Deriving optimal operation of reservoir proposing improved artificial bee colony algorithm: standard and constrained versions

F. Soghrati and R. Moeini

ABSTRACT

In this paper, one of the newest meta-heuristic algorithms, named artificial bee colony (ABC) algorithm, is used to solve the single-reservoir operation optimization problem. The simple and hydropower reservoir operation optimization problems of Dez reservoir, in southern Iran, have been solved here over 60, 240, and 480 monthly operation time periods considering two different decision variables. In addition, to improve the performance of this algorithm, two improved artificial bee colony algorithms have been proposed and these problems have been solved using them. Furthermore, in order to improve the performance of proposed algorithms to solve large-scale problems, two constrained versions of these algorithms have been proposed, in which in these algorithms the problem constraints have been explicitly satisfied. Comparison of the results shows that using the proposed algorithm leads to better results with low computational costs in comparison with other available methods such as genetic algorithm (GA), standard and improved particle swarm optimization (IPSO) algorithm, honey-bees mating optimization (HBMO) algorithm, ant colony optimization algorithm (ACOA), and gravitational search algorithm (GSA). Therefore, the proposed algorithms are capable algorithms to solve large reservoir operation optimization problems.

Key words | constraint, Dez reservoir, improved artificial bee colony algorithm, large-scale optimization, optimal operation, single-reservoir system

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INTRODUCTION

Nowadays, due to increasing population and available water resources limitations, humans should attend to optimal use of various water resources. In general, surface and groundwater are the main water resources. In order to use these resources, different structures should be constructed. Water flows in rivers are the most important part of surface water resources and therefore dams can be constructed to store them (Winter *et al.* 1998).

Due to the above, in recent decades, finding the optimal operation of reservoirs has been of more interest for water resources researchers. However, finding an optimal solution for the reservoir operation optimization problem is not an easy task and, therefore, various optimization methods have been proposed for this problem. Generally, these methods are classified as linear programming (LP), nonlinear programming (NLP), dynamic programming (DP), meta-heuristic algorithms (or evolutionary algorithms), and hybrid methods. Each of these methods has its own advantages and disadvantages (Moeini & Afshar 2009).

Nowadays, meta-heuristics algorithms are significantly used to solve optimization problems in which they have been proposed based on the natural behavior of organisms and real phenomenon (Ketabchi & Ataie-Ashtiani 2015a). These algorithms have some important advantages, such as

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no need for continuity, derivability, convexity of objective function and constraints. In addition, intelligent foraging behavior of these algorithms prevents the model from trapping in optimal local points. Owing to these capabilities, meta-heuristic algorithms have been greatly used to solve reservoir optimization problems for 40 years. Hossain & El-Shafie (2013), Ahmad *et al.* (2014), and Ketabchi & Ataie-Ashtiani (2015b) reviewed the capability of different meta-heuristic algorithms which are used to solve this optimization problem. In addition, many effective, improved and modified forms of these algorithms have been also proposed by many researchers. For example, different evolutionary and meta-heuristic algorithms such as genetic algorithm (GA), evolution strategy, ant colony optimization algorithm (ACOA), honey-bee mating optimization (HBMO) algorithm, elitist-mutated particle swarm optimization (EMPSO), shuffled frog leaping (SFL) algorithm, interactive multi-class algorithm, arc based constrained ant colony optimization algorithm (ABCACOA), particle swarm optimization (PSO) algorithm, harmony search (HS) algorithm, cuckoo search genetic algorithm (CSGA), and gravitational search algorithm (GSA) have been proposed and used for solving this problem, in which the details are presented in Table 1.

Table 1 | Different methods' application to solve reservoir operation optimization problem

Methods	Authors (year)
GA	Esat & Hall (1994), Rani & Moreira (2010), Chang *et al.* (2010), Hınçal *et al.* (2011), Liu *et al.* (2011), Zhang *et al.* (2013)
Evolution strategy	Runarsson & Yao (2005)
ACOA	Jalali (2005), Kumar & Reddy (2006), Jalali *et al.* (2007), Afshar & Moeini (2008), Madadgar & Afshar (2009), Afshar (2012, 2013), Moeini & Afshar (2013)
HBMO	Afshar *et al.* (2007), Bozorg-Haddad *et al.* (2008)
EMPSO	Kumar & Reddy (2007)
CSGA	Yasar (2016)
SFL	Li *et al.* (2010)
Interactive multi-class	Wang *et al.* (2011)
ABCACOA	Moeini & Afshar (2011)
HS	Bashiri-Atrabi *et al.* (2015)
PSO	Zhang *et al.* (2011), Moeini & Babaei (2017)
GSA	Moeini *et al.* (2017)

Reviewing the research literature shows the capabilities of meta-heuristic algorithms for solving reservoir operation optimization problems. Therefore, proposing a new meta-heuristic algorithm or improving and modifying the original form of meta-heuristic algorithm is an attractive research field for engineers. One of the new proposed meta-heuristic algorithms is artificial bee colony (ABC) algorithm, which was first proposed by Karaboga & Basturk (2007) and used to solve different engineering optimization problems. It is worth noting that the ABC algorithm is based on the natural behavior of a honey-bee colony which cooperates for food foraging. Akay & Karaboga (2010) proposed a modified ABC algorithm for parameter optimization problems and compared the performance of standard and modified versions of the ABC algorithm with other available algorithms. The results showed that the standard ABC algorithm was more effective to solve basic functions but using the modified ABC algorithm led to a better solution for combined functions. Sadhan & Subir (2012) used the ABC algorithm to optimize a dynamic power flow model for a pump reservoir system including stationary generator, wind speed, and hydropower reservoir. The obtained result showed better performance of the ABC algorithm in comparison with the GA and PSO algorithms with higher convergence rate. Sayyafzadeh *et al.* (2013) studied the reservoir operation optimization problem using the ABC algorithm and compared the results with the GA. Hossain & EI-shafie (2014a) solved the reservoir operation optimization using PSO, ABC, and GA. The results showed that the ABC algorithm was more appropriate for supplying water demand and management of water scarcity. Finally, Hossain & EI-shafie (2014b) determined the optimal policy of reservoir using the ABC algorithm and showed that the obtained policy could supply 98% of demands in the entire period of time.

Current research aims to assess and improve the capabilities of the ABC algorithm to solve the reservoir operation optimization problem. Here, two improved artificial bee colony algorithms (IABC) are proposed in order to increase the capabilities of ABC algorithm, in which they are denoted by suffix *1* and *2*, IABC1 and IABC2, respectively. In addition, the characteristics of the proposed IABCs are used here to propose a constrained version of

IABC applying the concept already used for other meta-heuristic algorithms (Afshar & Moeini 2008; Afshar 2012; Moeini *et al.* 2017; Moeini & Babaei 2017). Here, two constrained versions of IABC are proposed which are named partially and fully IABC, PCIABC and FCIABC, algorithms. In the PCIABC algorithm, local operation policies are created such that the continuity equation and the water release and storage volume constraints are satisfied simultaneously. However, in the FCIABC algorithm, the storage volume bounds are modified prior to the main search. It should be noted that in both constrained versions of IABC, only feasible operation of the reservoir is constructed. In other words, in the constrained algorithm, the feasible search space is constructed by recognizing infeasible components and excluding them from the search space. This proposed mechanism is very useful to solve large-scale optimization problems, in which it leads to smaller search space size. By considering water releases or storage volumes at each operation time period as a decision variable of the problem, two formulations are proposed here for each proposed algorithm, in which they are denoted by subscript R and S, respectively. Here, the simple and hydropower operation problems of Dez reservoir in Iran over 60, 240, and 480 monthly operation time periods are solved using the proposed algorithms and the results are presented and compared with other available results. The superior performance of the proposed algorithms is presented and highlighted in the section 'Results and discussion'.

