International Journal of GEOMATE, Dec., 2025 Vol.29, Issue 136, pp.113-120
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2025.136.g15107
Geotechnique, Construction Materials and Environment

SOLVING OPTIMAL RESERVOIR OPERATION PROBLEMS FOR WATER INFRASTRUCTURE USING GENETIC ALGORITHM AND KEPLER OPTIMIZATION ALGORITHM

Rittayut Gonthong[1], *Anujit Phumiphan[2], Nonthaphong Phonphuak[3], Siwat Lawanwadeekul[4] and Anongrit Kangrang[5]

[1,2] School of Engineering, University of Phayao, Phayao, Thailand; [3] Faculty of Engineering, Rajabhat Mahasarakham University, Mahasarakham, Thailand; [4] Faculty of Industrial Technology, Lampang Rajabhat University, Thailand; [5] Faculty of Engineering, Mahasarakham University, Mahasarakham, Thailand.

*Corresponding Author, Received: 30 May 2025, Revised: 30 Nov. 2025, Accepted: 02 Dec. 2025

ABSTRACT: Rule curves of reservoirs are necessary guides to operate reservoir in long term operation. This paper proposed an alternative approach of Genetic Algorithm (GA) and Kepler Optimization Algorithm (KOA) to connect with the simulation model for searching optimal reservoir rule curves as the flood control area. The proposed models were applied to determine the optimal flood rule curves of the Nam Oon Reservoir in the Northeast region of Thailand. Minimum average excess water and minimum frequency excess water were used as the objective functions for the searching procedure. The historic inflow, synthetic inflow data of 1,000 events and future inflow were used to evaluate efficiency of the flood control rule curves in showing situations of water shortage and excess water in term of frequency, magnitude and duration. The results showed that obtained rule curves were used to simulate the Nam Oon Reservoir system for reducing flood in long term operation. The results indicated that situations of excess water using the obtained rule curves from the proposed model were smaller than using the current rule curves both for the present and future situations. The new obtained rule curves from the proposed GA and KOA models were better than the existing rule curves in decreasing flood situation.

Keywords: Water Infrastructures, Non-Construction Reservoir Management, Rule Curves, Genetic algorithm, Kepler Optimization Algorithm.

1. INTRODUCTION

Many countries struggle with natural resource management, particularly water, vital for human welfare. The complexity of water resource issues is exacerbated by climate change and land use changes [1]. Effective water management requires both organizational frameworks and appropriate management tools. This includes both physical structures and non-structural organizational tools for water resource management [2].

Enhancing reservoir operations is an expedient technique that avoids construction. Reservoir operation rule curves (RORC) involve the optimization of multiple objectives under competing constraints. RORC aims to stabilize water levels and mitigate risks associated with exceeding control thresholds that may endanger the dam. Conversely, water levels must not fall below control thresholds to avert shortages. RORC consists of upper and lower curves for the long-term management of monthly water storage. Effective reservoir management entails adequate water allocation during normal conditions and minimizing water shortage impacts during crises [3-4]. Concurrently, during high water situations, water allocation should prevent harm to downstream communities. Nonetheless, their effectiveness may diminish over time or with data alterations, prompting the need for optimal value identification and enhancements [5-7].

Various optimization techniques, such as dynamic programming and simulated annealing, have been utilized to optimize RORC. Despite their effectiveness, these methods exhibit limitations, including sensitivity to initial conditions and local optima convergence [8]. Consequently, there is a necessity to investigate alternative optimization methods that are robust and efficient in identifying global solutions. This research centers on two such methods: Genetic Algorithm (GA) and Kepler Optimization Algorithm (KOA), which are effective for complex, multi-objective optimization challenges in water storage infrastructure management. Among the most prevalently employed and efficacious optimization methodologies, the Genetic Algorithm (GA) is distinguished by its inherent flexibility and robustness. GA constitutes a population-based metaheuristic, drawing inspiration from the mechanisms of natural selection. It employs operators such as selection, crossover, and mutation to progressively refine and enhance solutions across successive generations. Its efficacy is attributed to its capacity to navigate a broad search space and achieve convergence towards global optima without necessitating gradient information. In contrast, the Kepler Optimization Algorithm (KOA) represents a relatively novel physics-inspired methodology that is grounded in Kepler's laws of planetary motion. This algorithm conceptualizes candidate solutions as celestial bodies in orbit, dynamically modifying their positions in response to gravitational attraction towards the optimal known solution. KOA is particularly adept at circumventing local optima and has exhibited rapid convergence rates in high-dimensional search scenarios. By emulating celestial dynamics, it introduces a distinctive mechanism that balances the dual processes of exploration and exploitation.

