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Review on Dam and Reservoir Optimal Operation for Irrigation and Hydropower Energy Generation Utilizing Meta-Heuristic Algorithms

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ABSTRACT In engineering and scientific disciplines, there are extensive Optimization Application Problems (OAPs) such as economic dispatch, structural design, and water resources. One of the major OAPs is the operation of dams and reservoirs to minimize the gap between water supply for irrigation and demand patterns such as hydropower generation. Drawing optimal operation for dams and reservoirs is often categorized as discontinuity, multimodality, non-differentiability and non-convexity. Classical mathematical programming-based methods for optimization might be inappropriate or unrealizable in drawing optimal operation rules for dam and reservoir operation. During the last two decades, new optimization methods-based on nature-inspired meta-heuristic algorithms (MHAs) have motivated hydrologists to investigate MHAs as better alternative optimization tools for identifying the optimal dam and reservoir operation rules. To solve the dam and reservoir-optimization applications better, this review presents the past, present, and prospective research directions using MHAs. The problem of dam and reservoir optimization requires a fundamental shift of focus towards enhancing not only the problem formulation and decomposition but also the computational efficiency of MHAs.

INDEX TERMS Meta-heuristic algorithm, reservoir operation, optimization, water resources management.

ACRONYMS

ACO	Ant Colony Optimization
BA	Bat Algorithm
BBO	Biogeography-Based Optimization
CSO	Cat Swarm Optimization
CA	Cellular Automata
FA	Firefly Algorithm
GA	Genetic Algorithm
HBMO	HoneyBees Mating Optimization
MHA	Meta-heuristics algorithm
MSA	Moth Search Algorithm
PSO	Particle Swarm Optimization
SSO	Shark Smell Optimization
SA	Simulated Annealing
WCA	Water Cycle Algorithm
WSA	Wolf Search Algorithm

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I. INTRODUCTION

In the past 20 years, many researchers applied various nature-inspired MHAs to different classes of dam and reservoir water systems. (e.g., single reservoir, single-purpose; single reservoir, multipurpose; or multi-reservoir, multipurpose). The downside to linear programming (LP), for example, lies in its linear form rigidity as a prerequisite to perform well in an application. Linear programming, where a high

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nonlinear function is present, imposes a drawback in the performance rate in providing the optimum and computational time globally. Using nonlinear programming methods that are more advanced, they can overcome these limitations of LP. In the case of dynamic programming (DP), it has been used successfully in solving a variety of optimization problems. However, it still faces the problem commonly known as the curse of dimensionality [1]. When interacting with the increase in the number of state variables, this significant concern emerges as it restricts its implementation to deal with a separable optimization problem. For instance, multiple reservoir system operations might not be able to utilize the DP approach as well as in the case of a single reservoir. Because of the categorization of the reservoir storage portion as state variables, the number of reservoirs to be managed is strictly limited. Thus, it motivates many researchers to create novel approaches to deal with complicated issues to replace conventional methods. These approaches can develop the problems more realistically in comparison to traditional methods [2], [3]. There is no general algorithm for solving the optimization of the reservoir operation as proved in the no free lunch theorem, according to Reference [4].

Although previous and current studies have demonstrated that a particular algorithm could outperform others for a certain case study using evaluation performance indices, our understanding of the reasons behind such success is limited. Therefore, to step further in this area of research, it is necessary to understand the interrelationship between the reservoir water system's features of the case study being optimized, the searching mathematical procedure of the optimization algorithm, and the performance of the algorithm. With this understanding, a better conceptual understanding of the reasons behind a particular algorithm with a certain searching procedure performing worse or better for a particular case study under conditions could be made possible, instead of directly identifying and comparing the performance indices on specific case studies. Furthermore, this insightful assessment could motivate hydrologists to go beyond only knowing the performance indices of algorithm or case study to attain the near-full understanding that might be more general to be applicable for betterment selection of the compatibility between the optimization algorithm(s) for a certain case study. In the meanwhile, such reservoir systems need a further adaptation of the algorithm's mathematical technique and the need for them to be combined or hybridized with other MHAs to make such a special reservoir water system [5]–[7].

The structure of the paper is basically presented as follows. Section 2 introduces the main mathematical procedure for drawing the optimal operation for dams and reservoirs as the optimization problem. Section 3 discusses two main elements: 1) the working principle of the algorithms in reservoir optimization and 2) how certain aspects of the standard algorithms have been improved through a hybridization approach or adding/modifying the mathematical procedure for the internal operators. Section 4 provides an insight into how these algorithms play a role in handling problems in this field. Section 5 draws the recommendations for future research and conclusion.

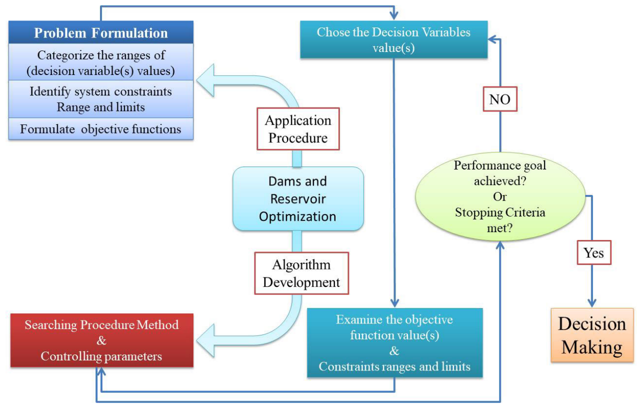

FIGURE 1. Steps in optimization procedure for dams and reservoirs operation.

II. UNDERSTANDING DAM AND RESERVOIR OPERATION: MATHEMATICAL FORMULATION AND OPTIMIZATION

This section provides a general guideline procedure for the dam and reservoir system and optimization problem formulation. The following steps are the most common procedure in the optimization process when classical optimization methods or MHAs are applied, as shown in Fig. 1:

1. Problem formulation (i.e., identification and definitions of the decision variables and formulation of the objective function and system constraints' limits and ranges).

2. Categorization of the ranges of the decision variable values.

3. Examination of the objective function and the constraint limits for the chosen decision variable values.

4. Selection of a set of decision variable values (among the updated set) according to assessment feedback from the evaluation process utilizing the search method.

5. A repeat of steps 3 and 4 until the performance goal is achieved or reaches the stopping criterion.

6. Storage of the optimal selection set of the optimal decision variables' solutions into an appropriate decision-making memory process.

Concerning the above stages, the distinct difference between algorithms is during the step 3 procedure. In this step, the searching procedure of the algorithm varies from one another. Generally, MHAs have a few advantages over the classical optimization-based mathematical programming methods [8]–[12] It motivates hydrologists to utilize and adapt the MHAs to dam and reservoir operation applications.

