S}_t$, is vectors of system storages in period t, $\boldsymbol{Q}_t$ and $\boldsymbol{R}_t$ are inflows and releases to/from system reservoirs at period t, respectively; $\boldsymbol{A}$ is a $K \times K$ connectivity matrix. All other parameters defined earlier for the single reservoir problem have the same meaning for reservoir k at period t in multi-reservoir problem.

It is worthwhile to note that the definition of objective function in form of Eq. (10) does not need more extensive data for the multi reservoir case study, while introduces the nonlinearity of real-world hydropower reservoir operation problems (Afshar 2013b).

4 Case Studies

4.1 Single Reservoir Operation

The hydropower operation of Dez reservoir in southern Iran is considered as a text example to illustrate the efficiency and effectiveness of the IWO for optimal hydropower operation of single reservoir problems. The monthly inflow to reservoir for a 480-month period is presented in Fig. 2. Average annual inflow to the reservoir is 5950 million cubic per meter (MCM). Total storage capacity, dead storage and effective storage of the reservoir are 3340, 830 and 2510 MCM, respectively.

The installed capacity of hydroelectric power plant is 650 MW which working 10 h per day, leading to plant factor of 0.417. The efficiency of power plant is 90 % and the downstream water level elevation of hydroelectric power plant is equal to 172. The constant coefficients of volume-elevation curve for Dez reservoir are as follos: a = 249.833, b = 0.05872, $c = -1.73 \times 10^{-5}$ and $d = 1.526 \times 10^{-9}$.

In order to test the capability of the IWO to capture the complexity of problems with different scales, the monthly operation of Dez reservoir is considered over 5, 20 and 40 years which lead to 60, 240 and 480 decision variables for optimization problems defined by Eqs. 3 to 9.

4.2 Multi-Reservoir Operation

A four-reservoir problem introduced into the literature by Larson (1968) and subsequently served as an illustrative example, and solved by various researchers to test different optimization algorithms. The schematic configuration of the reservoirs in this system is illustrated in Fig. 3. As shown in the figure, each reservoir has its own downstream hydropower plant and the outflow from the last reservoir may be used for irrigation. The objective function of this problem was proposed as

$$Max\ F = \sum_{k=1}^{K} \sum_{t=1}^{NT} B_{k,t} \times R_{k,t} \tag{17}$$

In this study, the problem objective function is modified by only replacing release volume with the produced energy as defined in Eq. (10) to keep the modification minimal while

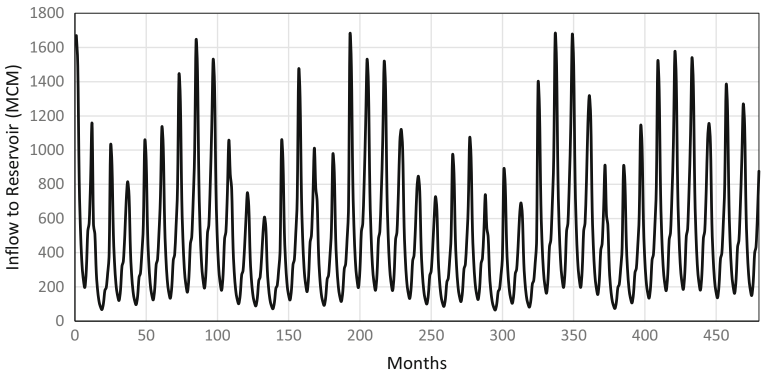
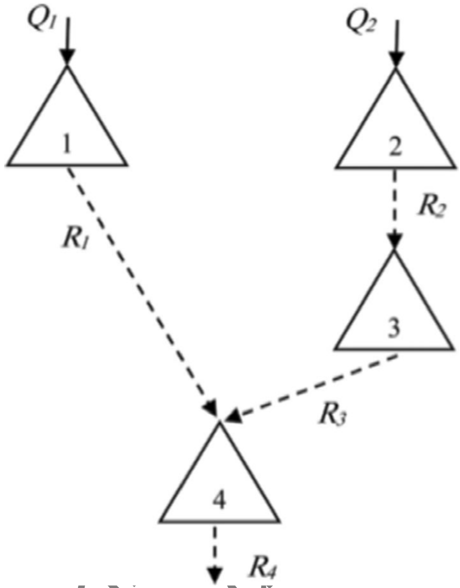


Fig. 2 Monthly inflow to Dez reservoir

Fig. 3 Reservoirs configuration in multi-reservoir problem



introducing the non-linearity of the real-world hydropower operation problems (Afshar 2013b). All data including allowable range of storage and release volumes, benefit functions, as well as volume elevation curve data can be found in (Afshar 2013b).