This article advocates for an alternative approach integrating GA and KOA with a reservoir simulation model (RSM) to optimize flood RORC in flood control regions. The study applied the proposed models to determine the optimal flood RORC for the Nam-Oon Reservoir (NOR) in Northeastern Thailand. The search methods were guided by two objective functions: minimizing average excess water and reducing the frequency of excess water.

2. RESEARCH SIGNIFICANCE

This study introduces the integration of Genetic Algorithm and Kepler Optimization Algorithm into reservoir rule curve development, offering a novel solution to the limitations of traditional reservoir operation methods. By addressing excess water management through adaptive and intelligent optimization, this research significantly contributes to enhancing long-term flood mitigation strategies. The results demonstrate practical improvements in water resource management under both current and future inflow conditions, providing a scalable framework for other flood-prone regions. The approach advances the state of practice in reservoir operations by bridging simulation models with robust optimization techniques.

3. MATERIALS AND METHODS

3.1 Research Area

This study was carried out in Sakon Nakhon Province, Thailand, during 2021–2022, with the primary aim of investigating water resources and irrigation management within the Nam-Oon Reservoir (NOR) area. Located in the Songkham Basin in northeastern Thailand, the reservoir supports an irrigation area of approximately 32,480 hectares and has a maximum storage capacity of 520 million cubic meters (MCM), with an average annual inflow of 404.835 MCM. Inflow data, systematically collected over a 28-year period from 1994 to 2021, were analyzed to identify long-term patterns in water availability and to inform sustainable water management strategies. The findings provide valuable insights to guide efficient irrigation planning and to promote the optimal, equitable, and sustainable utilization of water resources in the region.

3.2 Reservoir Operation Simulation Model

The reservoir system was modeled through the implementation of the water balancing principle, which required hydrological data, physical characteristics of the reservoir, water demand statistics pertinent to the reservoir, and other associated data. The quantification of the available water resources was derived utilizing Equation (1), which is predicated upon this principle. The assessment of the monthly water discharge considered the accessible water resources, the predetermined release obligations, established operating protocols, and the delineated Reservoir RORC as illustrated in Fig. 1.

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

The equation delineates the computation of the water resources accessible during the month τ, while considering various influencing factors. W_{τ} signifies the water availability for the month τ, whereas $S_{\tau-1}$ indicates the volume of water retained at the termination of the month $\tau - 1$, which is initially established at the maximum capacity of the reservoir. The computation is derived from the influx into the reservoir (I_{τ}), the volume of precipitation recorded during the month (P_{τ}), and the average evaporation losses incurred throughout the month (E_{τ}).

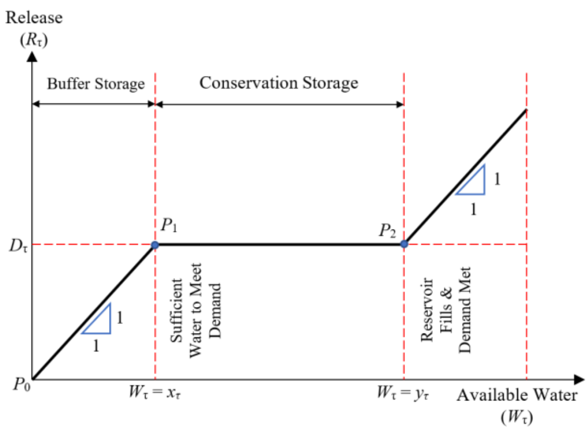

Fig. 1 Standard water allocation criteria

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 excess water amount (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 .

$$\text{Min } Avg_i = \left(\frac{1}{n} \sum_{v=1}^{n} Sp_v \right) \quad (2)$$

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

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

In this equation, Avg_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.

3.3 Genetic Algorithm (GA)

The Genetic Algorithm was first developed by John Holland [9] in the 1970s and has been widely applied in optimization problems due to its robustness and adaptability. GA is inspired by the principles of natural selection and genetics, simulating the process of evolution. It operates on a population of candidate solutions, evolving them over generations through biologically inspired operations. The algorithm is based on the following ideas: 1) individuals in the population represent potential solutions (called chromosomes), 2) better solutions have higher probabilities of being selected to reproduce, and 3) genetic operations such as crossover and mutation introduce diversity and drive the search process. The algorithm is described in the following steps:

Step 1: Define the objective function, constraints, and bounds of the problem.

