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COMPARATIVE ANALYSIS OF OPTIMIZATION ALGORITHMS FOR RESERVOIR OPERATIONS: A CASE STUDY ON UKAI DAM

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ABSTRACT

Effective reservoir operation is critical for managing water resources in the face of rising demand and limited supply. This study investigates the use of the Jaya Algorithm (JA), Invasive Weed Optimization (IWO) and Particle Swarm Optimization (PSO), to reduce irrigation deficits at the Ukai Dam on India's Tapi River. The algorithms were evaluated using a 45-year dataset that included irrigation deficiencies, convergence rates, and reliability and vulnerability indices. JA consistently outperformed PSO and IWO, demonstrating reduced deficiencies, faster convergence, and superior dependability. The work offers useful insights for improving reservoir operations in the context of water resource management, emphasizing the relevance of algorithm selection in producing robust and economical results.

Keywords: Jaya algorithm, Optimization, Irrigation, Reservoir operation.

INTRODUCTION

The increasing demand for water and the scarcity of current water sources, careful management, development, and preservation of water resources have become critical in the modern day (Tzanakakis et al., 2020). This condition puts a pressure on water supply infrastructure, resulting in disputes among diverse water consumers, fierce rivalry, and negative environmental consequences due to the mismatch between water demand and supply (Martínez-Valderrama et al., 2023, Mehta et al., 2023). Addressing these issues needs effective water distribution and management procedures, which is a daunting undertaking for policymakers (Adom and Simatele, 2022). Optimizing present projects is one possible method for addressing reservoir operation difficulties (Giuliani et al., 2021). Historically, reservoir operation has depended on methodologies such as linear programming (LP), non-linear programming (NLP), and dynamic programming (DP) (Kumar and Yadav, 2022). While these strategies have proven useful, each has its own set of restrictions. Linear programming requires a linear objective function and constraints; dynamic programming encounters dimensionality concerns; and non-linear programming struggles to solve non-convex issues efficiently (Xu et al., 2022).

Recognizing these limits, current research has focused on investigating heuristic and metaheuristic algorithms as alternatives (Abualigah et al., 2022). Although these algorithms do not always provide optimum global solutions, they regularly produce outstanding results within realistic calculation durations. This transition to heuristic and metaheuristic techniques reflects a larger recognition of the need for inventive and adaptive solutions in reservoir operation optimization (Jahandideh-Tehrani et al., 2021). As the demand for water grows and the issues of managing water resources become more complicated, the research of various optimization strategies becomes critical (Kumar et al., 2023). The combination of evolutionary algorithms, heuristic methods, and metaheuristic methodologies provides potential solutions to the complex difficulties involving water distribution and reservoir operation (Almubaidin et al., 2022). In the face of rising water scarcity and competition, policymakers and water resource managers must take into account these emerging techniques in order to establish viable and sustainable solutions (Zhang et al., 2020, Umrigar et al., 2023).

In recent decades, researchers have increasingly focused on evolutionary algorithms as helpful methods for handling complex problems, including reservoir operation optimization (Kumar and Yadav, 2020a). Notably, scholars have investigated numerous evolutionary algorithms to solve the issues of managing water resources. (Reddy and Kumar, 2007) used PSO to manage reservoir operations, with the goal of maximizing hydropower output and addressing irrigation deficits. In a comparable way, (Kim et al., 2008) used the genetic algorithm (GA) to develop optimal operating rules for reservoirs over the course of a year, with an emphasis on thoroughly investigating the reservoir operation problem. The adaptability of evolutionary algorithms was further proved by (Raju et al., 2012), who employed Differential Evolution (DE) algorithms to schedule irrigation planning within the framework of reservoir operations.

Hossain and El-Shafie (2014) work demonstrates that the use of evolutionary algorithms extends beyond standard methodologies. They investigated the effectiveness of the artificial bee colony (ABC) algorithm in improving the discharge strategy of the Aswan High Dam. This study demonstrated the applicability of evolutionary algorithms to real-world problems associated with huge reservoir systems. Ming et al. (2015) conducted a comparative research on the use of cuckoo search (CS) to optimized Wujiang's multi-reservoir scheme. The findings, which included a comparison with GA and PSO, showed that CS outperformed these established algorithms for optimizing reservoir operations. This demonstrates the ability of evolutionary algorithms, such as CS, to provide superior solutions in the complex job of managing multi-resource systems. The wide variety of evolutionary algorithms used in these works reflects the continuous search for novel and efficient ways to reservoir operation optimization. As researchers continue to investigate and enhance these algorithms, it is becoming clear that evolutionary techniques are important tools for tackling the complexity of water resource management and improving reservoir operations in the face of rising demands and uncertainties (Maier et al., 2014, Nicklow et al., 2010, Reed et al., 2013, Giuliani et al., 2016).

