Transforming Water Management: The Impact of Harris Hawks Optimization on Ubolratana Dam, Thailand

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Abstract. *Effective reservoir management is critical for addressing water scarcity and ensuring water security, especially in drought-prone regions. However, traditional reservoir operation methods, such as the Standard Operating Procedure (SOP), often fail to adequately balance water deficits and surpluses under changing climatic and demand conditions. This study addresses these limitations by integrating the Harris Hawks Optimization (HHO) algorithm with a reservoir simulation model, aiming to enhance operational efficiency at Ubolratana Dam in northeastern Thailand. The research evaluates the Hedging Rule (HR) against SOP benchmarks, highlighting its ability to reduce average water shortages and excessive water releases. Using historical management data, monthly inflow patterns, and current water demand, the proposed HR framework demonstrates a 53% reduction in water shortages and a 19% decrease in excessive releases compared to existing practices. These results underscore the significant potential of optimization-based approaches in improving reservoir resilience and reliability. This study fills a critical gap in sustainable water management by offering a robust and adaptable framework for optimizing reservoir operations in regions vulnerable to climate variability.*

Keywords:

Reservoir Operation, Hedging Rule, Standard Operating Policy, Harris Hawks Optimization, Reservoir Rule Curves

1. Introduction

Water, a vital but limited natural resource, is crucial for human and ecological well-being. Rapid climate changes are disrupting the water cycle, leading to floods, droughts, and societal conflicts over water usage [1-3]. Effective water resources management, which balances economic efficiency, social justice, and environmental sustainability, is essential. Strategies for better water management include optimizing supply and demand management and implementing non-structural measures to cut costs and reduce impacts. Improving reservoir operations is a key approach to enhance water resource management [4-6].

Reservoir management faces significant hydrological challenges, such as those seen at the Ubolratana reservoir in Thailand, necessitating adaptations to both droughts and floods. [7-9] Management must balance natural uncertainties with fluctuating water demands, employing tools like the rule curve for effective water balance analysis. Critical data, including downstream demand, reservoir levels, and rainfall-induced inflows, are essential, though often limited by inadequate historical records. Improved timing and scaling of water releases, tailored to current needs, can enhance operational efficiency and emphasize the necessity for customized strategies in water resource management [10-11].

Reservoir rule curves, comprising upper and lower thresholds, provide a framework for optimal water level control. However, while they offer long-term management benefits, their efficacy in reservoir operations may diminish over time. [12-15] Consequently, diverse rule curves have been developed, including release criteria to guide water discharge decisions [16-18].

Effective reservoir management relies heavily on the establishment of precise release criteria to balance water storage and release, ensuring a sustainable supply while minimizing risks of shortages and floods. The Standard Operating Procedure (SOP) has long been the prevailing approach in reservoir operations, offering a straightforward framework for water allocation. SOPs are typically designed based on static rule curves, which assume fixed conditions and uniform water release rates. While these methods are practical for routine operations, they are often insufficient in addressing dynamic inflow variability, particularly under conditions of climate change and growing water demand [19-21]. One of the most significant limitations of SOP is its inability to adapt to single-period water shortages caused by erratic inflows, resulting in frequent over-releases during wet periods and insufficient supply during droughts. This gap highlights the need for more adaptive policies that can mitigate these risks effectively.

To address these shortcomings, the hedging rule (HR) policy has been proposed as an alternative framework. Unlike SOP, HR introduces a more flexible and adaptive mechanism by prioritizing water allocation based on the severity of water scarcity. During periods of low inflow, HR strategically reduces water releases to conserve storage, thereby ensuring availability for critical demands in subsequent periods [22-25]. This proactive approach allows HR to mitigate the impact of droughts, particularly in dry seasons, which are common in regions like northeastern Thailand. While SOP relies on a fixed release schedule, HR dynamically adjusts its release strategy based on real-time conditions, making it a more robust solution for reservoirs facing high variability in inflow and demand.

Simulation models and advanced methods have significantly enhanced reservoir management by introducing data-driven decision-making frameworks. Dynamic programming (DP) [31], while effective for multi-stage optimization, faces computational limitations in complex systems. Heuristic and metaheuristic approaches, such as genetic algorithms (GAs) [32] and particle swarm optimization (PSO) [33], offer flexibility and efficiency in solving non-linear problems. However, these methods often require extensive parameter tuning and may struggle with adaptability to real-time inflow variability.

