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AN ASSESSMENT OF OPTIMAL OPERATION POLICIES FOR A RESERVOIR USING PARTICLE SWARM OPTIMIZATION

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ABSTRACT

Reservoirs play a major role in managing the available water resources. The scarcity of water has become a serious problem worldwide; therefore, reservoirs must be created, planned and managed efficiently. Water resource systems need to be planned in an optimal manner for a systematic study. The paper focuses on obtaining optimal monthly release policies for a reservoir using the particle swarm optimization algorithm with an elitism strategy. The model has been applied to the Ukai reservoir in Gujarat, India. The PSO algorithm works on the basis of swarm behavior, and due to its strong background to reach the optimum, it provides better operating policies than the standard continuity equation. The results obtained by PSO show that the demands were satisfied and compared with those obtained using the continuity equation based on reliability and vulnerability indices. Finally, implications of the results and suggestions for further research are discussed.

Keywords: Reservoir Operation, Particle Swarm Optimization Algorithm, Elitist Mechanism

INTRODUCTION

Water is a vital resource to support all forms of life (Rouissat and Samil, 2022; Derdour et al., 2022; Remini and Amitouche, 2023). Unfortunately, water is not evenly distributed by location or by season of the year. Some areas of the country (India) are more arid, and water is a scarce and precious commodity. Other areas of the country receive more than adequate amounts of rain, causing occasional floods and loss of life and property. Dams and reservoirs have been constructed to collect, store and manage the supply of water to sustain civilization since time immemorial. Reservoirs have a high level of multifunctionality and are used for water supply, energy production, flood protection, ecological services, and recreation. Due to the growing population and expanding economies, impounding reservoirs are necessary for the storage and transport of water to cover the continuous, anthropogenic demand for water from the noncontinuous, natural water supply and to attain and preserve the fundamental human right for access to clean water.

Due to increased consumption and climate change effect, optimal reservoir operation has become an interesting subject for water resource managers (Mezenner et al., 2022; Verma et al, 2023). The important issue in reservoir operation is to manage the water resource shortage by preparing a target function and optimal planning for operation. The significance of modeling in reservoir operation is identified over time because simulation and optimization are allowed to improve the management. Reservoir operation is complex due to challenging issues that involve several decision variables, risk and uncertainty. Thus, there is a need to address multiple and conflicting objectives. Reservoir operators address these challenges using numerical analysis and optimization methods, allowing decision-makers to develop optimal operating policies to judiciously utilize water and maintain the balance between release and demand for efficient water management. Many researchers have discussed the reservoir system analysis problem at length. Techniques involved in studying this crucial problem involve linear programming (LP), nonlinear programming (NLP), dynamic programming (DP), evolutionary computation, artificial neural networks (ANNs), fuzzy logic, simulation techniques, etc. In recent decades, the basic tools adopted in the planning, design and operation of reservoir system analysis have been classified into two categories: optimization and simulation. Optimization includes a diverse set of techniques that preferably include linear programming and dynamic programming. Simulation gives a better representation of the reservoir system and is based on trial and error to identify near optimal solutions. However, the configuration of the system, nature of the objective function, constraints involved, and availability of data are the deciding factors in choosing the technique.

