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Optimization model for integrated river basin management with the hybrid WOAPSO algorithm

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A R T I C L E I N F O

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A B S T R A C T

This work examines the effectiveness of a newly-developed optimization framework for river basin management. The proposed framework relies on the newly developed WOAPSO algorithm, which is a hybrid metaheuristic algorithm combining two conventional metaheuristic algorithms, namely the weed optimization algorithm (WOA) and the particle swarm optimization algorithm (PSO). Two case studies are presented in this study to evaluate the performance of the WOAPSO algorithm. The first case study consists of a ten-reservoir river basin example which compares the performance and reliability of the hybrid WOAPSO algorithm with that of linear programing (LP), non-linear programing (NLP), WOA, and the PSO algorithm. Results indicate the hybrid WOAPSO finds solutions meeting downstream water demands with 99.94% of reliability (with respect to the global optimum, as derived by LP) in the ten-reservoir system. It outperforms the WOA and PSO, which feature lower reliabilities than that achieved by WOAPSO. The second case study demonstrates failure of the conventional NLP optimization scheme in solving a real-world three-reservoir hydropower optimization problem which maximizes the efficiency index of hydropower production. The newly-introduced WOAPSO algorithm minimizes the objective function with superior efficiency compared with those of the WOA and PSO, in terms of the convergence rate and the achieved best values of the objective function. Furthermore, the WOAPSO is proven more reliable for solving complex multi-reservoir systems within the context of integrated river basin management than classic and evolutionary optimization algorithms.

1. Introduction

The optimization of multi-reservoir systems operation within the framework of integrated management for water supply and other functions, such as generating hydropower, improves the performance of water resources systems in arid in semi-arid regions with scarce natural sources of water. Classic optimization methods have found numerous applications in reservoir operation optimization. Barros et al. (2001, 2003), for example, applied nonlinear programming (NLP) to optimize hydropower production in reservoir systems in Brazil. Labadie (2004) presented a comprehensive review of mathematical and metaheuristic optimization rules for multi-reservoir systems. Mariano et al. (2008) adopted the NLP method to optimize reservoir operation for maximizing the benefit of hydropower production considering environmental requirements downstream of the reservoir. Baliarsingh (2010) employed stochastic dynamic programming (SDP) to optimize reservoir operation rules for a single-reservoir system for agricultural water supply and hydropower production. Bozorg-Haddad et al. (2013) applied NLP for the optimization of pumped storage in hydropower systems. Sharif and Swamy (2014) relied on the LINGO software package for resolving the optimal operation of a discrete four-reservoir system introduced by Larson (1968). Ji et al. (2015) employed linear programming (LP) to maximize hydropower production in the Han river, South Korea.

Various limitations hinder the application of classic methods such as LP and NLP to solve nonlinear reservoir operation problems of high dimensionality. Metaheuristic and evolutionary search algorithms have become commonly applied methodologies to solve such complex optimization problems. Sharif and Wardlaw (2000) implemented the genetic algorithm (GA) for the optimal operation of multi-reservoir systems and demonstrated the GA has better convergence capability than dynamic programming (DP). Ahmed and Sarma (2005) compared the

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GA with SDP in the optimization of multi-objective reservoir operation and reported that the GA method exhibited better performance than SDP. Tospornsampan et al. (2005) applied the simulated (SA) algorithm to the optimal operation of a ten-reservoir system to maximize hydropower production and compared their results with those obtained with the GA. Jothiprakash and Shanthi (2006) optimized operation rules for a single-reservoir system with the GA. Bozorg-Haddad et al. (2006) introduced the honey-bee mating optimization (HBMO) algorithm, inspired by the mating of bees, as a metaheuristic algorithm and applied it to several reservoir operation problems. Geem (2007) adopted the harmonic search (HS) algorithm for optimal operation scheduling of a multi-reservoir system for maximizing hydropower production and irrigation water supply. Bozorg-Haddad et al. (2008) reported the application of NLP and the HBMO algorithm for the optimal operation and design of single and multi-reservoir systems. Celeste and Billib (2009) implemented particle swarm optimization (PSO) to search for optimal operation policies of a single-reservoir system in Brazil. Wang and Qiu (2010) optimized reservoir operation in China with the aim of hydropower energy production relying on the PSO algorithm with adaptive random inertia weighting (ARIW). Zhang et al. (2011) applied PSO algorithm to the optimal operation of a multi-reservoir system with 25 hydroelectric power plants in the Mianjin basin of China. Vaghefi et al. (2012) implemented the imperialist competitive algorithm (ICA) for the optimal operation problem of the Sepidrood river reservoir for sediment extraction. Afshar (2012) developed long-term optimal operation rules for the Dez reservoir, Iran, for hydropower production with the PSO algorithm. Dariane and Sarani (2013) applied the intelligent water drops (IWD) and the Ant Colony Optimization (ACO) algorithms for long-term optimal operation of the Dez reservoir. Bozorg-Haddad et al. (2015a) developed optimal operation policies for the Karoon-4 reservoir in Iran with the water cycle algorithm (WCA). Bozorg-Haddad et al. (2015b) implemented the bat algorithm (BA) for the optimal operation of a four-reservoir system in continuous domain and of the Karoon-4 reservoir for hydropower production. Garousi-Nejad (2016) implemented the firefly algorithm (FA) for optimization operation of two different single-reservoir systems, one with the purpose of irrigation supply and the other one with the aim of hydropower generation. Solgi et al (2017) used an enhanced HBMO (EHBMO) to optimize a multi-reservoir system. Bozorgi et al (2017) applied the anarchic society optimization (ASO) to optimize the operation of a single-reservoir hydropower system (Karun-4 reservoir) and a four-reservoir system. Li et al. (2018) reported an improved shuffled frog leaping algorithm (SFLA), the chaos catfish effect SFLA (CCESFLA), to maximize the hydropower generation of three reservoirs in China. Jiang et al. (2018a,b) introduced an optimization model with early warning mechanism for hydropower stations considering the uncertainty of runoff forecast. Jiang et al. (2018a,b) implemented the multi-stage progressive optimality algorithm (POA) for optimizing energy storage a series of reservoirs. Jiang et al (2019) introduced a method of energy storage operation chart (ESOC) to analyze the influence of time scale on power generation of multiple reservoirs.

Mehrabian and Lucas (2006) introduced the weed optimization algorithm (WOA) inspired by the behavior of weeds. Mehrabian and Yousefi-Koma (2007) implemented the WOA to optimize the location of piezoelectric actuators on a smart fin. Sahraei-Ardakani et al. (2008) optimized electricity production with the WOA. Hajimirsadeghi and Lucas (2009) developed the hybrid WOAPSO algorithm by blending the weed optimization algorithm with particle optimization algorithm. Sedighy et al. (2010) applied the WOA to design and optimize a printer Yagi antenna. Other applications of the WOA in various fields can be found in Sharma et al. (2011), Jayabarathi et al. (2012), Ghasemi et al. (2014), Saravanan et al. (2014), Asgari et al. (2015), and Azizipour et al. (2016). Lenin et al. (2014) determined optimal power reactive dispatching (ORPD) with WOAPSO. Mohammadi et al. (2014) designed and optimized the operation of a fuzzy-based gas turbine engine (GTE) with hybrid WOAPSO algorithm.

A review of the available literature indicates the hybrid WOAPSO algorithm has not been applied in water resource systems analyses. Moreover, multi-reservoir systems with integrated river basin management are complex and their optimized operation is difficult to solve for with conventional optimization methods. Some optimization algorithms are unable to tackle these reservoir problems, or they converge to suboptimal solutions. This type of complex reservoir operation problems necessitate optimization frameworks driven by powerful algorithms. The hybrid WOAPSO algorithm is suitable to tackle complex water resources problems: it exhibits rapid convergence to near global optima. Also, the hybrid WOAPSO algorithm is herein demonstrated to obtain the best near optimal solutions to complex reservoir operation problems.

This work introduces an optimization model integrating river basin management focusing on multi-reservoir systems and, specifically, on hydropower operation that maximizes benefits with the hybrid WOAPSO algorithm. The performance of the hybrid algorithm is herein compared with those of NLP, LP, the WOA, and PSO algorithm. The comparison of these optimization methods is based on the solutions of two reservoir operation problems, namely, a river basin benchmark problem with ten-reservoir system and a three-reservoir system for hydropower generation.

2. Simulation and reservoir operation model

One ten-reservoir system benchmark and a three-reservoir hydropower production problems illustrate the implementation of the hybrid WOAPSO algorithm. The ten-reservoir problem maximizes the benefit from allocated reservoir releases:

$$Max.\ Be = \sum_{i=1}^{n}\sum_{t=1}^{T} b_{i,t} \times R_{i,t} \tag{1}$$

in which Be = objective function representing the income from water allocation to meet water demand, i = reservoir number, n = total number of reservoirs, $b_{i,t}$ = income in period t from reservoir i and $R_{i,t}$ = allocated water demand in t period from reservoir i (10^6 m^3).

The objective function for hydropower production is as follows:

$$Min.\ \ OF_{hydropower} = \sum_{i=1}^{I}\sum_{t=1}^{T} 1 - \frac{P_{i,t}}{PPC_i}^{\,2} \tag{2}$$

in which $OF_{hydropower}$ = objective function total efficiency index of hydropower production, i = reservoir index, $i = 1,\ 2,\ \ldots,\ T,\ I$ = total number of reservoirs, $P_{i,t}$ = generated power from reservoir i during operation period t (10^6 w), and PPC_i = power-plant installed capacity of reservoir i (MW). The objective function [Eq. (2)] minimizes the sum of square deviations between monthly generated hydropower and installed power-plant capacity during the period of operation.

