

Optimal operation of reservoir for sustainable water management using multi-criteria decision-making approach

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ABSTRACT

Reservoir operation optimization is crucial for sustainable water resource management, but resource competition can cause conflicts, necessitating bargaining solution approaches for optimal operational schemes. In the present study, three multi-objective algorithms, Non-Dominating Sorting Genetic Algorithm II (NSGA II), Non-Dominating Sorting Genetic Algorithm III (NSGA III), and multi-objective particle swarm optimization (MOPSO), were used for optimizing Ravishankar Sagar reservoir (RSSR), Chhattisgarh, India. Furthermore, a multi-criteria decision-making analysis was carried out using the entropy method compromise programming (EMCP) approach. The results obtained showed that 83% of the demand was met using NSGA II, while NSGA III and MOPSO methods were able to meet 68 and 44% of the demand. Based on the comprehensive evaluation, it may be said that NSGA II has better potential for complex optimization problems.

Key words: NSGA II, MCDM, MOPSO, NSGA III, multi-objective reservoir operation

HIGHLIGHT

- The novelty of the paper lies in the fact that the EMCP approach has not been used for reservoir operation problems, and in the present research work, the EMCP approach has been applied to the NSGA II, NSGA III, and MOPSO algorithms, and a detailed comparison has been carried out based on the results obtained.

1. INTRODUCTION

Water scarcity in cities is a major challenge due to limited resources, pollution, and increasing demand due to industrial growth, population, and living standards. Unequal distribution of water resources leads to disputes and calls for resource optimization. Because they store and redistribute available natural resources, reservoirs are crucial to the development of water resource systems. The decision-making process for managing water in multipurpose reservoirs is complicated and involves many goals that are frequently at odds with one another and suggest rivalry between stakeholders and water users. Therefore, the optimal allocation of the available water to various sectors/functions from the reservoir is crucial as it requires performing multiple functions simultaneously. It depends upon various social, economic, and environmental factors, among others.

In recent years, multi-objective algorithms have been used for optimizing multi-reservoir systems due to their great efficiency and rapid convergence. However, every reservoir has different problems and objectives, which pose new challenges for optimal reservoir operation.

Over the years, there has been extensive research on reservoir operation optimization using conventional and evolutionary methods. The conventional methods included research on problem statements using linear programming (LP), non-linear programming, and dynamic programming, which have proven to be useful in solving different optimization problems by being stable and derivative-based. However, these standard methods suffered from various disadvantages: limited exploration, certain types of objective functions, the complexity of the problem, and others (Lai *et al.* 2021). In recent decades, researchers

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have come across numerous meta-heuristic algorithms (MHAs) inspired by natural systems. These MHAs can be divided into three distinct categories, viz. evolution, physics, and swarm intelligence. Among them, multi-objective genetic algorithms (MOGAs), being the evolutionary algorithms, have proved well suited to solving reservoir operation problems of complex systems owing to their faster convergence and diversity of solutions (Wang *et al.* 2022). Numerous researchers have used different variants of genetic algorithms for optimization. Wardlaw & Sharif (1999) proposed a simple genetic algorithm (GA) to evaluate different formulations for reservoir systems to be used in real-time operations. Several researchers continued studying and exploring the model in this field, such as Jothiprakash & Shanthi (2006), Reddy & Kumar (2006), Cheng *et al.* (2008), and many others. Chen *et al.* (2016) proposed a computational strategy involving the parallel populations concept with a non-dominating sorting genetic algorithm (NSGA II), which enhanced the quality of the solution concerning convergence and diversity. Heydari *et al.* (2016) used NSGA II to solve the optimization model for two reservoir systems, and considerable decisions on the problem were taken. Later, Dai *et al.* (2017) used NSGA II for modeling reservoirs using Pareto optimal solutions. The results indicated that the model had the potential to improve the comprehensive benefits of the reservoirs. Another application of NSGA II was presented by Hojjati *et al.* (2018) for optimal reservoir operation to maximize power generation and flood control capacity. Also, the results were compared with the multi-objective particle swarm optimization (MOPSO) model and were found to be superior with better convergence. Furthermore, Wang *et al.* (2022) represented three variants of GA, NSGA II, NSGA III, and Reference Vector Guided Evolutionary Algorithm (RVEA), for the optimization of a multi-reservoir system. The results emphasized the significance of selecting the appropriate algorithm for the given problem. Chen *et al.* (2017) proposed an improved NSGA III to optimize flood control operation and it was found that the model produced well-distributed Pareto optimal solutions. Another application of NSGA III was used by Ni *et al.* (2019) to analyze power generation, flood control, and ecological maintenance. Non-inferior scheduling strategies were obtained with better convergence and more uniformity. Later, Zhang & Huang (2021) applied NSGA III to optimize the flow and water level of a river basin to restore ecological health. Dabral *et al.* (2024) employed Metaheuristics algorithms – GA, NSGA II, NSGA III, and Eps MOEA – to optimize the objective function for maximization of storage along with a different set of constraints and performed sensitivity analyses on all algorithms to calibrate different evaluation parameters. So far, NSGA III has been widely applied in the field of water resources. Besides, in recent years, numerous research studies have been conducted on complex reservoir operations employing MOPSO. Reddy & Kumar (2007) presented MOPSO to generate Pareto optimal solutions for reservoir operation. The results indicated that MOPSO can be used as a viable alternative for solving complex water resources problems. Another variant of MOPSO was again proposed by Reddy & Kumar (2009), i.e. elitist mutation multi-objective particle swarm optimization, and the model developed was concluded to be an effective aid for water resources management. Later, Fallah Mehdipour *et al.* (2011) used the MOSPO model to optimize multi-reservoir system operations and were found to be successful in finding an optimal Pareto front. Furthermore, Rahimi *et al.* (2013) applied the MOPSO model with time-variant inertia and acceleration coefficients for the derivation of optimal operating policies for the chosen reservoir system. Mansouri *et al.* (2022) applied MOPSO to minimize the violation of allowed capacity and maximize the supply, and it was found that the model was able to provide 20–35% more supply in dry months. These multi-objective algorithms can be further explored using a multi-criteria decision-making (MCDM) approach to analyze the decisions made. Although there has been less literature presenting the application of MCDM techniques in reservoir operation, several studies have applied them successfully to complex problems. Zhu *et al.* (2016) proposed an MCDM model for flood control operation using an improved entropy weight method. In the same area of flood control operation, Zhu *et al.* (2017) proposed another MCDM technique based on a back propagation neural network, which also was proved as an effective tool. Later, Yang *et al.* (2019) used an efficient MCDM technique based on a technique for order preference by similarity to the ideal solution (TOPSIS), gray correlation, and a combination weighted method, providing more reliable solutions. To address the uncertainties of reservoir operation problems, Zhu *et al.* (2020) proposed a stochastic MCDM framework based on stepwise weight information, which indicated that risk-informed decisions could be made with more reliability. Furthermore, Zhang *et al.* (2020) developed another MCDM model that could facilitate decision-makers to make balanced decisions considering the past and future.

Myo Lin *et al.* (2020) presented a multi-objective model predictive control scheme incorporating NSGA II and MCDM techniques to optimize existing reservoirs. Another MCDM technique based on a payoff matrix, objective weights, fuzzy technique, and compromise programming was used by Ramani & Umamahesh (2024) for designing three water distribution networks optimally. However, most existing studies lack an integrated approach that combines MCDM with multi-objective optimization algorithms such as NSGA-II, NSGA-III, and MOPSO. Our study bridges this gap by integrating the entropy

method and compromise programming (EMCP) with multi-objective optimization techniques to achieve a comprehensive evaluation of reservoir operations.

Multi-objective evolutionary algorithms (MOEAs) such as NSGA-II, NSGA-III, and MOPSO have been widely applied in reservoir optimization due to their ability to handle conflicting objectives. However, each algorithm has its own strengths and limitations, as shown in Table 1.

Relevant studies by Husain & Shrivastava (2020), Ma *et al.* (2023), and Hosseini Dehshiri *et al.* (2023) have demonstrated the applicability of these algorithms in water resource management, reinforcing their selection for this research.

In the present study, NSGA II is used to optimize the given reservoir operation problem and evaluate the results based on optimal solutions and certain indicators, which are then compared with NSGA III and MOPSO for validation. Furthermore, to analyze the Pareto optimal solutions, the concept of the EMCP was used with the chosen algorithms to implement the MCDM approach in reservoir operation problems (Ramani & Umamahesh 2024). The novelty of the paper lies in the fact that the EMCP approach has not been used for reservoir operation problems, and in the present research work, the EMCP approach has been applied to NSGA II, NSGA III, and MOPSO algorithms, and a detailed comparison has been carried out based on the results obtained.

