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An Alternative Approach Using the Firefly Algorithm and a Hybrid Method Based on the Artificial Bee Colony and Cultural Algorithm for Reservoir Operation

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Abstract: In reservoir operation rule curves, it is necessary to apply rule curves to guide long-term reservoir management. This study proposes an approach to optimizing reservoir operation rule curves (RORCs) using intelligent optimization techniques from the firefly algorithm (FA) and a unique combination method utilizing the artificial bee colony and cultural algorithm (ABC-CA). The aim is to establish a connection with the simulation model to determine the optimal RORCs for flood control. The proposed model was used to determine the optimal flood control RORC for the Nam-Oon Reservoir (NOR) in northeastern Thailand. A minimum frequency and minimum average of excess water were provided as an objective function for assessing the efficiency of the search process. The evaluation of the effectiveness of flood control RORCs involved expressing water scarcity and excess water situations in terms of frequency, magnitude, and duration using historical inflow data synthesized from 1000 events. The results demonstrated that when using the obtained RORC to simulate the NOR system for reducing flooding in long-term operations, excess water scenarios were smaller than those using the current RORC. The results showed that the excess water scenario using the RORC obtained from the proposed model can reduce the excess water better than the current RORC usage scenario. In decreasing flood situations, the newly acquired RORC from the suggested FA and ABC-CA models performed better than the current RORC.

Keywords: optimization techniques; cultural algorithm; firefly algorithm; artificial bee colony; reservoir operation rule curves

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1. Introduction

Numerous nations now face enormous difficulties in managing their natural resources, especially with regard to water resources, which are essential for improving human welfare and quality of life. The issue of water resources remains a serious and substantial concern, and its complexity makes it even more hazardous, owing to the influence of climate change and alterations in land use [1–14]. Adequate water management necessitates two essential components: proper water organization and suitable tools for managing water resources. Hardware, such as water control structures, and software, such as organizational structures and non-construction tools, are needed to manage water resources [2,3,15–26].

Frequently, enhancing the operation of reservoirs is a favored technique because it can be swiftly implemented and does not involve construction. RORCs are a complicated issue involving the optimization of multiple objectives with numerous competing constraints [27–30]. RORCs aim to control the water level in a reservoir to keep it stable

and reduce risks, such as the water level exceeding the control threshold, which may cause harm to the dam. On the contrary, the water level should not be lower than the control threshold to the point of risking water shortages. These RORCs comprise upper and lower curves for the long-term management of the monthly stored water. The principle of good reservoir management is to be able to allocate enough water to use as needed during normal conditions and to help reduce the severity of water shortages during crises. At the same time, during high water conditions, water can be allocated without causing damage to the lives and properties of people downstream. Nevertheless, their effectiveness can decrease over time or when there are any changes to the data [12], necessitating the search for optimal values and improvements [19–26].

Various optimization methods have been employed to find the optimal RORCs, including dynamic programming [31,32], the genetic algorithm [15–17,33–35], the simulated annealing algorithm [36], particle swarm optimization [4], ant colony optimization [37], the harmony search algorithm [38,39], and cuckoo searching [40]. Although the above-mentioned techniques can solve the RORC problem, they also have several disadvantages, such as convergence to the optimal solution often depending on the initial value. There is also the possibility of obtaining localized solutions rather than the most appropriate solution. Therefore, researchers have developed artificial intelligence (AI) techniques, or intelligent techniques, and the science of swarm intelligence. It is advisable to investigate an alternative optimization approach if it is user-friendly and suitable for the task at hand. Over the past decade, a novel method called the firefly algorithm (FA) has gained popularity. The FA is a swarm-based metaheuristic algorithm that is based on the flashing behavior of fireflies. It is a simple and efficient algorithm that can be readily implemented [41–46]. The cultural algorithm (CA) is a computational science of evolution that was developed by Reynolds in 1994 [47] to enhance the efficiency of the artificial bee colony algorithm (ABC), which is a form of evolutionary computation. By simulating social evolution and utilizing the information and experiences that accumulate over time, it integrates with the agent-based modeling (ABM) learning process [48,49]. Cultural processes are very helpful in reducing the difficulty of determining the right answers and increasing the efficiency of finding the best solution in a search space. The belief and population spaces are the two primary parts of the cultural process. Population space refers to all potential solutions within the search space. In contrast, belief space represents the knowledge or information that solutions gather while striving for the best possible answers. The information gathered in this belief space is shared throughout the population space and can be applied to all population-based optimization techniques [47].

This study presents a solution to the most suitable reservoir management problem by using cultural processes, which are an evolutionary computational science, to help improve the efficiency of finding solutions in the bee colony process. The artificial bee colony process is used as the population space for cultural processes. By using normative knowledge, which is knowledge or information about samples or important events, and situational knowledge, which is a group of solutions or a population with values that are within the desired range and are acceptable in the process of finding the most appropriate value, to increase the efficiency of finding a solution, the bee swarm process is used to find the solution within the search space and apply it to solve the reservoir management problem by calculating the minimum frequency value and the minimum average value of excess water, which are determined as objective functions to evaluate the efficiency of the search process. Through testing RORCs and comparing the results and efficiency in finding answers with the firefly algorithm technique, which has previously been used to solve the RORC problem in the Nam–Oon Reservoir, it is feasible to employ alternative techniques, such as the FA and ABC-CA, in combination with a reservoir simulation model (RSM), to identify the most favorable RORC. Cultural processes are very useful in improving the efficiency of finding the right answers in the search space and simplifying the creation of global answers. The bee colony process still has some limitations. In particular, there is the problem of convergence to global solutions, which can occur when the search space

becomes larger, resulting in slower computation. Therefore, to overcome these limitations, cultural process techniques have been introduced to increase efficiency.