The continuity equation expresses the mass-balance constraint in the reservoir by means of Eq. (3):

$$S_{i,t+1} = S_{i,t} + Q_{i,t} + M_{n\times n}R_{i,t} - L_{i,t} - Sp_{i,t} \tag{3}$$

in which, $S_{i,t+1}$ = storage volume of reservoir i at the beginning of the operation period $t+1$ (10^6 m^3), $S_{i,t}$ = storage volume of reservoir i at the beginning of the operation period t (10^6 m^3), $Q_{i,t}$ = monthly accumulation volume entering reservoir i during operation period t (10^6 m^3), M = a $n \times n$ matrix of water-release connections between reservoirs, $L_{i,t}$ = loss volume from reservoir i during operation period t (10^6 m^3), $Sp_{i,t}$ = water volume spilled from reservoir i in operation period t (10^6 m^3).

Upper and lower bounds of reservoir storage volume are written in Eq. (4):

$$Smin_i \leqslant S_{i,t} \leqslant Smax_i \tag{4}$$

in which $Smin_i$ = minimum storage capacity of reservoir I (10^6 m^3), and $S\max_i$ = maximum storage capacity of reservoir i (10^6 m^3).

Upper and lower bounds for water release are defined by Eq. (5):

$$Rmin_i \leqslant R_{i,t} \leqslant Rmax_i \tag{5}$$

in which $Rmin_i$ = minimum allowable release volume from reservoir i (10^6 m^3) and $Rmax_i$ = maximum allowable release volume from reservoir i (10^6 m^3).

Evaporative volume loss is determined according to Eq. (6):

$$L_{i,t} = A_{i,t} \times E_{i,t} \tag{6}$$

where $A_{i,t}$ = lake area of reservoir i during operation period t (km^2), and $E_{i,t}$ = average loss depth in reservoir i during operation period t (km). Lake area is a function of reservoir storage volume and is calculated using area vs. volume and area vs. water elevation functions found below.

The water spilled from reservoir i during operation period t ($Sp_{i,t}$) is calculated according to Eq. (7):

$$Sp_{i,t} = \begin{cases} S_{i,t} - Smax_i & if \quad S_{i,t+1} > Smax_i \\ 0 & else \end{cases} \tag{7}$$

In some cases, the initial and final reservoir storages are set constant according to Eqs. (8) and (9) (these are the so-called carryover constraints in reservoir operation studies):

$$S_{i,1} = Sinitial_i \tag{8}$$

in which $Sinitial_i$ = initial volume of reservoir i at the start of the operation periods (10^6 m^3), and:

$$S_{i,T} = S_{i,1} \tag{9}$$

The carryover condition expressed by Eq. (9) is commonly imposed when the reservoir operation time step is short.

The energy generated by reservoir i in each operation period t is as follows:

$$P_{i,t} = \frac{\gamma\,.\,\eta_i\,.\,\Delta H_{i,t}\,.\,RPH_{i,t}}{10^6\,.\,n_i} \tag{10}$$

in which γ = water unit weight (N/m^3), η_i = hydropower plant efficiency of reservoir i which is considered constant during all periods, $\Delta H_{i,t}$ = mean difference of water surface level between the beginning and ending of operation period t in reservoir i, $RPH_{i,t}$ = water discharge entering the hydropower plant at reservoir i during operation period t (m^3/s) and n_i = performance coefficient of hydropower plant in reservoir i. Eqs. (11)–(12) are employed to calculate $\Delta H_{i,t}$ in Eq. (10):

$$\Delta H_{i,t} = \overline{H_{i,t}} - Tw_{i,t} \tag{11}$$

in which $\overline{H_{i,t}}$ = average elevation of water at reservoir i at the beginning and end of operation period t in (m), and $Tw_{i,t}$ = downstream water elevation of reservoir i during operation period t (m), which is a function of the discharge to the river and is calculated from stage-discharge (rating curve) data.

$$\overline{H_{i,t}} = \frac{H_{i,t} + H_{i,t+1}}{2} \tag{12}$$

in which $H_{i,t}$ = water elevation of reservoir i at the beginning of operation period t(m), and $H_{i,t+1}$ = water elevation of reservoir i at the end of operation period $t + 1$ (m). $H_{i,t}$ and $H_{i,t+1}$ are calculated with the area-volume-height curves of the reservoirs expressed by Eq. (13):

$$H_{i,t} = g(S_{i,t}) \tag{13}$$

in which g = denotes the water elevation vs. storage function.

The volume of water entering the power plant of reservoir i during operation period t ($Re_{i,t}$) consists of $RPH_{i,t}$, which is the amount of required water for electricity production at power plant of reservoir i during operation period t (10^6 m^3), and $SpPH_{i,t}$which is the water volume bypassing the power plant of reservoir i during operation period of t (which has no role in hydropower production) (both in 10^6 m^3):

$$RPH_{i,t} = \frac{Re_{i,t} - SpPH_{i,t}}{CF_{i,t}} \tag{14}$$

where $CF_{i,t}$ = the conversion coefficient of 10^6 m^3 to m^3/s for reservoir i during operation period t which is calculated according to Eq. (15):

$$CF_{i,t} = \frac{24 \times 3600}{1'000'000} day_t \tag{15}$$

where day_t = denotes the number of days of operation periods (month) t.

Power generation is limited by constraint (16):

$$0 \leqslant P_{i,t} \leqslant PPC \tag{16}$$

A penalty function is added to the objective function to avoid violations of the carryover constraint violations:

$$P1_i = K1[S_{i,T+1} - Sinitial_i]^2 + D1 \tag{17}$$

in which $P1_i$ = penalty function for violating the carryover constraint, $K1$ = penalty coefficient, and $D1$ = a constant number.

In addition, if reservoir volume is less than minimum reservoir storage volume in any period then a penalty function is introduced:

$$P2_{i,t} = K2[Smin_i - S_{i,t}]^2 + D2 \tag{18}$$

in which $P2_{i,t}$ = penalty function for violation of minimum reservoir storage volume, $K2$ = penalty coefficient, and $D2$ = a constant number. A penalty constraint is likewise introduced to avoid violating maximum storage:

$$P3_{i,t} = K3[Smax_i - S_{i,t}]^2 + D3 \tag{19}$$

in which $P3_{i,t}$ = penalty function for violation of the maximum reservoir storage volume i during operation period t, $K3$ = penalty coefficient, and $D3$ = a constant number.

The sum of penalty functions defined by Eq. (20) is added to (under minimization) or subtracted from (under maximization) to the objective function:

$$P = \sum_{i=1}^{n} P1_i + \sum_{i=1}^{n}\sum_{t=1}^{T} P2_{i,t} + \sum_{i=1}^{n}\sum_{t=1}^{T} P3_{i,t} \tag{20}$$

where P = sum of penalty functions.

In reservoir operation systems the water releases from the reservoir are often the decision variables. Thus, upper and lower release constraints are defined as feasible intervals for selecting random release in the implementation of metaheuristic and evolutionary algorithms. In this manner these algorithms yield release values in the feasible ranges of release volumes. For this reason, there are no penalty constraints imposed on release violations.

3. Methods and materials

3.1. Optimization algorithms

3.1.1. The weed optimization algorithm (WOA)

The WOA models each weed as a member of a population or colony of potential solutions in which the weed positions constitute the decision variables of an optimization problem. Weeds are allowed to reproduce based on their quality (i.e., on their objective function values) in the colony. This means that the better the quality of a weed, the larger the number of seeds it produces. A seed is an improved solution arising from an existing weed. When the algorithm starts the weeds are in an unsuitable environment and attempt to distribute their seeds over a large space in search of a more suitable environment. This step of the WOA searches for an optimal space near (and including) the optimal point or solution. From this time onward the weeds distribute their seeds within a close range, which brings the newly produced weeds arbitrarily close to the best location or global optimal solution of the optimization problem being solved.

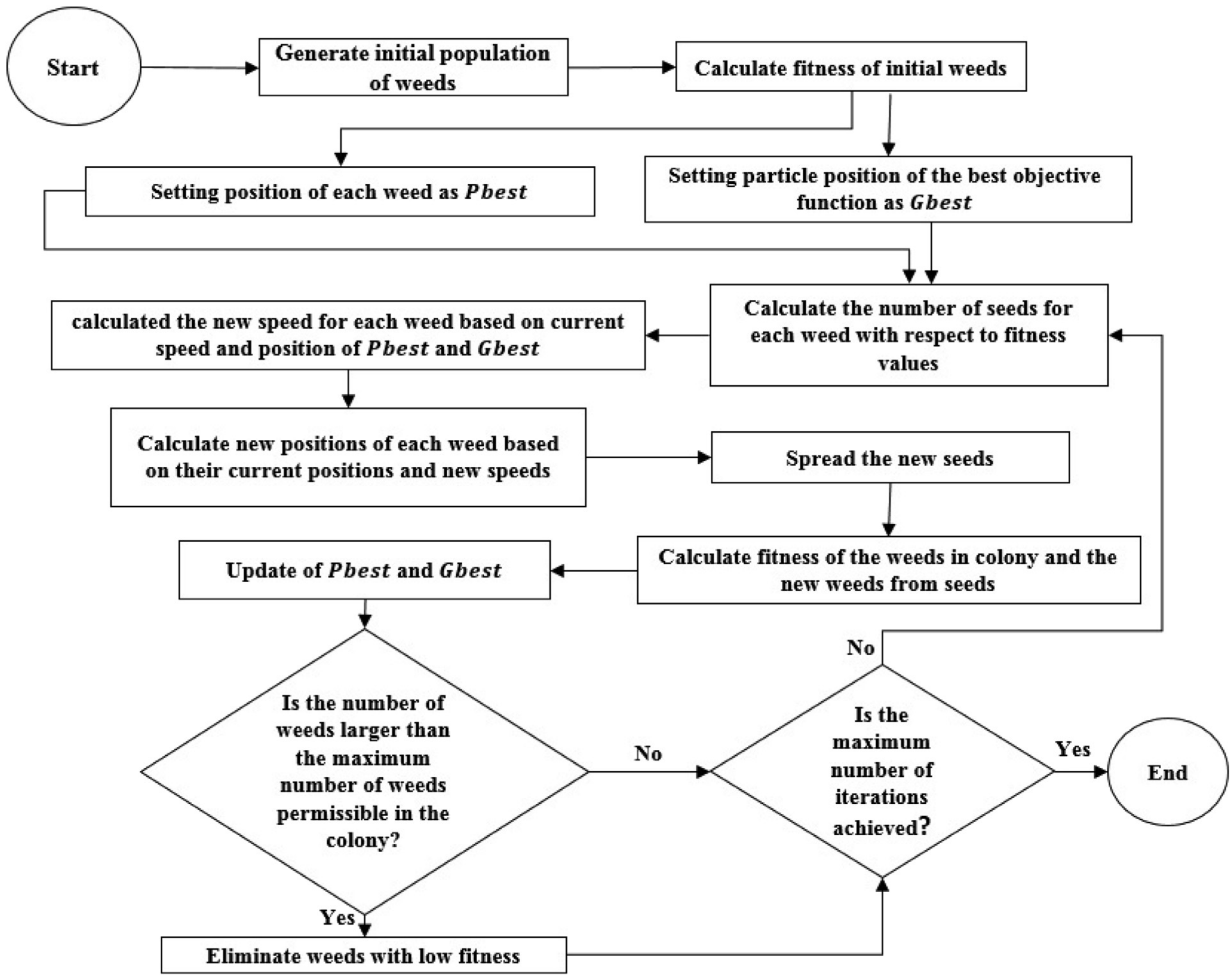


Fig. 1. Flowchart of the hybrid WOAPSO algorithm.

The WOA consists of the following steps:

1. An initial d-dimensional population ($P_{initial}$) of weeds is generated and distributed randomly in space.
2. Reproduction: in this step the current weeds produce seeds considering those weeds with the best and worst qualities. $NoS_{\max}$ and $NoS_{\min}$ denote respectively the number of weeds with best and worst qualities. $NoS_{\max}$ and $NoS_{\min}$ are user selected. Seed production is governed by Eq. (21):

$$NoS_i = \frac{OF_i - OF_{\min}}{OF_{\max} - OF_{\min}} \times (NoS_{\max} - NoS_{\min}) + NoS_{\min} \tag{21}$$

where NoS_i = the number of seeds produced by weed i, OF_i = value of the objective function of weed i, $OF_{\min}$ = minimum value of the objective function in the colony of weeds, $OF_{\max}$ = maximum value of the objective function in the colony of weeds. Eq. (21) prioritizes seed selection from the fittest weeds, which, in turn, more likely than not will yield an improved population of weeds, and so on and so forth until reaching a convergence criterion. This selection procedure of the WOA mimics the evolutionary principle of survival of the fittest.

3. Seed distribution, adaptation, and randomness: the seeds are distributed randomly with a zero-mean normal distribution. Their population's standard deviation is reduced from an initial (maximum) predefined value to a final (minimum) predefined value in each generation according to Eq. (22):

$$\sigma_{iter} = \frac{(iter_{\max} - iter)^n}{(iter_{\max})^n}(\sigma_{initial} - \sigma_{final}) + \sigma_{final} \tag{22}$$

where σ_{iter} = value of the standard deviation in the current iteration of the WOA, $iter_{\max}$ = maximum number of iterations (i.e., generation of seeds), $iter$ = iteration number, $\sigma_{initial}$ = initial standard deviation, σ_{final} = final standard deviation and n = a non-linear module (non-linear modulation index) which is selected by the user.

4. Competitive exclusion: the exclusion of evolutionarily undesirable weeds starts after a few iterations whenever the number of weeds in the colony exceeds its maximum possible number ($P_{\max}$). The exclusion is effected by steps outlined above to maintain the number of weeds in the population within limits. This process is iterated until the end of the algorithm.

3.1.2. The PSO algorithm

The PSO algorithm was developed by Eberhart and Kennedy (1995) inspired by the social behavior of fish and birds which live in groups. The PSO algorithm is applied to particles, thence its name particle search optimization. Each particle's value contributed to the objective function is calculated according to its position in the decision space. Thereafter any particle selects a direction to move along based on a combination of its current position, the best place it has ever occupied, and on the position of other particles which currently occupy the best positions in the population of particles. One step of the PSO algorithm is completed once all the particles in the current population have moved. Steps are repeated until the algorithm reaches the maximum iteration

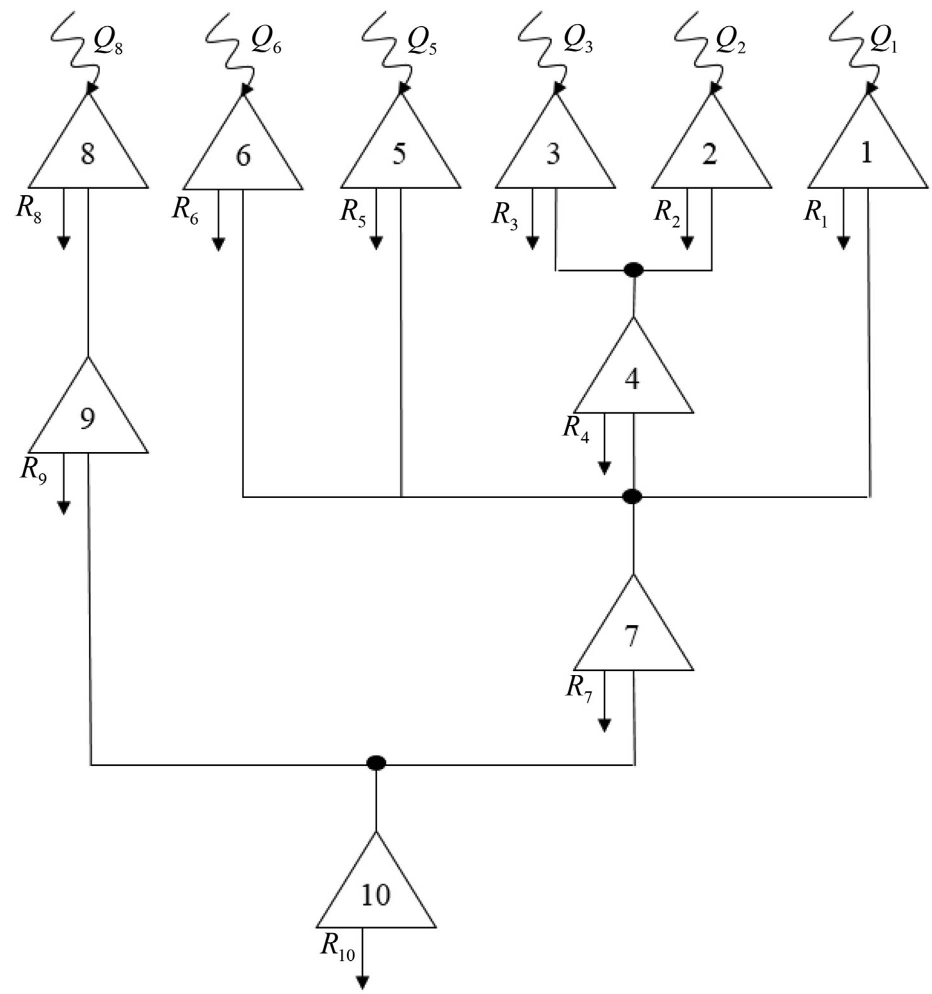


Fig. 2. Schematic of the ten-reservoir system.

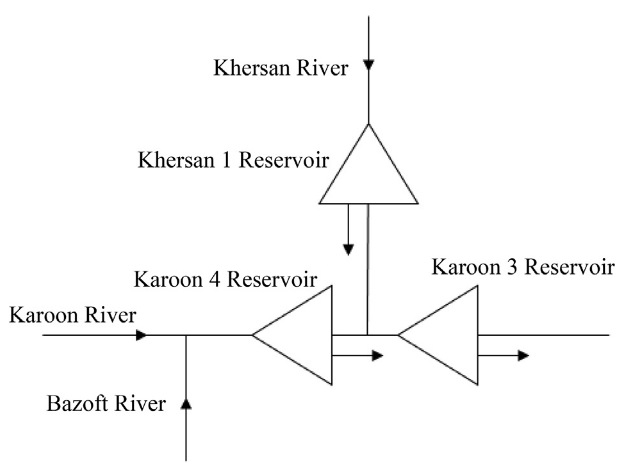


Fig. 3. Schematic of the Karoon 4, the Khersan 1, and the Karoon 3 reservoirs system.

number.

The PSO algorithm begins with a randomly generated population of particles. In the first iteration the initial state of each particle is the best position the particle has ever occupied (and is named *Pbest*), and the best particle with the best objective function value is determined (and is named *Gbest*). In the following iterations *Pbest* and *Gbest* are updated according to the positions occupied by the particles in the population judged by the values of their objective functions. A new velocity for each particle is calculated according to Eq. (23) considering *Pbest* and *Gbest*. The new position of each particle is then calculated according to Eq. (24) based on the new velocity and current position of the particle:

$$V_i(t+1) = \omega \quad V_i(t) + C_1 r_1 [Pbest_i(t) - X_i(t)] + C_2 r_2 [Gbest(t) - X_i(t)] \tag{23}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{24}$$

where $V_i(t+1)$ = velocity of particle i in iteration $t+1$, $V_i(t)$ = velocity of particle i in iteration t, $Pbest_i(t)$ = the best position which particle i has occupied until iteration t, $Gbest(t)$ = position of the best particle until iteration t, $X_i(t+1)$ = position of particle i in iteration $t+1$, $X_i(t)$ = current position of particle i in iteration t. Also ω = inertia coefficient, which is an index of convergence to local and global optima. C_1 and C_2 denote the personal learning and global learning factors, respectively, and are user defined. The parameters r_1 and r_2 are the numbers which are generated randomly in each iteration with a uniform distribution in the interval [0, 1].

