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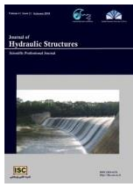

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Uncertainty analysis and risk identification of the gravity dam stability using fuzzy set theory

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Abstract

This paper introduces a methodology in which the fuzzy theory has been used along with numerical modeling of a gravity dam. For this purpose, using the fuzzy set theory method, the Folsom gravity dam in the USA, which is modeled in ANSYS and CADAM softwares, its uncertainties are analyzed. It is shown that with 10% variation in the input variables, about -92.31 to +78.6% uncertainty is created in the heel stability of the dam. Another part of this paper focuses on sensitivity analysis based on inputs and shows how inputs affect the outputs. From this sensitivity analysis can be proven that the output parameters have a monotonic behavior and the fuzzy outputs can be extracted without the need for an optimization algorithm. This paper also presents a new concept of risk identification derived from the fuzzy set theory to increase the stability awareness of the Folsom gravity dam. The minimum amount of uncertainty that leads to the risk area is 0.02%, which is related to S1 in loading condition 2.

Keywords: Uncertainty, Risk, Fuzzy set theory, Gravity dam, Numerical modeling.

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1. Introduction

Dams are structures built across rivers to stop the flow and create a reservoir or divert water from the natural path into the desired path. Dams are an essential part of any country's infrastructure that can be used for energy production, water supply, flood control, and other activities such as irrigation, navigation, tourism, etc. Various incidents such as human errors during operation and construction or natural incidents affect the performance of dams. It is expected that for various reasons such as population growth, growing water demand, climate change, etc., the construction of more dams in different parts of the world will be on the agenda of decision-makers and managers [1][2].

Like other structures, dams are exposed to various incidents that threaten the safety and stability of dams. These incidents can threaten the lives of many people who are living

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downstream of dams and are at risk of failure[3].That is why today, the analysis of dams in terms of uncertainty and risk is on the agenda of operators, and therefore, extensive researches have been done on the analysis of dam structure uncertainty [4-8]. In other words, coupling uncertainty and risk can provide valuable information for operators and decision-makers about how vital structures, such as dams, work. The impact of uncertain input parameters (e.g., different imposed loads, material properties, and geometric parameters) on the design of the dam as well as its impact on the stability of the dam against slip can be calculated, and then the amount of risk can be achieved through this way.

There are several ways to analyze uncertainty, such as the Monte Carlo Simulation Method, based on probability, Fuzzy Set Theory (FST), and Entropy Method. Fuzzy logic (FL) is a nascent method in uncertainty analysis and risk assessment recently welcomed to replace traditional methods. The FST and FL were first introduced by Zadeh (1965) [9], and their principles were then developed by his colleagues as well as by researchers such as Beit et al. (1992)[10] and Mamdani & Assilian (1975) [11]. Firstly FST was considered as a classic set theory, but over the past decades, the concept of fuzzy mathematics is rapidly developed. FST is very useful in interpreting uncertainties in a wide range of engineering problems. Up to now, a significant number of studies in fields of engineering has used fuzzy sets such as Beer et al. (2013), Hanss & Turrin (2010), Jahani et al.(2014), Li et al. (2015), Purba (2014a, 2014b), Reza et al.(2013), Xu et al.(2016), and Tee et al.(2018) [12-20].

Regarding the risk analysis of gravity dam's stability, Li et al. (2011) [21] investigated dam risk using fuzzy c-means clustering (FCM) which is the most widely used as a clustering algorithm. Because the FCM technique depends on the initialization of clustering centers for overcoming this shortage this method is coupled to an artificial intelligence technique. The artificial bee colony algorithm (ABC) is used as an artificial intelligence technique. Coupling the ABC with the DCM method (ABCFCM) is proposed for risk analysis of dams. Altarejos-García et al. (2012)[22] proposed a methodology for determining the probability of failure by sliding in concrete gravity dams using the concept of risk. They improved the conditional probability estimation of the gravity dam response using the Monte Carlo simulation method. They found that the conditional probability of dam failure would lead to results related to dam validity and safety that were of considerable importance. Peyras et al. (2012) [23] presented a combined method of risk analysis and reliability methods to assess the probability of dam safety. The results showed that the level of reliability is very high. Su & Wen (2013) [5] established a method that calculated the fuzzy risk for a gravity dam. In this study, they presented an analysis method to calculate the fuzzy risk and the probability of stability failure of gravity dams. As they claimed, randomness and fuzziness are two inseparable components that affect the stability of gravity dams. Haghighi & Ayati (2015) [2] used fuzzy theory and they linked it to genetic algorithm optimization model to address the uncertainties in the stability of the gravity dam. In the subsequent study by Haghighi & Ayati (2016) [25], they completed their previous research using a new multi-criteria genetic algorithm optimization model and its connection to the fuzzy theory. Alembagheri & Seyedkazemi (2015)[26] used probabilistic and stochastic methods to analyze the possible seismic performance of gravity dams. In this research, the Monte Carlo simulation method has been used to analyze the uncertainty of input parameters and their effect on the seismic performance of the gravity dam. Morales (2016) [27] proposed a method to analyze dam fragility and then identify uncertainties. Fragility curves provided valuable input for risk models to compare risk reduction versus reduced investment uncertainty. Jia et al. (2018) [28] investigate the failure probability of a dam using the FOSM-based method that is a mathematical model. Using the FOSM method, have been taken the uncertainties of material parameters and the different stress states and material zones into account. In this study for coding the FOSM method into a computer program, the MATLAB program is used. Finally, for verifying the proposed algorithm, the Monte Carlo Simulation Method is used as a benchmark method. Gavabar et al. (2018) [29] This study is studied probabilistic seismic in hazard of jointed gravity dams. The case study which is used for this study is Folsom dam. The Folsom dam is numerically modeled based on the finite element method. Two sources of nonlinearity in this study are material and geometric nonlinearly. Shu et al. (2020) [30] evaluate the safety reliability for dams based on interval-valued intuitionistic fuzzy set and evidence theory. In this research, the interval-valued intuitionistic fuzzy set is used to evaluate the uncertainty in heterogeneous information, and for modifying that information the supporting degree is used. For verifying the proposed algorithm, a multiple-arch dam is used as an example and the result has shown that there is a potential risk at the dam section and it must be reinforced to become safer. Majid Pouraminian et al. (2020) [31] Investigated the uncertainty analysis of the dam structure. They examined the uncertainty of the dam by considering the uncertainty in the physical and mechanical properties of the dam body materials as well as the reservoir water level. In this research, the coefficient of variation is 5 and 10%. The results indicate that the modulus of elasticity of concrete, concrete density, and hydrostatic pressure height are the most effective parameter and the Poisson ratio is an insignificant parameter in the dam response. Laifu Song et al. (2021) [32] analyzed the reliability of rockfill dam using Copula Function. In this paper, a radial basis function network (RBFN) and an intelligent response surface method are combined for the reliability analysis of rockfill dam slope stability. In this research, the nonlinear strength parameters are modeled using the Copula function. The results indicate that the Copula function unlike traditional independent normal distribution has resulted in a higher failure probability and overestimation of the reliability of the stability system of the dam slope. Hiroshi Takagi et al. (2021) [33] investigated the stochastic uncertainty in a Dam-Break. In this research, the uncertainty of gate-opening speeds in dam-break is investigated. For studying the uncertainty, in this study 290 tests were performed. Finally, statistical relationships are established between the gate speed and the maximum pressure, which has a very significant relationship.