Existing evolutionary methods used in reservoir operation optimization have limitations, particularly due to the wide range of parameters they need. These parameters are divided into two categories: general parameters, such as population size and number of iterations, which are shared by all evolutionary algorithms and algorithm-specific parameters that are unique to each approach (Kumar and Yadav, 2020b). In the case of common parameters, fundamental choices such as population size and iteration count have a significant impact on the overall performance of evolutionary algorithms. They define a basic structure that determines the algorithm's convergence and exploration capabilities. The actual problem, however, is properly selecting particular algorithm-specific parameters, which can have a major influence on the efficacy of the optimization process

For example, PSO considers internal characteristics such as social and cognitive parameters, as well as inertia weight. The values of these parameters affect how particles in the swarm interact and adjust their places (Gad, 2022). Similarly, GA uses characteristics such as mutation rates, crossover probabilities, and reproduction parameters to influence the exploration and exploitation balance within the genetic population (Shang et al., 2020). DE uses the crossover rate and scaling factor as critical factors to determine the level of disturbance in the solution space (Mei et al., 2023). The ABC algorithm includes characteristics including the number of hired bees, scout bees, and observers (Zarzycki and Skubisz, 2022). These settings specify the roles and duties of various bee kinds in the search process. The difficulty is to correctly configure these parameters to guarantee effective exploration of the solution space.

It is worth mentioning that other algorithms used in reservoir operations, such as, Bat Algorithm, Cuckoo Search and Weed Optimization, each have their own set of parameters. The selection and fine-tuning of these factors are crucial for attaining the best outcomes in reservoir operation optimization (Chong et al., 2021). The incorrect selection of algorithm-specific parameters might result in inferior solutions, slowed convergence, or even premature convergence. Researchers and practitioners must carefully adjust these parameters based on the unique peculiarities of the situation at hand. As the subject of reservoir operation optimization advances, tackling the problems of parameter selection and optimization is critical to realizing the full potential of these algorithms in real-world applications.

In this work, the Jaya algorithm (JA) was used to solve the problems related with method-specific parameters in existing optimization techniques. JA, created by (Rao 2016), is distinguished by its relentless pursuit of the best feasible solution while actively avoiding failure by staying clear of poor alternatives. Previous studies, such as those by (Rao et al., 2017) improving current machining methods and (Rao et al., 2018) optimizing plate-fin heat exchangers, have shown that JA is effective in increasing effectiveness. Huang et al. (2018) used JA to maximize power point tracking problem, demonstrating its capacity to achieve faster convergence and more efficacies. Building on this achievement, (Kumar and Yadav, 2018) applied JA to optimized reservoir operations and the results indicated superior performance. Kumar and Yadav (2019) presented a modified elitist JA, to optimize optimum cropping pattern problems.

Given JA's notable success in a variety of fields, including machining, heat exchangers, power point tracking, multi-reservoir operations, and optimal cropping patterns, the current study used JA to solve the complex problem of reservoir operation optimization with the specific goal of minimizing irrigation deficits. The fundamental element of the problem is the requirement for more water to satisfy irrigation needs and eliminate irrigation deficits. To evaluate JA's performance, comparisons were done with different optimization techniques, including IWO and PSO. The next part describes the methodology and materials used in this work.

MATERIAL AND METHODS

Jaya Algorithm (JA)

The Jaya algorithm is a population-based optimization algorithm introduced by (Venkata Rao, 2016). It is inspired by the natural process of individuals improving themselves to achieve better outcomes. The algorithm seeks to maximize the objective function by iteratively updating the solutions in the search space. The algorithm works as follows:

a) Initialize Population: Generate an initial population of candidate solutions.
b) Evaluate Objective Function: Evaluate the objective function for each candidate solution in the population.
c) Update Positions: For each pair of solutions, adjust the position of the solutions based on their respective performances. Move towards the better solution and away from the worse one.
d) For updating the position of a solution $\boldsymbol{X_i}$ toward a better solution $\boldsymbol{X_j}$ is given by:

$$X_i(t+1) = X_i(t) + r * (X_j(t) - X_i(t)) \quad (1)$$

e) where: $\boldsymbol{X_i(t+1)}$ is the updated position of solution $\boldsymbol{X_i(t)}$ at iteration $\boldsymbol{t+1}$, $\boldsymbol{X_i(t)}$ is the current position of solution $\boldsymbol{X_i}$ at iteration $\boldsymbol{t}$, $\boldsymbol{X_j(t)}$ is the position of the better solution $\boldsymbol{X_j}$ at iteration $\boldsymbol{t}$, $\boldsymbol{r}$ is a random number between 0 and 1.
f) Update Objective Function: Evaluate the objective function for the updated positions.
g) Repeat steps (c)-(d) for a certain number of iterations or until convergence criteria are met.

The algorithm is designed to move each solution toward the better solution in the search space, influencing the exploration-exploitation trade-off.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based optimization algorithm inspired by the social behavior of birds flocking or fish schooling. It was originally introduced by (Eberhart and Kennedy, 1995). PSO is widely used for solving optimization problems, particularly in the domains of engineering, data mining, machine learning, and other fields. The algorithm works as follows:

a) Initialization: Randomly initialize the position and velocity of each particle in the search space. Set each particle's personal best position ($pbest$) initially to its current position.
b) Evaluation: Evaluate the fitness of each particle based on its position in the search space.
c) Update Personal Best ($pbest$): If the current position yields a better fitness value than the stored $pbest$, update $pbest$.
d) Update Global Best ($gbest$): Identify the particle with the best fitness value in the entire population and designate its position as the global best.
e) Update Velocity and Position: Adjust the velocity and position of each particle using the following formulas:

$$velocity(t+1) = w \times velocity(t) + c_1 * rand(\,) * \left(pbest - position(t)\right) + c_2 * rand(\,) * (gbest - position(t)) \tag{2}$$

$$position(t+1) = position(t) + velocity(t+1) \tag{3}$$

Here, w is the inertia weight, c_1 and c_2 are acceleration coefficients, and $rand(\,)$ generates a random number between 0 and 1.

f) Repeat steps (b) - (e) until a termination condition is met (e.g., a maximum number of iterations or achieving a satisfactory solution).

