Title
Development and Application of the Bat Algorithm for Optimizing the Operation of Reservoir Systems

Journal
Journal of Water Resources Planning and Management, 141(8)

ISSN
0733-9496

Authors
Bozorg-Haddad, Omid
Karimirad, Iman
Seifollahi-Aghmiuni, Samaneh
et al.

Publication Date
2015-08-01

DOI
10.1061/(asce)wr.1943-5452.0000498

Peer reviewed

Development and Application of the Bat Algorithm for Optimizing the Operation of Reservoir Systems

Omid Bozorg-Haddad[1]; Iman Karimirad[2]; Samaneh Seifollahi-Aghmiuni[3]; and Hugo A. Loáiciga[4]

Abstract: Optimal utilization of water resources by means of water transfers and reservoirs in semiarid and arid regions is used to mitigate natural water scarcity. In this context, metaheuristic algorithms for optimum reservoir system operation have become an attractive alternative to traditional operations research algorithms such as linear programming (LP), nonlinear programming (NLP), and dynamic programming (DP). This paper presents the metaheuristic bat algorithm (BA) and its application to the optimal operation of the Karoun-4 reservoir system in Iran and to a hypothetical four-reservoir system. The merits of the performance of the BA in the optimization of reservoir operation are demonstrated by comparison to those of LP, NLP, and genetic algorithm (GA) in terms of the convergence to global optima and of the variance of results about global optima for reservoir optimization problems. **DOI:** 10.1061/(ASCE)WR.1943-5452.0000498.

Author keywords: Bat algorithm; Optimization; Reservoir operation; Nonlinear programming; Genetic algorithm.

Introduction

The use of reservoir systems to store and transfer water to provide multiple services (e.g, water supply, hydropower, flood control, flow regulation for ecologic functions, and recreation) is well established. There are numerous studies that optimize the operation of reservoir systems. Mujumdar and Ramesh (1997), for example, used dynamic programming (DP) to establish that optimized reservoir operation could increase agricultural yields by 40% in areas served by the Karnataka reservoir in India. Rashid et al. (2007) used stochastic dynamic programming (SDP) to optimize the operation rule curve of the Dokan reservoir in Iraq. The latter authors demonstrated that SDP-optimized production of hydropower is superior to nonoptimized production. Similar conclusions regarding the SDP-optimized production of hydropower were obtained by Liu et al. (2012) in the Three Gorges dam in China.

Recently, many optimization techniques have been developed and applied in all aspects of water resources systems such as reservoir operation (Bozorg-Haddad et al. 2011a; Fallah-Mehdipour et al. 2011b, 2012, 2013), hydrology (Orouji et al. 2013), water distribution networks (Bozorg-Haddad et al. 2008; Fallah-Mehdipour et al. 2011a; Seifollahi-Aghmiuni et al. 2011, 2013), and algorithmic developments (Shokri et al. 2013). Only a few of these works dealt with the application of the bat algorithm (BA) in water resources systems and especially for optimizing the operation of reservoir systems.

Several metaheuristic algorithms have been used to optimize reservoir operation and genetic algorithm (GA) is a frequent choice. As an example, Hormwichian et al. (2009) used GA to demonstrate the possible reduction in water shortages in areas served by the Lampao reservoir in Thailand. Chen et al. (2012) optimized the operation rule curve of the Qingshitan reservoir in southwest China using GA and proved that the optimized rule could reduce downstream water-level fluctuations substantially.

Metaheuristic algorithms such as particle swarm optimization (PSO), harmony search (HS), and the firefly algorithm (FA) are gaining prominence among methods used for solving many complex optimization problems (Kennedy and Eberhart 1995; Mitchell 1998; Deep and Bansal 2009). Most of these algorithms are derived from the characteristics of biological and physical systems in nature and other realms. A case in point is simulated annealing (SA), which is based on the annealing process of metals (Kirkpatrick et al. 1983). PSO was developed based on the swarm behavior of birds and fish (Kennedy and Eberhart 1995, 2001). HS was inspired by the process of composing music (Geem et al. 2001), and the FA was formulated based on the flashing behavior of fireflies (Yang 2008). Each of the mentioned algorithms has its advantages and disadvantages. For example, SA can almost guarantee finding the optimal solutions if the cooling process in metals is slow enough and the simulation runs long enough (Yang 2010).

The BA is a metaheuristic algorithm based on the echolocation features of microbats (Yang 2010). Among the applications of the BA, continuous optimization in the context of engineering design optimization has been extensively studied, which demonstrated that the BA can deal with highly nonlinear problems efficiently and can find the optimal solutions accurately (Yang 2010, 2012; Yang and Gandomi 2012). Case studies include pressure vessel design, automobile design, spring and beam design, truss systems, tower and tall building design, and others. Assessments of the BA features are found in Koffka and Ashok (2012), who compared the BA with the GA and PSO algorithms in cancer-research problems and provided evidence that the BA performs better than the

[1]Associate Professor, Dept. of Irrigation and Reclamation Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, Univ. of Tehran, Karaj, 31587-77871 Tehran, Iran (corresponding author). E-mail: OBHaddad@ut.ac.ir

[2]Ph.D. Student, Dept. of Irrigation and Reclamation Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, Univ. of Tehran, Karaj, 31587-77871 Tehran, Iran. E-mail: ikarimirad@ut.ac.ir

[3]Ph.D. Candidate, Dept. of Irrigation and Reclamation Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, Univ. of Tehran, Karaj, 31587-77871 Tehran, Iran. E-mail: seifollahi@ut.ac.ir

[4]Professor, Dept. of Geography, Univ. of California, Santa Barbara, CA 93106. E-mail: Hugo.Loaiciga@ucsb.edu

Note. This manuscript was submitted on April 25, 2014; approved on October 31, 2014; published online on December 3, 2014. Discussion period open until May 3, 2015; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496/04014097(10)/$25.00.

other two algorithms. Malakooti et al. (2012) implemented the BA to solve two types of multiprocessor scheduling problems (MSPs) and concluded that in the single-objective MSP the bat intelligence outperformed the list algorithm and the genetic algorithm. Reddy and Manoj (2012) used fuzzy logic and the BA to obtain optimum capacitor placement for loss reduction in electricity distribution systems.

Ramesh et al. (2013) reported a detailed study of combined economic load and emission dispatch problems using the BA. They compared this algorithm with the ant colony optimization (ACO) algorithm, hybrid genetic algorithm, and other methods, and concluded that the BA is easy to implement and much superior to the comparison algorithms in terms of accuracy and efficiency. Niknam et al. (2013) showed that the BA outperforms the GA and PSO in solving energy generation problems. Baziar et al. (2013) compared the BA with the GA and PSO in the management of a microgrid for various types of renewable power sources and concluded that BA has the best performance.

One advantage of the metaheuristic algorithms in comparison with the conventional optimization methods such as linear programming (LP), nonlinear programming (NLP), and DP is their superior capacity to find global optimal solutions of the optimization problems in various fields of water resources engineering, and, in particular, in the optimization of reservoir system operation. This study introduces the BA as a new and capable algorithm and evaluates its capacity to obtain optimal solutions to reservoir optimization problems. In this study, the BA's efficiency was first confirmed using a mathematical benchmark problem. Thereafter, its performance was evaluated in solving the reservoir operation optimization of a real single reservoir and a hypothetical multireservoir case study. The obtained results were compared with optimization results derived with GA.

Methodology

The BA algorithm is implemented in this study to optimize reservoir operation. Bats, the only winged mammals, can determine their locations while flying using sound emission and reception, which is called echolocation. Their population is approximately 20% of all mammal species. Bat sizes range from the tiny bumblebee bat (with mass ranging from 1.5 to 2 g) to the giant bats with wingspan of about 2 m weighing approximately 1 kg (Altringham 1996; Colin 2000).

