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Application of modified enhanced differential evolution algorithms for reservoir operation during floods: a case study

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ABSTRACT

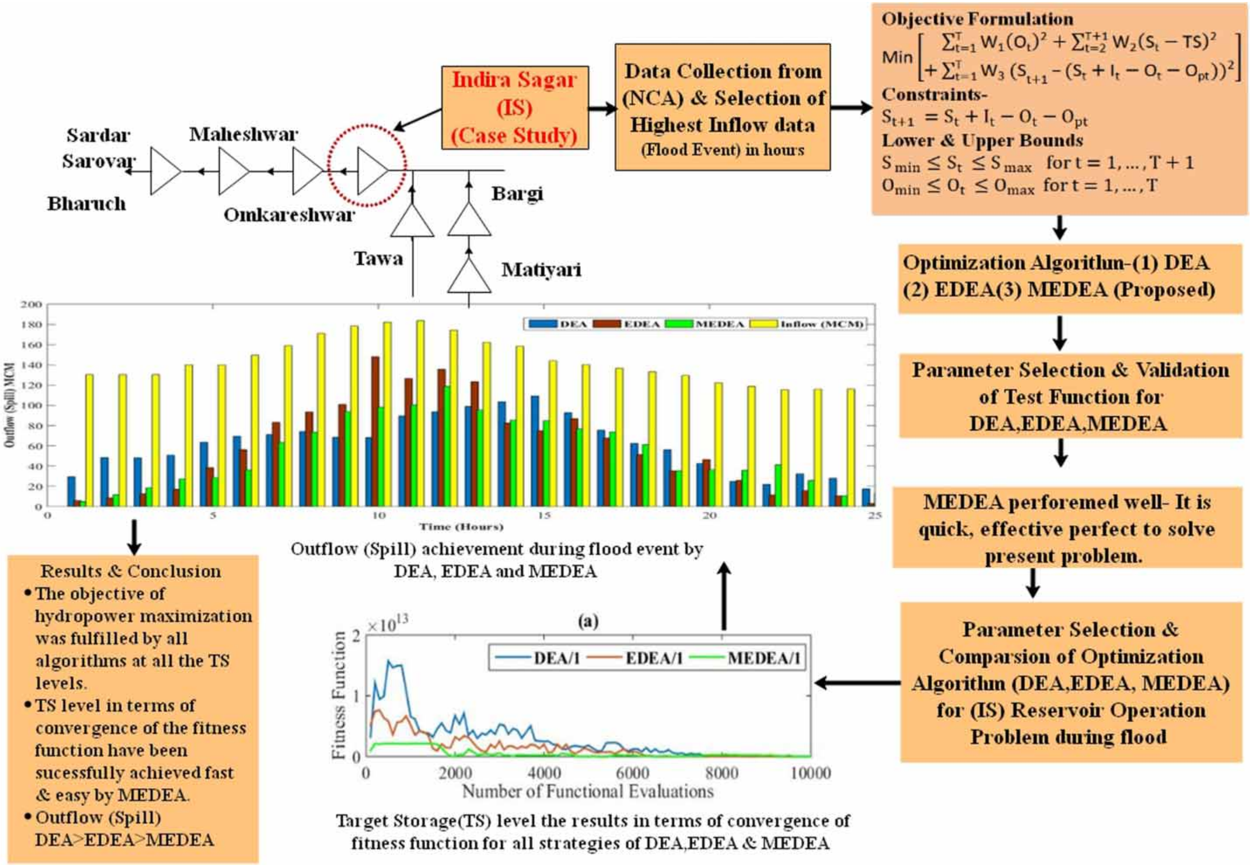
Operating a reservoir during flooding is a complex problem in which optimum decision-making is a difficult task. The present study demonstrates a solution for the operation of flooding problem in a multiple-purpose reservoir. A reservoir on River Narmada in central India is chosen as the case study. The multiple objective problems comprised maximization of hydropower releases, minimizing spills, and achieving stipulated target storage at the end of the operation period. The chosen optimization models are the Differential Evaluation Algorithm (DEA) and its variants: the Enhanced Differential Evolution Algorithm (EDEA) and the Modified Enhanced Differential Evaluation Algorithm (MEDEA). The EDEA model is modified in the present study to MEDEA. The results of all three models applied to the same case study are compared on convergence to an optimal solution. All three algorithms were tested on two of the popular benchmark functions that are Ackley and Sphere. The results of both applications demonstrated that MEDEA proved to be the best in terms of converging to the optimal solution, exhibiting better stability, and quality of final results. The outcomes of this study also provided an effective way to optimize large scale multi-purpose and multi-reservoir flood control operation problems.

Key words: Differential Evolution Algorithm (DEA), Enhanced Differential Evolution Algorithm (EDEA), Modified Enhanced Differential Evolution Algorithm (MEDEA), optimization, reservoir operation

HIGHLIGHTS

- The optimization algorithm DEA, EDEA and MEDEA was analyzed for reservoir flood control operation.
- The multiple objectives comprised for multi-purpose reservoir flood control operation.
- The challenge was selection of correct control parameters to achieve reservoir optimization.
- To evaluate the performance of algorithms two benchmark function was selected.
- The outcome of this research helps the operator's to control and operate the reservoir 0n hour or day wise during flood event.

GRAPHICAL ABSTRACT



LIST OF NOTATIONS

IS	Indira Sagar
DEA	Differential Evolution Algorithm
EDEA	Enhanced Differential Evolution Algorithm
MEDEA	Modified Enhanced Differential Evolution Algorithm
O_t	Outflow through spillway
t	Time steps in hours (t = 1,2,3, … T)
T	The time horizon for the problem
St	Initial storage at the beginning of time step t
TS	Target storage in the reservoir at the end of time horizon
MCM	Million cubic meter
Opt	Outflow through turbine
W_1	Weight assigned for the spillage
W_2	Vector of weights for achievement of target storage at the end of time horizon
W_3	Weight to meet the continuity constraint
exp	Exponential
bin	Binary
$rand_t[0,1]$	Uniformly distributed random numbers between 0 and 1 generated for each time step t.
D	Dimension of the problem
NP	Population size
F	Mutation factor
K	Scaling factor
CR	Crossover factor
G	Generation
G_{max}	Maximum number of iterations