Invasive Weed Optimization Algorithm (IWO)

The Invasive Weed Optimization (IWO) algorithm, proposed by (Mehrabian and Lucas, 2006), is a nature-inspired optimization technique drawing inspiration from the invasive characteristics of weeds in nature. IWO models the process of weeds spreading and colonizing an area to iteratively improve potential solutions in a search space. The algorithm works as follows:

a) Initialization: Initialize weed positions randomly in the search space.

b) Evaluation: Evaluate the fitness of each weed based on its position.

c) Reproduction (Seed Production): Assign reproductive success probabilities to each weed based on fitness. Generate random numbers to determine if a weed produces seeds. Create new weeds (seeds) based on the generated probabilities.

d) Seed Dispersal (Colonization): Disperse the seeds across the search space, emulating the invasive behavior of weeds. The process of seed dispersal in IWO can be represented by the formula:

$$X_{new} = X_{old} + R * (X_{best} - X_{old}) \tag{4}$$

e) Where, X_{new} is the new position (seed), X_{old} is the current position of a weed, X_{best} is the position of the weed with the best fitness, R is a random number between 0 and 1.

f) Weed Elimination: Eliminate certain existing weeds based on a criterion (e.g., worst fitness) to make room for new seeds.

g) Repeat: Iterate through steps (b) – (e) until a termination condition is met.

STUDY AREA DESCRIPTION AND DATA COLLECTION

The Tapi River is a west-flowing interstate river in India that passes through Maharashtra and Madhya Pradesh before finally pouring out of Gujarat. The Ukai Dam, built in 1972 along the Tapi River at coordinates 21°14'53.52"N and 73°35'21.84"E, has a maximum storage capacity of 8480.18 Mm^3, with a gross storage capacity of 7414.29 Mm^3. The dam, which was primarily constructed for irrigation, power production, and some flood control, is critical to the region's water management. Fig. 1 shows an index map of the research region. Water is distributed inside the irrigation system via three canal networks. The Ukai Left Bank Main Canal (ULBMC) diverts straight from the Ukai Dam, whereas the Kakrapar Left Bank Main Canal (KLBMC) and Kakrapar & Ukai Right Bank Main Canal (KURBMC) divert from the Kakrapar Weir, which is 29 kilometers downstream. The dam discharges water for energy generation, and the downstream city is Surat, which has a population of over 6.6 million.

The Singanpor Weir Cum Causeway, located near Rander in Surat City, was built on the Tapi River in 1995. The Ukai Dam guarantees that the minimal downstream discharge is sufficient to fulfill Surat City's household, industrial, and water quality requirements. Any overflow from the weir empties into the Khambhat Gulf in the Arabian Sea. The Surat Irrigation Circle and the Ukai Left Bank Division provided data for this study. The dataset contains the following: monthly inflow into the Tapi River (1972–2016), evaporation rates (1972–2016), reservoir areas (1972–2016), monthly levels and storage in the Ukai Reservoir (1972–2016), monthly discharge from Powerhouse (1976–2016), irrigation requirements, channel releases (1976–2016), and requirements for water quality for home, industrial, and domestic use. This large dataset is the basis for a thorough assessment of the many functions of the Ukai Dam and their impact on the neighboring towns.

