Larhyss Journal, ISSN 1112-3680, n°53, Mars 2023, pp. 73-93

RESERVOIR OPERATION OPTIMIZATION USING ANT COLONY OPTIMIZATION A CASE STUDY OF MAHANADI RESERVOIR PROJECT COMPLEX CHHATTISGARH - INDIA

VERMA S.[1]*, SAHU R.T.[1], PRASAD A.D.[1], VERMA M.K.[1]

[1] Civil Engineering Department, National Institute of Technology
District of Raipur, State of Chhattisgarh, India

(*) shashiv50@gmail.com

Research Article – Available at http://larhyss.net/ojs/index.php/larhyss/index
Received October 14, 2022, Received in revised form March 8, 2023, Accepted March 9, 2023

ABSTRACT

The significance of water resource management is undeniable, and optimizing reservoir operations for hydropower generation, irrigation, and flood mitigation is a profound task. To accomplish this, a variety of optimization approaches and procedures were employed. Ant colony optimization (ACO) techniques are employed in this study for reservoir operation, where a collection of cooperative agents called ants can achieve near-optimal reservoir operation. To use ACO algorithms, a finite horizon with an inflow time series is a primary assumption. The Mahanadi Reservoir Project comprises a multireservoir system, which makes the optimum operation complex and uncertain for such a reservoir. Furthermore, the ACO technique was employed to optimize the operation of the Mahanadi Reservoir Project Complex. Traditional water resource optimization models have failed due to the increasing number of decision variables and time constraints. The ACO model outperforms the existing operational policy, and the average percentage change in reliability, resilience, and sustainability suggests an increase of up to 12.79%, 3.98%, and 15.48%, respectively, while the vulnerability is reduced by up to 10.28%. Therefore, the ACO algorithm is a novel and promising method for finding optimal reservoirs. It is worth investigating for future applications in the field of water resource systems.

Keywords: Ant colony, Optimization, Reservoir operation, Water resource, Performance evaluation

INTRODUCTION

When managing water resources, a set of laws and regulations must be followed to attain a specified aim. As a result, when we talk about attaining a goal, it is clear that we are not talking about producing a perfect product but rather about determining the best way to achieve the goal within the restrictions of our resources (Opricovic et al., 1991). In recent environmental goals, large dams are frequently erected for many objectives, such as flood control, irrigation, and electricity generation, and a substantial study has been performed to optimize reservoir operation (Mezenner et al., 2022). The key research strategies aim to optimize release and storage volume by analyzing changes in inflow and demand (Reddy et al., 2005; Kapelan, 2005). Currently, due to water shortages, the global freshwater supply to fulfill the demands of different sectors is decreasing continuously (Jury and Vaux, 2007; Rijsberman, 2006; Sahu et al., 2022b; Mehta and Yadav, 2020). Thus, the factors that contribute to this include urbanization, land use and land cover changes, climate change, land degradation, population growth, and improper water resource management (Azharuddin et al., 2022; Larson et al., 2013; Sahu et al., 2021a; Ghashghaie et al., 2014; Sahu et al., 2022a; Mehta et al., 2013a). Therefore, to overcome these problems and fulfill the freshwater availability and energy demands of different sectors, it will be necessary to develop optimal operating policies for multireservoir systems (Guo et al., 2011; Zhou et al., 2014; Pandey et al., 2022).

Many researchers have studied the steady-state operation policies of reservoirs throughout the world to obtain the optimal release of water and storage volume considering inflows (Azizipour et al., 2016; He et al., 2014; Lu et al., 2013; Cheng et al., 2008). Furthermore, most reservoir operation research has focused on specific goals, such as irrigation systems (Birhanu et al., 2014; Mehta et al., 2013b), hydroelectric power production (Azizipour et al., 2016; Lu et al., 2013; Cheng et al., 2008), and flood control measures (He et al., 2014; Pradhan et al., 2022; Dhiwar et al., 2022; Sahu et al., 2021b; Patel et al., 2018; Mehta et al., 2022; Mehta et al., 2020; Mangukiya et al., 2022). Currently, the optimal operation policy for reservoir operation has become significantly important, and researchers are still searching for the best one. Many researchers have proposed and reviewed different reservoir operations models and algorithms (Rani and Moreira, 2010; Wurbs, 1993; Yeh, 1985). Labadie (2004) has extensively reviewed and examined the different optimization techniques and concluded that there are no universally specified techniques for the optimal operation of multireservoir systems, whereas Rani and Moreira (2010) have studied and evaluated that optimization models necessarily require simulation optimization models for verifying and testing the planned operating policies. Reservoir operators frequently use simulation models because they are easy to understand, reliable, and more relaxed than optimization models (Oliveira and Loucks, 1997; Labadie, 2004).

Due to the high variability of rainfall in a basin, the Mahanadi reservoir project complex is considered a case study, which affects the reservoir inflows. Additionally, a multireservoir system has not been optimally operated. Traditional nonlinear techniques have the problem of high computational time requirements and becoming stuck in a local minimum. To minimize this problem, many researchers are looking for new techniques and their advancements over the years. Various heuristic and metaheuristic algorithms have been introduced, which do not always obtain the global optimal solution but give quite good results in a considerable amount of computational time. Ant colony optimization (ACO) was first introduced by Dorigo (1992) as a random search technique for the solution of difficult combinatorial problems such as traveling salesman and quadratic assignment problems and is more efficient than other metaheuristic algorithms such as the WOA, GWO, and SA (Dorigo, 1992; 1996; 1997). Various researchers all over the world work on numerous heuristic and metaheuristic algorithms to derive steady-state operating optimization strategies due to the complexity of nonlinear interactions in model formulation and the number of decision variables subjected to constraints (Jalali et al., 2007). Different ACO algorithms are used to solve different water resource problems, for example, to predict the hydraulic conductivity of unsaturated soil samples (Blum, 2005), water distribution systems (Maier et al., 2003), long-term reservoir operation (Pohlheim, 2005), reservoir performance under the impacts of changing climate (Verma et al., 2021; 2022b; Sahu et al., 2021c; 2021d), and simulation-optimization problems to estimate groundwater parameters in a steady state manner (Socha and Dorigo, 2008).

The problem of an optimal operating policy of multireservoir systems involves many equality and nonequality constraints, dimensional instability, and time-consuming calculations, so the traditional method fails to produce global optimal solutions. Therefore, nature-inspired metaheuristics, such as the ant colony optimization (ACO) algorithm, are becoming an increasingly popular approach for finding the optimal operating policy for a multireservoir system to improve the efficiency of the optimization algorithm and avoid becoming trapped in local minima. The effectiveness of the algorithm is evaluated by comparing it to the results of an existing operational policy that corresponds to an optimal solution. The following section begins with an overview of the ACO process. A reservoir operation case study and how to make a model will then be discussed in more detail. Finally, the findings and conclusions are presented.