In this paper, unlike some of the abovementioned studies, all the forces included in the regulations are considered, which leads to a more comprehensive study. Another difference is that in some research papers, dam analysis has been done simply and assuming the dam is rigid and without considering the foundation, but in the present paper, dam modeling is done with the foundation and using the finite element method, which is a much more accurate method. This paper also develops the concept of dam stability risk identification in an innovative way resulting from fuzzy results. In general, the innovation of the present paper is summarized as follows:

1- Comprehensive dam analysis based on all loading modes of USACE regulation (American dam design regulation).
2- Dam analysis with foundation with finite element method using ANSYS.
3- Identify the risk of dam stability in an innovative way from fuzzy results.
4- Ability to identify risk in optimal design mode for design with acceptable confidence margins.

In the present study, at first, a typical gravity dam stability was modeled based on numerical modeling and then the fuzzy theory has been used along with numerical modeling. For this purpose, the dam is modeled in ANSYS software to calculate the critical stresses. Additionally, the dam stability safety factor was computed using CADAM software. Then, the uncertainty and risk of critical stresses and safety factors against sliding and overturning were recognized using the responses obtained from the fuzzy analysis. The second step in this research is to identify the risk area of the dam. To identify the risk area, after obtaining the fuzzy set theory outputs, the areas that exceed the boundaries obtained by the criteria of the regulations are known as the risk area.

2. Stability analysis of gravity dams

Gravity dams are dams that are constructed using concrete or stone, and their stability is based on their weight. Identifying critical forces and their combinations are essential parts of the analysis and design of a dam. The pressures and forces can be categorized as follows: (1) external water pressure, (2) temperature, (3) internal water pressure; i.e., pore pressure or uplift in the dam and foundation, (4) weight of the structure, (5) ice pressure, (6) silt pressure, (7) earthquake, and (8) forces from gates or other appurtenant structures.

Table 1: USACE (1995) [32] load conditions for stability analysis of gravity dams

Number	Class	Earthquake	Headwater	Tail Water	Silt	Ice	Uplift
1	Unusual	-	-	-	-	-	-
2	Usual	-	Crest (top of gate)	Minimum	Yes	Yes	Yes
3	Unusual	-	SPF	Flood elevation	Yes	-	Yes
4	Extreme	OBE (upstream direction)	-	-	-	-	-
5	Unusual	OBE (downstream direction)	Usual pool level	Minimum	Yes		Preearthquake level
6	Extreme	MCE (downstream direction)	Usual pool level	Minimum	Yes		Preearthquake level
7	Extreme	-	-	Flood elevation	Yes		Yes

SPF (Standard Project Flood), PMF (Probable Maximum Flood), OBE (Operating Basis Earthquake), MCE (Maximum Credible Earthquake

A gravity dam should satisfy the criteria against overturning and sliding. Safety factor against the overturning and sliding are calculated according to the following equations, respectively:

$$FS_0 = \frac{\sum M_p}{\sum M_a} \tag{1}$$

Where $\sum M_p$ is the total passive moments and $\sum M_a$ is the total active moments about the toe.

$$FS_s = \frac{T_F}{T} = \frac{Ntan(\varphi) + cL}{T} \tag{2}$$

In which, T_F is the maximum resisting shear, T is the applied shear, N is the resultant of the forces normal to the sliding plane, φ is the soil foundation angle of internal friction, c is the cohesion intercept and L is the length of the base in compression for a unit strip of the dam. The section should be so proportional that the stresses in both the concrete and the foundation should not exceed from the admissible values. There are two methods to analyze the stresses of gravity dams: namely the gravity method and the finite element method. where the latter is much more accurate from the former. To estimate the overall value of dam safety factor against sliding and over training, CADAM software was employed herein. In addition, to calculate the principle internal stresses, ANSYS software (formulated and developed on the basis of finite element method) was employed. CADAM software has been designed for evaluating the safety factors of stability of gravity dams. The CADAM software is developed using the Gravity method. USACE (1995) [32] has determined specific criteria for for dam stability against overturning and sliding as well as some other criteria for the critical internal stresses. The stability safety factor and stresses criterion for concrete gravity dams for each loading conditions is presented in Table(2).