$O_{(t,G)}$	Outflow at G generation within its feasible bounds
S_{t+1}	Final storage in the end of time step t + 1
O_{max}	Maximum outflow through spillway at time step t
O_{min}	Minimum outflow through spillway at time step t
S_{min}	Minimum permissible storage values capacity of reservoir (MCM) in *t*th hour
S_{max}	Maximum permissible storage values capacity of reservoir (MCM) in *t*th hour
It	Inflow to reservoir at time step t
$O_{(1,G)}$	1st random sample value of outflow through spillway at G generation
$O_{(2,G)}$	2nd random sample value of outflow through spillway at G generation
$O_{(3,G)}$	3rd random sample value of outflow through spillway at G generation
$O_{(4,G)}$	4th random sample value of outflow through spillway at G generation
$O_{(5,G)}$	5th random sample value of outflow through spillway at G generation
O_{best}	Best value from random sample of outflow through spillway
$O_{(worst,G)}$	Worst value from random sample of outflow through spillway at G generation
$MV_{(t,G+1)}$	Mutant vector of $(G+1)^{th}$ generation at time step t
$OV_{(t,G+1)}$	Target vector of $(G+1)^{th}$ generation at time step t
FP	Target or parent vector
FC	Trial or child vector
SFP	Fitness parent function
SFC	Fitness child function
TS-1	1st Target Storage i.e. 2281.96 MCM
TS-2	2nd Target Storage i.e. 4810.59 MCM
TS-3	3rd Target Storage i.e. 6969.22 MCM
TS-4	4th Target Storage i.e. 9744.57 MCM
TS-5	5th Target Storage i.e. 10754.51 MCM

INTRODUCTION

Reservoirs serve multiple purposes like hydropower generation, irrigation and municipal/industrial supplies along with flood control. Reservoirs also play a crucial role in flood reduction in a river. Operation of a reservoir is a tricky problem because of the uncertain inflows and varying demands. Maintenance of the storage for conservation and flood control are conflicting issues. Since the early 1970s, the reservoir operation problem has been solved using different Mathematical Programming (MP) techniques. The reviews published by Yeh (1985), Wurbs (1993), Labadie (2004), Rani & Moreira (2010) highlight the research progress in the development and applications of MP techniques for the optimization of reservoir operations. For reservoir operation during floods, various mathematical programming techniques such as Linear Programming (LP) (Windsor 1973), Nonlinear Programming (NLP) (Olcay & Larry 1990), Folded Dynamic Programming (Kumar *et al.* 2010), and Dynamic Programming (Mythili *et al.* 2013) can be cited as examples. There have been certain issues like function type, dimension of the problems and convergence to optimum value, etc., with the MP techniques despite having a strong mathematical foundation of MP techniques.

The Meta-Heuristic Algorithm (MHA) that was used to solve optimization problems have evolved in the last four decades with many advantages over the MP application to the optimization problems. MHAs are stochastic search algorithms used to obtain the optimum value of a given function. A detailed history and merit–demerits of MHAs can be found in Sorensen *et al.* (2018). The application of MHAs to water resources engineering is discussed by Reddy & Kumar (2020). A few examples of the applications of evolutionary algorithms to reservoir problems are Genetic Algorithms (GA) (Chang & Chen 1998; Jothiprakash & Shanthi 2006), Differential Evolution (DE) (Vasan & Raju 2004), Genetic Programming (GP) (Fallah-Mehdipour *et al.* 2012), Swarm Intelligence Algorithms such as Particle Swarm Optimization (PSO) (Moradi & Dariane 2009), Ant Colony Optimization (ACO) (Reddy & Kumar 2006), Honey Bee Mating Algorithm (HBMA) (Haddad *et al.* 2005), Bat Algorithm (BA) (Yang 2010; Ehteram *et al.* 2018), and Improved Bat Algorithm (IBA) (Ahmadianfar *et al.* 2016). Other algorithms include the Weed Optimization Algorithm (WOA) (Asgari *et al.* 2016), Harmony Search (HS) Algorithm (Bashiri-Atrabi *et al.* 2015), etc.

The Differential Evolution Algorithm (DEA) is a genetic-simulating stochastic population-based meta-heuristic technique developed by Storn & Price (1997). Brest *et al.* (2006) explained DEA as a powerful evolutionary algorithm for global optimization in many real-life complex problems. Das & Suganthan (2011) have compared DEA with other evolutionary as well as flock behaviour algorithms indicating that DEA is the most simple and easy to implement among all its kinds. The number of parameters is the lowest and the implementation requires simple coding.

Since the DEA method is a stochastic method based on either a random number generated or binary generation, the convergence parameters are crucial thus selection of these parameters is the crux of the versatility of DEA. Storn & Price (2004) mentioned that the performance of DEA depends upon the selection of control variables, viz. the population size (NP), mutation factor (F), crossover factor (CR), etc. From the literature review, it is clear that there is no standard procedure to determine the parameters, despite mentions of some tools and techniques for the determination of parameters. Storn & Price (2004) suggested ten different mutation strategies to increase the efficiency of DEA. These strategies approach the solution in slightly different ways in the mutation operation. An application of ten strategies to reservoir planning considering optimal cropping patterns with an aim of maximizing net economic benefits was presented by Vasan & Raju (2004). Regulwar *et al.* (2010) applied these strategies for the operation of multiple objective reservoir systems. Adeyemo & Otieno (2010) applied all strategies for the maximization of hydropower in a reservoir system.

The DEA has certain limitations like poor search capability, less population diversity, slow convergence rate, etc. Many different procedures to circumvent the limitations have been proposed. One of which is the Enhanced Differential Evolution Algorithm (EDEA) proposed by Ahmadianfar *et al.* (2017). While the algorithm was successful in its application, it had some minor limitations thatwere overcome by a better algorithm known as the Modified Enhanced Differential Evolution Algorithm (MEDEA). The introduction of this algorithm is a major contribution to the present study.

In the present study, the main focus is on the application of DEA and its variants the EDEA and MEDEA to solve the problem of reservoir operation during flood and compare the results. All five strategies have been implemented. The main criteria for comparison were the level of the solution achieved from the viewpoint of optimization and the required number of iterations in achieving the objectives of the formulated problem.

Case study and data acquisition

The Indira Sagar (IS) Reservoir situated on River Narmada in the central part of India is selected as a case study for the problem of flood operation. The reservoir is impounded with a 92 m high and 653 m long concrete gravity dam with a powerhouse capacity of 1,000 MW. There is also a canal from the reservoir to irrigate 0.99 Lakh Hectares of the land. Some salient details related to the IS reservoir are presented in Table 1. The IS Reservoir is the largest and most upstream storage in a cascade of four reservoirs of the Narmada Valley water resources management plan. The storage is used for conservation purposes as well as mandatory statutory releases to be made downstream through the hydropower plant. The Indian Monsoon Season spanning over 4 months is the only time when floods occur. The planners of the reservoir have specified a target storage value based on the fortnight of the season which has to be achieved after every flood event. The arrangement facilitates the operator to maintain space in the reservoir storage for future flood(s). Flood control is a significant aspect in the operation of IS Reservoir to protect the dams downstream. The basic objectives for the operation of IS reservoirs are releases for irrigation and hydropower generation. Flood mitigation is a secondary but important objective. During the flood period, the irrigation releases are zero and the reservoir is operated only for hydropower generation and flood protection. At present, the operations are based on heuristics and experience of the operators. A block diagram is shown in Figure 1 to indicate the relative position of the IS project and other reservoirs.

