University of Baghdad
College of Engineering
JOURNAL OF ENGINEERING

Journal of Engineering

journal homepage: www.jcoeng.edu.iq

Volume 32 Number 9 September 2026

Performance Comparison of Evolutionary and Nature Inspired Algorithms for Optimizing the Operation of Indira Sagar Reservoir

Ashwin Parihar *, **Shilpa Tripathi** , **Ruchir Lashkari**

Civil Engineering, Medicaps University, Indore, India

ABSTRACT

Efficient reservoir operation is an important aspect of sustainable water resources management in monsoon-driven river basins such as India, where hydrological variability and competing water demands present complex operating challenges. The present study is aimed to evaluate the comparative performance of evolutionary and nature inspired metaheuristic optimization approaches for the optimal operation of Indira Sagar Reservoir. The reservoir operation problem is formulated as a constrained multi-objective optimization problem to minimize water-supply deficits and improve hydropower related performance under the constraints of storage, dead-storage, release, spillway-capacity and storage-change. The selected algorithms represent different population-based evolutionary and nature-inspired search mechanisms and are evaluated under a common modelling framework using representative hydrological years. Performance is assessed based on deficit reduction, convergence behavior, reliability, resilience, vulnerability, and sustainability indicators. The existing operating policy exhibited low time-based reliability (0.4627) and volumetric reliability (0.6854), while resilience reached 1.0000, indicating rapid recovery following detected failures but frequent shortage occurrence. The comparative results showed that CSA achieved the lowest mean deficit of 966.8 MCM among the evaluated approaches, compared with approximately 14,220.14 MCM for the existing policy, followed by IWO and CA. The observed ranking was CSA > IWO > CA > TV-EM-MOPSO > EM-MOPSO > MO-PSO. These findings identify CSA as the most promising candidate among the evaluated approaches for further development and validation of an improved operating policy for Indira Sagar Reservoir.

Keywords: Crow search algorithm, Indira sagar reservoir, Metaheuristic optimization, Reservoir operation, Water resources management.

1. INTRODUCTION

Reservoirs are essential components of water resources systems, supporting irrigation, hydropower generation, domestic and industrial water supply, environmental

*Corresponding author
Peer review under the responsibility of University of Baghdad.
https://doi.org/10.31026/j.eng.2026.09.04

Article received: 25/06/2026
Article revised: 25/08/2026
Article accepted: 30/08/2026
Article published: 01/09/2026

requirements, and flood mitigation. Increasing water demand, hydrological variability, population growth, and competing water uses have made reservoir operation increasingly complex. Efficient reservoir management therefore requires appropriate operating policies that can balance water-supply requirements, storage conditions, hydropower generation, and environmental needs. Previous studies have demonstrated the importance of developing reliable and efficient operating policies for multipurpose and multi-reservoir systems **(Jothiprakash et al., 2011; Fayaed et al., 2013; Kumar et al., 2013).**

Optimal reservoir operation is generally formulated as a nonlinear, constrained, and multi-objective optimization problem involving conflicting objectives such as minimizing water-supply deficits, maintaining adequate storage, maximizing hydropower generation, and improving system reliability. Different optimization and computational approaches have therefore been applied to derive improved reservoir operating policies. Genetic Algorithm, Artificial Neural Networks, stochastic optimization, and hybrid optimization approaches have demonstrated the potential to improve reservoir operation under complex hydrological conditions **(Jothiprakash et al., 2011; Fayaed et al., 2013; Kumar et al., 2013).** Multi-objective optimization frameworks have also been developed to address competing reservoir-operation objectives and support more effective decision-making **(Giuliani et al., 2016).**

The increasing complexity of reservoir systems has further encouraged the application of metaheuristic and nature-inspired optimization techniques. Such methods provide flexible search mechanisms for nonlinear and constrained optimization problems and have been applied to reservoir release policy development and optimal reservoir operation. For example, multi-strategy optimization has been used for developing optimal reservoir policies **(Ahmadianfar et al., 2019),** while other studies have investigated machine-learning and metaheuristic approaches for reservoir operation and release optimization **(Allawi et al., 2018; Latif et al., 2021; Saham et al., 2022).** These studies demonstrate the potential of advanced optimization methods for improving reservoir operating policies under complex system conditions.

However, the reported performance of optimization algorithms is strongly problem-dependent. Most existing studies have concentrated on developing or applying a particular optimization technique, whereas comparatively less attention has been given to systematic performance comparison of different evolutionary and nature-inspired algorithms under an identical reservoir-operation framework. In particular, there remains a need to determine how different search mechanisms perform when the algorithms are subjected to the same objective functions, operational constraints, hydrological inputs, and evaluation criteria. This represents an important knowledge gap because selecting an appropriate optimization algorithm can influence the quality, feasibility, and robustness of the resulting reservoir operating policy.

In the present study, algorithm performance is not defined only by the ability to minimize water-supply deficits. It also involves the generation of feasible reservoir operating policies while maintaining appropriate storage and release conditions and achieving satisfactory reliability, resilience, vulnerability, and sustainability characteristics. Reliability, resilience, and vulnerability provide complementary measures of water-resource system performance by describing failure frequency, recovery behavior, and the severity of failures, respectively **(Hashimoto et al., 1982).** The importance of harmonizing reliability-based performance indicators for reservoir planning and operational evaluation has also been highlighted by **(Adeloye et al., 2017).** Therefore, these indicators, together with deficit and operational

feasibility, are considered for comparative evaluation in the present study.
The algorithms considered in this study were selected to represent different evolutionary and nature-inspired search mechanisms and their applicability to complex reservoir optimization problems. MOPSO, EM-MOPSO, and TV-EM-MOPSO represent particle-based multi-objective and evolutionary search mechanisms, whereas CA, IWO, and CSA represent alternative nature-inspired search strategies. The selection was motivated by the need to compare fundamentally different search behaviors within a common reservoir-operation framework rather than to assume that these methods are universally superior to other approaches such as Genetic Algorithm, Whale Optimization Algorithm, Ant Colony Optimization, or Sine Cosine Algorithm. Previous reservoir studies using evolutionary, multi-objective, and alternative optimization approaches provide a basis for such comparative assessment **(Jothiprakash et al., 2011; Giuliani et al., 2016; Ahmadianfar et al., 2019; Latif et al., 2021).**
Indira Sagar Reservoir is a major multipurpose reservoir in India with important roles in irrigation, hydropower generation, and regional water management. The operation is characterized by competing demands, variable inflows, storage constraints and multiple operational requirements, making it a suitable case to evaluate alternative optimization approaches. The present study compares MOPSO, EM-MOPSO, TV-EM-MOPSO, Cultural Algorithm (CA), Invasive Weed Optimization (IWO) and Crow Search Algorithm (CSA) for optimal operation of Indira Sagar Reservoir. The comparison is based on the reduction of water-supply deficit, the feasibility of reservoir operating and the resulting reliability, resilience, vulnerability and sustainability of the operating policies.
The study is subject to several assumptions and limitations. The optimization model is developed using available historical hydrological and demand data and represents reservoir operation at a monthly time scale. The analysis assumes that the adopted reservoir characteristics, demand representation, operating constraints, and model parameters adequately represent the system. The comparison is restricted to the selected algorithms and therefore does not establish universal superiority over all available optimization techniques. Furthermore, the resulting operating policies require further testing under alternative hydrological sequences, climate variability, demand uncertainty, and real-time operational conditions before practical implementation.

2. MODEL DESCRIPTION

2.1 Multi-Objective Particle Swarm Optimization (MO-PSO)

MO-PSO proposed by **(Coello et al., 2004)**, extends the conventional PSO framework to solve multi-objective optimization problems. In MO-PSO, a particle is a candidate solution that moves its position towards the personal best (Pbest) and the global best (Gbest) solutions. The particle velocity is calculated as

$$v_i^{t+1} = w\, v_i^t + c_1\, r_1 (pbest_i - x_i^t) + c_2\, r_2 (gbest - x_i^t) \tag{1}$$

and update the position as

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

where (w) is the inertia weight, (c_1) and (c_2) are acceleration coefficients, and (r_1) and (r_2)

are random numbers. The solutions are stored in an external archive until convergence is obtained.

2.2 Elitist Mutation Multi-Objective Particle Swarm Optimization (EM-MOPSO)

EM-MOPSO is a variant of MO-PSO that employs an elitist mutation operator to enhance population diversity and prevent premature convergence. Selected elite particles are mutated after the normal velocity and position update process.

$$[\ x_i^{new} = x^i + \delta] \tag{3}$$

Where δ is a random mutation factor. The mutated solutions are evaluated and stored in an external archive of non-dominated solutions. The optimization is repeated until the stopping criteria are reached.

2.3 Time Variance Elitist Mutation Multi-Objective Particle Swarm Optimization (TV-EM-MOPSO)

TV-EM-MOPSO enhances EM-MOPSO by using a time-varying inertia weight and an adaptive mutation mechanism used by **(Trivedi and Shrivastava, 2020)**. The inertia weight is renewed as

$$w(t) = w_{max} - \backslash\{(w_{max} - w_{min})t\}\{T_{max}\} \tag{4}$$

where w_{max} and w_{min} are maximum and minimum inertia weights respectively. The adaptive strategy promotes global exploration during the early search stage and local exploitation near convergence. Non-dominated solutions are updated during the optimization procedure. In the present implementation, the population consists of 20 particles, and the optimization is performed for 200 iterations. The elitist mechanism retains the best-performing solutions, while the mutation operation is applied to maintain population diversity and avoid premature convergence. Two elite particles were retained, a mutation size of 0.10 was adopted, and the algorithm was independently replicated over 50 runs to assess the consistency of the obtained solutions. The non-dominated solutions are retained and updated during the optimization process to maintain the Pareto-optimal solution set.

2.4 Cultural Algorithm (CA)

The Cultural Algorithm (CA), introduced by **(Chung and Reynolds, 1999)** is an evolutionary optimization method based on the interaction between a Population Space and a Belief Space. Candidate solutions evolve in the Population Space, whereas the Belief Space stores the knowledge acquired during the search and guides subsequent generations toward improved solutions. This knowledge-sharing mechanism enhances both exploration and exploitation during the optimization process.

$$\mathrm{BS_{t+1}} = \mathrm{Update(BS_t, Accepted\ Solutions)} \tag{5}$$

where (BS) is the space of beliefs. The information exchange between these two spaces drives the search process towards better solutions, until the termination criterion is satisfied.

