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A Systematic Review of Optimization of Dams Reservoir Operation Using the Meta-heuristic Algorithms

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Abstract

During the last two decades, the issue of optimal operation of dam reservoirs has received much attention among water resources management researchers. Also, the operation of dam reservoirs in terms of diversity of decision-making and target functions has complexities that sometimes cannot be solved with traditional optimization methods and requires a lot of time and money. Therefore, the use of new tools and advanced methods in solving such problems is inevitable. In this review article, 76 research articles from the most prestigious journals in the world between 2002 and 2021 have been reviewed. Meta-analysis method (PRISMA) has been used for systematic review and selection of the studied articles. This research includes a comprehensive review regarding the application of different optimization models in the exploitation of dam reservoirs and can provide a critical insight into the selection of used models and the accuracy of different modeling methods in the optimization of dam reservoirs. The investigated models include single-objective and multi-objective reservoirs, as well as single and multi-reservoirs. The results of this study show that researchers' interest and popularity in hybrid algorithms (HA) (18.68%) and GA (16.48%) were more than the traditional or improved versions. Also, hybrid algorithms showed better results than single meta-heuristic algorithms and traditional methods. According to the obtained results, it can be stated that the meta-heuristic algorithms used are capable of solving complex models in reservoir operation problems with a fast convergence rate.

Keywords Optimization · Dams reservoirs · Meta-heuristic algorithms · Review

Nomenclature

ABC	Artificial Bee Colony
ACDE	Adaptive Chaotic Differential Evolution
ACO	Ant Colony Optimization
ADE	Adaptive Differential Evolution

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AFSA	Artificial Fish Swarm Algorithm
AGA	Adaptive Genetic Algorithm
AI	Artificial Intelligence Algorithm
ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
AOA	Accompanying Progressive Optimality
APO	Artificial physics optimization
ARIW	Adaptive random inertia weight
BA	Bat Algorithm
BBO	Biogeography-based optimization
C-GA	Chaos-genetic algorithm
CGA	Constrained genetic algorithm
CIPSO	Constrained version of IPSO algorithm
COA	Chaos Optimization Algorithm
CPSO	Chaotic particle swarm optimization
CSA	Clonal Selection Algorithm
CSA	Cuckoo Search Algorithm
CSO	Cat Swarm Optimization
DE	Differential Evolution
DP	Dynamic Programming
ELM	Extreme Learning Machine
EMPSO	Elitist-mutated particle swarm optimization
FA	Firefly algorithm
FCACOA	Fully Constrained Ant Colony Optimization
FFNN	Feed-forward neural network
FIS	Fuzzy Inference System
FOA	Fruit Fly Optimization Algorithm
GA	Genetic Algorithm
GA–KNN	Genetic Algorithm–K Nearest Neighborhood
BSGA	Bayesian Stochastic GA
GAOM	Genetic Algorithm Optimization Model
GEP	Gene Expression Programming
GP	Genetic Programming
GPR	Gaussian Process Regression
GSA	Gravity Search Algorithm
GWO	Grey Wolf Optimizer
GWO	Grey Wolf Optimizer
HBMO	Honey-Bee Mating Optimization
HB-SA	Hybrid bat–swarm algorithm
HSA	Harmony Search Algorithm
HSLSO	Hybridizing sum-local search optimizer
HWGA	Hybrid whale-genetic algorithm
IBA	Improved bat algorithm
ICA	Imperialist Competitive Algorithm
IDEPSO	Improved hybrid DE and PSO
IDP	Incremental Dynamic Programming
IGWO	Improved Grey Wolf Optimization
IPSO	Improved particle swarm optimization
ISO	Implicit stochastic reservoir optimization

IWO	Invasive weed optimization
JA	Jaya Algorithm
KA	Kidney Algorithm
LBA	Lévy Flight Bat Algorithm
LFWOA	Lévy flight and distribution
LP	Linear Programming
LPA	Lion Pride Algorithm
LSO	Lion Swarm Optimization
LTHG	Long Term Hydropower Generation
LTMIF	Long-Term Mean Inflow Forecast
MA	Metaheuristic algorithms
MBA	Monarch Butterfly Algorithm
MFOA	Modified Fruit Fly Optimization Algorithm
ML	Machine Learning
MSA	Moth Swarm Algorithm
MS-DEPSO	Multi-strategy
NDSs	Nondominated solutions
NFIS	Neuro-Fuzzy Inference System
NFL	No Free Lunch theorem
NLP	Non-Linear Programming
NSGA-II	Non-Dominated Sorting Genetic Algorithm-II
NSGA-III	Non-Dominated Sorting Genetic Algorithm-III
PA-DDS	Pareto Archived Dynamically Dimensioned Search
PCACOA	Partially Constrained Ant Colony Optimization Algorithm
PFDO	Perfect-Forecast Deterministic Optimization
POA	Progressive Optimization Algorithm
PSO	Particle Swarm Optimization
R	Correlation Coefficient
R^2	Coefficient of Determination
RVM	Relevance Vector Machine
SA	Simulated ANeuro-Fuzzynnealing
SCE	Shuffled Complex Evolution
SDP	Stochastic dynamic programming
SLGA	Self-Learning Genetic Algorithm
SM	Simulation Model
SMA	Spider Monkey Algorithm
SMLA	Shark Machine Learning Algorithm
SOM	Self-Organizing Map
SOP	Standard reservoir operating policy
SOS	Symbiotic Organisms Search
SQP	Sequential Quadratic Programming algorithm
SVM	Support Vector Machine
SVR	Support Vector Regression
TLBO	Teaching Learning Based Optimization
VNS	Variable Neighborhood Search
WA	Weed Algorithms
WCA	Water Cycle Algorithm
WOA	Weed Optimization Algorithm
WOA	Whale Optimization Algorithm

1 Introduction

The limitation of water resources in the world and the increasing water needs in the fields of drinking, agriculture, industry, electricity generation, environmental issues, etc. require that studies of planning and management of water resources in order to store and optimally operate reservoirs of dams to The desired syntax and within the framework of the objectives of the plan and according to the priority of needs should be presented as a standard study method. Therefore, the operation of dam reservoirs with the correct use of modern studies in the world is of particular importance. Optimization can be considered a practical tool for simplifying and solving linear and non-linear formulas of big problems and interpreting the solutions. Optimization is an effective method of finding the answer that provides the best result with the highest profit and lowest cost. Today, in order to make optimal use of available resources, including water resources and related issues, it has led researchers use various optimization techniques around the world (Singh 2012). Optimization methods are a step forward in researchers' studies to solve reservoir exploitation problems and improve water resources management in water shortage situations. In the studies conducted, new optimization methods, including classical and evolutionary algorithms, have been used to improve the performance of the reservoir system (Ahmadi et al. 2014; Ashofteh et al. 2015). Zhang et al. (2014) used the tank optimization method for the optimal use of water resources in hydroelectric power plants during the operation period according to physical and operational limitations. The main purposes of the reservoir are to provide hydroelectric power and water supply, which is aimed at meeting human demand (Chang et al. 2010a, b). Today, evolutionary algorithms are considered efficient and effective methods in reservoir optimization and maximizing electricity production. Considering that traditional optimization is a complex and difficult task in solving high-dimensional non-linear problems in multi-reservoir systems and large-scale power plants, therefore, solving such a large problem with traditional approaches will be impractical. Therefore, it seems necessary to provide powerful dimensionality reduction techniques to improve the computational performance of conventional methods (Feng et al. 2019). Classical methods and evolutionary algorithms or meta-heuristics (EAs) are the main methods of reservoir operation optimization. Of course, the developed evolutionary algorithms are more useful in today's studies. High dimensions and slow convergence can be called the main reason why classical methods such as linear programming (LP), dynamic programming (DP), stochastic dynamic programming (SDP), and nonlinear programming (NLP) are not accepted by researchers. Therefore, EAs (inspired by biological phenomena) were developed and widely used due to their high search speed to find global nearly optimal solutions and have replaced classical methods (Bozorg-Haddad et al. 2015a, b; Neboh et al. 2015). To solve complex calculations, it is very useful to develop more efficient computational methods and developed intelligent control systems that are able to learn from different sources of knowledge and can be more suitable for the operation of reservoir systems (Rani and Moreira 2010). Singh (2012), studied several new evolutionary algorithms for reservoir optimization problem. Ahmad et al. (2014) gave a brief overview of the current optimization techniques developed in solving reservoir operation problems. They discussed the use of evolutionary and hybrid algorithms for single and multi-objective simulation and optimization of dam reservoirs. Evolutionary algorithms have the ability to solve non-linear problems and analyze multi-objective reservoirs. Recently, in order to find out the special and unique characteristics of modern techniques, the use of traditional and evolutionary, and hybrid optimization methods has become popular. Zhang et al. (2018) used two traditional artificial intelligence models, BPNN and SVR, with the aim of optimization. Also, learning models, including LSTM model, have been given much attention in helping the performance of the reservoir. Detailed recommendations have been provided in various reservoir optimization researches regarding the process of model parameter settings, simulation functions and applications of artificial intelligence models used under different flow regimes. In engineering and scientific topics, especially economic topics and structural design and water resources engineering, modern optimization methods are widely used to solve practical problems. One of the main topics of optimization in the problems of dam reservoirs is to minimize consumption in water supply for irrigation and demand patterns such as hydropower generation. Over the past two decades, new optimization methods based on nature-inspired meta-heuristic algorithms (MHAs) have emerged as suitable alternative optimization tools to identify optimal dam and reservoir rules (Chong et al. 2021). Hossain (2013) used several optimization techniques mainly artificial intelligence (AI) to model the reservoir operation of single and multi-reservoir systems. Optimizing reservoir operations can be seen as water release and transfer operations with the aim of water management to ensure reliable water supply, hydropower generation, reduce downstream floods, etc. Dobson et al. 2019 provided an extensive and useful collection of scientific literature on the development and application of various mathematical optimization methods for reservoir operational problems along with their advantages, limitations, and scope of application.

Jahandideh-Tehrani et al. (2019) showed in their review that non-animal EAs perform better than classical methods such as LP and NLP in solving reservoir optimization problems. Evolutionary algorithms used in solving reservoir operation problems have advantages and disadvantages. The best way to solve this problem, in order to provide an optimal solution, many researchers consider it appropriate to use hybrid models and believe that the disadvantages of one algorithm are corrected and completed by another algorithm. Hybrid algorithms have become widely used and common in solving complex water resource management problems. Hydropower, flood control, inflow forecasting, ecological base flow, and water distribution systems are a few of these operations (Adeyemo and Stretch 2018). Energy maximization is one of the objective functions of the meta-heuristic algorithms that have been widely used to manage operational policies for dam reservoirs. However, the continued advancement of meta-heuristic methods aids in the resolution of issues with real-time reservoir operation. (Azad et al. 2020). Perhaps the most important question and concern of most researchers in using optimization algorithms, especially metaheuristic algorithms, is choosing the right algorithm to solve the problem. It is not possible to say with certainty which optimization or metaheuristic algorithm is suitable for solving a problem, and only by comparing the results can it be claimed which algorithm offers a better method. Although previous and current studies have shown that a particular algorithm can be better for a particular case study using performance appraisal indicators than other algorithms, our understanding of the reasons for such success is limited and a comprehensive study is needed. Therefore, to take further steps in this area of research, it is necessary to better understand the interrelationships between the characteristics of the reservoir water system under optimization, the mathematical search method of the optimization algorithm, and the performance of the algorithm used. This article reviews studies on reservoir system operation optimization, including the use of conventional optimization methods as well as the range of computational intelligence methods like evolutionary computation, meta-heuristic algorithms, fuzzy set theory, and artificial neural networks. Since the use of meta-heuristic algorithms in reservoir system research has been used in the last few decades and the interest of researchers in this field has increased day by day, this study mainly focuses on the latest optimization algorithms for water resources, especially dam reservoirs. Review articles related to dam reservoirs optimization techniques are shown in Table 1.

2 Methodology of Survey

2.1 Collection of Studied Articles

In this review article, a systematic review has been conducted based on the PRISMA guidelines for a detailed review of the research conducted regarding the optimization of the reservoir performance of dams. For this purpose, the content of the articles related to the research subject, which includes the abstract, methods, results, discussion, and references, was carefully examined. The studied collection only included articles from reputable journals with an impact factor that have used meta-heuristic algorithms and intelligent models in research related to the optimization of reservoir performance of dams. Databases in Elsevier, ASCE, Springer, John Wiley, ICE, IWA, Taylor and Francis, Scopus, PubMed, Science Direct, IEEE Xplore, and Google Scholar were considered for the search, screening, and selection process. In the process of searching for relevant articles, there was no time limit for publication. To ensure the retrieval of all usable articles, the reference list of all articles was retrieved again. The keywords used in the mentioned databases were: “reservoir”, “optimization”, “dam”. Also, the combined words of “evolutionary algorithm”, “Meta-Heuristic algorithm”, “reservoir operation”, “optimization Algorithm”, “neural network”, and also some meta-heuristic algorithms such as PSO, ABC, ACO, etc. were used along with “reservoir optimization”. In the first stage, the number of 535 articles related to the review article was identified. The number of articles that were obtained through searching the database as well as additional records obtained through other sources is included. After that, there is the screening stage, and using Endnote and Excel software, duplicate articles were removed by searching the title and author, and finally, 187 articles unrelated to the subject of this article were removed. Of course, 11 new articles were retrieved from the list of sources of reviewed articles. Then, the full text of 123 eligible articles was examined, and among these complete articles, 47 articles were excluded by mentioning the reason and exclusion criteria. In the last stage, 76 articles were approved for compiling this review article (Fig. 1).

Figure 2 displays the number and proportion of articles published between 2005 and 2021.The general trend of publishing articles shows the popularity of meta-heuristic algorithms in dam reservoir optimization problems among researchers so it has increased by 69.74% in the last six years.

2.2 Region of Study

Out of a total of 73 case studies conducted in articles on dams reservoirs optimization using metaheuristic algorithms, 60.27% of the studies have been conducted in Iran. Limited water resources in Iran and increasing water demand in the fields of

Table 1 Review articles related to different optimization problems

Author(s) Year	Citing articles	Journal Title	Publisher	H-Index	Scopus Impact Factor/ WOS 2021	SJR (2020)
Rani and Moreira (2010)	312	Water Resources Management	Springer Netherlands	100	3.54/4.426	0.941 Q1
Singh (2012)	173	Journal of Hydrology	Elsevier	226	5.76/6.708	1.684 Q1
Ahmad et al. (2014)	166	Water Resources Management	Springer Netherlands	100	3.54/4.426	0.941 Q1
Zhang et al. (2018)	168	Journal of Hydrology	Elsevier	226	5.76/6.708	1.684 Q1
Hossain et al. (2013)	68	Water Resources Management	Springer Netherlands	100	3.54/4.426	0.941 Q1
Dobson et al. (2019)	44	Advances in Water Resources	Elsevier Ltd	138	4.71/5.361	1.314 Q1
Jahandideh-Tehrani et al. (2019)	28	Environmental Monitoring and Assessment	Springer Netherlands	109	2.52/3.307	0.59 Q2
Adeyemo and Stretch (2018)	17	South African Journal of Chemical Engineering	Elsevier BV	15	5.52/_	0.797 Q1
Azad et al. (2020)	28	Energy Reports	Elsevier Ltd	33	7.37/4.937	1.199 Q1
Chong et al. (2021)	8	IEEE Access	Institute of Electrical and Electronics Engineers Inc	127	4.48/3.476	0.587 Q1

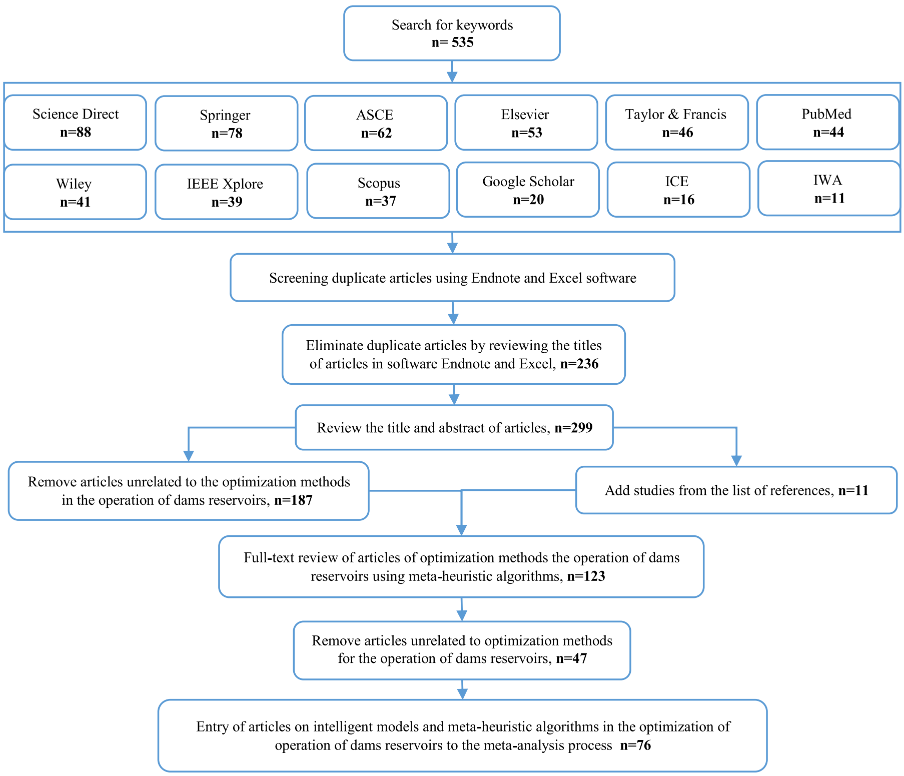

Fig. 1 Selected articles in databases based on PRISMA

drinking, agriculture, industry, electricity generation, environmental issues, etc. have led researchers to pay more attention to studies in the field of storage and optimal use of dam reservoirs Fig. 3.