Literally, values for the objective function, which are bounded by some constraints, are measured, and checked using a simulation technique for the reservoir. The simulation procedure could be formulated throughout a certain nonlinear mathematical procedure or a predefined simulation model approach. In general, it is free of mathematical errors and more straightforward in adding/integrating the optimization

TABLE 1. References with corresponding algorithm in reservoir operation optimization.

Algorithm	Author	Area of Application	Objective Function	Decision Variables	Assumption	Penalty Function	Important Factor	Comparison
GA	Reference [74]	Multiple reservoir	Multi-purpose	Release	No evaporation loss is considered, and release rule is assumed to be connected piece-wise linear functions		Crossover probability and mutation probability	
	Reference [26]	Karangkates and the Wonorejo and Beng reservoirs	Single- and multi-purpose	release	No linearity is used	Apply on irrigation demand only	Mutation probability	With DDDP
	Reference [27]	Fei-Tsui Reservoir	Multi-purpose	release			Blend crossover (α = 0.5) and macro evolutionary selection	No comparison (only between the internal parameters)
	Reference [75]	Pagladia reservoir	Multi-purpose	release	release rule is assumed to be connected piece-wise linear functions		Crossover probability and mutation probability	With SDP
	Reference [76]	Bhadra reservoir system	Multi-purpose	Release			crossover probability (pc) of 0.9 and a variable-wise mutation probability (pm) of 0.03	No comparison is made
	Reference [77]	multiple reservoir system at Mae Klong River Basin	Single-purpose	release		When final state of reservoir is less than target desired state	modified ranking selection approach, probability of crossover of 0.7, and a probability of mutation of 0.04	With standard GA
HBMO	Reference [78]	Dez single reservoir	Single-purpose	release		No penalty function used	Simulated annealing searching process and four arbitrary different cross-over operators	With LP (LINGO 8.0)
	Reference [35]	Dez single reservoir	Single-purpose	release	release is considered as linear function	No penalty function used (final storages can be set up as fixed values equal to the target final storages)	Simulated annealing searching process and four arbitrary different cross-over operators	With LP (LINGO 8.0)
	Reference [36]	Discrete and continuous 4RP and continuous 10RP	Single- and multi-purpose	Release	No evaporation is considered	When final state of reservoir is less than target desired state	Two mutation operators and four arbitrary different cross-over operators	better than GA
	Reference [37]	4 reservoir problem	Multi-purpose	Release	No evaporation is considered	No penalty function used (final storages can be set up as fixed values equal to the target final storages)	Proportionate selection and roulette wheel and dependency on the previous population	better than elitist genetic algorithm (EGA) and the standard HBMO
PSO	Reference [39]	single reservoir	Multi-purpose	Release	starting volume to be equal to the active volume	No penalty function		No comparison is made
	Reference [79]	Dez reservoir	Multi-purpose	Release		No penalty function	C1=1.5; C2 = 0.5; alpha = 0.9; w = 1.0; N = 50; NMax = 10; probability of mutation = 0.01	better than PSO, GA and ACOr
	Reference [40]	Single reservoir	Multi-purpose	Release	release is considered as linear function	No penalty function	Population size (50); velocity parameter (0.2)	With GA
	Reference [80]	Dez reservoir	Multi-purpose	Release	No evaporation is considered	Penalty function for violates storage constraints		unconstrained PSO and a genetic algorithm
ACO	Reference [13]	Hirakud reservoir	Multi-purpose	storage	Reservoir volume is classified into discrete domain	No Penalty function for violates storage constraints	Pheromone updating rules (global updating, p=0.1; local updating, q0==.0) and Pheromone trail (alpha=1; beta=4);	better than GA for long term
	Reference [81]	Dez reservoir	Single-purpose	storage	No evaporation is considered	No Penalty function for violates storage constraints since storage is taken as decision variable	Incorporate partial and fully constrained into ACO mechanism	better than unconstrained ACO
	Reference [14]	Dez reservoir	Multi-purpose	release	No evaporation is considered	No penalty function for violates storage constraints	multi-colony ant algorithm and Pareto-front approach	With GA
	Reference [82]	Dez reservoir	Single-purpose	release		No penalty function for violates storage constraints	Pheromone evaporation rate (ξ=1.35) and Locality of the search process (q=0.19)	with real coded GA
	Reference [16]	Dez reservoir	Single-purpose	release	No evaporation is considered	Penalty function for violates storage constraints	adaptation operator and explorer ant (mutation operators)	better than standard ACO
	Reference [83]	Cascade reservoirs of	Single-	storage	No evaporation is	No penalty function	local chaos	better than standard

TABLE 1. ***(Continued.)*** **References with corresponding algorithm in reservoir operation optimization.**

		Dadu River	purpose		considered	for violates storage constraints	optimization of ant colony	ACO
BA	Reference [17]	Karoun-4 reservoir in Iran, 4 reservoirs problem	Single- and multi-purpose	Release		Penalty function for violates storage constraints	Frequency (f); loudness (A)	better than LP, NLP and GA
FA	Reference [24]	1) erf Reservoir with Irrigation Purpose…2) Karun-4 Reservoir with Hydropower Production Purpose	Single- and multi-purpose	release		Penalty function for violates storage constraints	attractiveness of a firefly is determined by its brightness (Beta=1; alpha=0.005; gamma=5)	better than GA
CA	Reference [84]	Multi reservoirs	Single-purpose	Storage	No evaporation is considered		cell, cell neighborhood, cell state (decision variable) and update rule	better than PSO and GA in large scale problem

procedure to a predefined simulation model approach. If the MHAs could be easily added/integrated using the predefined simulation model approach, utilizing MHAs is advantageous. In this case, MHAs could be capable of addressing dam and reservoir cases that encounter difficult mathematical features without the need for simplifying the problem of the simulation procedure as required when most of the classical optimization methods are used and are unable to consider the nonlinearities.

The release policy for any month m is determined by conducting an online multidimensional search at the beginning of the month, with the previous month's inflow and the ending storage being known. The optimization of the objective function can be characterized by

$$\max\ or\ min \sum_{Tmin}^{Tmax} P\left(q_t \mid q_{t-1}\right).B\left(S_t, R_t\right) + V\left(S_{t+1}\right), \quad (1)$$

where R_t is a vector of releases during period t, T is the length of the operational time horizon, S_t is the vector of storage in each reservoir at the beginning of period t, $B(S_t, R_t)$ is the objective to be maximized or minimized (for E.g., minimizing total hydropower cost or maximizing irrigation demand), P is the conditional probability for inflow, q_t in any month to be connected to the outflow in the preceding month, q_{t-1}. V is the ending storage volume. Storages, releases, and inflows are related by several continuity relationships. The basic physical relationship of a reservoir operation study is the continuity equation:

$$S_{t+1} = S_t + I_t - R_t - E_t - O_t, \quad (2)$$

where S_{t+1} is the final storage during the month, I_t is inflow during month t, E_t is evaporation loss in the reservoir during time t, and O_t is overflow or surplus from the reservoir during time t.

