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Fast convergence optimization model for single and multi-purposes reservoirs using hybrid algorithm

Mohammad Ehteram [a,*], Sayed-Farhad Mousavi [a], Hojat Karami [a], Saeed Farzin [a], Mohammad Emami [a], Faridah Binti Othman [b], Zahra Amini [c], Ozgur Kisi [d], Ahmed El-Shafie [b]

[a] Department of Water Engineering and Hydraulic Structures, Faculty of Civil Engineering, Semnan University, Semnan, Iran
[b] Department of Civil Engineering, Faculty of Engineering, University of Malaya, Malaysia
[c] Department of Civil Engineering, Faculty of Engineering, University Technology Malaysia, Kuala Lumpur, Malaysia
[d] Center for Interdisciplinary Research, International Black Sea University, Tbilisi, Georgia

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ABSTRACT

Developing optimal operation policy for single or multi-purposes dams and reservoirs is a complex engineering application. The main reasons for such complexity are the stochastic nature of the system input and slow convergence of the optimization method. Furthermore, searching optimal operation for multi-purposes or chain reservoir systems, becomes even more complex because of interfering operations between successive dams. In this study, a new hybrid algorithm has been introduced by merging the genetic algorithm (GA) with the krill algorithm. In fact, the proposed hybrid algorithm amalgamates the advantages of both algorithms, first, the ability to converge fast for global optimum and, second, considering the effect of stochastic nature of the system. Three benchmark functions were used to evaluate the performance of this proposed optimization model. In addition, the proposed hybrid algorithm was examined for Karun-4 reservoir in Iran as an example for a hydro-power generation dam. Two benchmark problems of hydropower operations for multi-purposes reservoir systems, namely four-reservoir and ten-reservoir systems were considered in the study. Results showed that the proposed hybrid algorithm outperformed the well-developed traditional nonlinear programming solvers, such as Lingo 8 software.

1. Introduction

Several dams and reservoirs have been constructed around the world for better operation of available water for irrigation, domestic and industrial uses, hydropower generation and flood mitigation. Dams and reservoirs are the hydraulic structures designed for storing and regularly releasing water to meet the downstream water needs based on the operator's decisions [1,2,20]. Despite the need for dams and reservoirs to match the increasing of the water demands, their operation is a highly challenging task to achieve. In fact, optimizing the operation of the existing dams and reservoirs is essential to maximize their benefit and to cope with present and future water demands [1]. In most cases, the decision-makers for dams and reservoirs depend on their experience to decide the appropriate timing and amount of water release. The main challenge related to dam and reservoir operations is that the release decisions should be made in light of the system's physical constraints, including the stochastic nature of system parameters [3,21].

Over the last few decades, water resources managers have given serious attention to optimizing the operation policies of dams and reservoirs. Several optimization methods of this complex engineering application have been introduced due to improvements in analytical and computer technology [4]. Recently, evolutionary algorithms and other metaheuristics have been employed to achieve optimal operation and sustainable water resources management solutions for dam and reservoir operation [5]. In fact, evolutionary algorithms are iterative search strategies enclosing the following phases: consideration and explanation of decision variables and constraints; selection of the decision variables and corresponding values; computation of objectives and constraints for the selected decision variable values [6]. Furthermore, a simulation process is repeated and the set of decision values is updated until the values satisfy the selected stopping criteria; and the optimal solutions are obtained by a decision-making process [6].

Various metaheuristic methods have also been used to solve the optimization problems. Oliveira and Loucks [7] used a genetic

* Corresponding author.
E-mail address: eh.mohammad@yahoo.com (M. Ehteram).

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algorithm (GA) to develop optimal water release policies for the complex dam and reservoir systems. Furthermore, the honey-bee mating algorithm (HBMA) and bat algorithm (BA) have been investigated as alternative methods for searching optimal water release decisions [8,9]. A further step towards long-term optimization has been taken in the multi-tier interactive GA [10]. GA has been modified by integrating it with a stepwise simulation model to solve large-scale dam and reservoir systems that include up to 16 dams [11]. Bozorg Haddad et al. [12] used water cycle algorithm to determine reservoir policies for the optimal operation of Karun-4 reservoir in Iran. They also compared the results of the water cycle algorithm with those obtained with GA and nonlinear programming method.