An emphasis on optimization methods in reservoir system analyses is given by (Yeh, 1985). Schmidt and Plate (1983) used a stochastic simulation method for planning an irrigation system in the sense of maximizing crop production for the whole irrigation area. Mathematical optimization techniques such as LP and DP were used to study the operation and design of a single, multipurpose reservoir system by (Bhaskar and Whitlatch, 1987). Wang et al. (2005) employed a constraint technique, decomposition iteration, and simulation analysis to address multi-objective optimization, a multi-reservoir system, and the stochasticity of inflows. Later, Reddy and Kumar (2007) used a swarm optimization algorithm to optimize multiple crop irrigation. The model performance was tested under different water deficit conditions, and sensitivity analysis of the crop yield was performed for water shortages at various growth stages. Moradi and Dariane (2009) used the standard particle swarm optimization algorithm and the modified method named elitist-mutation particle swarm optimization (EMPSO) to determine the optimal operation of a single reservoir system. The results indicated optimization that the use of EMPSO in complex problems is remarkably superior to PSO in terms of run time and the optimal value of the objective function. (Bazargon et al., 2011) developed a nonlinear discrete-time dynamic model to describe the operation of a single-purpose reservoir during the irrigation season using particle swarm optimization (PSO). A multiswarm version of particle swarm optimization (MSPSO) in connection with the well-known HEC-ResPRM simulation model in a parameterization–simulation–optimization (parameterization SO) approach was presented by (Ostadrahimi et al., 2011). It was shown that the real-time operation of the three-reservoir system with the proposed approach may significantly outperform the common implicit stochastic optimization approach. (Jana et al., 2012) proposed an improved PSO, namely, PSO-APMLB, in which an adaptive polynomial mutation strategy was employed in the local best of particles to introduce diversity in the swarm space. From the experimental results, it was found that the proposed algorithms performed better than PSO. Two adapted versions of PSO were presented for the efficient solution of the large-scale reservoir operation problem by Afshar (2012). Chenari et al. (2016) adopted PSO to solve the operation problem of a multipurpose Mahabad reservoir dam in northwestern Iran. The results showed that in most of the scenarios for normal and drought conditions, the released water obtained by the PSO model was equal to the downstream demand. Jadhav (2018) used PSO and LINGO to develop releases for hydropower generation and concluded that PSO can be used for complex reservoir operation. Oussam et al. (2019) used PSO to optimize multi-reservoir operating rules in inter basin water transfer project and concluded that PSO gave good results. Raju et al. (2020) used linear programming to develop an operation policy for the Hemavathy Reservoir, Hassan District Karnataka, India. The results showed that the downstream irrigation demands were satisfied and that a considerable amount of water was conserved from reduced spills. Salmani and Shourian (2022) used multi-objective PSO for reservoir optimization and performed sensitivity analysis on the parameters. The results revealed the acceptable precision of the algorithm.

In the present study, an enhancement of standard PSO model has been proposed to develop optimal operating policies for ukai dam, India. Sonaliya and Suryanarayana (2014) used genetic algorithm (GA) for optimal operation of ukai reservoir and concluded that a considerable amount of water was saved by applying GA. Furthermore, Nigam et al. (2015) presented the climate change effect on Ukai reservoir based on trend analysis. Surat city belongs to the downstream side of the ukai dam which makes it important to analyze and manage the releases from the dam. The novelty of the present study lies in proposing the elitist mechanism in standard PSO for ukai dam to better manage the releases in an optimal manner.

METHODOLOGY

The study presents an efficient and reliable swarm intelligence-based approach to derive optimal operating policies for the Ukai reservoir, i.e., PSO has been developed in the study. Particle swarm optimization is a heuristic global optimization method developed by James Kennedy and Russell Eberhart in 1995 after being inspired by the study of bird flocking behavior by biologist Frank Heppner. As far as the particle swam optimization algorithm is concerned, the solution swam is compared to the bird swarm, the birds' moving from one place to another is equal to the development of the solution swarm, good information is equal to the most optimist solution, and the food resource is equal to the most optimist solution during the whole course. The most optimist solution can be determined in the particle swarm optimization algorithm by the cooperation of each individual. The particle without quality and volume serves as each individual, and the simple behavioral pattern is regulated for each particle to show the complexity of the whole particle swarm. PSO is initialized with a population of random solutions and searches for optima by updating generations. Each particle keeps track of its coordinates in the search space, which are related to the best solution (fitness) it has achieved thus far (the fitness value is also stored.) The optimization process in this algorithm starts with the collection of particles. Each particle is considered a candidate solution of the optimization problem and contains three vectors: the current position of the particle (X_i), the best obtained position of each particle in the previous iteration (Y_i) and the velocity vector. A central aim of each cycle in the algorithm is the identification of the best position of each particle. Following this, the best position of the particle (X_i^{iter+1}) is considered the new position of the new particle for the purpose of continuance in such a way that it yields two main equations:

$$V_i^{iter+1} = \left[wV_i^{iter} + c_1 rnd\left(Y_i^{iter} - X_i^{iter}\right) + c_2 rnd\left(Y_*^{iter} - X_i^{iter}\right)\right] \quad (1)$$

$$X_i^{iter+1} = X_i^{iter} + V_i^{iter+1} \quad (2)$$

where Y_i^{iter+1} is the new velocity vector for each particle, c_1 is the personal learning coefficient, c_2 is the global learning coefficient, rnd is a uniformly distributed random value between 0 and 1, Y_*^{iter} is the current best solution and w is the inertial coefficient.

