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Fuzzy rule based seismic risk assessment of one-story precast industrial buildings

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Abstract: Efficient tools capable of using uncertain data to produce fast and approximate results are more practical in rapid decision-making applications when compared to conventional methods. From this point of view, this study introduces a risk assessment model for one-story precast industrial buildings by fuzzy logic which builds a bridge between uncertainty and precision. The input, output and relations of the fuzzy based risk assessment model (FBRAM) were determined by reference buildings. The Monte Carlo simulation method was used to handle uncertainties associated with the structural characteristics of the reference buildings. Section dimension, longitudinal reinforcement ratio, column height related to building elevation, confinement ratio and seismic hazard are regarded as input and the plastic demand ratio is considered as the output parameter by the mathematical formulation of strength and deformation capacity of the buildings. The supervised learning method was used to determine the membership function of fuzzy sets. Fuzzy rules of FBRAM were constructed from Monte Carlo simulation by mapping of inputs and output. FBRAM was evaluated by a group of simulated buildings and two existing precast industrial buildings. Comparisons have shown significant agreement with analytical model results in both cases. Consequently, it is anticipated that the proposed model can be used for the seismic risk mitigation of precast buildings.

Keywords: fuzzy logic; supervised learning; precast buildings; risk assessment; Monte Carlo simulation

1 Introduction

Seismic evaluation of structures against earthquake-induced effects is an important issue to reduce economic and social losses. Many developing countries exposed to high seismic risk have improved or updated their own seismic codes (CEN, 2005; FEMA, 2004; TEC, 2007). On the other hand, seismic assessment of buildings requires a large amount of data and time as it needs to gather many types of information, such as geometry and structural characteristics of building components, geotechnical information, earthquake hazard of building site, etc. Furthermore, an appropriate structural model is needed to represent the behavior of the structure and a damage evaluation strategy compatible with hazard analysis should be developed. Although this type of analysis is building-specific and takes a considerable amount of time and data, some parametric studies at a regional level on these types of structures can be found in the literature (Babič and Dolšek, 2016; Kramar *et al.*, 2010).

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The engineering society has focused on the methodology to numerically quantify the damage in structures in the last decade. For this purpose, several researchers offered different local (Colombo and Negro, 2005; Mehanny and Deierlein, 2001; Park and Ang, 1985) and global (Bracci *et al.*, 1989; Park *et al.*, 1985) seismic damage indices and these indices use a non-dimensional index that normalizes structural damage from zero (represents undamaged state) to one (represents the collapse state of the structure). The drawback of these studies is that the intermediate values of both the local and global damage indices are not validated against the intermediate damage states of the structures (Shiradhonka and Sinha, 2012).

Developments in the field of earthquake engineering also increased the use of probabilistic methods instead of deterministic ones. By this way, uncertainty (aleatory and epistemic) is taken into account to some extent. The fragility and the vulnerability curves are the most common examples (Rossetto *et al.*, 2013) of the probabilistic methods and numerous studies are performed for various structures (Bosiljkov *et al.*, 2012; Cripstyani *et al.*, 2016; Palanci *et al.*, 2016). The ability of using ground motion or structural damage parameters (e.g. story drift, inter-story drift ratio) is another advantage of these tools. Probabilistic methods have also been adapted and used widely in many guidelines and technical manuals (ATC, 1985; FEMA, 2012; FEMA, 2016). Most of the functions given in these manuals are derived from expert opinions after post-earthquake observations, while some of them are based on structural analysis. Although the post-earthquake observations are more realistic and the expertise of professionals is a very efficient way to produce vulnerability functions, it also has some disadvantages: (a) rare occurrence of an earthquake that can cause damage to structures; (b) bias between the results due to the possibility of insufficient data for a specific type building or building groups; and (c) possibility of overstatements in the observations as experts often have their own ideas. In addition, Porter (Porter, 2016) also stressed that the probability of the underestimation of uncertainty is one of the drawbacks of this approach. Entire studies discussed earlier evidently emphasize the significance of building stock analysis, multi-criteria analysis or any other alternative techniques for developing the decision-making strategies. For this reason, instead of using detailed analysis methodologies, simpler and more rapid tools that require less information and allow to decide whether a detailed analysis is required or not can be more helpful in decreasing afforded information and efforts in the preliminary stages.

Fuzzy logic (FL), introduced by Lotfi Zadeh (Zadeh, 1965), on the other hand, has been used in a wide variety of scientific and engineering applications (Ross, 2010) in the recent years. The main advantages of FL are that it has the capability of modeling uncertain data (Sivanandam *et al.*, 2007), it is able to use vague or ambiguous data which real life problems possibly inherent to and also able to model and perform human reasoning by linguistic variables that can be interpreted by mathematical quantities. In addition, it is very useful to decrease the information afforded by the conventional models as it can provide balance between precision and uncertainty. For these reasons, it can be used in the approximate fast solutions with existing information within the acceptable uncertainty limits. FL and its integration with neural networks (NN) or genetic programming (GP) have also been used in solving various civil engineering problems such as structural engineering, earthquake engineering, etc. Some examples of fuzzy applications are: 1) Doran *et al.* (2015) applied fuzzy logic to predict the lateral confinement coefficient of RC columns wrapped with CFRP, 2) Bachi *et al.* (2014) used an adaptive neuro-fuzzy inference system to predict the dynamic behavior of beams, 3) Cevik (2011) modeled the rotation capacity of wide flange beams by the neuro-fuzzy approach, 4) Amani and Moeini (2012) conducted a study to predict the shear strength of reinforced concrete beams using an adaptive neuro-fuzzy inference system, 5) Alvanitopoulos *et al.* (2010) employed the neuro-fuzzy techniques for the classification of earthquake damage in buildings, and 6) Ozkul *et al.* (2014) presented a method for the prediction of inelastic displacement ratios of degrading RC structures.

In the last decade, fuzzy logic approaches have also been applied in damage detection. Sawyer and Rao (2000) used fuzzy logic for structural fault detection, Pawar and Ganguli (2003) proposed a genetic fuzzy system for damage detection using the natural frequencies in cantilever beams, Chandrashekhar and Ganguli (2009a) proposed a fuzzy logic system for damage detection in structures having uncertainty in material property as well as measurements, Chandrashekhar and Ganguli (2009b) presented a fuzzy logic system (FLS) for damage detection using curvature damage factor and used Monte Carlo simulation considering the uncertainty in the structural parameters, and Aydin and Kisi (2015) presented a hybrid neuro-fuzzy system to localize and predict the severity of cracks in beam-like structures. In addition to the damage detection in beam-like structures, Sen (2010) used fuzzy logic modeling to visualize the earthquake hazard of existing buildings. Furthermore, Sen (2011) proposed a supervised fuzzy model to classify the buildings that would be vulnerable to earthquake hazard and applied his model in the Zeytinburnu district of İstanbul, Turkey. All the studies mentioned above have greatly contributed to structural assessment studies and indicate that FL is a very efficient tool to solve problems in the field of civil/structural engineering. Although efficiency of fuzzy logic is validated by various studies, it is not explored in specific building types like precast buildings and assessment studies are mostly concentrated on using ground motion parameters like PGV to represent seismic hazard or to determine inelastic demands (Durucan and Gumus, 2018). In addition, the effect of uncertainties associated with the structural characteristics of the buildings is not discussed in structural response content. Considering this situation, the present study uses FL for the risk assessment of one-story precast buildings which frequently used reinforced concrete (RC) construction types for large-scale production activities in most industrialized countries.

