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Variance-based global sensitivity analysis for fuzzy random structural systems

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Abstract
There have been increasing advances in the sophisticated approaches like fuzzy randomness to handle different uncertainties in civil engineering; however, less attention has been paid to the formulation of a sensitivity analysis for fuzzy random structural systems. In this study, the main objective is to present the formulation of fuzzy Sobol sensitivity indices to quantify the influence of fuzzy random structural parameters. Meanwhile, uncertainty in derivation of limit states and acceptance criteria in collapse analysis is addressed briefly and treated using fuzzy model parameters. To show the application of the established sensitivity test, the collapse behavior of a steel moment frame subjected to sudden column removal is evaluated thoroughly. The proposed fuzzy sensitivity indices are determined for the problem and the overall influence of fuzzy acceptance criteria on the collapse assessment is shown using fragility analysis. The results show that the presented fuzzy sensitivity analysis can give detailed insight into the characteristics of fuzzy random systems, and the epistemic uncertainty in derivation of limit states can have significant effects on the reliability-based collapse analysis. It is worth mentioning that to alleviate high computational demands in fuzzy probabilistic collapse analysis, a neural network metamodel is applied in conjunction with the genetic algorithm which is also of practical value to engineers and researchers.

1 | INTRODUCTION

Many studies have been conducted in different fields of civil engineering based on the fuzzy set theory such as control of building structures (Jiang & Adeli, 2008; Nomura, Furuta, & Hirokane, 2007), life cycle cost optimization of structures (Sarma & Adeli, 2000, 2002), and decision making (Adeli & Sarma, 2006; D'Urso, Masi, Zuccaro, & De Gregorio, 2018; Jin & Doloi, 2009; Ponz-Tienda, Pellicer, Benlloch-Marco, & Andrés-Romano, 2015). Meanwhile, fuzzy random reliability has been developed in the past two decades to handle uncertainties in structural engineering and computational mechanics (Jahani, Muhanna, Shayanfar, & Barkhordari, 2014; Möller & Beer, 2004; Möller, Beer, Graf, & Hoffmann, 1999; Möller, Graf, & Beer, 2003; Muhanna & Mullen, 1999). Various sources of uncertainty can be categorized into two major groups, stochastic and informal uncertainties. Stochastic uncertainty is related to the intrinsic variability whereas informal uncertainty is associated with the lack of knowledge and modeling simplifications. Although stochastic uncertainty has been considered properly using probability theory, this approach is based on the presumption that there is sufficient information about the probability distribution parameters such as mean and standard deviation values. By using fuzzy randomness, insufficient knowledge about model parameters and informal uncertainty in distribution parameters are described using fuzzy numbers.

As a powerful uncertainty model, fuzzy randomness has been implemented in many studies to quantify uncertain parameters and conduct fuzzy reliability analysis

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(Graf, Hoffmann, Möller, Sickert, & Steinigen, 2007; Möller, Beer, Graf, & Sickert, 2006; Möller, Liebscher, Schweizerhof, Mattern, & Blankenhorn, 2008; Wang, Ma, Zhang, & Liu, 2012). Besides these research contributions, few attempts have been made to formulate sensitivity indices for fuzzy random structural systems. As mentioned by Saltelli, Tarantola, Campolongo, and Ratto (2004), sensitivity tests are conducted for several purposes which are quite useful for coping with uncertainties in any scientific model and risk management. For instance, sensitivity tests can indicate influential factors (Boscato, Russo, Ceravolo, & Fragonara, 2015; Castillo, Grande, Mora, Lo, & Xu, 2017) which need better control to decrease the output variability. In addition to reducing output variance below a given tolerance, they can be used for model simplification by identifying less important parameters. To this end, Cui, Lu, and Wang (2011) proposed a reliability sensitivity method to deal with systems consisting of fuzzy and random variables. Recently, Jafari and Jahani (2016) presented a gradient-based sensitivity test to find the influence of informal uncertainty of fuzzy distribution parameters on the failure probability. To have aforementioned applications, a general sensitivity test is required to address the influence of both informal and stochastic uncertainties not only on the failure probability, but also on any type of output variance for risk reduction, model simplification, or other applications.

In this study, a sensitivity test is proposed for fuzzy random structural systems, which in turn, yields fuzzy sensitivity indices. Effects of stochastic uncertainty in structural parameters are quantified using the variance-based global sensitivity analysis (Saltelli et al., 2008), and the intervals of these indices corresponding to each α-level show the overall effect of informal uncertainty in their contribution. The variance-based sensitivity test or the Sobol method, extended to fuzzy random systems, is one of the well-known methods which has been applied to structural engineering in recent years (Arwade, Moradi, & Louhghalam, 2010; Kala, 2011, 2016). In the present research, fundamentals of fuzzy randomness and fuzzy probabilistic collapse analysis are explained briefly. Then the implementation of fuzzy sensitivity indices for the uncertainty model is described. To demonstrate the proposed method, the collapse behavior of a steel moment-resisting frame is analyzed under sudden column removal using fragility analysis and the proposed sensitivity test. There is also a short discussion about incorporating informal uncertainty in derivation of limit states and acceptance criteria for the collapse analysis as fuzzy model parameters. As nonlinear dynamic collapse analysis is quite time-consuming especially for the considered probabilistic analyses, an artificial neural network (ANN) is applied systematically to the problem which can be also of practical value to engineers and researchers.

2 | FUZZY RANDOMNESS

2.1 | Fundamentals

Fuzzy randomness is an uncertainty model which can allow for different sources of uncertainty in the model and data. Stochastic and informal uncertainties are treated by representing parameters of probability distributions and model parameters using fuzzy numbers, respectively. A fuzzy number is a set of elements $\tilde{A}$ on the fundamental set U along with their corresponding functional values $\mu(a)$,

$$A = \{(a, \mu(a))|a \in U\} \tag{1}$$

where μ is called the membership function and the functional values show the achievement of assessment criterion and uncertainty level. For a fuzzy number, the membership function is piecewise continuous and it is normalized as

$$\forall a \in U, \mu(a) \in [0, 1] \tag{2}$$

The functional values should be convex which means they decrease monotonically on each side of the maximum value.

Two other definitions which are used subsequently for the treatment of uncertainty are support set and α-level set. The support $S(\tilde{A})$ of the fuzzy set $\tilde{A}$ is defined as a crisp set which contains all elements having membership values greater than zero,

$$S(A) = \{a \in U|\mu(a) > 0\} \tag{3}$$

The crisp subsets A_{α_k} of $\tilde{A}$ with elements having membership values greater than or equal to α_k are called α-level sets which are also subsets of the support $S(\tilde{A})$,

$$A_{\alpha_k} = \{a \in U|\mu(a) \geq \alpha_k\} \tag{4}$$

A fuzzy number with its membership function, support, and α-level set are shown in Figure 1. The α-level set A_{α_k} specifies the interval $[a_{\alpha_k,l}, a_{\alpha_k,r}]$ for the considered parameter with

