Water and Environment Journal
Promoting Sustainable Solutions
CIWEM

Water and Environment Journal. Print ISSN 1747-6585

A review of applications of animal-inspired evolutionary algorithms in reservoir operation modelling

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Keywords
animal-inspired EA; optimization; overview; reservoir operation; state-of-art review.

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doi:10.1111/wej.12657

Abstract

Successful operation of reservoir systems to guarantee the optimal use of available water resources has been the subject of many studies. The advent and applications of evolutionary algorithms (EAs) in the field of reservoir operation have led to significant advances in our capacity to improve the planning and management of complex reservoir systems. This study reports a review of the applications of animal-inspired EAs to reservoir operation optimization selected among a large number of available papers in this area of research. The animal-inspired EAs herein identified concern algorithms that mimic biologic traits of animal (wild) species. Among the animal-inspired EAs ant colony optimization (ACO), particle swarm optimization (PSO), shuffled frog leaping algorithm (SFLA), artificial bee colony (ABC), honey bee mating optimization (HBMO), firefly algorithm (FA), cuckoo search (CS) and the bat algorithm (BA) are the best-known ones selected for this review. This paper presents a brief description of the algorithmic characteristics and various employed improved versions or varieties thereof of each of the stated EAs. Furthermore, the differences between the proposed animal-inspired EAs and their improved versions are identified by comparing the performance of the implemented animal-inspired EAs in the reviewed literature. PSO and its varieties have the largest number of reported applications. Our comparison results revealed that constrained, discrete and randomized varieties of the animal-inspired EAs outperformed unconstrained, continuous and deterministic varieties, respectively because of larger feasible search space, better solution quality and shorter computational time. Moreover, all the animal-inspired EAs outperformed traditional methods of reservoir optimization, such as nonlinear programming (NLP) and dynamic programming (DP).

Introduction

Reservoirs are key components of water resources systems, which play an important role in efficient water allocation (Bozorg-Haddad *et al*., 2008a; 2013; Jahandideh-Tehrani *et al*., 2014). Different approaches for water management optimization have been developed to tackle a wide range of water resources issues, such as reservoir operation (Asgari *et al*., 2016), surface water (Bozorg-Haddad *et al*., 2011; Fallah-Mehdipour *et al*., 2011b; Hamedi *et al*., 2016; Jahandideh-Tehrani *et al*., 2015; 2020), groundwater (Bozorg-Haddad and Mariño, 2011; Fallah-Mehdipour *et al*., 2014; Ismail *et al*., 2019), construction scheduling (Orouji *et al*., 2014), as well as water distribution networks modelling and optimization in shortage, flooding and drought conditions and calibration (Creaco *et al*., 2019; Fallah-Mehdipour *et al*., 2011a; Sabbaghpour *et al*., 2012; Soltanjalili *et al*., 2011). The applied approaches for reservoir operation optimization are classified in two main categories, traditional (e.g. dynamic programming (DP), nonlinear programming (NLP) and stochastic dynamic programming (SDP)) and evolutionary algorithms (EAs) approaches. EAs mostly showed higher efficiency in solving complex multi-objective problems (high-dimensional, nonconvex, discrete and multimodal problems) compared to traditional techniques as EAs are able to evaluate all objective functions simultaneously in a Pareto sense (Jahandideh-Tehrani *et al*., 2019; Reddy and Kumar, 2006). Therefore, EAs commonly employed to solve complex optimization problems when traditional methods fail to find optimum solution (Bozorg-Haddad *et al*, 2016; Jahandideh-Tehrani *et al*., 2019). Basically, EAs mimic processes observed in natural evolution (e.g. mutation, crossover, selection and reproduction) (Nicklow *et al*., 2010) and operate on a population of

Water and Environment Journal **35** (2021) 628–646 © 2020 CIWEM.

tentative solutions/designs (Bozorg-Haddad *et al*., 2018). Back *et al*. (2000) stated that EAs are able to discover tentative solutions according to stochastic operators. These operators perform mutation and recombination to obtain new solutions. In case of optimization, fitness of individuals (solutions) improves by the selection process (Back *et al*., 2000). EAs have the ability to efficiently solve multi-dimensional, discrete and nonlinear problems with only having limited information about the mathematical structure of the problem (Fogel, 2000). EAs may require a heavy computational time and the adjustment of algorithmic parameters. Nevertheless, EAs are commonly superior over traditional optimization approaches in solving complex and high dimensional optimization problems (Blickle, 1997).

Some EAs are inspired by physical and chemical phenomena, such as the simulated annealing (SA) and harmony search (HS), which are inspired by homonymous thermodynamic process and musical phenomena, respectively (Jahandideh-Tehrani *et al*., 2019). Other evolutionary and metaheuristic algorithms are inspired by the biological traits of animals/plants, such as life cycles, predatorial behaviour, and mating and foraging strategies. Ant colony optimization (ACO) was applied to monthly operation of a reservoir system by Jalali *et al*. (2006). Particle swarm optimization (PSO), which is a population-based stochastic search technique, was proposed by Kennedy and Eberhart (1995). The firefly algorithm (FA) is inspired by the flashing behaviour of fireflies (Yang, 2008). Bozorg-Haddad *et al*. (2006) introduced honey bee mating optimization (HBMO), which is a swarm-based algorithm, and has been applied to reservoir and water distribution network operation. The artificial bee colony (ABC) and the shuffled frog leaping algorithm (SFLA) are other examples of animal-inspired EAs proposed by Karaboga (2005) and Eusuff and Lansey (2003), respectively. ABC was inspired by the foraging behaviour of honey bees, whereas the SFLA was formulated based on a set of interacting populations of virtual frogs apportioned into several groups.

Previous state-of-the-art studies have mostly focused on the overview of different fields of water resource management such as the applications of multi-objective EAs in water resources (Reed *et al*., 2013), reservoir optimization in water resources (Ahmad *et al*. 2014), the application of EAs to reservoir operation for hydropower production (Neboh *et al*., 2015), the optimal operation of multi-reservoir systems (Labadie, 2004), the application of non-animal-inspired EAs to reservoir optimization (Jahandideh-Tehrani *et al*., 2019) and the application of PSO to water management (Jahandideh-Tehrani *et al*., 2020b), whereas a review of the applications of animal-inspired EAs for optimization of reservoir operation has not been conducted yet. Many papers were investigated the applications of animal-inspired EAs to different types of reservoirs (e.g. single and multi-reservoir system) with different operation purposes (e.g. flood control and drinking water supply).

In addition to the applications of animal-inspired EAs to the water management area there have in-depth investigations that evaluated the efficiency of the animal-inspired EAs in other fields, specifically when coupling EAs with the fuzzy logic system (Olivas *et al*., 2017a; 2017b; Perez *et al*., 2016; Sanchez *et al*., 2017; Valdez *et al*., 2017). Fuzzy systems can efficiently facilitate the process of parameter adaptation through controlling the solution diversity of EAs, such as PSO, BA, bee colony optimization (BCO). Olivas *et al*. (2017a) compared the original and modified versions (coupled with interval type-2 fuzzy logic system) of PSO, BA and BCO to control the trajectory of an autonomous mobile robot. According to their results, PSO outperformed BA and BCO. The fuzzy logic system improved the performance of studied original EAs, such as ACO, PSO, BA and BCO (Olivas *et al*., 2017a; 2017b; Perez *et al*., 2016; Valdez *et al*., 2017).

