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DOI
10.1007/s11269-023-03517-w

Publication date
2023

Document Version
Final published version

Published in
Water Resources Management

Citation (APA)
Yildiz, B., Ulukok, M. K., & Bashiry, V. (2023). Bi-Attempted Base Optimization Algorithm on Optimization of Hydrosystems. *Water Resources Management*, *37*(9), 3585-3597. https://doi.org/10.1007/s11269-023-03517-w

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Bi-Attempted Base Optimization Algorithm on Optimization of Hydrosystems

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Received: 12 December 2022 / Accepted: 6 April 2023

Abstract

This study aims to search for optimum design parameters for a slurry pipeline problem and optimum operation parameters for a multi-reservoir scheduling problem by using Bi-Attempted Base Optimization Algorithm (ABaOA), which has been recently developed as a numerical bidirectional search algorithm. The slurry pipeline problem is a constrained non-linear cost minimization problem with constraints on facility capacities. It has two separate cost terms that behave differently with changes in decision variables. The problem includes several decision variables in addition to the fact that the objective function is highly non-linear. On the other hand, the multi-reservoir problem is a well-known problem in Hydraulics that aims to maximize benefit by optimizing the releases of each reservoir. The problem has a known global optimum, which is used to test the abilities of the ABaOA. The ABaOA is developed from Base Optimization Algorithm (BaOA) by transforming its operators with the aim to diversify the search paths to reach the global optimum. Its applications in hydrosystems show that it converges to the optimum solutions in reasonable times. The results from the first application are compared to the ones obtained from Genetic Algorithms (GA) application. It is observed that ABaOA outperformed GA in terms of speed of convergence and finding a better alternative solution. The ABaOA reaches the global optimum in the second application. In addition, alternatives with better benefit functions, including some penalties have been determined.

Keywords Numerical optimization · Evolutionary algorithms · Multimodal functions · Slurry pipelines · Reservoir optimization · Hydraulics

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Published online: 26 April 2023

1 Introduction

The application of a proper optimization method is essential in an efficient design and operation of most of the engineering systems. This application may aim to minimize the total cost or maximize the total benefit of the system by searching for an optimum set of decision variables. In this process, the system necessities or simply the constraints of the problem need to be considered. An optimization method may vary depending on the problem type, the properties of the candidate solutions, or the tools to be used during the search. Some optimization algorithms follow particular natural or artificial routines in their search mechanisms. Genetic Algorithms (GA) (Holland 1992) and Differential Evolution (DE) (Storn and Price 1997) follow the natural evolution processes and adapt crossover and mutation operators between their successive iterations. Particle Swarm Optimization (PSO) (Kennedy and Eberhart 1995), Ant Colony Optimization (ACO) (Dorigo et al. 1996), Artificial Bee Colony Algorithm (ABC) (Karaboğa 2005), Bat Algorithm (BA) (Yang 2010) and Directional Bat Algorithm (dBA) (Chakri et al. 2017) mimic the movement of swarms in approaching the optimum solution between the iterations. Cuckoo Search (CS) (Yang and Deb 2009) follows a particular cuckoo bird species with similar behaviour when searching for a host nest for their eggs to drop. Harmony Search (HS) (Geem and Kim 2001) is developed based on an artificial search mechanism: the musical harmony rules. On the other hand, Base Optimization Algorithm (BaOA) (Salem 2012) uses mathematical operators to form new candidate solutions on every iteration step.

The search continues for a better optimization method to converge to the optimum solution in a shorter search time. Recently, Hu et al. (2021), Zand et al. (2022), Mohammadi et al. (2022), Pathak and Srivastava (2022) and Liang et al. (2022) proposed their algorithms for better optimization with some capabilities. The Bi-Attempted Base Optimization Algorithm (ABaOA) is also a recently developed numerical search algorithm that uses mathematical operators to vary its candidate solutions among consecutive iterations (Ulukok 2021). It is based on BaOA (Salem 2012) and follows a bidirectional search by using two displacement parameters on all the candidate solutions at the initiation of the iterations. It was developed by removing two operators from BaOA and keeping only two mutation operators. These modifications increased the speed of convergence and gave a better ability to reach global optimum solutions. It overperformed BaOA, directional Bat Algorithm (dBA), Bat Algorithm (BA), Particle Swarm Optimization (PSO), Harmony Search (HS), Cuckoo Search (CS), Differential Evolution (DE) and Genetic Algorithms (GA) in 20 benchmark functions when using non-parametric statistical Friedman test to evaluate the results (Ulukok 2021).