By using Eqs. 1 and 2, the velocities and particle positions are updated repeatedly over the iterations to obtain the optimal solution. After updating each particle's velocity and position vector, the elitist mutation step executes by arranging or sorting the fitness function values in ascending order. The worst particle is identified depending on the problem formulation and updated using Eq. (3).

$$P_g^{`} = P_g + M * R * \eta \quad (3)$$

where R is the corresponding decision variable range, M is the mutating factor, and η (0,1) is a random number following a normal distribution. The worst particle has been replaced with a new position, giving better personal and global best values. Using the new position vector, the fitness function is evaluated again, thus obtaining improved personal and global best values.

FLOWCHART FOR THE PSO ALGORITHM

The algorithm flow or the stepwise procedure of the PSO method is given below:

Step 1: Input Data for the Model

The initial required inputs are: Monthly Inflows, Monthly Demands, Monthly Evaporation, Swarm Size (Number of particles), Number of Iterations, Parameters of the model; w, c_1, c_2

Step 2: Random Initialization of Particle Velocity and Position

For each particle, randomly generate two vectors, position vector X (0) and velocity vector V (0). In reservoir operation, each particle is analogous to release, R_t. In the present study, number of particles adopted is 20 based on the sensitivity analysis performed.

Step 3: Fitness Function Evaluation

The function value is determined for each particle based on the objective function and constraints according to the problem formulation discussed below.

Step 4: Set Personal Best values

At initial iter = 0, the current fitness is set to be the local best value for each particle and then proceed forward and record the corresponding particle position.

Step 5: Set Global Best values

During the first iteration, set pbest value as the global best value. For the rest of the iterations, each pbest values are compared with the other pbest values in the population. The best pbest value evaluated is recorded to be the gbest value.

Step 6: Update Position and Velocity

Evaluate new velocities of the particles using Eq.1 as described above and update the position of each particle using Eq.2. The parameters used in the equations above have already been described. New updated velocity and position vectors will be generated for each particle of the population moving towards a better solution.

Step 6: Elitist Mutation Step

After updating position and velocity of the particle, adjust the parameters and perform elitist mutation mechanism according to Eq. 3.

Step 7: Check the Stopping criteria

To check the optimality, either the number of iterations assigned is reached or a predefined value of the fitness function is obtained. The particle generating final global best value will be the optimal solution or else repeat steps 3 to 7.

The flow diagram below explains the stepwise procedure of the model used in the study.