Table 2: USACE (1995) [34] stability and stress criteria for concrete gravity dams

Loading Condition	Sliding Safety Factor	Overturning Safety Factor	Compress Stress	Tensile Stress
Usual	2	1.3	$0.5fc'$	0
Unusual	1.7	1.2	$0.3fc'$	$0.6fc'$^2/3
Extreme	1.3	1.1	$0.9fc'$	$1.5fc'$^2/3

Note: fc' is 1-year unconfined compressive strength of concrete. In this case fc'=35MP

3. Methodology

In the fuzzy set theory, uncertainty parameters can be presented in a new form that each parameter refers to a set of values instead of a single value. A fuzzy number, like N, is a subset of the real numbers. Each variable, like x, has a grade of membership, $x\epsilon N, \mu_N \epsilon [0,1]$, that declares the amount of membership grade to the fuzzy number. x is not included in the fuzzy set if $\mu_N(x) = 0$, x is a full included if $\mu_N(x) = 1$, and x will be the fuzzy member if $0 < \mu_N(x) < 1$. α_cut, N_α, is an operation that is applied to the fuzzy numbers and it divides, as shown in Fig 1, the fuzzy numbers into the crisp intervals as$[x_{a,a}, x_{b,a}]$.When $\alpha = 0$, the interval is $x_a, x_b$and called 'support' which has the highest uncertainty whereas when $\alpha = 1$,the interval has only one value, x_c, which called the 'crisp number'. For each parameter, like x, when α_cut is applied to x, the intervals can be shown as follows.

$$x_{a,\alpha} = x_c - \Delta x_\alpha$$
$$x_{b,\alpha} = x_c - \Delta x_\alpha \qquad (3)$$

In which Δx_α is the uncertainty amount at α_cut and $x_{a,\alpha}$ and $x_{b,\alpha}$ are the lower and upper bounds of x at α_cut, respectively. As said above the maximum membership value is one and can be shown as follows.

$$\exists x \in R, \mu_N(x) = 1 \qquad (4)$$

Considering two α_cut, α and α', and their intervals, the relationship between the intervals can be formulated in the following.

$$(N_\alpha = [x_{a,\alpha}, x_{b,\alpha}]): \alpha' < \alpha \ \rightarrow \ x_{a,\alpha'} < x_{a,\alpha}, x_{a,\alpha'} > x_{b,\alpha} \qquad (5)$$

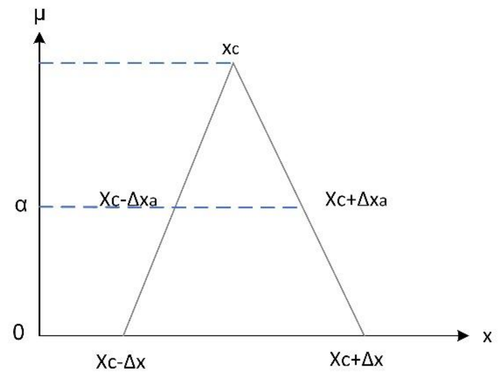


Figure 1. Triangular symmetric fuzzy number

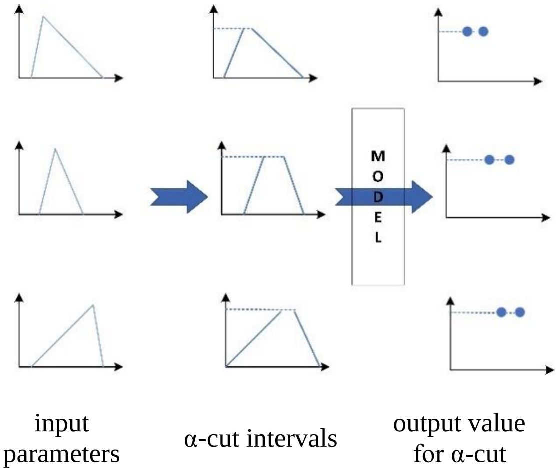


Figure 2. α_cut method

Two types of triangular and trapezoidal membership functions are very prevalent in the fuzzy set theory. In this study, the triangular membership function is utilized to represent the gravity dam's uncertainties. The fuzzy approach to uncertainty analysis of gravity dam is introduced as follows:

Specify the crisp values of input design variables (x_c).

The maximum uncertainty for each input design variable $\pm\Delta x$ is approximated based on expert knowledge.

A continuous triangular fuzzy membership function (Figure 1) can be attributed to each input design variable; so that the support of the fuzzy membership is $2\Delta x$.

At first, a limited number of α_cuts are specified, and then the membership functions of each input design variable is discretized by those α_cuts. (Figure 2)

In this step, for each output parameter, two optimization problems are solved. The safety factor and critical stress are defined by a nonlinear function $f(\vec{x})$ where $\vec{x}$ is the vector of decision variables (input uncertainties). $f(\vec{x})$ is evaluated through a simulation model, and for each α_cut, it is once maximized and once minimized by an optimization model.

If the optimization problem is one of a non-monotonic type, then an optimization algorithm will be required to solve it, in the otherwise if the problem has monotonic behavior, the maximization and minimization of output parameters could be obtained simply through the extremes of input parameters, and there is no need to use optimization algorithms. In the gravity dam model, assuming the dam geometry is a deterministic parameter, and the other input parameters are indeterminism so that this problem will be monotonic. This could be confirmed through the equations of the dam's safety factors (equations 3.1 and 3.2).

Finally, an area of the output figures that can be described as having gone beyond the allowable value in USACE will be recognized as the risk area.

Fuzzy analysis of gravity dam:

In this research, the study is carried out on the Folsom gravity dam. This dam was established, about 25 miles northeast of Sacramento, on the American River in the United States in 1955. The cost of construction of this dam is approximately 81.5 million dollars. Figure (3) shows a cross-section of the Folsom dam geometry. Because of the lack of access to enough information on the dam, the hypothetical numerical values in geometry have been used. To model, the dam's foundation in ANSYS software, the depth, and width at the downstream are equal to the dam's height, and the width at the upstream is two times higher than the dam's height.