The focus of this work is to review and compare the applications of the selected well-known animal-inspired EAs (ACO, PSO, SFLA, ABC, HBMO, FA, CS and BA) to reservoir operation optimization, and to identify the research gaps in this field through reviewing journal citation report (JCR) published literature. Several single- and multi-objective animal-inspired EAs are compared to provide a comprehensive overview of the application and performance assessment of the animal-inspired EAs in reservoir optimization. A comprehensive summary of the inspiration mechanisms and characteristics of the selected animal-inspired EAs is presented followed by the performance comparison of the proposed EAs in optimization of reservoir operation. This review's results highlight the leading algorithms in terms of convergence rate, objective evaluation and quality of solutions.

Algorithms

Recent and numerous studies indicate that evolutionary algorithms are efficient in solving complex and real word water resources problems, particularly those dealing with reservoir operation. The selected well-known animal-inspired EAs that have been applied to optimization of reservoir operation problems in the reviewed literature are listed in Table 1. The oldest among them is the ACO and the most recent is the BA. PSO is the animal-inspired algorithm with the largest number of improved versions, including the discrete PSO (DPSO) and Quantum-behaved PSO (QPSO). The ACO takes the second place in the number of improved versions of the original algorithm (i.e. the constrained ant colony optimization algorithm and the nondominated archiving ant colony optimization algorithm). The following section reviews a brief description of the inspiration mechanisms

Table 1 List of the animal-inspired EAs in chronologic order with the oldest listed at the top and the most recent listed at the bottom of the list

Algorithm	Acronym	Year of appearance
Ant Colony Optimization	ACO	1992
Particle Swarm Algorithm	PSO	1995
Shuffled Frog Leaping Algorithm	SFLA	2003
Artificial Bee Colony	ABC	2005
Honey Bee Mating Optimization	HBMO	2006
Firefly Algorithm	FA	2008
Cuckoo Search	CS	2009
Bat Algorithm	BA	2010

and features of main animal-inspired EAs implemented to reservoir optimization. The type of algorithm application, comparison with other methods, final superior algorithm and key findings of each paper are summarized in tables for each studied animal-inspired EA.

Ant colony optimization (ACO)

ACO was developed by Dorigo *et al*. (1991). It is a metaheuristic and discrete combinational algorithm, inspired by the collective behaviour of ants in search for food. ACO's search strategy is performed by artificial ants moving in the search space. Jalali *et al*. (2007) applied a special multi-colony ACO to a 10-reservoir problem operation optimization. The purpose of applying such special version of ACO was to generate a nonhomogeneous mesh in the search space in order to combine discrete and continuous decision variables. ACO efficiently minimizes the possibility of missing the global optimal region, which is highly probable in complex real-world problems with large continuous search space. Jalali *et al*. (2007) also demonstrated that the best objective value of a 10-reservoir problem operation was 99.8% of the known global solution. Wan *et al*. (2017) coupled ACO with artificial neural network (ANN) and applied it to a six-reservoir optimization problem. ACO was used as an optimization tool to estimate optimal weights and parameters of the ANN. The calibrated model was then applied to predict the runoff of the studied reservoir. Their results indicated that the error (difference) for estimated runoff is less than 10%. Different varieties of ACO were employed in other studies, which are listed in Table 2 in chronological order. The results of the reviewed literature,

Table 2 Varieties of ACO

Algorithm	Acronym	Year of appearance	Reference
Constrained Ant Colony Optimization Algorithms	CACOA	2004	Chu *et al*.
Partially Constrained Ant Colony Optimization Algorithm	PCACOA	2007	Afshar M. H.
Nondominated Archiving Ant Colony Optimization	NA-ACO	2009	Afshar A. *et al*.
Ant Colony Optimization Optimizer with a Virtual Linear Programming	Hybrid ACO-LP	2015	Afshar A. *et al*.

Table 3 Summary of the applications of ACO

ACO algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
Multi-colony ACO (Jalali *et al*., 2007)	A hypothetical 10-reservoir problem	–	–	• Efficient combination of discrete and continuous decision variables • Applicable to complex real word problems
CACOA (Moeini and Afshar, 2013)	Two hypothetical four and 10 reservoir hydropower system	Conventional unconstrained ACO	CACOA	• Superiority of CACOA in terms of lower computation effort and better quality solution s • Provision of an efficient method for large scale multi-reservoir operation
PCACOA (Afshar and Moeini, 2008)	A single hydropower reservoir	Conventional unconstrained ACOA and FCACOA	PCACOA	• Superiority of PCACOA because of reduction in the size of the search space
NA-ACO (Afshar *et al*., 2009)	Two single reservoirs	–	–	• NA-ACO generated improved nondominated solutions compared with those from the weighted-sum method.
Hybrid ACO-LP (Afshar *et al*., 2015)	A single reservoir	GA-LP	ACO-LP	• Superiority of ACO-LP in reservoir studies
Hybrid ACO-ANN (Wan *et al*., 2017)	A six-reservoir system	–	–	• Optimization weights and parameters of ANN

Table 4 Varieties of PSO

Algorithm	Abbreviation	Year of appearance	Reference
Discrete Particle Swarm Optimization	DPSO	1997	Kennedy and Eberhart
Multi-Objective Particle Swarm Optimization	MOPSO	1999	Moore and Chapman
Hybrid Artificial Neural Network and Particle Swarm Optimization	Hybrid ANN-PSO	2000	Zhang and Shao
Multi-Swarm Version of Particle Swarm Optimization	MSPSO	2004	Blackwell and Branke
Quantum-Behaved Particle Swarm Optimization Algorithm	QPSO	2004	Sun *et al*.
Chaotic Particle Swarm Optimization	Chaotic PSO	2005	Liu *et al*.
Elitist-Mutation and Multi-Objective Particle Swarm Optimization	EM-MOPSO	2007	Reddy and Kumar
Elitist-Mutated Particle Swarm Optimization	EMPSO	2007	Kumar and Reddy
Improved Adaptive Particle Swarm Optimization	IAPSO	2007	Li and Tang
Partially Constrained Particle Swarm Optimization I	PCPSO1	2013	Afshar
Improved Nondominated Sorting Particle Swarm Optimization Algorithm	I-NSPSO	2013	Guo *et al*.
Elite-Guide Particle Swarm Optimization	EGPSO	2014	Zhang *et al*.

including the type of ACO application, key findings and superior algorithm are summarized in Table 3.

The constrained ant colony optimization algorithm (CACOA)

Chu *et al*. (2004) proposed CACOA, which is an improved version of ACO developed through adding a quadratic distance metric, constrained addition of pheromone, the sum of the K nearest neighbour distances *(*SKNND*)* metric and a shrinking range strategy to modify data clustering. Moeini and Afshar (2013) applied the CACOA to a 4- and 10-reservoir hydropower system. They also compared the proposed CACOA with conventional unconstrained ACO. Their results and convergence curves comparison indicated that CACOA provided a feasible search space and the average objective function value was obtained after 96 and 12 operational periods for 4- and 10-reservoir systems, respectively. Furthermore, the CACOA achieved higher objective function compared to conventional unconstrained ACO because of complete feasible search space. Therefore, the latter authors reported that the CACOA performed much better than unconstrained ACO producing better-quality solutions with less computational effort.