This study suggests employing an alternative method that utilizes the FA and ABC-CA in combination with an RSM to identify the optimal flood RORC in flood control areas. In this study, we employed the proposed models to identify the optimal flood RORC for the NOR, situated in northeastern Thailand. Two objective functions—minimizing the average excess water and minimizing the frequency of excess water—directed the search methods.

2. Methodology

2.1. Research Area

The research area is situated in Sakon Nakhon province, Thailand, as shown in Figure 1. The research was conducted between 2021 and 2022. The NOR has an irrigation area of 32,480 hectares and is located in the Songkham Basin in northeastern Thailand. The storage capacity of the reservoir is 520.000 million cubic meters (MCM), while the average annual inflow is 404.835 MCM. Data on the inflow were collected over a period of 28 years, from 1994 to 2021. Schematic diagrams of the NOR system, which provides domestic water supply, irrigation, industry demand, and conservation of the environment, are shown in Figure 2.

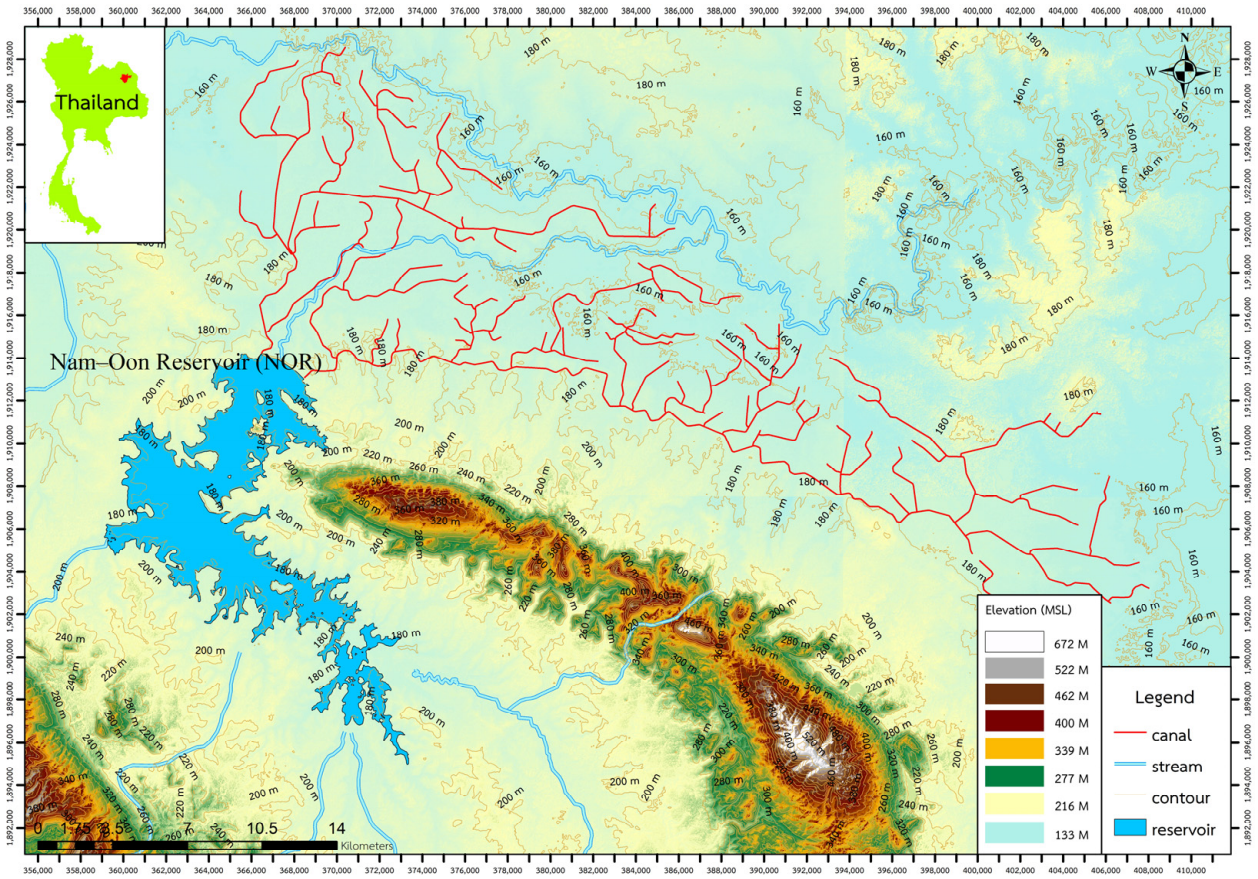


Figure 1. The location of the Nam–Oon Reservoir (NOR).