Other techniques, such as ant colony optimization (ACO) [34] and hybrid approaches combining simulation with optimization, have demonstrated potential in addressing uncertainties. Machine learning (ML), Artificial neural network, extreme learning machine (ANNs), has been employed for inflow prediction and optimization [35-36], but its dependency on large datasets and lack of interpretability remain challenges.

Despite these advancements, many existing methods are constrained by computational demands, static assumptions, or limited adaptability, particularly in multi-purpose reservoirs facing dynamic conditions. This study addresses these gaps by introducing the Harris Hawks Optimization (HHO) algorithm, a robust and flexible approach designed to optimize release rules effectively under uncertain and complex scenarios.

In this context, the quest for a more robust and versatile optimization method led to the emergence of the Harris Hawks Optimization (HHO) approach [37]. Inspired by the collaborative hunting strategies of Harris Hawks, HHO offers a novel solution that transcends the limitations of previous optimization techniques. Unlike its predecessors, HHO requires minimal parameterization and exhibits a remarkable balance between exploration and exploitation, thereby enhancing its adaptability and effectiveness in deriving optimal rule curves [38-41].

The literature review indicates that the HHO method outperforms other techniques under similar conditions and is highly effective when applied to various problems. Consequently, this study aims to identify optimal reservoir rule curves by integrating the HHO approach with the HR and SOP release criteria of the Ubolratana reservoir in Khon Kaen, Thailand. Additionally, the research will assess the effectiveness of the HHO-derived rule curves in minimizing water shortages and excesses, considering both HR and SOP criteria.

2. Material and Methodology

2.1 Study Area

The Ubolratana reservoir, located in Khon Kaen province in northeastern Thailand at a longitude of 102°37'06.0"E and latitude of 16°46'31.4"N, as shown in “Fig. 1” is a vital water resource. It boasts a normal storage capacity of 2,431 million cubic meters (MCM) and a dead storage capacity of 581.67 MCM. The water surface area at normal storage is 137.90 square kilometres.

As depicted in “Fig. 2” the reservoir supports a wide range of downstream water requirements, including power generation, agricultural irrigation, flood management, industrial processes, municipal water supply, and conservation efforts.