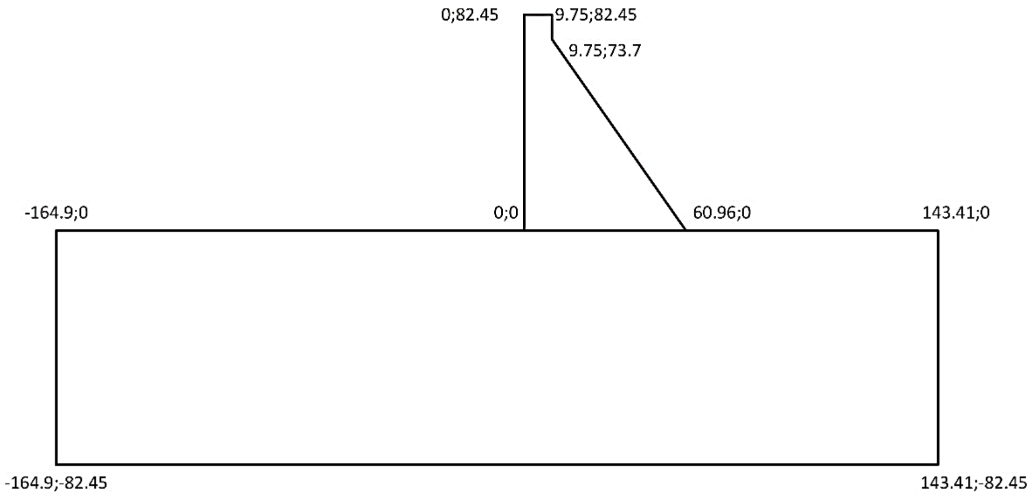


Figure 3. Geometry of Folsom Dam and Foundation

The design parameters are presented in Table 3. All design parameters have ±10% uncertainty. Table 3. Also contains the upper, crisp, and lower values of input uncertainties for each design parameter.

Table 3: Input fuzzy parameters variable

	Variable	unit (ISI)	lower limit	crisp value	upper value
1	unit weight of concrete	KN/m^3	24.67	25.97	27.27
2	unit weight of silt	KN/m^3	13.77	14.5	15.22
3	concrete elastic module of dam	Gpa	28.5	30	31.5
4	upstream normal level	m	66.5	70	73.5
5	standard project flood level	m	71.25	75	78.75
6	probable maximum flood level	m	74.57	78.5	82.42
7	downstream flood level	m	19	20	21
8	downstream minimum level	m	14.25	15	15.75
9	upstream silt level	m	23.75	25	26.25
10	operating basis earthquake coefficient		0.095	0.1	0.105
11	maximum credible earthquake coefficient		0.19	0.2	0.21
12	concrete elastic module of foundation	Gpa	-	20	-
13	Poisson's ratio of dam and foundation	-	-	0.2	-

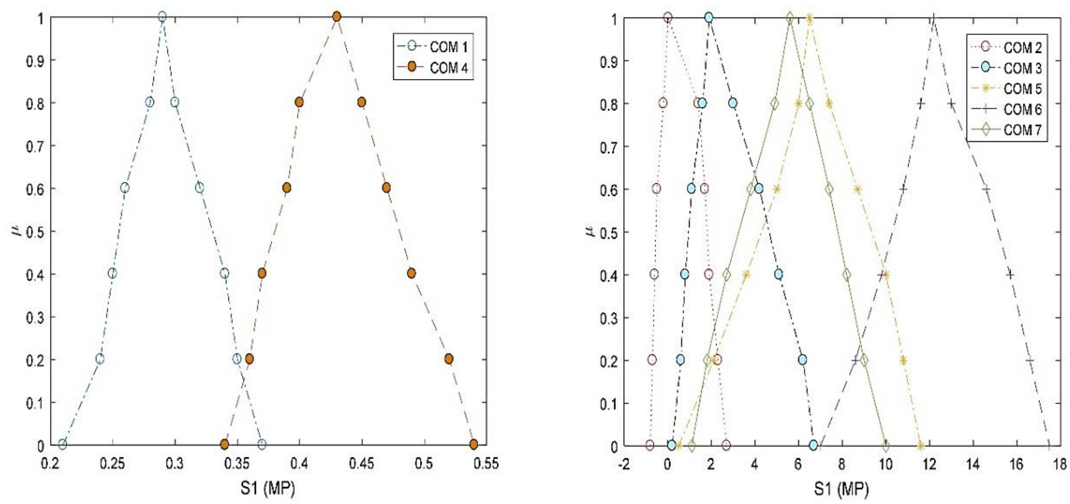
To obtain the impact of uncertainty of design parameters on the critical stresses, i.e. the principal stresses called S1 and S3, the input variables have been discretized with 6 $\alpha-$cuts including α =0 (the support), 0.2, 0.4, 0.6, 0.8 and 1 (the crisp). To obtain the impact of uncertainty of design parameters on the safety factors, i.e. the dam's sliding and overturning safety factor, the input variables have been discretized with 3 α−cuts including α =0 (the support), 0.5 and 1 (the crisp). Then, to find the extreme output values of each α-cut input, the incremental and decremental input parameters (table 4) must be identified and then the extremes of α- cuts must be estimated using the extremes from the input parameters. For finding the output values, the CADAM software and the ANSYS model, which includes the dam itself and the foundation , neglecting Dam-foundation interaction affects. To find the fuzzy functions of the dam's sliding and overturning safety factor through CADAM software, the input parameters were discretized using 3 a-cuts including α =0 (support), 0.5 and 1 (crisp).