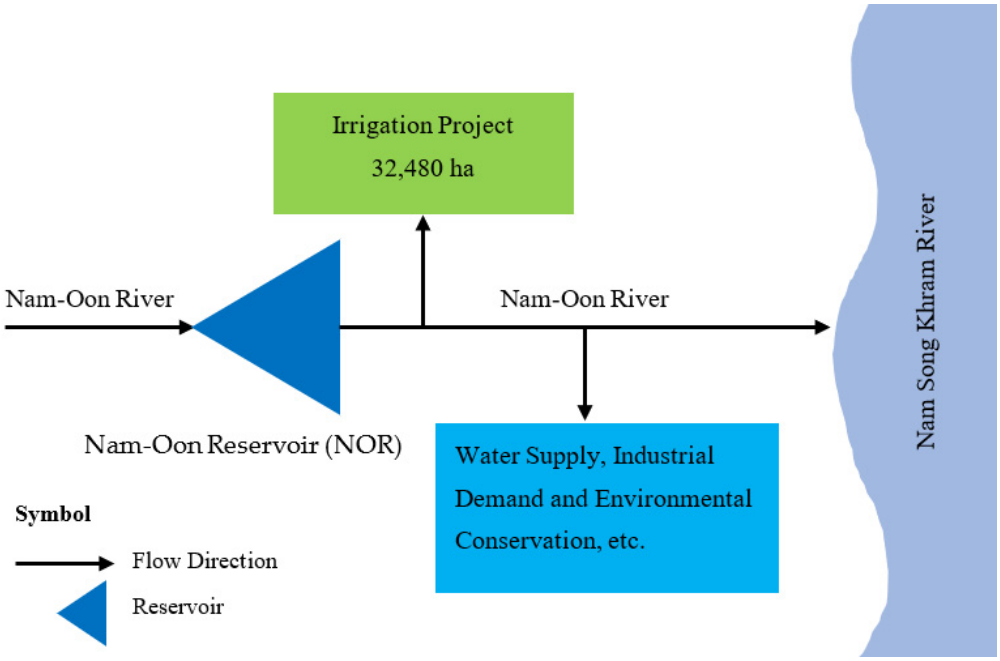


Figure 2. Illustration depicting a schematic diagram of the Nam–Oon Reservoir (NOR) system.

2.2. Model for Simulating Operation of Reservoir

The reservoir system was simulated by applying the water balancing concept, which necessitated hydrologic data, physical reservoir data, water demand data from the reservoir, and other relevant data. The available water was computed using Equation (1) based on this concept. The estimation of the monthly water release considered the available water resources, the specified release requirements, the standard operating procedures, and the represented RORC displayed in Figure 3.

$$W_\tau = S_{\tau-1} + I_\tau + P_\tau - E_\tau \quad (1)$$

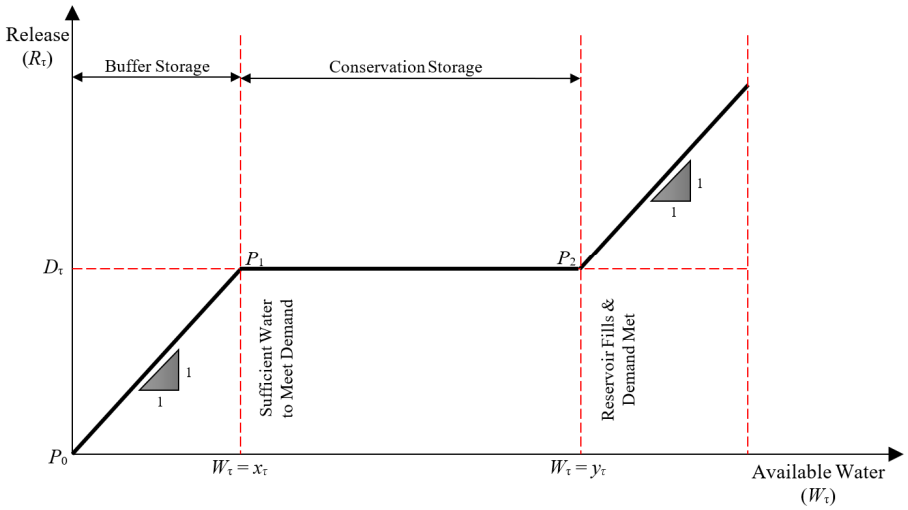


Figure 3. Standard operating reservoir rules.

This equation represents the calculation of available water during month τ, taking into account different parameters. W_τ refers to water availability during month τ, and $S_{\tau-1}$ denotes the amount of water that is stored at the conclusion of the month $\tau - 1$, which is initially set to full reservoir capacity. The calculation is derived from the inflow

into the reservoir (I_τ), the amount of precipitation during the month (P_τ), and the average evaporation loss during the month (E_τ).

Subsequently, the monthly water release rate (R_τ) was determined to calculate water scarcity and excess water levels. These levels are represented by the average yearly amount of excess water (the initial objective function in the search procedure) and the yearly frequency of excess water (the second objective function utilized during the search procedure), as shown in Equations (2) and (4), respectively. In these equations, x_τ refers to the lower RORC during month τ, while y_τ denotes the upper RORC during month τ.

$$Min\ Avr_i = \left(\frac{1}{n}\sum_{v=1}^{n} Sp_v\right) \tag{2}$$

$$\text{if } R_\tau > D_\tau;\ \text{Then } Sp_v = \sum_{v=1}^{n} (R_\tau - D_\tau) \tag{3}$$

$$\text{Min } Fre_i = \left(\frac{1}{n}\sum_{v=1}^{n} Sf_v\right) \tag{4}$$

In this equation, Avr_i represents the average amount of excess water per year during iteration i; Sp_v denotes the excess water during year v, where releases exceed the target demand; Fre_i is the frequency of excess water; Sf_v indicates the number of annual floods, which is the year when releases exceed the target demand; D_τ represents the monthly goal demand from the reservoir, which is determined by utilizing data from previous studies and calculating the water demand in the downstream area [50]. The variable i represents the iteration number.

2.3. Firefly Algorithm (FA)

The firefly algorithm was first proposed by Xin-She Yang in 2008 [51]. It was inspired by the flashing behavior of fireflies, where the intensity of the light emitted is proportional to the attractiveness of the firefly. This leads to fireflies that are closer together being more likely to fly toward one another. The algorithm is based on the following ideas: (1) no separation of sexes, where each firefly can attract others regardless of gender; (2) attraction of a firefly is proportional to its brightness, and fireflies with lower brightness move toward those with higher brightness; (3) brightness is determined by an objective function. The algorithm is described in the following steps.

Step 1: Define objectives, constraints, and boundaries for the function.