Reservoir constraints

- Release constraints

The release from the reservoir in a month should be less than or equal to an estimated or target release. The release constraint is expressed as

$$Rmin_t \leq R \leq Rmax_t. \quad (3)$$

- Reservoir storage constraints

The reservoir storage during a given month should neither be more than the maximum permissible storage capacity nor less than the minimum storage capacity. This constraint is mathematically described as

$$Smin_t \leq S_t \leq Smax_t, \quad (4)$$

where $Smin_t$ is the minimum storage capacity of the reservoir in million cubic meters (Mm^3), and $Smax_t$ is the maximum permissible storage capacity of the reservoir in Mm^3.

- Overflow constraints

The overflow constraints take care of the spills O_t as and when the storage in the reservoir exceeds the maximum capacity of the reservoir. The relevant constraint can be expressed as

$$O_t = S_{t+1} - \text{Smax}, \quad (5)$$

or

$$O_t \geq 0. \quad (6)$$

III. APPLICATION OF THE META-HEURISTIC ALGORITHMS IN RESERVOIR OPTIMIZATION

In this section, several algorithms are presented to show their effectiveness in reservoir operation optimization in comparison with one another using several evaluation metrics and how lacking in certain aspect of the algorithm can be solved either by modifying the algorithm itself or through hybridization with other another algorithm to achieve better performance. The advantages of one algorithm over the other are explored in one aspect of the problem while the other algorithm complements. In this way, better solutions are achieved that are superior to using one. To access the performances of these algorithms, several evaluation metrics were used such as the number of evaluation function, stability, convergence speed, exploitation ability, and exploration ability. To further illustrate the comparison between algorithms, a graphical method is adopted, as shown in figure 2.

TABLE 2. A summary of the application of each algorithm along with its hybridization/modification approaches in the optimization of reservoir operation.

Conventional algorithm	Evaluation metric	Comparison	Case study	Hybridization/modification	Area of improvement	Comparison	Case study
Ant colony optimization algorithm	1)Computation cost	Lower number of evaluation function needed than GA	Hirakud reservoir	Chaos ant colony optimization algorithm	Exploration search	1)Produce higher annual energy production than standard ACO. 2)Reduce the computation time needed	Hirakud reservoir
		Lower number of evaluation function needed than GA and HBMO	Hydropower reservoir system	Addition of two parameters: explorer ants and adaption operator	Exploration search	1)increase the stability. 2)able to reach higher global optimal.	Dez reservoir
Bat algorithm	1)Convergence characteristic 2)stability	a higher convergence speed to global optima and lower variance about global optima than GA	Karun-4 reservoir	BA + Differential algorithm	Exploration search	1)achieve better global optimal than standard BA	Four-reservoir and 10-reservoir problems
Biogeography based optimization	1)Parameter tuning process	Obtain higher objective function with faster convergence rate than GA	Four-reservoir and 10-reservoir problems	Further study	Low diversity in the generated solution – exploration search can be enhanced by introducing operator like reproduction strategy in GA.	Further study	Further study
Cat swarm optimization	1)Stability	Able to search higher global optimal with lower variance than GA	Karun-4 single reservoir	Further study	High computational time – no collaboration of local exploitation and global exploration	Further study	Further study
Cellular automata	1)Computation cost	Lower number of evaluation function than that of PSO, GA and ACO algorithm	Dez reservoir	Automata-harmony search hybrid	Local exploitation search	1)better global optimal 2)lower computational time than GA and PSO	Four-reservoir problem
	2)Convergence characteristic	Yielding better solution with higher convergence speed than GA	Single reservoir with water supply purpose				
Firefly algorithm	1)Convergence characteristic 2)stability	1)Converge to global optimal in a much faster rate than GA. 2)lower variance obtained for FA than GA	1)Aydoghmoush Reservoir Operation 2) Karun-4 Reservoir Operation	Modified firefly algorithm	2)searching process. 3)parameter tuning process	Converges more rapidly than standard FA and yield better solution	Discrete and continuous four-reservoir and continuous 10-reservoir
Honeybees mating optimization	1) computational cost	Lower number of evaluation function needed to reach global optimum than GA	Ten-reservoir problem	1)Enhanced HBMO	1)searching process- based on previous solution instead of randomly generated population	Decrease the number of evaluation function than standard HBMO	Four-reservoir problem
				2)Hybrid HBMO-SA	Local searching ability	Obtain better global optimal than GA and standard HBMO with same number of evaluation function	Dez and Karun reservoir
Particle swarm optimization	1)computational cost	higher computing efficiency than GA, but lower stability	A single reservoir with multi-purposes	EMPSO	Global searching ability- elitist-mutation strategy	Reach better global optimal than standard PSO with lesser number of function evaluations	Bhadra reservoir
Shark smell optimization	1)convergence characteristic 2)stability	1)Higher convergence speed than GA and PSO 2)yielding better global solution.	Four-reservoir problem	Further study		Further study	Further study
Genetic algorithm	None	No comparison work	Tsui-reservoir	1)GA and LP	Computation cost	Reduces the computation run time needed by GA.	Five-reservoir system (hypothetical)
				2)Sequential genetic algorithm	Computation cost	Reduces the computation run time needed by GA and yield better global solution.	Zayandeh-Rud river–reservoir system
				3)Varying chromosome length genetic algorithm (VLGA)	Computation cost	Reduces the computation burden of GA.	15-Khordad Reservoir
				4)Direct search genetic algorithm (DSGA)	stability	Obtain better global optimal with lower variance in the solutions than GA.	Dez reservoir
				5)Hybrid genetic algorithm and chaos	1)Stability 2)Convergence characteristic	1)Increase the population diversity of the GA. 2)Higher convergence speed than GA 3)Better global optimal	Chaishitan reservoir

FIGURE 2. The performance evaluation of algorithms in several case studies.

FIGURE 2. *(Continued.)* **The performance evaluation of algorithms in several case studies.**

A. ANT COLONY OPTIMIZATION (ACO)

In this study of Reference [13], an ACO technique was applied to optimize an operating rule for the multipurpose reservoir system. The case study of the Hirakud reservoir was carried out using ACO in comparison with GA. By conveying information to the next storage class from the previous storage, it can result in a better solution. The transmission of information is based on probabilistic transition rules, which improve the solution in a short amount of time at every interval. This is substantially useful for obtaining a solution, especially in long-term planning. Results revealed that ACO obtained more accurate solutions than GA can with a smaller number of function evaluations, especially in a long-term horizon operation where the number of decision variables and constraints increases in the problem domain. In this case, the average computational time requirements for ACO and GA are 32 min 28 sec and 80 min 54 sec to reach global optimum, respectively. Likewise, Reference [14] successfully applied the max-min ant system to solve constraint hydropower reservoir operation. When this algorithm is compared with Honeybees Mating Optimization (HBMO) and GA, the ACO has the least number of function evaluations due to low computational complexity, regardless of the number of decision variables. It is due to having high efficiency in the search space by virtue of a randomly generated initial population of ant solutions over the whole feasible region. It helps in maintaining a low computation burden, which corresponds to a low evaluation function.

