Metaheuristic algorithms for optimization of reservoir operations on Ravishankar Sagar reservoir

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ABSTRACT

Reservoir operations involve determining the quantity of water to be released or stored from the reservoir at any given time, based on the reservoir's current condition. This research presents optimizing techniques for reservoir operating policies on Ravishankar Sagar reservoir during monsoon season. Metaheuristics algorithms – GA, NSGA II, NSGA III, and Eps MOEA were used to optimize the objective function for maximization of storage along with a different set of constraints in Ravishankarsagar reservoir. Sensitivity analysis on all algorithms was performed to calibrate different evaluation parameters. The results were analyzed to find the effectiveness of soft computing algorithms in real-world problems. The standard deviation of 359.52, 351.93,349.68 and 361.09 and Median of 512.5, 525.36,568.96 and 433.79 was observed in GA, NSGA II, Eps MOEA, and NSGA IIII so all the algorithms performed well and were in close approximation, with the least standard deviation and the most optimum storage in Eps MOEA.

KEYWORDS
Eps MOEA; flood control; NSGA II; NSGA III; reservoir operations; sensitivity analysis

1. Introduction

Reservoir plays a crucial role in the management and planning of water resources systems. It stores the water during the monsoon season and further releases water during the dry seasons to meet the various conservational uses of the reservoir. Reservoir operations refer to specifying the amount of water that is to be released or stored from the reservoir at any time depending upon the state of the reservoir. Optimization of water entering the reservoir is a very important task as many stakeholders are directly or indirectly affected by the release from the reservoir. Optimal reservoir operations can increase sustainability and decrease the vulnerability of reservoirs against water-related disasters (Yekti 2017). Due to climate change, the importance of reservoirs is likely to increase not only for water storage purposes but also for maximizing water use benefits and mitigating climate extremes. Water deficit is one of the major issues for the stakeholders involved with the reservoir management system (Hamdy, Ragab, and Scarascia-Mugnozza 2003). Reservoir operation is the most advanced way to curtail water shortages and minimize the power production deficit. A managed reservoir operation can help in mitigating the adverse impacts on the river ecosystems during high or low flow conditions and provide a sustainable solution to water-related issues (Jager and Smith 2008). It can influence the flow pattern downstream which can further improve the water supply, and groundwater conditions and provide healthy riverine ecosystems (Suen and Eheart 2006).

Multi-purpose reservoirs are created to satisfy various purposes like meeting municipal demands, irrigation demands, industrial demands, hydropower generation, and flood control. These demands are often conflicting with each other and make reservoir operations a complicated task (Jain 2012). To operate the multi-purpose optimally it is essential to manage the trade-off among different objectives (Lin and Rutten 2016). The operation of reservoirs is defined with the help of rule curves and release policies. System Engineering techniques like simulation and optimization models are generally used to improve water management for multi-purpose reservoirs. Many attempts have been made over the past decades to continuously improve the release policies of the reservoirs by using different Meta Heuristic algorithms (MHAs) for water management over the basin. MHAs are divided into the following groups according to the theory of evolution (Lai et al. 2022) – Swarm (Particle swarm optimization), Bio (Weed Optimization), Probability (Entropy Method), Evolutionary (Coral Reef Optimization), Physics (Simulated annealing), System (Water Cycle), Math (Sine Cosine Algorithm), Music (Harmony Algorithm). These optimization algorithms have been successfully implemented in the field of reservoir operations by many researchers in recent years (Azizipour et al. 2016; Bashiri-Atrabi et al. 2015; Emami et al. 2021; Vasan and Raju 2009). Verma et al (2023) used Ant Colony optimization for the operation of Mahanadi reservoir project complex and it outperforms the concentional rule curve policies. Recently a new meta-heuristic algorithm, the spider monkey algorithm was used by Ehteram, Karami, and Farzin (2018) to reduce the irrigation deficiency of the multi-purpose reservoir with the improved convergence speed. Ferdowsi et al (2021) used meta-heuristic algorithms like multi-objective multi-verse (MOMVO) to reduce the construction cost of open channels and weirs. Alizamir et al (2021) used the bat algorithm for the water quality assessment

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with the help of chlorophyll concentration. Farzin et al (2022) used a new hybridization strategy along with the Harris hawk optimization model for the prediction of groundwater table and analysis of Drought. Danandeh Mehr et al. (2023) used two hybrid machine learning models based on the combination of an Extreme Learning Machine(ELM) along with Bacterial Foraging Optimization (BFO) and a Water Cycle Algorithm (WCA) for drought analysis. Kadkhodazadeh and Farzin (2021) used the Least square support vector machine along with a gradient-based optimizer algorithm for water quality parameters assessment in the Karun River basin. Wang et al. (2023) used the bald engine search algorithm coupled with the ε-constraint method for the flood control operation of a reservoir. Choi et al. (2023) used the recently developed Grey wolf optimizer for the development of the rule curve that maximizes the water supply reliability of the Hwacheon reservoir. Yasar and Mutlu (2016) used the cuckoo search algorithm for the development of rule curves of a reservoir with irrigation and hydropower generation as its main objectives. Afshar et al. (2007) used the Honey Bee Mating Optimization(HBMO) algorithm for the single reservoir operation with a non linear and continuous constrained problem. Numerous optimization algorithms have traditionally been employed to manage complex reservoir operations problems. The implementation of linear programming in the monthly operation of the reservoir has been done extensively in the past decades (Vedula, Mohan, and Shrestha 1986) (Tao and Lennox 1991). Due to non-linear constraints in the reservoir operations problem, Linear programming was not much applicable and there was increased use of dynamic programming in the complex non-linear reservoir system. In dynamic programming, complex problem is decomposed into subproblems that are solved successively. Dynamic programming was used in the single reservoir problem for resource allocation (Hall, Butcher, and Esogbue 1968). Dynamic programming faces the problem of the curse of dimensionality i.e. due to an increase in the number of state variables there will be an exponential increase in time (Yeh 1985). The use of Non-linear programming such as the Successive Quadratic programming method, Method of multipliers was also extensive in the Reservoir Operations problem but they have a problem of the slow rate of convergence, large computational cost, and converging in a locally optimal solution. To solve these problems many robust evolutionary algorithms have been proposed by researchers and have been applied successfully in the field of water resource engineering. A genetic algorithm is one such algorithm that comes up with the concept of survival of the fittest (Holland 1984). Various researchers have used Genetic Algorithm (GA) in the reservoir operation problem for the development of release policies (Hashemi, Barani, and Ebrahimi 2008; Hormwichian, Tongsiri, and Kangrang 2018; Kumar, Raju, and Ashok 2006; Sharif and Wardlaw 2000). In GAs sometimes to get an optimum solution the number of function evaluations is very large and the chances of getting global optima are also reduced due to the size of long chromosomes. New updated versions of GA, i.e. Non-Dominated Sorting Genetic Algorithm II (NSGA II) and Non-Dominated Sorting Genetic Algorithm III (NSGA III) are being used by researchers in water resource engineering systems to reduce the computational cost and time. The main advantage of these recently developed computing techniques is that these techniques can be used to get an optimal solution at a reduced computational time and cost (Cui et al. 2019; Deb et al. 2002). Another advantage of these robust algorithms is that these algorithms can efficiently handle large non-linear and uncertain data (Zhang 2007). Several papers have been published regarding the optimal operation of the reservoir. However, most of these studies focused on the Irrigation demands or the hydropower generation using the algorithms like GA and Multi Objective Evolutionary Algorithm (MOEA) (Mathur and Nikam 2009; Nagesh Kumar, Raju, and Ashok 2006; Reddy and Kumar 2006). In the present study, the applicability of the algorithms (NSGA II, NSGA III, and Eps MOEA), which are the improved version of the GA and MOEA, has been explored along with GA in reservoir operation problem for maximizing the storage and optimizing the outflow under the given set of constraints during the monsoon period where there may be a chance of flood due to uncertainties in inflow and other climatic factors.

