Larhyss Journal, ISSN 1112-3680, n°61, March 2025, pp. 31-52

OPTIMIZED OPERATION OF A MULTIPURPOSE RESERVOIR BY EVOLUTIONARY ALGORITHM FOR PANAM RESERVOIR PROJECT IN EASTERN GUJARAT, INDIA

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Research Article – Available at http://larhyss.net/ojs/index.php/larhyss/index
Received May 6, 2024, Received in revised form February 25, 2025, Accepted February 27, 2025

ABSTRACT

Survival of lives with satisfying their water-based demands becomes a challenging task for water resources engineers in upcoming times. The only way to optimize potential solutions is to manage current water resources with greater attention, plan ahead and conserve them by using appropriate optimization strategies. Owing to the drawbacks of traditional optimization methods, an evolutionary algorithm-based approach inspired by nature is implemented to determine the operational strategies of challenging reservoir systems that exist in real life. Evolutionary Algorithm (EA) namely Genetic Algorithm (GA) has been developed with primary objective to establish operational strategies for Panam reservoir project, located in eastern part of Gujarat, India. In this study, the objective function is to minimize the annual sum of squared deviation from intended irrigation release and desired storage volume. The GA model was run with ten years of inflow, release, demand, surplus and evaporation data to derive an optimal reservoir operational policy. Releases from the reservoir for domestic, industrial and irrigation purposes during concern time period are the decision variables; these are subject to restrictions on the reservoir's mass balance, storage capacity, release and surplus. The results obtained shows that a minimum of 46.67 Mm^3 and a maximum of 415.83 Mm^3 of water may be saved in the water year 2018-19 and 2019-20, respectively. When produced results were compared to the actual releases, it emerged that GA greatly outperformed traditional optimization techniques in satisfying downstream demands and the reservoir's optimal operation may save significant quantities of water.

Keywords: Evolutionary Algorithms (EA), Genetic Algorithm (GA), Reservoir optimization.

INTRODUCTION

Biologically motivated adaptive systems are becoming more and more popular for a means of resolving problems related to optimization. The genetic algorithm (GA) is gaining a lot of attention due to its versatility and efficiency in improving complicated systems, making it one of the most promising methods in the field of natural adaptive system evolutionary algorithms paradigm. Below is a discussion of several researchers' perspectives on applying the GA approach to reservoir optimization operations (Mezenner et al., 2022; Trivedi and Suryanarayana, 2023; Zegait and Pizzo, 2023; Verma et al., 2023a; Shaikh et al., 2024).

Multiple researchers found out that one of the more sophisticated strategies for attaining of water scarcities is to optimize the reservoir's operations (Remini and Ouidir, 2017; Boutoutaou et al., 2020; Hountondji et al., 2020; Remini, 2020). However, Reservoir operation management optimization is a collection of strategies that include optimizing or minimizing reservoir contributes without compromising the reservoir's objective functions and constraints. Traditional approaches, such as linear, non-linear, and dynamic programming, have limitations when it comes to resolving real-world, practical engineering issues (Lai et al., 2022). Also, several relevant studies, such as Ahmad et al. (2014), Singh et al. (2022), Kezzar and Souar (2024), Kouloughli and Telli (2023), and Berrezel et al. (2023), quoted that optimization is a tool for water resource system planning and management. Singh (2012) talked about how optimization approaches are used in a variety of contexts, including conjunctive planning, irrigation management (Faye, 2016; Rezzoug et al., 2016), optimal cropping patterns, groundwater intrusion (Morsli et al., 2017), management of reservoir system operation, resource management in arid and semi-arid regions (Boubakeur, 2018), and solid waste management (Ahmad et al., 2014).

Evolutionary algorithms have been proven to be more efficient than traditional approaches in tackling complicated multi-objective problems because they may evaluate all objective functions simultaneously in a Pareto sense (Jahandideh-Tehrani et al., 2019). Therefore, when traditional approaches are unable to provide the best response, evolutionary algorithms are frequently employed to address complex optimization problems (Haddad et al., 2016; Jahandideh-Tehrani et al., 2019, 2021). The implementation of evolutionary algorithms in the field of reservoir operation has greatly enhanced our ability to organize and manage intricate reservoir systems (Jahandideh-Tehrani et al., 2021).

Mohan and Vijayalakshmi (2009) said that Gas have been developed by Holland (1975), further developed by Goldberg (1989) and others in the 1980s. GA is an example of a search procedure that uses random choices as a tool to guide a highly exploitative search through the coding of a parameter space. Holland formulating genetic algorithms grounded in the principles of survival of the fittest and biologic advancement (Mohan and

Vijayalakshmi, 2009). Chang et al. (2010) stated that evolutionary computation methods, such genetic algorithms, have gained prominence recently in science and engineering for global optimization applications of reservoir planning and management. Furthermore, Gas can deal with challenging management and planning issues. A lot of interest has been paid to evolutionary computation approaches because of their potential for use in challenging system optimization (Chang et al., 2010). Chandwani et al. (2013) described that Inspired by Darwin's "Survival of the Fittest" theory, genetic algorithms that operate on the reproduction, crossover and mutation operators of natural evolution can determine the globally optimal solution to a given issue (Chandwani et al., 2013).