The IWO is applied for optimal multi reservoir hydropower operation over short, medium and long term operation periods with 12, 60 and 240 decision variables, respectively.

5 Results and Discussion

As an evolutionary method, IWO is a stochastic optimization algorithm which starts the search with random initial solutions, and it might provide different results at different runs. In order to

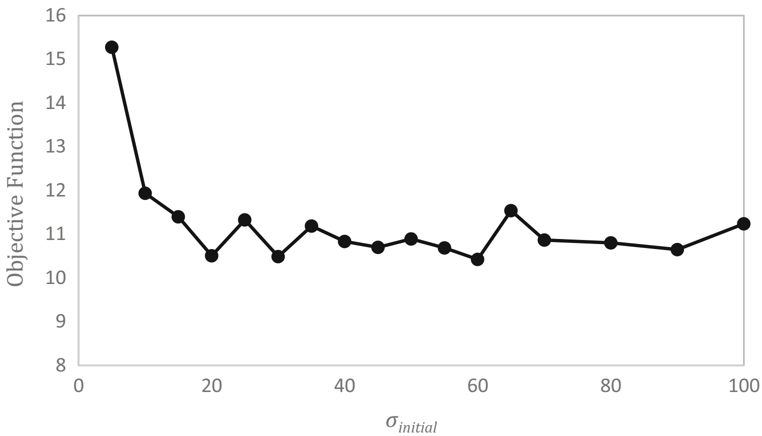


Fig. 4 Effect of $\sigma_{initial}$ on final solution for single-reservoir operation

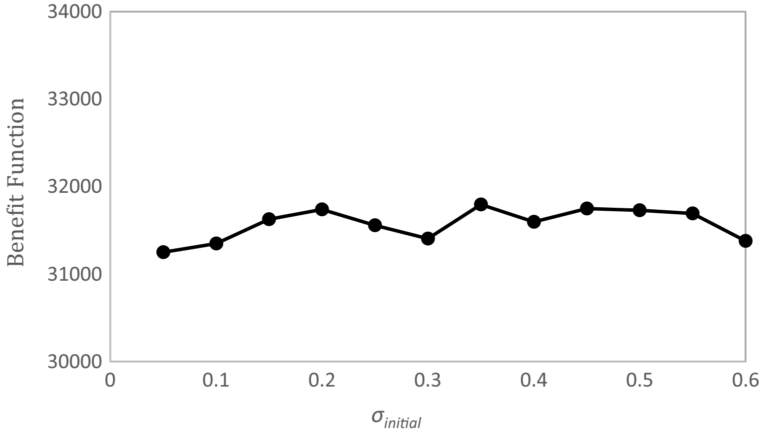


Fig. 5 Effect of $\sigma_{initial}$ on final solution for multi-reservoir operation

evaluate the algorithm fairly, 10 runs carried out for each problem, and the results are compared with those obtained out of 10 runs of PSO and GA.

Also, IWO, like other evolutionary algorithms, contains some free parameters which might affect the final solution. It is, therefore, important to investigate the effect of those parameters in quality of final solution. The less sensitive IWO parameters were chosen by trial and error as follows: the final standard deviation is set to as 0.01, the nonlinear modulation index is considered as $n = 2$ for both cases. Also, the maximum number of iteration ($iter_{max}$) is determined such that thorough exploration of the search space is ensured. A maximum number of iterations equal to 10,000, 20,000 and 40,000 are used for short, medium and long term operations for both cases of single reservoir and multi reservoir problems.