Most microbats are insectivores and use a type of sonar, called echolocation, to detect prey, avoid obstacles, and locate their roosting crevices in the dark. Bats emit sound pulses while flying and listen to their echoes from surrounding objects to assess their own location and those of the echoing objects (Yang and Gandomi 2012).

Each pulse has a constant frequency (usually in the range of 25×10^3 to 150×10^3 Hz) and lasts a few thousandths of a second (up to approximately 8 to 10 ms). About 10 to 20 sounds are emitted every second with the rate of emission up to approximately 200 pulses per second when they fly near their prey while hunting. If the interval between two successive sound bursts is less than 300 to 400 μs, bats cannot process them for path-finding purposes (Yang 2010).

As the speed of sound in air is typically $v = 340$ m/s, the wavelength (λ) of the ultrasonic sound bursts with a constant frequency (f) is given by (Yang and Gandomi 2012)

$$\lambda = \frac{\nu}{f} \tag{1}$$

λ is in the range of 2 to 14 mm for the typical frequency range from 25×10^3 to 150×10^3 Hz. Such wavelengths are of the same order of magnitude of their prey sizes.

Bats emit pulses as loud as 110 dB, which are in the ultrasonic region (frequency range of human hearing is between 20 and 20,000 Hz). The loudness also varies from the loudest when searching for prey to a quieter base when homing towards the prey. The travelling range of such short pulses is typically a few meters (Richardson 2008).

Microbats can avoid obstacles as small as thin human hairs. Such echolocation behavior of microbats can be formulated in such a way to make it possible to create the bat-inspired optimization algorithm using the following idealized rules (Yang 2010):

1. All bats use echolocation to sense distance and they can discern the difference between food or prey and background barriers.
2. Bats fly randomly with velocity ν_l at position y_l with a fixed frequency $f_{\min}$, varying wavelength λ, and loudness A_0 to search prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the pulsation rate, depending on the proximity of their target.
3. The loudness can vary from a large (positive) A_0 to a minimum constant value $A_{\min}$.

In general the frequency (f) is in the range of $[f_{\min}, f_{\max}]$ and corresponds to a range of wavelengths $[\lambda_{\min}, \lambda_{\max}]$. In actual implementations, one can adjust the range by adjusting the wavelengths (or frequencies) and the detectable range (or the largest wavelength) should be chosen such that it is comparable to the size of the domain of interest, and then toning down to smaller ranges. For simplicity, f has been assumed in the range of $[0, f_{\max}]$.

The pulsation rate (r) is in the range of [0, 1], where 0 means no pulses at all and 1 means the maximum pulsation rate. Based on these approximations and idealization, the basic steps of the BA have been summarized in the flowchart shown in Fig. 1 for minimization problems.

According to Fig. 1, after determination of prey (objective function) and producing the initial situation of bats (position, velocity, frequency, pulsation, loudness: y_l, ν_l, f_l, r_l, and A_l, respectively), the objective function is used to evaluate situations. The following are the rules to update the lth bat's position (y_l) and velocity (ν_l) in a d-dimensional search space ($l = 1, 2, \ldots, n$) (update situations). The new positions $[y_l(t)]$ and velocities $[\nu_l(t)]$ at time step (t) are given by (Yang and Gandomi 2012)

$$f_l = f_{\min} + (f_{\max} - f_{\min}) \times \boldsymbol{\beta} \tag{2}$$

$$\nu_l(t) = [y_l(t-1) - Y_*] \times f_l t = 1, 2, \ldots, T \tag{3}$$

$$y_l(t) = y_l(t-1) + \nu_l(t) t = 1,\ 2, \ldots, T \tag{4}$$

where $y_l(t-1)$ = position at time step $t-1$; $\boldsymbol{\beta}$ = random vector in the range of [0, 1] drawn from a uniform distribution; Y_* = current global best location (solution) determined after comparing all the solutions among all the n bats; and T = total period of assessment.

Because the product $\lambda_l \times f_l$ is the velocity increment, either f_l or λ_l can be used to adjust the velocity change while the other factor (λ_l or f_l) is assumed as a fixed value, depending on the type of problem of interest. In this implementation, the values of $f_{\min} = 0$ and $f_{\max} = 100$ were used based on the domain size of the problem. Initially, a frequency value drawn uniformly from the range of $[f_{\min}, f_{\max}]$ was assigned to each bat. In practical implementations, the positions of the bats are obtained from the solution of the optimization problem.

J. Water Resour. Plann. Manage., 2015, 141(8): 04014097

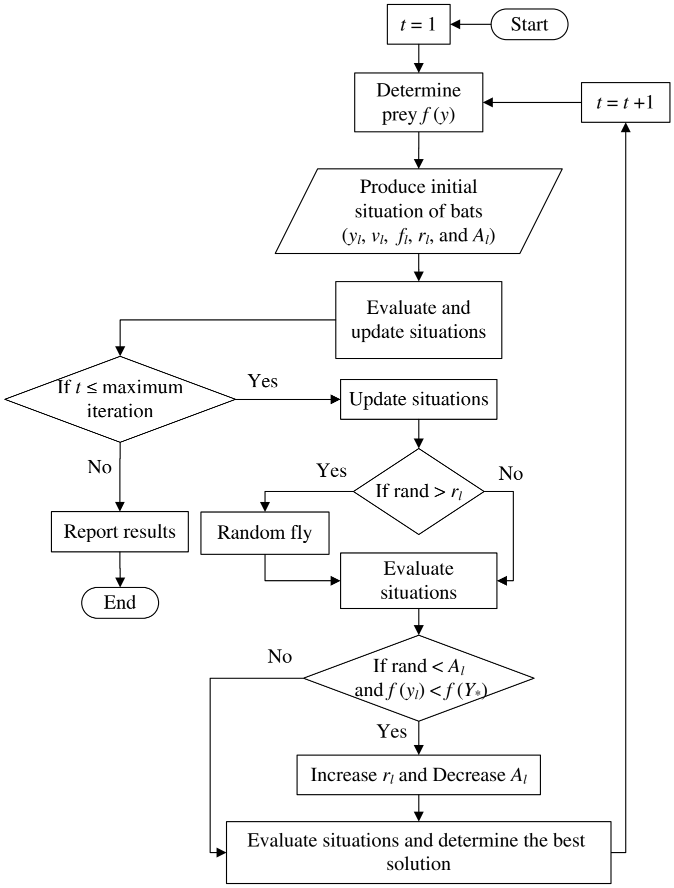

Fig. 1. Bat algorithm flowchart

For the local search part (random fly), once a solution has been selected among the current best solutions, a new solution for each bat is generated locally using random walk (Yang and Gandomi 2012)

$$y(t) = y(t-1) + \varepsilon A(t) t = 1,\ 2,\ \ldots, T \tag{5}$$

where ε = random number in the range of [−1,1]; and $A(t)$ = average loudness of all the bats at the tth time step. The value of $A(t)$ is reduced while approaching the optimum solution by using a rate called random walk rate.

Updating the velocities and positions of bats is similar to the procedure in the standard PSO algorithm (Kennedy and Eberhart 2001) because f_l essentially controls the pace and range of the movement of the swarming particles. So the BA can be considered as a combination of the standard PSO and intensive local search controlled by the loudness and pulsation rate.

