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Evaluating Expert Opinion-Based Reservoir Operation in Cfa/Csa Climatic Conditions

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Abstract: This study evaluates the application of an expert opinion-based fuzzy method for reservoir operation in humid subtropical climate/hot-summer Mediterranean climatic classes (Cfa/Csa in the Köppen–Geiger climate classification system), which are characterized by humid subtropical to Mediterranean conditions with ample rainfall and seasonal water availability challenges. Effective reservoir management in these regions is critical for balancing water storage and downstream release and maintaining ecosystem health under variable hydrological conditions. The performance of the fuzzy method was compared to two meta-heuristic algorithms: gravitational search algorithm (GSA) and shuffled frog leaping algorithm (SFLA). System performance was assessed using key indices such as the reliability index as a measure of meeting water demands. The fuzzy method achieved the highest reliability index of 0.690, outperforming GSA (0.677) and SFLA (0.688), demonstrating its superior ability to ensure consistent water supply downstream. The fuzzy method, leveraging expert knowledge, not only enhanced downstream water supply reliability but also reduced computational time compared to the meta-heuristic approaches. The incorporation of expert opinions provides a practical, robust, and efficient framework for reservoir management in challenging climate conditions such as Cfa/Csa classes. Additionally, the fuzzy solution demonstrated superior adaptability to diverse hydrological conditions, balancing ecological and water supply needs effectively. These findings highlight the potential of using expert opinions to support sustainable reservoir operations by achieving optimal trade-offs between competing objectives and addressing challenges in water resource management under varying climatic conditions.

Keywords: optimal reservoir operation; expert opinions; Cfa/Csa climate classes; shuffled frog leaping algorithm; gravitational search algorithm

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1. Introduction

The role of large dam reservoirs in water supply has been highlighted in previous studies [1–3]. Moreover, they have a considerable role in supplying electricity to urban and rural areas [4]. Due to the importance of large dam reservoirs, one of the most significant tasks after their construction is the management of release and reservoir storage [5]. it is proposed that a loss function applicable to manage release to the downstream of the dam [1]. This function, which has recently been used as the main component of the objective function, defines loss as zero when water demand downstream is equal to or more than the release. On the other hand, when release is less than demand downstream of the reservoir, loss would be more than zero. It is demonstrated that losses due to deviation from storage and release targets need to be incorporated into penalty or loss functions associated with the real-time operation of reservoir systems [3].

Disparate solutions have been employed for solving reservoir operation issues as an optimization problem. Linear programming (LP) was the first and simplest method to optimize reservoir operation that has been addressed in the literature [2]. Given the complexity of reservoir operation as a non-linear problem, linear programming was not able to handle it properly [5]. Hence, the development of non-linear programming was the next progressive step to solve the optimization problem of reservoir operation, which has been highlighted in some reservoir operation studies [2]. Dynamic programming, another intellectual solution that has widely been used, breaks a complicated reservoir operation problem into simpler sub-problems in a recursive manner [3]. The literature comprehensively reviewed the details of each method in reservoir optimization that may be used to perceive the details of the developed methods [2]. Undoubtedly, advances in computational methods through the development of evolutionary algorithms, called meta-heuristic algorithms, were a recent progressive step toward optimizing reservoir operation. The genetic algorithm (GA) was the frontier evolutionary algorithm utilized in reservoir operation. It was not, however, robust enough to handle complex systems such as long-term reservoir operations. Hence, hybrid algorithms were introduced as improved genetic algorithms [5,6]. Improving the efficiency of solutions and reducing computational time were the main reasons for the application of other meta-heuristic algorithms in reservoir optimization. As a general classification of meta-heuristic algorithms, they could be classified as animal-inspired and non-animal-inspired algorithms [2].

Animal-inspired algorithms imitate animals' social behaviours to find an optimized solution for the problem. Ant colony optimization and honeybee algorithms were the first employed in reservoir optimization [1,4]. Bat algorithms, firefly algorithms, cat swarms, and penguin search algorithms are meta-heuristic methods recently used to solve the optimization problem of reservoir operation [5–8].

The second set of algorithms are non-animal-based algorithms that may imitate physical laws in optimization. As an illustration of the application of non-animal-based algorithms in reservoir operation, some methods utilized for this purpose have been reviewed. One of the relatively older methods is the simulated annealing algorithm inspired by annealing in metallurgy, which has been implemented in reservoir operation properly [9]. The gravitational search algorithm (GSA) is based on the law of gravitational and mass interactions and it has been used to optimize release downstream of dams for the supply of hydropower plants [10]. Some algorithms are not inspired by physical laws, such as harmony search algorithms and teaching–learning-based algorithms, which were successfully used in reservoir operation [11,12].

Another aspect of advances in computational methods was using data-driven models in water engineering problems, which were applied as simulators in many hydrological processes. Unequivocally, one of the most important data-driven models is the fuzzy inference system, which is very applicable to engineering and industrial problems [13]. The theory of fuzzy sets was developed by Zadeh [14] applicable in industry and engineering. Two main approaches have been developed in fuzzy inference systems (FIS), namely the Mamdani and Sugeno approaches. The Mamdani approach focuses on creating a control system based on linguistic rules, which are in accordance with experts' opinions. The Sugeno approach, however, carries out the defuzzification process based on the weighted average or weighted sum of a few data points instead of the centroid of a two-dimensional area [15]. Fuzzy inference systems have been addressed for reservoir management in the literature. Fuzzy sets have been used to provide a viable alternative by developing fuzzy mathematical programming models [16]. A study on the comparison of fuzzy stochastic dynamic programming and stochastic dynamic programming demonstrated that both formulations provide similar measures of system performance [17].

Water management poses inherent challenges, particularly in the study area characterized by Cfa (humid subtropical) and Csa (Mediterranean) climatic conditions [14]. Understanding the distinct characteristics of these climates is essential for addressing water supply and flood control issues effectively. These regions often experience variability in precipitation patterns, including intense rainfall events and irregular temporal distribution of water resources, which contribute to significant management complexities. Flood risk is a critical concern in these areas, as sudden, heavy rainfall can overwhelm natural and engineered water systems, leading to devastating floods. The challenge of managing flood risks is compounded by the increasing unpredictability of weather patterns caused by climate change. In addition, these regions frequently face variability in water supply, even during periods of significant annual rainfall. This variability often results in water shortages during peak demand periods, impacting both urban water supplies and agricultural needs. Agriculture plays a dominant role in water use within these climatic regions, with high-consumption crops such as rice, citrus, and olives being widely cultivated. Despite the relatively high annual precipitation in Cfa and Csa climates, the demand for irrigation remains significant, particularly during dry summer periods. These dry spells, especially prevalent in Mediterranean climates, place additional pressure on already strained water resources, exacerbating challenges related to agricultural productivity and food security.

Climate variability further amplifies water management challenges, with both Cfa and Csa regions experiencing increasingly extreme weather events. For instance, Cfa climates may witness intensified rainfall and flooding, while Csa climates are susceptible to prolonged droughts, leading to heightened pressure on water storage and distribution systems. These extremes necessitate adaptive management strategies to mitigate risks and ensure sustainable water use. Considering these challenges, effective reservoir operation and water resource management have become paramount. Reservoirs play a pivotal role in regulating water storage and release, thereby addressing the dual objectives of flood control and water supply. Traditional management approaches often rely on evolutionary algorithms or optimization techniques to determine release schedules and storage strategies. However, these methods can sometimes fall short in addressing complex, multifaceted challenges unique to these climatic conditions.

This study proposes an approach to reservoir operation by incorporating expert opinion-based methods, specifically leveraging fuzzy logic frameworks. Unlike conventional methods, fuzzy-based approaches allow for the integration of qualitative expert insights into decision-making, offering a more nuanced and adaptive strategy for water management. The primary objective of this research is to evaluate the challenges of reservoir management in Cfa and Csa climatic conditions and assess the efficacy of expert opinion-based methods compared to traditional evolutionary algorithms in these climatic conditions. By developing and testing a fuzzy logic-based framework, this study aims to bridge the gap between theoretical optimization and practical, real-world applications. The findings of this research provide valuable insights into the potential of expert-driven methodologies to enhance water resource management, particularly in regions facing the dual challenges of flood risks and water scarcity. This novel approach underscores the importance of incorporating human expertise into advanced modelling techniques to achieve sustainable and resilient water management outcomes.