For the present study, inflow data of the IS Reservoir for a flood sequence was acquired from the Narmada Control Authority (NCA). The independent sequences of 25-h flow data are chosen for the present study starting from 0000 h on 29th August to 0000 h on 30th August in 2020. This flood is one of the highest floods in the past decades.

Table 1 | Salient features of Indira Sagar reservoir (*Source* – Narmada Control Authority, Indore)

Sr.no	Characteristics	Quantity
1	Gross storage capacity	12.220 Bm^3
2	Live storage capacity	9.750 Bm^3
3	Dead storage capacity	2.470 Bm^3
4	Total catchment area	61,642 km^2
5	Spillway capacity	83,000 cumecs
6	Hydropower capacity	1,000MW

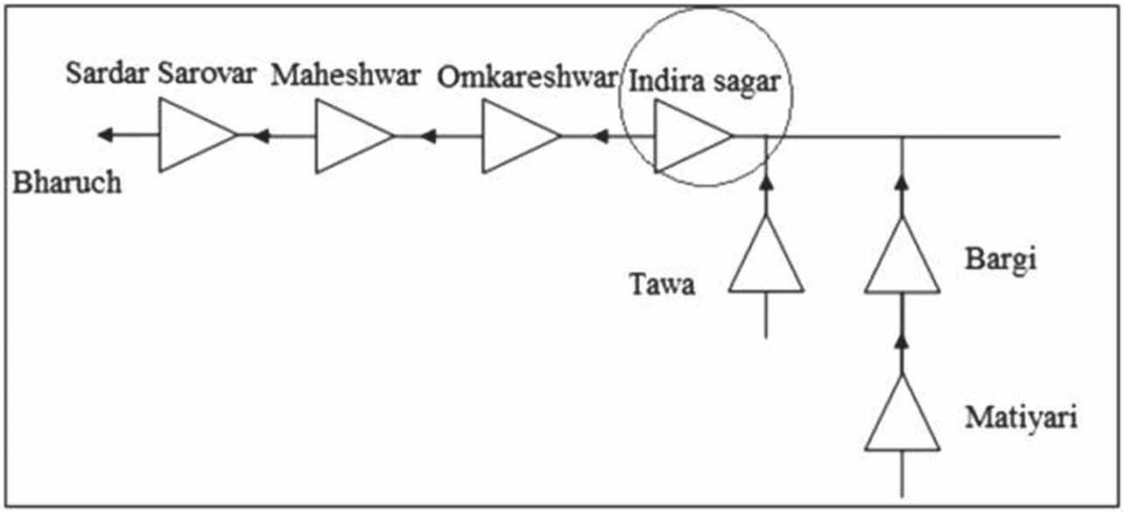


Figure 1 | Block diagram of the Narmada valley indicating the location of Indira Sagar Reservoir (*Source* – Narmada Control Authority, Indore).

MATERIALS AND METHODS

Model formulation

The order of meeting the objectives in operating the IS Reservoir during a flood is as follows:

(1) Maximize the releases through the turbine.
(2) Spillage of water to be controlled to maintain the discharge within the safe limits for the downstream.
(3) Bringing the reservoir to the level of target storage after the flood wave is over.

Keeping the priorities in mind the optimization problem is formulated. The optimization problem is discussed in the following paragraph.

The objective function

The objective function is a deterministic objective function with the minimization of the addition of a weighted sum of the square of spillway releases (O_t) and weighed sum of the squared difference of current storage (S_t) with the target storage (TS) at the end of the time horizon. The continuity equation or the storage conservation constraint has also been added as a component of the objective function as a weighted squared deviation to ensure continuity (Equation (1)).

$$\mathrm{Min}\left[\sum_{t=1}^{T} W_1(O_t)^2 + \sum_{t=2}^{T+1} W_2(S_t - TS)^2 + \sum_{t=1}^{T} W_3(S_{t+1} - (S_t + I_t - O_t - O_{pt}))^2\right] \quad (1)$$

where T is the time horizon for reservoir operation (25 h has been considered), O_t is spill outflow (MCM) in tth hour, S_t and S_{t+1} are the initial and final storage values of the reservoir in the beginning and end of tth hour (MCM), I_t is the inflow to the reservoir (MCM) in tth hour, O_{pt} is outflow through turbines (MCM) in tth hour (its value is taken as a constant value in the continuity equation which is equal to the maximum capacity of the turbines in an hour that is 7.92 (MCM), W_1 is the vector of weights for the spillage to be minimized (taken as a constant value of 100), W_2 is the vector of weights for meeting the target storage at the end of operation (which is varied at each time step from 1.00×10^{-6} at the start of an operation to 10,000 at the end of an operation) and W_3 is the vector of weights for assuring the continuity relationship to be satisfied (1,000). There is a single equality constraint that is the storage continuity constraint. This constraint is added as a third term in the objective function since the DEA model has limitation of accommodation of explicit constraint.

Bounds

The bounds on the storage and spills are specified as

$$S_{\min} \leq S_t \leq S_{\max} \quad \text{for } t = 1, \ldots, T+1 \tag{2}$$

and

$$O_{\min} \leq O_t \leq O_{\max} \quad \text{for } t = 1, \ldots, T \tag{3}$$

where $S_{\min}$ and $S_{\max}$ are minimum and maximum permissible storage values, respectively (MCM). $O_{\min}$ and $O_{\max}$ are minimum and maximum spills, respectively (MCM).

The optimization problem discussed in the preceding paragraph represented by Equations (1)–(3) is solved using DEA and its variants the EDEA and MEDEA in the present study. The techniques are discussed in the following paragraphs.

Steps of DEA adopted

The DEA model was adopted for the present study and a code is written on MATLAB. The following steps of optimization are discussed.

(1) Initialization: For the present problem the adopted time horizon (T) is 25 h. Thus, an initial population of 25 spill values $O_{t,G}$ are generated (for time step t and generation $G=0$) within the bounds. (Equation (4)).

$$(O_{t,G}) = O_{\min} + \mathit{rand}_t[0, 1].(O_{\max} - O_{\min}) \ \ \forall\, t = 1, T \tag{4}$$

The $O_{\min} = 0$ and $O_{\max} = 300.72$ (in MCM). The term $\mathit{rand}_t\,[0, 1]$ is set of 25 uniformly distributed random numbers between 0 and 1 generated for each time step t. From this vector of spill values the objective function is evaluated and stored in the form of the fitness parent function (SFP).