General Aspects: ACO Algorithm

Ant colony optimization (ACO) was proposed by Dorigo in the 1980s. It is a swarm intelligence-based and nature-inspired algorithm. Ants are known for their ability to locate the most efficient route to a food supply and mimic its behavior (Blum, 2005). Some ants return to their nest after locating food, leaving a chemical behind called pheromone. After finding such a route, additional ants will not remain scouting and wandering but will follow it. The density of pheromones increases on shorter and more traveled paths. Derivatives of pheromone evaporation have the advantage of avoiding local optimality and are artificial and used to solve optimization problems (Jalali et al., 2007). The likelihood of an ant moving from one state to another is determined by two factors: first, the move's attractiveness as determined by some heuristic, and second, the pheromone level or strength, which indicates how effective it has been in the past (Blum, 2005).

ACO algorithms seek high-quality solutions using a finite number of artificial agents with predetermined features. The algorithmic steps are given below:

1. Artificial ants travel from one point to the other, resulting in a series of incremental trial solutions.
2. The cost of the trial solution is determined, and each cycle (*k*) refers to developing a coherent trial solution and calculating the cost.
3. After each iteration (t), the pheromone is updated, which means that there are m cycles, where m is the number of ants in the group.

The component included in the trial solution at each point is selected randomly using Eq. (1),

$$P_{ij}^{k,t} = \frac{[\tau_{ij\,(t)}]^{\alpha}\,[\eta_{ij}]^{\beta}}{\sum_{l \epsilon N_i^k}[\tau_{ij}]^{\alpha}\,[\eta_{ij}]^{\beta}}, \text{ if } j \epsilon N_i^k \tag{1}$$

where $P_{ij}^{k,t}$ is the probability at cycle $\boldsymbol{k}$ and iteration *t*, $\boldsymbol{\tau_{ij\,(t)}}$ denotes pheromone concentration related to each iteration $\boldsymbol{t}$, is a heuristic factor, sometimes called local cost, and $\boldsymbol{N_i^k}$ represents nodes connected to the nodes *I* and *α*, *β* are the relative significance of pheromone and the local heuristic factor controlled by exponent parameters. It is worth noting that by adding the local heuristic component $(\boldsymbol{\eta_{ij}})$, which is equivalent to real ant sight and is sometimes called a visibility factor.

The pheromone trails have been updated to encourage positive solutions, and new trial solutions have been generated. The pheromone update equation is given below.

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\,\tau_{ij} \tag{2}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\,\tau_{ij} \tag{3}$$

where $\boldsymbol{\tau_{ij}}\ (\boldsymbol{t+1})$ is the pheromone concentration with an iteration of *(t+1)*; $\boldsymbol{\tau_{ij}}(\boldsymbol{t})$ is the pheromone concentration with an iteration of *t*; $\boldsymbol{\rho}$ consists of the pheromone persistence coefficient; and $\boldsymbol{\tau_{ij}}$ is a function of the trial solution to represent the change in pheromone concentration. Pheromone evaporation is simulated with a pheromone persistence factor of less than one.

Case study description

The Ravishankar Sagar reservoir, also known as the Gangrel Dam, is located in Chhattisgarh, India. It is built on the opposite bank of the Mahanadi River. It is in the Dhamtari district, approximately 17 kilometers from Dhamtari and 90 kilometers from Raipur, and it is located at 20^0 37' 36" N latitude and 81^0 33' 36" E longitude, as shown in Fig. 1. There were several reasons behind its construction, including a hydropower plant, an irrigation system, and flood control. It has a total design capacity of 910.5 Mm^3 when it is at its normal elevation of 333.00 m. Of this, 766.89 Mm^3 is used for active storage, and 144 Mm^3 is used for dead storage. Therefore, the study examines the reservoir performance from 1989–90 to 2019–20, when the reservoir maximum and minimum storage range from 950 Mm^3 to 144 Mm^3. By optimizing storage and release rates, the main objective will be to reduce the demand deficit.

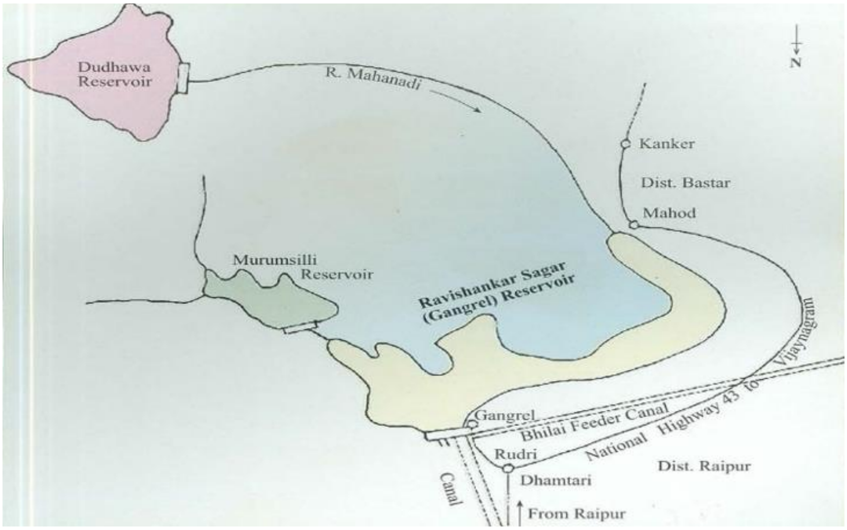

Figure 1: Location of the Ravishankar Sagar reservoir close to the Murumsilli and Dudhawa reservoirs (Desai and Shrivastava, 2004)

METHODOLOGY AND MODEL FORMULATION

Model application

The reservoir storage capacity ranges from 910 Mm^3 to 144 Mm^3. Therefore, a certain number of artificial ants are placed in different classes at random. Then, they start to decide which path to take. Based on these two variables, they select a transition point from one storage class to another time $(t+1)$. First, the transition edge heuristic is used to minimize the disparity between the amount of water released and the demand for water at that time. The second is the pheromone trail of that edge, which may have been acquired through successful ant migration across that edge in the past. Different ways exist for enhancing the edges. Fig. 2 shows the methodology flow chart. The route of a discretized graph and an artificial ant is illustrated in Fig. 3.