2. Application and Methodology

2.1. Study Area and Problem Definition

The present study was conducted in the Tajan River Basin, one of the most vital rivers in northern Iran, located in Mazandaran Province. The Tajan River originates in the Chahardangeh and Dodangeh Mountains and flows toward the Caspian Sea, passing through key cities such as Sari, the provincial capital of Mazandaran. Agriculture is the predominant economic activity in this region, underscoring the critical importance of water supply to meet irrigation demands. This catchment is fully located in Cfa/Csa climatic conditions. In other words, some limited upstream areas are located in Csa, and most midstream and downstream as well as some upstream areas are located in the Cfa climatic class.

To address these needs, the Rajaei Dam was constructed upstream, at the confluence of the Shirinrood and Sefidrood Rivers, which are the primary tributaries of the Tajan River. This dam plays a pivotal role in regulating and supplying irrigation water to the downstream agricultural lands. The location of the Rajaei Dam and the associated river basin are shown in Figure 1. Given the increasing frequency and severity of droughts in recent years, effective and accurate reservoir management has become essential. This study aims to explore and demonstrate the potential of a fuzzy inference system (FIS) to optimize water demand management for the downstream irrigated lands while ensuring efficient storage management within the reservoir. The simulation covers a four-year period, chosen to reflect the variability of the region's water demand and availability. During this period, the water demand of the irrigated land was estimated based on the area of the cultivated land and the agricultural water requirements for each unit. Additionally, the inflow to the reservoir, recorded by a hydrometric station upstream of the dam, was incorporated into the study. Figure 2 illustrates the maximum possible water demand alongside the recorded inflow to the reservoir over the 48 months of the simulation.

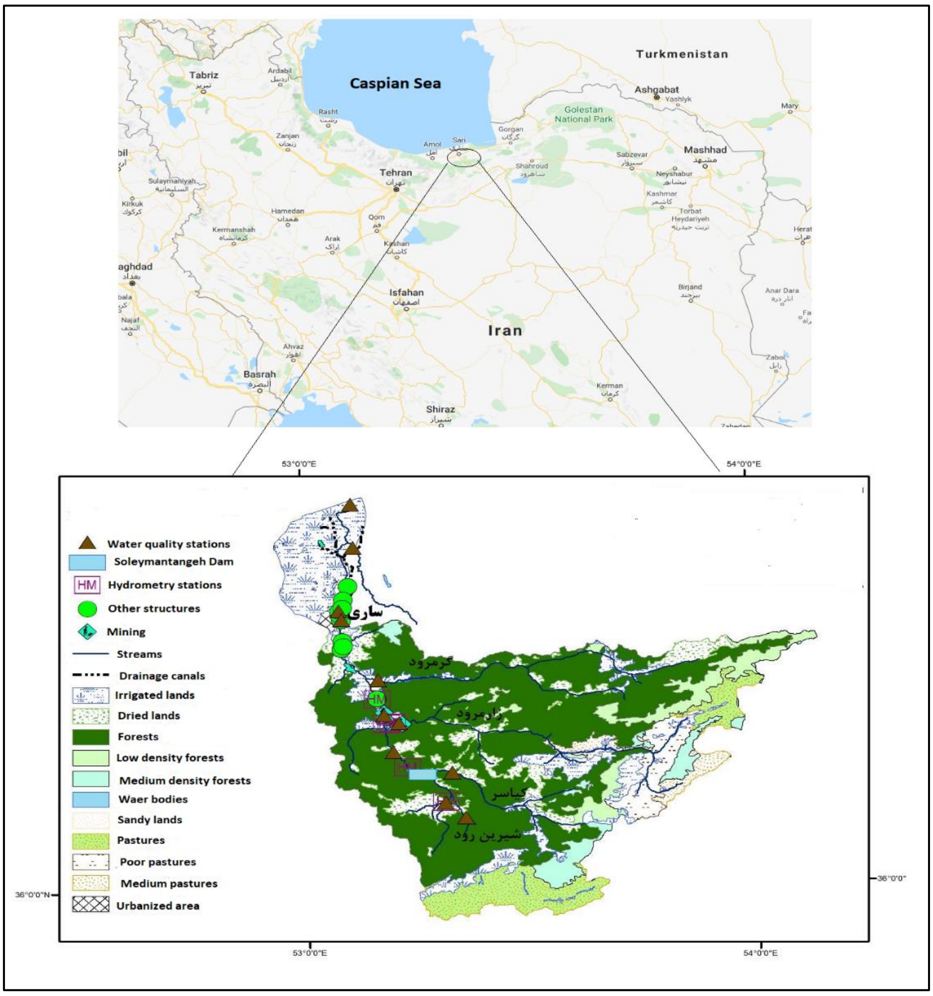

Figure 1. Land use and river network map of Tajan basin (from upstream to downstream non-translated names of the regions are Shirinrood, Kiasar, Zaremrood, Garmrood and Sary).

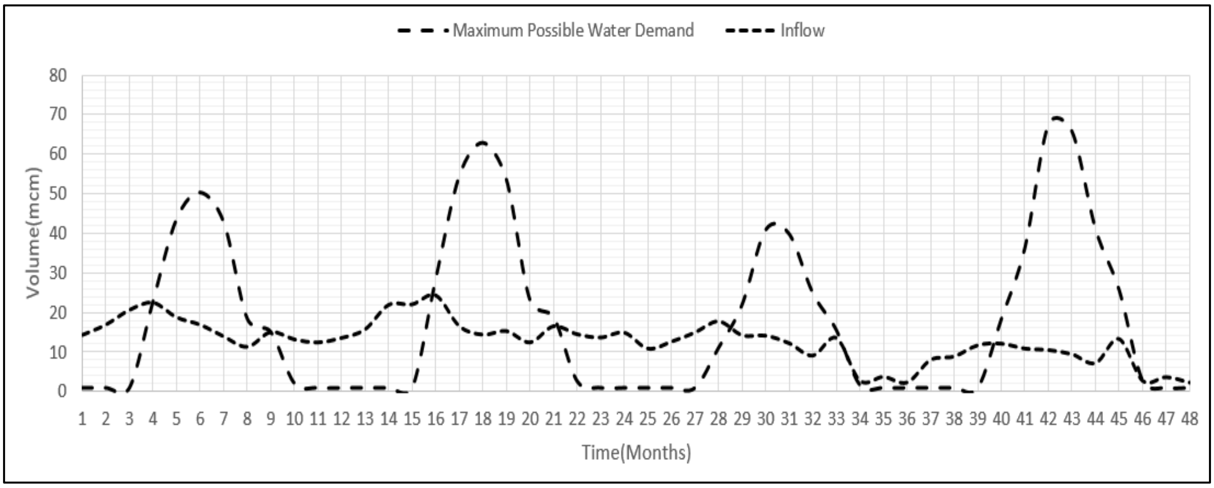

Figure 2. Maximum possible water demand and inflow to reservoir time series.

Based on the long-term record spanning 30 years, climate variability in this region has not been significant. Unlike many other regions in Iran, this area is not currently experiencing notable impacts from climate change. However, it is important to acknowledge that this situation could change in the future. For this study, we selected a four-year period to minimize the influence of other potential challenges, such as land-use changes. According to validated information, land use during these years remained relatively stable and did not undergo significant or impactful changes.

Another key factor influencing reservoir management is evaporation from the surface of the water body, which fluctuates seasonally. Figure 3 presents the average monthly evaporation rates throughout the year, providing further insight into the dynamics of water loss and its impact on reservoir management. By incorporating these various elements, the study seeks to develop a comprehensive strategy for efficient water use and reservoir optimization in the face of changing climate conditions and increasing water demand.