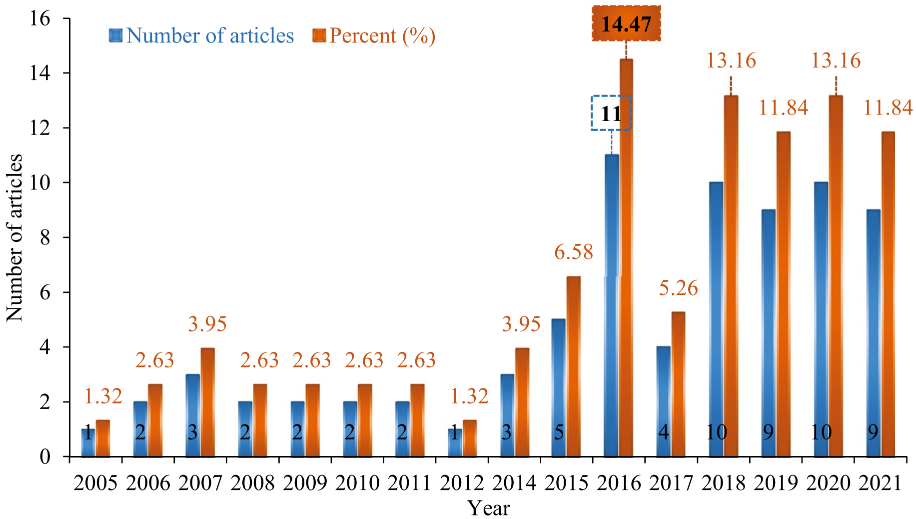

Fig. 2 Distribution of the total and percentage of articles that have been reviewed and published

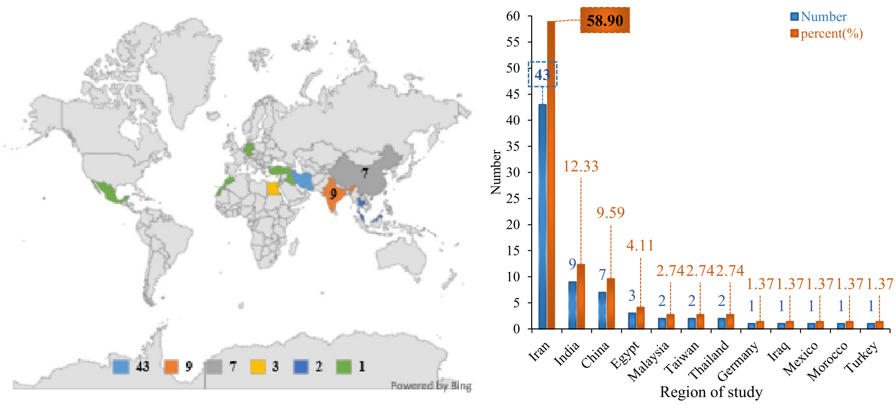

Fig. 3 Frequency of studied dams in optimization of dams reservoir operation using metaheuristic algorithms

Out of a total of 93 dams studied in dam reservoir optimization articles using metaheuristic algorithms (in several articles more than one dam or reservoir has been studied), in 11 articles Karun 4 dam has been selected as a case study. Karun 4 Dam is the largest double-arch dam in the Middle East. Various goals and benefits of Karun 4 dam (hydropower generation, surface water control of the region, water supply required by industry and agriculture in the downstream plains, and control of seasonal destructive floods), relatively large reservoir volume, location importance of the dam, and easy access to basic and hydrological data the dam can be considered as one of the main interests of researchers in its selection (Fig. 4).

2.3 Physical Specifications of the Reservoirs

2.3.1 Reservoir Capacity of the Studied Dams

The set of physical characteristics of reservoir includes reservoir volume at normal level, maximum reservoir volume, active storage, dead storage, reservoir capacity (useful volume),

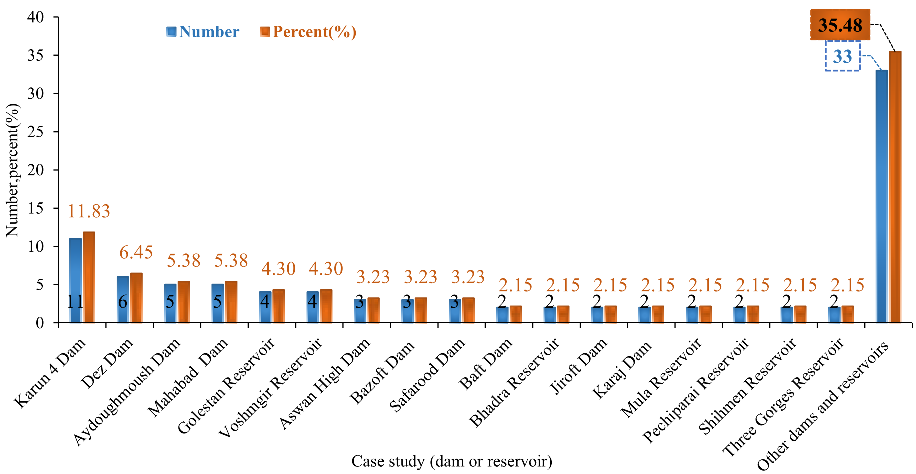

Fig. 4 Distribution of dams used in optimization studies

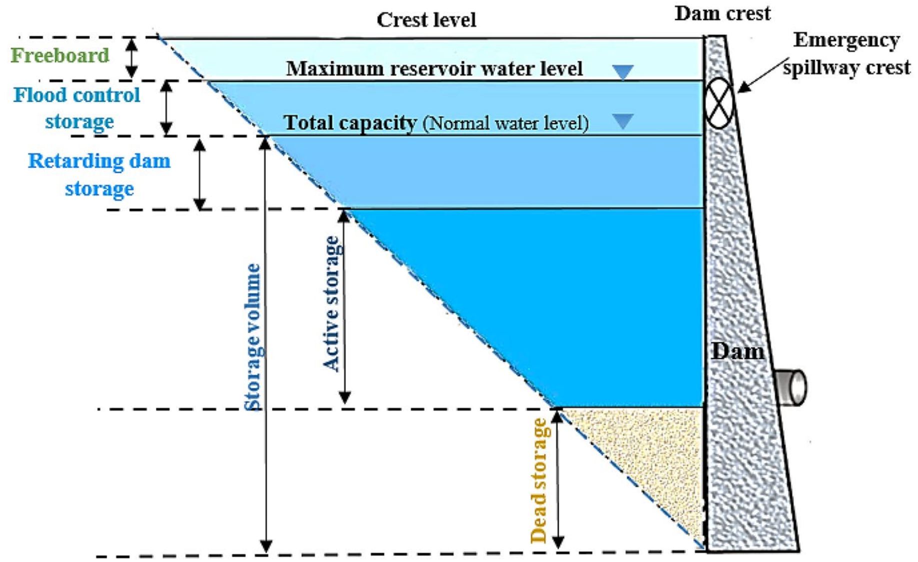

Fig. 5 Allocation of reservoir capacity of dams to different volumes

maximum and minimum operating level, flood control storage, and freeboard, which is shown in Fig. 5.

The different volumes of reservoir studied are shown in Fig. 6. The main part of the reservoir is active storage. The volume between the minimum operating level and the normal water level is called active storage, the main task of which is to regulate the output currents according to the input currents in the dry and high-water seasons. A noteworthy point in the table of the capacity of dam reservoirs is that Aswan Dam is a volume of 44.3 MCM that impounds a reservoir, Lake Nasser, that has a gross capacity of 169 BCM.

2.3.2 Classification of Dam Reservoirs

Dam reservoirs are divided into two main groups: single-purpose reservoirs and multi-purpose reservoirs. Also, reservoirs of dams are divided into single-reservoir systems and multi-reservoir systems according to their number on a river. The number and percent of dams reservoirs system, reservoir system operation, number of objective functions and purposes of the dam reservoir in the optimization of dam reservoirs using meta-algorithms (articles reviewed in the present article) are shown in Fig. 7. 65% of the studied dams are single reservoir and 74% are single purpose. Irrigation (23%), hydropower (19%), and drinking water supply (16%) are the three main objectives of the construction of the studied dams.

2.3.3 Baseline Period

The validity of dam reservoir optimization studies depends on the accuracy of the statistics and information used. Therefore, input and base data need to be accurate enough. In these studies, data collection and information such as topographic maps,

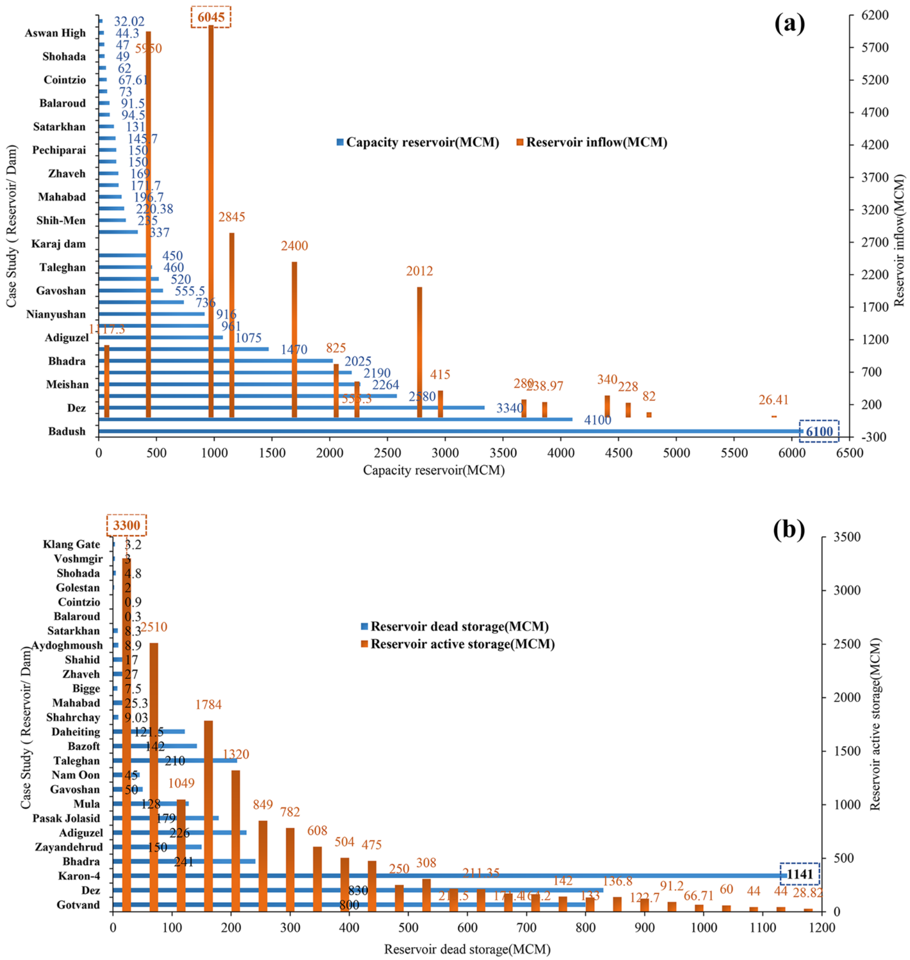

Fig. 6 Reservoir volumes of studied dams, **a** Capacity reservoir and reservoir inflow, **b** Active and dead storage

surface-volume-height curves, hydrological data (river discharge, river sediment, water infiltration in the reservoir), meteorological data (rainfall, reservoir evaporation losses), needs Water (drinking, industrial, agriculture, hydroelectric, environmental, flood control, shipping, recreation, etc.) is very important. Figure 8 shows that 44.59% of researchers used 60-month (24.32%) and 240-month (20.27%) data.

2.4 Analysis of the Selected Papers Based on Modeling Techniques and Publication Years

Information about the chosen articles concerning the optimal operation of dams reservoir employing meta-heuristic algorithms is presented in Table 2; it includes case study (dam/ reservoir system), author(s)(year), no. citations, journal name, impact factor,

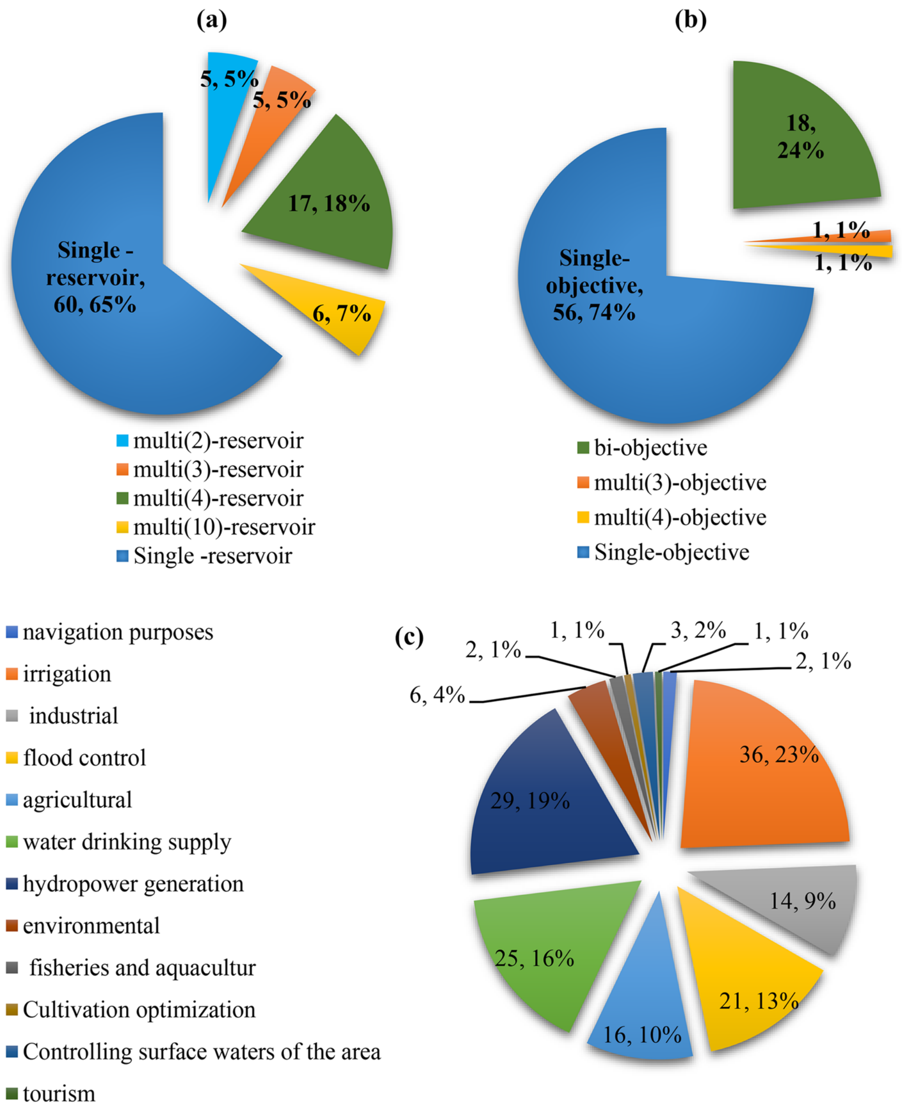

Fig. 7 Number and percent of dams reservoirs system in the present study, **a** Reservoir system operation, **b** Number of objective functions, **c** Purpose of the dam reservoir

period of study (month), reservoir capacity, reservoir inflow, active storage, dead storage, meta-heuristic algorithm, best (objective function/ solutions), global optimum, and objectives of the dam reservoir. The meta-heuristic algorithm for optimizing the operation of dam reservoirs is a hot topic, as shown by the number of citations in Table 2. However, articles published in recent years have been cited by few articles or have not yet been cited.

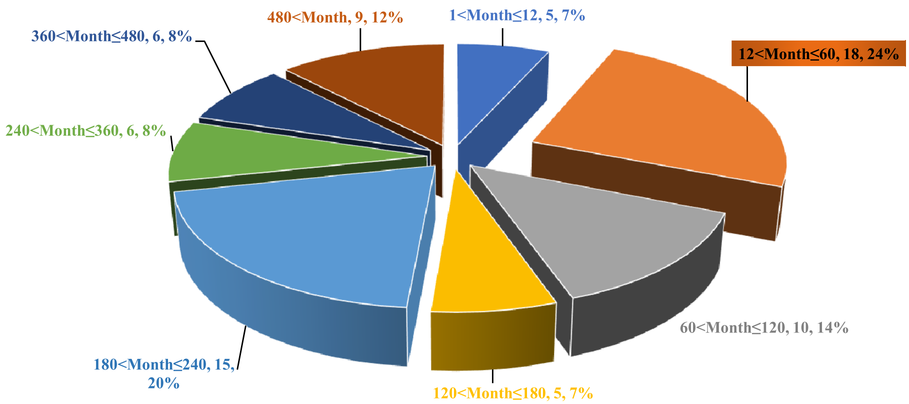

Fig. 8 Number and percent of Period of study

2.4.1 Review of Publications, Journals, Country, and Citations of the Studied Articles

Scimago Journal & Country Rank (SJR) is used to determine the validity and quality of the articles under review. Most articles (35.53% of articles) on optimization of dams reservoir operation using meta-heuristic algorithms have been published in the journal Water Resources Management. Springer Netherlands (39.47%) and the American Society of Civil Engineers (ASCE) (14.47%) also have the most publications on reservoir optimization and related topics, respectively. Quality journal articles were used in this study, and the journals' and articles' published quality was assessed using a Q or Quartile score. Out of 76 articles reviewed, 53 (69.74%) are Q1, 16 (21.05%) are Q2, 5 (6.58%) are Q3, and 2 (2.63%) are Q4, according to the Quartile scale. Engineering Applications of Computational Fluid Mechanics (9.55) and Knowledge-Based Systems (9.42) have the highest impact factors among the articles under review (Fig. 9).

Most articles in Netherlands magazines 38 articles (50%) have been published. It is clear that on the subject of dam reservoir optimization using ultra-innovative algorithms, the Netherlands magazines have received the most acceptance and publication of articles Fig. 10.

A total of 2688 citations from 2005 to 2021 were used for the selected articles in this review article, which are among the best and most cited articles that have been published so far. Figure 11 represents the annual cumulative citations. Eight of the papers published before 2015 stand out thanks to their high citation counts. These are Nagesh Kumar and Janga Reddy (2007) [322], Reddy and Kumar (2006) [163], Bozorg-Haddad et al. (2015a, b) [138], Ahmed and Sarma (2005) [131], Ashofteh et al. (2015)[119], Chang et al. (2010a, b) [119], Fallah-Mehdipour et al. (2012) [102], and Bozorg-Haddad et al. (2015a, b) [101] respectively.