The loudness (A_l) and the pulsation rate (r_l) are updated according to the iteration steps. The loudness usually decreases once a bat has found its prey, while the pulsation rate increases. Thus, the loudness can be chosen as any value of convenience. For example, the values of $A_0 = 1$ and $A_{\min} = 0$ can be used, where the zero value means that a bat has just found the prey and temporarily stops emitting any sound. The pulsation rate (r_l) at each time step is calculated as follows:

$$r_l^{t+1} = r_l^0[1 - \exp(-\gamma t)] A_l^{t+1} = \alpha A_l^t t = 1,\ 2,\ \ldots, T \tag{6}$$

where α and γ = constant values. In fact, α is similar to the cooling factor in the SA algorithm (Kirkpatrick et al. 1983). For any $0 < \alpha < 1$ and $\gamma > 0$, $A_l^t \to 0$ and $r_l^t \to r_l^0$ when $t \to \infty$.

Choosing the correct values for the parameters α and γ requires experimentation. Initially, each bat should have different values of loudness and pulsation rate, and this can be achieved by randomization. Their loudness and pulsation rates are updated only if the solutions improve, which means that the bats are moving towards the optimal solution.

Case Studies

Mathematical Benchmark Problems to Verify the BA Algorithm

Three benchmark functions (spherical, Rosenbrock, and Bukin-6) are introduced in this section (Fig. 2). They are useful to evaluate the BA in finding the optimum solutions of optimization problems. Eqs. (7)–(9) define the spherical, Rosenbrock, and Bukin-6 functions, respectively

$$f(x) = \sum_{j=1}^{m} x_j^2 - 5.12 \le x_j \le 5.12 \tag{7}$$

$$f(x) = \sum_{j=1}^{m-1} [100\,(x_{j+1} - x_j^2)^2 + (x_j + 1)^2] - 2.048 \le x_j \le 2.048 \tag{8}$$

$$f(x_1, x_2) = 100\sqrt{|x_2 - 0.01x_1^2|} + 0.01|x_1 + 10| - 15 \le x_1 \le -5, -3 \le x_2 \le 3 \tag{9}$$

where $f()$ = mathematical function; x = independent variable; j = index of x; and m = total number of the x. The spherical and Rosenbrock functions have one global minimum, whereas the Bukin-6 function has several local minima, which complicates finding its global optimal solution. The global optimal value of the spherical function (herein defined as a 20-dimensional function) is located at the origin of coordinates (at zero). The optimal value of the Rosenbrock and Bukin-6 functions, herein represented as two-dimensional functions, is equal to zero corresponding to the points (1,1) and (–10,1), respectively.

For comparison, the GA was also applied to obtain the optimal solutions of the previously mentioned benchmark functions. Because evolutionary algorithms generally start from a set of random solutions, assessing their performances needs multiple runs. Therefore, to test the effect of the initial starting points, 10 different runs for GA and BA were performed in this study.

Optimizing Reservoir System Operation with the BA Algorithm

Fig. 3 shows the schematic of a reservoir with its associated fluxes. Maximizing the total operation benefits constitutes the objective function of the reservoir operation problems

$$\text{Maximize } B = \sum_{i=1}^{N} \sum_{t=1}^{T} b_i(t)\,\mathrm{Re}_i(t) \tag{10}$$

where B = total benefit of the multireservoir system; i = index of reservoirs, $i = 1, 2, \ldots, N$; N = total number of reservoirs; t = operation periods; T = total number of operation periods; $b_i(t)$ = unit benefit function of the reservoir i during period t; and $\mathrm{Re}_i(t)$ = summation of release and spill of the reservoir i during period t.

J. Water Resour. Plann. Manage., 2015, 141(8): 04014097

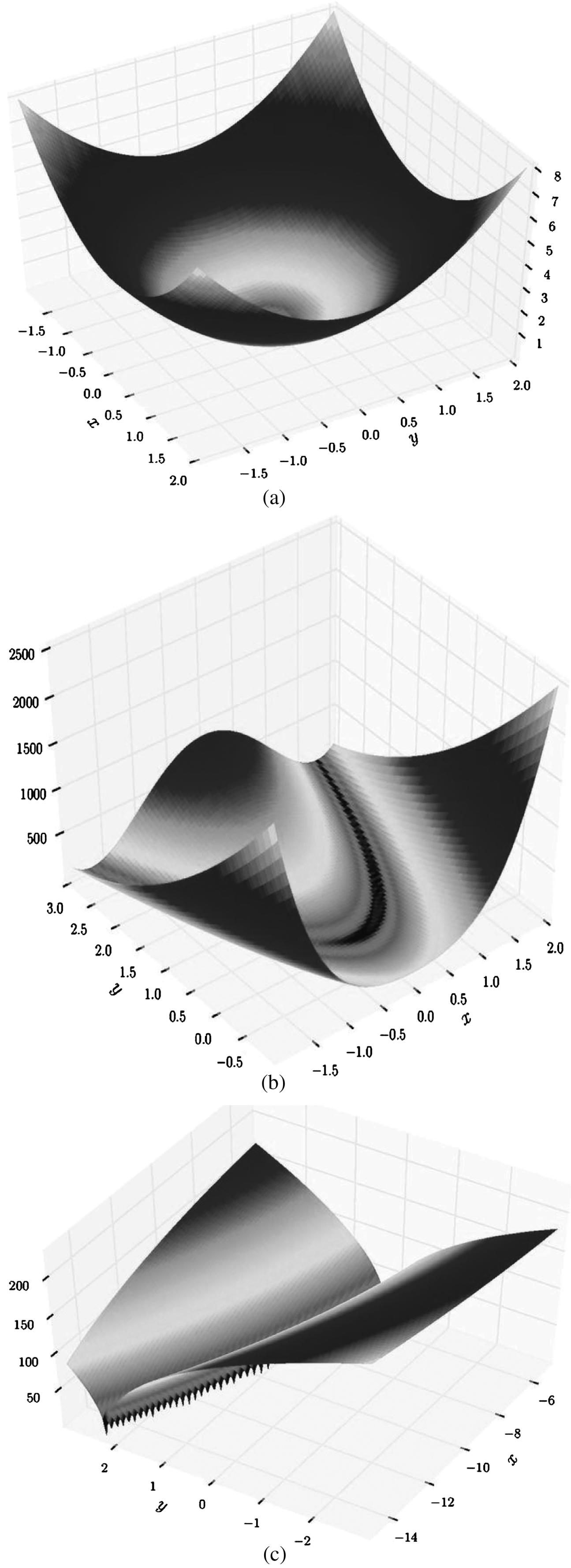

Fig. 2. Mathematical test functions: (a) spherical; (b) Rosenbrock; (c) Bukin-6

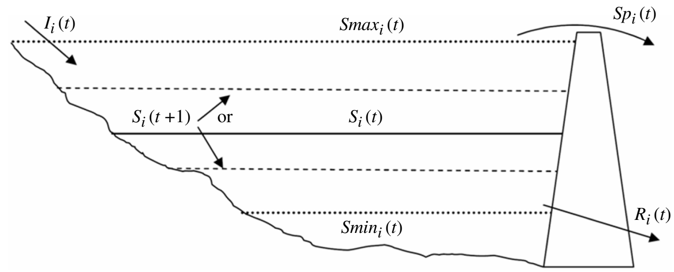

Fig. 3. Schematic of a reservoir with fluxes

There are several constraints imposed on reservoir operation. The continuity constraint over operating period t for reservoir i is

$$S_i(t+1) = S_i(t) + I_i(t) + \mathbf{M}_{N\times N}[R_i(t) + \mathrm{Sp}_i(t)]t = 1,\ 2,\ \ldots, T, i = 1, 2, \ldots, N \tag{11}$$

where $S_i(t)$ and $S_i(t+1)$ = storage of the reservoir i at the beginning of the periods t and $t+1$, respectively; $I_i(t)$ = net of the river flow, precipitation on lake, evaporation from lake, and groundwater losses and gains for the reservoir i during the period t; $R_i(t)$ = release of the reservoir i during the period t; $\mathrm{Sp}_i(t)$ = spill of the reservoir i during the period t; and $\mathbf{M} = N \times N$ matrix of indexes of reservoir connections describing the manner in which releases and spills from upstream reservoirs accrue to the ith reservoir.