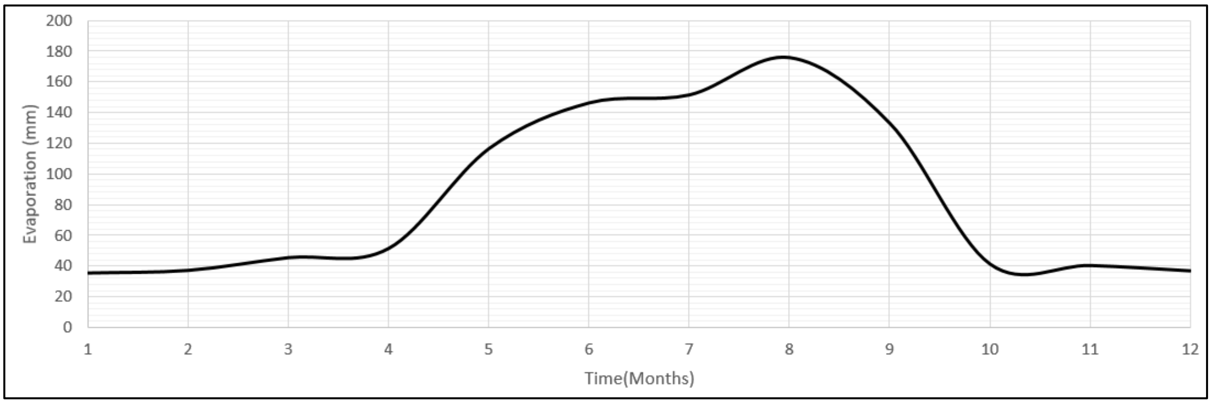

Figure 3. Evaporation from reservoir surface in different months (January to December).

2.2. Expert Opinion-Based Solution

This section presents the structure of the proposed expert opinion-based method for optimizing reservoir management. Two key parameters have been selected as inputs to the fuzzy inference system: water demand downstream of the reservoir and available storage within the reservoir. To build the Mamdani fuzzy inference system, the first step involves defining the membership functions for these inputs, as shown in Figure 4.

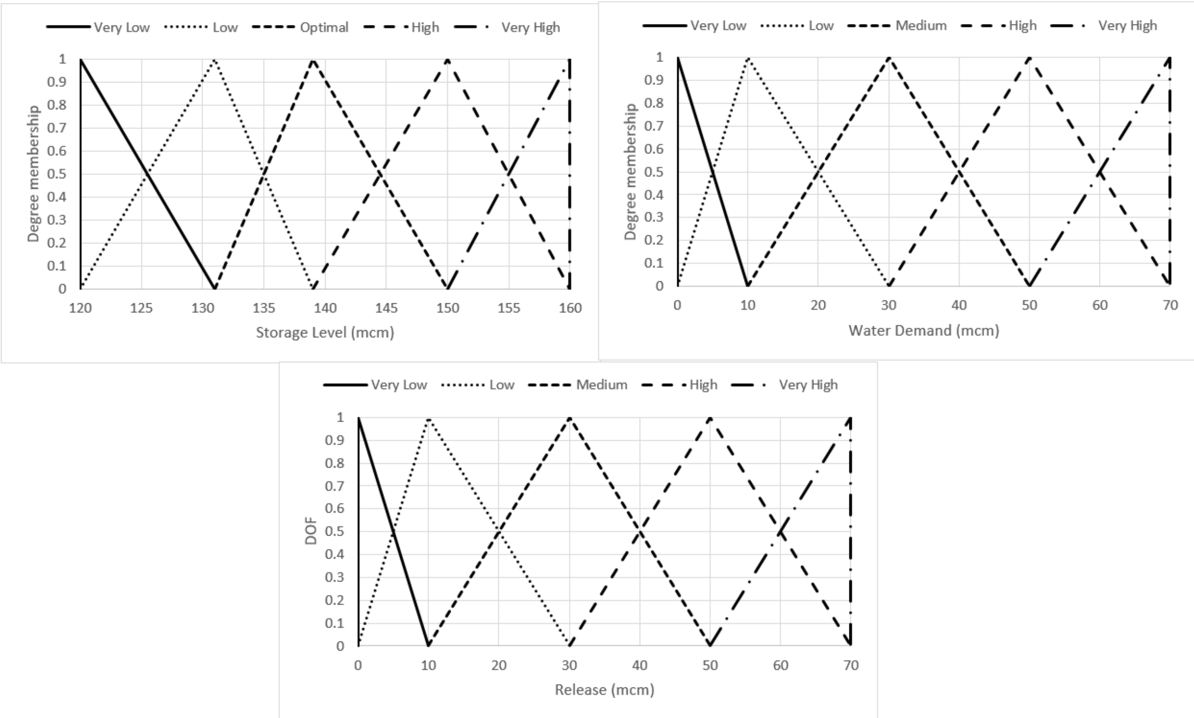

Figure 4. Developed degree membership and degree of fulfillment.

For water demand, a triangular fuzzy membership function was used, which is a commonly applied model in fuzzy logic systems. The membership classes were defined based on the maximum water demand and expert opinions, ensuring that the system accurately reflects the variability in demand over time. Similarly, the membership function for storage in the reservoir was developed based on the minimum and maximum water levels defined as necessary to ensure the efficient operation of the associated hydropower plant. The "objective level" refers to the initial water level or storage that is required to meet the planned electricity generation by the plant. The "maximum storage" corresponds to the water level at which the reservoir would overflow or spill, while the "minimum storage" is the lowest permissible water level that ensures the plant can still function effectively.

A key component of the Mamdani fuzzy system is the degree of fulfillment (DOF), which pertains to the release of water downstream. Since the release must be sufficient to meet the estimated water demand, its fuzzy levels were defined in a manner similar to the water demand, ensuring that the system can adjust water releases accordingly. Throughout the simulation, the reservoir storage was continuously updated based on the release of water and other operational factors. The new storage level at each step of the simulation can be calculated using Equation (1), which incorporates the inflow, release, and evaporation components, ensuring that the system dynamically adjusts to changing conditions and demands as follows:

$$S_{t+1} = S_t + I_t - R_t - \left(\frac{E_t \times A_t}{1000}\right), t = 1, 2, \ldots, T \tag{1}$$

where S_t is storage at time period t, I_t is inflow to reservoir at time t, E_t is evaporation from reservoir surface at time t, A is area of reservoir surface, R_t is total release in time period t, which includes release and overflow that are useable as source of water for downstream irrigated lands, T is the time horizon. Overflow (F_t) could be defined by Equation (2).

$$\begin{cases} if\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right) - S_{max} \\ if\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) < S_{max} \rightarrow F_t = 0 \end{cases} \tag{2}$$

The inputs and outputs of the fuzzy system were selected based on extensive experience and insights gained from water supply management in the region. Two major input parameters were identified as particularly influential: the available storage in the reservoir and the existing water demand. These inputs reflect critical factors in water resource management, such as balancing supply and demand and ensuring efficient distribution. The fuzzy system's output was considered to be the release selected to align with downstream operational goals. This decision ensured that the system provided actionable insights for practical water management applications.

An essential consideration in the development of the fuzzy system was the selection of membership functions. The number of membership functions plays a critical role in the system's accuracy and interpretability. If the number is too high, the system becomes overly complex and computationally expensive. Conversely, with too few membership functions, the system lacks precision and fails to capture the nuances of the input-output relationships. Striking the right balance is essential to achieve optimal performance. After careful evaluation, five membership functions were selected for the development of the fuzzy models. This choice was informed by an initial study that demonstrated its effectiveness in accurately modelling the system. These membership functions, spanning from "very low" to "very high", provided a clear and interpretable representation of the input and output parameters. As depicted in Figure 4, this configuration captures the range of variability in both inputs and outputs, ensuring a robust and adaptable fuzzy system for water resource management.

It is important to note that Equation (2) was not utilized in the fuzzy optimization method. The maximum storage was defined in such a way that the overflow would be zero, meaning it is indirectly accounted for in the system. While this equation is not part of the fuzzy optimization process, it is crucial for traditional optimization methods where it forms part of the objective function, which is outlined in the subsequent section.

Fuzzy rules are a fundamental component of the proposed fuzzy-based methodology and are established using the IF-THEN logic. For instance, one example of a fuzzy rule is:

> **IF** water demand is "high" and storage is "low", **THEN** the release would be "very low".