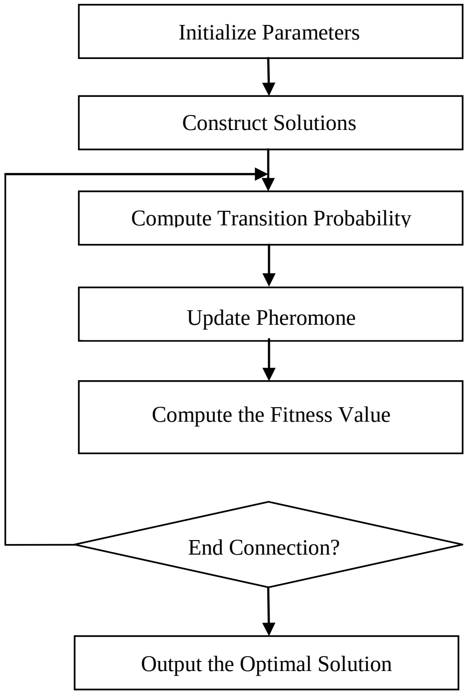

Figure 2: Methodology flow chart

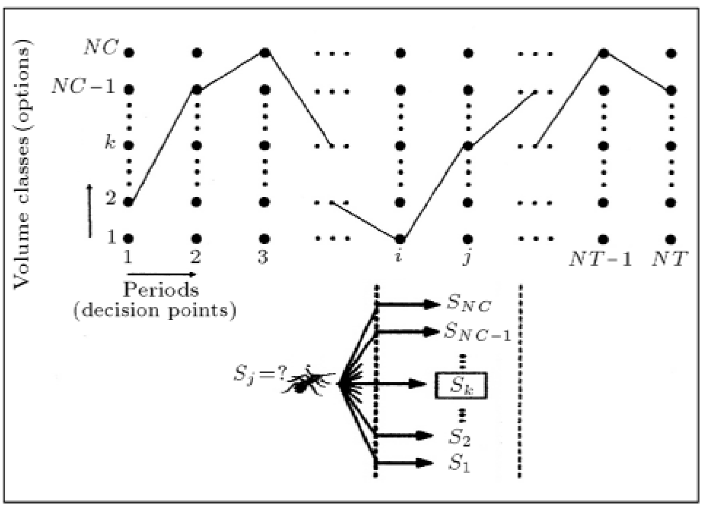

Figure 3: Route of a discretized graph and an artificial ant (Mohammed, 2018)

Heuristic information

In this study, the heuristic information $\boldsymbol{\eta_{ij}(t)}$ is determined by considering the criterion of minimum deficit.

$$\eta_{ij}(\mathrm{t}) = \frac{1}{\left[R_{ij}(\mathrm{t}) - D_{ij}(\mathrm{t})\right]^2} \text{ for all t} = 1, 2, 3 \ldots\ldots\ldots\ldots, \mathrm{NT} \tag{4}$$

where $\boldsymbol{R_{ij}}(\mathbf{t})$ is a release at period $\boldsymbol{t}$ depending upon the initial and final storage volume at classes $\boldsymbol{i}$ and $\boldsymbol{j}$, respectively; $\boldsymbol{D_{ij}}(\mathbf{t})$ is a demand at period $\boldsymbol{t}$. Although the release $\boldsymbol{R_{ij}}(\mathbf{t})$ is determined by using the continuity equation

$$R_{ij}(\mathrm{t}) = S_i - S_j + I_{(t)} \tag{5}$$

which is subjected to the following constraints:

$$S_{min} \le S_i \le S_{max} \tag{6}$$

$$S_{min} \le S_j \le S_{max} \tag{7}$$

where $\boldsymbol{S_i}$ and $\boldsymbol{S_j}$ denote the initial and final storage volumes in terms of classes $\boldsymbol{i}$ and $\boldsymbol{j}$, respectively, and S_{min} and S_{max} are the minimum and maximum allowed storage capacities, respectively.

Fitness function

The fitness function aims to assess the efficiency of the generated solutions. The total square deviation (TSD) was chosen as the objective function in this study.

$$\mathrm{TSD} = \sum_{t=1}^{NT}\left[R_{ij}(\mathrm{t}) - D_{ij}(\mathrm{t})\right]^2 \tag{8}$$

where $\boldsymbol{R_{ij}}(\mathbf{t})$, and $\boldsymbol{D_{ij}}(\mathbf{t})$ represent release and demand at period $\boldsymbol{t}$ for storage volume classes $\boldsymbol{i}$ and $\boldsymbol{j}$, respectively, and $\boldsymbol{NT}$ denotes the total number of periods.

Reservoir performance evaluation

A suitable approach is to classify a system's performance as either satisfactory or unsatisfactory. When the whole annual demand (D) is not fulfilled, the situation is considered unsatisfactory or a failure (Ahmadianfar and Zamani, 2020; Alameddine et al., 2018; Fowler et al., 2003; Goharian 2018; Bayazit and Ünal, 1990). Reservoir reliability is determined by its ability to supply the given demand at any moment during the simulation. Frequency and probability are two ways to represent how reliable a system is (Hashimoto et al., 1982). Referring to Eq. 9 for reliability, where $\boldsymbol{X_t}$ and S is a system output state at time $\boldsymbol{t}$ and a group of all satisfactory outputs. Resilience assesses how rapidly a system recovers, and the ability to bounce back from a failure is called resilience (Hashimoto et al., 1982). Referring to Eq. 10 for reliability, where $\boldsymbol{d_j}$ and M denote the duration of failure and the number of failure events, respectively. Sustainability is defined as measures of long-term viability such as reliability, resiliency, and vulnerability (Loucks, 1997). Referring to Eq. 11 for reliability, where D is a target demand. Vulnerability assesses the likelihood of an event going wrong and causing harm. An inadequate succession of events results in vulnerability. Referring to Eq. 12 for reliability, where $\boldsymbol{v_j}$ is the defect volume of the failure events.

$$\alpha = Prob\ [X_t \ \epsilon\ S] \tag{9}$$

$$Res = \left\{ \frac{1}{\frac{1}{M}} \textstyle\sum_{j=1}^{M} d_j \right\} \tag{10}$$

$$k = \ Res_t \times Res\ \left(1 - \frac{Vul}{D}\right) \qquad 0 \le \mathrm{k} \le 1 \tag{11}$$

$$Vul = \frac{1}{M} \textstyle\sum_{j=1}^{M} v_j \tag{12}$$

OPTIMIZATION MODEL PERFORMANCE MEASURES

The statistical evaluation index, which includes the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute percentage error (MAPE), was used to check the accuracy of the employed algorithm, as shown in equations 13-15 (Willmott, 1981).

$$\mathrm{R}^2 = \left[\frac{\sum\left(Re_{opt(i)} - \overline{Re_{opt}}\right)(Re_t - \overline{Re})}{\sqrt{\sum(Re_{opt(i)} - \overline{Re_{opt}})^2 \ \sum(Re_t - \overline{Re})^2}} \right]^2 \tag{13}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \textstyle\sum_{t=1}^{n} (Re_{opt(i)} - \ Re_t)^2} \tag{14}$$

$$\mathrm{MAPE} = \frac{100}{n} \ \textstyle\sum_{i=1}^{n} \left| \frac{Re_{opt(i)} - Re_t}{Re_{opt(i)}} \right| \tag{15}$$

In the above equation, $\boldsymbol{Re_t}$ is a release at time $\boldsymbol{t}$ for the optimized algorithm, $\overline{\boldsymbol{Re}}$ is the mean of the release, and $\boldsymbol{Re_{opt(i)}}$ denotes the optimum release at time *t*. Similarly, $\overline{\boldsymbol{Re_{opt}}}$ is the mean of the optimum release, and *n* is the number of total periods. A lower value of RMSE and a higher value of R^2 represent the accepted accuracy of the algorithm and a good correlation between the data, which also judges its superiority over the other algorithms. The MAPE parameters represent the deviation between the release and the release made by the optimized algorithms. Hence, the lower the values of these parameters are, the more efficient the algorithm.