(2) Mutation: From the string of the spill values $O_{t,G}$ the mutation operation was carried out. The mutant vector $\mathrm{MV}_{(t,G+1)}$ for $(G+1)$th generation for different strategies was computed from the formulae presented in Table 2.

From the vector $O_{t,G}$, 5 values were chosen randomly ($O_{(i,G)}$ ($i = 1$–5)). The value $O_{(best,G)}$ was chosen to be the highest value from the vector $O_{t,G}$. The mutation factor F (value between 0.15 and 0.18) and the scaling factor K (value between 0.135 and 0.265) are the controlling variables used in DEA. After each run these values are varied to get better convergence. The Mutant Vector $\mathrm{MV}_{(t,G+1)}$ for $(G+1)$th generation was subjected to check with the bounds.

$$\begin{aligned}&\text{If} \quad \mathrm{MV}_{(t,G+1)} < O_{\min} \ \text{then}\ \mathrm{MV}_{(t,G+1)} = O_{\min}\\ &\text{and If} \quad \mathrm{MV}_{(t,G+1)} > O_{\max} \ \text{then: } \mathrm{MV}_{(t,G+1)} = O_{\max}\end{aligned} \tag{5}$$

Table 2 | Mutation for differential evolution strategies

Differential evolution strategies	DEA	Equation for mutation operation
DE/rand/1/exp	DEA/1	$\mathrm{MV}_{(t,G+1)} = O_{(1,G)} + F(O_{(2,G)} - O_{(3,G)})$
DE/rand/2/exp	DEA/2	$\mathrm{MV}_{(t,G+1)} = O_{(1,G)} + F(O_{(2,G)} - O_{(3,G)} + O_{(4,G)} - O_{(5,G)})$
DE/best/1/exp	DEA/3	$\mathrm{MV}_{(t,G+1)} = O_{(best,G)} + F(O_{(2,G)} - O_{(3,G)})$
DE/best/2/exp	DEA/4	$\mathrm{MV}_{(t,G+1)} = O_{(best,G)} + F(O_{(2,G)} - O_{(3,G)} + O_{(4,G)} - O_{(5,G)})$
DE/rand to best/1/exp	DEA/5	$\mathrm{MV}_{(t,G+1)} = O_{(1,G)} + F(O_{(2,G)} - O_{(3,G)}) + K(O_{best} - O_{(1,G)})$

(3) Crossover: The crossover operation is applied to enhance the diversity of the population. Initially, a vector (of dimension T) of uniformly distributed random numbers between 0 and 1 are generated ($rand_t[0,1]$). These random numbers were compared with the crossover factor CR (in a range of 0.135–0.265) and the final trial vector $OV_{t,G+1}$ is obtained as follows.

$$\text{If } rand_t[0,1] < \text{CR then } OV_{t,G+1} = MV_{t,G+1} \quad \text{(Mutant Vector)}$$

$$\text{and If } rand_t[0,1] > \text{CR then } OV_{t,G+1} = (O_{t,G=0}) \quad \text{(Target Vector)} \tag{6}$$

The obtained trial vector $OV_{t,G+1}$ is used to evaluate the objective function for the selection of next generation vector.

(4) Selection: Before invoking the selection process the objective function value is evaluated from the trial vector $OV_{t,G+1}$ as the fitness child function SFC. For the selection of the final value of spills for the next generation the objective function values SFP and SFC are compared using the greedy criterion for the minimization problem as follows:

$$\text{If SFP} \leq \text{SFC then } OV_{(t,G+1)} = OV_{(t,G+1)} \text{ and If SFP} \geq \text{SFC then } OV_{(t,G+1)} = (O_{(t,G)}) \tag{7}$$

Thus, a new vector of spills $OV_{(t,G+1)}$ is generated which is termed as the final vector. With these values, the mutation operation (step 2) is performed again. The Mutation, Crossover, and Selection operations are sequentially repeated until the final objective function SFC is minimized and the target storage is achieved. In the present study, the process is truncated after 10,000 iterations up to which the problem finds an optimum value is obtained. The flowchart for the solution to the present problem is indicated in Figure 2.

The DEA strategies involve exponential as well as binomial functions for mutation. However, in the present study, only exponential functions for all the 5 strategies have been adopted and reported. This is because the binomial functions lead to premature convergence and get stuck in the local optimum. This was mentioned by Qin *et al.* (2009) and the experience gained in the present study.

Enhanced differential evolution algorithm and suggested modification

The convergence of DEA harps on the efficiency of the mutation operation. The traditional DEA has a limitation of weak local search ability and slow convergence rate despite the fact that it is a simple and efficient evolutionary algorithm. (Fan & Lampinen 2003; Ahmadianfar *et al.* 2017). This limitation escalates when complex optimization problems are solved. To improve the performance of DEA Ahmadianfar *et al.* (2017) introduced an Enhanced Differential Evolution Algorithm (EDEA) with changes in the mutation operation of the traditional DEA. They mention that the improvement in mutation will only be possible if the exploration and exploitation path is invoked. In the DEA, the first and the second strategies (Table 2) select the random variables from the vector of the initial population. The approach is exploratory. The exploratory approach adopted by the other strategies use the best individuals with randomly selected variables. They combined the mutation strategy used by Fan & Lampinen (2003) and Mohamed & Sabry (2012) to generate a new mutation strategy using an exponential formula. In the present study, the mutation strategy of EDEA was further modified to enhance the efficiency of the process of mutation. For the modification placement of the variable $O_{(i,G)}$ was changed. Further, the scaling factor K is introduced and used with F in the mutation operation of a new method named as Modified Enhanced Differential Algorithm (MEDEA). The difference between the two methods is shown in Table 3.

In Table 3, $P_{\max}$ and $P_{\min}$ are two constants within the range between 0 and 1, respectively, $nMut_{cur}$ is the current generation number and $nMut_{\max}$ is the maximum number of generations for mutation operation of EDEA and MEDEA. $O_{(best,G)}$, $O_{(better,G)}$, $O_{(worst,G)}$ are the tournaments best, better and worst five randomly selected vectors, respectively.

