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WASPAS Application and Evolutionary Algorithm Benchmarking in Optimal Reservoir Optimization Problems

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Abstract: This study applies a recently developed evolutionary algorithm (EA) called state of matter search (SMS) to minimize the total energy deficit in the Karun4 reservoir, Iran. The operation of the Karun4 reservoir is influenced by several factors, which requires a multiple criteria framework for selecting the most suitable solution EA. Five EAs, in addition to the SMS, were evaluated for the reservoir operation problem on the basis of four performance criteria and the fitness function (FF) value. The priority assessment on the basis of FF value revealed that the SMS outperformed the other EAs in converging to the optimal solution. However, judged by the other four performance criteria, based on weighted aggregates sum product assessment (WASPAS) technique, particle swarm optimization (PSO) proved superior to the other EAs. This paper's results show that the selection of a solution EA for solving complex reservoir optimization problem requires a multicriteria decision-making process. Multiobjective evolutionary algorithms (MOEAs) are well-suited for the task. **DOI: 10.1061/(ASCE)WR.1943-5452.0000716.** © *2016 American Society of Civil Engineers.*

Author keywords: Optimal reservoir operation; Algorithm benchmarking; States of matter search algorithm; Performance criteria; Weighted aggregates sum product assessment (WASPAS) technique.

Introduction

Evolutionary algorithms (EAs) and other metaheuristics are useful tools in achieving sustainable water resources management under growing water use and limited water resources. EAs have been widely applied in various real-life water resources management problems such as reservoir system operation (Tu et al. 2003; Dariane and Momtahen 2009; Li et al. 2010; Fallah-Mehdipour et al. 2011, 2012; Steinschneider et al. 2014; Taghian et al. 2014; Aboutalebi et al. 2015; Giuliani et al. 2015; Asgari et al. 2015; Schardong and Simonovic 2015; Ashofteh et al. 2015; Hidalgo et al. 2014; Ahmadianfar et al. 2015; Tsai et al. 2015; Bozorg-Haddad et al. 2011, 2016; Ahmadi Najl et al. 2016; Garousi-Nejad et al. 2016).

EAs apply an iterative search including the following phases: (1) selection and definition of decision variables, objectives, and constraints; (2) selection of the values of decision variable; (3) evaluation of objectives and constraints for the selected decision variable values through a simulation process; (4) selection of an updated set of decision variable values on the basis of feedback received from the simulation process; (5) repetition of simulation and updating the set of decision variable values until satisfying the selected stopping criterion; and (6) passing the optimal solutions into an appropriate decision-making process (Maier et al. 2014). Several advantages of EAs have been identified in previous studies. EAs can be linked with simulation models that raise the confidence of the results and facilitate the "straightforward treatment of parallel computing" (Maier et al. 2014, p. 273). EAs are capable of solving complex problems with difficult mathematical properties (Reed et al. 2013). Owing to this capability, EAs are not plagued by non-linearities and discontinuities during the process of optimization that beset classical/traditional optimization methods that require problem simplification to search for the global optimal solution of one or more objective functions (Zufferey 2012).

According to the "no free lunch" theorem, there is not a single EA that performs better than alternative ones in solving all conceivable, well-defined, optimization problems (Wolpert and Macready 1997). Hence, in addition to well-known EAs such as the genetic algorithm (GA) and particle swarm optimization (PSO), new ones like the bat algorithm (BA), biogeography-based optimization (BBO), and the water cycle algorithm (WCA) have been developed in recent years.

Hashimoto et al. (1982) proposed that the performance of a reservoir system operation should be assessed according to three criteria: (1) how likely a system is to fail, (2) how quickly it recovers from failure, and (3) how severe are the consequences of failure. In order to apply the performance criteria besides the objective function through an EA benchmarking problem, multicriteria decision making (MCDM) techniques can be used. MCDMs assist decision makers in selecting an alternative among several competing ones that best satisfies the objectives of an optimization problem by

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ranking the alternatives on the basis of properly chosen evaluation criteria, such as those proposed by Hashimoto et al. (1982) for reservoir operation. Bolouri-Yazdeli et al. (2014) ranked various real-time reservoir operation rules extracted from standard operation policy (SOP), stochastic dynamic programming (SDP), linear decision rules (LDR), and nonlinear decision rule (NLDR) by a MCDM technique according to three performance criteria namely, reliability, resiliency, and vulnerability. Sawicka and Zak (2014) reported a combination of MCDMs and classification algorithms to prioritize the redesign scenarios of an existing distribution system. Azarnivand et al. (2014) ranked eight strategies on the basis of sustainable development criteria to find out the most comprehensive solution for reviving a drying lake. Walker et al. (2015) developed a multicriteria framework based on a weighted aggregation of 10 water quality parameters to visualize the status of water quality in Serbia. Bozorg-Haddad et al. (2016) applied several MCDMs with different assumptions for conflict resolution in a complex multiobjective problem. Malekian and Azarnivand (2016) recommended application of MCDMs that have a sensitivity parameter in their computational mechanism, such as VIKOR, Compromise programming, etc. One of the recently developed MCDMs, benefitted from the sensitivity parameter, is the weighted aggregates sum product assessment (WASPAS, Zavadskas et al. 2012). WASPAS has been employed in an ecological–economic evaluation of multidwelling modernization (Staniūnas et al. 2013), for selecting a deep-water port (Bagočius et al. 2013), in the assessment of alternative facades (Zavadskas et al. 2013), in site selection (Vafaeipour et al. 2014), and for supply-chain management (Hashemkhani Zolfani et al. 2015).

This paper applies a recently developed EA that has not been previously implemented in water resources systems optimization. The algorithm was developed by Cuevas et al. (2014) and is called states of matter search (SMS). The SMS algorithm attempts to balance between global and local searches for optimal solutions by emulating the physical principles of thermal-energy motion mechanism that increase the population diversity of solutions while avoiding the concentration of particles within a local minimum (Tan et al. 2009).

In addition, this work evaluates the performance of five EAs besides the SMS, namely, the GA, PSO, BBO, BA, and WCA. Unlike conventional EA benchmarking studies that compared EAs only on the basis of the optimal solution to optimization problems, this study employs MCDM to render a novel and multicriteria EA selection framework. The authors are not aware of previous applications of the SMS algorithm to the optimization of water recourses systems. The performance assessment implemented in this study relies on the WASPAS technique, which is a recently developed model that has not been employed in water resources studies. The contributions of this paper are (1) introducing the SMS algorithm and the WASPAS technique to water resources, (2) presenting simulation and optimization models for a single reservoir system with hydropower generation objective, (3) comparing the results from the SMS and five other EAs with respect to performance criteria, and (4) analyzing the EAs' efficiencies with consideration of performance criteria.

Methods and Materials

The SMS algorithm is summarized in this section. A complete description of the SMS is found in Cuevas et al. (2014). The details regarding the GA, PSO, BBO, BA, and WCA can be found in Holland (1975), Kennedy and Eberhart (1995), Simon (2008), Yang (2010), and Eskandar et al. (2012), respectively. Two optimization problems were tackled in this study: (1) a hypothetical benchmark problem to assess the capability of the SMS in finding near optimal solution, and (2) a real-life optimization problem first optimized on the basis of the objective function. Subsequently, the performance of several EAs (SMS, GA, PSO, BBO, BA, and WCA) is assessed throughout a multicriteria framework by taking four performance criteria into account. The remainder of this section presents concepts and formulas regarding simulation and optimization models of reservoir operation along with the formulas used by the proposed MCDM (WASPAS) technique.