2.5 Invasive Weed Optimization (IWO)

IWO, introduced by **(Mehrabian and Lucas, 2006),** mimics the colonization behavior of invasive weeds. Candidate solutions are replicated according to their fitness and the number of seeds it produces is determined by

$$S_i = S_{min} + ((f_{best} - f_{worst})/(f_i - f_{worst}))(S_{max} - S_{min}) \quad (6)$$

where (S_i) is the seed production of the weed (i). The seeds are spread at random, and the principle of competitive exclusion ensures that only the strongest individuals will survive to the next generation. The procedure is repeated until convergence.

2.6 Crow Search Algorithm (CSA)

The Crow Search Algorithm (CSA) proposed by **(Askarzadeh, 2016)** is inspired by the intelligent behavior of crows, particularly their ability to hide and retrieve food from memorized locations. Each crow represents a candidate solution, while its memory stores the best previously visited position. During the search process, a crow follows another crow to approach its memorized hiding location. The position of a crow is updated according to:

$$X_i^{t+1} = \{X_i^t + r_i \, FL_i^t(M_j^t - X_i^t), r_j >= AP_j^t; a\ random\ position, r_j < AP_j^t\} \quad (7)$$

where α is the step size, λ is the Levy distribution. Bad nests are abandoned with fixed probability while better solutions are retained. CSA employs iterative Levy flight exploration and nest replacement to efficiently trade-off exploration and exploitation in searching for near-optimal reservoir operating policies.

3. STUDY AREA DESCRIPTION

The Indira Sagar Reservoir is a large multipurpose project constructed on the Narmada River in Madhya Pradesh, India, near Punasa in Khandwa district at about 22.25° N latitude and 76.47° E longitude **(Fig. 2).** It is a critical component of the Narmada Valley Development Project and is vital for irrigation, hydropower generation and flood control in central India. The reservoir has a large catchment area of 61,642 km^2 and a gross storage capacity of 12,220 Million m^3, comprising 9,750 Million m^3 of live storage and 2,470 Million m^3 of dead storage, thereby providing substantial water availability for multi-sectoral demands. The Full Reservoir Level is at 262.13 m and the Minimum Drawdown Level is at 237.00 m, providing operational flexibility under varying hydrological conditions. The dam is a 92-m high and 653-m long concrete gravity dam, which was commissioned in 2005. The dam has a gated spillway system with 20 gates to regulate the floods efficiently. **Fig. 1** shows the main elements of the reservoir system, including the spillway, intake structure, powerhouse, and canal network, which allow for integrated water storage, controlled release, and power generation. The hydropower has an installed capacity of 1000 MW generated by eight turbines of 125 MW each. It is one of the region's most significant power-generating infrastructures. The reservoir's hydrological regime is predominantly influenced by monsoonal rainfall, leading to distinct seasonal variability in inflow patterns that requires optimized reservoir operation to balance competing objectives **(Neelakantan et al., 2013; Sinha et al., 2023).**

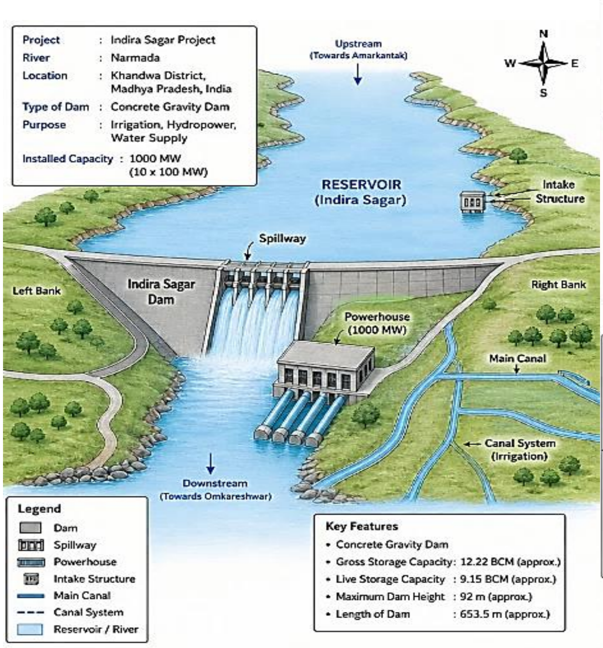

Figure 1. Layout of the Reservoir System

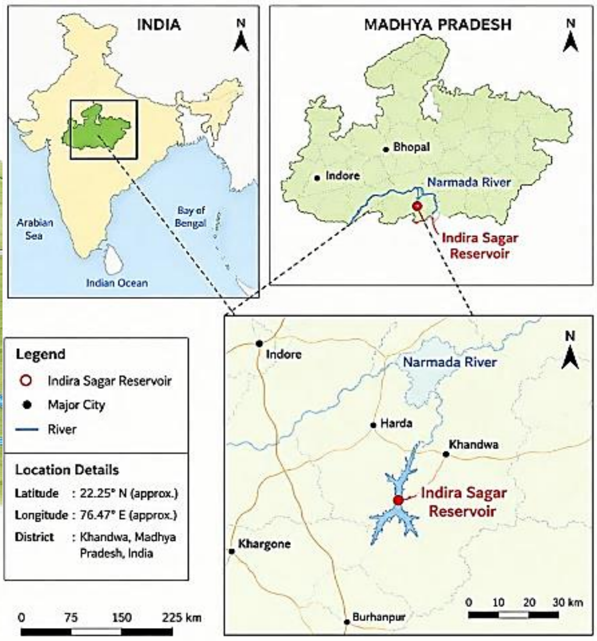

Figure 2. Location Map of Indira Sagar Reservoir

Table 1. Reservoir Technical Details

Parameter	Description	Value
River	River on which dam is constructed	Narmada
Location	Geographic location	Punasa, Khandwa (M.P.)
Latitude	Latitude of dam site	22.25° N
Longitude	Longitude of dam site	76.47° E
Type of Dam	Structural classification	Concrete Gravity Dam
Year of Commissioning	Year of completion	2005
Area of Catchment	Upstream drainage area	61,642 km^2
Gross Storage Capacity	Total storage capacity	12,220 MCM
Live Storage Capacity	Usable storage	9,750 MCM
Dead Storage Capacity	Non-usable storage	2,470 MCM
Full Reservoir Level (FRL)	Maximum water level	262.13 m
Minimum Drawdown Level (MDDL)	Minimum operating level	237.00 m
Dam Height	Height above foundation	92 m
Dam Length	Length across river	653 m
Spillway Type	Type of spillway	Gated spillway
Number of Spillway Gates	Total gates	20
Installed Power Capacity	Hydropower generation capacity	1000 MW
Number of Turbines	Powerhouse units	8 (125 MW each)
Purpose	Primary functions	Irrigation, Hydropower, Flood Control

3.1 Development of Reservoir Operation Optimization Model

The objective of this study was to develop an optimization model for determining the monthly reservoir releases that minimize the water-supply deficit while maintaining feasible conditions for storage and operation. The model was applied to the Indira Sagar Reservoir and verified with the observed series of inflow, demand, storage and release. The optimization problem was formulated as a constrained multi-objective reservoir operation problem.

3.1.1 Overall Methodological Framework

The overall methodological framework used in this study provides a systematic workflow for optimizing reservoir operation and comparing the selected metaheuristic algorithms. The framework comprises research objective definition, data collection and preprocessing, optimization model development, algorithm implementation, simulation, and comparative performance evaluation. The complete workflow adopted in the study is presented in **Fig. 3.**

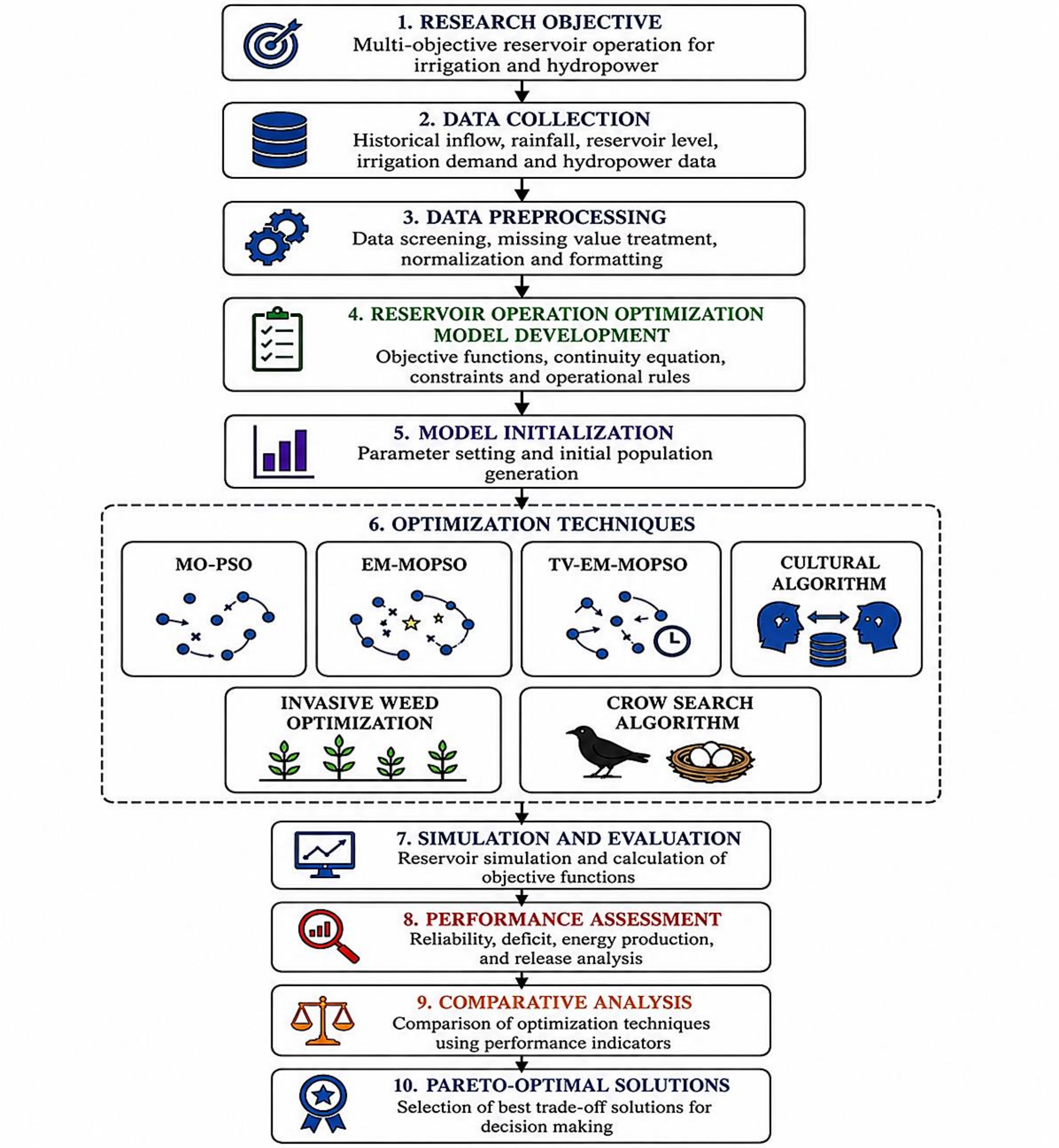

Figure 3. Overall methodological framework adopted for reservoir operation optimization and comparative evaluation of the selected metaheuristic algorithms.