2. MATERIALS AND METHODS

2.1. Study area

Ravishankar Sagar Reservoir (RSSR), located in Chhattisgarh, India, serves as a vital water resource for irrigation, drinking water supply, and hydropower generation. However, the reservoir faces several operational challenges, including seasonal water scarcity, conflicting water demands, and ecological sustainability concerns.

The selection of RSSR for this study is based on the following factors:

- *Multi-purpose utility*: RSSR supports irrigation, drinking water, and hydropower, making optimization crucial for sustainable management.
- *Hydrological variability*: The reservoir experiences significant seasonal inflow variations, requiring robust optimization strategies.
- *Environmental concerns*: Maintaining environmental flow (E-flow) requirements while meeting water demand is a key challenge.

These complexities make RSSR an ideal case study for developing and testing multi-objective optimization strategies aimed at sustainable water resource management. RSSR is built on the river Mahanadi, which originates in Pharsia village of Raipur (Madhya Pradesh, India). It is situated in the Dhamtari district within the geographical coordinates of 20° 34' latitude and 81° 34' longitude. The reservoir was mainly constructed for irrigation purposes and partially hydel, but at present, it serves many purposes, including municipal and industrial as well as domestic demands, with a catchment area of 3670 km². RSSR is used to satisfy the Municipal and Industrial and Irrigation demands, with municipal demands to be fulfilled at the first priority level.

The study area's location map is shown in Figure 1.

2.2. Data collection

The data used in the current study are monthly inflows, monthly demands, reservoir storage data, and evaporation data. The data were acquired from the Central Water Commission (CWC), India, and the Centre for Development of Advanced Computing, Pune, for the period 1989 to 2016. Figure 2 shows the data collected for the study.

Table 1 | Advantages and disadvantages of selected algorithms

Algorithm	Advantages	Disadvantages
NSGA-II	Well established, and widely used, maintains a good balance between exploration and exploitation	Can converge prematurely in highly complex problems
NSGA-III	Designed for many-objective optimization, maintains diversity well	Computationally expensive, requires careful tuning
MOPSO	Fast convergence, easy parameter tuning	Prone to premature convergence, less effective for diverse Pareto solutions

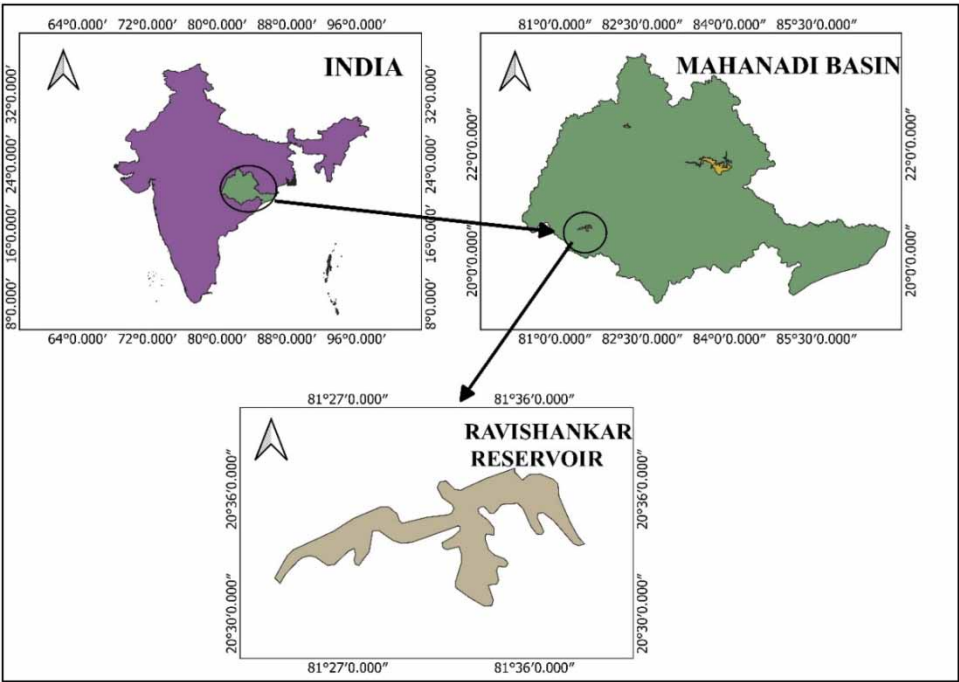


Figure 1 | Location map of RSSR.

PHYSICAL DATA	• Storage capacities of Reservoir • Elevation-Area-Volume curves for key levels(EAV) • Channel Capacity(Downstream)
HYDRO-METEOROLOGICAL DATA	• Inflow to Reservoir • Losses (Evaporation)
WATER DEMAND DATA	• Environmental Flow targets • Water demand series(Irrigation, water supply and Municipal Demand)
OPERATIONAL DATA	• Key Reservoir Levels • Minimum Operational Levels • Maximum Flood Control Level

Figure 2 | Data collection.

Average annual rainfall is about 1,250 mm with vast variations during the whole year, which can be seen in Figure 1. Monthly inflows and demands are shown in Figure 3, which indicates that the distribution of rainfall is quite uneven and needs to be optimized to meet the demands in dry periods.

The area–elevation–volume (AEV) curve is presented in Figure 4. The main features of the reservoir are shown in Table 2. The AEV curve and salient features are essential for the problem formulation and were obtained from the data acquired for the chosen reservoir.

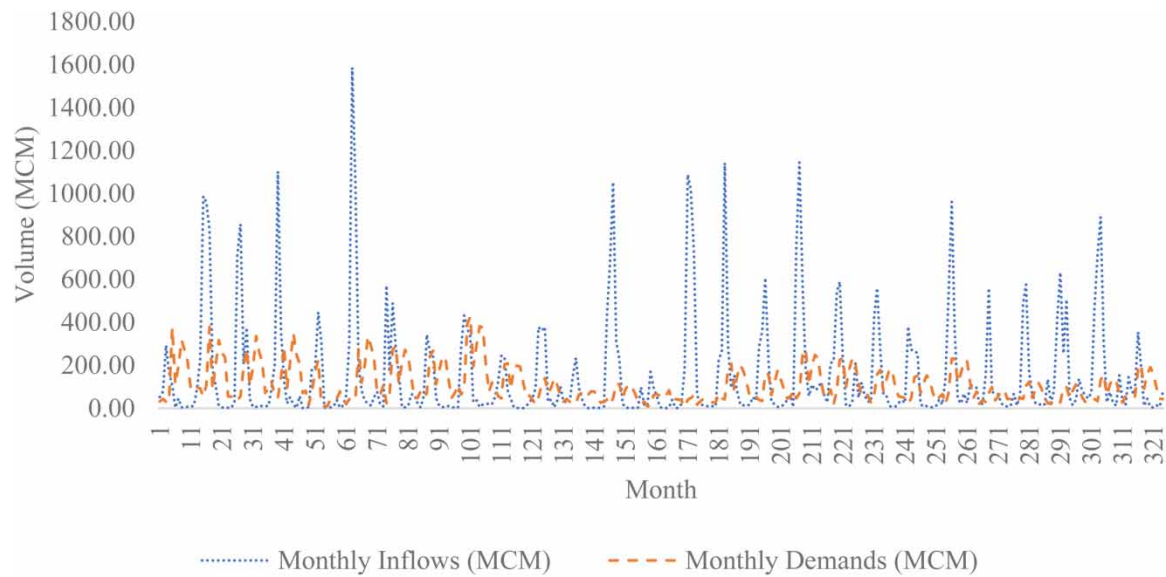


Figure 3 | Average monthly inflows and demands.

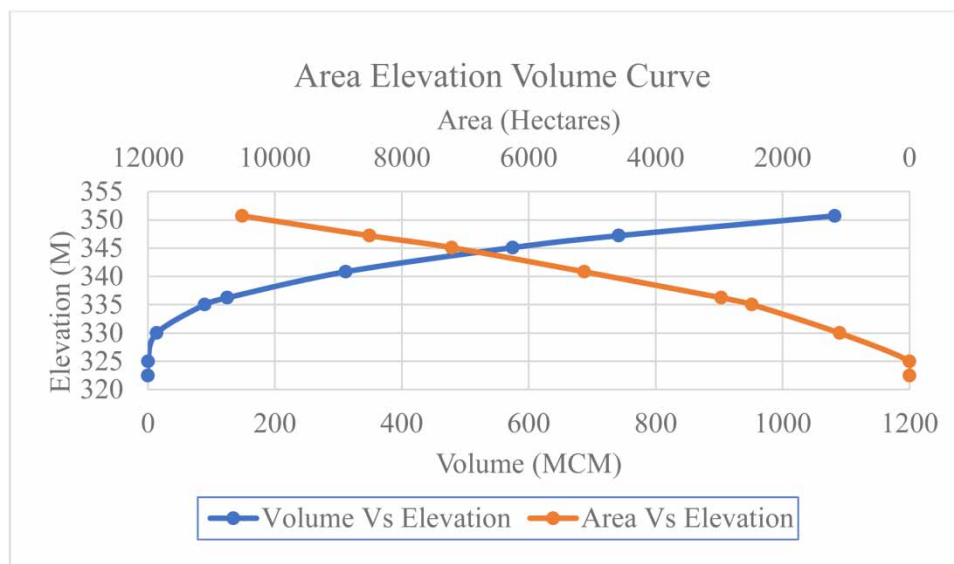


Figure 4 | Area elevation volume curve.