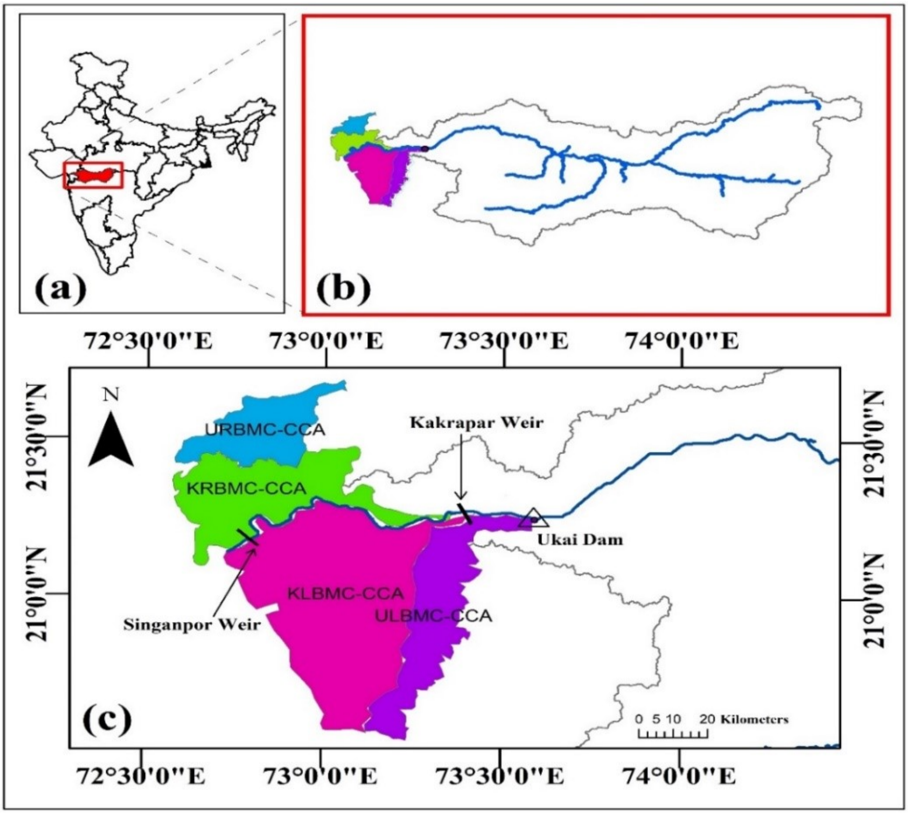

Figure 1: Study area index map

MATHEMATICAL MODEL FORMULATION

The aim of this research is to reduce irrigation deficits, as measured by Square Deviations of Irrigation Demand and Release (SQDV). The SQDV is defined as the total of squared differences between irrigation demands (D) and irrigation releases (IR) for three canals during a 12-month period:

$$\text{Minimize } SQDV = \sum_{t=1}^{12}(D_{1,t} - IR_{1,t})^2 + \sum_{t=1}^{12}(D_{2,t} - IR_{2,t})^2 + \sum_{t=1}^{12}(D_{3,t} - IR_{3,t})^2 \tag{5}$$

Here, $D_{1,t}$, $D_{2,t}$, and $D_{3,t}$ represent the irrigation demands for ULBMC, KLBMC, and KURBMC, respectively, during the time period t, in Mm^3. Similarly, $IR_{1,t}$, $IR_{2,t}$ and $IR_{3,t}$ represent the corresponding irrigation releases.

The objective is contingent upon the following constraints:

Continuity constraints

$$ST_{t+1} = ST_t + I_t - \left(R_{1,t} + IR_{1,t} + IR_{2,t} + IR_{3,t}\right) - Ev_t - O_t \quad (6)$$

Where, ST_{t+1} is the storage during period $t+1$ in Mm^3. ST_t is the reservoir storage, I_t is the inflow, $R_{1,t}$ is the release to the river bed turbine, Ev_t is the evaporation, O_t is the overflow from the reservoir during period t in Mm^3.

Evaporation constraints

$$Ev_t = \frac{E_t}{1000} * \frac{A_t + A_{t+1}}{2} \quad (7)$$

Where, E_t and A_t are the reservoir evaporation and area from the reservoir during period t in Mm^3 and 10^6 m^2 respectively. A_{t+1} is the reservoir areas at t+1 in 10^6 m^2.

Storage constraints

$$ST_{min} \leq ST_t \leq ST_{max} \quad (8)$$

Where, ST_{min} and ST_{max} are the minimum and maximum storage capacities, during period t in Mm^3.

Canal Capacity constraints

$$IR_{1,t} \leq CL_{1,t,max} \quad (9)$$

$$IR_{2,t} \leq CL_{2,t,max} \quad (10)$$

$$IR_{3,t} \leq CL_{3,t,max} \quad (11)$$

Where, $CL_{1,t,max}$, $CL_{2,t,max}$ and $CL_{3,t,max}$ are the maximum canal carrying capacities in ULBMC, KLBMC, and KULBMC, respectively in Mm^3.

Overflow constraints

$$O_t \geq ST_t + I_t - \left(R_{1,t} + IR_{1,t} + IR_{2,t} + IR_{3,t}\right) - E_t - ST_{max} \tag{12}$$

Where, $O_t > 0$, ST_{max} is the maximum storage in Mm^3.

Irrigation demands

$$D_{1,t,min} \leq IR_{1,t} \leq D_{1,t,max} \tag{13}$$

$$D_{2,t,min} \leq IR_{2,t} \leq D_{2,t,max} \tag{14}$$

$$D_{3,t,min} \leq IR_{3,t} \leq D_{3,t,max} \tag{15}$$

Where, $D_{1,t,min}$, $D_{2,t,min}$ and $D_{3,t,min}$ are the minimum irrigation demands and $D_{1,t,max}$, $D_{2,t,max}$ and $D_{3,t,max}$ are the maximum irrigation demands for ULBMC, KLBMC, and KULBMC, respectively, in time period t.

Water Quality Requirements

$$R_{1,t} \geq D_{min,t} \tag{16}$$

Where, $D_{min,t}$ is the minimum downstream release in the river.

MODEL EVALUATION

Statistical efficiency parameters

Root mean square error (RMSE)

RMSE is a widely used statistical measure of the accuracy of a predictive model or an estimator. It quantifies the average magnitude of the errors between water demand and water released. A smaller RMSE indicates better model performance, with 0 representing a perfect fit.

$$RMSE = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(D_i - R_i)^2} \tag{17}$$

Where, D_i is the water demand and R_i is the water released, during $t = 1, 2, \ldots \ldots 12$, in Mm^3.

Mean absolute error (MAE)

Mean Absolute Error is another statistical measure of the accuracy of a predictive model or estimator. It computes the average difference between the water demand and water released. MAE is less sensitive to outliers compared to RMSE, making it suitable for scenarios where outliers are a concern. The MAE may vary from 0 to ∞.

$$MAE = \sum_{i=1}^{t} \frac{|D_i - R_i|}{t} \tag{18}$$

Nash Sutcliff efficiency (NSE)

It is described as one minus ration of the sum of the difference square between demand and releases water to the demand water variance. The NSE varies from 1 to -∞, here one value shows the perfect fit.

$$NSE = 1 - \frac{\sum_{i=1}^{t}(D_i - R_i)^2}{\sum_{i=1}^{t}(D_i - \overline{D}_i)^2} \tag{19}$$

Where, $\overline{D}_i$ is the average water demand.