In order to determine the parameters of a fuzzy logic based risk assessment model (FBRAM) and to establish a background for fuzzy rule relations, reference building models were generated and a Monte Carlo simulation method was used to handle the uncertainties associated with the structural characteristics of the buildings. Thus, a mathematical model of reference buildings was created and the seismic assessment of the buildings was estimated analytically by nonlinear analyses. Based on the theoretical background supported by mathematical operations, capacity and demand related parameters are determined and assigned to a fuzzy assessment model. The section dimension parallel to earthquake direction, the column height related to building elevation, the longitudinal reinforcement ratio, confinement ratio and seismic hazard are defined as input fuzzy sets. The plastic demand ratio is regarded as the output fuzzy set and the outcomes of Monte Carlo simulation are used to organize the membership functions, sets and fuzzy rule relations. In order to examine the fuzzy rule based assessment model, the FBRAM estimations are compared with the results obtained from the reference buildings. Furthermore, the reliability of the risk assessment model is verified by two distinct precast industrial buildings located in the Aegean part of Turkey.

2 Precast industrial buildings and damage assessment

The first part of this section describes the selection of structural properties for construction of a reference hinge jointed one-story precast industrial buildings by the Monte Carlo method. The second part is concentrated on determination of the strength and displacement capacity of the reference industrial facilities. Finally, a seismic demand estimation procedure and performance assessment strategy is described.

2.1 Reference building models

In order to determine distinct building models, various section dimensions, longitudinal reinforcement ratios and confinement ratios should be used. Square sections (B = H) are generally used in the precast buildings (Senel and Palanci, 2011) and cross-sectional dimensions of precast columns range between 350 mm and 600 mm. In addition to the member dimensions, the strength of the precast columns is affected by the longitudinal reinforcement ratio, so this parameter should also be included in the building models. Previous studies implied that the longitudinal reinforcement ratio of the precast members are rather high (around 2.0-2.5%) and columns are arranged by S420 hot-rolled steel grade type (Senel and Palanci, 2011; Palanci, 2010). However, lower ratios should also be included to cover all possible conditions and as a consequence of this situation, allowable maximum (4%) and minimum (1%) longitudinal reinforcement ratios are used for the reference precast buildings. As one-story precast industrial facilities are constructed with a hinge jointed at the roof level, precast columns are singly curved if the roof is assumed as rigid in its own plane; in other words, they can be treated as a single-degree-of-freedom (SDOF) member and hence the column height (L) becomes an important parameter to define the slenderness of these buildings. Due to the importance of column height on structural behavior and considering the study by Senel and Palanci (2011), the minimum and the maximum column heights are taken as 6 m and 9 m, respectively.

It is a known fact that the transverse reinforcement ratio has positive effects on section deformation capacity. For this reason, the other input parameter is regarded as confinement ratio (ρ_s/ρ_{sm}) as suggested in TEC (2007) and it is assumed that it ranges between 0% and 100%. Note that 100% is used to describe that the relevant member (precast column) provides the required level of confinement given by TEC (2007). The terms ρ_s and ρ_{sm} define the existing and the required volumetric transverse reinforcement ratios in the cross-section according to TEC (2007), respectively. Selection of this parameter is based on the study conducted by Palanci and Senel (2013). Palanci and Senel (2013) divided the confinement ratio into three classes as “Poor”, “Average” and “High”. Although the crisp values of each group are described by Palanci and Senel (2013), the advantage of this parameter is that the prescribed statements are akin to fuzzy statements and they can be used as an input fuzzy set in the current study.

Although the effect of parameters discussed above is individually known, the combination of these parameters and their influence on the structural behavior is a more complex issue. For this reason, numerous structures covering the various aforementioned parameters are needed to express all the possible responses. This is also necessary to validate the reliability of the assessment model. For this purpose, the Monte Carlo simulation method is used to construct reference precast building models considering the parameters given earlier. The Monte Carlo method is highly effective to determine how variability of input relates to output variability under a variety of conditions and it is easy to generate a vast amount of input values to produce a simulated distribution of the possible outcomes. In addition, there are commercial computer programs that perform the calculations and present results in simple graphs and tables and it is worth noting that alternative methods such as the direct simulation method, bootstrap method and moment matching, can also be used for such purposes.

During the construction of the reference buildings by the Monte Carlo method, it is assumed that all structural parameters are normally distributed (Table 1). Normal distribution parameters of sectional properties are given in Table 1. The attributes of normal distribution (mean and standard deviation) are assigned by considering the minimum and maximum limits of each parameter. Note that negative values are excluded in expressing the physical dimensions. By this way, the uncertainties associated with the structural properties are taken into account during the modeling of the reference precast buildings.

Typical configuration of a one-story hinge jointed

Table 1 Distribution parameters of the considered structural properties

Normal distribution parameters	Section dimensions (B = H) mm	Column height (L) m	Longitudinal reinforcement ratio (ρ_l) %	Confinement ratio (ρ_s/ρ_{sm}) %
Mean (μ)	475	7.5	2.5%	50%
Std. deviation (σ)	30	0.3	0.3%	10%

precast industrial facility is also illustrated in Fig. 1. Various span lengths are available to construct industrial buildings, but span lengths are commonly between 18 m and 25 m (Senel and Palanci, 2011). The other structural elements such as number of purlins, gutter beams and cladding materials have an effective role on the axial load level of precast columns. Palanci (2010) stressed that the axial load ratio of precast columns is mainly around 5% by using the data obtained from approximately 100 existing precast buildings. In this study, the strength and deformation capacities of the reference buildings were determined by considering the previous study (Palanci, 2010).

2.2 Capacity determination

Moment-curvature analysis was performed to determine the strength and inelastic deformation capacity of precast columns. Regardless of intermediate damage levels, ultimate deformation capacity of members was determined by strain limits of confined concrete (ε_{cu}, see Eq. (1)) and tensile longitudinal reinforcement (ε_{su} = 0.06). Strain limits of both concrete and steel is provided from TEC (2007). Obtained moment-curvature relations were represented by bilinear curves (Priestley *et al.*, 1996) (Fig. 2) to increase the simplicity of computations and then converted to moment-plastic rotation curves. Plastic rotation capacity (θ_{p}) of members was computed by the multiplication of plastic hinge length (L_{p}) and plastic curvature capacity (ϕ_{p}) of the column (Eq. (2)). If yield curvature (ϕ_{y}) is subtracted from ultimate curvature capacity (ϕ_{u}), plastic curvature is obtained (Eq. (3)). In the equations, subscript "*i*" defines the label of the member existing in the precast frame (see Fig. 3 for illustration).

$$\varepsilon_{\text{cu}} = 0.004 + 0.014\frac{\rho_{\text{s}}}{\rho_{\text{sm}}} \le 0.018 \tag{1}$$

$$\theta_{\text{p}i} = \phi_{\text{p}i} L_{\text{p}i} \tag{2}$$

$$\phi_{\text{p}i} = \phi_{\text{u}i} - \phi_{\text{y}i} \tag{3}$$

After the determination of individual precast column responses, the base shear and roof displacement (i.e. capacity curve) of precast industrial buildings were determined. The capacity curves of buildings were constructed by performing pushover analysis. During the analysis, the lumped plasticity model was used and plastic hinges (expressed as moment-plastic rotation curves) were assigned to the critical regions of columns (i.e. lower end of members) where plastic deformation occurs. Furthermore, plastic hinge length was computed as half of the section dimension parallel to earthquake direction. Maximum displacement capacity of buildings was attained when the ultimate capacity of any member existing in the frame was first reached. Mathematical expression of this condition is given in Eq. (4) and represented in Fig. 4. Determination of intermediate damage levels of the pushover curve will be described in Section 2.4. In the equation, $\delta_{\text{u}i}$ expresses the member displacement capacity of the *i*th member at the ultimate and Δ_{u} inelastic capacity of building.

$$\Delta_{\text{u}} = \min\left(\delta_{\text{u}1}, \ldots, \delta_{\text{u}n}\right) \tag{4}$$

2.3 Determination of seismic demand

Estimation of seismic demand has always been an attractive topic for researchers in the field of earthquake engineering and several studies have been conducted (Benazouz *et al.*, 2012; Chopra and Chintanapakdee, 2004; Garcia and Miranda, 2007). In addition, seismic assessment and/or rehabilitation of buildings require