Definition of the SMS Operators

Three following operators mimic the behavior of the laws of thermodynamics applied to particles of gases, liquids, and solids.

1. The direction vector (d_i): During development of evolution process, particles' positions are changed because of existing attraction forces. Each of the direction vectors ($D = \{d_1, d_2, \ldots, d_{N_p}\}$) emulates the direction of these changes, where N_p is the number of population. The d_i parameter is randomly selected within the range $[-1, 1]$. The following formula is used to simulate the attraction phenomenon that leads the particles toward the best-so-far particle:

$$d_i^{k+1} = \frac{d_i^k}{2} \cdot \left(1 - \frac{k}{\text{gen}}\right) + a_i \qquad a_i = \frac{(p^* - p_i)}{\|p^* - p_i\|} \tag{1}$$

where k and gen = iteration number and total iteration number, respectively. a_i denotes the attraction unitary vector; p_i = molecule i of population P; and p^* = best individual.

The d_i operator is used to compute the velocity (v_i) of each particle as follows:

$$v_i = d_i \cdot v_1 \tag{2}$$

$$v_1 = \frac{\sum_{j=1}^{n}(b_j^u - b_j^l)}{m} \cdot \beta$$
$$\text{where } \beta\text{: configuration parameter} \in [0, 1] \tag{3}$$

where v_1 = initial velocity; b_j^u and b_j^l = upper and lower bounds of the jth decision variable, respectively; and m = number of decision variables.

The new position is updated for each particle based on their permissible displacement (ρ) as follows:

$$p_{i,j}^{k+1} = d_{i,j}^k + v_{i,j} \cdot \text{rand}(0,1) \cdot \rho \cdot (b_j^u - b_j^l), \quad \text{where } 0.5 \le \rho \le 1 \tag{4}$$

where rand(0,1) denotes a function that generates a random number between 0 and 1 with the uniform distribution.

2. The collision: Provided that the distance between two particles such as p_i and p_q is shorter than an obtained proximity value (i.e., $\|p_i - p_q\| < r$), collisions are taken into account. The occurrence of collisions changes the particles' respective direction vectors in the following way: $d_i = d_q$ and $d_q = d_i$. The collision radius (r) is evaluated as follows:

$$r = \frac{\sum_{j=1}^{n}(b_j^u - b_j^l)}{m} \cdot \alpha, \quad \text{where } \alpha \in [0, 1] \tag{5}$$

where α = configuration parameter. Given that r predetermines the rate of increase or decrease of diversity, it controls the diversity of population solutions and improves the exploratory capability during the searching process.

3. The random behavior of particles is modeled via a probabilistic criterion in the search space. In so doing, if a uniform random number in the range of [0, 1] is smaller than a probability threshold (H), then the random particles' positions are simulated as follows:

$$p_{i,j}^{k+1} = \begin{cases} b_j^l + \mathrm{rand}(0,1)\cdot(b_j^u - b_j^l) & \text{with probability } H \\ p_{i,j}^{k+1} & \text{with probability}(1-H) \end{cases} \quad i \in \{1,2,\ldots,N_p\};\ j \in \{1,2,\ldots,n\} \tag{6}$$

Implementation of the SMS Algorithm

The aforementioned operators portray a general sketch of the SMS algorithm. Based on Cuevas et al. (2014), the operators participate in five computational steps: (1) investigating the best element of population P; (2) evaluation of v_1 [Eq. (3)], and r [Eq. (5)]; (3) evaluation of the new particles according to the directional vector operator [Eqs. (1), (2), and (4)]; (4) solving the collisions by applying the collision operators; and (5) generating the new random positions on the basis of the random position operator [Eq. (6)]. According to Fig. 1, the optimization process

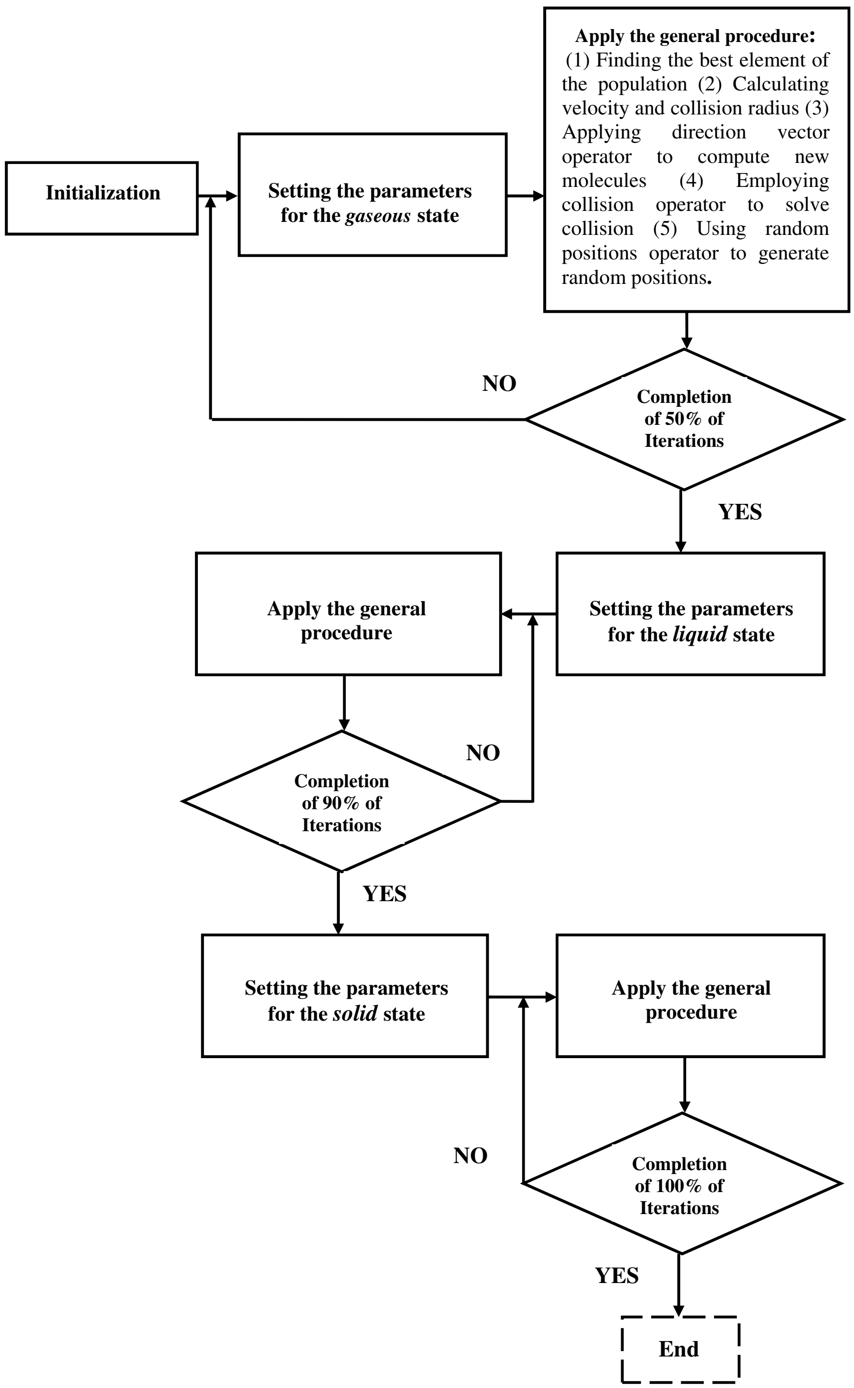

Fig. 1. Flowchart of the SMS algorithm

starts by initializing a set P of N_p particles to optimize the parameters of an n-dimensional particles' position. The initialization is simulated as follows:

$$p_{i,j}^0 = b_j^l + \text{rand}(0,1) \cdot (b_j^u - b_j^l), \quad i \in \{1, 2, \ldots, N_p\}; \quad j \in \{1, 2, \ldots, n\}, \tag{7}$$

where i, j, and zero represent parameter index, particle index, and the initial population, respectively.