Table 4. Incremental and decremental input parameter

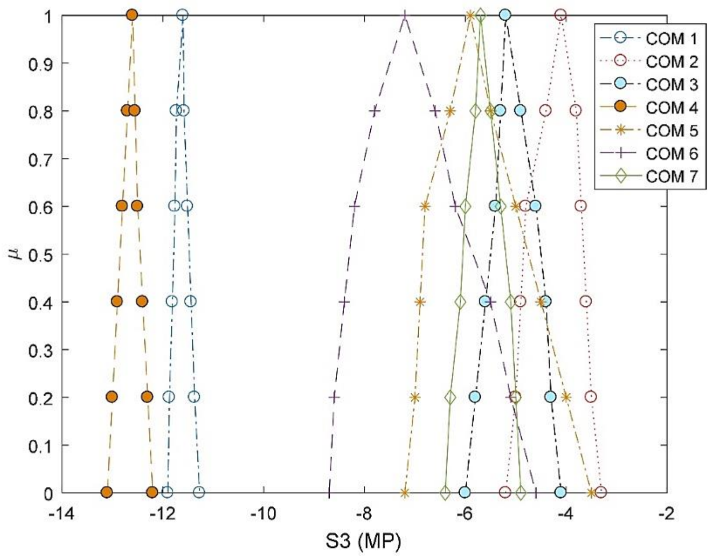
Input Variable	Max Tensile Stress (S1)	Max Compress Stress S3	Sliding Safety Factor	Overturning Safety Factor
Upstream Water Level	Incremental	Incremental	Decremental	Decremental
Upstream Silt Level	Incremental	Incremental	Decremental	Decremental
Unit Weight of Concrete	Decremental	Incremental	Incremental	Incremental
Unit Weight of Silt	Incremental	Incremental	Decremental	Decremental
Earthquake Coefficient	Incremental	Incremental	Decremental	Decremental
Concrete Elastic Module of Dam	Incremental	Incremental	-	-

4. Results and discussion

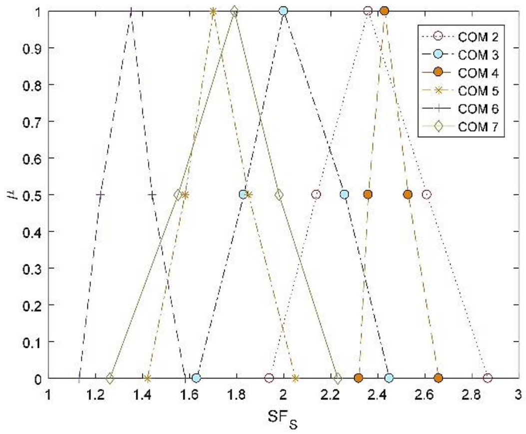
The fuzzy function of the principal stresses, i.e. S1 and S3, and the safety factors, i.e. sliding safety factor and overturning safety factor, are presented in figure 5 for all possible loading conditions, respectively. The results of α=0 (the uncertainty of input variable is 10%), which are more important for uncertainty analysis, are presented in the figure 6.



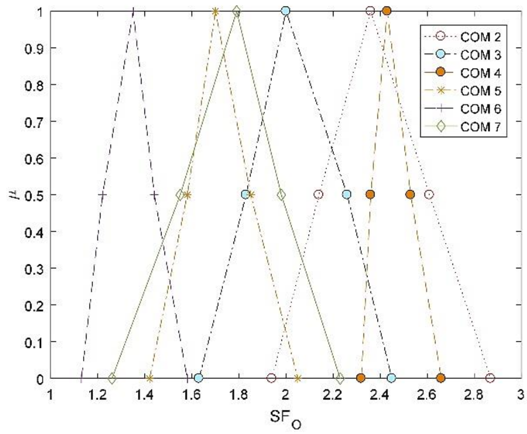
a. Fuzzy maximum stress (S1)



b. Fuzzy minimum stress (S3)