2. Materials and methods

The literature review was carried out to understand the problem and monthly (Hydrological and Reservoir) data sets for the Ravishankar Sagar reservoir were obtained from June 1989 to May 2016. After preprocessing the data, mathematical problem formulation was carried out. Problem formulation consists of Objective Functions (OF) and constraints associated with the reservoir. An objective function is a variable of type scalar that enhances the performance of the system. The main target of the problem formulation is to either maximize or minimize the objective function as per the benefits associated with the reservoir (Irrigation, Environmental, Municipal, Hydropower, Flood control, etc.). The mathematical model is the mathematical performance of the real problem and can perform different aspects of the situation in an interpretable form. In the present study, our main concern is to Maximize storage under a given set of constraints in the Ravishankarsagar reservoir during high inflow or floods using metaheuristic algorithms. The objective function as shown in equation 1 is to maximize the difference between the storage and the outflow so that the maximum amount of storage within the limits of the reservoir can be utilized during floods.

$$\boldsymbol{Maxz} = \sum_{t=1}^{N} \boldsymbol{S_t} - \boldsymbol{Q_t} \tag{1}$$

$\boldsymbol{S_t}$ = Storage at each period t (MCM)
$\boldsymbol{Q_t}$ = Outflow from a reservoir in each period (MCM)
$\boldsymbol{t}$ = Time period in months

The hydrological constraints that are used in the reservoir operations include the mass balance constraint, equation 2 which describes the continuity equation of the reservoir and the Storage constraint as shown in equation 3 which defines that the storage is always in between the permissible storages of the reservoir and overflow constraints as shown in equation 4 and equation 5.

2.1 Mass balance constraint

$$\boldsymbol{S_{t+1} = S_t + I_t - Q_t - E_t - O_t} \tag{2}$$

$\boldsymbol{S_t}$ = Storage in each period t (MCM)
$\boldsymbol{S_{t+1}}$= Storage at next period t (MCM)
$\boldsymbol{I_t}$ = Inflow during the period t (MCM)
$\boldsymbol{E_t}$ = Evaporation from the reservoir during the time t (MCM)
$\boldsymbol{O_t}$ = Overflow at period t (MCM)

2.2 Storage constraints

$$\boldsymbol{S_{min}} \leq St \leq \boldsymbol{S_{max}} \tag{3}$$

$\boldsymbol{S_{min}}$= Minimum Drawdown Level
$\boldsymbol{S_{max}}$= Full Reservoir Level

2.3 Overflow constraints

$$O_t = S_{t+1} - S_{Max} \tag{4}$$

$$\boldsymbol{O_t \geq 0} \tag{5}$$

The selected model was then implemented on all four optimization algorithms i.e. GA, NSGA II, NSGA III, and Eps MOEA for the Ravishankar Sagar reservoir which is a multi-objective reservoir with various conflicting objectives. All four algorithms were then compared with the help of box plots. The detailed methodology flowchart is shown in Figure 1. The main aim of the present study is to maximize the storage and optimize the outflow from the Ravishankarsagar reservoir during the flood seasons under the given storage, overflow, and mass balance constraints as a release from the Ravishankarsagar reservoir highly influence the inflow to the downstream Hirakud reservoir. This study also finds the use and effectiveness of soft computing algorithms in the field of reservoir operations that would help the decision-maker to raise the water level to the maximum limit considering the safety of the dam and to store flood waters during monsoon season and to release it during the non-monsoon periods.

2.4 GA

The heuristic search and optimization methods known as genetic algorithms 'Select the best, discard the rest' to mimic natural evolution (Kumar Bhattacharjya and Holland 1992; Sastry, Goldberg, and Kendall 2005). John Holland developed GA in 1960. GA offers a group of highly prospective alternatives in which a suitable and effective solution to a specific issue can be found. GAs are a part of evolutionary computation, a considerably more diverse computing field. It is based on biologically inspired operators like mutation, crossover, and selection as shown in Figure 2. In the Genetic algorithm first initialization is done in which the initial population is generated randomly across the search space. After this, the offspring population is formed and the fitness value of solutions is evaluated. Then selection is performed which chooses the better solutions over the worse ones. Parent population crossover is performed to generate a new child population with possible better offspring solutions. Finally, the mutation is performed which modifies the solution. These steps are repeated until the termination criteria are met.

2.5 NSGA II

NSGA II is the updated and robust variant of the Genetic Algorithm due to its fast-sorting techniques. Its main parameters are feed rate, rotational speed, cutting speed, etc. Unlike the other optimization approaches, NSGA-II simultaneously optimizes each goal without being influenced by

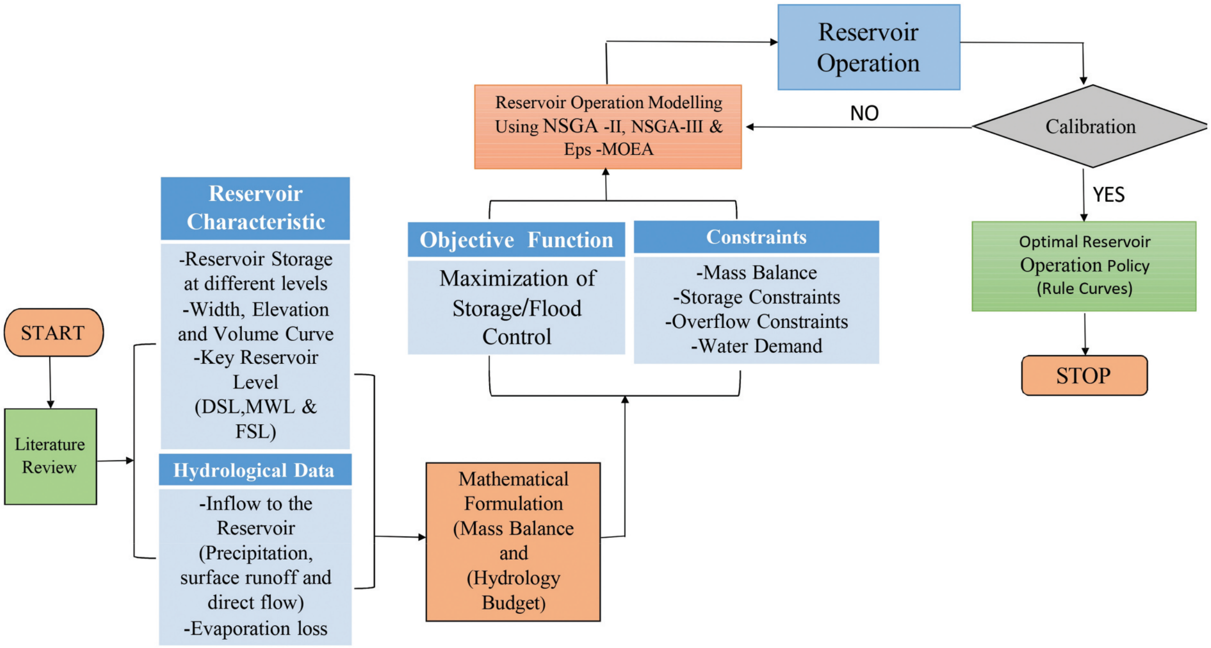

Figure 1. Flowchart of the applied methodology.