On the other hands, due to the lack of dynamic adjustments between global searches and local optimization, it is difficult to maintain high diversity and overcome local optimum problems for ACO. Like in PSO, no operators can aid in promoting sudden changes in the set of solutions. Due to an inadequate global search, there is an increase in iteration times, which quickly reduces ant colony diversity, trapping the ant in the local optimum.

For this reason, Reference [15] presented a chaos ant colony optimization (CACO) algorithm to optimize the reservoir operation problem with hydropower purposes. The proposed algorithm was much superior compared to the classical ACO with the improvement in the stagnation; thus, it avoided getting trapped in local optima. Given half of the computation time needed, CACO obtained higher annual energy production (8582.7 million kw·h) than standard ACO (8567.8 million kw·h). Following the same trend, Reference [16] presented a modified ACO algorithm to optimize the hydropower reservoir operation problem. The addition of operators such as explorer ants and adaption operators significantly improved the basic ACO algorithm effectiveness; that is, there were chances of generating diverse solutions even in local trapped conditions regardless of the amount of pheromone value. The proposed method outperformed the original ACOR in achieving a better global solution and lower variance over the best solution due to its stronger global searching ability.

B. BAT ALGORITHM (BA)

BA practices fine-tuning of frequency like that in the features used in PSO and HA. Frequency tuning in BA behaves as a mutation by varying the solutions locally. When optimality is approaching, the range of frequencies can be decreased, switch from exploration to exploitation. This provides an additional benefit of BA as an optimization method comparable to another swarm intelligence algorithm.

Reference [17] employed the BA to optimize a system of reservoir operation. The proposed algorithm was applied on a real case Karoun-4 reservoir operation and a benchmark of four-reservoir problems. Results showed that the BA algorithm outperformed GA by having a higher convergence speed to global optima and lower variance about global optima due to its BA. This is because BA can perform automatic zooming, which allows it to zoom into a region with a high potential to locate good solutions.

However, standard BA seems to be relatively poor in exploration ability despite its good performance in exploitation due to the lack of crossover operation (unlike GA and DE). Consequently, BA maintains the same members of the whole population through the search procedure. There is a need to improve the control strategy to switch between exploration and exploitation at the right moment.

Reference [18] presented an improved BA on optimization of a multi-reservoir operation. The proposed method exploited the hybridization of BA with the DE algorithm. It has been tested on two benchmark multi-reservoir problems for the hydropower generation purpose. The proposed method introduced an additional six mutation strategies to standard BA for achieving better global optimal. The result obtained was satisfactory and compared well with that of the LP method used to solve these problems.

C. BIOGEOGRAPHY-BASED OPTIMIZATION (BBO)

Another evolutionary algorithm is known as BBO which optimizes a function by stochastically and iteratively improving candidate solutions regarding a given measure of quality. To show the performance of BBO in a water-related field, Reference [19] simulated the water release from a powerhouse using a BBO algorithm to be applied to two reservoir operation problems. The proposed algorithm could supply different demands better than GA due to the former the algorithm is better in terms of the parameter-tuning procedure. Since minor changes in parameters do not have much effect on the BBO performance, the optimization process turns into a simpler mechanism that relies on a simpler algorithmic structure.

Nonetheless, in the mutation of BBO, there is a lack of exploration in the search process. This is because the BBO mechanism involves an exact procedure as migration that induces a random process in the mutation. Owing to the lack of corresponding exploration to balance its exploitation, BBO is easily trapped in the local optimum. Moreover, the migration process in BBO manages the solution directly without using any reproduction strategy such as GA. Thus, the low diversity of the algorithm is mainly due to the creation of similar habitats (solutions), leading to slow convergence and the local optimum. Therefore, the aspect of exploration in BBO can be the focus to improve its performance.

D. CAT SWARM OPTIMIZATION ALGORITHM (CSO)

CSO has good local and global search abilities. It avoids the prolix limits, i.e., the maximum velocities, in all iterations, and it could discover a better solution than PSO-type algorithms. This enhances the possibility for it to reach the global optimal solution. Reference [20] employed the cat algorithm on the application of a single-reservoir optimization (Karun-4 single reservoir) and a benchmark multi-reservoir operation problem (four-reservoir problems). The proposed method showed promising results as another alternative optimization method when compared to GA. Having both the good local and global search, CSO obtained results with a lower variance, approximately twice as low as GA.

On the other hand, there is still room for improvement. For instance, the difficulty of CSO to handle complex optimization problems with many local extreme values. This is because there is no collaboration in the local exploitation and global exploration searches when carried out. They perform independently, resulting in higher computation time to reach the global optimum.

E. CELLULAR AUTOMATA (CA)

Several studies used CA in the application of reservoir operation optimization. Reference [21] applied CA on the optimization of a reservoir operation. The proposed method was applied on a Dez reservoir in Iran for three different periods. CA is well competent in solving the complex problem as it does not affect the number of iterations. One reason is that each cell can comply with complex systems behavior using a simple rule. This is important as it does not require any breakdown of the whole system into sub-components. The algorithms, PSO, GA, and ACO, were used to validate the performance of CA. The proposed method could provide a better solution compared to that of the mentioned methods. Results have shown that in operating long-term planning rules, CA only requires a low number of function evaluations as compared to the high number of function evaluations by the GA, PSO, and ACO algorithms. Another CA application was also carried out by Reference [22] on chance-constraint water-supply reservoir operation problem. The proposed model was tested out on the Dez reservoir operation to optimize the water supply for three different time periods. CA outperformed GA by yielding a better solution with a higher convergence speed in optimizing the water supply under the constraint condition. This shows that CA could perform efficiently even in the long-term planning of reservoir operation.

Another hybrid algorithm called the cellular automata-harmony search approach was demonstrated by Reference [23] on a four-reservoir system for hydropower optimization of different time periods. A standard CA has difficulty in governing the rules for local updates. An extensive effort is needed for the success of local rule development. This might formulate an improper rule, which leads to system failure. It is sometimes not easy to obtain perfect rules governing the evolution of the system. There is a lack of comprehensive understanding in the CA model, whether the system dynamicity has been considered thoroughly or needs a superficial dynamics component. Therefore, by incorporating HS into CA, it improved the local search of decomposed sub-problems whose solutions would then pass to CA iteratively. The proposed method showed superiority over other optimization methods such as GA, PSO, and CA–NLP in terms of their efficacy to locate the near-local optimal solution. The results showed that CA–HS performed better than the mentioned methods.