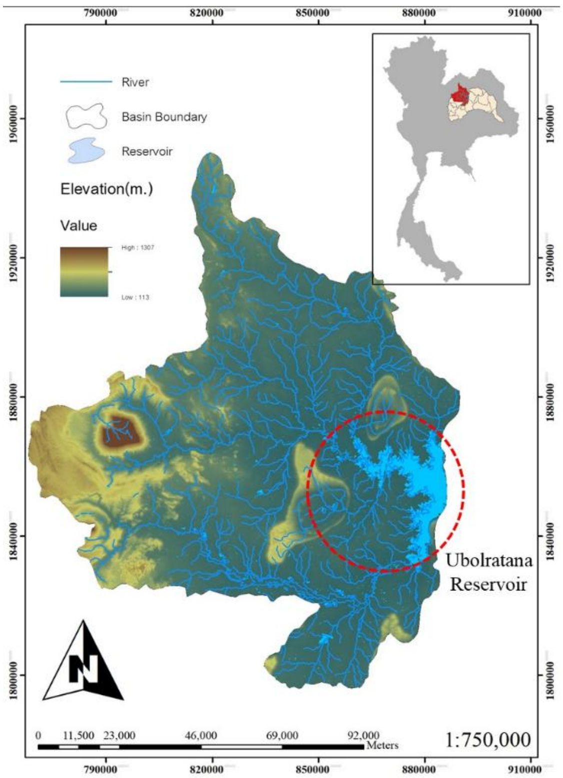


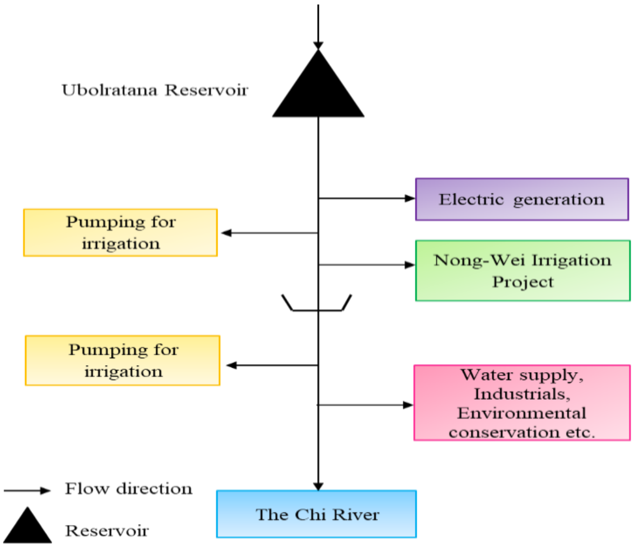
Fig. 1 The Location of Ubolratana Reservoir.

The hydroelectric power plant at the reservoir plays a crucial role in meeting local energy requirements. Additionally, the reservoir's irrigation system boosts agricultural productivity and supports local farmers. It is also vital for flood control, helping to manage water flow and prevent flooding in downstream areas.

Furthermore, the Ubolratana reservoir meets the water demand of various industries and provides a reliable domestic water supply, ensuring access to clean and safe drinking water for the local population. It also supports environmental conservation efforts, maintaining ecological balance and supporting diverse habitats.

2.2 Inflow Data

The Ubolratana reservoir, situated in Khon Kaen province in northeastern Thailand, spans an upper watershed area of 11,960 square kilometers across Nong Bua Lamphu, Chaiyaphum, and Khon Kaen provinces. Historical inflow data from 1972 to 2023, as illustrated in "Fig. 3," reveals an average annual inflow of 2,465 MCM. The highest recorded inflow was 5,884 MCM in 1978, while the lowest was 387 MCM in 2019.These inflows play a critical role in managing water resources for flood and drought control and are vital for supporting regional needs such as irrigation, power generation, and environmental conservation.



supporting various regional needs including irrigation, power generation, and envirconservation.

Fig. 2 Schematic Diagram of the Ubolratana Reservoir [9].

2.3 Reservoir Simulation Model

The management of the Ubolratana reservoir relies on an advanced simulation model that incorporates a water balance equation, along with reservoir rule curves and defined release criteria. The model begins by calculating the aaccessible water using the water balance approach, which takes into account monthly inflow and downstream water requirements. The estimated monthly water release is then determined by applying the release criteria and the established rule curves for the reservoir.

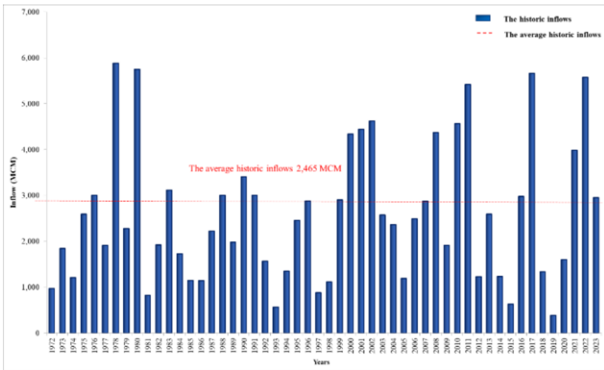


Fig. 3 The annual historical inflow into the Ubolratana reservoir, as reported by EGAT of Thailand.

2.3 Reservoir Simulation Model

The operation of the Ubolratana reservoir is governed by an advanced simulation model that utilizes a water balance equation, integrating reservoir rule curves and specific release criteria. The model begins by calculating the available water using the water balance approach, which takes into account monthly inflow and downstream water requirements. The estimated monthly water release is then determined by applying the release criteria and the established rule curves for the reservoir.

In this study, the reservoir operation model was developed based on the water balance principle and includes both HR and SOP as the criteria for release. The HR and SOP differ significantly in their approach to water release management. HR aims to conserve water by restricting discharge during dry seasons, ensuring sufficient water availability during low inflow periods. In contrast, SOP focuses on meeting target water demands throughout the year, often resulting in less conservative water management compared to HR. Both the HR and SOP criteria were evaluated for performance, with their one-point representations illustrated in "Fig. 4," with their formulations presented in "Eqs. (1) – (2)." equation, detailed in these equations, considers stored water from the previous month, current inflow, and average evaporation loss to determine the available water each month.