The partially constrained ant colony optimization algorithm (PCACOA)

Afshar (2007) introduced this algorithm, which satisfies constraints by providing a tabu list for each ant. Afshar and Moeini (2008) optimized power generation of a single-reservoir hydropower system in Iran. They also compared PCACOA with unconstrained ACOA and fully constrained ACOA (FCACOA). The same authors demonstrated that the minimum, maximum and average computation cost of FCACOA were better than those produced by PCACOA. Also, the average solution costs calculated with the FCACOA and PCACOA were 68.086 and 230.66 over 480 operation periods, respectively. This difference was observed as all the performed runs for FCACOA produced feasible solutions over all periods while PCACOA produced only two feasible solutions for the hydropower operation problem. Therefore, Afshar and Moeini (2008) indicated that the PCACOA and FCACOA outperformed the unconstrained ACOA by reducing the size of the search space.

Nondominated archiving ant colony optimization (NA-ACO)

Afshar *et al*. (2009b) proposed NA-ACO which consists of a multi-colony ant algorithm and a new policy of information exchange. This new policy leads to a set of nondominated solutions. They applied this algorithm to a two-reservoir hydropower system. The first case study minimized irrigation water supply deficits and maximized hydropower generation, which are conflicting objectives. The second case study defined flood control and hydropower generation as objective functions. NA-ACO algorithm produced 19 nondominated points in the first case study, whereas the weighted sum method generated three nondominated points. Similarly, the nondominated solutions were improved applying NA-ACO.

Ant colony optimization optimizer with a virtual linear programming (hybrid ACO-LP)

This approach was introduced by Afshar *et al*. (2015). They combined ACO optimizer with a virtual LP model to handle constraints in the solution methodology. The same authors applied this model to a single reservoir to minimize reservoir capacity under reliability and volumetric deficit constraints. After comparing the proposed ACO-LP with GA-LP, it was concluded that ACO-LP is superior over GA-LP in terms of locating the reliability optimal reservoir capacity

Table 5 Summary of the applications of PSO

PSO algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
DPSO (Noory *et al*., 2012)	A single reservoir	CPSO	DPSO	• Superiority of DPSO because of faster convergence, more accurate solutions, more stability
MOPSO (Baltar and Fontane, 2008)	A test function (proposed by Kita *et al*. 1996)	NSGA-II, Micro GA and PAES	MOPSO	• Superiority of MOPSO in terms of Closeness to the true Pareto front and distribution along the front in solving the test function
MOPSO (Fallah-Mehdipour *et al*., 2011b)	A three reservoir hydropower system	–	–	• Improvement of the quality and quantity of the Pareto fronts • Prevention of premature convergence
MOPSO-EDA (Lou *et al*.)	Six test problems	NSGA-II, RMMEDA and Clust MPSO	MOPSO-EDA	• Superiority of MOPSO-EDA in terms of uniformity
MSPSO (Ostadrahimi *et al*., 2012)	A three reservoir system	Implicit stochastic optimization (ISO)	MSPSO	• Superiority of MSPSO in terms of smaller penalties deviations from target releases and storages • Reduction in the average, minimum and maximum possible penalties
QPSO (Wang *et al*., 2015)	A multi-reservoir system	–	–	• Robust application of QPSO in estimating operating rule curves coupled with multiple hedging rules
Chaotic PSO (He *et al*., 2014)	A multi-reservoir hydropower system	GA, DE and PSO	Chaotic PSO	• Superiority of chaotic PSO in terms of minimum flood peak and minimizing the maximal upstream water level
EM-MOPSO (Reddy and Kumar, 2007a)	A single multi-purpose reservoir	NSGA-II	EM-MOPSO	• Superiority of EM-MOPSO in terms of provision of a wide spread of solutions with good convergence to the optimal Pareto-front
EMPSO (Kumar and Reddy, 2007)	A single multi-purpose reservoir	GA and PSO	EMPSO	• Superiority of EMPSO in terms of better quality solutions with fewer functional evaluations.
EMPSO (Afshar, 2009)	A single reservoir	–	–	• Maximization of total relative crop yields through efficient reservoir releases and crop water allocations
EMPSO (Ghimire and Reddy, 2014)	A single hydropower reservoir	–	–	• Improvement of power generation by applying EMPSO
IAPSO (Zhang *et al*., 2014a)	A multi reservoir hydropower system	BPSO, APSO and WPSO		• Superiority of IAPSO in terms of power generation benefit and convergence performance
PCPSOI (Afshar, 2013)	Hypothetical 4 and 10 reservoir system	FCPSO, unconstrained PSO and PCPSO2	FCPSO	• Superiority of FCPSO in terms of yielding optimal solution for 4 and 10 reservoir system
I-NSPSO (Guo *et al*., 2013)	A multi-reservoir system	–	–	• Obtained efficient operating policy through I-NSPSO • Prevention of the occurrence of single periods of severe short supply during droughts
EGPSO (Zhang *et al*., 2014b)	Large-scale cascaded hydropower systems	DPSA	EGPSO	• Superiority of EGPSO because of increase in power production, decrease in wasted water and shorter computational time • Applicable to high dimensional and complex problems with low computation time
Parallel MOPSO (Niu *et al*., 2018)	A multi-purpose reservoir system	MOPSO	Parallel MOPSO	• Superiority of the Parallel MOPSO because of stronger search capacity and shorter computational time
Improved PSO (Moeini and Babaie, 2017)	A single hydropower reservoir	Fully and partially constrained and unconstrained PSO	Fully constrained PSO	• Superiority of the fully constrained PSO because of more feasible search space and best solution provision

under variable reliability and normalized deficit index in their case study.

The particle swarm optimization (PSO) algorithm

The PSO algorithm was introduced by Kennedy and Eberhart (1995). PSO is a population-based algorithm inspired by the group behaviour of animals, for instance, bird flocks and fish schools. PSO is the most frequently applied animal-inspired EA to reservoir optimization. Varieties of the PSO algorithm are listed in Table 4. Most PSO applications concern single-objective optimizations involving varieties of the PSO. The results of the reviewed literature, including the type of PSO application, key findings and superior algorithm are summarized in Table 5. Several varieties of PSO are discussed in the following sections.

Discrete particle swarm optimization (DPSO)

This algorithm was first applied by Kennedy and Eberhart (1997). DPSO operates with discrete binary variables. Noory *et al*. (2012) applied this algorithm to a single reservoir in Iran. They optimized their model with LP and with the continuous particle swarm optimization (CPSO) algorithm and found that the number of functional evaluations (for optimizing annual net benefit) and the standard deviations of the results over 50 independent runs were 167 000 and 0.81, respectively, while CPSO obtained 200 000 functional evaluations and 1.09 standard deviation for the same number of runs. Therefore, the DPSO algorithm converged to the optimal solution faster and more accurately than CPSO.