These verbal fuzzy rules, which guide the inference system, are displayed in Table 1. The storage levels are defined using a set of membership functions labelled from SF1 to SF5, representing very low, low, optimal, high and very high of storage, respectively. Similarly, water demand is categorized using DF1 to DF5, corresponding to very low, low, medium, high, and very high demands. The release values, which correspond to the water release adjustments, are defined in a similar manner to the water demand categories, using the labels RF1 to RF5.

Table 1. Developed verbal fuzzy rules.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25
Storage	SF1	SF1	SF1	SF1	SF1	SF2	SF2	SF2	SF2	SF2	SF3	SF3	SF3	SF3	SF3	SF4	SF4	SF4	SF4	SF4	SF5	SF5	SF5	SF5	SF5
Water Demand	DF1	DF2	DF3	DF4	DF5	DF1	DF2	DF3	DF4	DF5	DF1	DF2	DF3	DF4	DF5	DF1	DF2	DF3	DF4	DF5	DF1	DF2	DF3	DF4	DF5
Release	RF1	RF1	RF1	RF1	RF1	RF1	RF1	RF2	RF5	RF2	RF2	RF5	RF4	RF5	RF3	RF1	RF2	RF3	RF4	RF5	RF1	RF2	RF3	RF3	RF5

These fuzzy rules provide the basis for the Mamdani fuzzy inference system, enabling it to respond dynamically to changes in water demand and storage conditions, with appropriate adjustments to the downstream release. The system is designed to optimize water management by balancing storage and demand based on predefined fuzzy categories, ensuring efficient operation of the reservoir while meeting downstream irrigation needs.

2.3. Meta-Heuristic Algorithms

The objective function was defined by an improved loss function, which was initially developed in the literature [1,18]. This function is displayed in Equation (3).

$$OF = \sum_{t=1}^{T} \left(\frac{D_t - R_t}{D_t} \right)^2 \quad (3)$$

In the optimization model, **D** represents the water demand, and **R** denotes the water release. It is important to highlight the first constraint related to the application of the proposed objective function, which involves the upper and lower limits of the release. These limits are constrained between zero and the maximum demand for each month in the algorithms employed.

Another critical constraint is the storage level in the reservoir, which must remain within the predefined minimum and maximum storage values. While these limits are essential for managing the reservoir, they may not be directly considered in the developed programming by the algorithm. To address this, a commonly used approach to transform a constrained optimization problem into an unconstrained one is the penalty function method. This method introduces penalty functions that penalize any violations of constraints, effectively guiding the optimization process toward feasible solutions.

In this study, two penalty functions denoted as **P1** and **P2** have been incorporated into the main objective function, as shown in Equation (4). These penalty functions serve to penalize any violations of the release and storage constraints, ensuring that the optimization process stays within acceptable bounds while still striving to meet the desired objectives.

Furthermore, Equations (1) and (2) were used to update the reservoir's storage at each time step, reflecting changes in the water release and inflow. This dynamic update process ensures that the system continuously adjusts to the evolving conditions, maintaining an optimal balance between water release, demand, and storage management throughout the simulation period.

$$\begin{cases} if S_i > S_{max} \rightarrow P1 = c1\left(\frac{S_i - S_{max}}{S_{max}}\right)^2 \\ if S_i < S_{min} \rightarrow P2 = c2\left(\frac{S_i - S_{min}}{S_{min}}\right)^2 \end{cases} \quad (4)$$

Two meta-heuristic algorithms were used to solve the resulting defined objective function and the optimization problem. The first one is a known non-animal-inspired evolutionary algorithm called the gravitational search algorithm (GSA). This applicable algorithm, which is based on law of gravitational in physics has originally been developed and has been utilized in reservoir management for optimized release for the hydropower plan [19]. Its flowchart is displayed in Figure 5.

Additionally, an animal-inspired algorithm called the shuffled frog leaping algorithm (SFLA) has been used to solve the proposed objective function. The algorithm is shown in Figure 6.

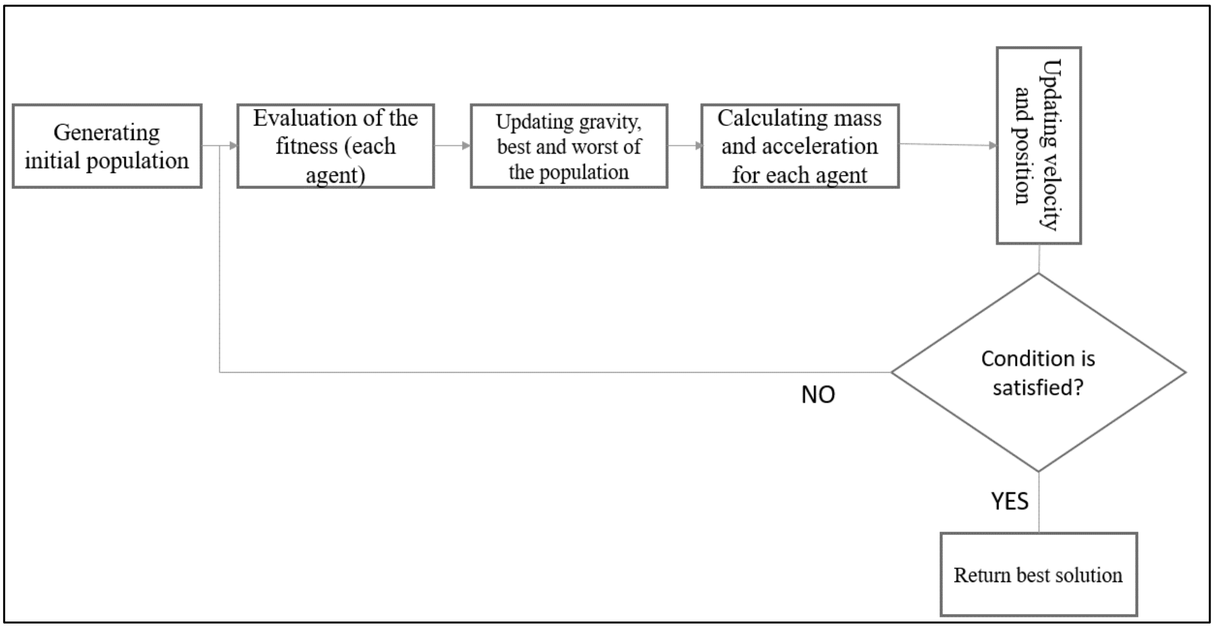

Figure 5. Flowchart of GSA [20].

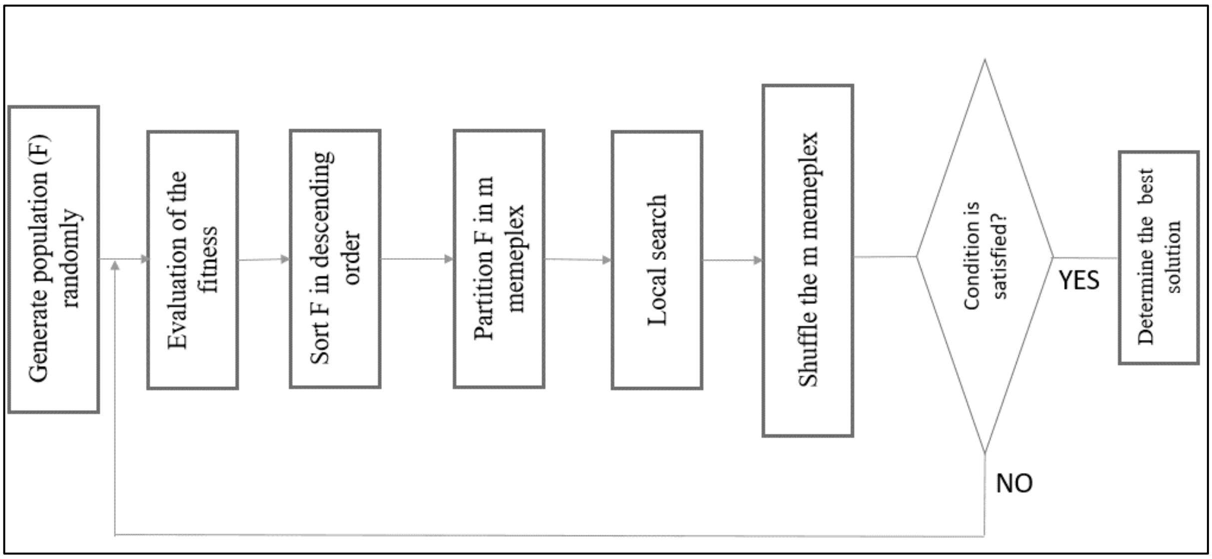

Figure 6. Flowchart of SFLA [21].