Releases from the reservoirs (through the turbines or diverted for irrigation) are constrained as

$$R_i^{\min}(t) \le R_i(t) \le R_i^{\max}(t)t = 1, 2, \ldots, T, i = 1, 2, \ldots, N \tag{12}$$

in which $R_i^{\min}(t)$ and $R_i^{\max}(t)$ = minimum and maximum allowable releases of the reservoir i during period t, respectively. The constraint on reservoir storage is defined as

$$S_{\min_i}(t) \le S_i(t) \le S_{\max_i}(t)t = 1, 2, \ldots, T, i = 1, 2, \ldots, N \tag{13}$$

where $S_{\min_i}(t)$ and $S_{\max_i}(t)$ = minimum and maximum allowable storages of the reservoir i during period t, respectively. The spill $[\mathrm{Sp}_i(t)]$ occurs when the storage exceeds its maximum value

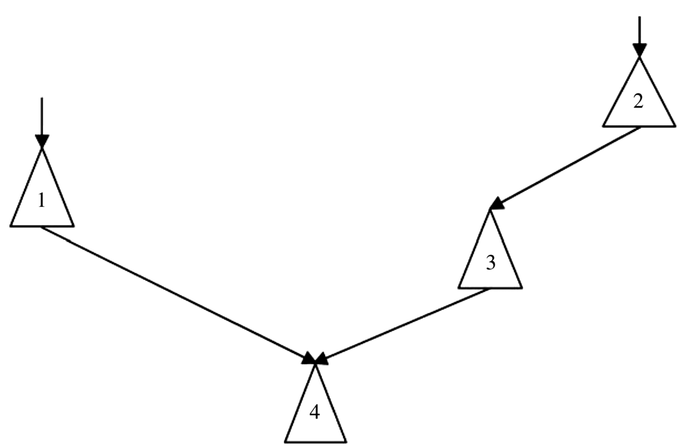

Fig. 4. Schematic of the four-reservoir system

$$\mathrm{Sp}_i(t) = S_i(t) + I_i(t) - S_{\max_i}(t) t = 1,2,\ldots,T, i = 1,2,\ldots,N \tag{14}$$

In some cases, the initial and final storages of each reservoir are considered as fixed values (called carryover)

$$S_i(1) = S_i^{\text{initial}} i = 1,2,\ldots,N \tag{15}$$

$$S_i(T+1) = S_i^{\text{target}} i = 1,2,\ldots,N \tag{16}$$

in which S_i^{initial} and S_i^{target} = initial and target storages of the reservoir i. If the reservoir storage does not meet the constraints in Eqs. (15) and (16), the results are infeasible and a penalty function is applied. The penalty function, $g_i(t)$ applied to the constraint in Eq. (16) is expressed as follows:

$$g_i(t) = k_1[S_i(T+1) - S_i^{\text{target}}]^2 S_i(T+1) \neq S_i^{\text{target}} \tag{17}$$

in which k_1 = penalty constant. Moreover, if the reservoir storage violates its minimum or maximum values, the following penalty functions [$h_i(t)$ and $w_i(t)$] are applied:

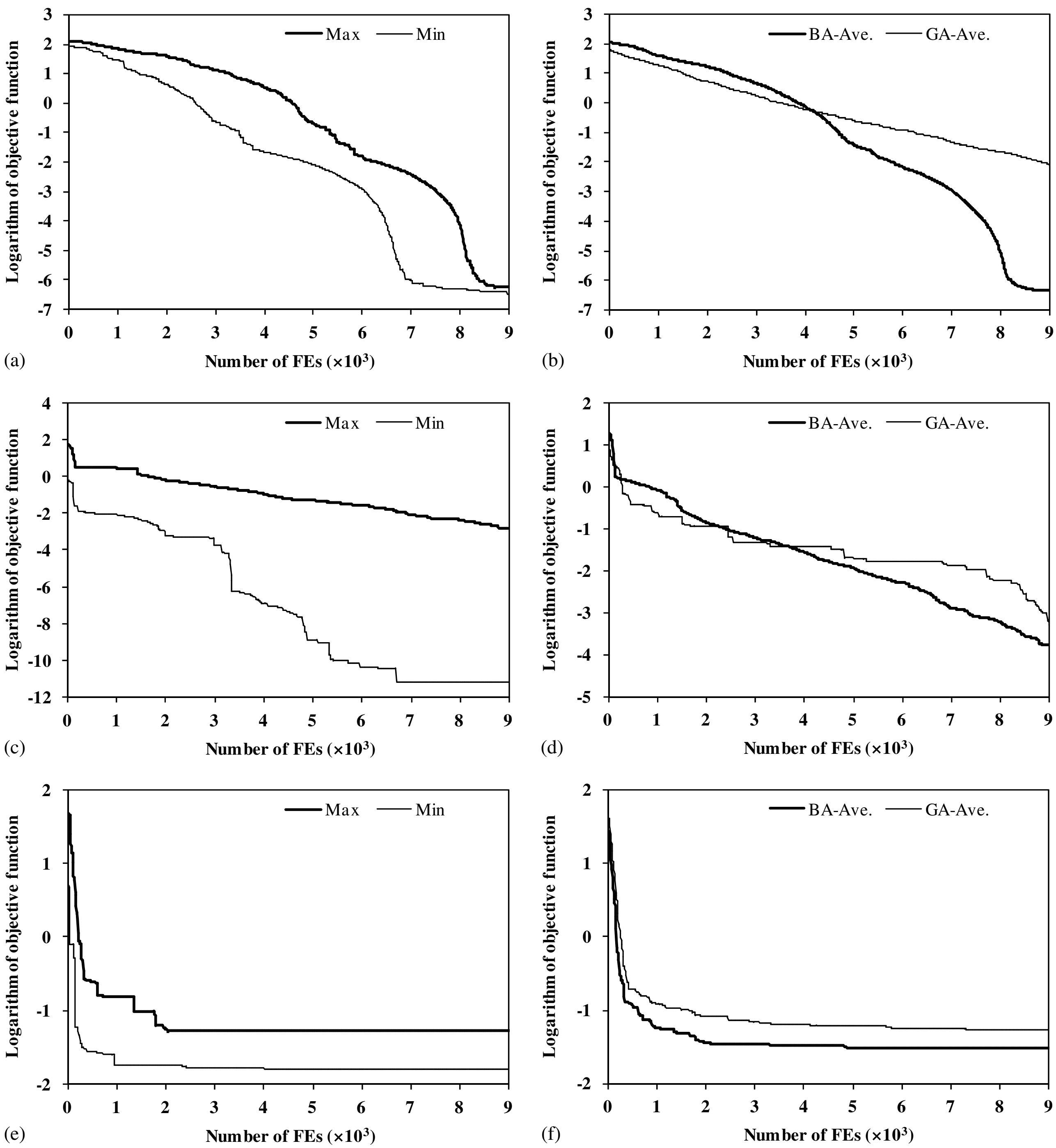

Fig. 5. Minimum (best) and maximum (worst) rates of convergence of the BA algorithm from 10 runs for the (a) spherical function; (c) Rosenbrock function; (e) Bukin-6 function; average rates of convergence of the GA and BA algorithms from 10 runs for the (b) spherical function; (d) Rosenbrock function; (f) Bukin-6 function