Recently, in a study of Verma et al. (2024), the robust metaheuristic algorithm whale optimisation algorithm (WOA) was compared to the assessment of an existing operating strategy for a multi-reservoir system performed by employing grey wolf optimisation (GWO) and findings indicated that GWO was the most effective approach and it is recommended as a trustworthy and promising technique for optimising multi-reservoir systems (Verma et al., 2024).

Hınçal et al. (2011) discovered the efficiency and effectiveness of GA in optimization of multi reservoirs in the Colorado river storage project, U.S. for maximization of energy production. Their study determined that The GA proved to be efficacious and offers a viable substitute for conventional optimization methods since the sensitivity analysis of the GA model suggested optimal values for population size, generation number, crossover frequency and mutation (Hinçal et al., 2011). To determine optimal reservoir operating policies, Momtahen and Dariane (2007) proposed a real coded GA based optimization method. In which a single reservoir system is subjected to several reservoir release rules, including linear, piecewise linear, fuzzy rule base, and neural network, and the results are compared with traditional models such as stochastic dynamic programming, dynamic programming and regression. The current and previous study's outcomes indicated GA models were generally superior in identifying better expected system performance (Momtahen and Dariane, 2007).

Moreover, following are the major differences that exist between Genetic Algorithm and conventional optimization techniques (Ahmed and Sarma, 2005; Chang et al., 2005; Jothiprakash and Shanthi, 2012; Mohan and Vijayalakshmi, 2009; Sivanandam and Deepa, 2008):

1. GAs utilize coded representations of the problem's parameters rather than the parameters themselves; in other words, they deal with the solution set's coding rather than the solution itself.
2. Although almost all traditional optimization methods start their search at a single point, GAs always works on a population of points or strings; in other words, GAs uses a population of solutions rather than a single result from searching. This robustness of genetic algorithms helps to avoid local stationary points and increases the probability of achieving the global optimum.
3. GAs evaluates utilizing a fitness function as instead of derivatives. They can therefore, be applied to any kind of optimization problem.

4. Conventional approaches for continuous optimization employ deterministic transition operations, whereas GA applies probabilistic ones.

In order to determine the best operating methods for the objective function of minimizing the annual sum of squared deviation from the target irrigation release and desired storage volume, a GA model was established and applied to the Pechiparai reservoir and Kodaiyar basin in Tamil Nadu, India by Jothiprakash and Shanthi (2012). The reservoir's releases for irrigation and other demands (which include demands from industry and municipalities) are the decision variables. Lastly, determined that GA model could give better performance in real world operation of the reservoir (Jothiprakash and Shanthi, 2006; 2012).

Adeyemo (2011) developed EAs for reservoir operations and their results display EAs are useful tools for addressing multidimensional, non-linear, convex and complex reservoir problems and produce trade-offs to reservoir operation problems for which a reservoir operator can choose the solution applicable to situation (Adeyemo, 2011). Another study explained that a comprehensive review of innovative methods and their applications in the field of water resources planning and management is offered by evolutionary algorithms (EAs), along with the scope of EAs in the areas of groundwater systems (Zegait et al., 2021; Deb, 2024), urban drainage and sewer systems, water distribution systems (Pandey et al., 2022; Rouissat and Smail, 2022; Patel and Mehta, 2022), hydrologic and fluvial modelling (Qureshi et al., 2024), wastewater treatment (Aroua-Berkat and Aroua, 2023; Mumthaj et al., 2023; Zaid et al., 2023; Yadav et al., 2024), water strategy (Aroua, 2022), and irrigation and methods of water harvesting (Derdour et al., 2022). Evolutionary algorithms have consistently shown themselves to be adaptable and powerful tools in solving complex water resources problems.

Verma et al. (2022) employed simulated annealing (SA), a popular heuristic technique, to determine the best operating strategy for multi-reservoir systems, especially the Ravishankar Sagar, Dudhawa, and Murumsilli reservoirs in Chhattisgarh, India. The results indicate that the current multireservoir system's overall performance has improved by an average of 28.09%, 10.12%, and 36.49% in the areas of sustainability, resilience, and dependability, respectively, while vulnerability has decreased by up to 11.83%. In a nutshell SA represents an exciting and promising strategy for reservoir optimization search. Another Modified particle swarm optimization (MPSO) algorithm was also established by Verma et al. (2023b) for Mahanadi reservoir complex in Chhattisgarh and found to be performed better than PSO. (Verma et al., 2022; 2023).

The GA approach is also presented by Sharif and Wardlaw (2000) for the optimization of multi reservoir systems in Indonesia. They developed the GA model for reservoir system optimization that is easily adaptable to any reservoir system and offers the unique advantage of employing a genetic algorithm (Sharif and Wardlaw, 2000). Additionally, a number of GA alternatives for reservoir systems are developed by both and the four-reservoir, deterministic, finite-horizon problem is applied to assess them. Their study concluded that, real-value coding provides superior outcomes and works much faster than binary coding. Furthermore, the GA technique is a viable substitute for stochastic dynamic programming techniques since it is reliable, simple to apply to complex systems (Wardlaw and Sharif, 1999).