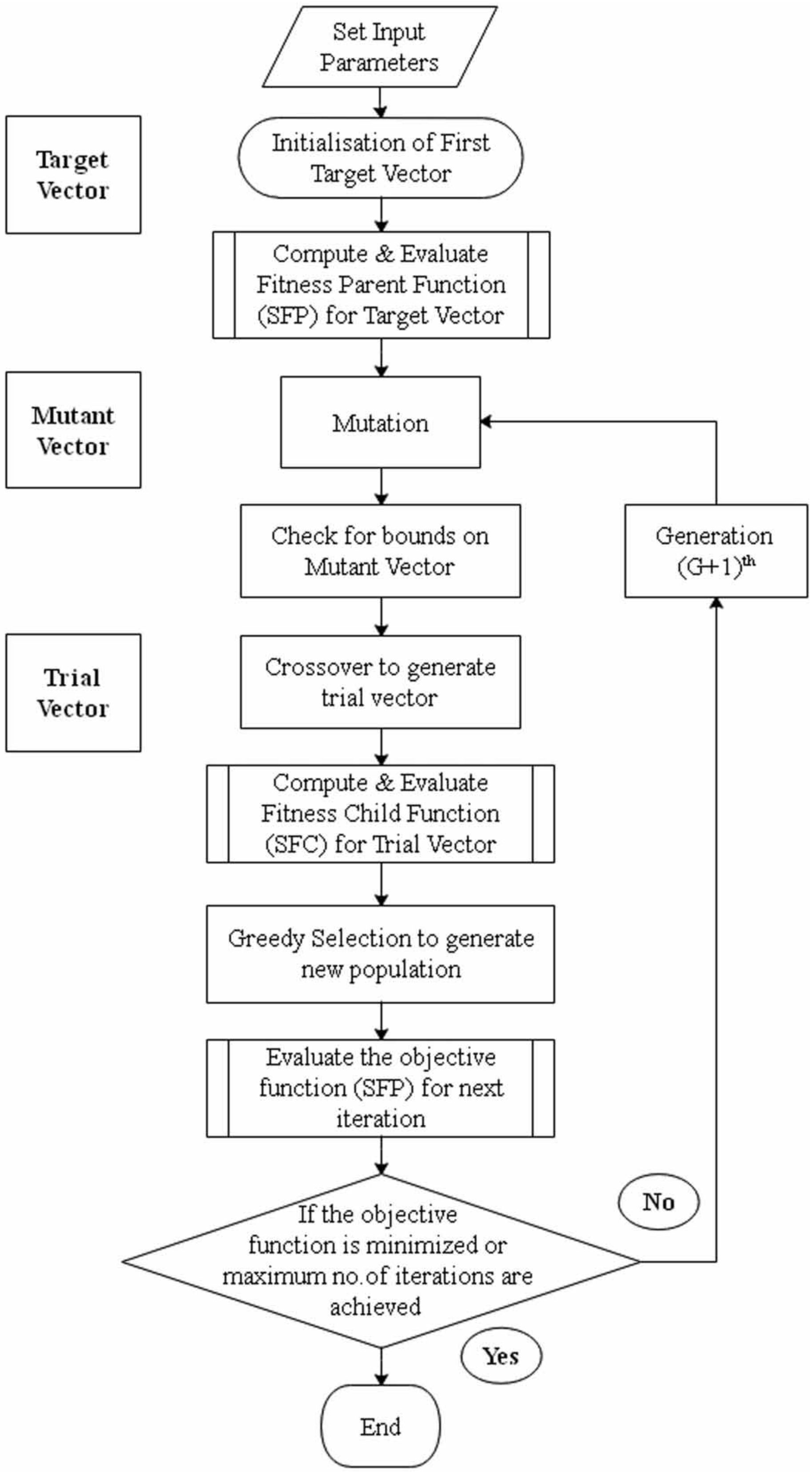


Figure 2 | General flow chart of the DEA.

Table 3 | Comparison of mutation operation of EDEA and MEDEA

EDEA (Ahmadianfar *et al.* 2017)	MEDEA (Suggested in present study)

if $rand_t[0, 1] < \left(P_{\max} + (P_{\max} - P_{\min}) * e^{\left(\frac{-nMut_{cur}}{nMut_{\max}}\right)}\right)$
 $MV_{(t,G+1)} = O_{(1,G)} + F(O_{(2,G)} - O_{(3,G)}) + F(O_{(4,G)} - O_{(5,G)})$
 $MV_{(t,G+1)} = O_{(best,G)} + F(O_{(r_1,G)} - O_{(r_2,G)}) + F(O_{(r_3,G)} - O_{(r4,G)})$
 $MV_{(t,G+1)} = O_{(r_i,G)} + F(O_{(best,G)} - O_{(r_i,G)}) + F(O_{(r_1,G)} - O_{(r_2,G)})$
 else
 $MV_{(t,G+1)} = O_{(avg,G)} + F_1(O_{(lbest,G)} - O_{(better,G)}) + F_2(O_{(lbest,G)} - O_{(worst,G)}) + \frac{F1 + F2}{2}(O_{(better,G)} - O_{(worst,G)})$
 $MV_{(t,G+1)} = O_{(avg,G)} + (P_2 - P_1)(O_{(lbest,G)} - O_{(worst,G)}) + (P_3 - P_2)(O_{(better,G)} - O_{(worst,G)}) + (P_1 - P_3)(O_{(worst,G)} - O_{(best,G)})$
 $MV_{(t,G+1)} = O_{(best,G)} + F_1(O_{(lbest,G)} - O_{(better,G)}) + F_2(O_{(lbest,G)} - O_{(worst,G)})$
 endif
	if $rand_t[0, 1] < (P_{\max} + (P_{\max} - P_{\min}) * e^{\left(\frac{-nMut_{cur}}{nMut_{\max}}\right)})$
	 $MV_{(t,G+1)} = O_{(1,G)} + F(O_{(2,G)} - O_{(3,G)} + O_{(4,G)} - O_{(5,G)})$
	 $MV_{(t,G+1)} = O_{(best,G)} + F(O_{(2,G)} - O_{(3,G)} + O_{(4,G)} - O_{(5,G)})$
	 $MV_{(t,G+1)} = O_{(1,G)} + F(O_{(2,G)} - O_{(3,G)}) + K(O_{(best,G)} - O_{(1,G)})$
	 else
	 $MV_{(t,G+1)} = O_{(avg,G)} + F(O_{(best,G)} - O_{(better,G)}) + K(O_{(best,G)} - O_{(worst,G)}) + \frac{F + K}{2}(O_{(better,G)} - O_{(worst,G)})$
	 $MV_{(t,G+1)} = O_{(avg,G)} + F(O_{(best,G)} - O_{(worst,G)}) + K(O_{(better,G)} - O_{(worst,G)}) + \frac{F + K}{2}(O_{(worst,G)} - O_{(best,G)})$
	 $MV_{(t,G+1)} = O_{(best,G)} + F(O_{(best,G)} - O_{(better,G)}) + K(O_{(best,G)} - O_{(worst,G)})$
	 endif