3.1.3. The hybrid WOAPSO algorithm

Hajimirsadeghi and Lucas (2009) developed the hybrid WOAPSO algorithm by combining the WOA and the PSO algorithm. The WOA converges to the optimal area of solutions relatively slowly. However, after finding the optimal area the WOA approaches the global optimum accurately because of its effective and diverse search capacity. The PSO algorithm the changes of the particles' positions within the search space are based on the social psychological of individuals to emulate the success of other individuals. The PSO algorithm converges to the

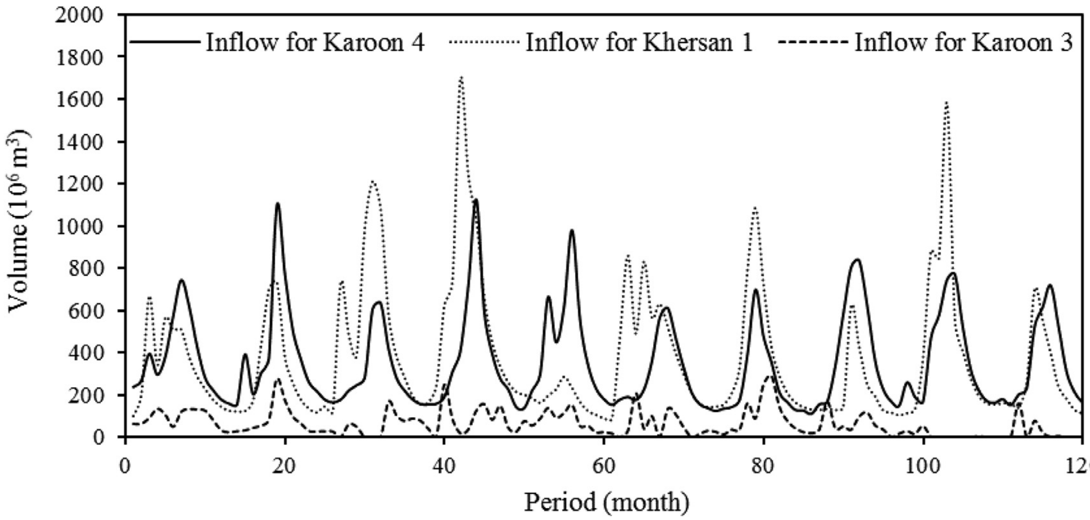


Fig. 4. Monthly discharge for the Karoon 4 reservoir, the Khersan 1, and the Kariin 3 in the 10-year operational period.

Table 1
The best parameters of the WOA, PSO algorithm, and hybrid WOAPSO algorithm for the ten-reservoir system operation.

	WOA	PSO	Hybrid WOAPSO algorithm
$P_{initial}$	50	250	30
$P_{\max}$	120	–	90
$iter_{\max}$	20,000	27,000	17,000
$NoS_{\min}$	1	–	1
$NoS_{\max}$	5	–	3
n	4	–	4
$\sigma_{initial}$	5.5	–	1.5
σ_{final}	0.01	–	0.01
ω	–	0.72	0.7
C_1	–	1.49	2
C_2	–	1.49	0.5

Table 2
Results of 10 runs of the WOA, the PSO algorithm, and the hybrid WOAPSO algorithm for the ten-reservoir system operation.

	WOA	PSO algorithm	Hybrid WOAPSO algorithm	LP
1	1160.38	1150.64	1191.86	
2	1142.57	1148.23	1191.77	
3	1153.92	1156.33	1190.67	
4	1155.52	1142.54	1193.76	
5	1144.93	1156.24	1193.51	
6	1147.91	1150.58	1189.75	
7	1136.63	1153.76	1190.09	
8	1145.81	1154.05	1190.89	
9	1146.30	1154.66	1191.03	
10	1145.38	1150.64	1193.06	
Minimum	1136.63	1142.54	1189.75	
Average	1147.93	1151.77	1191.64	
Maximum	1160.38	1156.33	1193.76	1194.44
Standard Deviation	6.537758	4.000601	1.339579	
Coefficient of Variation	0.005695	0.003473	0.001124	
Number of functional evaluations	6,597,742	6,750,000	6,523,664	

optimal area of solutions fast with fairly deliberate particle movements in each iteration. The hybrid WOAPSO exhibits rapid and accurate convergence to near global optimal solution. The interaction between the dispersion method of the WOA algorithm and the speed of the PSO algorithm produces an effective balance between local and global exploration of the problem space. Furthermore, Hajimirsadeghi and Lucas (2009) reported the hybrid WOAPSO algorithm results indicating faster convergence to superior optima than the WOA and PSO algorithm could achieve individually by testing them with mathematical benchmark functions.

The steps of the hybrid WOAPSO algorithm are as follows:

An initial population of weeds is randomly generated and distributed in a d-dimensional space. The objective function value is calculated for each weed. The number of seeds (i.e., new weeds or potential solutions) generated by each weed is calculated with Eq. (21). The positions of weeds are assessed in terms of *Pbest* and *Gbest* as done with the PSO algorithm as explained above. New solutions (seeds) are generated with Eqs. (23) and (24) employed in PSO algorithm. The objective function values are calculated for each generated weed. Their positions are changed with the PSO algorithm. This is followed by seed generation with the WOA. Subsequently, the PSO algorithm updates the positions *Pbest* and *Gbest*. Competitive exclusion is performed by the WOA. Whenever the number of weeds in a colony reaches the allowed number the exclusion process is affected and the weeds that have lower objective function values are removed from the colony.

Fig. 1 illustrates graphically the steps of the hybrid WOAPSO algorithm.

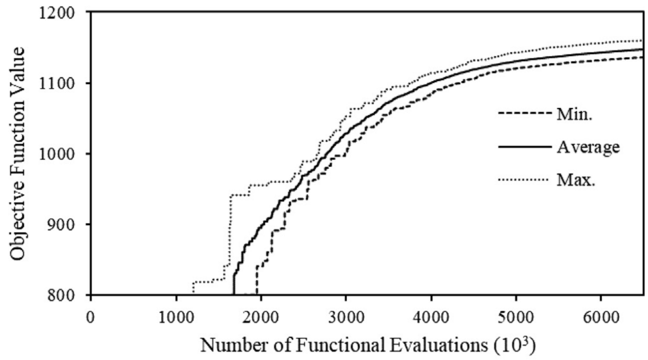
3.2. Case studies

3.2.1. Ten-reservoir problem

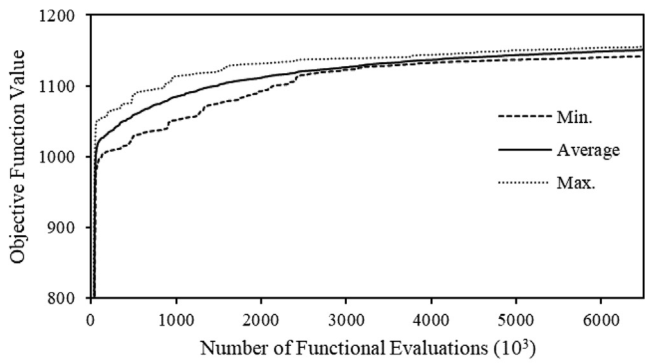
The ten-reservoir system problem for integrated river basin management was introduced by Murray and Yakowitz (1979) solved it with the constrained differential DP (CDDP) method. Afterwards, Wardlaw and Sharif (1999) solved this problem with the GA. Recently; Bozorg-Haddad et al. (2011) applied the HBMO algorithm to solve the same problem.

The ten-reservoir system and river basin schematic is displayed in Fig. 2 where it is seen that optimized management of the system of reservoirs are integrated for river basin management. The reservoirs 1, 2, 3, 5, 6, and 8 have natural inflow whereas the inflow to reservoirs 4, 7, 9, and 10 are from upstream reservoir releases. The ten-reservoir system operation is performed during a 12-month period and released water generates hydropower whose revenue is a linear function of release. Releases from reservoir 10 also deliver agricultural water (Murray and Yakowitz 1979).

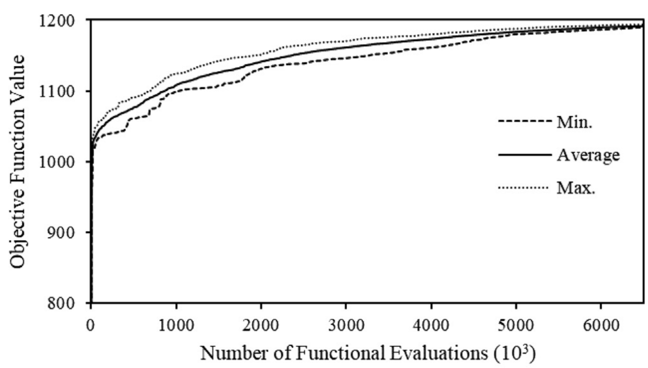
The matrix of releases connectivity for this system is given by Eq. (25). In this matrix the ten rows and columns account for the presence of the ten reservoirs. A + 1 matrix element means a reservoir receives



(a)



(b)



(c)

Fig. 5. Convergence for 10 runs of the ten-reservoir operation problem for the (a) WOA, (b) PSO algorithm, and (c) hybrid WOAPSO algorithm.

water from upstream, -1 means water is released from a reservoir, and 0 means reservoirs are not connected to each other. For example, reservoir number 4 which is represented by row 4 receives releases from reservoirs 2 and 3. Also, this reservoir is not directly connected to reservoirs 1, 5, 6, 7, 8, 9 and 10.

$$M = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & +1 & +1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 \\ +1 & 0 & 0 & +1 & +1 & +1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & +1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & +1 & 0 & +1 & -1 \end{bmatrix} \tag{25}$$

The penalty coefficients in Eqs. (17)–(19) equal $K1 = K2 = K3 = 60$, $D1 = D2 = D3 = 0$ (Bozorg-Haddad et al., 2011). This problem features 120 decision variables, and the number of constraints based on Eqs. (4), (5), and (9) equals 30.