RESULTS AND DISCUSSION

The model was tested using several approaches and aspects. As a preliminary step, the model's code is executed in the MATLAB programming language. Parameter Tune-Up and Ants-Iterations tests were then carried out in two distinct stages. In addition, the IAP method has been used to initiate pheromone trail updates at each of the abovementioned test stages.

Tuning of parameters

The experiments were carried out by fine-tuning the primary parameters employed in ACO, namely, $\boldsymbol{\alpha}$ (determines the importance of the pheromone trail), $\boldsymbol{\beta}$ (determines the strength of the heuristic value), and $\boldsymbol{\rho}$ (determines the pheromone increment). Only the different-class model was used for these tests, and the ant count and iterations were both set to 100 and 500, respectively. The literature on ACO suggests that the parameter was adjusted within the ranges α = [1, 2, 3, 4], β = [1, 2, 3, 4], ρ = [0.1, 0.5, 0.9], and q_o = [0.80, 0.90] (Jalali et al., 2006; Dorigo et al., 1996; Reddy and Kumar, 2006; Dorigo and Gambardella, 1997; Zecchin et al., 2005; Mohammed et al., 2018). In contrast, the parameter in the present study was set to one of the following values: α ([1, 0.8, 0.6, 0.4], β [1, 0.8, 0.6, 0.4, 0.2], and ρ [0.4, 0.2, 0.1]). Table 1 shows the results of 10 independent runs of the algorithm for each set of parameters and signifies the best-selected parameters, which include $\alpha = 0.8$, $\beta = 0.2$, $\rho = 0.1$, $q_o = 0.8$, number of ants =100, and max iteration = 500. For an objective function with 500 iterations, the ACO model could obtain the optimal value, but with each additional iteration, the algorithm's execution time increases, and the objective function values decrease. In other words, the ACO algorithm goes through a total of 1000 iterations. Fig. 4 shows the objective function values for the multireservoir system.

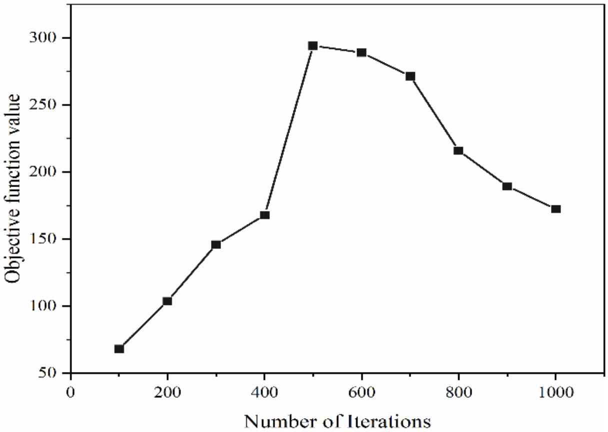

Figure 4: Objective function values concerning the number of iterations (Source: own study).

Table 1: TSD results for parameter tuning for the IAP method

α, β, ρ	IAP Method				
	Best	Worst	Mean	SD	TSD
1, 0.2, 0.4	0.145	0.894	0.520	0.2459	2.0061
1, 0.2, 0.2	0.135	0.645	0.390	0.2531	2.0226
1, 0.2, 0.1	0.175	0.565	0.370	0.2410	1.9770
0.8, 0.2, 0.4	0.185	0.795	0.490	0.2225	1.9583
0.8, 0.2, 0.2	0.148	0.879	0.513	0.2358	1.9491
0.8, 0.2, 0.1	0.121	0.79	0.455	0.2206	1.9465
0.6, 0.2, 0.4	0.224	0.748	0.486	0.2521	1.9722
0.6, 0.2, 0.2	0.154	0.754	0.454	0.2530	1.9807
0.6, 0.2, 0.1	0.214	0.764	0.489	0.2537	1.9904
0.4, 0.2,0.4	0.224	0.678	0.451	0.2531	1.9696
0.4, 0.2, 0.2	0.211	0.851	0.531	0.2457	1.9599
0.4, 0.2, 0.1	0.211	0.851	0.531	0.2416	2.0054
1, 1, 0.4	0.214	0.782	0.498	0.2607	2.0007
1, 1, 0.2	0.21	0.698	0.454	0.2627	2.0037
1, 1, 0.1	0.186	0.654	0.420	0.2584	1.9747
1, 0.8, 0.4	0.421	0.524	0.473	0.2401	1.9599
1, 0.8, 0.2	0.214	0.654	0.434	0.2574	1.9979
1, 0.8, 0.1	0.246	0.647	0.447	0.2658	2.0698
1, 0.6, 0.4	0.135	0.691	0.413	0.2764	2.1374
1, 0.6, 0.2	0.125	0.687	0.406	0.2803	2.1519
1, 0.6, 0.1	0.154	0.582	0.368	0.2842	2.1706
1, 0.4, 0.4	0.214	0.421	0.318	0.2437	2.0745
1, 0.4, 0.2	0.124	0.542	0.333	0.2362	2.0392
1, 0.4, 0.1	0.185	0.655	0.420	0.2288	2.0154

For IAP pheromone updates, the 100-class model gave the best results when the parameters were fixed to (α =0.8; β =0.2; ρ =0.1) and the mean total square deviation was 0.455 units. Using the 100-Class model's parameter tune-up, the mean TSD results are shown in Fig. 5. During this test, the number of ants that are generating solutions and the number of iterations they execute to find better solutions were assessed. IAP pheromone updating methods are used to update the models in this phase using both 100-Class and 200-Class discretization resolutions. In the meantime, the values of parameters (α, β, ρ) were specified based on the best tunes from the previous test. For this test, the number of ants and number of iterations were as follows: Ants [10, 20, 50, 100], Iterations [50, 100, 200, 500]. Each combination of ants and iterations is shown in Table 2, together with the mean and standard deviation of the obtained results across 10 runs, to indicate which combinations produced the best and worst outcomes.

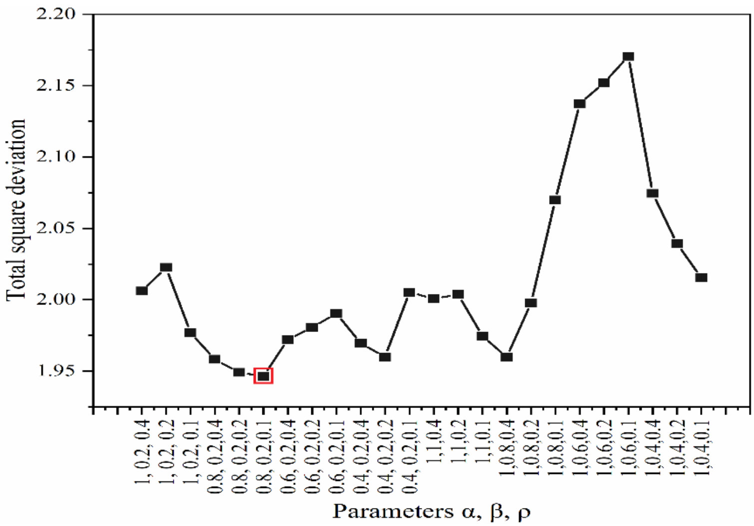

Figure 5: TSD results for parameter tuning for the IAP method

Table 2: TSD results for different numbers of ants and iterations using the IAP method in 100 class and 200 class models.