To change the searching method of new trial vectors $OV_{(t,G+1)}$, a polynomial mutation concept (Ahmadianfar *et al.* 2017) was used.

$$OV_{(t,G+1)} = \begin{cases} MV_{(t_j,G+1)} + \sigma(U_b - L_b) & \text{if } rand_t < C_r \text{ or } j = j_{rand}[1, D] \\ MV_{(t_j,G+1)} & \text{if } rand_t > C_r \text{ and } rand_t \le 0.5 \\ MV_{(t_j,G+1)} & \text{if } rand_t > C_r \text{ and } 0.5 < rand_t \le 0.75 \\ O_{(r1,G)} & \text{otherwise} \end{cases} \quad (8)$$

$$\text{With } \sigma = \begin{cases} (2 * rand_t[0, 1])^{1/(\eta+1)} - 1 & \text{if } rand_t[0, 1] < 0.5 \\ 1 - (2 - 2 * rand_t[0, 1])^{1/(\eta+1)} & \text{otherwise} \end{cases} \quad (9)$$

where j_{rand} = randomly generated interger from 1 to D, σ is polynomial mutation, η is a distribution index (equal to 10), U_b and L_b is the lower and upper bounds of decision variable, respectively.

Benchmark testing

All the techniques that are DEA, EDEA, and MEDEA which are used for the optimization of the reservoir operation problem under consideration are tested on the benchmark mathematical (Ackley and Sphere) functions (Equations (10) and (11)). The Ackley function is a multimodal function in which local minima rise with the dimensions of the problem. On the other hand, sphere function is a continuous function in which local minima except for the global one with the dimensions of the problem.

$$f_1(x) = 20 + e - 20 \exp\left(-0.2\sqrt{\frac{1}{D}\left(\sum_{i=1}^{D} x_i^2\right)}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D} \cos(2\pi x_i)\right) \quad (10)$$

$$f_2(x) = \sum_{i=1}^{D} x_i^2 \quad (11)$$

The dimensions, search space and global optimum values are shown in Table 4 and other parameters with the ranges are shown in Table 5. The computed results of the application of DEA, EDEA, and MEDEA on these functions are presented in Table 6. Due to the lowest average results and the standard deviation values, the MEDEA is quick in convergence and effective in determining the results in comparison to both other techniques.

Table 4 | Dimensions, search spaces, global optimum values, and acceptance level of test functions

Test function	Function	Dimension	Search space	Global optimum
Ackley	f1	25	$[-32, 32]^D$	0
Sphere	f2	25	$[-5.12, 5.12]^D$	0

Table 5 | Range of parameters of DEA, EDEA, MEDEA used for Ackley and Sphere functions as well as reservoir operation problem

Algorithm	Parameter	Values
MEDEA and EDEA	Population size (NP)	25
	Mutation factor (F)	0.15–0.80
	Scaling factor (K)	0.135–0.265
	Crossover rate (CR)	0.395–0.500
	No. of functional evaluations	10,000
	$nMut_{max}$	400
	$nMut_{cur}$	100
	η	10
DEA	Population size (NP)	25
	Mutation factor (F)	0.15–0.80
	Scaling factor (K)	0.135–0.265
	Crossover rate (CR)	0.395–0.960
	No. of functional evaluations	10,000

Table 6 | Value of fitness calculated with , EDEA, and MEDEA in different runs for (Ackley and Sphere) benchmark function

Function	Algorithm	Best	Worst	Average	Standard deviation
Ackley	DEA	1.24×10^{-11}	7.32×10^{-7}	1.37×10^{-7}	2.56662×10^{-7}
	EDEA	1.17×10^{-14}	4.81×10^{-11}	5.92×10^{-12}	1.49138×10^{-11}
	MEDEA	$\mathbf{8.08\times10^{-16}}$	$\mathbf{8.08\times10^{-16}}$	$\mathbf{8.08\times10^{-16}}$	**0**
Sphere	DEA	1.24×10^{-12}	6.92×10^{-7}	1.17×10^{-7}	2.37499×10^{-7}
	EDEA	4.09×10^{-15}	6.70×10^{-11}	6.77×10^{-12}	2.11689×10^{-11}
	MEDEA	$\mathbf{7.46\times10^{-18}}$	$\mathbf{7.46\times10^{-18}}$	$\mathbf{7.46\times10^{-18}}$	$\mathbf{1.62409\times10^{-33}}$

Bold text emphasizes MEDEA outperforms EDEA and DEA in solving Ackley and Sphere function with better convergence accuracy.

RESULTS AND DISCUSSIONS ON RESERVOIR OPERATION OPTIMIZATION

Though the MEDEA technique performs better, DEA and EDEA are both used to determine the optimal operation of the reservoir in the study. The models were run for all five strategies with DEA, EDEA, and MEDEA for five target storage values. Each of the problems was solved with a sufficient number of iterations. The major issue was to choose a proper set of parameters for all three models. Storn & Price (1997) initially suggested the population size (NP) between 5*D and 10*D (where D is the dimension of the problem), values of Mutation Factor (F) to be in the range of 0–2 and the Crossover Factor (CR) in the range between 0 and 1. Storn & Price (2008) while discussing the application of ten strategies recommend revised values of NP as 10D, and reduced the range of F and CR between 0.5 and 1.0. Vasan & Raju (2004) have mentioned the range of CR between 0.4 and 1.0 and that of F between 0.4 and 1.0 at an increment of 0.5. Regulwar *et al.* (2010) adopted CR values from 0.7 to 0.95 at a discrete increment of 0.05 and F values ranging from 0.2 to 0.9 with a discrete increment of 0.05. All these values were not found to be suitable in the present study thus a trial and error procedure was adopted. For the present problem, the selection of control parameters for DEA, EDEA, and MEDEA is shown in Table 5.