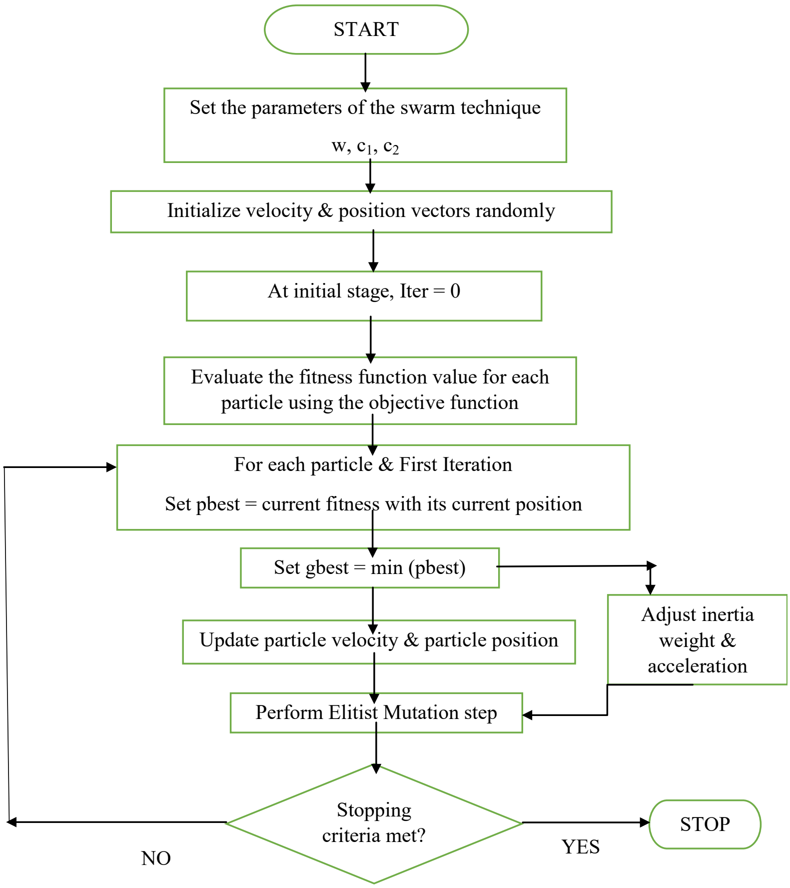

Figure 1: Flowchart for the PSO Algorithm

CASE STUDY DESCRIPTION

The Ukai Dam is located across the River Tapi near Ukai village in Surat District, Gujarat State, with a catchment area of approximately 62,255 km^2 and a water spread of approximately 52,000 hectares. It is located between longitudes 73°32'25"-78°36'30"E and latitudes 20°5'0"-22°52'30"N. The Ukai dam has a maximum storage capacity of 8,480.18 MCM and a gross storage capacity of 7,414.29 MCM at full reservoir level. The active storage capacity of the Ukai reservoir is 6730 MCM. Water stored in the reservoir is used for irrigation purposes and drinking water needs in the Surat, Ankleshwar, Tapi, Navsari and Valsad districts of South Gujarat. The catchment of the dam covers large areas of 12 districts of Maharashtra, Madhya Pradesh and Gujarat. The districts that lie in the catchment include Betul, Hoshangabad, Khandwa, and Khargaon of Madhya Pradesh; Akola, Amravati Buldhana, Dhule, Jalgaon and Nasik of Maharashtra and Bharuch and Surat of Gujarat state. The command area of 66,168 Ha is spread over the districts of Surat, Tapi, Navsari and Valsad. The dam is an earth-cum-masonry dam. Its embankment wall is 4,927 m long. Its earth dam is 105.156 meters high, whereas the masonry dam is 68.68 meters high. The dam's left bank canal feeds water to an area of 1,522 km^2. and its right canal provides water to 2,275 km^2 of land. The Ukai reservoir has two power plants, one on the main dam with an installed capacity of 300 MW since 1974, and another, the ULBMC mini station which has been oper-ating since 1988 with an installed capacity of 5 MW. In 1995, the Singanpor Weir cum causeway was built on the Tapi River near Rander Surat. A limited downstream release from the Ukai dam is performed to meet the domestic demands, industrial demands and water quality requirements of the region. The surplus water from the weir goes into the Arabian Sea.

The data acquired for the present study were the monthly inflow, demand, storage, evaporation and release data for the monsoon months for years 2007-2011 and was collected in 2014. The location map of ukai dam is presented below in figure 2.