2.4. Analysis of System Performance

Previous studies initially developed three main indices to measure the system performance of reservoirs that have been improved in recent studies [1,18]. These indices include reliability, resiliency, and vulnerability indices, which have mathematically been expressed, respectively, in Equations (5) through (7):

$$\alpha_R = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t} \tag{5}$$

$$\beta_R = \frac{f_s}{F} \tag{6}$$

$$\gamma_R = Max_{t=1}^{T}\left(\frac{D_t - R_t}{D_t}\right) \tag{7}$$

where D and R have previously been defined, f_s is the number of failure series, and F is the number of failure periods during the operation period. Moreover, the root mean square error and absolute mean error have been utilized as additional indices to compare actual release and maximum water demand which are respectively displayed in Equations (8) and (9).

$$RMSE_R = \sqrt{\sum_{t=1}^{T} \frac{(D_t - R_t)^2}{T}} \quad (8)$$

$$MAE_R = \frac{\sum_{t=1}^{T} |D_t - R_t|}{T} \quad (9)$$

In addition to the optimization and management strategies, it is essential to assess the performance of the reservoir's storage system, which is defined in terms of storage loss. To measure this performance, several indices are employed, including resiliency, vulnerability, root mean square error (RMSE), and mean absolute error (MAE). These indices were used to evaluate both the storage and release performance of the system. It is important to note that for the purposes of this analysis, water demand was substituted by the optimal storage level, while the total release was replaced by the actual available storage at each time step.

Given the use of various methods for managing the release and storage of water in the reservoir, it becomes crucial to implement a decision-making system to select the best approach. In this context, the fuzzy technique for order of preference by similarity to the ideal solution (fuzzy TOPSIS), as proposed, was applied to make decisions among different alternatives [22,23]. The framework for this decision-making process is shown in Figure 7.

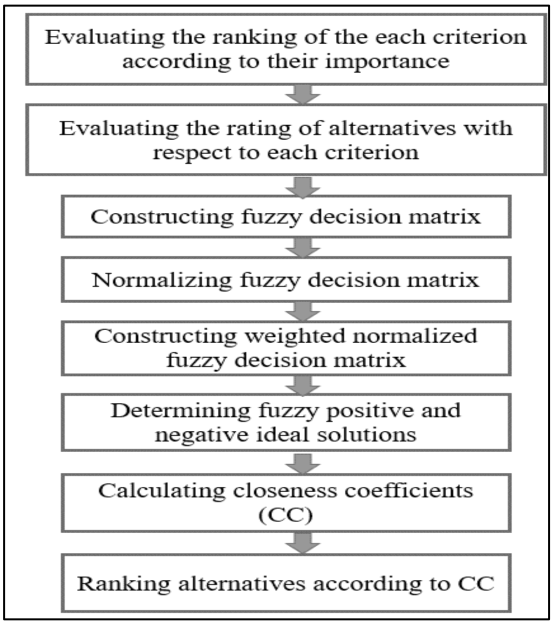

Figure 7. Flowchart of fuzzy TOPSIS [22].

The criteria for comparison include the previously discussed indices, such as resiliency and vulnerability, which reflect the system's ability to adapt and manage water efficiently. The alternatives or candidates considered in this decision-making process include GSA (gravitational search algorithm), SFLA (shuffled frog leaping algorithm), and fuzzy solutions. By applying the fuzzy TOPSIS method, the study aims to identify the most effective strategy for reservoir management based on these diverse criteria, ultimately selecting the alternative that best aligns with the system's performance objectives.

3. Results

The direct outputs of the reservoir optimization process, utilizing the three proposed solutions, are presented in Figures 8 and 9, which show the total release to downstream and the storage levels during the simulated period, respectively. The different methods lead to varying scenarios in terms of water supply demand downstream, and consequently, result in different storage levels throughout the operating period.

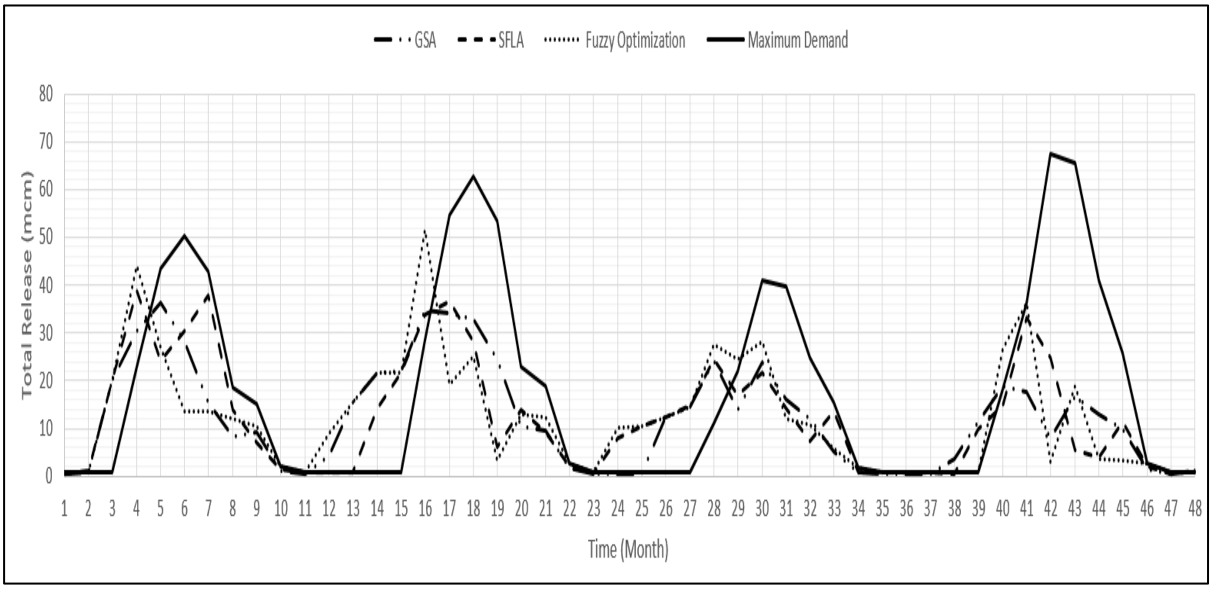

Figure 8. Optimum total release to downstream.

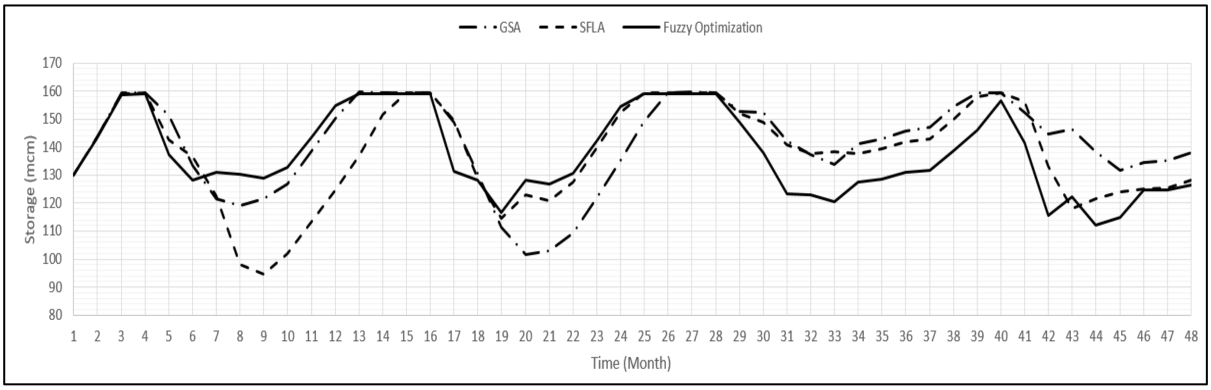

Figure 9. Optimum storage level.

