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Original Article

Optimization of Reservoir System Operation using Fuzzy Set Theory

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Abstract - *This study demonstrates running a complicated multi-reservoir system with numerous goals. The multi-reservoir system heavily incorporates demand and input uncertainties. Fuzzy set theory, which is a robust theory, is significantly impacted by this uncertainty. The fuzzy linear programming method is utilized in this study to find the best course of action for the system's functioning when there is uncertainty in various parameters, including the availability of resources, technological advancements, and objective function coefficients. As a case study, a composite parallel and series four reservoir system are chosen, and the system is tested with the fuzzification objective function. The effects on the goals, such as maximizing irrigation release and maximizing power release returns, are also examined. The operational guidelines that resulted from this process improve comprehension of the issue, its numerous complexity, and repercussions. This gives policymakers (decision makers) a variety of possibilities for their elimination of taking appropriate action.*

Keywords - *Fuzzy set theory, Optimization, Linear programming, Reservoir operation.*

1. Introduction

In the past, the development of water resources has focused on a single, primarily financial goal like anticipated net benefits. The gains or losses resulting from various uses of water resources, development, and water-related risks were expressed in monetary terms. Real economic benefits can be seen for uses including hydropower, irrigation, and water delivery. The use of monetary terms is frequently artificial and unable to convey the true nature of other advantages, such as those related to flood control, water quality management, or recreation. Similarly, there is a significant non-monetary component to the environmental impact of water resource development on the physical system. In these circumstances, utilizing physical units (indicators) like the number of individuals sheltered from flooding, the amount of silt or dissolved oxygen, or visitor days seems appropriate. Economic efficiency measures, such as predicted net benefits or the benefit-cost ratio, can be used for economic benefits.

2. Literature Review

Several methods have successfully tackled the non-linearity-constrained optimization problem during the past few decades. The classic models come first in the progression of innovations and strategies for reservoir operation optimization. The reservoir models that have been used extensively in the past include linear programming (LP), non-linear programming (NLP), dynamic programming, Lagrange relaxation (Pan Liu et al. 2012), and network optimization (Zeng Xiang et al. 2019, Tongtiegang Zhao et. al. 2012, Xiang Li et al. 2014, Chunlong Li et al. 2014). As a result of the ongoing advancement of artificial intelligence since the turn of the twenty-first century, some of the more well-known models have been enhanced to attain their higher precision. Genetic algorithms (GA), genetic programming (GP), and differential evolution (DE) are some of the evaluation algorithms.

Evolutionary algorithms in swarm intelligence (EAs-SI), such as particle swarm optimization (PSO), are currently used to determine the time order for reservoir models. After that, in order to overcome the inadequacies of the current algorithms, a hybrid or combination of the EA or EA-SI has been widely utilized in the optimization of reservoir operation, including parameter tuning ([9] Wen-jing Niu, and Zhong-kai Feng 2021), premature convergence issues (Xiaohui Lei et al. 2018), shortcomings in complex optimization problems like dimensionality (Zhiqiang Jiang et al. 2018), and substantial processing efforts (Shiqin Wang et al. 2020). Because of this, academics have significantly increased the range of MHAs to enhance reservoir operation, especially during the past ten years.

The works by Regulwar and Anand Raj (2007), Sumant A. Chaudhari and Anand Raj (2009), Kamodkar and Regulwar (2014), and Gurav and Regulwar (2012) all demonstrate the application of fuzzy set theory to reservoir system optimization and irrigation planning. Anand Raja and Nagesh Kumar (1998, 1999) presented a novel fuzzy ranking algorithm based on maximizing and minimizing sets.

The RANking FUzzy Weights (RANFUW) method is straightforward to compute. The suggested method (the RANFUW) was used to plan and manage a river basin for a system with many parallel reservoirs upstream and one reservoir downstream; Jairaj and Vedula (2000) and Barathi (2019) were developed a fuzzy mathematical programming model. The study's final objective was to find the least yearly mean monthly irrigation withdrawal departure from the desired level. A thorough overview of the state of the art for managing a system with numerous reservoirs was given by John W Labadie (2004) and Thlama Mperiju Mainta, Yahi Ali Dzakwa, and Yakubu Ishaku (2022). This article assesses current methods for managing and operating reservoir systems while optimizing them and suggests further research and real-world application directions.