F. FIREFLY ALGORITHM (FA)

Unlike PSO, FA does not depend on either the historical best or the global best. This helps to reduce the chance to trap the potential solutions in premature convergence. This is because FA does not need to be concerned about the initialization of velocity, especially at high velocities that are relatively unstable to control. With this FA ability, Reference [24] applied FA to the optimization of complex multiple reservoir operations with multiple purposes: hydropower and irrigation purposes. As previously described, FA was indeed able to converge to the global optimal at a much faster rate than GA. Besides, the local attraction is more robust than the long-distance attraction. This enables the division of multiple subgroups in the population, leading to higher chances to reach a global solution as each generated group has the potential to do so. This gives the FA more flexibility in searching the problem spaces effectively, especially in multimodal objectives.

On top of that, Reference [25] further explored the application of FA in the optimization of multi-reservoir discrete variables operation and continuous states. They developed an improved version of FA and tested out on three benchmark reservoir operation problems. These problems were to maximize the total benefits from hydropower generation. This modified version of ACO highlighted the downside of standard ACO, where its performance depends highly on the parameters' values that require extensive turning of the parameters. One of the adjustments made in this study was that the parameters setting of the standard FA. MFA can set the parameters more readily and properly than FA. The results obtained were compared with other alternatives, such as the BA, the BBO algorithm, LP, differential dynamic programming (DDP), discrete DDP (DDDP), the multi colony ant algorithm, the GA, the HBMO algorithm and the WCA, and fund FA to be capable of providing a better global optimal solution to the test problems.

G. GENETIC ALGORITHM (GA)

Applications of GA in reservoir optimization are extensive and are usually used as a benchmark for testing other algorithm effectiveness. Reference [26] conducted a study to investigate the potential of GA in real multi reservoir case. This case study was carried out in a continuous domain without discretization. When the complexity increases, the amount of discretization work intensifies, resulting in more computation time. Thus, without discretization, results showed a significant improvement in computation time to converge the searching process and quality of solution for GA compared to NLP.

Reference [27] showed that to decide the optimum operating rule in a reservoir environment, the combination of a simulation model and GA works better. The proposed model tested on the multipurpose Fei–Tsui reservoir, namely for irrigation, hydropower, and water supply. The objective was to meet different demands by minimizing the deficit of water shortage. The proposed method can satisfy the objective function, demonstrating its superiority in managing complex reservoir operations.

Despite that, GA has low computation efficiency and slow optimization speed, especially when dealing with large and complex problems. Thus, for a large number of chromosomes, the chances that they can trap the solution in the local optimum are very high. Apart from that, it needed a high amount of computation cost too. Since GA needs a high number of function evaluations for a large-scale optimization problem, it increases the time needed to compute the global optima. Moreover, the lack of the capability to maintain diversity in GA's population of the solution has led to a premature local optimum. In GA, the population has no memory of its previous state; this results in an independent event for each generation. Therefore GA, in general, can have difficulty obeying equality constraints.

Reference [28] defined a different evolutionary method with a combination of the GA and LP for optimization of hydropower reservoir operation. In this proposed method, in the beginning, GA optimized a set of complicating variables, then followed up by LP. The hybrid method could overcome the problem of the long computation time needed to reach an optimal solution. Reference [29] solved the application of the reservoir operation problem by developing an improved version of the simple GA, called the sequential genetic algorithm (SGA). The proposed method showed superiority over the conventional GA by having a lower computational run time. The dynamic update of the length of a chromosome in the SGA is the main contributor to the significant reduction in computation run time. Reference [30] optimized the reservoir operation rules by developing a varying chromosome length GA (VLGA). The VLGA has modified the GA by improving the initial solution by increasing the chromosome length sequentially. They applied the proposed method on the 15-Khordad Reservoir in Iran. A modified version of GA, the direct search (DSGA) approach, proposed by Reference [31], was used to optimize the multipurpose reservoir operation, which had higher efficiency than nonlinear programming and the standard GA. NLP initiates the search from a random single point that needs a good initial solution to converge to a global optimum, while GA can search a population of initial solutions in which all these solutions are evaluated in the search space. Reference [32] employed an application of a chaos GA on the reservoir operation problem so that the new method could possess higher abilities than the simple GA. The annealing chaotic mutation operation as a replacement to the standard mutation operator improves the initialization of the solution, thus avoiding the chances of being trapped in the local optimum. The hybridization method obtained a better solution and converged to the global optimum faster than standard GA.

H. HONEYBEES MATING OPTIMIZATION (HBMO)

HBMO does not impose much difficulty in dealing with the problem of discrete or continuous decision variables. Besides, HBMO requires less computational effort in tackling different problems with different characteristics due to the utilization of several operators. Reference [33] employed HBMO on the optimization of a single-reservoir operation. He demonstrated that the proposed algorithm could compete well with other heuristic methods, such as GA, in optimizing reservoir operation with a discrete search space. Reference [34] also presented an application of the HBMO algorithm on reservoir operation optimization. The proposed algorithm produced results, showing that it was not limited to discrete decision variables. Another application of the HBMO algorithm on reservoir operation optimization, performed by Reference [35], was used to compute the optimal solution for irrigation and hydropower purposes. The performance of HBMO was computationally more efficient compared to that of NLP due to the presence of several operators. Moreover, Reference [36] demonstrated that HBMO requires less computational effort than an evolutional algorithm such as GA on reservoir-optimization problems through a sensitivity analysis.

Despite these advantages, the computational work imposed during the modeling process of the honeybee's mating ritual in HBMO is high. This is due to a large number of evaluations of the objective function required by taking into account the unsuccessful drones throughout the process. Therefore, it decreases the search ability at the local level. Besides, the queen should choose from the existing population instead of the entire decision space. Thus, there is no direct link between the current solutions with the previously generated solution in the iteration process.

Reference [37] presented a newly enhanced HBMO and evaluated it by solving several mathematical benchmark problems and a multi-reservoir problem. In terms of computation efficiency and convergence of global optimal, ENHBMO outperformed the other mentioned methods. The difference between the modified proposed method and the standard method is in the mating process. Instead of performing a random search on the entire decision space, the ENHBMO generates a new solution based on a previously found solution. Reference [38] proposed an improved version of the HBMO algorithm in solving the optimization of multi-reservoir system's operation. The modified method is a combination of two different algorithms, namely SA and the queen GA. This hybrid method improves the local searching ability of HMBO. They tested the proposed method on a benchmark single-reservoir problem in comparison with real-coded GA and original HBSM. The results showed that the proposed method could obtain a better solution than the other comparative algorithms.

I. PARTICLE SWARM OPTIMIZATION (PSO)

PSO has lower computational work than GA due to the random order of the fitness solution in the searching process that reduces computational time, especially for large population sizes. Another contribution to the computational work is the simple arithmetic operation of the velocity update parameter of PSO. PSO is also simpler than GA because of its ability to communicate globally among the particles without a need for mutation or crossover operators. Besides, PSO requires much fewer parameters to tune; this speeds up the convergence rate and can attain good global searching ability. Moreover, PSO is less likely to fall into the local minima problem since it does not rely on the initial population. PSO uses a population search instead of point searches to identify a wider promising region in the whole designated space at the initial stage. Besides, the randomness in the initial set of the solution has given many credits to derivative-free algorithms as they do not rely on initial guesses.