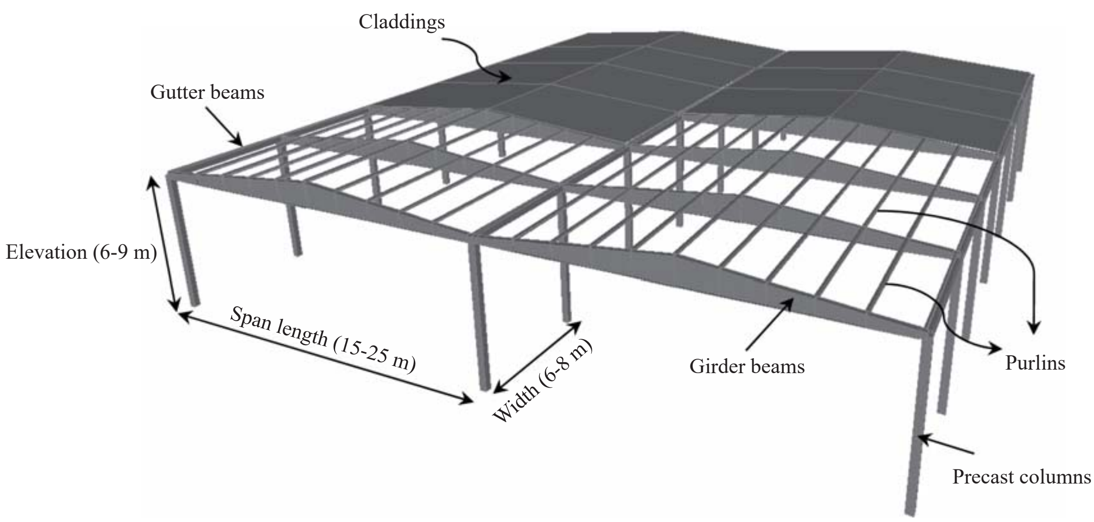


Fig. 1 Typical elements and configuration of one-story precast industrial facilities

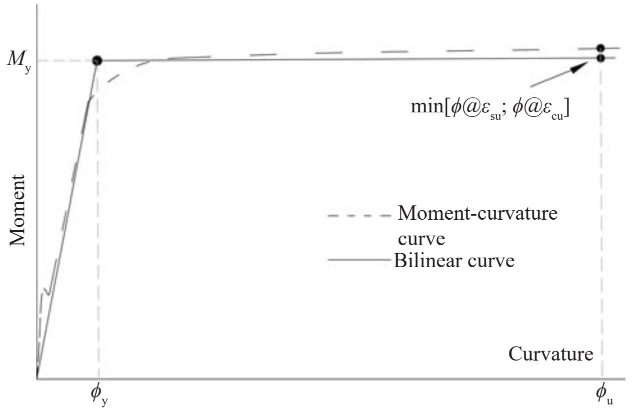


Fig. 2 Typical section moment-curvature relation and bilinear curve

the determination of the seismic displacement demand to make a decision on the performance of buildings. Many earthquake prone countries have improved their earthquake regulation codes (CEN, 2005; FEMA, 2004; TEC, 2007; ATC, 1996) for seismic assessment or retrofitting of buildings.

In this study, seismic displacement demand of buildings was calculated by using the Eurocode-8 calculation method (CEN, 2005). In order to determine seismic displacement, target demand spectrum is defined in terms of an earthquake that has a 10% probability of exceedance in 50 years. This spectrum also corresponds to a 5% damped elastic design spectrum. For this purpose, the target spectrum adapted from the Turkish Earthquake Code (TEC, 2007) shown in Fig. 5 was used. In the figure, a_g is the reference ground acceleration and it varies according to the seismicity (earthquake zone) of the region (Table 2). Characteristic periods of spectrum (T_B and T_C) that correspond to lower and upper limits of the constant spectral acceleration region are given in Table 2 for different soil types. In the figure, S_a and T define the elastic response spectrum and vibration period of a linear single-degree-of-freedom (SDOF) system, respectively.

According to the Eurocode 8 (CEN, 2005), if the period of the building is higher or equal to T_C, the "Equal displacement rule" is used and the inelastic displacement demand (S_{dil}) is equal to the elastic displacement demand (S_{del}). Otherwise, the inelastic displacement is calculated by Eq. (5b), but note that S_{dil} should be higher than S_{del}. In the equation, $S_a(T)$ represents the elastic acceleration response spectrum at the period T and q_u defines the

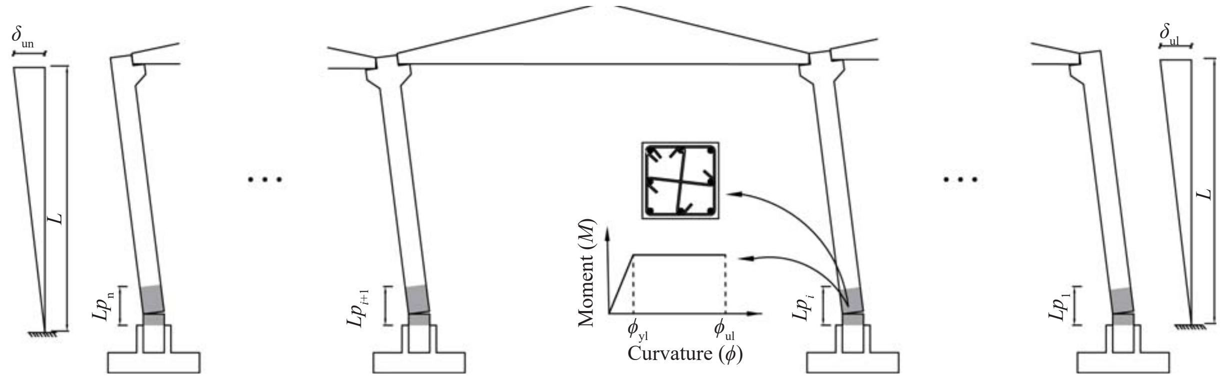


Fig. 3 Typical deformation form of one-story precast industrial frame

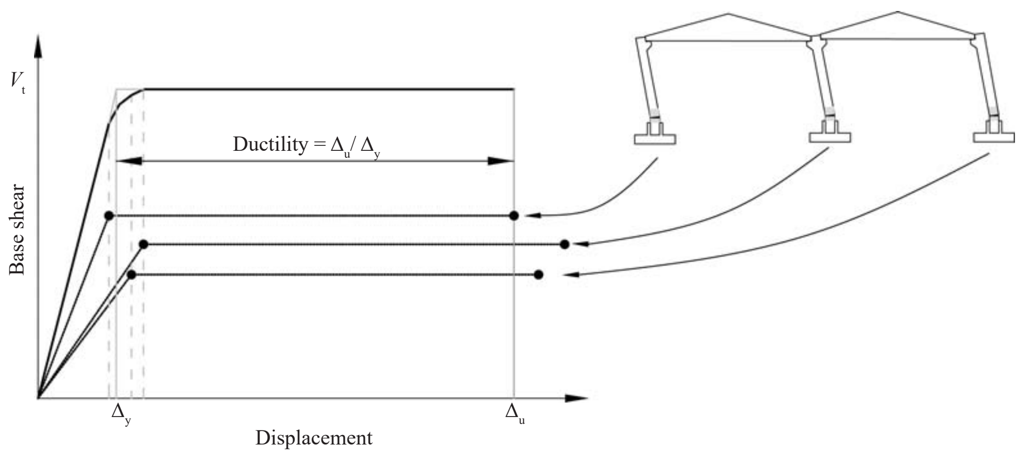


Fig. 4 Determination of yield and ultimate displacement capacity of precast buildings

Table 2 Ground accelerations (a_g) and characteristic periods of soil types for response spectrum

Earthquake zone	a_g (g)	Soil type	T_B (s)	T_C (s)
1	0.4	Z1	0.10	0.3
2	0.3	Z2	0.15	0.4
3	0.2	Z3	0.15	0.6
4	0.1	Z4	0.20	0.9