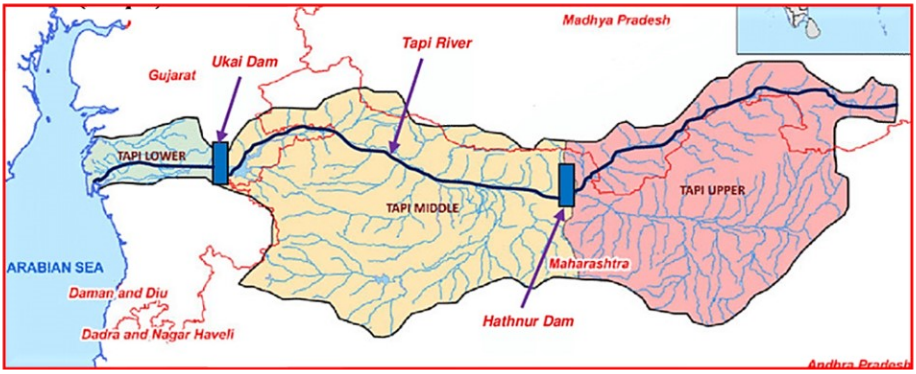

Figure 2: Location Map

Figure 3 below represents the statistical information of inflows corresponding to the data acquired.

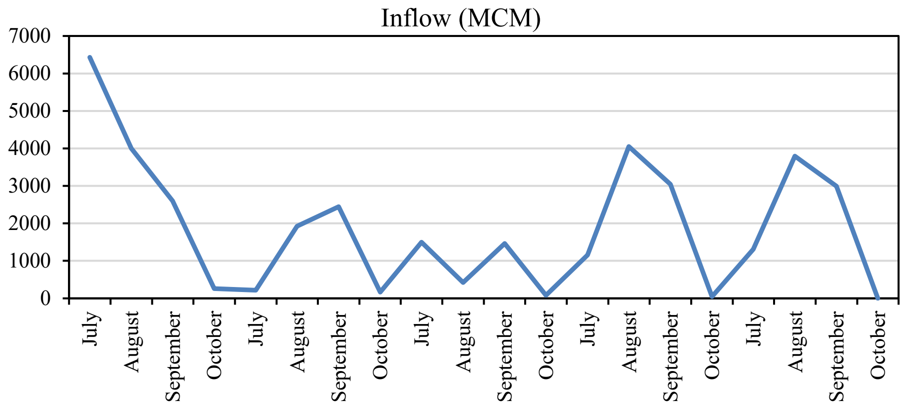

Figure 3: Location Map

Problem Formulation

The Ukai reservoir system considered monthly inflows for optimal reservoir operation. To manage the targets, the model is formulated with the objective of minimizing the annual sum of the deviation of release and demand. The objective function is expressed as follows:

Minimize $|R_t - D_t|$

The constraints are as follows:

$S_{t+1} = S_t + I_t – R_t - E_t$

$0 \leq Rt \leq Dt$

$S_t^{min} \leq S_t \leq S_t^{max}$

where R_t is the volume released during month t, D_t is the monthly demand during time t, S_{t+1} is the volume stored at the end of a time, S_t is the reservoir storage in a period t, S_t^{min} is the minimum reservoir storage volume during time t, S_t is the volume stored during time t, S_t^{max} is the maximum reservoir storage volume during time t and E_t is the evaporation loss during time t. The model was run using MATLAB to obtain the results in the form of monthly releases, which were then compared with the standard continuity equation to validate the performance of PSO. The performance of the model was also evaluated based on reliability and vulnerability, where reliability signifies the probability with which the reservoir system will perform the required function, while vulnerability implies the probability of failure of an event.

Data Processing

The data analysis and processing were done using the following procedure:

- The input data was acquired for the model i.e., the Monthly inflows, demands and evaporation data for the given periods.
- The state continuity equation was used to fulfill the monthly demands for all the years
- using MS Excel keeping $S_t = 0$.
- The months with reservoir storage exceeding the live storages were considered under Spill.
- The models were developed for the monsoon months for all the years and obtained results were then compared.

Performance Indices

To evaluate the performance of a water resource system, some performance indicators can be used for analysis of the obtained results.

Reliability

Reliability Index is explained as the ratio of volume of water released over the entire period to the total demand volume expressed as:

$$RI = \left(\frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t}\right) * 100 \tag{4}$$

where, R_t is the release of water for the period t = 1,2, 3, …, T

D_t is the water demand for the same period

Vulnerability

Vulnerability Index is given by the sum of the volume of all the water deficit events and is mathematically expressed as:

$$VI = Max_{t=1}^{T} \left(\frac{D_t - R_t}{D_t}\right) * 100 \tag{5}$$

where, $D_t - R_t$ will represent the water deficit event i.e., water demand and release for time period t

RESULTS AND DISCUSSION

To apply the particle swarm algorithm, the input data were the monthly inflows and demands and actual releases from 2007-2011 for the monsoon season. The objective of the present study was to obtain monthly releases to meet the demands and then compare them with the actual releases as per the continuity equation.