Multi-objective particle swarm optimization (MOPSO)

Moore and Chapman introduced MOPSO in (1999). Several researchers have applied MOPSO to single hydropower reservoir with multiple objectives (Baltar and Fontane, 2008; Fallah-Mehdipour *et al*., 2011b; Lou *et al*., 2015). Baltar and Fontane (2008) applied MOPSO to a single reservoir considering four objectives: (1) maximizing annual firm water supply; (2) maximizing annual firm energy production; (3) minimizing flood risk; and (4) maximizing the overall reliability of the system. MOPSO was also compared with nondominated sorting genetic algorithm (NSGA-II), Micro genetic algorithm (GA) and Pareto Archived Evolution Strategy (PAES). The latter authors reported that MOPSO outperformed other algorithms in solving test functions in terms of closeness to the true Pareto front and distribution along the front. Fallah-Mehdipour *et al*. (2011b) employed MOPSO to a three-reservoir hydropower system considering three objectives: minimizing the sum of squared deviations of: (1) release from demand; (2) storage from target storage; and (3) generated power from instaled capacity. Their results indicated that applying a warm-up technique (using the search mechanism of single-objective PSO to find a uniform Pareto front in space) improved the quality and quantity of the Pareto fronts and prevented premature convergence. Lou *et al*. (2015) compared MOPSO-EDA (combined MOPSO and estimation of distribution algorithm) with the NSGA-II, regularity model-based multi-objective estimation of distribution algorithm (RMMEDA) and Clust MPSO (a multiple swarm multi-objective particle swarm optimization) using six test problems. The results demonstrated that MOPSO-EDA outperforms other methods and can obtain nondominated fronts with good coverage and uniformity. Niu *et al*. (2018) implemented a parallel MOPSO to Lancang cascade hydropower system in southwest China. The latter authors divided the large-population swarm into smaller sub-swarms to be optimized parallelly. Their study indicated that parallel MOPSO overcomes conventional MOPSO because of improved search ability and less computation time.

Multi-swarm version of particle swarm optimization (MSPSO)

Blackwell and Branke (2004) introduced MSPSO. Ostadrahimi *et al*. (2012) applied MSPSO to a three-reservoir system located in the United States considering four test problems and calculated reservoir operating rules. Their results suggested that real time operation with MSPSO outperformed the implicit stochastic optimization (ISO) by reducing the error in estimating target releases and storages. They also noted that in some cases there was a 10-fold increase in error with the ISO technique, which made MSPSO superior over the ISO in their comparison.

Quantum-behaved particle swarm optimization (QPSO) algorithm

The QPSO algorithm was introduced by Sun *et al*. (2004). QPSO is based on the concept of a quantum machine and is applied for nonlinear and nonconvex optimization problems. Wang *et al*. (2015) applied QPSO to a multi-reservoir system to calculate operating rule curves coupled with multiple hedging rules. They defined the objective function as minimization of the sum of squared deficits for agricultural and public demands of system. They found QPSO as a robust global optimization tool to deal with their complex nonlinear system. They concluded that considering bidirectional inter-basin water transfer and water supply simultaneously is an efficient approach.

Chaotic particle swarm optimization (chaotic PSO)

Liu *et al*. (2005) proposed chaotic PSO. This is a hybrid approach designed to escape from local optima that strikes a balance between global and local searches. He *et al*. (2014) applied this algorithm to a multi-reservoir hydropower system and compared the chaotic PSO with the GA, differential evolution (DE) and PSO. In order to make this comparison, two typical floods (5% and 0.2% frequency flood) were considered and the square sum of the discharge flow process was calculated over simulation period. The results indicated that chaotic PSO generates the most efficient solutions for the minimum flood peak (49 300 m^3/s) and the maximal peak-clipping rate (22.85%) than the other three algorithms for 5% frequency flood. The minimal flood peak and the maximal peak-clipping rate were 53 494 m^3/s and 34.04%, respectively, for a 0.2% frequency flood.

Elitist-mutation and multi-objective particle swarm optimization (EM-MOPSO)

Reddy and Kumar (2007a) introduced EM-MOPSO. An innovative strategic mechanism named Elitist-mutation (EM) was coupled with the multi-objective PSO (MOPSO) algorithm to preserve diversity in the population of solutions and to explore the search space. EM improved the performance of PSO with the EM operator, which uniformly distributes the non-dominated solutions along the optimal Pareto-front. Reddy and Kumar (2007a) applied EM-MOPSO to single hydropower reservoir optimization with irrigation, hydropower generation and environmental release purposes. They calculated and compared EM-MOPSO results with those of NSGA-II. The average spacing metric of EM-MOPSO (258.28) was lower than that for NSGA-II (504.32), which meant that the best distribution of Pareto solutions was reached by EM-MOPSO. Hence, it was concluded that EM-MOPSO was more efficient than NSGA-II in terms of providing a wide spread of solutions with good convergence to the optimal Pareto-front.

Elitist-mutated particle swarm optimization (EMPSO)

Kumar and Reddy (2007) introduced EMPSO. The elitist-mutation strategy improves the PSO approach and is capable of replacing the worst particle solutions by the best solution within a swarm of solutions. The solution is improved by maintaining the diversity in the population. This approach was applied to a single hydropower reservoir (Afshar, 2009a; Ghimire and Reddy, 2014; Kumar and Reddy, 2007). Kumar and Reddy (2007) applied EMPSO to a multi-purpose reservoir to minimize sum of squared deficits for irrigation annually and to maximize annual energy production. They compared EMPSO with real coded GA and PSO. The average number of functional evaluations over 10 trial runs were 85 440, 83 280 and 95 660 with EMPSO, PSO and GA, respectively. Furthermore, the total annual irrigation deficits (squared deficits) were 141 601.94, 147 300.87 and 145 180.93 for the EMPSO, PSO and GA, respectively, which confirmed the superiority of EMPSO. Regarding the other objective (hydropower production maximization) of the model it was observed that the average annual hydropower productions were 1820.71, 1802.58 and 1805.91 × 10^6 kWh corresponding to the EMPSO, PSO and GA, respectively. Therefore, the EMPSO outperformed PSO and GA in terms of generating better quality solutions with fewer functional evaluations. Reddy and Kumar (2007b) applied EMPSO to a nonhydropower single reservoir to maximize the total relative yield from crops. The model calculated efficient reservoir releases and crop water allocation over a 10-day period for several crops (sorghum, pulses, wheat, safflower and cotton). Ghimire and Reddy (2014) studied the annual hydropower production optimization of a reservoir using EMPSO. The objective function was to maximize annual hydropower production considering flood control restrictions, irrigation requirements and various other physical and technical constraints. It was concluded that EMPSO improves power generation significantly after comparing the optimization results with historical power production.

Improved adaptive particle swarm optimization (IAPSO)

Li and Tang (2007) introduced IAPSO. IAPSO applies an adaptive dynamic parameter control mechanism to identify model parameters. Zhang *et al*. (2014a) compared this approach with basic PSO (BPSO), adaptive PSO (APSO) and W linearly decreasing PSO (WPSO). They applied three different population sizes (50, 100 and 150) to compare the maximum hydropower generation of the four stated algorithms for the studied reservoir. Their results revealed that IAPSO algorithm generated the largest amount of hydropower, 42.23, 41.77 and 42.12 billion kWh for population size of 50, 100 and 150, respectively. Therefore, IAPSO gave better operational results with more efficient convergence, performance and robustness than other methods. Moeini and Babaie (2017) implemented an improved PSO to optimize large scale hydropower-reservoir operation through unconstrained and two (partially and fully) constrained versions of PSO. Their results indicated that the fully constrained PSO provided more feasible search space and the best solution, compared with partially constrained and unconstrained PSO.