Each combination of the adopted strategy and the stipulated target storage level are shown in Table 7. The results in terms of convergence of the fitness function for the highest value of Target Storage TS-5 are shown in Figure 3(a)–3(e). Figures 3(a)

Table 7 | The target storage levels to achieve optimaztion of the reservoir system

Target storage (TS)	Target storage (MCM)
TS-1	2,281.96
TS-2	4,810.59
TS-3	6,969.22
TS-4	9,744.57
TS-5	10,754.51

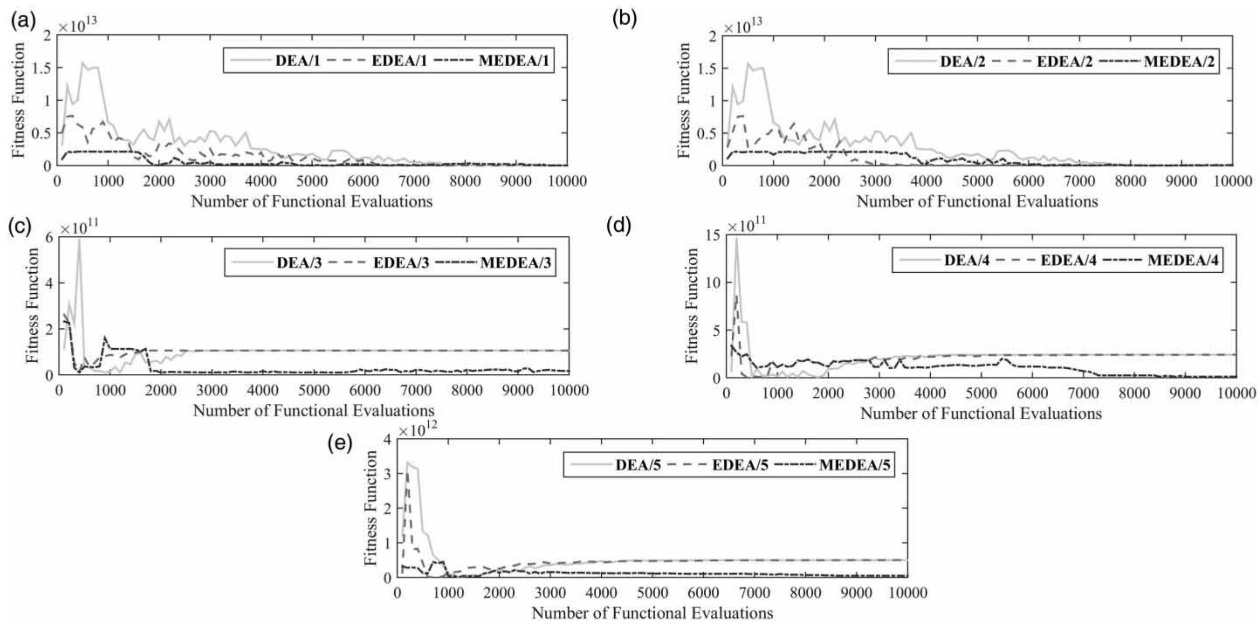


Figure 3 | Number of functional evaluations vs. fitness functions of all strategies of DEA,EDEA, and MEDEA for TS-5 in 2020.

and 3(b) indicate that for strategies 1 and 2, almost same results are achieved with all three algorithms indicating convergence. However, in strategies 3, 4, and 5, the application of algorithms DEA and EDEA are trapped in the local optimum much before the global optimum. The algorithm MEDEA performed well and converged.

The optimization results of fitness functions of all strategies of DEA, EDEA, and MEDEA for the reservoir system are calculated as shown in Table 8. The standard deviation of the fitness function of MEDEA is lower than EDEA and DEA. It is also recommended that a low standard deviation qualifies the convergence ability, stability and precision of MEDEA. It is also clear that the worst solution of MEDEA (equal to 4.13×10^{10}) was better than the best solution of EDEA (equal to 8.83×10^{10}).

The computed outflow hydrographs derived from different models for a target storage of 10,754.34 MCM are shown in Figure 4. The figure indicates that the MEDEA generates a proper outflow sequence which is more akin to a reservoir flood routing outflow hydrograph. The outflow (Spill) sequence generated by MEDEA has a gradual rise and fall whereas the DEA and EDEA generate a bit fluctuating sequence. The overall outflow values are within safe limits as they will not cause extreme conditions downstream. The total outflow achieved by MEDEA, EDEA, and DEA is 1,341.78 MCM; 1,450.65 MCM; 1,511.20 MCM, respectively.

Table 9 indicates a comparison of the achievement of different Target Storage values with various strategies of DEA, EDEA and MEDEA for the year 2020. According to the percentage deviation of target storage the MEDEA attains lowest values in comparison to the strategies of EDEA and DEA. In the hierarchy MEDEA performed the best, EDEA performed better than DEA.

Table 8 | Fitness function values of DEA, EDEA, and MEDEA for the reservoir system

Algorithm	Best	Worst	Average	Standard deviation
DEA/1	7.88×10^{9}	1.57×10^{13}	2.85×10^{12}	3.56×10^{12}
EDEA/1	6.17×10^{9}	7.64×10^{12}	1.43×10^{12}	1.86×10^{12}
MEDEA/1	3.68×10^{9}	2.13×10^{12}	5.07×10^{11}	7.12×10^{11}
DEA/2	7.88×10^{9}	1.57×10^{13}	2.85×10^{12}	3.06×10^{12}
EDEA/2	8.40×10^{9}	7.65×10^{12}	1.05×10^{12}	1.90×10^{12}
MEDEA/2	2.53×10^{9}	2.13×10^{12}	9.09×10^{11}	9.05×10^{11}
DEA/3	1.04×10^{10}	5.92×10^{11}	1.03×10^{11}	9.09×10^{10}
EDEA/3	1.27×10^{10}	2.62×10^{11}	1.04×10^{11}	2.51×10^{11}
MEDEA/3	$1.00\text{E}\times10^{10}$	2.32×10^{11}	2.97×10^{10}	4.13×10^{10}
DEA/4	6.80×10^{9}	1.47×10^{12}	2.14×10^{11}	$1.58\text{E}\times10^{11}$
EDEA/4	6.46×10^{9}	8.66×10^{11}	2.11×10^{11}	$8.83\text{E}\times10^{10}$
MEDEA/4	1.01×10^{10}	3.36×10^{11}	1.05×10^{11}	$6.75\text{E}\times10^{10}$
DEA/5	7.00×10^{9}	3.31×10^{12}	5.23×10^{11}	$5.15\text{E}\times10^{11}$
EDEA/5	7.35×10^{9}	3.09×10^{12}	4.55×10^{11}	2.99×10^{11}
MEDE/5	5.00×10^{9}	4.50×10^{11}	1.18×10^{11}	7.82×10^{10}