Sensitivity analysis and Model parameters

The parameters of the model used in the PSO algorithm were selected based on sensitivity analysis (Reddy and Kumar, 2007) and are demonstrated below in Table 1. Sensitivity analysis is associated with examining the effects of different values of parameters on the objective function values. After scrutinizing these effects, the optimized values of the parameters have been obtained for the models. For PSO model, after performing several trial runs inertia weight is fixed to 0.4 and c_1 & c_2 are found to be 1.2 and 1.6 respectively.

Table 1: Model Parameters for the PSO algorithm

Parameter	Population size	No. of iteration	c_1	c_2	W
Value	20	200	1.2	1.6	0.4

The sensitivity analysis of the number of iterations and population size is shown below in Figures 4 and 5, respectively. Figure 4 shows the sensitivity for number of iterations, from which it is observed that the minimum fitness value is observed at maximum of 200 iterations. Figure 5 represents the sensitivity to population size, from which optimum fitness is at swarm size of 20. As can be seen in figures 4 and 5, that after a certain value fitness value does not change and converges to a straight line after that value for number of iterations and swarm size. Thus, those values represent the optimum value of the parameter for the model.

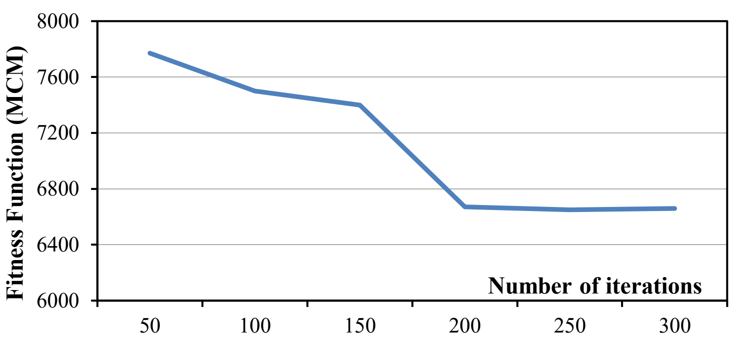

Figure 4: Sensitivity analysis for number of iterations

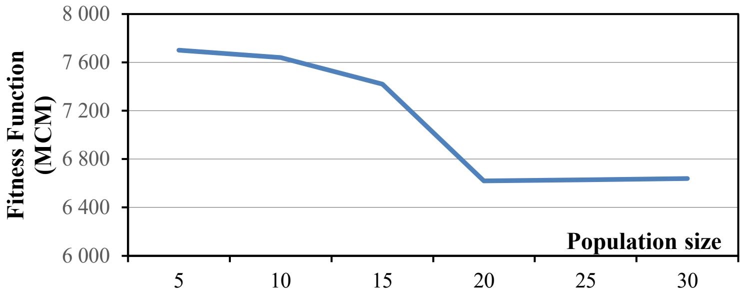

Figure 5: Sensitivity analysis for population size

Optimal Policy

The optimal releases obtained using the PSO model are compared with the actual releases, as explained below in Figures 6 and 7 based on the regression plot. From the regression plot, it has been observed that the releases obtained using the PSO model satisfy the demands. Additionally, it can be seen in figure 3 that points are less scattered and correlate in a better way than observed in figure 4. In figure 3, the model releases scatter quite close to regression line indicating a better relation between release and demand obtained using the PSO model that the actual releases. The optimal policy for the monsoon months for the considered period i.e., 2007-11 is presented below in figure 8. The releases obtained using the model are more efficient regarding better management of the releases and direct towards optimum decision making for future works in the reservoir.