Reference [39] presented the Particle Swarm Algorithm (PSO) for a problem with multi objective functions. The results showed that the PSO has a faster convergence speed than a GA. Reference [40] tested out the performance of GA and PSO on reservoir operation with multipurpose functions. Since both algorithms have different features, their performances on reservoir operation optimization are varied. If one preference is on the stability of the solution obtained, GA is a better choice, whereas, for the computational efficiency and accuracy to compute a globally optimal solution, PSO can satisfy the condition better.

Nevertheless, PSO is weak in exploration; this leads to its convergence to local optima. This is because there is no operator that can stimulate abrupt changes that can enhance the exploration in the set of potential solutions; consequently, the solutions are easily trapped in local minima. Another major factor to the convergence to local optima is the strong connection among the particle members.

Reference [41] applied the proposed EMPSO over the standard PSO and GA to optimize the multipurpose single-reservoir (Bhadra) system in India. The proposed weighted approach can alter the velocity of the particle when handling multiple objectives. This allowed local search to be supervised in parallel with the global search, thus keeping the balancing point between them. Through this implementation of work, the proposed algorithm could easily find the global optimum. The proposed EMPSO implemented a new strategy, the elitist-mutation strategy, which replaces the worst solutions with the best solution during the mutation process. The results showed that EMPSO outperformed the standard PSO and GA by increasing exploration in the search space while maintaining the population's diversity, resulting in a better solution with higher computation efficiency. Reference [42] applied the EM–MOPSO algorithm to optimize the multipurpose reservoir operation problem. The proposed method surpassed the performance of NSGA-II in providing a wider range of feasible solutions with a higher convergence rate.

J. SHARK SMELL OPTIMIZATION ALGORITHM (SSO)

One of the advantages is the high exploration and exploitation ability of the shark algorithm. It is due to momentum-incorporated gradient-based forward movement and a rotational movement-based local search.

An application of the SSO for optimizing reservoir operation, presented by Reference [43], was adopted on two hypothetical reservoir operation problems. For comparison purposes, two algorithms, PSO and GA, was used to optimize the same problems. The results obtained demonstrated the SSO's superiority over the other methods in locating a better global solution at a higher convergence speed rate due to its strong exploration and exploitation process.

However, SSO's search performance depends on the randomness in the initial population of solutions. Consequently, it might have the possibility for solutions to be trapped in the local optima during the searching process. This drawback is also possibly due to gradient behavior, which is the movement of solutions along with the objective function, even though it speeds up the convergence rate. Another probable disadvantage of gradient-based methods is that they are weak in handling problems such as objective functions with noise, inaccurate gradients, and an irregular shape of problem layout. In addition, gradient-based methods require tremendous computational work; for example, each time the code is altered, the adjoint computations may need to be revised.

K. SIMULATED ANNEALING (SA)

SA is flexible and able to approach global optimality. Reference [44] verified the applicability of SA on a 10-reservoir problem in comparison with constraint differential dynamic programming and a hybrid of GA and linear programming (LP). The proposed SA outperformed the above-mentioned techniques. He then developed a model using SA as the optimization method on a multi-reservoir system in Thailand to minimize irrigation deficits. The result obtained by SA has shown that SA is more efficient than GA in providing a better solution and had high computational efficiency. The performance of SA in the reservoir was quite favorable and showed a promising sign to address large and complex problems. Reference [45] applied SA on a single reservoir on the Havrias River for optimal irrigation reservoir operation. The developed model consists of two stages: SA initiates the search for the optimal global solution, initially, then refined by the stochastic gradient descent (SGD) algorithm. The results showed that this approach managed to compute proper water release to satisfy the irrigation requirement and total farm income.

In addition, SA can improve its computational efficiency through hybridization with GA. As reported by Reference [46], a hybrid GA–SA algorithm was used to optimize the operation rule based on fuzzy programming of the Shihmen Reservoir was used in Taiwan. The proposed method outperformed the existing reservoir operating in terms of short and long-term reservoir operation performance. The GA algorithm strengthened the global search ability, while the SA algorithm improved the local search ability in the proposed method. Additionally, the proposed method increased the chances to converge to the global optimum, and at the same time, reduced the computational time.

L. OTHER META-HEURISTIC ALGORITHMS

Recently, there are a few algorithms which are relatively new to the water related field have been used to optimize the reservoir operation. One of these algorithms is the water cycle algorithm (WCA). Reference [47] applied the WCA to optimize a multi-reservoir system in Iran. The proposed method showed promising results in solving the reservoir operation problem with a higher convergence speed than GA in reaching the global optimum. Since there is no direct link between the current solutions with the previously generated solution in the iteration process, it reflects a weak connection between the generated solutions (streams) with their best solution, followed by the second and third best solution. Therefore, improving the comparison of the updated solution (streams/rivers) with their existing conditions can be the future work.

Another recently implemented algorithm in reservoir optimization was the moth search algorithm (MSA). In this study of reference [48], they used an improved and standard version of MSA to optimize the reservoir operation. They compared with GA, a commonly used algorithm in reservoir operations. One of the two main working principles is the utilization of the quazi-opposite method to improve the exploration of the standard algorithm. The second working principle is the adoption of a chaos hypothesis to improve the diversity of the search process. The improvement in the global exploration search in MSA has a significant impact, especially in terms of the stability in obtaining global optimum. Results showed that improved MSA could yield higher objective function and lower standard deviation among the mentioned algorithms.

In the same way, another algorithm that was applied in this reservoir optimization was the wolf search gray algorithm (WSA) by Reference [49]. They tested the efficiency of the proposed algorithm on a Karun-4 reservoir system. Three algorithms, namely, GA, BBO, and WCO, were used to compare with the proposed algorithm. Results revealed that the strong exploration search of WSA was sufficient for the proposed algorithm to reach the global optimal efficiently without getting trapped in the local optimal. The proposed algorithm can reach 99.91% of the global optimum, while the other can only reach up to 79, 96, 98, and 99.90% of the global optimum, respectively. It is also noteworthy that WCA and WSA have only a slight difference in the result obtained due to their search process of having a strong global characteristic.

IV. CHALLENGES IN THE RESERVOIR OPTIMIZATION

As shown in section III, each algorithm has its own merit and has been successfully applied to reservoir optimization. These algorithms can be further classified into several categories in accordance with the way they are used to optimize the reservoir operation. It is worth noting that the groupings here are not distinctive as some algorithms can be characterized into different categories at the same time. Generally, classifications rely to a great extent upon what the focus or emphasis and the viewpoint might be. Thus, this section intends to provide insight into how these algorithms play a role in handling problems in this field.