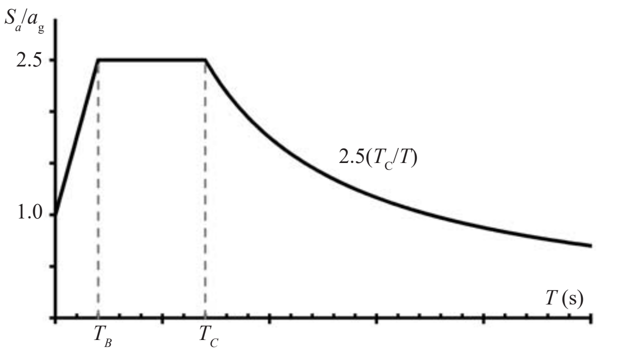


Fig. 5 Target response spectrum (5% damped) for seismic demand estimation

ratio between $S_a(T)$ and the yield acceleration (S_{ay}) of the equivalent SDOF system. Graphical representation of these explanations is also demonstrated in Fig. 6, where S_{dy} represents the yield displacement capacity of the equivalent SDOF system.

$$S_{\mathrm{del}} = S_a(T)(T/2\pi)^2 \tag{5a}$$

$$S_{\mathrm{dil}} = \frac{S_{\mathrm{del}}}{q_{\mathrm{u}}}\left(1+(q_{\mathrm{u}}-1)\frac{T_C}{T}\right) \geq S_{\mathrm{del}} \tag{5b}$$

2.4 Performance assessment of precast buildings

The objective of assessment studies is to check whether structures satisfy the desired performance level under the considered earthquake hazard. Multiple performance criteria can be defined for any building according to its priority. Hence, severity of the earthquake hazard may differ for distinct performance levels. As mentioned in the earlier section, determination of seismic demand is a key parameter in seismic assessment studies and it is mostly desired that “Life Safety” performance level should be satisfied under the consideration of 5% damped target elastic design spectrum. Although similar performance levels are sought, different seismic codes and documents may use different definitions for similar performance levels (TEC, 2007; ATC, 1996; FEMA, 1997). Despite this situation, there is also a general consensus on performance objectives and it is expected that structure should maintain its vertical and lateral load resistance, and structural components should be deformed within acceptable damage limits.

In this study, seismic performance evaluation of one-story precast buildings is determined by using the plastic demand ratio ($\mu_{\Delta p}$) and this parameter is also used as an output for FBRAM. Precast columns are the main components of the bearing system and they have primary importance on the stability of these buildings. The other possible damage cases, such as overturning of girder beams or shear resistance between beam-column joints, are not of primary concern of this study as they have different data entry and need special consideration of possible failure modes for these buildings. In the literature, the effect of beam-column joints and other possible failure cases are investigated and evaluated by various studies (Decanini *et al.*, 2012; Senel *et al.*, 2013; Magliulo *et al.*, 2015).

A typical bilinear form of the building capacity curve is shown in Fig. 7. The figure illustrates the elastic and plastic parts. It can be seen that permanent deformations occur beyond the elastic part and after this

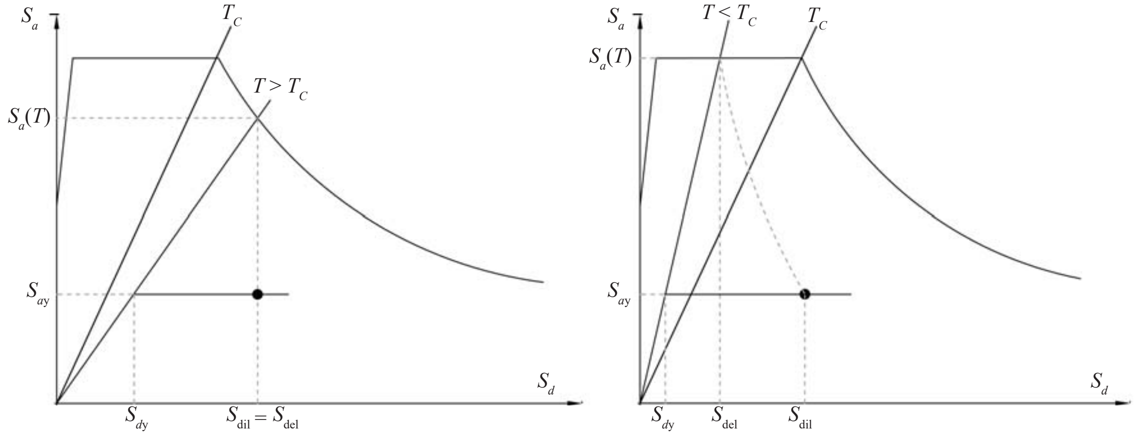


Fig. 6 Seismic demand estimation in Eurocode 8 (CEN, 2005) (left: medium and long period range; right: short period range)

level, deformations should be restricted to the acceptable limits to maintain the stability of the structure. Within the frame of structural engineering, performance of buildings is defined in different performance levels beyond the yield point. "Slight", "Moderate", "Extensive" and "Collapse" terms can be considered as general descriptions in expressing the performance states. However, it is also important to define the threshold values of intermediate damage levels in percentage of plastic deformation capacity. In a general sense, 75% of total plastic deformation can be acceptable to distinguish "Moderate" and "Extensive" damage regions. On the other hand, the limit of "Extensive" damage level describes the beginning of "Collapse" damage. Although representative expressions for other damage levels "Slight" and "Moderate" are specified for structural components, there is no apparent expression pointed out for structural response and they are mostly assigned intuitively by analysts or experienced engineers. In this study, 10% of plastic deformation is defined as the limit for "Slight" damage level to distinguish "Slight" and "Moderate" damage. Consequently, the values of damage levels used for the seismic assessment of one-story precast buildings are plotted in Fig. 7 by considering the discussions above. Note that in some seismic codes (TEC, 2007) even the elastic part is included in the slight damage level.

Plastic demand ratio ($\mu_{\Delta p}$) is calculated by Eq. (6). In the equation, S_{du} and S_{dy} donate the ultimate and yield spectral displacement capacity and the inelastic displacement demand is represented by S_{dil}. Note that S_{dy} and S_{du} are equal to the yield (Δ_y) and the ultimate displacement capacity (Δ_u) of the building since the hinge jointed one-story precast buildings can be represented as equivalent SDOF systems if the roof is assumed as rigid in its own plane. In the equation, the numerator expresses the amount of plastic demand while the denominator corresponds to the plastic deformation capacity. This ratio also provides insight about the energy dissipation of structures

$$\mu_{\Delta p} = \left(S_{dil} - S_{dy}\right) / \left(S_{du} - S_{dy}\right) \quad (6)$$

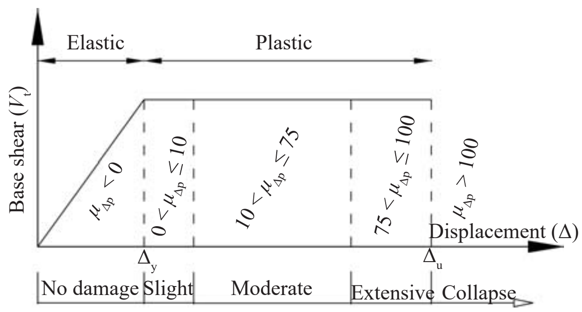


Fig. 7 Typical representation of building capacity curve and damage limits

Note that the applicability of the proposed FBRAM is neither restricted to the expressions of damage levels discussed above nor to the use of seismic demand and/or damage assessment method. The introduced model can easily be adapted to any variables (e.g. inputs and outputs) by the re-evaluation of the results. Therefore, it can be said that the proposed model can be applied to all type of structures without any restriction and with this aspect, it may be of interest to a wider audience.