Investigating the capabilities of optimization algorithms in particular areas is also needed. Water resources engineering projects are particularly essential in this regard due to the limited resources and increasing demand. Furthermore, considering the cost of the projects due to their large scale, finding a better solution for them would increase the benefit significantly (Goodarzi et al. 2014). Particularly in hydraulics, interesting optimization problems exist with complex fitness function formulations or application domains. The complexity of mathematical formulations lies in the fact that some formulas are still based on empirically derived functions with high degrees. The complexity in the application is mainly observed in river engineering problems with long reaches when several independent hydrosystems influence the performance of others. Some recent studies related to the optimization of hydrosystems can be given as follows: Bajany et al. (2021) used several nonlinear optimization techniques to minimize water cost in arid to semiarid areas. Zhao and Yang (2021) applied a comparative analysis to optimize curve fitting in determining soil water parameters by minimizing the error sum. They have used Newton-Rhapson method, PSO, DE and Jaya algorithms. Choi et al. (2023) used Improved Grey Wolf Optimizer to maximize water supply reliability of a reservoir which underwent a purpose change.

Among the hydrosystem applications, slurry pipeline optimization problem is a typical example for a complex one including a multi-phase flow, highly non-linear problem functions and several decision variables (Yildiz et al. 2014). Another complexity of the hydrosystem applications can be seen at optimal reservoir scheduling problems when the system includes several reservoirs (Cascade or parallel systems). This problem has many application cases worldwide. A search for a better optimum for this problem would affect the added benefit highly. Among the early works, Heidari et al. (1971) defined a case study that aims to maximize the benefit from hydropower and irrigation activities having the release amounts from each reservoir as decision variables. This case has a known global optimum which would make it a good benchmark test for the algorithms. In this study, the capabilities of a newly proposed algorithm, ABaOA were tested on optimum design and operation of these two hydrosystems. We aim to show the strengths and weaknesses of the algorithm in these applications. This study includes the first two applications of the ABaOA in design and operation of engineering systems. In the first application, the results of ABaOA were compared with those of GA. Here, ABaOA managed to supply a better result than the one provided by GA in a shorter time. In the second application, a more detailed analysis was carried out having known the global optimum of the problem. The application limits and the practical advantages of the algorithm were demonstrated. The comparison of the algorithms in terms of convergence time shows that ABaOA can be a solid option at areas which require repetitive applications like reservoir operation studies.

2 Bi-Attempted Base Optimization Algorithm

The Bi-Attempted Base Optimization Algorithm (ABaOA) was developed by Ulukok (2021) by adapting the Base Optimization Algorithm (BaOA), which was proposed by Salem (2012) (abbreviated initially as BOA) (Xing & Gao 2014). The Base Optimization Algorithm (BaOA) is a population-based algorithm that uses arithmetic operators to guide its candidate solutions to the global optimum solution. In this regard, some candidate solutions are produced at the start of the first iteration. Then, the corresponding fitness function for each of them are calculated. The best one is carried to the next iteration. Mutation is applied to the rest of the individuals. It uses four arithmetic operators as displacement parameters with two range limiters defining the boundaries of the search space. The best individual is checked at the end of each iteration. Salem (2012) shows that, applying eight benchmark functions, the BaOA performed better than GA and ACO in finding the global optimum and the solution convergence time. The ABaOA was proposed by Ulukok (2021) by removing two mutation operators from the BaOA namely multiplication and division operators. Instead, the ABaOA adds two more displacement parameters (δ_1, δ_2) in the addition and subtraction operators to provide more intensification and diversification to the search process. It is aimed to reach optimum points in the search space at the early iterations. Therefore, it is suggested that one large and one small range limiter to be used depending on the domain of the individuals. The multiplication and division operators are removed to increase the computational speed.