METHODOLOGY

In this paper, the improved version of the ABC algorithm named IABC has been proposed to solve the reservoir operation optimization problem which is based on the original form of ABC algorithm. Therefore, in this section, first the standard form of ABC algorithm and then the IABC algorithm are presented.

Artificial bee colony (ABC) algorithm

ABC algorithm can be considered as one of the newest meta-heuristic algorithms due to the fact that it was proposed based on the natural behavior of real bees. However, this algorithm can also be considered as one of the evolutionary algorithms due to the fact that it generates a random initial population of possible solutions and improves it iteratively through evolutionary-type processes. This algorithm was proposed first by Karaboga & Basturk (2007). The algorithm is based on the natural behavior of a group of bees to find food together and it was modeled as an artificial system. In this algorithm, three categories of employed, onlooker, and scout bees are defined. In the ABC algorithm, employed bees are defined as moving to different food sources and gathering information, including amount of nectar, direction, and distance to the hive, so play a role in the cycle of bees searching for food. When employed bees return to the hive, they share information with other bees. This mechanism leads onlooker bees to find food sources which are more likely to have nectar. When these bees gather information, spectator bees move to the food sources that are more likely to have existent nectar. Finally, the scout bees task is started, in which, regardless of other bees' information, the random search of food sources is done by these bees so that the bees do not miss a good food source (Karaboga & Basturk 2007).

In order to simulate the performance of bees in nature, in the ABC algorithm different parameters are defined. It is worth noting that in this algorithm, the numbers of defined parameters are less than other meta-heuristic algorithms. This fact is one of the main advantages of this algorithm. These parameters include the bees' numbers (BN), the food sources' numbers (SN), the number of repetitions (MCN), amount of variables that vary to produce new answer (Ndim), and the allowed number of failure of a source (Limit). This algorithm was fully described by Karaboga & Basturk (2007) and therefore it is not completely presented here. However, a brief description of this algorithm is presented as follows.

The three basic steps of finding the optimal solution process using the ABC algorithm are presented as follows:

1. Sending the employed bees to food sources and determining their nectar.
2. Choosing food resources by the onlooker bees. Then, sharing information with employed bees. Finally, determining the amount of nectar of food resources.
3. Sending a scout bee to possible food sources.

According to these steps, the process of finding the optimal solution using the ABC algorithm can be explained as follows. At first, half of the total number of bees is considered and some random answers are generated and finally the objective functions values are calculated. These values are nectar food source. Then, the main process begins to find the optimal solution. It should be noted that, initially, each bee chooses an initial response as the main food source. Therefore, in order to change it and look around for finding a better solution, another initial solution is randomly selected as auxiliary food source. One of the most important parameters of this algorithm is the number of changes in the initial solution to find a new solution at each stage. In this algorithm, it is randomly selected and, therefore, a specified number of variables has been chosen and taken into account in both the main and auxiliary solutions by using the following equation (Naveena *et al.* 2015):

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{1}$$

where, v_{ij} = the new food source, φ_{ij} = a random number between [−1, 1] and x_{ij} = the solution j from food source i. Among the ABC algorithm process, if the new objective function value indicates improved conditions, a new solution replaces the old ones and the main solution is removed. However, if the new objective function value does not show any improvement, the main solution remains. Therefore, the onlooker bees start their work in which they help each other to find the optimal solution. For this reason, each of them goes to a food source once, and the best solution is chosen by changing the chosen solution. The mechanism is similar to the mechanism that was mentioned before for employed bees. In this algorithm, onlooker bees go towards food sources with higher possibility. Here, the likelihood of choosing any food source is calculated using the following equation (Naveena *et al.* 2015):

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{2}$$

where, p_i = a numerical value chance food source i, fit_i = objective function value for the food source i and SN = the number of food sources. Accordingly, each onlooker bee considers a food source that is more likely than a random number and therefore some food sources can be checked several times. This process is contained until the stop criterion is reached.

Improved artificial bee colony (IABC) algorithm

In this paper, an IABC algorithm is proposed to improve the performance of the standard ABC algorithm. Here, two improved algorithms, named IABC1 and IABC2, have been proposed. In general, in the ABC algorithm the number of employed bees is equal to onlooker bees and therefore their numbers are equal to half of the total number of bees. Here, this ratio has been changed and therefore the first version of IABC algorithm, IABC1, is proposed. In other words, in IABC1 the number of spectator bees is equal to the different percentage of the total number of bees. However, in the second version of the IABC algorithm, IABC2, the new parameter named neighborhood radius parameters is defined for the standard ABC algorithm. Therefore, Equation (1) is modified as follows:

$$v_{ij} = x_{ij} + R \times \varphi_{ij}(x_{ij} - x_{ki}) \tag{3}$$

where, R = the neighborhood radius and other parameters were previously defined. In the proposed IABC2 algorithm, the following equation is proposed to determine the neighborhood radius:

$$R = G \times \exp\left(-A \times \left(\frac{\text{cycle}}{\text{MCN}}\right)\right) \tag{4}$$

where, cycle = iteration number, MCN = total number of iteration, A and G = the constant values.

It is worth nothing that the specific advantage of the proposed IABC algorithm in comparison with standard ABC is as follows. In the IABC algorithm, better interaction between the concept of exploration and exploitation is done using proposed approaches. It should be noted that exploration is the ability of the algorithm to extensively explore the space search of the problem. However, the exploitation is the ability of the algorithm to explore around the neighborhoods of local solutions. In other words, the previously obtained solutions are used to find the optimal solution. Although these concepts conflict with each other, effective interaction between these two concepts is one of the main challenges to provide new meta-heuristic algorithms. Here, by proposing two IABC algorithms this interaction is well established. The superior performance of the proposed IABC algorithms to solve optimization problems will be shown when they are used to solve benchmark test examples.

RESERVOIR OPERATION OPTIMIZATION PROBLEM

In this paper, the reservoir operation optimization problems for water supply and hydropower generation are solved using the proposed algorithms. The mathematical formulations of these problems are presented as follows. The mathematical formulation should be presented by defining decision variables, objective function and constraints.

Reservoir operation for water supply

The objective function of this problem is minimizing the sum of the shortage from specific demand at each operation time period. Therefore, the mathematical formulation can be presented as follows (Afshar & Moeini 2008):

$$\text{minimize } F = \sum_{t=1}^{NT}\left[\frac{D_t - r_t}{D_{\max}}\right]^2 \tag{5}$$

where, NT = the total operation time period, D_t = water demand at operation time period t, r_t = water release from reservoir at operation time period t, $D_{\max}$ = maximum water demand during all operation time periods.