Table 1. Characteristics of the BA and GA Used with the Test Functions

Characteristic	Spherical	Rosenbrock	Bukin-6
Population	10	10	10
Minimum frequency ($f_{\min}$)	0	0	0
Maximum frequency ($f_{\max}$)	1	1	2
Number of evaluation	9,010	9,010	9,010
Maximum loudness (A_0)	0.9	0.95	0.9
Minimum loudness ($A_{\min}$)	0.03	0.05	0.1
Random walks factor	0.03	0.01	0.05
Random walks rate	5	6	5
Number of dimensions (variables)	20	2	2
Number of constraints	2	2	2
Average time of calculation	6 s	11 s	27 s

$$h_i(t) = k_2[S_{\min_i}(t) - S_i(t)]^2 S_i(t) < S_{\min_i}(t) \tag{18}$$

$$w_i(t) = k_3[S_i(t) - S_{\max_i}(t)]^2 S_i(t) > S_{\max_i}(t) \tag{19}$$

in which k_2 and k_3 = penalty constants. Thus, the penalized objective function is written in the following form:

$$\text{Maximize } B = \sum_{i=1}^{N}\sum_{t=1}^{T} b_i(t)\text{Re}_i(t) - \sum_{i=1}^{N}\sum_{t=1}^{T} g_i(t) - \sum_{i=1}^{N}\sum_{t=1}^{T} h_i(t) - \sum_{i=1}^{N}\sum_{t=1}^{T} w_i(t) \tag{20}$$

Single-Reservoir System Operation

The Karoun-4 reservoir in Iran is herein used as the case study for single-reservoir operation applying the BA. This reservoir was built on the Karoun River for hydropower generation. The Karoun-4 reservoir generic location is specified by coordinates 31°35′ N and 50°24′ E. The minimum and maximum reservoir volumes are $1{,}141 \times 10^6$ and $2{,}190 \times 10^6$ m^3, respectively. In addition, its power plant capacity (PPC) is equal to $1{,}000 \times 10^6$ W. This reservoir's operation is herein simulated for the 5-year period 1975–1980, with a monthly time step. The objective function of this operation problem is the maximization of generated power, which is equivalent to the minimization of the deficit with respect to the installed capacity [Eq. (21)], with constraints presented in the previous section [Eqs. (11)–(19)] with one reservoir ($N = 1$)

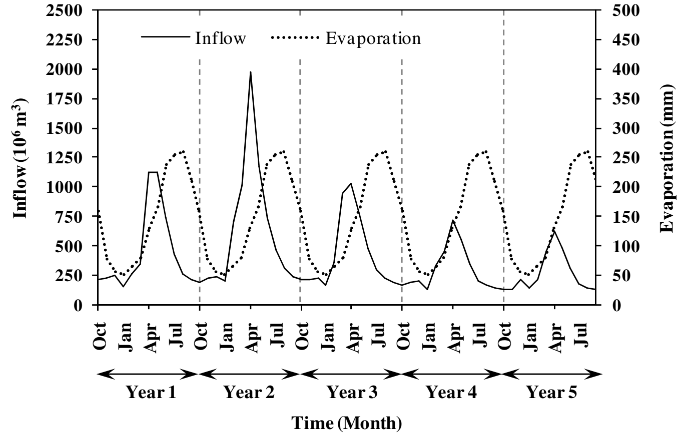

Fig. 6. Average volume of inflow and evaporation depth in the Karoun-4 reservoir

Table 3. Parameters of the GA and BA Used in the Reservoir System Problems

Parameter	Karoun-4	Four-reservoir system
Population	70	50
Minimum frequency ($f_{\min}$)	0	0
Maximum frequency ($f_{\max}$)	5	5
Number of evaluation	70,070	500,050
Maximum loudness (A_0)	0.95	0.95
Minimum loudness ($A_{\min}$)	0.1	0.1
Random walks factor	0.1	0.1
Random walks rate	5	5
Number of dimensions (variables)	61	48
Number of constraints	361	196
Average time of calculation	767 s	1,582 s

$$\text{Minimize } D = \sum_{t=1}^{T}\left[1 - \frac{P(t)}{\text{PPC}}\right] \tag{21}$$

in which D = total power deficit (objective function); and $P(t)$ = generated power in period t.

Table 2. Statistical Measures from 10 Runs of the GA and BA for the Spherical, Rosenbrock, and Bukin-6 Functions

Run number	Spherical GA (10^{-3})	Spherical BA (10^{-7})	Rosenbrock GA (10^{-4})	Rosenbrock BA (10^{-7})	Bukin-6 GA (10^{-2})	Bukin-6 BA (10^{-2})	Global
1	5.78	4.31	26.90	482.00	8.6	2.5	0
2	6.81	4.12	4.76	0.00007	4.8	1.7	
3	6.98	5.60	2.36	1.32	5.4	2.8	
4	6.37	3.98	10.55	0.0139	2.3	3.3	
5	9.85	4.29	0.37	0.00008	4.5	3.1	
6	8.80	4.20	0.11	555.00	5.7	1.8	
7	8.10	4.02	0.14	136.00	6.7	1.6	
8	7.36	4.20	4.86	0.0938	6.3	4.9	
9	15.14	4.97	1.38	16,000.00	4.8	3.9	
10	1.38	3.36	0.55	0.00014	5.2	5.3	
Best	1.38	3.36	0.11	0.00007	2.3	1.6	
Average	7.66	4.31	5.20	1,720.00	5.4	3.1	
Worst	15.14	5.60	26.90	16,040.00	8.6	5.3	
Standard deviation	3.47	0.60	8.29	5,030.00	8.6	2.5	
Coefficient of variation	0.45	0.14	1.59	0.00292	1.6	0.8	

Four-Reservoir System Operation

This (maximization) problem was introduced and solved by Chow and Cortes-Rivera (1974). This problem is a hypothetical example of a four-reservoir system operation with the aim of maximizing the total benefit during the operation period (equal to 1 year). A schematic model of this problem is shown in Fig. 4. Eqs. (11)–(20) constitute the simulation and optimization equations for this problem. The data required for modeling the system such as inflows, reservoir storages, and other features are available in Murray and Yakowitz (1979).

Table 4. Statistical Outputs from 10 Runs of the GA and BA for the Reservoir System Problems

	Karoun-4			Four-reservoir system		
Run number	GA (10^{-4})	BA (10^{-10})	Global	GA	BA	Global
1	1.6726	1.2330	1.2132	280.25	308.20	308.29
2	1.5491	1.2351		280.12	307.12	
3	1.8647	1.2544		273.94	307.41	
4	1.7521	1.2355		281.12	307.93	
5	1.9867	1.2366		272.62	308.09	
6	1.7530	1.2502		279.61	307.95	
7	1.9312	1.2367		282.90	308.09	
8	1.5697	1.2340		275.89	308.03	
9	1.8418	1.2351		277.47	307.62	
10	1.5350	1.2405		279.74	308.02	
Best	1.5350	1.2330		282.90	308.20	
Average	1.7456	1.2391		278.37	307.84	
Worst	1.9867	1.2544		272.62	307.12	
Standard deviation	0.1617	0.0073		3.30	0.35	
Coefficient of variation	0.0926	0.0059		0.0118	0.0011	

Results and Discussions

The results obtained for the optimization of the benchmark mathematical functions, single-reservoir, and multireservoir systems are presented in the next three sections.

Results of the BA Verification Using the Mathematical Benchmark Functions

Fig. 5 shows the maximum and minimum of the objective function using the BA and the average rate of convergence using the BA and GA achieved for the three benchmark functions.

Fig. 5 depicts a more rapid convergence of the BA than the GA. Also, the former algorithm approaches the global optimum more closely than the latter. This figure demonstrates that the BA converges faster to more accurate solutions than the GA.

