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Review article

# Optimization of the hydropower energy generation using Meta-Heuristic approaches: A review

Abdus Samad Azad [a], Md Shokor A. Rahaman [b,*], Junzo Watada [c], Pandian Vasant [d], Jose Antonio Gamez Vintaned [e]

[a] Department of Fundamental and Applied Sciences, Universiti Teknologi Petronas, 31750 Tronoh, Malaysia
[b] Shale Gas Research Group, Institute of Hydrocarbon Recovery, Universiti Teknologi Petronas, 31750 Tronoh, Malaysia
[c] Invited Researcher, IPS Research Center, Waseda University, Japan
[d] Universiti Teknologi Petronas, 31750 Tronoh, Malaysia
[e] Department of Petroleum Geosciences, Universiti Teknologi Petronas, 31750 Tronoh, Malaysia

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ABSTRACT

Whatever the exact figures, world energy consumption, particularly electricity consumption, can increase significantly during couple of decades. It is not possible solely due to demographic pressure, but also due to expansion of living standards within the less developed countries. Hydropower has reached high levels of technical sophistication in power generation as compared with other renewable energy sources. The paper discusses recent hydropower optimization research and development activities using metaheuristic approach. The article discusses emerging attempts to promote the optimization of hydropower. It provides a comprehensive analysis of recent attempts to extend the operating policies of hydraulic structures to reach extraordinary degrees of versatility, a subject of many recent research projects using metaheuristic algorithms. In addition, groundbreaking technologies for hydroelectric energy production are also discussed with the study based on reservoir operation and scheduling of flow and energy.

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**Contents**



* Corresponding author.
*E-mail addresses:* Azadutp@gmail.com (A.S. Azad), md_17009796@utp.edu.my (M.S.A. Rahaman), junzo.watada@gmail.com (J. Watada), pvasant@gmail.com (P. Vasant), jose.gamez@utp.edu.my (J.A.G. Vintaned).

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## 1. Introduction

Electricity has become a very important need of life and controls the stable functioning of any society. It can be generated through various resources e.g. renewable and non-renewable resources. Global status report on renewable energy stated that recently most part of electricity is generated through renewable energy resources as compared to previous years. In 2018 power sector had an increased power installation of 18 GW using renewable resources (Hannah E. Murdock and André, 2019). Hydropower has gained most attention among all other resources due to its large load handling capacity, minimum fluctuation of electric energy and minimum adverse environmental impacts as compared to fossil fuels (Feng et al., 2020b). Hydropower is the power generated by head difference of flowing water. This head difference can be generated with reservoir or without reservoir depending on the type of hydropower plant (Karaeren, 2014). It accounts a share of 15.8% of total electricity production worldwide as shown in Fig. 1.

Hydropower generation is currently facing few challenges e.g. environmental regulations, operational constraints, limited equipment capabilities, flow uncertainties and regulatory constraints (Stoll et al., 2017; leten et al., 2010). All these challenges limit the power generation capability of a reservoir. As construction of new reservoirs is an expansive task, it is needed to properly manage the existing hydropower resources to obtain the maximum power potential of the reservoir. Few studies have reported energy complementation through incorporating wind and solar energy into the electric grid. Both wind and solar sources are unpredictable and unknown, meaning that their performance varies with time because of their reliance on environmental conditions and cannot be entirely reliable option of energy maximization (Ibanez et al., 2014). Two most reported solution for power optimization are (i) reservoir operation optimization and (ii) scheduling the water flow. Hydropower production maximized by optimizing the river annual flow and reservoir operating conditions can be considered as reliable option in this regard. However, these factors contain many uncertainties e.g. unpredictable future demand, flow, climate conditions and economic factors. Utilization of various models used at planning stage help in handling such uncertainties (Neelakantan, 2013). These models help in optimizing reservoir size, water demand and release scheduling while satisfying the constraints. Parallel to these factors risk of cost management is also needed to be dealt by the plant manager (Fleten et al., 2010). Scheduling the reservoir operation helps in minimizing the operational cost of plant and can be achieved by traditional or modern techniques (Sharma, 2002). Handling all such factors makes hydropower production process complex in nature. Sometimes it becomes impossible to solve these complex problems using traditional techniques (Nkechi Neboh et al., 2015) e.g. linear, nonlinear (NL) and dynamic programming (DP) (Yoo, 2009). Linear programming-based approaches can provide the optimal global solution for problems where the objective function and constraints can be represented linearly via decision variables (Feng et al., 2019c). Complex nature of hydropower planning, nonlinear objective functions and limitations make linear programming unreliable to guarantee the precision of optimal solution for power generation (Feng et al., 2017c). A nonlinear model describes more accurately the characteristics of hydroelectric power production, and the impact of head shift can be properly considered, which is one of the key challenges associated with the short term hydropower scheduling problem. However, it fails to address the question of infinite quadratic programming within finite time (Catalão et al., 2010). Dynamic programming has no strict constraint on the unsmooth and non-convex characteristics of the hydropower scheduling problem, which makes it highly common in water resource fields (Feng et al., 2017b). The parallel DP algorithm takes advantage of the distributed memory structure and aims to reduce the processing time and enhance the RAM need (Feng et al., 2019c). In orthogonal discrete differential dynamic programming (ODDDP), orthogonal experiment architecture is adopted to minimize the quest space in each step while building the corridor around the current trajectory, and then the classical dynamic programming recursive equation is used to check for a better trajectory, slowly increasing the consistency of the solution by iterative computation. However, owing to the extreme curse of dimensionality, conventional discrete differential dynamic programming cannot produce optimization outcomes within a reasonable period (Feng et al., 2017a). Therefor solving complicated hydropower functional difficulties, the problem of dimensionality remains the largest challenge to dynamic programming. It has been reported that DP variants can reduce the dimensions to certain degrees but the computational obligation can always increase dramatically as the problem size expanded (Feng et al., 2017b). So, dimensionality always remains biggest curse in solving high-dimensional optimization problems of hydropower (Li et al., 2014). Therefore, a growing interest has been developed for doing research in developing novel approaches to solve complex natured optimization problems e.g. artificial neural network (ANN) (Hammid et al., 2018), real time optimization algorithms (Cordova et al., 2014), heuristic, hyper heuristic (Kheiri, 2014) and metaheuristic approaches (Tsoukalas and Makropoulos, 2015; Yang et al., 2015). Meta heuristic approach is gaining most interest in this regard because of its minimum cost and time. It is a high level approach towards problem solving which is independent of the nature of the problem (Kheiri, 2014). The benefit of metaheuristic approaches over traditional methods is the extraneity to establish a unique initial condition, convexity, continuity and differentiability (Ehteram et al., 2019). Meta heuristic algorithms are classified in many classes as shown in Fig. 2.

Multiple reservoirs e.g. cascade reservoir has better power generation capacity than single reservoir (XingLi Yin et al., 2019). It can be calculated as follows:

$$P_O(t) = \sum_{i=1}^{n} K_i Q_i(t) H_i(t) \tag{1}$$

where, $P_O$ (t) is power generated in time t; $Q_i(t)$ is the water discharge at ith reservoir in time t; $H_i(t)$ is net head of water at ith reservoir in time t; n is the number of reservoirs; and $K_i$ is the coefficient of power generation. Power generation is function of turbine discharge and net head. It is obvious that net head varies largely with reservoir storage and power generation can also be calculated integrating storage variable into Eq. (1).

**Nomenclature**

| | |
|---|---|
| ACDE | Adaptive Chaotic Differential Evolution |
| ADE | Adaptive Differential Evolution |
| ANN | Artificial Neural Network |
| AOA | Accompanying Progressive Optimality Algorithm |
| AGA | Adaptive Genetic Algorithm |
| BA | Bat Algorithm |
| COA | Chaos Optimization Algorithm |
| CS | Cuckoo Search Algorithm |
| CSA | Clonal Selection Algorithm |
| DE | Differential Evolution |
| DP | Dynamic Programming |
| GA | Genetic Algorithm |
| GAOM | Genetic Algorithm Optimization Model |
| GSA | Gravitational Search Algorithm |
| GWO | Grey Wolf Optimizer |
| HBMO | Honey-Bee Mating Optimization |
| HS | Harmony Search Algorithm |
| IDP | Incremental Dynamic Programming |
| KA | Kidney Algorithm |
| LPA | Lion Pride Algorithm |
| LP | Linear Programming |
| LSO | Lion Swarm Optimization |
| LTHG | Long Term Hydropower Generation |
| MA | Metaheuristic algorithms |
| MBA | Monarch Butterfly Algorithm |
| MSA | Moth Swarm Algorithm |
| 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 |
| PSO | Particle Swarm Optimization |
| POA | Progressive Optimization Algorithm |
| SCE | Shuffled Complex Evolution |
| SOM | Self-Organizing Map |
| SM | Simulation Model |
| SLGA | Self-Learning Genetic Algorithm |
| SQP | Sequential Quadratic Programming algorithm |
| VNS | Variable Neighborhood Search |
| WCA | Water Cycle Algorithm |
| WOA | Weed Optimization Algorithm |

The goal of planning the operation of a hydropower plant is to optimize the overall profit generated from the selling of the electricity provided to the National Grid. It is the application's objective function, which is determined by combining the monthly hydropower output with the corresponding electricity prices (Ho and Ioannis Kim, 2014). It can be calculated by Eq. (2) as follows:

$$\max B = \sum_{j=1}^{12} E_j P_j \tag{2}$$

where B is the profit; E is the energy generated; P is the energy price; j is the time period. Various constraints must be considered for a real time optimal solution of hydropower generation such as water head, turbine discharge, reservoir level, water balance and storage capacity constraints. The validity of simulated results can be verified by root mean square error (RMSE), Pearson correlation coefficient (r) or efficiency index (E). If RMSE $= 0$, $r^2 = 1$ and E $=$ 1 then it shows reliable simulation, also r should be higher than E should be greater than 0.7 for suitable model (Sorachampa et al., 2020).