Step 2: Generate an initial population of chromosomes randomly, each representing a candidate solution.

Step 3: Evaluate the fitness of each chromosome using the defined objective function.

Step 4: Select parent chromosomes for reproduction based on fitness (e.g., roulette wheel selection or tournament selection).

Step 5: Apply crossover operation to selected parents to create offspring, combining parts of their genetic material.

Step 6: Apply mutation to some offspring to introduce random variations and maintain diversity in the population.

Step 7: Evaluate the fitness of new offspring.

Step 8: Form a new population by selecting the fittest individuals from the combined set of parents and offspring.

Step 9: Check the stopping criteria (e.g., maximum number of generations or convergence). If not met, return to Step 4.

Step 10: Use the best chromosome in the final population as the optimal solution.

3.4 Kepler Optimization Algorithm (KOA)

The Kepler Optimization Algorithm (KOA) was inspired by Kepler’s laws of planetary motion and is a physics-based metaheuristic introduced to solve complex optimization problems. It models candidate solutions as orbiting bodies influenced by gravitational forces. Each solution adjusts its position based on a set of rules derived from celestial mechanics, aiming to converge toward the optimal point, much like planets orbiting a focus. The algorithm is based on the following ideas: 1) each candidate solution is treated as a body in motion around a central point (the best solution), 2) the velocity and position of each body are updated according to Keplerian dynamics, and 3) movement is guided by an attraction toward better solutions within the search space. The algorithm is described in the following steps:

Step 1: Define the objective function, constraints, and boundaries of the search space.

Step 2: Initialize a population of orbiting bodies (candidate solutions), each with initial position, velocity, and gravitational parameters.

Step 3: Evaluate the fitness of each candidate using the objective function.

Step 4: Identify the best candidate solution (analogous to the central mass or gravitational focus).

Step 5: Update the position and velocity of each candidate based on Keplerian equations of motion, incorporating gravitational pull toward the best-known solution.

Step 6: Apply boundary checks to ensure all updated solutions remain within the feasible search space.

Step 7: Evaluate the new fitness values and update the global best solution if a better candidate is found.

Step 8: Recalculate orbital parameters and repeat movement updates for each candidate based on their new positions.

Step 9: Check the stopping conditions (e.g., maximum iterations or fitness convergence). If not met, repeat from Step 5.

Step 10: Use the best-found solution as the final optimal result and terminate the search.

3.5 Genetic Algorithm Incorporating Reservoir Simulation Model (RSM)

In this study, the Genetic Algorithm (GA) was integrated with the Reservoir Simulation Model (RSM) to optimize monthly reservoir operation rule curves (RORCs). The process begins with initializing key parameters, including full storage capacity, normal high-water level, dead storage level, and monthly water demands. An initial population of chromosomes is then generated, each representing a complete RORC for the year, consisting of 24 decision variables—12 for the upper curve and 12 for the lower curve, corresponding to each month. Each chromosome is evaluated using the RSM, which simulates monthly water releases based on the encoded RORC and standard operating rules. The simulated releases are subsequently used to calculate objective functions, namely average annual excess water and the frequency of excess water events.

Following fitness evaluation, chromosomes are ranked, and genetic operations are applied. Parent chromosomes are selected based on their fitness and undergo crossover to produce offspring, while mutation introduces variability to explore the search space. The newly generated offspring are re-evaluated with the RSM, and their fitness scores are updated. The population is then revised by retaining the best-performing chromosomes from both the previous and current generations. This iterative process—comprising selection, crossover, mutation, simulation, and fitness evaluation—continues until the stopping criteria, such as a maximum number of generations or convergence, are met.

The optimal RORC is identified from the best-performing chromosome, ensuring a balance between water supply and flood mitigation objectives. By integrating GA with RSM, this framework provides an adaptive and robust approach for reservoir operation, capturing seasonal inflow variability and operational constraints. The method enhances both the efficiency and reliability of reservoir management by systematically searching for RORCs that minimize excess water while maintaining operational feasibility. Fig. 2 illustrates the GA-RSM framework employed in the RORC optimization process.