Step 2: Specify the attractiveness of the light source, the number of fireflies, the filter efficiency of the medium, and the variables for movement distance, number of movements, or stopping conditions of the fireflies.

Step 3: Create an initial population of fireflies using non-chance-based random sampling, where each firefly represents the answer to the considered problem, and store the locations of all fireflies.

Step 4: Check if the randomly generated fireflies are within the constraint function or not. If not, generate a new set of fireflies until all of them meet the constraint function.

Step 5: Move the firefly with the least brightness toward the firefly with the greatest brightness among all fireflies.

Step 6: Check if the variables are within the defined boundaries. If not, adjust them to be within the boundaries.

Step 7: Check if all fireflies are within the constraint function. If not, adjust them to be within the constraint function.

Step 8: Compare the values of all fireflies to find the most suitable value for this movement.

Step 9: Check the stopping conditions. If met, proceed to Step 10. If not, repeat from Step 5.

Step 10: Use the value obtained from Step 9 as the optimal solution, and the calculation is completed.

2.4. Artificial Bee Colony and Cultural Algorithm (ABC-CA)

2.4.1. Cultural Algorithm (CA)

Cultural evolution is a computational science of evolution that was developed by Reynolds in 1994 [47,48]. It is a simulation of the social evolution model that is integrated with various agent-based learning techniques. It utilizes experience and knowledge gained over time. Cultural evolution is highly beneficial in developing the effectiveness of finding appropriate answers within search spaces, making global answers more easily accessible. Generally, cultural evolution can be divided into two main components: belief space and population space. Population space is the space of possible solutions in the search space, while belief space is the space of knowledge or information that is accumulated during the search process for the most appropriate solution. The information accumulated in the belief space is shared with the population space and can be used to simulate and apply all techniques for finding the most appropriate solution in a population-based manner.

2.4.2. Artificial Bee Colony (ABC)

The ABC algorithm is a smart and intelligent group-based technique developed by Pham in 2005 [34] to simulate the process of bees searching for food sources. The efficiency of the bee colony optimization algorithm is comparable to other intelligent group-based techniques, but it requires the configuration of various parameters, such as the number of bees (n) that explore the environment, the number of food sources (m) that bees investigate, the number of best food sources (e), the number of bees selected for the best food sources (nep), the number of bees selected for other food sources (nsp), the initial size of the flower petals (ngh), and the criteria for stopping all processes. The bee colony optimization algorithm starts by randomly placing n bees in the search space and then finding the fitness values of the number of food sources investigated by the bee colony. Although the bee colony optimization algorithm has been used to solve various optimization problems, including the control and planning of power systems, and is an interesting intelligent group-based technique, it still has some limitations, especially in converging to the global optimum, which may occur when the search space is large, leading to slower computation time. Therefore, various techniques, such as the cultural algorithm, have been used to overcome these limitations and improve efficiency.

In this article, the artificial bee colony process was used as a population model for cultural processes, while normative knowledge, which is knowledge or information about various important examples or events, and situational knowledge, which is a group of solutions or populations that are valuable in the desired range and are acceptable in the process of finding the most appropriate value, were used to help improve the efficiency of bees. It explores finding solutions within the search space and applies them to solve the problem of reservoir operation by calculating the appropriate control curve of the reservoir using the bee colony process as a cultural model.

2.5. Firefly Algorithm-Incorporating Reservoir Simulation Model (RSM)

The FA and RSM are linked by first initializing the essential data, including the full capacity level, normal high-water level, dead storage level, and monthly water demands. Subsequently, a starting population of fireflies is generated by the model, where each firefly symbolizes the monthly RORC of the reservoirs, which defines the upper and lower RORCs. To find the optimal value for RORCs, there are 24 decision variables, namely, 12 for the upper RORCs and 12 for the lower RORCs, depending on the number of months in a year. The first set of fireflies in the initial population consisted of 24 decision variables, which were used in the RSM to obtain the monthly release of water based on those RORCs and the standard operating rules. The discharged water was employed to calculate the previously described objective functions. Subsequently, fitness evaluations and updates of the fitness

values were performed for the objective function. Subsequently, the fireflies were assigned rankings, their locations were updated, and the stop criterion was checked. This process was iterated until the criteria were satisfied, achieving the most optimal RORC values. Figure 4 depicts the FA and RSM utilized for searching the RORCs.