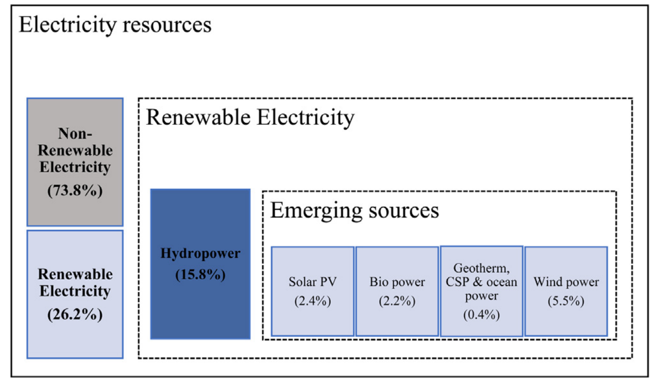


**Fig. 1.** Worldwide Electricity Production-End of 2018 (Hannah E. Murdock and André, 2019).

## 2. Reservoir operation optimization

The optimization of water supply facilities needs to do not only with the physical facilities and their operating features but also with the parameters under which the network is run. A concern with the operation of a reservoir can be considered as an issue with other constraints in policymaking. The reservoir management program is a series of rules, also referred to as the operating protocol or the release scheme (Hınçal et al., 2010). Reservoir operation management (ROM) involves allocating water for the required usage depending on the type of reservoir, optimizing the energy production; while minimizing the possibility of floods, cost of operation, adverse environmental effects and water shortage (Wurbs, 1993). A wise decision for water release operation is needed to be taken for a good ROM on monthly or yearly basis. General flowchart for ROM is shown in Fig. 3. It shows that ROM needs to schedule the reservoir flow and storage balance throughout year to optimize the power generation, flood mitigation and water supply. Unit commitment (UC) is also important parameter for decision makers for optimal operation of reservoir system. UC of hydropower is subject to data variability: water inflows into reservoirs, electricity demand, run-of-river and wind generation, and equipment failures. While this variation may be compensated for by stochastic simulations, in reality it is more common to change plans depending on the most up-to-date details, often several times a day (Marchand et al., 2019). When reservoir inflows are predicted accurately using good optimization techniques, more balanced and effective solutions can be achieved for a reservoir multipurpose system. Generation of hydropower can also be enhanced and improved (Zhang et al., 2020a).

The management of reservoir activities is widely researched, with original research concentrating mainly on water volume limits and more recent experiments integrating ecology and water quality parameters (Shaw et al., 2017). Many rule curves and regulation rules, such as normal procedure regulation, hedging law, space law, pack rule, linear decision rule, neural network dependent rule, etc., are applied and investigated for efficient

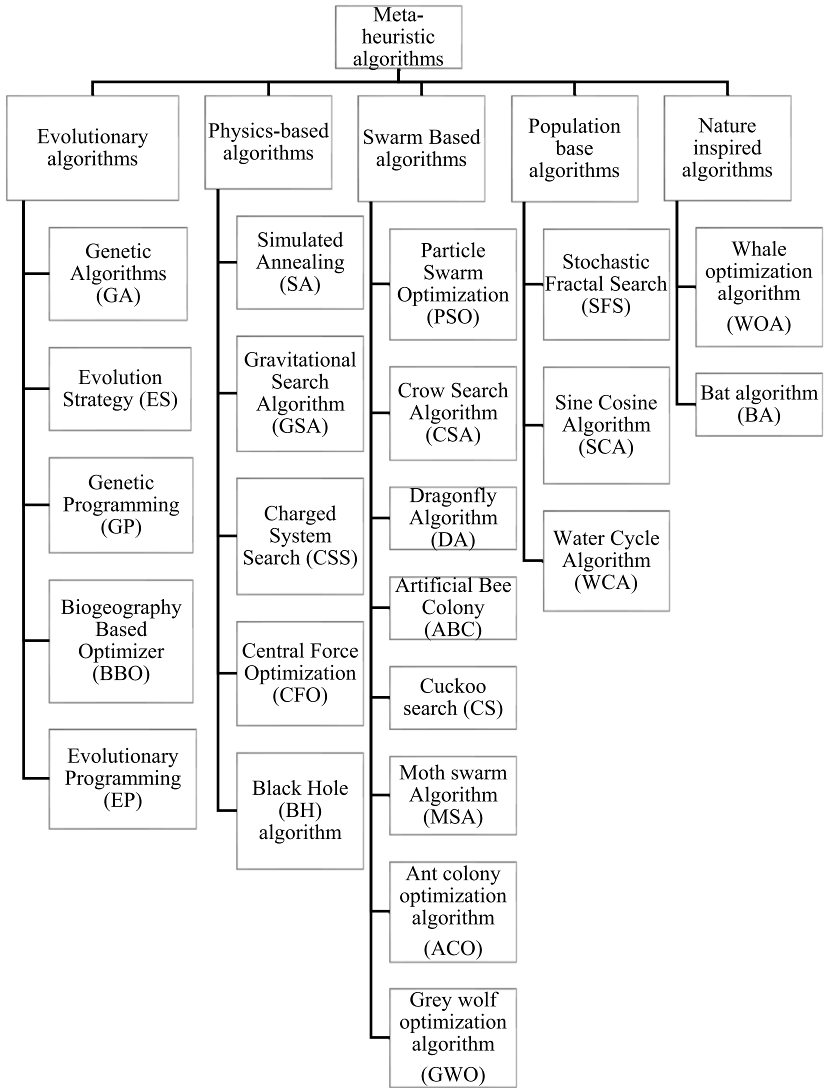


**Fig. 2.** Categories of meta heuristic algorithms.

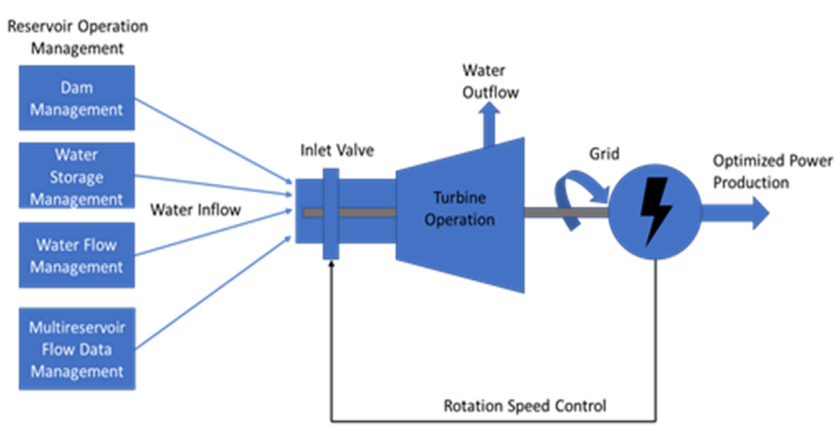


**Fig. 3.** Schematic diagram of a hydro power plant (Geng Feng and Beer, 2015).

reservoir operation system (Tayebiyan et al., 2019). Hedging policy has gained most attention in this regard. Wang et al. in their study proposed a hedging model using nonlinear programming (NLP) to determine the end of year storage that can be utilized during dry period in next year. This hedging rule was found better in performance than standard operating policy (SOP) (Jian Wang et al., 2019). To make the power production reliable during all time period following equation (Eq. (3)) was used as objective function:

$$\min(L_t\ (Q_t.S_t) + L_{t+1}\ (S_t)) \tag{3}$$

where $L_t$ and $L_{t+1}$ are current and future loss in storage; $Q_t$ and $S_t$ are water flow and storage at end of period, respectively. Water release policies (Tayebiyan et al., 2016) and hedging rule have also been optimized by genetic algorithm (GA) (Chiamsathit et al., 2014; Tayebiyan and Mohammad, 2016). Researchers aim to apply the most efficient procedure to achieve the maximum operation efficiency to maximize effective performance with the lowest energy consumption. Various approaches are used in this regard including artificial neural network (ANN) (Shaw et al., 2017; Xu et al., 2020), dynamic programming (DP) (Li et al., 2014), dynamic optimization algorithm (DP) (Rooholla kolbadi nezhad, 2016), stochastic dynamic programming (Wu et al., 2018), nonlinear programming (NLP) (Jothiprakash and Arunkumar, 2013), Shuffled Complex Evolution (SCE) algorithm (Wu and Chen, 2013), Genetic algorithm (Olukanni et al., 2018), Particle swarm optimization algorithm (PSO) (Lu et al., 2013).

Reservoirs can vary in function e.g. Reservoirs which are multipurpose. Numerous studies revealed that integrating effective river inflow forecasting procedures with efficient management strategies can provide reliable and sustainable approaches to enhance the economy of hydropower output for multi-purpose reservoir structures (Olofintoye et al., 2016). Large-scale hydropower and reservoir system's activity is known as a traditional high-dimensional nonlinear and multi-stage optimization problem, and solving such a broad problem is very complicated or even impractical with current approaches. Therefore Feng et al. suggested some powerful dimensionality reduction techniques to improve conventional methods' computational performance (Feng et al., 2019b). Meta heuristic algorithms have shown efficiencies for managing operation policies of such reservoirs with energy maximization as one of the objective functions. However, more development in meta heuristic techniques will help further to solve real time reservoir operation problems. The metaheuristic approaches application in reservoir operation management and scheduling are discussed in further sections.

## 3. Evolutionary algorithms (EAs)

Recently there has been widespread use of evolutionary and meta-heuristic algorithms as search and optimization methods in different problem areas. Evolutionary algorithms have been particularly applied widely in hydropower sector for various optimal problems. Such as Grey wolf optimization (GWO) algorithm was applied in reservoir study for data forecasting (Dehghani et al., 2019), Power generation scheduling was done by adaptive chaotic differential evolution algorithm (ACDE) (Lu et al., 2010b), multi objective optimal scheduling was done based on differential evolution with adaptive Cauchy mutation (MODE-ACM), short term hydrothermal scheduling was reported using clonal selection algorithm (CSA) from the group of evolutionary computation (Swain et al., 2011), reservoir operation was optimized by an evolutionary algorithm named Borg MOEA (Al-Jawad and Tanyimboh, 2017; Zatarain Salazar et al., 2017) and accompanying progressive optimality algorithm (APOA) (Ji et al., 2018), optimal operation of spillway was determined by the progressive optimality algorithm (POA) (Liu et al., 2017), multi-stage progressive optimality algorithm (POA) in the optimization of energy storage operation chart (Jiang et al., 2018), currently pareto front (PF)-based multi-objective evolutionary algorithms (MOEAs) are frequently used in hydropower optimization problems. MOEAs have ability to solve multiple problems simultaneously such as NSGA-II, NSGA-III, multi-objective particle swarm optimization algorithm based on decomposition (dMOPSO), Moth–flame Optimization Algorithm based on R-domination (R-IMOMFO) etc. Zhang et al. (2020). Hence wide application of EAs in hydropower optimization problems make them an important part of literature to solve optimization problems.

### 3.1. Genetic algorithm (GA)

Genetic algorithm relates to the probabilistic algorithm category. It is referred as stochastic optimization techniques whereby candidate solutions are created to search the solution space. It is represented by a chromosome using binary coding encoding various numbers, integers or any variable (Robin Wardlaw, 1999). Advantage of GA over traditional optimization is its treatment of more practical, dynamic, and highly nonlinear problems. In this process, an initial population is created; each individual is coded to be numerically represented; then each person in the population is given a fitness value which is a metric in relation to which each entity is determined whether or not to survive in subsequent generations. Genetic operators, discovery, crossover, and mutation perform the classification and placement of entities that will be rewarded to exist in subsequent generations (Hınçal et al., 2010). A general flowchart of GA is shown in Fig. 4. Many studies have been found for optimization of hydropower by crossover and mutation operation in the simple genetic algorithms and modified one.

#### 3.1.1. Modified genetic algorithms

As GAs are versatile enough to handle a large range of complex problems still it is anticipated that increasing complexity of problem causes more cost in terms of the calculation time needed and premature convergence (Tospornsampan et al., 2005). Alterations in GA and hybridization has helped to overcome this problem. Yeng et al. proposed new trigonometric selective operators in GA to advance its convergence speed for optimal operation of cascade reservoir (Yang et al., 2013b). An improved adaptive genetic algorithm (AGA) was capable of fitting negative data by sine roulette selective operator. The algorithm provided good results for Qing River cascade hydropower system during the scheduled period (Yang et al., 2013a). An increased hydropower generation was achieved by adding two simulation algorithms in genetic algorithm optimization model (GAOM) (Al-Aqeeli et al., 2016). The added algorithms changed the population value of GA and provided the optimal solution for the single reservoir. Optimized operation policy for a system of four reservoirs was also determined by using genetic algorithm optimization model (GAOM) and increased hydropower generation was achieved. The optimized policy was evaluated by a simulation model (SM) and $R^2$ value of 0.99 confirmed the performance of GAOM in hydropower optimization (Al-Aqeeli, 2016). Maximization of hydropower production was achieved by Zhou et al. by combining the non-dominated sorting genetic algorithm-II (NSGA-II) with a successive approximation for mega cascade reservoir in China (Zhou et al., 2018). The NSGA-II model has two major defects: one is that with the rise in iteration levels, population variation may slowly decline and all entities will have the same or identical genes, resulting in the premature convergence problem; another flaw is the execution time, using serial computing, shows an average square growth as the number of people in the population grows (Feng et al., 2018a). Liu et al. proposed NSGA-II framework-based lion pride algorithm (LPA) and tested for reservoir operation problem (Liu et al., 2020a). The proposed algorithm performed well in diversity and convergence and showed 2–4 times better run time than NSGA-II for dual objective optimization problem. The new form, Self-Learning Genetic Algorithm (SLGA), which is an updated version of the SOM-based Multi-Objective GA (SBMOGA), was introduced in a study for optimization of multipurpose reservoir operation (Hakimi-Asiabar et al., 2010). The algorithm used Self-Organizing Map (SOM) and Variable Neighborhood Search (VNS), to add memory to the GA and increase its local search precision.

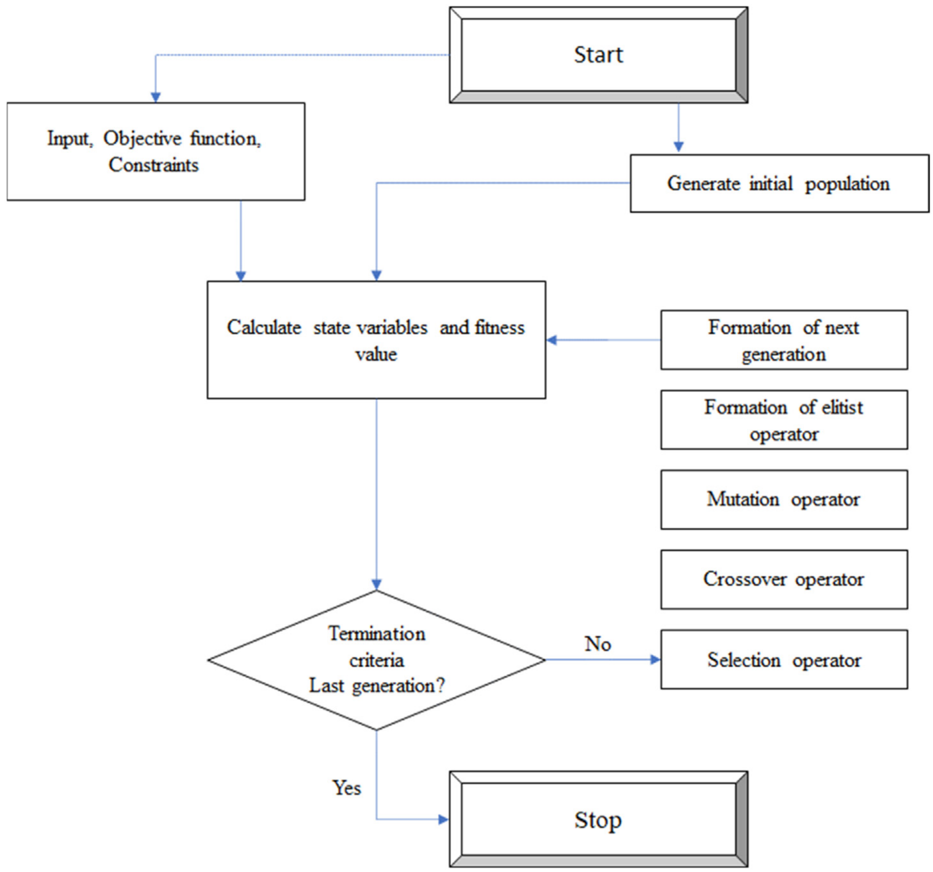


**Fig. 4.** Flowchart of genetic algorithm (GA).

### *3.2. State of the art evolutionary algorithms*

Comprehensive learning particle swarm optimization (CLPSO) is a state-of-the-art algorithm that is effective in exploration. Zhang et al. proposed an improved CLPSO (ECLPSO) to increase the efficiency of CLPSO in exploitation and related the ECLPSO to the optimal activity of hydropower systems with multi-reservoirs (Zhang et al., 2016). Two new approaches to address the various physical and organizational limitations were introduced in CLPSO. Firstly, the limits on outflow and storage capacity were sufficiently applied to accomplish an exchange-off between maintaining flexibility and promoting convergence. Second, the penalty factor was dynamically modified to facilitate initial quest space exploration and slowly direct the quest to focus on the suitable region. Strawberry optimization algorithm also a state of the art algorithm based on bio-inspired framework was developed to help the optimal release pattern of reservoir (Asvini and Amudha, 2017). Single and multiple objective optimization problems were considered, and results showed highly reliable performance of the algorithm. The kidney algorithm (KA) has been found to be an incredibly efficient state-of-the-art optimization algorithm ideal for tackling a wide variety of engineering applications. Zhou et al. proposed an improved KA by adding three strategies; (i) exploration and exploitation strategy (ii) adaptive strategy and (iii) the elitism strategy, into the existing KA and optimized the energy production policy of cascade reservoir with 7.8% increased energy production compared to the standard operation policy (Zhou et al., 2020).

## 4. Physics based algorithms

### *4.1. Gravitational search algorithm*

Gravitational Search Algorithm (GSA) is a popular evolutionary algorithm based on the Newtonian mechanics laws of gravity and mass interactions. Although GSA surpasses traditional PSO and GA approaches in many issues, there are still some shortcomings such as exploration–exploitation discrepancy and local convergence. To strengthen the efficiency of GSA standard system, Feng et al. proposed an enhanced GSA algorithm (EGSA) with three updated approaches (opposition learning strategy, mutation search strategy, and elastic-ball modification strategy) was implemented to reduce the phenomenon of premature convergence (Feng et al., 2019a). The proposed algorithm found satisfying results for multi objective operation of Cascade hydropower dams. Moeini et al. applied two constraint versions of GSA to tackle the problem of large-scale hydropower optimization and satisfying the constraints (Moeini et al., 2017). The proposed algorithms were able to reduce the size of the search space while considering water release and storage volume at each running period as decision variables. Bozorg-Haddad et al. discussed Achievement in the gravity search algorithm (GSA) using LP and NLP in addressing problems of benchmark functions, single reservoirs, and optimal management of four reservoirs. The findings of GSA in minimizing test functions were nearer to the optimum remedies than the findings of the GA. During its overall effective period, the GSA converge to 99.97 percent of the global solving, during the time that the GA converged to 97 percent of the global solving (Omid Bozorg-Haddad and Loáiciga, 2016). Feng et al. presented a multi-strategy gravitational search algorithm (MGSA) whether the Lévy flight with self-adaptive modification technique used to enhance

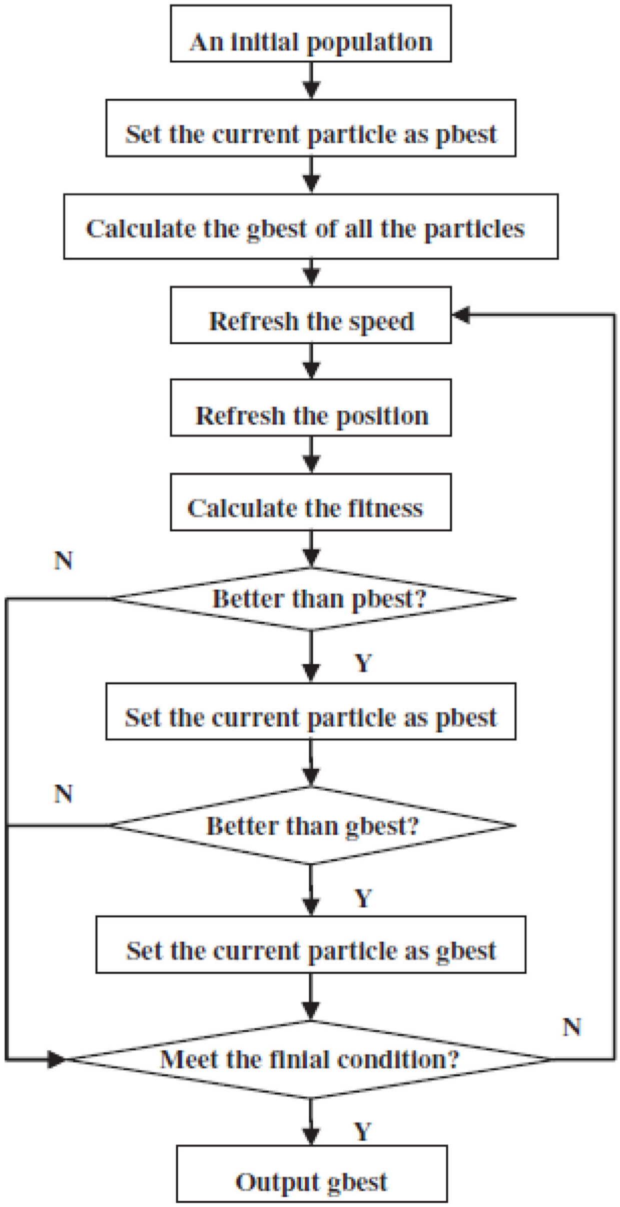


**Fig. 5.** Flowchart for PSO algorithm (Lu et al., 2013).

local swarm exploration. The algorithm proposed to overcome the limitations in premature integration of GSA algorithm for the ecological function of cascade hydropower reservoirs. In various cases, MGSA can achieve optimized scheduling schemes to allow clear cuts in the inadequate ecological water volume (Feng et al., 2020a).

## 5. Swarm based algorithms

### 5.1. PSO

As with other meta heuristic approaches PSO is implemented by a stochastic optimization based on the population. Every point in the problem space is taken as a particle in this algorithm, and all the points are taken as swarm, identical to pack of birds or fish school rushing towards the food or its habitat. Flow chart of PSO is shown in Fig. 5.

The viable solution can be expressed by the position vector of the particle $x_i(t)$ in the standard particle swarm optimization (SPSO) with N particles in the D-dimensional search space. The position of the ith particle, $x_i(t)$, is determined by a stochastic velocity $v_i(t)$ that is modified by the distance the particle is from its own best solution and that of its vicinity. The particle therefore travels according to the equation (Lu et al., 2010a) that follows:

$$v_{i,j}(t+1) = \omega.v_{i,j}(t) + c_1.r_{1,j}(t).\left(pbest_{i,j}(t) - x_{i,j}(t)\right) + c_2.r_{2,j}(t).\left(gbest_j(t) - x_{i,j}(t)\right) \quad (4)$$

where $i = 1, 2,\ldots, N$; $j = 1, 2,\ldots, D$; t is the iteration pointer; $c_1$ is the rationality learning factor and $c_2$ is the social learning factor; $\omega$ is the weight of inertia which varies from $\omega_{max}$ to $\omega_{min}$ linearly (Feng et al., 2019d); $r_{1,j}(t)$ and $r_{2,j}(t)$ are the random numbers equally distributed in range from 0–1; $x_{i,j}(t)$ is the jth dimension of position vector $x_i(t)$ at iteration t and $v_{i,j}(t)$ is the jth dimension of the vector $v_i(t)$ at iteration t; $Pbest_{i,j}(t)$ is the jth element of the best possible solution vector that particle i accessed before iteration t, and $gbest_j(t)$ is the jth element of the best possible solution vector that the entire swarm at iteration t obtains. PSO has been widely used in hydropower optimal problems with various programming models e.g. mixed integer nonlinear program (MINLP) (Zadeh et al., 2016) and WEAP model (Hatamkhani et al., 2020).

An improved Particle swarm optimization (IPSO) algorithm was also suggested by combining competitive evolution, decomposition, and dynamic shuffling into the traditional PSO algorithm by Feng et al. A simulation–optimization model was developed based on proposed IPSO to refine the main point of the water diversion curves, the hedging law curves and the target storage curves (Hong-bin Fang et al., 2014). The model's general context is expressed in Fig. 6.

Quantum-behavior particle swarm optimization (QPSO) has been widely developed recently to enhance PSO's efficiency to tackle a large number of continuous optimization problems (Xia et al., 2019) QPSO 's iterative formula differs much from PSO's, it needs no velocity vectors for particles, has fewer parameters to adjust and can be implemented more easily. Sun et al. (2012) Improved nested particle swarm optimization (PSO) algorithm was proposed to control and optimize spatial and temporal water scarcity distribution by exploiting reservoir compensation and cascade reservoir hydrology compensation (Peng Shaoming et al., 2018). Multi-objective particle swarm optimization (MOPSO) has also been proposed for hydropower planning (Wu et al., 2020), Hydroelectric power production, water management and floods protection (Bai et al., 2019).

### 5.2. Artificial bee colony

Haddad et al. demonstrated application of honey-bee mating optimization (HBMO) algorithm with Fetcher Powell function for optimization problem of a single reservoir (Bozorg Haddad et al., 2009). The "Fletcher–Powell" method tests indicated precision and higher convergence speed when using HBMO algorithm rather than GA. Both NLP solver and HBMO resulted in nearly the same optimal solutions, disregarding evaporation from the model structure. Through using migration and modification operators and applying parallel processing, the monarch butterfly algorithm (MBA) was created to keep a balance between the discovery and extraction capacities for purpose of energy optimization of multi-reservoir (Ehteram et al., 2017a). The proposed algorithm performed better, in terms of exploration and exploitation, than GA and PSO during all wet and dry period. Choong S.-M. et al. implemented ABC algorithm designed to minimize the operating system's water deficit and examining its efficiency implications focusing on weekly and monthly input of data. For optimum

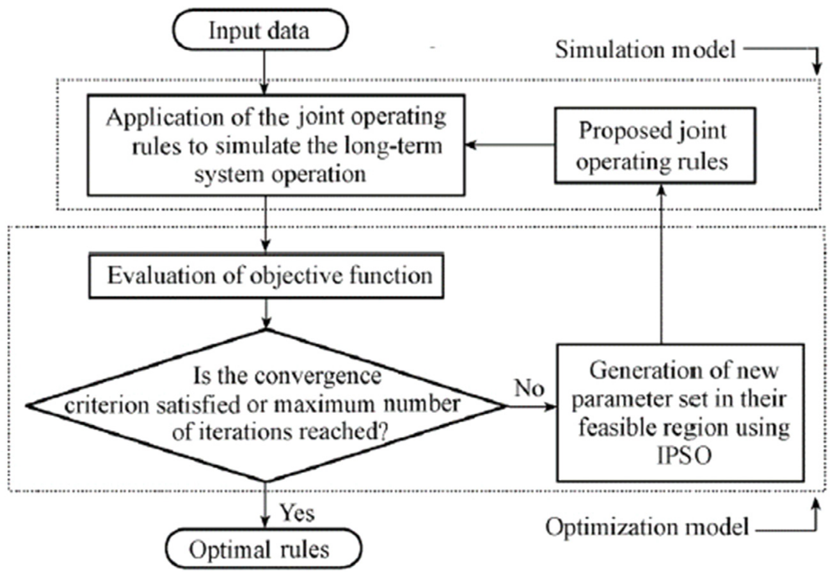


**Fig. 6.** General flow diagram of application of IPSO in reservoir operation optimization.

release curves, the ABC algorithm provides promising and comparable solutions which were then used under various inflow conditions to induce the release of the reservoir at different operational periods. The weekly ABC optimization model achieves better performance with better quality consistency and less uncertainty than ABC 's monthly optimization method (Choong et al., 2017).

### 5.3. Cuckoo Search Algorithm (CS)

Cuckoo Search Algorithm (CS) is one of the new versions of PSO algorithm. CS is an optimization algorithm that was developed in 2009. This was inspired by the compulsory parasitism of certain cuckoo species by laying their eggs in the nests of other host birds. Any host birds can require direct clash with the interfering cuckoos (Layeb, 2011). Imperialist competitive algorithm (ICA) and cuckoo optimization algorithm (COA) were used for optimal reservoir operation for power maximization (Hosseini-Moghari et al., 2015). To enhance the performance of Cuckoo Search Algorithm R. Salgotra et al. proposed three new modification of the original algorithm. Compared to the state-of-the-art algorithms, the improved algorithms were statistically tested particularly grey wolf optimization (GWO), differential evolution ( DE), firefly algorithm (FA), flower pollination algorithm (FPA) and bat algorithm (BA). The computational and statistical findings show the supremacy of the models suggested in comparison to other algorithms found in the literature (Salgotra et al., 2018). Average performance values obtained were 6.461 and 5.454 for both algorithms, respectively. It shows better performance of COA. Cuckoo search algorithm also applied as improved multi-objective cuckoo search (IMOCS) algorithm for multi objective hydropower station optimal operation (Meng et al., 2019). Three improvement strategies in the algorithm and their outcomes are mentioned as follows:

- The search efficiency was improved by group constraints technique and population initialization strategy.
- Convergence and quality of solutions was improved by flock search strategy.
- Global optimal solution was obtained by dynamic adaptive probability.