For more sensitive parameters of IWO, a series of preliminary runs was carried out to assess the effect of $\sigma_{initial}$ on the final solution obtained by IWO. The periods of 60 and 12 months of operation considered for single-reservoir and multi-reservoir problems, respectively; with different values of $\sigma_{initial}$. Figures 4 and 5 show the average value of 10 runs for each $\sigma_{initial}$ for single-reservoir and multi-reservoir cases, respectively. Based on the results of sensitivity analysis of IWO to $\sigma_{initial,}$ the initial standard deviation is set to 25 and 0.2 for single reservoir and multi reservoir cases, respectively.

Also, to show the sensitivity of the IWO to initial population size, maximum population size (P_{max}) and maximum number of seeds (S_{max}), three different sets of parameters (PS) are used as summarized in Table 1. The PS1 and PS3 have the minimum and maximum number of function evaluations, respectively.

Table 1 Characteristics of different parameters' sets

PS	Initial Population Size	Maximum Population Size	Maximum Number of Seeds
1	2	5	2
2	5	10	5
3	10	15	10

Table 2 Results of IWO for Dez reservoir operation over periods of 60, 240 and 480 months

Month	PS	Objective Function			SD	Average Computational Time(s)
		Minimum	Maximum	Average		
60	1	10.3	12.3	11.2	0.7	0.9
	2	8.3	9.7	8.8	0.4	2.2
	3	7.8	8.5	8.2	0.3	4.6
240	1	49.3	–	–	–	2.4
	2	29.6	36.3	32.7	2.2	6.2
	3	25.9	30.9	29.2	1.4	13.9
480	1	–	–	–	–	–
	2	101.9	–	–	–	16.2
	3	63.3	75.7	70.4	3.8	42.7

5.1 Results for Single Reservoir Problem

The IWO algorithm is used to optimally operate Dez reservoir for hydropower purposes, over periods of 60, 240 and 480 months so that the capabilities of IWO can be assessed for operation problems of different scales.

The minimum, maximum and average objective function of 10 runs for hydropower operation over periods of 60, 240 and 480 months presented in Table 2, with different sets of IWO free parameters. This table also shows the standard deviation (SD) and average computational time. Although IWO produced feasible solutions for shortest period of 60 months for three sets of parameters (shown in Table 1), however, for the longer period of 240 months, the IWO only produced 1 feasible solution per 10 runs by using parameters of PS1, while all solutions obtained by using PS2 and PS3 are feasible. For the longest period of operation, namely 480 months, IWO failed to produce any feasible solution using parameters set 1 (PS1)., and achieved only one feasible solution out of 10 runs using PS2. This failure can