The characteristics of the BA and GA used in this study are listed in Table 1. A summary of the results of the 10 different intercomparison runs are shown in Table 2. The low value of the standard deviation for the BA proves the high reliability of its

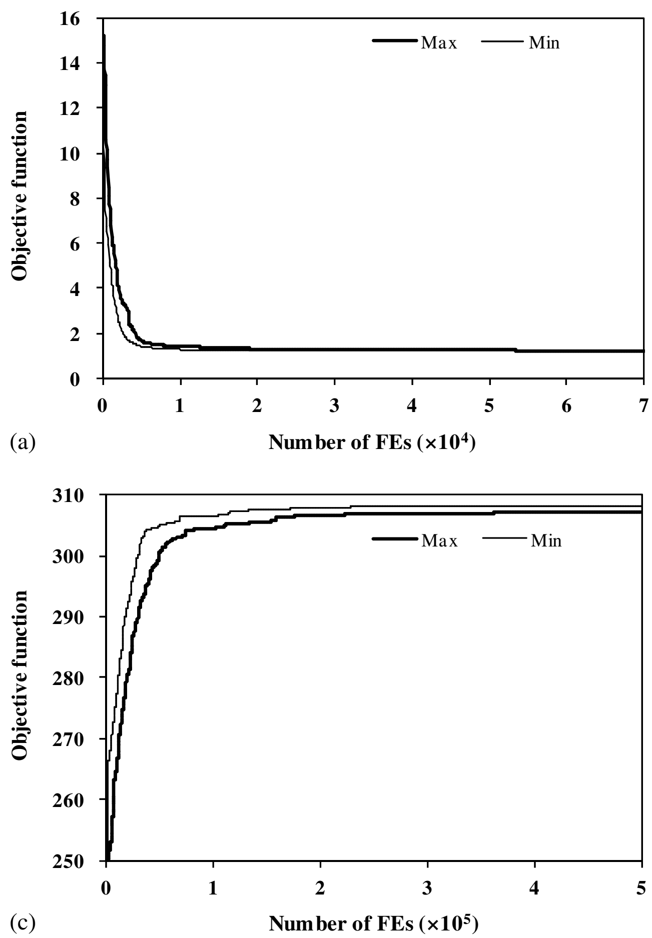

Fig. 7. Minimum (best) and maximum (worst) rates of convergence of the BA algorithm over 10 runs for the (a) Karoun-4 reservoir; (c) four-reservoir system; average rates of convergence of the GA and BA algorithms from 10 runs for the (b) Karoun-4 reservoir; (d) four-reservoir system

results for the previously mentioned functions, which show negligible differences between results obtained from various runs of the BA.

Results for the Single-Reservoir (Karoun-4) System Operation

Fig. 6 shows the average volume of inflow and evaporation depth in the Karoun-4 reservoir during the 5-year study period.

The GA and NLP were applied to optimize the Karoun-4 reservoir operation and compared with the results from the BA. The *MATLAB 7.6* optimization toolbox was used to implement the GA and the BA. The NLP method was implemented with the *Lingo 11.0* optimization software. The NLP method's solution is considered the global optimum and was used to evaluate the BA's ability to approach a global solution. The parameters for the GA and BA algorithms were determined by a trial-and-error technique (Table 3).

The objective function value from the NLP method equals 1.213, herein considered as the global optimal solution for this problem in this study. The GA and BA converged to 1.535 and 1.233 after approximately 70,000 objective-function evaluations (FEs), respectively. Table 4 shows the results for this problem. According to the latter results, the amount of variation of the objective function obtained from the BA in 10 different runs is insignificant and close to zero. Calculating close solutions in different runs is considered as a self-validating property (precision) of an algorithm. In this problem, the coefficient of variation of the BA in 10 runs is approximately 16 times smaller than that of the GA (Table 4).

Fig. 7 shows the maximum and minimum objective function rates of convergence of the BA for Karoun-4 hydropower reservoir and the four-reservoir system. This figure depicts the convergence of the GA and BA after approximately 70,000 FEs. The BA's convergence rate is superior to that of the GA in addition to yielding a better objective function value. Fig. 8 illustrates the amount of release from the reservoir, variation of reservoir storage, and generated power during the operation period. Based on Fig. 8, the output variables from the BA are very close or identical to the NLP outputs. With regards to the GA, there are differences between the solution variables obtained with this method and the optimal variables obtained with the NLP in some months.

Results for the Four-Reservoir System Operation

This problem has been studied by several researchers. Chow and Cortes-Rivera (1974) solved the mentioned problem using the LP method and reported the optimal value of the objective function as being equal to 308.26. Murray and Yakowitz (1979) offered the optimal objective function for this problem being equal to 308.23 using the differential dynamic programming (DDP) method. Bozorg-Haddad et al. (2011a) solved this problem using the honey-bee mating optimization (HBMO) algorithm. They used 220 and 5,000 for the population size and the number of iterations in the HBMO algorithm, respectively (approximately 1 million FEs). The latter authors presented an average value equal to 307.50 for the objective function from 10 runs of the HBMO algorithm. Moreover, they solved this problem using the LP method with the *Lingo 8.0* software. LP produced 308.29 as the optimal objective function for this problem. In the present study, the value of 308.29 achieved with the BA is considered to be the global optimal solution and the comparisons are made based on it.

The parameters of the GA and BA used in this study are written in Table 3 (approximately 500,000 evaluations for both methods). The values of these parameters were determined by trial and error. The average values of the objective function from 10 runs of the GA and BA are equal to 299.70 and 307.84, respectively. Table 4 shows the summary of results calculated with the two algorithms.

With respect to the results in Table 4, in addition to a suitable performance of the BA in reaching a global optimal solution, the variation of the objective function in 10 different runs of this algorithm is low with a standard deviation equal to 0.35, while the GA exhibits a standard deviation equal to 3.30. Based on the standard deviation, the GA shows results' variations approximately 9.5 times larger than those of the BA results in 10 runs. The average values of the objective function from 10 different runs of the GA and the BA are 90.30 and 99.86% of the global optimal solution, respectively. Fig. 7 also illustrates the BA's convergence characteristics and the GA's and BA's average convergence characteristics from 10 runs for the four-reservoir system. Fig. 8 shows calculated monthly reservoir releases, storages, and power production using the BA for the