The flowchart of the ABaOA algorithm is given in Fig. 1. It uses the same algorithm as BaOA except for the mutation operators. A user-defined number of individuals are developed randomly (S_i). Then, the fitness values of each individual ($f(S_i)$) are calculated, where f is the test function. The individual which returns with the best fitness is selected. For each individual, mutation operators are applied using two addition and two subtraction operators by using two displacement parameters (δ_1, δ_2) each. Then, the individuals for the next iteration are obtained (S_i^{+}, S_i^{++}, S_i^{-}, S_i^{--}) within the limits (R_{min} and R_{max}). Finally, each individual is evaluated, and the best individual is updated if applicable.

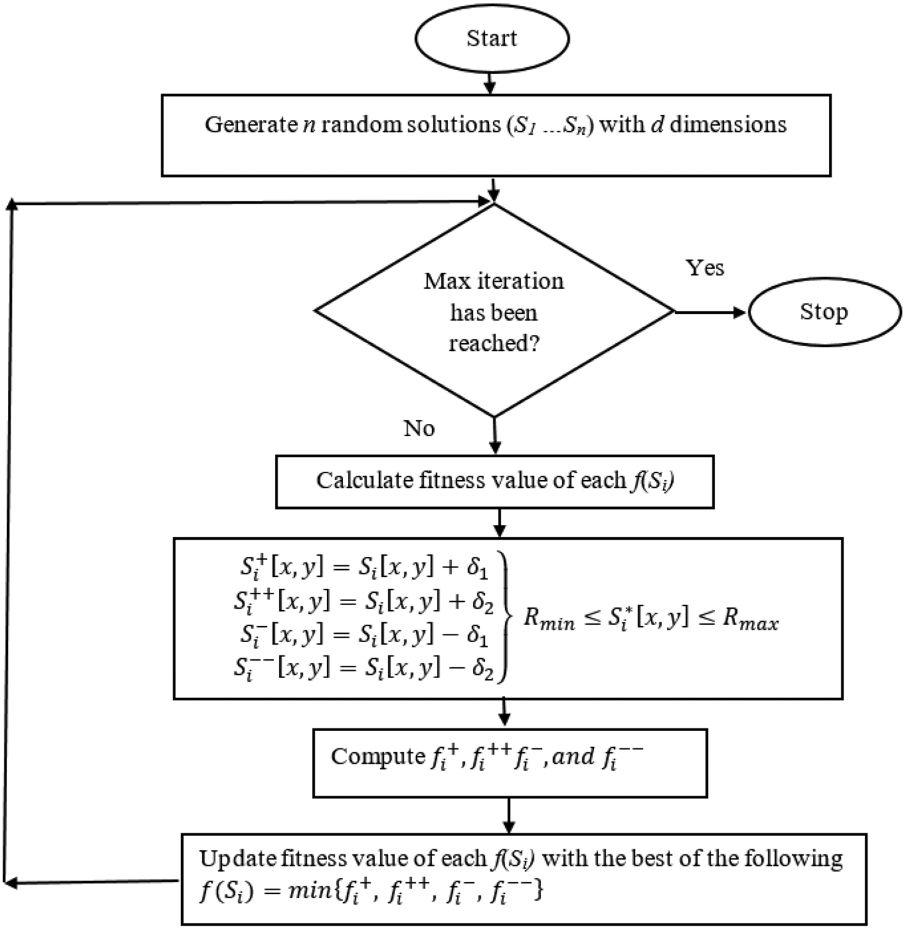

Fig. 1 Bi-Attempted Base Optimization Algorithm (ABaOA) Flow Chart

The abilities of ABaOA were tested on the 20 benchmark functions of the CEC'2005 benchmark suite (Suganthan et al. 2005) at Ulukok (2021). The functions were selected as a combination of uni-modal or multi-modal ones. The performance of ABaOA was compared with eight search algorithms (BaOA, dBA, BA, PSO, HS, CS, DE and GA). In 15 functions out of 20, the ABaOA obtained better results than the others did. The results were further analysed using the best, worst, and mean values of the solutions obtained by each algorithm. The applications of the non-parametric Friedman and Wilcoxon tests were done. Both tests showed that ABaOA is superior, with a level of significance $p < 0.05$.