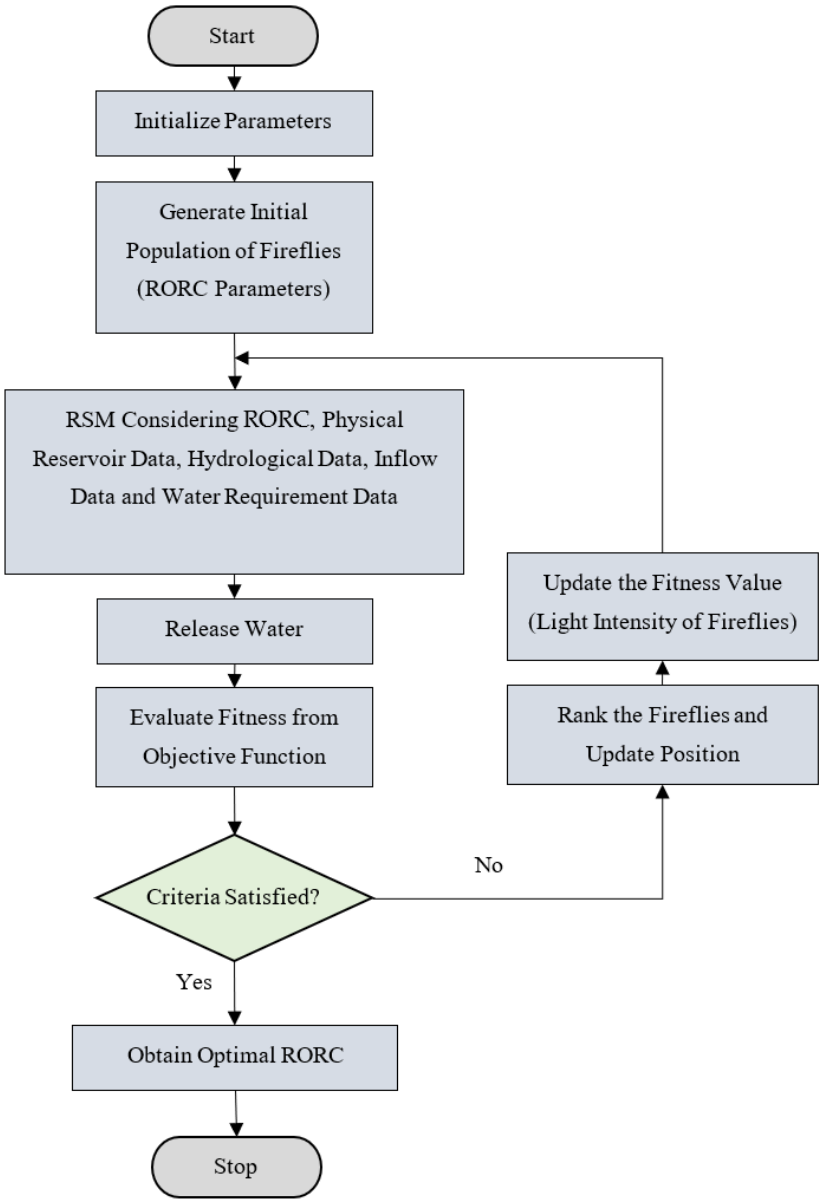


Figure 4. Firefly algorithm incorporating the RSM into the search for optimal RORCs.

2.6. Artificial Bee Colony and Cultural Algorithm Incorporating RSM

The ABC-CA and reservoir simulation model were linked, starting with initializing the essential data, including the full capacity level, normal high-water level, dead storage level, and monthly water demands. Next, the initial population of the ABC and belief space from CA were generated by the model, where each ABC denotes the monthly RORC of the reservoirs that define the upper and lower RORCs. To find the optimal value for the RORCs, there are 24 decision variables, namely, 12 for the upper RORCs and 12 for the lower RORCs, depending on the number of months in a year. The initial population of the ABC consisted of 24 decision variables, which were then used in the RSM to obtain the monthly release of water based on those RORCs and the standard operating rules. The discharged water was employed to calculate the previously described objective functions.

Subsequently, fitness evaluations and updates of the fitness values were performed for the objective function. The ABC parameters were reassigned to new values using the situational and normative knowledge of CA. Subsequently, their ranking and position were revised, and the stopping criterion was evaluated. This process was iterated until the criteria were satisfied, achieving the most optimal RORC values. Figure 5 depicts the ABC-CA and RSM utilized for searching the RORCs.