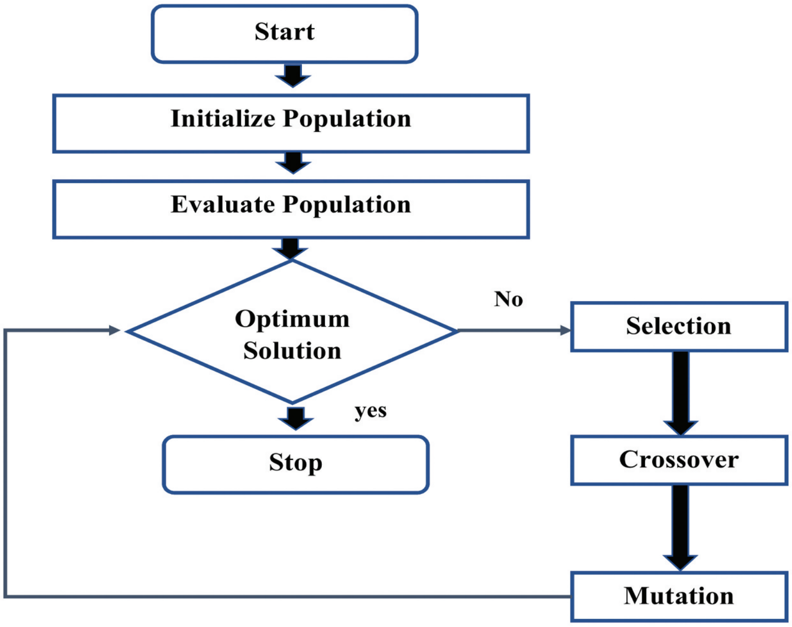

Figure 2. Concept diagram of GA.

other solutions (Deb et al. 2000; Murugan, Kannan, and Baskar 2009). At first, population initialization is done similarly to the earlier version of the non-dominated sorting Genetic algorithm, and a population Rt of size 2N is formed from the union of Pt and Qt as shown in Figure 3. The Rt population is then sorted using the non-domination criteria. F1 contains the best solutions from the combined population and as its size is smaller than that of N all the members of F1 will be selected for the new population Pt + 1. Similarly, the remaining members of population Pt + 1 are chosen from other fronts F2 and F3 according to their non-domination ranking. This process continues until there is no more space for the new solution. Generally, the total count of a solution is larger or smaller than that of the population size N. To overcome this, sorting from the last front F3 is done using the Crowded-Comparison operator which chooses the best solution from the last front and fills all the slots of size N. Further, Pt + 1 of size N is utilized for the Selection, Crossover, and Mutation to generate a new population of the same size N. Same process repeats till we reach the optimal solution. The concept diagram of NSGA II is demonstrated in Figure 4.

2.6 NSGA III

The NSGA-III is based on Reference Directions, which must be provided when the algorithm is in the initial state (Yuan, Xu, and Wang 2014). The initial population is made up of several solutions, and it is then expanded to include a number of child solutions (produced by crossover) and several mutant solutions (produced by population mutation). These make up the extended population, which is ranked according to dominance (to coincide with each front). The process is then

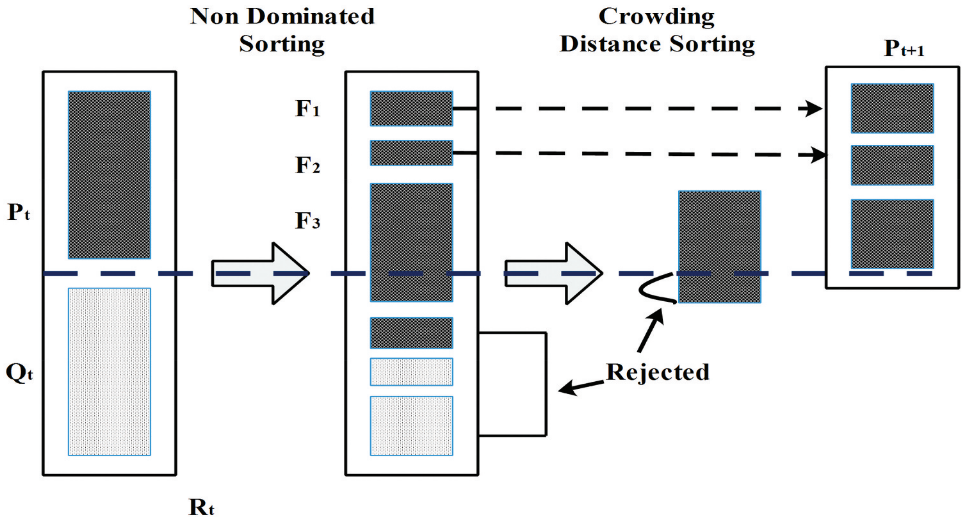

Figure 3. Process flow of NSGA II.

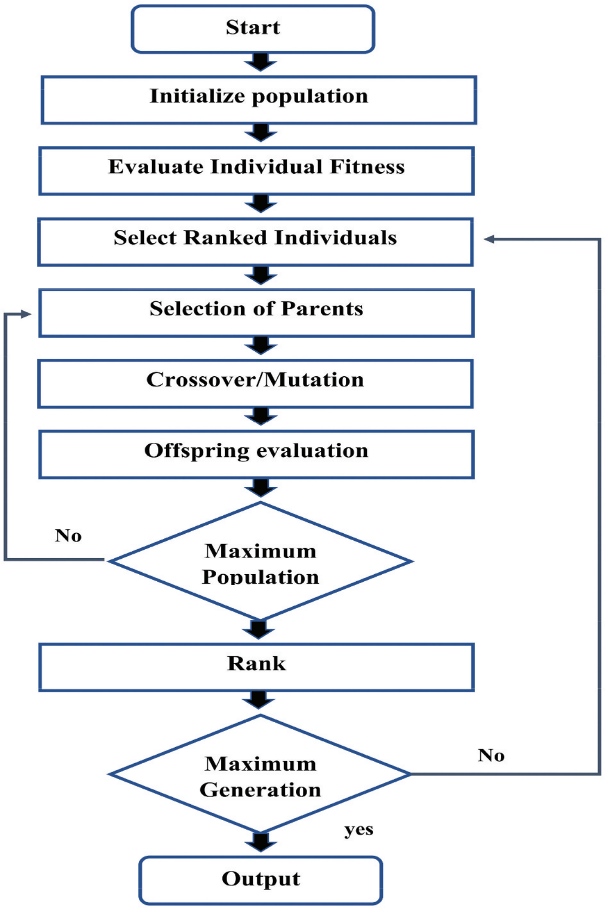

Figure 4. Concept diagram of NSGA II.

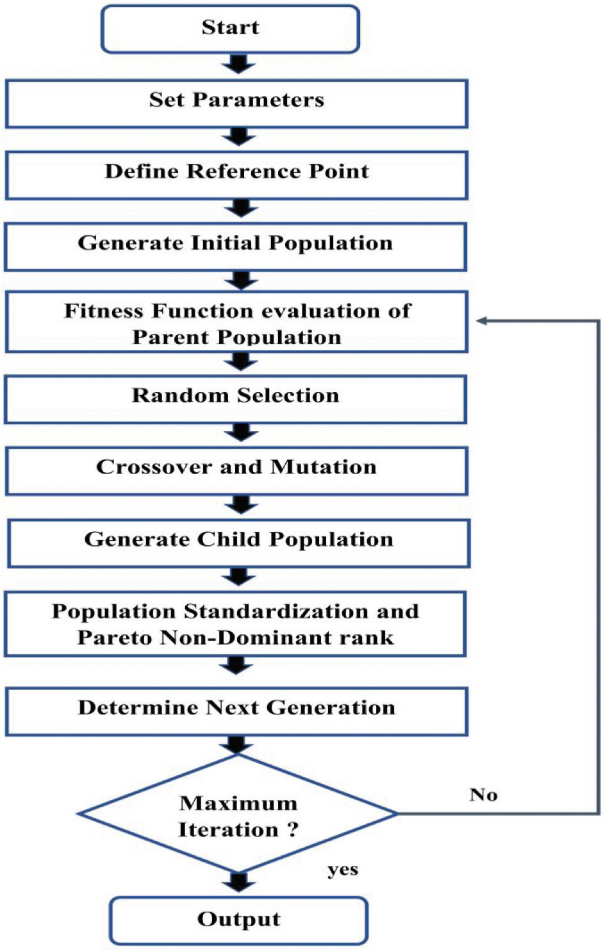

Figure 5. Concept diagram of NSGA III.

repeated with a truncation of the enlarged population to its original size. First, the non-dominated sorting is done like in NSGA-II. Second, some solutions must be chosen from the splitting front. The underrepresented reference direction is first filled by NSGA-III. The solution with the lowest perpendicular distance in the normalized objective space is the one that survives if the reference direction has no solutions assigned. If this reference line receives a second solution, it is given at random. The concept diagram of NSGA III is shown in Figure 5.

2.7 Eps MOEA

In Eps MOEA, two populations evolve concurrently. Two offspring are produced using one solution from each population. After that, each offspring is used to update both the parent and archive populations. To update the archive population the E-dominance concept is used, whereas the parent population is updated using a standard dominance concept (Fan et al. 2019). As the E dominance approach reduces the cardinality of the Pareto optimal set and a steady-state EA is proposed, maintaining a diverse group of solutions with a short computation time is possible. The concept diagram of Eps MOEA is shown in Figure 6.