After initialization, the gaseous state is the first phase that employs 50% of the total algorithmic iterations within the optimization process. The task of the gaseous state in the optimization scheme is executing the exploration process (global search of solutions). The gaseous state includes three phases: (1) setting the parameters (Table 1); (2) applying the aforementioned five steps of the computational process of SMS algorithm; and (3) provided that 50% of all iterations are completed, the exploration process continues to a mild transition between exploration (global search) and exploitation (local search) processes in the liquid state. Otherwise, return to the previous computational step.

The liquid state intensifies the exploration–exploitation processes by applying 40% of the total number of iterations. The first and second phases of the liquid state are similar to those of the gaseous phase. In the third phase, provided that 90% of all iterations (50% in the gaseous state) are completed, the exploration process continues to an exploitation process in the solid state. Otherwise, return to the previous computational step.

The solid state's task is investigating the solutions by focusing on the exploitation process. The first and second phases of the solid state are similar to those of the gaseous and liquid phase. This state employs 10% of the total number of iteration numbers to complete the optimization process. In the third step, provided that 100% of all iterations (90% from the gaseous and liquid states) are completed (0.9% total iteration number < iteration number ≤ total iteration number), the optimization process ends. Otherwise, return to the general procedure of SMS algorithm.

Reservoir Simulation Model

In general, a reservoir system is simulated as follows:

$$S_{(z,t+1)} = S_{(z,t)} + Q_{(z,t)} + M_{(z,y)} \cdot R_{(z,t)} + M_{(z,z')} \cdot Sp_{(z',t)} - \text{Loss}_{(z,t)}$$
$$\text{for } z = 1, 2, \ldots, n_r, \quad z' = 1, 2, \ldots, n_r, \quad t = 1, 2, \ldots, T \tag{8}$$

where t = index for simulation periods; z = reservoir number; $S_{(z,t)}$ and $S_{(z,t+1)}$ = storages of zth reservoir, respectively, at the beginning and end of period t (10^6 m^3); $Q_{(z,t)}$ = inflow volume into the zth reservoir during period t (10^6 m^3/s); $M_{(z,z')}$ = fourth-order

Table 1. Parameter Values of Each EA

Algorithm	Parameter	Karun4 reservoir system	Benchmark problem
GA[a]	NFE	100,000	500,000
	Mutation rate	0.05	0.06
	Mutation function	Uniform	Uniform
	Selection function	Roulette wheel	Roulette wheel
	Crossover fraction	0.6	0.7
	Crossover function	Two-point crossover	Two-point crossover
PSO	NFE	100,000	500,000
	Cognitive parameter	2	1.5
	Social parameter	1.5	1.5
	Minimum inertia weight	0.15	0.2
	Maximum inertia weight	0.95	0.9
	constriction factor	1	1
BBO[a]	NFE	100,000	500,000
	Mutation rate	0.07	0.05
	Mutation function	Gaussian	Gaussian
	Selection function	Roulette wheel	Roulette wheel
	Alpha	0.6	0.4
WCA[b]	NFE	100,000	500,000
	Number of rivers	28	35
	$d_{\max}$ (controls the search intensity)	2	2.7
BA[c]	NFE	100,000	500,000
	Minimum frequency	0	0
	Maximum frequency	1	5
	Minimum loudness	0.05	0.1
	Maximum loudness	0.75	0.95
	Random walks factor	0.1	0.1
	Random walks rate	5	5
SMS	NFE	100,000	500,000
	$\rho[x,y,z]$[d]	[0.8, 0.5, 0.1]	[0.9, 0.5, 0.1]
	$\alpha[x,y,z]$	[0.3, 0.05, 0.4]	[0.3, 0.1, 0.3]
	$\beta[x,y,z]$	[0.8, 0.3, 0.2]	[0.8, 0.4, 0.1]
	$H[x,y,z]$	[0.65, 0.5, 0.1]	[0.6, 0.4, 0.1]

[a]Based on Bozorg-Haddad et al. (2015) in case of multiple reservoir system.
[b]Based on Bozorg-Haddad et al. (2014b) in case of multiple reservoir system.
[c]Based on Bozorg-Haddad et al. (2014a) in case of multiple reservoir system.
[d]x = gaseous state; y = liquid state; z = solid state.

matrix of input–output connectivity among reservoirs with −1's along the diagonal denoting releases from reservoirs, and off-diagonal +1s denoting transfers of water from one reservoir to another; $R(z',t)$ = release volume from z'th reservoir during period t (10^6 m^3); $Sp_{(y,t)}$ = overflow volume from yth reservoir during period t (10^6 m^3); $\text{Loss}_{(z,t)}$ = evaporation loss from the zth reservoir surface during the operational period (10^6 m^3); n_r = number of reservoirs; and T = total number of operation periods (months).

The evaporation volume and the average surface are evaluated as follows:

$$\text{Loss}_{(z,t)} = Ev_{(z,t)} \cdot \bar{A}_{(z,t)} \qquad \bar{A}_{(z,t)} = \frac{A_{(z,t)} + A_{(z,t+1)}}{2}$$
$$\text{for } z = 1,2,\ldots,n_r, \quad t = 1,2,\ldots,T \tag{9}$$

where $Ev_{(z,t)}$ = net evaporation depth (evaporation minus precipitation) from the zth reservoir surface during the period t (km); $\bar{A}_{(z,t)}$ = average zth reservoir area during period t (km^2); and $A_{(z,t)}$ and $A_{(z,t+1)}$ = zth reservoir areas, respectively, at the beginning and end of period t.

$A_{(z,t)}$ is evaluated by the area-storage formula

$$A_{(z,t)} = \xi_{(z,1)} S^3_{(z,t)} + \xi_{(z,2)} S^2_{(z,t)} + \xi_{(z,3)} S_{(z,t)} + \xi_{(z,4)}$$
$$\text{for } i = 1,2,\ldots,n_r, \quad t = 1,2,\ldots,T \tag{10}$$

where $\xi_{(z,1)}$, $\xi_{(z,2)}$, $\xi_{(z,3)}$, and $\xi_{(z,4)}$ = constant coefficients of the area-storage equation.

The overflow (spill) from the reservoir should also be taken into account as follows:

$$S_{P_{(z',t)}} = \begin{cases} S_{(z',t+1)} - S_{\max(z',t)} & \text{if } S_{(z',t+1)} > S_{\max(z',t)} \\ 0 & \text{otherwise} \end{cases} \quad \text{for } z' = 1,2,\ldots,n_r, \quad t = 1,2,\ldots,T \tag{11}$$

where $S_{\max(z,t)}$ = maximum storage amount of zth reservoir during period t.