The most important problem constraints are continuity constraint and upper and lower limitations for the water storage volume and release from the reservoir, which are defined as follows:

$$S_{t+1} = S_t + I_t - r_t - L_t \tag{6}$$

$$r_{\min} \le r_t \le r_{\max} \tag{7}$$

$$S_{\min} \le S_t \le S_{\max} \tag{8}$$

where, S_t = reservoir storage volume at the beginning of the operation time period t, I_t = inflow into the reservoir at operation time period t, S_{t+1} = reservoir storage volume at the beginning of the operation time period $t+1$ (end of the operation time period t), L_t = water losses at operation time period t, r_{min} = minimum water release from reservoir, r_{max} = maximum water release from reservoir, S_{min} = minimum water storage volume of reservoir, S_{max} = maximum water storage volume of reservoir.

Reservoir operation for hydropower generation

The objective function of this problem is minimizing the sum of the shortage of the hydropower generated from plant capacity at each operation time period, which is defined as follows (Afshar & Moeini 2008):

$$\text{minimize } F = \sum_{t=1}^{NT}\left[1 - \frac{P_t}{\text{Power}}\right] \tag{9}$$

where, P_t = hydropower generated at operation time period t and power = installation power plant capacity. It is worth noting that the P_t can be calculated as follows:

$$P_t = \min\left[\left(\frac{g \times \eta \times R_t}{PF}\right) \times \left(\frac{h_t}{1000}\right),\ \text{power}\right] \tag{10}$$

$$\text{in which, } h_t = \left[\frac{H_t + H_{t+1}}{2}\right] - \text{TWL} \tag{11}$$

$$H_t = f(S_t) \tag{12}$$

where, h_t = effective head of water at operation time period t, g = gravity acceleration, η = power plant efficiency, PF = plant factor coefficient, H_t = water storage level above sea level that is generally a function of reservoir storage volume (Equation (12)), R_t = water discharge passing through the turbine at operation time period t and TWL = tail water level above sea level.

The problem constraints are the continuity equation and upper and lower limitations for water storage and release which are presented as Equations (6)–(8).

CONSTRAINED IMPROVED ARTIFICIAL BEE COLONY (CIABC) ALGORITHM

Some problems such as reservoir operation optimization problem are naturally sequential and therefore the trial solution can be incrementally constructed using a component by component approach. This approach is very useful for solving a large-scale reservoir operation optimization problem in which some of the problem constraints can be explicitly satisfied and therefore the search space size of the problem can be extremely reduced. This approach leads to better solutions and improves the convergence characteristics of the algorithm. Therefore, two constrained versions of IABC algorithms, named PCIABC and FCIABC, are proposed here based on this approach.

Generally, water releases or storage volumes at each operation time period can be considered as decision variables of the reservoir operation optimization problem. In this paper, two formulations are proposed for each proposed algorithm, considering water releases or storage volumes at each operation time period as decision variables of the problem, in which they are denoted by subscript R and S, respectively. It should be noted that each solution j from food source i, x_{ij} presents with a vector of decision variables $x_{ij} = (x_{ij}^1, \ldots, x_{ij}^d, \ldots, x_{ij}^D)$ where d $(d = 1, L, D)$ is the number of decision variables (problem dimension). Here, the operation time periods define the dimensions of the problem solution ($D = NT$) in which the dimensions are treated in a sequence defined by the operation time periods. Furthermore, the storage volume at the beginning of the first operation time period is assumed to be pre-defined. A brief description of the proposed algorithms is presented as follows.

Partially constrained improved artificial bee colony (PCIABC) algorithm

Here, two partially constrained improved artificial bee colony (PCIABC) algorithms are proposed denoted by suffix *1* and *2* and therefore they are named PCIABC1 and PCIABC2.

In the first formulation of PCIABCs, named $\text{PCIABC1}_{\text{R}}$ and $\text{PCIABC2}_{\text{R}}$, each dimension of the solution presents the water release from the reservoir at each operation time period. Assuming known water storage volume value at the start of the operation time period, a new bound for each dimension of the solution, representing the water release form reservoir at each operation time period, is calculated using the continuity equation and water storage volume constraints. In other words, a continuity equation is used to calculate the water storage volume at the end of the time period t (S_{t+1}) and this value is replaced in water storage volume constraint. Therefore, the following equation is obtained:

$$\mathrm{s}_{t+1,min} \leq s_t + I_t - r_t \leq \mathrm{s}_{t+1,max} \tag{13}$$

This equation leads to the following equation for water release from the reservoir at each operation time period t:

$$r_t \leq s_t + I_t - s_{t+1,min} \;\&\; r_t \geq s_t + I_t - s_{t+1,max} \tag{14}$$

Combining this new bound (Equation (14)) with original water release constraint (Equation (7)) leads to the new constraint for water release as follows:

$$max\,(s_t + I_t - \mathrm{s}_{\mathrm{t+1,max}}, r_{min}) \leq r_t \leq min\,(s_t + I_t - s_{t+1,min}, r_{max}) \tag{15}$$

It should be noted that using Equation (15), the resulting solutions are feasible.

However, in the second formulation of PCIABCs, named $\text{PCIABC1}_{\text{S}}$ and $\text{PCIABC2}_{\text{S}}$, each dimension of the solution presents the water storage of the reservoir at the end of each operation time period. Assuming known water storage volume value at the start of the operation time period, new bound for each dimension of the solution, representing the water storage volume of reservoir at the end of each operation time period, is calculated using the continuity equation and water release constraints. In other words, the continuity equation is used to calculate the water release at the operation time period t (r_t) and this value is replaced in the water release constraint. Therefore, the following equation is obtained:

$$r_{min} \leq s_t + I_t - s_{t+1} \leq r_{max} \tag{16}$$

This equation leads to the following equation for water storage volume of the reservoir at the end of each operation time period t:

$$s_{t+1} \leq s_t + I_t - r_{min} \;\&\; s_{t+1} \geq s_t + I_t - r_{max} \tag{17}$$

Combining this new bound (Equation (17)) with the original water storage volume constraint (Equation (8)) leads to the new constraint for water release as follows:

$$max\ (s_t + I_t - \mathrm{r}_{\max}, s_{min}) \leq s_{t+1} \leq min\ (s_t + I_t - r_{min}, s_{max}) \tag{18}$$

It should be noted that using Equation (18), the resulting solutions are feasible.

Fully constrained improved artificial bee colony (FCIABC) algorithm

Sometimes, a condition might occur in the PCIABC algorithm that some of the solutions are infeasible. This condition generally depends on the magnitude of the inflow at any operation time period. In this condition, the new calculated bounds, Equation (14) or (17), are above or below the original bounds and therefore an empty allowable range is obtained (using Equations (15) and (18)). Here, this problem is resolved by proposing another algorithm, named fully constrained improved artificial bee colony (FCIABC) algorithm. Two FCIABC algorithms are proposed here denoted by suffix *1* and *2* and therefore they are named FCIABC1 and FCIABC2. In addition, two formulations are proposed for each FCIABC algorithm, named $\mathrm{FCIABC1_R}$ ($\mathrm{FCIABC2_R}$) and $\mathrm{FCIABC1_S}$ ($\mathrm{FCIABC2_S}$), considering water release or storage volume at each operation time period as decision variables of the problem, respectively.