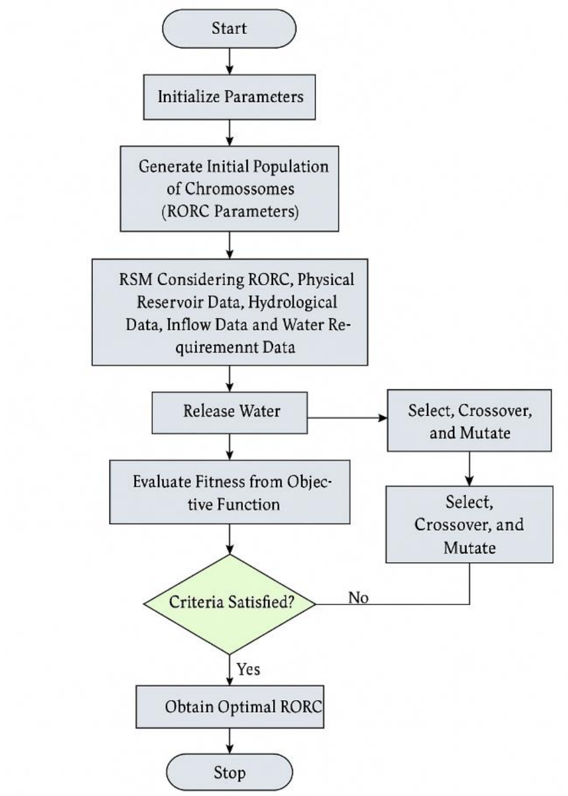

Fig. 2. Genetic Algorithm incorporating RSM to search for optimal RORC.

3.6 Kepler Optimization Algorithm Incorporating Reservoir Simulation Model (RSM)

The integration of the Kepler Optimization Algorithm (KOA) with the Reservoir Simulation Model (RSM) begins by initializing key reservoir parameters, including full storage capacity, normal high-water level, dead storage level, and monthly water demand. An initial population of Kepler agents is generated, where each agent encodes a set of 24 decision variables—12 upper and 12 lower RORC values corresponding to each month of the year. Each candidate solution is evaluated using the RSM, which simulates monthly water release operations based on the encoded RORC and operating rules. The performance of each solution is assessed through predefined objective functions such as minimizing the average volume and frequency of excess water. Based on these evaluations, the fitness of each agent is determined, reflecting its gravitational quality in the KOA framework. Positions and velocities of the agents are updated according to Keplerian dynamics, guided by gravitational attraction toward the best-performing solution. Agents are then ranked, and their parameters adjusted accordingly. This process of simulation, evaluation, and orbital update continues iteratively until a specified stopping condition is met (e.g., maximum iterations or convergence threshold). The optimal RORC is then selected from the best agent in the final population. Fig. 3 illustrates the framework of KOA integrated with RSM for optimizing reservoir operation rule curves.

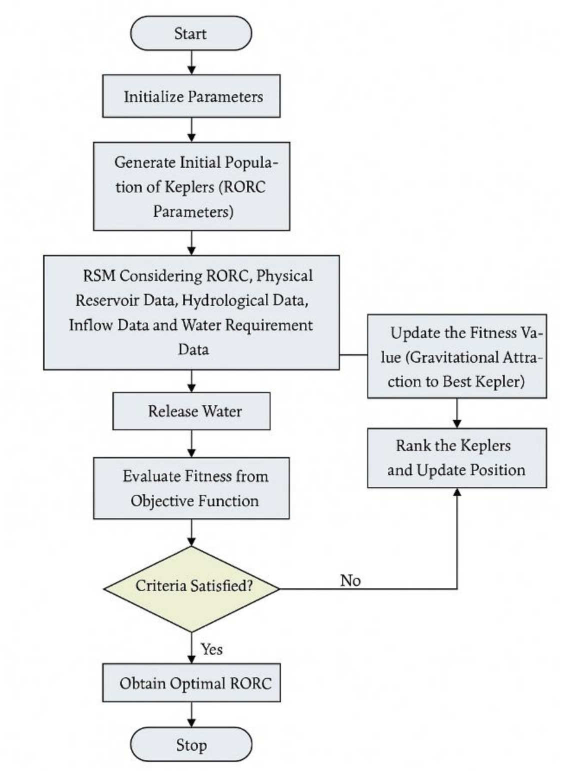

Fig. 3. Kepler Optimization Algorithm incorporating RSM to search for optimal RORC.