Table 2 Details of the reviewed papers' optimization of dams reservoir operation using the meta-heuristic algorithms

No.	Case study (dam/ reservoir system)	Author(s)(year)/ No. Citations	Journal Name	Scopus Impact Factor / SJR(2020)/ Quartile	Period of study (Month)	Reservoir capacity/ Reservoir inflow (MCM)
1	Mula Reservoir (India)	Bilal et al. (2021)/(1)	Memetic Computing	**5.42** 0.825 Q1	360	736 825
2	Klang Gate Dam (KGD) (Malaysia)	Lai et al. (2021)/(0)	Engineering Applications of Computational Fluid Mechanics	**9.55** 1.347 Q1	264	32.02 –
3	Cointzio Dam (Mexico)	Mendoza Ramírez et al. (2021)/(2)	Water Resources Management	**3.54** 0.941 Q1	900	67.61 –
4	Halilrood Basin (Baft, Safarood, and Jiroft Dams) (Iran)	Sharifi et al. (2021)/(2)	Scientific Reports	**4.13** 1.24 Q1	223	–
5	Mahamed Dam (Morocco)	El Harraki et al. (2021)/(3)	Environmental Monitoring and Assessment	**2.52** 0.59 Q2	936	239.5 830
6	Halilrood Basin (Baft, Safarood, and Jiroft Dams) (Iran)	Yavari and Robati (2021)/(2)	Water Resources Management	**3.54** 0.941 Q1	223	–
7	Mahabad Dam (Iran)	Sharifazari et al. (2021)/(0)	Water Science and Engineering	**3.06** 0.716 Q1	288	196.7 280
8	Single reservoir (India)	Wang et al. (2021)/(2)	Water Resources Management	**3.54** 0.941 Q1	–	2797 –
9	Multi(4), (10)-Reservoir	Akbarifard et al. (2021)/(4)	Water Science and Technology: Water Supply	**1.18** 0.318 Q3	–	–
10	Shahrchay Dam (Iran)	Nourani et al. (2020)/(10)	Journal of Hydrology	**5.76** 1.684 Q1	588	220.38 –
11	Dez Dam (Iran)	Soghrati and Moeini (2020)/(8)	Journal of Hydroinformatics	**2.38** 0.654 Q2	60 240 480	3340 5950

Table 2 (continued)

No.	Case study (dam/ reservoir system)	Author(s)(year)/ No. Citations	Journal Name	Scopus Impact Factor / SJR(2020)/ Quartile	Period of study (Month)	Reservoir capacity/ Reservoir inflow (MCM)
12	Karaj Dam (Iran)	Tabari et al. (2020)/(3)	Soft Computing	**3.86** 0.626 Q2	69	– –
13	Nianyusha, Meishan Reservoir (China)	Chen et al. (2020a, b)/(7)	Journal of Hydrology	**5.76** 1.684 Q1	–	916, 2264 –
14	Zayandehrud Dam (Iran)	Moeini and Babaei (2020)/ (5)	Applied Soft Computing Journal	**7.71** 1.29 Q1	528	1470 –
15	Safarood Dam (Iran)	Rezaei-Estakhroueiyeh et al. (2020)/(0)	Data in Brief	**1.13** 0.212 Q4	223	73 –
16	Karun 4 Dam (Iran)	Akbarifard et al. (2020)/(11)	Data in Brief	**1.13** 0.212 Q4	106	2190 6045
17	Nagarjunasagar Reservoir (India)	Karnatapu et al. (2020)/(1)	Journal of The Institution of Engineers (India): Series A	**0.96** 0.205 Q2	–	11560 –
18	Panjiakou, Daheiting, Taolinkou Reservoir (China)	Chen et al. (2020a, b)/(0)	Water Science and Engineering	**3.06** 0.716 Q1	12	337 –
19	Mosul Reservoir/Mosul and Badush Reservoirs (Iraq)	Al-Aqeeli et al. (2020)/(8)	Water Resources Management	**3.54** 0.941 Q1	–	11100 2135.4 6100 117.3
20	Voshmgir-Golestan Reservoir (Iran)	Karami et al. (2019)/(11)	Water Resources Management	**3.54** 0.941 Q1	60	47,62 –
21	Multi(4), (10)-Reservoir	Mohammadi et al. (2019)/ (14)	Water Resources Management	**3.54** 0.941 Q1	–	–

Table 2 (continued)

No.	Case study (dam/ reservoir system)	Author(s)(year)/ No. Citations	Journal Name	Scopus Impact Factor / SJR(2020)/ Quartile	Period of study (Month)	Reservoir capacity/ Reservoir inflow (MCM)
22	Taleghan Dam (Iran)	Mohammadrezapour et al. (2019)/(15)	Neural Computing and Applications	**5.4** 0.713 Q1	12	460 –
23	Aswan High Dam (Egypt)	Silva Santos et al. (2019)/(3)	Journal of Applied Water Engineering and Research	0.94 0.241 Q3	1200	–
24	Zhaveh Dam (Iran)	Jamshidi and Shourian (2019)/(3)	Water Resources Management	3.54 0.941 Q1	240	169 –
25	Shahid Dam/ Multi(4)-reservoir (Iran)	Zarei et al. (2019)/(19)	Water Resources Management	3.54 0.941 Q1	60	150 –
26	Voshmgir-Golestan Reservoir (Iran)	Yaseen et al. (2019)/(32)	Neural Computing & Applications	5.4 0.731 Q1	60	47, 62 –
27	Mahabad Dam (Iran)	Rouzegari et al. (2019)/(7)	Water Resources Management	3.54 0.941 Q1	252	196.7 280
28	(Karun1, Dez, Godar) and Balaroud Reservoir (Iran)	Ahmadianfar et al. (2019)/ (12)	Applied Soft Computing Journal	7.71 1.29 Q1	120 180 240	91.5 for Balaroud reservoir
29	Karun 4 Dam/ Aydoughmoush Dam (Iran)	Ehteram et al. (2018b)/(14)	Environmental Earth Sciences	2.76 0.641 Q2	120	2190,145.7_/228
30	Aswan High Dam (Egypt)	Allawi et al. (2018)/(8)	Environmental Earth Sciences	2.76 0.641 Q2	216	162300 84000
31	Aydoghmoush Dam (Iran)	Ehteram et al. (2018a)/(23)	Water Resources Management	3.54 0.941 Q1	120	145.7 228
32	Gotvand Dam (Iran)	Shenava and Shourian (2018)/(7)	Water Resources Management	3.54 0.941 Q1	72	4100 14000
33	Karun 4 Dam (Iran)	Bahrami et al. (2018)/(22)	Journal of Irrigation and Drainage Engineering—ASCE	**1.3** 0.527 Q2	60 12	2190 6045

Table 2 (continued)

No.	Case study (dam/ reservoir system)	Author(s)(year)/ No. Citations	Journal Name	Scopus Impact Factor / SJR(2020)/ Quartile	Period of study (Month)	Reservoir capacity/ Reservoir inflow (MCM)
34	Karun 4 Dam (Iran)	Yaseen et al. (2018)/(14)	KSCE Journal of Civil Engineering	**1.97** 0.503 Q2	60	2190 6045
35	Voshmgir-Golestan Reservoir (Iran)	Ehteram et al. (2018c)/(21)	Water Resources Management	**3.54** 0.941 Q1	60	47, 62 –
36	Multi(4), (10) -Reservoir	Kumar and Yadav (2018)/ (24)	Water Resources Management	**3.54** 0.941 Q1	–	–
37	Gavoshan and Shohada Dam (Iran)	Azari et al. (2018)/(12)	Water Resources Management	**3.54** 0.941 Q1	72	49, 555.5 26.41,555.3
38	Voshmgir-Golestan Reservoir/ Multi(4), (10) -Reservoir (Iran)	Qaderi et al. (2018)/(20)	Water Management	**1.06** 0.27 Q3	60	47, 62 –
39	Chenderoh Reservoir (Malaysia)	Choong et al. (2017)/(15)	Water Resources Management	**3.54** 0.941 Q1	156	94.5 –
40	Danjiangkou, Ankang Reservoir (China)	Yang et al. (2017)/(23)	Journal of Water Resources Planning and Management—ASCE	**2.89** 0.917 Q1	684	33910,3340 –
41	Bazoft Dam (Iran)	Ehteram et al. (2017a)/(53)	Knowledge-Based Systems	**9.42** 1.587 Q1	60	450 2012
42	Karun 4 Dam (Iran)	Ehteram et al. (2017b)/(19)	Advanced Engineering Informatics	**6.41** 1.107 Q1	60	2190 6045
43	Karun 4 Dam (Iran)	Bozorg Haddad et al. (2016a, b)/(51)	Journal of Water Resources Planning and Management—ASCE	**2.89** 0.917 Q1	60	2190 –
44	Adiguzel dam (Iran)	Yasar (2016)/(14)	Mathematical Problems in Engineering	**1.42** 0.626 Q3	183	1075 –

Table 2 (continued)

No.	Case study (dam/ reservoir system)	Author(s)(year)/ No. Citations	Journal Name	Scopus Impact Factor / SJR(2020)/ Quartile	Period of study (Month)	Reservoir capacity/ Reservoir inflow (MCM)
45	Bazoft dam (Iran)	Asgari et al. (2016)/(80)	Journal of Irrigation and Drainage Engineering—ASCE	**1.3** 0.527 Q2	60	450 2012
46	Three Gorges Reservoir (China)	Dai et al. (2016)/(13)	Environmental Earth Sciences	**2.76** 0.641 Q2	600	39300 _
47	Mahabad dam (Iran)	SaberChenari et al. (2016)/ (23)	Environmental Monitoring and Assessment	**2.52** 0.59 Q2	384	196.7 280
48	Xiluodu– Xiangjiaba–Threegorges (China)	Zhang et al. (2016)/(36)	Journal of Hydro-Environment Research	**2.46** 0.68 Q2	-	-
49	Dez Dam (Iran)	Azizipour et al. (2016)/(42)	Water Resources Management	**3.54** 0.941 Q1	12 60 240	3340 5950
50	Mula Reservoir (India)	Rani and Srivastava (2016)/ (8)	Water Resources Management	**3.54** 0.941 Q1	216	736 _
51	Karun4 Dam/ Aydoughmoush Dam (Iran)	Garousi-Nejad et al. (2016)/ (56)	Journal of Irrigation and Drainage Engineering—ASCE	**1.3** 0.527 Q2	120 504	2190,145.7_/228
52	Multi(4), multi(10) -reservoir	Ahmadianfar et al. (2016)/ (60)	Journal of Water Resources Planning and Management—ASCE	**2.89** 0.917 Q1	_	
53	Karun 4 Dam, multi(4)-reservoir (Iran)	Bozorg-Haddad et al. (2016a, b)/(41)	Advances in Water Resources	**4.71** 1.314 Q1	60	2190 6045
54	Aydoghmoush Dam (Iran)	Ashofteh et al. (2015)/(119)	Journal of Water Resources Planning and Management—ASCE	**2.89** 0.917 Q1	156	145.7 _
55	Karun 4 Dam (Iran)	Bozorg-Haddad et al. (2015a, b)/(101)	Journal of Water Resources Planning and Management—ASCE	**2.89** 0.917 Q1	60	2190 6045

Table 2 (continued)

No.	Case study (dam/ reservoir system)	Author(s)(year)/ No. Citations	Journal Name	Scopus Impact Factor / SJR(2020)/ Quartile	Period of study (Month)	Reservoir capacity/ Reservoir inflow (MCM)
56	Karun 4 Dam,multi(4)-reservoir (Iran)	Hosseini-Moghari et al (2015)/(51)	Water Resources Management	**3.54** 0.941 Q1	360	2190 6045
57	Dez Dam (Iran)	Afshar et al. (2015a, b)/(17)	Water Resources Management	**3.54** 0.941 Q1	480	3340 5950
58	Karun 4 Dam, Multi(4)-reservoir (Iran)	Bozorg-Haddad et al. (2015a, b)/(138)	Journal of Irrigation and Drainage Engineering—ASCE	**1.3** 0.527 Q2	60	2190 6045
59	Three Gorges Reservoir (China)	He et al. (2014)/(55)	Applied Mathematical Modelling	**5.4** 1.101 Q1	_	39300 45290
60	Bigge Reservoir (Germany)	Elabd and El-Ghandour (2014)/(4)	Journal of Hydrologic Engineering—ASCE	**2.02** 0.595 Q2	12	171.7 238.97
61	Aswan High Dam (Egypt)	Hossain and El-shafie (2014)/(32)	Neural Computing and Applications	**5.4** 0.713 Q1	216	162300 84000
62	Karaj Dam (Iran)	Fallah-Mehdipour et al. (2012)/(102)	Water Resources Management	**3.54** 0.941 Q1	108, 36	415
63	Pechiparai, Perunchani and Chittar-I, Chittar-II (India)	Jothiprakash et al. (2011)/ (25)	Water Resources Management	**3.54** 0.941 Q1	156	_ 692.39
64	Multi (4), (10)-Reservoir	Bozorg-Haddad et al. (2011)/ (88)	Water Management	**1.06** 0.27 Q3		_
65	Satarkhan Dam (Iran)	Ahmadi et al. (2010)/(19)	Water Resources Management	**3.54** 0.941 Q1	204	131 82
66	Shih-Men Reservoir (China)	Chang et al. (2010a, b)/(119)	Journal of Hydrology	**5.76** 1684 Q1	240	235

Table 2 (continued)

No.	Case study (dam/ reservoir system)	Author(s)(year)/ No. Citations	Journal Name	Scopus Impact Factor / SJR(2020)/ Quartile	Period of study (Month)	Reservoir capacity/ Reservoir inflow (MCM)
67	Pasak Jolasid Reservoir (Thailand)	Pinthong et al. (2009)/(19)	Water Resources Management	**3.54** 0.941 Q1	60	961 2400
68	Dez Dam (Iran)	Afshar and Shahidi (2009)/ (41)	Engineering Optimization	**3.2** 0.601 Q2	60 240 480	3340 5950
69	Shihmen Reservoir (Taiwan)	Chaves and Chang (2008)/ (73)	Advances in Water Resources	**4.71** 1.314 Q1	–	–
70	Dez Dam (Iran)	Afshar and Moeini (2008)/ (42)	Water Resources Management	**3.54** 0.941 Q1	60 240 480	3340 5950
71	Nam Oon Reservoir (Thailand)	Suiadee and Tingsanchali (2007)/(34)	Hydrological Processes	**3.39** 1.222 Q1	276	520
72	Shihmen Reservoir (Taiwan)	Chiu et al. (2007)/(35)	Hydrological Processes	**3.39** 1.222 Q1	120	–
73	Bhadra Reservoir (India)	Nagesh Kumar and Janga Reddy (2007)/(322)	Journal of Water Resources Planning and Management—ASCE	**2.89** 0.917 Q1	180	2025 2845
74	Bhadra Reservoir (India)	Reddy and Kumar (2006)/ (163)	Water Resources Management	**3.54** 0.941 Q1	828	2025 2845
75	Pechiparai Reservoir (India)	Jothiprakash and Shanthi (2006)/(87)	Water Resources Management	**3.54** 0.941 Q1	384	150 –
76	Pagladia Reservoir (India)	Ahmed and Sarma (2005)/ (131)	Water Resources Management	**3.54** 0.941 Q1	240	–

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
608 128	DE, GA, PSO, ABC, SA, CS	DP			irrigation, industrial

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
28.82 3.2	LFWOA	WOA, ABC, PSO, GA (real coded), GA (binary, DP			flood control
66.71 0.9	GA	SDP, DP			domestic water, irrigation
_	HHO, SOA, STOA, TSA, MSA	GA, PSO			Baft dam: agricultural, drinking, and industrial purposes, Jiroft dam: drinking, industrial, agricultural, electricity generation, flood control purposes, Safarood dam: agricultural, drinking, industrial
229.5 10	GA	_			water supply, irrigation
_	MOWCA	NSGA-II	236.07 for MOWCA, 268.01 for NSGA-II		Baft dam: agricultural, drinking, and industrial purposes, Jiroft dam: drinking, industrial, agricultural, electricity generation, flood control purposes, Safarood dam: agricultural, drinking, industrial
171.4 25.3	ACO, GA	_	0.9868 for ACO, 0.9969 for GA		agricultural, industrial, domestic, environmental
2137.1 659.9	DE, PSO, APO	_			hydropower generation, agricultural, irrigation, water supply
_	MSA	HS, ICA	(308.83 for MSA, 264.61 for HS, 306.47 for ICA) for CFRO problem, (1195.58 forMSA, 1060.76 for HS, 1136.22 for ICA) for TRO problem		_

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
211.35 9.03	GA	–			drinking, industrial, agricultural
2510 830	ABC	–			hydropower
176 –	GA	–			drinking, agricultural
–	NSGA-III	–			flood control
1320 150	**Hybrid Algorithm (HA)**(SVM-CIPSO)	IPSO			agricultural, drinking, industrial water, flood controlling, and storage the water for drought seasons
–	SOS	–	10.89		–
1049 1141	MSA	PSO, GA	0.1470 for MSA, 0.1584 for PSO,0.3026 for GA	Lingo 0.110	hydropower, controlling surface waters of the area, flood control, irrigation
5730 –	**Hybrid Algorithm (HA)** (GA–NLP)	–		308.292 for FRBS, 1194.441 for TRBS	hydropower generation and agricultural irrigation
215.5 121.5	ARIW-PSO	GA, PSO, IPSO,			flood control, water supply, hydroelectric power, river ecological water supply, irrigation
8150 2950 5931.73168.27	PSO	–			water supply, hydropower generation, flood control, irrigation, fishery development, and recreation
44,60 3,2	**Hybrid Algorithm (HA)** (GS + PSO)	GA, GS, PSO, NLP	0.111 for HA 0.212 for PSOA 0.221 for GA 0.178 for GSA		irrigation

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
_	HWGA	GA, WOA, LP	(247.447 for WOA,286.596 for GA, 289.906 for HWGA) for FRBS, (826.772 for WOA,1010.244 for GA, 1115.674 for HWGA) for TRBS	308.29 for CFRO problem	_
250 210	COA	GA		0.11	cultivation optimization, irrigation
_	**Hybrid Algorithm (HA)**(ISO–LTF–ANN)	SOP, SDP, PFDO			water demands of irrigation, industrial and domestic use (water supply), and hydropower generation
142 27	BA	NLP	105.3, 102.8, and 80.5 for the first to the third scenarios	_	Irrigation and agriculture
133 17	**Hybrid Algorithm (HA)**(BA-PSO)	BA, PSO	(0.98 for (HA)(BA-PSO), 1.12 for BA, 1.22 for PSO) for Shahid Dam, (308.28 for (HA)(BA-PSO), 308.20 for BA, 308.99 for PSO) for CFRO problem	Lingo (1.77 for Aydoughmoush dam,1.18 for Karoun 4 reservoir)	agricultural, urban, industrial and environmental
44,60 3,2	**Hybrid Algorithm (HA)**(HB-SA)	NLP, PSOA, BA, WCA	0.156	Lingo 0.112	irrigation
171.4 25.3	SA	NLP, GAMS	18.37		agricultural, drinking, and industrial water, and control the flood

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/solutions)	Global optimum	Objectives of the dam reservoir
91.2 0.3	**Hybrid Algorithm (HA)** (MS-DEPSO)	DE, PSO, ABC, HSLSO, CS, IDEPSO4	(7.55 for MS-DEPSO, 10.28 for DE, 9.52 for PSO, 11.51 for ABC, 8.29 for HSLSO, 8.35 for IDEPSO4, 10.99 for CS) for single-reservoir, (77.95 for 120 months, 113.63 for 180 months, 147.58 for 240 months) for 3-reservoir		_
1049,136.8 1141/8.9	BA	NLP	1.78 for Aydoughmoush dam,1.19 for Karoun 4 reservoir	NLP (1.213 for Karun4,308.29for CFRO problem)	Aydoghmoush Reservoir: Irrigation, Karun 4 Dam: Hydropower, Controlling surface waters of the area, flood control
_	SMLA	GA, NLP	0.114 for SMLA, 0.143 for GA		irrigation and industrial uses, navigation purposes, and energy production
136.8 8.9	KA	BA, GA, PSO, SA, WA, NLP	1.789 GA,0.789 KA, 1.111 SA, 1.655 WA, 1.422 BA, 1.765 PSA	0.11	Aydoghmoush Reservoir: irrigation, Karun 4 Dam: hydropower, controlling surface waters of the area, flood control
3300 800	**Hybrid Algorithm (HA)**(ICA-MODSIM)	_		(401.33: TLBO,401.44: JA) for DFRO problem (308.30: TLBO, 308.40: JA) for CFRO problem, (1194.44: TLBO, 1194.59: JA)for TRO problem	water supply enhancement and flood mitigation