Performance evaluation indicators

Reliability index

The reliability index is a performance evaluation indicator that assesses the ability of a system, process, or structure to function without failure or breakdown over time. It is often used in engineering, reliability engineering, and risk analysis. This index illustrates the correlation between the water released and the water demand, and it is anticipated to exhibit a substantial value.

$$\alpha_v = \frac{\sum_{i=1}^{t} R_i}{\sum_{i=1}^{t} D_i} \tag{20}$$

Where, α_v is the reliability index.

Vulnerability index

The vulnerability index is a performance evaluation indicator that measures the susceptibility or sensitivity of a system, process, or entity to adverse effects or disruptions. This index is associated with the degree of failures occurring in the system, and a lower value of this index is preferable.

$$\lambda = Max\left(\frac{D_i - R_i}{D_i}\right) \tag{21}$$

Where, λ is the vulnerability index.

RESULTS AND DISCUSSION

Model Development and Parameters

In this study, a reservoir operation model was developed to minimize irrigation deficits, employing an average monthly inflow dataset spanning 45 years (1972-2016). All algorithms were implemented using MATLAB R2014b software. The common control parameters, termination criteria 100,000 and a population size of (25, 50, 75, and 100), were systematically varied to assess algorithmic efficiency across 10 distinct runs. Notably, it was observed that all algorithms exhibited enhanced performance with a population size of 75. Specifically, for the PSO algorithm, internal parameters such as the cognitive parameter (c_1) and social parameter (c_2) were set to 1.3 and 2.0, respectively. The inertia weight $w(i)$ was assigned a value of 1. For the IWO algorithm, parameters like the minimum and maximum seed numbers $Seed_{min}$ and $Seed_{max}$ were configured as 0 and 3, respectively. The non-linear modulation index (a) was chosen as 2, with initial standard deviation $(\sigma_{initial})$ and final standard deviation (σ_{final}) set at 0.6 and 0.001, respectively.

To ensure compliance with reservoir storage constraints, a penalty mechanism was incorporated. The penalty parameter $g(m)$ was fixed at 5. The penalty function $p_{(m,t)(c)}$, where c denotes the constraint, is defined in Eq. (22) and (23), showcasing the penalty features:

$$\textit{If } f(p_{(m,t)(c)}) == 0\textit{, then } penalty\ function = 0 \tag{22}$$

$$\textit{Else if } f(p_{(m,t)(c)}) \neq 0\textit{, then } penalty\ function = abs\left(f(p_{(m,t)(c)})\right)^2 \tag{23}$$

These adjustments and configurations were made to fine-tune the algorithms and account for the unique characteristics of the reservoir system, demonstrating a comprehensive approach to optimizing reservoir operations while minimizing irrigation deficits.

Analysis of Irrigation Deficiencies

The outcomes derived from 10 distinct runs of JA, PSO and IWO in the pursuit of minimizing irrigation deficiencies are subject to detailed examination. Across individual runs, JA demonstrated a range of deficiencies from 0.01 to 18.10, exhibiting variability in its performance. In contrast, PSO displayed a broader spectrum, with deficiencies spanning from 1.27 to 259.61, indicating a higher degree of variability. Meanwhile, IWO consistently showcased competitive performance, maintaining irrigation deficiencies within the range of 0.14 to 60.52. Examining specific metrics, the "Best" result illuminated the algorithm's minimum deficiency achieved in any single run, with JA achieving an impressive 0.01. Conversely, the "Worst" result highlighted the algorithm's maximum deficiency, revealing PSO's susceptibility with the highest deficiency recorded at 259.61. The "Mean" deficiency, providing an average across all runs, revealed JA with the lowest at 3.31, followed by IWO at 6.96, and PSO with a substantially higher mean deficiency of 123.62. The "Standard Deviation" metric, which gauges the variability of results, pointed to JA's consistent performance with a relatively low standard deviation of 6.12, while PSO exhibited a wider variability with a standard deviation of 117.39.

JA emerged as a robust and competitive algorithm, consistently achieving low irrigation deficiencies. PSO, while showcasing a broader range of performance, demonstrated higher variability and mean deficiencies. IWO, on the other hand, presented stable and effective performance. The choice of algorithm depends on specific requirements, balancing factors such as consistency, performance, and variability.

Table 1: Results for 10 different runs of JA, PSO and IWO for irrigation deficiencies

Sr No.	JA	PSO	IWO
1	0.01	217.58	0.74
2	10.43	217.67	1.60
3	0.40	18.41	0.19
4	0.01	20.15	0.21
5	0.18	259.61	0.14
6	1.32	257.23	0.89
7	18.10	217.67	2.35
8	1.32	18.41	1.60
9	0.01	1.27	60.52
10	0.38	8.13	1.37
Best	0.01	1.27	0.14
Worst	18.15	259.61	60.52
Mean	3.31	123.62	6.96
Standard Deviation	6.12	117.39	18.83

Fig. 2 illustrates the convergence rates of the various algorithms employed in the study. The convergence rate is a critical metric that signifies how quickly or efficiently each algorithm reaches its optimal or near-optimal solution. The plotted data provides a visual representation of the convergence behaviour of JA, PSO and IWO over the course of the optimization process. By examining the convergence rates depicted in the figure, one can gain insights into the efficiency and effectiveness of each algorithm in reaching the desired solution for minimizing irrigation deficiencies. Here JA convergence rates was faster as compared PSO and IWO.