3 Application #1: Slurry Pipeline Optimization

Slurry pipelines are used to transport ore materials from mine pits to the processing factories. In this method, the solid ore materials are broken into the desired amount of particle diameters and a slurry is formed after mixing with a carrier liquid. In transportation, this slurry is pumped to the demand nodes through pipelining. Then, at the exit, the liquid is removed for the further processing part of the job. Slurry pipelining is done by burying the pipelines in the ground, resulting in less air pollution, noise, traffic, and carbon emission rather than transporting the same amount with trucks, rail, or ships. Compared with the same methods, slurry pipelining requires less energy to transport the same amount (Gopaliya and Kaushal 2016). Due to those advantages, slurry pipelining is widely used in mining, chemical and petroleum industries (Zambrano et al. 2017). The hydraulics of slurry pipelines is analysed following two-phase (solid–liquid) flow conditions. The critical velocity of the flow below which the settlement starts is defined with the help of empirical studies (Smith 1970; Schriek 1973). Besides, head loss is essential in terms of energy costs. Empirical methods were employed to search for head loss estimation methods (Wasp et al. 1978; Yücel et al. 1978; Coffey and Partridge 1982; Doron et al. 1987; Wilson et al. 2006; Cowper et al. 2009).

Concerning slurry transportation, an optimization problem is formulated using multi-source and demand nodes (Yildiz et al. 2014). The aim is to minimize the cost, which includes the pipeline layout cost and the energy requirement cost, by concerning the capacity constraints of the facilities. The decision variables of the problem are the pipe diameters and the solid concentration rates at each pipeline. The constructed optimization problem is multi-modal, which means that it has local optimum solutions in the search space. It may have several decision variables and it includes high non-linearity in the equations. When pipe diameters increase, the energy losses decrease; so, does the energy cost. However, it increases the pipe costs. This behaviour of the cost function and the variety of decision variables increase the complexity of finding an optimum solution. Therefore, the employed optimization technique plays an essential role in the solution.

The optimization problem aims to minimize the cost subject to the capacity constraints of each facility. The cost function here will be simplified to the sum of the energy and pipe layout costs at each pipeline.

$$C = \sum_{i=1}^{m} \sum_{j=1}^{n} C1_{ij} + \sum_{i=1}^{m} \sum_{j=1}^{n} C2_{ij} \tag{1}$$

where, $C1_{ij}$ and $C2_{ij}$ stand for energy and pipe costs, at the pipeline connecting the i^{th} mine pit and the j^{th} factory, with m and n corresponding to the total number of the mine pits and the factories, respectively. The energy cost can be computed by multiplying the total energy needed by the unit price of the energy, CE. The total energy needed can be calculated from hydraulic calculations. Here, the total energy need, E, is obtained from the total energy losses in the pipelines. The pump power, P_p, which is required to generate that amount of energy is calculated, and the energy spent to generate that much power is calculated.

$$\begin{gathered} H = iL \\ P_p = \frac{g\rho_m Q_m H_P}{\eta} \\ E = 7884 P_P \\ C1 = CE * E \end{gathered} \tag{2}$$

where H is the total head loss, i is the loss coefficient, L is the pipe length, g is the gravitational acceleration, ρ_m is the mixture density, Q_m is the volumetric discharge of the flow which can be calculated as the velocity of the mixture, $V_{m,}$ times the cross-section of the pipe, H_P is the pump power, which is simply equated to the head loss (H) and η is the efficiency of the pump, which is taken as 1.0 for simplicity. The mixture density can be calculated by using the concentration by volume as given below;

$$\rho_m = \rho_w\left[C_V S_S + \left(1 - C_V\right)\right] \tag{3}$$

The head loss coefficient in solid–liquid mixture flows is formulated empirically by Schriek (1973) as follows:

$$i = 0.0039{C_V}^{0.803}D^{-1.25}{V_m}^{1.77} \tag{4}$$

where C_v is the volumetric concentration, D is the pipe diameter, and V_m is the velocity of the mixture. In this equation, the mixture velocity must be equated to the critical mixture velocity to preserve the non-settling flow. It is defined by Smith (1970) and Schriek (1973) as;