In the FCIABC algorithm, at first, the storage volume bounds are modified before starting the PCIABC algorithm process. Here, the operation time periods are swept in reverse order to calculate a set of new bounds for storage volume constraints in order to find and remove the infeasible regions. In other words, by starting from the last operation time period, the continuity equation and the water release and storage volume constraints are used to calculate the water storage volume at the operation time period t as follows. This process is continued until all operation time periods are covered:

$$s_t \leq s_{max,t+1} - I_t + r_{max}\ \ \&\ \ s_t \geq s_{min,t+1} - I_t + r_{min} \tag{19}$$

This equation (Equation (19)) should be combined with the original box water storage volume at operation time period t leading to the following constraint:

$$\begin{aligned} &max\ (s_{t+1,min} - I_t + r_{min},\ s_{min}) \leq s_t \\ &\quad \leq min\ (S_{t+1,max} - I_t + r_{max}, s_{max}) \end{aligned} \tag{20}$$

These new calculated bounds are used by the PCIABC algorithm leading to an algorithm named FCIABC, in which no infeasible solutions will be created during the search process.

CASE STUDY

In this paper, the simple and hydropower reservoir operation optimization problems of Dez reservoir, in southern Iran, are solved for 60, 240, and 480 monthly operation time periods using the proposed algorithms. Therefore, the details and information about these problems are presented in this section. The active (live) storage of this reservoir is 2,510 million cubic meters (MCM) and the average annual inflow is 5,900 MCM in 40 years. In addition, the initial reservoir storage volume is equal to 1,430 MCM and the minimum and maximum allowable water release from the reservoir are equal to zero and 1,000 MCM, respectively. Here, the minimum and maximum allowable water storages of the reservoir are equal to 830 and 3,340 MCM. An assumption is considered here that water loss (l_t) is equal to zero. It should be noted that the hydro-electric plant of this reservoir consists of eight units, in which the capacity of each is equal to 80.8 mega watt (MW). Furthermore, the installation power plant capacity is equal to 650 MW. In addition, the plant factor coefficient and power plant efficiency are equal to 0.417 and 90%, respectively. For this reservoir, the tail water level (TWL) is 172 m above sea level. Here, the following equation is used to determine the water storage level (Afshar & Moeini 2008):

$$H_t = a + b \times S_t + c \times s_t^2 + d \times s_t^3 \tag{21}$$

where, *a, b, c*, and *d* are constant confidence levels with the values of $a = 249.83364$, $b = 0.0587205$, $c = -1.37 \times 10^{-5}$, and $d = 1.529 \times 10^{-9}$.

RESULTS AND DISCUSSION

In order to solve these optimization problems, at first, a set of preliminary runs should be done to find the proper values of the proposed algorithms' parameters. Proper values of these parameters are presented in Table 2. A maximum number of 1,000 iterations and 100 populations amounting to 100,000 function evaluations for each run are used here to solve these problems. Tables 3 and 4 are presented to show the maximum, minimum, and average cost values, the scaled standard deviation of the solutions, and the number of feasible runs obtained in 10 runs for the simple and hydropower operation of Dez reservoir, respectively, over 60, 240, and 480 monthly operation time periods using all the proposed algorithms. Comparison of the results shows that all qualities of the solution are increased when the improved version of ABC is used to solve these problems, in which the quality of the solution of the second improved version is better than the first one due to the fact that effective interaction between exploration and exploitation concepts occurs by using the proposed improved versions. In addition, both fully and partially constrained versions of the proposed algorithms have the ability to produce better results in comparison with the original standard form of the proposed algorithms; the results of the fully constrained version are significantly better due to the fact that using the proposed mechanism leads to smaller search space size for the problem, especially for longer 480 monthly operation time periods.

It is worth noting that the results of the first (second) formulation of the IABC1 algorithm are improved 12.5% (4.1%) and 7.03% (12.46%) in comparison with the first (second) formulation of ABC algorithm over 60 and 240 monthly operations time periods of simple reservoir operation, respectively. Furthermore, using the ABC algorithm leads to an infeasible solution for longer operation time periods (480 months) of simple reservoir operation problem; however, using the $IABC1_S$ algorithm for this problem leads to four feasible solutions in 10 runs. In addition, the results of the first (second) formulation of the IABC1 algorithm are improved 4.46% (14.28%) and 1.6% (4.03%) in comparison with the first (second) formulation of the ABC algorithm over 60 and 240 monthly operations time periods of hydropower reservoir operation, respectively. Furthermore, using the ABC algorithm leads to an infeasible solution for longer operation time periods (480 month) of hydropower reservoir operation problem. However, using $IABC1_R$ ($IABC1_S$) algorithms for this problem leads to six (five) feasible solutions in 10 runs. It should be noted that this improvement is particularly remarkable when the second improved version (IABC2) is used to solve these problems. Here, the results of the first (second) formulation of the IABC2 algorithm are improved 16.85% (3.92%) and 18.32% (15.52%) in comparison with the first (second) formulation of the ABC algorithm over 60 and 240 monthly operations time periods of simple reservoir operation, respectively. Furthermore, using the ABC algorithm leads to an infeasible solution for longer operation time periods (480 months) of simple reservoir operation problem. However, using the $IABC1_S$ algorithm for this problem leads to five feasible solutions in 10 runs. In addition, the results of the first (second) formulation of the IABC2 algorithm are improved 5.39% (14.33%) and 2.31% (5.39%) in comparison with the first (second) formulation of the ABC algorithm over 60 and 240 monthly operation time periods of hydropower reservoir operation, respectively. Using the ABC algorithm leads to an infeasible solution for longer operation time periods (480 months) of hydropower

Table 2 | Proper values of algorithm parameters

Operation time periods (month)	Formulation	Limit	Ndim	Percentage of employed bees	A	G	R
60	*I*	120	6	0.8	0.001	1	1
	II	6,000	1	0.67	0.001	1	1
240	*I*	6,000	4	0.8	0.00001	1	1
	II	6,000	4	0.8	0.00001	1	1
480	*I*	6,000	4	0.67	0.00001	1	1
	II	110	2	0.8	0.00001	1	1

Table 3 | Results of proposed algorithms to solve simple reservoir operation problem