A. COMPLEXITY

Real-life engineering optimization problems often deal with problems that involve the regulation of decisions made. This issue usually determines the number of decisions in accordance with the problem faced [50]. For short-term real-life reservoir operation, comprises a time step of hours, days, or at most a week. Operating a short-term reservoir requires tremendous work as it involves objectives and constraints that are contradictory to one another, in which decisions must be taken in real-time [51]. Rapid changes such as floods and droughts are short episodes of system operation. This helps in long-term optimization that is intended to improve the operation of the system on average over a representative range of wet, dry, and normal conditions [52].

Besides, reservoir operations in real-life cases are complex and have high time complexity. In fact, the computational time is also proportional to the cost needed. Practically, minimizing the computing time and cost can have a drastic effect on any optimization system [53]. Therefore, many have brought in nature-inspired algorithms with stochastic search abilities; by randomly transferring solutions to solutions in a progressive manner toward a better solution. Although they are competent in the optimization process, they still need a large number of function evaluations to reach the global optimum. It has a major contribution to the intensive computational approach of simulation optimization [54], [55].

In view of the importance of these complexities, algorithms such as ACO, PSO, and CA that can reduce the number of function evaluations would contribute greatly to particularly real-time optimization.

An ACO algorithm analyses the problem slightly more complex that of than classical evolutionary and genetic algorithms. Instead of formulating the subsequent generation population using the Markov chain principle, ACO uses pheromone traces, which evaporate slowly, resulting in a longer-term effect. By doing so, the previous iterations solution has a significance impact on the next iteration's state.

Similarly, PSO contains fewer parameters, unlike other evolutionary algorithms (e.g., no crossover, mutation, and selection). Due to this, its searching process depends solely on the iteration procedure, which decreases the calculation burden.

The computing aspect of cellular automation is essential not only for functional implementation but also for fundamental study. It is possible to view cellular automata as a computer system that processes the information encrypted in their structure. Their fundamental construction is quite straightforward and yet their overall performance is highly complicated and can mimic the phenomena that have been observed in many physical and other systems.

In most real-world applications, the dynamics of the system are continuously changing. The developed meta-heuristic techniques should be substantially able to adapt themselves to these changes and to generate adequate responses and reactions to them. In other words, they could be applied in online (real-time) or offline (simulation) learning. Using RL in online learning from scratch (without any prior knowledge) could be very expensive and troublesome; therefore, it could be initially used as offline learning during which a basic understanding of the environment is achieved. This knowledge could be eventually useful in starting online learning.

B. PARAMETER TUNING PROCESS

Most optimization problems found in the real world cannot be solved using analytical methods. Most metaheuristics have their control parameters to modify how the heuristics perform their search. This is necessary because different problems may require different search strategies to be solved effectively. The control parameters allow for the optimization algorithm to be adapted to the problem at hand [56]. It is, however, difficult to predict what the optimal control parameters are for any given problem. The problem of finding these optimal control parameter values is known as parameter tuning. The significance of the parameter tuning process would be great, especially in multi-reservoir cases. Reservoir optimization is a problem-specific type that varies from case to case. The conditions faced in each case might not be the same as those in another; thus, it is time-consuming to find a new set of parameters for the specific problem.

PSO implementation is simpler and easier than GA as it deals with few parameters (like position and velocity only). In contrast to GA, PSO does not use any genetic kind of operator, i.e., crossover and mutation. Particles update themselves using the internal velocity, and they also have a memory that is important to the algorithm. Apart from that, an algorithm like BBO is slightly different than PSO in terms of segregation in which clumping the solutions together does not exist (without following the global best). The relatively slow transfer rate of information avoids the formation of comparable particles that can clump the solutions together. The presence of redundant solution can decrease the population diversity.

In HBMO, four arbitrary different crossover operators are employed. The differences between these four operator types include the different strategies in generating the new solutions based on the previous solutions. For instance, in the first and second types, a one-point cut crossover is applied, but in each one, the queen's genes are placed in the right part and left part of the new solution. In the last two types, a two-point cut crossover occurs, but the queen's genes are placed in the middle and sides of the new solution. Moreover, HBMO does not require parameters' sensitivity analysis. It is due to independence from its related parameters, thus reducing the tuning process of the parameters.

To sum up, the operation of a reservoir involves a complex decision that should be made, integrating many variables and objectives and significant risk [57]–[59]. Inaccurate tuning of the parameter-specific algorithm on cases such as reservoir optimization only intensifies the computation effort or traps into the local optimal [60]. With respect to the points mentioned above, algorithms such as WCA, BBO, PSO, and HBMO can be beneficial in this situation. Since they often share some parameters, including the number of individual in the population or random factors to introduce diversity, they are less likely susceptible to failure in the parameter tuning process. Thus, if the number of variables and parameters in this model makes the problem intractable and too large, existing software or hardware might not be able to find an optimal solution using conventional optimization methods in a reasonable time.

C. EXPLORATION AND EXPLOITATION

A meta-heuristic algorithm performs two major searches in the problem space: a global search is performed to obtain multiple solutions and local searches in the neighborhoods of the existing solutions [61], [62]. This allows improvement to be made in the obtained solutions. Finding a proper balance between exploitation and exploration makes solving the problems much more difficult when a certain meta-heuristic algorithm is used [63], [64]. The difficulty in the adjustment process is due to the failure of the two processes to occur simultaneously. However, if a meta-heuristic algorithm can only perform the best in either one of them, then it is still relatively lacking in obtaining a good solution. For example, poor exploitation can reduce the searching ability to convergence to the global optimum, whereas poor exploration can decrease the chances to escape from the local optimum [65]. Facing a problem with many local optima, the meta-heuristic algorithm that has poor exploitation will find it hard to get to the global optimum [66]. It can be seen based on the previous study, algorithms such as WCA, CA, HBMO, BA, BBO, PSO, ACO, and FA could solve reservoir optimization problems even though they are either weak in exploitation or exploration search ability. And through hybridization or modification, these algorithms showed even better performance by enhancing their respective shortcoming.

The algorithm that is strong in both search abilities without hybridization such as CSO can be proved suitable in han-

TABLE 3. Criteria based on the reservoir characteristic optimization.

criteria	algorithm	
	advantage	disadvantage
Exploitation (local search)	SSO BA BBO CSO ACO	WCA CA HBMO
Exploration (global search)	SSO SA CSO GA	BA BBO PSO ACO
Parameter tuning	WCA BBO HBMO Jaya	FA GA
Complexity	CA PSO ACO	SA CSO GA HBMO
Convergence speed	BA FA	GA Jaya

dling reservoirs that contain several conflicting objectives and constraints. These objective functions are always nonlinear, nonconvex, and contain multiple local optima [67]. The presence of multi-objective optimization problems signifies the importance of MHAs, especially in real-world optimization. There are always trade-offs between these objectives such as that between maximizing benefits from hydropower and fulfilling the demand for irrigation. Such objectives are often conflicting with each other, resulting in the existence of multiple optimal solutions [68].