The three following constraints also play roles in the optimization process:

$$R_{\min(z,t)} \le R_{(z,t)} \le R_{\max(z,t)} \quad \text{for } z = 1,2,\ldots,n_r, \quad t = 1,2,\ldots,T \tag{12}$$

$$S_{\min(z,t)} \le S_{(z,t)} \le S_{\max(z,t)} \quad \text{for } z = 1,2,\ldots,n_r, \quad t = 1,2,\ldots,T \tag{13}$$

$$S_{(z,1)} = S_{(z,T+1)} \quad \text{for } z = 1,2,\ldots,n_r \tag{14}$$

where $R_{\min(z,t)}$ and $R_{\max(z,t)}$ = minimum and maximum permissible release of the zth reservoir during the period t, respectively; $S_{\min(z,t)}$ = minimum storage value of zth reservoir at the beginning of the period t; $S_{(z,1)}$ = storage of zth reservoir at the beginning of the operational period; and $S_{(z,T+1)}$ = storage of zth reservoir at the initial of the following period.

Case Study: Operation of Karun4 Reservoir

The Karun4 reservoir is located in the upper part of Karun River's basin, southwestern Iran. The minimum and maximum of reservoir storage varies between $1{,}141 \times 10^6$ and $2{,}190 \times 10^6$ m^3, respectively. The Karun4 reservoir was constructed for hydropower purposes and its power-plant capacity (PPC) is equal to $1{,}000 \times 10^6$ W. The optimal operation of the Karun4 reservoir is solved from 1991–1992 to 2000–2001. The optimization problem for the case study is as follows:

The reservoir's power plant generation is calculated by the following formula:

$$P_{(t)} = \text{Minimize}\left[\left(\frac{g \times \eta \times Rp_{(t)}}{PF \times \text{Mul}_{(t)}}\right) \times \left(\frac{\bar{H}_{(t)} - Tw_{(t)}}{1000}\right), \text{PPC}\right]$$
$$\text{for } t = 1,2,\ldots,T \tag{15}$$

where $P_{(t)}$ = hydropower generation in period t (10^6 W); g = acceleration of gravity (m/s^2); η = efficiency of power plant; $Rp_{(t)}$ = release water from the power plant in period t (10^6 m^3; PF = plant functional coefficient; $\text{Mul}_{(t)} = 10^6$ times of the number of seconds in period t; $\bar{H}_{(t)}$ = average reservoir water level during period t (m); $Tw_{(t)}$ = reservoir tail-water level during period t (m); and PPC = power plant capacity.

The storage-height formula for the Karun4 reservoir is given by:

$$H_{(t)} = \zeta_1 S^3_{(t)} + \zeta_2 S^2_{(t)} + \zeta_3 S_{(t)} + \zeta_4 \quad \text{for } t = 1,2,\ldots,T \tag{16}$$

where ζ_1, ζ_2, ζ_3, and ζ_4 = storage-height constant coefficients.

The objective of the optimization is to minimize the total energy deficit (TED):

$$\text{Minimize TED} = \sum_{t=1}^{T}\left(1 - \frac{P_{(t)}}{\text{PPC}}\right)^2 \tag{17}$$

Two penalty functions for $t = 1,2,\ldots,T$ were introduced to penalize the constraints violations:

$$P1 = K_1[S_{(T+1)} - S_{(1)}]^2 \quad \text{if } S_{(T+1)} < S_{(1)} \tag{18}$$

$$P2_{(t)} = K_2[S_{\min} - S_{(t+1)}]^2 \quad \text{if } S_{(t+1)} < S_{\min} \tag{19}$$

where $P1$ and $P2_{(t)}$ = penalty functions, in which the former penalizes reservoir storage the end of the entire operational period being different from the beginning storage, and the latter penalizes reservoir storage in any period t being less than the minimum reservoir storage; K_1 and K_2 = constants of the penalty functions.

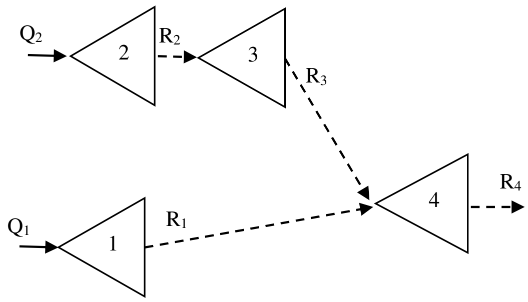

Fig. 2. The four-reservoir system

The penalized objective function is given by the following formula:

$$\text{Minimize TED} = \sum_{t=1}^{T}\left[\left(1-\frac{P_{(t)}}{\text{PPC}}\right)^2 + (P1 + P2_{(t)})\right] \tag{20}$$

Benchmark Problem: Operation of a Four-Reservoir System

The SMS is verified by a multiple-reservoir hypothetical benchmark problem introduced by Chow and Cortes-Rivera (1974). The required data, namely, inflows and reservoir storage were obtained from Murray and Yakowitz (1979). In this system, on the basis of the connectivity among reservoirs (Fig. 2), the matrix determining relationship between reservoirs is as follows:

$$M = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 1 & 0 & 1 & -1 \end{bmatrix} \tag{21}$$

Unlike the Karun4 reservoir problem, the objective function (B) for operation of this hypothetical four-reservoir system example is the maximization of the revenue during the operational period.

$$\text{Maximize } B = \sum_{t=1}^{T}\sum_{z=1}^{n_r} p_{r(z,t)} \cdot R_{(z,t)} \tag{22}$$

where $p_{r(z,t)}$ = profit related to the zth reservoir in period t.

Three penalty functions for $z = 1, 2, \ldots, n_r$, $t = 1, 2, \ldots, T$ are introduced to penalize violations of storage constraints:

$$P3_{(z)} = K_3[S_{(z,T+1)} - S_{(z,\text{target})}]^2 \quad \text{if } S_{(z,T+1)} < S_{(z,\text{target})} \tag{23}$$

$$P4_{(z,t)} = K_4[S_{\min(z,t)} - S_{(z,t+1)}]^2 \quad \text{if } S_{(z,t+1)} < S_{\min(z,t)} \tag{24}$$

$$P5_{(z,t)} = K_5[S_{(z,t+1)} - S_{\max(z,t)}]^2 \quad \text{if } S_{(z,t+1)} > S_{\max(z,t)} \tag{25}$$

where $P3_{(z)}$, $P4_{(z,t)}$, and $P5_{(z,t)}$ = penalty functions of the four-reservoir system operation related to the beginning storage not equaling the ending storage during the operational period, storage being less than the minimum storage, and storage exceeding maximum reservoir storage, respectively; K_3, K_4, and K_5 = constants of the penalty functions; and $S_{(z,\text{target})}$ = desirable volume of zth reservoir at the end of operation period ($S_{(z,\text{target})} = S_{(z,1)}$).

The objective function with penalties becomes

$$\text{Maximize } B = \sum_{t=1}^{T}\sum_{z=1}^{n_r}[p_{r(i,t)} \cdot R_{(i,t)} - (P3_{(i)} + P4_{(i,t)} + P5_{(i,t)})] \tag{26}$$

Performance Criteria

The following dimensionless criteria in the range of [0,1] were employed (Hashimoto et al. 1982).

Reliability is evaluated on the basis of the probability that a reservoir generate power equal to PPC during the operational period in two different ways:

Temporal Reliability (TR): It measures the number of periods in which the generated power from the reservoir exceeds the threshold [Eq. (27)]

$$\text{TR} = \frac{\overset{T}{\underset{t=1}{N}}(P_t \geq \text{PPC})}{T} \tag{27}$$

where $\overset{T}{\underset{t=1}{N}}(P_t \geq \text{PPC})$ = number of periods in which the generated power exceeds PPC.