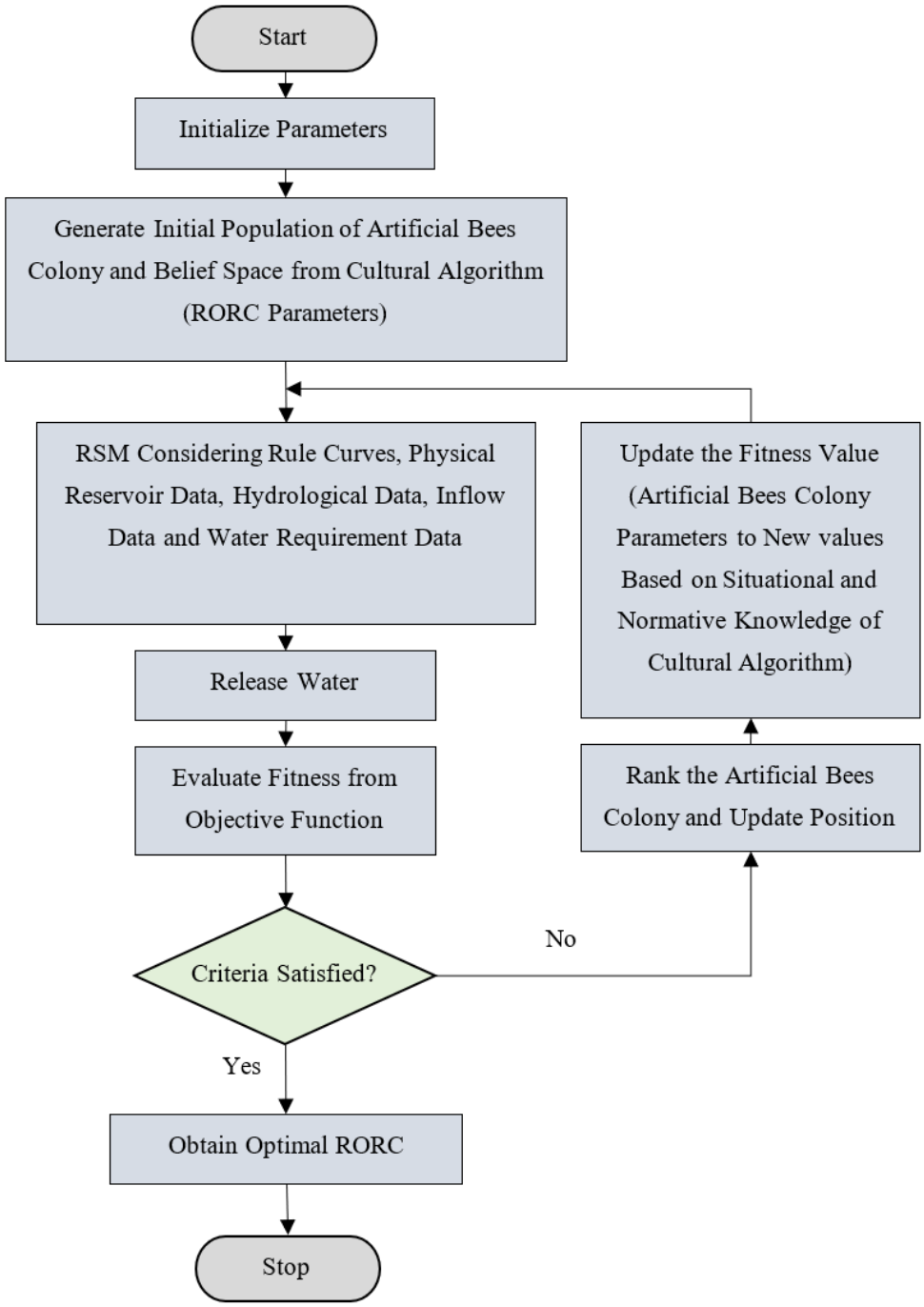


Figure 5. ABC-CA incorporating the RSM into the search for optimal RORCs.

2.7. Assessment of Obtained RORCs

The RORCs obtained through the FA, ABC-CA, and RSM were tested by applying them to the reservoir system for each inflow scenario. Initially, the historic inflow data of 28 years were used in the RSM, followed by the evaluation of 1000 synthetic inflow events

generated from the same historic inflow data under the same conditions in the RSM using the HEC-4 model. For the operation of the HEC-4 model, statistical principles were used in the analysis. These principles can analyze models with only one water metering station or with many stations combined in the same basin. In cases where there are more than one runoff station, the model synthesizes missing or incomplete data for the station under consideration on the basis of both runoff data for the month under consideration at the other stations and statistical relationships between the runoff measurement stations used for analysis. In addition, the amount of synthetic runoff may be determined by determining statistical characteristics. The HEC-4 model calculates the mean standard deviation and skew coefficient of the runoff for each month and each runoff station by adding 1% of the runoff to the average runoff. The model calculates the regression equation from the correlation matrix using the Crout method for each station and month. Then, it calculates the runoff volume of each station by calculating each consecutive month. It starts from the average of all stations in the first month and calculates subsequent months. Finally, the evaluation results were presented, considering the occurrence, magnitude, and duration of water scarcity and excess water situations.

2.8. Analysis of Data Using Statistical Methods

The frequency was determined by dividing the number of annual floods or droughts by the total number of years considered. The magnitude of water scarcity or excess water was determined by dividing the total water scarcity or excess water by the total number of years considered. The maximum magnitude of water scarcity or excess water was determined by selecting the yearly water scarcity or excess water with the highest value for all years considered. The duration of water scarcity or excess water was determined by dividing the number of consecutive years with floods or droughts by the total number of groups of successive years with floods or droughts. The maximum duration of water scarcity or excess water was determined by selecting the maximum number of consecutive years with floods or droughts for all years considered. The results are presented as the mean $\pm$ standard deviation for synthetic inflow cases.

3. Results

3.1. Optimal RORCs

The FA model introduced in this research produced optimal RORCs, as depicted in Figure 6. The search process employed the objective of minimizing yearly excess water, considering historical and projected inflow data. The RORCs labeled RC2-Avr_FA and RC3-Avr_ABC-CA, and the existing ones (RC1-Current) displayed a similar trend. The lower RORCs derived from both historical and projected inflow data surpassed the current RORCs from March to July. However, the upper RORCs of the newly optimized rules exceeded the current ones from June to September. It is important to highlight that the obtained upper RORCs (RC3-Avr_ABC-CA) were below the current upper RORCs from October to November.

The optimal RORCs generated by the FA and ABC-CA models introduced in this study are illustrated in Figure 6. The search procedure involved utilizing the objective function to minimize annual excess water, using historical inflow data as a basis. The RORCs obtained from the FA model (RC2-Avr_FA), the RORCs derived from the ABC-CA model (RC3-Avr_ABC-CA), and the current RORCs (RC1-Current) all exhibited similar trends. Nonetheless, the RORCs resulting from the FA and ABC-CA models surpassed the current RORCs between March and July. On the contrary, the novel optimal RORCs surpassed the current RORCs from June to September. It is important to highlight that the upper RORCs derived from the ABC-CA model (RC3-Avr_ABC-CA) were lower than the current upper RORCs throughout the October–November period.

