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ORIGINAL ARTICLE

A hybrid bat–swarm algorithm for optimizing dam and reservoir operation

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Abstract

One of the major challenges and difficulties to generate optimal operation rule for dam and reservoir operation are how efficient the optimization algorithm to search for the global optimal solution and the time-consume for convergence. Recently, evolutionary algorithms (EA) are used to develop optimal operation rules for dam and reservoir water systems. However, within the EA, there is a need to assume internal parameters at the initial stage of the model development, such assumption might increase the ambiguity of the model outputs. This study proposes a new hybrid optimization algorithm based on a bat algorithm (BA) and particle swarm optimization algorithm (PSOA) called the hybrid bat–swarm algorithm (HB-SA). The main idea behind this hybridization is to improve the BA by using the PSOA in parallel to replace the suboptimal solution generated by the BA. The solutions effectively speed up the convergence procedure and avoid the trapping in local optima caused by using the BA. The proposed HB-SA is validated by minimizing irrigation deficits using a multireservoir system consisting of the Golestan and Voshmgir dams in Iran. In addition, different optimization algorithms from previous studies are investigated to compare the performance of the proposed algorithm with existing algorithms for the same case study. The results showed that the proposed HB-SA algorithm can achieve minimum irrigation deficits during the examined period and outperforms the other optimization algorithms. In addition, the computational time for the convergence procedure is reduced using the HB-SA. The proposed HB-SA is successfully examined and can be generalized for several dams and reservoir systems around the world.

Keywords Particle swarm optimization · Multireservoir system · Bat algorithm · Optimization model

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1 Introduction

Water resource management is a science that attempts to perform comprehensive planning to prevent water scarcity in current and future periods [1, 2]. The water stored upstream of dams is considered to be an important manageable water resource that can be controlled to supply the water demands for different uses, such as domestic, agricultural, and industrial purposes, and the environmental requirements for effective operations [3, 4]. The construction of large dams provides decision makers with flexible tools for meeting downstream demands using only the water stored upstream of the dam and by optimizing the operations for the available water resources [5, 6]. In recent years, optimal operational planning and management have been achieved by utilizing mathematical models or optimization algorithms. Each problem in the optimal operation of dams and reservoirs can be defined within the mathematical procedure of the optimization algorithm and by identifying problems with single or multiple objective functions considering the system constraints [7, 8]. The water supply, hydropower production or responsiveness of the environmental demands can be considered as different aims or objective functions in a problem of a particular dam and reservoir system. In addition, dam and reservoir systems are considered to be highly nonlinear, stochastic and multidimensional problems; they are highly complex optimization applications. Therefore, there is a need to develop an effective optimization algorithm that can address such highly complex applications to achieve optimal planning. Evolutionary algorithms with high computational speeds have been used to obtain the most accurate solutions [9–15].

Recently, evolutionary algorithms have shown stronger potential for solving such complex problems with multiobjective functions than traditional optimization models such as nonlinear or linear programming [11, 13, 14, 16]. Traditional methods experience convergence problems, especially in complex applications and when allocating the global solution to multiple reservoirs under different nonlinear constraints [9, 10, 12, 13, 15, 17]. Therefore, evolutionary algorithms that require less computational time and have a good search ability for the global optima can be applied to generate the optimal operation rules for dams and reservoirs. Managing the available water resources at the dams and reservoirs water systems is considered as a vital challenges and might be a source of planning difficulties for the decision makers. For example, different water's stakeholders downstream the dam and reservoir water system experienced problem regarding the mismatch between the water supply and demands. In addition, it is difficult to develop a model that able to generate operation rules and respond well to all the system's needs and constraints. Furthermore, each dam and reservoir water system has specific climate and hydrological conditions, so the model must be adopted for each case individually [3, 18]. The existing evolutionary algorithms (EA) as one of the most recent optimization algorithms used to develop optimal operation rules for dam and reservoir water systems, they have several internal random parameters. The value of these parameters have to be assumed at the initial stage of the model development, such assumption might increase the ambiguity of the model outputs. Finally, these problems may incorporate system's parameters with uncertainties, such as the inflow to the reservoir. Therefore, there is a need to formulate an optimization algorithm that able to solve these challenges with the dam and reservoir water system operation.

1.1 Background

Afshar et al. [19] applied honey bee mating optimization (HBMO) to solve the multireservoir system problem. The goal was to increase the power produced for downstream requirements. The results showed that the HBMO can obtain a solution that was close to the global solution with less computational time than the genetic algorithm (GA). Genetic programming (GP) can optimize the operation of a reservoir to supply irrigation requirements. This method operates based on genes and chromosomes to optimize continuous optimization problems. The results showed that the GP can decrease the vulnerability index by considering the water supply downstream for more operational periods [20]. Hossain and El-Shafie [21] considered reservoir operations with different categories of inflow, and the results showed that the artificial bee colony (ABC) method can provide operational rules for water releases to supply water demands. In addition, the ABC algorithm converged more quickly than the GA and PSO.

Nonlinear rule curves have been considered for optimal reservoir operation based on a genetic algorithm (GA). The results indicated that third-order rule curves based on the GA can supply the demands better than nonlinear programming based on lower deficiency values [22]. Biography-based optimization (BBO) was used to decrease the power deficiencies for a reservoir and hydropower in Iran. The results showed that the annual power production based on BBO was 12 and 14% more than with GA and particle swarm optimization (PSO), respectively [23].

The weed algorithm (WA) was used to increase power generation in a multireservoir system, and the results indicated that the WA could obtain the best solution based on a lower number of functional evaluations. The design of the algorithm is inspired by the properties of a weed's life. In addition, the power production for the multireservoir system based on the WA increased by 12% and 15% more than with the GA and PSO, respectively [24]. Hosseini-Moghari et al. [25] applied the imperialist competitive algorithm (ICA) to manage a reservoir for irrigation. The results indicated that the ICA could optimize the objective function of the problem of decreasing irrigation demands, so the volume deficiencies were ignored by the ICA, in contrast with the GA and PSO. Hossain et al. [26] applied the ABC method to reservoir operation to extract the rule curves for the released water volume. The results indicated that the ABC method, which is based on a volumetric reliability index, could better supply the downstream irrigation demands than the particle swarm algorithm and genetic algorithm. Mohammadrezapour et al. [27] applied the cuckoo algorithm to the water allocation controlled by a dam. The results showed that the cuckoo algorithm achieved a higher reliability index than the PSOA and GA.

Another study considered the optimization of multireservoir operations in China. The aim of the study was to maximize power generation by a multireservoir system using the shark algorithm (SA), which is based on the rotational movement of sharks. The SA increased the power production by 12% more than the GA [28].

The Krill algorithm (KA) was used to optimize an irrigation system by decreasing the deficiency volume, and the results indicated that the KA had a faster convergence speed than other methods; furthermore, it could supply the demand volumes with a higher reliability index [29]. Ming et al. [30] used the PSOA to solve multiobjective optimization problems. The results showed that the PSOA, which is based on the modification of the inertial weights, could cover the irrigation and environmental demands better than the GA, which is based on a higher certainty index. Karami et al. [31] applied the WA for the irrigation and hydropower generation management of two reservoirs in Iran. The model was mainly designed to minimize the total water deficit based on only one decision variable—the water released. The released water based the generated operation rule using the WA could meet the required water demands for irrigation and hydropower with the least risk.

The results of these studies show that soft computing methods and artificial intelligence methods based on the least computational time and the ability to receive large data and adapt to different hydrological and climate conditions are powerful tools for solving dam and reservoir problems with objective functions and constraints.

1.2 Problem statement and innovation

Evolutionary algorithms outperform traditional methods in generating optimal operation rules for dams and reservoirs; however, each algorithm has specific drawbacks that negatively influence the overall model performance. This study proposes a method for hybridizing the PSOA with the BA to overcome these drawbacks. The BA is considered a successful algorithm for several engineering optimization applications, including dams and reservoirs [32–34]. However, the results of previous studies have indicated that the BA may become trapped in local optima when solving multireservoir problems and requires more computational time to obtain converged solutions [32, 33, 35]. Although several studies have used either the BA or the PSOA for dam and reservoir water system, the main goal of this paper is to integrate the advantages of the two algorithms and then generate a more effective hybrid algorithm based on both the BA and PSO.

The BA has the capability of automatically zooming in on the region where the optimal solution can be identified; however, this feature gives it the ability to converge quickly in the early stage and dramatically more slowly in later stages. As a result, the BA experiences a slow convergence rate when searching for the optimal solution. In addition, no mathematical analyses are available to accelerate the convergence rate. Furthermore, the attained accuracy for the global optimal solution is insufficient, especially for large-scale and highly complicated applications, because several parameters must be tuned and controlled within the algorithm procedure. Therefore, there is a need to improve the performance of the BA to ensure high performance and accuracy to achieve the optimal solution [36]. On the other hand, the PSOA acts based on global and local leader procedures, which ensures the sharing of information among all particles. Utilizing this feature allows the PSOA to adopt the solution achieved using the BA procedure in terms of its control parameters and frequency tuning. In terms of the BA parameter control, the PSOA can be adapted to provide automatic switching from exploration to exportation when approaching the optimal solution, which improves the convergence process and accurately identifies the optimal solution. The PSOA can be used to adjust the frequency variation to mimic the true system functions. However, the PSOA suffers from partial optimism because it experiences an irregular direction toward the optimal solution. Fortunately, such drawbacks can be adjusted by the BA using the pulse emission mechanism. Thus, the hybridization of the BA with the PSOA could result in a new hybrid algorithm that acts in parallel to replace the suboptimal solution attained by one algorithm with one that is closer to the optimal solution of the other algorithm. This parallel structure for the BA and PSOA algorithms results in the hybrid bat–swarm algorithm (HB-SA), which integrates the advantages of both algorithms and overcomes their disadvantages. As a result, the HB-SA can guarantee a faster convergence rate and more accurate identification of the global optima for large-scale engineering applications with highly nonlinear complex systems.

1.3 Objective

The main objective of this study is to generate an optimal operational policy for dam and reservoir operation to minimize the irrigation deficit downstream of the dam. The potential of the hybrid bat and particle swarm optimization algorithm (HB-SA) is evaluated. The proposed HB-SA is then applied to the Golestan and Voshmgir dams as a case study to evaluate the ability of the HB-SA to derive a reliable, highly resilient and low-vulnerability release policy to minimize the irrigation deficit downstream of the dams. The multireservoir system problem is considered to be one of the most difficult problems in water resource management, so when decision makers are given a new method, they prefer to test it in a real-life scenario, such as an actual multireservoir system. Allocating water fairly in these problems is very difficult; thus, developing mathematical models for problems with numerous complex constraints is important for designers. The reservoir operation problem and the evolutionary algorithms have several uncertainties. Some of these uncertainties are related to the random parameters used in the algorithms, which can be computed based on accurate sensitivity analyses, and other uncertainties are related to the hydrological parameters and reservoir-related issues. This study focuses on the capabilities of the new evolutionary algorithm and compares the results with those of other methods from the literature. It considers the uncertainties related to the optimization algorithms and random parameters and identifies future projects that consider other uncertainties such as inflow and evaporation.

2 Methodology

2.1 Bat algorithm

Bats can generate loud sounds to separate obstacles from prey based on the reception of echoes generated by the surroundings. Thus, bats have a powerful auditory ability for sound reception. The BA applies the mathematical concepts of a bat's life based on the following assumptions [33]:

1. All bats use their echolocation ability based on sounds received from their surroundings to identify prey from obstacles.
2. The velocity, position, wavelength, frequency, and loudness for a random flight of bats are represented by y_l, λ_l, $f_{\min}$ and A_o, respectively.
3. The loudness varies between the initial value ($A_{\min}$) and a large value (A_0).

The pulsation rate (r_l) is considered for each bat, and the value of this parameter is in the interval [0, 1]; 0 means that the bat has not received any pulse, and 1 means that the bat received the maximum pulsation rate. The frequency, velocity, and position of the bat are updated based on the following equations:

$$f_l = f_{\min} + (f_{\max} - f_{\min}) \times \beta_l \tag{1}$$

$$v_l(t) = [y_l(t-1) - Y_*] \times f_l, t = 1, \ldots, T \tag{2}$$

$$y_l(t) = y_l(t-1) + v_l(t) * t \tag{3}$$

where f_l is the frequency, $f_{\min}$ is the minimum frequency, $f_{\max}$ is the maximum frequency, β is a random vector within the interval [0, 1], which take different value at each iteration, $v_l(t)$ is the bat's velocity, Y_* is the best position, t is the time step, and T is the total of the assessment periods. The local search for the BA is considered based on a random walk and the following equation:

$$y(t) = y(t-1) + \varepsilon A(t) \tag{4}$$

where ε is a random value between − 1 and 1, and $A(t)$ is the loudness. The loudness and pulsation rate are updated for each level. When a bat finds prey, the pulsation rate increases, and the loudness decreases. The pulsation rate is updated based on the following equation:

$$r_l^{t+1} = r_l^0[1 - \exp(-\gamma t)]A_l^{t+1} = \alpha A_l^t \tag{5}$$

where r_l^{t+1} is the new pulsation rate, r_l^0 is the initial pulsation rate, and α and γ are constants. The chart of the algorithm is shown in Fig. 1.

2.2 Particle swarm optimization algorithm

The search space is based on D dimensions; the position vector is $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, and the velocity vector is $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The best previous position for the bat is considered based on $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$. The g index shows the best particle with the best position among the other particles. The velocity and position will be updated based on following equation [28]:

$$v_{id}^{n+1} = \chi \left[w v_{id}^n + \frac{c_1 r_1^n (p_{id}^n - x_{id}^n)}{\Delta t} + \frac{c_2 r_2^n \left(p_{gd}^n - x_{id}^n\right)}{\Delta t} \right] \tag{6}$$

$$x_{id}^{n+1} = x_{id}^n + \Delta t v_{id}^{n+1} \tag{7}$$

where v_{id}^{n+1} is the new velocity of the particle, χ is the constriction coefficient, w is the inertia weight, c_1 and c_2 are the acceleration coefficients, r_1, and r_2 are random numbers, Δt is the time step, n is the iteration number, and x_{id}^{n+1} is the new position of the particle. First, the random

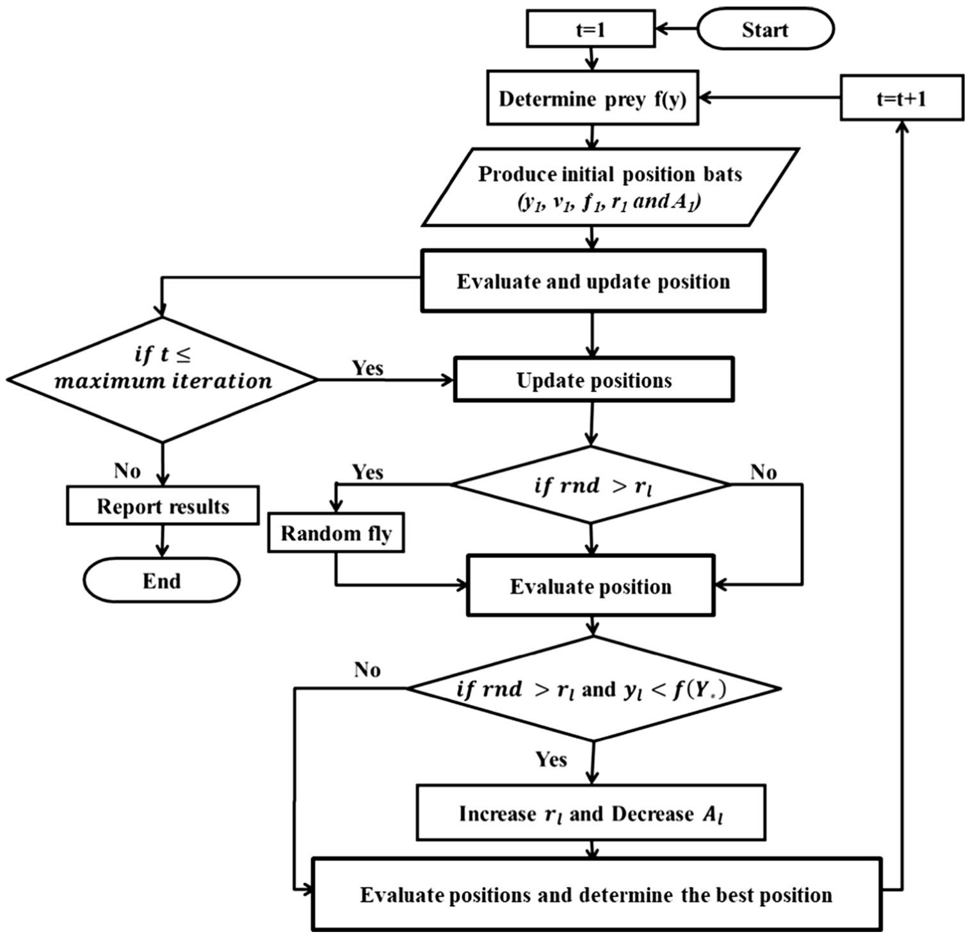

Fig. 1 Flowchart for the BA

parameters are initialized, and the size of the population is then determined. The objective function is computed for each particle, and the best particle is then determined. The velocity and position are computed using Eqs. (6) and (7), respectively. The convergence criterion is checked; if it is satisfied, the algorithm finishes.

2.3 Hybrid bat–swarm algorithm

The weaknesses of the BA, such as being trapped in a local optimum and the slow convergence speed, can be improved using a hybrid and parallel structure. A communication strategy is used between the BA and the PSOA. The value of the objective function is computed for each member, and these solutions are then sorted based on the best quality. The main idea is to replace the weak solution of one algorithm with the best solution of the other algorithm. The population of algorithms is divided into different subgroups, and the subgroups act independently for each iteration. When the communication strategy is triggered, the information exchange between the algorithms occurs.

The substitution of the weaker solutions of each algorithm allows the method to obtain the benefits of the cooperation. When the substitution of the solutions occurs, information is exchanged between the BA and the PSOA. In addition, each algorithm acts based on the optimization process and its independent performance.

Considering both algorithms independently, the k agents are the best solutions and will be selected based on the quality of the computed objective functions for both algorithms. These k agents will be copied and will replace the worst solutions of the other algorithms. The k agents are divided into subgroups, which will share their information with the subgroups of the other algorithm; this is shown in Fig. 2, in which R is the number of the communication strategy between the different groups.

The different levels of the hybrid algorithm are considered based on the following steps:

1. First, the random parameters for both algorithms are determined independently.
2. The objective function will be computed for both algorithms.
3. The bat and particle with the best position based on the computed objective functions are determined.
4. The velocity and position for the BA and PSOA are computed based on step 3.