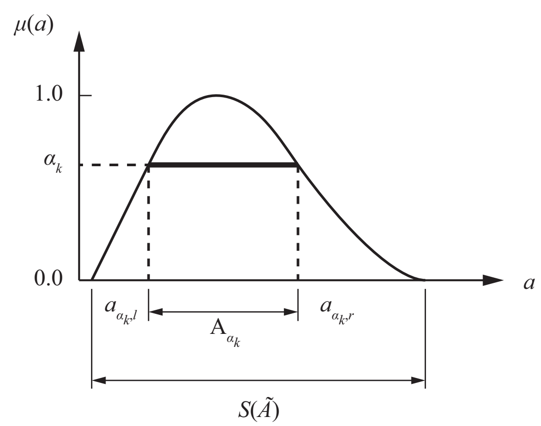

FIGURE 1 A fuzzy number and its support and α-level set

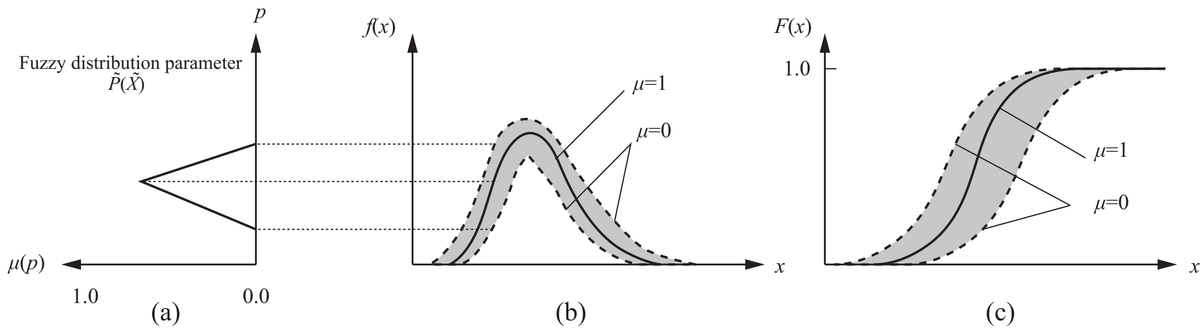

FIGURE 2 Fuzzy probabilistic basic variable: (a) fuzzy distribution parameter; (b) fuzzy probability density function; and (c) associated fuzzy probability distribution function

regard to the uncertainty level α_k. To approximate the membership function, a triangular membership function is usually used which is also utilized in this study. A fuzzy number with a triangular membership function is called fuzzy triangular number and is represented by

$$\tilde{A} = < a_1, a_2, a_3 > \tag{5}$$

where a_1 and a_3 are, respectively, the smallest and the largest values of the support and a_2 corresponds to the maximum membership value $\mu(a_2) = 1$.

2.2 | Stochastic and informal uncertainty

Informal uncertainties in the model can be accounted for by representing model parameters as fuzzy numbers. On the other hand, stochastic uncertainty and imperfect knowledge about distribution parameters can be treated using fuzzy random numbers which consider stochastic characteristics of a parameter using classical probability models and imprecision of the considered probability models using fuzzy distribution parameters. Considering distribution parameters, such as mean and standard deviation for a probabilistic basic variable in structural analysis, leads to the fuzzy probabilistic basic variable $\tilde{X}$ with the fuzzy distribution parameter $\tilde{P}(\tilde{X})$. This definition characterizes the fuzzy probability density function $\tilde{f}(x)$ and the associated fuzzy probability distribution function $\tilde{F}(x)$. Probability functions for a fuzzy probabilistic basic variable are depicted in Figure 2. The solid curves represent the probability functions corresponding to the membership value of 1, and the dashed curves correspond to the membership value of zero. Therefore, all possible probability functions called trajectories are contained between the dashed curves.

3 | FUZZY PROBABILISTIC COLLAPSE ANALYSIS

In this part, fuzzy probabilistic collapse analysis is described briefly using the Zadeh's general extension principle (Zadeh, 1965) with the aim of providing better insight into the fuzzy input space and mapping onto the output space of failure probability. After the reader becomes familiar with the problem at hand and the fuzzy input space, determining fuzzy sensitivity indices for the input space is explained in the same way and then the efficient α-level optimization method is explained in the next part.

In fuzzy probabilistic collapse analysis, model parameters are described using fuzzy numbers and probabilistic basic variables are defined using fuzzy distribution parameters. The jth fuzzy model parameter is denoted using $\tilde{M}_j$ and the ith fuzzy probabilistic basic variable along with its corresponding fuzzy distribution parameter is shown by $\tilde{X}_i$ and $\tilde{P}(\tilde{X}_i)$, respectively. Originals of input variables are defined with small letters without tilde, for example, m_j and $p(\tilde{X}_i)$. The general way of conducting numerical solution is to define the fuzzy input space by assigning fundamental sets of fuzzy distribution parameters $\tilde{P}(\tilde{X}_i)$ and fuzzy model parameters $\tilde{M}_j$ to axes of the Cartesian coordinate system. The coordinates of points in this space characterize a Cartesian product space. The membership degree of each point, that is, each original, in this space is equal to the minimum membership value of its components. This procedure forms the fuzzy input space which is illustrated for two input variables in Figure 3.

The coordinates $p(\tilde{X}_i)$ of an arbitrary point in this fuzzy input space specifies exactly one original for each fuzzy probabilistic basic variable and therefore one trajectory of the joint fuzzy probability density function. The coordinates m_j give precisely one element for each fuzzy model parameter in structural analysis and thus one crisp limit state function. Accordingly, the joint probability density function and the limit state give in turn one element of fuzzy failure probability $\tilde{P}_f$ which can be found by conventional reliability methods. By having virtually infinite originals in the fuzzy input space, failure probability elements are obtained and the final membership degree for each element is equal to the maximum membership value of originals leading to the same element (Figure 3). This procedure using the max-min operator is called Zadeh's extension principle (Zadeh, 1965).

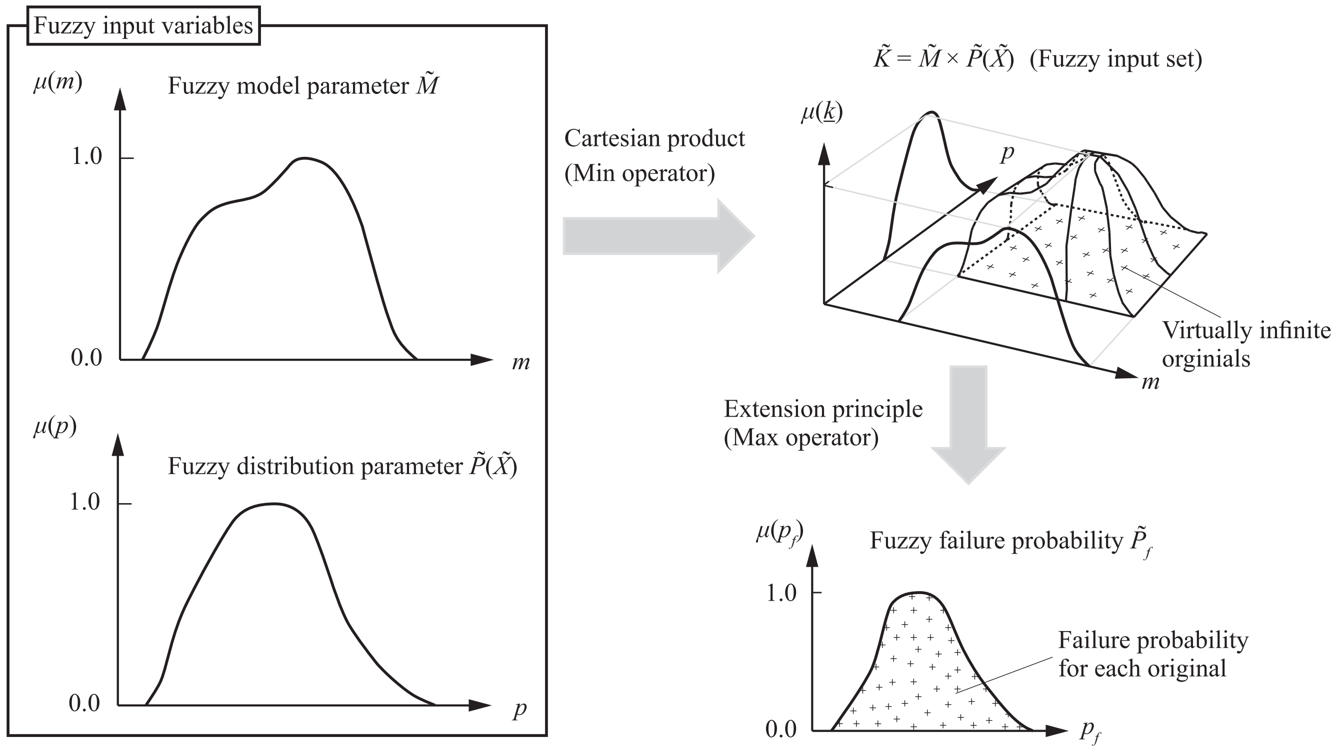

FIGURE 3 Fuzzy probabilistic collapse analysis

Failure probability elements can be approximated using reliability methods such as the first-order reliability method or the Monte Carlo simulation (MCS). Although MCS requires high computational demands, it provides a general solution for any kind of problems regardless of nonlinearity and complexity (Jahani et al., 2014).