3.1.2 Objective Function

The first objective function minimizes the normalized water-supply deficit:

$$F_1 = \min\{(D-R_1)/D\}^2 \quad (8)$$

where: D = water demand during period t, R = reservoir release during period t.
The second objective function represents the hydropower-related objective:

$$F_2 = (E_{max} - (PPC*R_2*H)/E_{max}) \quad (9)$$

The objective functions are optimized subject to the physical and operational constraints of the reservoir system.

MIN F=(F1+F2)

3.1.3 Reservoir Storage Continuity

The reservoir water balance is governed by the continuity equation:

$$S_{t+1} = S_t + I_t - R_t - E_t - Sp_t \quad (10)$$

where: S_t = Storage at time t ,I_t = Inflow E_t = Evaporation losses, Sp_t = Spill

3.1.4 Reservoir Operating Constraints

The optimization model incorporates the following constraints.

(a) Storage constraint

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

$S_{min} \le S_{t+1} \le S_{max}$

For Indira Sagar Reservoir, the minimum and maximum operating storage limits are defined according to the adopted reservoir operating characteristics.

(b) Dead storage constraint

$S_t \ge S_{Dead}$

(c) Change in storage constraint

$\Delta S_{minj} \le S_{t+1} - St \le \Delta S_{max}$

(d)Spillway capacity constraints

$0 \le R_t \le R_{max}$

In the case of the Reservoir Operation problem, several constraints are taken into account when an optimization process is applied.

3.2 Optimization Algorithms

Six optimization methods were selected for comparative evaluation: MO, EM, TV-EM, CA, IWO, and CSA. The selection was made to compare conventional, modified, time-varying, and population-based search strategies within the same reservoir-operation problem. The algorithms differ in how they balance exploration of the search space and exploitation of promising solutions. This comparison is important because reservoir operation is nonlinear, constrained, and multi-period, and the best solution may be difficult to obtain using a single search mechanism. MO and EM were included as baseline. TV-EM was added to study if a time-varying search parameter can improve the trade-off between global exploration and

local refinement. Other population-based techniques, CA, IWO and CSA were selected because they are based on different mechanisms for updating and diversifying candidates. The idea was not to assume that one algorithm is the best in general, but to find out which method gives the most consistent solutions (feasible solutions) for the reservoir model under equal computational conditions.
All methods were compared on the same population size, number of iterations, independent random runs, decision variable bounds, objective functions, constraint handling procedure, and termination rule for fairness. The parameters that are specific to the algorithm and that are reported in **Table 2** were held constant for all water years evaluated.

Table 2. Parameter settings of the optimization algorithms

Algorithm	Population size	Maximum iterations	Main algorithm-specific parameters
MO-PSO	20	200	(w=0.4,; c_1=1.257,; c_2=1.6)
EM-MOPSO	20	200	(w=0.4,; c_1=1.257,; c_2=1.6); elitist mutation
TV-EM-MOPSO	20	200	Time-varying (w); (c_1=1.257, c_2=1.6); elitist adaptive mutation
CA	20	200	Population space + belief space acceptance influence functions
IWO	20	200	Seed production, dispersal in space, competitive exclusion
CSA (Crow Search Algorithm)	20	200	Awareness probability + flight-length parameter

Six metaheuristic optimization algorithms were employed to compare their performance in reservoir operation optimization. Algorithms were implemented under a common modeling framework with identical objective functions and identical operational constraints. The main computational steps and solution-updating mechanisms of the algorithms are shown in **Fig. 4.**

3.3 Model Application

In this section, the developed optimization model is applied to the reservoir data rather than a separate statistical data-analysis procedure. The dataset was checked for consistency, units, time-step alignment and missing or unrealistic values. The inflow and demand data on monthly basis for the period 2009-2025 was collected from Narmada Control Authority (NCA), Indore; Narmada Valley Development Authority (NVDA), Indore and Narmada Hydroelectric Development Corporation (NHDC), Khandwa. The inflow, demand, storage, evaporation and release data were then converted to a common monthly time step and used as inputs to the reservoir optimization.
The model was first run using the current or baseline operating policy. This was the gap in reference and performance levels. Then the same model and data were used to run the six optimization algorithms. Each candidate solution was simulated throughout the study horizon and its objective values were computed only after checking storage, release, spill and water-balance constraints. The best solution of each independent run was retained for comparison.
The performance indicators obtained from the model were time-based reliability, volumetric reliability, resilience, vulnerability, normalized vulnerability, sustainability

index, total deficit, annual deficit, and percentage deficit reduction. These indicators were selected because they measure different aspects of operation. Reliability measures the frequency or volume of demand satisfaction, resilience measures recovery after failure, vulnerability measures the severity of failure, and the sustainability index provides a composite comparison **(Hashimoto et al., 1982; Kjeldsen et al., 2004; Adeloye et al., 2017).**

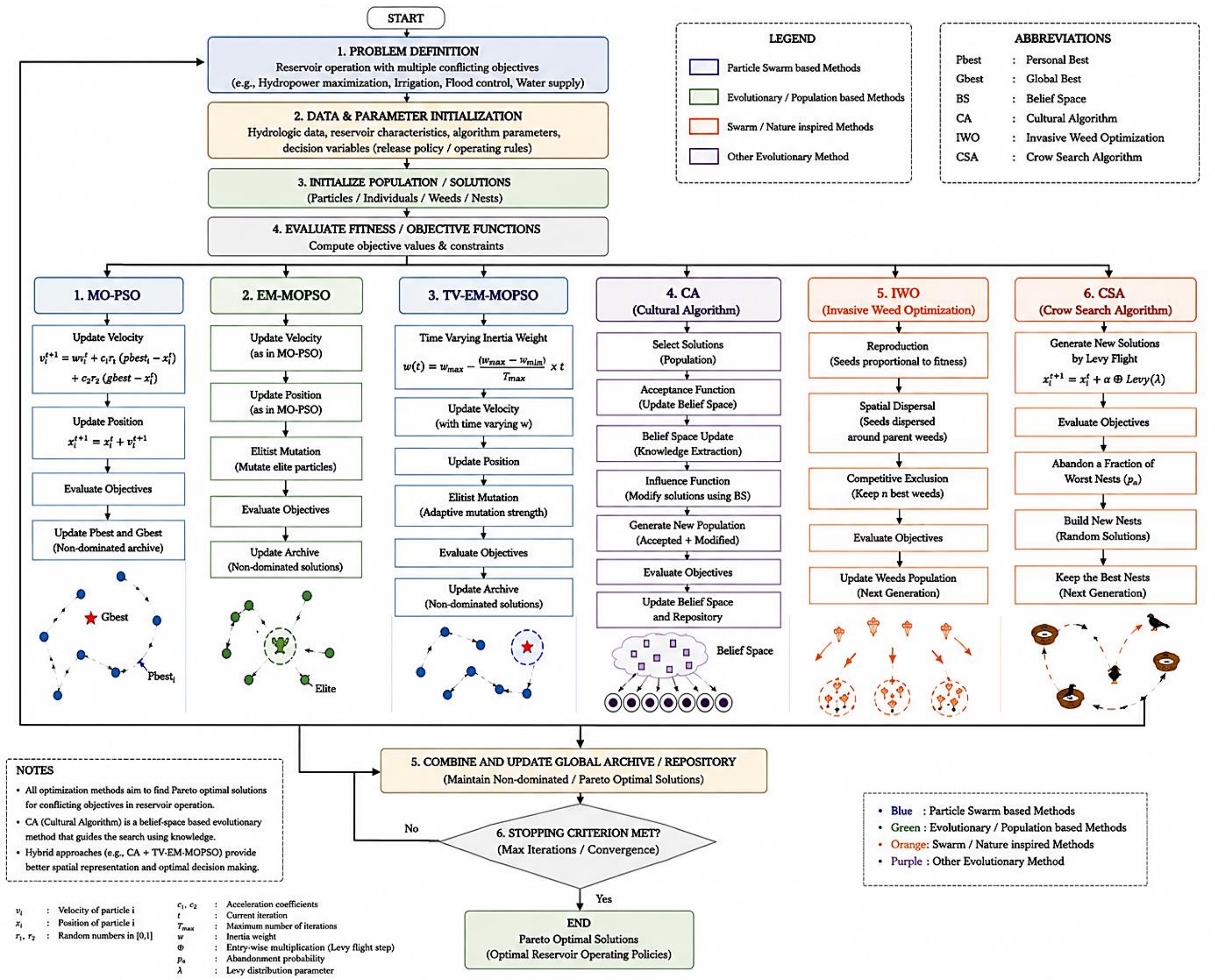

Figure 4. Computational framework of the metaheuristic optimization algorithms used in this study.

3.4 Performance Evaluation

The selected performance indicators follow the reliability–resilience–vulnerability framework of **(Hashimoto et al., 1982)**. Reliability measures the probability that the system remains in a satisfactory state, resilience measures the likelihood or speed of recovery after failure, and vulnerability measures the severity of the failure. These indicators are complementary and should be interpreted together rather than used independently **(Hashimoto et al., 1982; Kjeldsen et al., 2004).** The screening targets in **Table 3** are used as engineering benchmarks for interpretation, not as universal regulatory standards. There is no one international pass/fail limit for all reservoir systems, as acceptable performance depends on type of demands, drought tolerance, environmental requirements, storage capacity and stakeholder priorities. Targets for individual studies should therefore be transparently reported and tested in sensitivity analysis. Generally, the sustainability index is constructed using reliability, resilience, and inverse vulnerability, and it is bounded by a value ranging from 0 to 1, where a higher value corresponds to more stable performance **(Sandoval-Solis et al., 2011; Adeloye et al., 2017).** The final comparison was based on the deficit magnitude, percentage reduction in the deficit, reliability, resilience, vulnerability, sustainability index, and constraint feasibility. The algorithm is not judged only on a low deficit that might be achieved at the expense of storage security or other operating objectives because of the use of multiple indicators.