It is important to clarify that the total release includes both the actual water release and any overflow directed downstream. This distinction is critical because given the substantial water demands downstream—primarily driven by irrigation needs—either the release or the overflow is used to fulfill the irrigation requirements. As a result, the total release to downstream in certain months exceeds the defined maximum water demand, which is an essential aspect to consider in the evaluation of system performance.

A key factor for further analysis is the potential for storage in agricultural pools located downstream. These pools provide a valuable opportunity for storing excess water, which can then be used in subsequent months. This capability is advantageous for managing water demand more effectively, especially during periods when water availability may fluctuate.

It is also important to recognize that the reservoir is not the sole water source for meeting downstream demands. The downstream branches of the river also contribute to satisfying irrigation needs. However, the primary goal remains for the reservoir to supply as much of the downstream water demand as possible, optimizing its contribution to the overall water management strategy. This dual-source approach—combining reservoir release with water from downstream branches—ensures greater flexibility and resilience in meeting agricultural water requirements.

Figure 9 illustrates the optimum storage levels of the reservoir under the different methods used. The results indicate that the shuffled frog leaping algorithm (SFLA) leads to significant fluctuations in the reservoir's storage, especially during the first year of the operational period. In contrast, the gravitational search algorithm (GSA) shows more pronounced changes in storage levels during the middle months of the simulation period. Both GSA and SFLA exhibit less variability in storage levels during the third year of the simulation. The fuzzy method, however, results in a more uniform pattern of storage level changes throughout the simulation period. While differences in storage behaviour among the methods are observable from the time series, they do not allow for direct, quantified comparisons. Therefore, a comprehensive analysis of system performance is necessary to evaluate the effectiveness of each method in optimizing reservoir management.

As discussed in the previous section, the system's performance has been assessed in terms of both water release and storage. Figure 10 presents the system performance indices related to the water released downstream. The reliability index reveals that the fuzzy method achieves the highest reliability release among the methods tested. This reliability index is a crucial measure for evaluating reservoir optimization, as ensuring the maximization of total water demand downstream is the primary objective of the release optimization process. Furthermore, this index plays a sensitive role in decision-making for reservoir management, reflecting the system's consistency in meeting water release targets.

The resiliency index, which measures the beneficial operation of the reservoir, mirrors the reliability index in its importance. A higher resiliency index indicates better recovery capabilities in the system after any failure, and the fuzzy method demonstrates the best performance in this regard. This result suggests that the fuzzy method can most effectively recover from any disruptions, maintaining stable water management operations.

On the other hand, the vulnerability index, which assesses the magnitude of the worst-case failure in release, shows that the fuzzy method performs the weakest in this area. The GSA method, in contrast, achieves the highest performance, minimizing the magnitude of failure. While this is an advantage, it should be noted that the vulnerability index is less critical and sensitive in this specific problem setup. This is because the possibility of storing water in downstream pools provides a buffer, helping stakeholders mitigate the impacts of failure.

The other indices, root mean square error (RMSE) and mean absolute error (MAE), suggest that either GSA or SFLA delivers better performance in terms of release accuracy, as indicated by the obtained release time series. Similar to the vulnerability index, the impact of these errors is reduced due to the availability of downstream storage, which minimizes the importance of these indices when compared to the reliability index. In conclusion, while GSA shows the best performance in minimizing failure magnitude and improving accuracy, the fuzzy method excels in terms of reliability and resiliency, making it the most robust approach for optimizing reservoir management in this study.

Figures 10 and 11 presents the system performance indices related to the reservoir's storage and release, which are crucial for minimizing storage loss. When selecting indices for storage loss analysis, it is important to note that the reliability index is not suitable for evaluating system performance in this context, as defined by Equation (5). This is because the changes in storage levels at each time step directly impact storage loss, and simply summing the storage levels across time would provide little meaningful insight. Unlike release, where the reliability index is a key factor, vulnerability becomes an essential index for storage performance analysis. The vulnerability index reflects the maximum magnitude of failure in storage management, indicating weaknesses in the proposed method for managing reservoir storage.

Figure 10. System performance indices of release.

Additionally, the resiliency indices of root mean square error (RMSE) and mean absolute error (MAE) help quantify the discrepancies between the objective storage level and the actual storage level. These indices act as "cost" indicators, meaning that increases in vulnerability, RMSE, or MAE indicate a worsening performance that results in greater storage losses. In contrast, the resiliency index is considered a "benefit" measure, as a higher resiliency indicates better recovery from storage losses, making it a desirable outcome in reservoir management.

Based on the results, the fuzzy method delivers the best performance among the "cost" indices related to storage loss. This suggests that it minimizes storage loss more effectively compared to the other methods. However, when calculating the resiliency index, it becomes clear that the GSA method achieves the highest resiliency rate, indicating that it can recover more effectively from storage losses. Nonetheless, the resiliency rate of the fuzzy solution is quite close to that of GSA, suggesting that while GSA may excel in resiliency, the fuzzy method also performs well in terms of maintaining a stable storage system and minimizing losses.

Figure 11. System performance indices of storage.

Not only are values of disparate indices for release and storage different but they could also propose different analyses of used methods to optimize operating reservoir. As a result, the application of a decision-making system is indispensable to selecting the best method and the proposed management scenario for operating reservoirs. Figure 12 displays the structure of fuzzy TOPSIS for the present study. As can be observed, level 1 (highest row) shows the goal of structure, which is selecting the best solution for optimizing reservoir operation. Moreover, level 2 shows all the criteria that are effective in selecting the best method. All nine calculated criteria can be seen at this level. Finally, the lowest level displays possible alternatives which include used solutions. We used the fuzzy TOPSIS method based on one expert as the decision maker. Hence, the first step is to determine the weight for different criteria. Our discussion on indices for release and storage would be helpful to determine the weights of each criterion. Used notations include ML, M, H, and VH representing moderately low, medium, high, and very high, respectively (Tables 2 and 3 show weight of importance and rating of the alternatives).

Due to our discussion about release to downstream, the reliability index must, unsurprisingly, be considered as VH because a dearth of the reliability index for release in our problem would significantly damage crops at downstream agricultural lands. Meanwhile, the vulnerability index has been allocated at the ML level of importance because the possibility of storage would reduce the magnitude impact of failure on irrigation demand. Either RMSE or MAE were considered at the M level of importance due to the positive effect of storage downstream, although their importance is clearly more than the vulnerability index. The allocation of weights to storage indices is another story. As discussed, the vulnerability index is very sensitive and crucial in the analysis of storage alterations because a high rate of vulnerability would considerably reduce benefits associated with storage levels in the reservoir. Others have been considered at the H level of importance because their role in storage loss is similar.

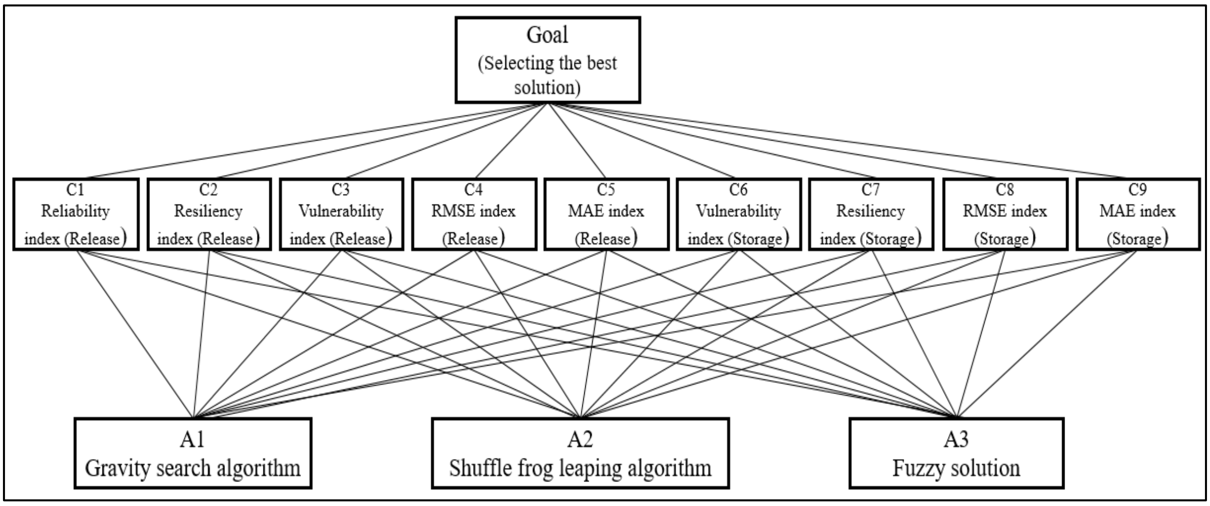

Figure 12. Developed structure for fuzzy TOPSIS analysis.