The Evolutionary Algorithms (EAs), specifically Differential Evolution (DE) (Cantún-Avila et al. 2021, Phil Husbands et al. 2007, Regular Choudhari, and Anand Raj 2010), Genetic Algorithm (GA), and Genetic Programming (GP) are where the evolution of metaheuristics starts. The evolutionary theory by Charles Darwin has led to the development and learning of numerous cultures. The fundamental tenet of the EA is to initially generate a population of potential solutions through a selective mechanism like natural selection, evolution, and reproduction.

3. Model (MOFUOPT) Development

The Multiobjective Fuzzy Optimisation (MOFUOPT) model is generated monthly to produce an operational strategy for making the most of the sub-basins water resources as demand exceeds supply.

4. Objective Functions

The two goals that this study took into account are

1. Increase the amount of water that is released for use in irrigation (i.e., Release for Irrigation - RI)
2. Increase the amount of water released in order to generate electricity (i.e., Release for Power - RP)

$$Maximize\ Z = \sum_i^4 \sum_j^{12} (RI)_{ij} \quad (1)$$

$$Maximize\ Z = \sum_i^4 \sum_j^{12} (RP)_{ij} \quad (2)$$

In the case where i varies from 1 to the number of reservoirs (in this case, four reservoirs) and j ranges from 1 to the number of time steps (in this case, 12 months),

5. Constraints

5.1. Turbine Release-Capacity Constraints

Discharges into turbines for power generation must be lower or equal to the discharge of Turbine Capacities (TC) for all months. The power output must also meet or surpass monthly Releases for Firm Power (RFP) requirements. These constraints are as follows:

$$\mathrm{RP(i,j)} \leq \mathrm{TC}(i) \qquad \forall \quad i = 1,2,\ldots,4. \quad (3)$$

$$\mathrm{RP(i,j)} \geq \mathrm{RFP}(i) \qquad \forall \quad j = 1,2,3,\ldots\ldots,12. \quad (4)$$

5.2. Irrigation Release-Demand Constraints

Throughout the year, flows into irrigation canals (RI) should be below or equal to all reservoirs' peak Irrigation Requirement (IDmax).

In addition, canal irrigation flows must be more than or equivalent to the baseline irrigation need. We assume a minimum irrigation demand of 30% for this study. As a result, the restriction on irrigation release and demand can be stated as

$$\mathrm{RI(i,j)} \leq \mathrm{ID_{max}(i,j)} \qquad \forall \quad i = 1,2,\ldots,4. \quad (5)$$

$$\mathrm{RI(i,j)} \geq \mathrm{ID_{min}(i,j)} \quad \forall \quad j = 1,2,3,\ldots\ldots\ldots,12. \quad (6)$$

5.3. Reservoir Storage- Capacity Constraints

Every month, the storage level (S) in the reservoirs must be higher than the minimum storage level (Smin) and either below or equivalent to the maximum storage level (SC). Every month on the first, the storage is collected. The following phrases describe these constraints:

$$S\mathrm{(i,j)} \leq \mathrm{SC}(i) \qquad \forall \quad i = 1,2,\ldots,4. \quad (7)$$

$$S\mathrm{(i,j)} \geq S_{\min}(i) \qquad \forall \quad j = 1,2,3,\ldots\ldots\ldots\ldots,12. \quad (8)$$

5.4. Hydrologic Continuity Constraints

Reservoir storage (S), inflows (IN), and monthly losses from reservoir storage (S) are all subject to these limitations, as releases from the turbines (RP), releases for irrigation (RI), and releases for drinking water supply (RWS), all of which are considered to be constant. The hydrologic continuity restrictions for all reservoirs can thus be stated as follows:

(i) Reservoir (R1):

$$\left(1+a_j(1,j)\right)\ S(1,j+1)=\left(1-a_j(1,j)\right)\ S(1,j)+IN(1,j)-RP(1,j)-RI(1,j)$$
$$-SPILL(1,j)-RWS(1,j)-FCR(1,j)+\phi_1 RP(1,j)-A_0 e_j(1,j)\quad j=1,2,3,\ldots\ldots\ldots,12 \tag{9}$$

(ii) Reservoir (R2):

$$\left(1+a_j(2,j)\right)S(2,j+1)=\left(1-a_j(2,j)\right)\ S(2,j)+IN(2,j)+\phi_2 FCR(1,j)-RP(2,j)$$
$$-RI(2,j)-SPILL(2,j)-RWS(2,j)-A_0 e_j(2,j)\quad \forall j=1,2,3,\ldots\ldots\ldots,12 \tag{10}$$