2.3. Multi-criteria decision-making methods

The study focuses on using the MCDM technique for optimal reservoir operation utilizing NSGA II, NSGA III, and MOPSO algorithms.

2.3.1. NSGA II

NSGA II has been widely used in various engineering problems, including optimal reservoir operation. NSGA II is an important enhancement of the standard GA proposed by *Deb et al. (2022)*. In addition to the basic concept of the GA, an elite strategy based on the crowding distance was introduced in NSGA II to explore the sampling space to a greater extent, thereby increasing the speed and robustness of the algorithm. The proposed algorithm is explained as follows:

Table 2 | Characteristics of dam

Characteristics	RSSR
Type of dam	Embankment
Height	30.5 m
Length	1830 m
Total capacity	909.3 MCM
Spillway capacity	766.89 MCM
Full reservoir level	348.70 m
Dead storage level	336.21 m

- (i) Random generation of the initial population and initialization of parameters.
- (ii) Classification of the first generation based on non-dominated sorting and genetic operations.
- (iii) Sort the new merged population, i.e. the parent population and the sub-population, on the basis of crowding distance to generate a new parent population.
- (iv) Perform genetic operations on the new parent population to produce a child population for the next iterations.

The algorithm is explained in [Figure 5](#).

2.3.2. NSGA III

NSGA III is another enhancement of the GA based on the NSGA II framework and was proposed by [Deb & Jain \(2013\)](#). The main feature of NSGA III is that it replaces the concept of crowding distance for the selection mechanism with a uniformly distributed reference point concept to improve solution diversity. The algorithm is explained as follows:

- (i) Random generation of the initial population and initialization of parameters.
- (ii) For each individual reference points are generated to determine the mating parent and then selected.
- (iii) Offspring populations are formed on the basis of crossover and mutation operations.
- (iv) Parent and offspring populations are merged through non-dominated sorting.
- (v) New individuals are selected on the basis of reference point operation to enter the next generation population.

The algorithm is explained in [Figure 6](#).

2.3.3. MOPSO

The particle swarm optimization algorithm is another evolution-based technique inspired by the movement of birds and was introduced by [Eberhart & Kennedy \(1995\)](#), for multi-objective problems. The Particle Swarm Optimization (PSO) algorithm considers every solution as a particle moving with some velocity toward optimality. The position and velocities of the particle and the whole population set are updated with every iteration to evolve and move toward the optimal destination. The algorithm is explained as follows:

- (i) Initialization of population with velocity and position vectors.
- (ii) Simulate the movement of the particles individually and globally.
- (iii) Update the population to form new solutions toward optimality.
- (iv) Perform mutating operations on the new population to produce optimal solutions for the next iterations.

The algorithm is demonstrated in [Figure 7](#).

2.3.4. MCDM

Once the formulated set of equations for the multi-objective problems has been optimized using the soft computing algorithms, a set of best possible solutions known as Pareto fronts can be found for the given optimization problem. It becomes important to choose the preferred solution among these based on quality. To perform this task, the MCDM technique is used for performance evaluation of the obtained solutions through multiple criteria. For this decision-making

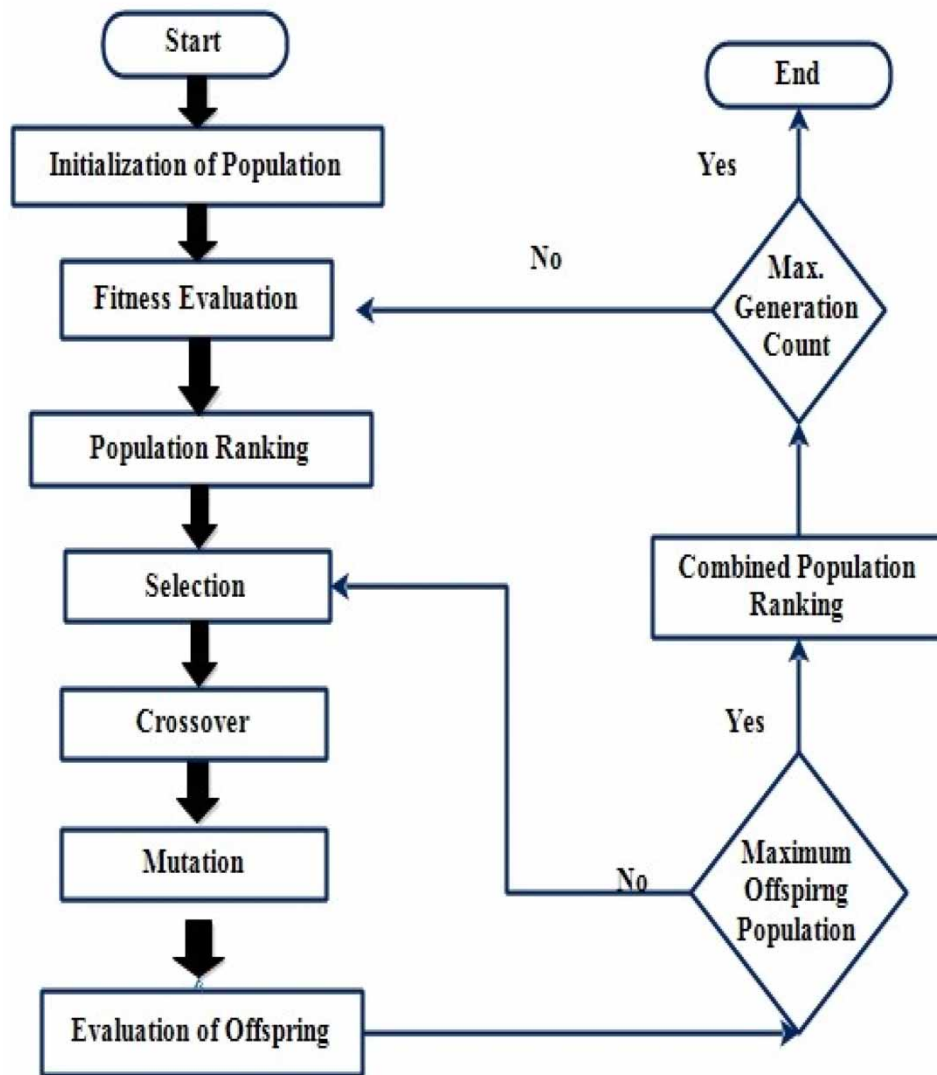


Figure 5 | Flowchart of NSGA II.

process, several MCDM methods are available, like the weighted sum method, TOPSIS, Visekriterijumsko Kompromisno Rangiranje, and fuzzy analytic network process, mentioned by [Taherdoost & Madanchian \(2023\)](#). Other methods, viz. weightage allocation criteria and compromise programming, were used by [Ramani & Umamahesh \(2024\)](#).

To comprehend the Pareto fronts, the optimal solutions were summarized and ranked using the EMCP approach. The proposed approach is based on the degree of uncertainty, which quantifies itself within the context of probability theory. First, a payoff matrix (M) is generated, and the values of the matrix M are normalized to a range between 0 and 1. The normalized element (N_{xy}) can be calculated from the following equation:

$$N_{xy} = \frac{M_{xy}}{\sum_{i=1}^t M_{xy}} \quad (1)$$

where N_{xy} is the normalized element and M_{xy} is the value of the solution at the x row of the performance indicator at the y column of the matrix from the Pareto front. For different criteria, relative entropies are computed to allocate the weightage of

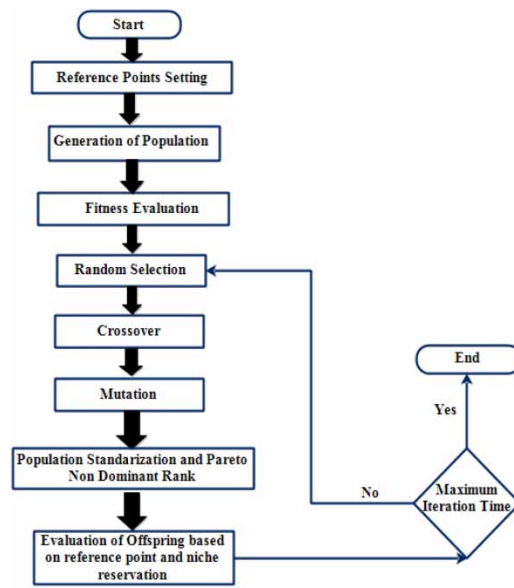


Figure 6 | Flowchart of NSGA III.