3. Study area

Ravi Shankarsagar Reservoir is one of the largest storage structures formed by the construction of Gangrel Dam in 1978 (Pandya 1994). Figure 7 shows its location in the Mahanadi River basin in the Dhamtari District of Chhattisgarh, India. It is a multipurpose reservoir that serves irrigation, municipal, and industrial needs. Murumsilli and Dhudhawa are two reservoirs of the Mahanadi Basin that feeds the Ravi Shankar Sagar reservoir. The Ravi Shankar Sagar reservoir meets demand via two service canals: the Mahanadi Main Canal (MMC) and the Mahanadi Feeder Canal (MFC) (Anusha and Verma 2020). Ravishankar Sagar Reservoir has a surface area of 95.40 km^2 and a storage capacity of 910 MCM at the Full Reservoir Level (FRL) and 144 MCM at the Minimum Drawdown Level. The total catchment area of the Ravishankar Sagar Project is approximately 3,600 km^2, with the Dhudhawa reservoir intercepting 625 km^2 and the Murumsilli reservoir intercepting 486 km^2. Figure 8 depicts a schematic diagram of the Ravishankar reservoir.

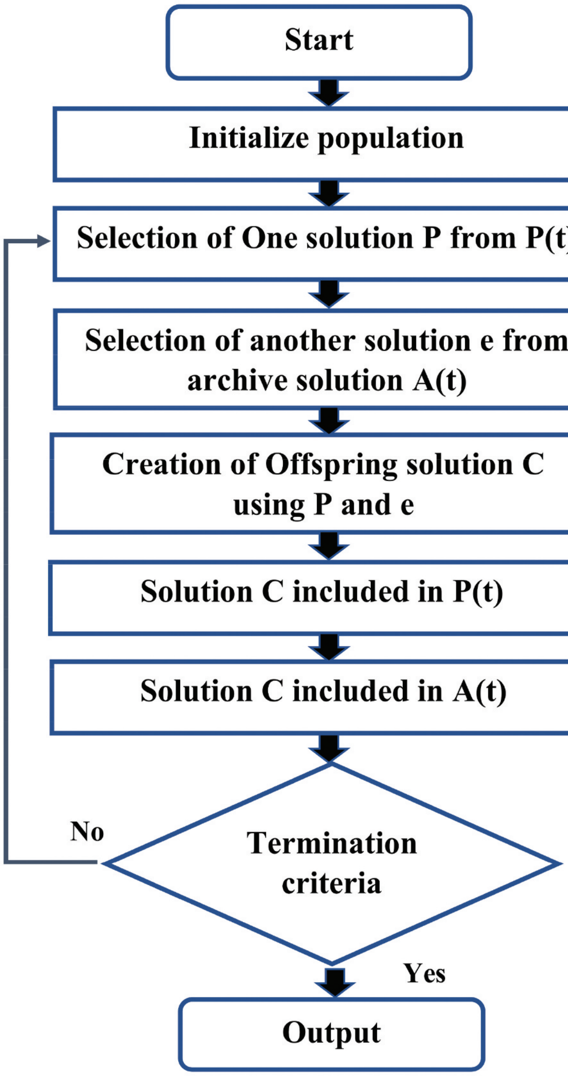

Figure 6. Concept diagram of eps MOEA.

4. Data collection

Reservoir operation requires a humungous amount of data which also depends on the number of stakeholders involved in the project. The model's capabilities to switch from planning to seasonal operations are defined by data, where planning includes historical data and seasonal operations include input data based on existing demand and inflow forecasts. Data required for Reservoir Operation includes Physical Data, Hydro-Meteorological Data, and Water Demand Data. Physical data refers to reservoir storage capacities as well as diversion channel flow capacities. The network definition is one of the most important aspects of the physical model data. Physical data includes the storage of reservoirs, Elevation Area Volume curves, Key reservoir Levels, and Channel capacity. Hydro-Meteorological Data comprises various input files in the form of time series. This data covers time series inflow to the reservoir and Evaporation and precipitation data time series. Reservoir outflows are influenced by water demands as a result of a variety of factors in any River Basin Network. Demands must be met regularly to assess the viability of any model. Water demand depends on the type of topography, climatic conditions, and anthropogenic conditions of the geographical area. This data includes Environmental flow targets and reservoir conservational demand time series data. Data on a monthly time-step basis was used from June 1989 to May 2016 as a simulation period. The time series plot of the storage data is shown in Figure 9. The mean of the storage values comes to be 570.1 MCM with a minimum value of 149.3 MCM and a Maximum value of 920.6 MCM.

5. Results and discussions

5.1 Sensitivity analysis

Sensitivity analysis can be used to screen out the sensitive parameters of the algorithm used in nonlinear reservoir operations problems. Sensitivity analysis helps in finding parameters, especially in large-size real-world problems (Srinivas et al. 2014). Sensitivity analysis was performed for all three algorithms to find out the sensitive parameters and tune them to get optimal results. A code for sensitivity analysis was written in Python and later on, the calibration of the model was performed.

5.1.1 Sensitive analysis of GA

Population size was varied from 100 to 1200 and peak was observed in the range of 1050 to 1150. Later the population size was again varied from 1050 to 1150 to find the optimal population size and the peak was observed at 1140 as shown in Figure 10. The model run was performed at a population size of 1200.

5.1.2 Sensitive analysis of NSGA II

Trial runs of Population size were done from 100 to 1200 to get the optimal results. Peak was observed from 50 to 150. Later again, the population size varied from 50 to 150, and a population size of 100 was taken for the model run as shown in Figure 11.

5.1.3 Sensitive analysis of Eps MOEA

In Eps MOEA, population size, and another parameter, epsilon, were varied for the different ranges to get the optimal values of the parameters. Epsilon is one of the main parameters of the Eps MOEA algorithm which allows the good diversity of solutions to be maintained in the population size. The epsilon dominance concept is used to update the archive population while the usual dominance concept is used to update the parent population in this algorithm. Population size was varied from 100 to 1200, and the maximum value of the objective function comes at the population size of 190, as shown in Figure 12. The maximum objective function value was observed at the epsilon of 0.05, as shown in Figure 13.

5.1.4 Sensitive analysis of NSGA III

In NSGA III, population size varied from 100 to 1200 and an optimal value of objective function was observed around 1110, as shown in Figure 14. Division outer was varied from 1 to 20. The maximum value of the objective function was achieved at a value of 12, as shown in Figure 15