The HR constraints are as follows:

When $0 \leq (1\text{-}DDIt).Dt \leq SWAt$

$$R_{v,\tau} = \begin{cases} WA_\tau & \text{if } WA_\tau < SWA_\tau \\ D_\tau + (SWA_\tau - D_\tau)\dfrac{WA_\tau - EWA_\tau}{SWAt_\tau - EWA_\tau} & \text{if } SWA_\tau \leq WA_\tau \leq EWA_\tau \\ D_\tau & \text{if } EWA_\tau \leq WA_\tau < D_\tau + C \\ WA_\tau - C & \text{if } WA_\tau \geq D_\tau + C \\ 0, \text{ otherwise} & \end{cases} \quad (1)$$

Here, $R_{v,\tau}$ represents the total release from the aggregated reservoir at time τ; SWA_τ and EWA_τ denote the starting and ending water availability of the aggregated reservoir at time τ, respectively; and D_t indicates the water demand for the supply system at time τ.

The SOP constraints are as follows:

$$R_{v,\tau} = \begin{cases} D_\tau + W_{v,\tau} - D_\tau + C,\ for W_{v,\tau} \geq D_\tau + C + D_\tau \\ D\tau,\ for D_\tau \leq W_{v,\tau} < D_\tau + C + D_\tau \\ D_\tau + W_{v,\tau} - D_v\, for D_\tau - D_\tau \leq W_{v,\tau} < D_\tau \\ 0, otherwise \end{cases} \tag{2}$$

In this context, $R_{v,\tau}$ denotes the water release during year ν and month τ (where τ ranges from 1 to 12, corresponding to January through December). D_τ represents the net water demand for month τ; D_t+C indicates the upper rule curve for month τ; D_t is the lower rule curve for month τ and $W_{v,\tau}$ refers to the available water, calculated using the water balance concept for year ν and month τ, as outlined in "Eq. (3)" [15].

$$W_{v,\tau}=S_{v,\tau+}Q_{v,\tau}\text{-}R_{v,\tau}\text{-}E_\tau \tag{3}$$

Here, $S_{v,\tau}$ represents the volume of water stored at the end of month τ; $Q_{v,\tau}$ is the monthly inflow to the reservoir; and E_τ denotes the average evaporation loss. The operating policy typically allocates the available water $W_{v,\tau}$ to manage the risk of future water shortages, particularly when when $0 \leq W\nu,\tau < Dt - D\tau$ in the context of long-term operations.

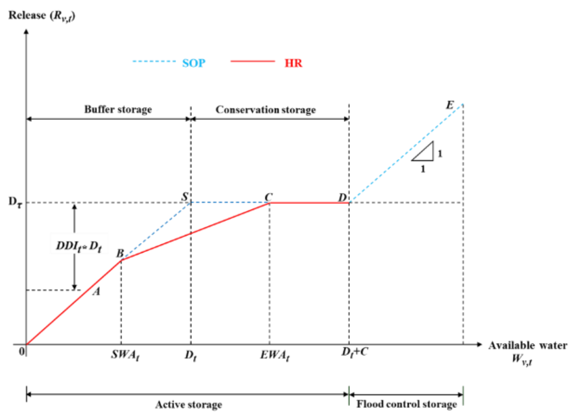


Fig. 4 The HR and SOP. [9]

2.4 Objective Functions for Optimizing Rule Curves

In this study, the objective functions employed for identifying optimal rule curves were to minimize the average water shortage, as outlined in "Eq. (4)", and to reduce the frequency of water shortages, as described in "Eq. (5)". These functions were utilized in the calculations performed using the HHO method.

The minimal average water shortage per year

$$MinH_{(avr)} = \frac{1}{n}\sum\nolimits_{v=1}^{n} Sh_V \tag{4}$$

The minimal average excess water per year

$$Min\ P_{(avr)}=\frac{1}{n}\sum\nolimits_{v\text{-}1}^{n} Spv \tag{5}$$

Here, *H (avr)* represents the average annual water shortage, \(n\) denotes the total number of years examined, and *ShV* indicates the minimized average water shortage in year *v* (the year when releases fall short of the target demand). *P(avr)* refers to the average annual excess water to be minimized, while *Spv* denotes the excess release of water during year *v* (the year when releases exceed the target demand).