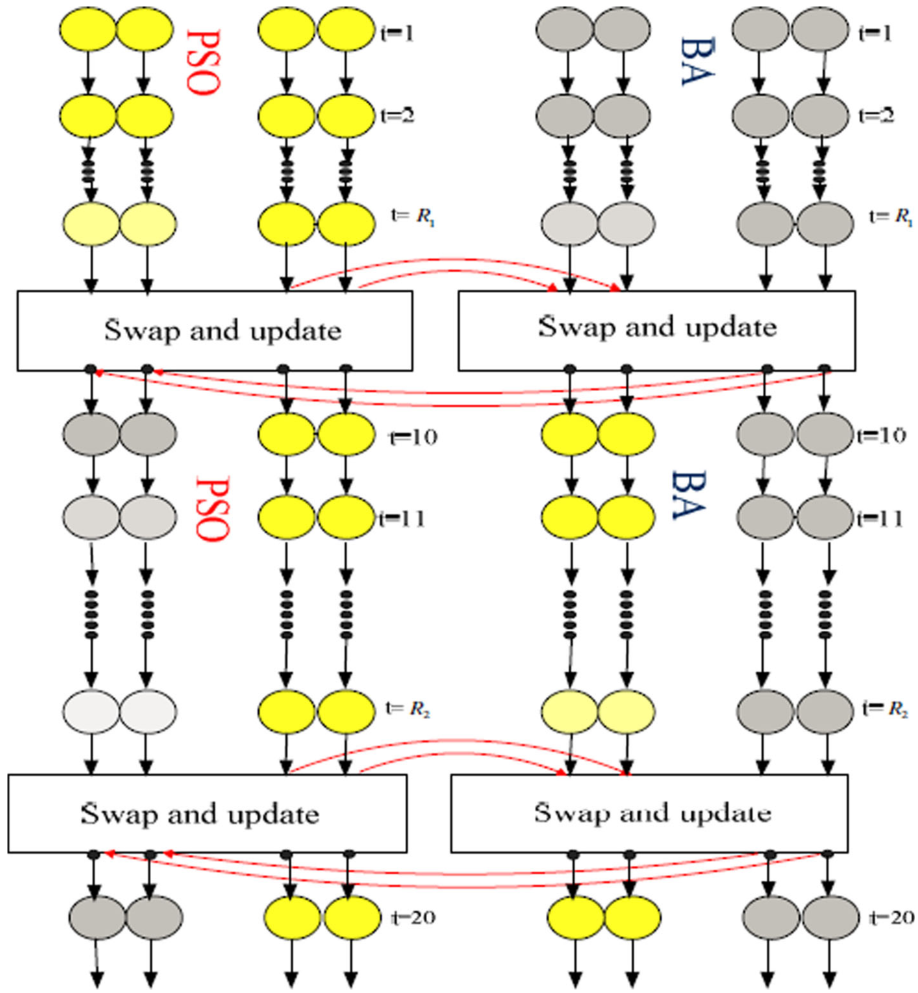

Fig. 2 Communication strategy

5. The velocity and position for the BA and PSOA are computed using Eqs. (2), (3), (6), and (7).
6. After the position and velocity updating, as well as the computation of the objective function for the BA and PSO, k particles and bats are selected. These agents are the best particles or bats.
7. These agents are copied into the other algorithms, where they replace the worst solutions of the other algorithms.
8. The convergence criteria are checked. If they are satisfied, the algorithm finishes; otherwise, the algorithm returns to step 2.

3 Case study

The Gorganrood Basin is an important basin in Northern Iran that contains one of the main arteries that discharge into the Caspian River. The Gorganrood River is 359.4 km long. Two important dams (Golestan and Voshmgir) are located in the basin (Fig. 3).

The Voshmgir Dam is the oldest dam in this basin and in Golestan state. It was constructed in 1969, and irrigation supply is an important duty of this dam. The reservoir storage capacity is 47 MCM, and the annual adjustment capacity for the dam is 117 MCM. The Golestan Dam is located upstream of the Voshmgir Dam. It has a reservoir capacity of 86 MCM, but this volume has been reduced to 62 MCM because of sedimentation. The characteristics of these dams are shown in Table 1. Data from 2007 to 2012 are considered for this case study. This period was selected due to the high confidence in the data from the stations, so planning and management strategies can be developed based on accurate information. In addition, a 5-year period is sufficient for decision makers to evaluate the capabilities of new method. Finally, accurate data are not available for other years; thus, this period is considered for this study.

In fact, dam and reservoir water system includes a few parameters that are stochastic in nature. For example, one of the major parameters that influence the operation of such system is the river streamflow to the reservoir, one of the system input. This parameter is stochastic in nature as it

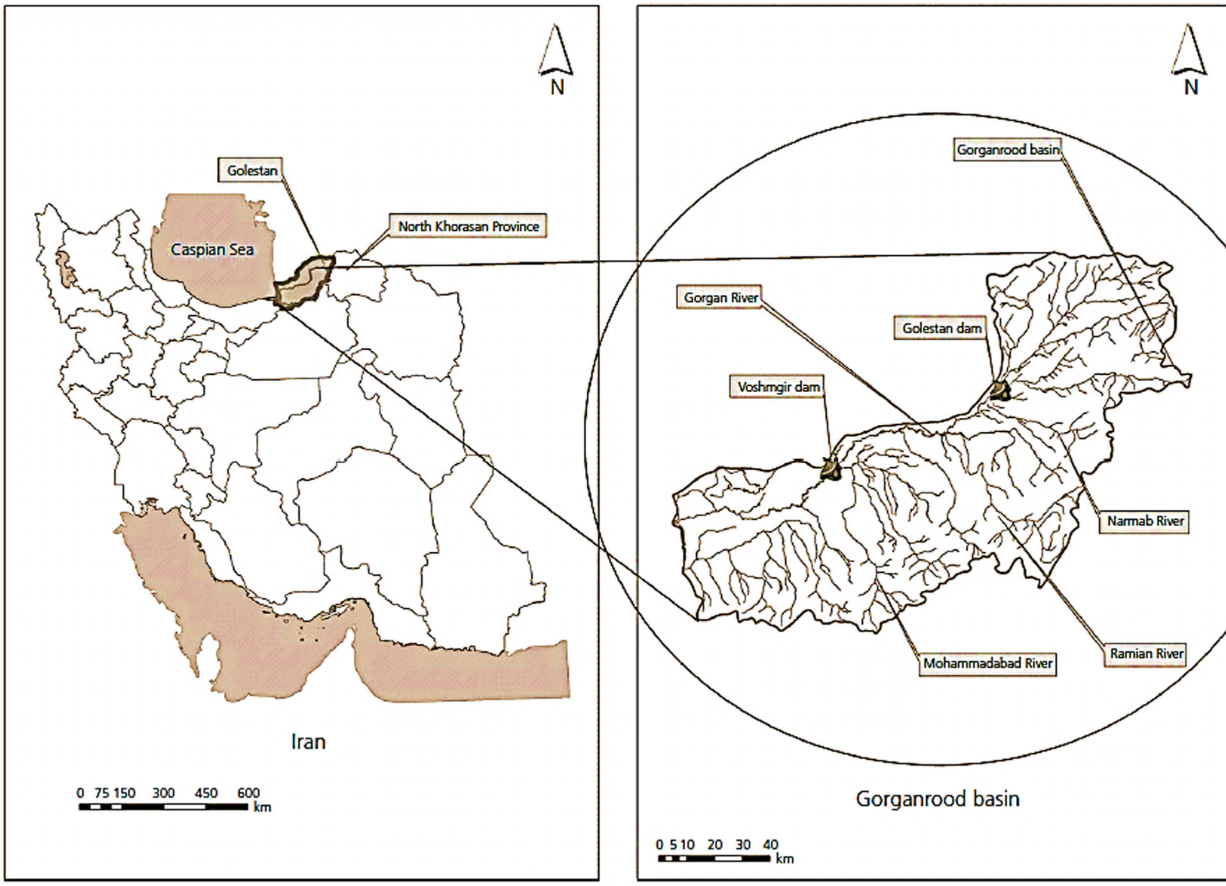

Fig. 3 Golestan and Voshmgir dams

Table 1 Main characteristics of the Golestan and Voshmgir dams

Characteristics	Voshmgir Dam	Golestan dam
Type of dam	Earth dam	Earth dam
First year of operation	1970	1999
Height from foundation (m)	17.8	17
Crest length (m)	430	1367
Total storage capacity (mcm)	47	62
Irrigation land area (km^2)	210	270
Spillway discharge capacity (m^3/s)	935	1550
Average water level (m)	10	49

takes different pattern on daily, weekly, monthly, seasonally and even yearly basis. In addition, one of the system losses is the evaporation losses from the surface area from the reservoir which is affecting the reservoir water balance and simulation. The evaporation water loss is mainly based on the evaporation rate which is affected by the air temperature. Similarly as the river streamflow, the air temperature is considered as highly stochastic parameter because its value is fluctuated over the year. Therefore, dam and reservoir water system is considered highly stochastic system and required a special modeling procedure that able to consider the stochastic nature of the system's variables.