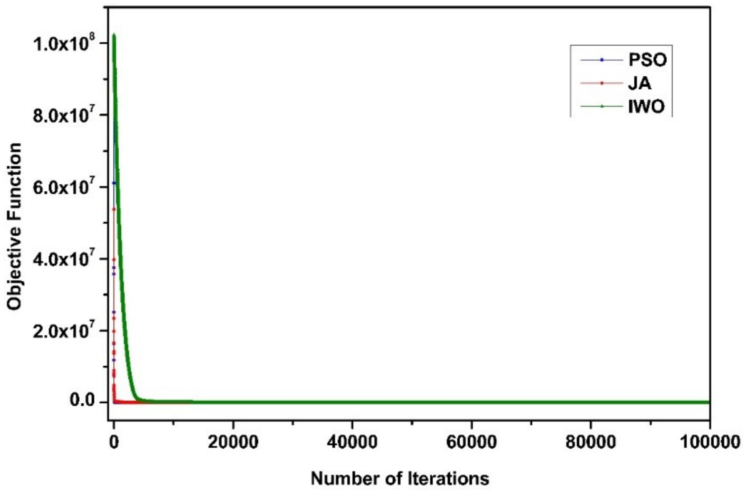

Figure 2: Convergence rate of the various algorithms

Statistical efficiency parameters

Table 2 presents the results of various algorithms based on error indexes, providing a comprehensive overview of their performance metrics. The NSE, RMSE, and MAE serve as key indicators for assessing the accuracy and reliability of the algorithms in minimizing irrigation deficiencies. The NSE values reveal the overall goodness-of-fit, with JA achieving a perfect score of 1, indicating an excellent match between observed and simulated values. Both PSO and IWO closely follow suit, attaining high NSE values of 0.99, denoting strong model performance across the algorithms. Moving on to RMSE, which quantifies the average magnitude of the model's errors, JA exhibits an impressively low value of 0.000429, suggesting minimal deviations between predicted and observed values. In comparison, PSO and IWO show higher RMSE values of 0.311 and 0.120, respectively, indicating slightly larger errors in their predictions. The MAE values further corroborate the accuracy of the algorithms. JA records the smallest MAE at 0.000340, signifying minimal absolute errors. PSO and IWO, while displaying slightly higher MAE values of 0.348 and 0.178, respectively, still maintain commendable accuracy in predicting irrigation deficiencies. Overall, JA particularly stands out with its perfect NSE score and exceptionally low RMSE and MAE values, emphasizing its accuracy and reliability in reservoir operation optimization.

Table 2: Results of various algorithms based on error indexes

Error Indexes	JA	PSO	IWO
NSE	1	0.99	0.99
RMSE	0.000429	0.311	0.120
MAE	0.000340	0.348	0.178

Performance evaluation indicators

Table 3 encapsulates the outcomes with a focus on performance indicators such as the Reliability Index and Vulnerability Index. These indices serve as pivotal metrics for evaluating the effectiveness and robustness of JA, PSO and IWO in the context of reservoir operation optimization. The Reliability Index, expressed as a percentage, gauges the dependability and consistency of each algorithm in meeting water release demands. JA leads with an exceptional Reliability Index of 99.99%, signifying an almost perfect reliability in fulfilling water release requirements. PSO and IWO closely follow suit with high Reliability Indices of 99.93% and 99.96%, respectively, underscoring their reliability in reservoir operation. Complementing the Reliability Index, the Vulnerability Index assesses the intensity of system failures, with lower values indicating a more robust and resilient algorithm. JA demonstrates an incredibly low Vulnerability Index of 0.000675427, suggesting a minimal likelihood of failure in meeting water release demands. In comparison, PSO and IWO exhibit higher Vulnerability Indices of 0.361047 and 0.124685, respectively. Although higher than JA, these values still indicate satisfactory robustness in handling reservoir operation challenges. The performance indicators reveal that all three algorithms – JA, PSO, and IWO – exhibit high levels of reliability in meeting water release demands, with JA showcasing nearly flawless performance. Additionally, the algorithms demonstrate varying degrees of system robustness, with JA demonstrating an exceptionally low vulnerability to failure. These findings collectively contribute to a comprehensive understanding of the algorithms' performance in optimizing reservoir operations.

Table 3: Results of different algorithm based on performance indicators

Performance Index	JA	PSO	IWO
Reliability index %	99.99	99.93	99.96
Vulnerability index %	0.000675427	0.361047	0.124685

CONCLUSION

In conclusion, this research methodically evaluated how well the Jaya Algorithm (JA), Invasive Weed Optimization (IWO), and Particle Swarm Optimization (PSO), performed in improving reservoir operations to reduce irrigation deficits. JA constantly showed strong performance with low deficiencies and quick convergence. PSO demonstrated a broad spectrum of results, indicating flexibility, although with increased unpredictability. IWO has always operated in a steady and efficient manner. JA stood out with a perfect Nash Sutcliff efficiency and exceptional reliability, making it suitable for minimizing irrigation deficiencies. PSO shown adaptability, whereas IWO demonstrated dependability. This study highlights the significance of choosing the right algorithm based on particular optimization targets and limitations in the challenging field of water resource management, offering insightful information to practitioners and decision-makers.