2.5 Utilizing HHO and Reservoir Simulation Models to Identify Optimal Rule Curves

The HHO algorithm is a swarm-based optimization technique that does not rely on gradient information, drawing inspiration from the collaborative hunting behaviours of Harris hawks. It mimics the surprise pounce strategy, where hawks coordinate attacks on their prey from various angles. By dynamically adjusting its parameters, HHO effectively balances exploration and exploitation, making it highly efficient for solving complex optimization challenges [10].

- **Initialization:** In this step, the reservoir simulation model parameters and HHO algorithm settings are defined. The population size (N) represents the number of hawks (solutions) in the search space. The boundaries (Xu, Xl) set the limits within which the solutions can vary. The total number of iterations (T) determines how many times the algorithm will update the solutions to find the new optimal rule curves.
- **Reservoir simulation:** Using the initial parameters, the reservoir simulation model calculates the initial fitness of each hawk based on the water releases computed from the HR and SOP rule curves. This simulation considers monthly inflow data, water demands, and the rule curves to estimate how much water should be released each month.
- **Evaluation:** The suitability of each solution is determined through objective functions that gauge performance indicators, such as reducing the average water deficit and surplus. The Elite Matrix is constructed from the best-performing solutions, guiding the optimization process in subsequent iterations.
- **Optimization:** The HHO performs optimization in three phases: exploration (searching for new solutions), transition (balancing between exploration and exploitation), and exploitation (refining solutions). Hawks adjust their positions based on their fitness, with the goal of converging on the best rule curves.
- **Objective Function:** The objective functions evaluate the fitness of solutions by minimizing water shortages and excesses (Eqs. (4) – (5)). These functions ensure that the reservoir management goals are achieved, balancing the need to supply water while preventing shortages and excessive releases.
- **Iteration and Convergence:** During each iteration, the HHO algorithm updates the rule curves, refining the solutions based on the fitness evaluations. Convergence occurs when the algorithm reaches a state where further iterations do not significantly

improve the solutions, meeting the predefined stop criteria. This indicates that the optimal rule curves for the reservoir have been found, ensuring efficient and effective water management