Volumetric Reliability (VR): It represents the percentage of the total generated power to the maximum generable power in all operational periods. Eq. (28) indicates that the PPC is applied whenever the generated power is equal to or larger than PPC:

$$\text{VR} = \frac{\sum_{t=1}^{T}[(P_t|P_t < \text{PPC}) \vee (\text{PPC}|P_t \geq \text{PPC})]}{T \cdot \text{PPC}} \tag{28}$$

where $\sum_{t=1}^{T}(P_t|P_t < \text{PPC}) \vee (\text{PPC}|P_t \geq \text{PPC})$ = total generated power in all operational periods; and $T \cdot \text{PPC}$ = maximum generable power in all operational periods.

Resiliency (R): It measures the reservoir's ability to recover from failure as follows:

$$\text{R} = \frac{\overset{T-1}{\underset{t=1}{N}}(P_t < \text{PPC}|P_{t+1} \geq \text{PPC})}{\overset{T}{\underset{t=1}{N}}(P_t < \text{PPC})} \tag{29}$$

where $\overset{T-1}{\underset{t=1}{N}}(P_t < \text{PPC}|P_{t+1} \geq \text{PPC})$ = number of periods when the system recovers from failure; and $\overset{T}{\underset{t=1}{N}}(P_t < \text{PPC})$ = total failures in all operational periods. $P_{t+1} < \text{PPC}$ means that the period of failure (there may be more than one) has not ended yet. N (the counter of successes) is increased if $P_{t+1} \geq \text{PPC}$.

Vulnerability (V): It expresses the average amount of failures/deficits during operation periods as follows:

$$\text{V} = \frac{\sum_{t=1}^{T}[(\text{PPC} - P_t|P_t < \text{PPC}) \vee (0|P_t \geq \text{PPC})]}{T} \tag{30}$$

where $\sum_{t=1}^{T}[(\text{PPC} - P_t|P_t < \text{PPC}) \vee (0|P_t \geq \text{PPC})]$ = total deficits of generated power.

The optimization maximizes TR, VR, and R, and minimizes V.

WASPAS

WASPAS was developed by combining two conventional models, namely the weighted sum model (WSM) and the weighted product model (WPM), which were developed by Fishburn (1967) and Miller and Starr (1969), respectively. Zavedaskas et al. (2012) discovered that the efficiency and accuracy of the combined WSM-WPM are higher those of the separate models. In this paper the proposed EAs are the alternatives while the objective function value along with four performance criteria namely, TR, VR, R, and V are considered as evaluation criteria. Letting x_{ef} denotes the performance value of alternative e with respect to the evaluation criterion f.

The WASPAS steps are as follows (Zavadskas et al. 2012):

1. Normalize all the entries of the decision matrix:

$$\bar{x}_{ef} = \frac{x_{ef}}{\text{Max}_e x_{ef}} \text{ For beneficial criteria}$$

$$\bar{x}_{ef} = \frac{\text{Min}_e x_{ef}}{x_{ef}} \text{ For nonbeneficial criteria} \quad (31)$$

2. Compute the WASPAS weighted and normalized decision making matrix for summation ($\phi_e^{(1)}$) and multiplication ($\phi_e^{(2)}$) parts:

$$\phi_e^{(1)} = \sum_{f=1}^{n_c} \bar{x}_{ef} w_f$$

$$\phi_e^{(2)} = \prod_{f=1}^{n_c} (\bar{x}_{ef})^{w_f} \quad (32)$$

The total number of the evaluation criteria is denoted by n_c. Moreover, w_f = criterion's weight, which is considered equal for all the used performance criteria.

3. Assessment of the alternatives:

$$\phi = \lambda(\phi_e^{(1)}) + (1 - \lambda)(\phi_e^{(2)}) \quad (33)$$

The value of λ determines the fractions of WSM and WPM that make up the final assessment, ϕ. Usually, λ is assumed equal to 0.5, while this work evaluated ϕ in the range of $\lambda = \{0, 0.1, 0.2, \ldots, 1\}$ to gain insight of the alternative-prioritization process. However, applying different values of λ might cause various rankings. The aggregation of different ranks was achieved with Copeland's procedure (Copeland 1951), in which the best alternative is the one that beats all remaining contenders in pairwise contests. Copeland's procedure has been successfully applied to prioritization of flood alleviation alternatives (Chitsaz and Banihabib 2015) and urban water management scenarios (Motevallian et al. 2014). If VI indicates the number of victories and L represents the number of losses in pairwise contests, the highest rank belongs to the alternative that gains the largest number of VI-L. In the current study, the EAs are the alternatives that participate in pairwise comparisons, and are assessed according to their ranks for each value of λ.

Results and Discussion

The evaluation process was undertaken with the *MATLAB* software. More than one run (repetition) is needed owing to the random nature of the EAs' computations. Therefore, this paper applied 10 runs to obtain the optimal values of five evaluation criteria. Moreover, for the real-world single reservoir problem, the population size was made equal to 100 and the number of objective-function evaluations was set equal to 100,000. The number of objective-function evaluations (NFE) for the benchmark problem was equal to 500,000. The results attributed to the benchmark problem are presented first. The prioritization on the basis of objective function values follows. Lastly, the results of the multiple criteria assessment of the proposed EAs are evaluated to identify the most suitable EA for optimal operation of the Karun4 reservoir. The parameters of the EAs are listed in Table (1). Moreover the K_1, K_2, K_3, K_4, and K_5 values are set equal to 50, 20, 60, 40, and 40, respectively.

Table 2. Summarized Results of 10 Runs of the Six Proposed EAs' Optimal Fitness Function Values of the Benchmark Problem

Number of runs	GA[a]	PSO	BBO[a]	WCA[b]	BA[c]	SMS
1	300.42	306.68	308.00	306.83	308.20	307.87
2	298.89	306.91	308.02	302.40	307.12	307.71
3	300.09	307.07	308.12	303.65	307.41	308.26
4	300.47	307.65	307.56	303.60	307.93	306.15
5	298.46	306.31	307.11	302.38	308.09	306.40
6	300.00	307.43	307.88	306.01	307.95	307.33
7	299.22	308.15	307.57	304.05	308.09	308.01
8	299.87	307.72	308.08	306.75	308.03	307.83
9	299.20	307.58	308.00	306.63	307.62	308.06
10	300.35	308.18	306.55	306.92	308.02	308.20
Average	299.70	307.37	307.69	304.92	307.85	307.58
Worst	298.46	306.31	306.55	302.38	307.12	306.15
Best	300.47	308.15	308.12	306.83	308.20	308.26
Standard deviation	0.71	0.62	0.51	1.89	0.35	0.74
Coefficient of variation	0.002	0.002	0.002	0.006	0.001	0.002

[a]Based on Bozorg-Haddad et al. (2015).
[b]Based on Bozorg-Haddad et al. (2014b).
[c]Based on Bozorg-Haddad et al. (2014a).

EAs Prioritization Based on the Objective Function Value

Benchmark problem: The global optimal value of the four-reservoir system problem equaled 308.29 (Bozorg-Haddad et al. 2011). All the applied EAs could approximate the solution accurately. Table 2 lists the performance of the SMS in the hypothetical problem associated with its best, worst, and average performances through 10 repetitions. In general, the SMS performed well in optimizing the revenues from the multireservoir system. Because of the fact that SMS's best-performing value of the objective function among the 10 runs equaled 308.26, it outperformed other EAs in its best run. The BA was the second-best performance with a value of the objective function equal to 308.20. Meanwhile, with respect to average-performing values, the BA and BBO, respectively, converged to 307.85 and 307.69, which were superior to the SMS's 307.58. Moreover, compared with other EAs (except the WCA), the SMS had the larger standard deviation, which is undesirable. For instance, the standard deviation of the SMS's results was more than two times greater than the BA's.