4 | FUZZY GLOBAL SENSITIVITY ANALYSIS

Each original of the fuzzy input space $\tilde{K}$ outlines a reliability problem for an uncertain output response. In the aforementioned fuzzy input space, the coordinates of each original consists of distribution parameters $p(\tilde{X}_i)$ for probabilistic basic variables and model parameters m_j. As the coordinates m_j do not contribute to the output variability for the current original of the fuzzy input space, the sensitivity indices are not calculated for them. The coordinates $p(\tilde{X}_i)$ of each original in the fuzzy input space specify precisely one element of the joint fuzzy probability density function. This joint density function leads to the variability in the output response which stems from the role of probabilistic basic variables in the model and their distribution parameters $p(\tilde{X}_i)$. To evaluate the influence of probabilistic basic variables on the current output variance, Sobol's sensitivity indices are determined for this original of the joint fuzzy probability density function. Given z as the output and function of input variables, the main contribution of the ith probabilistic basic variable to the total variance of the considered output $V(Z)$ is termed the first-order index in the literature and can be calculated as

$$s_i = \frac{V(E(z|x_i))}{V(z)} \tag{6}$$

The numerator indicates that the variance of the inner expectation is determined by only changing x_i and for each fixed x_i the output is averaged for all possible variation of other variables. Therefore, the effects of the ith probabilistic basic variable on the total variance are quantified and the influence of other variables is excluded by averaging which is called the conditioned variance.

When there is no interaction between input variables, the model is called additive and summing up the first-order sensitivity indices will be equal to one,

$$\sum s_i = 1 \tag{7}$$

When the above-mentioned equation does not hold for obtained first-order indices, it indicates that the model is non-additive and the interaction of input variables also influences the output variability. The interaction here does not refer to the mutual dependency of input variables that must be considered in mapping or generating the fuzzy input set or probabilistic samples. In fact, it is the interaction of input variables inside the model for generating the output response. The interaction between the ith and the lth probabilistic basic variables can be obtained similarly using higher order indices as

$$s_{i,l} = \frac{V(E(z|x_i, x_l))}{V(z)} - s_i - s_l \tag{8}$$

However, determining all higher order indices for a function with n probabilistic basic variable requires to calculate $2^n - 1$ terms which seems impossible due to the curse of dimensionality. Hence, another measure termed the total effect is utilized which is obtained as

$$s_{Ti} = 1 - \frac{V(E(z|x_{\sim i}))}{V(z)} \tag{9}$$

where $x_{\sim i}$ indicates that the expectation in the numerator is conditional upon all probabilistic basic variables excluding the ith variable. Hence, $V(E(z|x_{\sim i}))$ contains the output variance from all input variables except the ith probabilistic basic variable, and therefore the total effect of the variable is obtained by deducting the conditioned variance from the total variance. It has been shown that the first-order sensitivity indices along with the described total effects can clearly indicate the general characteristics of a model (Saltelli et al., 2004). These indices can be determined using estimators recommended by Saltelli et al. (2008). For further information on global sensitivity and calculations, readers are referred to Saltelli et al. (2008).

For each original of the fuzzy input space, the previous procedure is done, which provides one sensitivity index for each probabilistic basic variable. Each calculated sensitivity index is an element of the fuzzy sensitivity index $\tilde{S}_i$ for the ith fuzzy probabilistic basic variable. By applying the Max operator, membership degrees for each element of fuzzy sensitivity indices are determined.

5 | FUZZY GLOBAL SENSITIVITY ANALYSIS USING α-LEVEL OPTIMIZATION METHOD

As stated before, the aforementioned procedure was mentioned using the general extension principle for the sake of clarity. Although this approach is a general procedure for mapping fuzzy input variables onto fuzzy results and provides clear understanding, it is a computationally inefficient approach (Möller & Beer, 2004). In this reference, two reasons are mentioned: first one is that the precision of the membership of a fuzzy result highly depends on the number of originals evaluated, and the next one is the curse of dimensionality. Therefore, the α-level optimization method is usually employed instead which employs a search algorithm (Möller, Graf, & Beer, 2000). The main idea in this approach is that instead of a large number of numerical evaluations from the input space and finding the membership function using the envelope of functional values corresponding to the obtained results (Figure 3), an optimization can be done to find the range of the fuzzy value corresponding to each α-level. In this approach, all fuzzy input variables, $\tilde{P}(\tilde{X}_i)$ and $\tilde{M}_j$, are divided similarly into r α-level sets, $k = 1, 2, \ldots, r$. The α_k level of input variables represents the crisp subspace K_{α_k} of the fuzzy input space $\tilde{K}$ and can be mapped onto the corresponding crisp subspaces S_{i,α_k} and P_{f,α_k} of the fuzzy sensitivity indices and fuzzy failure probability. As S_{i,α_k} can be fully described by finding the maximum $s_{i,\alpha_k,r}$ and the minimum $s_{i,\alpha_k,l}$ for each α-level subspace, there is no need to find all other elements $s_{i,\alpha_k,l} < s_i < s_{i,\alpha_k,r}$. Therefore, K_{α_k} is considered as the search domain for finding the boundaries of S_{i,α_k}. As shown in Figure 4, each α-level subspace of fuzzy input variables is considered as the search domain and the maximum and minimum of each sensitivity index are found for the corresponding α-level of each fuzzy probabilistic basic variable. There are different search algorithms and optimization methods that can be applied. In this research, the genetic algorithm (GA) (Adeli & Kumar, 1995; Adeli & Sarma, 2006) which is inspired by the natural selection was utilized. To give a better understanding of conducting fuzzy global sensitivity test using GA, the flowchart of the procedure is illustrated in Figure 5.

6 | APPLICATION TO MODEL STRUCTURE

6.1 | Structural properties

To show the application of the proposed method, a hypothetical steel structure subjected to sudden column removal on the first story was assumed and assessed in this research. The structure is a three-story moment frame designed for the dead load of $5\,\text{kN/m}^2$ and the live load equal to $3\,\text{kN/m}^2$. The height of all stories is 4 m except the first story which is 5 m. The nominal dimensions of the used sections and the plan layout are depicted in Figure 6. The nominal elastic modulus of all structural members is equal to 2×10^5 MPa whereas the yield strengths of beams and columns are 330 and 370 MPa, respectively.