3 Fuzzy logic and rules definition

In a typical fuzzy logic system, there are four main parts (see Fig. 8): fuzzification interface, fuzzy inference unit (engine), a set of fuzzy rules that associates the inputs and outputs (fuzzy rule base) and defuzzification interface. The fuzzification interface is used to transform crisp input variables into corresponding linguistic values. Fuzzy inference unit can be considered as the core of fuzzy logic and it performs inference operations for decision-making. The fuzzy rule base involves the fuzzy conditional statements (***IF-THEN*** rules). The defuzzification interface allows the transformation of the fuzzy results into crisp output.

Fuzzy rules are described in terms of linguistic statements to associate the input and output. The fuzzy rule base is mostly constructed by expert opinion or sense of knowledge. As it involves conditional statements, necessary connectors are needed and mostly "***AND***" or "***OR***" conjunctives are used. Fuzzy rules are typed as follows (antecedent–consequent form):

if (*input 1 is membership function 1*) ***and/or*** (*input 2 is membership function 2*) ***and/or***. . . ***then*** (*output$_n$ is*

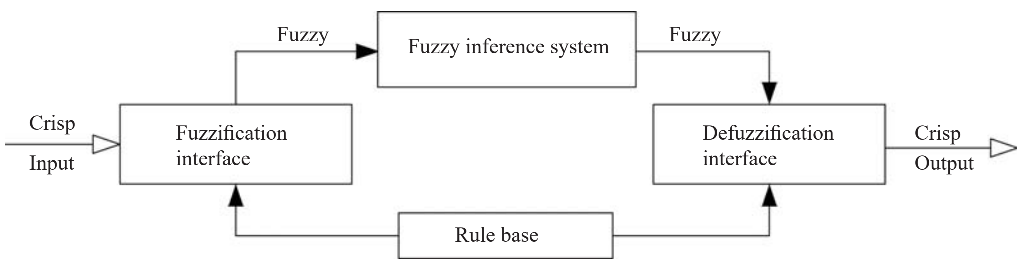


Fig. 8 Typical form of fuzzy logic system

output membership function$_n$).

In this fuzzy based rule form, the *membership function* is written to express fuzzy sets of the considered input (antecedent) or fuzzy set of output, and the given example rule contains one conclusion (consequent) which is described by more than one antecedent. If "***AND***" is used as a logical connective, the minimum membership value of antecedents intersects the membership function of the consequent in the rule. The maximum value of antecedents intersects the consequent membership function by "***OR***" connective. Detailed information on the aforementioned descriptions is graphically illustrated in Fig. 9 for dual-input and single-output fuzzy system. The other important component of fuzzy logic systems is the fuzzy inference engine and some inference methods are introduced by several researchers (Mamdani Method: (Mamdani and Assilian, 1975), Sugeno Method: (Sugeno and Kang, 1988; Takagi and Sugeno, 1985)). The most commonly used technique is the Mamdani method as it has widespread acceptance and is suited to human input (Sivanandam *et al.*, 2007). In this study, the Mamdani method is also employed as

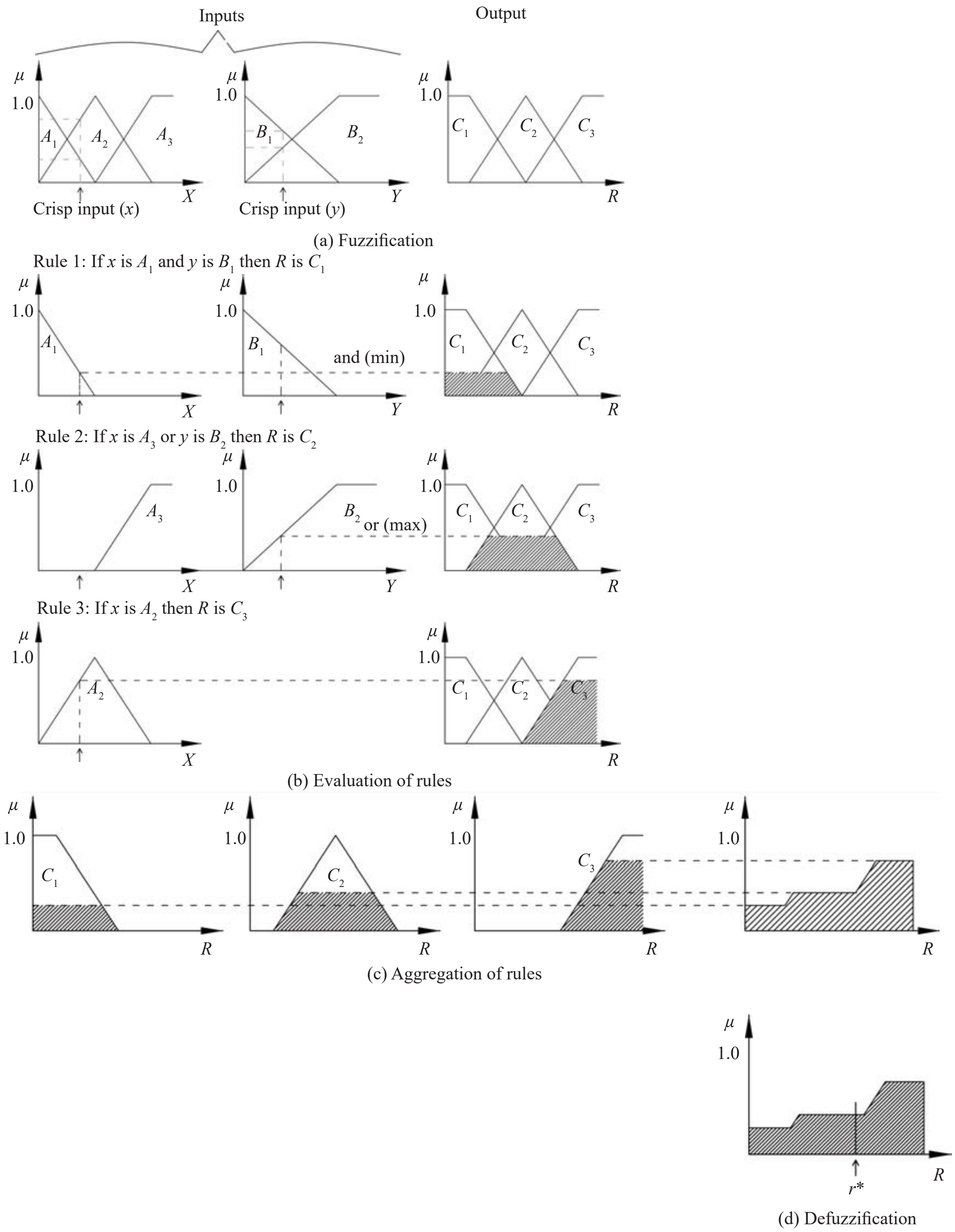


Fig. 9 Mamdani based fuzzy inference method

the fuzzy inference technique (Fig. 9).

In Mamdani's model, the minimum operator is used for the conjunction of rules (Iancu, 2012). In other words, "***AND***" operator transmits the minimum membership value of the antecedents to the consequent. This situation is plotted in Fig. 9(b) by **Rule 1**. On the contrary, "***OR***" operator is the maximum operator used for disjunction of rules as shown in Fig. 9(b) by **Rule 2**. As the fuzzy logic systems consist of more than one rule (as given in the example in Fig. 9), the rule outputs are required to be evaluated and this task is conducted in an aggregation step and the *max* operator is used. As can be seen in Fig. 9(c), that aggregated output is still in fuzzy quantities and it should be converted to crisp output. For this purpose, the defuzzification process is used and there are various techniques for defuzzifying: (1) Centroid method, (2) Weighted average method, (3) Centre of sums, (4) Max-membership principle etc. The most common method, also the one used in this study, is the centroid method and it focuses on finding the center of gravity of aggregated fuzzy output (Fig. 9(d)). Algebraic expression of the centroid method is given in Eq. (7).

$$r^* = \int \frac{\mu_C(r) \cdot r\mathrm{d}r}{\mu_C(r) \cdot \mathrm{d}r} \tag{7}$$

In the equation, r^* is the crisp value of the aggregated fuzzy output, μ_C defines the union of rule outputs or membership function of the aggregated output in the fuzzy set C, and r is the element of universe or subsets of R.