Iterations	Status	Number of ants							
		10		20		50		100	
		100 class	200 class	100 class	200 class	100 class	200 class	100 class	200 class
50	Best	0.391	0.397	0.388	0.390	0.376	0.396	0.373	0.397
	Worst	0.646	0.651	0.704	0.718	0.756	0.855	0.799	0.811
	Mean	0.519	0.523	0.546	0.565	0.566	0.573	0.586	0.610
	SD	0.328	0.361	0.324	0.331	0.323	0.379	0.318	0.330
100	Best	0.352	0.410	0.353	0.361	0.366	0.414	0.369	0.397
	Worst	0.978	0.992	0.615	0.625	0.782	0.789	0.852	0.870
	Mean	0.665	0.678	0.484	0.492	0.574	0.584	0.611	0.628
	SD	0.306	0.356	0.305	0.353	0.290	0.341	0.284	0.314
200	Best	0.220	0.262	0.211	0.235	0.214	0.319	0.211	0.271
	Worst	0.978	0.993	0.832	0.892	0.782	0.839	0.852	0.892
	Mean	0.599	0.622	0.522	0.562	0.498	0.543	0.532	0.536
	SD	0.284	0.297	0.281	0.302	0.278	0.290	0.271	0.275
500	Best	0.185	0.223	0.175	0.252	0.135	0.185	0.011	0.117
	Worst	0.795	0.831	0.565	0.569	0.689	0.719	0.768	0.771
	Mean	0.490	0.513	0.370	0.377	0.412	0.452	0.390	0.394
	SD	0.262	0.270	0.252	0.274	0.249	0.262	0.247	0.253

Table 3: Water demand for the year 2019-20 with the optimized suggestion of release in million Mm³ using the two different approaches

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Demand	14	35.05	9	10	175	384	287.4	165.34	82.18	64.11	67.85	45
100 class IAP	30.38	32.48	47.34	81.3	247.48	277.32	108.34	124.84	89.34	80.43	43	45
200 class IAP	27.59	32.48	47.34	86.97	237.65	270.54	103.97	122.44	89.34	83.65	43	45

Table 2 shows that the more ants employed to search for solutions, the better the mean total square deviation. Therefore, 50 ants outperform 10 ants. Increasing the number of iterations also improves the mean total square deviation for a given number of ants. On the other hand, for pheromone updates, however, the IAP approach provides better results. Additionally, one can observe that the results have not improved significantly, especially with 500 iterations when using the 200-Class model instead of the 100-Class model. The Ravishankar Sagar reservoir's water demand (in million M^3) for the 12 months of 2019-20 is shown in Table 3 following the two different approaches used in this study. Table 3's statistics are shown in Fig. 6, which depicts the performance of the two different approaches, as well as how optimum results are achieved.

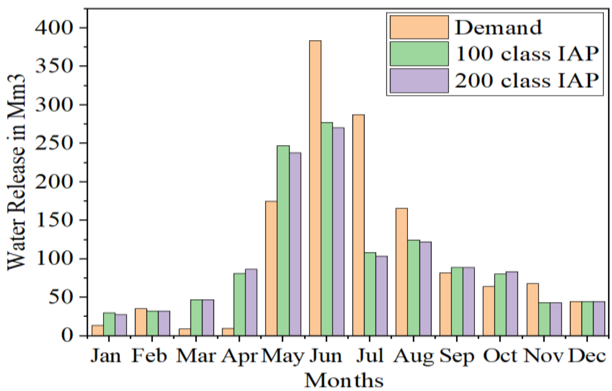

Figure 6: Optimized water release using the two approaches compared with the demand during the 12-month period of 2019-20

Performance measures

Based on historical data, the model simulation and optimization were performed for over 31 years (372 months) from June 1989-90 to May 2019-20. The performance of the model simulation, as discussed in Section 4.1, is evaluated by calculating different performance indices. Fig. 7 shows the graphical representations of reliability, resilience, sustainability, and vulnerability indices for ant colony optimization operation policy releases compared to existing releases. Fig. 7a shows that the average reliability over the entire study period is 0.74, which is somewhat higher than the reliability of the existing policy of 0.66. The peak discharge at the Ravishankar Sagar Reservoir is in October and November, according to the optimal solution, which means that the reservoir will be more reliable in those months than in any other month because there will be more water available for irrigation. However, based on historical data, more peak discharge is available in August and September, indicating that the existing reservoir is more reliable during those months. The availability of water in the reservoir diminishes in comparison to other months, implying that the present reservoir is less reliable. The reservoir is also reliable in terms of storage capacity, but it has to be extended to reduce excessive demand by optimizing the operation policy. To enhance reservoir reliability, the disparity between antecedent and standard operating policies needs more storage.

According to Fig. 7b, the optimized model's resilience is quite similar to that of the existing model, which is 3.98% higher than the existing model, implying that the reservoir's ability to bounce back from failure events is not significantly improved when compared to the existing model, and the average resilience indices of the optimized and existing models are 0.64 and 0.62, respectively. In addition, for increased water supply, reliability and resilience were achieved by confining all releases from outlet structures rather than spillways under historical conditions and maximizing releases from outlet structures under future climatic and demand conditions. The water supply was boosted as a result of the turbines that were placed at the outlet structure. A high reservoir level during the wet season and a shift in the minimum reservoir level in April and May also helped farmers provide excess water.

The sustainability pattern followed by the optimized model is similar to the existing model, as shown in Fig. 7c. According to Fig. 7c, a reservoir system is more sustainable in the monsoon season when the reservoir storage ratio increases and demand drops, but it is less sustainable in February, March, April, and May, based on historical and optimal solutions. According to the standard operating policy, which is shown in Fig. 7c, an increase in the storage ratio is required during months with low flow and in anticipation of dry periods. Furthermore, because of the low available storage, the existing reservoir operating policy (0.37) is less sustainable.

According to Fig. 7d, the average vulnerability of the existing model is higher than that of the optimized model, suggesting that the optimized model is less vulnerable than the existing model. In the case of the monsoon (June, July, and August) and autumn seasons (September and October), the vulnerability of the optimized model decreases compared to the existing model. Thus, the system is found to be less reliable, resilient, sustainable, and more vulnerable when used with historical data, but it exhibits enhanced reliability, resilience, and sustainability with good recovery time and is less vulnerable when used with an optimal solution. As a result, in the overall scenario, the ACO model outperforms the existing operational policy in terms of performance as well as the average percentage change in reliability, resilience, and sustainability. Reliability, resilience, and sustainability all increase by 12.79%, 3.98%, and 15.48%, respectively, while vulnerability decreases to 10.28%. The statistics in Table 4 demonstrate the accuracy assessment of the multireservoir system, which suggests that the ACO model lies in the range of satisfactory conditions (> 0.70) in terms of the coefficient of determination. Additionally, good agreement is observed between the existing and the simulated output, which records a root mean square error (RMSE) of 2.3993 and a mean absolute percentage error (MAPE) of 0.3866.