(iii) Reservoir (R3):

$$\left(1+a_j(3,j)\right)\ S(3,j+1)=\left(1-a_j(3,j)\right)S(3,j)+IN(3,j)-RP(3,j)$$
$$-SPILL(3,j)-RWS(3,j)-A_0 e_j(3,j)\quad \forall j=1,2,3,\ldots\ldots\ldots\ldots,12 \tag{11}$$

(iv) Reservoir (R4):

$$\left(1+a_j(4,j)\right)\ S(4,j+1)=\left(1-a_j(4,j)\right)\ S(4,j)+IN(4,j)+\phi_3 SPILL(3,j)$$
$$+\phi_4 RP(3,j)-RI(4,j)-RWS(4,j)-SPILL(4,j)-A_0 e_j(4,j)$$
$$\forall\ j\ =\ 1,2,3,\ldots\ldots\ldots,12. \tag{12}$$

and

$$(v)\ S(i,1)=S(i,13) \tag{13}$$

The reservoir's condition at the end of the year must equal the initial storage at the start of the following year; thus, an equation is required to accomplish this.

Reservoir R1 is part of a pumped storage system. Transition loss accounts for 10% of pumping turbine discharges back into the reservoir. Therefore, the value of φ1 in the constraint for reservoir R1 is 0.9. The RWS releases are projected to remain at 30.00 Mm3 for reservoir R1, 3.55 Mm3 for reservoir R2, and 2.0 Mm3 for reservoirs R3 and R4. The transition loss from R1 to R2 is projected to be 10% of FCR (Feeder Canal Release). Therefore, the value of φ2 in the constraint for reservoir R2 is set to 0.9. It is assumed that 10% of the SPILL from R3 to R4 is lost in the changeover. Therefore, the value of φ3 in the constraint for reservoir R4 is 0.9. The transitional loss for turbine releases (RP) from R3 to R4 is expected to be 10% of RP. This means that the constraint value for reservoir R4's φ is 0.9.

The annual operation policy corresponding to the first objective function, i.e., irrigation maximization, has a high value of 1983.24 Mm3. The corresponding annual release value for power is 907.77 Mm3. For R1, the irrigation demands are fully met from June to December, but in the remaining months, they are not. There is a deficit of about 62% in January and 30% in the remaining months. For R2 in August and September, the demands are fully met, and for the remaining periods, a deficit is observed. For R4, irrigation demands are fully met.

This is because R3 has power demands only, whereas R4, which is downstream of R3, has irrigation demands. The spills from R3 are sufficient to meet the irrigation demands of R4. It is also clearly observed that the turbine releases are minimum. Spills that go out of the system under consideration are only observed in June (i.e., spills from R4). RWS on all the reservoirs is fixed for all months, depending upon the annual demands. Just like in the previous case (i.e., maximization of irrigation), it is observed that power releases are made maximum wherever possible, and irrigation releases are given the least preference.

Reservoir storages are found to be maximum to maintain high heads over the turbines to make power generation high. The maximum value of the objective function, i.e. maximization of power releases, is 1552.89 Mm3. The corresponding release for irrigation is 803.87 Mm3. In the first case, the spills in reservoir R1 are zero, but for the second case, the spills increase (710.5 Mm3) as less water is diverted towards irrigation due to less preference for irrigation. There are no spills from reservoir R2. For reservoir R3, there are spills for the first case (420.8 Mm3), but for the second case, there are no spills as more preference is for power releases, and R3 is only a hydropower reservoir. The spills from R4 increased from 11.0 Mm3 to 449.6 Mm3.

After determining the maximum and minimum values of Z1 and Z2, the objectives are fuzzified, while the model's other parameters are deemed crisp. The linear membership function is used to fuzzify the objectives. The following equations (1) and (2) yield the membership functions for irrigation and hydropower discharges, respectively.

$$\mu_{Z_1}(x) = \begin{cases} 0 & Z_1 \leq 803.87 \\ \frac{(Z_1-803.87)}{(1983.24-803.87)} & 803.87 < Z_1 < 1983.24 \\ 1 & Z_1 \geq 1983.24 \end{cases} \quad (14)$$

$$\mu_{Z_2}(x) = \begin{cases} 0 & Z_2 \leq 907.77 \\ \frac{(Z_2-907.77)}{(1552.89-907.77)} & 907.77 < Z_2 < 1552.89 \\ 1 & Z_2 \geq 1552.89 \end{cases} \quad (15)$$