$$V_{cr} = 2966.45f(C_w)d^{0.75}{s_s}^{0.5}D^{0.5} \tag{5}$$

where d is the d_{50} of the material size distribution, s_s is the specific gravity of the solid material, and $f(C_w)$ is a function of concentration by weight which is given below;

$$\begin{array}{c} f\left(C_w\right) = 0.2067C_w + 1.035 \rightarrow 0.30 \le C_w \le 0.45 \\ f\left(C_w\right) = 1.52C_w + 0.444 \rightarrow 0.45 \le C_w \le 0.55 \\ f\left(C_w\right) = 6.1C_w + 2.075 \rightarrow 0.55 \le C_w \le 0.70 \end{array} \tag{6}$$

The pipe laying cost is calculated using Bhave's (1985) equation, which simplifies it to a function depending on the pipe diameter (D) and pipe length (L).

$$C2 = 210.89D^{1.3744}L \tag{7}$$

where $C2$ is in USD when D is in m and L is in m. The constraints of the problem are the capacities. The amount of material transported at each pipe is formulated. The term W_{ij} is defined as the total weight transported from the mine pit i to the factory j and formulated as below:

$$W_{ij} = \left(C_v\right)_{ij}\rho_w s_s \frac{\pi {D_{ij}}^2}{4}\left(V_m\right)_{ij} \tag{8}$$

where, D_{ij} and $(V_m)_{ij}$ are the diameter and the mixture velocity at the pipe connecting the mine pit i and to the factory j, respectively. C_v can be written in terms of C_w as:

$$\left(C_v\right)_{ij} = \frac{\left(C_w\right)_{ij}}{\left(\left(C_w\right)_{ij} + s_s\left(1 - \left(C_w\right)_{ij}\right)\right)} \tag{9}$$

Then, p_i, which is the total weight of ore material transported from the production point i (mine pit), and c_j, which is the total weight of ore material transported to the consumption point j (factory), are formulated with the below equations:

$$\begin{array}{l} p_i = \sum_{j=1}^{n} W_{ij} \text{ for } i = 1, 2, \dots, m \\ c_j = \sum_{i=1}^{m} W_{ij} \text{ for } j = 1, 2, \dots, n \end{array} \tag{10}$$

Then, the optimization problem can be formulated as follows:

$$\textbf{Min}\ C \text{ subject to}\\ 0 \le p_i \le \left(p_{cap}\right)_i \text{ and } 0 \le c_j \le \left(c_{cap}\right)_j \tag{11}$$

where p_{cap} and c_{cap} are the capacities of the production and consumption nodes. The unknowns in the problem remain as, D_{ij}, and $(C_W)_{ij}$, at each pipeline, which are the decision variables of the problem. The lower and upper boundaries of them are set. For the pipe diameters, the limits are determined as [0,1] and the results are selected from a set of pipe diameters that are available on the market. The limits for the C_W are determined as [0, 0.7] considering the hydraulic transportation limits. The capacities of the mine pits and the factories and the distances between each node, which would be used as the pipe length among those nodes, are given in Table S.1 and Table S.2 of the Supplementary Information File, respectively.

3.1 Results for Application#1

In this application, the displacement parameters of ABaOA were selected as 0.05 and 0.01 m for the pipe diameters and 0.01 and 0.005 for C_v. The diameters were restricted to the commercially available pipe sizes (0.1, 0.12, 0.15, 0.20, 0.25…,1.00 in meters). The population size was selected as 10,000 and 100 iterations were set. The algorithm reached a better solution than GA did (266 M USD total cost decreased by more than 6 M USD) after the 13th iteration in a reasonable run time (318.7 s), and no progress was recorded afterwards. The related values are given in Table S.3 of the Supplementary Information File. The resulting cost function value and the corresponding decision variables are given in Table S.4 of the Supplementary Information File, along with the GA results obtained by Yildiz et al. (2014). In the reference study, GA operators were selected as follows: tournament type selection with a tournament size of three, a population size of 9000, BLX-0.5 type of crossover with 75% crossover rate and 6% mutation rate. The optimal solution was obtained after the 100th generation at GA. Besides, GA could not reach the optimum found by ABaOA. The computational facilities used in Yildiz et al. (2014) and the present study are not identical. Therefore, a comparison of the computation times of the algorithms may not make sense. However, GA has more operators compared to ABaOA, which increases the runtime of GA for identical problem solutions with the same population number. Yildiz et al. (2014) applied more than 400 tests to estimate the optimum combination of the GA operators. However, as the number of operators in ABaOA is just four, around ten trials were sufficient to reach a better result in this study.