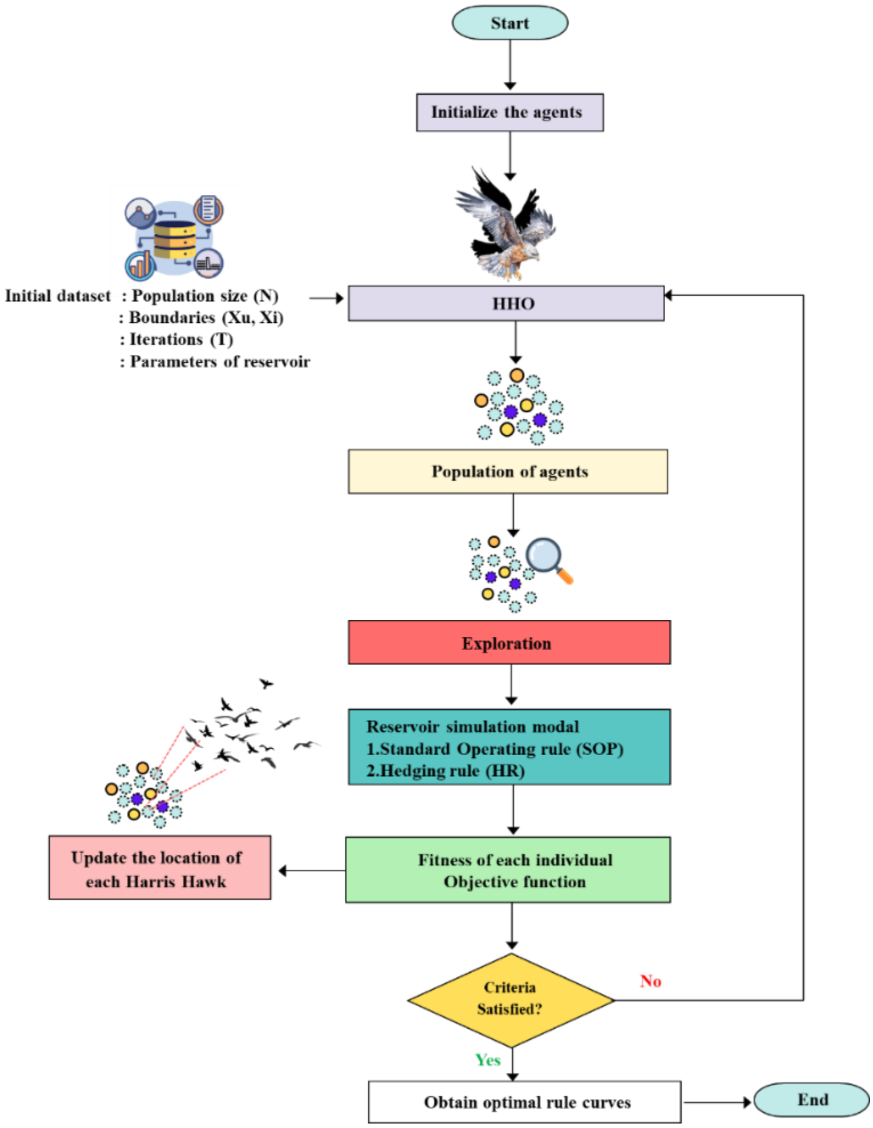


Fig. 5 The application of the HHO method with the reservoir simulation model for determining the optimal rule curves. [10]

3. Results and Discussion

3.1 Efficiency of HHO Rule Curves Considering HR and SOP

Figure 6 displays the optimal rule curves obtained through the HHOmethod, applied with the reservoir simulation model under both HR and SOP conditions. The rule curves derived using the HHO technique under HR conditions (RC1-HR-Avs, RC3-HR-Fqs) demonstrate higher levels compared to those obtained under SOP conditions (RC2-SOP-Avs, RC4-SOP-Fqs) and the existing rule curves.

Notably, the lower rule curves determined by HR criteria are elevated in comparison to those determined by SOP criteria, particularly during the dry season (April–May). This suggests that the HR-based optimal rule curves are designed to conserve water by restricting water discharge during the dry season, aligning with the principles of HR [7]. This approach aims to enhance water retention within the reservoir, ensuring sufficient water availability during periods of low inflow. The higher levels of the lower rule curves under HR criteria indicate a proactive strategy to prevent reservoir depletion, which is critical for sustaining water supply and maintaining ecological balance during dry spells.

Additionally, the upper rule curves under HR criteria are higher than those under SOP criteria at the end of the rainy season (October–November). This indicates a more conservative approach to water release, allowing for greater storage capacity as the wet season concludes. By maintaining higher upper rule curves, the HR-based strategy ensures that the reservoir can store more water, which is vital for reducing the risk of water shortages in the subsequent dry season. This increased storage capacity at the end of the rainy season provides a buffer against potential drought conditions, thereby enhancing the resilience of the water management system.

As a result, the storage capacity at the end of the rainy season is higher with HR criteria compared to SOP criteria and the existing rule curves, which helps in alleviating severe water shortages during the following dry season. This highlights the main goal of using HR criteria along with rule curves for optimizing reservoir operations [16]. The implementation of HR criteria seeks to optimize the balance between water conservation and supply, ensuring that the reservoir can meet water demands even during prolonged dry periods. This approach not only enhances water security but also supports sustainable water management practices.