3.7 Assessment of the obtained RORC

The RORC was tested through GA, KOA, and RSM on a reservoir system for various inflow scenarios. Historic inflow data spanning 28 years informed the RSM, which subsequently evaluated 1,000 synthetic inflow events based on this data using the HEC-4 model. Statistical principles guided the analysis conducted by the HEC-4 model. The model accommodates analyses involving either a single water metering station or multiple stations within the same basin. When multiple runoff stations exist, the model synthesizes missing data based on runoff data from other stations and their statistical interrelationships. Furthermore, synthetic runoff amounts are derived from established statistical characteristics. The HEC-4 model computes the mean, standard deviation, and skew coefficient of monthly runoff, augmenting the average runoff by 1%. Ultimately, the evaluation results addressed the frequency, intensity, and duration of both water scarcity and excess situations [10].

4. RESULTS AND DISCUSSION

4.1 Optimal RORCs

The GA model introduced in this research produced the optimal RORCs, as depicted in Fig. 4. The search process employed the objective of minimizing yearly excess water, considering historical and projected inflow data. The RORCs labeled GA-Avg., KOA-Avg., and the existing ones (RC1- Existing) displayed a similar trend. The lower RORCs derived from both historical and projected inflow data surpassed the cur-rent 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 (KOA-Avg.) were below the current upper RORCs for October to November.

The optimal RORCs generated by the GA and KOA models introduced in this study are illustrated in Fig. 4. The search procedure involved utilizing the objective function to minimize the annual excess water, using historical inflow data as a basis. The RORCs obtained from the GA model (GA-Avg.), the RORCs derived from the KOA model (KOA-Avg.), and the current RORCs (RC1- Existing) all exhibited similar trends. Nonetheless, the RORCs resulting from the GA and KOA models surpassed the current RORCs between March and July. On the contrary, the novel optimal RORCs will surpass the current RORC from June to September. It is important to highlight that the upper RORCs derived from the KOA model (KOA-Avg.) were lower than the current upper RORCs throughout the October–November period.

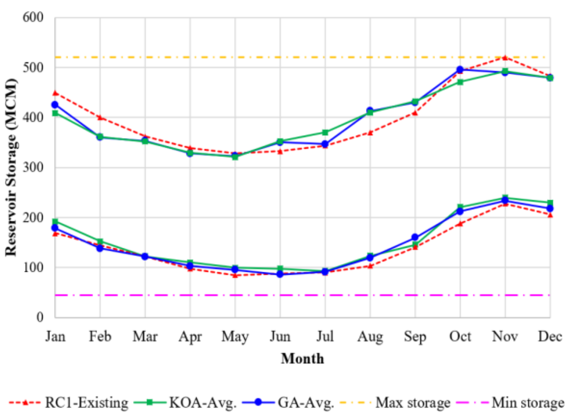

Fig. 4. Optimal RORCs of the NOR using the objective function of minimizing the average excess water in the search procedure.

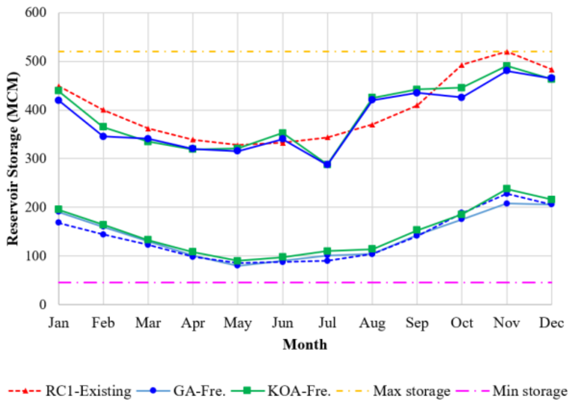

Fig. 5. Optimal RORCs of the NOR using the objective function of minimizing the frequency of excess water in the search procedure.

Fig. 5 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 GA-Fre., KOA-Fre., and the existing RORCs are resembling. They also demonstrate that the lower RORCs resulting from the utilization of historical and future inflow data (GA-Fre. and KOA-Fre.) 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.