3.2.2. The Karoon-4, Khersan-1, and Karoon-3reservoir system

The Karoon river basin provides essential hydropower in Iran. Its management poses unique challenges. The Karoon-4, Khersan-1, and Karoon-3 reservoirs generate hydropower in the Karoon basin. The three-reservoir system is depicted in Fig. 3. The releases of the Karoon-4 and Khersan-1 reservoirs are inputs to the Karoon-3 reservoir. Natural inflow enters all three reservoirs. The optimization of this three-reservoir system applies 10 years of data (i.e., 1988 through 1998) or 120 monthly periods. The connectivity matrix for this system is given by Eq. (26), in which Rows and Columns 1, 2, and 3 represent reservoirs Karoon 4, Khersan 1, and Karoon 3, respectively. Reservoir Khersan 1, for instance, is represented by Row 2, and is not connected to other reservoirs and does not receives inputs from them. Reservoir Karoon 3 (Row 3) receives releases from the two other reservoirs. This problem has 360 decision variables, and the number of constraints based on Eqs. (4), (5), (9), and (16) equals 12.

$$M = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ +1 & +1 & -1 \end{bmatrix} \tag{26}$$

The Karoon-4's double-arched concrete dam has a maximum elevation of 1025 m above sea level. The Karoon-4 reservoir serves flood control, flow regulation, and hydropower generation functions. Minimum and maximum storage volumes for this reservoir are 1144.29 and 2019 million cubic meters, respectively, and the maximum release from this reservoir equal 450 million cubic meters. The power plant installation equals 1000 MW. I Its performance coefficient and hydropower plant efficiency equal 20 and 88%, respectively.

The Khersan-1 reservoir is located in the Sofla area of the Khersan river in Chararmahal-Bakhtiari province 14 km upstream of the Karoon and Khersan rivers intersection. The Khersan-1's concrete dam rises to a maximum elevation from sea level equal to 1013 m above sea level. This reservoir generates hydropower. Minimum and maximum storage volumes are 262.68 and 332.55 million cubic meters, respectively, and the maximum release from reservoir equals 400 million cubic meters. In addition, its power-plant capacity is 584 MW, and its performance coefficient and hydropower plant efficiency are equal to 25 and 93%, respectively.

The Karoon-3 reservoir is located 28 km east of the city of Izeh and 610 km along the Karoon river in north eastern Khuzestan province. The Karoon-3 reservoir has a double-arch concrete dam with maximum elevation above sea level equal to 840 m. Its main functions are water storage, flood control, water regulation municipal and agricultural uses, and hydropower production. Minimum and maximum storage volumes are 1110.12 and 2252.58 million cubic meters, respectively, and maximum release is 1000 million cubic meters. Furthermore, its power-plant capacity equals 2000 (10^6 w), and the performance coefficient and hydropower plant efficiency are 25 and 92%, respectively.

The monthly reservoir inflows to the three reservoirs are plotted in Fig. 4. The minimum and maximum river inflows to the Karoon-4 reservoir are 112.4 and 1123.3 million cubic meters, respectively. Minimum and maximum river inflows to Khersan-1 reservoir equal 85.5 and 1694.3 million cubic meters, respectively. Also, the minimum and maximum river inflows to the Karoon-3 reservoir are 0 and 288.51 million cubic meters, respectively.

4. Results and discussions

4.1. Ten-reservoir problem

Murray and Yakowitz (1979) reported the optimal value of the objective function equal to 1190.62. Wardlaw and Sharif (1999) solved this problem with the GA and LP methods and reported global optimal answers equal to 1194.44 and 1190.25 by LP and GA, respectively.

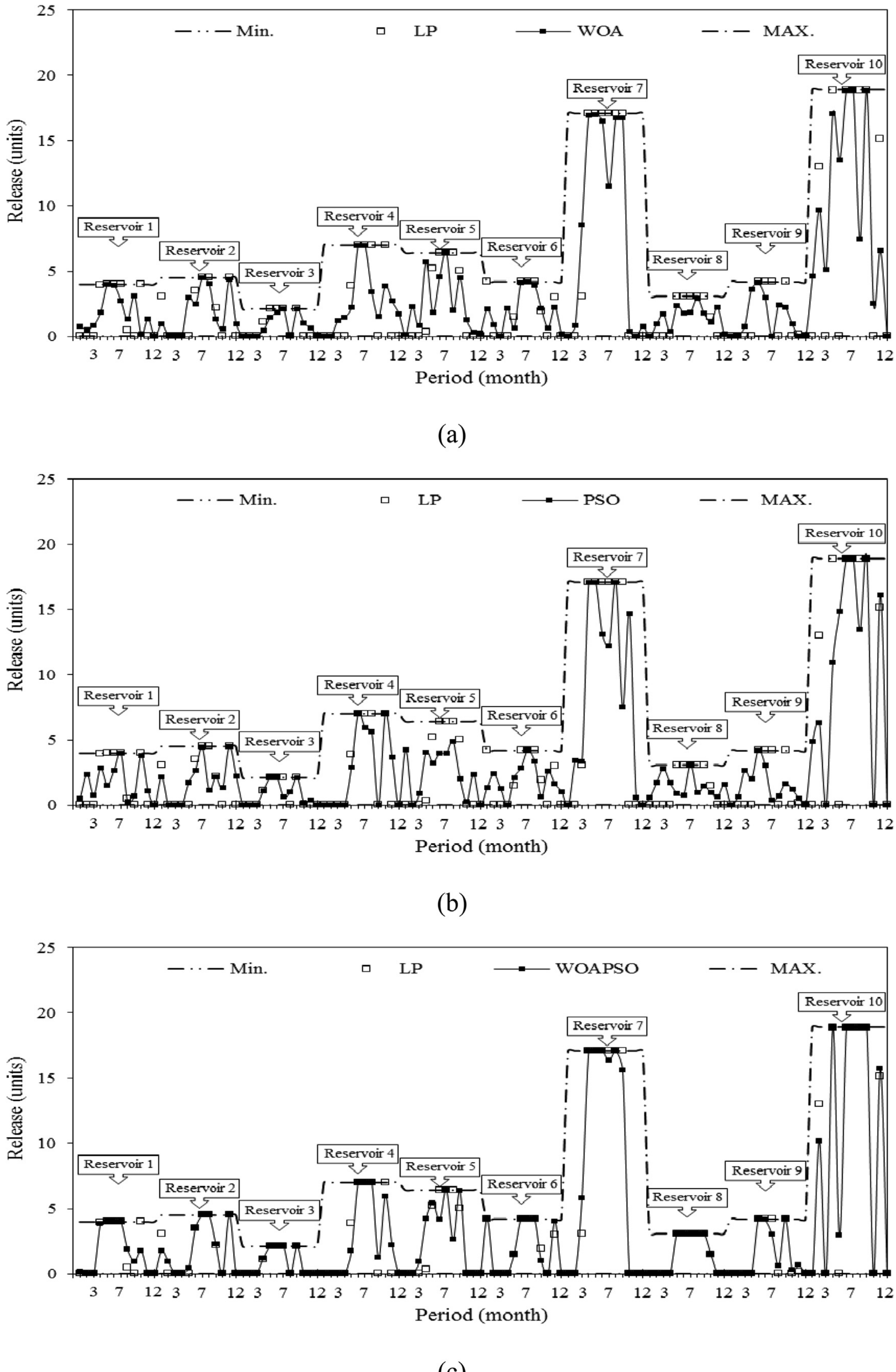


Fig. 6. Results of release volumes with the (a) WOA, (b) PSO algorithm, and (c) hybrid WOAPSO algorithm against LP for ten-reservoir operation problem.