Table 2. Weights of importance for criteria.

Criteria	**Release**					**Storage**			
	Reliability	**Resiliency**	**Vulnerabili**	**RMSE**	**MAE**	**Resiliency**	**Vulnerabili**	**RMSE**	**MAE**
Weight	VH	M	ML	M	M	H	VH	H	H

Table 3. Rating of alternatives (right: storage, left release).

Criteria	**Alternatives**	**Rating**
Reliability (Benefit)	GSA	G
	SFLA	VG
	Fuzzy	VG
Vulnerability (Cost)	GSA	G
	SFLA	VG
	Fuzzy	VG
Resiliency (Benefit)	GSA	RG
	SFLA	G
	Fuzzy	VG
RSME (Cost)	GSA	RG
	SFLA	RG
	Fuzzy	VG
MAE (Cost)	GSA	G
	SFLA	G
	Fuzzy	VG
Vulnerability (Cost)	GSA	VG
	SFLA	RG
	Fuzzy	F
Resiliency (Benefit)	GSA	VG
	SFLA	F
	Fuzzy	G

Table 3. *Cont.*

Criteria	Alternatives	Rating
RSME (Cost)	GSA	G
	SFLA	VG
	Fuzzy	RG
MAE (Cost)	GSA	VG
	SFLA	RG
	Fuzzy	RG

Another issue that deserves mention is the rating of alternatives for each criterion as the next step in the development of the fuzzy TOPSIS method. Notations include F, RG, G, and VG, which mean fair, relatively good, good, and very good. Our estimation of rates was based on absolute values and differences among methods. Furthermore, it should be noted that cost indices impact the system. For instance, if a fuzzy solution demonstrates an F rating for the vulnerability index of storage, it will indicate the best performance and other indices as well. Table 4 displays D+ and D− for alternatives and consequently Figure 13 displays the final ranking of the used optimization methods of reservoir management. Moreover, Figure 14 shows the irrigation deficiencies of different methods.

Table 4. D+ and D− of alternatives.

Alternatives	D+	D−
GSA	1.10	2.14
SFLA	1.27	1.93
Fuzzy	0.96	2.26

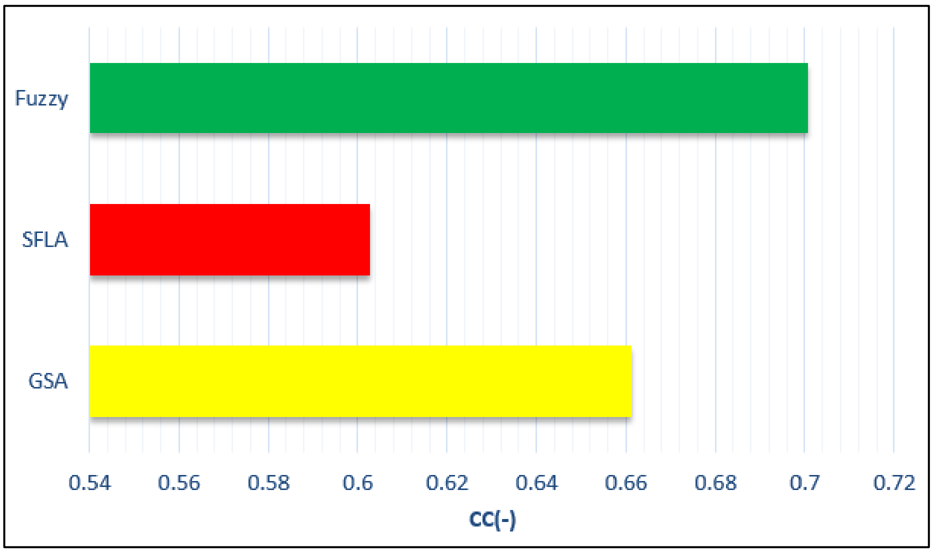

Figure 13. Final ranking on optimization method solutions.

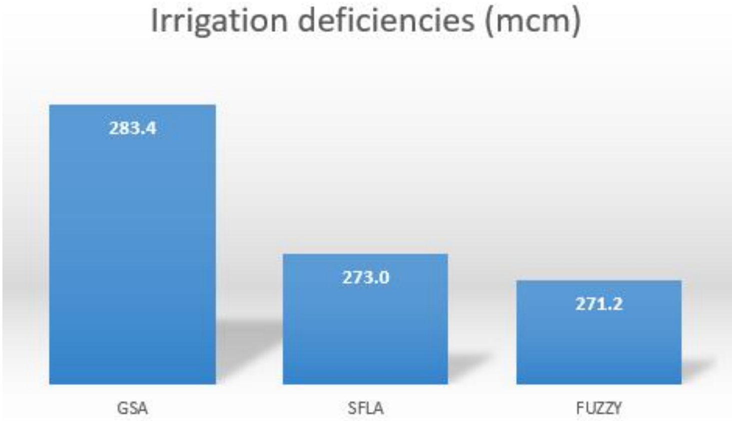

Figure 14. Irrigation deficiencies of different methods.

4. Discussion

In the context of reservoir operation within Cfa (humid subtropical climate) and Csa (Mediterranean climate) climatic conditions, the proposed fuzzy-based expert opinion method offers an adaptable, efficient, and robust solution for managing water release and storage. These climatic classes, characterized by distinct seasonal precipitation patterns and temperature fluctuations, present unique challenges for reservoir management.

In Cfa climates, where summers are hot and humid and winters are mild with significant rainfall, managing water resources presents several challenges. The high evaporation rates during summer and lower water inflows in winter complicate water storage management. There is a need to maintain sufficient storage during dry periods and prevent overflow during the wet season. The inconsistency in precipitation and the seasonal fluctuations in temperature and humidity make it difficult to predict water demand and reservoir storage, often resulting in the under- or over-release of water. In Csa climates, which experience hot, dry summers and mild, wet winters, the primary challenge is efficient water storage and distribution, especially during the extended dry season. The concentrated rainfall in winter means that reservoirs must store enough water to supply demand during the summer months, while also accounting for the potential of high evaporation losses. Reservoir management in these regions requires careful balancing to meet the demands of agricultural irrigation, which often peaks during dry months.

Given these challenges, the fuzzy-based method, developed in this study, demonstrates significant potential for improving reservoir management in Cfa and Csa climates. The Mamdani fuzzy approach, with its ability to incorporate expert opinion-based rules and pragmatic constraints, makes it especially effective for regions where climatic uncertainty and water demand variability complicate decision-making processes. The fuzzy-based method is well-suited for Cfa and Csa climates due to its flexibility in accommodating seasonal variations in precipitation and temperature. By incorporating expert knowledge into the fuzzy rules, it can adjust water release schedules to avoid water shortages during dry periods and prevent overflow during wet seasons. The system can continuously update the release and storage strategies based on real-time data, ensuring timely decisions to handle unexpected climatic changes.