Hakimi et al. (2010) stated Probabilistic search algorithms known as genetic algorithms can be used to solve a wide range of challenging multi-objective optimization problems, including those involving non-linear, non-convex, and multimodal functions. Moreover, GA is a population-based approach to global search that can identify the global optima while avoiding local optima traps (Hakimi et al., 2010). Another GA optimized rule curve model established by SeethaRam for multipurpose Bhadra Reservoir Project in Karnataka State, India to generate far more power than the previous operation did without sacrificing the irrigation demands, and to optimize the amount of hydropower generated while satisfying the needs for irrigation (SeethaRam, 2021). A set of optimal operation policies for a multipurpose reservoir system, namely Bhadra Reservoir system, in India is derived by Reddy and Kumar. Multi-objective Genetic method (MOGA), an evolutionary method created by Reddy and Kumar, provides a Pareto optimal set for reservoir operation (Reddy and Kumar, 2006). Ahmad et al. (2014) quoted that researchers Chang and Chen (1998) who compared real-coded GA and Binary-coded GA in the optimization of flood control reservoir model and concluded that compared to binary-coded GA, real-coded GA is more accurate and efficient (Ahmad et al., 2014).

Mehta et al. (2023) reviewed reservoir operation policies employing a variety of algorithms, such as the genetic algorithm (GA), the artificial fish swarm algorithm (AFSA), the particle swarm optimization algorithm (PSOA) (hybrid approach), the Jaya algorithm, the multiobjective evolutionary algorithm (MOEA), and the honey-bee mating optimization (HBMO) algorithm. They were able to successfully demonstrate the effectiveness and utility of multiple algorithms for evolving multiobjective reservoir operation policies (Mehta et al., 2023).

Researchers Hossain and El-Shafei (2013) reviewed the paper of Deepti and Maria (2009) and found that since GA uses a population of responses rather than a single solution to search for the optimum, it is more likely to find a global optimal solution that is closer to or accurate than conventional optimization or gradient search approaches (Hossain and El-Shafei, 2013). Maliwal et al. (2019) created a genetic algorithm-based system for calculating real-time reservoir release schedules before and after heavy flooding (Maliwal et al., 2019).

The GA model has been created in this work to guide operational strategies for a reservoir system in Panam This paper aims to illustrate the suitability of the GA approach for optimizing a multipurpose reservoir system. Specifically, it will determine an objective function that minimizes reservoir releases while satisfying demands and conserving water for future use. Release of the reservoir for irrigation, domestic and industrial water demand in each month of the water year starting from 2011-12 to 2020-21 subject to constraints on reservoir storage capacity, release, surplus, and mass balance are the decision variables. Each decision variable is coded into strings, with the upper and lower bounds specified. The fitness of each string is then calculated. Reproduction, crossover, and mutation functions are employed to operate these strings.

STUDY AREA AND DATA COLLECTION

Panam Reservoir Project is the study area that was selected for the purpose of this study.

It comprises of construction of a masonry dam across river Panam, a tributary of river Mahi near village Kel-Dezer of Shahera taluka of Panchmahal district, located on eastern part of the state of Gujarat, India, as seen in Fig. 1.

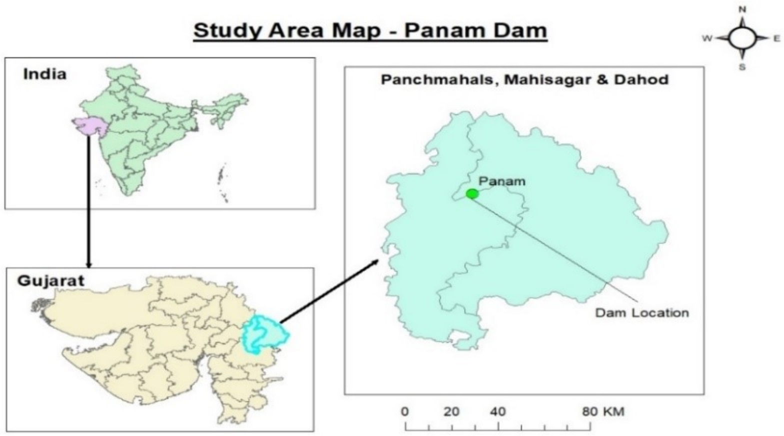

Figure 1: Location map of Panam Reservoir Project

Panam reservoir project details

The Panam River, a tributary of the Mahi River that originates in the Devgadh Baria Taluka of District Dahod, is covered by the Panam Dam. Twenty-five kilometers downstream of the Panam Dam, the Panam River enters the Mahi River. Table 1 displays key information regarding Panam Dam while Tables 2, 3 and 4 illustrate the silent features of the Panam Dam, Panam Reservoir and Panam Canal respectively (Patel and Parekh, 2022).

Table 1: Panam dam basic information

Basic Information	
Location	Vill.: Kel Dezar, Tal: Santrampur Dist.: Panchmahals
Purpose	Irrigation, Water Supply, Power Generation and Fisheries
River	Panam (Tributary of Mahi)
Area of catchment	2312 km^2
Mean annual rainfall in the catchment	26 MCM
Mean annual rainfall	940 mm
Year of commencement of construction work	1971
Year of completion	1999

Table 2: Panam dam construction data

Dam	
Type	Masonry
Bed Rock	Quartzite and Phyllite
Maximum height above the lowest point of foundation	56.36 m
Length at the top of the dam	269.45 m
Total Volume Content:	
Concrete	0.71 MCM
Masonry	2.88 MCM
Earthwork	2.68 MCM