Table 3. Performance indicators, interpretation, and screening targets

Indicator	Interpretation	Preferred direction	Screening target used in this study
Time-based reliability (R_t)	Fraction of periods in which demand is fully satisfied.	Higher is better.	$R_t \geq 0.90$
Volumetric reliability (R_v)	Fraction of total demand volume supplied.	Higher is better.	$R_v \geq 0.95$
Resilience (R_{es})	Ability to return to a satisfactory state after failure.	Higher is better.	$R_{es} \geq 0.50$; $R_{es} = 1.00$ is ideal
Normalized vulnerability (Vul_n)	Relative magnitude of shortage during failure.	Lower is better.	$Vul_n \leq 0.10$
Sustainability index (SI)	Composite measure of reliability, resilience, and low vulnerability.	Higher is better.	SI ≥ 0.75 preferred; SI < 0.25 indicates very poor combined performance

4. RESULTS AND DISCUSSION

4.1 Behavior of the Existing Operating Policy

Figs. 5 to 8 show that the current policy does not break down by one isolated shortage event. The annual deficit results, in contrast, point to a chronic failure for meeting demand in water stressed years. The baseline deficits range from 7,450.66 MCM in 2014-15 to 19,921.68 MCM in 2018-19. The average is around 14,220.14 MCM for the five years evaluated. The large contrast between the lower- and higher-deficit years suggests that the policy is sensitive to hydrological variability and has limited buffering capacity when inflows are insufficient.

This result is important for the interpretation of the following optimization results. A policy may look good in average or wet years but will have unacceptable shortages in critical drought years. So, the baseline should be used as a benchmark for stress-testing, not as evidence of satisfactory operation. The water-balance residual shown in **Fig. 9** should be examined as part of the model verification, because a low optimization deficit is meaningful only if mass conservation and all constraints on release, storage, spill, and demand are met.