Algorithm (operation time period)	Minimum	Maximum	Average	Standard deviation	Number of feasible solutions
ABC_R (60)	1.049	1.1864	1.11886	0.040811	10
ABC_S (60)	0.86262	1.0735	0.950023	0.085447	10
ABC_R (240)	29.4198	1,247.776	167.5886	2.270481	8
ABC_S (240)	11.5443	16.9025	14.3858	0.132041	6
ABC_R (480)	3,685.781	6,47.194	5,199.72	0.200693	–
ABC_S (480)	59.7352	669.2162	293.2189	0.827879	–
$IABC1_R$ (60)	0.91804	1.1588	1.027592	0.086565	10
$IABC1_S$ (60)	0.82758	0.98054	0.89556	0.046508	10
$IABC1_R$ (240)	27.3537	870.3015	116.5645	2.272028	9
$IABC1_S$ (240)	10.1057	13.8914	11.91257	0.106541	7
$IABC1_R$ (480)	1,237.615	4,549.996	2,993.546	0.361448	–
$IABC1_S$ (480)	68.3634	251.9125	636.2861	0.712515	4
$IABC2_R$ (60)	0.8723	1.1103	1.040184	0.073236	10
$IABC2_S$ (60)	0.82888	0.97369	0.897984	0.053131	10
$IABC2_R$ (240)	24.029	50.6253	34.3812	0.26071	8
$IABC2_S$ (240)	9.7527	11.8684	10.68809	0.071266	8
$IABC2_R$ (480)	1,237.592	4,549.945	2,971.977	0.371165	–
$IABC2_S$ (480)	50.689	297.6383	102.6883	0.755918	5
$PCABC_R$ (60)	0.87464	1.1418	1.005303	0.098996	10
$PCABC_S$ (60)	0.83042	0.91752	0.86251	0.036191	10
$PCABC_R$ (240)	10.653	13.0897	12.06441	0.074897	10
$PCABC_S$ (240)	7.7916	9.2908	8.43671	0.053071	10
$PCABC_R$ (480)	36.1205	52.1871	41.9684	0.136512	10
$PCABC_S$ (480)	18.6388	21.2698	19.70712	0.045879	10
$PCIABC1_R$ (60)	0.87063	1.071	0.953022	0.05323	10
$PCIABC1_S$ (60)	0.80783	0.90785	0.866042	0.039072	10
$PCIABC1_R$ (240)	10.1023	11.7898	11.19185	0.051275	10
$PCIABC1_S$ (240)	7.4704	9.1638	8.3209	0.06928	10
$PCIABC1_R$ (480)	35.097	41.1112	36.54984	0.047703	10
$PCIABC1_S$ (480)	17.9201	19.5474	18.89014	0.03003	10
$PCIABC2_R$ (60)	0.83087	0.90349	0.861378	0.040868	10
$PCIABC2_S$ (60)	0.80726	0.97369	0.897984	0.042373	10
$PCIABC2_R$ (240)	9.9851	12.1366	11.08865	0.062614	10
$PCIABC2_S$ (240)	7.1631	9.091	8.1313	0.090821	10
$PCIABC2_R$ (480)	34.9191	39.67999	37.65551	0.051027	10
$PCIABC2_S$ (480)	17.9201	19.9127	18.8688	0.036662	10
$FCABC_R$ (60)	0.74027	1.049	0.880873	0.105388	10
$FCABC_S$ (60)	0.79309	1.0683	0.949524	0.101065	10
$FCABC_R$ (240)	10.0326	12.8257	12.7806	0.078072	10
$FCABC_S$ (240)	7.4924	8.4241	8.10631	0.035398	10

(continued)

Table 3 | continued

Algorithm (operation time period)	Minimum	Maximum	Average	Standard deviation	Number of feasible solutions
$FCABC_R$ (480)	32.994	39.0395	36.56369	0.050851	10
$FCABC_S$ (480)	18.1941	19.8948	19.02434	0.026817	10
$FCIABC1_R$ (60)	0.73838	1.017	0.928392	0.102393	10
$FCIABC1_S$ (60)	0.76829	0.86858	0.817643	0.03925	10
$FCIABC1_R$ (240)	9.9898	12.769	11.48224	.084602	10
$FCIABC1_S$ (240)	7.2471	8.2881	7.86143	0.035911	10
$FCIABC1_R$ (480)	31.3308	38.2045	35.74124	0.060099	10
$FCIABC1_S$ (480)	17.9179	20.28247	19.28269	0.041335	10
$FCIABC2_R$ (60)	0.72759	1.0408	0.8666424	0.115566	10
$FCIABC2_S$ (60)	0.76349	0.88014	0.822284	0.048232	10
$FCIABC2_R$ (240)	9.8091	12.0552	11.16271	0.070444	10
$FCIABC2_S$ (240)	7.1107	8.3556	7.77864	0.061344	10
$FCIABC2_R$ (480)	30.1656	37.0888	33.80038	0.083557	10
$FCIABC2_S$ (480)	16.9104	19.7904	18.91875	0.043669	10

reservoir operation problem; however, using $IABC1_R$ ($IABC1_S$) algorithms for this problem leads to five (five) feasible solutions in 10 runs.

Comparison of the results of Tables 3 and 4 shows the remarkable performance of the constrained version of the proposed algorithms and especially the fully constrained version in comparison with the original standard form of these algorithms. In other words, the results of the first (second) formulation of the PCIABC2 algorithm are improved 4.75% (2.61%), 58.46% (26.55%), and (64.65%) in comparison with the first (second) formulation of the IABC2 algorithm over 60, 240, and 480 monthly operation time periods of simple reservoir operation, respectively. In addition, the results of the first (second) formulation of the FCIABC2 algorithm are improved 16.59% (7.89%), 59.18% (27.09%), and (66.64%) in comparison with the first (second) formulation of the IABC2 algorithm over 60, 240, and 480 monthly operation time periods of simple reservoir operation, respectively. Furthermore, by using both formulations of the constrained versions (PCIABC2 and FCIABC2) to solve simple reservoir operation optimization problem, all results are always feasible. However, by using $IABC2_R$ ($IABC2_S$) to solve this problem over 60, 240, and 480 monthly operation time periods, the number of feasible solutions are 10 (10), eight (eight), and zero (five), respectively. In addition, the results of the first (second) formulation of the PCIABC2 algorithm are improved 2.32% (3.82%), 2.98% (31.35%), and 16.35% (12.65%) in comparison with the first (second) formulation of the IABC2 algorithm over 60, 240, and 480 monthly operation time periods of hydropower reservoir operation, respectively. In addition, the results of the first (second) formulation of the FCIABC2 algorithm are improved 4.94% (5.13%), 9.15% (34.79%), and 33% (28.42%) in comparison with the first (second) formulation of the IABC2 algorithm over 60, 240, and 480 monthly operation time periods of hydropower reservoir operation, respectively. Furthermore, by using both formulations of the constrained versions (PCIABC2 and FCIABC2) to solve hydropower reservoir operation optimization problem, all results are always feasible; however, by using IABC2R (IABC2S) to solve this problem over 60, 240, and 480 monthly operation time periods, the number of feasible solutions are 10 (10), nine (eight), and five (five), respectively.

The convergence curves of minimum solution cost values for the simple and hydropower operation problems over 240 operation time periods are shown in Figures 1 and 2, respectively, using the original and two improved versions of ABC (IABC1 and IABC2) algorithms. It is seen from these figures that the best solution cost values obtained with improved ABC algorithms stays way below that of the original standard ABC algorithm in which the improvement of

Table 4 | Results of proposed algorithms to solve hydropower reservoir operation problem