Table 3: Panam reservoir data

Reservoir		
Area at full reservoir level		89.80 Km^2
Gross storage capacity @ FRL		578.18 MCM
Effective storage capacity (Live storage)		552.96 MCM
Dead storage		25.22 MCM
Reservoir Levels		
River bed level		86.50 m
M.D.D.L.		108.20 m
Crest level of spillway		116.730 m
F.R.L.		127.41 m
H.F.L.		128.015 m
Top of Dam		131.50 m
Area under submergence		
a) Forest	b) Waste land	c) Culturable
a) 1686 ha	b) 2075 ha	c) 5229 ha
No. of villages under submergence		6 partial, 36 full

Table 4: Panam canal data

Canal	
Length of canal	99.725 km
Capacity	21.00 m3/s
Gradient	1:7500
Gross command area	58273 ha
Culturable command area	36405 ha

DATA COLLECTION

To run GA model through MATLAB software, data collected from Panam river basin. In present study, monthly actual total release, irrigation and other demands (includes domestic and industrial demand), evaporation, spill out, previous month and current month reservoir storage etc. in Million Cubic Meter (MCM) are collected. The storage capacity bounds are determined by the reservoir's capacity at dead storage and full reservoir level, while the monthly actual release statistics are taken into consideration when making decisions about monthly demands. For the water years 2015-16 to 2019-20, Table 5 displays monthly actual release and monthly demand information in MCM.

Table 5: Monthly actual release and demand in MCM for water year from 2015-16 to 2019-20.

	2015-16		2016-17		2017-18		2018-19		2019-20	
Month	Actual Release	Demand	Actual Release	Demand	Actual Release	Demand	Actual Release	Demand	Actual Release	Demand
Jun	14.81	23.37	15.68	21.52	16.81	13.36	20.81	19.70	26.92	36.32
Jul	21.66	19.60	14.35	14.53	27.85	25.60	19.80	20.54	18.35	18.30
Aug	30.57	22.80	13.17	11.37	39.35	23.70	31.10	20.90	14.00	16.20
Sep	30.69	23.72	27.77	11.70	58.51	21.82	34.78	20.40	164.86	20.56
Oct	21.56	26.76	31.96	14.66	36.29	24.93	29.24	21.32	213.93	22.17
Nov	23.15	31.50	38.75	24.27	34.83	26.10	36.81	26.70	100.09	28.22
Dec	21.76	33.00	41.46	30.67	33.94	30.30	32.85	28.53	34.91	29.30
Jan	22.41	39.72	34.60	36.12	30.25	37.23	37.89	33.20	36.92	36.32
Feb	29.42	43.60	38.99	49.17	48.97	41.67	44.81	34.14	28.35	18.30
Mar	22.81	37.80	29.71	22.10	28.48	19.40	34.53	33.12	24.00	16.20
Apr	21.71	33.94	25.96	16.60	25.05	16.46	27.81	36.83	21.86	20.56
May	24.85	26.30	25.37	20.22	20.82	19.65	25.85	34.20	23.93	22.17

METHODOLOGY AND MODEL DEVELOPMENT

In the Panam reservoir system, total ten water years from 2011-12 to 2020-21 are considered to develop GA model. The process of solving a GA problem involves creating a string that can represent the decision variables that need to be recognized. According to the release rule for that month, the release will be determined by the amount of water in the reservoir that is available (initial storage and inflow during the current month). The chromosome that represents a solution to such a problem is made up of twelve genes (sub-string) that reflect the problem's decision variables (releases). There are twelve monthly releases for every year in the optimization process. The reservoir optimization process' methodology is better understood via the flowline displayed in Fig. 2.

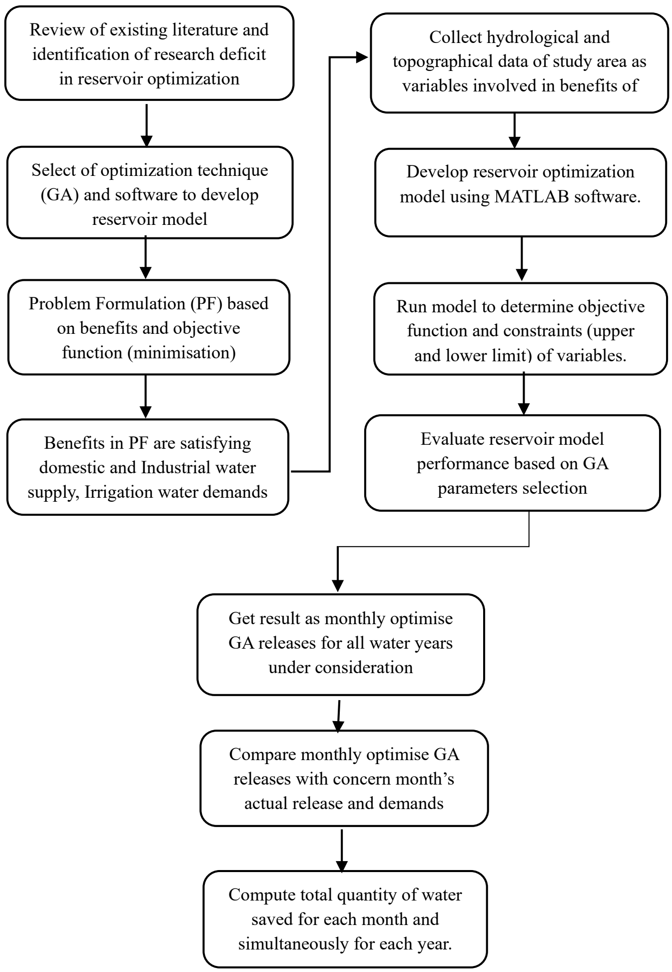

Figure 2: Flowline of Reservoir Operation Optimization Process

Genetic algorithm model development

The implementation of a genetic algorithm through self-developed MATLAB code offers complete control over genetic operations, including population, cross-over and mutation, as well as greater flexibility for developing constraints and penalty methods.