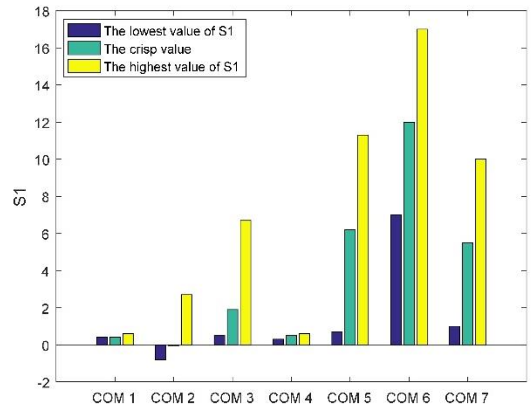


c. Fuzzy sliding safety factor

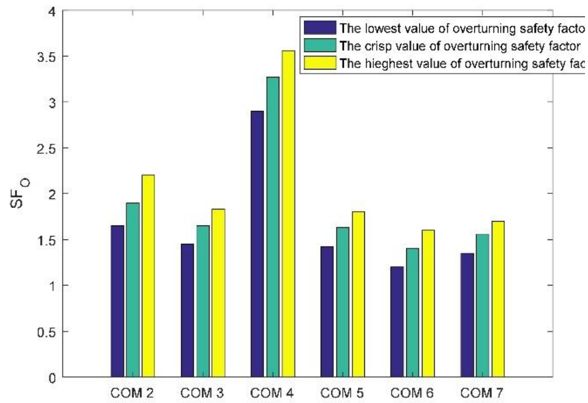


d. Fuzzy overturning safety factor

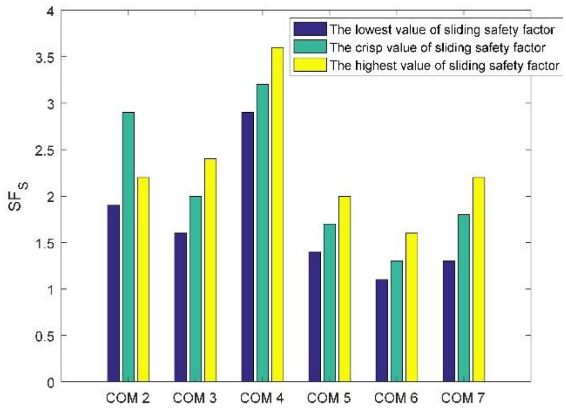
Figure 5. Fuzzy outputs



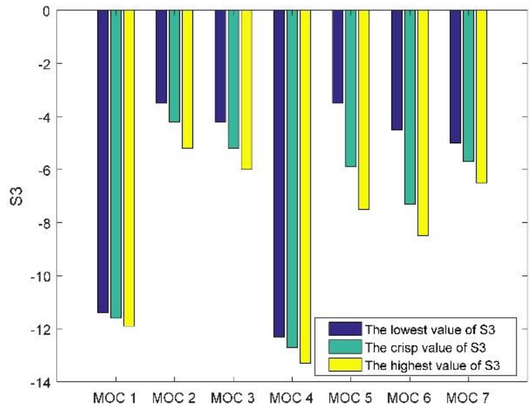
a. Value of S1



b. Value of overturning safety factor



c. Value of sliding safety factor



d. Value of S3

Figure 6. Comparing the lowest, crisp and highest value of fuzzy outputs for α=0

5. Uncertainty analysis, Risk identification from results, and sensitivity analysis

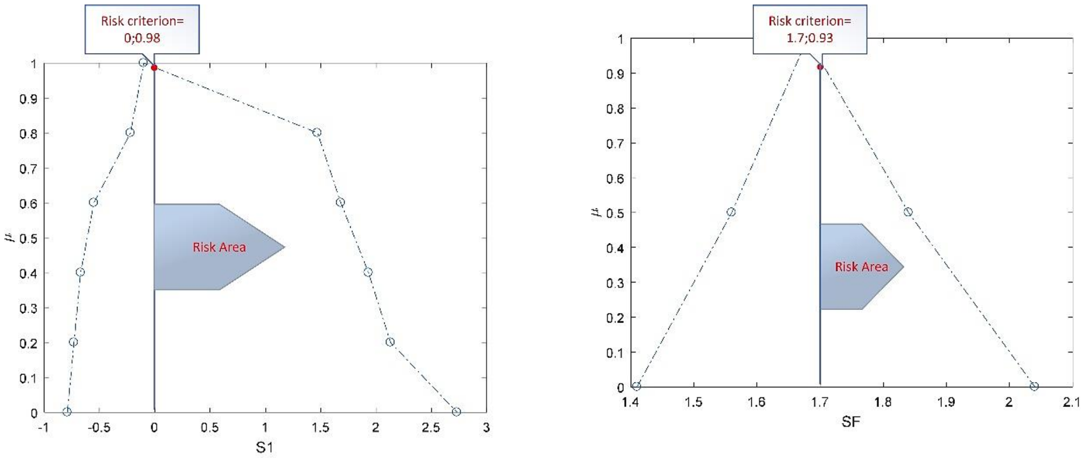
Table 5 reports the maximum uncertainty of principal stresses and safety factors for α=0 with their associated loading conditions. It clearly shows that how the small uncertainty, ±10%, in input variables is spread out over the system and leads to such large uncertainty in the output responses. As can be seen from this table, S1 has the maximum uncertainty that this value is 92.31% and the minimum uncertainty is for SFo with the value 13.3%. Among the stresses and safety factors, tensile stress has the highest positive and negative value of uncertainty. As a result, it indicates that with the same amount of uncertainty in the inputs, the propagation of uncertainty on the tensile stress is higher than other stresses and safety factors. Among the different loading conditions, the loading conditions 5 and 7 have the highest number of critical uncertainties. As can be seen from Table (5), the only Loading condition that causes the most positive and negative uncertainty for sliding safety factor and min Compress stress are 7 and 5 respectively. But for max tensile stress, the combination of these loading conditions causes the most positive and negative uncertainty.

Table 5: The maximum uncertainties of safety factors and principle stresses

Output parameter	Uncertainty (%)	Loading condition
Overturning safety factor	+18.8	3
	-13.3	6
Sliding safety factor	+24.61	7
	-29.58	7
MIN Compress stress (S3)	+40.68	5
	-22.03	5
MAX tensile stress (S1)	+78.6	7
	-92.31	5

In general, the fuzzy responses of the model are more practical than the classical responses. The fuzzy responses provide more insight into future dam performance. As can be seen from Figure 5, uncertainty causes changes in output of S1, S3, SFo and SFs under different loading conditions. This fact indicates that if the design is done without considering the uncertainty, it will cause instability in the operation of the structure. Figure 6 has the same meaning in a different way. This figure shows a comparison between crisp values and maximum and minimum values under different loading conditions for different stresses and different safety factors. This figure shows the maximum amount of positive and negative violations of crisp values that are likely to occur. As can be seen from Figures 5 and 6, the least uncertainty in S1 is for the combination of loads 1 and 4, which are equal to 25% and 30%, respectively. It should be noted that this amount of uncertainty is the average of the amount of positive and negative uncertainty. Also, the least uncertainty in S3 is for the combination of loads 1 and 4, which is equal to 2.1% and 3.9%, respectively. For overturning safety factor and sliding safety factor, the least uncertainty for the load combination is 7, 3 and 5,6 which are equal to 11.21%, 11.51% and 17.64%, 19.26% respectively.