3.1 Discretization of structural parameters for input and output of FBRAM

In this section, two important parameters that have a strong impact on the inputs of a fuzzy based risk assessment model (FBRAM) are discussed. First, the study by Palanci and Senel (2013) is utilized for the investigation of capacity related parameters. In their study, Palanci and Senel introduce a rapid seismic assessment model and propose some salient equations to obtain lateral strength, yield and ultimate displacement capacity of precast industrial buildings. The authors have stated that the yield strength of precast columns is affected by section dimensions (B and H^2), longitudinal reinforcement ratio (ρ_l), column height (L) and axial load ratio, but the axial load ratio was taken as equal to 5%. In previous work, the yield displacement capacity of members was described as directly proportional to the strain capacity of longitudinal reinforcement (ε_{sy}) and column height (L), and inversely proportional section dimension (H) parallel to earthquake direction. Yield displacement capacity of building was set to the minimum yield deformation of the precast column.

It should be stressed that the determination of the yield displacement capacity of the building is the key factor to reveal whether or not plastic deformation occurs. In Eq. (8), typical risk of permanent deformations is expressed mathematically and if the seismic demand (S_{dil}) is equal to or higher than the yield capacity of the structure (S_{dy}), plastic deformations occur.

$$S_{dil} \geq S_{dy} \tag{8}$$

If the structure is under the risk of plastic deformations, the severity of damage should be determined. In this case, effective parameters on the ultimate displacement capacity of the structure should be determined. Palanci and Senel (2013) also showed that the ultimate displacement capacity of members is affected by the confinement ratio (ρ_s/ρ_{sm}), section dimension (H) parallel to earthquake direction, longitudinal reinforcement ratio (ρ_l) and column height (L). This situation implies that similar parameters, except the confinement ratio, have an important role on the capacity of precast buildings. From the overall implications, it can be said that section dimensions (B and H), longitudinal reinforcement ratio (ρ_l), column height (L) and confinement ratio (ρ_s/ρ_{sm}) are the primary parameters to construct the capacity of single story precast industrial buildings and these parameters are used as inputs in FBRAM.

Secondly, demand related parameters are investigated and according to the Eurocode-8 method, the period of the structure should be obtained. Furthermore, the natural period of the structure can be determined from the elastic slope of the capacity curve (see Fig. 4) by Eq. (9). In the equation, V_t is the base shear and Δ_y is the yield displacement capacity of building.

$$T = 2\pi\sqrt{\frac{m\Delta_y}{V_t}} \tag{9}$$

However, structural period is not adequate to describe the demand related parameters and seismic hazard; the severity of the earthquake and soil type conditions are also needed. This situation implies that multiple parameters should also be involved and this threatens the simplicity of FBRAM. For simplification, the number of parameters should be reduced, but some mathematical operations are required. For this purpose, expansion of Eq. (8), which indicates the damage potential risk of structures, is used in Eq. (10). In Eq. (10), the left and the right sides describe the seismic demand and yield capacity of structure, respectively. In the equation, inelastic demand is estimated by dividing the acceleration response spectrum to the square of angular frequency (w) of the structure and angular frequency can be converted to natural period of the structure by Eq. (11).

$$\frac{S_a(T)}{w^2} \geq \frac{\phi_y \cdot L^2}{3} \tag{10}$$

$$w = \frac{2\pi}{T} \tag{11}$$

If the elastic acceleration response spectrum ($S_a(T)$) is expanded, it will be determined that the demand is related to the design ground acceleration (a_g), soil factor (S), characteristic period of soil type (T_C) and damping correction factor (η) parameters (see Eq. (12)). In the equation, $\eta = 1$ for 5% viscous damping and $S = 1$ since the maximum elastic acceleration is taken as equal to 1g. Reference design ground acceleration values, (a_g) and the characteristic periods (T_C) were provided in Table 2.

$$S_a(T) = a_g S\eta 2.5\left[\frac{T_C}{T}\right] \tag{12}$$

If Eq. (12) is substituted into Eq. (10) and period term (T) is replaced by Eq. (9), the following equation is determined by doing some simplifications:

$$2.5T_C a_g \frac{\sqrt{m\Delta_y / V_t}}{2\pi} \geq \Delta_y \tag{13}$$

If the square of both sides is taken and some simplifications are made, then Eq.(14) is obtained.

$$\left(\frac{1.25}{\pi} T_C a_g\right)^2 \geq \Delta_y \frac{V_t}{m} \tag{14}$$

In Eq. (14), the weight of structure is g (acceleration of gravity) times of mass ($W = m$g). Yield capacity of the building can also be determined by the moment-area theorem (Eq. (15)). In Eq. (15), yield curvature can be replaced with Eq. (16) given by Palanci and Senel (2013) for one-story precast industrial buildings. According to Eq. (16), yield capacity is proportional to the constant value "c" (ranging between 1.90~2.0) and the yield strain of longitudinal reinforcement and is inversely proportional to the section dimension (H) parallel to the earthquake direction.

$$\Delta_y = \frac{\phi_y L^2}{3} \tag{15}$$

$$\phi_y = c\frac{\varepsilon_y}{H} \tag{16}$$

If Eq. (15) and Eq. (16) are substituted into Eq. (14) and conversion of mass is made, Eq. (17) is obtained as follows:

$$\overbrace{\left(\frac{1.25}{\pi}\right)^2}^{\text{constant}} \left(T_C a_g\right)^2 \geq \overbrace{\left(cg\frac{\varepsilon_y}{3}\right)}^{\text{constant}} \left(\frac{L^2}{H}\right)\left(\frac{V_t}{W}\right) \tag{17}$$

Equation (17) clearly indicates that demand related parameters are the design ground acceleration and the characteristic periods defined according to soil type. Thus, seismic hazard (SH) can be expressed by multiplication of T_C and a_g.

Following the determination of input parameters, output of the FBRAM is investigated. As the performance of one-story precast industrial buildings is determined by the plastic deformation demand ratio (see Eq. (6)) one output ($\mu_{\Delta p}$) is assigned to FBRAM and secondary parameters such as natural period (T) and mass of structure (m) are not considered. By this way, the simplicity of the model is greatly increased while the calculation efforts are decreased.

3.2 Input and output membership functions of FBRAM

In the previous section, capacity and demand related parameters are discussed and the results indicated that section dimensions (B and H), longitudinal reinforcement ratio (ρ_l), column height (L) and confinement ratio (ρ_s/ρ_{sm}) are required for both capacity and demand estimations. On the other hand, SH is the demand related parameter and regarded as the input parameter. Since it is assumed that columns have square dimensions ($B = H$), section dimensions are represented by H which is parallel to the earthquake excitation.

In order to determine membership functions of these parameters and fuzzy relations of the proposed model, Monte Carlo results were utilized by using the following steps:

(1) All possible damage conditions (slight, moderate, extensive and collapse) were categorized.

(2) The output, plastic demand ratio ($\mu_{\Delta p}$), related with damage conditions of buildings were categorized into nine parts with increments of 12.5% to capture smaller changes in the plastic region.

(3) The value range of inputs related to damage type involved (e.g. slight, moderate etc.) was determined by mapping of input and output. By this way, each input is divided into different sub-categories.

(4) Membership function of SH and relations of inputs and outputs are determined by using the supervised learning method considering the categorization of inputs (L, H, ρ_s/ρ_{sm}, ρ_l), output ($\mu_{\Delta p}$) and hazard classes given in Table 3.