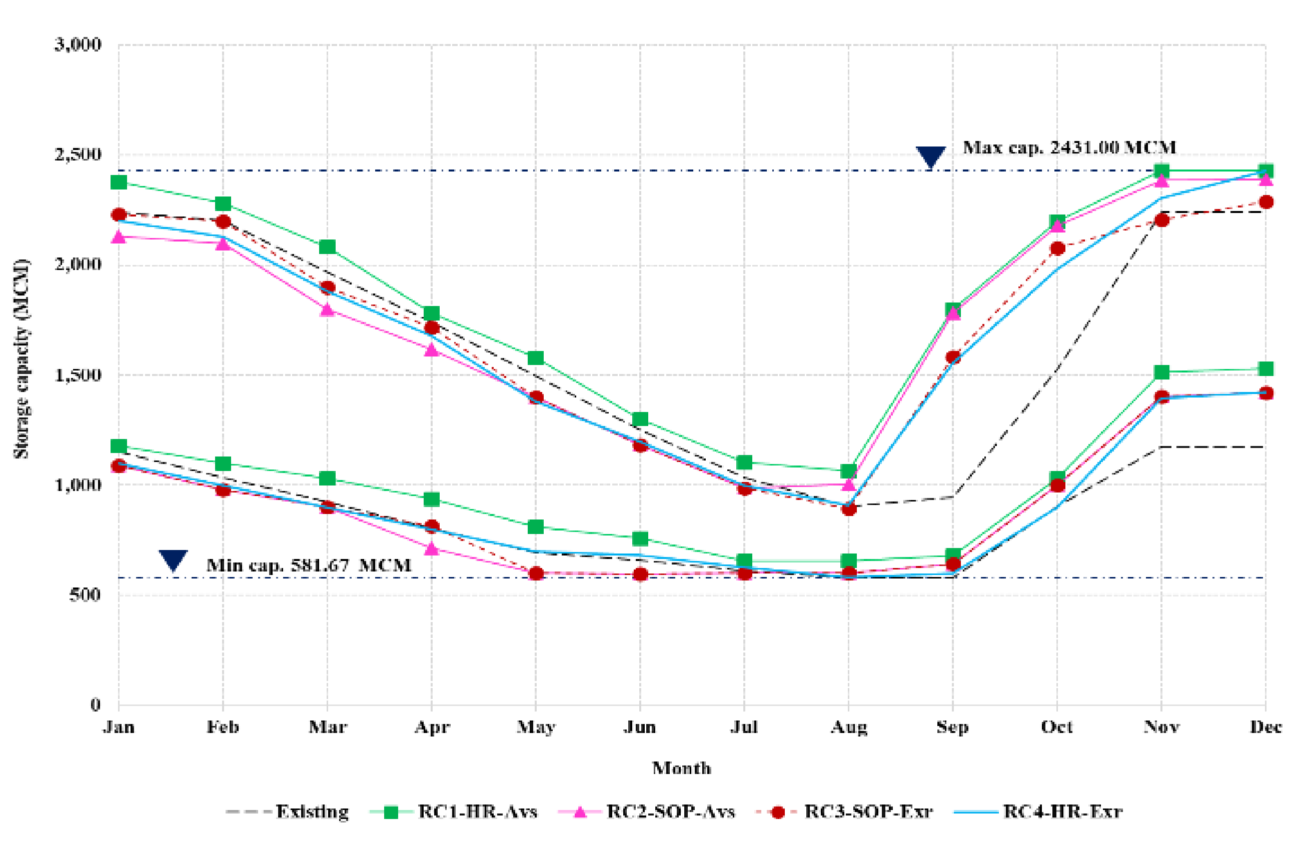


Fig. 6 The optimal rule curves for the Ubolratana reservoir, taking into account both the HR and the SOP.

Tables 1 and 2 present the scenarios of water shortages and excess releases resulting from the new rule curves developed using the HHO method with HR and SOP criteria. It is noted that, using historic inflow data and applying the HR criteria with the fitness functions of minimal average water shortage (RC1-HR-Avs), the average annual water shortage is minimized to 115.769 MCM, while the maximum water shortage reaches 742.00 MCM per year. However, the frequency of water shortages is highest at 0.654 occurrences per year, as detailed in Table 1. This suggests that although HR criteria effectively reduce the magnitude of shortages, they do not completely eliminate their frequency.
Similarly, the use of historic inflow data with HR criteria and the objective functions of minimal average water shortage (RC1-HR-Avs) also minimizes excess water situations. The average annual excess water is reduced to 1,107.54 MCM, with the maximum excess water being 4,113.159 MCM per year, as shown in Table 2. This highlights the HR criteria's effectiveness in managing excess water releases, thus minimizing wastage and improving water conservation within the reservoir system.

In conclusion, the HR criteria provide a more controlled approach to water release, aiming to save water for the subsequent dry season and alleviate potential water deficits [22]. Conversely, SOP criteria focus on meeting target demand across all considered durations, as highlighted in numerous previous studies [33]. As a result, SOP criteria might be less effective compared to HR criteria for reservoirs that frequently experience drought conditions. The findings suggest that adopting HR criteria in the rule curves developed through HHO can lead to more efficient reservoir operations, particularly in regions prone to frequent droughts. This aligns with the broader goals of sustainable water management, emphasizing the need for adaptive strategies to address varying hydrological conditions effectively.