Additionally, software comes with an integrated toolbox for genetic algorithms, which offers an efficient method to do GA quickly and easily. The user has to input the upper bound, lower bound, constraints, objective function and other selection parameters in the GA toolbox. The toolbox itself offered strategies for conducting GA operations, including crossover, mutation, encoding, population and selection (Anas et al., 2019).

First, a random population is created using the genetic algorithm, and strings (also referred to as chromosomes) are used to code the variable sets as a set of solutions to the problem. The GA begins a problem's trial solution and applies an objective function to determine the problem's worth or "fitness." (Chang et al., 2005). The member with the highest fitness value survives for the new generation. After that, parents are selected according to their fitness value to perform crossing over (crossover). Children are produced either by making a random change in any parent (mutation) or interchanging the vector entries between a pair of parents (crossover). The next generation is then created by the algorithm substituting the children for the existing population. The procedure is repeated until the criteria are satisfied (Hossain and El-Shafei, 2013). Furthermore, Fig. 3 displays flowchart of genetic algorithm.

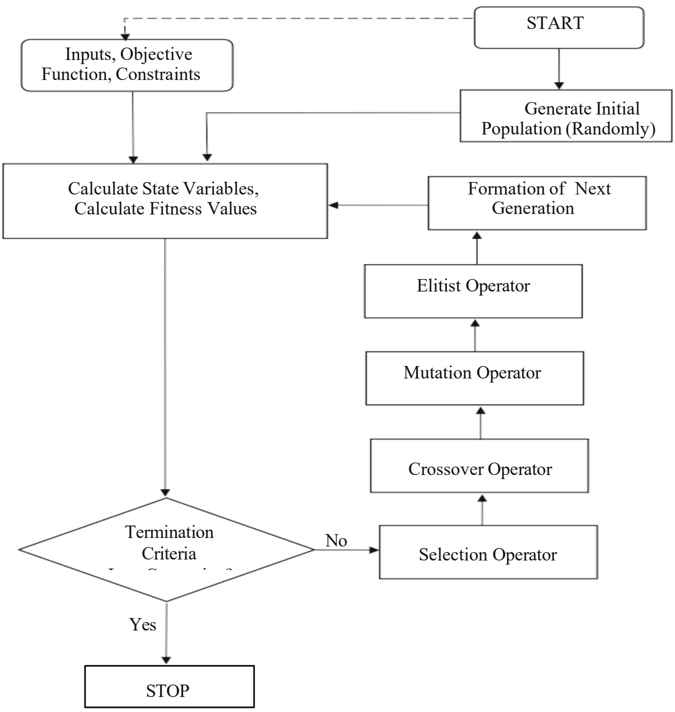

Figure 3: Flowchart of Genetic algorithm cycle (Hinçal et al., 2011)

In this GA formulation reservoir release rule is assumed to be connected piece-wise linear functions. The coordinates of the end points of the connected piece-wise linear functions should be determined since it is expected that the release rule comprises the connected piece-wise linear functions. Each endpoint consists of two coordinates viz. water available and release, which, in the GA formulation are unknown variables of the optimization problem. The operating policy that minimizes the fitness function is defined by the connected piece-wise linear release rule functions, and the objective is to find the coordinate of each end point.

The targeted irrigation release and storage volume's annual sum of squared deviations is used as the fitness function. The essential approach known as "Survival of the fittest" is applied to the strings to create the next generation followed the evaluation of the fitness function. More probable to be transmitted over to the subsequent generation are the strings with higher fitness. The following parameters needs to be chosen from a defined range in order to implement the genetic algorithm approach (Chang et al., 2005).

1. Population size (n) – usually 30–200.
2. Probability of crossover (Pc) – usually 0.5–1.0.
3. Probability of mutation (Pm) – usually 0.01–0.1.

Value of Pm are Pm ≥ 1/n and Pm ≤ 1/l, where n = population size and l = length of string.

Nonetheless, the coordinate values of the release rule function's extreme endpoints are known. Coordinates of the first point correspond to the condition, where no release can be made as water level reach to dead storage as 25.22 MCM. The coordinates of the last point refer to the situation of having maximum possible water available. At this point water available in excess of storage at full reservoir level as 578.18 MCM and must be released to avoid violating constraints of upper limit of reservoir storage.

The present evaluation adopts the monthly continuity equation for the system to relate release and storage at each period to inflow and spill. (Haddad et al., 2016, 2017; Jahandideh-Tehrani 2019).

$$Sr\,(t) - Sr\,(t+1) + Inf\,(t) - Ep(t) - R\,(t) - Sp(t) = 0 \tag{1}$$

According to the optimization model, the primary goal of reservoir operation is to determine the optimal water allocations to meet individual demands without compromising the system and to conserve water for future needs (Patel and Parekh, 2022). However, Fitness function for reservoir operation that should be minimized and can be Mathematically expressed as per below equation (Sonaliya and Suryanarayana 2014). Objective function develop for GA model is express below.

$$Z = \sum_{t=1}^{12}[R(t) - D(t)]^2 + \sum_{t=1}^{12}[Sr(t) - Sr(t+1) + Inf\,(t) - Ep(t) - R(t) - Sp(t)]^2 \tag{2}$$

Where:

Z = system performance (Objective function)

R(t) = Monthly release during time period/month ‘t’

D(t) = Monthly demands during time period/month ‘t’

$Sr(t)$ = Initial storage of reservoir at the beginning of month ‘t’

Sr (t +1) = Final storage of reservoir at the end of preceding month ‘t’

$Inf(t)$ = Monthly inflow into reservoir during time period/month ‘t’.