It was assumed that the reproduction conditions for the aforementioned properties were unknown, and the influential parameters in collapse analysis were described using fuzzy random variables. The stochastic uncertainty of parameters was considered based on distribution types and parameters recommended in the codes, and the coefficient of variations was assumed to be a constant. Based on informal uncertainty and the subjective assessment of the objective data, the parameters were fuzzified and the results of fuzzification are summarized in Table 1. Distribution types and all related assumptions considered are based on the literature (CEN, 1993; Ellingwood, Galambos, MacGregor, & Cornell, 1980; Javidan, Kang, Isobe, & Kim, 2018; JCSS, 2001). The live

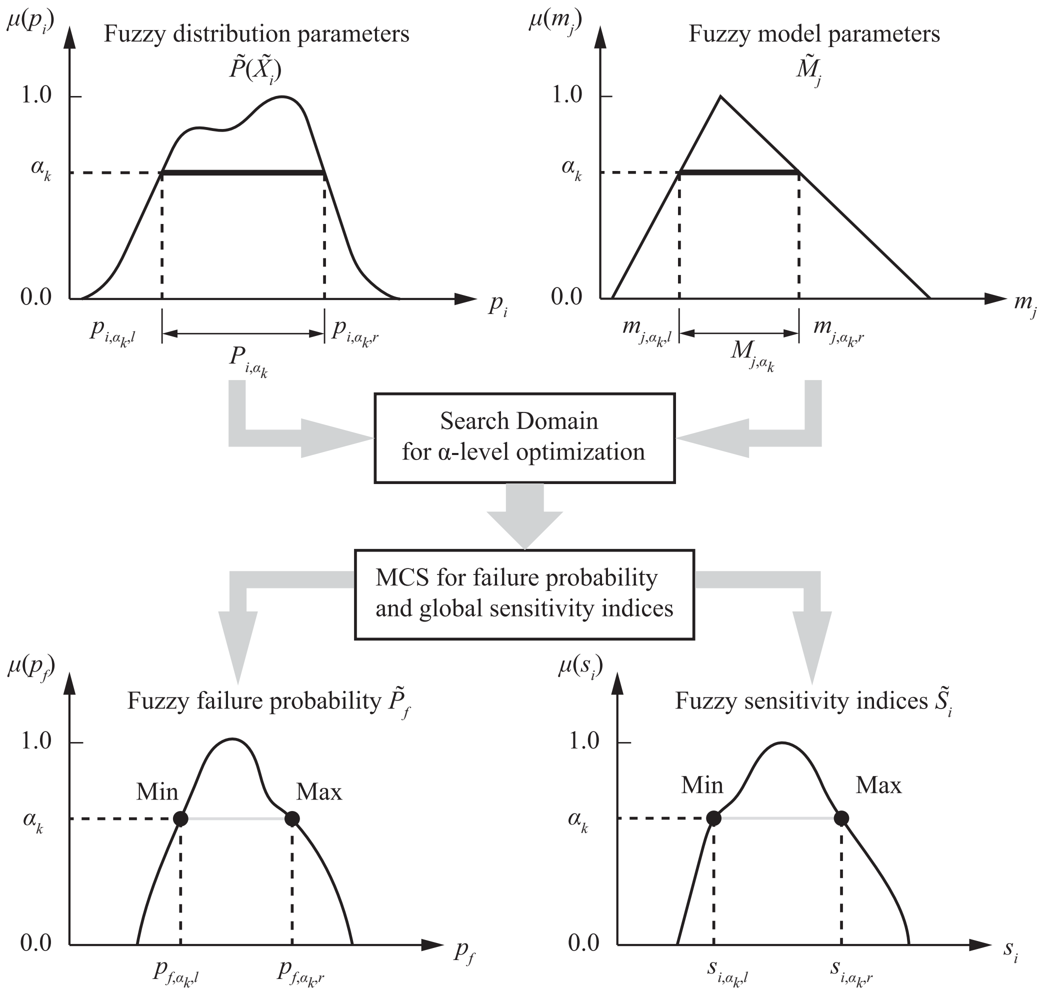

FIGURE 4 α-level optimization

load consists of two components, the intermittent load and the arbitrary-point-in-time load (JCSS, 2001). The latter denotes the average load during lifetime of the structure with a specific occupancy whereas the intermittent load is associated with a short time like renovation or special events (Ellingwood et al., 1980). As extreme events are indeed a type of arbitrary-point-in-time accident, the only source of variability was assumed to be the sustainable component of the live load. It was assumed that there is no spatial variation in the parameters.

The corner column on the first story marked in Figure 6b was assumed to be removed suddenly under an extreme action. The damage states of structural members were evaluated using the limit states specified in the ASCE 41-13 (ASCE, 2013). Another uncertainty considered herein is the informal uncertainty in derivation of acceptance criteria and limit states for collapse analysis. Acceptance criteria for strength and deformation in guidelines are based on idealized experimental force-deformation curves. However, there is no denying that this evaluation of objective information entails informal uncertainty. Moreover, these criteria are designated for deterministic geometrical properties whereas analyses in this study were conducted in a probabilistic fashion. Therefore, as can be seen in Table 2, limit states provided in ASCE 41-13 were adopted while allowing for the informal uncertainty. These criteria are associated with three performance levels which are immediate occupancy (IO), life safety (LS), and collapse prevention (CP) levels. The same criteria are also recommended in guidelines (DoD, 2016; GSA, 2016) for progressive collapse which is the subject of this section. The fuzzy limit state enters the numerical solution as a fuzzy model parameter. Because it solely affects the fuzzy limit state surface which divides the joint fuzzy probability density function into the survival region and the failure region.

It should be noticed that the viewpoint on limit states is different from the fuzzy performance level which has been addressed in the previous studies (Kirke & Hao, 2004; Thinley & Hao, 2017) and it should not be misunderstood. In those studies, the probability density function $f(x)$ of the structural output response was determined using the classical probabilistic analysis while having a specific performance level was considered as a fuzzy variable. The degree of truth, that is, the membership degree, for each performance