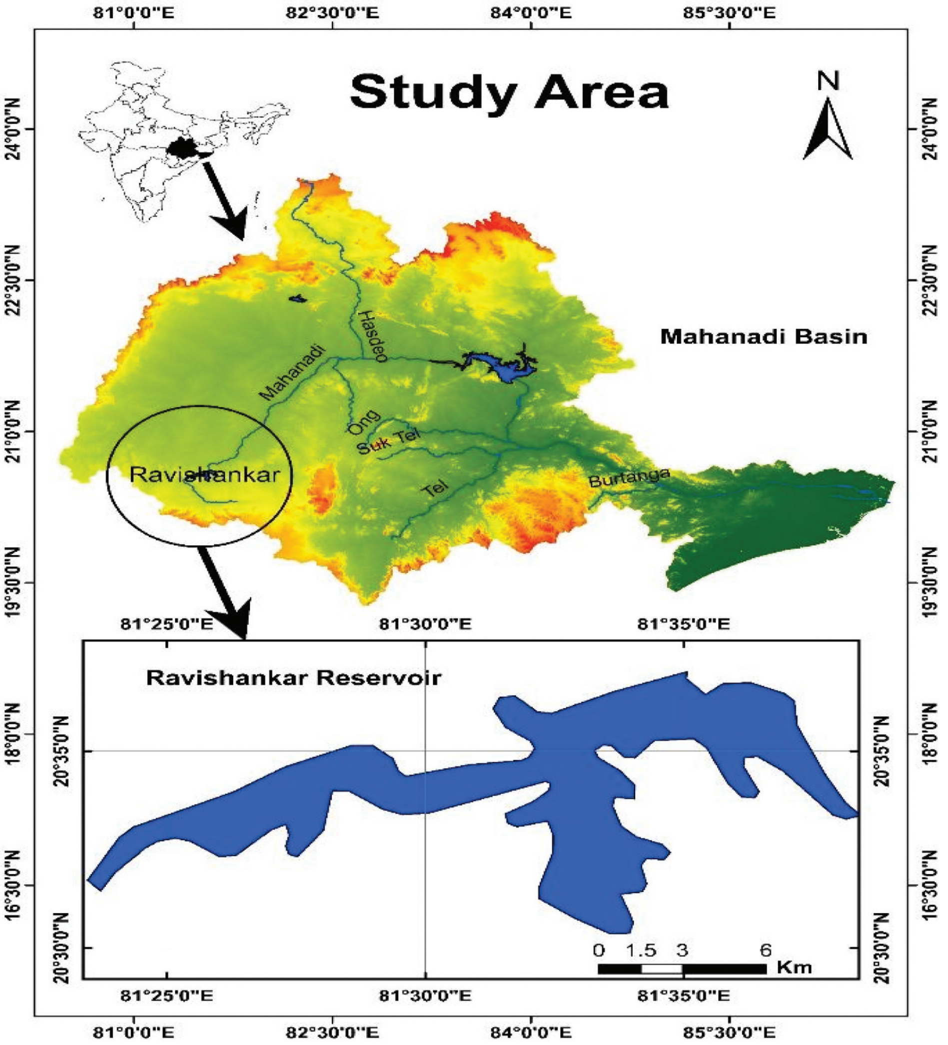

Figure 7. Map of study area.

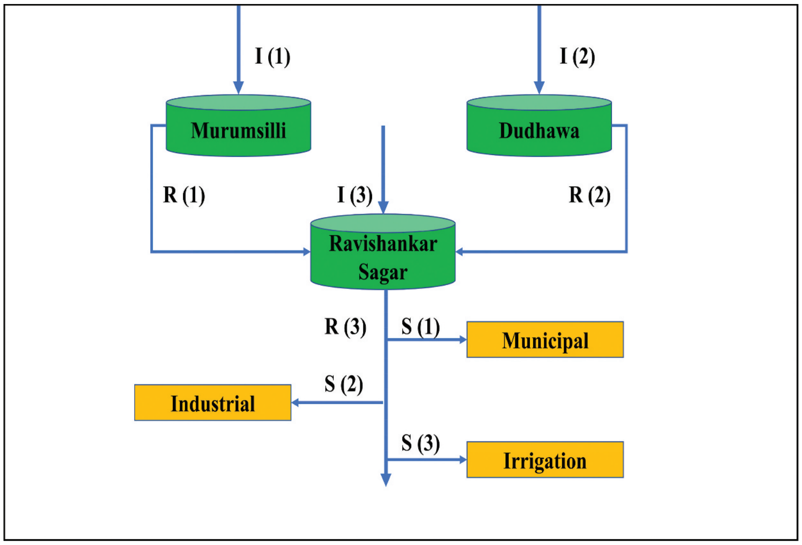

Figure 8. Schematic diagram of Ravishankar Sagar Reservoir.

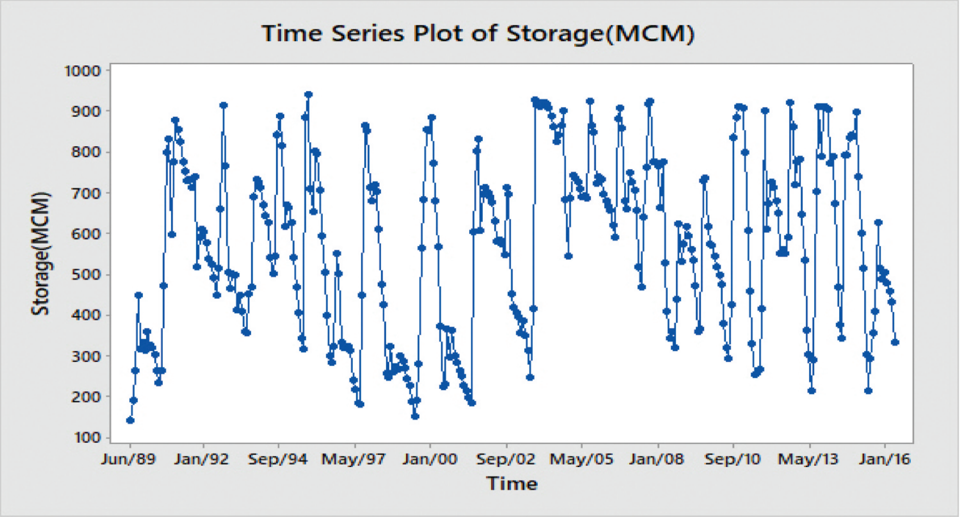

Figure 9. Time series plot of storage data.

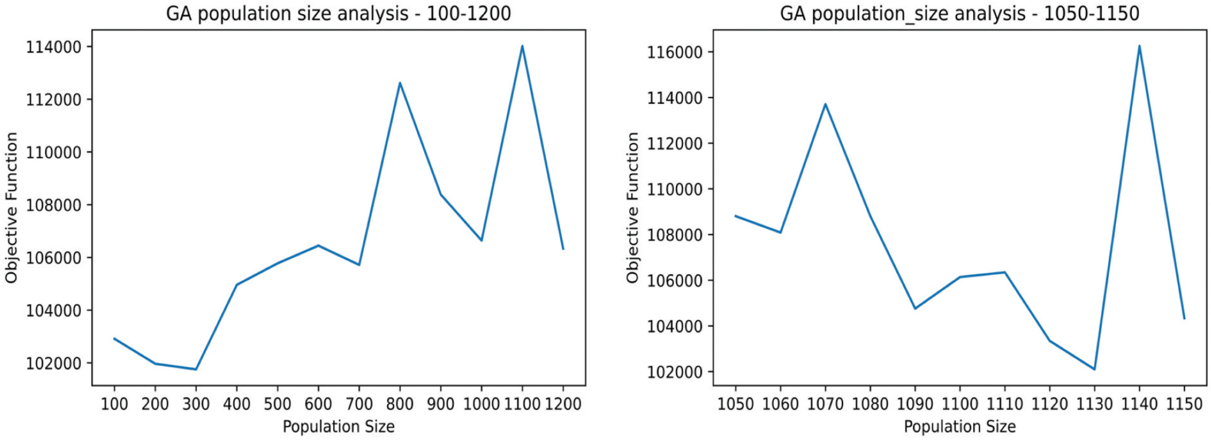

Figure 10. Variation of population size - GA.

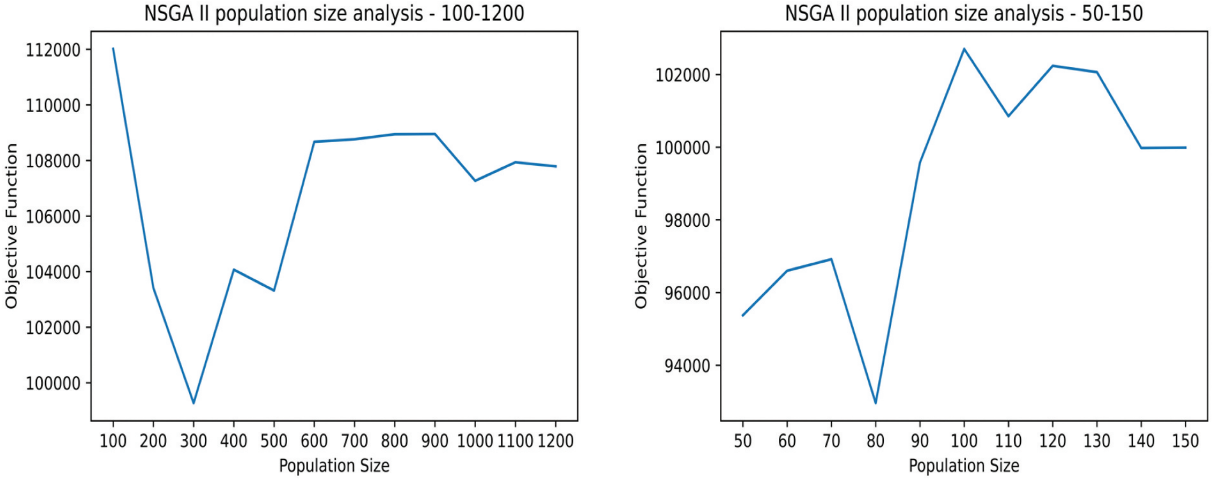

Figure 11. Variation of population size - NSGA II.