Table 3. Summarized Results of 10 Runs of the EAs Optimal Fitness Function Values of the Karun4 Reservoir Problem

Number of runs	GA	PSO	BB0	WCA	BA	SMS
1	1.029	0.982	0.975	0.950	0.963	0.949
2	0.985	0.970	0.976	0.958	0.962	0.952
3	0.977	0.961	0.958	0.985	0.967	0.949
4	0.975	0.961	0.959	0.979	0.961	0.953
5	0.970	1.049	0.952	0.978	0.961	0.953
6	0.982	0.965	0.968	0.954	0.957	0.956
7	0.972	0.959	0.953	0.966	0.961	0.966
8	0.969	0.982	0.970	0.981	0.963	0.948
9	0.972	0.994	0.955	0.974	0.978	0.964
10	0.992	0.970	0.968	0.964	0.951	0.952
Average	0.982	0.979	0.963	0.969	0.962	0.954
Best	0.969	0.959	0.952	0.950	0.951	0.948
Worst	1.029	1.049	0.976	0.985	0.978	0.966
Standard deviation	0.018	0.027	0.009	0.012	0.007	0.006
Coefficient of variation	0.018	0.028	0.009	0.013	0.007	0.006

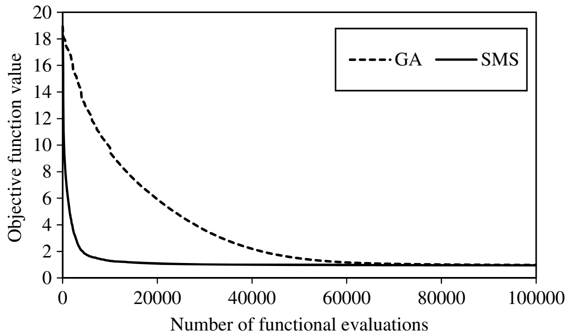

Fig. 3. Convergence of the SMS and the GA to the average optimal function of the Karun4 reservoir

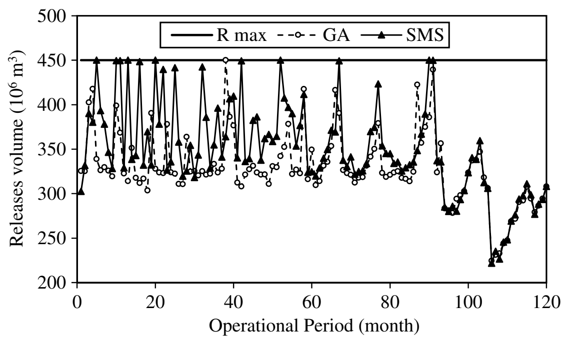

Fig. 4. Optimal release during the operational period of the Karun4 reservoir

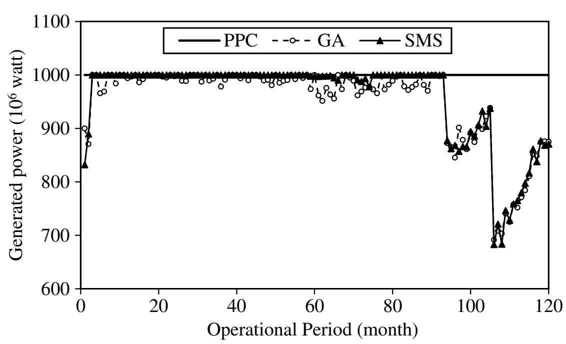

Fig. 5. Optimal generated power during the operational period of the Karun4 reservoir

Real-world problem: Table 3 lists the results of the Karun4 reservoir problem, which leads to the following insights: (1) considering the fact that the optimization direction was minimization, the average values of fitness function (objective function) demonstrated the superiority of the SMS over all other rival EAs; (2) even the worst performance of the SMS outdid the best performance of the GA (the SMS reached 0.966 in its worst run whereas the GA converged to 0.969 in its best performance); and (3) the coefficient of variation of SMS was almost five times smaller than the PSO's. Fig. 3 depicts the convergence trend of the best EA (SMS) versus the worst one (GA) with respect to their best parameters' values. It is shown in Fig. 3 that the SMS converged to optimal solution after almost 20,000 functional evaluations, whereas the GA reached the optimal value after 70,000 functional evaluations.

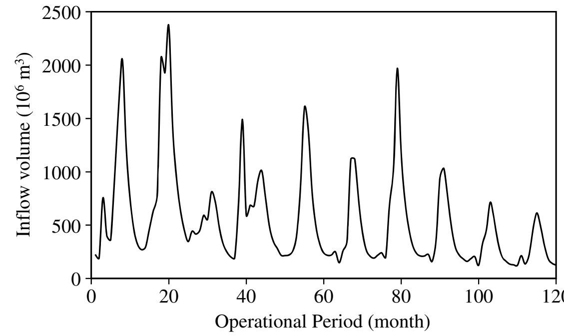

Fig. 6. Inflow volume during the operational period of the Karun4 reservoir

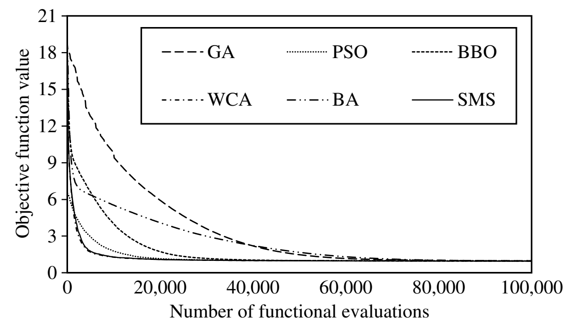

Fig. 7. Convergence of the SMS versus the other EAs to the average optimal function of the Karun4 reservoir

Table 4. Karun4 Reservoir Decision Matrix of the EAs according to the Evaluation Criteria

Algorithms	Temporal reliability (%)	Volumetric reliability (%)	Resiliency (%)	Vulnerability (%)	Fitness function
Decision matrix					
GA	29.167 (6)	95.194 (6)	29.412 (1)	4.806 (6)	0.982 (6)
PSO	60.000 (2)	95.814 (4)	27.083 (2)	4.186 (4)	0.979 (5)
BBO	56.667 (4)	95.937 (1)	11.538 (5)	4.063 (1)	0.963 (3)
WCA	58.333 (3)	95.815 (3)	26.000 (3)	4.185 (3)	0.969 (4)
BA	39.167 (5)	95.613 (5)	19.178 (4)	4.387 (5)	0.962 (2)
SMS	65.833 (1)	95.911 (2)	7.317 (6)	4.089 (2)	0.954 (1)
Normalized decision matrix					
GA	0.4430	0.9923	1	0.8454	0.9715
PSO	0.9114	0.9987	0.9208	0.9707	0.9745
BBO	0.8608	1	0.3923	1	0.9906
WCA	0.8861	0.9987	0.8840	0.9709	0.9848
BA	0.5949	0.9966	0.6521	0.9263	0.9917
SMS	1	0.9997	0.2488	0.9937	1

Note: The numbers within parentheses refer to the rank of each EA corresponding to the evaluation criteria.