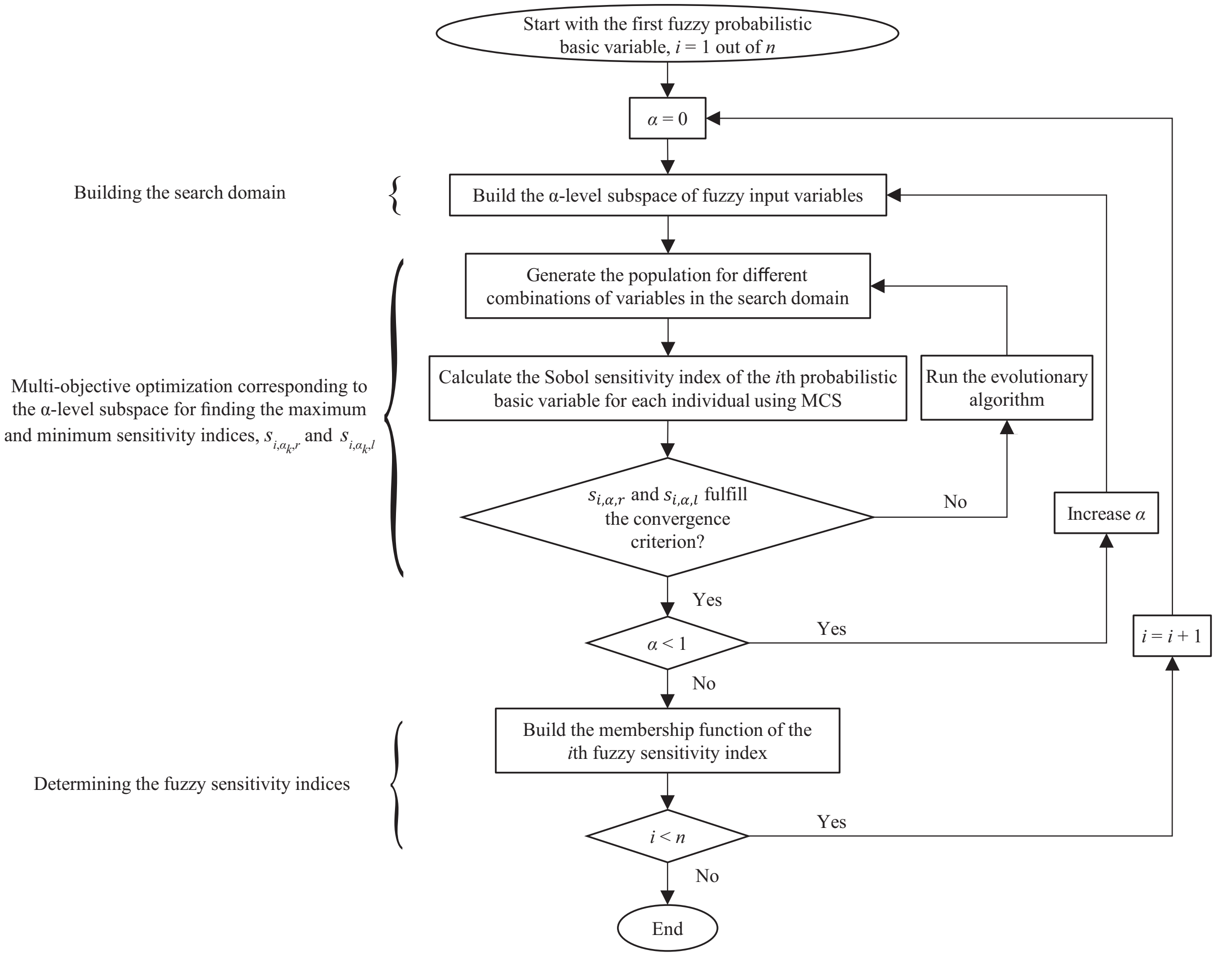

FIGURE 5 Flowchart of α-level optimization for fuzzy global sensitivity analysis using GA

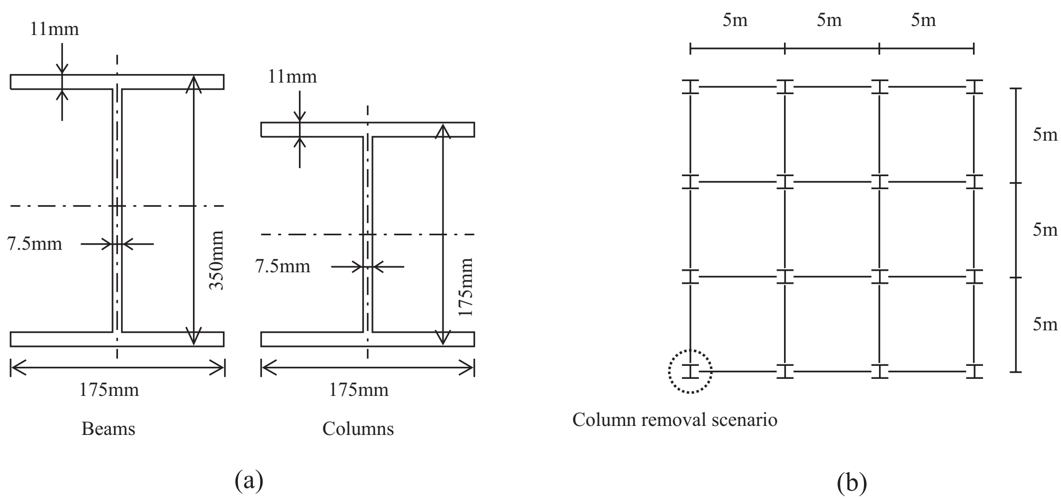

FIGURE 6 Details of the considered structure: (a) nominal dimensions of beam and column sections; (b) plan of the structure and the considered column removal scenario

level was calculated using the expectation of the membership function,

$$E[\mu(x)] = \int_{D_L}^{D_U} \mu(x) f(x) dx \tag{10}$$

where D_U and D_L are the upper and lower boundaries of the fuzzy limit state, respectively. In the present research, informal uncertainty in derivation of definitive limit states was taken into account.

TABLE 1 List of uncertainty parameters

Category	Parameter	Mean	Standard deviation	Distribution
Gravity loads	Dead load DL	$< 4.2, 5.25, 6.3 >$ kN/m^2	$< 0.4, 0.5, 0.6 >$ kN/m^2	Normal
	Live load LL_{apt}	$< 0.4, 0.57, 0.7 >$ kN/m^2	$< 0.16, 0.23, 0.28 >$ kN/m^2	Gamma
Construction tolerances	Beam length L	$< 4{,}800, 5{,}000, 5{,}100 >$ mm	30.4 mm	Normal
Beam properties	Yield strength f_{yb}	$< 300, 346, 375 >$ MPa	$< 21, 24.2, 26.25 >$ MPa	Lognormal
	Elastic modulus E_b	$< 1.9, 2, 2.1 > \times 10^5$ MPa	$< 57, 60, 63 >$ MPa	
Dimensions of beam sections	Outside height t_{1b}	$< 348, 350, 354 >$ mm	$< 17.4, 17.5, 17.7 >$ mm	Normal
	Flange width t_{2b}	$< 173, 175, 179 >$ mm	$< 8.65, 8.75, 8.95 >$ mm	
	Flange thickness t_{fb}	$< 9.5, 11, 13.5 >$ mm	$< 0.47, 0.55, 0.67 >$ mm	
	Web thickness t_{wb}	$< 6.5, 7.5, 8.5 >$ mm	$< 0.32, 0.37, 0.42 >$ mm	

TABLE 2 Fuzzy limit states corresponding to damage of steel beams

		Damage		
Element	Failure type	IO	LS	CP
Beams	Flexure	$< 0.2\theta_y, 0.25\theta_y, 0.3\theta_y >$	$< 2.8\theta_y, 3\theta_y, 3.2\theta_y >$	$< 3.8\theta_y, 4\theta_y, 4.2\theta_y >$

6.2 | Analysis model

The three-dimensional (3D) model structure was established in OpenSees (Mazzoni, McKenna, Scott, Fenves, et al., 2006) which is a versatile platform with different materials, elements, and solution algorithms. Beam-column elements were modeled using the force-based *nonlinearBeamColumn* elements with the fiber section and the *Steel02* material. Applicability and accuracy of this element and material for different nonlinear analyses have been validated previously (Amini, Bitaraf, Eskandari Nasab, & Javidan, 2018; Shayanfar & Javidan, 2017). The dead and live loads with the load combination of $1.05DL + 0.3LL$ (Xu & Ellingwood, 2011) were distributed directly to beams based on the tributary area.

To evaluate the general behavior of structures under progressive collapse, codes and guidelines (DoD, 2016; GSA, 2016) recommend the alternate path method in which the triggering extreme action is not specified and the structure is analyzed under a sudden column removal scenario (Ahmadi, Rashidian, Abbasnia, Mohajeri Nav, & Usefi, 2016; Kim, Park, & Lee, 2011; Mohajeri Nav, Abbasnia, Rashidian, & Usefi, 2016; Usefi, Nav, & Abbasnia, 2016). The structure was evaluated only under sudden removal of the corner column, because structures are generally more vulnerable for the corner column removal case (Shayanfar & Javidan, 2017). To simulate the sudden column removal for each realization, the intact model structure was analyzed under gravity loads using nonlinear static analysis, and the internal forces of the corner column were obtained. Then, the column was replaced with its reaction forces on the beam-column joint and the structure was reanalyzed under gravity loads which in turn produces the same response. Last, by performing nonlinear dynamic analysis using 2% modal damping ratio, the reaction forces were removed in 10 ms to simulate the phenomenon of sudden column removal. The structure was simulated under the column removal scenario for 5 s with a time step of 0.01 s and the maximum vertical deflection above the removed column was determined for each realization.