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
1049 1141	CSO	GA, NLP	(1.218 for CSO, 1.547 for GA) for Karun4, (308.20 for CSO, 307.32 FOR GA) for CFRO problem	_	hydropower, controlling surface waters of the area, flood control, irrigation
1049 1141	**Hybrid Algorithm (HA)**(AFSA-PSOA)	GA, PSOA, AFSA	1.500 for GA, 1.320 for AFSA, 1.299 for PSOA	_	hydropower, controlling surface waters of the area, flood control, irrigation
44,60 3,2	SMA	PSO, GA	0.112 for SMA, 0.212 for PSOA, 0.221 for GA		irrigation
_	TLBO, JA	LP	(401.33 for TLBO, 401.44 for JA) for DFRO problem(308.30 for TLBO, 308.40 for JA) for CFRO problem,(1194.44 for TLBO, 1194.59 for JA)for TRO problem		_
44,504 4.8, 50	NSGA-II	PESA-II and SPEA-II	_		supply drinking water, meeting the irrigation water demand
44, 60 3, 2	WCA	ICA, HS, PSO, GA	0.157 WCA, 0.74 GA, 0.23 PSO, 0.48 ICA,0.81 HS	NLP (1.213 for Karun-4,308.29 for CFRO problem, 1194.44 for TRO problem)	irrigation

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
_	ABC	_		Lingo (1.213 for Karun4, 308.29 for CFRO problem)	domestic and industrial water supply, irrigation, flood mitigation, recreation, fisheries, aquaculture
_	PA-DDS	NSGA-II, NDSs			danjiangkou reservoir: flood control, water supply, hydropower generation, Irrigation. ankang reservoir: hydropower generation, flood control, navigation, irrigation, tourism
308 142	SA	GA, PSO	0.40 for Bazoft dam reservoir, (308.29 for SA, 285.16 for GA) for CFRO problem	Lingo (0.1614 for Single-Reservoir, 401.3for DFRO problem, 308.29 for CFRO problem)	irrigation, agricultural
1049 1141	**Hybrid Algorithm (HA)** (GA-Krill)	NLP	(1.212 for Hybrid, 1.300 for Krill, 1.610 for GA) for Karun-4, (308.29 for Hybrid, 307.54 for Krill, 307.12 for GA) for CFRO problem, (1194.44 for Hybrid, 1190.12 for Krill, 1190.01 for GA) for TRO problem		hydropower, controlling surface waters of the area, flood control, irrigation
1049 1141	BBO	GA, NLP	(1.535 for GA, 1.223 for BBO) for Karun4, (300.47 for GA, 308.12 for BBO)for CFRO problem		hydropower, controlling surface waters of the area, flood control

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
849 226	CS	–			Hydropower, irrigating
308 142	WOA	GA, LP, NLP	(0.2250 for GA, 0.1624 for WOA) for Single-Reservoir, (Not reported for GA, 401.1 for WOA) for DFRO problem (298.36 for GA, 306.99 for WOA) for CFRO problem		irrigation, agricultural
26900 12400	**Hybrid Algorithm (HA)**Chaos-GA (CGA)	SVR		DP (70.313)	meet the ecological water demands of the lake, to achieve maximum hydropower production
171.4 25.3	PSO	–		NLP (3.3727 for FA and GA) for Aydoghmoush dam, (0.0045 forfor FA and GA) for Karun 4 Reservoir)	drinking water, prepare agricultural water, control seasonal floods, and generate electricity
-	PSO	–		922.324 for 4-reservoir	hydrothermal power system
2510 830	IWO	GA, PSO	32017 for 12 months, 153318 for 60 months, 823287 for 240 months	1.213 for Karun4,308.20 for CFRO problem	hydropower
609 127	**Hybrid Algorithm (HA)** (DP–GA)	–	0.043 for DP–GA, 0.826 for GA		irrigation, water supply

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
1049,136.8 1141,8.9	FA	GA, NLP	(3.5365 for FA and 6.3790 GA) for Aydoghmoush Reservoir, (0.0078 for FA and 0.0089 GA) for Karun 4 Reservoir	Lingo (1.2132 for Karun4, 308.29 for CFRO problem)	Aydoghmoush Reservoir with Irrigation, Karun 4 DamHydropower, Controlling surface waters of the area, flood control
	Hybrid Algorithm (HA) (IBA)	LP	308.4 for CFRO problem, 1194.44 for TRO problem	NLP (5.243 for Karun4 dam, 308.29CFRO problem)	
1049 1141	GSA	GA, NLP	(1.239 for BA,1.260 for WLA,1.239 for BBO,1.218 for GSA) for Karun4, (307.84 for BA,302.38 for WLA,306.55 for BBO, 308.10 for GSA) for CFRO problem		Hydropower, Controlling surface waters of the area, flood control, irrigation
136.8 8.9	GP	–		1.213 for Karun4, 308.29 for CFRO problem	irrigation
1049 1141	BA	GA, LP, NLP, DP	(1.5350 for GA, 1.223 for BA) for Karun4, (282.90 for GA, 308.20 for BA) for CFRO problem		Hydropower, Controlling surface waters of the area, flood control,

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
1049 1141	GA, ICA, COA	NLP	(6.196 for GA, 5.586 for ICA, 5.246 for COA) for Karun4 dam, (302.42 for GA, 306.76 for ICA, 307.92 for COA) for CFRO problem		Hydropower, Controlling surface waters of the area, flood control, irrigation
2510 830	**Hybrid Algorithm (HA)**(ACO-LP)	_			hydropower
1049 1141	WCA	GA	(1.260 for WCA and 1.52 for GA) for Karun4, (306.92 for WCA and 300.47 for GA) for CFRO problem		Hydropower, Controlling surface waters of the area, flood control, irrigation
26900 12400	CPSO	PSO, GA, DE			flood protection for its downstream area
164.2 7.5	GA	_		(401.30 for DFRO problem, 308.29 for CFRO problem, 1194.44 for TRO problem) for HBMO	water compensation, flood control, hydropower generation, and water recreation
_	ABC	GA			generating hydropower, irrigation water, annual flood control, and water supply for domestic/industrial uses

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
176	GP	GA, NLP	35.763 for GA, 31.333 for GP including stochastic variable, 32.147 for GP including deterministic variable		drinking, agricultural
_	GA, SDP	_			irrigation, domestic, livestock, small industry, and large industry
_	HBMO	GA	401.30 for DFRO problem, 308.29 for CFRO problem, 1194.44 for TRO problem		_
122.7 8.3	**Hybrid Algorithm (HA)**(GA–KNN), (BSGA)	_			agricultural, industrial, domestic, and environmental
_	CGA	_			hydropower generation, agriculture, and industry use together with drinking water
782 179	**Hybrid Algorithm (HA)**(GA-NF)	_			reduce flood risk in downstream, water supply, irrigation, industrial, domestic, and ecological
2510 830	Cellular Automata	GA, AC, PSO			hydropower
_	ANN, GA	DP, M5			domestic, industrial, agriculture, hydropower generation
2510 830	ACO (PCACOA, FCACOA)	_			hydropower
475 45	GA	_			Irrigation, Agricultural

Table 2 (continued)

Active storage/Dead storage (MCM)	Meta-heuristic algorithms	Compared models	Best (objective function/ solutions)	Global optimum	Objectives of the dam reservoir
_	**Hybrid Algorithm (HA)** (GA-SA)	_		_	irrigation water supply, flood control, power generation, and recreation
1784 241	EMPSO	PSO, GA			irrigation and hydropower generation
1784 241	GA	_			irrigation and hydropower generation
_	GA	_			irrigation, domestic, livestock, small industry, and large industry needs
_	GA	SDP	_		irrigation and hydropower

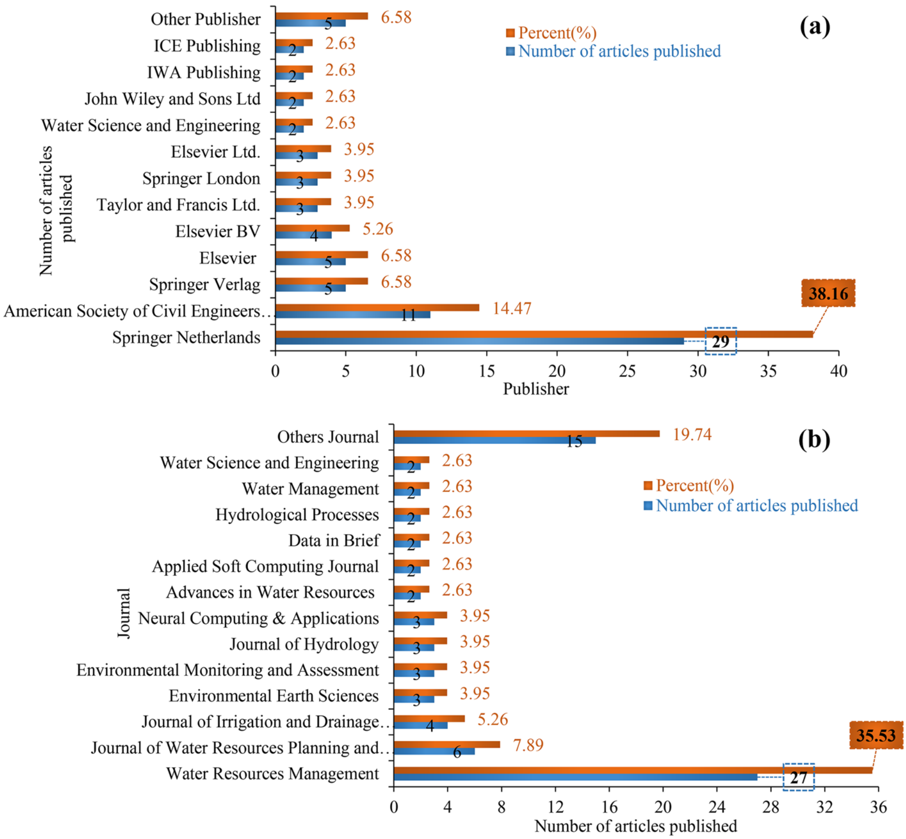

Fig. 9 The most reviewed articles **a** in publications; **b** in journals

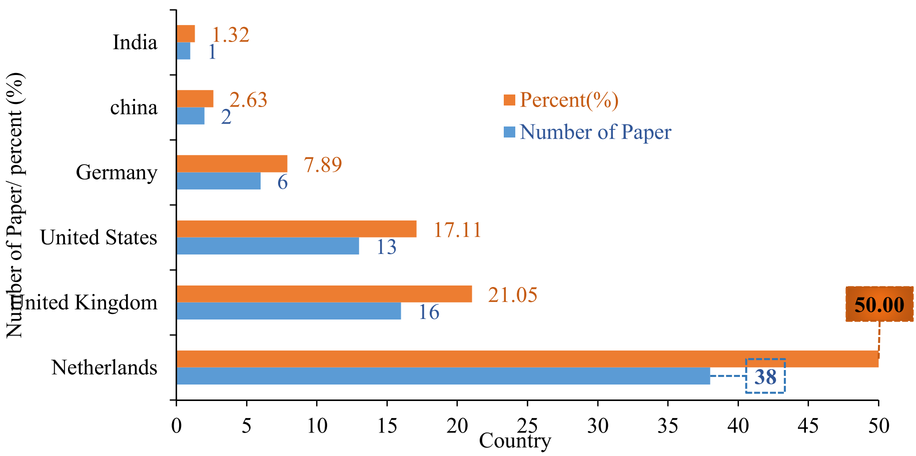

Fig. 10 Case studies published in different countries

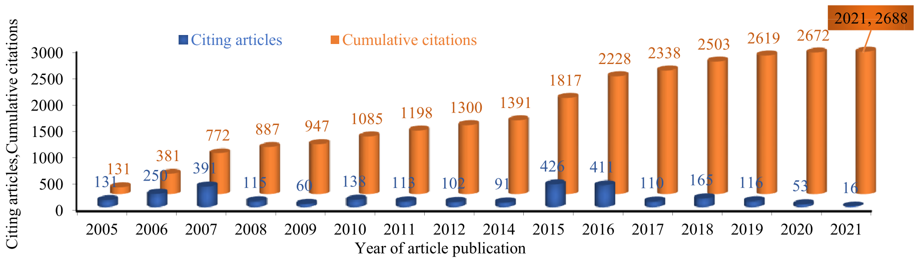

Fig. 11 Cumulative citations of selected articles published

3 Different Modeling Techniques to Optimize the Operation of Dam Reservoirs

Implicit stochasticoptimization (ISO) and explicit stochastic optimization (ESO) are two types of optimization techniques that can be used to optimize reservoir systems. In reality, ISO methods are deterministic methods that employ extremely long representative hydrology to achieve optimal operation. Although historical records can also be used, synthetic streamflow generators are frequently used to create hydrology. Following that, reservoir operating policies are typically inferred from optimized model solutions using regression techniques. In other words, to iteratively improve promising operating rules, ISO applications have combined optimization, regression, and simulation techniques. (Bhaskar and Whitlatch 1980). The explicit representation of probabilistic streamflows or other ambiguous problem parameters is necessary for ESO formulations. Because they can be written to more accurately represent a problem, some comparative studies have found that ISO methods are preferable to ESOs (Karamouz and Houck 1987). Classical optimization techniques are briefly discussed in this review article since they have already been covered in sufficient detail in other review articles. However, emerging techniques, particularly meta-heuristic algorithms used by researchers to operate reservoir systems, are covered in more detail in Fig. 12.

3.1 Linear Programming

One of the most frequently used optimization techniques for modeling reservoir system optimization issues is linear programming (LP). It has been used to solve a variety of problems involving reservoir systems with a variety of objectives, including figuring out the best operating procedures (Crawley and Dandy 1993), sizing reservoir capacities (Loucks et al. 1981), yield evaluation (Dahe and Srivastava 2002), flood control (Needham et al.

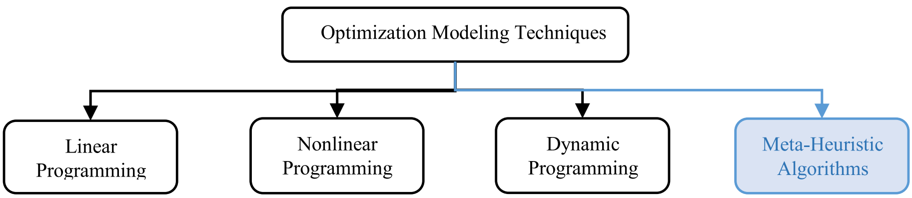

Fig. 12 Modeling techniques for optimizing dam reservoirs

2000), and concurrent use planning (Vedula et al. 2005). The flexibility of this technique in the application of complex programs, convergence to the global optimal solution, and access to cost-effective software solutions, such as LINDO, and LINGO. The limitations on linear and convex objective functions and linear constraints are the primary drawbacks of LP. However, nonlinearity in some reservoir problems (e.g., nonlinear benefit or cost functions) can be tackled by approximation and extension of LP to separable LP (Crawley and Dandy 1993) and successive LP (Mousavi and Ramamurthy 2000; Barros et al. 2003).

3.2 Nonlinear Programming

Due to complex relationships between various physical and hydrological variables or because the system is designed to achieve a specific goal, nonlinearity is present in the problems of many reservoir systems. The majority of hydropower generation issues are nonlinear, which makes finding solutions challenging. LP (discussed in the previous section) is typically applied in successive steps to these problems or by approximating a nonlinear problem to a linear problem. Additionally, dynamic programming (see Section 3.3) can deal with nonlinearities. Nonlinear programming (NLP) techniques, however, are employed specifically for a certain class of issues. The generalized reduced gradient (GRG) method and successive or sequential quadratic programming (SQP) are two examples of these algorithms. Large-scale nonlinear optimization problems can currently be solved using a variety of general-purpose software packages, e.g., LINGO, and LANCELOT.

3.3 Dynamic Programming

The Bellman (1957) method of dynamic programming (DP) is an optimization technique for resolving multistage decision-making processes. The most appealing aspect of the DP algorithm is that a complex multistage problem is broken down into several smaller, simpler problems that are then solved one at a time, recursively. Additionally, nonlinear problems and problems involving stochastic variables can be easily accommodated within the general framework of DP. Even nonconvex and discontinuous functions are capable of being solved by discrete DP. Yakowitz (1982) gave a thorough analysis of DP and how it was applied to numerous problems involving water resources. The applicability and restrictions of DP methods, specifically regarding problems with reservoirs, are presented by Nandalal and Bogardi (2007).

3.4 Bibliographic Review on Optimization of Dams Reservoir Operation Using the Meta-heuristic Algorithms

Research in this field has shown that linear and nonlinear optimization methods have made significant progress. But using these methods to optimize large structures is difficult and sometimes impossible. To solve this problem, new meta-heuristic algorithms with high convergence capability can be a suitable solution. Meta-heuristic (MH) methods are discussed in this section. In general, there has been an exponential increase in the use of MH techniques to solve various applications. They are free gradient methods that produce better results than conventional techniques when used to solve extremely challenging optimization issues (Abualigah and Diabat 2021). Additionally, they are quicker and easier to implement than traditional optimization techniques (Abualigah and Diabat

2020). MH techniques can be divided into various groups according to a variety of inspirations. According to Abd Elaziz et al. 2021, these categories include human inspiration algorithms, swarm intelligence (SI) techniques, evolutionary algorithms (EAs), and approaches to natural phenomena. Figure 13 depicts the standard procedures for using meta-heuristic techniques to improve dam reservoirs. Meta-heuristic algorithms typically fall into one of two categories: single-solution based (like simulated refrigeration, SA), or population-based (like genetic algorithm, GA). As the name suggests, the optimization phase for the first type only considers one solution. At each iteration of the optimization process, a population of solutions (the second type) evolves. Population-based methods frequently discover an optimal or suboptimal solution that is identical to or very close to the precise optimal. The main sources of inspiration and models for population-based metaheuristic methods (P-metaheuristics) are phenomena in nature. The optimization process is started by these algorithms by creating a set (population) of individuals, each of whom represents a potential solution to the optimization problem. This population changes frequently by exchanging the existing population for a brand-new population that was created using some of the frequently random operators. Additionally, the optimization procedure goes on until the stop criteria (i.e., the maximum number of iterations) is met. The first set of calculations draws its inspiration from biological phenomena and the biological evolution of the natural world. These algorithms are Invasive Weed Optimization (IWO), Bat algorithm (BA), Whale Optimization Algorithm (WOA), Water Cycle Algorithm (WCA), Symbiotic Organisms Search (SOS), and Shark Machine Learning (SML). The algorithms in the second class of systems, known

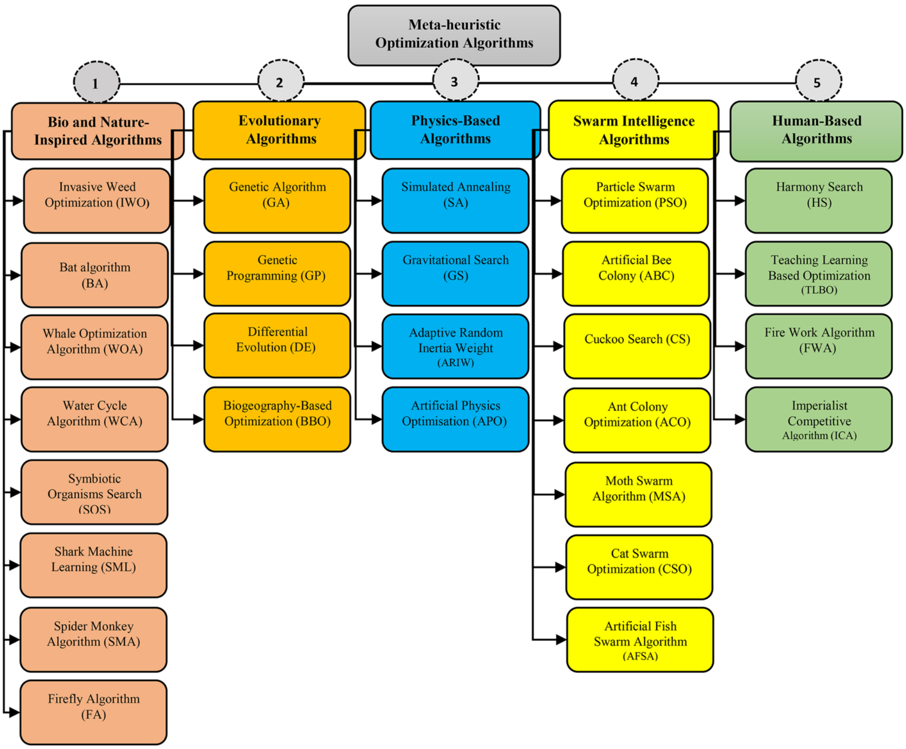

Fig. 13 Meta-heuristic methods in optimizing dam reservoirs

as EAs, were developed by simulating natural genetic principles like crossover, mutation, and selection. The Genetic Algorithm (GA), Differential Evolution (DE), Genetic Programming (GP), and Biogeography-Based Optimization (BBO) are a few MH techniques that fall under this category. Physics-based algorithms make up the third category. The laws of physics serve as a source of inspiration for physics-based algorithms. Simulated Annealing (SA), Artificial Physics Optimization (APO), Adaptive Random Inertia Weight (ARIW), and Gravitational Search (GS) are a few examples of these algorithms. The fourth class of P-meta-heuristic algorithms is social imitation (SI) algorithms, which imitate the social behavior of organisms that live in herds, flocks, or groups (e.g., decentralized, self-organized systems). For instance, Eberhart and Kennedy's Particle Swarm Optimization (PSO) algorithm was primarily influenced by the group behaviors of birds. A candidate solution to the optimization problem is represented by each particle in the congestion in PSO. Each particle is updated during the optimization process based on both its best (local) position and the position of the best global particle. Additional examples of SI techniques include artificial bee colonies (ABC), cuckoo search (CS), and ant colony optimization (ACO). A group of algorithms that resemble some aspects of human behavior is included in the fifth category of P-meta-heuristic algorithms. The Fire Work Algorithm (FWA), Harmony Search (HS), Teaching Learning Based Optimization (TLBO), and Imperialist Competitive Algorithm (ICA) are a few examples of human-based algorithms.