4.2 Efficiency of the obtained RORCs

The effectiveness of the newly derived RORCs from all search scenarios was evaluated using the Reservoir Simulation Model (RSM) with historical inflow data for the Nam-Oon Reservoir (NOR) over a 28-year monthly record. The evaluation focused on occurrences of water scarcity and excessive water within each RORC, with results summarized in Table 1. Among the RORCs, the one generated by the KOA approach (KOA-Avg. and and KOA-Fre.), using minimization of average excess water as the optimization objective, demonstrated the best performance. It exhibited the lowest frequency, magnitude, and duration of water scarcity, at 0.464 times per year, 19.926 MCM per year, and 1.684 years, respectively. Similarly, it minimized excessive water releases, with values of 0.627 times per year, 85.641 MCM per year, and 2.00 years for frequency, magnitude, and duration, respectively. Comparative analysis further revealed that the newly developed RORCs outperformed existing curves under historical inflow conditions, providing improved mitigation of both water shortage and excessive water events. These results highlight the effectiveness of the proposed optimization approach in generating RORCs that enhance reservoir operation reliability, ensuring a more balanced management of water resources across varying seasonal and annual inflow conditions, while reducing risks associated with both deficit and surplus water situations.

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 ± 7.224 MCM/year) and excessive water (66.221 ± 17.001 MCM/year) using the KOA RORCs, obtained by minimizing average excess water as the optimization objective (KOA-Avg.), were the lowest in comparison to the other RORCs. Conversely, when the current RORCs were employed for assessment, the outcomes indicated the highest values.

4.3 Discussion

The patterns of the newly derived RORCs from all search scenarios and the current RORCs (as depicted in Figs. 4 and 5) exhibited similarities due to the impact of season-al inflow patterns and consistent conditional effects, which align with findings from other studies [11]. 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 up-dated 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 KOA RORCs, which were developed by incorporating historical inflow data in 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 [12, 13]. It is crucial to conduct a comparative analysis between the results of the proposed GA and KOA techniques and the outcomes of alternative methods.

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

Situation	RORC	Frequency (times/year)	Volume (MCM)		Time period (year)	
			Average	Maximum	Average	Maximum
Water scarcity	RC1- Existing	0.962	45.884	154.000	13.500	14.000
	GA-Avg.	0.584	21.378	130.000	2.500	3.000
	GA-Fre.	0.782	38.411	142.000	6.000	8.000
	KOA-Avg.	0.464	19.926	126.000	1.684	3.000
	KOA-Fre.	0.994	38.407	140.000	10.500	12.000
Excess water	RC1- Existing	0.754	113.402	476.959	4.000	6.000
	GA-Avg.	0.794	89.226	479.080	3.000	5.000
	GA-Fre.	0.797	86.844	465.867	3.000	4.000
	KOA-Avg.	0.704	89.381	465.083	2.000	4.000
	KOA-Fre.	0.627	85.641	436.372	2.000	3.000

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- Existing	μ	0.971	42.445	131.774	17.442	22.637
		σ	0.032	6.831	36.226	6.804	4.937
	GA-Avg.	μ	0.673	18.014	110.824	2.653	5.292
		σ	0.109	8.224	29.344	0.968	2.447
	KOA-Avg.	μ	0.473	16.271	108.097	2.307	4.065
		σ	0.106	7.224	27.744	0.747	2.044
	GA-Fre.	μ	0.811	33.227	120.224	6.242	10.388
		σ	0.108	7.723	34.220	3.584	4.335
	KOA-Fre.	μ	0.989	33.407	119.379	15.124	18.066
		σ	0.051	6.837	30.055	7.225	5.097
Excess water	RC1- Existing	μ	0.699	91.994	358.622	3.009	7.717
		σ	0.107	20.931	77.022	1.554	2.249
	GA-Avg.	μ	0.638	68.734	328.771	2.557	5.334
		σ	0.155	18.984	81.229	0.899	2.227
	KOA-Avg.	μ	0.557	66.221	324.073	2.458	5.365
		σ	0.104	17.001	80.177	0.975	2.005
	GA-Fre.	μ	0.687	80.812	350.401	2.844	6.113
		σ	0.110	19.003	79.773	1.098	2.502
	KOA-Fre.	μ	0.644	79.991	345.374	3.009	6.302
		σ	0.105	20.224	77.780	1.224	2.708

μ = mean
σ = standard deviation

5. CONCLUSION

This study applied the Genetic Algorithm and Kepler Optimization Algorithm with RSM to identify optimal RORCs. The approach, using two objective functions, produced novel RORCs with similar patterns driven by seasonal inflow dynamics, though variations occurred during the rainy season. RORCs generated by minimizing average excess water and incorporating historical inflow data were more effective in mitigating excessive water events under both historical and synthetic inflow scenarios.