The amount of water release from the reservoir and the generated power during the operational period are depicted with Figs. 4 and 5, respectively. According to Fig. 5, the generated power saw a marked decline in the end of operational period. Assessment of inflow volume to the Karun4 reservoir at the end of operational period revealed a similar decline (Fig. 6). In that period, Iran faced a severe drought. Because of the fact that the Karun4 reservoir was

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Table 5. Values of ϕ^1 and ϕ^2 for Each EA

Parts of decision making matrix	EAs					
	GA	PSO	BBO	WCA	BA	SMS
ϕ^1	0.850	0.955	0.849	0.945	0.832	0.848
ϕ^2	0.816	0.955	0.803	0.944	0.813	0.756

Table 6. Performance of Each EA for Different Values of λ

Values	ϕ_{GA}	ϕ_{PSO}	ϕ_{BBO}	ϕ_{WCA}	ϕ_{BA}	ϕ_{SMS}
$\lambda = 0$	0.8157	0.9546	0.8033	0.9436	0.8130	0.7561
Rank	3	1	5	2	4	6
$\lambda = 0.1$	0.8191	0.9547	0.8078	0.9437	0.8149	0.7653
Rank	3	1	5	2	4	6
$\lambda = 0.2$	0.8226	0.9547	0.8124	0.9438	0.8169	0.7746
Rank	3	1	5	2	4	6
$\lambda = 0.3$	0.8261	0.9548	0.8169	0.9440	0.8188	0.7838
Rank	3	1	5	2	4	6
$\lambda = 0.4$	0.8296	0.9549	0.8215	0.9441	0.8207	0.7930
Rank	3	1	4	2	5	6
$\lambda = 0.5$	0.8331	0.9549	0.8260	0.9442	0.8227	0.8023
Rank	3	1	4	2	5	6
$\lambda = 0.6$	0.8365	0.9550	0.8306	0.9444	0.8246	0.8115
Rank	3	1	4	2	5	6
$\lambda = 0.7$	0.8400	0.9550	0.8351	0.9445	0.8265	0.8207
Rank	3	1	4	2	5	6
$\lambda = 0.8$	0.8435	0.9551	0.8396	0.9446	0.8285	0.8300
Rank	3	1	4	2	6	5
$\lambda = 0.9$	0.8470	0.9552	0.8442	0.9448	0.8304	0.8392
Rank	3	1	4	2	6	5
$\lambda = 1$	0.8504	0.9552	0.8487	0.9449	0.8323	0.8484
Rank	3	1	4	2	6	5

built on the upper reach of the Karun River only for hydropower purposes (not water allocation), drought is the only driving force of this decline. The release and reservoir storage were reduced, and consequently the power generation declined.

The results indicate that the SMS performed better than other EAs on the basis of fitness function (FF) evaluation (Fig. 7). The next subsection applies four performance criteria to determine the robustness of the proposed EAs.

EAs Prioritization Based on the Objective Function value and Performance Criteria

The evaluation criteria TR, VR, R, V, and FF have equal significance in this paper. The decision matrix that reveals the value of each EA according to the evaluation criteria is presented in Table 4. Table 4 shows that the SMS could rank first with respect to the TR criterion and FF. The GA, which had the lowest performance with the FF criterion, stood superior to the other EAs according to the R criterion. The GA's performance in satisfying the R criterion was approximately four times better than the SMS's. The BBO performed best with the V and VR criteria.

The $\phi_e^{(1)}$ and $\phi_e^{(2)}$ values are presented in Table 5 as the prerequisites to evaluate the ϕ parameter with respect to different values of the sensitivity parameter of WASPAS. Table 6 demonstrates the values of the ϕ parameter and ranks of each EA according to different values of $\lambda = 0.1, 0.2, \ldots, 1$. An unanticipated finding was the low rank of SMS in all λ-based scenarios. When $\lambda < 0.8$, SMS was the sixth ranked while for $\lambda \geq 0.8$ it ascended to the fifth rank. The PSO and the WCA ranked first and second, respectively in all scenarios. For instance, when $\lambda = 0.5$, the ϕ values for the PSO and

Table 7. Pairwise Contests Based on Copeland's Procedure

Contender A	Contender B	Number of victories for A	Number of victories for B	Winner
GA	PSO	0	11	PSO
GA	BBO	11	0	GA
GA	WCA	0	11	WCA
GA	BA	11	0	GA
GA	SMS	11	0	GA
PSO	BBO	11	0	PSO
PSO	WCA	11	0	PSO
PSO	BA	11	0	PSO
PSO	SMS	11	0	PSO
BBO	WCA	0	11	WCA
BBO	BA	7	4	BBO
BBO	SMS	11	0	BBO
WCA	BA	11	0	WCA
WCA	SMS	11	0	WCA
BA	SMS	8	3	BA

Table 8. Final Ranks Based on Copeland's Procedure

EAs	Rank
GA	3
PSO	1
BBO	4
WCA	2
BA	5
SMS	6

WCA equaled to 0.955 and 0.944, which were 1.19 and 1.18 times larger, respectively, than ϕ value of the SMS. Notice that the PSO and WCA were not chosen as the highest priority EAs with any of the criterion rankings. Another significant result of the MCDM was related to the performance of the GA. Although the GA had the lowest performance with the FF criterion, it outperformed the SMS when in all scenarios. From a methodological point of view, employment of WASPAS provided a variety of ranking lists. The λ parameter of WASPAS provided three lists of rankings for the policy makers.

Because of the fact that 11 different λ values were used, 11 pairwise contests among the EAs were held (Table 7). The PSO, WCA, GA, BBO, and BA won 5, 4, 3, 2, and 1 contests, respectively, while the SMS was defeated in all contests. The aggregated ranking list of the proposed EAs with Copeland's method is presented by Table 8. The aggregated ranking is analogous to the final prioritization list when $0.4 \leq \lambda \leq 0.7$ (Table 6). Copeland's method revealed a successful application in the present study for providing an aggregation of the diverse ranking lists of a MCDM on the basis of the sensitivity parameter.

The rankings listed in Table 4 are not all equal to the rankings of Table 8. In other words, the current study noted that none of the five proposed criterion could be individually taken as a sole and sufficient evaluation criteria in EA selection/algorithm benchmarking. The Copeland's ranking shown in Table 8 illustrates that complex reservoir systems require a multicriteria assessment to choose the best-suited EA.

Previous papers have proven the superiority of the BBO (Bozorg-Haddad et al. 2015), BA (Bozorg-Haddad et al. 2014a), and WCA (Bozorg-Haddad et al. 2014b) over the GA in reservoir management employing the FF criterion solely. However, the multicriteria framework of the current research demonstrates that the

EA selection in reservoir operation problems is a complex task that requires consideration of performance criteria. This paper's results revealed the multiobjective nature of reservoir operation problems. Therefore, this paper's findings suggest that multiobjective evolutionary algorithms (MOEAs) capture the multiplicity of criteria that arise in complex optimization problems, in agreement with recommendations by Deb (2008), Nicklow et al. (2010), Reed et al. (2013), Maier et al. (2014), and Giuliani et al. (2014), among others.

Concluding Remarks

This work presented a comparison among six EAs, including a recently developed EA called SMS, assessing their capacity to solve the optimal operation of the Karun4 reservoir for hydropower generation. Unlike conventional approaches that prioritize EAs on the basis of the FF, the current study benefited from a MCDM framework for EA evaluation. WASPAS, a new MCDM technique, was used to rank the proposed EAs according to five evaluation criteria including the FF. The conventional assessment on the basis of FF criterion revealed that the SMS outperformed other EAs in converging to the optimal solution. However, application of the MCDM framework did not favor the SMS. Because of the computational algorithmic nature of WASPAS, which employs the λ parameter in the range of $\{0, 0.1, 0.2, \ldots, 1\}$, the aggregated ranks of the EAs were determined based on Copeland's procedure. The MCDM illustrated that the PSO and WCA performed better than the other EAs, including SMS. Furthermore, SMS showed the worst performance among all EAs in satisfying the resiliency criterion.