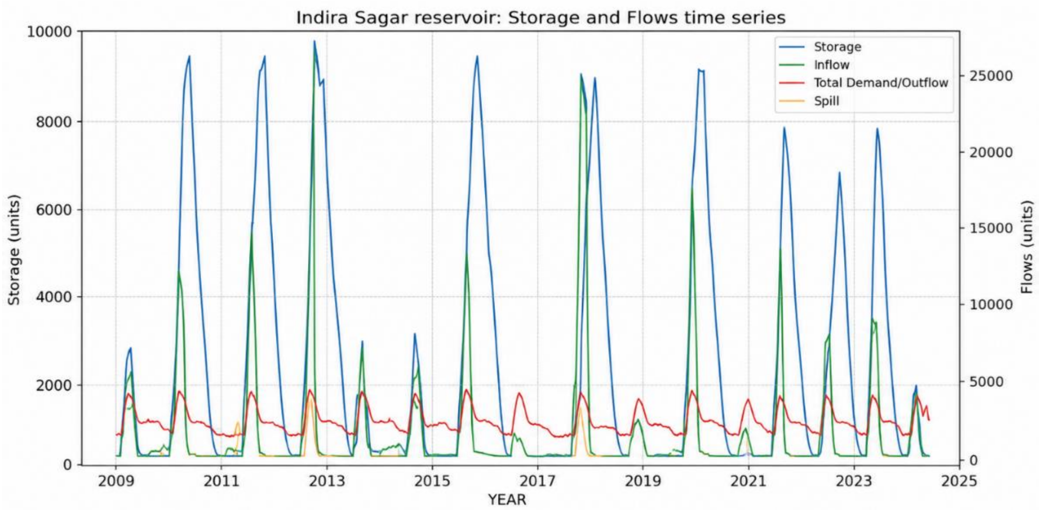

Figure 5. Time-series overview

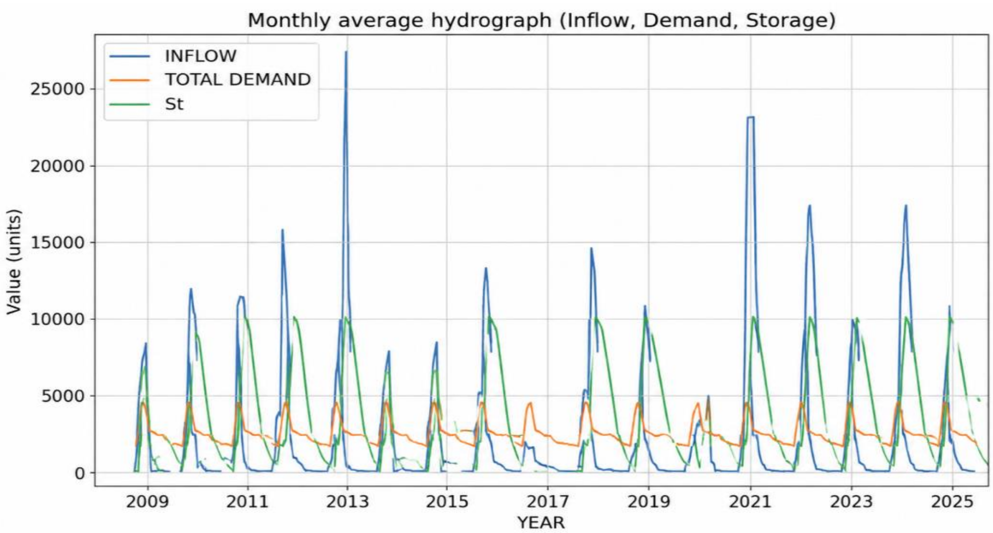

Figure 6. Mean Monthly Hydrograph

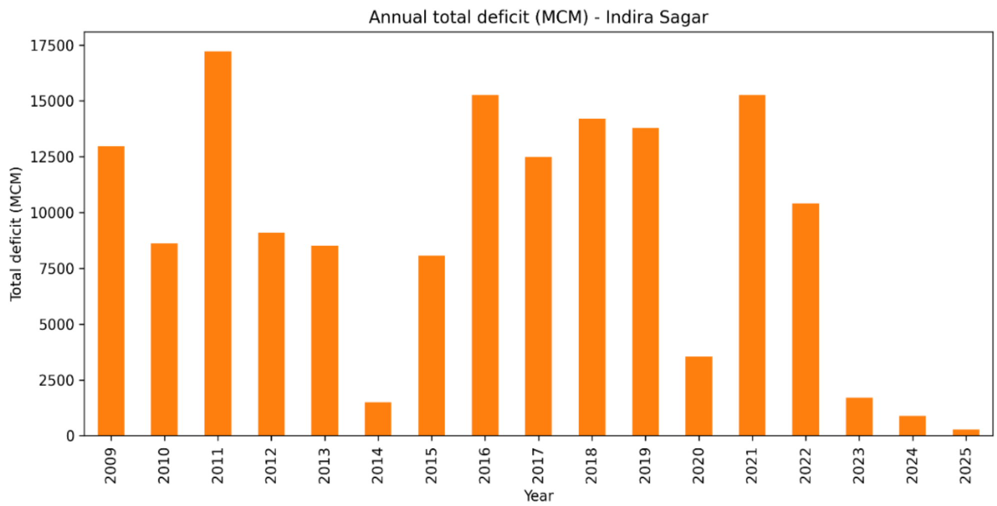

Figure 7. Annual Total Deficit

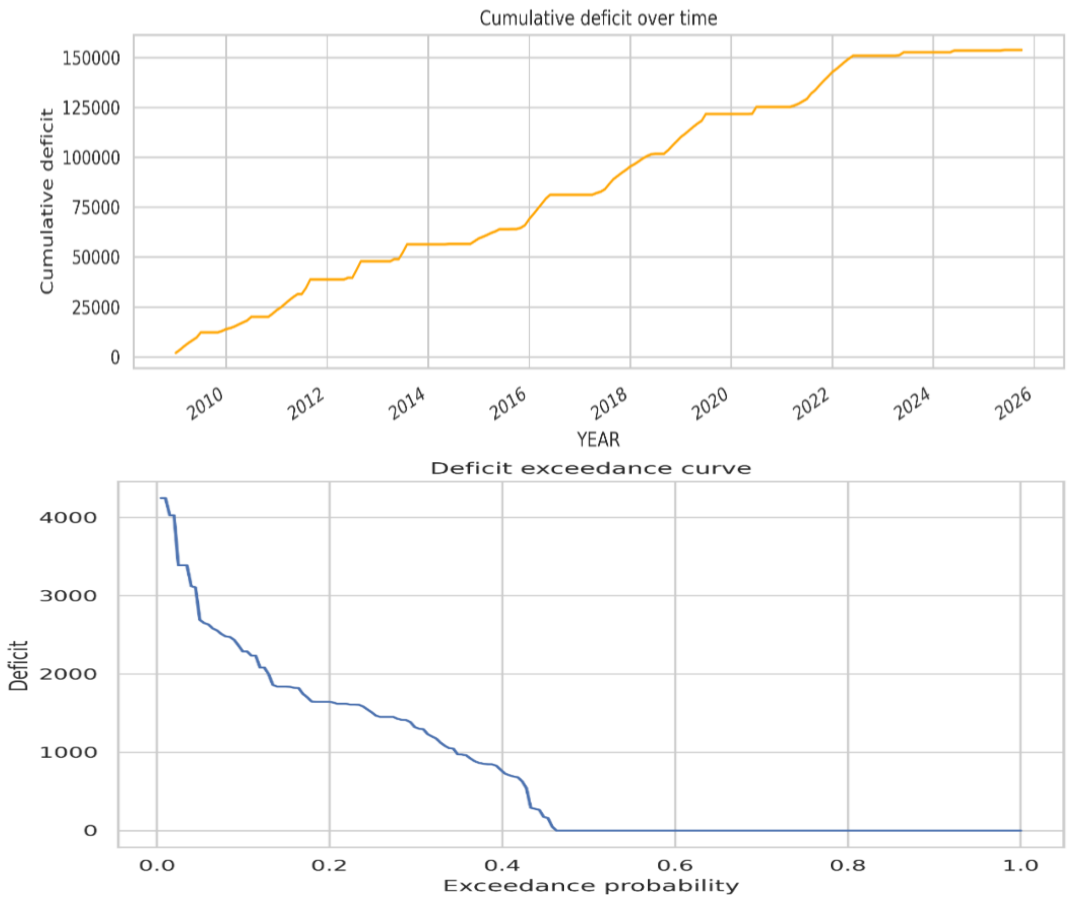

Figure 8. Risk and accumulation

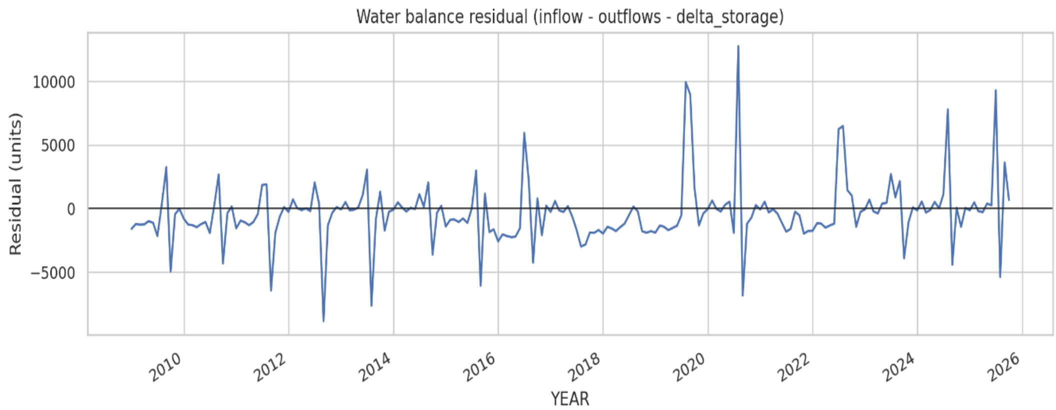

Figure 9. Water-balance residual

4.2 Interpretation of System Performance Indicators

Table 4 and **Fig. 10** show the time-based reliability of 0.4627 indicate that demand was fully satisfied in fewer than half of the evaluation periods. This demonstrates frequent operational failures. The higher volumetric reliability of 0.6854 shows that most of the total demand volume was supplied, but the difference between the two indicators indicates that supply was not distributed consistently over time. Users may therefore experience repeated period-level shortages even when the overall delivered volume appears relatively high. The resilience value of 1.0000 indicates successful recovery after detected failures. However, this result should not be interpreted as evidence of satisfactory overall performance because resilience does not measure how often failures occur or how large the associated deficits are. The vulnerability value of 1,424.39 MCM confirms that shortages were substantial when failures occurred. Consequently, the existing policy can recover from failure but does not prevent frequent and severe shortages. The low sustainability index of 0.1918 supports this interpretation and indicates that the combined performance of the policy remains weak.

Table 4. Performance Index Details

Performance Index	Value
Time-based Reliability	0.4627
Volumetric Reliability	0.6854
Resilience	1.0000
Vulnerability (MCM)	1424.39
Normalized Vulnerability	0.5855
Sustainability Index	0.1918

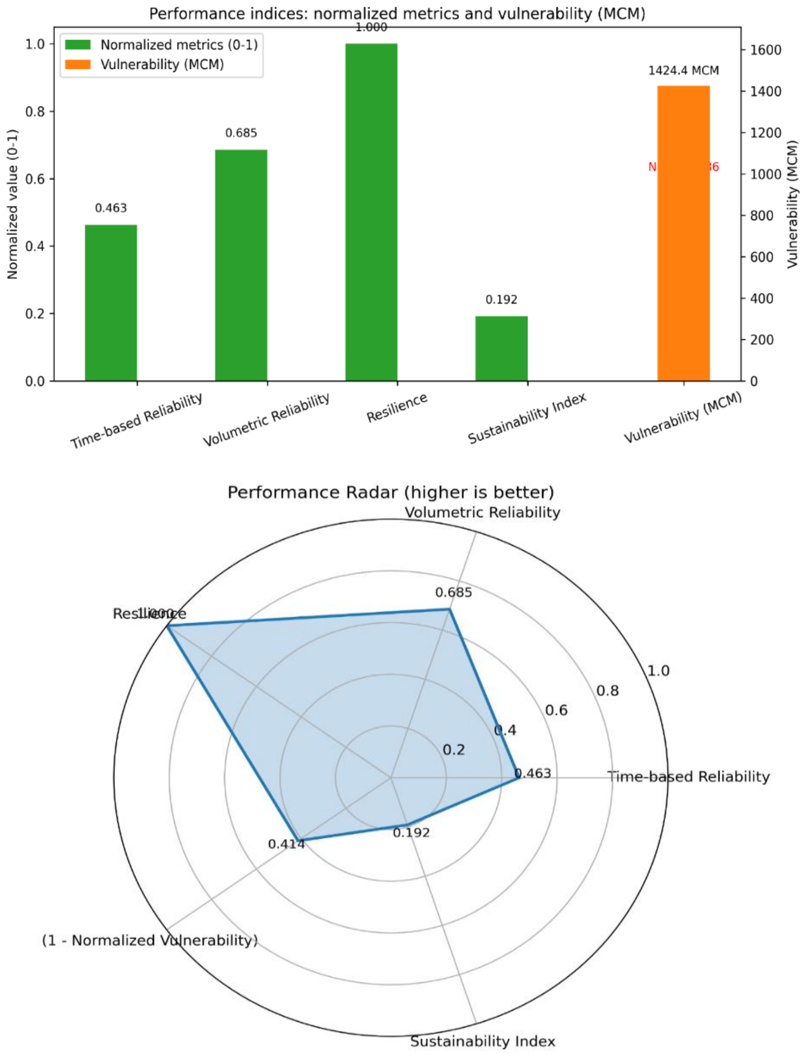

Figure 10. Performance Index Radar

4.3 Comparative Evaluation of Optimization Algorithms

All six optimization methods in **Table 5** reduced the baseline deficit, confirming that improved release scheduling can enhance reservoir performance, as shown in **Figs. 11 to 16.** However, the methods did not perform equally. CSA produced the lowest deficit in all five evaluated water years, followed by IWO, CA, TV-EM, EM, and MO. The mean deficits were approximately 966.8 MCM for CSA, 1,563.2 MCM for IWO, 2,019.8 MCM for CA, 2,509.0 MCM for TV-EM, 3,517.8 MCM for EM, and 4,321.6 MCM for MO.

Table 5. Comparison of Water Deficits Computed by Different Algorithms (MCM)

Water Year	Baseline	MO	EM	TV-EM	CA	IWO	CSA
2009–10	7,762.84	2,419	1,900	1,453	1,201	1,001	700
2010–11	18,778.64	5,690	4,976	3,700	2,603	1,789	1,175
2014–15	7,450.66	2,187	1,870	1,289	1,103	1,010	704
2015–16	17,186.86	5,340	4,098	2,870	2,313	1,768	1,065
2018–19	19,921.68	5,972	4,745	3,233	2,879	2,248	1,190

All values are expressed in million cubic meters (MCM).

The results therefore support an empirical conclusion that CSA provides the strongest deficit-reduction performance for the tested formulation and hydrological scenarios. Relative to the MO solution, CSA reduced the deficit by approximately 67.8% to 80.1% across the five years. That's not a small numerical difference, it is a major operational improvement. The baseline deficit was reduced by about 90.6-94.0% in the years chosen with a mean reduction of about 93.2%. **Fig. 16** and **Table 6** shows that it performs well in both low and high deficit years, indicating the method is appropriate for the tested reservoir model and constraint structure. Significant improvement was also observed for IWO and CA while the conventional MO and EM approaches were less effective. TV-EM was better than EM and MO, which suggests the time-varying search mechanism was useful, but it was not as good as CSA, IWO and CA. The results show that CSA has the best performance among the evaluated methods.

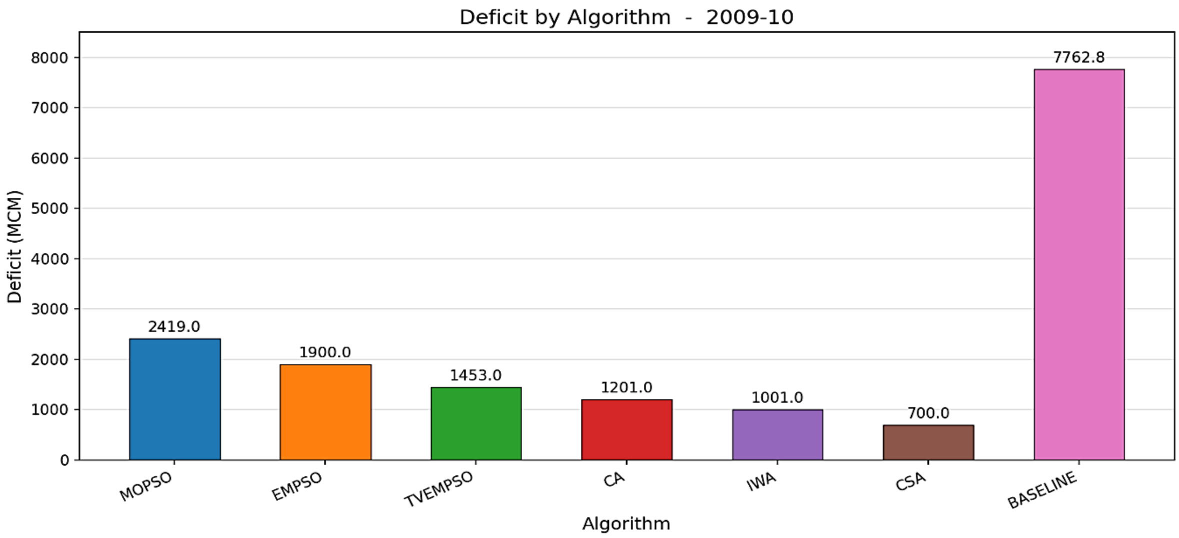

Figure 11. Comparison of Deficit Values Obtained by Different Optimization Algorithms for Water Year 2009–10