Partially constrained particle swarm optimization I (PCPSOI)

Afshar (2013) introduced PCPSOI which is associated with a new set of bounds for the decision variable to satisfy constraints on the corresponding state variables. Afshar

Table 6 Summary of the applications of the SFLA

SFLA Algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
MOSFLA (Li *et al*., 2010)	A single multi-purpose reservoir	NSGA-II and DP	MOSFLA	• Superiority of MOSFLA because of the generation of uniform spread solutions and closer convergence to true Pareto frontier
SFLA (Fallah-Mehdipour *et al*., 2013)	A single reservoir	GA and PSO	SFLA	• Superiority of SFLA because of obtaining maximum objective function for both linear and nonlinear multi-crop planning rules
Improved SFLA (Li *et al*. 2018)	A multi-reservoir hydropower system	SFLA, PSO, immune SFLA and cloud SFLA,	Improved SFLA	• Superiority of the improved SFLA because of increased power generation and faster and more stable convergence to solutions

(2013) applied this approach to a hydropower multi-reservoir system and two benchmark problems and compared PCPSOI with fully constrained PSO (FCPSO), unconstrained PSO (UCPSO) and PCPSO2. It was observed that FCPSO obtained the best optimal solutions with 308.4 and 1194.05 for the 4- and 10-reservoir systems, respectively. Therefore, the constrained algorithms, especially FCPSO, performed better than UCPSO.

Improved nondominated sorting particle swarm optimization (I-NSPSO) algorithm

Guo *et al*. (2013) applied this algorithm to a multi-reservoir system considering two test problems. The I-NSPSO algorithm was proposed to preserve the diversity of non-dominated solutions in multi-objective optimization problems. The multi-population mechanism was combined with nondominated sorting particle swarm optimization to generate the I-NSPSO algorithm. Guo *et al*. (2013) demonstrated that that I-NSPSO is capable of finding optimal Pareto fronts. The calculated policy rule prevented single periods of severe short supply of water during droughts.

Elite-guide particle swarm optimization (EGPSO)

Zhang *et al*. (2014b) introduced EGPSO. This approach avoids trapping in local optima by means of an external archival set. Elite solutions are maintained during the evolutionary search process. They compared EGPSO with DPSA, where EGPSO improved energy production by 0.34% and deserted water by 6.48%. The computing time of the EGPSO (40.09 s) was lower than the DPSA's (118.75 s). Therefore, it was revealed that the EGPSO is efficient in high-dimensional and complex optimization problems with regard to convergence and computing time.

The shuffled frog leaping algorithm (SFLA)

The SFLA was introduced by Eusuff and Lansey in (2003). The SFLA is a population-based algorithm inspired by natural memetics that involve interacting virtual populations of frogs partitioned into different memeplexes. The applications of this algorithm are summarized in Table 6. Li *et al*. (2010) and Fallah-Mehdipour *et al*. (2013) applied SFLA to nonhydropower optimization problems. Li *et al*. (2010) compared the multi-objective SFLA (MOSFLA) with NSGA-II and DP employing Three Gorges Reservoir, including reservoir, hydropower station and navigation structures in China. Two conflicting objectives (minimization the highest reservoir water level and minimization of the peak flow discharge) over two typical floods (the 5 and 0.2% frequencies in 1954) were investigated in the Three Gorges project. Their results indicated that MOSFLA outperforms NSGA-II in terms of convergence and distribution. The computational time of NSGA-II was twice that of MOSFLA, because NSGA-II lacks the archival maintenance feature. MOSFLA also outperformed DP as several solutions were far from the Pareto front obtained by DP, whereas MOSFLA produced solutions that were distributed uniformly in the feasible space and had better convergence to the Pareto front. In summary, they concluded that multi-objective SFLA is capable of generating a uniform spread of solutions and exhibited better convergence than NSGA-II and DP. Fallah-Mehdipour *et al*. (2013) applied and compared three EAs (SFLA, GA and PSO) in a reservoir irrigation problem to obtain optimal linear and nonlinear multi-crop planning rules. The estimated maximal (best) objective function (total net benefit) of the GA and PSO were 65.53 and 62.34% worse (less) than the best (maximal) value obtained by SFLA, respectively. Similarly, concerning nonlinear planning the best (maximum) values of objective functions were 73.63 and 72.29% for GA and PSO, respectively, which were lower than that obtained by SFLA. Therefore, it was reported that the SFLA obtained the best solution for linear and nonlinear planning rules in comparison with the GA and PSO. Li *et al*. (2018) implemented an improved SFLA through coupling a local 'refine search' mechanism and a 'global incentive adjustment' mechanism. In this improved version of SFLA, more frogs were motivated to jump out of the local steady state and a more refined local search was applied near the optimal individuals. The Li Xianjiang cascade reservoirs in China were the selected case study. The average annual power generations calculated with SFLA with SFLA, PSO, immune SFLA and cloud SFLA increased the average annual power generation by 6.7, 7.5, 3.0 and 0.8%, for the stated algorithms, respectively. Also, the convergence of the improved SFLA was more stable and faster than that of SFLA, PSO, immune SFLA and cloud SFLA with shorter computational time. This review indicates the SFLA can outperform GA and PSO in reservoir optimization problems, yet, it is not applied frequently.

The artificial bee colony (ABC) algorithm

The ABC algorithm was introduced by Karaboga (2005). The ABC is a population-based algorithm that imitates the natural foraging behaviour of honey-bees. Previous applications of this algorithm are listed in Table 7. Chen *et al*. (2016) applied ABC to optimize multi-crop irrigation scheduling and to obtain optimal operation policy model considering conjunctive operation of reservoirs and ponds. They concluded that ABC can potentially solve this nonlinear, high-dimensional and complex optimization problem in terms of fast convergence and reaching global optimal value. Hossain and El-Shafie (2014) and Ahmad *et al*. (2016) compared the ABC algorithm with the GA in obtaining monthly release curves of a reservoir in Egypt. The total estimated RMSEs for obtained rule curves by ABC were 9.81, 4.78 and 5.90 billion cubic meters (BCM) for high, medium and low flow conditions, respectively. The stated RMSE values were lower than those of obtained by GA (10.18, 5.38 and 6.39 BCM for high, medium and low flow conditions). Also, the reservoir reliability, resilience and vulnerability were 98.14%, 1 month and 1.11% of demand for ABC, respectively, whereas GA obtained 91.6%, 2 months and 57.75% of demand for the reservoir reliability, resilience and vulnerability, respectively, which were significantly worse than ABC's performance criteria. Ahmad *et al*. (2016) compared the performance of the ABC with the Gravitational Search Algorithm (GSA) in minimizing the irrigation release deficit of the Timah Tasoh Dam located in the Northern part of Peninsular Malaysia. ABC achieved faster convergence rate and better fitness function values with lower standard deviation, which confirmed the high stability of the ABC. The latter authors analysed the reservoir performance criteria (reliability, vulnerability and resiliency indexes) of ACB and GSA. The estimated reliability, vulnerability and resiliency indexes were 60.19, 3.01 and 0.33 for ABC, and 58.33, 3.22 and 0.40 for GSA, respectively. The ABC algorithm exhibited faster convergence rate, stability, higher reliability and lower vulnerability indexes; however, the GSA performed better with respect to the resiliency indicator measure. ABC was also used for water supply deficit purposed in another study by Choong *et al*. (2017). They used ABC as an optimization tool to investigate the performance of both monthly and weekly release curve in the Chenderoh Reservoir, Malaysia. ABC was found to be an efficient tool to extract the variant of the reservoir release for operating policies. They also indicated that weekly ABC optimization model outperformed the monthly model in terms of reliability and vulnerability indexes. Hossain *et al*. (2018) applied ABC to the Aswan High Dam, Egypt,