6.3 | ANN metamodel

As mentioned earlier, each realization of sudden column removal needs two nonlinear static analyses and one nonlinear dynamic analysis which are quite time-consuming. On the other hand, finding one element of failure probability or sensitivity index using MCS requires thousands of analyses, let alone employing a search algorithm for finding their maxima and minima corresponding to each α-level and also conducting fragility analysis. To alleviate this problem, different approaches can be adopted. Among these methods, ANNs have gained a prominent position (Chojaczyk, Teixeira, Neves, Cardoso, & Soares, 2015; Javidan et al., 2018; Mitropoulou & Papadrakakis, 2011; Möller et al., 2008). It has been shown that the multilayer feed forward network architecture can estimate functions with high nonlinearity (Cardoso, de Almeida, Dias, & Coelho, 2008). Since the efficiency of this type of ANN in reliability analysis has been demonstrated, it is utilized here to predict the structural response. The method was shown here by implementing the ANN and the GA in MATLAB. It is worthwhile mentioning that although there is a growing trend toward deep neural networks and more sophisticated methods in civil engineering (Cha, Choi, Suh, Mahmoudkhani, & Büyüköztürk, 2018; Hashemi and Abdelghany, 2018; Nabian & Meidani, 2018; Rafiei & Adeli, 2018), the conventional backpropagation neural network was used here because the main scope of this study is the formulation of fuzzy Sobol indices and the considered metamodel is proven to be accurate enough to reduce the computational effort of the example.

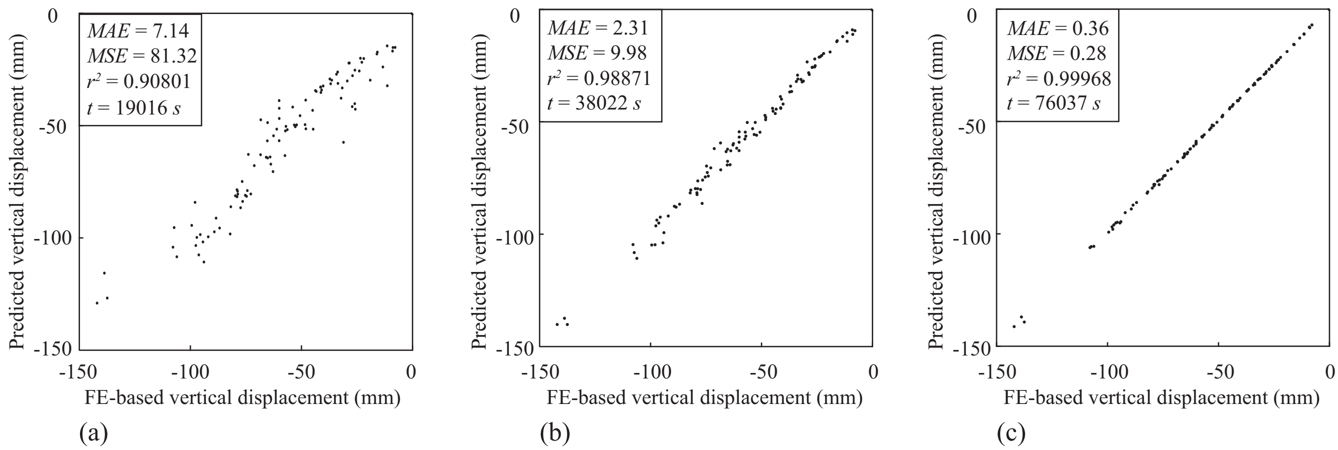

FIGURE 7 Precision of ANN metamodels: (a) trained by 100 samples; (b) trained by 200 samples; and (c) trained by 400 samples

The maximum vertical deflection above the removed column, during 5 s after sudden column removal, was considered as the output of the ANN and was used to find the maximum demand of beam rotations. By trial and error, ANNs with one hidden layer and 10 neurons seemed to be applicable. Tan-sigmoid was used as the transfer function because of continuity and nonlinearity. Three training sets with 100, 200, and 400 samples were prepared by utilizing Latin-hypercube sampling uniformly all over the support space of input variables and considering 99.9% confidence interval (CI) for probabilistic variables. Each set of samples were generated after five iterations for maximizing the minimum distance between samples, to provide samples with good space-filling characteristics. The Levenberg–Marquardt algorithm was chosen to train the ANN metamodels.

The accuracy of the ANNs trained with three different sets was evaluated using another 100 samples, and the results are shown in Figure 7. The mean absolute error MAE, mean squared error MSE, and coefficient of determination R^2 were used to quantify the goodness of prediction. The computational time is also shown in the results. It can be observed that the ANN trained with 400 samples is able to produce quite accurate results and it was employed for further analyses.

7 | RESULTS AND DISCUSSION

7.1 | Fuzzy fragility analysis

Quantifying the robustness of the structure at this stage can provide a better understanding for sensitivity analysis at the next stage. The general collapse performance of the structure was evaluated by fragility analysis. Given x as the intensity measure IM, the fragility curve $F_d(x)$ here was obtained based on the probability that the damage measure DM is larger than the considered damage state d,

$$F_d(x) = P(DM \geq d | IM = x) \tag{11}$$

As mentioned earlier, the maximum demand of beam rotations was considered as the damage measure, and was determined using the maximum vertical deflection above the removed corner column. The limits for the damage states were previously explained and listed in Table 2. The intensity measure was assumed to be the gravity load, and was normalized to the nominal gravity load with the aforementioned load combination. The failure probabilities were determined using MCS up to the load factor of 4.0 for which the ANN was trained practically. The range of the load factor was divided into steps of 0.1, and the fuzzy failure probability corresponding to each load factor was determined when $\alpha = 0$ and $\alpha = 1$. The GA was employed using 100 individuals and 10 generations for both fragility and sensitivity analysis in this research. The *DoubleVector* option was chosen for the population type and the mutation function was chosen to be the *adaptive feasible* function which provides step lengths satisfying the constraints and adaptive generations based on the success of the previous generation. The scattered crossover option with the fraction of 0.8 was used. To carry out the MCS while applying search algorithm, 10^5 samples were used to find each failure probability. The fragility analysis was performed for crisp limit states and also fuzzy limit states to compare the results.

The fragility curves for three damage states are shown in Figure 8. It is observed that the fuzzy collapse probabilities under the nominal gravity load are zero for the LS and CP damage states and the structure is robust against the progressive collapse. The fuzzy median collapse load factors related to the LS damage state are, respectively, $< 2.29, 2.87, 4.08 >$ and $< 2.37, 2.87, 3.89 >$, with and without consideration of fuzzy limit states. The same trend can be observed for the IO damage state with the load factors of $< 0.18, 0.25, 0.41 >$ and $< 0.2, 0.25, 0.34 >$. As can be seen, consideration of the informal uncertainty in derivation of limit states and acceptance criteria can widen the support of the fuzzy load factor related to a specific collapse probability. Therefore, the fragility curves with consideration of fuzzy limit states include a wider