The objective function based on minimizing the irrigation deficits is determined based on the following equation:

$$Minimize(F) = \sum_{t=1}^{T}\sum_{i=1}^{2}\left(\frac{D_{i,t} - R_{i,t}}{D_{\max,i}}\right)^2 \quad (8)$$

where F is the objective function, T is the number of operational periods, $D_{\max,i}$ is the maximum demand in the operational period for each dam, $D_{i,t}$ is the downstream demand for each dam, and $R_{i,t}$ is water released by each dam. The continuity constraints are defined for each dam as follows:

$$S_{1,t+1} = S_{1,t} + I_{1,t} - R_{1,t} - L_{1,t} - Sp_{1,t} \quad (9)$$

$$S_{2,t+1} = S_{2,t} + I_{2,t} - R_{2,t} - L_{2,t} - Sp_{2,t} \quad (10)$$

where $S_{1,t+1}$ is the storage volume of the Golestan Dam, $I_{1,t}$ is the inflow to the Golestan Dam, $R_{1,t}$ is the water released by the Golestan Dam, $L_{1,t}$ is the loss volume for the Golestan Dam, $Sp_{1,t}$ is the loss overflow volume for the

Golestan Dam, and the variables in Eq. (10) are similar to those in Eq. (9) but are related to the Voshmgir Dam. The loss volume is computed using the following equation:

$$L_{i,t} = A_{i,t}\left(E_{i,t}\right) \tag{11}$$

where $A_{i,t}$ is the area of each reservoir, and $E_{i,t}$ is the evaporation from each reservoir.

Qaderi et al. [37] reported the following equations between the reservoir area and the storage based on regressions between these parameters;

$$A_1 = -0.0037S_1^2 + 0.4568S_1 + 1.2026 \quad \text{(Golestan)} \tag{12}$$

$$A_2 = -0.00114S_2^2 + 0.464S_2 - 0.5056 \leftarrow (Voshmgir) \tag{13}$$

In addition, the constraints for the released water and reservoir storage were considered based on the following equations:

$$S_{\min(i)} \le S_{i,t} \le S_{\max,i} \tag{14}$$

$$R_{\min(i),t} \le R_{i,t} \le R_{\max(i),t} \tag{15}$$

where $S_{\min(i)}$ is the minimum storage, $S_{\max,i}$ is the maximum storage, $R_{\min(i),t}$ is the minimum amount of water released from the dams, and $R_{\max(i),t}$ is the maximum amount of water released from the dams.

The penalty functions are considered based on the following equations:

$$P_{1i,t} = \begin{bmatrix} \sum_{t=1}^{T}\sum_{i=1}^{2}\left(\frac{\left(S_{i,t} - S_{\max(i)}\right)^2}{S_{\max(i)}}\right) \leftarrow \text{if}\left(S_{i,t} > S_{\max(i)}\right) \\ \sum_{t=1}^{T}\sum_{i=1}^{2}\left(\frac{\left(S_{i,t} - S_{\min(i)}\right)^2}{S_{\min i}}\right) \leftarrow \text{if}\left(S_{i,t} < S_{\min(i)}\right) \end{bmatrix} \tag{16}$$

$$P_{2i,t} = \begin{bmatrix} \sum_{t=1}^{T}\sum_{i=1}^{2}\left(\frac{\left(R_{i,t} - R_{\max(i)}\right)^2}{R_{\max(i)}}\right) \leftarrow \text{if}\left(R_{i,t} > R_{\max(i)}\right) \\ \sum_{t=1}^{T}\sum_{i=1}^{2}\left(\frac{\left(R_{i,t} - R_{\min(i)}\right)^2}{R_{\min i}}\right) \leftarrow \text{if}\left(R_{i,t} < R_{\min(i)}\right) \end{bmatrix} \tag{17}$$

The mathematical model for the operation of the two reservoirs is considered based on the following factors:

1. The released water is considered as a decision viable to simplify the computations; in addition, this is the first priority for the decision makers.
2. The initial positions of the particles and bats (released water) are considered as the initial populations for both algorithms.
3. The continuity equation is considered, and the storage volume is computed based on this equation.
4. The storage and released water volumes should be checked with the permissible domain, and the penalty functions will be computed if necessary.
5. The objective function is computed for each member and both algorithms independently.
6. The best positions for the particles and bats are determined based on the previous step.
7. The velocity and position are updated for the BA and PSOA.
8. The k agents for both algorithms are selected based on the best values for the objective functions, and they are copied and transformed to the other algorithm to replace the worst solutions of the other algorithm.
9. The convergence criterion is checked. If it is satisfied, the algorithm finishes; otherwise, it returns to step 2.

4 Model evaluation

Golestan and Voshmgir Dam are designed as a single purpose water system for supplying water to irrigation based on the irrigation water demand pattern. However, after generating the operation rule using particular optimization algorithm, this operation rule should be examined using certain performance indexes that could measure how effective is this operation rule. Afterward, for the comparison purpose, the operation rules that have been generated using the other optimization algorithms should be examined using the same performance indexes as well. From these two steps, the effectiveness of the proposed model in this study could be examined against the performance from the other optimization algorithms.

The following indexes are defined for the investigation of the different algorithms used to optimize reservoir operation. These indexes are widely used to determine the capabilities of new methods for water resource management problems based on the water release volume, water release time and the ability to address drought periods or critical periods:

1. Volumetric reliability index: this index is based on the released water and downstream demand. If the released water can supply the demand well, the value of this index will be high [29].

$$\alpha_{\mathrm{V}} = \frac{\sum_{i=1}^{2}\sum_{t=1}^{T} R_{i,t}}{\sum_{i=1}^{2}\sum_{t=1}^{T} D_{i,t}} \times 100 \tag{18}$$

where α_{V} is the volumetric reliability index.