### 5.4. Grey wolf optimization algorithm (GWO)

Grey Wolf Optimizer is a recently developed meta-heuristics search algorithm based on swarm intelligence, inspired by the hunting process and leading framework of grey wolves in nature and requiring minimal control parameters (Kamboj et al., 2018). It has been applied widely in many engineering problems. It consists of four main steps e.g. population initialization, social leadership hierarchy, encircling prey and hunting (Liu et al., 2020c). GWO mimics the grey wolf 's hunting conduct and social control, which has been tested to be more efficient than other outstanding current optimization algorithms such as PSO, DE and many others (Mirjalili et al., 2014).

## 6. Nature inspired algorithms

Nature-inspired computing has gained tremendous popularity in recent years as its high performance and adaptation in solving problems of optimization which are computationally difficult to solve by traditional mathematical programming methods. Borrowing the inspiration from natural evolutionary mechanisms, due to their simplicity and versatility, these algorithms have a range of applications including science and engineering (Wang et al., 2019).

The bat algorithm is an evolutionary algorithm. It has a simplified mechanism in deciding the method's initial parameters also Have the intrinsic value over other algorithms of specifying the parameter's right value and can match the discovery and exploitation ability. Additionally, the algorithm has a higher rate of convergence than genetic algorithms, particle swarm, and bug (Ehteram et al., 2018). Improved bat algorithm (IBA) was introduced to accurately direct the evolution and improve the convergence of optimal operation of multireservoir system (Ahmadianfar et al., 2016). The spatial features of each bat's Socio-cognitive experiences were established in the population by the differential evolution (DE) algorithm.

Yin et al. proposed a modified non-dominated sorting whale optimization algorithm for maximizing the power generation of hydro, Photovoltaic and wind system hybrid. The model was inspired by the whale behavior. The proposed model showed a good performance in handling the large population and high dimensional problems of optimization. To avoid falling in premature solution, exploration ability (a) of whale optimization algorithm was improved (XingLi Yin et al., 2019).

Performance of Lion swarm optimization (LSO) algorithm built on pack of lions was measured using quantitative, convergence, mathematical and robustness analyze to automate cascade hydroelectric power station dispatch. The comparative findings showed that the LSO produced substantially preferable results as for convergence speed, robustness, rate of success, and optimization fidelity relative existing optimizers (Liu et al., 2020b).

## 7. Population based algorithms

### 7.1. Water cycle algorithm (WCA)

The WCA is an effective optimization algorithm that is acquired by the water cycle phenomena. It incorporates an operator to investigate the suitable locations close to the best solution and applies an exploration operator to introduce an evaporation method to explore the feasible solutions thoroughly. Despite this, the algorithm still undergoes to premature convergence or stuck in local optima in attempting to solve problems and requires a substantial calculation time (Ahmadianfar et al., 2019). Xu et al. offered an updated WCA based on the Diversity Evaluation and Chaos Theory (DC-WCA) for multi-reservoir optimization problems to prevent premature convergence. The optimization results revealed that DC-WCA optimized annual hydropower generation was better compared to those optimized using the other reported optimizers, and DC-WCA's convergence rate was higher than other observed optimizers (Xu and Mei, 2018).

### 7.2. Sine Cosine Algorithm (SCA)

Sine Cosine Algorithm (SCA) employs computational formula focused on sine and cosine functions. It established several initial random candidate solutions and allows them to fluctuate outwards or into the best solution for solving optimization problems. When the iteration counter heads above the maximum number of iterations SCA algorithm stops the optimization by default. Unimodal test feature study concludes that the SCA algorithm converged considerably faster than FA, BA, FPA, GSA, PSO, and GA (Mirjalili, 2016). To increase the quality Z.-k. Feng et al. suggested an Adaptive Sine Cosine Algorithm (ASCA) whether SCA improved by three approaches (elite mutation strategy, simplex dynamic search and neighborhood search strategy). Test analysis showed that ASCA approach provide improved scheduling outcomes in different runoff situations, illustrated its strong robust efficiency and global search capabilities (Feng et al., 2020c).

## 8. Hybrid algorithms

Present heuristic optimization algorithms can solve limited number of problems. It has been demonstrated that there is no algorithm that can work enough wide to solve all optimization problems (Seyedali Mirjalili, 2010). Hybrid algorithms are a blend of two algorithms, or more and help in dealing with complex multi-objective optimization problems. Hybridization of algorithms has similar benefits as individual, additionally it incorporates the strengths of one method to solve the shortcomings of other. Hybrid algorithms have been applied for estimation of energy production (Uzlu et al., 2014), reservoir operations and scheduling problems. Evolutionary algorithms with other local search algorithms have been successfully hybridized and used in hydropower optimization. Genetic algorithm often falls in premature convergence when applied to complex optimization problems. Hybrid of Chaos optimization algorithm (COA) and GA highly improved the convergence speed of GA when applied to hydropower optimization problem (Cheng et al., 2007). The ability of COA to reduce the search space, ignore the minimum values of solution set and change drastically with change in initial value overcame the convergence problem of GA. While GA overcame the limitations of COA for utilizing previous data and offered a highly optimal solution for hydropower optimization problem. Efficiency of GA was also enhanced by a SOM-Based Multi Objective GA (SBMOGA) hybrid algorithm (Hakimi-Asiabar et al., 2009). For hybridization, neurons in GA were trained and SOM based multi objective rule was adopted, which improved the solution diversity and convergence rate of global optimal solution for hydropower system.

Ho et al. optimized a reservoir operation using hybrid of Harmony search algorithm (HS), incremental dynamic programming (IDP) and genetic algorithm (GA). The hybrid algorithms established were shown to be stable tools, converged into outstanding operational policies, and displayed better efficiency compared to basic metaheuristics and the current policy of the reservoir. The algorithms were used for optimization of Huong Dien reservoir data and forecasted more hydropotential of the structure (Ho and Kim, 2015).

A hybrid of multi ant colony system (MACS) and adaptive differential evolution (ADE) algorithm was applied for short term hydro generation scheduling. MACS and ADE solved the unit commitment and economic load dispatch problems respectively for three Gorges–Gezhouba cascaded hydropower plants. The hybrid method revealed best convergence property and computational effort while utilizing minimum water (Mo et al., 2013).

Asgari et al. proposed a new hybrid algorithm WOAPSO of weed optimization algorithm (WOA) and the particle swarm optimization algorithm (PSO) with the aim of optimizing downstream water demand for a river system of 10 reservoirs. The results of proposed algorithm were reported with 99.4% reliability as compared to LP, NLP, WOA and PSO (Asgari et al., 2019).

## 9. The benefits and drawbacks of metaheuristic algorithms

Metaheuristics are built to look for near-optimum solutions, since they are not capable of finding the optimal solution. Nonetheless, metaheuristics have several characteristics that can be used either separately or in conjunction against several conventional approaches on a wide variety of problems (Pei et al., 2019). The genetic algorithm is most studied metaheuristic algorithm. It is convenient to update and also has many other positive aspects e.g. high potential to manage nonlinear or discontinuous objectives and constraints. It can be used for solving a specified problem individually and to overcome computational efforts of complex problems (Deb, 1999). On the other hand, GA is inefficient in mathematical terms, i.e. higher time consumption (Beg and Islam, 2016). Cuckoo search Algorithm (CSA) meets the demands of global convergence, helps research abilities at local and global stages, uses Lévy flights as a tool for global searching (Wang Fan et al., 2012)., CSA has some obstacles including weak performance, low convergence rate and ability of dropping to optimum local value (Qu and He, 2015). Differential evolution (DE) has the capability to handle non-convex, nonlinear and multidimensional cost functions. It is simpler in use, it just takes a few parameters, capable of converging to the global solution. DE is perfect for exploring and diversifying, can accommodate extremely computationally complex cost functions. On the contrary, convergence of DE is not robust, it falls quickly into a regionally optimal solution and needs parameter adjustment (Wu et al., 2009). Particle swarm optimization (PSO) is important in both science and technical works and also its computation is fast (Zhigang Lian et al., 2008; Park, 2006). In contrast, there is a shortage of a robust quantitative foundation for the theory to be resolved in the possible advancement of the hypothesis involved (Park, 2006). Firefly algorithm (FFA) has the capability to divide the population into distinct groups, and is thus ideal for diversifying (Pal et al., 2012). However, FFA is not really good for coping with complicated scenarios, as it can be stuck in several local optima (Pal et al., 2012; Ali et al., 2014). Ant colony optimization (ACO) is used to overcomes premature convergence problem. The development cycle for ACO is essentially concurrent, because ants produce solutions separately and concurrently. In spite of this the nature of ACO is hard to analyze technically, since ACO is focused on sequence of spontaneous actions of different individual artificial ants (Selvi and Umarani, 2010). Bat algorithm (BA) is fast, versatile and convenient to deploy. It is used to tackle a large number of problems, has the potentiality to zoom in dynamically to locations with appropriate solutions. BA does not use any permanent parameter, but has command on its parameters to adjust the values at various iterations. In that case BA has the opportunity to move from exploration phase to exploitation phase instantly and rapidly. But the traditional BA follows constant values, and it can effectively be extended to questions with nonlinear global optimization process (Kongkaew, 2017). Conversely, BA is not integrated to resolve discrete problems, several parameters which need to be tuned (Sheng Xiao-hua, 2013). Artificial bee colony algorithm (ABC) algorithm is extremely robust, converges rapidly, needs few parameters and is feasible (Yan, 2011). However, in the later period of its exploration, the ABC algorithm does have premature convergence and the classification accuracy. Its best achieved value might not be reasonably big to satisfy the objectives (Abu-Mouti and El-Hawary, 2012).