3.4.1 Bio and Nature-Inspired Algorithms

Invasive Weed Optimization (IWO) A population-based optimization algorithm called the Invasive Weed Meta-heuristic finds the general optimum of a mathematical function by modeling the compatibility and randomness of weed colonies. Weeds are strong plants with aggressive growth patterns that pose a serious threat to crops. They have proven to be very resistant to environmental changes and adaptable. Consequently, a potent optimization algorithm is obtained by taking into account their characteristics. The resistance, adaptability, and randomness of a sample of weeds are attempted to be replicated by this algorithm. A phenomenon in agriculture known as colonies of invasive weeds served as the inspiration for this technique. A plant that grows erratically is what is commonly understood by the term "weed". Even though weeds may be useful in some areas, when the same plant grows in an area that obstructs human needs and activities, it is referred to as a weed. The "Invasive Weed Optimization Algorithm" is a straightforward numerical optimization algorithm based on colonized weed that was introduced by Mehrabian and Lucas (2006). Using fundamental characteristics like seeding, growth, and competition in a weed colony, this algorithm is straightforward but effective in convergent to optimal solutions. Some fundamental aspects of the process are taken into consideration to simulate the habitat behavior of weeds:

1. Primary population initialization: A small number of seeds are dispersed throughout the search area.
2. Reproduction: Based on their fitness value, every seed develops into a flowering plant that then produces seeds. As we move from S_{max} to S_{min}, the quantity of grass grains decreases linearly as follows:

$$n(w_i) = \frac{S_{max}(\max fit - fit(w_i)) + S_{min}(fit(w_i) - \min fit)}{\max fit - \min fit} \quad (1)$$

3. Spectral Spread: The following equation results in the seeds produced by the group in the normal distribution with a mean planting position and standard deviation (SD):

$$\sigma_t = \left(\frac{T-t}{T}\right)^n (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \quad (2)$$

where n is the nonlinear modulation index, T is the maximum number of iterations, and _t is the current standard deviation (Mehrabian and Lucas 2006). His conversion ensures that the fall of grain in the range decreases nonlinearly at each step, producing more suitable plants while removing unsuitable plants, and displays the transfer mode from r to a choice of K.
4. Competitive deprivation: If the number of grasses in the colony exceeds the maximum allowable number (Pmax), the grass with the worst fitness is eliminated from the colony, leaving a fixed number of herbs.
5. The minimum colony cost function of the grasses is then stored after this process is completed in the maximum number of iterations (Misaghi and Yaghoobi 2019). Asgari et al. (2016) developed a study that applied the WOA algorithm to an ideal reservoir operation. Azizipour et al. (2016) presented the use of the invasive IWO algorithm, a novel evolutionary algorithm motivated by colonizing weeds, for the best performance of hydropower reservoir systems in their paper. The outcomes are contrasted with those currently available from the two most popular evolutionary algorithms, GA and PSO. The findings demonstrated that for both single-reservoir and multi-reservoir hydropower operation issues, the IWO is more efficient and effective than PSO and GA.

Bat Algorithm (BA) The echolocation of microbats serves as the basis for the bat algorithm (BA) (Yang 2010). The echolocation technique used by bats is called the bat algorithm. Echolocation is a type of sonar that bats use to find prey and avoid obstacles. These bats use echolocation, which involves emitting a very loud sound pulse and listening for the echo that is reflected from nearby objects. Their pulses vary in properties and can be correlated with their hunting strategies, depending on the species. Most bats sweep through a range of about an octave using brief, frequency-modulated signals. Each species' signal bandwidth is different, and it is frequently widened by adding more harmonics. The following rules can be used to represent the echolocation traits of microbats in BA.

1. All bats use echolocation to gauge distance, and somehow, they can distinguish between background barriers and food/prey.
2. To find prey, bats randomly fly with a speed of Vi at a position Xi while using a fixed frequency fmin, variable wavelength k, and loudness $A0$. Depending on how close their target is, they can automatically change the pulses' wavelength (or frequency) and rate of emission r ∈ [0; 1].
3. Although there are many possible ways for the loudness to change, it is assumed that it ranges from a large (positive) $A0$ to a small constant value $Amin$. At position Xi, the ith bat flies at a fixed frequency of fmin at a random velocity of Vi. To find food, the bat changes its wavelength and loudness A_0. The rules that determine how their positions Xi and velocities Vi in a D-dimensional search space are updated must be specified. The current best location (solution), known as $Xbest$, was found by comparing all other

locations among all n bats (Yang 2010). When g is defined as the index of the best bat in the population and the iteration number is denoted by superscripts, the new solutions X_i^t and velocities V_i^t at time step t are then provided by Eqs. (3) and (4). The wavelength λ of the ultrasonic sound bursts with a constant frequency f is given by

$$\lambda_i = \frac{V_i}{f_i} \tag{3}$$

$$f_i = f_{min} + \left(f_{max} - f_{min}\right) \times \beta \tag{4}$$

$$V_i^t = V_i^{t-1} + (X_i^{t-1} - X_{best}) \times f_i$$

where $\beta \in [0; 1] = a$ random vector drawn from a uniform distribution. X_{best} is the current global best location (solution), which is located after comparing all the solutions among all the n bats. The new solutions of the *ith* bat at time step t are given by X_i^t and V_i^t

$$X_i^t = X_i^{t-1} + V_i^t \tag{5}$$

The loudness is presumptively assumed to range from a large (positive) $A0$ to a small constant value $Amin$. The values of $fmin$ and $fmax$ depend on the problem's domain size. Each bat is initially given a frequency that is uniformly drawn from $[fmin, fmax]$ at random. For local search procedure (exploitation), each bat takes a random walk creating a new solution for itself based on the best selected current solution ($Xbest$)

$$X_{new} = X_{best} + \varepsilon A^t \tag{6}$$

where the random number ε is drawn from $[-1; 1]$; and A^t= the average loudness of all bats at this time step. The loudness decreases as a bat tend closer to its food and pulse emissions rate increases

$$A_i^{t+1} = \alpha A_i^t \tag{7}$$

$$r_i^t = r_i^0[1 - \exp(-\gamma t)] \tag{8}$$

where α and γ = constants and $r_i^0 \in [0; 1]$.

The optimal operation of a reservoir by incorporating the hedging policy and the Bat Algorithm (BA) was investigated in Jamshidi and Shourian's (2019) study. Three operation rules determine and compare the ideal monthly releases from the reservoir while minimizing the deficit in the water supply provided by the dam. Yaseen et al. (2019) in their studies propose the hybrid bat-swarm algorithm (HB-SA), a new hybrid optimization algorithm built on the BA and PSO algorithms. The primary goal of this hybridization is to enhance the BA by replacing the BA's suboptimal solution with an optimal one obtained from the PSOA. By avoiding the trapping in local optima brought on by using the BA, the solutions effectively quicken the convergence process. The proposed HB-SA is successfully examined and can be generalized for several dams and reservoir systems worldwide, which reduces the computational time for the convergence procedure. Ehteram et al. (2018a, b, c) research findings demonstrated that the bat algorithm with a third-order rule curve that converged to the minimum objective function achieved the highest values of the reliability index and resiliency index and the lowest value of the vulnerability index.

As a result, the bat algorithm with a third-order rule curve can be thought of as a suitable optimization model for reservoir operation. Ahmadianfar et al. (2016) To enhance its global searchability, introduced an improved bat algorithm (IBA) with a hybrid mutation strategy. The explorative and exploitative mutation operators are two of the six DE mutation mechanisms used in the original BA algorithm. The four-reservoir and ten-reservoir systems' benchmark hydropower operation problems were both solved using the suggested approach. To replace conventional operations research algorithms like LP, NLP, and DP, metaheuristic algorithms for optimal reservoir system operation have grown to be desirable alternatives. Bozorg-Haddad et al. (2015a, b) in their paper present the metaheuristic BA algorithm and its application to a hypothetical four-reservoir system as well as to the best operation of the Karoun-4 reservoir system in Iran.

Whale Optimization Algorithm (WOA) The humpback whale algorithm serves as the basis for the recently proposed meta-heuristic known as the whale optimization algorithm (Mirjalili and Lewis 2016). In the WOA algorithm, humpback whales approach their prey by spinning them up in the water and surrounding them with spherical bubbles.

Encircling the Prey Encircling their prey is the first step in the humpback whales' hunting ritual. It implies that the target prey is the best solution available and that each whale in the current population is attempting to better define its location relative to the desired solution. The mathematical representations of this are given by Eqs. (9) and (10).

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{X^*}(t) - \vec{X}(t) \right| \tag{9}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} \tag{10}$$

where, t is current iteration,$\vec{A}$ and $\vec{C}$ are coefficients vectors, $\overrightarrow{X^*}(t)$ is the position vector ofthe best solution achieved so far, $\vec{X}$ is the position vector, || is absolute value and. is the element-by-element multiplication.

The vectors $\vec{A}$ and $\vec{C}$ are calculated by Eqs. (11) and (12) (Mirjalili and Lewis 2016):

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{11}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{12}$$

where $\vec{a}$ is linearly reduced from 2 to 0 during the iterations (in both phases of exploration. and exploitation), and $\vec{r}$ is a random vector between 0 and 1.

Bubble-Net Attacking Method (Exploitation Phase) Along with swimming in a converging circle, whales also follow a spiraling path as they circle their prey. The WOA is assumed to choose between the spiral model or the shrinking encircling mechanism (50:50) to update the position of the whales to model this simultaneous behavior. Eq. The mathematical model is described by (13) (Mirjalili and Lewis 2016):

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*(t)} - \vec{A} \cdot \vec{D} & if\ p < 0.5 \\ \vec{D} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) & if\ p \geq 0.5 \end{cases} \tag{13}$$

where p is a random number [0, 1], $\vec{D} = \left|\vec{C} \cdot \vec{X^*}(t) - \vec{X}(t)\right|$ represents the distance between whale and the prey (best solution achieved so far), b is the constant defining the shape of logarithmic spiral, l is the random number between − 1 and + 1, is the element-by-element multiplication, and $\vec{A}$ is used with the random values between − 1 and + 1 to move whales toward a reference whale.

Search for prey (Exploration Phase) Instead of using the best whale that has been discovered thus far, a whale that is chosen at random updates the position of a whale. Eqs. The mathematical model is described in (14) and (15) (Mirjalili and Lewis 2016):

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_{rand}} \cdot \vec{X}\right| \tag{14}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A} \cdot \vec{D} \tag{15}$$

where $\overrightarrow{Xrand}$ is a random position vector (the random whale) selected from the current population and $\vec{A}$ is used with random values greater than 1 or less than − 1 to move whales far away from the reference whale.

Complex technical problems are resolved by the WOA algorithm. The aim of Lai et al. (2021) using WOA and LFWOA algorithms, is to reduce the water deficit of KGD. Muhammad et al. (2019), the whale-genetic hybrid algorithm (HWGA), a combination of WOA and GA algorithms, was used to examine the optimal performance of a four-reservoir system (FRBS) and ten-reservoir system (TRBS).

Other Bio and Nature-Inspired Algorithms Water Cycle Algorithm(WCA), Symbiotic Organisms Search (SOS), Shark Machine Learning (SML), Spider Monkey Algorithm(SMA), and Firefly Algorithm (FA) are very popular among researchers for dams reservoirs optimization studies. Yavari and Robati (2021) used the evolving multi-objective water cycle algorithm (MOWCA) to ensure Jiroft Dam's reservoir system operated as efficiently as possible for downstream demand–supply, flood control, and hydropower energy generation. In the study of Qaderi et al. (2018), the operating policy for a multi-reservoir system was derived using a novel metaheuristic optimization algorithm called the WCA algorithm. The outcomes of WCA were compared to those of other developed evolutionary algorithms, such as the genetic algorithm, harmony search algorithm, particle swarm optimization algorithm, and imperial competitive algorithm. The results showed that WCA is superior to other algorithms in calculating the annual deficit. Bozorg-Haddad et al. (2015a, b), used the WCA algorithm to determine the best operational plans for the Karon-4 reservoir and a four-reservoir system in Iran. The outcomes show the WCA's high effectiveness and dependability in resolving reservoir operation problems. Rezaei-Estakhroueiyeh et al. (2020) presented a model based on the SOS algorithm for the optimal operation of Safarud Reservoir. These datasets' analyses demonstrated that the SOS algorithm was effective in solving the reservoir problem in the best possible way. Allawi et al. (2018) suggested using the SML algorithm to build the best rule possible for reservoir operation. The SML started with a set of randomly generated potential solutions and then interactively searched for the best one. The findings of their studies demonstrate that the SML procedure is appropriate for use in a reservoir system because it can address the stochastic characteristics of dam and reservoir systems. The shark algorithm is a stochastic search optimization algorithm that begins with a set of randomly generated potential solutions and then interactively searches for the best one. Given that the reservoir system is a stochastic system by nature, such a procedure is appropriate for its system characteristics. The studies of Ehteram et al. (2017a), examine the shark algorithm's potential as an optimization algorithm for reservoir operation. Ehteram et al. (2018a, b, c) to optimize the operations of the Golestan and Voshmgir dams, compared SMA's capabilities to those of well-known optimization algorithms. The SMA, with its high rate of convergence, is recommended as an appropriate tool for optimizing the operation policy of cascade reservoirs by the findings of their studies. Garousi-Nejad et al. (2016) in their paper applies a metaheuristic algorithm called the firefly algorithm (FA) to reservoir operation and show the effectiveness of this algorithm over the GA using (1) five mathematical test functions, (2) the operation of a reservoir system for irrigation supply, and (3) the operation of a reservoir system for hydropower production. The outcomes show that, when compared to the outcomes of the GA, the FA performs better in terms of the convergence rate to global optimum and the variance of the outcomes regarding global optimum.

3.4.2 Evolutionary Algorithms

Genetic Algorithm (GA) A search that produces successive "generations" of answers starting with an initial set of the randomly chosen population. The primary distinction between GA and traditional optimization techniques is this. Darwin's theory of evolution's "survival of the fittest" serves as the inspiration for GA. The methods used in this approach are crossover, mutation, and selection. By carrying out the aforementioned operations to enhance the quality of the solution, the fittest individuals will be chosen and produce new populations. Parents must be chosen from the initial population in the selection process based on their fitness. The chromosomes with better fitness have more opportunities to serve as parents. There are many ways to select parents for crossover, including tournaments, roulette wheels, ranking systems, Boltzmann selection algorithms, and steady-state selection. Crossover probability exists between the parents to produce offspring (children). In the absence of crossover, children are exact replicas of their parents. There are various crossover operations, including single-point, two-point, multipoint, uniform, and matrix crossover. Each locus in offspring has a low mutation probability. To keep population diversity high, the mutation is used to help the search algorithm escape local minima. The initial population is replaced with fresh offspring, and until the termination criteria are met, the aforementioned operations must be carried out on the new population. An unconstrained problem can be solved by GA by incorporating a penalty function into the objective function to transform the constrained problem into an unconstrained problem. The GA model could perform better if used in the reservoir's real-world operation, according to the Jothiprakash and Shanthi (2006) study. Reddy and Kumar (2006) used a population-based search evolutionary algorithm called Multiobjective Genetic Algorithm (MOGA) to create a Pareto optimal set in their study to outperform the traditional methods for Multi-objective Optimization Problems (MOOP). Chang et al. (2010a, b) suggested using a constrained genetic algorithm (CGA) method to identify the best reservoir operation strategy to facilitate decision-making. When maximizing the reservoir's 10-day storage, their suggested method takes the ecological base flow requirements into account as a restriction on the amount of water that can be released from the reservoir. According to the studies of Jothiprakash et al. (2011) by using the GA model, an attempt was made to derive the optimal operating policies of multiple reservoirs. The outcomes of the GA model were then contrasted with those of the traditional stochastic dynamic programming model. To determine the best time for the Bigge Reservoir in Germany to be released, Elabd and El-Ghandour (2014) proposed a multi-objective genetic algorithm optimization model, assuming two input flow scenarios for dry seasons. The outcomes show the effectiveness of the developed model, which successfully determines the optimal releases in the two inflow scenarios of dry seasons while meeting all constraints. Nourani et al. (2020), to provide agricultural and municipal water supplies in both the base period and future periods, the GA optimization model developed the best rule curves for the reservoir. Results indicate that the methodology for evaluating and optimizing current systems provided by the framework developed in this work emphasizes the need to take projected climate change into account as an assessment tool for reservoir management in the future. Mendoza Ramírez et al. (2021) simulated the operation of a reservoir in Michoacán, Mexico, using genetic algorithms and two methods of dynamic random programming optimization. El Harraki et al. (2021) to optimize multi-objective reservoir operation, proposed an objective function combining two competitive shortage indicators. To address this issue, a more advanced genetic algorithm that reduces impractical fluctuations in the operation of the policy is created. In their studies, operating curves were jointly optimized to hedging factors to avoid severe droughts and high user damage.