In synthesis, this paper's results highlight the significance of implementing a practical computational method for robust decision making. The sole application of the objective function value as an evaluation criterion does not lead to adequate prioritization of alternative EAs.

Appendix. Parameter Values for Karun4 Reservoir

$$A_{(z,t)} = \xi_{(z,1)} S^3_{(z,t)} + \xi_{(z,2)} S^2_{(z,t)} + \xi_{(z,3)} S_{(z,t)} + \xi_{(z,4)} \quad \text{for } i = 1, 2, \ldots, n_r, \quad t = 1, 2, \ldots, T$$

$$\xi_{(z,1)} = 2.08 \times 10^{-9}$$

$$\xi_{(z,2)} = -9.79 \times 10^{-6}$$

$$\xi_{(z,3)} = 2.42 \times 10^{-2}$$

$$\xi_{(z,4)} = 1.82$$

$$H_{(t)} = \zeta_1 S^3_{(t)} + \zeta_2 S^2_{(t)} + \zeta_3 S_{(t)} + \zeta_4 \quad \text{for } t = 1, 2, \ldots, T$$

$$\zeta_1 = 1.74 \times 10^{-8}$$

$$\zeta_2 = -8.60 \times 10^{-5}$$

$$\zeta_3 = 17.71 \times 10^{-2}$$

$$\zeta_4 = 869.55$$

$$S_{\min} = 1{,}441 \times 10^6 \text{ m}^3$$

$$S_{\max} = 2{,}190 \times 10^6 \text{ m}^3$$

$$R_{\min} = 0 \times 10^6 \text{ m}^3$$

$$R_{\max} = 450 \times 10^6 \text{ m}^3$$

$$Tw_{(t)} = 845 \quad \text{for } t = 1, 2, \ldots, T$$

$$\text{PPC} = 1{,}000 \times 10^6 \text{ W}$$

$$\eta = 0.88$$

$$PF = 0.20$$

Acknowledgments

The authors are thankful for the insightful and constructive comments submitted by two anonymous reviewers and the associate editor.

Notation

The following symbols are used in this paper:

$\bar{A}_{(z,t)}$ = average zth reservoir area during the period t;
$A_{(z,t)}$ and $A_{(z,t+1)}$ = zth reservoir areas, respectively, at the beginning and end of the period;
a_i = attraction unitary vector;
b^l_j = lower j decision variable bound;
b^u_j = upper j decision variable bound;
BA = bat algorithm;
BBO = biogeography-based optimization;
d_i = direction vector;
EA = evolutionary algorithms;
$Ev_{(z,t)}$ = net evaporation (evaporation minus precipitation) from zth reservoir surface during the period of t;
FF = fitness function;
g = acceleration of gravity;
GA = genetic algorithm;
gen = total iteration number;
$\bar{H}_{(t)}$ = average reservoir water level during period t;
H = threshold;
k = iteration number;
K_1, K_2, K_3, K_4, and K_5 = constants of penalty function;
L = loss;
LDR = linear decision rules;
$\text{Loss}_{(z,t)}$ = evaporation loss from zth reservoir surface during the operational period;
m = number of decision variables;
$M_{(z,z')}$ = matrix of input-output connectivity among reservoirs;
MCDM = multicriteria decision making;
MOEAs = multiobjective evolutionary algorithms;
$\text{Mul}_{(t)}$ = 10^6 times of the number of seconds in period t;
n = number of particles;
n_c = number of criteria;
$\underset{t=1}{\overset{T}{N}} (P_t \geq \text{PPC})$ = number of periods in which the generated power exceeds PPC;

$\underset{t=1}{\overset{T-1}{N}}(P_t < \text{PPC}|P_{t+1} \geq \text{PPC})$ = number of periods when the system recovers from failure;
$\underset{t=1}{\overset{T}{N}}(P_t < \text{PPC})$ = total failures in all operational periods;
NFE = number of objective-function evaluations;
NLDR = nonlinear decision rule;
N_p = number of population;
n_r = number of reservoirs ;
$P_{(t)}$ = hydropower generation at period t;
p^* = best individual;
$P1$ = penalty functions related to not being equal the storages of beginning and end of operation period (in real-world problem);
$P2_{(t)}$ = penalty functions related to becoming less the reservoir storage than minimum storage of reservoir (in real-world problem);
$P3_{(z)}$ = penalty functions related to not being equal the storages of beginning and end of operation period (in benchmark problem);
$P4_{(z,t)}$ = penalty functions related to becoming less the reservoir storage than minimum storage of reservoir (in benchmark problem);
$P5_{(z,t)}$ = penalty functions related to becoming more reservoir storage than maximum storage of reservoir (in benchmark problem);
PF = plant functional coefficient;
p_i = molecule i of population P;
$p_{i,j}^{k+1}$ = random particles' positions;
PPC = power plant capacity;
$p_{r(z,t)}$ = profit related to the zth reservoir in period t;
PSO = particle swarm optimization;
$Q_{(z,t)}$ = inflow volume into zth reservoir during period t;
r = collision radius;
R = resiliency;
$R_{(z',t)}$ = release volume from z'th reservoir during the period t;
$R_{\min(z,t)}$ and $R_{\max(z,t)}$ = minimum and maximum permissible release of the zth reservoir during the period t, respectively;
$Rp_{(t)}$ = release water from plant at period t;
$S_{(z,1)}$ = storage of zth reservoir at the beginning of operational period;
$S_{(z,t)}$ and $S_{(z,t+1)}$ = storages of zth reservoir, respectively, at the beginning and end of period t;
$S_{(z,T+1)}$ = storage of zth reservoir at the end of the operation period;
$S_{(z,\text{target})}$ = desirable volume of zth reservoir at the end of operation period;
SDP = stochastic dynamic programming;
$S_{\max(z,t)}$ = maximum storage amount of zth reservoir during the period t;
$S_{\min(z,t)}$ = minimum storage value of zth reservoir at the beginning of the period t;
SMS = states of matter search;
SOP = standard operation policy;
$Sp_{(z',t)}$ = overflow volume from z'th reservoir during the period t;
T = operational period;
t = number of operational period;
TED = total energy deficit;
TR = temporal reliability;
$Tw_{(t)}$ = reservoir tail-water level during period t;
V = vulnerability;
v_1 = initial velocity while;
v_i = velocity;
VI = victory;
VR = volumetric reliability;
WASPAS = weighted aggregates sum product assessment;
WCA = water cycle algorithm;
w_f = criterion's weight;
WPM = weighted product model;
WSM = weighted sum model;
x_{ef} = value of alternative e with respect to evaluation criterion f;
$\bar{x}_{ef}$ = normalized element of decision matrix;
z = reservoir number;
α and β = configuration parameters;
η = efficiency of power plant;
λ = parameter of sensitivity;
$\xi_{(z,1)}$, $\xi_{(z,2)}$, $\xi_{(z,3)}$, and $\xi_{(z,4)}$ = constant coefficients of area-storage equation;
ρ = permissible displacement;
ζ_1, ζ_2, ζ_3, and ζ_4 = constant coefficients of storage-height equation;
ϕ = weighted aggregates sum product parameter;
$\phi_e^{(1)}$ = summation part; and
$\phi_e^{(2)}$ = multiplication part.

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