Typical representation of the procedure followed is also shown in Fig. 10. It can be seen from the figure that although plastic demand ratios were divided into smaller increments, moderate damage constitutes the important part (65%) of the plastic region. The figure also indicates that the plastic region is arranged between 0% and 125%. Observations of Monte Carlo simulations have indicated that plastic demand ratios of some buildings may be extremely high (> 150%). Even if the damage state of these buildings is collapse, this condition should also be covered. Evaluations have indicated that plastic demand ratios of such buildings could be fixed to 125%

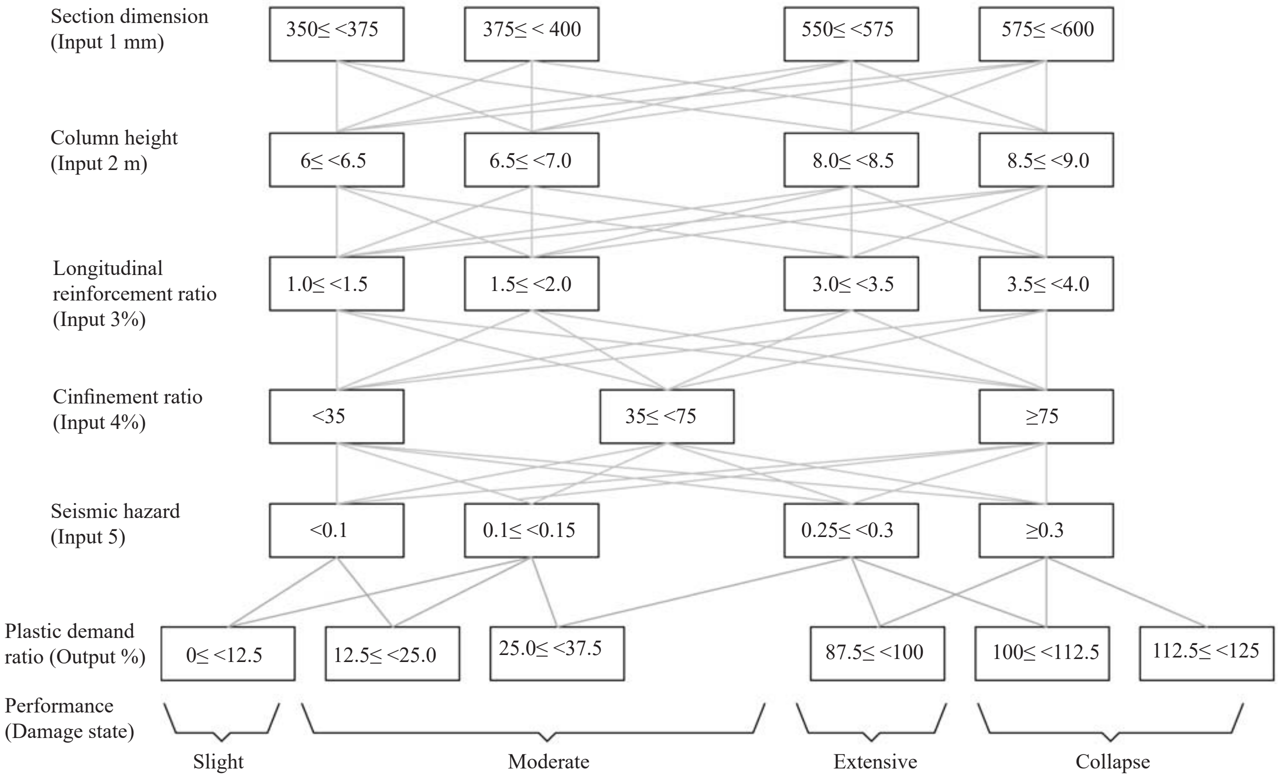


Fig. 10 Mapping of relations between inputs and output using Monte Carlo method results

in the proposed model.

During the mapping of input and output, it was observed that section dimension, building elevation similar to column height (L) and longitudinal reinforcement ratios could be commonly categorized with constant ranges. For example, section dimension (H) can be categorized with increments of 50 mm. Similarly, longitudinal reinforcement ratio and column height was categorized with increments of 1% and 1m, respectively. Thus, membership function of central values was taken as equal to one and a triangular curve was used to describe fuzzy sets of these inputs (Figs. 11-13).

In order to categorize the confinement ratios, the study of Palanci and Senel (2013) was used. Palanci and Senel (2013) defined the crisp range of the confinement ratio as follows: if the confinement ratio (ρ_s/ρ_{sm}) is equal and lower than 35%, then it is “poor”, or if this ratio is equal and higher than 75%, it is accepted as “good” in terms of confinement. Otherwise (35% < ρ_s/ρ_{sm} <75%), the confinement ratio was described as “average”. Considering the previous expressions, the membership function of the confinement ratio fuzzy set is defined as shown in Fig. 14. The fuzzy subsets of confinement and the longitudinal reinforcement ratios are represented in terms of percentage (%) in Fig. 13 and Fig. 14.

In order to determine the membership function of seismic hazard (SH) by the supervised learning method, initial central values were required. For this purpose, multiplication of T_C and a_g (Table 3) was used. It was

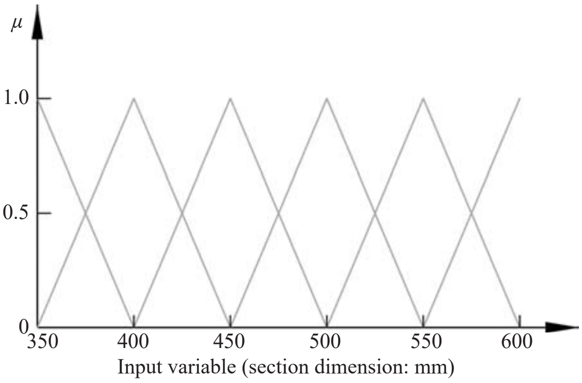


Fig. 11 Membership function and fuzzy sets of section dimension (H)

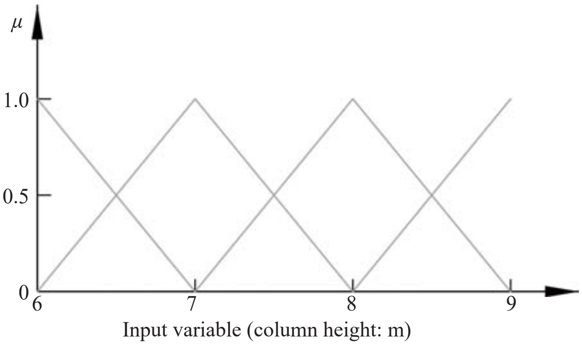


Fig. 12 Membership function and fuzzy sets of column height (L)

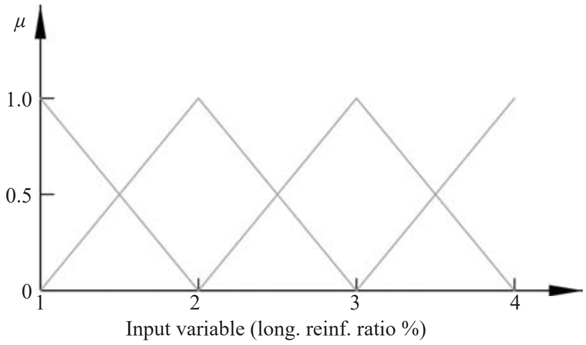


Fig. 13 Membership function and fuzzy sets of longitudinal reinforcement ratio (ρ_l)

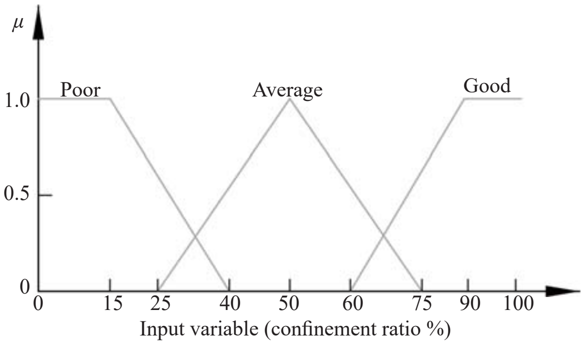


Fig. 14 Membership function and fuzzy sets of confinement ratio (ρ_s/ρ_{sm})

observed that *SH* ranges between 0.03 and 0.36 if the intermediate values of both parameters were used. Regarding these values, fuzzy statements of *SH* and their initial central values were described as given in the Table 3. As seen from the table, six fuzzy statements: "very low", "low", "low-medium", "medium", "high" and "very high" are used to express *SH*. Considering the initial range of prescribed fuzzy statements, the supervised learning method was used and fuzzy sets of *SH* were assigned by comparing them with the results of the reference buildings produced by Monte Carlo method. Eventually, the membership function and fuzzy set of *SH* shown in Fig. 15 is determined.