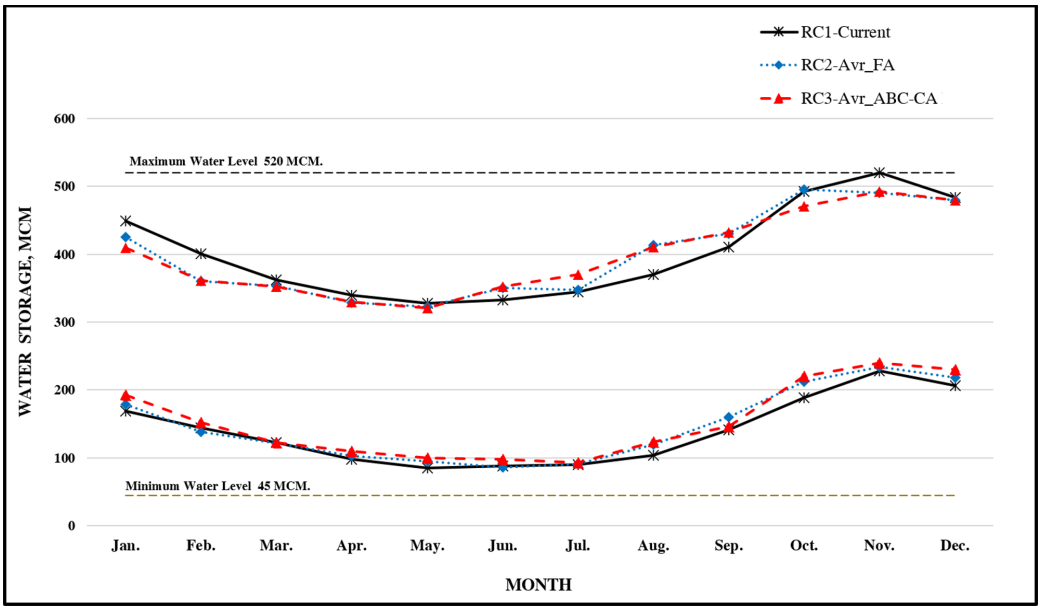


Figure 6. Optimal RORCs of the NOR using the objective function of minimizing the average excess water in the search procedure.

Figure 7 illustrates the optimized RORCs for the NOR. These curves were obtained by minimizing the frequency of excess water through a search process that considered historical data as the optimization objective. The patterns observed in RC4-Fre_FA, RC5-Fre_ABC-CA, and the current RORCs are resemblant. They also demonstrate that the lower RORCs resulting from the utilization of historical and future inflow data (RC4-Fre_FA and RC5-Fre_ABC-CA) were greater than the current RORCs from January to June. Conversely, the upper RORCs of the newly derived optimal RORCs were lower than the current RORCs in July.

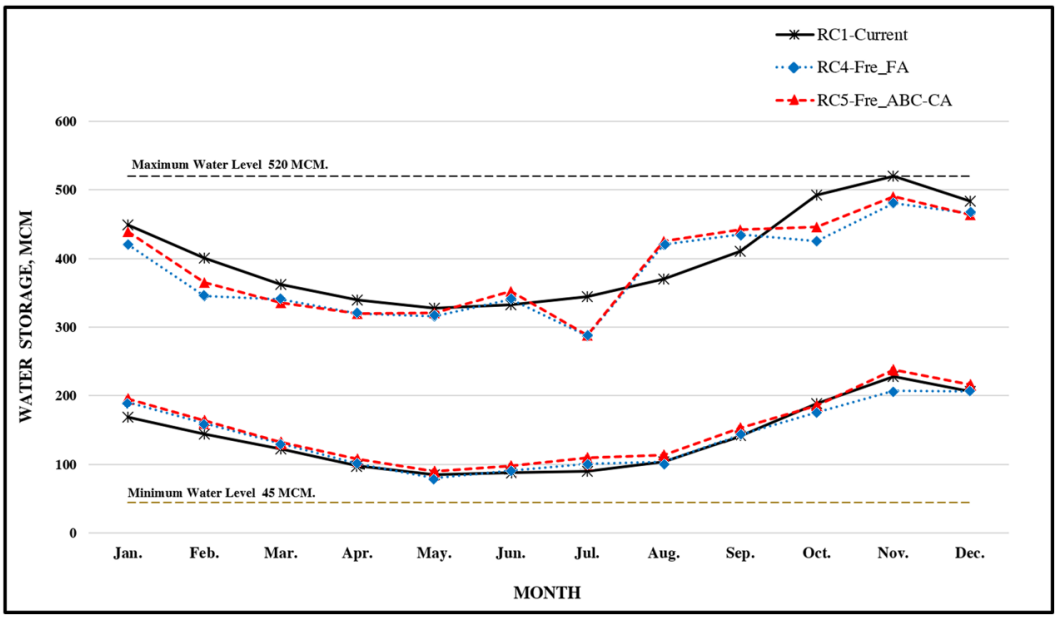


Figure 7. Optimal RORCs of the NOR using the objective function of minimizing the frequency of excess water in the search procedure.

3.2. Efficiency of Obtained RORCs

The effectiveness of the recently derived RORCs from all search scenarios was assessed through an RSM that considered historical inflow data for the NOR, spanning 28 years on a monthly basis. The assessment considered instances of water scarcity and excessive water within the RORCs, and the results are outlined in Table 1. These findings indicate that the RORC based on ABC-CA (RC5-Fre_ABC-CA), generated by minimizing average excess water as the optimization goal, yielded the lowest occurrences of water scarcity (0.464 times per year, 19.926 MCM per year, and 1.684 years for frequency, magnitude, and duration, respectively), as well as excessive water release (0.627 times per year, 85.641 MCM per year, and 2.00 years for frequency, magnitude, and duration, respectively) in comparison to the other RORCs. Moreover, the analysis demonstrated that the newly developed RORCs were more effective in mitigating both water scarcity and excessive release situations than the existing RORCs within the historic scenario.

Table 1. Situations of excess water and water scarcity in the NOR, considering historical inflow during the past 28 years.