These membership functions' graphical representation is given in Figures 1(a) and 1(b), respectively. Next, with this information, the modified optimization problem is formulated as Maximize λ Subjected to,

$$\frac{(Z_1-803.87)}{(1983.24-803.87)} \geq \lambda \quad (16)$$

$$\frac{(Z_2-907.77)}{(1552.89-907.77)} \geq \lambda \quad (17)$$

and all the original constraints in the model and $\lambda \geq 0$

λ is believed to be the degree of satisfaction obtained by optimizing both the fuzzified objectives Z1 and Z2.This problem is solved, and the most significant value of λ (i.e., λ^*) is discovered to be 0.9479.

The maximum values of Z_1 and Z_2 corresponding to λ^* are Z_1^* (Irrigation releases corresponding to the maximum level of satisfaction) =1921.87 Mm^3 and Z_2^* (Hydropower releases corresponding to the maximum level of satisfaction) = 1519.30 Mm^3.

In this fuzzified case, irrigation has reached 97% of the maximum observed, and power releases also reached 97% of the maximum. A better (compromise) solution is obtained when the objectives are fuzzified simultaneously than the individual objectives considered one at a time. These formulations lead to a non-dominated solution as both objectives are converted to constraints, and a new objective λ (level of satisfaction) is assumed as shown eq. 2. There has been a significant reduction in reservoir spills of R_1 (equal to zero) compared to the power maximization, which is 710.5 Mm^3.

The spills from R3 are reduced to zero when compared with spills from the operation policy for irrigation, where it is 420.8 Mm^3. The spills are less in reservoir R4 when compared with power maximization, which is 449.6 Mm^3. If the storage is focused, the reduction of spills accounts for the increased rise in the storage values of the reservoirs. This reduction of spills is indirectly increasing the total irrigation and power releases. The graphical representation of the results is shown below.

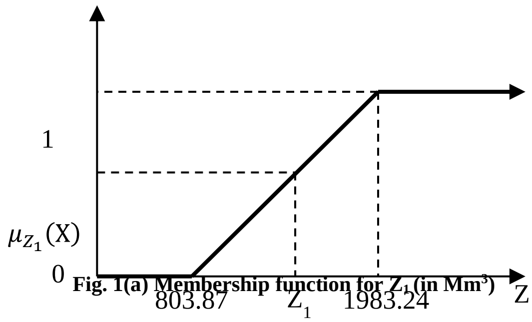

Fig. 1(a) Membership function for Z_1 (in Mm^3)

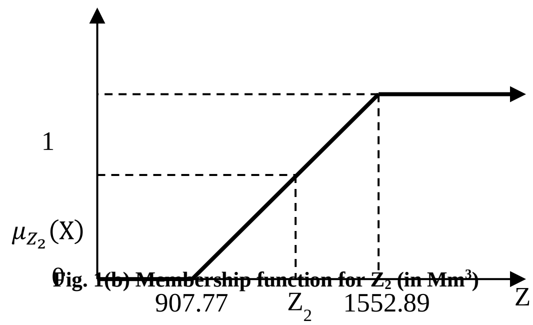

Fig. 1(b) Membership function for Z_2 (in Mm^3)

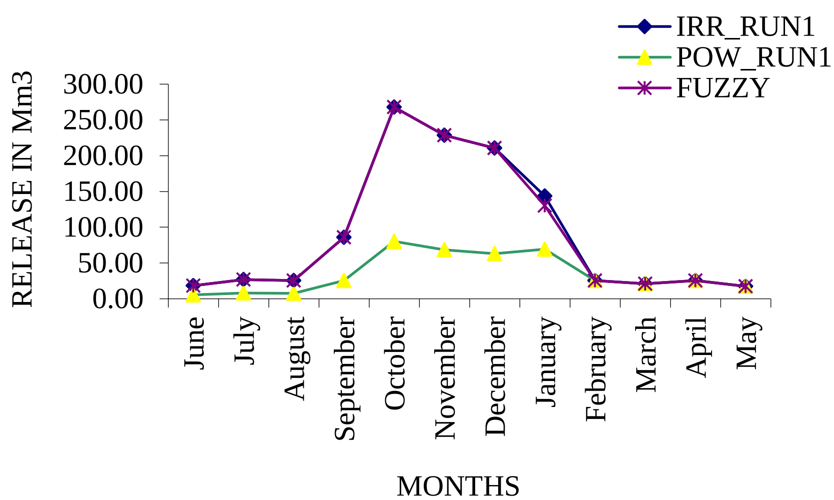

Fig. 2 Irrigation releases for jayakwadi stage-I (R1)