## 10. Comparative studies for application of metaheuristic algorithms in hydropower optimization

Akbarifard et al. conducted a comparative study between Moth swarm algorithm (MSA), Genetic algorithm (GA) and Particle swarm optimization (PSO) algorithm for optimal hydropower operation of Karun-4 reservoir (Akbarifard et al., 2020). The results revealed that MSA had the capacity to generate superior solutions for the hydropower reservoir as compared to other algorithms with coefficient of variance of 0.0192 and best CPU time of 19.7 s The results are shown is Table 1 for values of objective functions in 10 runs. Another study on same reservoir using ICA and COA proved COA to be best in achieving global optimum as compared with GA and NLP (Hosseini-Moghari et al., 2015).

Ehteram et al. used Shark Algorithm for optimization of water scarcity and power generation of same reservoir. The findings observed from the algorithm was 100 percent accordance to the complete optimal solution Acquired by Lingo applications and non-linear process. It was reported that the results were ideal solution in published researches to date for that problem (Ehteram et al., 2017b).

Another comparative study conducted by Ghodousi et al. concluded that dynamic programming (DP) requires very high volume of storage and data as compared to meta heuristic algorithms e.g. GA, PSO and ACO (Kolbadi Nezhad and Hesam, 2016). Barros et al. conducted a hydropower optimization study for a large-scale hydropower system consisting of 75 plants. Linear, nonlinear, and successive linear programming models were applied. It was concluded that linear programming gave better results than other models in term of energy production, while SLP model reduced the solution time (Mario et al., 2003).

Swain et al. proposed clonal selection algorithm (CSA) for short term scheduling optimal solution of a hydrothermal plant (Swain et al., 2011). The findings of the suggested method Was identical to the ones of gradient search (GS), synthetic annealing (SA), evolutionary programming (EP), dynamic programming (DP), nonlinear programming (NLP), genetic algorithm (GA), improved fast EP (IFEP), differential evolution (DE) and improved particle swarm optimization (IPSO) strategies. Through the numerical tests, it was observed that, at less computational effort, the CSA-based method would provide better solution.

Three optimization algorithms were implemented in an analysis including progressive optimization algorithm (POA), particle swarm optimization (PSO), and genetic algorithm (GA). The minimization of water usage rate was chosen as the objective function, along with other physical and operational restrictions, according to a long discharge data set (Lu et al., 2013). The modified genetic algorithm (GA) was used for reservoir activities, and the optimization method was regarded for various flows in river regimes. For the development of hydropower, nonlinear rule curves focused on the GA were derived, and the enhanced elitism-dependent algorithm obtained further hydropower generation without trapped optimum local solutions (Pimenta and Assireu, 2015; Jahandideh-Tehrani et al., 2014; Babel et al., 2012). The modified PSO focused on inertia coefficient adjustment had faster convergence over other PSO models. In contrast, hydropower output attained hydropower plant efficiency concentrated on modified PSO (Wu and Chen, 2013). In addition , multi-reservoir operations focused on a hybrid PSO and GA improved efficiency with the objective of enhancing generation of hydropower. The findings showed that the latest hybrid algorithm could obtain further hydropower generation and quicker integration by covers the GA and PSO vulnerabilities, focused on growing population density (Yang et al., 2015; Chang et al., 2013). Optimal scheduling of hydropower system.

Scheduling of hydropower production is a complex nonlinear task. It involves application of water balance equation for a certain period. For a complete optimization problem short-term, mid-term and long-term scheduling is needed to be considered which makes the computation very extensive. Most researchers have considered either short term, mid-term or long term scheduling to minimize the computation effort and time (Belsnes and Fosso, 2005). Purpose of short-term scheduling is to maximize the income of energy production by minimizing the grid start up and power fluctuation. Cost can also be minimized by taking hybrid system of energies e.g. hybrid solar, wind and hydro power plant (Acakpovi et al., 2015; Kapsali and Kaldellis, 2010). Mid-term hydropower scheduling (MTHS) aims at controlling both hydropower production and water release with full benefit while satisfying multiple network constraints on an annual horizon (Ge et al., 2018). Energy production is generally maximized by long term or mid-term basis (Jinwen Wang and Zhang, 2004). Scheduling has been done by various methods such as mathematical techniques including artificial neural network (ANN) (Joy, 2020), stochastic models (SM) (Fodstad et al., 2015), nonlinear programming (NLP) (Pérez-Díaz et al., 2010), logical optimization (Gupta et al., 2019), Sequential Quadratic Programming algorithm (SQP) (Finardi et al., 2005) and heuristic techniques including progressive optimality algorithm (POA) (Cheng et al., 2017), Grey wolf optimization (GWO) algorithm (Li et al., 2019b), particle swarm optimization (PSO) (Madhuri et al., 2013), dragonfly algorithm (DA) (Li et al., 2019a), and multi-objective evolutionary algorithms (MOEA) (Liu et al., 2019). Some simplified approaches have also been adopted (Kjaerland and Larsen, 2012). Mathematical techniques take few assumptions or generalizations to solve the complex equations which lead towards partial optimal solutions. Whereas heuristic techniques enable global optimal solutions to problems (Fu et al., 2011).

Xie et al. proposed a hybrid algorithm of Genetic algorithm (GA) and progressive optimality algorithm (POA) for short-term

**Table 1**
Data value for optimization study at karun-4 hydropower reservoir (Akbarifard et al., 2020).

| Number of runs | MSA | | GA | | PSO | |
|---|---|---|---|---|---|---|
| | Optimal value | CPU time (s) | Optimal value | CPU time (s) | Optimal value | CPU time (s) |
| 1 | 0.1559 | 21.82 | 1.6918 | 48.71 | 0.1584 | 28.99 |
| 2 | 0.1473 | 20.12 | 1.4352 | 47.79 | 1.0708 | 30.35 |
| 3 | 0.1470 | 21.46 | 1.9616 | 40.88 | 0.2499 | 28.88 |
| 4 | 0.1486 | 22.53 | 1.4702 | 37.16 | 0.5463 | 28.93 |
| 5 | 0.1508 | 21.58 | 0.3762 | 48.23 | 0.2756 | 29.03 |
| 6 | 0.1472 | 20.66 | 0.6623 | 47.99 | 0.1704 | 29.01 |
| 7 | 0.1506 | 19.7 | 1.3717 | 47.93 | 0.2570 | 29.62 |
| 8 | 0.1470 | 21.24 | 0.9225 | 48.09 | 0.1591 | 29.6 |
| 9 | 0.1473 | 20.42 | 0.5495 | 47.14 | 0.732 | 29.17 |
| 10 | 0.1471 | 21.76 | 0.3026 | 47.62 | 0.1823 | 28.93 |

hydropower generation (STHG) scheduling. Objective the of study was to maximize the power generation. It was obtained by analyzing the runoff data using algorithm and obtaining the optimal scheduling process. Later scheduling rules were defined using statistical tools and formulas were developed for power maximization of cascade hydropower station (Wei Xie et al., 2012). Fu et al. reported a new approach termed as immune algorithm-based particle swarm optimization (IA-PSO) for short term hydropower scheduling (Fu et al., 2011). IA-PSO was used by integrating the method of immune information retrieval with the particle swarm optimization algorithm. From the comparative analysis, the IA-PSO method was found to have the most globally optimal solution at a higher rate of convergence. Long term hydropower generation (LTHG) scheduling was reported by series division method (SDM) established on the practical swarm optimization and the firefly algorithm. The results find out that Firefly Algorithm with series division (SDFA) is stable and has strong performance and supremacy (Hammid and Sulaiman, 2018). Feng et al. conducted their study on LTHG scheduling considering the climate change and various stream flows on Jinsha River using gravitational search algorithm (GSA). The reported results were able to present decision supporting for the potential balancing of the Jinsha River's water supplies (Feng et al., 2018c). Neu et al. introduced a parallel multi-objective particle swarm optimization (PMOPSO) in which the large population swarm was separated in many smaller subswarms can be managed simultaneously through separate worker channels. The findings demonstrated that PMOPSO could produce adequate scheduling results with power optimization in different situations (Niu et al., 2018).

## 11. Discussion

Table 2 demonstrates the results of various metaheuristic algorithms applied recently for hydropower optimization. It is found in the recent study pattern that work is interested in using some new metaheuristic and mixing existing metaheuristic algorithm to address the optimization of the hydropower and reservoir operation. Various objective functions are utilized for this purpose such as flow scheduling, reservoir operating rules modification, reservoir design parameters tuning, and cost optimization etc. All algorithms performed well in this regard particularly multiple objective function design. GA and PSO are mostly used traditional algorithms with various modifications in this regard. They have shown reduced convergence and computation time. Emerging new algorithms such as BA, KA, MOSBO and GSA etc. have outperformed than these traditional algorithms recently and authors have demonstrated various modern algorithms with new computational techniques for hydropower optimization.

There is a difference between practical real-world execution and theoretical knowledge in reservoir operation. The reason for this disparity is because certain reservoir managers lose trust in the simplified problem model, which is meant to override decision-makers' findings and recommended solutions (Yang et al., 2015). Moreover, application of metaheuristic algorithms for large scale hydropower optimization problems has certain limitations e.g. premature convergence due to stochastic analysis mechanism (Feng et al., 2018b). In real hydropower operations, it has been observed, some techniques are very powerful and able to provide a robust modeling on reservoir application, but normally too powerful technique can consume a lot of operational times. No algorithm with polynomial time exists except non-deterministic polynomial-time hardness (NP-Hard) for complicated optimization problems. For practical purposes this issue often takes a long time to compute. Therefore, during the past 30 years, the use of provisory approaches became noticed mostly (Othman et al., 2012). To narrow the gap between theoretical knowledge and practical application of evolutionary algorithms Yang et al. built an optimization model based on real time constraints and reservoir system (Yang et al., 2015). It was suggested that the proposed solution, which blended the strengths of advanced multi-objective optimization algorithms with more practical (i.e., including nonlinearity and complexity) method formulations, can offer a clearer image for decision-makers of the variety of choices to choose from. However environmental constraints and uncertain turbine efficiency constraints were not considered in this study. Asgari et al. (2019) revealed that the hybrid of weed optimization algorithm (WOA) and the particle swarm optimization algorithm (PSO) worked very well to solve a real-world three-reservoir hydropower optimization issue that maximizes the hydropower output capacity index, while NLP optimization scheme failed. In some papers nature of problems is not considered as key point in deciding the algorithm and same algorithm is applied to solve many problems and made comparison. That is not an appropriate technique towards comparison of results. Table 2 states that state of the art algorithms have shown highly accurate results particularly hybrid algorithms are most efficient in real time problem solving. Evolutionary algorithms have been found to be very efficient in solving real world hydropower generation problems particularly GA has been applied widely. Biggest advantage of these algorithms is their higher capacity in handling complex natured problems particularly when hybridized. However, the cost and variability in various natural factors have not been much discussed in research works using EAs', which should be addressed in future works. Also, the lack of interaction between algorithm developers and decision makers limits the application of EAS in handling real world optimization problems.