$Ep(t)$ = Monthly mean evaporation loss that occurs during time period/month ‘t’.

$Sp(t)$ = Monthly surplus of water that eventually flows during time period/month ‘t’

Thus, Under the constraints stated in Eq. (3), (4) and (5) the fitness function, Eq. (2) seeks to minimize the total annual imbalance between the monthly reservoir releases and water demands, including deficits and spill outs.

Release Constraint

Total release for that month should be either less than or equal to overall demand.

(irrigation, domestic and industrial) and the constraint is stated below.

$$0 \leq R(t) \leq D(t);\ for\ all\ t = 1, 2....,12. \quad (3)$$

Reservoir Storage Capacity Constraint

The amount of storage in the reservoir over the given time period/month $'t'$ must not be less than the reservoir's dead storage nor more than its maximum storage. The constraint is expressed mathematically below.

$$Sr_{min} \leq Sr(t) \leq Sr_{max};\ for\ all\ t = 1, 2....,12. \quad (4)$$

Where, Sr_{max} stands for the reservoir's maximum capacity for storage during that period/month ‘t’ in MCM and Sr_{min} denotes minimum storage capacity of the reservoir during time period/month ‘t’ in MCM.

Surplus Constraints

During heavy rainy season, the reservoir would get filled beyond full reservoir level, such excess water should be released as surplus. This surplus constraint is given by the following:

$$Sp(t) \geq 0;\ for\ all\ t = 1, 2....,12. \quad (5)$$

RESULTS AND DISCUSSION

Based on monthly demand data and available release data, within maximum and minimum storage capacity of reservoir, for each water year monthly decision variable for release and storage are utilized to minimise value of objective function

The monthly releases generate using GA model for each of the water year from 2015-16 to 2019 -20 are compared with the actual releases and also with the actual demand data form each year. The amount of water that can be conserved or left over has been calculated based on the parameters needed to meet the specified demands. The actual release and demand from 2015–16 to 2019–20, as well as the GA releases for each of the water years, are presented below.

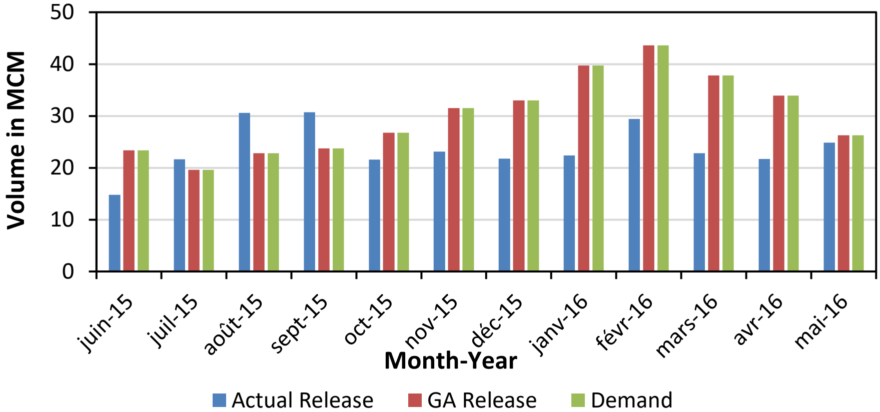

Figure 4: Actual release, GA release, and demand comparison on a monthly basis during the water year 2015–16

Fig. 4 displays the monthly comparison of actual releases, releases obtained by GA and Demand for all the months from June 2015 to May 2016 for water year 2015-16. It has been noted that the GA releases obtained for the months of June, October, November, December, January, February, March, April and May exceed the actual releases; however, every attempt is made to fulfil the demands during these months. Conversely, the GA releases during the months of July, August and September are optimized to a certain extent such that considerable amount of water saving can be done. The amount of water saved in respective months is 10.45%, 34.07% and 29.38%.

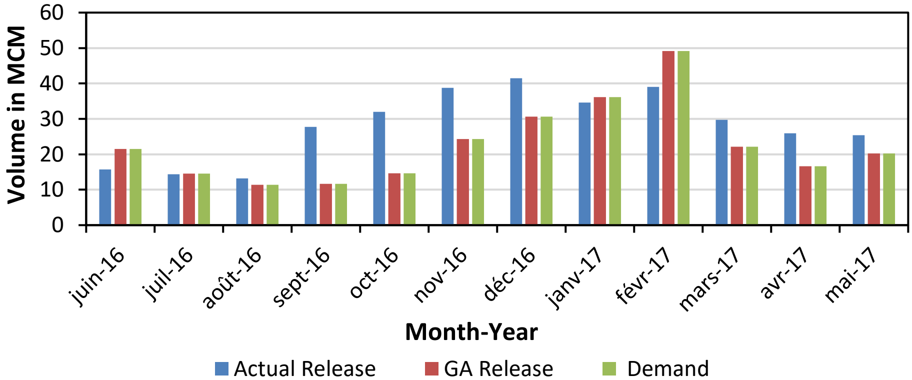

Figure 5: Monthly comparison actual release, GA release and demand for water year 2016-17

Fig. 5 demonstrates the monthly comparison of actual releases, releases obtained by GA and demand for all the months from June 2016 to May 2017 for water year 2016-17. Although more GA releases were obtained for the months of June, July, January and February than there were actual releases, each effort is made to satisfy demand during these times. On the contrary, for the months of August to December and March to May the GA releases are optimised to an amount such that considerable amount of water saving can be done. The maximum and minimum amount of water saved in month of September 137.35% and in month of August is 15.83% respectively.