One of the core strengths of the fuzzy-based method is its ability to integrate expert opinions from reservoir operators, hydrologists, and agricultural stakeholders. This feature is particularly important in regions with high climate variability, where precise water demand forecasting is difficult. Experts can help define the verbal fuzzy rules, which guide water release decisions in response to changing climatic conditions, such as fluctuating rainfall and temperature patterns. This approach ensures that the model reflects real-world challenges and incorporates knowledge about local water usage practices. The fuzzy-based method's ability to minimize irrigation deficiencies is highly relevant for Cfa and Csa regions, where agriculture is a primary water user. By optimizing water distribution, the fuzzy system ensures that irrigation demands are met efficiently, especially during the peak demand seasons of summer. As evidenced in the study, the fuzzy method outperforms algorithms like GSA and SFLA in minimizing irrigation deficiencies. This makes the fuzzy method an excellent tool for regions where agriculture is the dominant water demand.

It is important to highlight that modifying the input parameters or adjusting the membership function data in fuzzy systems can significantly influence the water release. Given the dynamic and interdependent nature of water resource systems, other factors might need to be integrated into the model. For instance, in regions where evaporation is particularly high—though not applicable to the current study area—this parameter could be incorporated into the fuzzy modelling framework. Such additions can substantially affect the release, either increasing or decreasing them, depending on the specific conditions of the system.

As emphasized, the quality and structure of the input data play a pivotal role in the system's performance. In the present study, an optimal number of five membership functions was selected for the fuzzy system. This choice reflects a balance between model complexity and accuracy. Increasing the number of membership functions adds sophistication to the system, improving its ability to capture nuances in water resource exploitation. However, it also increases computational complexity. Conversely, if the number of membership functions is set too low, the model's accuracy and reliability for practical application diminish, rendering it less effective in managing water resources.

The fuzzy system's resiliency index, which measures how well the system recovers after failures, is particularly important in climates prone to droughts or flooding—events that are common in both Cfa and Csa climates. By adapting to changing conditions and optimizing release and storage decisions, the fuzzy-based method helps minimize the impacts of extreme climatic events. Whether managing water scarcity during droughts or excess water during flooding, the fuzzy method ensures that the reservoir can respond flexibly to these challenges.

In Cfa and Csa climates, high evaporation rates during the warmer months can result in significant water losses from reservoirs. The fuzzy-based method takes evaporation into account, adjusting storage and release strategies to minimize these losses. Using performance indices like RMSE and MAE, the fuzzy-based method ensures that actual storage levels remain close to optimal levels, minimizing storage loss. This is critical in regions where evaporation significantly impacts the available water supply, and managing storage loss is essential for meeting long-term water demand.

The system performance of the fuzzy-based method is evaluated using various indices, including reliability, resiliency, vulnerability, and storage loss indices. The results show that the fuzzy-based method outperforms other algorithms such as GSA and SFLA in key performance areas, particularly in terms of release reliability and irrigation supply maximization. The fuzzy system achieves the highest resiliency index, indicating its capacity to recover from system failures, while its vulnerability index demonstrates its robustness in minimizing the impact of water release failures. Although GSA performs better in terms of vulnerability, the fuzzy system's overall performance, particularly in storage management and irrigation optimization, makes it a superior choice for Cfa and Csa climates.

The adoption of the proposed fuzzy-based reservoir operation system has the potential to yield significant benefits, particularly for the downstream areas. These areas, including agricultural lands and natural pastures, rely heavily on consistent and adequate water supply. Ensuring sufficient water distribution to these zones is essential for meeting agricultural demands. One of the primary strengths of this operation system lies in its reliance on expert insights. These experts possess an in-depth understanding of the unique requirements of downstream water users, enabling the system to be tailored to their needs effectively. The integration of expert opinions ensures that the system is responsive to the diverse demands of downstream water resources. Additionally, this approach incorporates valuable feedback from farming communities and other stakeholders, allowing the system to reflect the perspectives and practical experiences of those directly affected by reservoir management decisions. By facilitating a more direct involvement of downstream communities in the reservoir exploitation process, this system is expected to promote more sustainable water management practices. It ensures that the operational strategies align with the broader goals of environmental sustainability while addressing the socio-economic needs of the local population. Moreover, fostering such participatory decision-making processes helps to build trust and satisfaction among stakeholders, enhancing the overall acceptance of the system.

Based on the conducted study and the evaluation of the implemented models in specific scenarios, it is evident that one of the key advantages of employing a fuzzy system lies in its ability to significantly reduce computational time compared to conventional optimization methods, such as used algorithms. The results indicate that achieving optimal outcomes with the optimization models requires approximately two hours of computational time. This duration depends on several factors, including the complexity of the system, the iterations involved, and the computational resources available.

In contrast, the newly developed fuzzy system reduces this computational time to just a few minutes, making it a powerful and efficient alternative. This remarkable efficiency is due to the inherent nature of fuzzy systems, which rely on expert-derived rules and approximate reasoning rather than exhaustive computational iterations. In situations where numerous simulations or real-time evaluations are required, the fuzzy system's reduced computational demand becomes a transformative advantage. Moreover, in scenarios where evolutionary algorithms are used for optimization, the computational cost can become even more prohibitive. These algorithms often involve extensive iterations and population-based simulations, resulting in considerable time investment. The fuzzy system addresses this bottleneck effectively by delivering rapid, approximate solutions without compromising the reliability of the results.

Fuzzy systems have been widely applied in various engineering fields, demonstrating significant utility in addressing complex water resources problems [24,25]. However, it is important to acknowledge the inherent limitations of these systems, as outlined in previous studies. One notable limitation is that fuzzy systems are inherently approximate in nature, offering a framework for approximate modelling rather than precise or deterministic solutions. This characteristic makes them particularly suitable for scenarios where exact models are difficult or impossible to develop due to system complexity or limited data availability.

The reliance on expert input is a defining feature of fuzzy systems. Expert opinions are typically based on objective observations, but these observations often involve a degree of subjectivity and qualitative judgment. Consequently, the models constructed using fuzzy systems may reflect this inherent subjectivity. Despite this, such approximate models serve as effective substitutes for exact models, particularly in situations where capturing all variables and interactions in an exact form is impractical or infeasible. Fuzzy systems are particularly valuable in situations requiring flexibility and adaptability, where the dynamics of the system under study are not fully understood, or where there is a high degree of uncertainty.

All types of modelling, including those related to water resources, involve inherent uncertainties and require a thorough examination to assess their reliability and applicability. Water resource models must be designed to provide users with reliable, long-term insights, enabling accurate decision-making. In this study, two critical issues related to the uncertainties are emphasized: the quality of the available data and the accuracy of fuzzy-based models for reservoir exploitation. With respect to the available data, attention must be paid to the inherent errors present in these datasets. For instance, inaccuracies may arise in the inflow time series to reservoirs, which are derived from a series of flow measurements and estimates. Similarly, sedimentation in reservoirs impacts the estimation of storage capacity and must be carefully considered in the modelling process. These factors significantly influence the accuracy of the models and highlight the importance of accounting for such uncertainties during analysis which should be incorporated into the analysis to ensure a realistic estimation of storage capacity. While other potential sources of uncertainty such as surface evaporation exist, they should not be considered primary contributors to uncertainty in the present models. Another key source of uncertainty arises from the fuzzy nature of the models themselves, which rely on the quality of observations and actual reservoir exploitation data. Fuzzy models inherently approximate the behaviour of complex systems and are influenced by the quality of input data. This implies that even with advanced modelling techniques, uncertainties will persist, particularly regarding the accuracy of predictions derived from these models.

5. Conclusions

This study evaluated a Mamdani fuzzy solution for optimizing reservoir release and storage, comparing it with the shuffled frog leaping algorithm (SFLA) and gravitational search algorithm (GSA), specifically in Cfa and Csa climatic classes. The results revealed that while the fuzzy solution was robust in managing release and storage, evolutionary algorithms like SFLA and GSA performed better in certain release system indices. A fuzzy TOPSIS decision-making method was used to rank the methods, with the fuzzy solution emerging as the best for optimization, followed by GSA. Analysis of irrigation deficiencies showed that GSA was less effective in minimizing deficiencies, while the fuzzy solution excelled in maximizing agricultural water supply. This study confirms the efficiency of fuzzy methods in reservoir management under Cfa and Csa climates, offering a computationally efficient alternative that incorporates expert knowledge, making it a promising solution for optimizing water resource management in dynamic climatic conditions.

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