2. Problem statement and objectives

The above-mentioned optimization algorithms have several advantages and disadvantages. The major advantage in these algorithms is their ability to be adjusted to include several nonlinear systems in parallel or series with different constraints and objective functions. The major disadvantage is the difficulty of addressing the stochastic pattern of the system parameters, slow convergence and lack of ability to distinguish the optimal global solutions. In this context, this study introduces an improved krill algorithm in combination with GA to address the stochasticity pattern and improve the ability of the search procedure to return global optima with relatively faster convergence. The krill algorithm was first introduced in 2012 by Gandomi and Alavi [13]. It is a novel biological-based algorithm that considers time-independent parameters while searching for the optimal solution. In the krill algorithm, time interval can be fine-tuned to reflect the stochastic behavior of the system parameters, which is a unique advantage over other algorithms [14]. However, the krill algorithm is slow to converge, especially when applied to a complex stochastic system such as dam and reservoir system.

In this study, a proposal for improvement of krill algorithm has been made. It is necessary to integrate differential evaluation for the global numerical optimization to accelerate the convergence procedure. The proposed hybrid algorithm in the present research is different from standard krill algorithm in a few aspects. The major function of GA is to assure the uniformity of krill population by finding a starting candidate solution without prior knowledge of the solution. Such integration for both algorithms guarantees fast convergence and avoids trapping in local optima.

In this study, the proposed hybrid algorithm was introduced to investigate its ability to optimize single and multi-purposes dams and reservoirs operation. The efficiency and reliability of the proposed hybrid algorithm were first verified using three mathematical benchmark functions. Then, its performance was evaluated by using real case studies of dam and reservoir applications. These case studies are well-known which were selected primarily by other researchers to introduce a comparative analysis on the performance of the proposed hybrid algorithm and previously-developed optimization models.

3. Materials and methods

3.1. Krill algorithm

The krill algorithm is based on krill's food search behavior. The shortest distance of each krill from both the food and the center of krill community is taken as the target function for krill's movement.

In the krill optimization algorithm, krill movement is categorized by three factors:

1. The motion created by other organisms,
2. Food-finding behavior, and
3. Random distribution.

Krill swarm is aiming at increasing density and finding more food. Krill attraction to high-density locations is considered as the target function. In natural systems, the fitness of every creature is a combination of distance from food and the concentration in the krill swarm. In multidimensional spaces, the algorithm should be able to search multiple dimensions. Therefore, the following Lagrangian model is used for decision making in multidimensional space:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{1}$$

where N_i is the motion made by other creatures, F_i is the food-finding movement, and D_i is the physical distribution. Krill movements are explained as follows:

- Movements of other creatures: According to theory, krill tries to move towards the density center. The α_i movement direction is approximated through the local density swarm, the swarm movement destination, and the factors avoided by the swarm. This movement is shown as: ω_n

$$N_i^{new} = N^{\max}\alpha_i + \omega_n N_i^{old} \tag{2}$$

$$\alpha_i = \alpha_i^{local} + \alpha_i^{t\arg et} \tag{3}$$

where $N_{\max}$ is maximum speed, and is usually taken 0.01 m/s, ω_n is the inertia weight, in the range of zero and one, N_i^{old} is the last movement, $\alpha_i^{t\arg et}$ is the target direction effect, which is showcased by the best krill. Neighborhood effects are the ratio of how much creatures are attracted to or repelled by certain areas for the local search. Neighbors' effects can be modeled as:

$$\alpha_i^{local} = \sum_{i=1}^{NN} \widehat{K}_{ij}\widehat{X}_{ij} \tag{4}$$

$$\widehat{X}_{ij} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \tag{5}$$

$$\widehat{K}_{ij} = \frac{K_j - K_i}{k^{worst} - k^{best}} \tag{6}$$

where k^{best} and k^{worst} are the best and worst values for krill fitness and K_i represents the fitness value of the current target function, K_j is the current neighbor's fitness value, X represents the corresponding position of the fitness value, and NN is the number of neighbors. There are several strategies for neighbor selection, one of which is related to the feel distance. Feel distance can be determined by the following equation:

$$d_{s,i} = \frac{1}{5N}\sum_{j=1}^{N}\|X_i - X_j\| \tag{7}$$

where $d_{s,i}$ is the feel distance for getting the i^{th} krill and N is the krill population. Fig. 1 shows this distance. The five factors in the denominator are derived empirically. According to the above relation, if the distance between two krills is less than the one as yielded by Eq. (7), these two krills are neighbors. The following relation indicates the effect of the best-fitting function:

$$\alpha_i^{t\arg et} = C^{best}\widehat{K}_{i,best}, \widehat{X}_{i,best} \tag{8}$$

where C^{best} is the most fitting krill impact index. This index is defined on the basis that the solution converges to the global optimum. C^{best} is calculated as follows: