Uncertainty analysis through development of seismic fragility curve for a SMRF structure using adaptive neuro-fuzzy inference system based on fuzzy c-means algorithm

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Abstract. The present study is mainly focused on development of the fragility curves for the sidesway collapse limit state. One important aspect of deriving fragility curves is how uncertainties are blended and incorporated into the model under seismic conditions. The collapse fragility curve is influenced by different uncertainty sources. In this paper in order to reduce the dispersion of uncertainties, Adaptive Neuro Fuzzy Inference System (ANFIS) based on fuzzy C-means algorithm used to derive structural collapse fragility curve, considering effects of epistemic and aleatory uncertainties associated with seismic loads and structural modeling. This approach is applied to a Steel Moment Resisting Frame (SMRF) structural model whose relevant uncertainties have not been yet considered by the others in particular by using ANFIS method for collapse damage state. The results show the superiority of ANFIS solution in comparison with excising probabilistic methods e.g., First Order Second Moment Method (FOSM) and Monte Carlo (MC)/Response Surface Method (RSM) to incorporate epistemic uncertainty in terms of reducing computational effort and increasing calculation accuracy. As a result, it can be concluded that comparing with proposed method rather than Monte Carlo method, the mean and the standard deviation are increased 2.2 % and 10 % respectively.

Keywords. ANFIS C-means algorithm, Collapse fragility curve, First order second moment method, Epistemic uncertainty, Aleatory uncertainty, Incremental dynamic analysis.

1. Introduction

Seismic fragility curves describe probability of structures bearing assorted damage steps versus seismic intensity [1]. Sideway collapse that is described as lateral instability of structures excited by strong earthquake is the concern of many recent studies [2]. Complete evaluation of the risk of earthquake-induced structural collapse demands a robust analytical model with nonlinear behavior and at the same time a clear observation of the various significant sources of uncertainty [3]. Factors leading to changes in collapse capacity of a building are divided into two categories: aleatory and epistemic uncertainties. Accordingly, aleatory (record-to-record) uncertainty consists of factors that possess random features or according to our current knowledge and data, cannot be accurately predicted. As far as is known, the earthquake ground motions contain of the main source of uncertainty regarding to other identified sources. Site-specific seismic hazard curve describes uncertainties in ground motion intensity, which maintains a connection between the spectral intensity and the mean annual frequency of exceedance.

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Record-to-record variability stands for the extra uncertainties allied with frequency content and other characteristics of the ground motion records. There are other uncertainties associated with the simulation of the structural responses in the analysis approaches and development of idealized model describing real behavior. The epistemic uncertainties can be reduced by developing knowledge boarders. The effect of this uncertainty factors can be reduced by collecting more data or using more appropriate analytical model. The parameters of modeling assumptions (analytical model) are mainly sources of epistemic uncertainties, which are propagated into the structure responses through numerical analysis [4]. To simulate structural responses, detailed nonlinear response history analysis is usually applied and the source of elementary uncertainty modeling is placed in description of the model parameters especially the strength, the deformation capacity, the stiffness and energy absorption properties of the building components [5].

Some simple methods from First-Order-Second-Moment to more complicated method like crude Monte Carlo method have been used to combine such uncertainties [6]. Crude Monte Carlo simulation method needs a lot of simulation to cover all probabilistic distributions allied with each source of uncertainty, which would be completely time-consuming. For solving this problem, the response surface in combination with Monte Carlo simulation method has been suggested to reduce computing effort. Besides, the response surface method could be replaced with Artificial Neural Network method (ANN) to imply effects of uncertainties in reliability models[7-8]. The prediction of the mean and standard deviation of collapse fragility curve using permanent function is the most important limitation of response surface method. Moreover, taking advantage of the higher level of response functions demands more data to compute coefficients. It was represented that ANNs can be applied to any estimated form of functions. ANN approaches have been applied for deriving fragility curves in a limited number of studies. Lagaros and Fragiadakis [9] used ANN for the quick assessment of the exceedance probabilities for each limit state at a particular hazard level. They have applied Monte Carlo simulation based on ANN while randomness incorporated in material and geometry parameters in addition to considering uncertainty in seismic loading. Mitropoulou and Papadrakakis [10] suggested Monte Carlo simulation based on ANN for the sensitivity analysis of large concrete dams. ANN method was used by Mitropoulou and Papadrakakis [10] to establish fragility curves for different limit states of concrete structures. They suggested that strong ground motion parameters and the spectral acceleration at different limit states were regarded as input and output layers, respectively. This study was expanded by deriving the fragility curve considering various uncertainties. Cardaliaguet and Euvrand [11] applied an ANN algorithm to estimate a function and its derivatives in control theory. Li [12] indicated that any multivariate performance measure and its existing derivatives could be coincidentally estimated by a radial basis ANN while the presumption on the performance were relevantly mild. Chapman and Crossland [13] showed an example of ANN application for prediction of the failure probability of pipe work under different working situation.

While ANN was employed to develop fragility curves in mentioned several works, using Adaptive Neuro Fuzzy Inference System (ANFIS) in this respect to the author’s knowledge, was not reported. Advantages such as better matching between input and output, faster computation in complex problems, lower encountered error and hence more accrued results may be considered for ANFIS in comparison to ANN in various application fields [14, 15]. The main objective of this paper is to show effectiveness of ANFIS method in deriving collapse fragility curves. Moreover, modeling parameter uncertainty effects are incorporated in this study. ANFIS is trained and tested according to limited numbers of simulations derived from nonlinear analyses of structure under strong ground motion excitations. The responses of
structure simulated by modeling parameters under ground motion excitation are acquired through application of Incremental Dynamic Analysis (IDA) method. The mean and the standard deviation of collapse capacity ($S_{\text{collapse}}^0$) are derived as the results of implementing ANFIS. To explain the capability of the suggested method, a three-story moment-resisting steel frame is modeled as the case study in this work. Results of proposed method are compared against results of FOSM and Monte Carlo simulation along with response surface method in view of developing collapse fragility curves. In this study, ANFIS with Grid Partition (GP), Subtractive Clustering (SC) and FCM algorithm are applied to predict mean and standard deviation of fragility curve for the first time and finally compared with Monte Carlo and FOSM methods.

2. Development of analytical fragility curves

IDA is a common method in evaluating fragility curves for different limit states of structures affected by different earthquake intensity. Each IDA curve is developed by implementing successive nonlinear dynamic analyses of structure, while it is influenced by amplifying intensities of strong ground motions [16]. These curves show structural response parameter (deformation or force quantity), named as Engineering Demand Parameter (EDP), versus features of affected strong ground motion, named as Intensity Measure (IM).

2.1. Collapse fragility curve

Based on selection of key variables, the collapse fragility function can be written in IM-Based or EDP-Based formats [14]. IM-Based formulation, which uses IM as controlling variable, is exhibited by equation (1):

$$P(\text{Collapse}|IM=im_i) = P(im_i > IM_{LS}) = F_{IM_{LS}}(im_i)$$  (1)

Using EDP as intermediate variable, EDP-Based formulation is presented by equation (2):

$$P(\text{Collapse}|IM = im_i) = \sum_{all \, edp_c} P(EDP_d > EDP_c | EDP_c = edp_c, IM = im_i) \cdot P(EDP_c = edp_c)$$  (2)

Where, $P(\text{Collapse} \mid IM=im_i)$ estimates probability of collapse given IM. $P(EDP_d > EDP_c \mid EDP_c = edp_c, IM = im_i)$ specifies the probability of applied engineering demand ($EDP_d$) exceeding associated collapse capacity of structure in the form of Engineering demand parameter ($EDP_c$). Each random value of capacity ($edp_c$) and intensity measures ($im_i$) should be calculated in above equation. Moreover, the expression $P(EDP_c = edp_c)$ specifies the probability that the structure's capacity equals the specific capacity of $edp_c$.

In equation (1), $F_{IM_{LS}}(im_i)$ is the cumulative probability distribution function for the specific limit state, described by intensity measure of imposed strong ground motion, which is obtained through application of IDA to the structure. Derivation of the parameters of this probability distribution function demands an explanation of IM and a process to propagate the epistemic and aleatory uncertainties involved in IM [6]. The collapse limit state, considered in this paper, is described as the IM of strong ground motion in which the structure experiences the lateral dynamic instability in a sidesway collapse mode. In other words, IM$^C$ is described as the last-converged result on an IDA curve through implementation of successive nonlinear dynamic analyses [17]. In this study, IM-based formulation is used to calculate collapse fragility curve of structures. Using this approach, for a set of IDA curves points which is indication of specified IM
exceeded probability of collapse limit state. In this method, the random variable is defined as the collapse capacity in the form of intensity measure $(IM)$. The collapse fragility curves are often defined by lognormal probability distributions [4]. The fragility curves obtained from IDA analysis is represented by equation (3)

$$P(C|IM) = \Phi\left(\frac{\ln(IM) - \ln(\eta_c)}{\beta_{RC}}\right)$$

In this equation, $\Phi(.)$ is the standard Gaussian distribution function and, $\eta_c$ and $\beta_{RC}$ are the mean and the standard deviation of collapse fragility curve, respectively [18].

2.1.1. Treatment of epistemic uncertainty

There are different types of methods for incorporating epistemic uncertainties in a seismic reliability analysis, like the sensitivity analysis, the mean estimate method [19], the First-Order-Second-Moment Method (FOSM), the Monte Carlo simulation methods along with the Response Surface Method (RSM) [20, 21] or other inference methods such as the Artificial Neural Network (ANN) [7, 10]. In sensitivity analysis, the effect of each random variable on structural response is distinguished by changing a single model parameter and re-evaluating the structure’s performance. This method has been used to choose the most influential parameters affecting performance assessment of structures. In the mean estimate method, it is assumed that only variance of fragility curves is changed by epistemic uncertainties; on the contrary, in the confidence interval method, the mean values are affected by epistemic uncertainties and variance remains unchanged. Unlike these simplifying assumptions, it is shown that epistemic uncertainty causes a shift in both the mean and the standard deviation values of collapse fragility curves.

A general version of the FOSM method is formulated in standard Gaussian space [20, 21], and has an advantage in comparison with some other methods since it involves a small number of structural analyses. Moreover, the mean seismic capacity and its variance can be estimated without understanding the actual probability distribution of the performance function $Z(Q_1, Q_2, \ldots, Q_n)$ where $Q_1, Q_2, \ldots, Q_n$ represent a set of input random variables [22]. FOSM is an approximation method for computing the mean and the standard deviation of a function of variables, which are shown by probability distributions. Considering variable $Z$, which is a function of $n$ random variables $Q_i$, the mean and the standard deviation of $Z$ can be approximated by expansion of function $Z$ using Taylor’s series, about the expected values of random variables. In FOSM method, first-order terms of Taylor series and the first two moments of expected function $Z$ are considered. The mean and the standard deviation of $Z$ is computed as follows [4, 23].

$$\mu_Z = Z(\mu_Q)$$

$$\sigma_Z^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{\partial Z}{\partial Q_i} \frac{\partial Z}{\partial Q_j} \rho_{Q_iQ_j} \sigma_{Q_i} \sigma_{Q_j}$$

In equations (4) and (5) $\mu_Z$ and $\sigma_Z^2$ are the first two moments of function $Z$, $\rho_{Q_iQ_j}$ stands for the correlation coefficient between two variables $Q_i$ and $Q_j$, $\sigma_{Q_i}$ is variance of $Q_i$ and $n$ is the number of input variables.
In this study, the output function is the mean of collapse fragility curve and input variables composed of \( \{ \theta_p, \theta_{pc}, \Lambda \} \) are defined in Section 3. Equations (6) are written as follows for evaluation of the mean and the standard deviation of output function.

\[
\mu_{\text{Ln}(\text{IM}_C)} = \text{IM}_C \left( \mu_{\theta_p}, \mu_{\theta_{pc}}, \mu_{\Lambda} \right)
\]

\[
\sigma^2_{\text{Ln}(\text{IM}_C)} = \left( \frac{\partial g}{\partial \theta_p} \right)^2 \sigma^2_{\ln \theta_p} + \left( \frac{\partial g}{\partial \theta_{pc}} \right)^2 \sigma^2_{\ln \theta_{pc}} + \left( \frac{\partial g}{\partial \Lambda} \right)^2 \sigma^2_{\ln \Lambda} + 2 \left( \frac{\partial g}{\partial \theta_p} \right) \left( \frac{\partial g}{\partial \theta_{pc}} \right) \rho_{\theta_p, \theta_{pc}} \sigma_{\ln \theta_p} \sigma_{\ln \theta_{pc}}
\]

\[
2 \left( \frac{\partial g}{\partial \theta_{pc}} \right)^2 \left( \frac{\partial g}{\partial \Lambda} \right)^2 \rho_{\theta_{pc}, \Lambda} \sigma_{\ln \theta_{pc}} \sigma_{\ln \Lambda}
\]

Equation (6) is written as follows for evaluation of the mean and the standard deviation of output function.

According to advantages such as capability of modeling various modes of component deterioration, refinement of parameters definition, Modified Ibarra-Krawinkler model is used here. Modeling parameters of steel moment resisting connections are considered as epistemic uncertainties, and their effects on collapse fragility curves are investigated in this study \( \{ \theta_p, \theta_{pc}, \Lambda \} \). Calculation of derivatives requires determination of the mean values of \( \text{IM}_C \) for various values of modeling variables. Derivatives may be computed by one-side method or two-side method which, is shown by equation (7) and (8), respectively

\[
\frac{\partial Z(\mu_0)}{\partial Q} = \frac{Z(\mu_0) - Z(\mu_0 \pm n\sigma_Q)}{\pm n\sigma_Q} \quad (7)
\]

\[
\frac{\partial Z}{\partial Q} = \frac{Z(\mu_0 - n\sigma_Q) - Z(\mu_0 + n\sigma_Q)}{2n\sigma_Q} \quad (8)
\]

In Crude Monte Carlo method, thousands of simulations for modeling parameter values based on their statistic distributions are implemented and then the structure is analyzed based on these simulated values. Thousands of the probability of collapse versus \( IM \) values denoted as collapse fragility curves involving effects of epistemic uncertainties resulted from this rigorous analyses. This method is very elaborative in practice due to the runtime needed for several time-consuming nonlinear dynamic analyses of structure for each simulated value of modeling parameter. Derivatives method in combination with Monte Carlo simulation is used for seismic vulnerability assessment in several structure e.g., steel framed structure [24], horizontally curved steel bridges [25] and concrete building structures [26]. In addition, response surface method has been used to derive the fragility curves [27]. Monte Carlo simulation
applying a predefined regressed function, as response surface, has been proposed as an alternative to substitute time history dynamic analysis and to reduce the computational effort in the context of the previous researches. In this method, first, fixed formats of functions were interpolated to the limited number of simulations of modeling variables as inputs, which lead to resultant means and standard deviations of collapse fragility curves and as outputs of the function. In the next step, means and standard deviations of collapse fragility curves for a large number of simulations of modeling parameters are calculated applying derived analytical functions. The cost of reducing analysis time in the response surface–based method is loss of accuracy in approximated collapse fragility curves. To overcome this deficiency and to reduce the simulation runtime, the Monte Carlo along with inference method such as ANN and ANFIS Methods in lieu of Response Surface method may be suggested. In this paper, ANFIS Method is used for prediction the mean and the standard deviation of fragility curves for the first time.

2.1.2. The ANFIS method

ANFIS is a fuzzy inference system performed in the structure of adaptive networks. The presented model can build an input-output mapping based on both human knowledge in the form of fuzzy rules and stipulated input-output data pairs. In the present study, it proposed a Sugeno-type fuzzy system in five-layer network (Figure 1) [28]. The node functions in the same layer are of the same function family as explained below:

Layer 1: Every node $i$ in this layer is a square node with a node function:

$$O_i^1 = \mu_{A_i}(x)$$  \hspace{1cm} (9)

In which $x$ is the input to node $i$ and $A_i$ is the linguistic label (such as “small” or “large”) associated with this node function. In other words, $O_i^1$ is the membership function of $A_i$ and it defines the degree to which the given $x$ fulfills the quantifier $A_i$. Any continuous and various function, such as generally applied bell-shaped, trapezoidal or triangular-shaped membership functions are efficient candidates for node function in this layer.

Layer 2: Every node in this layer is a circle node termed $\Pi$ that multiples the incoming signals and sends the product out. For example:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \hspace{1cm} i = 1, 2.$$  \hspace{1cm} (10)

Each node output describes the T-norm operators that combine the probable input membership grades in order to calculate the firing strength of a rule.

Layer 3: Every node in this layer is a circle node termed $N$. The $i^{th}$ node computes the ratio of the $i^{th}$ rule’s firing strength to the sum of all rules’ firing strengths:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \hspace{1cm} i = 1, 2.$$  \hspace{1cm} (11)

For accessibility, outputs of this layer will be labeled normalized firing strengths (Figure 2).

Layer 4: Every node $i$ in this layer is a square node with a node function:
\[ O_i^4 = \bar{w}_i f_i = \bar{w}_i \left( p_i x + q_i y + r_i \right) \]  \hspace{1cm} (12)

Where \( \bar{w}_i \) is the output of layer 3, and \( \{p_i, q_i, r_i\} \) is the parameter set. Parameters in this layer will be applied as consequent parameters that are adaptable.

Layer 5: The single node in this layer is a circle node (adaptive node) termed \( \Sigma \) that calculates the total output as the summation of all incoming signals, i.e.

\[ O_i^5 = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i} \]  \hspace{1cm} (13)

It is not adaptable.

[Figure 1, near here]

[Figure 2, near here]

For having knowledge of ANFIS, a combination of two methods of back-propagation (gradient descent) and least squares estimation are applied. First, parameters of the introduction section are assumed stable, and final parameters are estimated applying least squares method. Then, final parameters are assumed stable and error back-propagation is applied to correct the parameters of introduction. This procedure is repeated in each learning cycle [29].

Two methods are generally applied to create ANFIS: Grid Partition (GP) and Subtractive Clustering (SC). ANFIS with GP algorithm apply a hybrid-learning algorithm to recognize parameters of inference system. It uses a combination of the least square method and the back-propagation gradient descent method for training ANFIS membership function parameters.

Grid partition divides the data space into rectangular sub-spaces applying axis-paralleled partition based on pre-defined number of MF and their category in each dimension. The number of rules is based on the number of input variables and on the number of MF applied per variable, and this partition strategy requires a small number of membership function for each input. It faces problems when we have a moderately large number of inputs [30].

Clustering is a task of selecting a set of data into groups named clusters to find structures and patterns in a dataset, and the radius of a cluster is the maximum distance between all the points and the centroid. There are two most important clustering methods: the hard clustering and the fuzzy clustering. The hard clustering is based on categorize each point of the dataset just to one cluster. In fuzzy clustering, objects on the borderlines between several clusters are not forced to fully relate to one of them. The subtractive clustering method (SC) as a hard clustering was suggested [31].

The SC method supposes that per data point is a potential cluster center and computes the potential for each data point based on the density of surrounding data points. The capacity of potential for a data point is a function of its distances to all other data points. A data point with many surrounding data points will have a high potential value. The data point with highest potential is chosen as the first cluster center, and the potential of data points near the first cluster center is demolished. Therefore data points with the
highest remaining potential as the next cluster center and the potential of data points near the new cluster center are demolished.

It is remarkable that the important radius of cluster is vital for deciding the number of clusters and data points outside this radius has little effect on the potential decision. Also, a smaller radius results in many smaller clusters in the data space, which leads to more rules [31].

In this study, GP, SC, and another technique which is named Fuzzy C-means (FCM) are applied to generate the ANFIS model. FCM is a strong unsupervised algorithm. FCM clustering was first informed by Dunn [32]. It was extended by Bezdek (1981). FCM is an algorithm where per data point has a membership degree between 0 and 1 to each fuzzy subset. In other words, each data in FCM can be related to all groups with various membership grades. The algorithm generates an optimal c partition by minimizing the weighted within group sum of squared error function $J_m$ [32]:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m d^2(x_i, v_j)$$

In which, $X = \{x_1, x_2, ..., x_N\} \in \mathbb{R}^m$ is the dataset in the m-dimensional vector space, $N$ is the number of data items, $c$ is the number of clusters within $2 < c < N$, $u_{ij}$ is the degree of membership of $x_i$ in the $j^{th}$ cluster, $m$ is the weighting proponent on each fuzzy membership, $v_j$ is the prototype of the center of cluster $j$, $d^2(x_i, v_j)$ is distance measure between object $x_i$ and cluster center $v_j$.

To generate an ANFIS with FCM, data are clustered by FCM algorithm and then ANFIS method is used for clustering data.

3. Case study and analytical modeling

To evaluate the effects of various sources of uncertainties and their interaction on the collapse fragility curves, a 3-storey intermediate moment steel buildings is designed for a specified site (Tehran) where located in a high seismic zone. The seismic design of case study structure is performed based on UBC-97 provisions [33]. This building assumed to be constructed on soil type B (the average velocity of shear waves in the top 30 m of soil would be 360-750 m/s) and located in seismic zone 4. The buildings are square in plan and it consists of three bays of 5.0 m in each direction and having the story heights of 3.2 m that are shown in Figures 3 and 4.

A rigid diaphragm can be assumed according to the floor building systems existing in common steel concrete composite floor structural systems. The values of response modification factors (i.e. R) which are utilized by UBC-97 (considering R=8.5 for special moment resisting frame) [33]. Gravity loads are supposed to be similar to common residential buildings in Iran. Table 1 give cross sections for all members. The fundamental period of the frame is 1.075 s.
OpenSees finite element program is employed for modeling and analysis of the structures. All frame members are modeled with the two-dimensional prismatic beam element consists of semi-rigid rotational springs at the ends and an elastic beam element in the middle (see Figure 5). The analytical model developed by Ibarra et al. referred to as Ibarra-Medina- Krawinkler (IMK) model, is applied in this study[34]. It has been shown that \( \{ \theta_p, \theta_{pc}, \Lambda \} \) have more effects than other modeling parameters on collapse performance of structures [34]. It simulates nonlinear behavior of frame members. The IMK model creates strength bounds based on a monotonic curve as shown in Figure 6.

Definitions of modeling parameters, shown in Figure 6, are as follows:

- \( \theta_c \): Cap rotation
- \( M_y \): Effective yield moment
- \( \theta_y \): Effective yield rotation
- \( \theta_u \): Ultimate rotation capacity, \( \theta_p \): Plastic rotation capacity, \( \theta_{pc} \): Post-Capping rotation capacity.

The hysteretic behavior of the connection is defined based on deterioration rules, which are defined according to hysteretic energy dissipated in each load-deformation cycle.

The deterioration of basic strength, post capping strength, unloading stiffness and reloading stiffness could be considered in this model.

The energy dissipation capacity of the component, by which deterioration rules are formulated, is described as [35]:

\[
E_t = \Lambda M_y
\]  

(15)

In equation (15), \( \Lambda \) is the rate of cyclic deterioration and is estimated according to calibration of experimental results. It has been represented that \( \theta_p, \theta_{pc} \) and \( \Lambda \) have more influences than other modeling parameters on collapse performance of structures. Lognormal probability distribution function is employed to show uncertainties due to \( \theta_p, \theta_{pc} \) and \( \Lambda \). The parameters of these probability distributions, based on laboratory tests, are presented in Table 2.

The inelastic beam-column joint behavior of the steel frame is simulated by nonlinear panel zone of Krawinkler model, which is shown in Figure 7. This model holds the full dimension of the panel zone with rigid links and controls the deformation of the panel zone by using two bilinear springs that simulate a tri-linear behavior [36].

A set of 40 strong ground motions represented by Medina [37], named as LMSR records, is chosen to consider record-to-record variability in estimating collapse capacity of the structure. IM-based
formulation is used to derive collapse fragility curves from performing IDA of the sample structure. These records are normal strong ground motions recorded in California region and do not involve pulse – type near-field features that is introduced in Table 3. The hunt&fill tracing algorithm is used to scale records in IDA method to achieve good performance [16].

Fragility curves are developed by ANFIS based on fuzzy C-means algorithm. To achieve input data and train ANFIS, five realizations for each modeling random variables \((\theta_p, \theta_{pc}, \Lambda)\) are considered. It is to be noted that they are related to mean, mean minus and plus one standard deviation and mean minus and plus two standard deviations (mean, mean \(\pm 1\times\) standard deviation, mean \(\pm 2.0\times\) standard deviation, Totally 125 simulations). The tree diagram of realizations for input variables is shown in Figure 8. Each branch of the tree shows a value for one of input variables. For each realization of input variables, IDA is performed and collapsed fragility curves are derived based on equation (3). The selected parameters for intensity measure (IM) and damage measure (DM) should appropriately indicate the impact of an earthquake and behavior of a construction, respectively. Maximum inter-story drift ratio among the common parameters is chosen for estimating DM. For IM parameter, spectral acceleration \(S_a(T_1, 5\%)\), at fundamental elastic natural period among other intensity measures is selected. It was indicated that both advantages of efficiency and sufficiency for \(S_a\) intensity measure while used versus Maximum inter-storey drift ratio [16].

A total of number of \(40\times125\) IDA curves are developed to train and test the proposed ANFIS network which 125 various of these \(\theta_p, \theta_{pc}, \Lambda\) parameters are input data for ANFIS system. Objective data in ANFIS method are mean and standard deviation of collapse fragility curves, which are similar to output functions in FOSM method.

A sample of IDA curves and fragility curves for 10 cases are presented in Figures 9 and 10, and the architecture of represented neural networks to predict mean and standard deviation values of collapse fragility curves is shown in Figure 11. As it is shown in this figure, after analyzing for each scenario, which includes epistemic uncertainty, ANFIS predicts mean and standard deviation of collapse fragility curves. There are 125 available data for ANFIS while 88 cases are applied for training, 37 remaining data are used for testing the model.

The performance of model configuration is estimated based on coefficient (R) and Mean-Square Error (MSE) of the linear regression between the predicted values from the neural network model and the desired outputs, as follows:

\[
RMSE = \frac{n_i \sum_{i=1}^{n_i} (y_i - \hat{y_i})^2}{(n_i - 1) \sum_{i=1}^{n_i} (y_i)^2}
\]  

(16)
\[ R^2 = 1 - \frac{\sum_{i=1}^{n_i} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n_i} \hat{y}_i^2} \]  

(17)

Where \( y \) and \( \hat{y} \) are actual and predicted values, respectively; and \( n_i \) is the number of testing samples. The smaller \( RMSE \) and the larger \( R^2 \) are generally indicative of better performance. To find the best results based on GP, SC, and FCM methods, datasets are applied randomly and many models are established. It is discovered that the FCM model is much faster than the other two methods and the algorithm of GP was more time-consuming process than others. Moreover, the results of the best models that obtained from SC method is lower than both GP and SC methods. In the SC method, radius of the cluster should be defined before modeling. The smaller radius will create the greater number of unknown parameters. In Table 4, the best results obtained by the SC algorithm for the test phase are presented. According to this table, the best model has 0.89 and 0.029 for \( R \) and \( RMSE \) of the mean value of fragility curve, respectively. It is found that the GP algorithm had less error, but needed more rules to solve the problem. It is observed that to evaluate standard deviation, FCM algorithm has better efficiency than other two methods. To create ANFIS with FCM algorithm, the number of clusters is predefined for the model. Therefore, to get the proper state, many models with various number of clusters are established. The best model in the test and the train properties for the mean and the standard deviation are presented in Table 5.

The performance of ANFIS for evaluating the mean values of test data for developing fragility curve is shown in Figure 12. The relevant value for the standard deviation is shown in Figure 13, where ANFIS output values are plotted versus the results achieved by performing full IDA.

Two different training sets of the mean and the standard deviation have been tested. It is found that both performed equally well; hence, ANFIS with FCM is chosen, since it requires less computing time and better performance for preparing the training and testing set. To predict the means and the standard deviations of collapse fragility curves, ANFIS based on fuzzy C-means algorithm simulation is applied. These models are calibrated from 10000 realizations of input random variables that located inside interval \([-2s, +2s]\) and then, collapse fragility curve is derived through fitting a log-normal probability distribution. It is observed in Table 6 that the mean and the standard deviation of fragility curve in ANFIS method with FCM, are 0.47623 and 0.4256, respectively. As a result, it can be concluded that comparing with ignorance of modeling uncertainties, the mean is reduced 25 % and the standard deviation is increased 9.3 %. The comparison between FOSM approximation in inclusion of modeling uncertainties in developing fragility curves and resulted fragility curve with neglecting modeling uncertainties is noteworthy. The mean value doesn't change using FOSM approximation. As it is presented in Table 6,
mean and standard deviation of collapse fragility curve of sample structure with neglecting modeling uncertainties are 0.6292 and 0.3894, respectively. Application of FOSM method to involve modeling uncertainty remains mean value unchanged and standard deviation is changed to 0.5190 and 0.4417, for one-side and two-side formulations represented by equations (7) and (9), respectively. Results of quadratic response surface method and proposed method are compared in view of collapse fragility curves. To obtain input data to evaluate response surface, five realizations for each modeling random variables \((\theta_p, \theta_{pc}, \Lambda)\) are considered, which corresponds to mean, mean minus and plus one standard deviation and mean minus and plus two standard deviations (totally 125 simulations). For each realization of input variables, IDA is implemented and collapse-capacity spectral acceleration is derived for each record.

Response functions, applied to estimate mean and standard deviation of collapse fragility curves, are shown in equations (18) and (19). The constant coefficients of these equations are evaluated through implementing nonlinear regression analysis. Estimated coefficients are listed in Tables 7. Implementing response surface functions in conjunction with Monte Carlo simulation derived the mean and the standard deviation of fragility curve of 0.4866 and 0.4762 respectively (depicted in Table 6).

\[
\eta_c = C_0 + C_1 \theta_p + C_2 \theta_{pc} + C_3 \Lambda + C_4 \theta_p \theta_{pc} + C_5 \theta_p \theta_{pc}
+ C_6 \theta_{pc} \Lambda + C_7 \theta_p^2 + C_8 \theta_{pc}^2 + C_9 \Lambda^2
\]

\[
\beta_c = C_0' + C_1' \theta_p + C_2' \theta_{pc} + C_3' \Lambda + C_4' \theta_p \theta_{pc} + C_5' \theta_p \theta_{pc}
+ C_6' \theta_{pc} \Lambda + C_7' \theta_p^2 + C_8' \theta_{pc}^2 + C_9' \Lambda^2
\]

Resulted collapse fragility curves using (ANFIS) based on fuzzy C-means algorithm simulation in addition to collapse fragility curve ignoring effects of modeling uncertainties (while modeling parameters are set as their mean values) are presented in Figure 14 and 15.

4. Conclusion

In this paper, ANFIS and FCM training/validation algorithm as an efficient and effective method are introduced to predict the mean and the standard deviation values of collapse fragility curves of a case study three-story SMRF building. The modified Ibarra–Medina–Krawinkler moment rotation model are considered as modeling parameters for frame’s members. The fragility curves are derived through implementation of IDA on the structure, while limited realizations of values for modeling parameters are
presumed. To this end, three inputs \((\theta_p, \theta_{pc} \text{ and } \Lambda)\) and two output data values (mean and standard deviation) are considered. The system is trained by a dataset of 125 values obtained from 5000 IDA curves. Then, dataset consisting of 10000 inputs are applied to predict a basis fragility curve with aleatory and epistemic uncertainty. As a result, involvement of modeling uncertainties reduces the mean and increases the standard deviation of obtained fragility curves. To compare the results, collapse fragility curves of sample frame are derived using other approaches such as FOSM and RSM methods. Modeling parameters involved in moment-rotation relationship of connections, entitled \((\theta_p, \theta_{pc} \text{ and } \Lambda)\) are considered as epistemic uncertain parameters. The effects of epistemic uncertainties, on collapse fragility curves, are estimated by aforementioned methods. Many ANFIS models based on GP, SC, and FCM are expanded, and it is understood that the ANFIS-FCM predicts the fragility curve with higher accuracy than other methods (GP, SC). GP is more time-consuming process than other methods and needs more rules to solve the problem and in the SC method, the problem is radius value of the cluster, which should be defined before modeling, hence the smaller radius will create the greater number of unknown parameters. In this respect, FCM algorithm has better efficiency than other two methods. Therefore, FCM algorithm in comparison with Monte Carlo method are known as precise methodology. Nevertheless, the proposed method presented here demonstrates a small prediction error and leads to comparable results with those obtained using Monte Carlo method.

5. References


**Biographies**

**Fooad Karimi Ghaleh Jough** was born in 1982. He obtained his BS degree in Civil Engineering from Tabriz Azad University, Iran in 2006, and MSc degree in Structural Engineering from Sistan & Baluchestan University, Zahedan, Iran in 2008. He received his PhD in earthquake engineering from Eastern Mediterranean University, Famagusta, Turkey in 2016 and has been a faculty member at Sarab branch of Islamic Azad University. His research interests include vulnerability assessment of existing buildings and using metaheuristic algorithms in seismic risk analysis.

**Seyed Bahram Beheshti Aval** is associate professor at Civil Engineering Department at the K.N. Toosi University of Technology. He received his PhD degree from the Sharif University of Technology (SUT) in 1999. He is responsible for teaching of courses in design of reinforced concrete structures, energy methods in finite element analysis, seismic rehabilitation of existing buildings, structural reliability, and probabilistic seismic analysis of structures. His research activities have included studies of seismic reliability analysis of structures, composite structures, and various problems in seismic design of structures. He has authored more than 50 published papers and two textbooks entitled Energy Principles and Variational Methods in Finite Element Analysis and Seismic Rehabilitation of Existing Buildings.
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Table 1. Design sections for the case study structure

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Table 2. Mean and dispersion and correlation calibration of modeling parameters

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Table 3. Strong ground motions used for dynamic Analyses

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Table 4. The results of the best models that obtained from ANFIS by SC algorithm

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Table 5. The results of the best models that obtained from ANFIS by FCM algorithm

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### Table 6. Results of FOSM, ANFIS and RSM on parameters of collapse fragility curves

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### Table 7. The coefficients of RSM functions for mean and standard deviation of fragility curves

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