In order to identify the dam risk, the allowable stresses and the minimum values of the dam's stability against sliding and overturning according to the USACE regulation (is mentioned in table 2) are considered to be criteria for recognizing the dam's stability risk. The risk criterion is shown in figure 7. In figure 7-a the risk criterion is (0;0.98) and this criterion is (1.7;0.93) for figure 7-b. An area of the fuzzy function diagram whose output parameter values exceeding the risk criteria values has been identified as the risk area. As shown in Figure 7, this area can be displayed to the right of the risk criterion. Then the amount of uncertainty of the output parameter that leads to the risk in the dam, i.e. the boundary of the risk area specified by the risk criterion, is identified. These values are given in Table 6. According to this table, the minimum amount of uncertainty that leads to the risk is 0.02%, which is related to S1 in loading condition 2, which is shown in Figure 7-a. The least uncertainty that leads to sliding risk is 0.06%, which is related to loading condition 3 and shown in Figure 7-b. In the case of S3 and the overturning stability coefficient, no uncertainty in the range of zero to ten per cent leads to risk, and in fact uncertainty that is greater than this range will lead to risk. The results show that the risk of S1 is higher than S3 and the risk of sliding is higher than overturning, which shows that S1 is more sensitive than S3 and also sliding is more sensitive to overturning too.



a. Risk area in fuzzy function of S1 COM 2 **b. Risk area in fuzzy function of SF COM 5**

Figure 7. Risk area

Table 6: The minimum uncertainty that lead to risk of dam

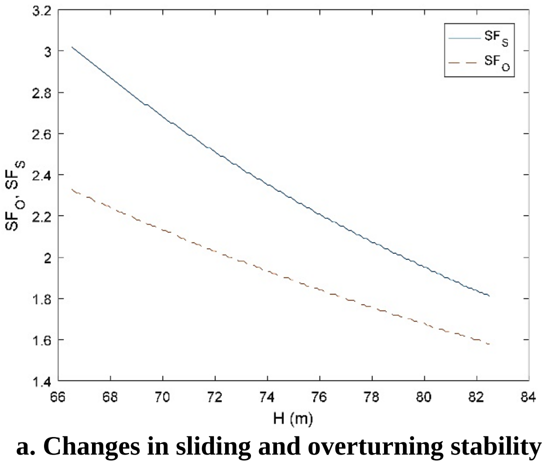
loading combination	1	2	3	4	5	6	7
The value of uncertainty which causes tensile stress risk	>10%	0.02%	8.95%	>10%	1.75%	8.10%	>10%
allowable tensile stress	6.42	0	6.42	16.05	6.42	16.05	16.05
The value of uncertainty which causes compress stress risk	>10%	>10%	>10%	>10%	>10%	>10%	>10%
allowable compress stress	17.5	10.5	17.5	31.5	17.5	31.5	31.5
The value of uncertainty which causes sliding risk	>10%	8%	>10%	>10%	0.06%	0.05%	9.98%
The least SFs to stability	1.7	2	1.3	1.3	1.7	1.3	1.3
The value of uncertainty which causes overtraining risk	>10%	>10%	>10%	>10%	>10%	>10%	>10%
The least SFo to stability	1.2	1.3	1.2	1.1	1.2	1.1	1.1

Note: >10% uncertainty means it is not obvious that which value of uncertainty lead to risk but it is clear that this value is more than 10%

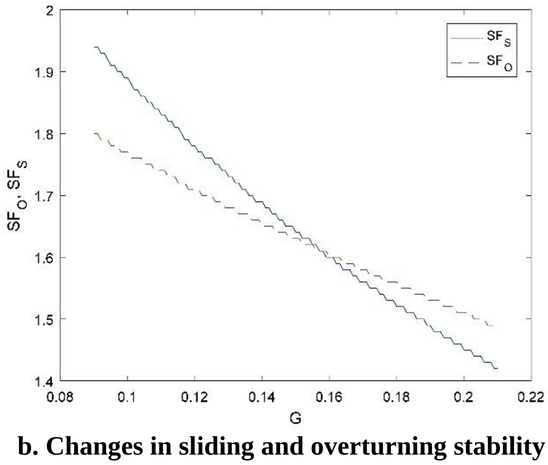
Finally, the sensitivity analysis of the gravity dam is investigated. This sensitivity analysis is so important because it gives a good view of the effects of each parameter on the output and can also be proof of the monotonicity of the problem.

Sensitivity analysis of S1, S2, SFo, and SFs values for important input parameters such as water level height, concrete modulus of elasticity, concrete specific gravity and earthquake acceleration separately in loading conditions 3, 7, and 5, which according to Table 5 have the most uncertainties of output parameters in fuzzy analysis in these loading conditions are investigated. The results of the sensitivity analysis are shown in Figure 8 for SFo and SFs values and in Figure 9 for S1 and S3 values. In these figures, the monotonicity of the model relative to the input parameters can be clearly seen. As can be seen, the values are strictly descending or ascending, which proves logically that the problem is monotonic. As can be seen from Figure

(8), with increasing water level height in the reservoir, the safety factors decrease. This indicates that the resistant forces to tipper forces are reduced. The same reason is true for increasing the acceleration of an earthquake. Another thing is worth mentioning is that the sensitivity of SFS to water level is greater than its earthquake acceleration so as can be seen from figure (8-a), its changes against (H) is about 1, whereas its changes against (G) is 0.5. Like SFS, SFO has the same trend against (H) and (G). This can be deduced from Figure (8-a) that its change against (H) is about 0.8, whereas its change against (G) is 0.3. According to Figure (9), it can be seen that in general, the stress s1 is more sensitive to the input parameters than s3. Figure (9-a) shows that with increasing the modulus of elasticity of the dam body, the values of stresses S1 and S3 increase. The reason for this increase is that with increasing the modulus of elasticity of the dam body, energy absorption in the dam body is higher than the foundation, which leads to an increase in tension and pressure in the dam. S1 and S3 have opposite directions in the junction of the dam and the foundation, so with increasing both of them the balance of forces is still statically maintained. Figures (9-b) and (9-c) show that with increasing the earthquake acceleration and water level behind the dam, both stresses S1 and S3 increase in quantity. This is an obvious fact and for this reason in gravity dam design regulation, the values of these two parameters are intentionally increased to make the stresses more critical to make the design more secure. Also, these two figures show that the range of changes (sensitivity) of S1 to the water level behind the dam is greater than the earthquake acceleration. Figure (9-d) shows that increasing the weight of the dam reduces the value of S1 and increases the absolute value of s3. This means that increasing the weight of the dam increases the stability of the dam against traction at the dam heel, which is obvious. Also, as it turns out, S1 is much more sensitive to the weight of the dam than S3. The slope value of s1 changes decreases when it reaches zero, which is because when the value of s1 is greater than zero, it means cracking and lifting of part of the heel of the dam. In this case, due to the reduction of the contact surface between the dam and the foundation, the stability of the dam decreases, and the process of crack expansion occurs faster in the heel of the dam.