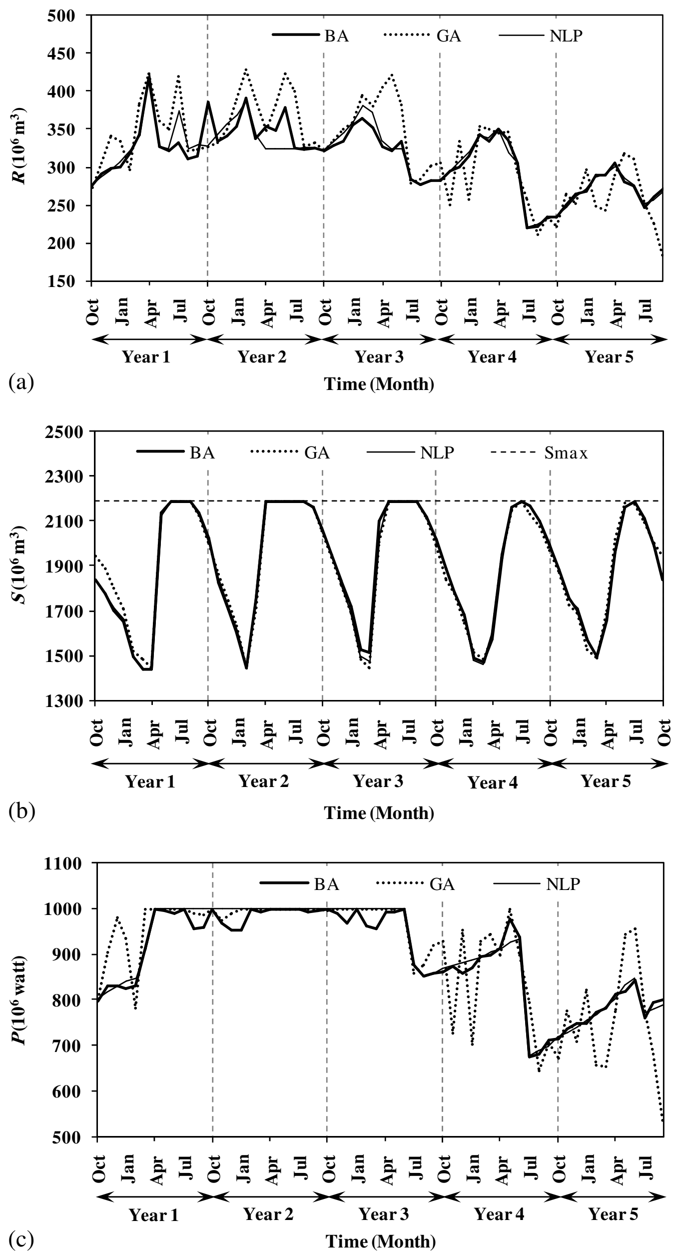

Fig. 8. Monthly reservoir (a) releases; (b) storages; (c) power production from the BA for the Karoun-4 reservoir problem

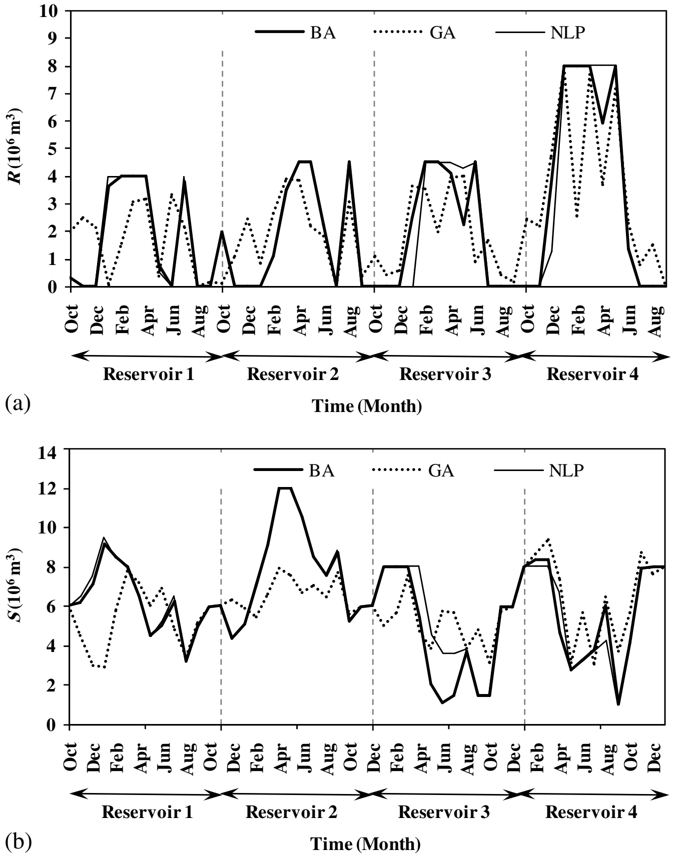

Fig. 9. Monthly reservoir (a) releases; (b) storages obtained from GA, BA, and LP for the four-reservoir problem

Karoun-4 reservoir problem. Graphs of release and storage variation in each reservoir of the four-reservoir system obtained using the GA and BA are plotted in Fig. 9.

Concluding Remarks

Evolutionary and metaheuristic algorithms are powerful and versatile optimization methods. These algorithms overcome the shortcomings of the traditional optimization methods and help managers and engineers deal with complex engineering optimization problems. The BA's accuracy as a new metaheuristic algorithm was verified in this research with several mathematical benchmark optimization problems, and its superior performance was proved by comparing its results with those of other well-known optimization methods.

In addition, the developed and verified BA was applied to a real case study. The BA demonstrated its applicability in achieving optimal operation rules for the Karoun-4 reservoir in Iran. The standard deviation of results obtained from several runs was approximately equal to zero, which shows high reliability of the BA in achieving the global optimum of this optimization problem. Also, the average of different results (1.24) was closer to the global result (1.21) than the GA's (1.75). Moreover, the BA's advantages and superior performance were highlighted by employing a complex engineering problem in the field of multireservoir operation. The BA achieved closer values (with average equal to 307.84) to the NLP solution (308.29) than the GA (with average equal to 278.37) for the multireservoir operation problem. The BA was capable of reaching better optimal solutions compared with the conventional optimization methods that are commonly applied in reservoir operation problems.

Notation

The following symbols are used in this paper:

$A_{\min}$ = minimum loudness (dB);
A_0 = maximum loudness (dB);
$A(t)$ = average loudness of all the bats during the tth time step (dB);
B = total benefit of the multireservoir system;
$b_i(t)$ = unit benefit function of the reservoir i during period t;
D = total power deficit;
f = wave frequency (1/s);
$f_{\max}$ = maximum wave frequency (1/s);
$f_{\min}$ = minimum wave frequency (1/s);
$f(x)$ = mathematical function;
$g_i(t)$ = penalty functions;
$h_i(t)$ = penalty functions;
i = index of reservoirs;
$I_i(t)$ = net of the river flow, precipitation on lake, evaporation from lake, and groundwater losses or gains for the reservoir i during period t;
j = index of the mathematical independent variables;
k_1, k_2, and k_3 = penalty constant;
l = index of bats;
$\mathbf{M}$ = $N \times N$ matrix of indexes of reservoir connections;
m = total number of the mathematical independent variables;
N = total number of reservoirs;
n = total number of bats;
$P(t)$ = generated power during period t (W);
PPC = power plant capacity (W);
r_l = lth bat's pulsation rate;
$R_i(t)$ = release of the reservoir i during the period $t(\times 10^6\ \mathrm{m}^3)$;
$R_i^{\max}(t)$ = maximum allowable release of the reservoir i during period $t(\times 10^6\ \mathrm{m}^3)$;
$R_i^{\min}(t)$ = minimum allowable release of the reservoir i during period $t(\times 10^6\ \mathrm{m}^3)$;
$\mathrm{Re}_i(t)$ = summation of release and spill of the reservoir i during period $t(\times 10^6\ \mathrm{m}^3)$;
$S_i(t)$ = storage of the reservoir i at the beginning of the period $t(\times 10^6\ \mathrm{m}^3)$;
$S_i(t+1)$ = storage of the reservoir i at the beginning of the period $t+1(\times 10^6\ \mathrm{m}^3)$;
S_i^{initial} = initial storage of the reservoir $i(\times 10^6\ \mathrm{m}^3)$;
$S_{\max_i}(t)$ = the maximum allowable storage of the reservoir i during period $t(\times 10^6\ \mathrm{m}^3)$;
$S_{\min_i}(t)$ = minimum allowable storage of the reservoir i during period $t(\times 10^6\ \mathrm{m}^3)$;
S_i^{target} = target storage of the reservoir $i(\times 10^6\ \mathrm{m}^3)$;
$\mathrm{Sp}_i(t)$ = spill of reservoir i during period $t(\times 10^6\ \mathrm{m}^3)$;
T = total number of operation periods;
t = index for the operation periods;
$w_i(t)$ = penalty functions;
x = mathematical independent variable;
y_l = lth bat position;
Y_* = current global best position;
α = constant value;
$\boldsymbol{\beta}$ = random uniform vector in the range of [0, 1];
ε = random number in the range of [−1,1];
γ = constant value;

λ = wavelength (m);
λ_{max} = maximum wave length (m);
λ_{min} = minimum wave length (m); and
ν = wave velocity (m/s).