As reservoir operation is a complex task hence hybrid algorithms provide multiple solutions. Some algorithms provide efficiency for short term planning and some perform better in long term planning scenario. There are several real field constraints and restrictions, and the results are observed under them. The researcher also mentioned the optimization of hydropower

**Table 2**
Problem formulation and results of optimal study on hydropower system.

| Optimization methods | Objective of study | Techniques adopted | Outcomes | Ref. |
|---|---|---|---|---|
| Genetic algorithm (GA) | 1. A nonlinear four-reservoir problem, along with extended time horizons.<br>2. A more complex ten-reservoir problem | Alternative representation, selection, crossover, and mutation schemes were considered. | This was concluded that the most encouraging solution to the four-reservoir problem for genetic algorithms involved real-value encryption, tournament discovery, uniform crossover and adjusted uniform mutation. Real-value coding worked much quicker than binary coding and generates improved performance. Genetic algorithm method was robust, and was easily extended with stochastically generated operations, complex structures, to real-time operations. | Robin Wardlaw (1999) |
| Improved Kidney Algorithm (KA) | Joint operation of mega cascade reservoirs. | This research presented a strategy that merged three auxiliary techniques into the Kidney Algorithm (KA) to maximize the hydropower production to overcome the KA's inefficiencies regarding the combined activity of six mega cascade reservoirs located in China's Jin-Sha River basin. | The improved KA significantly improved hydropower production efficiency and stability as well as decreased hydropower production vulnerability to a large degree. The KA and improved KA were able to boost the hydropower production by 4.7% and 7.8% respectively. CO2 emission was reduced. | Zhou et al. (2020) |
| Lion swarm optimization algorithm (LSO) | Maximize the yearly output of hydro power channels by the cascade, subject to other restrictions (along with technological and physical). | LSO is an effective approach for overcoming complicated problems with basic form and outstanding convergence speed for qualitative decisions parameters. | The findings obtained by the LSO algorithm were satisfactory as comparing to GA, improved CS and PSO, that indicates that LSO had good success in dynamic issues with qualitative decisions parameters. | Liu et al. (2020b) |
| Multi-objective hybrid grey wolf optimization algorithm | Economic Emission Dispatch (EED) for two competing goals Minimizing the expense of gasoline while Minimizing pollutions. | Continuous and distinct variables of optimization are configured and synchronously optimized. | 1. Compared to its opponents, the suggested algorithm has been able to obtain the strongest Pareto front for economic/emissions bi-objectives.<br>2. Tests show that the scheduling schemes are entirely underneath the feasible range.<br>3. Analysis shows that the combined activity of RE and hydropower stations benefits both the economic and environmental goals and reduces operating expenses and carbon emissions by 11.9 percent and 17.4 percent, accordingly, as the RE potential of the hybrid model rises from 50 percent to 100 percent cent. | Li et al. (2019b) |
| PSO | Hydrothermal scheduling problem | PSO technique was applied and illustrated to tackle the hydrothermal scheduling problem with polynomial thermal cost method. | PSO algorithm was comparable through a well-known heuristic process, and outcomes were consistent with the success of order to solve nonlinear optimization problem. Perhaps even, PSO algorithms could identify almost global solutions in a short period of time. | Madhuri et al. (2013) |
| A progressive optimality algorithm (POA) | Maximizing the overall consumption of energy that requires maintaining maximum level water heads with reservoir spills. | Using a progressive optimality algorithm (POA), the system was solved in two-stage optimizations based on a multidimensional search. | The proposed model could obtain higher overall absorption of energy, thus minimizing leakage efficiently. | Cheng et al. (2017) |
| Multi-objective method based on differential evolution with adaptive Cauchy mutation (MODE-ACM) | Short-term multi-objective optimal hydro-thermal scheduling (MOOHS) | The suggested multi-objective optimization algorithm focused on DE — multi-objective differential evolution with adaptive Cauchy mutation (MODE-ACM) has adapted an elitist archive to maintain the non-dominated solutions acquired throughout the evolutionary phase. An efficient way of addressing restrictions was used to overcome the dynamic conditions of equity and inequalities. | The findings obtain by MODE-ACM appeared better in terms of fuel cost and also emissions performance with a shorten computational period, which confirmed that MODE-ACM may have been a feasible option to produce optimized trade-offs for the optimum hydrothermal scheduling short-term multi-objective problem. | Qin et al. (2010) |

(continued on next page)

**Table 2** (*continued*).

| Optimization methods | Objective of study | Techniques adopted | Outcomes | Ref. |
|---|---|---|---|---|
| Adaptive chaotic differential evolution algorithm (ACDE) | Shor-term hydropower scheduling reservoirs. | (1) To gain the parameter settings in the Differential Evolution Algorithm (DE) and a Chaotic Local Search (CLS) procedure were combined with DE to effectively prevent premature convergence.<br>(2) New heuristic constraint approaches have been introduced, without any penalty factor settings. | Smaller fuel costs, lower computing time and faster convergence properties compare to other existing approaches in both test systems, resulting in a fresh and efficient approach to solving SHGS problem. | Lu et al. (2010b) |
| Immune algorithm-based particle swarm optimization (IA-PSO) | Short-term hydropower scheduling of reservoirs. | The reservoir hydroelectric optimizing method was conceived as a question of high-dimensional, complex, nonlinear, and stochastic global optimization of a multi-reservoir hydropower network. | It was observed that, at a fast pace of convergence, the IA-PSO method offered the most globally efficient solution. | Fu et al. (2011) |
| Quantum-behaved particle swarm optimization (QPSO) | Short-term combined economic emission scheduling (CEES) of hydrothermal power systems with many limitations in terms of sustainability and inequalities. | (1) The stated methodology, defined as QPSO-DM, merged the QPSO algorithm with the differential mutations process to boost global search capabilities.<br>(2) Heuristic methods are introduced to address the constraints of equity, in particular the constraint of water dynamic equilibrium and active power equilibrium.<br>(3) A feasibility-based assessment strategy was often used to fulfill the limitations on reservoir capacity capacities. | The simulation research indicates that in the short-term hydrothermal scheduling, the suggested approach was able to produce high-quality approaches optimally and effectively than all other algorithms evaluated for optimization. | Lu et al. (2010a) |
| Non-dominated sorting whale optimization algorithm (NSWOA) | 1. Maximization of the electricity system's gross cumulative power output.<br>2. To minimize the variation of power production of the system. | An improved model of the non-dominated whale optimization algorithm (updated NSWOA) was introduced in order to achieve a solution range of the long-term multi-objective optimization framework of the hydro-photovoltaic (PV)-wind power grid, under which the cascade hydropower station serves as the power system compensate. | The observations indicate that the adjusted NSWOA could provide decision-makers with a set of options for optimum choice, and the hydroelectric power could decently balance for PV power and wind power due to its strong adjustment capacity. | Xingli et al. (2019) |
| Series division method (SDM) based on the practical swarm optimization and the firefly algorithm | Long-Term Hydro Generation Scheduling (LHGS) | The suggested SDM was evaluated on both actual Observed System Operator (AOSO) and Standard System Operation (SSO) test structures and contrasted to a certain latest research works in the area. | 1. Sometimes, the magnitude of the SDM was given a faster convergence to achieve the strongest initial procedure in swarm's algorithm research.<br>2. The findings demonstrate that the Series Division Firefly Algorithm (SDFA) has been reliable and seems to have strong performance and supremacy. | Hammid and Sulaiman (2018) |
| Particle swarm optimization (PSO) and Firefly algorithm (FA) | Strong value for producing power at its optimum point. | Hybrid algorithm was proposed. | 1. For certain respects the level of success of FA was higher than the PSO.<br>2. In conclusion, the outcomes demonstrated FA's intensity, as well as its performance and dominance. | Sakidin et al. (2017) |

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under uncertainty. They also used clustering strategies to reduce the search space. So, the approaches that the researchers reported to be doing well might not work effectively when the problem level is very high. On a reservoir model of broad scale, however, less research is found and more research work is needed to be done in this domain to address gap between theoretical knowledge and practical application. It can be concluded that future hydropower sustainability is highly dependent on real development and control of water capacity and efficient artificial intelligence techniques e.g. metaheuristic techniques play important role in this regard.