Genetic Programming (GP) A type of EC called GP employs the same searching technique as GA. The initial GP assertion was made by Cramer in 1985, and Koza later added to it in 1992 and 1994. They were the ones who first applied GP to a variety of challenging optimization and search issues. Each solution from GP is provided as a tree structure. The evaluation of mathematical and logical expressions is required because each tree node has an operator function and each terminal node has an operand. Two examples of mathematics are shown in the GP in Fig. 14. As it is shown, {x,5} and {x,12} are respectively the terminal sets of $y(x) = \frac{1}{5}\exp(x) + xsin(x)$ and $y(x) = 2x + 12$ expressions. The arithmetic operators $(\pm, \times, \div)$ are internal nodes called functions. The mathematical operations (e.g., sin, and cos), Boolean operators (e.g., And, Or), as well as logical expressions (e.g., If—Then—Else), are recognized as the function set. During the GP searching process, a set of trees is generated at random, and each tree's fitness function is calculated. Using strategies like the roulette wheel, tournaments, or ranking methods, better individuals have a higher chance of surviving for the next generation in most EC. Using crossover and mutation operators, the following generation is created (Fallah-Mehdipour et al. 2012).

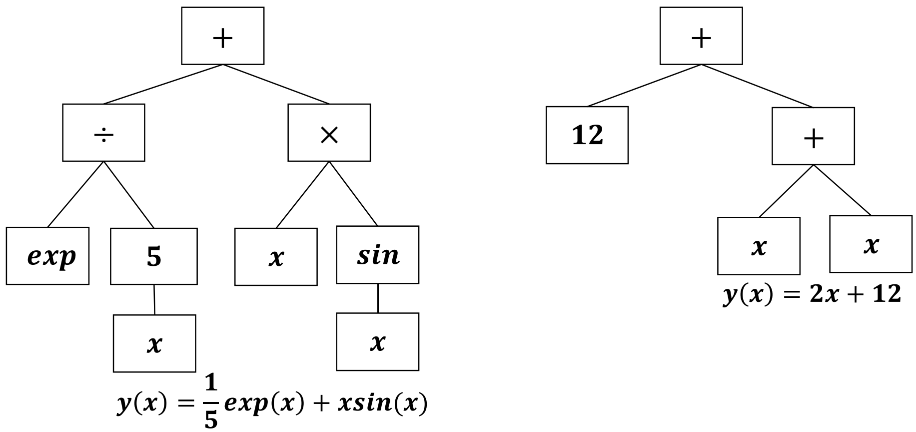

Fig. 14 GP mathematical expression examples

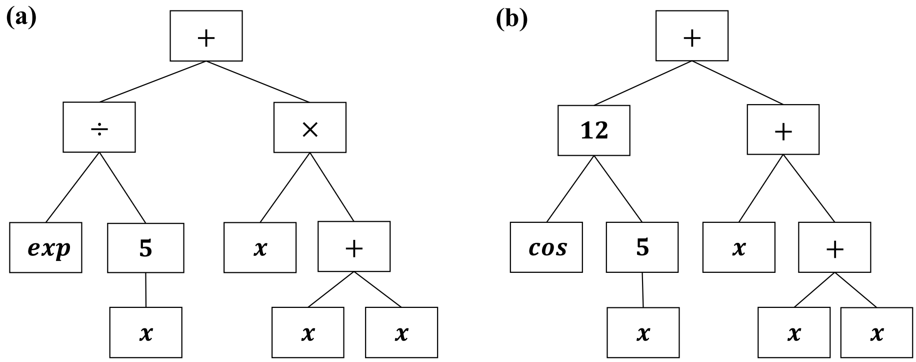

Fig. 15 Tree structures a) before and b) after mutation

In the crossover operator, two parents are chosen, and the sub-tree crossover randomly (and independently) chooses a crossover point (a node) in each parent tree. Point mutation is applied to each node individually in the mutation operator. That is, as shown in Fig. 15, every node is randomly taken into account and, with a certain probability, it is exchanged for another random variable. The input for the following generation is the trees that were produced using genetic operators. This procedure continues until the termination criterion, which might specify a maximum number of generations to run as well as a success criterion specific to the problem, like when the error is less than one percent. Then, two offspring are created by swapping out the sub-tree rooted at the crossover point in a copy of the first parent with a copy of the sub-tree rooted at the crossover point in the second parent.

Ashofteh et al. (2015) used an optimization MO-GP algorithm in their paper to increase the reliability index and decrease the reliability index of the irrigation supply provided by the Aidoghmoush Reservoir system (East Azerbaijan, Iran). Fallah-Mehdipour et al. (2012) the use of GP to create a reservoir operation policy concurrent with inflow prediction is discussed in their paper.

Other Evolutionary Algorithms In studies about dam reservoir optimization problems, members of the Evolutionary Algorithms group have utilized differential evolution (DE) and biogeography-based optimization (BBO). The purpose of the study by Ahmadianfar et al. (2019) is to create a powerful hybrid of DE and PSO with a multi-strategy (MS-DEPSO) to optimize the operating policies for reservoir systems. The basic DE algorithm's local and global search capabilities are encouraged by the proposed MS-DEPSO to produce an efficient optimal operating policy. To evaluate the effectiveness of the suggested optimization method, fourteen mathematical functions were used. To assess the effectiveness of MS-DEPSO in the production of hydropower energy, a multi-reservoir hydropower system with three different monthly operation periods over 10, 15, and 20 years were used as a real-world case study. Bozorg-Haddad et al. (2016a, b) used the BBO algorithm to address reservoir operation issues in their paper. The BBO algorithm is first tested by minimizing three mathematical benchmark functions (Sphere, Rosenbrock, and Bukin6). To a system with one reservoir and one with four reservoirs, they applied the BBO algorithm. The BBO algorithm's effectiveness in resolving the three optimization problems was compared to that of the GA. The outcomes demonstrate that the BBO algorithm outperformed the GA in accurately minimizing the benchmark functions. The BBO successfully solved the hydropower optimization problem for a single reservoir.

3.4.3 Physics-Based Algorithms

Simulated Annealing (SA) SA is similar to the metallurgical annealing process, in which a metal object is heated to almost its melting point and then slowly cooled. As a result, metal atoms can align, crystallize, and reach a minimum energy state. Kirpatrick et al. (1983), the initial proposal for the SA algorithm is a multipurpose heuristic searching technique for optimizing functions of many variables and will assess a series of local optimum in search of the global optimum. On the limited but expansive space of workable solutions, the SA algorithm imposes a neighborhood structure (Chiu et al. 2007). SA is based on the annealing process, which was inspired by the study of metallurgy. The SA Algorithm includes the following steps (Bilal et al. 2021):

1. Create a haphazard first solution for the problem.
2. For the initialized solution Fi, determine its fitness.
3. Create a new solution for the problem, then determine fitness for the new solution Fj.
4. If Fj is strictly better than Fi, accept the new solution.
5. When the comparison between "acceptance probability" and "random number" yields a favorable result, the new solution is accepted even if Fj is not strictly superior to Fi.

Following is a calculation of the new solution's acceptance probability.

$$P = e^{-\frac{\Delta E}{T}} \tag{16}$$

where ΔE: Energy difference;T: Temperature; e: 2.71828.

6. Update temperature using the following formulawhere ΔT: Temperature change.

$$T = T - \Delta T \tag{17}$$

7. Up until the allotted iterations are used up or the stopping criteria are satisfied, repeat steps 3–6.

In their study, Bilal et al. (2021) investigated the implementation and comparison of six well-known meta-heuristics, namely: simulated annealing, genetic algorithms, particle swarm optimization, differential evolution, and artificial bee colony to optimize reservoir operation policy. In the research done by Rouzegari et al. (2019) by utilizing the SA and NLP methods, the optimal operating model of the reservoir was created with the goals of reducing the deficiencies and taking into account the downstream demands of the reservoir, particularly the environmental water Mahabad River demands. Chiu et al. (2007) introduced a method for optimizing reservoir operation using fuzzy programming and hybrid evolution algorithms SA and GA. In the hybrid search process, the GA provides a global search and the SA algorithm provides a local search. According to the findings of their studies, the hybrid GA-SA model performs parallel analyses that raise the likelihood of locating an ideal solution while decreasing the amount of time needed for reservoir operation.

Gravitational Search Algorithm (GSA) The GSA, the second component of our hybrid algorithm, looks for the best solution in the problem's search space using physical laws. The GSA is based on Newton's theory of gravity. Accordingly, the gravitational force of each mass acts to absorb the others during the algorithm's execution. Let's say there is a system with N masses. The expression $x_i = (x_i^1, \dots, x_i^d \dots, x_i^n)$ displays the location of each mass, with x_i^d denoting the mass's position in dimension d and N denoting the problem's dimensions. The algorithm begins the search by dispersing the objects throughout the problem space at random. The following equation is then used to define the gravitational force of the j-th factor at each iteration's step:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{\alpha j}(t)}{R_{ij}(t)^{R_{power}}} \times \left(x_j^d(t) - x_i^d(t)\right) \tag{18}$$

where $M_{\alpha j}(t)$ is the active gravitational mass of mass j; $M_{pi}(t)$ is the inactive gravitational mass of i-th mass; $G(t)$ is the gravitational constant at time t; $R_{ij}(t)$ is the distance between the two masses i and j; R_{power} is the power of the distance between the two masses; and $F_{ij}^d(t)$ is the force between the two particles. Following that, using the following equations, the gravitational constant and the separation between two particles are calculated.

$$R_{i,j}^t = \|x_i(t), x_j(t)\|_2 \tag{19}$$

$$G(t) = G_0 \times \exp\left(\frac{-k \times iter}{\max iter}\right) \tag{20}$$

where max iter is the number of iterations that can be made, G_0 is the initial gravitational constant, and K is the descending coefficient. The general force that is posed over i in the d-dimensional problem space is based on the following equation:

$$F_i^d(t) = \sum\nolimits_{j=1, j\neq 1}^{N} rand_j F_{ij}^d(t) \tag{21}$$

A random number between 0 and 1 is represented by $rand_j$ in this scenario. The second law of Newton states that each mass accelerates in the direction of the d dimension proportional to the force applied to it in that direction and the inverse mass of its inertia. Thus:

$$\alpha_{i,j} = \frac{F_i^d(t)}{M_{ii}(t)} \tag{22}$$

d stands for the problem's dimension, and $M_{ii}(t)$ is the mass of the inertia of the system. The i-th object. Based on the following equations, the object's position and velocity are determined.

$$v_i^d(t+1) = rand_i \times v_i^d(t) + \alpha_i^d(t) \tag{23}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{24}$$

where $rand_i$ is a random number ranging between 0 and 1, $v_i^d(t+1)$ is the new velocity of each mass α: mass acceleration, and $x_i^d(t+1)$ is the new position of each mass. GSA considers both gravitational objects and inertial objects according to Eq. (25), which is used to change the objective function value of objects according to Eq. (26). After that, Eq. (27) is used to normalize the object values:

$$M_{\alpha i} = M_{pi} = M_{ii} = M_i \tag{25}$$

$$q_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{26}$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^{N} q_j(t)} \tag{27}$$

where $M_{\alpha i}$ is the active gravitational mass, M_{pi} is the inactive gravitational mass, and M_{ii} is the mass of inertia, all of which are equal to M_i. $q_i(t)$ is meanwhile the value of the objective function at time t, $fit_i(t)$ is the value of the i-th mass at time t, $M_i(t)$ are the normalized mass at time t, and $worst(t)$ and $best(t)$ are the worst and best values of the objective function respectively. The steps for running the GSA are as follows:

1. A random state is used to create the initial population and particle positions.
2. Based on a sensitivity analysis, the parameters α, R_{power}, and G_0 are computed at their initial values.
3. Each mass has its objective function value calculated.
4. The masses are specified with the best and worst values of the objective function, and G's value is updated accordingly.
5. Eqs. (21), (22) and (27) are used to determine the acceleration and mass values.
6. Updates the position and speed.
7. The convergence condition is examined. The algorithm is finished if it meets the requirements. Otherwise, we proceed to step 3 (Karami et al. 2019).

An evolutionary optimization algorithm called the GSA is based on mass interactions and the law of gravity. Bozorg-Haddad et al. (2016a, b) investigated the GSA's performance in their paper for optimization problems, single reservoir, and four-reservoir operations. In three optimization problems, the GSA's solutions were contrasted with those of the well-known GA. The outcomes demonstrated that the GSA's results in minimizing the optimization problems are closer to the optimal solutions than the GA's results. Karami et al. (2019) to reduce irrigation deficiencies in a multi-reservoir system, introduced a hybrid algorithm (HA) including GSA and PSO algorithms. Iran's Golestan Dam and Voshmgir Dam system, a significant multi-reservoir system, served as the test case for the proposed algorithm. The results of HA demonstrated that it was capable of guaranteeing a high volumetric reliability index (VRI) to satisfy the pattern of water demand downstream from the dams, as well as outperforming the other algorithms on other crucial indices. As a global optimizer for dam and reservoir operations, the proposed HA appears to have a lot of potentials.

Other Physics-Based Algorithms In the Physics-Based Algorithms group, Adaptive Random Inertia Weight (ARIW) and Artificial Physics Optimisation (APO) have been used in studies related to dam reservoir optimization problems. The paper by Chen et al. (2020a, b) is based on traditional PSO and describes an effective and trustworthy heuristic method for building a multi-objective optimization model for reservoir operation using PSO with an adaptive ARIW strategy, known as the ARIW-PSO algorithm. In their research, the effectiveness of the ARIWPSO algorithm was examined using a few traditional test functions, and the outcomes were compared to those of the GA, the traditional PSO, and other enhanced PSO methods. In research, Wang et al. (2021) The use of representative heuristic algorithms from the DE, PSO, and APO categories for reservoir optimal operation was reviewed, and their performance was evaluated using a designed experiment. Additionally, a general solution procedure for the application of HAs was created for the MOROO problem, along with the necessary tools for handling constraints and designing fitness functions.

3.4.4 Swarm Intelligence Algorithms

Particle Swarm Optimization (PSO) PSO shares many similarities with evolutionary computation techniques such as GA. PSOs are initialized with a population of random solutions and search for optima by updating generations. Algorithms and distributed problem solvers that were motivated by the cooperative behavior of insect colonies and other animal societies are referred to as "swarm intelligence". According to this perspective, PSO is a swarm intelligence technique for resolving optimization issues. An algorithm for population-based heuristic search and particle swarm optimization was first proposed by Eberhart and Kennedy (1995) and was modeled after the social behavior of flocking birds. PSO and evolutionary computing methodologies like GA have many similarities. PSOs start with a population of random solutions and update generations to look for optimum solutions. Contrary to techniques like GAs, basic PSO does not employ any operators based on the principles of natural evolution to find a new batch of candidate solutions. PSO, on the other hand, is dependent on the communication of individual population swarm particles. According to Parsopoulos and Vrahatis (2004), each particle effectively modifies its trajectory to move toward both its own current best position and the best position previously attained by any other members in its neighborhood. The following formulas are used in this algorithm to determine each particle's velocity and new location based on the position of the best particle in the group and the best location that the particle has personally experienced.

$$v_i^{t+1} = wv_i^t + c_1 rand\left(p_{best} - x_i^t\right) + c_2 rand(g_{best} - x_i^t) \tag{28}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{29}$$

Here, v_i^{t+1} is the velocity at time t + 1, w is the inertial coefficient, c_1 and c_2 are the acceleration coefficients, a rand is a random number between 0 and 1, p_{best} is the best particle in the i-th iteration, g_{best} is the best particle among all the iterations, and x_i^{t+1} is the position of the particle at time t + 1. The PSO begins by dispersing particles at random throughout the issue area. With each iteration, the particle velocity is determined using Eq. (28), and the particle position is then updated using Eq. (29). Up until it satisfies the requirements, the particle position is changed (Karami et al. 2019). By combining an enhanced PSO algorithm with an SVM technique, Moeini and Babaei (2020) proposed new hybrid methods to address the challenges of optimizing reservoir operations for water inflow conditions. The IPSO algorithm's efficiency was increased by using the constrained version, or CIPSO. The CIPSO algorithm explicitly satisfies the problem constraints, which results in a smaller search area and, ultimately, a lower computational cost. The Chen et al. (2020a, b) paper is based on traditional PSO. To create a multi-objective optimization model for reservoir operation, present an effective and trustworthy heuristic method using PSO in conjunction with an adaptive ARIW strategy. This method is known as the ARIW-PSO algorithm.

In their studies, the effectiveness of the ARIWPSO algorithm was examined using a few traditional test functions, and the outcomes were compared with those of the GA, the traditional PSO, and other enhanced PSO methods in the research done by Al-Aqeeli et al. (2020), to maximize annual hydroelectric generation, the PSO model for a single reservoir (PSOS) was developed. In their paper, SaberChenari et al. (2016) to operate the multipurpose Mahabad reservoir dam in the northwest of Iran, researchers adopted the PSO method. The operation problem of the multipurpose Mahabad reservoir dam in northwest Iran was solved using the PSO method. The goal is to reduce the discrepancy between downstream monthly demand and release, which is the desired outcome or target function. The approach was used by taking into account the likelihood that inflow would decrease under each of the four normal and drought-related scenarios. The findings of their studies demonstrated that the PSO model performs well in minimizing reservoir water losses, and this can be a good operation strategy for the reservoir in drought conditions. He et al. (2014) proposed an improved logistic map-based chaotic particle swarm optimization (CPSO) algorithm that uses the discharge flow process as the decision variable in conjunction with the penalty function.

Artificial Bee Colony (ABC) The ABC algorithm uses the search method with the intelligent behavior of the honey bee swarm to find and exploit the impossible region. This algorithm imitates the self-organization, division of labor, and foraging strategies used by honey bee swarms. Employed bees (EB), onlookers (O), and scouts (S) make up the three bee swarm groups. The EB is the type of bee that uses the food sources (possible solutions) from the designated area of the search area. The bee known as the O waits for the EB to bring back the information while remaining inside the hive. The bees use a waggle dance to exchange information about the sources of food. Poor food sources are avoided in favor of high-quality ones, which the O memories for future use. Once their food source has been fully utilized and abandoned, S is the bee that is used to randomly search for a new food source (Choong et al. 2017). A set of release options was used as the food source mathematically. Each source is expressed as Eq. (30):

$$y_i = (i = 1, 2, \dots, F) \tag{30}$$

where yi is the ith member of a single food source for the population size of F. The best source with the finest fitness value in the population is recorded. EB improved its current location using local search steps as described by Diwold et al. (2011) in each iteration where yi is the ith member of a single food source for the population size of F. The best source with the highest recorded fitness value in the population. EB improves its current position using local search steps in each iteration (Diwold et al. 2011).

$$x_{ij} = y_{ij} + \theta_{ij}(y_{ij} - y_{kj}) \tag{31}$$

where y_{ij} is the current single release of the jth source, j stands for the dimensional vector, x_{ij} is the newly updated value of the release for the ith location of the jth source, and y_{kj} stands for additional randomly selected releases. It must be obtained from an alternative nearby source. In the range of -1 and 1, θ_{ij} is chosen at random. The best fitness value that is compatible with the ideal solution will determine whether to choose an endurance solution. The O, on the other hand, decides which food source to pursue based on its likelihood of being picked once the EB has updated its position. The following equation, first presented by Eiben and Smith (2003), uses a standard roulette wheel selection to draw in more O:

$$P_i = \frac{f(y_i)}{\sum_{j=1}^{N} f(y_j)} \tag{32}$$

where N is the total amount of the food source and P_i, the probability of any ith source, is the ratio of its fitness to the sum of all the other sources' fitnesses. S needs to find a new food source to come up with a better solution if the source has a low fitness value. Soghrati and Moeini (2020) used the ABC algorithm to optimize the reservoir. Choong et al. (2017) the ABC algorithm was created to solve the problem of optimizing Chenderoh reservoir operations in the Malaysian state of Perak. In their study, the suggested algorithm sought to reduce the reservoir water deficit and analyze the performance impact based on input from weekly and monthly data. The ABC algorithm offers promising and comparable solutions for ideal release curves because it can identify various potential events occurring in the reservoir. Then the release of the reservoir was done using the ideal release curves at different operating times and different inflow scenarios.