4 Application #2: Optimization of a Multi-Reservoir System

The water reservoirs either naturally or artificially created by constructing dams are used for water storage and supply when anticipated. The stored water can be used for irrigation, clean water supply or hydropower generation (Mays 2010). When using water for hydropower generation, an optimization study is needed to maximize the profit from energy production. In this problem, essential parameters are hourly energy unit price changes, reservoir water levels and the incoming flow to the reservoir (Ak et al. 2017). Besides, in some rivers with high hydropower potential, dams follow each other. Thus, the release from one reservoir highly influences the inflow of the reservoirs on the downstream side of it. Then, optimizing the releases of each reservoir becomes more critical considering their effect in total benefit. Optimum operation of reservoirs has been studied a lot recently. A review article covered 50 scientific papers that were dealing with optimum operation studies for single, parallel and cascade reservoirs and were published between years 2011 and 2021 (Lai et al. 2022). Among the cascade and parallel reservoir handled ones, Al-Aqeeli and Mahmood Agha (2020) used PSO to maximize generated power from a two-reservoir system. Later, Zhu et al. (2022) used a nonlinear model (Gurobi solver) to maximize total generated power at a multi reservoir system. Zhang et al. (2022) searched for an optimal operation strategy for a cascade sluice reservoir system including the water quantity, water quality and socioeconomic aspects. Chen et al. (2023) used Multi-Objective Genetic Algorithms to maximize generated power and ecological flow at a cascade reservoir system.

Among the first applications, an optimization problem considering a combined parallel and cascade four-reservoir system was developed by Larson (1968) as delivered by Heidari et al. (1971). A representative scheme of it is given in Fig. 2. In the same figure, four reservoirs as RES1 to RES4 and the releases from each as R1 to R4 are indicated. The inflows of RES1 and RES2 are given as 2, and 3 unit discharges, respectively. The inflow of RES3 equals the release of RES2, and the inflow of RES4 equals the summation of the releases from RES1 and RES3. RES1, RES2, and RES3 operate for only hydropower purposes, while RES4 has irrigation purpose besides hydropower. Therefore, there are four benefit terms for hydropower and one for irrigation. The benefit functions are defined in the problem as a function of releases from the reservoirs. The system is operated for a 12-time-increment period. According to these, the total benefit function, B, of the problem is defined as follows:

$$B = \sum_{i=1}^{4} \sum_{t=1}^{12} b_{i,t} R_{i,t} + \sum_{t=1}^{12} b_{5,t} R_{4,t} \tag{12}$$

where, index i corresponds to the reservoir number, index t corresponds to time instant, and b_i is the benefit multiplier for hydropower activity up to $i=4$ and for irrigation activity when $i=5$. These multipliers are given as a function of time and provided in Table S.5 of the Supplementary Information File. The global optimum value of this function is known (401.3) for the given parameters below. It was previously obtained using dynamic programming

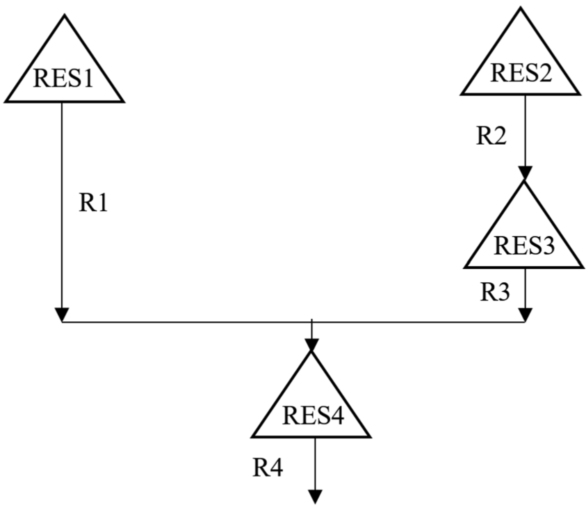

Fig. 2 Four-reservoir system as given by Heidari et al. (1971)