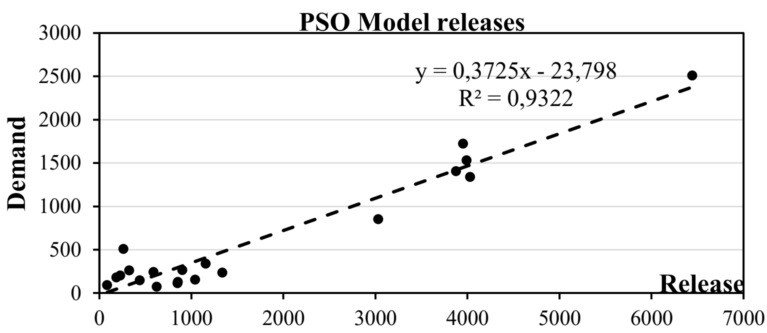

Figure 6: Regression of model releases and demand

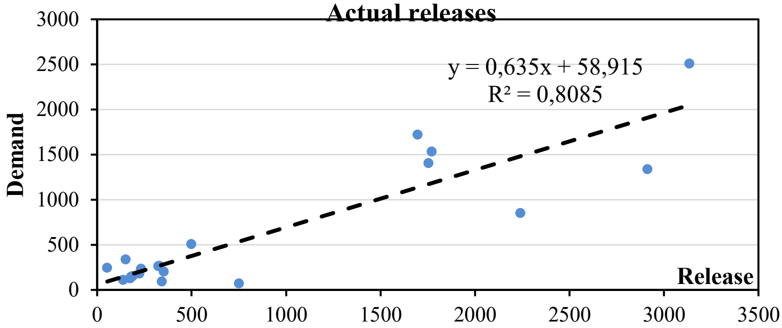

Figure 7: Regression of actual releases and demand

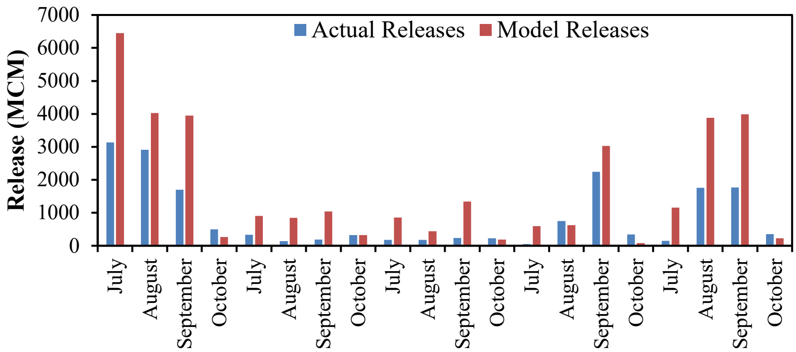

Figure 8: Releases for monsoon months

Performance measuring indices

In order to evaluate the performance of the models, Reliability Index, Vulnerability Index and RMSE has been calculated. Table 8 shows the performance of the algorithm used in the study for reservoir operation of ukai dam using the reliability and vulnerability. The model releases are significantly performing better in comparison to the actual releases with higher reliability and less vulnerability. The value of R^2 is better for model releases indicating good correlation between releases obtained using PSO model than the actual releases.

Table 2: Comparative analysis of reservoir releases

Performance Indices	Actual Releases	Model Releases
R^2	0.808	0.932
Reliability	1.4	2.7
Vulnerability	0.03	0.02

CONCLUSION

The releases obtained using the PSO algorithm completely satisfy the monthly demands for all the years considered in the study. The coefficient of determination of model releases has been improved by 14% compared with the actual releases. The reliability for model and actual releases is 2.7 and 1.4, respectively, while vulnerability is 0.02 and 0.03 for model and actual releases, respectively. This implies that the reliability is higher and vulnerability is lower for model releases than for actual releases, although to a small extent, some improvement is seen. Therefore, it can be concluded that the PSO technique can be effectively applied for such reservoir operation optimization problems. Besides PSO, some other enhancements of basic model can be used to further improve the obtained results and direct towards a better optimization of the reservoir. Also, other meta-heuristic models can be applied and compared to develop more potential models for optimal operation.

Declaration of competing interest

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

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