Other Physics-Based Algorithms In the swarm intelligence algorithms group, cuckoo search (CS), ant colony optimization (ACO), moth swarm algorithm (MSA), cat swarm optimization (CSO), and artificial fish swarm algorithm (AFSA) have been used in studies related to dam reservoir optimization problems. In Hosseini-Moghari et al (2015), the imperialist competitive algorithm (ICA) and cuckoo optimization algorithm (COA), which are two evolutionary methods, are used in the optimal operation of the reservoir. Firstly, these algorithms were used in solving several benchmark problems. Afterward, the optimal operation policy of the Karun4 reservoir was extracted. Finally, results obtained from these methods were compared with GA algorithm and NLP. To solve the mixed integer nonlinear programming problem, To solve the mixed integer nonlinear programming problem, a hybrid algorithm of ACO and LP model was proposed. The water supply and hydropower operation of the Dez reservoir in Iran over operation periods are problems that must be solved as efficiently as possible using the methods put forth by Afshar and Shahidi (2009). The solutions obtained using the three methods of GA, ACO, and PSO are also presented. Afshar and Moeini (2008) presented the ACO algorithm for the optimization of complex reservoir operation problems. The research studies of Akbarifard et al. (2021), on two powerful meta-heuristic algorithms HS and ICA, were used to compare the performance of the butterfly swarm algorithm (MSA) with each other. First, seven benchmark functions with dimensions ranging from 2 to 30 were used to evaluate how well these algorithms performed. They were then contrasted to optimize the operation of four-reservoir and ten-reservoir systems, which is a challenging problem. Overall, the comparison found that MSA was the best of the 12 algorithms examined, and it is advised as a reliable and promising tool for the best operation of multi-reservoir systems. Akbarifard et al. (2020) in their paper claim that created a model based on the MSA algorithm to optimize water resources. The analysis of these datasets showed that the MSA algorithm outperformed the GA and PSO algorithms in the hydropower reservoir problem's optimal operation. In the research by Bahrami et al. (2018), using a single reservoir system and a hypothetical four-reservoir system, the CSO algorithm was used to calculate the reservoir systems' optimal performance. The superiority of this metaheuristic algorithm is shown by comparison with GA. Yaseen et al. (2018) found in their study that it is possible to optimize the Karun-4 reservoir by using a combined strategy of AFSA and PSOA algorithms. In their optimization method, energy production is increased and water shortage is minimized. Khorsandi et al. (2022) integrated the multi-objective firefly with the K-nearest neighbor to accelerate the optimal operation of multi-objective reservoirs. Rahmati et al. (2021) applied the Grasshopper Optimization Algorithm (GOA) to the optimal operation of hydropower reservoir systems under climate change. Moghadam et al. (2022) performed the optimal allocation of surface and ground water resources with Invasive Weed Optimization Algorithm (IWOA) modeling. Azadi et al. (2021b) presents a simulation–optimization approach linking the CE-QUAL-W2 with the firefly algorithm k-nearest neighbor (FA-KNN) model to obtain optimal reservoir discharges to achieve water quality objectives. Azadi et al. (2021a) evaluated the effects of climate change on thermal stratification of reservoirs using FA-KNN.

3.4.5 Human-Based Algorithms

Harmony Search (HS) Geem et al. (2001) proposed the harmony search (HS) It was used to solve optimization problems. The HS is a population-based metaheuristic algorithm that draws its inspiration from musical phenomena that seek out the most harmonious condition. In two studies, the HS technique was used to optimize the reservoir (Dariane and Karami 2014; Bashiri-Atrabi et al. 2015). The latter authors contrasted the HS and HBMO and found that the HS displayed promising results in terms of convergence speed.

Imperialist Competitive Algorithm (ICA) Atashpaz-Gargari and Lucas (2007a, b) introduced ICA. The population-by-population approach used by this algorithm is similar to that of many other evolutionary algorithms. ICA simulates political–social evolution. A population of initial solutions (countries) is generated at the start of the ICA process (much like a chromosome in GA). Some nations are viewed as colonies, while others are seen as imperialists. N decision variables may include variables such as culture, language, etc. for each optimization problem. Each nation is defined as an array of 1 × N as follows (Hosseini-Moghari et al 2015):

$$country = \left[V_1, V_2, \dots, V_N\right] \tag{33}$$

$$cost = F(country) \tag{34}$$

where F is the objective function, cost is the value of F, and $V_1, V_2, \dots, V_N$ are decision variables. The imperialists then recruit colonies into their empires through a process known as assimilation policy (colonies are impacted by the imperialists' culture and language). In this phase, colonies with θ deviation of and x units transfer to the imperialists. A more thorough search in the decision space results from this deviation. Both x and θ are uniformly distributed random variables.

$$x \sim U(0, \beta \times d) \tag{35}$$

$$\theta \sim U(-\gamma, \gamma) \tag{36}$$

where $\beta = a$ number greater than one which makes colonies close to imperialists from two sides, d is a distance between imperialists and colonies and γ is a parameter that determines the amount of deviation from the original direction. Some nations that don't make much progress each generation experience revolution. The revolution operator stops the algorithm from becoming stuck at the local optimum. One of the colonies may end up in a better situation than its imperialist after moving colonies toward imperialist or revolution events. It might swap colonial and imperialist stances. Imperialistic competition, in which all empires compete to have more colonies, is the most crucial stage of ICA. This procedure is carried out by the weakest colony leaving the realm of the weakest empire and affiliating with stronger empires. Colonies are merged with stronger empires based on probability. This probability is proportional to each imperialist power plus a random percentage from the average power of colonies.

$$T.C_n = cost\left(imperialist_n\right) + \xi mean\left\{cost(colonies\ of\ empire_n)\right\} \tag{37}$$

where $T.C_n$ = total cost of the nth empire, and ξ = a positive number less than one, which is a user-defined parameter.

Afshar et al. (2014) compared the ICA and ACO algorithms' performance in a case study involving a single-objective hydropower reservoir and found that the ICA showed quick convergence to nearly optimal solutions for linear operating rule curves and outperformed ACO. The ideal reservoir operation curve was obtained in Shenava and Shourian (2018) study with the dual goals of increasing water supply and lowering flood damage. The operation of the Gotvand Reservoir in Iran was optimized in this way by simultaneously increasing the downstream water supply and decreasing flood damage using the ICA algorithm.

3.4.6 Hybrid Algorithm (HA)

There are only certain problems that can be solved by current heuristic optimization algorithms. No algorithm can sufficiently solve all optimization problems (Mirjalili and Hashim 2010). Hybrid algorithms, which combine two or more algorithms, are useful for handling challenging multi-objective optimization problems. Algorithm hybrid offers the same advantages as individual algorithms, plus it builds on one approach's advantages to address another's weaknesses. The estimation of energy production reservoir operations and scheduling issues have both been addressed using hybrid algorithms (Uzlu et al. 2014). The combination of evolutionary algorithms with other local search algorithms has been successfully used in the optimization of hydropower. Zarei et al. (2019) investigated the performance of a multi-purpose water tank to meet agricultural, urban, industrial and environmental needs. The total monthly water release was first determined by a new evolutionary hybrid algorithm (BA algorithm and PSA) to operate the best reservoir and satisfy the total monthly needs (agricultural, urban, industrial, and environmental). By removing the weak responses of one algorithm and substituting the strong responses of the other, the new Hybrid Algorithm (HA) assists BA and PSA in accelerating convergence and achieving an ideal solution. In the study of Karnatapu et al. (2020) to determine the best operating policies for a multi-purpose reservoir, a hybrid genetic and algorithmic programming (GA-NLP) model was proposed. Results show that the GA-NLP model can be successfully applied for the best distribution of limited available water resources to any reservoir. Mohammadi et al. (2019) in their paper by examining the optimal operation of continuous-time four-reservoir systems (FRBS) and ten-reservoir systems (TRBS) using a hybrid whale optimization algorithm (HWGA) that combines GA and WOA algorithms.

3.4.7 Other Meta-heuristic Optimization Algorithms

Ehteram et al. (2018a) used the kidney algorithm (KA) in their study to optimize the operation of the reservoir of the Aydoghmoush dam in the eastern Azerbaijan province of Iran to lower the irrigation deficit downstream of the dam. The algorithm's outcomes were compared with those of other evolutionary algorithms, such as the BA, GA, PSO, SA, and WA algorithms. Tabari et al. (2020) integrated the reservoir structure simulation model and the optimization approach to creating a multi-objective model that would meet the demands for water supply while maintaining the structural stability of the dam. A dynamic artificial neural network was also employed for this reason as an interfaced model to connect the outcomes of the simulator model to those of the suggested strategy. A non-dominated sorting genetic algorithm (NSGA-II) and multi-criteria decision-making techniques were used to create the optimal trade-off curve, from which the best solution was extracted. The findings demonstrated that, given the stability of the dam, the downstream water demand allocation was utilized to the fullest extent possible. The reliability and vulnerability coefficient values in the optimal conditions are higher than those in the existing conditions, according to a comparison between the existing and optimal conditions. The results show that, in comparison to the optimal conditions, the fuzzy stability index increased by 7%, indicating that the optimal model performs better. With a water supply of 30%, summer had the highest deficiency, and spring with a water supply of 30% had the lowest deficiency when compared to downstream water demands. During summer, the average optimal allocation and the average demands were 20.51 MCM and 67.50 MCM, respectively. Chen et al. (2020a, b) suggested using the NSGA-III algorithm to optimize a multi-objective risk management model for real-time flood control operations. Sharifi et al. (2021) in their study from 2021, five recently-introduced robust evolutionary algorithms (EAs) of Harris hawk's optimization algorithm (HHO), seagull optimization algorithm (SOA), sooty tern optimization algorithm (STOA), tunicate swarm algorithm (TSA). The moth swarm algorithm (MSA) was used for the first time to optimize the Halilrood multi-reservoir system.

4 Comparative Performance Analysis and Discussion

4.1 Interpretation of Algorithms Used in Dam Reservoir Optimization

Figure 16 demonstrates the results of various metaheuristic algorithms applied recently for dam reservoir optimization. In the recently studied patterns, it has been determined that interest in using some new meta-heuristic algorithms and combined meta-heuristic algorithms to optimize reservoirs, dams, and reservoir operations has increased. Results indicate that cutting-edge algorithms, particularly hybrid algorithms, have produced results that are incredibly accurate when solving problems in real-time. Reduced convergence and computation time is the main goal of algorithms. This study demonstrates hybrid algorithms have grown in popularity for solving reservoir optimization issues and have outperformed more traditional approaches like LP and NLP as well as other meta-heuristic algorithms. After hybrid algorithms in this study, GA has been the most well-liked evolutionary algorithm among researchers in reservoir optimization because it is one of the most established and effective evolutionary algorithms. Recent studies have paid more attention to hybrid algorithms and meta-heuristic algorithms, particularly non-animal ones. GA and PSO algorithms have been used in more comparative studies, totaling 67.21 percent of new studies that have compared

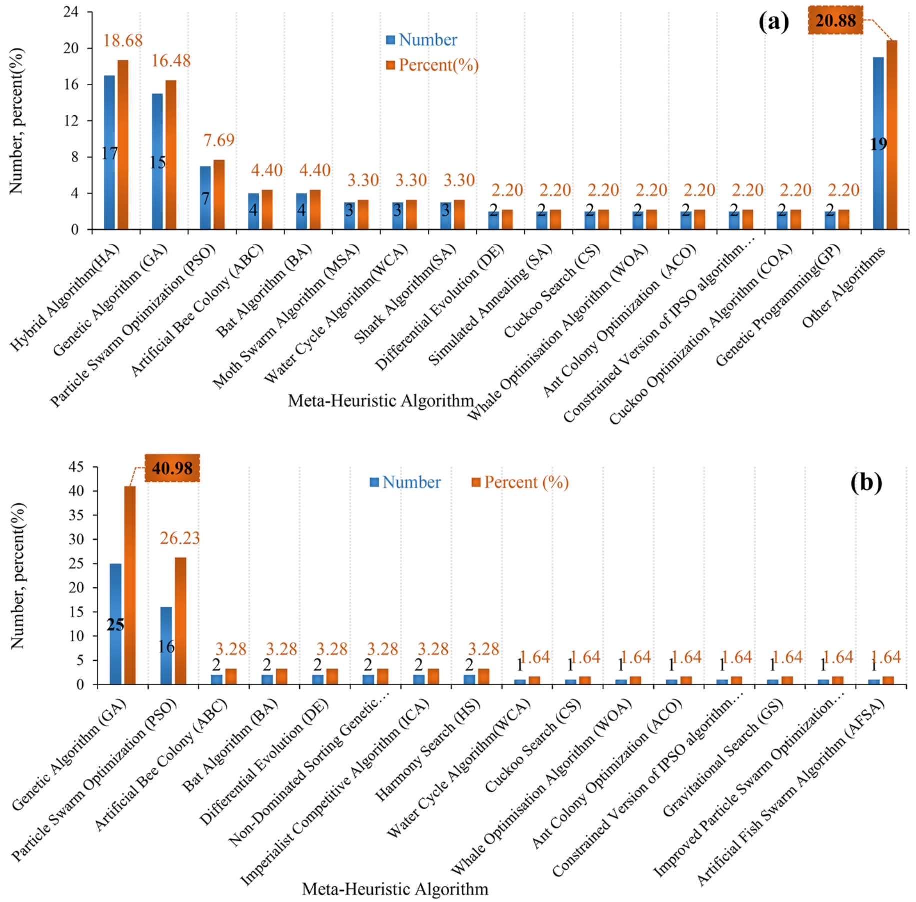

Fig. 16 Meta-heuristic algorithms in dam reservoir optimization **a** The most optimal algorithm, **b** Compared algorithms

these two algorithms. In general, it is impossible to pinpoint precisely which algorithm is superior to the others. As a result, using techniques like hybrid algorithms can be a useful way to solve this issue. Figure 15 shows that more research has been done using hybrid algorithms than other single meta-heuristic algorithms. In the present review study regarding the optimization of reservoirs of dams, 76 articles were reviewed, of which 17 articles (18.68 percent of the articles) were done using hybrid algorithms.

4.2 Statistical Criteria

The statistical indices of root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2) and Nash–Sutcliffe efficiency (NSE) are more than other evaluation indices in the problems of optimizing reservoirs, meeting water needs, and managing reservoirs of dams using Meta-heuristic algorithms are used (Fig. 17).

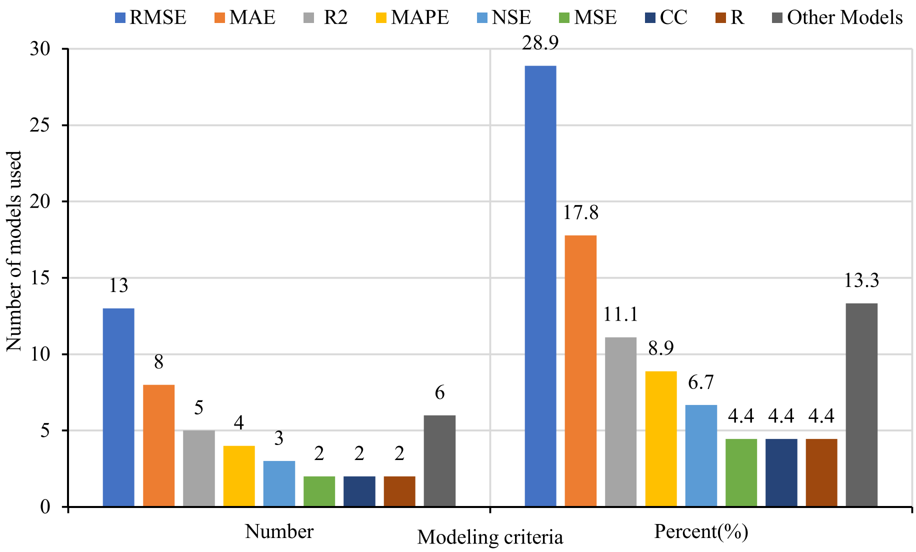

Fig. 17 The most important criteria for evaluating the performance of dams reservoir optimization using meta-heuristic algorithms

The most important criteria for evaluating the performance of dam reservoir optimization studies using meta-heuristic algorithms are shown (Eq. 38 to 40):

$$RMSE = \sqrt{\frac{1}{N}(\sum_{i=1}^{N}(f(i) - y(i))^2} \tag{38}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|f_i - y_i| \tag{39}$$

$$R^2 = \frac{\left[\sum_{i=1}^{N}(f_i - \overline{f})(y_i - \overline{y}\right]^2}{\sum_{i=1}^{N}(f_i - \overline{f})^2 \sum_{i=1}^{N}(y_i - \overline{y})^2} \tag{40}$$

where N is the number of observations, f_i and y_i (i = 1; 2;...; N) represent the predicted and observed values, respectively; f¯and_y¯represent the predicted and observed average values, respectively; RMSE is a popular and reliable measure of researchers in most studies to measure the standard deviation between estimated values and observed values. The closer the RMSE is to zero, the less deviation there is between the predicted and observed results. The coefficient of determination (R^2) is a good measure of the fit of a statistical model. MAE indicates the average absolute value of the difference between the observed and modeled values of the independent variable. Nash–Sutcliffe efficiency (NSE) is a very important evaluation criterion in issues related and compatible with water engineering sciences, which has been used in only two papers (Azari et al. 2018; Ehteram et al.2018a, b, c) (Eq. 41).

$$NSE = 1 - \frac{\sum_{i=1}^{N} (\overline{y}_i - y_i)^2}{\sum_{i=1}^{N} (y_i - \overline{y})^2} \tag{41}$$

In NSE, the efficiency coefficient of the numerical model is between 5 and negative infinity, which is introduced as a measure to measure the prediction ability of the model, the explanation coefficient close to one indicates the success of the model in modeling.

4.3 Evaluation Indices

Multiple indicators can be used to evaluate the performance of the dam reservoir and the evolutionary algorithms used in management studies (Hashimoto et al. 1982):

4.3.1 Volumetric Reliability

This index is based on downstream demand and the amount of water released. The value of this index will be high if the released water can adequately meet demand (Ehteram et al. 2017a, b, c, d):

$$\alpha_V = \frac{\sum_{i=1}^{2} \sum_{t=1}^{T} R_{i,t}}{\sum_{i=1}^{2} \sum_{t=1}^{T} D_{i,t}} \times 100 \tag{42}$$

where α_V is the volumetric reliability index.