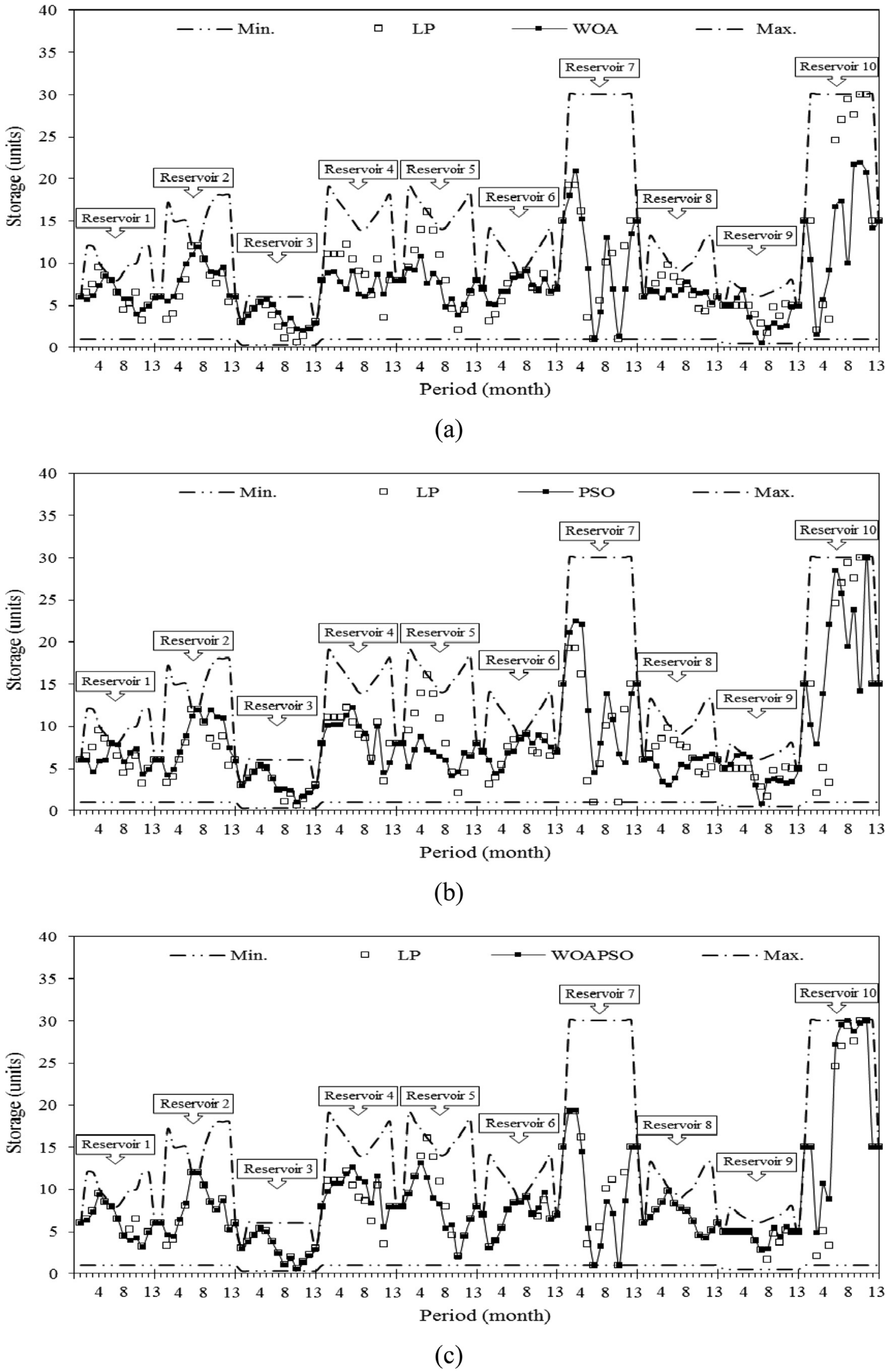


Fig. 7. Results of storage volumes with the (a) WOA, (b) PSO algorithm, and (c) hybrid WOAPSO algorithm against LP for ten-reservoir operation problem.

Table 3
The best parameters of the WOA, PSO algorithm, and hybrid WOAPSO algorithm for the Karoon 4, the Khersan 1, and the Karoon 3 reservoir system operation.

	WOA	PSO algorithm	Hybrid WOAPSO algorithm
$P_{initial}$	20	100	10
$P_{\max}$	40	–	25
$iter_{\max}$	10,000	12,000	10,000
$NoS_{\min}$	1	–	1
$NoS_{\max}$	5	–	4
n	3	–	4
$\sigma_{initial}$	20	–	10
σ_{final}	1	–	1
ω	–	1	0.7
C_1	–	1.5	1.3
C_2	–	2	2

Table 4
Results of 10 runs of the WOA, the PSO algorithm, and the hybrid WOAPSO algorithm for the Karoon 4, the Khersan 1, and the Karoon 3 reservoir system operation.

	WOA	PSO algorithm	Hybrid WOAPSO algorithm	NLP
1	0.093725	0.114149	0.088186	
2	0.094844	0.131040	0.091607	
3	0.096041	0.115912	0.088194	
4	0.094529	0.162364	0.085955	
5	0.094069	0.170331	0.087815	
6	0.092552	0.134613	0.090218	
7	0.094049	0.182686	0.087644	
8	0.093002	0.144576	0.087345	
9	0.093177	0.173956	0.083341	
10	0.091863	0.153752	0.091083	
Minimum	0.091863	0.114149	0.083341	–
Average	0.093785	0.148338	0.088139	
Maximum	0.096041	0.182686	0.091607	
Standard Deviation	0.001145	0.022952	0.002319	
Coefficient of Variation	0.012211	0.154726	0.026314	
Number of functional evaluations	1,088,479	1,200,000	1,022,226	

Recently Bozorg-Haddad et al. (2011) solved this problem with LP and HBMO whose optimal objective values equaled 1194.44 and 1192.56, respectively.

A global solution to this problem was calculated with the LP method in Lingo 14.0. The global optimal value was 1194.44, that was equal to that reported by Wardlaw and Sharif (1999) and Bozorg-Haddad et al. (2011). The hybrid WOAPSO algorithm was implemented to this 10-reservoir problem with the parameters listed in Table 1 calculated with sensitivity analysis. In addition, sensitivity analysis of the WOA parameters and the hybrid WOAPSO algorithm were performed according to procedures by Mehrabian and Lucas (2006) and Hajimirsadeghi and Lucas (2009), respectively.

The results of the calculated objective function from ten runs of the WOA, PSO algorithm, and hybrid WOAPSO algorithm include the values of maximum, average, minimum, standard deviation, coefficient of variation, and number of functional evaluations (which is independent of computer used and form of writing the code of algorithms) listed in Table 2. It is seen in Table 2 that the best values of the objective function for the WOA, PSO algorithm, and hybrid WOAPSO algorithm equal 1160.37, 1156.33, and 1193.76, respectively. Furthermore, the hybrid WOAPSO algorithm reached 99.94% of the global optimum obtained with the LP method. The corresponding best values for the WOA and PSO algorithm were 97.16 and 96.80% of the global optimum, respectively. The calculated values of the standard deviation and coefficient of variation for the hybrid WOAPSO algorithm are much smaller than those obtained with the WOA and PSO algorithm, which

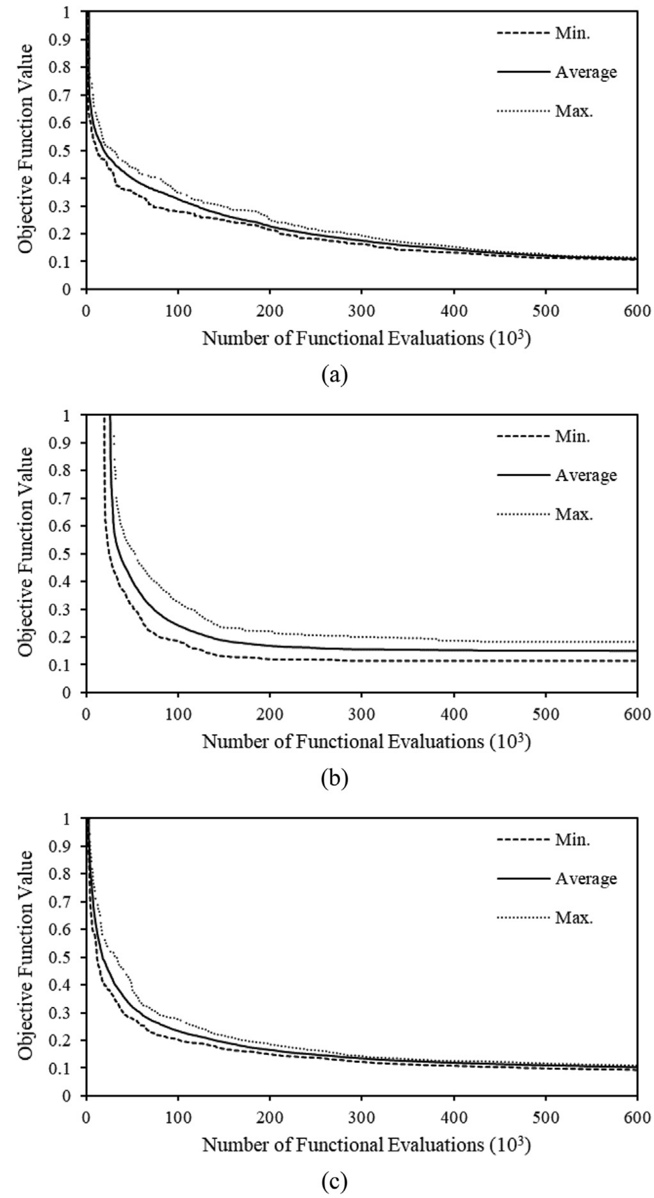
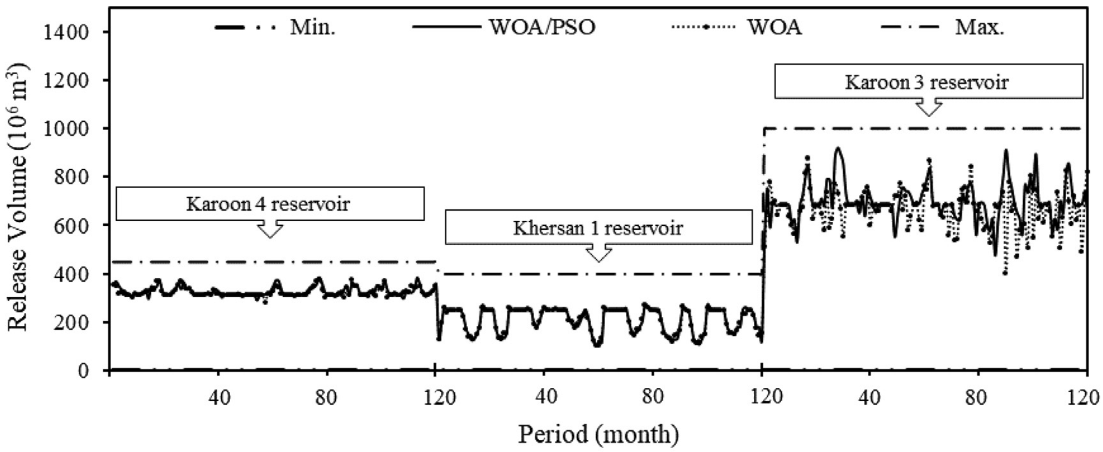