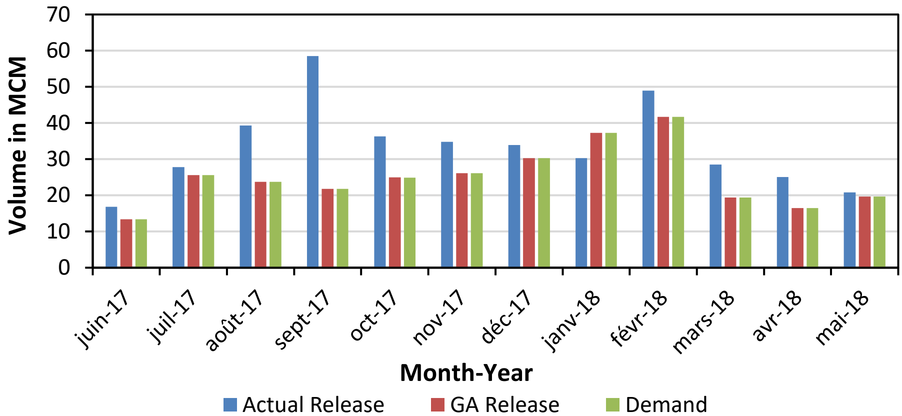

Figure 6: Actual release, GA release, and demand assessment for each month over the water year 2017–18

Actual release, GA release, and demand assessment for each month over the water year 2017–18 shows in Fig. 6. It is detected that only for the months of January the GA release obtained is more than actual release but, complete consideration is taken to satisfy the demands in this month. For remaining months from July to December and February to May the GA releases are optimised to an amount such that considerable amount of water saving can be done. The largest amount of water saved in September was 168.15%, whereas marginal amount of water saved in month of May is 5.95 %.

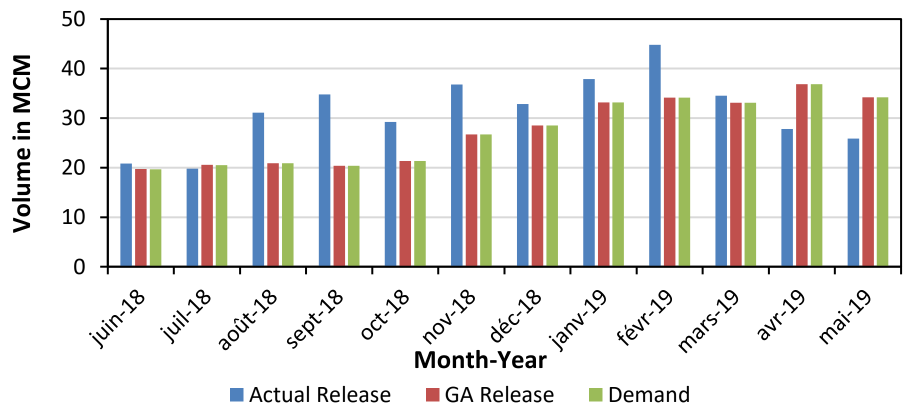

Figure 7: A month wise analysis of the water year 2018–19's actual, GA release and demand

The monthly comparison of actual releases, releases obtained by GA and demand for all the months from June 2018 to May 2019 for water year 2018-19 demonstrates in Fig. 7. While it is noted that in July, April and May, the number of GA releases obtained exceeds the numbers of actual releases, every effort is made to meet demand during these months. However, for the months of June and August to March the GA releases are optimised to an amount such that reasonable amount of water saving can be done. The highest amount of water saved in September month is 70.49% while marginal amount of water saved in month of March is 4.25 %.

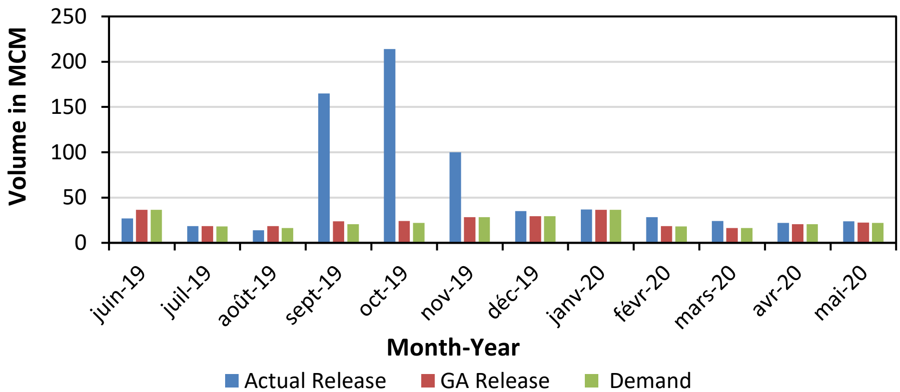

Figure 8: Month by month comparison of actual release, GA release and demand for water year 2019-20

The monthly assessment of actual releases, releases obtained by GA and demand for all the months of water year 2019-20 shows in Fig. 8. It is found that the quantity of GA releases obtained in June, July and August exceeds the quantity of actual releases; yet, every effort is taken to satisfy the needs during these months. Conversely, for the months of September to May the GA releases are optimised to an amount such that considerable amount of water saving can be done. During a month of September and October because of heavy rainfall reservoir reach to its highest capacity. The amount of water saved in October is more than seven times of average monthly demand while due to controlled releases marginal amount of water saved in month of January is 1.51 %.