Situation	RORC	Frequency (Times/Year)	Volume (Million Cubic Meter)		Time Period (Year)	
			Average	Maximum	Average	Maximum
Water scarcity	RC1-Current	0.962	45.884	154.000	13.500	14.000
	RC2-Avr_FA	0.584	21.378	130.000	2.500	3.000
	RC3-Avr_ABC-CA	0.464	19.926	126.000	1.684	3.000
	RC4-Fre_FA	0.782	38.411	142.000	6.000	8.000
	RC5-Fre_ABC-CA	0.994	38.407	140.000	10.500	12.000
Excess water	RC1-Current	0.754	113.402	476.959	4.000	6.000
	RC2-Avr_FA	0.794	89.226	479.080	3.000	5.000
	RC3-Avr_ABC-CA	0.797	86.844	465.867	3.000	4.000
	RC4-Fre_FA	0.704	89.381	465.083	2.000	4.000
	RC5-Fre_ABC-CA	0.627	85.641	436.372	2.000	3.000

Additionally, 1000 sets of simulated inflow data were generated for each reservoir based on their historical inflow records. Table 2 presents the frequency of excessive water and water scarcity in the NOR region. This analysis was based on the synthetic inflow data of 1000 instances in the RORC simulation. The findings revealed that the instances of water scarcity (16.271 $\pm$ 7.224 MCM/year) and excessive water (66.221 $\pm$ 17.001 MCM/year) using the ABC-CA RORCs, obtained by minimizing average excess water as the optimization objective (RC3-Avr_ABC-CA), were the lowest in comparison to the other RORCs. Conversely, when the current RORCs were employed for assessment, the outcomes indicated the highest values.

Table 2. Situations of excess water and water scarcity in the NOR region, considering 1000 synthetic inflow samples.

Situation	RORC		Frequency (Times/Year)	Volume (MCM)		Time Period (Year)	
				Average	Maximum	Average	Maximum
Water scarcity	RC1-Current	μ	0.971	42.445	131.774	17.442	22.637
		σ	0.032	6.831	36.226	6.804	4.937
	RC2-Avr_FA	μ	0.673	18.014	110.824	2.653	5.292
		σ	0.109	8.224	29.344	0.968	2.447
	RC3-Avr_ABC-CA	μ	0.473	16.271	108.097	2.307	4.065
		σ	0.106	7.224	27.744	0.747	2.044
	RC4-Fre_FA	μ	0.811	33.227	120.224	6.242	10.388
		σ	0.108	7.723	34.220	3.584	4.335
	RC5-Fre_ABC-CA	μ	0.989	33.407	119.379	15.124	18.066
		σ	0.051	6.837	30.055	7.225	5.097

Table 2. *Cont.*

Situation	RORC		Frequency (Times/Year)	Volume (MCM)		Time Period (Year)	
				Average	Maximum	Average	Maximum
Excess water	RC1-Current	μ	0.699	91.994	358.622	3.009	7.717
		σ	0.107	20.931	77.022	1.554	2.249
	RC2-Avr_FA	μ	0.638	68.734	328.771	2.557	5.334
		σ	0.155	18.984	81.229	0.899	2.227
	RC3-Avr_ABC-CA	μ	0.557	66.221	324.073	2.458	5.365
		σ	0.104	17.001	80.177	0.975	2.005
	RC4-Fre_FA	μ	0.687	80.812	350.401	2.844	6.113
		σ	0.110	19.003	79.773	1.098	2.502
	RC5-Fre_ABC-CA	μ	0.644	79.991	345.374	3.009	6.302
		σ	0.105	20.224	77.780	1.224	2.708

Notes: μ: mean; σ: standard deviation.

4. Discussion

The patterns of the newly derived RORCs from all search scenarios and the current RORCs (as depicted in Figures 6 and 7) exhibited similarities due to the impact of seasonal inflow patterns and consistent conditional effects, which align with findings from other studies [2,33,34,52–54]. The updated lower RORCs surpassed the current lower RORCs during dry seasons. This setup helps regulate the amount of released water by reducing water discharge to conserve more water during periods of low rainfall, a strategy observed in similar studies. In contrast, the newly established upper RORCs for the months of June to September exceeded the corresponding current upper RORCs. These arrangements enable greater water conservation by mitigating excessive water release and maintaining elevated water levels. On the contrary, the newly obtained upper RORCs were lower than the existing upper RORCs for the months of October to November. As a result, these updated RORCs have the potential to better manage flood scenarios compared to the current RORCs, as they involve increased water release to create additional reserve volume.

The outcomes from assessing the newly acquired RORCs (presented in Tables 1 and 2) revealed that the occurrences of water scarcity and excessive water using the ABC-CA RORCs, which were developed by incorporating historical inflow data into the search process, were the lowest compared to the other RORCs. This similarity arises from their creation, involving the utilization of historical inflow data, a strategy akin to other studies [34,55–57]. It is crucial to conduct a comparative analysis between the results of the proposed FA and ABC-CA techniques and the outcomes of alternative methods.

Integration of FA and ABC-CA improves the efficiency of reservoir operation rule curves, reducing water shortages and excess water compared to traditional methods.

In this research, we did not take situations of extreme weather conditions or unexpected environmental changes into consideration. However, the approach presented in this research can accommodate situations of extreme weather conditions or inflow uncertainty. The reason for this is that such situations only involve changes in the data used in the reservoir model. Therefore, there will be no negative impact on the surrounding ecosystem.

5. Conclusions

In this study, the firefly algorithm (FA) and the artificial bee colony combined with the cultural algorithm (ABC-CA) were employed alongside an RSM to search for the optimal RORCs. The findings highlighted that the proposed approach, utilizing two distinct objective functions, yielded novel RORCs. The similarities in the patterns of these RORCs are attributed to seasonal inflow dynamics and consistent search conditions. Nonetheless, there exist variations, particularly notable during the rainy season. Additionally, the results demonstrated that the RORCs generated by minimizing average excess water and incorporating historical inflow data into the search process are more effective in mitigating

excessive water scenarios compared to the other RORCs, in both historical and synthetic inflow scenarios.

This research revealed the utilization of the FA and the combination of the ABC-CA in conjunction with a simulation model to explore flood control RORCs that offer potential benefits in terms of optimization. The RORC derived from the newly proposed FA and ABC-CA models outperformed the current RORCs in mitigating flood scenarios. This study serves as a valuable resource for researchers engaged in the pursuit of optimal flood control RORCs for reservoirs situated in flood-prone regions.

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