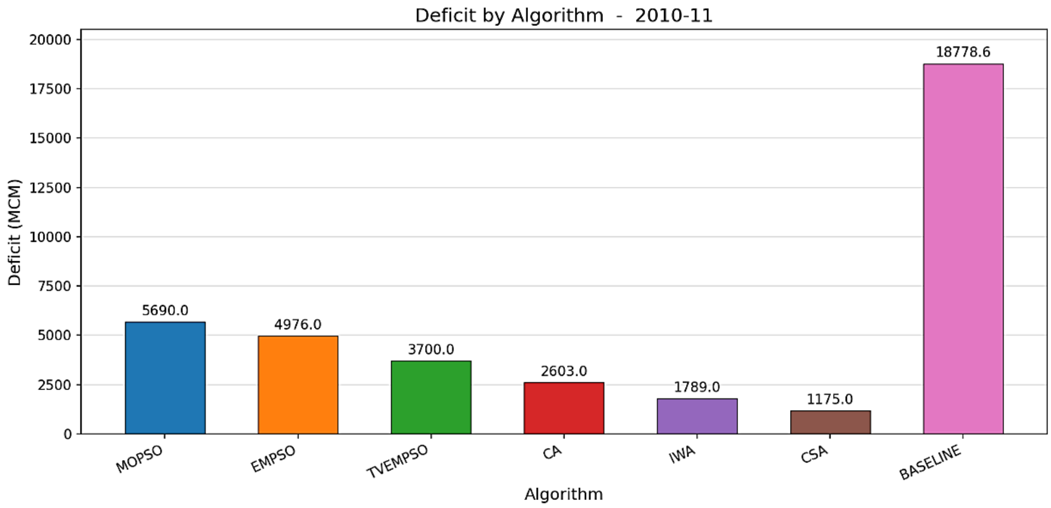

Figure 12. Comparison of Deficit Values Obtained by Different Optimization Algorithms for Water Year 2010-11

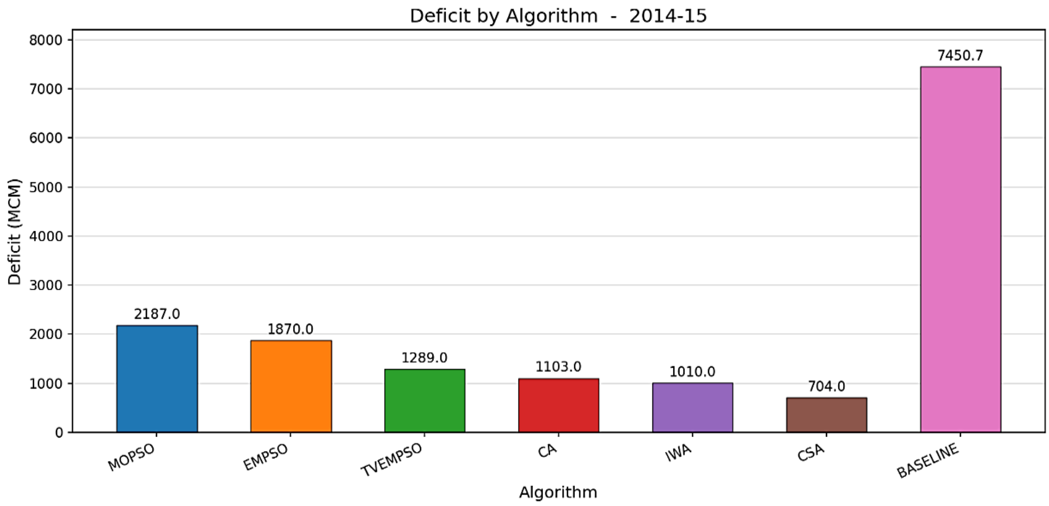

Figure 13. Comparison of Deficit Values Obtained by Different Optimization Algorithms for Water Year 2014-15

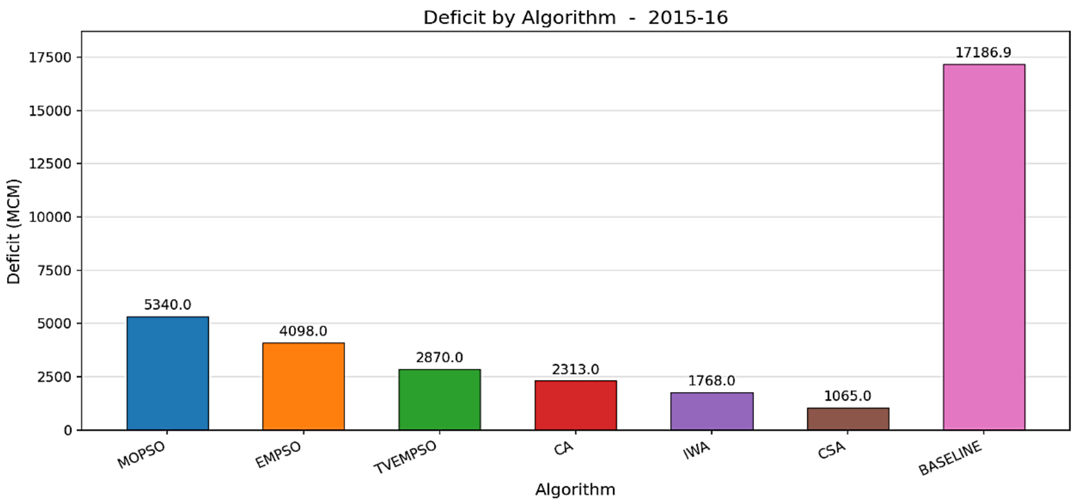

Figure 14. Comparison of Deficit Values Obtained by Different Optimization Algorithms for Water Year 2015-16

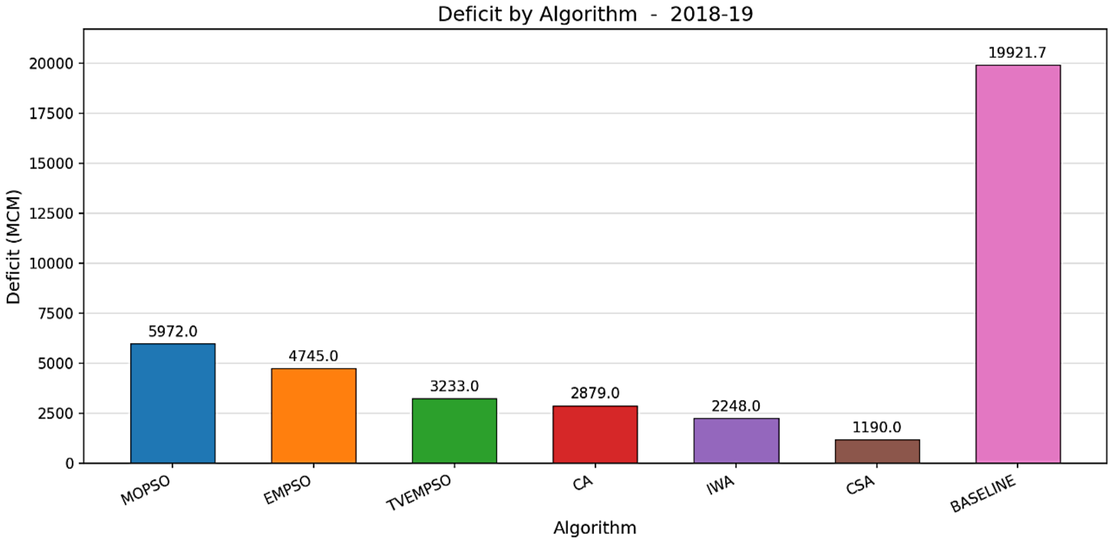

Figure 15. Comparison of Deficit Values Obtained by Different Optimization Algorithms for Water Year 2018-19

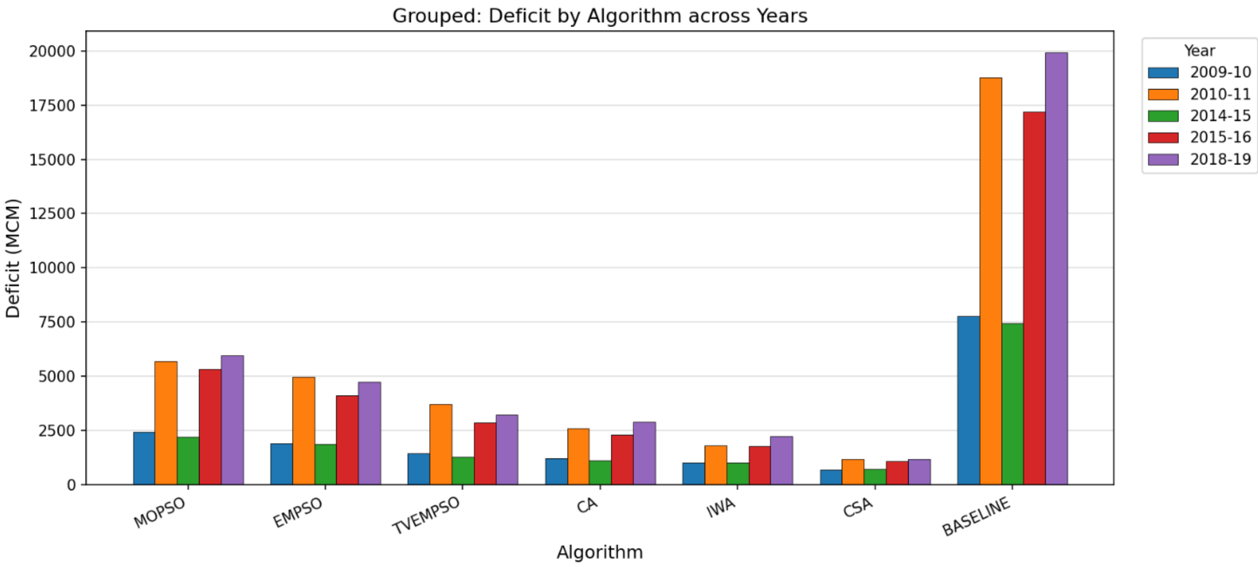

Figure 16. Performance Comparison of Deficit Assessment Algorithms across Selected Water Years

Table 6. Comparison of Percentage Water Deficits Computed by Different Algorithms for all year (MCM)

Water Year	MO Deficit Percentage	EM Deficit Percentage	TV-EM Deficit Percentage	CA Deficit Percentage	IWO Deficit Percentage	CSA Deficit Percentage
2009-10	68.83870418	75.5244059	81.2826115	84.5288482	87.105226	90.9826759
2010-11	69.6996211	73.5018128	80.2967659	86.1385086	90.47322	93.7428919
2014-15	70.64690172	74.9015575	82.6995228	85.1959454	86.444157	90.5511746
2015-16	68.92974444	76.1561971	83.3011922	86.542041	89.713069	93.8034041
2018-19	70.02261446	76.1817323	83.7714522	85.5484104	88.715813	94.0266094

However, the conclusion is limited with the objective functions, parameter settings, constraints and hydrological scenarios used in this study. To test whether the observed ranking is robust to different experimental conditions, multiple stochastic runs and statistical tests would have to be performed.