Algorithm (operation time period)	Minimum	Maximum	Average	Standard deviation	Number of feasible solutions
ABC_R (60)	7.9845	10.3801	9.69217	0.078141	10
ABC_S (60)	9.4005	10.3313	9.86679	0.035238	10
ABC_R (240)	36.1193	54.5524	41.57314	0.152168	8
ABC_S (240)	42.5412	63.3729	49.9541	0.164008	8
ABC_R (480)	141.518	1,730.324	607.2727	0.825621	–
ABC_S (480)	97.1981	103.192	99.85743	0.021523	–
$IABC1_R$ (60)	7.628	10.2991	9.6871	0.100425	10
$IABC1_S$ (60)	8.0585	10.0486	9.43491	0.076251	10
$IABC1_R$ (240)	35.5495	42.3033	37.89781	0.053643	8
$IABC1_S$ (240)	40.8285	62.3627	47.44364	0.162969	9
$IABC1_R$ (480)	124.1598	197.5901	377.9581	0.34356	6
$IABC1_S$ (480)	93.9587	102.6383	98.60451	0.022746	5
$IABC2_R$ (60)	7.5543	10.5822	8.78804	0.110237	10
$IABC2_S$ (60)	8.0531	9.94501	8.87048	0.058631	10
$IABC2_R$ (240)	35.2872	41.3792	37.81296	0.053078	9
$IABC2_S$ (240)	40.2496	60.7114	46.26197	0.147072	8
$IABC2_R$ (480)	123.9756	834.6815	298.3928	0.73599	5
$IABC2_S$ (480)	93.5975	101.8695	98.35106	0.043561	5
$PCABC_R$ (60)	7.60801	8.768	8.20586	0.048159	10
$PCABC_S$ (60)	8.0273	9.98661	8.4726	0.066694	10
$PCABC_R$ (240)	35.13	41.0809	39.4709	0.046272	10
$PCABC_S$ (240)	28.4836	30.9068	29.6338	0.027533	10
$PCABC_R$ (480)	104.5659	110.7172	107.2959	0.017487	10
$PCABC_S$ (480)	84.7147	102.2468	95.21455	0.063369	10
$PCIABC1_R$ (60)	7.4498	8.1106	7.78571	0.027833	10
$PCIABC1_S$ (60)	7.9335	9.1527	8.559967	0.04161	10
$PCIABC1_R$ (240)	34.7391	40.5617	38.36536	0.049174	10
$PCIABC1_S$ (240)	27.7312	29.1691	28.79674	0.014851	10
$PCIABC1_R$ (480)	104.0206	109.1881	106.7662	0.015627	10
$PCIABC1_S$ (480)	83.7037	101.827	93.30147	0.084055	10
$PCIABC2_R$ (60)	7.3789	7.94	7.66611	0.027504	10
$PCIABC2_S$ (60)	7.7457	9.1375	8.636944	0.030578	10
$PCIABC2_R$ (240)	34.2363	38.76664	37.0185	0.039611	10
$PCIABC2_S$ (240)	27.631	29.0833	28.75991	0.01518	10
$PCIABC2_R$ (480)	103.7	108.2621	106.2968	0.014971	10
$PCIABC2_S$ (480)	81.7538	100.3918	90.86011	0.087466	10
$FCABC_R$ (60)	7.3695	8.92	8.69172	0.051976	10
$FCABC_S$ (60)	7.7305	9.1001	8.27981	0.049975	10
$FCABC_R$ (240)	33.9958	37.9021	35.87202	0.038547	10
$FCABC_S$ (240)	26.993	29.0105	28.15381	0.0230534	10

(*continued*)

Table 4 | continued

Algorithm (operation time period)	Minimum	Maximum	Average	Standard deviation	Number of feasible solutions
$FCABC_R$ (480)	84.6598	89.8492	87.12874	0.021458	10
$FCABC_S$ (480)	67.4359	70.6739	68.78317	0.012923	10
$FCIABC1_R$ (60)	7.2921	8.2284	7.75551	0.036499	10
$FCIABC1_S$ (60)	7.6949	9.0692	8.22376	0.052063	10
$FCIABC1_R$ (240)	33.6455	36.5682	34.72254	0.037113	10
$FCIABC1_S$ (240)	26.3232	28.9238	27.71237	0.03437	10
$FCIABC1_R$ (480)	83.744	89.8085	87.71257	0.023147	10
$FCIABC1_S$ (480)	67.0775	70.5848	68.65065	0.013286	10
$FCIABC2_R$ (60)	7.1814	8.2503	7.555167	0.049637	10
$FCIABC2_S$ (60)	7.6401	9.0316	8.14697	0.051156	10
$FCIABC2_R$ (240)	32.0582	36.5682	33.98562	0.037525	10
$FCIABC2_S$ (240)	26.245	28.877	27.86639	0.030269	10
$FCIABC2_R$ (480)	83.0658	89.3052	86.23375	0.020504	10
$FCIABC2_S$ (480)	67	70.303	68.75653	0.0122544	10

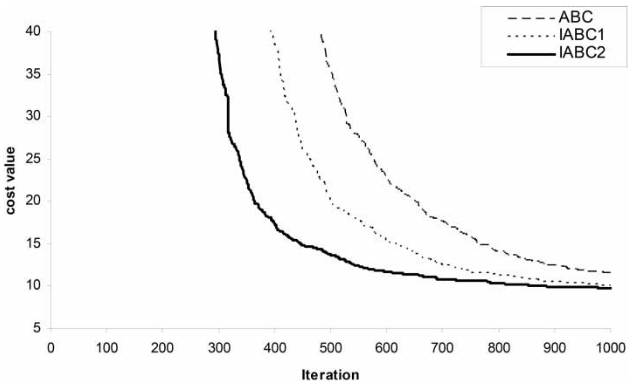

Figure 1 | Variation of minimum solution cost values of simple reservoir operation over a 240 monthly operation time period using the second formulation of ABC, IABC1, and IABC2.

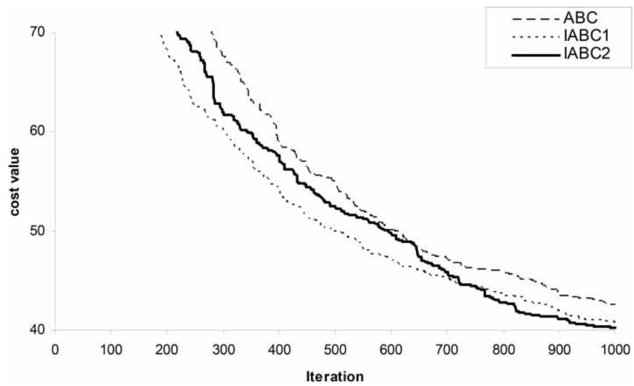

Figure 2 | Variation of minimum solution cost values of hydropower reservoir operation over a 240 monthly operation time period using the second formulation of ABC, IABC1, and IABC2.

the second ones (IABC2) are better due to effective interaction between exploration and exploitation concepts.

Figures 3 and 4 show the convergence curves of minimum solution cost values for the simple and hydropower operation problems over 240 operation time periods, respectively, using the second formulation of FCIABC2, PCIABC2, and IABC2. These figures indicate that the solution cost of the FCIABC2 algorithm always stays way below that of PCIABC2 and IABC2 algorithms due to a unique feature of the proposed mechanism in which it leads feasible and smaller search space for the problem to be created.

It is worth noting that the simple and hydropower operation problems of Dez reservoir were solved using different methods. Table 5 is presented to compare the best obtained results using FCIABC2 with other available results. It should be noted that 200,000 and 1,000,000 function evaluations (for ACOA and IACOA of Jalali (2005), 6,000,000 function evaluations (for GA and HBMO of Bozorg-Haddad *et al.* (2006)), 400,000 function evaluations (for FCACOA of Afshar & Moeini (2008)) and 100,000 function evaluations (for GA and FCPSO of Afshar (2012), FCGSA of Moeini *et al.* (2017), and FCIPSO of Moeini & Babaei (2017)) were

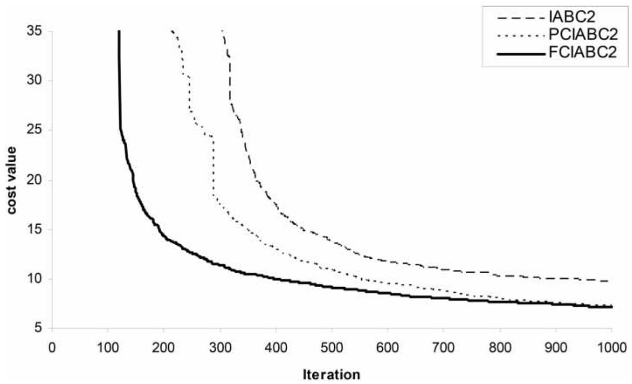

Figure 3 | Variation of minimum solution cost values of simple reservoir operation over a 240 monthly operation time period using the second formulation of IABC2, PCIABC2, and FCIABC2.