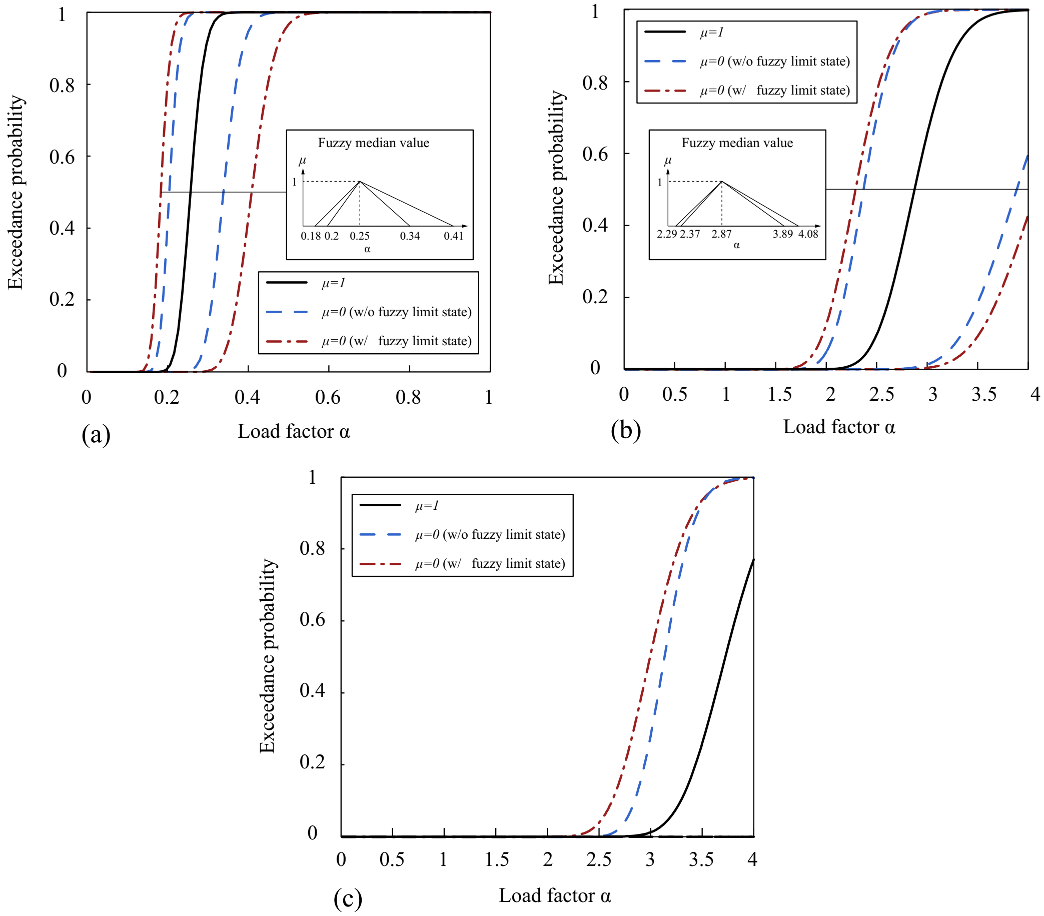

FIGURE 8 Fragility curves of the model structure: (a) IO damage level; (b) LS damage level; and (c) CP damage level

interval due to the other source of informal uncertainty which is the fuzzy limit state. The difference between failure probabilities of a specific load factor for fuzzy and crisp limit states could seem more significant. Based on the fragility curves, it can be conceived how considering the informal uncertainty in definitive limit states can affect the results and incorporating them as a fuzzy model parameter in the numerical solution is quite practical and useful.

The fuzzy fragility curve can describe the whole response of the system considering both informal and stochastic uncertainties. Conventional fragility curves only consider stochasticity and in some cases implicitly informal uncertainty. However, fuzzy probabilistic collapse analysis leads to fuzzy fragility curves which account for informal uncertainty in another dimension and the stochastic output response varies in this dimension. Given $\mu = 1$ the fragility curve is the same as the result of a conventional fragility analysis. At this α-level, there is only one original in the fuzzy input space and the system seems similar to an ordinary stochastic problem.

As can be seen above, fuzzy fragility curves determine how the informal uncertainty affects the intensity measure corresponding to a certain exceedance probability. This can be used when epistemic uncertainty exists, and for decision making the effect of this uncertainty needs to be determined. The results can be also defuzzified and turned into the conventional fragility curves in which the informal uncertainty is also incorporated, however, the current format also contains interesting information on the uncertainties involved in the model.

7.2 | Fuzzy global sensitivity analysis

The fuzzy sensitivity indices including the total effects and the first-order sensitivity indices of the considered variables were obtained using the MCS approach recommended by Saltelli et al. (2008). In this way, the total number of runs is $N(K+2)$, where N and K are the number of samples and variables, respectively. The fuzzy sensitivity indices were calculated when $\alpha = 0$ and $\alpha = 1$. To find the appropriate number of samples N by calculating the CI, different number of samples were considered and the fuzzy sensitivity analysis was conducted 100 times for each considered N and the 95% CI was calculated. The CI for the fuzzy sum of first-order indices corresponding to each number of samples is demonstrated in Figure 9. It is observed that by increasing the samples in abscissa, the CI converges and the MCS provides a better accuracy. According to the results, 10^5 samples were utilized

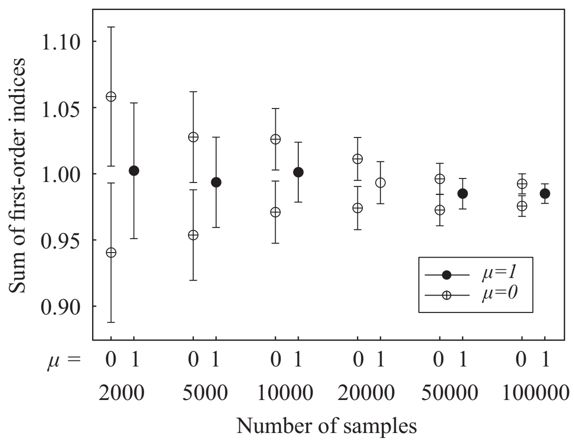

FIGURE 9 Fuzzy sum of first-order sensitivity indices and convergence of the 95% CI

to give an acceptable approximation, and the fuzzy sensitivity indices were calculated using this number of samples.

The fuzzy sum of first-order sensitivity indices is equal to $< 97.5\%, 98.5\%, 99.2\% >$. As this sum is close to unity, the interaction between variables has subtle effects on the output variance and the fuzzy number implies that it can account for 2.5% *at most*. Hence, there is not noticeable difference between the results of first-order sensitivities and total effects. These results are depicted in Figure 10 and as can be seen the main variables contributing to the output variance are the dead load, modulus of elasticity, and the height of the beam section. Their fuzzy first-order indices are $< 31.5\%, 35.4\%, 38.3\% >$, $< 26.2\%, 31.5\%, 36.8\% >$, and $< 20.6\%, 22.9\%, 26.2\% >$, respectively, which implies that they can alone account for *at least* 73.8% of the output variance. These three parameters are followed by the beam length, width and thickness of the beam flange, sustainable live load, web thickness of the beam section, and last the yield strength of the beam. Based on these results and the results from the fragility analysis, it is conceived that the structure is completely robust against progressive collapse and it mostly remains elastic under gravity loads. As a result, the modulus of elasticity and the height of the beam section play the most significant roles among structural properties whereas the yield strength has the lowest effect. Although the dead load is the most influential input variable, the sustainable component of the live load has minute contribution to the output variance. The reason is that this component is very small with slight variation and the main part of the live load is dedicated to the intermittent component. Finally, as beams need to span the damaged part and the flexural action is dominant, it is quite rational that the properties of the beam flange are more influential compared to that of the beam web.

The total effects of the dead load, modulus of elasticity, and the height of the beam section are, respectively, $< 32.5\%, 36.1\%, 38.7\% >$, $< 27.8\%, 31.9\%, 38.1\% >$, and $< 20.6\%, 23.3\%, 26.7\% >$. It is seen that there are 6.2%, 10.3%, and 6.1% differences between the lower and upper boundaries of their fuzzy total effects, respectively. It can be seen that the effects of informal uncertainty associated with a specific uncertainty level could be significantly different, which should be quantified. This shows the ability of the fuzzy global sensitivity analysis to quantify *the maximum and minimum possible contribution* of fuzzy random input variables.