The practical meaning of the comparison is made clear in **Table 7** and **Fig. 17**. All the optimization methods are better than the baseline but they do not give equal benefits. CSA results in the greatest reduction in low volume and is the best candidate policy for further validation. Prior to implementation, the improvement should be assessed for computational cost, operational simplicity, robustness to forecast error, and impact on hydropower, environmental releases, and storage security.

Table 7. Mean deficit and relative reduction compared to baseline for the five water years analyzed

Algorithm	Mean deficit (MCM)	Mean reduction vs baseline (%)
CSA	966.8	93.2
IWO	1,563.2	89.0
CA	2,019.8	85.8
TV-EM	2,509.0	82.4
EM	3,517.8	75.3
MO	4,321.6	69.6

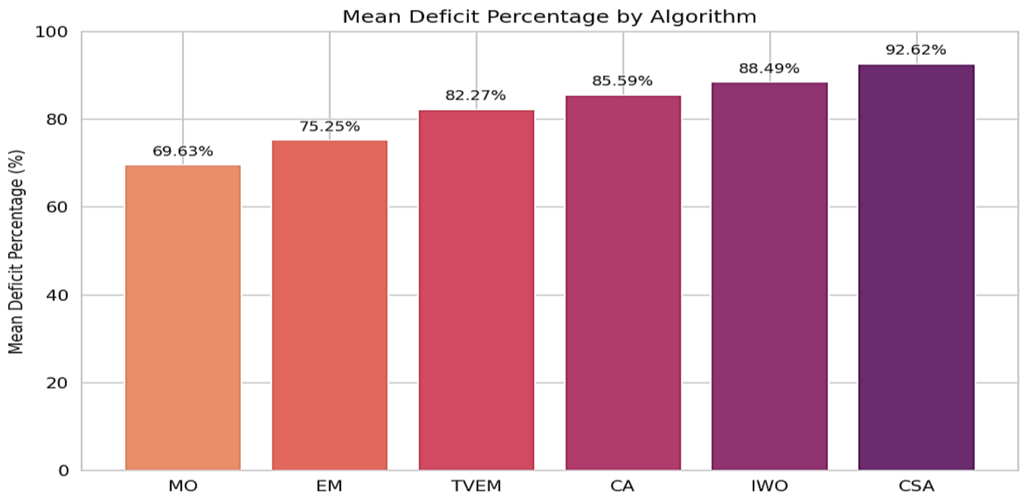

Figure 17. Mean Deficit Percentage by All Algorithms

4.4 Interpretation of the Pareto and Knee-Point Solution

Pareto analysis indicates that reservoir operation is a trade-off between deficit reduction and other objectives such as storage deviation, hydropower production and release requirements. Therefore, the solution based on the knee is more valuable for practical decision making than the solution based on minimum deficit only. The reported knee solution has an annual deficit of 7989.672 MCM, no annual spill, storage deviation of 1511.211 MCM, hydropower production of 2474.335 and average release of 3756.493, as shown in **Figs. 18** and **19**. The results indicate that the selected policy improves the balance among competing objectives, but it does not eliminate shortage completely. Hence, the policy should be seen as a compromise solution that needs to be further validated under different inflow and demand scenarios.

So, **Fig. 20** should be interpreted as a step of validation and not as an additional claim of universal optimality. The credibility of the optimized schedule is only guaranteed if it reproduces the reported annual deficit when simulated independently with the same initial storage, inflow sequence, demand series, operating constraints and decision variables. In addition, a final implementation study should be conducted to test the knee solution on unseen inflow sequences and perturbed demand to study robustness, as shown in **Table 8**

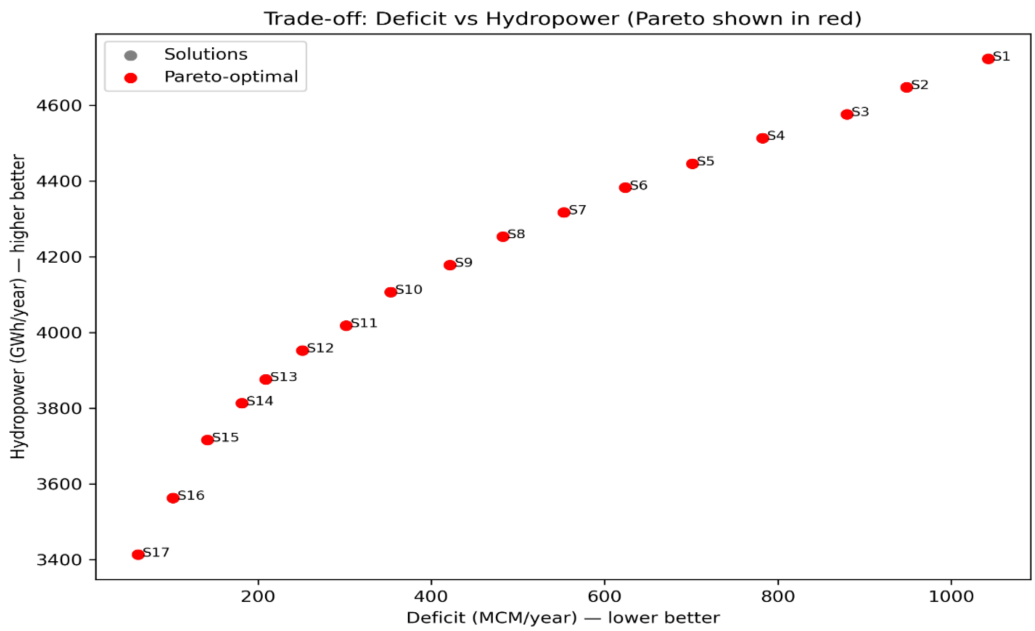

Figure 18. Pareto trade-offs and knee

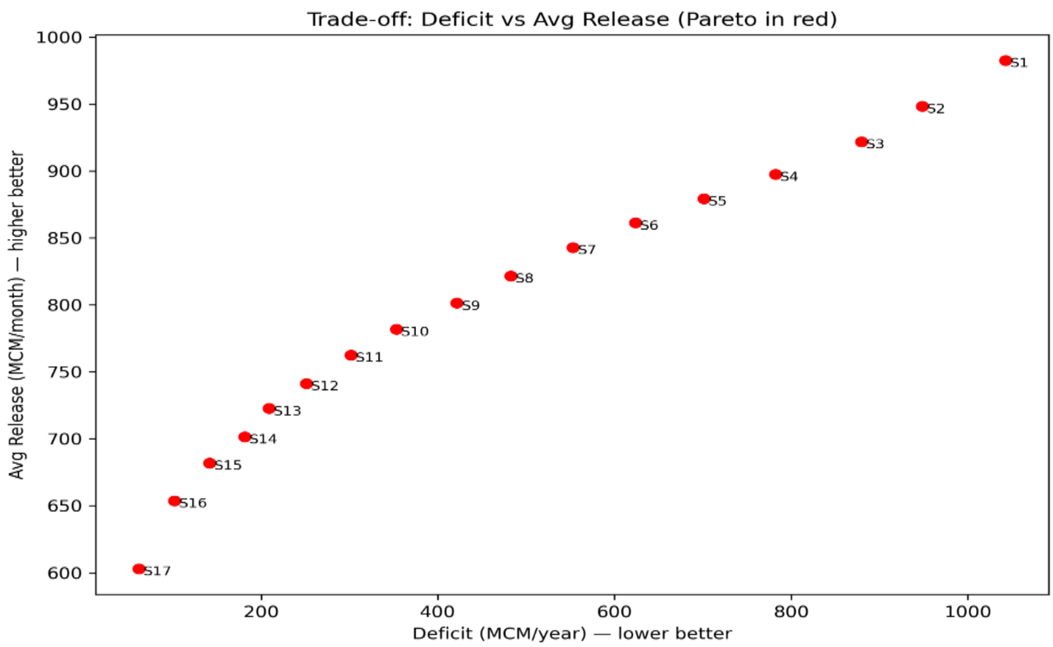

Figure 19. Pareto trade-offs and knee

Table 8. Knee solution Monthly Schedule

R1	5880.906	**R10**	2106.997
R2	2425.602	**R11**	2589.825
R3	1820.527	**R12**	4030.491
R4	4901.539	**Deficit**	7989.672
R5	0	**Annual_Spill**	0
R6	3079.423	**Storage_Dev**	1511.211
R7	4662.17	**Hydro**	2474.335
R8	7310.713	**Avg_Release**	3756.493
R9	6269.722		