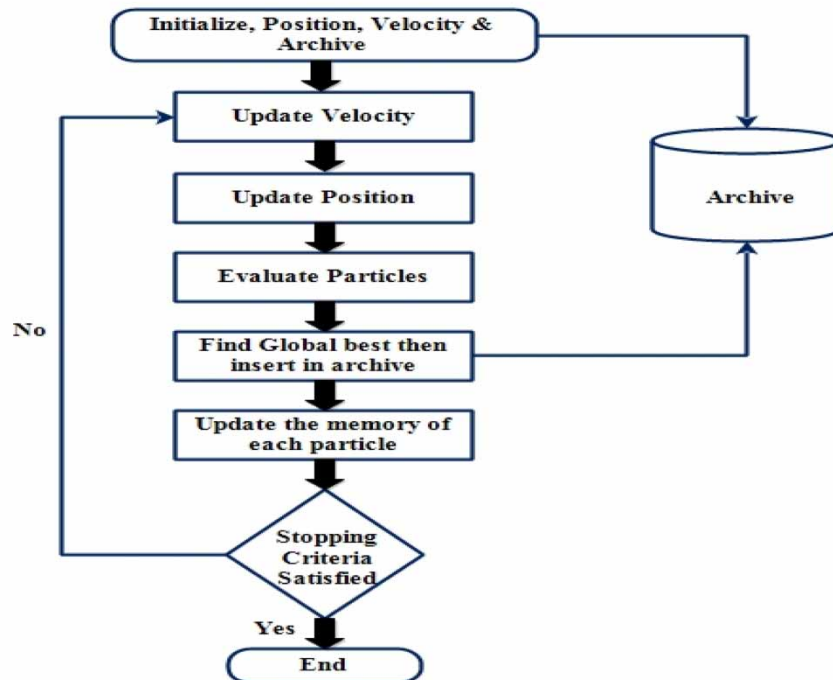


Figure 7 | Flowchart of MOPSO.

each criterion, using the equations mentioned in the following:

$$E_i = (-1/A) \times \sum_{i=1}^A N_{ij} \log_e N_{ij} \quad (2)$$

$$D_i = 1 - E_i \quad (3)$$

$$W_i = \frac{D_i}{\sum_{i=1}^C D_i} \quad (4)$$

where E_i is the entropy, D_i is the degree of divergence, W_i is the weight of the indicator (i), C is the total amount of criteria, A is the total amount of options, and N_{ij} is the normalized element of the payoff matrix of Pareto front solutions and performance indicators.

After weighting allocation, another compromise programming concept is implemented to obtain the solution when the criteria conflict with each other by aggregating all the multiple criteria, and another distance metric (DM) value is obtained using the following equation:

$$DM = \left[\sum_{i=1}^C W_i |N_j^* - N_j(i)|^p \right]^{1/p} \quad (5)$$

where p is the parameter (for linear distance, 1 and for Euclidean distance, 2), N_j^* is the ideal value of the membership function of N_{ij} .

The alternative criteria with minimum distance from the Pareto front solutions are considered to be the best alternative. The flowchart of the MCDM technique is shown in Figure 8.

2.4. Data analysis and methodology

In the present study, the mathematical problem formulation for the RSSR was done on the basis of monthly inflow and demand data. Problem formulation consists of objective functions and constraints associated with the reservoir. After the

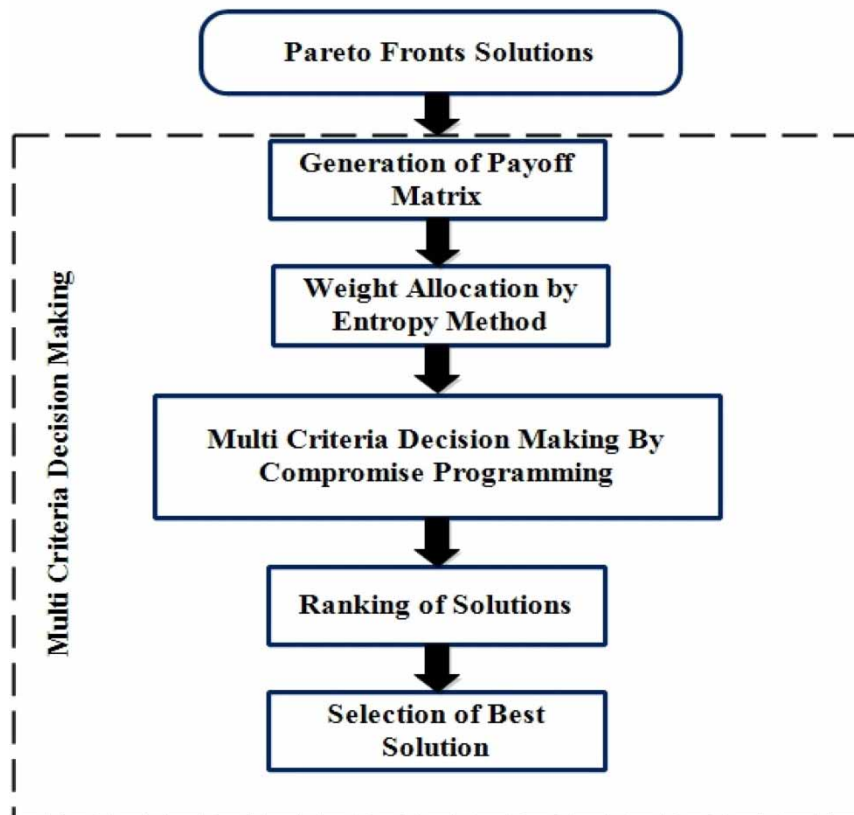


Figure 8 | Multi-criteria decision-making.

problem formulation, the set of equations was optimized using the soft computing techniques (NSGA II, NSGA III, and MOPSO) to derive the release policies and rule curves for the RSSR. The methodology adopted is summarized in the flow-chart shown in Figure 9.

The simple stepwise procedure of the adopted methodology is given as follows:

1. On the basis of an extensive literature review, the proposed models were adopted for the given formulated problem.
2. The data collected was analyzed and prepared to form input to the models developed.
3. The models were then run with specified parameter values, which were selected after performing sensitivity analysis; objective function, and constraints to obtain Pareto optimal solutions.
4. Once the solutions were obtained, the EMCP approach was incorporated to identify the best solutions. The EMCP is used to rank Pareto optimal solutions by considering the relative importance of objectives. The methodology follows these steps:
 - Normalize the objective function values using the min-max normalization method.
 - Compute entropy weights for each criterion to reflect their relative importance.
 - Apply compromise programming to select the solution closest to the ideal point based on the weighted Euclidean DM.
5. It is this structured approach that ensures an unbiased selection of the best reservoir operation strategy while balancing tradeoffs among conflicting objectives.

3. PROBLEM FORMULATION

In the present study, three objective functions were formulated and stated:

$$\text{Min } z_1 = \sum_{t=1}^N (D_i - R_i)^2$$

$$\text{Min } z_2 = \sum_{t=1}^N (D_m - R_m)^2$$

$$\text{Min } z_3 = \sum_{t=1}^N (D_f - R_f)^2$$

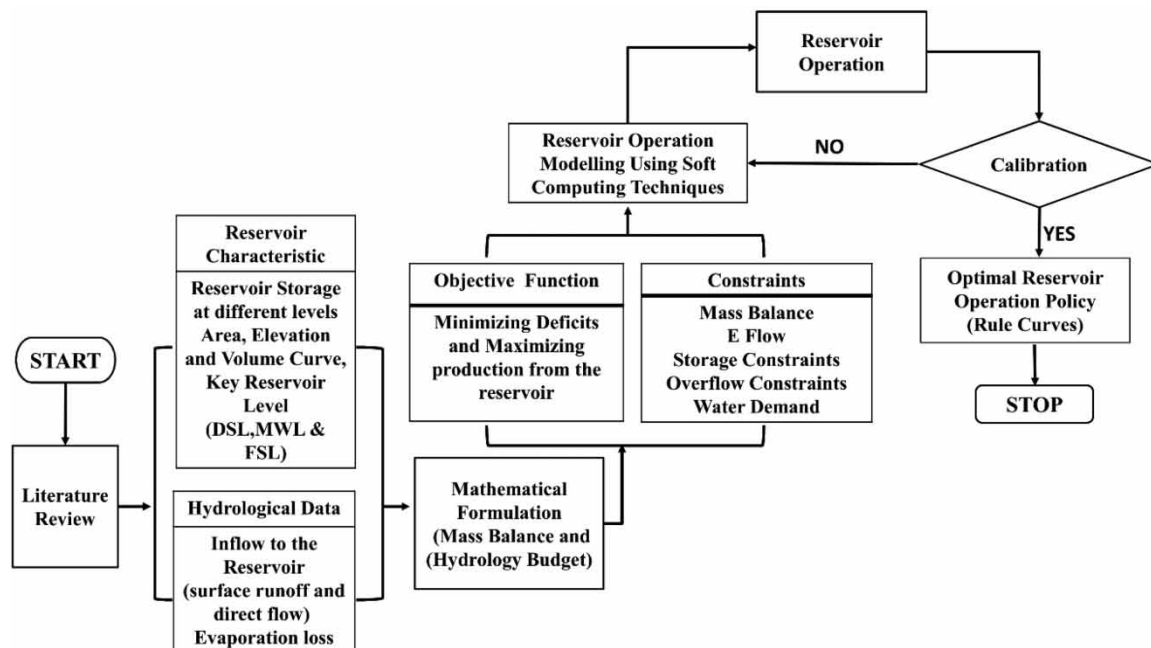


Figure 9 | Methodology.

where D_i is the irrigation demand at each time period t (million m^3); R_i is the irrigation release at each time period t (million m^3); D_m is the municipal demand at each time period t (million m^3); R_m is the municipal release at each time period t (million m^3); D_f is the industrial demand at each time period t (million m^3); and R_f is the industrial release at each time period t (million m^3).