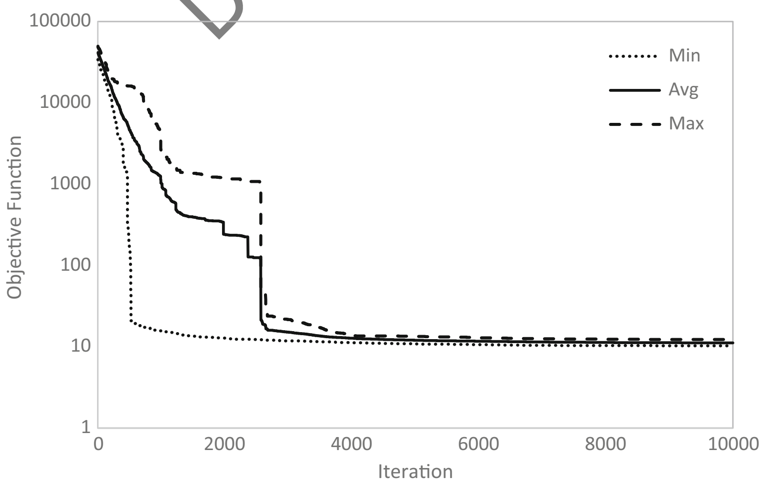


Fig. 6 Convergence curve for operation over 60-month period

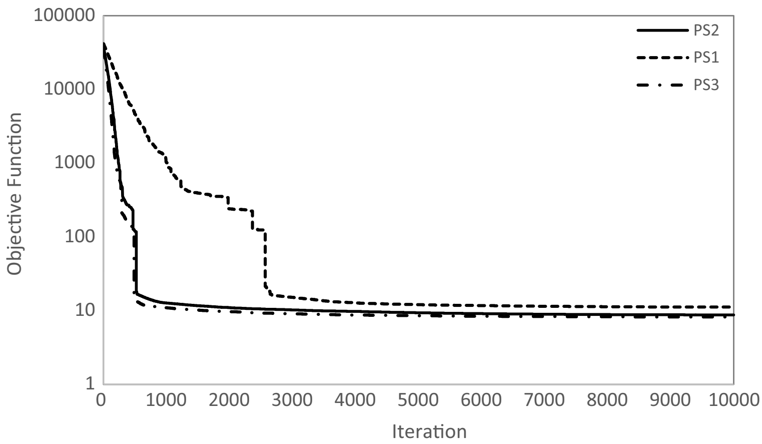


Fig. 7 Average of the objective function of 10 runs with different sets of parameters of IWO, for single-reservoir operation

be attributed to the larger scale of these problems compared to the 60-month problem. AS shown in Table 2, this issue is solved by increasing the initial population size, maximum population size and maximum number of seeds. In other words, for large scale problems, IWO needs to do more function evaluation to find the optimal or near optimal solution.

Figure 6 shows typical convergence curve for the hydropower operation of Dez reservoir over 60 months of operation, considering PS1. Also, the average of objective function of 10 runs with different sets of parameters are illustrated in Fig. 7. The curve emphasizes the fact that the solution obtained by more function evaluations, namely PS3, is closer to near optimal solution than those obtained by PS1 and PS2.

This problem was already solved by Afshar and Shahidi (2009) using two evolutionary algorithms GA and PSO. Here, the results of that study are only used for comparison purposes. Details of parameters of these methods used for solving the problem can be found in (Afshar and Shahidi 2009). Results shown in Table 3 demonstrate that IWO produced superior solutions than those obtained by GA and PSO. While only the GA and PSO solutions of 8.1 and 9.3 for the shortest period of 60 months are comparable to the IWO solutions of 7.8,

Table 3 Comparison of IWO with GA and PSO for solving single-reservoir hydropower operation problem

Month	Model	Objective Function			Average Computational Time(s)
		Minimum	Maximum	Average	
60	IWO	7.8	8.5	8.2	4.6
	GA	8.1	9.1	8.5	7
	PSO	9.3	14.3	11.3	9
240	IWO	25.9	30.9	29.2	13.9
	GA	55.1	617.0	159.0	27
	PSO	221.0	4320.0	1600.0	36
480	IWO	63.3	75.7	70.4	42.7
	GA	27,300.0	61,700.0	40,000.0	54
	PSO	25,100.0	70,400.0	41,800.0	73

Table 4 Results of IWO for multi-reservoir operation over periods of 12, 60 and 240 months

Month	PS	Objective Function			SSD	Computational Time(s)
		Maximum	Minimum	Average		
12	1	32,321	30,495	31,585	0.016	2.1
	2	33,041	31,684	32,410	0.013	6.6
	3	33,551	32,017	32,795	0.012	17.1
60	1	148,938	144,976	146,775	0.010	7.7
	2	154,347	149,652	152,161	0.009	27.8
	3	157,614	153,318	155,201	0.009	81.3
240	1	812,786	656,725	771,652	0.052	33.4
	2	835,580	790,679	812,383	0.017	155.9
	3	859,285	823,287	838,661	0.015	448.3

none of the solutions obtained by GA and PSO for 240 and 480 months of operation periods even approach the optimal solutions obtained by IWO.

5.2 Results for Multi Reservoir Problem

In order to show the capability of the IWO for solving multi reservoir hydropower operation problems, a four-reservoir benchmark problem is considered, and the results obtained for 12, 60, and 240 periods of operation presented in Table 4. The table shows maximum, minimum and average of objective function for ten runs with random initial solutions. Also, scaled standard deviation (SSD) and average computational time for ten runs are presented in this table. It should be mentioned that all runs of IWO lead to feasible solutions for three different operation periods with three different size of parameters (PS).

The characteristic of convergence of IWO for multi-reservoir problem, for shortest period of 12 month with PS3, is illustrated in Fig. 8. Also, the effect of size of parameters on IWO convergence characteristics is shown in Fig. 9.