Table 4: Performance measures for the multireservoir system.

Case study	Algorithm	Performance measures		
		R^2	RMSE	MAPE
Multireservoir system	Ant Colony Optimization	0.7129	2.3993	0.3866

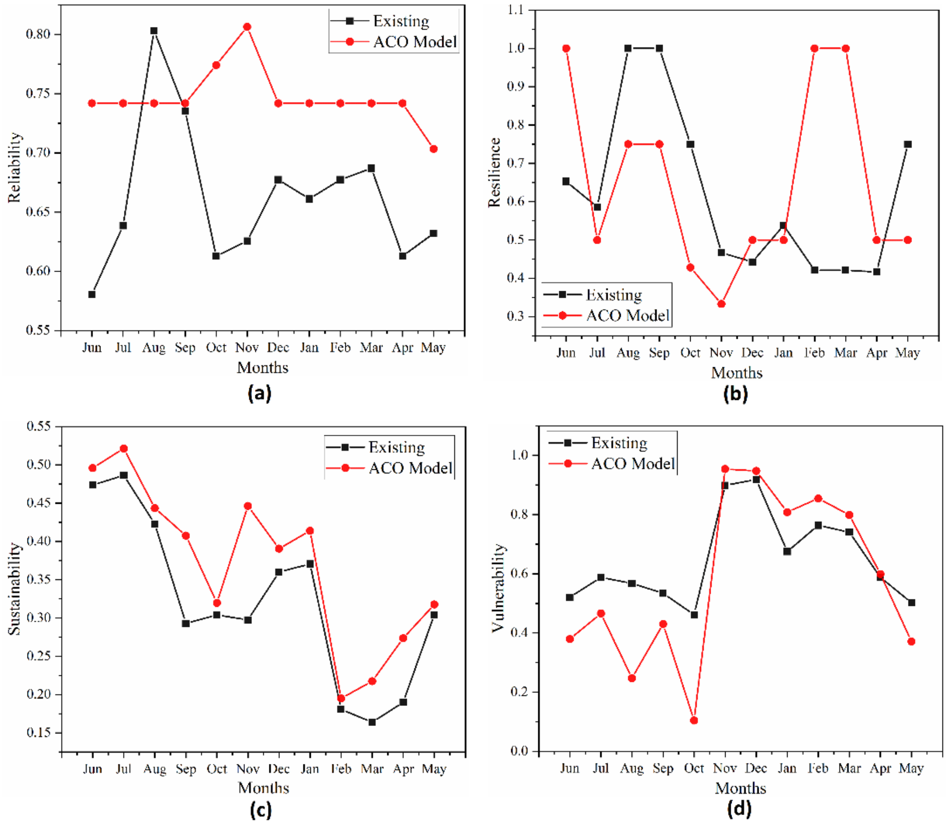

Figure 7: (a), (b), (c), and (d) Graphical representation of reliability, resilience, sustainability, and vulnerability measures for ant colony optimization operation policy release concerning existing releases (Source: own study)

Reservoir system operation model

The existing operating policy of a multireservoir system release policy derived from the ant colony optimization algorithm is displayed in the graph shown in Fig. 7. According to Fig. 8, the ACO model's primary benefit is its robust search, which frequently yields solutions that are nearly globally optimal. As long as the reservoir system operation model is compared to the water release model as per existing policy, there have been no water shortages, except in 1989-1990, 1990-1991, 2002-03 to 2005-06, and 2016-17. The total squared deviations were minimized by carefully planning the release and demand. Therefore, the ACO model has been able to provide enough monthly releases for multireservoir systems compared to the existing reservoir operating policy.

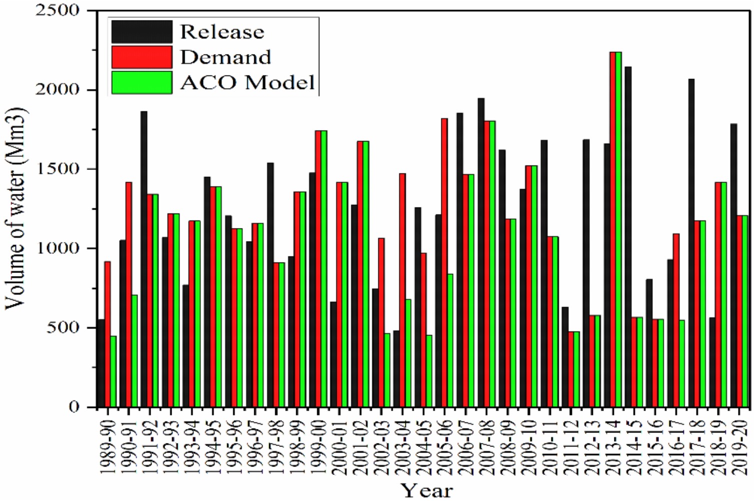

Figure 8: Graphical representation of release made by the ant colony optimization model concerning actual release and demand (Source: own study)

CONCLUSIONS

The optimal operating strategy for three reservoir systems in Chhattisgarh state, namely, Ravishankar Sagar, Dudhawa, and Murumsilli, was determined using an ant colony optimization model. Accordingly, the design of both the release and demand was based on minimizing squared deviations. The ACO model had many restrictions put on it, such as those about when it could be released and when it could be used. The key advantage of the model is its ability to find near-globally optimal solutions and can be employed to solve reservoir optimization problems. The results of this study and the adaptation of the same methodology for multireservoir systems show that ACO outperforms the existing operating policy concerning computational cost and convergence speed and reduces the deficits between downstream release and demand. As a result, the methodology given to water managers, water resource planners, and water decision-makers helps them make educated decisions about water development in light of growing water demand and increased scarcity. In addition, the ACO algorithm is easy to code and produces acceptable results when tackling optimization problems and has become a very useful technique for developing the steady-state operating policy for multireservoir systems, especially in water resource engineering.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

AFSHAR M. H., MARIÑO M.A. (2006). Application of an ant algorithm for layout optimization of tree networks, Engineering Optimization, Vol. 38, Issue 3, pp. 353-369.

AHMADIANFAR I., ZAMANI R. (2020). Assessment of the hedging policy on reservoir operation for future drought conditions under climate change, Climatic Change, Vol. 159, Issue 2, pp.253-268.

ALAMEDDINE I., FAYYAD A., ABOU NAJM M.A.J.D.I., EL-FADEL M., (2018). Sustainability of basin level development under a changing climate, Water Studies, Vol. 13, Issue 3, pp. 394-405.

ANANDA BABU, K., SHRIVASTAVA R.K., DIKSHIT M. (2015). Optimal Operation policies for Ravishankar Sagar reservoir-A case study, Journal of Indian water resources Society, Vol. 35, Issue 1, pp. 33-41.