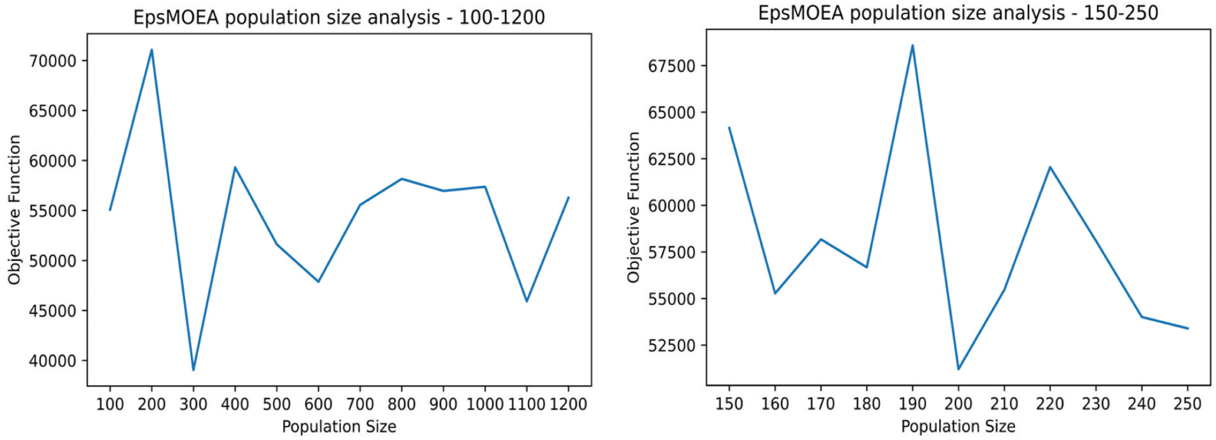

Figure 12. Variation of population size- eps MOEA.

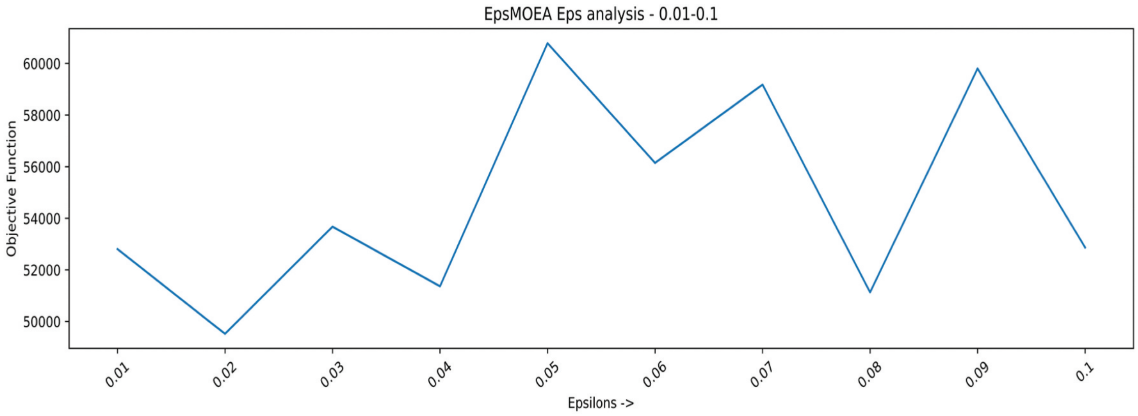

Figure 13. Variation of epsilon – eps MOEA.

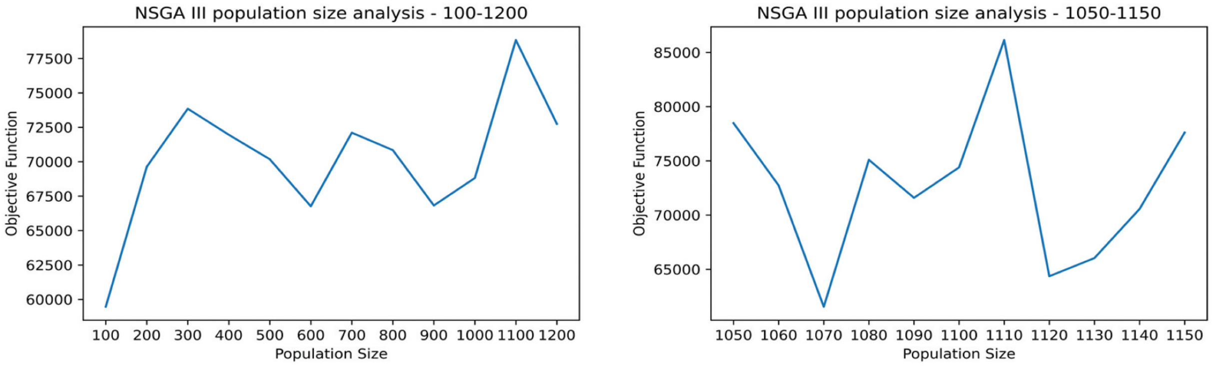

Figure 14. Variation of population size - NSGA III.

5.2 Optimization results

After sensitivity analysis, the model run was performed from June 1989 to May 2016. The release policy from all three algorithms is in terms of Storage (MCM) and Outflow (MCM). The objective function is the maximization of Storage under a given set of constraints. Figure 16 compares the Storage and outflow policy obtained from the GA, NSGA II, Eps MOEA, and NSGA III during the study period. The variability of the storage policies of the Ravishankar Sagar Reservoir is presented as a box plot. Figure 17 represents the storage values from the GA, NSGA II, Eps MOEA, and NSGA III for the study period in the box plot. The middle line of the box plot represents the median value, while the lower and upper boxes represent 25% and 75% of the whole data. The comparison is made for a precise analysis of the optimization techniques. Based on the evaluation

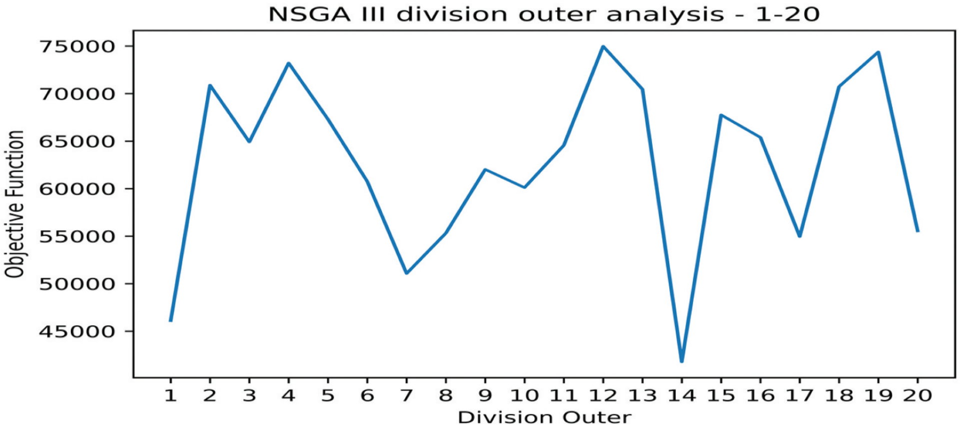

Figure 15. Variation of division outer.