References

Altringham, J. D. (1996). *Bats: Biology and behavior*, Oxford University Press, U.K.

Baziar, A., Kavoosi-Fard, A., and Zare, J. (2013). "A novel self adaptive modification approach based on bat algorithm for optimal management of renewable MG." *J. Intell. Learn. Syst. Appl.*, 5(1), 11–18.

Bozorg-Haddad, O., Adams, B. J., and Mariño, M. A. (2008). "Optimum rehabilitation strategy of water distribution systems using the HBMO algorithm." *J. Water Supply Res. Technol. AQUA*, 57(5), 337–350.

Bozorg-Haddad, O., Afshar, A., and Mariño, M. A. (2011). "Multireservoir optimisation in discrete and continuous domains." *Proc. Inst. Civ. Eng. Water Manage.*, 164(2), 57–72.

Chen, Q., Chen, D., Han, R., Li, R., Ma, J., and Blanckaert, K. (2012). "Optimizing the operation of the Qingshitanreservoir in the Lijiangriver for multiple human interests and quasi-natural flow maintenance." *J. Environ. Sci.*, 24(11), 1923–1928.

Chow, V. T., and Cortes-Rivera, G. (1974). "Application of DDDP in water resources planning." *Research Rep. No. 78*, Univ. of Illinois at Urbana-Champaign, Water Resources Center, Urbana-Champaign, IL.

Colin, T. (2000). *The variety of life*, Oxford University Press, U.K.

Deep, K., and Bansal, J. C. (2009). "Mean particle swarm optimization for function optimization." *Int. J. Comput. Intell. Stud.*, 1(1), 72–92.

Fallah-Mehdipour, E., Bozorg-Haddad, O., Beygi, S., and Mariño, M. A. (2011a). "Effect of utility function curvature of Young's bargaining method on the design of WDNs." *Water Resour. Manage.*, 25(9), 2197–2218.

Fallah-Mehdipour, E., Bozorg-Haddad, O., and Mariño, M. A. (2011b). "MOPSO algorithm and its application in multipurpose multireservoir operations." *J. Hydroinf.*, 13(4), 794–811.

Fallah-Mehdipour, E., Bozorg-Haddad, O., and Mariño, M. A. (2012). "Real-time operation of reservoir system by genetic programming." *Water Resour. Manage.*, 26(14), 4091–4103.

Fallah-Mehdipour, E., Bozorg-Haddad, O., and Mariño, M. A. (2013). "Developing reservoir operational decision rule by genetic programming." *J. Hydroinf.*, 15(1), 103–119.

Geem, Z. W., Kim, J. H., and Loganathan, G. V. (2001). "A new heuristic optimization algorithm: Harmony search." *Simulation*, 76(2), 60–68.

Hormwichian, R., Kangrang, A., and Lamom, A. (2009). "A conditional genetic algorithm model for searching optimal reservoir rule curves." *J. Appl. Sci.*, 9(19), 3575–3580.

Kennedy, J., and Eberhart, R. (1995). "Particle swarm optimization." *Proc., IEEE Int. Conf. of Neural Networks*, IEEE, New York, 1942–1945.

Kennedy, J., and Eberhart, R. (2001). *Swarm intelligence*, Academic, CA.

Kirkpatrick, S., Gelatt, C. D., and Vecchi, M. P. (1983). "Optimization by simulated annealing." *Science*, 220(4598), 671–680.

Koffka, K., and Ashok, S. (2012). "A comparison of BA, GA, PSO, BP, and LM for training feed forward neural networks in e-learning context." *Int. J. Intell. Syst. Appl.*, 4(7), 23–29.

Lingo 8.0 [Computer software]. Lingo Systems, Chicago.

Lingo 11.0 [Computer software]. Lingo Systems, Chicago.

Liu, P., Zhao, J., Li, L., and Shen, Y. (2012). "Optimal reservoir operation using stochastic dynamic programming." *J. Water Resour. Prot.*, 4(6), 342–345.

Malakooti, B., Kim, H., and Sheikh, S. (2012). "Bat intelligence search with application to multi-objective multiprocessor scheduling optimization." *Int. J. Adv. Manuf. Technol.*, 60(9–12), 1071–1086.

MATLAB 7.6 [Computer software]. Mathworks, Natick, MA.

Mitchell, M. (1998). *An introduction to genetic algorithms*, MIT Press, MA.

Mujumdar, P. P., and Ramesh, T. S. V. (1997). "Real-time reservoir operation for irrigation." *Water Resour. Res.*, 33(5), 1157–1164.

Murray, D. M., and Yakowitz, S. J. (1979). "Constrained differential dynamic programming and its application to multireservoir control." *Water Resour. Res.*, 15(5), 1017–1027.

Niknam, T., Sharifinia, S., and Azizipanah-Abarghooee, R. (2013). "A new enhanced bat-inspired algorithm for finding linear supply function equilibrium of GENCOs in the competitive electricity market." *Energy Convers. Manage.*, 76, 1015–1028.

Orouji, H., Bozorg-Haddad, O., Fallah-Mehdipour, E., and Mariño, M. A. (2013). "Estimation of Muskingum parameter by meta-heuristic algorithms." *Proc. Inst. Civ. Eng. Water Manage.*, 166(6), 315–324.

Ramesh, B., Mohan, V. C. J., and Ressy, V. C. V. (2013). "Application of bat algorithm for combined economic load and emission dispatch." *J. Electr. Eng. Telecommun.*, 2(1), 1–9.

Rashid, K. A., Al Diacon, G., and Popa, B. (2007). "Optimal operation of large hydropower reservoirs with unregulated inflows." *U.P.B. Sci. Bull., Ser. C*, 69(2), 25–36.

Reddy, V. U., and Manoj, A. (2012). "Optimal capacitor placement for loss reduction in distribution systems using bat algorithm." *IOSR J. Eng.*, 02(10), 23–27.

Richardson, P. (2008). *Bats*, Natural History Museum, London.

Seifollahi-Aghmiuni, S., Bozorg-Haddad, O., Omid, M. H., and Mariño, M. A. (2011). "Long-term efficiency of water networks with demand uncertainty." *Proc. Inst. Civ. Eng. Water Manage.*, 164(3), 147–159.

Seifollahi-Aghmiuni, S., Bozorg-Haddad, O., Omid, M. H., and Mariño, M. A. (2013). "Effects of pipe roughness uncertainty on water distribution network performance during its operational period." *Water Resour. Manage.*, 27(5), 1581–1599.

Shokri, A., Bozorg-Haddad, O., and Mariño, M. A. (2013). "Algorithm for increasing the speed of evolutionary optimization and its accuracy in multi-objective problems." *Water Resour. Manage.*, 27(7), 2231–2249.

Yang, X. S. (2008). *Nature-inspired meta-heuristic algorithms*, Luniver Press, U.K.

Yang, X. S. (2010). "A new metaheuristic bat-inspired algorithm." *Nature inspired cooperative strategies for optimization (NISCO 2010)*, J. R. Gonzalez, et al. eds., Springer, Berlin, 284, 65–74.

Yang, X. S. (2012). "Meta-heuristic optimization with applications: demonstration via bat algorithm." *Proc., 5th Bioinspired Optimization Methods and Their Applications (BIOMA2012)*, Bohinj, Slovenia, 23–34.

Yang, X. S., and Gandomi, A. H. (2012). "Bat algorithm: A novel approach for global engineering optimization." *Eng. Comput.*, 29(5), 464–483.