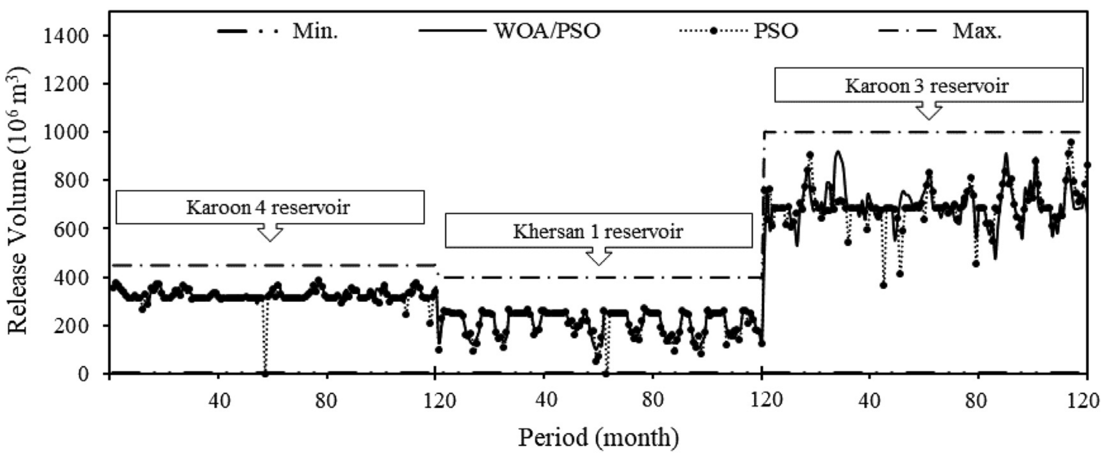
Fig. 8. Convergence for 10 runs of the Karoon 4, the Khersan 1, and the Karoon 3 reservoir system operation problem for the (a) WOA, (b) PSO algorithm, and (c) hybrid WOAPSO algorithm.

indicates the superior performance of the hybrid WOAPSO algorithm in this instance, and reaching more similar solutions in different runs.

Convergence curves of the WOA and hybrid WOAPSO algorithm are depicted in Fig. 5a, b, and c for the minimum, average, and maximum values calculated in ten runs, respectively. It is seen in Fig. 5 the hybrid WOAPSO algorithm converged to the optimal solution much faster than the WOA and PSO algorithm, and the WOA and PSO algorithm converged after 3,000,000 and 2,500,000 functional evaluations, respectively, whereas the hybrid WOAPSO algorithm achieved convergence after 1,000,000 functional evaluations. In addition, according to Fig. 5, the convergence curve for WOAPSO is more convex than the WOA's and PSO's. This indicates the hybrid WOAPSO algorithm converges in fewer number of functional evaluations to the optimal area of solutions. This result proves that combining WOA with the PSO algorithm leads to finding the optimal area faster than the WOA and PSO algorithm. This is so because the process of generating new solutions and directing them towards the global optimum is executed effectively. Also, it can be seen in Fig. 5c that minimum, average, and maximum values calculated



(a)



(b)

Fig. 9. Results of release volumes with (a) WOA against hybrid WOAPSO algorithm and (b) PSO algorithm against hybrid WOAPSO algorithm for the Karoon 4, the Khersan 1, and the Karoon 3 reservoir system operation problem.

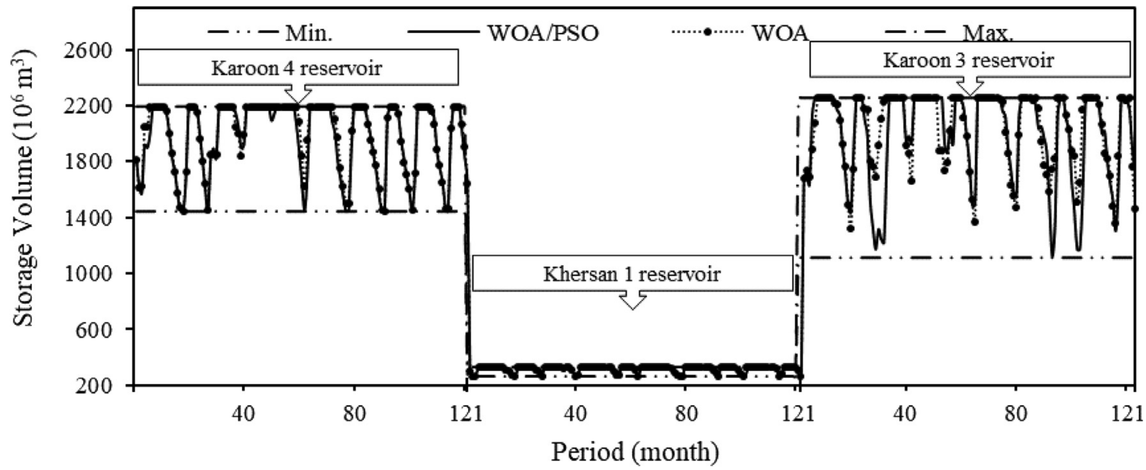
by the hybrid WOAPSO algorithm are close to each other, closer than those of the WOA and thePSO algorithm, which indicates that the hybrid WOAPSO algorithm is more reliable than the WOA and the PSO algorithm in computing similar objective function values in different runs (recall evolutionary and metaheuristic algorithms start the optimization search by generating random solutions, one new initial solution in each of several runs, therefore the final objective function values obtained in different runs differ from each other).

Graphs of reservoir release for the best run out of ten runs associated with the WOA, PSO algorithm, and hybrid WOAPSO algorithm against the results obtained with the LP method are presented in Fig. 6a, b, and c, respectively, for the ten-reservoir system problem, where it is seen all releases obtained with three algorithms satisfy the constraint for releases based on equation (5), and the release results obtained by the hybrid WOAPSO algorithm conform better with the release results calculated by the LP method than the WOA's and PSO's. In addition, as it can be seen from Fig. 2, the releases from reservoirs 1–6 are the input for reservoir 7, and releases from reservoirs 1–9 affect the release values from reservoir 10 since they directly and indirectly have effects on inputs to reservoir 10. Consequently, the release results obtained with the hybrid WOAPSO algorithm and LP for reservoirs 7 and 10 are exemplary of their comparative performances in solving integrated river basin management problems. Fig. 6c indicates that releases obtained with the hybrid WOAPSO algorithm, except for periods 3, 9, and 11 match the releases values obtained with LP. The hybrid WOAPSO algorithm calculated releases values in periods 3 and 9 that are less than those of LP by 1.034 and 0.943, respectively. In period 11 the hybrid WOAPSO algorithm obtained release value that exceeds the LP's by 2.472, thus increasing the objective function. Moreover, the hybrid WOAPSO algorithm calculated releases value in period 2 less than the LP's by 1.731 less than LP; yet, the hybrid WOAPSO algorithm calculated release value in period 11 in excess of the LP's by 2.315. It can be concluded from comparing release values obtained with the hybrid WOAPSO algorithm to those of LP that the former algorithm is efficient and effective in solving complex reservoir problems.

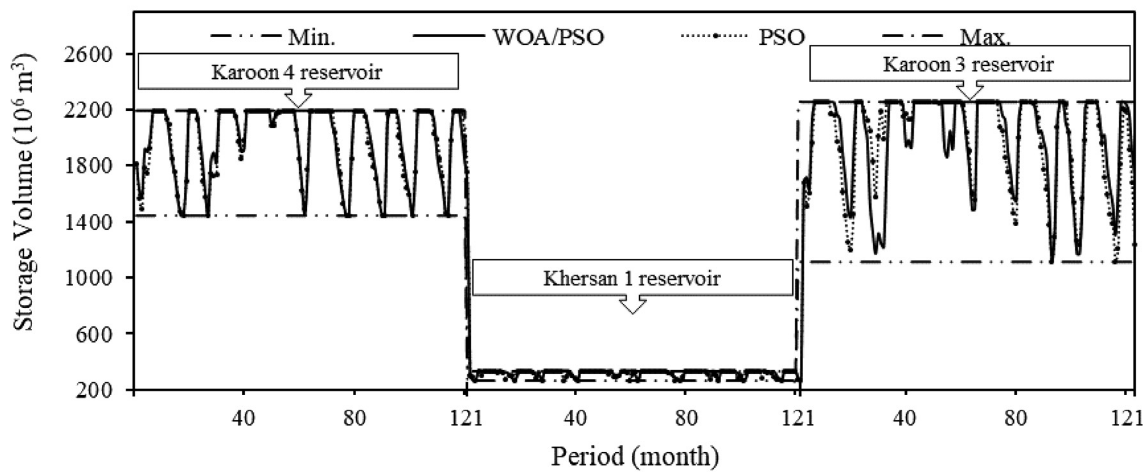
Graphs of reservoir storage for each reservoir of the ten-reservoir problem corresponding to the best run in 10 runs of the WOA, PSO algorithm and hybrid WOAPSO algorithm against the results from LP method are shown in Fig. 7a, b, and c respectively. The results of Fig. 7 indicate that reservoir storage volumes obtained with these three algorithms fall in the feasible range of reservoir storage. However, the storage volumes calculated with the hybrid WOAPSO algorithm are closer to those of the LP method than those obtained with the WOA and PSO algorithm.