2. Resiliency index: this index indicates the speed of the system to recover from a failure. It is important that a

system recovers after a single failure during an operational period. A high value of this index is desirable [28].

$$\gamma_i = \frac{f_{si}}{F_i} \tag{19}$$

where γ_i is the resiliency index, f_{si} is the number of failure series generated in the ith reservoir, and F_i is the number of failure periods generated in the ith reservoir.

3. Vulnerability index: this index indicates the maximum failure percentage generated during operational periods. Thus, a low value of this index is desirable.

$$\lambda = \mathrm{Max}_{i=1}^{2}\left(\mathrm{Max}_{t=1}^{T}\left(\frac{D_{i,t} - R_{i,t}}{D_{i,t}}\right)\right) \tag{20}$$

where λ is the vulnerability index.

5 Results and discussion

The irrigation supply is an important issue when operating multiple reservoirs, especially during periods of drought. The negative influences of droughts on irrigation management is the reason that decision makers for water resources pay particular attention to optimally operating multireservoir systems to avoid irrigation deficits. Thus, the proposed HB-SA will be applied mainly to minimize the water deficit for the irrigation demands downstream of the reservoir. In the following subsections, the procedure of the proposed hybrid algorithm will be evaluated followed by a direct application to the proposed case study presented in Sect. 3.

5.1 Initialization and validation of the HB-SA

Meta-heuristic algorithms have random parameters that should be predetermined and initialized before application to real problems. However, accurate initial values of these parameters are not specified for users due to the high uncertainties of these parameters. Thus, sensitivity analyses are often used to accurately determine these parameters. Although some studies use reported values for the parameters or use the trial and error process, a sensitivity analysis is the best method because it shows the variation of the objective function caused by variations of the values of the parameters.

For example, an accurate determination of the population size in meta-heuristic algorithms is an important step to initialize the minimization/maximization purpose of the objective function. Population sizes between 10 and 70 were examined to minimize the objective function. The results show that the initial population size of 50 provided the minimum value of the objective function, as shown in Table 2. Similarly, the proposed algorithm was examined for maximum and minimum frequency ranges from 3 to 9 and from 1 to 4, respectively. Table 2 shows that the maximum frequency is 7. The other initial parameters, including the maximum loudness, acceleration coefficient and inertia weight, are 0.7, 2 and 0.7, respectively (Table 2). The other parameters of the different methods are based on reported values and the permissible ranges from previous studies. In addition, some of the parameters do not affect the results, which is shown by the sensitivity analysis.

The next step in the parameter initialization is to examine the potential of the algorithm to identify the global optimum. Qaderi et al. [37] reported that the global solution of this problem, based on the Lingo software and nonlinear programming, was 0.110 (Table 3). The proposed HB-SA was examined for the same application and compared with the performances of other optimization algorithms, including the water cycle algorithm (WCA), harmony search (HS), intelligent colony algorithm (ICA), bat algorithm (BA) and particle swarm optimization algorithm (PSOA). All of the algorithms described in the literature review section have been shown to have good ability for solving complex water resource management problems. Thus, the new hybrid method can be compared with these methods to demonstrate its capabilities.

The algorithms were examined for 10 different runs via two different index average solutions and the variation coefficient. The proposed HB-SA outperformed the other algorithms and achieved a closer value of the minimum objective function than the other algorithms. Specifically, the proposed HB-SA attained an average value within the 10 runs of 0.115, which is approximately 95% of the global optimal value. In contrast, when using the PSOA and BA, the average values of the minimum objective function are 0.212 and 0.156, respectively, which are 88% and 47% greater, respectively, than the global solution. Similarly, the average solutions for the minimal objective functions achieved using the other algorithms (WCA, ICA, and HS) are less accurate than the proposed HB-SA based on the variation coefficient index. The HB-SA gave a value of 0.005, which is lower than the other algorithms and shows that the HB-SA gives the most reliable solution, as shown in Table 3.

In order to examine the proposed optimization algorithm against the existing ones for the ability to search for the global optima in reasonable time, the reference optimal objective function that has been achieved using the nonlinear programming using LINGO optimization software has been considered. In fact, all the details of the case study have been used and adjusted within the LINGO

Table 2 Sensitivity analysis of the HB-SA

Group size	Objective function	Maximum frequency	Objective function	Minimum frequency	Objective function	Maximum loudness	Objective function
10	0.215	3	0.221	1	0.167	0.3	0.178
30	0.198	5	0.178	**2**	**0.115**	0.5	0.154
50	**0.115**	**7**	**0.115**	3	0.124	**0.70**	**0.115**
70	0.117	9	0.124	4	0.132	0.90	0.124

Acceleration coefficient ($c_1 = c_2$)	Objective function	Inertia weight	Objective function
1.6	0.187	0.3	0.188
1.8	0.176	0.5	0.165
2.0	**0.114**	**0.7**	**0.115**
2.2	0.134	0.90	0.124

The variations of the values of different parameters versus the variations of values of the objective function

Table 3 Average optimal objective functions using different algorithms compared to the proposed HB-SA

Run	PSOA	BA	WCA	HB-SA
1	0.214	0.165	0.157	0.115
2	0.216	0.155	0.170	0.117
3	0.212	0.155	0.157	0.115
4	0.212	0.155	0.157	0.115
5	0.212	0.155	0.157	0.115
6	0.212	0.155	0.157	0.115
7	0.212	0.155	0.157	0.115
8	0.212	0.155	0.157	0.115
9	0.212	0.155	0.157	0.115
10	0.212	0.155	0.157	0.115
Average	0.212	0.156	0.158	0.115
Variation coefficient	0.008	0.018	0.042	0.005
Global solution [37]	0.110			

optimization software and an optimal objective function value of 0.11 has been successfully attained. However, the LINGO optimization software experienced a few limitations that should be carefully considered every time while using it when applying for generating optimal operation rule for dam and reservoir water system. First, the solution algorithm within the nonlinear programming process required very extensive CPU time to achieve the performance goal, which could be around 1 h. In fact, the required time-consuming to achieve the global optima is an essential factor in operating dam and reservoir water system as it might effect on the proper timing to functionalize the value of the decision variable. In fact, it might negatively influence on the whole operation performance and the system's objective function. Second, in most cases while real operation, there is a need to carry out some adjustments for the water system setup due to unexpected changes in the operation, at that time, there is a need to make readjust the whole case study within the software from the beginning which requires very long time to perform. On the other hand, for the meta-heuristics algorithm, it is only required to adjust the corresponding variable in the algorithm procedure without need to re-setup the whole case study.