The objective here is the minimization of the squared deviation between releases and demands subjected to various constraints.

3.1. Constraints of the model

3.1.1. Mass balance

The water mass balance in the reservoir is regulated by the continuity equation:

$$S_{t+1} = S_t + I_t - Q_t - E_t - O_{ft}$$

where S_t is the storage in each time period t (MCM); S_{t+1} is the storage for next time period $t + 1$ (MCM); I_t is the inflow to the reservoir at time period t (MCM); Q_t is the outflow from the reservoir in each time period; E_t is the loss from evaporation of the reservoir at period t (MCM); O_{ft} is the overflow at time period t (MCM); t is the time period.

3.1.2. Storage constraints

Reservoir storage is restricted between dead storage and live storage.

$$S_{\min} \leq S_t \leq S_{\max}$$

$S_{\min}$ is the dead storage (MCM); $S_{\max}$ is the maximum capacity of reservoir (MCM).

3.1.3. Overflow constraints

The overflow from the reservoir cannot be less than zero and is formulated as follows:

$$O_{ft} = S_{t+1} - S_{\max}$$

$$O_{ft} \geq 0$$

3.2. Environmental flow constraints

The CWC advises that the E-flow conditions for Himalayan rivers should be established as follows: (1) the minimum E-flow should be greater than 2.5% of the 75% dependable annual flow; (2) Additionally, during the monsoon season, a flushing flow with a peak of at least 250% of the 75% dependable annual flow is necessary. For rivers outside the Himalayan region, the recommendations are as follows: The minimum E-flow should not fall below 0.5% of the 75% dependable annual flow, and a flushing flow with a peak of no less than 600% of the 75% dependable annual flow is required during the monsoon period (Dabhade & Regulwar 2021).

$$Q_t \geq 0.005 \text{ of } 75\% \text{ of Dependent Annual Flow}$$

3.2.1. Release constraints

The constraint for reservoir release is stated as:

$$Q_t \leq \text{Canal Capacity in MCM}$$

The final models were then run to minimize the objective functions, duly satisfying the given constraints using NSGA II, NSGA III, and MOPSO models in MATLAB. In the present study, the first priority is given to the E-flow condition, and then the next priority is to meet first the municipal demand, secondly the irrigation demand, and then the industrial demand.

3.3. Performance indicators

The most commonly used performance measuring indicators for reservoir operation are reliability, vulnerability, and resilience (Anusha *et al.* 2017).

3.3.1. Reliability

Reliability defines the probability of a system being in a satisfactory state and is estimated as the ratio of the amount of released water, and required water.

$$R_e = \frac{(Tr)t}{(Td)t}$$

where $(Tr)t$ is the amount of water discharged during the time period t ; $(Td)t$ is the amount of water required during the time period t .

3.3.2. Vulnerability

Vulnerability indicates the severity of damage of an event, which is estimated as the ratio of water deficit events for the operation period and the volume of water required.

$$V_n = \frac{D}{(Td)t}$$

where D is the deficit volume of the event t ; $(Td)t$ is the required volume for the same period.

3.3.3. Resilience

Resilience indicates the water storage measured after recovery from any failure event. It is expressed as follows:

$$R_s = \frac{1 - y_i}{C_v}$$

where y_i is the annual yield divided by the inflows; C_v is the variation coefficient for optimal inflows

4. RESULTS AND DISCUSSION

Based on the problem formulation, results were obtained using the three evolutionary algorithms, which were then run in MATLAB for RSSR. The inputs used for the models were the monthly inflows and demands. The first priority in the formulated problem was to fulfill the E-flow criteria followed by the municipal, irrigation, and industrial demand. The given set of equations was applied to the proposed models NSGA II, NSGA III, and MOPSO to fulfill the given demands.

4.1. Sensitivity analysis of model parameters

Model parameters play a crucial role in governing the function of the algorithm, as each parameter has its contribution to the process. To validate the rationality of parameter settings, a sensitivity analysis was conducted by varying key algorithm parameters such as population size, mutation rate, and crossover probability, and with various simulations (Vojinovic *et al.* 2003), the parameter values were obtained. The following tests were performed, as shown in Tables 3–5.

The key parameters of the models are shown in Table 6.

4.2. Comparison of Pareto front solutions

After running the models for the respective number of iterations, several solution sets were obtained, from which the decision had to be made using the MCDM technique to reduce the large solution set to a smaller number of solutions.

For this process, the EMCP approach has been used in the present study, and the decision is taken accordingly. Figures 10–12, represent the Pareto Front solution sets acquired using NSGA II, NSGA III, and MOPSO, respectively. As can be seen in the figures, there is one solution set among all the Pareto Front sets, which is the best solution obtained using the EMCP approach.

Table 3 | Sensitivity analysis for NSGA II

Parameter	Range tested	Value tested	Municipal	Irrigation	Industrial	Remarks
Population size	10–150	10	1,150,000	5,500	5,600	Poor diversity
		50	1,050,000	3,800	3,900	Insufficient exploration
		100	890,000	2,200	2,300	Optimal, matches the red dot
		150	910,000	2,400	2,600	Slight overfitting
Iterations	100–700	100	1,100,000	4,500	4,600	Early stopping
		300	950,000	3,000	3,100	Suboptimal convergence
		500	900,000	2,000	2,500	Optimal, matches the red dot
		700	895,000	2,050	2,550	Minor gain
<i>M</i> prob.	0.1–0.5	0.1	1,000,000	2,800	2,900	Less exploration
		0.2	870,000	2,600	2,300	Optimal, matches the red dot
		0.5	980,000	3,200	3,300	Excessive mutation
<i>C</i> prob.	0.6–0.9	0.6	970,000	2,900	3,000	Lower diversity
		0.8	885,000	2,100	2,300	Optimal, matches the red dot
		0.9	910,000	2,200	2,600	Minor deviation

Bold values indicate the values adopted for model run after performing the sensitivity analysis.

Table 4 | Sensitivity analysis for NSGA III

Parameter	Range tested	Value tested	Municipal	Irrigation	Industrial	Remarks
Population size	50–150	50	680,000	6,700	6,200	Poor diversity
		80	675,000	6,500	6,100	Suboptimal exploration
		92	670,000	5,800	6,000	Optimal, matches the red dot
		120	682,000	5,900	6,050	Slight overfitting
Iterations	100–700	100	688,000	6,200	6,150	Early stopping
		300	693,000	5,800	6,280	Suboptimal convergence
		500	668,000	5,500	6,100	Optimal, matches the red dot
		700	699,500	5750	6,810	Minor gain
<i>n</i> _partitions	6–20	6	685,000	6,100	6,500	Coarser reference points
		10	692,000	6,300	6,650	Suboptimal distribution
		12	672,000	5,700	6,300	Optimal, matches the red dot
		20	681,000	5,100	6,420	Minor deviation

Bold values indicate the values adopted for model run after performing the sensitivity analysis.

4.3. Comparison of optimal operating policies

Optimal operating policies for any reservoir involve forming rule curves that specify how much water to store at different periods in a year while maintaining specific storage levels. In the present study, after obtaining the best solution from the EMCP approach, the rule curves are derived from the three selected algorithms as discussed in the following section.