4.2. The Karoon-4, Khersan-1 and Karoon-3 reservoir system

The optimization of this system for hydropower production was not solvable with NLP (using the Lingo 14.0 software package), due to its complex nonlinear nature. The search algorithm iterated for 36 h about



(a)



(b)

Fig. 10. Results of storage volumes with (a) WOA against hybrid WOAPSO algorithm, (b) PSO algorithm against hybrid WOAPSO algorithm for the Karoon 4, the Khersan 1, and the Karoon 3 reservoir system operation problem.

a local optimal point. Hence, there is no known solution to this problem with NLP. The optimization was tackled with the WOA, PSO algorithm, and hybrid WOAPSO algorithm, whose best parameters were calculated after sensitivity analysis and are listed in Table 3.

The calculated objective functions from 10 runs of the WOA, PSO algorithm, and the hybrid WOAPSO algorithm include the minimum, average, maximum, standard deviation, coefficient of variation, and the number of functional evaluations (which is independent of computer model and of the coding of algorithms) are reported in Table 4. It is seen in Table 4 the best value of the objective function for the hybrid WOAPSO algorithm equaled 0.08334, while the WOA's and PSO algorithm's values are 0.0916 and 0.14414, respectively, which are 9.02 and 36.90% larger (that is, inferior, under minimization) than the values calculated by the hybrid WOAPSO algorithm. This demonstrates the hybrid WOAPSO model and the WOA and PSO can solve this complex multi-reservoir problem where NLP fails. The hybrid WOAPSO algorithm reached the lowest f objective function value compared with the WOA and PSO algorithm. In addition, smaller standard deviation and coefficient of variation were achieved with the hybrid WOAPSO algorithm compared to those calculated with the WOA and PSO algorithm. This provides further evidence of the superiority and reliability of the hybrid WOAPSO algorithm in this instance.

Convergence graphs of the WOA, PSO algorithm, and hybrid WOAPSO algorithm are graphed in Fig. 8a, b, and c for the minimum, average, and maximum values calculated in 10 runs respectively. It is evident in Fig. 8 the hybrid WOAPSO algorithm and the WOA achieved convergence after 250,000 functional evaluations, whereas the PSO algorithm converged more slowly than the hybrid WOAPSO algorithm and the WOA. The hybrid WOAPSO is evidently faster converging to a near global optimum than the other two optimization algorithms. Also, the hybrid WOAPSO algorithm is faster in finding the optimal area of solutions and converging closer to the global optimum since its convergence curve is more concave than those of WOA and PSO algorithm.

Graphs of reservoir release, reservoir storage, and hydropower production for best runs of the WOA, PSO algorithm, and hybrid WOAPSO algorithm are portrayed in Figs. 9, 10, and 11 respectively. It is evident in Fig. 9 the release values calculated fall within the feasible range of minimum and maximum release. The releases calculated by WOA are in better agreement with those calculated by hybrid WOAPSO algorithm than those from the PSO algorithm. However, for the Karoon-3 reservoir the releases from the PSO algorithm are more consistent with those from the hybrid WOAPSO algorithm in many periods.

Reservoir storage calculated in the best run of 10 runs of the WOA and PSO algorithm are compared with those from hybrid WOAPSO algorithm in Fig. 10 where it is seen the reservoir storages obtained for all three reservoirs by the WOA are in better agreement with those calculated by the hybrid WOAPSO algorithm than with the PSO algorithm's.

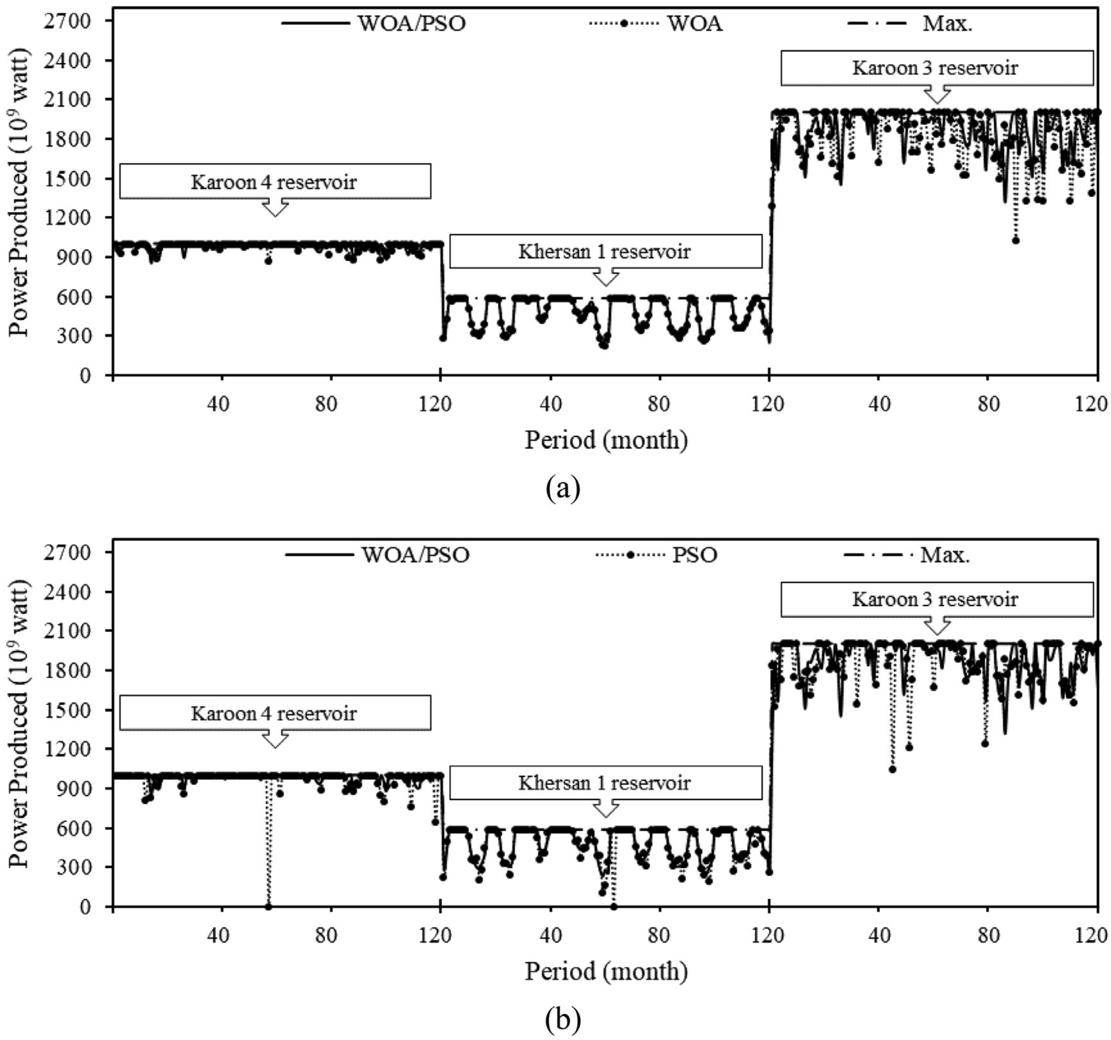


Fig. 11. Results of power produced with (a) WOA against hybrid WOAPSO algorithm and (b) PSO algorithm against hybrid WOAPSO algorithm for the Karoon 4, the Khersan 1, and the Karoon 3 reservoir system operation problem.

Hydropower production graphs calculated in the best run of 10 runs of the WOA and PSO algorithm are compared with the hybrid WOAPSO algorithm's in Fig. 11, where it is evident the hybrid WOAPSO algorithm achieved the largest hydropower production in reservoir Karoon-4 in many periods. Reservoirs Khersan-1 and Karoon-3 exhibited large production deficits in several periods. The WOA shows better agreement in hydropower production with the hybrid WOAPSO algorithm than does the PSO algorithm for reservoirs Karoon-4 and Khersan-1. The PSO algorithm exhibited better agreement of results with hybrid WOAPSO algorithm with respect to the Karoon-3 reservoir than the WOA.

5. Conclusions

This work developed a new optimization model called the hybrid WOAPSO algorithm. The performance of the hybrid WOAPSO was compared with those of the WOA and PSO algorithm based on two multi-reservoir optimization problems, one dealing with hydropower generation and the other maximizing the benefit from allocated reservoir releases, for integrated river basin management. The hybrid WOAPSO algorithm exhibited overall superior performance than the two other algorithms in this comparative study. This paper's comprehensive evaluation of the WOA, PSO algorithm, and hybrid WOAPSO algorithm established the latter optimization algorithm as a strong and comparatively efficient solver of complex and high dimension nonlinear multi-reservoir optimization problems.

Concerning the ten-reservoir benchmark problem our results indicate the optimal solution obtained with the hybrid WOAPSO algorithm (1193.76,) is 99.94% of the LP solution (1194.44), and is larger than those reported by previous studies published in the literature. This performance of the developed hybrid WOAPSO algorithm reveals the hybrid WOAPSO algorithm is effective and reliable in solving multi-reservoir operation problems nvolving integrated river basin management. The efficiency of the developed optimization model was tested with a real-world three-reservoir hydropower problem that cannot be solved with NLP, and whose optimal solution is unknown. The solving capacity of the newly developed optimization model was demonstrated by achieving the best value of the objective function (i.e., 0.08334) of this complex nonlinear optimization problem compared with the solutions by the WOA and PSO algorithm (0.0916 and 0.14414, respectively).

The hybrid WOAPSO algorithm could be applied in future studies to solve other water resources problems involving urban water distribution networks, or climate change impacts on water resources management. The WOA and PSO algorithm have been modified in some studies to improve their performance and efficiency. Combining these newly improved WOA and PSO algorithms may lead to more powerful hybrid algorithms compared with the hybrid WOAPSO proposed in the present study.

Declaration of Competing Interest

None.

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