This research revealed the utilization of the GA and the combination of the KOA 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 GA and KOA 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.

6. ACKNOWLEDGMENTS

The author gratefully acknowledges the University of Phayao and the Regional Irrigation Office 5 for their essential support, data, and technical assistance, which were vital for the successful completion and quality of this study.

7. REFERENCES

1. Nuannukul W., Phumiphan A., and Kangrang A. Cross-Drainage Culvert Design Under Global Climate and Land Use Changes. ARPN Journal of Engineering and Applied Sciences, 16(10), 2021, pp.1036-1044. http://www.arpnjournals.org/jeas/research_papers/rp_2021/jeas_0521_8587.pdf
2. Suwannachai L., Phumiphan A., Kuntiyawichai K., Supakosol J., Sriworamas K., Sivanpheng O., and Kangrang A., Integrating Hydrological Models for Improved Flash Flood Risk Assessment and Mitigation Strategies in Northeastern Thailand. Atmosphere, Water, 17(3), 2025, pp.1-33. https://doi.org/10.3390/w17030345
3. Xepapadeas A., Uncertainty and climate change: The IPCC approach vs decision theory. Journal of Behavioral and Experimental Economics, Vol. 109, 2024, pp.1-10. https://doi.org/10.1016/j.socec.2024.102188
4. Kosasaeng, S., Popila, E., Gonthong, R., and Phumiphan, A. Hybrid Modeling for Future Inflow Prediction of Huai Luang Reservoir under Climate Change. International Journal of GEOMATE, 29(132) 2025, pp. 98-109. https://doi.org/10.21660/2025.132.4978
5. Oyelakin R., Yang W., and Krebs P., Analysing Urban Flooding Risk with CMIP5 and CMIP6 Climate Projections. Water, 16(3), 2024, pp.1-20. https://doi.org/10.3390/w16030474
6. Raja D. L., Sukiyah E., Sulaksana N., and Endyana C., Morphometric and Land Use Analysis to Estimate Flood Hazard–A Case Study of Upper Cimanuk Watershed in Garut Regency, Indonesia. International Journal of GEOMATE, 19(73), 2020, pp. 126-133. https://doi.org/10.21660/2020.73.52312
7. Tanachaichoksirikun P., Jiao J., Sirikaew U., and Seeboonruang U., Flood and Drought Preliminary Assessment in the Bank Pakong River Basin Using the Weighed Factor Index Method. International Journal of GEOMATE, 28(127), 2025, pp. 79-87. https://doi.org/10.21660/2025.127.g14124
8. Can M., Invasive-Weed-Optimization-Based Extreme Learning Machine for Prediction of Lake Water Level Using Major Atmospheric–Oceanic Climate Scenarios. Sustainability 16(27), 2024, pp. 1-13. https://doi.org/10.3390/su16177825
9. SeethaRam, K. V. Three level rule curves for optimum operation of a multipurpose reservoir using genetic algorithms. Water Resources Management, 35(1), 2021, pp.353-368. https://doi.org/10.1007/s11269-020-02738-7
10. Wongarmart P., Kaewhanat A., Phumiphan A., Kosasaeng S., Sivanpheng O., and Kangrang A., Improving Reservoir Operation Efficiency Using Electric Eel Foraging Optimization and Transit Search Algorithms with Standard Operating Policy: Nong Han-Kumphawapi Case Study. ARPN Journal of Engineering and Applied Sciences, 20(6), 2025, pp.300-313. https://doi.org/10.59018/032543
11. Phumiphan A., and Kangrang A., Development of Decision-Making Support Tools for Future Reservoir Management Under Climate and Land Cover Variability: A Case Study. International Review of Civil Engineering, 12(4), 2021, pp. 271-283. https://doi.org/10.15866/irece.v12i4.20303
12. Phumiphan A., Kosasaeng S., Sivanpheng O., Hormwichian R., and Kangrang A., An Alternative Approach Using the Firefly Algorithm and a Hybrid Method Based on the Artificial Bee Colony and Cultural Algorithm for Reservoir Operation. Water, 16(6), 2024, pp.1-15. https://doi.org/10.3390/w16060816