This study systematically assessed the performance of Jaya Algorithm (JA), Particle Swarm Optimization (PSO), and Invasive Weed Optimization (IWO) in optimizing reservoir operations to minimize irrigation deficiencies. JA consistently demonstrated robust performance with low deficiencies and fast convergence. PSO exhibited a diverse range of outcomes, showcasing adaptability, albeit with higher variability. IWO consistently maintained stable and effective performance. JA stood out with a perfect Nash Sutcliff efficiency and exceptional reliability, making it suitable for minimizing irrigation deficiencies. PSO showed versatility, while IWO presented reliability. This study contributes valuable insights for practitioners and decision-makers, underscoring the importance of selecting the appropriate algorithm based on specific optimization objectives and constraints in the complex domain of water resource management.

Declaration of competing interest

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

REFERENCES

ABUALIGAH L., ELAZIZ M.A., KHASAWNEH A.M., ALSHINWAN M., IBRAHIM R.A., AL-QANESS M.A.A., MIRJALILI S., SUMARI P., GANDOMI A.H. (2022). Meta-heuristic optimization algorithms for solving real-world mechanical engineering design problems: a comprehensive survey, applications, comparative analysis, and results, Neural Computing and Applications, Vol. 34, Issue 6, pp. 4081–4110.

ADOM R.K., SIMATELE M.D. (2022). The role of stakeholder engagement in sustainable water resource management in South Africa, Natural Resources Forum, Vol. 46, Issue 4, pp. 410–427.

ALMUBAIDIN M.A.A., AHMED A.N., SIDEK L.B.M., ELSHAFIE A. (2022). Using Metaheuristics Algorithms (MHAs) to Optimize Water Supply Operation in Reservoirs: a Review. Springer Netherlands, Archives of Computational Methods in Engineering Vol. 29, Issue 6, pp. 3677-3711.

CHONG K.L., LAI S.H., AHMED A.N., ZAAFAR W.Z.W., RAO R.V., SHERIF M., SEFELNASR A., EL-SHAFIE A. (2021). Review on Dam and Reservoir Optimal Operation for Irrigation and Hydropower Energy Generation Utilizing Meta-Heuristic Algorithms, IEEE Access, Vol. 9, pp. 19488–19505.

EBERHART R., KENNEDY J. (1995). A new optimizer using particle swarm theory. In MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science IEEE, pp.39–43.

GAD A.G. (2022). Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review, Archives of Computational Methods in Engineering, Vol. 29, Issue 5, pp. 2531–2561.

GIULIANI M., CASTELLETTI A., PIANOSI F., MASON E., REED P.M. (2016). Curses, Tradeoffs, and Scalable Management: Advancing Evolutionary Multiobjective Direct Policy Search to Improve Water Reservoir Operations, Journal of Water Resources Planning and Management, Vol. 142, Issue 2, Paper ID 04015050.

GIULIANI M., LAMONTAGNE J.R., REED P.M., CASTELLETTI A. (2021). A State-of-the-Art Review of Optimal Reservoir Control for Managing Conflicting Demands in a Changing World, Water Resources Research, Vol. 57, Issue 12.

HOSSAIN M.S., EL-SHAFIE A. (2014). Evolutionary techniques versus swarm intelligences: Application in reservoir release optimization, Neural Computing and Applications, Vol. 24, Issues 7–8, pp. 1583–1594.

HUANG C., WANG L., YEUNG R.S.C., ZHANG Z., CHUNG H.S.H., BENSOUSSAN A. (2018). A prediction model-guided jaya algorithm for the PV system maximum power point tracking, IEEE Transactions on Sustainable Energy, Vol. 9, Issue 1, pp. 45–55.

JAHANDIDEH-TEHRANI M., BOZORG-HADDAD O., LOÁICIGA H.A. (2021). A review of applications of animal-inspired evolutionary algorithms in reservoir operation modelling, Water and Environment Journal, Vol. 35, Issue 2, pp. 628–646.

KIM T., HEO J.-H., BAE D.-H., KIM J.-H. (2008). Single-reservoir operating rules for a year using multiobjective genetic algorithm, Journal of Hydroinformatics, Vol. 10, Issue 2.

KUMAR V., SHARMA K.V., YADAV S.M., DESHMUKH A. (2023). Self-adaptive metaheuristic optimization technique for multi-objective reservoir operation, AQUA — Water Infrastructure, Ecosystems and Society, Vol. 72, Issue 8, pp. 1582–1606.

KUMAR V., YADAV S.M. (2018). Optimization of Reservoir Operation with a New Approach in Evolutionary Computation Using TLBO Algorithm and Jaya Algorithm, Water Resources Management, Vol. 32, Issue 13, pp. 4375–4391.

KUMAR V., YADAV S.M. (2019). Optimization of Cropping Patterns Using Elitist-Jaya and Elitist-TLBO Algorithms, Water Resources Management, Vol. 33, Issue 5, pp. 1817–1833.