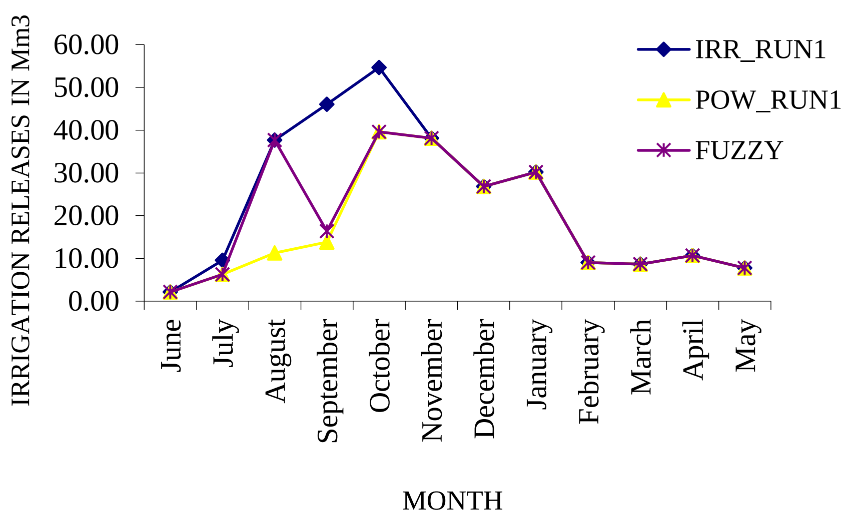

Fig. 3 Irrigation releases for jayakwadi stage-II (R2)

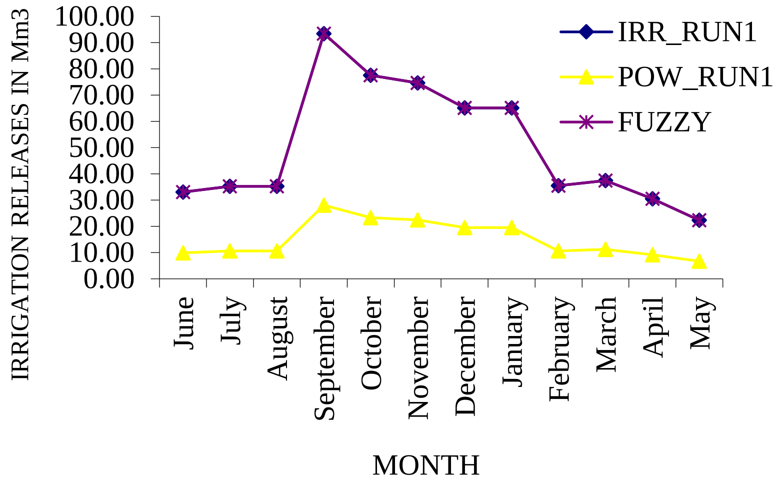

Fig. 4 Irrigation releases for siddheshwar (R4)

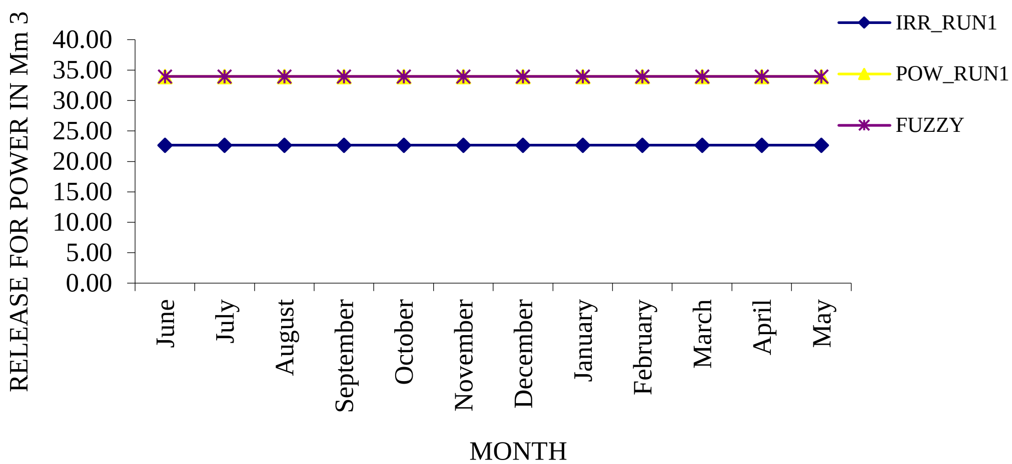

Fig. 5 Power releases for jayakwadi stage-I (R1)