4.3.1. Rule curves

Rule curves are derived on the basis of historical data, inflow forecasts, reservoir operation policies, and optimization techniques. In the present study, the goal is to balance conflicting objectives of municipal, irrigation, industrial, and environmental needs. Rule curves derived from these algorithms are shown in [Figures 13–15](#). The rule curves obtained using NSGA II show different peaks as well as filling and decline periods that are well defined. As can be seen in [Figure 12](#), the release model indicates that NSGA II is more sensitive to changes in inflow and manages the reservoir well by storing

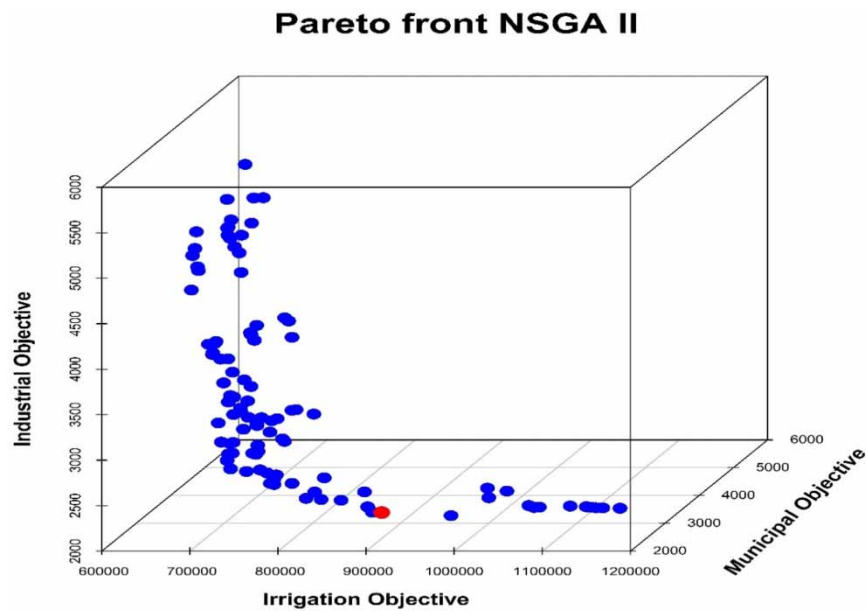
Table 5 | Sensitivity analysis for MOPSO

Parameter	Range tested	Value tested	Municipal	Irrigation	Industrial	Remarks
Swarm size	50–300	50	1,200,000	14,000	15,000	Poor exploration
		100	1,100,000	12,000	13,000	Suboptimal swarm
		200	1,080,000	13,500	11,000	Optimal, matches the red dot
		300	11,10,000	14,100	11,100	Slight overfitting
Iterations (Maxgen)	100–700	100	1,150,000	15,000	14,000	Early convergence
		300	1,050,000	14,500	12,000	Suboptimal
		500	1,000,000	13,800	11,500	Optimal, matches the red dot
		700	1,095,000	14,050	11,950	Minor gain
Inertia weight	0.4–0.9	0.4	1,180,000	12,000	12,500	Slow movement
		0.6	1,130,000	11,000	11,500	Suboptimal balance
		0.7	1,050,000	10,000	11,200	Optimal, matches the red dot
		0.9	1,080,000	10,200	11,300	Overshooting

Bold values indicate the values adopted for model run after performing the sensitivity analysis.

Table 6 | Key parameters for the three algorithms

NSGA II		NSGA III		MOPSO	
Parameter	Value	Parameter	Value	Parameter	Value
Population size	100	Population size	92	Swarm size	200
Number of iterations	500	Maxiter	500	Maxgen	500
M prob.	0.2	n_partitions	12	F_{cnt}	3
C prob.	0.8	Type	Real valued	Inertia weight	0.7
S_{min}	144 MCM	S_{min}	144 MCM	S_{min}	144 MCM
S_{max}	910 MCM	S_{max}	910 MCM	S_{max}	910 MCM

**Figure 10** | Pareto solution set for NSGA II.

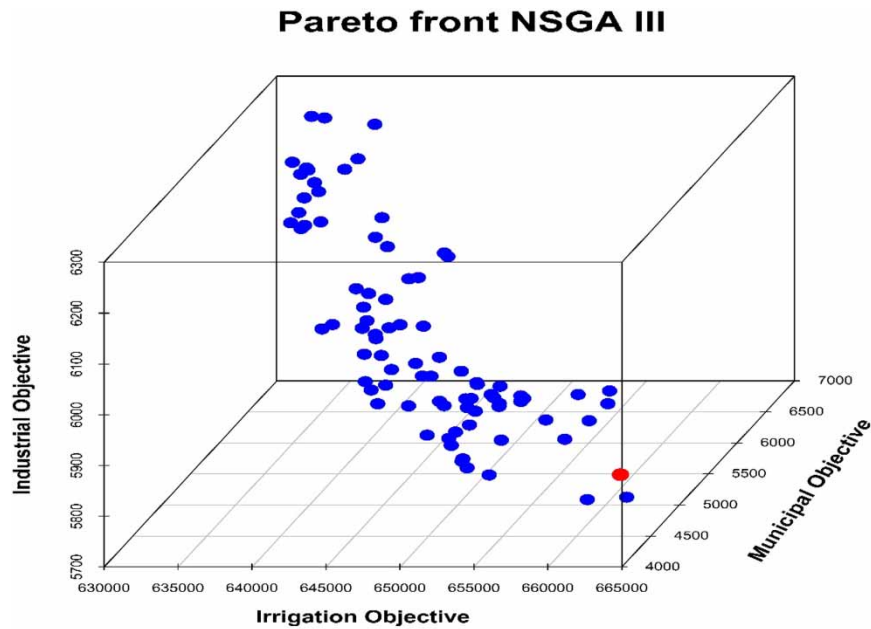


Figure 11 | Pareto solution set for NSGA III.

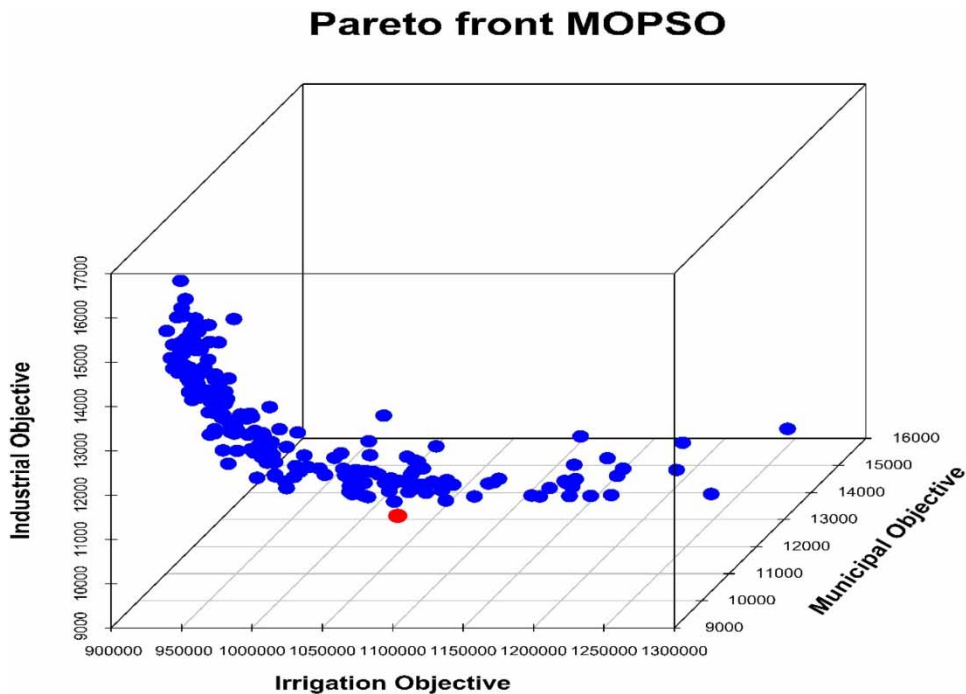


Figure 12 | Pareto solution set for MOPSO.

adequate amounts of water during high inflows and controlling releases during dry periods. The rule curves obtained using NSGA III and MOPSO exhibit less responsive behavior than NSGA II. The curves obtained are slightly flattened, indicating less variation in the available inflows. MOPSO produced a significantly flatter curve than NSGA III with lower peaks and variations.

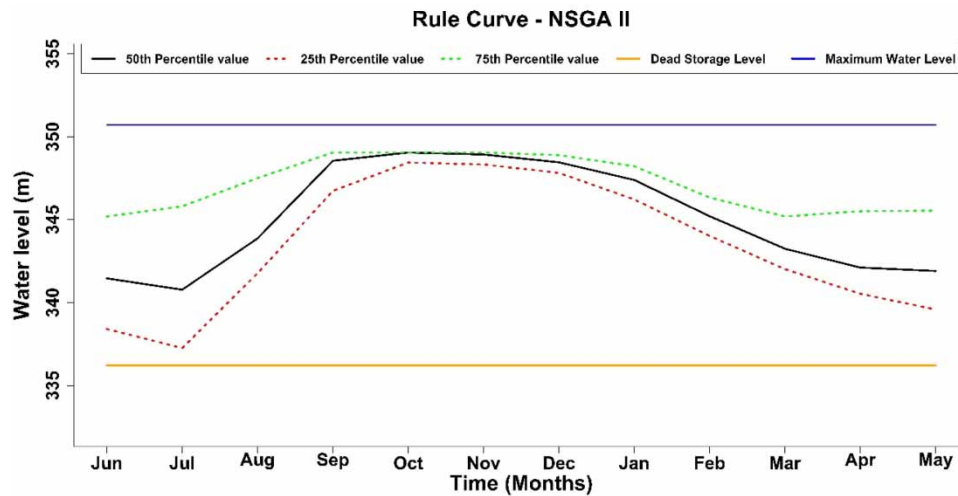


Figure 13 | Rule curve for reservoir using NSGA II.