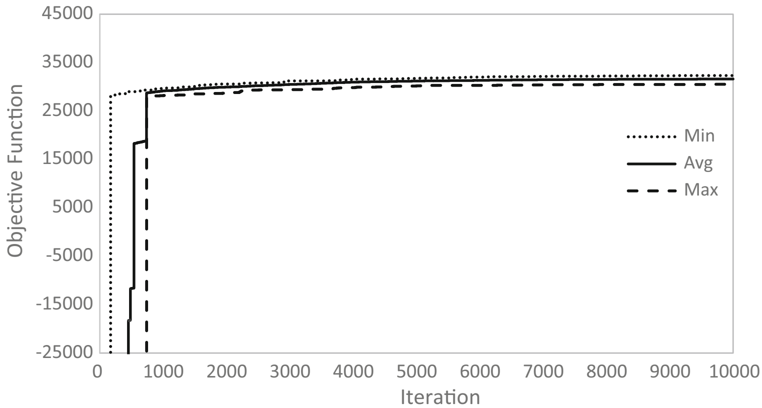


Fig. 8 Convergence curve for multi-reservoir operation over 12-month period

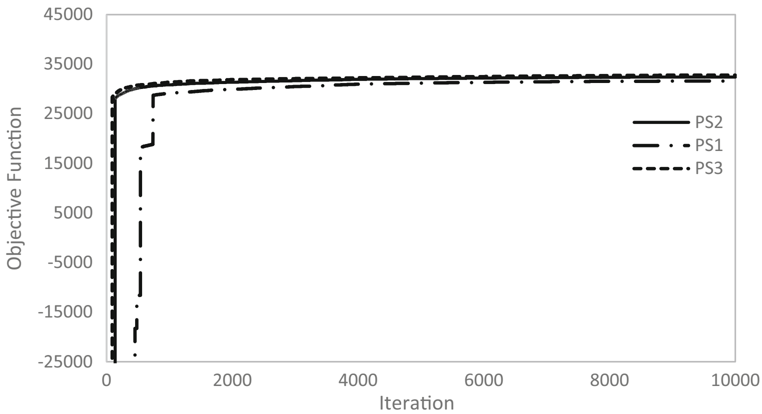


Fig. 9 Average of the objective function of 10 runs with different sets of parameters of IWO, for multi-reservoir problem

The results of IWO compared with those obtained by GA and PSO and presented by Afshar (2013b) are presented in Table 5. As shown in the table, IWO produced superior solutions than GA and PSO for shortest period of 12 months. However, it needs more computational time than GA and PSO to achieve this solution. In case of 60 months of operation, the solution obtained by IWO is about 6 % better than those obtained by PSO, but the IWO produced inferior solution than those achieved by GA. In longest period of operation, namely 240 months, IWO produced better solutions than GA and PSO in less computational time.

6 Conclusion

Application of IWO for optimal hydropower operation of reservoirs was presented in this study. IWO has been recently introduced as an optimization technique and has been successfully used to solve many optimization problems in various disciplines. In this study, IWO was applied to optimal hydropower operation of single reservoir and multi-reservoir systems for

Table 5 Comparison of IWO with GA and PSO for solving multi-reservoir hydropower operation problem

Month	Model	Objective Function			Average Computational Time(s)
		Minimum	Maximum	Average	
12	IWO	33,551	32,017	32,795	17.1
	GA	33,400	32,600	32,100	6.9
	PSO	33,400	31,600	32,400	9.6
60	IWO	157,614	153,318	155,201	81.3
	GA	164,000	161,000	162,000	126.7
	PSO	149,000	145,000	148,000	181.8
240	IWO	859,285	823,287	838,661	448.3
	GA	650,000	645,000	651,000	1487.0
	PSO	589,000	578,000	585,000	2208.0

short, medium and long term periods of operations. The results obtained by IWO was compared with existing results of two well-known evolutionary algorithms, namely GA and PSO. It was seen that IWO produced superior results than those obtained by PSO and GA for hydropower reservoir operation. Since it was shown that IWO is a potential powerful optimization technique for water resources problems, it is suggested to develop and apply the IWO to solve more practical problems in field of water resources management.

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