ANUSHA N., VERMA M. K., BAJPAI S. (2017). Performance measures for Ravi Shankar Sagar reservoir using simulation-optimization models, Water Utility Journal Vol. 15, pp. 67-79.

ANUSHA N., VERMA M., BAJPAI S. (2016). Developing of monthly steady state optimum operating policies for Ravishankar Sagar Reservoir using stochastic Dynamic Programming, 4th Indian Water Week Conference, April, New Delhi, India.

AZHARUDDIN M., VERMA S., VERMA M.K., PRASAD A.D. (2022). A Synoptic-Scale Assessment of Flood Events and ENSO—Streamflow Variability in Sheonath River Basin, India, In: Rao C.M., Patra K.C., Jhajharia D., Kumari S. (eds) Advanced Modelling and Innovations in Water Resources Engineering. Lecture Notes in Civil Engineering, Vol. 176, pp. 93-104.

AZIZIPOUR M., GHALENOEI V., AFSHAR M. H., SOLIS S. S. (2016). Optimal operation of hydropower reservoir systems using weed optimization algorithm, Water Resources Management, Vol. 30, Issue 11, pp. 3995-4009.

BAYAZIT M., ÜNAL N.E. (1990). Effects of hedging on reservoir performance, Water resources research, Vol. 26, Issue 4, pp.713-719.

BLUM C. (2005). Ant colony optimization: Introduction and recent trends, Physics of Life reviews, Vol. 2, Issue 4, pp. 353-373.

CHENG C.T., WANG W.C., XU D.M., CHAU K.W. (2008). Optimizing hydropower reservoir operation using hybrid genetic algorithm and chaos, Water Resources Management, Vol. 22, Issue 7, pp. 895-909.

DESAI V.R., SHRIVASTAVA N.P. (2004). Ecology and fisheries of Ravishankar Sagar Reservoir, Central Inland Fisheries Research Institute, Indian Council of Agricultural Research, Barrackpore, Lolkata, Wes Bengal, India, pp. 1-60.

DHIWAR B.K., VERMA S., PRASAD A.D. (2022). Identification of Flood Vulnerable Area for Kharun River Basin by GIS Techniques, In: Rao C.M., Patra K.C., Jhajharia D., Kumari S. (eds) Advanced Modelling and Innovations in Water Resources Engineering. Lecture Notes in Civil Engineering, Vol. 176, pp. 385-408.

DORIGO M. (1992). Optimization, learning and natural algorithms, Ph.D. Thesis, Politecnico di Milano.

DORIGO M., BLUM C. (2005). Ant colony optimization theory: A survey, Theoretical computer science, Vol. 344, Issue 2-3, pp. 243-278.

DORIGO M., GAMBARDELLA L.M. (1997). Ant colonies for the traveling salesman problem, biosystems, Vol. 43, Issue 2, pp. 73-81.

DORIGO M., MANIEZZO V., COLORNI A. (1996). Ant system: optimization by a colony of cooperating agents, IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), Vol. 26, Issue 1, pp. 29-41.

FOWLER H.J., KILSBY C.G., O'CONNELL P.E. (2003). Modeling the impacts of climatic change and variability on the reliability, resilience, and vulnerability of a water resource system, Water resources research, Vol. 39, Issue 8, pp. 1-11.

GHASHGHAIE M., MAROFI S., MAROFI H. (2014). Using system dynamics method to determine the effect of water demand priorities on downstream flow, Water resources management, Vol. 28, Issue 14, pp. 5055-5072.

GOHARIAN E., BURIAN S.J., KARAMOUZ M. (2018). Using joint probability distribution of reliability and vulnerability to develop a water system performance index, Journal of Water Resources Planning and Management, Vol. 144, Issue 2, Paper 04017081.

GUO S., CHEN J., LI Y., LIU P., LI T. (2011). Joint operation of the multireservoir system of the Three Gorges and the Qingjiang cascade reservoirs, Energies, Vol. 4, Issue 7, pp.1036-1050.

HASHIMOTO T., STEDINGER J.R., LOUCKS D.P. (1982). Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation, Water resources research, Vol. 18, Issue 1, pp.14-20.

HE Y., XU Q., YANG S., LIAO L. (2014). Reservoir flood control operation based on chaotic particle swarm optimization algorithm, Applied Mathematical Modelling, Vol. 38, Issue 17-18, pp. 4480-4492.

JALALI M.R., AFSHAR A., MARINO M.A. (2007). Multicolony ant algorithm for continuous multireservoir operation optimization problem, Water Resources Management, Vol. 21, Issue 9, pp. 1429-1447.

JALALI M. (2007). Salinization of groundwater in arid and semiarid zones: an example from Tajarak, western Iran, Environmental Geology, Vol. 52, Issue 6, pp.1133-1149.

JURY W.A., VAUX Jr H.J. (2007). The emerging global water crisis: managing scarcity and conflict between water users, Advances in agronomy, Vol. 95, pp.1-76.

KAPELAN Z.S., SAVIC D.A., WALTERS G. A. (2005). Multiobjective design of water distribution systems under uncertainty, Water Resources Research, Vol. 41, Issue 11, p. w11407.

LABADIE J.W. (2004). Optimal operation of multireservoir systems: State-of-the-art review, Journal of water resources planning and management, Vol. 130, Issue 2, pp.93-111.

LARSON K.L., POLSKY C., GOBER P., CHANG H., SHANDAS V. (2013). Vulnerability of water systems to the effects of climate change and urbanization: A comparison of Phoenix, Arizona and Portland, Oregon (USA), Environmental management, Vol. 52, Issue 1, pp. 179-195.

LI S., LIU Y., YU H. (2006). Parameter Estimation Approach in Groundwater Hydrology Using Hybrid Ant Colony System, In: Huang DS., Li K., Irwin G.W. (eds) Computational Intelligence and Bioinformatics, ICIC 2006. Lecture Notes in Computer Science, Vol. 4115, pp. 182-191.

LOUCKS D.P. (1997). Quantifying trends in system sustainability, Hydrological Sciences Journal, Vol. 42, Issue 4, pp. 513-530.

LU B., LI K., ZHANG H., WANG W., GU H. (2013). Study on the optimal hydropower generation of Zhelin reservoir, Journal of Hydro-Environment Research, Vol. 7, Issue 4, pp. 270-278.

MAIER H.R., SIMPSON A.R., ZECCHIN A.C., FOONG W.K., PHANG K.Y., SEAH H.., TAN C. (2003). Ant colony optimization for design of water distribution systems, Journal of water resources planning and management, Vol. 129, Issue 3, pp. 200-209.

MANGUKIYA N.K., MEHTA D.J., JARIWALA R. (2022). Flood frequency analysis and inundation mapping for lower Narmada basin, India, Water Practice & Technology, Vol. 17, Issue 2, pp. 612-622.