(Heidari et al.) and GA (Hınçal et al. 2011). The problem's constraints are storage capacities, release capacities and anticipated minimum end storage values. The storage capacities of RES1, RES2 and RES3 are given as 10-unit-volume and it is 15-unit-volume for RES4. The release capacities of RES1 to RES4 are 3-, 4-, 4- and 7-unit discharges respectively. The target minimum end storages are given as 5-unit-volume for RES1 to RES3 and 7-unit-volume for RES4. They are formulated below.

$$\begin{gathered} 0 \le S_{1,t}, S_{2,t}, S_{3,t} \le 10 \\ 0 \le S_{4,t} \le 15 \\ S_{1,12}, S_{2,12}, S_{3,12} \ge 5 \\ S_{4,12} \ge 7 \\ 0 \le R_{1,t} \le 3 \\ 0 \le R_{2,t}, R_{3,t} \le 4 \\ 0 \le R_{4,t} \le 7 \end{gathered} \tag{13}$$

where, $S_{i,t}$ denotes the storage of the reservoir i at time t. Storages are formulated using the continuity principle as;

$$S_{i,t+1} = S_{i,t} + I_{i,t} - R_{i,t} \tag{14}$$

where, I denotes inflow to the reservoir. Penalty functions for each constraint are developed according to the bracket penalty function method (Li and Mays 1995) and added to the benefit function to estimate the fitness function. The bracket penalty function is defined as below;

$$P = C \sum_{l} \left[\max(0, V_l)\right]^2 \tag{15}$$

where, V_l is the violation of the constraint l, C is the penalty multiplier which needs to be negative for maximization problems. The violation term shows the amount of violation of the constraint. For example, the violation for the end storage constraint can be calculated as (7-$S_{4,12}$) for RES4 if $S_{4,12}$ is larger than 7. C was taken as -40 in the end storage violation penalty by Heidari et al. (1971).

4.1 Results for Problem#2

The algorithm was run by using the penalty multiplier (C) value (-40) for minimum end storage constraint violations, as given by Heidari et al. (1971). For the other two constraint violations, C was selected as -100. The displacement parameters were used as 0.1 and 0.001. We have observed that if the small displacement parameter is selected close to the large one, the algorithm does not work efficiently, and convergence time increases. The population and iteration numbers were selected as 5000 for each. We obtained fitness function values above the known global optimum (like 401.748, while the known global optimum value is 401.300). Therefore, the algorithm converges to the better benefit function values with slightly violating the constraints. The release values giving the 401.748 fitness value are given in Table S.6 of the Supplementary Information File. These release values result in a benefit function value of 402.1973 with a -0.4495-penalty value. Figure 3 shows the variation of water volume at each reservoir with time. The results of this run are compared with the global optimum results as given by Heidari et al. (1971). The storage values of RES1 and RES4 are very close in both