Table 1 The scenarios of water shortages and excess water, based on 52 years of historical inflow data, using HR criteria.

Situations	Rule curves	Frequency (times/year)	Volume (MCM.)		Time period (year)	
			Average	Maximum	Average	Maximum
Shortage	Existing	0.673	204.308	865.000	3.889	8.000
	RC1-HR-Avs	0.654	115.769	742.000	3.778	7.000
	RC2-SOP-Avs	0.692	126.865	832.000	3.600	7.000
	RC3-HR-Exr	0.615	124.692	772.000	3.556	7.000
	RC4-SOP-Exr	0.592	140.577	813.000	4.000	7.000
Excess water	Existing	0.923	1,230.310	4,126.736	9.600	21.000
	RC1-HR-Avs	0.865	1,107.549	4,113.159	6.143	10.000
	RC2-SOP-Avs	0.808	1,118.634	4,152.957	5.250	9.000
	RC3-HR-Exr	0.865	1,119.433	4,155.656	9.000	13.000
	RC4-SOP-Exr	0.808	1,118.634	4,152.957	5.250	9.000

Table. 2 The scenarios of water shortages and excess water, based on 52 years of historical inflow data, using SOP criteria.

Situations	Rule curves	Frequency (times/year)	Volume (MCM.)		Time period (year)	
			Average	Maximum	Average	Maximum
Shortage	Existing	0.865	349.654	870.000	7.500	19.000
	RC1-HR-Avs	0.752	203.558	766.000	4.000	7.000
	RC2-SOP-Avs	0.673	247.962	900.000	4.111	7.000
	RC3-HR-Exr	0.768	220.941	834.000	3.924	7.000
	RC4-SOP-Exr	0.655	258.364	813.000	4.910	8.000
Excess water	Existing	0.962	1,189.589	4,150.361	16.667	25.000
	RC1-HR-Avs	0.942	1,191.718	4,113.159	16.000	25.000
	RC2-SOP-Avs	0.902	1,220.490	4,152.957	25.000	25.000
	RC3-HR-Exr	0.941	1,210.420	4,161.760	16.035	25.000
	RC4-SOP-Exr	0.923	1,253.280	4,164.330	25.035	25.000

4. Conclusion

This study demonstrated that the proposed model, utilizing two objective functions and the Harris Hawks Optimization (HHO) technique, successfully generated optimal rule curves that consistently outperformed existing rule curves under various reservoir conditions. Inspired by the cooperative hunting behavior of Harris hawks, the HHO algorithm efficiently explored and exploited the solution space, resulting in rule curves that significantly improved reservoir performance.

The findings revealed that while the rule curves based on the Hedging Rule (HR) criteria exhibited a higher frequency of water shortages compared to those based on the Standard Operating Policy (SOP), the average duration of shortages was notably shorter under the HR criteria. This outcome aligns with the primary goal of HR, which aims to mitigate the overall impact of water shortages by conserving water during critical periods. Furthermore, HR-based rule curves provided more accurate and realistic simulations of reservoir behavior across all historical inflow samples. This level of accuracy, often unattainable with static approaches like SOP, underscores the adaptability of HR when combined with advanced optimization techniques like HHO.

The dual functionality of the HHO-derived HR rule curves, effectively mitigating both excessive flooding and water scarcity, highlights their value in sustainable water management. By balancing the competing objectives of flood control and water conservation, particularly during the rainy season, this approach ensures reservoirs are optimally prepared to handle variable inflows while minimizing risks.

Nevertheless, this study recognizes certain limitations. The reliance on historical inflow data may not fully capture future hydrological variability influenced by climate change. To address this, future research should integrate predictive climate models for better inflow forecasting. Additionally, engaging local stakeholders in the development process could enhance the practical applicability of the proposed approach. Expanding the application of this method to a variety of reservoir systems will also help validate its broader applicability. Finally, leveraging advancements in heuristic and hybrid optimization methods presents opportunities to further improve rule curve development and reservoir operation strategies.

In conclusion, the integration of HHO with HR criteria offers a robust and adaptive framework for optimizing reservoir management. This approach not only enhances water allocation efficiency but also contributes to the sustainable management of water resources, making it a valuable tool for addressing complex hydrological challenges and increasing climate variability.

Acknowledgements

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