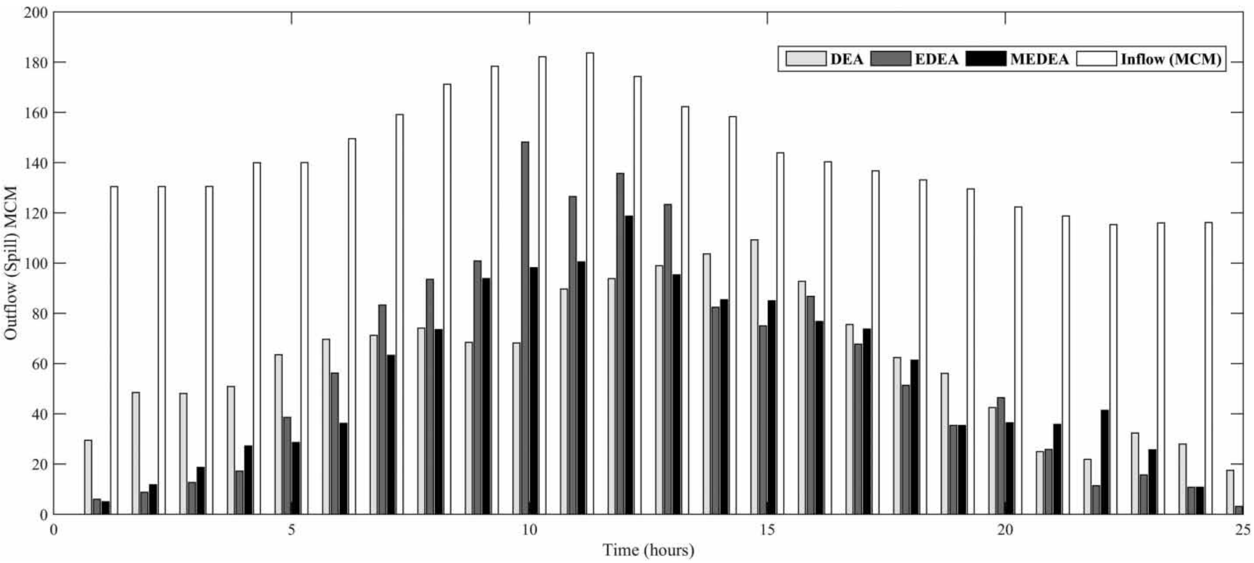


Figure 4 | Hourly inflow (input) and spill (output) by all the three algorithms for the target storage TS-5.

CONCLUSIONS

The present study demonstrates an application of three variants of DEA, viz. the DEA, EDEA, and MEDEA to derive short-term operation policies for a single reservoir during a flood event. The EDEA technique was proposed by Ahmadianfar *et al.*(2017), and the MEDEA technique is a major contribution of the present study. The techniques were first tested on benchmark optimization functions, namely the Ackley and Sphere functions, to establish their suitability. The main objective of the present study was to solve multiple objective optimization problems of reservoir operation during a flood event. A case study of Indira Sagar Reservoir in India was considered for a single flood event for the year 2020. The problem had three major objectives in the following order: to maximize the hydropower generation by passing maximum discharge through

Table 9 | Comparison of achievement of different target storage values with various DEA, EDEA, and MEDEA strategies for the year 2020

Target storage (MCM)	MEDEA	Storage achieved (MCM)	% deviation from target storage	EDEA	Storage achieved (MCM)	% deviation from target storage	DEA	Storage achieved (MCM)	% deviation from target storage
2,281.96	MEDEA/1	2,290.00	0.352	EDEA/1	2,296.00	0.615	DEA/1	2,313.34	1.38
4,810.59		4,818.33	0.161		4,824.46	0.288		4,846.41	0.74
6,969.22		6,971.22	0.029		6,975.14	0.085		6,988.59	0.28
9,744.57		9,745.55	0.010		9,748.41	0.039		9,757.71	0.13
10,754.51		10,810.33	0.519		10,841.60	0.810		10,906.46	1.41
2,281.96	MEDEA/2	2,298.66	0.732	EDEA/2	2,305.48	1.031	DEA/2	2,348.47	2.91
4,810.59		4,840.44	0.621		4,853.78	0.898		4,866.47	1.16
6,969.22		7,012.33	0.619		7,037.22	0.976		7,048.27	1.13
9,744.57		9,823.99	0.815		9,834.35	0.921		9,963.59	2.25
10,754.51		10,855.65	0.940		10,975.44	2.054		11,140.00	3.58
2,281.96	MEDEA/3	2,298.66	0.732	EDEA/3	2,323.49	1.820	DEA/3	2,357.65	3.32
4,810.59		4,817.44	0.142		4,829.52	0.393		4,850.84	0.84
6,969.22		6,996.40	0.390		7,006.40	0.533		7,088.88	1.72
9,744.57		9,767.89	0.239		9,777.67	0.340		9,786.47	0.43
10,754.51		10,860.26	0.983		11,051.26	2.759		11,060.00	2.84
2,281.96	MEDEA/4	2,292.56	0.465	EDEA/4	2,302.56	0.903	DEA/4	2,310.55	1.25
4,810.59		4,835.16	0.511		4,850.76	0.835		4,855.39	0.93
6,969.22		7,020.08	0.730		7,035.48	0.951		7,047.48	1.12
9,744.57		9,830.31	0.880		9,894.71	1.541		9,928.75	1.89
10,754.51		10,811.64	0.531		10,843.64	0.829		10,866.57	1.04
2,281.96	MEDEA/5	2,298.89	0.742	EDEA/5	2,298.89	0.742	DEA/5	2,301.21	0.84
4,810.59		4,840.21	0.616		4,850.27	0.825		4,860.69	1.04
6,969.22		6,985.13	0.228		7,021.93	0.756		7,045.32	1.09
9,744.57		9,797.41	0.542		9,897.41	1.569		9,909.60	1.69
10,754.51		10,824.76	0.653		10,864.76	1.025		10,901.91	1.37

turbines, to minimize the spills and attainment of stipulated target storage level at the end of the time horizon. The values of five target storage were specified by the state government. Weighing technique was used to solve the multi-objective problem. The weights were heuristically chosen to ascertain the fulfilment of the objectives according to the hierarchy. All the models were solved for five strategies. The choice of the optimization parameters was difficult and a tricky issue. Trial and error procedure has been adopted to finalize the parameters for all the algorithms. The study results indicate that the objective of hydropower maximization was fulfilled in all the algorithms at all the target storage values. The flood releases were also within the limits of the spillway capacity. The target storage values achieved were compared in the form of percentage deviations at the final iteration of all three algorithms with all the strategies. In this regard, the MEDEA technique performed better than EDEA. The DEA did not perform up to the mark in all the strategies. It is established that in all the strategies the MEDEA performed better since the solutions are stable and achieved fast convergence of optimization in comparison with DEA and EDEA. It can be recommended as a successful, quick converging, fast computing, and stable algorithm for solving large-scale reservoir operation problems.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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