4.3.2 Resiliency Index

This index shows how quickly a system can recover from a failure. A system must be capable of regaining functionality following a single failure while it is in operation. A high value of this index is desirable.

$$\gamma_i = \frac{f_{si}}{F_i} \tag{43}$$

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

4.3.3 Vulnerability Index

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

$$\lambda = Max_{i=1}^{2}(Max_{t=1}^{T}\left(\frac{D_{i,t} - R_{i,t}}{D_{i,t}}\right)) \tag{44}$$

where λ is the vulnerability index.

The results of evaluation indicators in dam reservoir optimization studies show that hybrid algorithms show better results than other single metaheuristic algorithms (Table 3). Also in single metaheuristic algorithms, SML and SMA algorithms show better results than other algorithms.

4.4 Investigate the Performance of Some Meta-heuristic Algorithms According to Optimal Value and Best CPU Time

The performance of some metaheuristic algorithms according to the optimal amount and optimal CPU time for single-reservoir system operation, four-reservoir system operation, and ten-reservoir system operation is reviewed (Table 4).

4.4.1 Single-Reservoir System Operation

Research by Sharifi et al. (2021) showed that the MSA algorithm had the best objective function value (6.96), the shortest run-time (6738 s), and the fastest convergence rate (< 2000 iterations) compared to HHO, GA, PSO, SOA and STOA algorithms. Yavari and Robati (2021) showed that the MOWCA algorithm with a total of 236.07 objectives performed better than the NSGA-II algorithm with a total of 268.01 objectives. In the studies of Wang et al. (2021), it was found that DE, PSO, and APO algorithms have similar performance in terms of optimal objective value criterion. DE and PSO algorithms are not much affected by population size, while APO is affected by population growth. In the DE algorithm, the diversity and stability of the population are preserved better than in the PSO or APO algorithms. With the performed evaluations, the use of the DE algorithm is more suitable than PSO and APO for the reservoir operation optimization problem.

4.4.2 Discrete-Time Four-Reservoir Operation (DFRO) Problem

The DFRO problem was introduced by Larson (1968) using a discrete-time formulation. After that, Murray and Yakowitz (1979) used dynamic differential programming (DDP) in studying the DFRO problem. In the last two decades, many researchers, including Bozorg-Haddad et al. (2011); Asgari et al. (2016); Kumar and Yadav (2018) have used this problem to investigate the performance of different algorithms.

4.4.3 Continuous-Time Four-Reservoir Operation (CFRO) Problem

The CFRO problem was introduced by Chow and Cortes-Rivera (1974). The difference between the CFRO problem and the discrete problem is in the constraints and input parameters. CFRO problem by researchers including Bozorg-Haddad et al. (2011, 2015a, b); Hosseini-Moghari et al (2015); Bahrami et al. (2018); Akbarifard et al. (2021) has been solved using different algorithms.

4.4.4 Ten-Reservoir Operation (TRO) Problem

Ten-reservoir system was presented by Murray and Yakowitz (1979). Ten-reservoir system is considered a complex system due to the parallel and series reservoirs. TRO problem by researchers including Wardlaw and Sharif (1999); Jalali et al. (2007); Ahmadianfar et al. (2016); Ehteram et al. (2017a, c) has been solved using different algorithms.

Table 3 Results of evaluation indicators in dam reservoir optimization studies

Author(s)(year)	Meta-heuristic algorithms	Reliability (%)	Resilience (%)	Vulnerability (% of demand)
Sharifi et al. (2021)	HHO, SOA, STOA, TSA, MSA	(MSA 73.99, HHO 67.26, SOA53.81, STOA56.95, TSA40.81, GA61.88, PSO 62.02) for Baft,(MSA49.35, HHO22.45, SOA32.74, STOA25.56, TSA32.29, GA22.42, PSO34.53) for Safarood,(MSA99.55, HHO92.83, SOA56.05, STOA63.68, TSA49.01, GA63.68, PSO62.78) for Jiroft	(MSA34.91, HHO38.43, SOA19.18, STOA22.12, TSA23.08, GA24.22, PSO25.37) for Baft,(MSA29.77, HHO15.99, SOA14.41, STOA12.16, TSA15.28, GA15.70, PSO18.40) for Safarood,(MSA73.65, HHO49.79, SOA20, STOA21, TSA23.51, GA29.08, PSO36.67) for Jiroft	(MSA24.97, HHO50.19, SOA96.64, STOA94.26, TSA96.88, GA76.20, PSO56.38) for Baft, (MSA63.97, HHO75.36, SOA75.54, STOA75.20, TSA75.66, GA75.36, PSO75.66) for Safarood, (MSA12.99, HHO27.34, SOA96.15, STOA93.38, TSA91.81, GA84.92, PSO36.33) for Jiroft
Nourani et al. (2020)	GA	75	25	_
Tabari et al. (2020)	GA	24.23	15.21	98.88
Chen et al. (2020a, b)	NSGA-III	63.9	95.8	1.31
Moeini and Babaei (2020)	Hybrid Algorithm (HA)(SVM-CIPSO)	51.95	45.95	3.539 MCM
Karami et al. (2019)	Hybrid Algorithm (HA):(GS + PSO)	(HA 97, GA 59, PSOA 88, GSA 89) for Voshmgir Dam, (HA 96, GA 56, PSOA 87, GSA 89) for Golestan Dam	(HA 56, GA 47, PSOA 52, GSA 53) for Voshmgir Dam, (HA 54, GA 45, PSOA 51, GSA 52) for Golestan Dam	(HA 9, GA 32, PSOA 12, GSA 11, Lingo 9) for Voshmgir Dam, (HA 10, GA 34, PSOA 14, GSA 12, Lingo 11) for Golestan Dam
Zarei et al. (2019)	Hybrid Algorithm (HA) (BA-PSO)	0.98 for Urban, 0.90 for Environmental, 0.89 for Industrial, 0.65 for Agricultural	0.99 for Urban, 0.87 for Environmental, 0.75 for Industrial, 0.61 for Agricultural	0.005 for Urban, 0.21 for Environmental, 0.22 for Industrial, 0.24 for Agricultural
Yaseen et al. (2019)	Hybrid Algorithm (HA)(HB-SA)	96 for Voshmgir Dam, 94 for Golestan Dam	55 for Voshmgir Dam, 56 for Golestan Dam	10 for Voshmgir Dam, 11 for Golestan Dam
Rouzegari et al. (2019)	SMLA	25	22.22	35.87
Ehteram et al. (2018b)	BA	98	45	7
Allawi et al. (2018)	SMLA	99.72	100	20.7

Table 3 (continued)

Author(s)(year)	Meta-heuristic algorithms	Reliability (%)	Resilience (%)	Vulnerability (% of demand)
Ehteram et al. (2018a)	KA	GA 45, KA 95, SA 77, WA 54, BA 87, PSA 53	GA 18, KA 44, SA 32, WA 28, BA 46, PSA 16	GA 20, KA 14, SA 27, WA 18, BA 12, PSA 19
Yaseen et al. (2018)	Hybrid Algorithm (HA)(AFSA-PSOA)	89	_	_
Ehteram et al. (2018c)	SMA	96 for Voshmgir Dam, 95 for Golestan Dam	58 for Voshmgir Dam, 56 for Golestan Dam	10 for Voshmgir Dam, 12 for Golestan Dam
Ehteram et al. (2017a)	SA	96	31	31
Hossain and El-shafie (2014)	ABC	98.14	_	1.11
Ahmadi et al. (2010)	Hybrid Algorithm (HA)(GA–KNN), (BSGA)	GA-KNN 69, BSGA 73	GA-KNN 47, BSGA 45	GA-KNN 3.3, BSGA 2.9
Pinthong et al (2009)	Hybrid Algorithm (HA)(GA-NF)	91.52	24	40.98

Table 4 Performance of some algorithms according to global optimum, best optimal value, and best CPU time

Author(s) (year)	Meta-heuristic algorithms	Global optimum	Best (objective function/ Optimal value/solutions)	CPU time(s)
Bilal et al. (2021)	DE, GA, PSO, ABC, SA, CS		ABC 133,690.61, DE 130,689.35, GA 135,285.11, PSO 129,776.77, SA 137,977.14, CS 135,327.37	ABC 2.05, DE 1.31, GA 0.83, PSO 1.61, SA 0.60, CS 0.83
Sharifi et al. (2021)	HHO, SOA, STOA, TSA, MSA			MSA 6738.56, HHO 10,223.4, SOA12971.24, STOA13762.63, TSA14416.42, GA11781.62, PSO 9347.28
Yavari and Robati (2021)	MOWCA		MOWCA 236.07, NSGA-II 268.01	
Sharifazari et al. (2021)	ACO, GA		ACO 0.9868, GA 0.9969	
Wang et al. (2021)	DE, PSO, APO			DE 3, PSO 3, APO 6.8
Akbarifard et al. (2021)	MSA		(MSA 308.83, HS 264.61, ICA 306.47) for **CFRO problem**, (MSA 1195.58, HS 1060.76, ICA 1136.22) for **TRO problem**	(MSA 269.71, HS 638.61, ICA 486.73) for **CFRO problem**, (MSA 722.55, HS 1963.41, ICA 1421.62) for **TRO problem**
Akbarifard et al. (2020)	MSA		MSA 0.1470, PSO 0.1584, GA 0.3026	MSA 19.7, PSO 28.88, GA 37.16
Karami et al. (2019)	Hybrid Algorithm (HA) (GS-PSO)	Lingo 0.110	HA 0.111, PSOA 0.212, GA 0.221, GSA 0.178	HA 45, GA 52, GS 117, PSO 172
Mohammadi et al. (2019)	HWGA	308.292 for CFRO, 1194.441 for TRO	(WOA 247.447, GA 286.596, HWGA 289.906) for **CFRO problem**, (WOA 826.772, GA 1010.244, HWGA 1115.674) for **TRO problem**	
Zarei et al. (2019)	Hybrid Algorithm (HA) (BA-PSO)	308.29 for CFRO problem	(HA 0.98, BA 1.12, PSO 1.22) for Shahid Dam, (HA 308.28, BA 308.20, PSO 308.99) for **CFRO problem**	HA 12, BA 15, PSO 17

Table 4 (continued)

Author(s) (year)	Meta-heuristic algorithms	Global optimum	Best (objective function/ Optimal value/solutions)	CPU time(s)
Ehteram et al. (2018b)	BA	Lingo (1.77 for Aydoughmoush dam,1.18 for Karoun 4 reservoir)	1.78 for Aydoughmoush dam,1.19 for Karoun 4 reservoir	
Allawi et al. (2018)	SMLA	Lingo 0.112	SMLA 0.114, GA 0.143	
Ehteram et al. (2018a)	KA		KA 1.789, GA 0.789, WA 1.111, SA 1.655, BA 1.422, PSA 1.765	GA 38, KA 34, SA 36, WA 37, BA 37, PSA 40
Bahrami et al. (2018)	CSO	NLP (1.213 for Karun4, 308.29 for CFRO problem)	(CSO 1.218, GA 1.547) for Karun4, (CSO 308.20, GA 307.32) for **CFRO problem**	
Yaseen et al. (2018)	Hybrid Algorithm (HA)(AFSA-PSOA)		GA 1.500, AFSA 1.320, PSOA 1.299	Improved GA 4.12, Dynamic PSO 3.67, HAS 4.12, BFA 4.11, ICA 3.97, HBO 3.78, FuzzyPSO 3.77, Chaotic ACO 2.12, AFSA 5.55, SOA 2.12, DABC 3.33, PABC 3.30, CABC 3.17, IABC 3.09, RABC 2.98, MABC 2.97, HBMO 3.16 IHBMO 3.11, PSOA 3.44, Hybrid 1.12
Ehteram et al. (2018c)	SMA	0.11	SMA 0.112, PSOA 0.212, GA 0.221	SMA 50, WCA 72.6, GA 172.6, PSOA 117.4, ICA 117.4, HAS 164.8
Kumar and Yadav (2018)	TLBO, JA	(TLBO 401.33, JA 401.44) for DFRO problem, (TLBO 308.30, JA 308.40) for CFRO problem, (TLBO 1194.44, JA 1194.59) for TRO problem	(TLBO 401.33, JA 401.44) for **DFRO problem** (TLBO 308.30, JA 308.40) for **CFRO problem**, (TLBO 1194.44, JA 1194.59) for **TRO problem**	

Table 4 (continued)

Author(s) (year)	Meta-heuristic algorithms	Global optimum	Best (objective function/ Optimal value/solutions)	CPU time(s)
Qaderi et al. (2018)	WCA	_	WCA 0.157, GA 0.74, PSO 0.23, ICA 0.48, HS 0.81	(WCA 72.6, GA 172.6, PSO 117.3, ICA 94.6, HS 164.8) for Golestan–Voshmgir, (WCA 24.56, GA 34.63, PSO 40.17, ICA 21.61, HS 121.98) for **CFRO problem**, (WCA 74.91, GA 121.84, PSO 116.19, ICA 63.88, HS 156.71) for **TRO problem**
Ehteram et al. (2017a)	SA		0.40 for Bazoft dam reservoir, (SA 308.29, GA 285.16) for **CFRO problem**	
Ehteram et al. (2017b)	Hybrid Algorithm (HA) (GA-Krill)	NLP (1.213 for Karun-4, 308.29 for CFRO problem, 1194.44 for TRO problem)	(HA 1.212, Krill 1.300, GA 1.610) for Karun-4, (HA 308.29, Krill 307.54, GA 307.12) for **CFRO problem**, (HA 1194.44, Krill 1190.12, GA 1190.01) for **TRO problem**	HA 20, GA 35, krill 30
Bozorg Haddad et al. (2016a, b)	BBO	Lingo (1.213 for Karun4, 308.29 for CFRO problem)	(GA 1.535, BBO 1.223) for Karun4, (GA 300.47, BBO 308.12) for **CFRO problem**	
Asgari et al. (2016)	WOA	Lingo (0.1614 for Single-Reservoir, 401.3 for DFRO problem, 308.29 for CFRO problem)	(GA 0.2250, WOA 0.1624) for Single-Reservoir, (GA Not reported, WOA 401.1) for **DFRO problem** (GA 298.36, WOA 306.99) for **CFRO problem**	
Rani and Srivastava (2016)	Hybrid Algorithm (HA)(DP–GA)	DP (70.313)	0.043 HA, 0.826 GA	345 GA, 24 HA

Table 4 (continued)

Author(s) (year)	Meta-heuristic algorithms	Global optimum	Best (objective function/ Optimal value/solutions)	CPU time(s)
Garousi-Nejad et al. (2016)	FA	NLP (3.3727 for FA and GA) for Aydoghmoush dam, (0.0045 for FA and GA) for Karun 4 Reservoir	(FA 3.5365, GA 6.3790) for Aydoghmoush Reservoir, (FA 0.0078, GA 0.0089) for Karun 4 Reservoir	
Ahmadianfar et al. (2016)	Hybrid Algorithm (HA)(IBA)	(308.29 for CFRO problem, 1193.92 for TRO problem) for IBA	308.4 for **CFRO problem**, 1194.44 for **TRO problem**	1560
Bozorg-Haddad et al. (2016a, b)	GSA	1.213 for Karun4, 308.20 for CFRO problem	(BA 1.239, WLA 1.260, BBO 1.239, GSA 1.218) for Karun 4, (BA 307.84, WLA 302.38, BBO 306.55, GSA 308.10) for **CFRO problem**	
Bozorg-Haddad et al. (2015a, b)	BA	Lingo (1.2132 for Karun4, 308.29 for CFRO problem)	(GA 1.5350, BA 1.223) for Karun 4, (GA 282.90, BA 308.20) for CFRO problem	767 for Karoun-4, 1582 for **CFRO problem**
Hosseini-Moghari et al (2015)	GA, ICA, COA	NLP (5.243 for Karun4 dam, 308.29 for CFRO problem)	(GA 6.196, ICA 5.586, COA 5.246) for Karun 4 dam, (GA 302.42, ICA 306.76, COA 307.92) for **CFRO problem**	
Bozorg-Haddad et al. (2015a, b)	WCA	1.213 for Karun4, 308.29 for CFRO problem	(WCA 1.260, GA 1.520) for Karun 4, (WCA 306.92, GA 300.47) for **CFRO problem**	
Fallah-Mehdipour et al. (2012)	GP		GA 35.763, GP including stochastic variable 31.33, GP including deterministic variable 32.147	
Bozorg-Haddad et al. (2011)	HBMO		(401.30 for **DFRO problem**, 308.29 for **CFRO problem**, 1194.44 for **TRO problem**) for HBMO	

5 Conclusions

In the past two decades, the use of modern methods of meta-heuristic optimization in various topics of water resources systems has increased to overcome the shortcomings of traditional methods and the inefficiency of mathematical methods due to the increase in the dimensions and complexity of the problem. Perhaps the most important concern of researchers in optimization issues and especially meta-heuristic algorithms is to choose the best algorithm considering their high number, but considering the nature of different reservoirs, it is not possible to say which algorithm is the most suitable. The best solution of the meta-heuristic algorithm is possible by finding the best speed and accuracy the in convergence and optimization of models. The results showed that the use of hybrid algorithms (18.68%) in reservoir optimization studies has obtained better results than traditional methods and other single algorithm methods. Considering that each algorithm has its advantages and disadvantages, combining them to find the best solution can be useful. In hybrid methods, the disadvantages of one algorithm are supplemented by another algorithm, and it is possible to modify the algorithms with the features of another algorithm. According to the obtained results, hybrid algorithms can be recommended to solve the complex problem of water resource management and reservoir operation. Among individual algorithms, GA algorithm (16.48%) has been the most popular model among researchers. Of course, in recent years, the GA algorithm has been used more to compare with other modern meta-heuristic algorithms, so 40.98 of the studied articles consider this algorithm as the best comparison option. GA and PSO algorithms are the best comparison options with modern models considering that they have been used in many articles. Evolutionary algorithms such as GA, ACO, and PSO have great potential to solve nonlinear multi-objective problems. An important issue in optimization modeling is considering the physical characteristics of the dam and reservoir to generalize the process. To measure reservoir performance indicators (such as reliability, flexibility, and vulnerability), the optimization operation must be accompanied by a simulation to be able to optimize and compare each hydrological model. In this review study, an attempt has been made to review all possible literature sources regarding the optimization of reservoirs, however, some issues may have been ignored or briefly stated and can be investigated separately and comprehensively in future studies.

Authors Contributions Behrang Beiranvand developed the theory and performed the computations. Parisa-Sadat Ashofteh verified the analytical methods. Parisa-Sadat Ashofteh encouraged Behrang Beiranvand to investigate a specific aspect. Parisa-Sadat Ashofteh supervised the findings of this work. All authors discussed the results and contributed to the final manuscript. Behrang Beiranvand wrote the manuscript with support from Parisa-Sadat Ashofteh. Parisa-Sadat Ashofteh conceived the original idea.

Availability of Data and Materials Those will be made available on reasonable request.

Declarations

Ethical Approval The paper is not currently being considered for publication elsewhere. All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Consent to Publish The participant has consented to the submission of the case report to the journal.

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