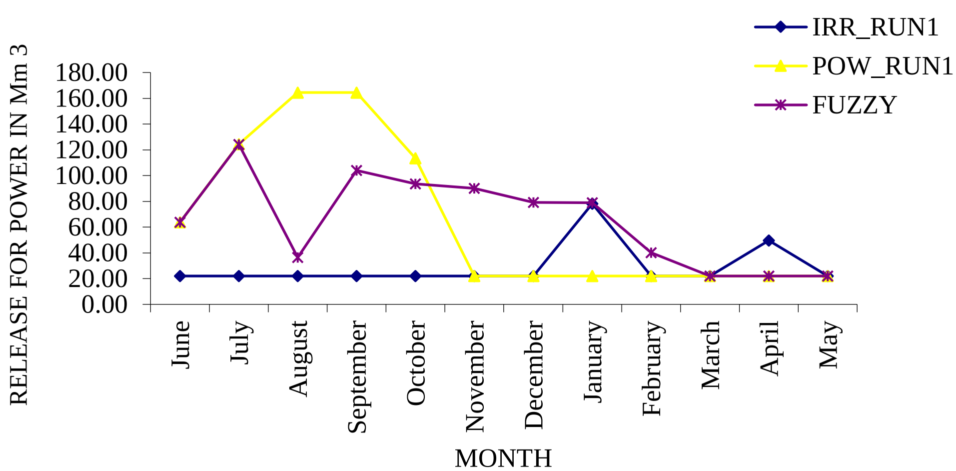

Fig. 6 Power releases for jayakwadi stage-II (R2)

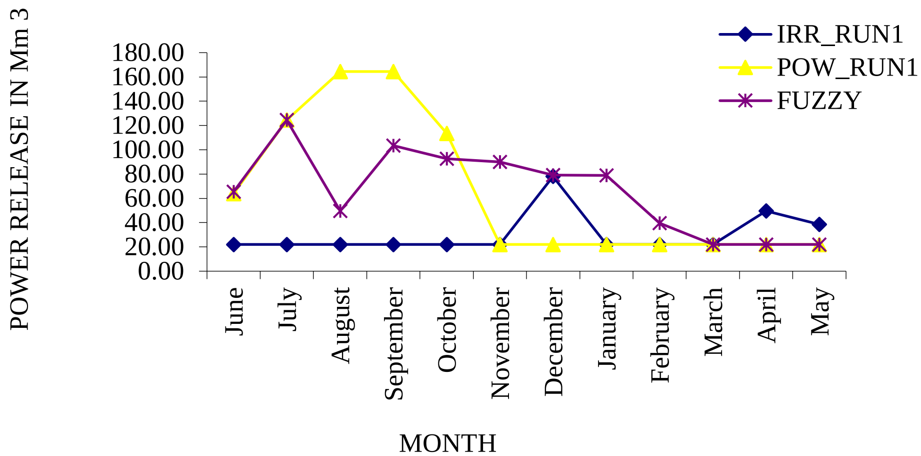

Fig. 7 Power releases for yeldari (R3)

6. Conclusion

Here, we highlight the advantages of fuzzy logic modelling and the problems with crisp logic modelling. Improving upon previous conventional methods is the driving force behind the development of Multiobjective Fuzzy Optimization (MOFUOPT). During integrated reservoir operations, the Godavari River sub-basin is considered in India's Maharashtra state. The problem is formulated with four reservoirs, and a satisfaction level of 0.94794 is reached after running the objective function fuzzification model. Irrigation releases for the year are recorded at 1921.87 Mm3, while electricity releases are recorded at 1519.30 Mm3. This demonstrates how the answer is enhanced by considering multiple goals at once. Fuzzifying the objective function yields a solution that sacrifices one goal to achieve the other.

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