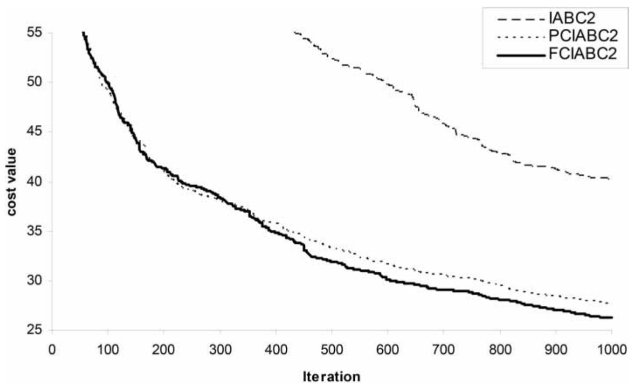

Figure 4 | Variation of minimum solution cost values of hydropower reservoir operation over a 240 monthly operation time period using the second formulation of IABC2, PCIABC2, and FCIABC2.

used to solve these optimization problems. Here, the best solutions of the proposed algorithms, such as FCIABC2, are obtained with 100,000 function evaluations. Comparison of the results of Table 5 shows the superiority of the proposed FCIABC2 algorithm to the other available results in nearly all operation time periods of simple and hydropower operation problems of Dez reservoir except for 240 and 480 month time periods of simple reservoir operation using FCGSA.

Finally, it should be noted that the performance of the proposed algorithm to solve models of water resource systems can be evaluated by performance criteria calculation. The most common criteria are reliability (how likely a system is to fail), resiliency (how quickly it recovers from failure), and vulnerability (how severe are the consequences of failure) proposed by Hashimoto *et al.* (1982). Therefore, a reservoir should be managed such as to have maximum reliability and resiliency and minimum vulnerability during an operation time period. In addition, all the components in the system should also be in balance in order to achieve sustainability. Therefore, Loucks (1997) defined a new criterion named the sustainability index (SI). Tables 6 and 7 are presented here to show the values of these criteria for the simple and hydropower operation of Dez reservoir, respectively, over 60, 240, and 480 monthly operation time periods using all the proposed algorithms. Comparison of the results shows that all criteria values are improved

Table 5 | Obtained solution cost values using different methods for simple and hydropower Dez reservoir operation over all operation time periods

	Methods									
Operation time periods	**ACOA (Jalali 2005)**	**IACOA (Jalali 2005)**	**HBMO (Bozorg-Haddad *et al.* 2006)**	**GA (Bozorg-Haddad *et al.* 2006)**	**FCACOA (Afshar & Moeini 2008)**	**GA (Afshar 2012)**	**FCPSO (Afshar 2012)**	**FCIPSO (Moeini & Babaei 2017)**	**FCGSA (Moeini *et al.* 2017)**	**FCIABC2 (present work)**
Simple reservoir operation problem										
60	0.926	0.804	0.81	1.1	0.782	0.807	0.744	0.7356	0.731	0.72759
240	–	–	–	–	6.798	38	10.7	5.9101	4.892	7.1107
480	In[a]	36.46	–	–	18.706	In	33.9	18.542	11.801	16.9104
Hydropower reservoir operation problem										
60	In	7.504	–	–	7.889	8.29	7.72	7.571	7.386	7.1814
240	–	–	–	–	25.785	53.1	33.7	25.303	26.730	26.245
480	In	In	–	–	66.809	In	85.7	71.104	67.957	67

[a]Infeasible solution.

Table 6 | Performance criteria values obtained with proposed algorithms for simple reservoir operation problem

Algorithm (operation time period)	Reliability	Vulnerability	Resiliency	Sustainability index
ABC_R (60)	58.33%	25.67%	44%	19.07694%
ABC_S (60)	63.33%	23.25%	45%	21.8726%
ABC_R (240)	41.67%	36.33%	41%	10.87783%
ABC_S (240)	43.75%	34.83%	42%	11.97499%
ABC_R (480)	–	–	–	–
ABC_S (480)	–	–	–	–
$IABC1_R$ (60)	63.33%	24.33%	50%	23.96091%
$IABC1_S$ (60)	66.67%	22.67%	50%	25.77796%
$IABC1_R$ (240)	45.67%	35.71%	47.70%	14.00531%
$IABC1_S$ (240)	47.50%	34.33%	49%	15.28469%
$IABC1_R$ (480)	41.67%	53.33%	46.40%	9.023588%
$IABC1_S$ (480)	42.71%	51.04%	48%	10.03719%
$IABC2_R$ (60)	68.33%	23.83%	53%	27.58489%
$IABC2_S$ (60)	71.67%	21.67%	53%	29.75373%
$IABC2_R$ (240)	47.50%	35.04%	49%	15.11944%
$IABC2_S$ (240)	50%	33.83%	51.60%	17.07186%
$IABC2_R$ (480)	43.75%	52.83%	48.84%	10.07905%
$IABC2_S$ (480)	45.83%	50.50%	50%	11.34293%
$PCABC_R$ (60)	75%	22.67%	60%	34.7985%
$PCABC_S$ (60)	80%	20.83%	58.30%	36.92489%
$PCABC_R$ (240)	49.58%	34.33%	52.80%	17.19125%
$PCABC_S$ (240)	53.33%	33.04%	53.60%	19.14044%
$PCABC_R$ (480)	45.83%	51.33%	50.03%	11.15942%
$PCABC_S$ (480)	47.92%	49.83%	52%	12.50156%
$PCIABC1_R$ (60)	76.67%	21.33%	64%	38.60242%
$PCIABC1_S$ (60)	81.67%	20%	63%	41.16168%
$PCIABC1_R$ (240)	52.08%	33.92%	53%	18.23967%
$PCIABC1_S$ (240)	56.67%	32.67%	54.50%	20.79497%
$PCIABC1_R$ (480)	47.92%	51.04%	51.20%	12.01236%
$PCIABC1_S$ (480)	50%	49.33%	53.30%	13.50356%
$PCIABC2_R$ (60)	80%	20%	66%	42.24%
$PCIABC2_S$ (60)	83.33%	19.67%	70%	46.85729%
$PCIABC2_R$ (240)	54.58%	33.67%	54%	19.54957%
$PCIABC2_S$ (240)	56.97%	33.33%	55.70%	21.15592%
$PCIABC2_R$ (480)	48.95%	50.08%	53%	12.951%
$PCIABC2_S$ (480)	51.67%	48.50%	53.80%	14.31621%
$FCABC_R$ (60)	80%	20%	66.60%	42.624%
$FCABC_S$ (60)	83%	18.83%	70%	47.15977%
$FCABC_R$ (240)	52.93%	32.04%	56.60%	20.35895%
$FCABC_S$ (240)	60.42%	31.33%	57.80%	23.98146%
$FCABC_R$ (480)	52.08%	50.13%	54.30%	14.10296%
$FCABC_S$ (480)	54.17%	48.33%	54.50%	15.25435%
$FCIABC1_R$ (60)	83.33%	19.33%	70%	47.05562%
$FCIABC1_S$ (60)	86.67%	18.33%	75%	53.08754%
$FCIABC1_R$ (240)	58.75%	31.33%	60.60%	24.44824%
$FCIABC1_S$ (240)	68.33%	29.83%	59.20%	28.38472%
$FCIABC1_R$ (480)	54.17%	49.04%	58.60%	16.17655%
$FCIABC1_S$ (480)	58.33%	46.17%	59%	18.52543%
$FCIABC2_R$ (60)	88.33%	18.67%	71.40%	51.2929%
$FCIABC2_S$ (60)	90%	18.04%	83.30%	61.44541%
$FCIABC2_R$ (240)	62.50%	30.75%	62.30%	26.96422%
$FCIABC2_S$ (240)	71.25%	29.17%	60.80%	30.68356%
$FCIABC2_R$ (480)	57.30%	48.13%	56%	16.64259%
$FCIABC2_S$ (480)	61.04%	45.83%	60.40%	19.97148%

when the improved version of ABC is used to solve these problems and in which the values of the second improved version are better that first ones. In addition, using both fully and partially constrained versions of the proposed algorithms leads to better values in comparison with the original standard form of the proposed algorithms and the values of the fully constrained versions are significantly better.