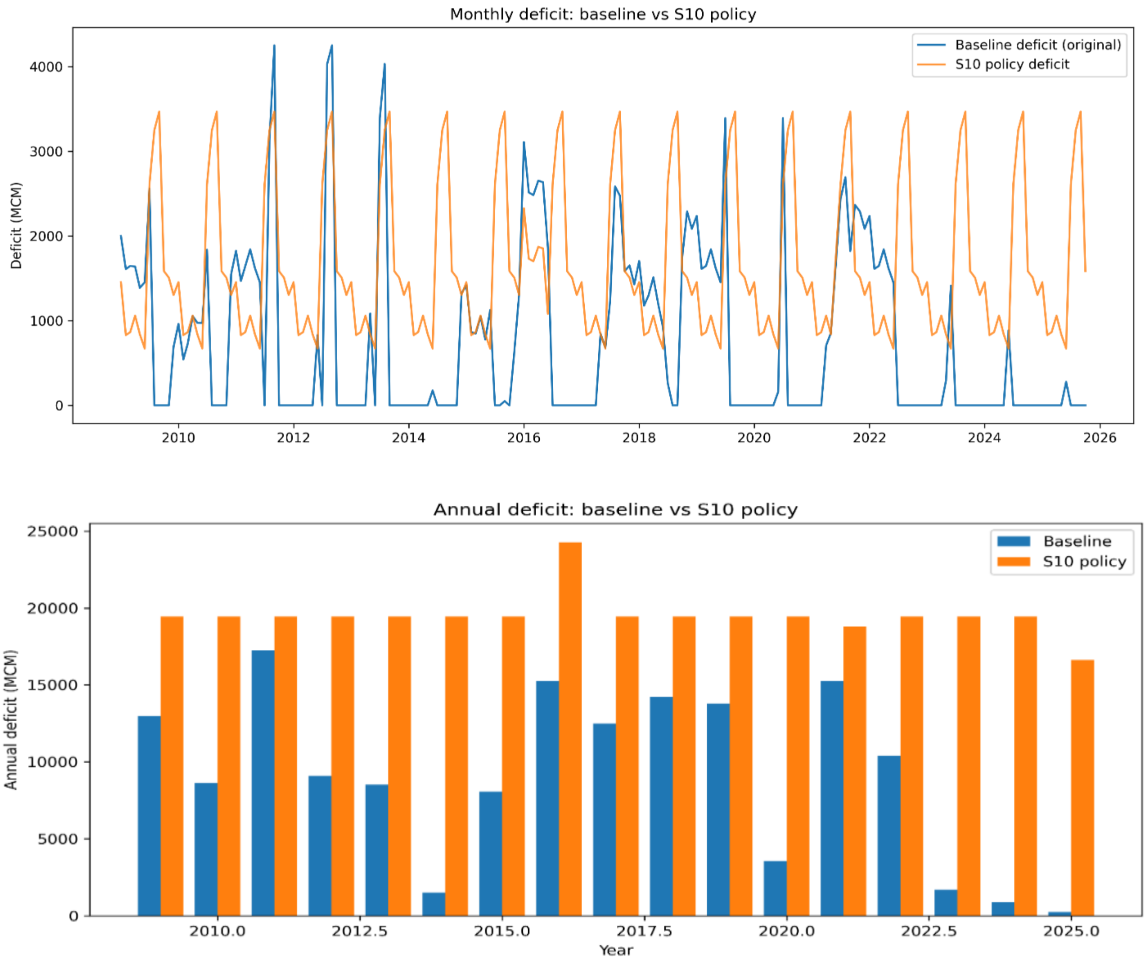

Figure 20. Policy validation annual deficit comparison

4.5 Discussion in Relation to Established Criteria and Previous Studies

The interpretation adopted here follows the widely used reliability, resilience, and vulnerability criteria introduced for water-resource system evaluation by **(Hashimoto et al., 1982).** Their framework emphasizes that a satisfactory policy must address all three dimensions: avoiding failure, recovering after failure, and limiting the consequences of failure. The present results illustrate why this multidimensional view is necessary. Resilience is perfect under the adopted definition, but the policy remains weak overall because failure frequency and failure magnitude are unfavorable.

The difference between time-based and volumetric reliability is also consistent with later reservoir-performance research, which notes that these indices are not interchangeable and commonly satisfy a volume-based reliability greater than or equal to time-based reliability **(Kjeldsen et al., 2004)**. Thus, the two reliability values reported here should not be treated as contradictory. They describe different operational risks: frequent period-level shortages versus the fraction of total demand volume delivered. For water-supply planning, both are needed because users experience the timing of shortages, whereas system planners also need the cumulative shortage volume.

The results are also consistent with good performance-monitoring practice in water management. International guidance emphasizes the use of measurable indicators for reliability, service quality, and sustainability rather than relying on a single aggregate outcome **(Sandoval-Solis et al., 2011).** In that context, the present study is strongest when it reports the full indicator set, the annual deficit pattern, the algorithm comparison, and the policy-validation result together. The study should avoid presenting the sustainability index as a standalone certification of sustainable operation, because no universal threshold is established by the results themselves and the composite value depends on the adopted formulation.

In general, the evidence favors CSA as the preferred candidate among the algorithms tested but not as a finished operating rule. The algorithm yields consistently large deficits, but the final policy must still be tested for mass-balance closure, constraint compliance, stochastic repeatability, hydropower and environmental-release impacts, and robustness to non-stationary inflows. This distinction makes the difference between a promising optimization result and an operationally defensible reservoir-management policy.

4.6 Final Overall Interpretation

The current operating policy of Indira Sagar Reservoir is not robust enough for the demand and inflow conditions evaluated. The major disadvantage is not the ability to recover after a shortage, but the combination of frequent failures and large volumes of shortage when failures occur. The time-based reliability of 0.4627 and vulnerability of 1,424.39 MCM indicate that the existing policy subjects water users to frequent and significant shortfalls. The resilience value of 1.0000 is encouraging but it describes recovery after failure and therefore cannot make up for poor failure prevention. This diagnosis is overall consistent with the low sustainability index of 0.1918. The optimization comparison gives a clear improvement path. All these six methods reduce the baseline deficit, and the CSA is the best performing method in all the tested cases with the lowest deficit in all the selected water years with a mean reduction of about 93.2% as compared to the baseline. Next most effective method is IWO, then CA, TV-EM, EM and MO. The conclusion is not that CSA yields the lowest numerical value in a single table but that CSA provides the most consistent reduction of shortage severity across contrasting hydrological years within the specified model framework.

However, the final conclusion should be expressed with the proper scope. CSA is a promising prospect for developing a better reservoir operating policy but its adoption requires independent validation and a sensitivity analysis. The most defensible management recommendation is to test the CSA-derived Pareto or knee-point policies as candidate rules while continuing to evaluate reliability, volumetric reliability, resilience, vulnerability, storage security, hydropower, and environmental requirements together.

4.7 Practical Implications

The results have three direct implications for management of a reservoir. First, operational monitoring should be on the frequency and magnitude of the shortages. A policy that produces a high share of annual demand may be unacceptable if users are subject to repeated monthly or seasonal failures. Managers need to track time-based reliability, volumetric reliability, deficit duration, deficit magnitude, and recovery time metrics separately.

Secondly, CSA can be used as a decision-support tool to generate candidate operating policies, especially for drought sensitive years. The results justify moving CSA forward to a validation stage, but they do not justify immediate adoption of the optimized schedule without checking downstream release obligations, hydropower requirements, environmental flows, rule-curve restrictions, and safety-related storage limits. The optimization output should be transformed into a deployable rule curve, release policy, or forecast-informed operating procedure, rather than a stand-alone monthly schedule.

Third, the framework can be used to support adaptive management under uncertainty. The next stage should include multiple inflow traces, climate change scenarios, demand-growth cases, parameter sensitivity and repeated stochastic optimization runs. The deciding criterion should be robustness across scenarios not best historical deficit. For a multipurpose reservoir, the final policy should also indicate the trade-off between water-supply reliability and hydropower or environmental performance. This is in line with the current water-sector practice where reliability and sustainability are viewed as monitored performance objectives and risk-informed planning is promoted under uncertainty **(Sandoval-Solis et al., 2011; Adeloye et al., 2017).** Thus, the practical value of this study is to narrow the set of plausible operating policies and to identify the trade-offs that managers must resolve. It does not remove the need for engineering judgment, stakeholder priorities, or operational safeguards. It provides a quantitative basis for transparent comparison of those choices.

5. CONCLUSIONS

The results indicate that the existing operating policy of Indira Sagar Reservoir is not sufficiently reliable under the evaluated hydrological conditions. Although the system shows good recovery after failure, the low time-based reliability and considerable vulnerability indicate that shortages occur frequently and remain significant. All optimization methods improved the baseline operation, but CSA consistently produced the lowest deficits across the evaluated water years, followed by IWO and CA. This confirms that CSA is the most promising method among the tested algorithms for improving reservoir operation under the adopted model conditions. However, the CSA-based policy should be further validated under different inflow, demand, and climate scenarios before practical implementation. Overall, the findings demonstrate that optimization-based reservoir operation can improve water-supply reliability and reduce deficit severity.

Credit Authorship Contribution Statement

Ashwin Parihar: Conceptualization, Methodology, Software, Numerical Simulation, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. Shilpa Tripathi: Methodology, Investigation, Supervision, Technical guidance, Validation, Writing – review & editing. Ruchir Lashkari: Methodology, Investigation, Supervision, Technical guidance, Writing – review & editing.

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.

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مقارنة أداء الخوارزميات التطورية والخوارزميات المستوحاة من الطبيعة لتحسين تشغيل خزان إنديرا ساغار

أشوين باريهار*، شيلبا تريباثي، روتشير لاشكاري

قسم الهندسة المدنية، جامعة ميدكابس، إندور، الهند

الخلاصة

يُعد التشـــغيل الفعّال للخزانات أمرًا بالغ الأهمية لتحقيق الإدارة المســـتدامة للموارد المائية في أحواض الأنهار التي تعتمد على الأمطار الموسمية، مثل الهند، حيث يؤدي التباين الهيدرولوجي وتعدد متطلبات المياه إلى خلق تحديات تشغيلية معقدة. تهدف هذه الدراســة إلى تقييم الأداء المقارن لأســاليب التحســين الاســتكشــافية التطورية والخوارزميات الميتاهيوريســتية المســتوحاة من الطبيعة لتحديد التشـغيل الأمثل لخزان إنديرا سـاغار.تمت صـياغة مشـكلة تشـغيل الخزان باعتبارها مسـألة تحسـين مقيدة متعددة الأهداف، تهدف إلى تقليل العجز في إمدادات المياه وتحســـين الأداء المرتبط بتوليد الطاقة الكهرومائية، مع الالتزام بقيود التخزين، والتخزين الميت، والتصـــريف، وســـعة المفيض، والتغير في حجم التخزين. وتمثل الخوارزميات المختارة آليات بحث ســكانية مختلفة، تطورية ومســتوحاة من الطبيعة، وقد جرى تقييمها ضــمن إطار نمذجة موحد باســتخدام ســنوات هيدرولوجية ممثلة.تم تقييم أداء الخوارزميات اســتنادًا إلى مؤشــرات تقليل العجز، وســلوك التقارب، والموثوقية، والمرونة، والقابلية للتعرض للمخاطر، والاســتدامة. أظهرت ســياســة التشــغيل الحالية موثوقية زمنية منخفضــة بلغت 0.4627وموثوقية حجمية بلغت 0.6854، في حين بلغت المرونة 1.0000، مما يشير إلى سرعة التعافي بعد حدوث حالات الفشل المكتشفة، ولكن مع تكرار حدوث حالات النقص.أظهرت النتائج المقارنة أن خوارزمية بحث الغراب (CSA) حققت أقل متوسط للعجز، حيث بلغ 966.8 مليون متر مكعب (MCM) بين الأساليب التي تم تقييمها، مقارنةً بحوالي 14,220.14مليون متر مكعب في سياسة التشغيل الحالية، تلتها خوارزمية IWOثم CA.وكان ترتيب أداء الخوارزميات كما يلي: CSA > IWO > CA > TV-EM-MOPSO > EM-MOPSO > MO-PSO وتشـير هذه النتائج إلى أن CSAتمثل المرشـح الأكثر promising بين الأسـاليب التي تم تقييمها لمزيد من التطوير والتحقق من صحتها بهدف وضع سياسة تشغيل محسّنة لخزان إنديرا ساغار.

الكلمات المفتاحية :خوارزمية بحث الغراب، خزان إنديرا ســاغار، التحســين الميتاهيوريســتي، تشــغيل الخزانات، إدارة الموارد المائية.