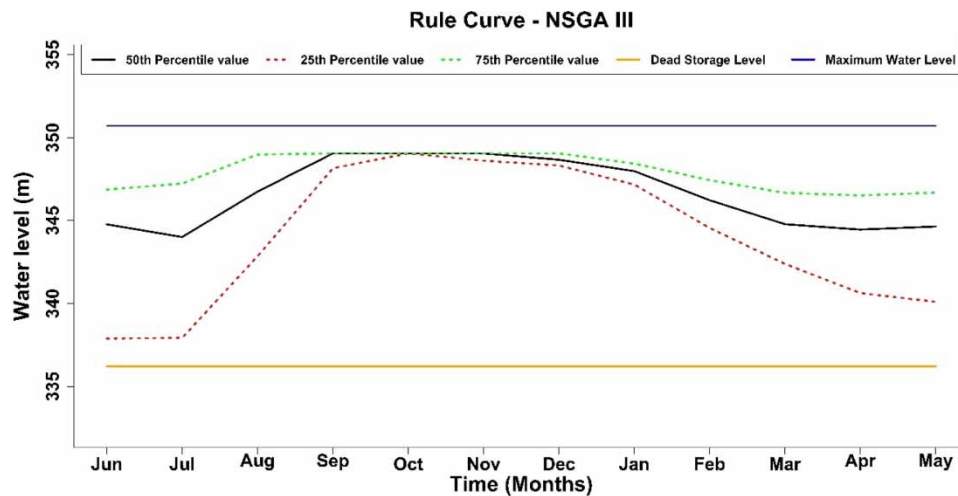


Figure 14 | Rule curve for reservoir using NSGA III.

4.3.2. Releases

The annual release volumes generated for the three objectives, municipal, irrigation, and industrial, are represented graphically in Figure 16. The releases obtained using NSGA II appear better than the other two models for the given period. It is evident from the figure that NSGA II releases have successfully met almost all the demands, particularly in the later years of the considered study period, because of high inflows. It was concluded that only 17% of the demand was not met using NSGA II, while for NSGA III and MOPSO, 32 and 46% of demands were not satisfied.

4.3.3. Deficit

Figures 17–19, show the monthly deficits obtained for the years 1991, 1997, and 2005, which were selected as samples. Figure 20 represents the annual deficits obtained for all years using the proposed models. The figure below shows that the deficits are minimal for NSGA II. The deficits were reduced up to 70% using NSGA II, while for NSGA III and MOPSO, the reductions were 42 and 25%, respectively.

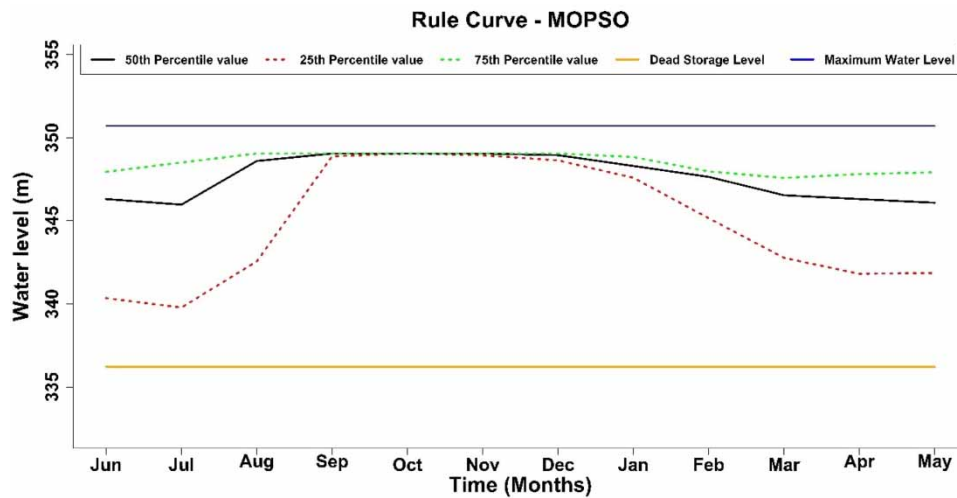


Figure 15 | Rule curve for reservoir using MOPSO.

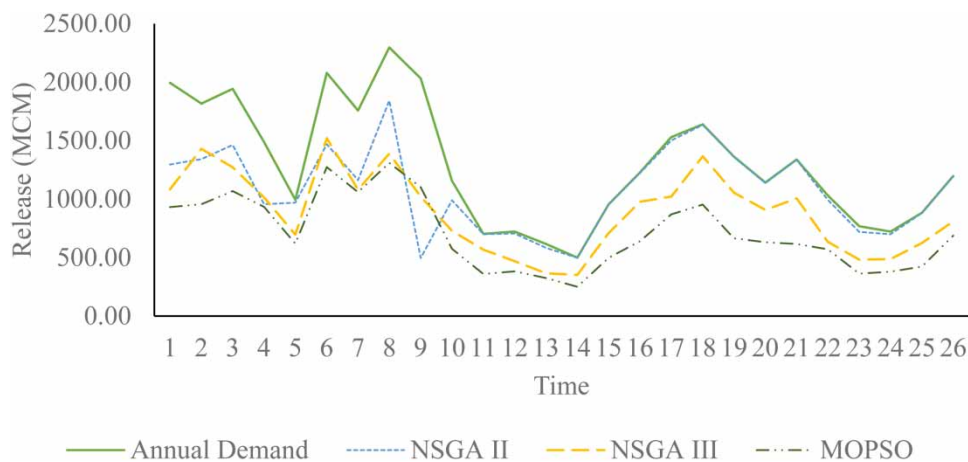


Figure 16 | Comparison of demand and releases using the three algorithms.

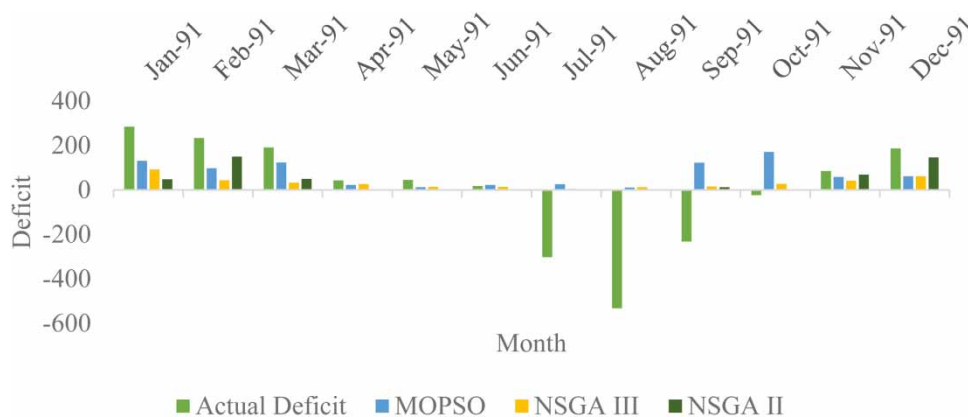


Figure 17 | Comparison of deficits using the three algorithms for the year 1991.

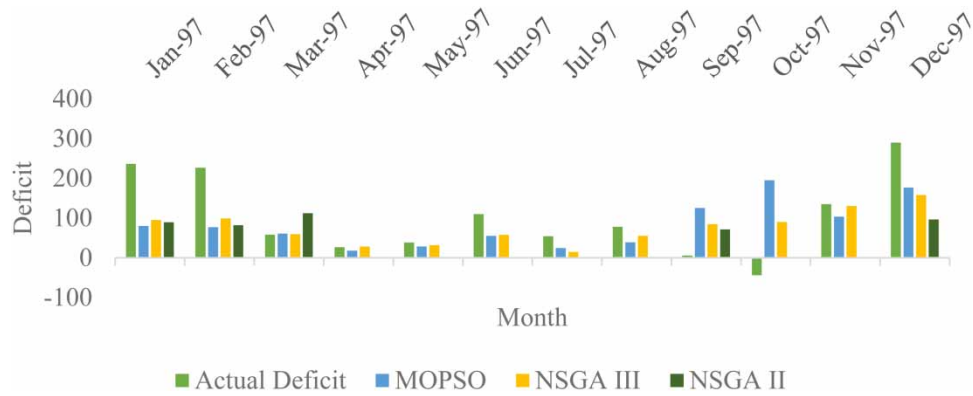


Figure 18 | Comparison of deficits using the three algorithms for the year 1997.