CONCLUDING REMARKS

The artificial bee colony (ABC) algorithm was used here for solving the operation optimization problem of single-reservoir system which is based on the natural behavior of a group of bees to find food together. In addition, in this paper, two IABC algorithms were proposed in order to improve the performance of this algorithm. Finally, in order to improve the performance of the proposed algorithms to solve large-scale problems, here, two constrained versions of these algorithms were also proposed, in which in these algorithms the problem constraints were satisfied

Table 7 | Performance criteria values obtained with proposed algorithms for hydropower reservoir operation problem

Algorithm (operation time period)	Reliability	Vulnerability	Resiliency	Sustainability index
ABC_R (60)	60.00%	23.33%	46%	21.16092%
ABC_S (60)	66.67%	21.16%	47%	24.70444%
ABC_R (240)	50.00%	34.00%	42%	13.86%
ABC_S (240)	52.33%	32.83%	43%	15.23052%
ABC_R (480)	–	–	–	–
ABC_S (480)	–	–	–	–
$IABC1_R$ (60)	65.00%	21.83%	51.00%	25.91336%
$IABC1_S$ (60)	68.00%	20.00%	52.67%	28.65248%
$IABC1_R$ (240)	51.67%	32.67%	48.00%	16.69892%
$IABC1_S$ (240)	54.33%	31.16%	50.00%	18.70039%
$IABC1_R$ (480)	48.66%	37.16%	47.66%	14.57345%
$IABC1_S$ (480)	50.00%	35.83%	48.33%	15.50658%
$IABC2_R$ (60)	67.66%	20.00%	53.33%	28.86646%
$IABC2_S$ (60)	70.00%	19.67%	53.33%	29.98799%
$IABC2_R$ (240)	53.66%	31.33%	48.66%	17.93039%
$IABC2_S$ (240)	55%	30.00%	51.66%	19.8891%
$IABC2_R$ (480)	50.00%	36.67%	48.00%	15.1992%
$IABC2_S$ (480)	51.66%	35.00%	50.00%	16.7895%
$PCABC_R$ (60)	70%	19.16%	55.00%	31.1234%
$PCABC_S$ (60)	75%	18.83%	57.66%	35.10197%
$PCABC_R$ (240)	55.00%	30.00%	50.00%	19.25%
$PCABC_S$ (240)	58.33%	28.67%	52.16%	21.7021%
$PCABC_R$ (480)	53.33%	35.00%	50.00%	17.33225%
$PCABC_S$ (480)	55.00%	33.33%	51.33%	18.82194%
$PCIABC1_R$ (60)	75.00%	18.33%	58.33%	35.72858%
$PCIABC1_S$ (60)	78.33%	18%	60.00%	38.52426%
$PCIABC1_R$ (240)	57.67%	29.16%	52.33%	21.3786%
$PCIABC1_S$ (240)	60.00%	27.16%	54.16%	23.67009%
$PCIABC1_R$ (480)	55.00%	34.16%	52.67%	19.07286%
$PCIABC1_S$ (480)	57%	32.63%	54.16%	20.91834%
$PCIABC2_R$ (60)	78%	18%	60.00%	38.29236%
$PCIABC2_S$ (60)	80.00%	17.67%	65.00%	42.8116%
$PCIABC2_R$ (240)	58.33%	28.00%	53.67%	22.54011%
$PCIABC2_S$ (240)	62.66%	26.67%	55.00%	25.27172%
$PCIABC2_R$ (480)	56.67%	33.67%	54.33%	20.42222%
$PCIABC2_S$ (480)	60.00%	32.00%	58.16%	23.72928%
$FCABC_R$ (60)	81%	17%	63.16%	42.80498%
$FCABC_S$ (60)	83.670%	16.16%	67.66%	47.46276%
$FCABC_R$ (240)	62.33%	26.16%	58.00%	26.69419%
$FCABC_S$ (240)	65.00%	25.00%	60.00%	29.25%

(*continued*)

Table 7 | continued

Algorithm (operation time period)	Reliability	Vulnerability	Resiliency	Sustainability index
$FCABC_R$ (480)	60.00%	31.16%	58.33%	24.09262%
$FCABC_S$ (480)	62.00%	30.00%	60.00%	26.04%
$FCIABC1_R$ (60)	82.25%	16.33%	65.00%	44.73207%
$FCIABC1_S$ (60)	85.00%	15.83%	70.00%	50.08115%
$FCIABC1_R$ (240)	64.66%	25.67%	60.00%	28.83707%
$FCIABC1_S$ (240)	67.00%	24.67%	63.16%	31.87755%
$FCIABC1_R$ (480)	61.16%	30.00%	60.00%	25.6872%
$FCIABC1_S$ (480)	65.00%	28.83%	62.16%	28.75553%
$FCIABC2_R$ (60)	85.33%	15.16%	67.16%	48.61979%
$FCIABC2_S$ (60)	88.67%	15.00%	72.33%	54.51476%
$FCIABC2_R$ (240)	67.67%	25.00%	63.33%	32.14156%
$FCIABC2_S$ (240)	70.00%	24.33%	66.16%	35.04429%
$FCIABC2_R$ (480)	63.33%	29.16%	62.67%	28.11562%
$FCIABC2_S$ (480)	66.67%	27.43%	65.00%	31.44857%

explicitly. Here, two formulations were proposed for each proposed algorithm considering water release or storage volumes as decision variables of the problem. The simple and hydropower operation optimization problems of Dez reservoir, in southern Iran, were solved over 60, 240, and 480 monthly operation time periods and the results were presented and compared. Comparison of the results showed that using the proposed improved versions of the ABC algorithm led to better results with low computational costs in comparison with the standard form of the ABC algorithm, especially for longer operation period. In other words, using the ABC algorithm led to an infeasible solution for 480 monthly operation period of simple and hydropower reservoir operation problems; however, using IABC algorithms led to some feasible solutions for both problems. In addition, by using the constrained versions, this improvement was remarkable and therefore the proposed constrained improved ABC algorithm was capable of solving large reservoir operation problems. In other words, the results of the second formulation of the FCIABC2 algorithm were improved 2.61% (5.13%), 26.55% (34.79%), and 64.65% (28.42%) in comparison with the second formulation of IABC2 algorithm over 60, 240, and 480 monthly operation time periods of simple (hydropower) reservoir operation, respectively.

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