The above-mentioned results can be used in simplifications for further analysis or controlling the considered output response. For instance, one might want to retrofit the case study structure against progressive collapse to reach the IO performance level. To control the vertical displacement under the column removal, the sensitivity indices show that the dead load, modulus of elasticity, and the height of the beam are

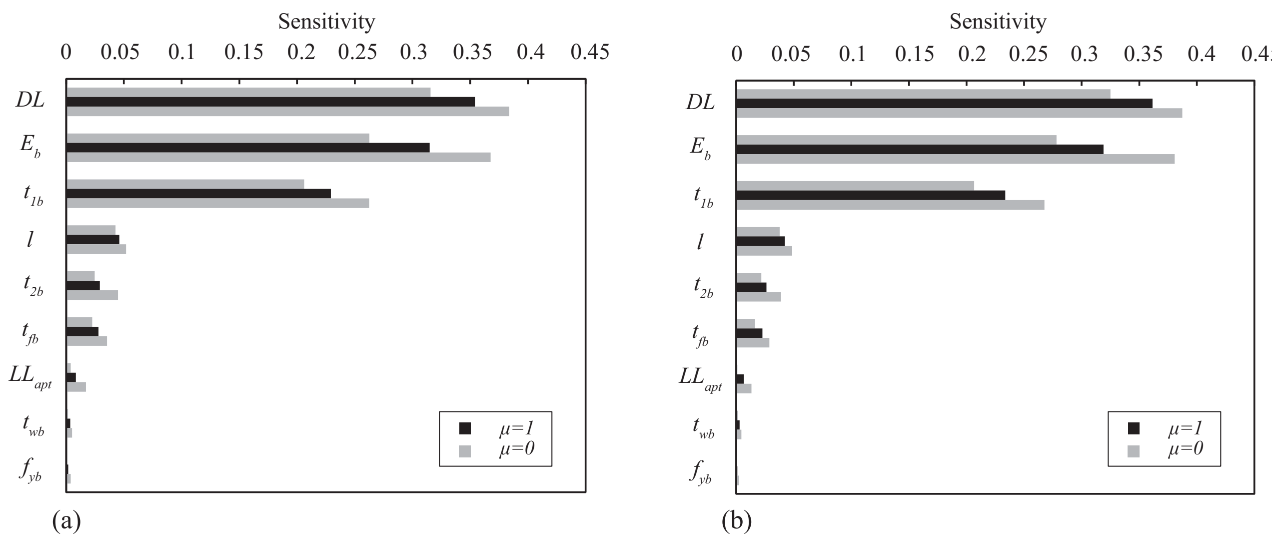

FIGURE 10 Fuzzy sensitivity indices: (a) first-order sensitivities and (b) total effects

the most influential parameters. Thus, one possible option is to reduce mass. It is observed that the beams remain elastic and the yield strength does not contribute very much to the output variance. Instead the height of the beam is the second influential parameter; therefore the next option can be increasing the stiffness by strengthening the beams and increasing their moment of inertia using plate. Because other six parameters have little or no influence, it is possible to omit six other parameters for the computational efficiency in further analysis. This simplification based on Sobol indices can be also used for the reliability-based design, and it is possible to reduce the input variables according to the desired accuracy.

To summarize, any system having input parameters with stochastic and informal uncertainties can be analyzed to quantify the influence of input uncertainties on the variance of the output responses. The fuzzy sensitivity index for an input parameter developed here has two components as a fuzzy number, that is, elements of sensitivity indices and their corresponding functional values which show the degree of truth. The former, the value of each element, is resulted from the stochastic nature of the considered input parameter, and the latter, the degree of truth, ensues from the informal uncertainty. The values of the sensitivity index are between 0 and 1, showing the influence of the considered input parameter as a percentage of the total output variance compared to other input parameters. These elements also provide a range showing the maximum and the minimum possible impact of the considered variable on the output variability. The degree of truth for possible sensitivity indices in this range is indicated by the membership function. As mentioned earlier, the effects of interaction between input parameters can be also quantified using total effect indices. Although fuzzy sensitivity indices contain important information, they can be also defuzzified to help decision making. In general, it is seen that the suggested fuzzy global sensitivity analysis can provide detailed insight into the characteristics of fuzzy random structural systems, and it can be also used in other types of systems as well.

At last it should be mentioned that the fuzzy fragility curves were obtained using 40 load factors, and for each load factor the search algorithm was utilized when $\alpha = 0$. It was conducted using 100 individuals and 10 generations for two times to find maximum and minimum failure probabilities. Failure probabilities corresponding to $\alpha = 1$ were obtained using one MCS. Bearing in mind that each MCS was carried out using 10^5samples and three limit states, a total number of $3 \times 40 \times (2 \times 100 \times 10 + 1) \times 10^5 \approx 2.4 \times 10^{10}$ analyses were conducted using the ANN. To find the proper number of samples for fuzzy global sensitivity analysis, the fuzzy sum of first-order sensitivity indices was calculated 100 times for each number of samples using the same search algorithm and the same two α-levels. Each fuzzy sum of the first-order sensitivity indices was determined by calculating the nine first-order sensitivity indices using the estimators with the mentioned total cost of $N(K+2)$ runs, where N is the number of samples and K is the number of variables. Hence, the total number of analyses for $N = 2 \times 10^3, 5 \times 10^3, 1 \times 10^4, 2 \times 10^4, 5 \times 10^4, 1 \times 10^5$, can be found by

$$\sum_N 100 \times (2 \times 10 \times 100 + 1) \times (N \times (9+2)) \approx 4.1 \times 10^{11} \tag{12}$$

Therefore, in this study, a total number of 4.3×10^{11} analyses were conducted approximately using the ANN. The ANN metamodel was trained with 400 samples from the 3D collapse simulation consisting of two nonlinear static analyses and one nonlinear dynamic analysis, which takes around 190 s for each collapse simulation using a PC with the Intel® Core i7 3.40 GHz. On the other hand, 10^5 simulations using the ANN metamodel take 0.041 s. Based on this, the effectiveness of the ANN in probabilistic analyses, especially for time-consuming analyses, can be seen clearly.

8 | CONCLUSIONS

In this study, a variance-based global sensitivity analysis was presented to evaluate quantitatively the effects of fuzzy random structural variables on a considered output response. To this end, the formulation of fuzzy Sobol sensitivity indices for fuzzy random structural systems was presented, which can show the influence of epistemic and aleatory uncertainties of the input parameters on the variance of output responses. Then the informal uncertainty in derivation of distinct limit states for collapse analysis was addressed briefly. These results can be used for simplification in reliability-based analysis and design by reducing noninfluential input variables. They also can be used for limiting the output results by controlling the input parameters. The formulation was provided using both the extension principle and the α-optimization method. The α-level optimization method was applied using the GA due to the advantages such as ability of finding global optima, having good performance in highly nonlinear problems, and easy-to-understand concept.

The proposed method was applied to the collapse assessment of a steel moment resisting frame subjected to a sudden column removal. An ANN metamodel was utilized to investigate the structural behavior thoroughly and reduce the costly probabilistic collapse analysis. The overall collapse behavior and the influence of fuzzy limit states were evaluated using fuzzy fragility curves to compute the fuzzy sensitivity indices. The developed sensitivity test showed that the most influential input variables were related to the elastic behavior of the structure, and therefore it was conceived that the case study structure remained in the elastic range when subjected to the sudden removal of the corner column. The results were consistent with the fuzzy fragility curves because the exceedance probability of the LS performance level under the load factor of 1 is almost zero. However, the structure failed to meet the IO performance level. One can retrofit the structure by directly controlling the influential parameters obtained using the computed fuzzy sensitivity indices. In this way, the proposed fuzzy global sensitivity analysis can provide detailed insight into the behavior of a fuzzy random structural model. Finally, it was observed that the informal uncertainty in derivation of acceptance criteria and limit states could affect the reliability analysis considerably, and the application of the ANN could reduce the computational cost drastically. Nevertheless, the high computational cost for nonlinear structural analysis is still a barrier to practical applications. Sensitivity analysis is commonly utilized in the context of stochasticity and therefore the sensitivity indices here were formulated for fuzzy random input variables. Some models may contain both fuzzy random and fuzzy input variables and the effects of fuzzy input variables should be quantified in addition to fuzzy random input variables. The formulation of such sensitivity analysis still needs further research.

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