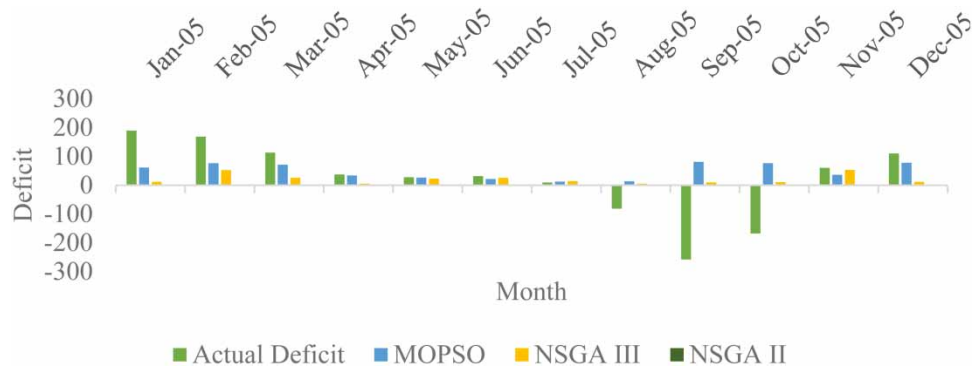


Figure 19 | Comparison of monthly deficits using the three algorithms for the year 2005.

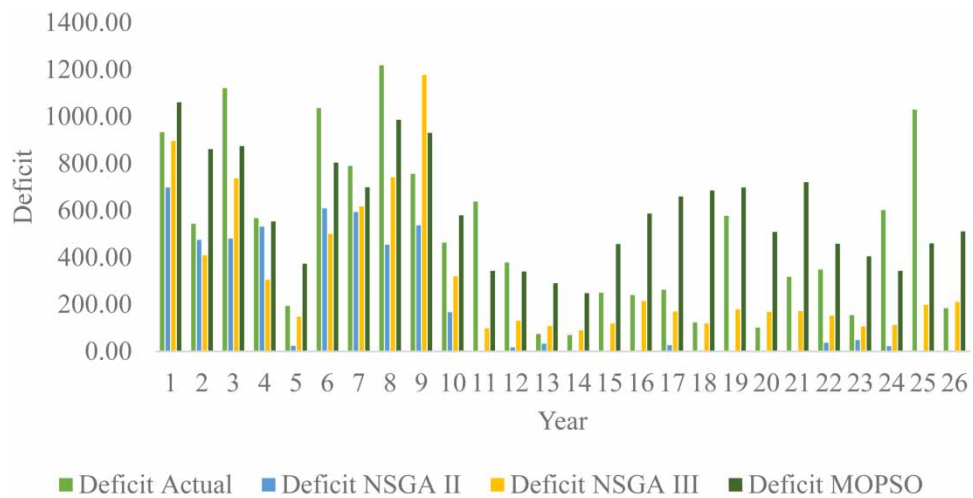


Figure 20 | Comparison of annual deficit using the three algorithms.

4.3.4. Environmental flow

In the case of the Himalayan rivers, the CWC recommends the E-flow conditions as follows: the minimum E-flow should be greater than 2.5% of the 75% dependable annual flow. E-flow when calculated from the Weibull method is equal to 6.4 MCM.

Maintaining E-flow constraints is crucial for sustaining aquatic ecosystems and ensuring social well-being. The results indicate that NSGA-II outperformed NSGA-III and MOPSO in minimizing E-flow violations, ensuring greater compliance with ecological requirements. The practical significance of this finding is that optimized reservoir operation strategies must consider municipal, irrigation, and industrial demands along with downstream ecological needs, which include:

- *Biodiversity conservation*: Ensuring adequate water levels for aquatic habitats.
- *Fisheries management*: Supporting livelihoods dependent on reservoir fisheries.
- *Community water access*: Balancing ecosystem conservation with water supply to rural communities.

This study underscores the need for a balanced water management strategy that integrates ecological sustainability into decision-making. The comparison of e-flow criteria satisfied by different algorithms and original policy is shown in Table 7.

4.4. Performance assessment of models

For performance assessment of the proposed models, the basic indices, viz. reliability, vulnerability, resilience, and Root Mean Square Error (RMSE) were estimated and are shown in Table 8. The release policies and rule curves obtained using NSGA II are more reliable than the other two models. For NSGA II, the resilience index is closer to one, indicating higher resilience and less vulnerability.

5. LIMITATIONS OF THE STUDY

While this study presents an efficient reservoir optimization framework, certain limitations must be acknowledged, which are discussed as follows.

5.1. Computational complexity

The application of NSGA-II, NSGA-III, and MOPSO requires significant computational resources, especially for large-scale reservoirs. The soft computing techniques applied in this study require considerable computational resources. The complexity grows with increasing population sizes, more iterations, and additional objectives, leading to longer computation times and less flexibility in trying more complex configurations. High computational demand leads to increased processing time, high dependence on advanced hardware, and a lack of scalability for more significant systems or real-time applications. In this line of thought, this study also highlights the need for strategies to overcome such challenges by using parallel computing to reduce processing times, integrating data-driven models for approximating objective functions, and refining algorithms to eliminate redundant computations.

Table 7 | Criteria for E-flow

Model	No. of months E-flow criteria not met	Percent of times E-flow not satisfied
Actual policy	52	16.05%
NSGA II	6	1.85%
NSGA III	7	2.16%
MOPSO	15	4.63%

Table 8 | Performance indicators of three algorithms

Algorithm			
Indicator	NSGA II	NSGA III	MOPSO
Reliability index	0.82	0.68	0.55
Vulnerability index	0.18	0.32	0.45
Resilience index	1.01	1.25	1.47
RMSE	11.59	13.22	17.61

5.2. Lack of real-time integration

One major limitation of this study is the lack of a real-time decision-making framework, mainly because real-time data are unavailable. Reservoir operations are very dynamic, given the changing patterns of inflows, demands for water use, and E-flow requirements. However, this study had to rely on historical data to develop operational policies, which, although useful for long-term planning, lack the responsiveness required for real-time scenarios.

5.3. Reservoir-specific study

Each reservoir is influenced by its unique hydrological inputs. The specific characteristics of the reservoir influence modeling. The performance of the algorithms and approaches presented may vary when applied to other reservoirs with different inflow patterns, catchment characteristics, and operational constraints.

6. CONCLUSIONS

Reservoir operation plays a crucial role in water resources management. The goal of optimizing reservoir operations is to lower risks and maximize reservoir benefits without compromising the reservoir's objective functions and constraints.

The present study employs three multi-objective algorithms, NSGA-II, MOPSO, and NSGA-III, to optimize the RSSR located in Chhattisgarh, India.

A detailed comparative analysis was executed for the proposed models. Based on the Pareto front solutions, rule curves, release policies, monthly deficits, E-flow criteria, and performance indices, NSGA II outperforms the other algorithms and produces the most reliable results across a variety of objectives due to its diverse solutions and Pareto fronts handling. The dynamic behavior of NSGA II enhances the potential of the model to manage the reservoir operation rules in a better way. NSGA III performs adequately, especially in handling higher-dimensional objective problems. However, it does not outperform NSGA-II in terms of overall solution quality. In some other studies, NSGA III does not necessarily outperform NSGA II; it also depends on the type of problem (Ishibuchi *et al.* 2016). MOPSO shows a lower degree of variety and convergence than NSGA II and NSGA III. However, it provides logical solutions for the reservoir operation issue.

7. PRACTICAL RECOMMENDATIONS

Based on the results, the following recommendations are proposed for policymakers and reservoir managers:

- *Adopt NSGA-II for operational decision-making:* Given its superior reliability and resilience performance, NSGA-II can serve as a baseline algorithm for optimizing reservoir operations.
- *Implement dynamic water allocation strategies:* Flexible reservoir release schedules should be designed to accommodate seasonal variations in water demand while maintaining ecological balance.
- *Incorporate stakeholder perspectives:* Decision-making processes should involve local communities, agricultural stakeholders, and environmental agencies to ensure equitable water distribution.
- *Enhance climate resilience in water management:* Future policies must consider climate-adaptive reservoir operation strategies, integrating real-time hydrological forecasting.

These insights provide a roadmap for sustainable reservoir management while balancing competing water-use priorities.

CONSENT TO PUBLISH

The authors have given consent and approved for manuscript submission.

AUTHORS CONTRIBUTIONS

All authors contributed to the study's conception and design. Methodology development was done by R.D., application, and data analysis were done by R.D., and data collection and conceptualization were done by H.A.S Sandhu. Draft preparation and review were done by M.T. and C.C.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

All data used during the study were provided by a third party. Direct requests for these materials may be made to the provider.

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