Table 7 Summary of the applications of ABC

ABC algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
ABC (Hossain and El-Shafie, 2014)	A single reservoir	GA	ABC	• Superiority of ABC because of lower estimated RMSE for computed rule curve and more efficient reliability, resilience and vulnerability
ABC (Chen *et al*., 2016)	A single reservoir	–	–	• Applicability of ABC in nonlinear, high dimensional and complex problems to optimize multi-crop irrigation scheduling and operation policy
ABC (Ahmad *et al*., 2016)	A single reservoir	GSA	–	• Superiority of the ABC in terms of faster convergence rate, stability, higher reliability and lower vulnerability indexes • Superiority of the GSA in terms of the resiliency indicator measure
ABC (Choong *et al*., 2017)	A single reservoir	–	–	• Applicability of the ABC in extracting weekly and monthly release curves
ABC (Hossain *et al*., 2018)	A single reservoir	PSO, GA and NN-SDP	ABC	• Superiority of the ABC in terms of achieving minimum water deficit, less waste of water and capacity to handle critical situations

to extract optimal water-release policies. The ABC, GA and PSO release policies were compared and it was concluded that ABC failed four times to meet the demand targets, compared to PSO, real coded GA and binary coded GA with 5, 18 and 63 times of failure in meeting the demand, respectively. ABC provided higher reliability (14%) than the Neural Network Stochastic Dynamic Programming (NN-SDP).

Honey-bee mating optimization (HBMO)

HBMO was developed by Bozorg-Haddad *et al*. (2006). HBMO is a swarm-based algorithm that is inspired by the mating strategies of honey-bees. This behaviour is based on genetic potentially, ecological and physiological environments and social conditions. The reported archival applications of this algorithm are listed in Table 8.

Several papers compared the HBMO's performance with the GA algorithm in reservoir optimization using test problems and benchmarks (Afshar *et al*., 2011b; Bozorg-Haddad *et al*., 2006; 2009; Solgi *et al*., 2017). All the papers showed the superiority of HBMO over GA in terms of convergence speed, search capacity and accuracy, which is the result of the fact that the GA uses only the best combination of probability for crossover and mutation that leads to premature convergence and, therefore, the GA may converge to local optima. On the contrary, the best heuristic functions were adapted by HBMO for the next generations, which consequently avoided trapping in local optima. Afshar *et al*. (2007), Bozorg-Haddad

Table 8 Summary of the applications of HBMO

HBMO algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
HBMO (Bozorg-Haddad *et al*., 2006)	A single hydropower reservoir	GA	HBMO	• Superiority of the HBMO by obtaining the best solutions based on the Pareto front
HBMO (Afshar *et al*., 2007)	A single reservoir	LP	HBMO	• Superiority of the HBMO in minimizing the total squared deviations of releases from the target demands because of more efficient fitness function
HBMO (Bozorg-Haddad *et al*., 2008b)	A multi-reservoir hydropower system and a single hydropower reservoir	NLP	HBMO	• Superiority of the HBMO in minimizing the total present net cost of the system and maximizing possible ratio for generated power to installed capacity • Failure of the NLP in finding a feasible solution in a hydropower multi-reservoir system • Poor performance of NLP in the single hydropower reservoir
HBMO (Bozorg-Haddad *et al*., 2008c)	A single hydropower reservoir	NLP	HBMO	• Superiority of the HBMO in extracting the linear monthly operation rules for irrigation in terms of lower water shortage • Failure of NLP in finding feasible solution for making the power generation as close to the instaled capacity as possible
HBMO (Bozorg-Haddad *et al*., 2009)	A single hydropower reservoir and a test problem	GA and NLP	HBMO	• Superiority of the HBMO over GA in the test problem because of faster convergence • Superiority of the HBMO over NLP in maximizing the power generation of a real word problem because of more efficient performance indices
HBMO (Afshar *et al*., 2011)	A multi-reservoir hydropower system and a test problem	GA	HBMO	• Superiority of the HBMO over GA in a single reservoir test problem because of better fitness function • Efficient operating rule curves by using HBMO
HBMO (Tică *et al*., 2017)	A multi-purpose reservoir	FA, CS and BA	–	• Superiority of the HBMO in terms of power generation • Superiority of the BA in terms of reservoir performance
EHBMO (Solgi *et al*., 2017)	A multi-reservoir system	HBMO and EGA		• Superiority of the EHBMO with fewer number of functional evaluations and less variance in results

Table 9 Summary of the applications of the FA

FA algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
FA (Garousi-Nejad *et al*., 2016a)	A single reservoir irrigation supply purpose and a single reservoir with hydropower production purpose	GA	FA	• Superiority of the FA in terms of the convergence rate to global optima and of the variance of the results about global optima
MFA (Garousi-Nejad *et al*., 2016b)	Three test problems	LP, DDP, DDDP, GA, MCAA, HBMO, WCA, BA and BBO	MFA	• Superiority of the MFA because of the least difference of the estimated objective function from the LP global optimal solutions
MODFA (Bozorg-Haddad *et al*., 2017)	A three reservoir system	MOGA and MOFA	MODFA	• Superiority of the MODFA because of the capability of achieving near-optimal solutions, high-speed convergence rate and higher reliability

et al. (2008b) and Bozorg-Haddad *et al*. (2008c) applied the HBMO algorithm. Afshar *et al*. (2007) and Bozorg-Haddad *et al*. (2008c) compared HBMO with LP and NLP, respectively. They reported that the HBMO is capable of solving discrete and continuous decision variables and obtains better local optima than LP and NLP. Bozorg-Haddad *et al*. (2008b) demonstrated that NLP fails to obtain feasible solution in a five-multi-reservoir system, which confirmed limited application of NLP in high non-linear and complex optimization problems. Bozorg-Haddad *et al*. (2008c) applied HBMO to a single reservoir with irrigation and hydropower purposes. The latter authors also compared their results with NLP. Regarding the irrigation purpose, NLP and HBMO obtained the values 26.08 and 18.15 for the fitness functions (minimizing the total squared deviation of releases from the target demands) over 480 operation periods, respectively. Concerning hydropower generation HBMO obtained 57.40 for objective function (making the power generation as close to the instaled capacity as possible), while NLP failed to find feasible solution. Generally, all the reviewed studies revealed that HBMO can outperform the GA algorithm, LP and NLP. Tică *et al*. (2017) applied HBMO to a simple hydropower reservoir and compared results with the FA, cuckoo search (CS) and bat algorithm (BA) algorithms. They demonstrated that HBMO was the best performing algorithm and produced the closest annual energy production to the reference value of 400 GWh, while BA yielded the best objective function. Solgi *et al*. (2017) also applied Enhanced HBMO (EHBMO), which is based on a new mating process, to a four-reservoir problem and compared results with HBMO and Enhanced GA (EGA). The EHBMO reduced the common computational demands of the HBMO and EGA while achieving a closer solution to global optimum, which confirms the superiority of the EHBMO over HBMO and EGA.