5.2 Analysis of irrigation deficiencies

After initializing the proposed HB-SA parameters and validating its performance, the HB-SA was applied to the case study. The main purpose of the proposed HB-SA is to optimize the operation of the Golestan and Voshmgir dams by minimizing the irrigation deficit, which minimizes the difference between the dam releases and the irrigation demand considering monthly time increments. Figure 4a and b shows the distributions of the irrigation deficit in MCM on a yearly basis (for 5 years) based on the examined optimization algorithms for the Golestan and Voshmgir dams, respectively. Figure 4a shows that the operation rule generated utilizing the proposed HB-SA achieved the minimum irrigation deficit. During the 5 years of operation using the HB-SA, the irrigation deficits ranged between 1 and 2.3 MCM in the first and fourth years of operation. In contrast, considering the operation rules attained using the BA and PSOA individually, the irrigation deficits ranged between 4 and 12 MCM for the BA and between 12 and 17 MCM using the PSOA. For example, the average deficit for the HB-SA is 1.86 MCM for the Golestan Dam, which is 87%, 62% and 40% less than those of the BA, WCA and PSOA, respectively.

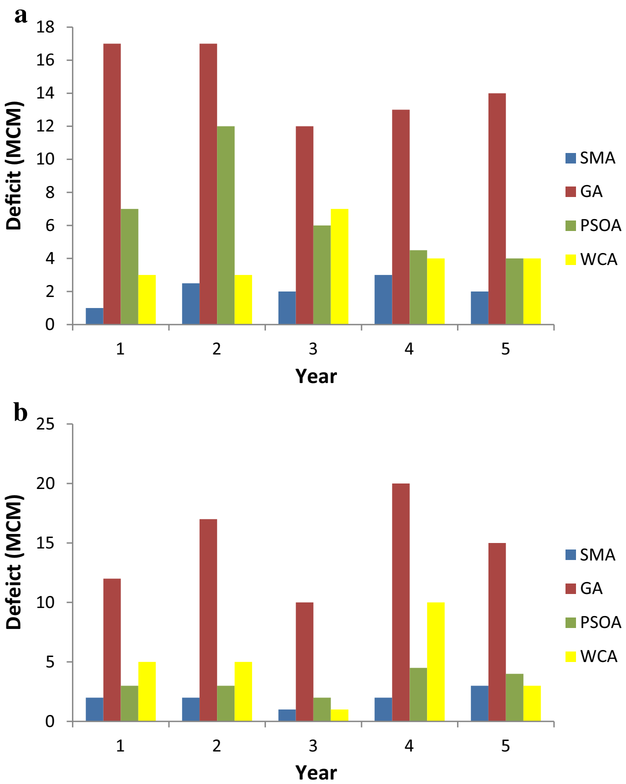

Fig. 4 Computed deficits for **a** the Golestan Dam and **b** the Voshmgir Dam

These results showed that the operation rule using the proposed HB-SA could reduce the irrigation deficit better than using the BA and PSOA alone. Furthermore, the results showed that the proposed HB-SA achieved better performance than that reported for the same case study by Qaderi et al. [37], which proposed using the WCA to optimize the operation. The range of the irrigation deficit using the WCA was between 3 and 7 MCM during the 5 years of operation, which is nearly 3 times the irrigation deficits achieved using HB-SA.

The same performance for the HB-SA was observed for the Voshmgir Dam, although during the 5 years of operation, the minimum irrigation deficit achieved using the WCA was 1 MCM, which is equal to the results achieved using the proposed HB-SA. The maximum irrigation deficits are 10 MCM using the WCA and 4 MCM using the HB-SA. These results demonstrate that the proposed HB-SA can be applied to different case studies and achieve the same level of performance.

For further analysis, the proposed algorithms were evaluated based on error indexes, including the correlation coefficient R^2, the root mean square error (RMSE) and the mean absolute error (MAE). The coefficient of determination (R^2) is used to examine the linear relationship between the water released and the irrigation demand. R^2 is calculated by dividing the covariance of the water released and the irrigation demand by the product of the standard deviation of those values. This indicator illustrates the precision of the linear fit and is a representation of the variance between the water released and the irrigation demand. The second indicator is the root mean square error (RMSE), which is used to measure the variation between the observed values of the required variable (irrigation demand) and the values (water released) from the model. The RMSE aggregates the individual differences into a single measure of the difference between the water released and the irrigation demand. Finally, the mean absolute error (MAE) was considered to examine how the operation rules of the model (water released) are biased with the system requirements (irrigation demand) while considering the deficit and the surplus. The RMSE value from the HB-SA for Golestan Dam was 6.8%, 10% and 22.1% lower than those from to the BA, WCA and PSOA, respectively, which demonstrates that the released water volume from the HB-SA responds to the demands better than those from the other methods. The MAE value for the Golestan Dam based on the HB-SA was 27%, 28% and 32% lower than those from the BA, WCA and PSOA, respectively. Similar results were given for the Voshmgir Dam, which demonstrated that the HB-SA had better performance than the other methods.

The indexes are used to compare the capabilities of the hybrid method with those of the other algorithms. Based on the reliability and vulnerability values for the water supply for the downstream demands, these indexes allow an accurate comparison of the capabilities of the methods. Table 4 shows the error indexes described above for the different algorithms for both dams. The highest value of R^2 is 0.93, which is the result for the water release pattern attained using the HB-SA. In other words, the water release pattern-based operation rule provided by the HB-SA closely matches the irrigation demand pattern with a minimal variance and a nearly linear relationship. Moreover, higher values of R^2 were achieved for the Voshmgir Dam (0.97) using the HB-SA, which indicates the suitability for this algorithm for other case studies. The minimum values of the RMSE were attained using the HB-SA for the Golestan Dam and Voshmgir Dam (4.1 and 3.9 MCM, respectively). The low RMSE values reflect the ability of the HB-SA to match the temporal patterns of the downstream irrigation demand and water release. Finally, the minimum values of the MAE are 3.2 and 2.1 MCM for the Golestan and Voshmgir dams, respectively, which demonstrates the advantage of the HB-SA over the other algorithms to derive the operation rule that minimizes the bias between the irrigation demand and the water released. The indexes shown in Table 5 can be defined based on the objective functions, but the aim of the decision makers is to decrease

Table 4 Evaluation of the algorithms based on the error indexes

Correlation coefficient $\bar{D}_t$: average monthly demand $\bar{R}_t$: average released water	$R^2 = \left[\frac{\sum_{i=1}^{n} (D_t - \bar{D}_t)(R_t - \bar{R}_t)}{\sqrt{\sum_{i=1}^{n} (D_t - \bar{D}_t)^2 (R_t - \bar{R}_t)^2}} \right]^2$
Root mean square error	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (D_t - R_t)^2}$
Mean absolute error	$MAE = \frac{\sum_{i=1}^{n} \lvert (D_t - R_t) \rvert}{n}$

Algorithm	R^2	RMSE	MAE
Golestan Dam			
HB-SA	0.93	4.1	3.2
BA	0.9	4.4	4.5
PSOA	0.65	5.3	5.1
WCA [37]	0.89	4.6	4.4
Voshmgir Dam			
HB-SA	0.97	3.9	2.9
BA	0.91	4	4.1
PSOA	0.68	5.1	5
WCA [37]	0.92	4.3	4.2

Table 5 Computation of the volumetric reliability, vulnerability and resiliency index

Index	Volumetric reliability %	Resiliency index %	Vulnerability index
Golestan Dam			
HB-SA	94	56	11
PSOA	57	47	34
BA	88	50	10
WCA [37]	89	49	14
Voshmgir Dam			
HB-SA	96	55	10
PSOA	60	48	32
BA	89	51	10
WCA [37]	90	50	12

the irrigation deficits and compare the results with those from other studies; thus, these indexes are computed without inserting them into the objective function.