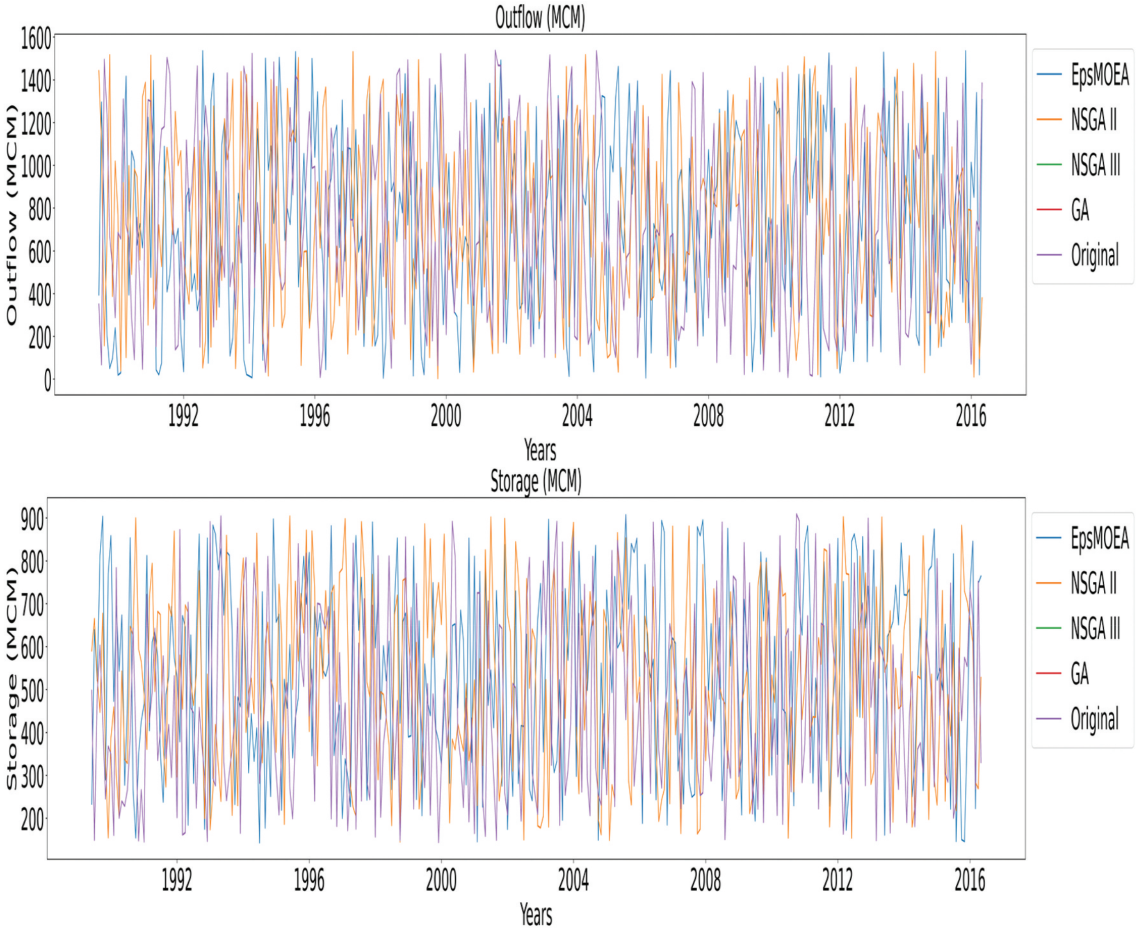

Figure 16. Comparison of three algorithm.

parameters for lowest Standard Deviation, highest Median, and Minimum lowest Storage, Eps MOEA shows the least standard deviation and highest Median as per the formulated objective function for flood control. NSGA III might work better than NSGA II in multi-objective optimization problems, but NSGA II results in a less standard deviation as per the present research compared to NSGA III. NSGA II has a high median and less standard deviation than that of GA. In the case of a single objective function also NSGA II outperforms GA in terms of median and standard deviation. Maximum and Minimum storage values of all the algorithms are in a similar range with a significantly less difference of around 20 MCM. All the algorithms perform almost equally with very little difference in storage values with the most optimum storage obtained from the Eps MOEA algorithm. The effectiveness of these algorithms in reservoir operation problems is also reported in other literature with different objective functions and constraints (Chen et al. 2020; Lei et al. 2018; Reddy and Kumar 2006). The table for

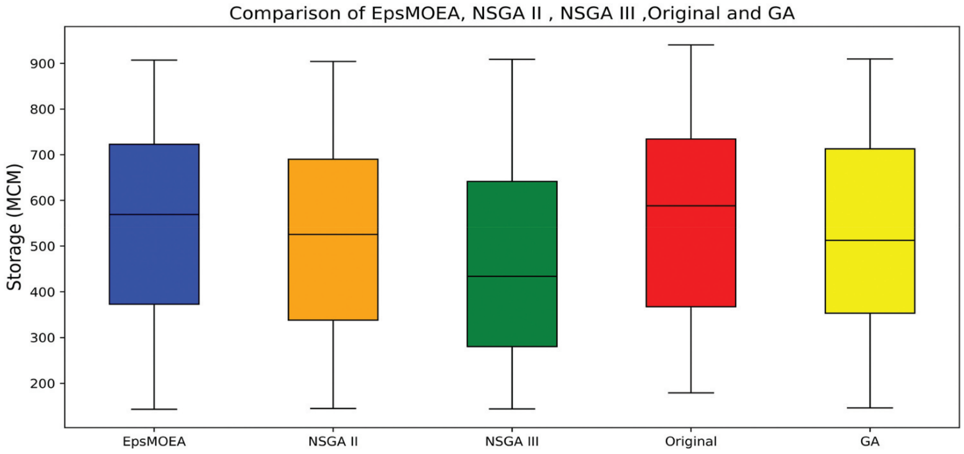

Figure 17. Box plots.

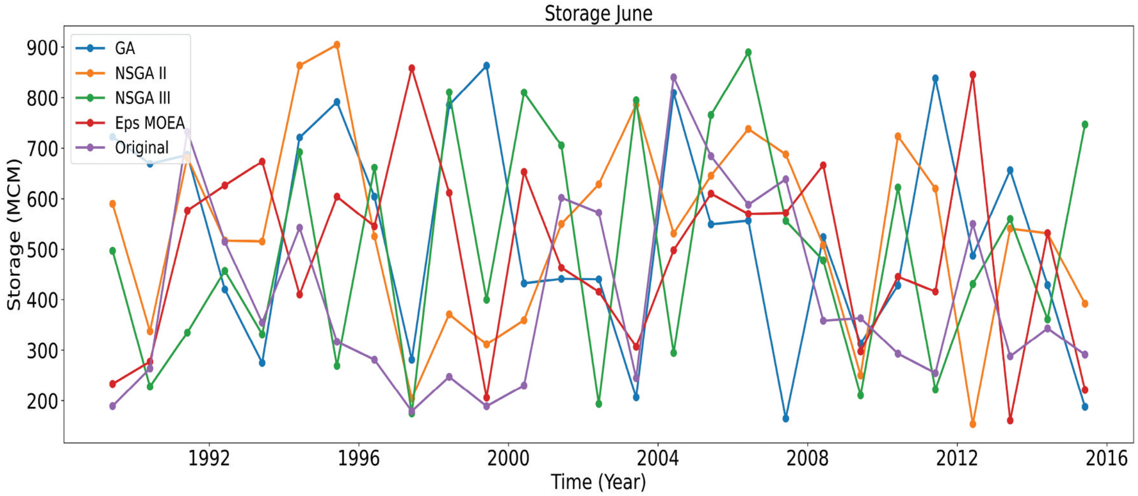

Figure 18. Graphical representation of algorithms storage with actual storage for June.