KUMAR V., YADAV S.M. (2020a). Optimization of Water Releases from Ukai Reservoir Using Jaya Algorithm. In Advanced Engineering Optimization Through Intelligent Techniques, Springer Singapore, pp. 323-336.

KUMAR V., YADAV S.M. (2020b). Self-adaptive multi-population-based Jaya algorithm to optimize the cropping pattern under a constraint environment, Journal of Hydroinformatics, Vol. 22, Issue 2, pp. 368–384.

KUMAR V., YADAV S.M. (2022). Multi-objective reservoir operation of the Ukai reservoir system using an improved Jaya algorithm, Water Supply, Vol. 22, Issue 2, pp. 2287–2310.

MAIER H.R. ET AL. (2014). Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions, Environmental Modelling and Software, Vol. 62, pp. 271–299.

MARTÍNEZ-VALDERRAMA J., OLCINA J., DELACÁMARA G., GUIRADO E., MAESTRE F.T. (2023). Complex Policy Mixes are Needed to Cope with Agricultural Water Demands Under Climate Change, Water Resources Management, Vol. 37, Issues 6–7, pp. 2805–2834.

MEHRABIAN A.R., LUCAS C. (2006). A novel numerical optimization algorithm inspired from weed colonization, Ecological Informatics, Vol. 1, Issue 4, pp. 355–366.

MEHTA D., DHABUWALA J., YADAV S.M., KUMAR V., AZAMATHULLA H.M. (2023). Improving flood forecasting in Narmada River basin using hierarchical clustering and hydrological modelling, Results in Engineering, Vol. 20, Paper ID 101571.

MEI, J., WU, L., CHEN, E., XIAO, W., ZHONG, L., GUO, J., LI, W. (2023). A novel structural damage detection method using a hybrid IDE–BP model, Knowledge-Based Systems, Vol. 273, Paper ID 110606.

MING B., CHANG J. XIA, HUANG Q., WANG Y. MIN & HUANG S. ZHI. (2015). Optimal Operation of Multi-Reservoir System Based-On Cuckoo Search Algorithm, Water Resources Management, Vol. 29, Issue 15, pp. 5671–5687.

NICKLOW J., REED P., SAVIC D., DESSALEGNE T., HARRELL L., CHAN-HILTON A., KARAMOUZ M., MINSKER B., OSTFELD A., SINGH A., ZECHMAN E. (2010). State of the Art for Genetic Algorithms and Beyond in Water Resources Planning and Management, Journal of Water Resources Planning and Management, Vol. 136, Issue 4, pp. 412–432.

RAJU K.S., VASAN A., GUPTA P., GANESAN K., MATHUR H. (2012). Multi-objective differential evolution application to irrigation planning, ISH Journal of Hydraulic Engineering, Vol. 18, Issue 1, pp. 54–64.

RAO R.V., RAI D.P., BALIC J. (2017). A multi-objective algorithm for optimization of modern machining processes, Engineering Applications of Artificial Intelligence, Vol. 61, Issue 8, pp. 103–125.

RAO R.V., SAROJ A., OCLOŃ P., TALER J., TALER D. (2018). Single- and Multi-Objective Design Optimization of Plate-Fin Heat Exchangers Using Jaya Algorithm, Heat Transfer Engineering, Vol. 39, Issue 13–14, pp. 1201–1216.

REDDY M.J., KUMAR D.N. (2007). Multi-objective particle swarm optimization for generating optimal trade-offs in reservoir operation, Hydrological Processes, Vol. 21, Issue 21, pp. 2897–2909.

REED P.M., HADKA D., HERMAN J.D., KASPRZYK J.R., KOLLAT J.B. (2013). Evolutionary Mult objective optimization in water resources: The past, present, and future, Advances in Water Resources, Vol. 51, pp. 438–456.

SHANG L., SHANG Y., HU L., LI J. (2020). Performance of genetic algorithms with different selection operators for solving short-term optimized reservoir scheduling problem, Soft Computing, Vol. 24, Issue 9, pp. 6771–6785.

TZANAKAKIS V.A., PARANYCHIANAKIS N. V., ANGELAKIS A.N. (2020). Water Supply and Water Scarcity, Water, Vol. 12, Issue 9, pp. 2347.

UMRIGAR J., MEHTA D.J., CALOIERO T., AZAMATHULLA H.M., KUMAR V. (2023). A Comparative Study for Provision of Environmental Flows in the Tapi River, Earth, Vol. 4, Issue 3, pp. 570–583.

RAO R.V. (2016). Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems, International Journal of Industrial Engineering Computations, Vol. 7, Issue 1, pp. 19–34.

XU S., XIONG G., MOHAMED A.W., BOUCHEKARA H.R.E.H. (2022). Forgetting velocity based improved comprehensive learning particle swarm optimization for non-convex economic dispatch problems with valve-point effects and multi-fuel options, Energy, Vol. 256, Paper ID 124511.

ZARZYCKI H., SKUBISZ O. (2022). A New Artificial Bee Colony Algorithm Approach for the Vehicle Routing Problem. In Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation: Proceedings of the INFUS Conference, pp. 562-569.

ZHANG D., SIAL M.S., AHMAD N., FILIPE A.J., THU P.A., ZIA-UD-DIN M., CALEIRO A.B. (2020). Water Scarcity and Sustainability in an Emerging Economy: A Management Perspective for Future, Sustainability, Vol. 13, Issue 1, Paper ID 144.