D. STABILITY AND CONVERGENCE SPEED

The conventional algorithms are said to be deterministic, i.e., they require gradient information to find function values or derivatives. Usually, they are also known as gradient-based algorithms. By contrast, gradient-free algorithms use only the function values without relying on any derivative information. In every optimization problem, the objective function can be considered as a mathematical model (function) that allocates a fitness value to each solution in the search space. Meta-heuristic algorithms begin their searching process with an initial population of variables in the direction toward the maximum/minimum of the objective function until a stopping criterion is met. Although each meta-heuristic algorithm has its specific way of conducting the search process, it can find a good solution intelligently. However, there is no guarantee that the achieved solution is the best.

Reference [69] stated: "Objective functions used in reservoir system optimization models should incorporate measures such as efficiency (i.e., maximizing current and future discounted welfare), survivability (i.e., assuring future welfare exceeds minimum subsistence levels), and sustainability (i.e., maximizing cumulative improvement over time)." Sustainability is one popular concept delineated by Reference [70].

Therefore, it is imperative to find methods that can induce randomness in their search process and at the same time obtain global optimum with a fast convergence rate. Among the mentioned algorithms in section III, there a few algorithms that fit this characteristic. Some algorithms are slow to convergence at the beginning, while some algorithms convergence faster than the other.

Algorithms that have a high convergence rate would be BA and FA. In BA, it possesses a unique feature that is also known as automatic zooming (i.e., higher convergence speed). This ability allows zooming into a region where there is a potential solution to be found. BA can perform parameter control in which the value of the variable can be altered as iterations proceed. This allows the exploration process to be switched to an exploitation process as the global solution is impending. Coupled with the automatic switching, it speeds up the convergence rate. Similarly, the high speed of convergence is easily attainable in PSO because the process is a single-directional flow of information, which allows passing the information from one particle to another. Meanwhile, FA could perform well without the need of incorporating the personal and global best of solution like in PSO. This allows FA to iterate quicker to the global optimal.

V. THE ALTERNATIVE METAHEURISTICS ALGORITHM FOR RESERVOIR OPTIMIZATION

The Jaya Algorithm applications relatively cover a wide range of domains by many researchers with backgrounds in different fields. The working principle of JA is rather straightforward, where for a given problem, the solution obtained should move towards the best solution, thus avoiding the worst solution. The beauty of JA lies in its characteristic of a parameter-less algorithm. It does not possess specific control parameters like the above-mentioned algorithms. Like any other algorithms, it requires typical control parameters, namely, the number of maximum generation and population size. After the parameter setting of population size and number of iterations, the solution is evaluated based on the equation below:

$$X_{new,i,j,k} = X_{i,j,k} + r_{1,i,j}\left(X_{i,best,j,k} - |X_{i,j,k}|\right) - r_{2,i,j}\left(X_{i,worst,j,k} - |X_{i,j,k}|\right). \quad (7)$$

There are two main operations in Jaya which are the $r_{1,i,j}\left(X_{i,best,j,k} - |X_{i,j,k}|\right)$ and $r_{2,i,j}\left(X_{i,worst,j,k} - |X_{i,j,k}|\right)$. The former term moves the candidate solutions towards the better solution, while the latter term moves the candidate solutions away from the worse solution. To examine its efficiency and effectiveness, the Jaya algorithm has been evaluated in comparison with other optimization methods. Several case studies have been carried out that involved dealing with the large-scale optimization problem. Reference [71] applied the Jaya algorithm to the optimization of a truss structure with many design variables to be considered and showed its superiority over other optimization methods. Despite that the Jaya algorithm prevailed over other MHAs in many other disciplines, it is still new in water-resource problems. Its application to the groundwater management problem was presented by Reference [72]. They optimized the cropping pattern problem to maximize the net annual returns by incorporating the Jaya algorithm into a mathematical model. The results showed that the proposed algorithm could compete well with the commonly used PSO algorithm in water-resource management. In addition, the computation time needed for the Jaya algorithm is less compared to that for PSO; this showed Jaya algorithm's applicability to be more suitable for real-time engineering applications such as the dam and reservoir water system.

VI. RECOMMENDATIONS AND CONCLUSION

The optimization process of reservoir operation involves several aspects of the characteristics of reservoir operation. The tuning process of parameters speeds up the decision-making process of the release rule. Meanwhile, as stated by Reference [73], through an exhaustive search method, the time of finding the exact solution is high, especially in the NP-hardness problem. Therefore, finding a solution using metaheuristics involves a compromise between the speed of finding and the accuracy of the obtained solution. As aforementioned, several techniques, including the hybridization approaches, have been seen to work efficiently in the reservoir operation. Recently, the rapid development of optimization methods and their application in numerous water-resource systems have successfully overcome the shortcoming of traditional methods. The commonly known meta-heuristic methods are evolutionary algorithms such as the GA and the swarm intelligence-based algorithm (e.g., PSO). A common point that these algorithms shared is that their performances depend heavily on the parameters used. One of the drawbacks of parameter-tuning process is that these parameters might lead to the convergence of the local optima solution or an increase in computational burden if one fails to tune them properly.

The proposed method for future study can be a fully developed parameter-less algorithm. It should not possess specific control parameters like the above-mentioned algorithms. Having an efficient tuning parameter-less algorithm, the proposed method will overcome the difficulty of finding optima for tuning specific control parameters. By outperforming the previous techniques with modern algorithms, the inability of the former methods to address multidimensional problems has been successfully dealt with using meta-heuristic methods. The efficiency of the MHAs at the early stage of development is considerably low due to limitations in computation work. As technology advances, complex problems become solvable by meta-heuristic methods; however, this requires extensive tuning of parameters; the associated algorithm is also referred to as the problem-based algorithm. The tuning process of the existing MHAs is seemingly unavoidable. Therefore, the proposed meta-heuristic algorithm has the potential to be an alternative optimization method because of its uniqueness as a parameter-less algorithm.

In conclusion, a number of meta-heuristic algorithms are useful for addressing reservoir operation problem. The strength of these optimization algorithms opens up a new avenue and many opportunities in the water-related field. Through a deeper understanding of the applicability of one algorithm, it allows the algorithm to be modified. The modification can be the addition of a new operator to the existing algorithm or incorporation of a different algorithm. Subsequently, it improves the efficiency of the modified algorithm to provide a better solution. The areas of improvement are usually the computational cost, parameter setting, convergence speed, local and global searching ability.

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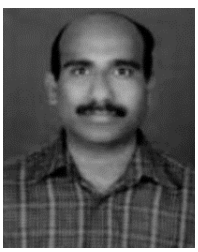

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