Table 5 shows the performance of the different algorithms based on the different evaluation indexes presented in Sect. 4. These evaluation indexes were calculated based on the simulation of the generated operation rules for the optimization algorithms from 2012 to 2017 on a monthly basis. The volumetric reliability (Table 5) ranged between 57% based on the PSOA and 94% based on the proposed HB-SA. The volumetric reliabilities associated with the BA and WCA are 88 and 89%, respectively, for the Golestan Dam. Thus, the allocated water release based on the proposed operation rule (HB-SA) was equal to or greater than the required irrigation demands during the examined 5-year period and outperformed the other algorithms. This observation shows that the proposed HB-SA effectively integrates the advantages of the BA and PSOA and achieves a higher volumetric reliability. In addition, the proposed HB-SA outperformed the recent WCA that was applied to the same case study and achieved a 5% improvement in the volumetric reliability. Likewise, the proposed HB-SA achieved a volumetric reliability of 97% for the Voshmgir Dam, which was higher than the other algorithms. The resiliency index for the HB-SA for the Golestan and Voshmgir dams are 56 and 55%, respectively, which shows that the system based on the HB-SA can exit from the drought periods earlier than other methods and can recover more quickly than the other methods.

Although the HB-SA has the best performance in terms of the reliability, the ultimate goal is to minimize the magnitude of the irrigation deficit. Therefore, there is a need to examine the vulnerability and resilience of the system. In fact, the operation rules might tend to hedge the policy (supply less than the full demand) to avoid severe irrigation deficits in future events. As a result, the operation rule could accept low reliability to enhance the resilience and vulnerability. However, the proposed HB-SA still derived an operation rule that was better than those of the other algorithms in terms of the vulnerability and resilience. These observations ensured the ability of the HB-SA to achieve the global solution for the system's operation.

Figure 5 shows the convergence procedure for the examined optimization algorithms for the dam and reservoir system. The convergence procedure is one of the most essential indicators for evaluating an optimization model, especially for real-time engineering applications such as dam and reservoir operations. It is difficult to determine the exact reason for the divergence or convergence of the convergence rate for the global optimal search procedure. All of the algorithms successfully converge and reach a particular solution, which may be the global optimum or a non-optimal solution. All of the algorithms run several times until convergence occurs with the convergence parameter set for each algorithm as presented in Sects. 2.1, 2.2 and 2.3. Two main points can be considered to differentiate between the performances of two different convergence curves for the optimization algorithms. One index is the number of iterations required for an algorithm to achieve the solution, and the second is the time required to reach the solution without considering the number of iterations required. Figure 5 shows that the HB-SA converged to the smallest value of the objective function in fewer

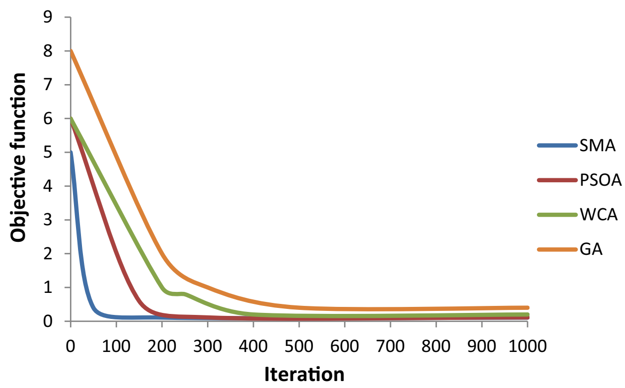

Fig. 5 Convergence rates of different algorithms

iterations than the other algorithms. In addition, the required time for the HB-SA to achieve the minimum value of the objective function was 75 s, whereas it was 78, 82 and 102 s for the BA, WCA, and PSO, respectively. These results demonstrate that the proposed HB-SA can determine the optimal solution in a lower number of iterations but also in a shorter time, which is considered an additional benefit of the proposed HB-SA for real-time dam and reservoir operations.

This study corroborates the previous study of Qaderi et al. [37] and showed the benefits of the proposed HB-SA approach over the WCA for achieving a better operating policy for the Golestan and Voshmgir dams. The proposed HB-SA is more complicated to adapt but is much more effective at deriving optimal operation rules for dams and reservoirs and could serve as and be generalized as an alternative to the more complicated stochastic dynamic programming (SDP) for reservoir operation. Finally, based on the observed advantages of the proposed HB-SA, it could be applied to several dam and reservoir water systems around the world.

6 Conclusion

This study introduced a procedure for developing a new hybrid optimization algorithm based on the BA and PSOA, namely, the hybrid bat–swarm algorithm (HB-SA). The goal of this work was to present an optimal operation rule for dam and reservoir systems that is reliable, robust and effective at minimizing irrigation deficits. The idea behind the developed HB-SA is to assimilate the advantages of both the bat and particle swarm algorithms and overcome their drawbacks when they are used in isolation. The proposed HB-SA was applied to the Golestan and Voshmgir dams in Iran. The reliability, resilience and vulnerability indexes used to evaluate the proposed algorithm showed that the operation rules achieved using the HB-SA outperformed those derived using the BA and PSOA independently. To validate the performance of the proposed algorithm, its derived operation rule was compared with those generated by applying the water cycle algorithm (WCA) to the same case study. The results showed that the proposed algorithm could achieve operation rules that minimize the irrigation deficit by almost 50% compared to those achieved using the WCA. Particularly for an intermittent irrigation schedule, which is often the case for irrigated crops downstream of dams, the proposed algorithm had a faster rate of convergence, which leads to a usable real-time optimal solutions for dams and reservoirs. The HB-SA algorithm further improved other metaheuristic algorithms and had reduced computational requirements for reaching a global optimal solution. However, one of the limitations of this study is related to the lack of sufficient climate conditions, so the effects of climate on reservoir operations should be considered in future studies.

Future research will extend the proposed HB-SA by including the uncertainty of the stochastic process to mimic the stochastic pattern of reservoir inflow by integrating inflow forecasting model and uncertainty technique with the optimization algorithm. Furthermore, the proposed HB-SA can be extended to more be applied for complicated dam and reservoir systems that have multiple purposes such as hydropower generation and domestic water usage.

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