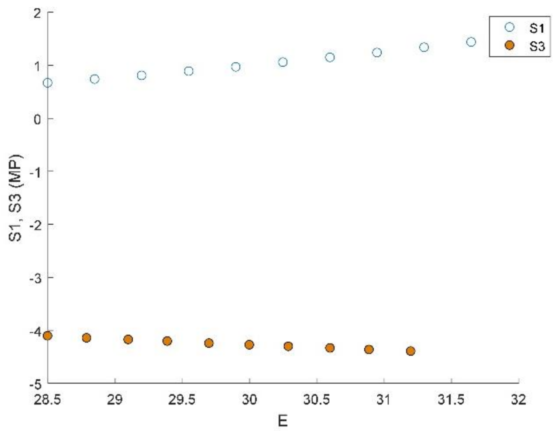


a. Changes in sliding and overturning stability coefficients against changes in water level

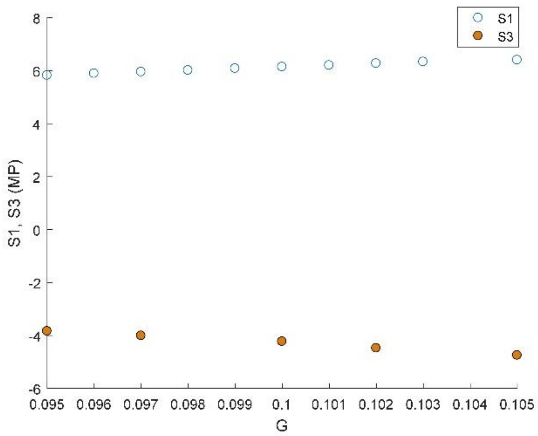


b. Changes in sliding and overturning stability coefficients against changes in earthquake acceleration

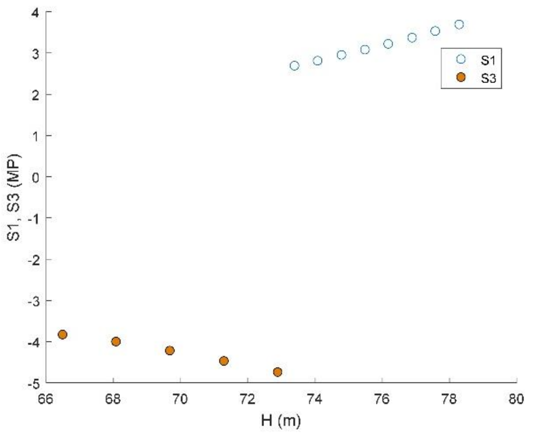
Figure 8. Changes in sliding and overturning stability coefficients against changes in water level and earthquake acceleration in loading condition 7.



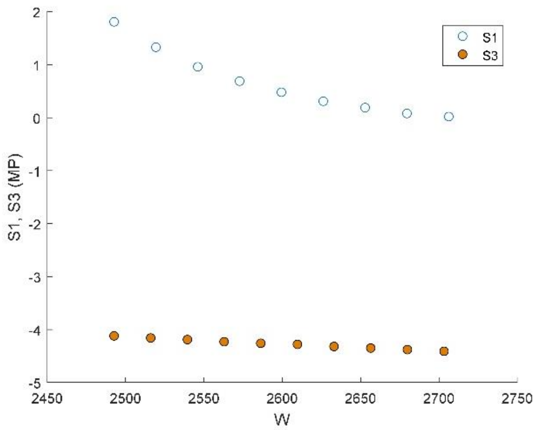
a. Stress changes against changes in the modulus of elasticity of concrete in the loading condition 3.



b. Stress changes against changes in earthquake acceleration in loading condition 5.



c. Stress changes against changes in water level in loading condition 3.



d. Stress changes against changes in specific gravity of concrete in loading condition 3.

Figure 9. Stress changes against changes in the modulus of elasticity of concrete (a), earthquake acceleration (b), water level (c), and specific gravity of concrete (d)

6. Conclusion

Dams are obviously an integral part of any country's infrastructure and their safety is one of the most critical issues, so all countries faced with this problem that how they can promote and guarantee the dam safety. Based on some of the uncertain input parameters on the design of the dams, some of the dams are at risk of failure. In this research, a method for uncertainty analysis and risk identification using fuzzy set theory is presented. For this purpose, the uncertainties were introduced to the model in the form of fuzzy triangles, then the fuzzy functions were discretized by the alpha cut method, and the model was developed as an optimization problem. Each alpha cut is applied to the input parameters, which are in the form of fuzzy functions, and then they are converted to intervals. Then the output parameters, i.e., the stabilities, are considered as the objective functions of the optimization model, and finally, the problem is optimized. Assuming that the dam geometry is constant, it is proved that the output parameters have a monotonic behavior and the fuzzy outputs can be extracted without the need for an optimization algorithm. Folsom gravity dam was analyzed by the mentioned method, and the obtained fuzzy results were used to analyze the uncertainty and identify the risk area. The results showed that minor uncertainties such as 10% could lead to significant uncertainties; for example, 10% uncertainty caused 92.31% uncertainty in S1 stability. Then, after obtaining fuzzy outputs, the risk area was identified. In order to identify the risk area of dam, the allowable stresses and the minimum values of the dam stability against sliding and overturning of the dam were obtained, which were considered as the risk criteria. Then the area of the fuzzy function diagram that output parameter values are more significant than the values of the risk criteria is identified as the risk area. Then the amount of uncertainty of the output parameter that leads to the risk area is identified. These values are listed in Table 6. The minimum amount of uncertainty that leads to the risk area is 0.02%, which is related to S1 in loading condition 2.

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