Table 6: Data for monthly GA releases in MCM throughout the water year 2015-16 to 2019-20

	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
2015-16	23.4	19.6	22.8	23.7	26.8	31.5	33.0	39.7	43.6	37.8	33.9	26.3
2016-17	21.5	14.5	11.4	11.7	14.7	24.3	30.7	36.1	49.2	22.1	16.6	20.2
2017-18	13.4	25.6	23.7	21.8	24.9	26.1	30.3	37.2	41.7	19.4	16.5	19.7

2018-19	19.7	20.5	20.9	20.4	21.3	26.7	28.5	33.2	34.1	33.1	36.8	34.2
2019-20	36.3	18.4	18.6	23.6	24.0	28.2	29.3	36.4	18.3	16.2	20.6	22.2

Monthly year wise GA releases obtained from GA model for water year 2015-16 to 2019-20 shows in table 6 while Fig. 9 gives graphical explanation of a comparison of actual releases and demands over a ten-year period with GA releases.

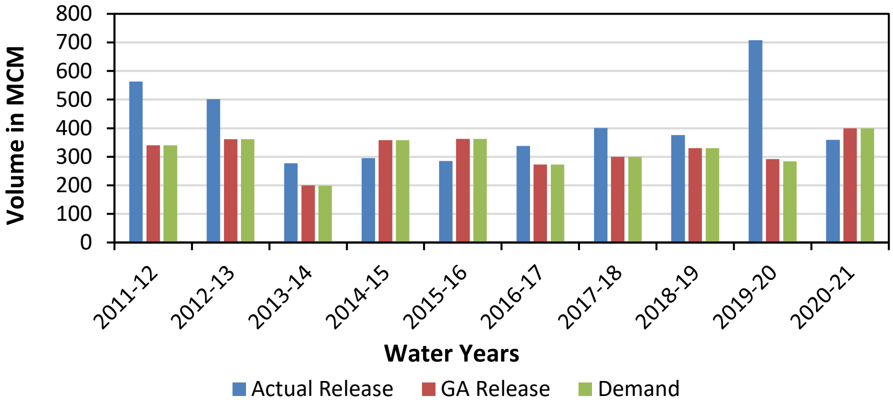

Figure 9: Annual comparison of actual release, GA release and demand for water year 2011-12 to 2020-21

According to Fig. 9, historical annual releases during the water years 2011-12, 2013-14, and 2016-17 to 2019-20 exceeded demand, resulting in an excess release of water. However, by monitoring monthly historical releases, it is possible that there will be some months when demand is unsatisfied in which case GA releases will be vital. Historical releases in the remaining water years, 2014-15, 2015-16 and 2020-21 were less than the demand; thereby, GA releases will fulfil the demand in those years without any water savings.

Table 7: Water saved annually in MCM from water year 2011-12 to 2020–21.

Water Year	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
Water Save (MCM)	223.32	140.15	78.1	-62.8	-76.72	64.81	100.92	46.67	415.83	-40.67

Table 7 illustrates the annual water savings in MCM for water years 2011-12 to 2020-21 obtained by comparing the historical water release of the ten water years under consideration with releases that are GA optimized. By using the GA optimum model for the current reservoir project, 889.63 MCM of water will be conserved overall, compared to 4105.8 MCM of all past releases, indicating 26.64% of the water saved during the water years under consideration. Water year 2019-20 saw the greatest water savings of 415.83 MCM or 142.26%, while 2018-19 saw the lowest water savings of 46.47 MCM or 14.16%. Although there is no water saving in 2014-15, 2015-16 and 2020-21, demand is satisfied by GA releases.

CONCLUSIONS AND FUTURE DIRECTION

Comparing traditional optimization techniques to natured inspired evolutionary algorithms, give thoughtful responses by optimizing real-time complex multi objectives reservoir operation systems. It is quite challenging to deal with different reservoir operations, such as managing various demands and manually establishing regulating curves to route floods with numerous constraints and variables involved rather than adopting advanced computer based soft optimizing approaches. Considering the GA model in this study, an effective release policy over a ten- water year from 2011-12 to 2020-21 can be developed, which satisfies the demand for irrigation, domestic use and industrial supply. The GA model has been proven to be able to save 27.64% more water annually in the ten water years under assessment than historical releases made in concern years by authorities. Of which the highest percentage of water saved was 142.26% in 2019-20 and the lowest percentage was 14.16% in 2018-19. However, for sustainable water management, there is ample opportunity for improvement in the use of optimization techniques through the adoption of a few modified versions of GA, animal-inspired metaheuristic algorithms, and hybridizations.

Declaration of competing interest

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

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