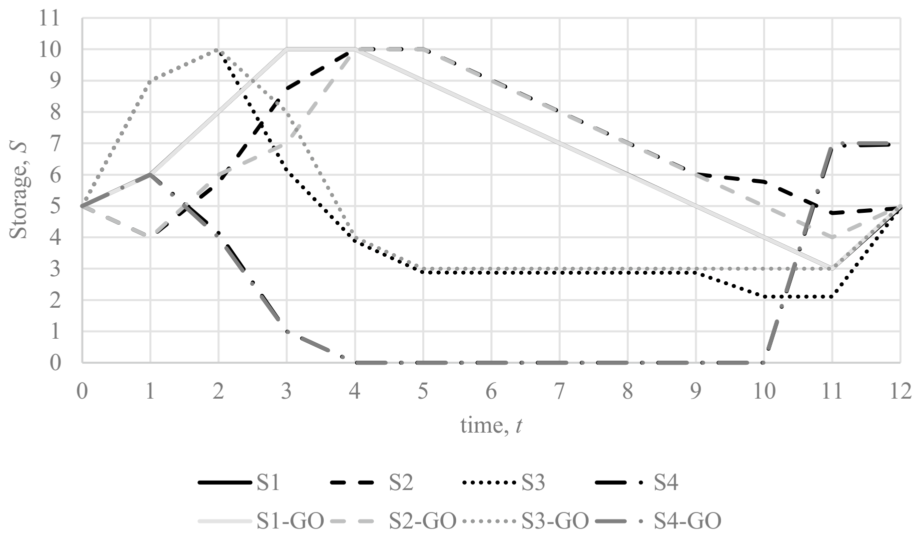

Fig. 3 The comparison of the results with those of the global optimum as given by Heidari et al. (1971) on the variation of reservoir storage values with time (Global optimum results are labelled with GO on the legend.)

solutions. Storage values of RES2 and RES3 slightly diverge from the global optimum results. As a result, the algorithm gave better benefit values than the global optimum, slightly violating the minimum end storage constraint at each reservoir.

The algorithm starts searching with randomly generated initial population values. Therefore, it should be repeated to see its actual performance. The algorithm was run ten times using the above algorithm parameters. Besides, it was observed that penalty multipliers were essential in convergence. Therefore, two more sets were run by using all penalty multiplier values equal to -100 and -200 separately. The best, mean and worst fitness values obtained from each set are given in Table 1. Increasing the penalty multipliers limits the algorithm to find individuals with better benefits and slight penalties. Besides, it also pushes the search away from the boundaries of the domain. As we used a precision of 1/1000, the algorithm had difficulties reaching the global optimum within the limited iteration number. While increasing C values further, the algorithm did not converge to better results. Therefore, the results regarding the larger penalty multipliers were excluded from the analyses. Clearly, the algorithm converged to better results than the global optimum within the given problem parameters. If one compares all fitness function values after each iteration, alternative solutions, including the global optimum can be obtained.

Table 1 The best, mean and worst fitness values after 10 runs for various penalty multipliers (C)

	Best Fitness	Mean Fitness	Worst Fitness
$C_1=-100$, $C_2=-100$, $C_3=-40$	401.748	401.740	401.730
$C_1=C_2=C_3=-100$	401.076	401.975	400.035
$C_1=C_2=C_3=-200$	399.925	399.783	399.689

5 Conclusion

In this study, two applications of ABaOA, a recently developed search algorithm, were achieved on the optimum design and operation of hydrosystems. The results were compared with those obtained from Genetic Algorithms in the first application (slurry pipeline optimization). The ABaOA outperformed GA in terms of finding a better solution. Besides, it required fewer iterations than GA did when the initial population sizes were the same. ABaOA was also found more user friendly. While the GA application required more than 400 tests to reach optimum operator values, ABaOA application needed only 10 tests owing to its low number of operators. By that means, ABaOA was proved applicable to complex non-linear optimization problems easily. The results of the second application were compared with the known global optimum. ABaOA provided alternative results, some resulting in better fitness values than the global optimum with small penalty values. Therefore, it provides the user with alternatives to select one among the possible solutions. Furthermore, the second application results show that if the precision of the decision variables is unknown, ABaOA may need more time to converge as the precision used during the search is defined at the beginning of the search. Two applications of ABaOA in the optimum design and operation of hydrosystems show signs that this search algorithm can be a decent alternative in optimizing non-linear and complex engineering problems. In addition, it has provided faster convergence than GA, which is practical in repetitive applications like optimum reservoir operation problems.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11269-023-03517-w.

Authors Contributions B. Y. and V. B. selected the application problems and organized the optimization problems. B. Y. and M. K. U. prepared the ABaOA code for applications. B. Y. and M. K. U. analysed and processed the results. B. Y. wrote the first draft of the manuscript. M. K. U. and V. B. reviewed and edited the text.

Funding The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Availability of Data and Materials The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request. The code developed in this paper for the application of the ABaOA is available online in GitHub directory and can be reached through this link: (https://github.com/burhanyildiz/ABaOA).

Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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