The firefly algorithm (FA)

The FA was introduced by Yang (2008). This algorithm is inspired by the behaviour of fireflies in nature. The list of application of FA to reservoir optimization problems is shown in Table 9. Garousi-Nejad *et al*. (2016a) compared the FA and GA using two different single reservoirs with irrigation and power generation purposes. The reservoir problem with irrigation purpose had best estimated values of the objective function (minimization of the irrigation deficit) equal to 6.38 and 3.54 for the GA and the FA, respectively. The FA generated the objective function with lower standard deviation (0.06) compared to that of GA (0.31). The reservoir problem with hydropower purpose indicated the best objective function value (minimization of the hydropower deficits) equal to 0.0089 and 0.0078 for the GA and the FA, respectively. The FA yielded the objective function with lower standard deviation (0.0003) than the GA (0.0004). Therefore, it was reported that the FA indicated the best performance considering convergence rate to global optima. In another study by the same researchers (Garousi-Nejad *et al*., 2016b) the superiority of the improved FA (MFA) over the GA, multi-colony ant algorithm (MCAA), HBMO, water cycle algorithm (WCA), BA, biogeography-based optimization (BBO), LP, improved differential dynamic programming (DDP) and discrete differential dynamic programming (DDDP) was established. The optimization of three well-known benchmark multi-reservoir operation problems were studied and it was reported that estimated objective functions of MFA differed from LP global optimal solutions by 0.01

and 0.79% for a continuous four-reservoir problem (CFP) and a continuous 10-reservoir problem (CTP), respectively. The computed objective function of MFA was equal to that of LP. Consequently, MFA was considered as a competitive optimization approach for multi-reservoir system problems. Bozorg-Haddad *et al*. (2017) implemented an extended multi-objective developed firefly algorithm (MOFDA) to a three-reservoir system in Iran. Two objective functions (maximization of power generation reliability and minimization of power deficits vulnerability) were considered and results were compared with multi-objective GA (MOGA) and MOFA. The optimal Pareto points of the MODFA dominated the MOGA and MOFA's optimal Pareto fronts. The optimal Pareto points of the MODFA were well-distributed compared to those of MOGA and MOFA. Therefore, MODFA was superior over MOGA and MOFA because of the capability of achieving near-optimal solutions, high-speed convergence rate and higher reliability.

Cuckoo search (CS)

The CS was developed by Yang and Deb (2009). This algorithm is inspired by the obligate brood parasitic behaviour of some cuckoo species. A summary of applied the CS to reservoir optimization is indicated in Table 10. Kangrang *et al*. (2017) published a paper dealing with the application of the CS to reservoir optimization. The conditional cuckoo search (CCS) was applied to derive rule curves for a single reservoir in Thailand. Kangrang *et al*. (2017) showed that the CCS is efficient in calculating adaptive rule curves under variable inflows. Ming *et al*. (2015) employed the CS to maximize the power generation of a multi-reservoir system in China. They also compared the performance of CS with GA and PSO for the same objective. Their results revealed that CS provided higher energy production with satisfied convergence performance. CS provided higher energy production by 0.52, 0.32 and 1.64% for three different scenarios than that of the GA. Overall, given the simple structure, excellent search efficiency and strong robustness of CS, this algorithm has performed efficiently in solving complex reservoir operation optimization. Meng *et al*. (2019) proposed a new improved multi-objective cuckoo search (IMOCS) algorithm to address the shortcomings of the multi-objective cuckoo search (MOCS). They applied a population initialization strategy based on constraint transformation and the individual constraints and group constraints technique (ICGC). They also applied a dynamic adaptive probability (DAP) to improve the quality of solutions and compared the performance of the IMOCS with MOCS and NSGA-II., IMOCS was the best-performing algorithm converging to a steady hyper volume, whereas MOCS applied more iterations for such convergence and the final achieved hyper volume was smaller. The Pareto front of the NSGA-II was similar to IMOCS in terms of convergence and diversity. However, the convergence of NSGA-II was worse than IMOCS's in earlier generations.

The bat algorithm (BA)

The BA was introduced by Yang (2010). The BA is inspired by the echo-location behaviour and predatorial strategies of bats in complete darkness. Bozorg-Haddad *et al*. (2015) and Ahmadianfar *et al*. (2016) applied the single-objective BA to optimize hydropower reservoir operation in Iran using test problems and benchmark functions. Bozorg-Haddad *et al*. (2015) compared the BA performance with that of GA's for operation rules extraction. The average results of BA (1.24) was closer to that of the global result (1.21) compared to the GA result (1.75). The latter authors indicated the convergence rate to global optima was also faster with the BA, which confirmed the superiority of the BA over the GA. Ahmadianfar *et al*. (2016) solved 4- and 10-multi-reservoir problems and reported suitable capability of the BA in global searching of solutions. Ehteram *et al*. (2018) also employed BA in two separate reservoirs (one

Table 10 Summary of the applications of CS

CS algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
CCS (Kangrang *et al*., 2017)	A single reservoir	CPSO	–	• Smaller water shortage and water excess for obtained rule curves of CCS, CPSO and CACO compared to the current rule curves • Applicability of both CCS and CPSO in rule curve improvement
CS (Ming *et al*., 2015)	A hydropower multi-reservoir system	GA and PSO	CS	• Superiority of the CS in optimizing energy production because of satisfactory convergence
IMOCS (Meng *et al*., 2019)	A multi-purpose reservoir	MOCS and NSGA-II	IMOCS	• Superiority of the IMOCS in terms of convergence speed, convergence property and diversity of solutions

with irrigation purpose and the other with power generation purpose) to obtain different rule curves, including first-, second- and third-order rule curves. Three performance criteria (reliability, resilience and vulnerability) were calculated. Concerning the first studied reservoir (Aydoughmoush dam) the third-order rule curve reduced the irrigation deficit object by 6.3 and 16% compared with the first- and second-order rule curves, respectively. Similarly, concerning the other studied reservoir (Karoun 4) the third-order rule curve generated the best average objective function with smaller coefficient variation (5.33 and 3.66 smaller than first-order and second-order rule curves, respectively). In addition to the conventional BA many researchers have employed the improved versions of this algorithm, including improved BA (IBA) and Hybrid Bat–Swarm Algorithm (HB-SA) (Table 11). Zarei *et al*. (2019) implemented the PSO, BA and Hybrid Algorithm (HA) to a multi-purpose reservoir. The HA obtained volumetric reliabilities equals 0.92, 0.89, 0.79 and 0.75 for urban, environmental, agricultural and industrial demands, respectively, similar to those of the BA and PSO. The obtained mean water release values of the HA met more demand targets than those of BA and PSO. In summary, the results of the reviewed literature, including the type of BA applications, key findings and superior algorithm features are listed in Table 12.

Improved bat algorithm (IBA)

Wang *et al*. (2018) optimized medium and long-term operation of a hydropower reservoir system using the BA algorithm. They applied an improved version of the BA by generating uniform distributed initial population rather than randomly scattered (unevenly) populations and compared the performance of improved BA with DP and GA. They concluded that improved BA optimized total power production by 1.6 and 4.2% compared to DP and GA, respectively. It was also proved that adding uniform scatter points to the initial population of the BA improves solutions' distribution and computational time.

Hybrid bat–swarm algorithm (HB-SA)

Yaseen *et al*. (2019) proposed a new hybrid algorithm (HB-SA), which was obtained by coupling the BA and PSO. The purpose of such coupling was to improve the conventional BA through using PSO to replace the sub-optimal solutions generated by the conventional BA for the purpose of addressing slow convergence rate and local optima trapping in the conventional BA. The Golestan and Voshmgir reservoirs in Iran were selected to evaluate the new proposed algorithm. Their results indicated that the HB-SA outperformed WCA, HS, Intelligent Colony Algorithm (ICA), BA and PSO and obtained a closer value of the minimum objective function (minimization of irrigation deficit). The HB-SA produced the average objective function equal to 0.115, which was almost 95% of the global optimal value, whereas the best objective function of the PSO and BA were 0.212 and 0.156, respectively.

Table 11 Varieties of the BA

Algorithm	Acronym	Year of appearance	Reference
Improved Bat Algorithm	IBA	2018	Wang *et al*.
Hybrid Bat–Swarm Algorithm	(HB-SA)	2019	Yaseen *et al*.