**Table 2** (*continued*).

| Optimization methods | Objective of study | Techniques adopted | Outcomes | Ref. |
|---|---|---|---|---|
| Improved bat algorithm (IBA) with a hybrid mutation strategy | To develop effective strategies for realistic issues in the control of waterways. | Modified bat algorithm (IBA) with a hybrid mutation approach was used to overcome four-reservoir and 10-reservoir problems in water resources management. The contextual attributes of increasing bat's social and cognitive experiences within the population with the differential evolution (DE) algorithm were formed to lead the evolution and significantly improve the convergence. | 1. The tests showed the newest bat algorithm performed well for several of the testing parameters than the former bat algorithms.<br>2. IBA can hold bats diverse and have a good result in global search.<br>3. The suggested BA is able to obtain very small standard deviation for 15 production cycles.<br>4. The approach presented was used to tackle two standard challenges of multireservoir hydroelectric operations, namely four-reservoir and 10-reservoir systems. | Ahmadianfar et al. (2016) |
| Particle swarm optimization (PSO), genetic algorithm (GA), and hybrid PSO-GA | Development of the reservoir operation rules. Maximize the power production efficiency. | To find the much more efficient algorithm, three optimization algorithms, namely particle swarm optimization (PSO), genetic algorithm (GA), and hybrid PSO-GA, were connected to any of the designed frameworks (1PHP as a test). | 1. The findings revealed that, around 2003–2009 and 2010–2012, there was no substantial gap among the production of the average monthly power production.<br>2. The findings indicated that the productivity of energy production might improve by 13 per cent with regards to traditional operation by implementing the recommended policy.<br>3. In comparison, the differences among average energy generations from the peak to the lower month have been narrowed from 49 MW to 26 MW, amount is nearly half that. | Tayebiyan et al. (2019) |
| The approach of Grey Wolf Optimization (GWO) paired with an adaptive neuro-fuzzy inference system (ANFIS) | To forecast the hydropower generation. | To predict hydropower production, the Grey Wolf Optimization (GWO) technique, combined with an adaptive neuro-fuzzy inference system (ANFIS) been used. | Studies demonstrated potential for the process. GWO-ANFIS was able to satisfactorily forecast the hydropower production whereas ANFIS struggled in nine variations of input–outputs. | Dehghani et al. (2019) |
| Hybrid of weed optimization algorithm (WOA) and the particle swarm optimization algorithm (PSO) | To establish a system for optimization of river basin operations. | In this observation two analyses were introduced to test the WOAPSO algorithm's efficiency. The first study consists of an analysis of a ten-river basin reservoir that contrasted the efficiency and accuracy of the WOAPSO hybrid algorithm with those of linear programming (LP), nonlinear programming (NLP), WOA, and PSO. | 1. Result suggested that the hybrid WOAPSO finds explanations in the ten-river basin reservoir that met downward water requirements with 99.94 percent consistency (in terms of the global maximum, as inferred from LP).<br>2. In the form of adaptive river basin management, WOAPSO has proved to be more efficient than classical and evolutionary optimization algorithms for overcoming complicated multi-reservoir operations. | Asgari et al. (2019) |
| Genetic Algorithm (GA) | To analyze the operating law for the reservoirs; design the parameters of the reservoir. | Accessible 27-year records (1984–2011) was collected from the Reservoir Station for statistical analysis & Genetic Algorithm (GA) MATLAB software, and a related optimization program (LINGO) was used for evaluation and testing. | The implementation of GA would lead-in a more practical and effective optimum value for enhancing hydroelectric power production and flood control, that will further influence hydropower decision-makers. | Olukanni et al. (2018) |

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## 12. Limitations

This comprehensive review has limits, as it relies exclusively on methods for optimization. The authors did not systematically scan a broad literature that aimed at modeling variables and handling uncertainty. Study based on reservoir surrogate modeling was not, however, deliberately omitted and many such studies were included in this analysis. A complete further review can be suggested on uncertainty analysis. In this review, articles published in web of science and Scopus are considered only during past 20 years.

## 13. Conclusion and future works

Optimization models are commonly used to assist decision taking. In several cases, however, the problems to be solved are complex, non-linear, little known and, most likely, marked by incredibly wide spaces for solutions. This finds it virtually difficult to find a range of solutions that offer great exchange-offs between conflicting goals, such as mitigating costs and optimizing environmental results, exploiting an implicit "optimization" approached, as part of that the optimal result was found surrounded by the help of domain expertise, experience and judgment, combined

**Table 2** (*continued*).

| Optimization methods | Objective of study | Techniques adopted | Outcomes | Ref. |
|---|---|---|---|---|
| A hybrid version of Grey Wolf Optimizer algorithm combined with pattern search (hGWO-PS) algorithm | To resolve the benchmark problems such as difficulties with product architecture and optimizing problems. | The Grey Wolf Optimizer's discovery process had been further enhanced by using pattern search algorithm, that is a derivative-free search tool. | 1. The exploitation process in the hypothesized GWO-PS hybrid algorithm was found to be stronger than the typical Grey Wolf Optimizer algorithm, Ant Lion Optimizer algorithm, Moth–Flame Optimization algorithm, sine–cosine optimization algorithm, and certain currently documented heuristics and meta-heuristics search algorithm.<br>2. Furthermore, leading to an improvement in the number of fitness tests the processing period of the algorithm has been marginally decreased. Therefore, the suggested algorithm indorses its usefulness in the area of meta-heuristics search algorithms influenced from nature. | Kamboj et al. (2018) |
| Series division method (SDM) based on the practical swarm optimization and the firefly algorithm | Long-Term Hydro Generation Scheduling (LHGS). | The suggested SDM is evaluated on the actual observed system operator (AOSO) and Standard System Operation (SSO) test platforms and contrasted of several existing research works in the field. | The tests find out that the Firefly Algorithm in the Series Division (SDFA) is stable and seems to have strong performance and supremacy. | Hammid and Sulaiman (2018) |
| Bat algorithm (BA) | Minimize irrigation deficit. Maximizing the power generation. | The BA is integrated through various rule curves including first-, second-, and third-order rule curve. To evaluate the efficiency of the algorithm, three distinct testing measures, respectively reliability, resilience, and vulnerability were examined. | Analysis found that the third-order rule curve bat algorithm obtained the maximum return for the indexes of durability and stability, and the lowest value for the index of vulnerability in these case studies. So it could be stated that the bat algorithm with the third-order rule curve worked faster than the rule curves of the other order in generating the optimum reservoirs operational strategy. | Ehteram et al. (2018) |
| Progressive optimality algorithm (POA) | Flood control and hydropower generation optimization. | Progressive optimality Algorithm (POA) was used to decide the optimum activity of spillways A smooth support vector machine (SSVM) method was employed for the real-time reservoirs activity to derive the optimized operating regulations that take into account the order and amount of spills used. | Studies indicate that the usage of multiple spillways has a noticeable effect on reservoir activity. Consequently, the order and number of spillways that will be included must be considered. Rather than optimizing the overflow, significant order optimization and number of spillways will produce the most rational outcomes. | Liu et al. (2017) |
| Genetic algorithm (GA) | Maximize total production of energy in horizontal timeframe. | This analysis constructs methods of simulation–optimization representing a discrete hedging policy (DHP). Consequently, the single reservoir structures and multi-reservoir systems of three operating model have been developed and optimized via the genetic algorithm (GA). | As shown in the details presented, the use of DHP for the activity of the hydropower reservoir system can rise the power generation production in the observed reservoir system to nearly 13 per cent given the current operational policy (TNB service). These can be stated that DHP is an effective and viable policy that may be used to run current or future reservoir hydropower systems. | Tayebiyan and Mohammad (2016) |
| Gravity search algorithm (GSA) | To tackle the problems such as complexities in river discharge, variable rainfall regime, and drought severity merit | This study discusses the usefulness of the gravity search algorithm (GSA) in finding solutions of benchmark functions, single reservoir, and operation optimization of four reservoirs. For three optimization problems, the GSA's approaches are equivalent to those of the well-known genetic algorithm (GA). | 1. The analyses reveal that the GSA outcomes in decreasing the test functions are nearer to the optimum solutions than the GA performance.<br>2. This should be stated that the GSA will pursue approaches quicker and with more specificity than the GA. | Bozorg-Haddad et al. (2016) |

(*continued on next page*)

with the outcomes from one or more simulation models. Evolutionary algorithms yet more metaheuristics offer the way by overcoming the aforementioned drawbacks, when it should be closely related for applications of ecological modeling included as apart of it is widely implemented non-formal optimization method discussed over, thus authorizing for computationally efficient exploration of broad search spaces. Mostly researches have centered on the exploit of hydroelectric power scheme for electricity supply through the application of different modeling strategies giving consideration to environmental effects. This

**Table 2** (*continued*).

| Optimization methods | Objective of study | Techniques adopted | Outcomes | Ref. |
|---|---|---|---|---|
| Genetic algorithm optimization model (GAOM) and Second algorithm (Salg) | Attainment of maximum hydropower production from water storage service. | During 20 scenarios (years) for the activity of Mosul reservoir, northern Iraq, two simulation algorithms was designed and implemented separately inside that GAOM. | The observations have proven the Salg's efficacy in growing the production of hydropower via the GAOM's improved method. Therefore, the findings showed the significance of having the Evaporation and Precipitation to consideration in reservoir simulation activity. | Al-Aqeeli et al. (2016) |
| Multi-objective surrogate based optimization (MOSBO) | Designing long-term principles of action for multi-reservoir structures. | Using a multi-objective parameterization–simulation–optimization (PSO) parsimonious system that integrates hydrological instability by stochastic simulation and makes the use of objective probabilistic functions. | Analysis revealed that MOSBOs will potentially have even more stable, uncertainty-aware operating laws, without any degradation of either the generality of evolutionary algorithms or the information contained in domain-specific models. | Tsoukalas and Makropoulos (2015) |
| Improved multi-objective cuckoo search (IMOCS) | Resolve MOCS limitations. In particular, a population initialization approach focused on restriction transformation and the individual constraints and group constraints technique (ICGC) and a dynamic adaptive probability (DAP) are used to increase the search productivity and the consistency of solution, simultaneously. | A flock search strategy (FSS) has been introduced to speeding up convergence dramatically and increase the efficiency of non-dominated solutions. | The findings indicate that IMOCS works well on converge rate, convergence attribute and solutions diversity than most other algorithms. | Meng et al. (2019) |

review provided a condensed analysis of various mathematical models developed for the process of hydropower generation. It was noticed whether there several parameters, including turbine and penstock size, quantity of turbines, turbine scheduling were not previously explored for optimum process of hydroelectric power station and hence more research is needed to understand the impact of those parameters. It can also be noted from previous research very few of these researches are accessible for optimal short-run activity of hydroelectric power stations. Hence more research is needed in this regard. State of the art algorithms have high potential to be used with modern programming skills and modifications that should be explored. Cost optimization using modern metaheuristic techniques also need to be explored.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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