MEHTA D.J., YADAV S.M. (2020). Hydrodynamic simulation of river Ambica for riverbed assessment: a case study of Navsari Region, In Advances in Water Resources Engineering and Management, Vol. 39, pp. 127-140.

MEHTA D.J., ESLAMIAN S., PRAJAPATI K. (2022). Flood modelling for a data-scare semiarid region using 1-D hydrodynamic model: a case study of Navsari Region, Modeling Earth Systems and Environment, Vol. 8, Issue 2, pp. 2675-2685.

MEHTA D.J., RAMANI M.., JOSHI M.M. (2013a). Application of 1-D HEC-RAS model in design of channels, Methodology, Vol. 1, Issue 7, pp. 4-62.

MEHTA D.J., YADAV S.., WAIKHOMS. (2013b). Geomorphic channel design and analysis using HEC-RAS hydraulic design functions, International Global Journal of Research Analysis, Vol. 2, Issue 4, pp. 90-93.

MEHTA D.J, YADAV S.M., WAIKHOM S., PRAJAPATI K. (2020). Stable channel design of Tapi River using HEC-RAS for Surat Region, In Environmental processes and management Vol. 91, pp. 25-36.

MEZENNER N., BENKACI T., BERMAD A., DECHEMI N. (2022). Dam reservoir operation optimization using genetic algorithm and principal component analysis simulation model - case of dam Ghrib reservoir, Larhyss Journal, No 51, pp. 145-160.

MOHAMMED M.N., DAHAM B.F. A., MOHAMMED K.S. (2018). Darbandikhan reservoir operation optimization using ant colony optimization algorithm, Zanco Journal of Pure and Applied Sciences, Vol. 30, Issue 1, pp. 135-141.

OLIVEIRA R., LOUCKS D.P. (1997). Operating rules for multireservoir systems, Water resources research, Vol. 33, Issue 4, pp. 839-852.

OPRICOVIC S., ECCHER L., ISAILOVSKI M. (1991). An optimization procedure for water reservoir planning, Yugoslav Journal of Operations Research, Vol. 1, Issue 2, pp. 225-233.

PANDEY P., MISHRA R., CHAUHAN R.K. (2022). Future prospects in the implementation of a real-time smart water supply management and water quality monitoring system, Larhyss Journal, No 51, pp. 237-252.

PATEL S.B., MEHTA D J., YADAV S. M. (2018). One dimensional hydrodynamic flood modeling for Ambica River, South Gujarat, Journal of Emerging Technologies and Innovative Research, Vol. 5, Issue 4, pp. 595-601.

POHLHEIM H. (2005). Geatbx introduction–evolutionary algorithms: Overview, methods and operators, Documentation for: GEATbx version, 3.5a, pp. 1-79.

PRADHAN D., SAHU R.T, VERMA M.K. (2022) Flood inundation mapping using GIS and Hydraulic model (HEC-RAS): a case study of the Burhi Gandak river, Bihar, India. In: Kumar R, Ahn CW, Sharma TK, Verma OP and Agarwal A (eds) Soft Computing: Theories and Applications. Lecture Notes in Networks and Systems, Vol. 425, pp. 135-145.

RANI D., MOREIRA M.M. (2010). Simulation–optimization modeling: a survey and potential application in reservoir systems operation, Water Resources Management, Vol. 24, Issue 6, pp.1107-1138.

REDDY M.J., KUMAR D.N. (2006). Optimal reservoir operation using multiobjective evolutionary algorithm, Water Resources Management, Vol. 20, Issue 6, pp.861-878.

RIJSBERMAN F.R. (2006). Water scarcity: fact or fiction? Agricultural water management, Vol. 80, Issue 1-3, pp. 5-22.

SAHU R.T., VERMA M.K., AHMAD I., (2021a). Some nonuniformity patterns spread over the lower Mahanadi River basin, India, Geocarto International.
https://doi.org/10.1080/10106049.2021.2005699

SAHU R.T., VERMA M.K., AHMAD I., (2021b). Segmental variability of precipitation in the Mahanadi River basin during 1901-2017, Preprint (Version 1) available at Research Square. https://doi.org/10.21203/rs.3.rs-542786/v1

SAHU R.T., VERMA M. K., AHMAD I. (2021c). Characterization of precipitation in the subdivisions of the Mahanadi River basin, India, Acta Scientific Agriculture, Vol. 5, Issue 12, pp. 50-61.

SAHU R.T., VERMA M.K., AHMAD I. (2021d). Regional Frequency Analysis Using L-Moment Methodology—A Review, In: Pathak KK, Bandara JMSJ and Agrawal R (eds) Recent Trends in Civil Engineering, Lecture Notes in Civil Engineering, Vol. 77, pp.811-832.

SAHU R.T., VERMA M.K., AHMAD I. (2022a). Interpreting different timeslot precipitation characteristics in the Seonath River basin, Chhattisgarh during 1901-2017, In: Reddy K.R., Kalia S., Tangellapalli S., Prakash D. (eds Recent Advances in Sustainable Environment, Lecture Notes in Civil Engineering, Vol. 285, pp. 21-37.

SAHU R.T., VERMA S., KUMAR K., VERMA M. K., AHMAD I. (2022b). Testing some grouping methods to achieve a low error quantile estimate for high resolution (0.25° x 0.25°) precipitation data, Journal of Physics: Conference Series, Vol. 2273**,** Paper 012017.

SECKLER D., BARKER R., AMARASINGHE U. (1999). Water scarcity in the twenty-first century, International Journal of Water Resources Development, Vol. 15, Issue 1-2, pp. 29-42.

SOCHA K., DORIGO M. (2008). Ant colony optimization for continuous domains, European Journal of Operational Research, Vol. 185, Issue 3, pp. 1155-1173.

VERMA S., PRASAD A.D., VERMA M.K. (2021). Trend Analysis and Rainfall Variability of Monthly Rainfall in Sheonath River Basin, Chhattisgarh, In: Pathak K.K., Bandara J.M.S.J., Agrawal R. (eds) Recent Trends in Civil Engineering. Lecture Notes in Civil Engineering, Vol. 77, pp. 777-790.

VERMA S., PRASAD A.D., VERMA M.K. (2022b). Trends of Rainfall and Temperature over Chhattisgarh During 1901–2010, In: Rao C.M., Patra K.C., Jhajharia D., Kumari S. (eds) Advanced Modelling and Innovations in Water Resources Engineering. Lecture Notes in Civil Engineering, Vol. 176, pp. 3-19.

WILLMOTT C.J. (1981). On the validation of models, Physical geography, Vol. 2, Issue 2, pp. 184-194.

ZECCHIN A.C., SIMPSON A.R., MAIER H.R., NIXON J.B. (2005). Parametric study for an ant algorithm applied to water distribution system optimization, IEEE transactions on evolutionary computation, Vol. 9, Issue 2, pp. 175-191.

ZHOU Y., GUO S., LIU P., XU C. (2014). Joint operation and dynamic control of flood limiting water levels for mixed cascade reservoir systems, Journal of Hydrology, Vol. 519, pp. 248-257.