Comparison of animal-inspired EAs

All the discussed animal-inspired EAs (ACO, PSO, SFLA, ABC, HBMO, FA, CS and BA) are population-based stochastic techniques, which are inspired by the interactions of individuals' behaviour in groups. The PSO and ACO are data clustering algorithms through swarm behaviour modelling; yet, the PSO is more efficient in fuzzy nature problems (Selvi and Umarani, 2010). PSO and SFLA are initialized with random positions of particles and frogs, respectively, while ACO first determines pheromone concentration, followed by initializing random positions for ants (El-Ghandour and Elbeltagi, 2018). The SFLA couples the local-search tool-based PSO benefits with the genetic-based memetic algorithm to derive optimal global solutions (El-Ghandour and Elbeltagi, 2018). The GA implements crossover operators to generate new candidate solutions, while the ABC employs its parent to generate new candidate solutions through a simple operation process (using the difference of randomly selected solutions from the population and randomly identified parts of the parents). The stated simple operation improves the convergence speed to local optima (Karaboga and Akay, 2009). PSO and GA keep the best found solution in the population (used for generating new solutions) whereas ABC does not always keep the best found solution and the best solution can be replaced by a new randomly generated solution by scout (Karaboga and Akay, 2009). Fister *et al*. (2013) claimed that FA does not consider historical individual best optimal solution and there is also no defined explicit global best solution, which prevents FA from premature convergence. Premature convergence is also common in PSO. The comparison of CS with PSO and GA revealed that the number of tuning parameters in CS is less than those of PSO and GA, which makes CS more applicable to a wider class of optimization problems, specifically, multimodal objective functions (Roy and Chaudhuri, 2013).

Table 12 Summary of the applications of BA

BA algorithm	Type of application	Comparison with traditional methods/EAs	Superior EA	Key findings
BA (Bozorg-Haddad *et al*., 2015)	A single hydropower reservoir	GA and LP	BA	• Superiority of the BA in minimizing power generation deficit because of faster convergence and lower deviation of results from the global optima
BA (Ahmadianfar *et al*., 2016)	Two hypothetical four and 10 reservoir hydropower systems	–	–	• Suitable capability of BA in searching global solutions
IBA (Wang *et al*., 2018)	A hydropower multi-reservoir system	DP and GA	IBA	• Superiority of the IBA because of fast convergence and short computational time of BAT
BA (Ehteram *et al*., 2018)	A single reservoir irrigation supply purpose and a single reservoir with hydropower production purpose	–	–	• Achievement of high performance criteria (reliability, resilience and vulnerability) in third-order rule curve
HB-SA (Yaseen *et al*., 2019)	A multi-reservoir system	WCA, HS, ICA, BA and PSO	HB-SA	• Superiority of the HB-SA because of faster convergence rate, prevention of trapping in local optima and shorter computational time
BA (Zarei *et al*., 2019)	A multi-purpose reservoir system	PSO and HA	HA	• Superiority of the HA because of higher reliability in meeting water demands

Our literature review also indicates that among the animal-inspired EAs the PSO has the largest number of applications and improved algorithmic versions. PSO has been improved over time through various modifications. For instance, the EM method is capable of replacing the worst particle solutions by the best ones, which can provide a uniform distribution of the nondominated solutions along the optimal Pareto front. Furthermore, chaotic, discrete and constrained versions of PSO improved the performance of the conventional PSO in solving reservoir optimization problems. Such improvements are reflected in calculated lower standard deviations (more stability), faster convergence rate, higher solution quality and comprehensive Pareto solutions. Furthermore, it has been reported that implementing a warm-up technique (using the search mechanism of single-objective PSO to find a uniform Pareto front in space) to MOPSO can improve the quality and quantity of the Pareto fronts as well as preventing premature convergence. The BA, for example, adds uniform scatter points to the initial population which significantly improves solutions' distribution and computational time.

The comparison made between constrained and unconstrained animal-inspired EAs revealed that provision of more feasible search space, higher solution quality, shorter computational time and reduction in the size of search space established the superiority of the constrained versions. It was determined from reported studies that the discrete versions of animal-inspired EAs outclass their continuous versions because of faster convergence rate and better quality of solutions. The GA is among the oldest and most widely applied evolutionary algorithms, yet, our survey revealed that ACO, chaotic PSO, SFLA, ABC, HBMO, FA, CS and BA outperform the GA in terms of the quality of solutions, faster convergence and feasible search space. ACO and ABC outperformed the GA with respect to calculated higher reservoir performance indices (reliability, resiliency and vulnerability) and chaotic PSO and HBMO were superior to the GA by obtaining better and more efficient solutions for flood control and power generation functions, respectively. The SFLA calculated more efficient linear and nonlinear operation policies compared to the GA. Our review revealed that the FA and the BA outperform the GA by achieving lower standard deviations and more efficient solutions in reservoir operation and rule extraction problems. Similarly, CS also performed better than the GA by providing more energy production in hydropower reservoir problems. This paper's survey of multi-objective optimization problems indicates that MOPSO and EM-MOPSO are superior to the classic NSGA-II. The previous conclusion is based on a limited number of applications reported to reservoir optimization problems. Generally, it was found that more recent proposed EAs (e.g. FA and BA) produce more efficient solutions to reservoir system problems compared to old EAs (e.g. the GA and PSO).

Conclusions

(1) Our review of published EAs revealed that the animal-inspired EAs have shown higher efficiency in optimizing reservoir operation problems than traditional approaches (e.g. DP and NLP). The inspiration mechanisms and characteristics of the selected well-known animal-inspired EAs (ACO, PSO, SFLA, ABC, HBMO, FA, CS and BA) were addressed. Several improved versions of each animal-inspired EA and their applications to reservoir system optimization were reviewed. Comparisons between different EAs indicate that the constrained versions of EAs outperformed the unconstraint versions because of provision of more feasible search space, higher solution quality, shorter computational time and reduction in the size of search space. Additionally, the discrete versions of animal-inspired EAs outperform their continuous versions because of faster convergence rate and better quality of solutions. Overall, our review revealed that more recent proposed EAs (e.g. BA and FA) indicate higher efficiently in reservoir operation optimization compared to older EAs (e.g. GA and PSO).

(2) This paper highlighted the importance of the animal-inspired EAs in improving the optimization of the reservoir operation problems. This was conducted with the purpose of identifying research gaps and new fields of inquiry in the area of applying EAs to reservoir optimization problems. These findings may serve as an incentive for future research. Given the increasing impacts of climate change, which is expected to lead to more droughts and extreme floods in different regions, efficient EAs must be identified and applied to reservoir operation to obtain optimal operation policies to deal with the extreme hydrologic events in the future. Moreover, the most efficient and accurate EAs must be identified and applied to optimize regional water allocation to different sectors (e.g. agriculture, municipal and industrial, environmental demand) through reservoir operation. Therefore, future research in the area of reservoir operation must emphasize the development and implementation of efficient (that is, fast converging) and accurate optimization EAs. It is also recommended that more effort be devoted to developing and improving recent proposed EAs, as it was found that recently introduced EAs have exhibited improved efficiency in solving reservoir system problems, particularly complex, high-dimensional, real-world ones.

Acknowledgement

The authors thank Iran's National Science Foundation (INSF) for its financial support of this research.

Conflict of interests

There are no conflict of interest.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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