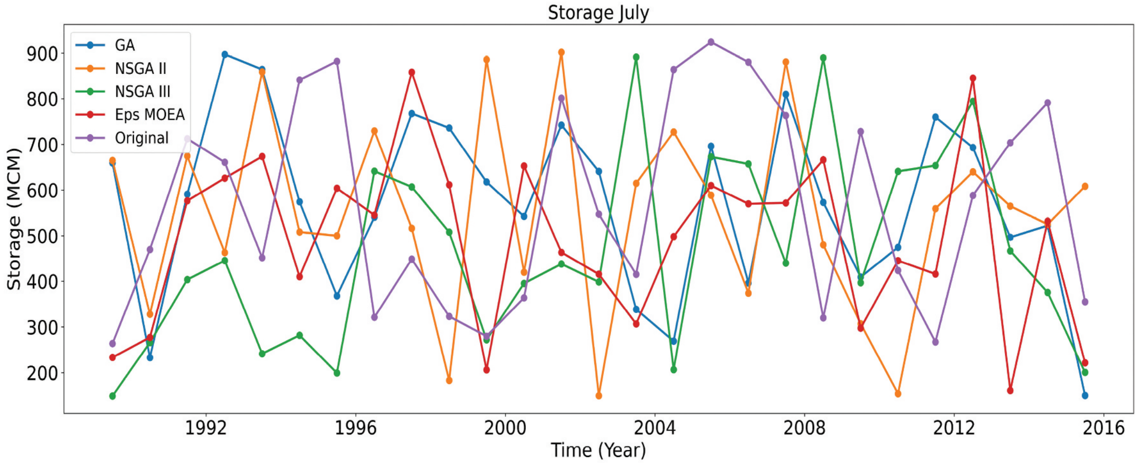

Figure 19. Graphical representation of algorithms storage with actual storage for July.

comparison of algorithms evaluation parameters is shown below as Table 1.

A graphical representation of the monthly operating policy during the monsoon season (June–September) obtained by the four algorithms after sensitivity analysis along with the original storage are shown in the figures below (Figures 18-21). Monsoon season is only considered as the prime objective of this research was to maximize the

Table 1. Evaluation parameters of algorithms.

Algorithms	GA	NSGA-II	Eps MOEA	NSGA-III
Standard Deviation	359.52	351.93	349.68	361.09
Median	512.5	525.36	568.96	433.79
Minimum	146.11	144.83	143.02	143.95
Maximum	909.8	904.28	907.21	909.7

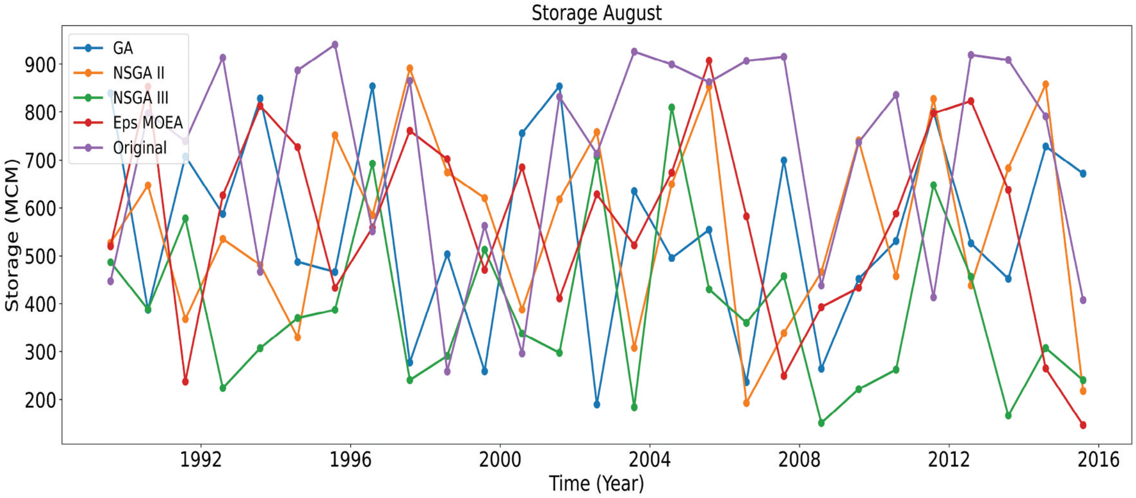

Figure 20. Graphical representation of algorithms storage with actual storage for August.

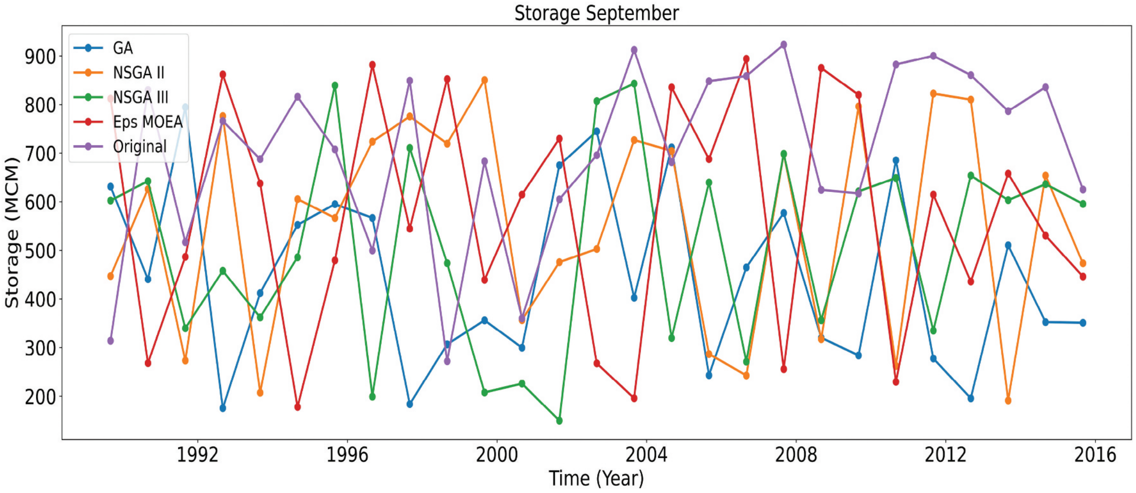

Figure 21. Graphical representation of algorithms storage with actual storage for September.

storage and store water during the monsoon season and to avoid floods in the downstream regions. The mean during only four monsoon seasons (June–September) was 525.85 for GA, 538.67 MCM for NSGA II, 465.46 MCM for NSGA III, 553 MCM for Epsilon MOEA, and 522 MCM for original storage. During the Monsoon season, NSGA II and Epsilon MOEA performed very well. It has been observed in Figures 20 and 21 that there are some points in the conventional policy in which storage exceeds 909 MCM but all three algorithms performed well and were under the full reservoir level. These algorithms performed well under the given set of constraints and have a huge application in the real-world problem of water resource engineering.

6. Conclusions

Decision-making is frequently and wisely supported by the use of optimization models in the field of Water Resources Management (Abdulbaki et al. 2017; Eusuff 2004). Many times, the issues that need to be solved are intricate, non-linear, and most likely sold as an extraordinarily vast variety of possible solutions. Because of this, it is practically impossible to find a range of alternatives that offer a wide range of trade-offs between challenging goals, such as minimizing costs and increasing production. There are some manipulating and implicit optimizing strategies, where the best result discovered is surrounded by domain expertise, practice, and intuition. In this study, four metaheuristic optimization techniques, GA, NSGA II, NSGA III, and Eps MOEA, are applied to the reservoir operations problem; and the usefulness of these algorithms is explored. In this model, the Storage is maximized, satisfying the flood control rules within the limitations of other reservoir physical constraints. After applying sensitivity analysis to all four algorithms, the storage policies from the algorithms are compared. The results of all four models showed closer matching. From the box plot, the most optimal Storage values were observed in Eps MOEA, with the least standard deviation making it quite promising and useful in the generation of reservoir operational policies. All the four algorithms performed well under a given set of constraints and can be effectively used in water resources management and planning. However, it may be inferred that the future scope should be more concentrated on and concerned with examining the relationship between hydrological variables and the impacts of climate change on the future operation of Reservoirs under different climate scenarios under climate change strategies. As climate change can greatly influence the operation of reservoirs.

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Disclosure statement

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Conceptualization Rajan Dabral; Methodology Rajan Dabral.; Software, Rajan Dabral; Validation Rajan Dabral and Har Amrit Singh Sandhu.; Formal analysis, Claudia Cherubini.; Investigation Har Amrit Singh Sandhu.; Resources Rajan Dabral and Har Amrit Singh Sandhu.; Data curation Rajan Dabral and Har Amrit Singh Sandhu.; Writing – original draft preparation, Rajan Dabral; Writing – Rajan Dabral and Har Amrit Singh Sandhu.; Claudia Cherubini; supervision Har Amrit Singh Sandhu.; project administration Har Amrit Singh Sandhu and Rajan Dabral.; funding acquisition Har Amrit Singh Sandhu. All authors have read and agreed to the published version of the manuscript"..

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