Following the determination of input parameters, the output fuzzy set is identified by plastic deformations. Fuzzy subsets of plastic deformations are expressed in terms of plastic ratios and identification of these ratios are used to encounter smaller changes in the plastic region, which may be critically important (Palanci, 2010; Palanci and Senel, 2013) on the seismic performance of one-story precast buildings. Thus, nine fuzzy statements: "very light", "light", "light-medium", "medium", "medium-high", "high", "very high", "excessive" and "very excessive" were assigned to output fuzzy set in FBRAM.

The results of Monte Carlo simulation have shown that some of the simulated buildings remain elastic ($\mu_{\Delta p} \leq 0\%$) while some are exposed to very excessive damage ratios ($\mu_{\Delta p} \geq 100\%$). For simplification, a very light deformation ratio ($\mu_{\Delta p} = 0$) is accepted for buildings which remains elastic. On the other hand, damage state of buildings which have very excessive damage ratios was assumed as "Collapse" ($\mu_{\Delta p} = 125\%$). By this way, all statements are designated as fuzzy sets as a percentile (%) of plastic deformation region and arranged between 0% and 125% with increments of 12.5%. Membership function of the output fuzzy set is given in Fig. 16.

In the study, fuzzy rules of FBRAM were also developed. In the proposed model, six statements for section dimension (*H*) and seismic hazard (*SH*), four for column height related to building elevation (*L*) and longitudinal reinforcement ratio (ρ_l) and three for confinement ratio (ρ_s/ρ_{sm}) are defined. As a result of the

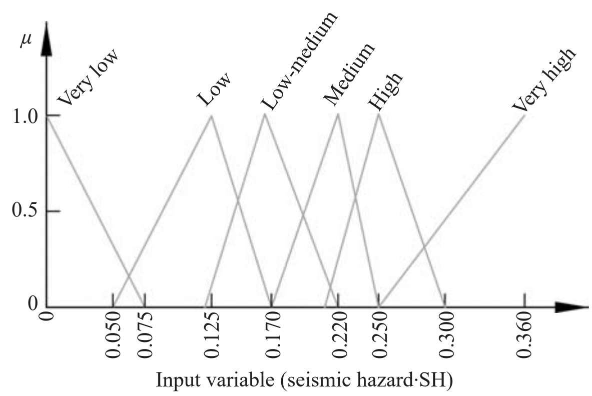
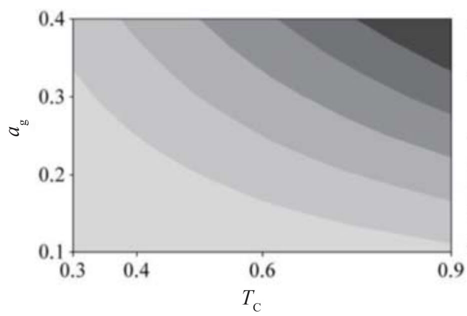


Fig. 15 Membership function and fuzzy sets of seismic hazard (*SH*)

Table 3 Initial central values for fuzzy SH statements



Fuzzy statements of SH	Crisp range of SH
Very low	SH <0.10
Low	0.10≤ SH <0.15
Low-Medium	0.15≤ SH <0.20
Medium	0.20≤ SH <0.25
High	0.25≤ SH <0.30
Very high	SH ≥0.30

multiplication of these inputs, 1728 rules were described and these rules were defined by "***IF-THEN***" conditional statements using the mapping of input and output. During the designation of fuzzy rules, again the Monte Carlo simulation results were utilized. In Table 4, each rule number describes the individual input and output fuzzy sets of FBRAM.

4 Application of fuzzy based risk assessment model

In this part of the study, the proposed risk assessment model is evaluated and validated by comparison of reference building results. Later, seismic assessment of two existing precast buildings in the Denizli Organized Industrial Zone (DOIZ) is performed.

In order to apply FBRAM and investigate the efficiency of the model, a group of buildings elected from the simulation model is used. Buildings are elected according to cross-section characteristics of their precast columns. The cross-section properties considered in the application of FBRAM are shown in Table 5. Plastic demand ratios and hence, the performance of selected buildings, were previously determined analytically via Monte Carlo method by considering all possible seismic

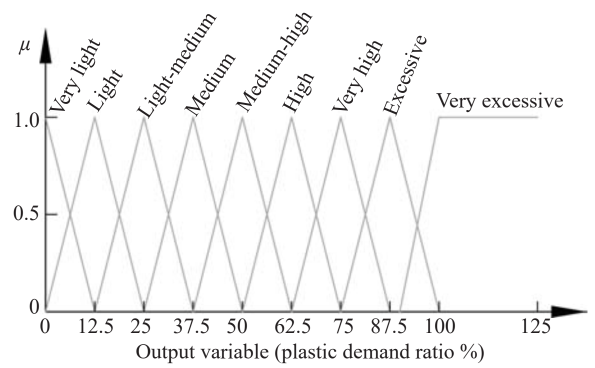


Fig. 16 Membership function and fuzzy sets of plastic demand ratio output ($\mu_{\Delta p}$)

hazard conditions.

During the evaluation of FBRAM, plastic demand ratios and building performance states are used and the results are compared with analytical analysis results (see Fig. 17). Comparison of plastic demand ratios of FBRAM and analytical analysis results is shown in Fig. 17(a) by constant (25%) plastic demand ratio intervals. For any building, if the plastic demand ratio is higher than 100%, eventual damage of the building is identified as "Collapse". As the maximum plastic demand ratio of FBRAM was set to 125%, the plastic demand ratio of analytical models higher than this value was fixed to this ratio.

It can be seen from Fig. 17(a) that the linear correlation coefficient (ρ) between analysis and FBRAM is very high (ρ = 0.99) and the trend line (dashed red line) is almost compatible with the linear curve (thick black line). In addition, plastic demand ratio intervals of analysis and FBRAM fit fairly well.

In Fig. 17(b), the performance of selected buildings is also compared. In some cases, plastic demand ratios determined from analysis seem slightly higher than FBRAM between damage intervals of 50%-75% and 100%-125%, but this situation has not affected their eventual damage levels as observed from the Fig. 17(b). In addition, Fig. 17(b) indicates that performance prediction of FBRAM shows good agreemnt with the analysis results. According to the figure, FBRAM predicts similar damage levels with analysis for "Extensive" damage. On the other hand, percentage of "Moderate" and "Collapse" damage is slightly higher in FBRAM compared to the analytical model results, but lower in "Slight" damage. This situation implies that the plastic demand ratio of some buildings may be overestimated by FBRAM. Observations on this issue have shown that this situation is encountered especially between the adjacent damage types such as "Slight" and "Moderate".

The fuzzy based assessment model is also applied to two existing precast industrial buildings to verify

Table 4 Fuzzy rules of FBRAM

Rule No#	Input1 H (mm)		Input2 L (m)		Input3 ρ_1 (%)		Input4 ρ_s/ρ_{sm}		Input5 SH		Output $\mu_{\Delta p}$ (%)
1	IF H is 350	and	L is 6	and	ρ_1 is 1	and	ρ_s/ρ_{sm} is poor	and	SH is very low	Then	$\mu_{\Delta p}$ is very light
…	…	…	…	…	…	…	…	…	…	…	…
100	IF H is 350	and	L is 7	and	ρ_1 is 2	and	ρ_s/ρ_{sm} is average	and	SH is high	Then	$\mu_{\Delta p}$ is very excessive
…	…	…	…	…	…	…	…	…	…	…	…
440	IF H is 400	and	L is 8	and	ρ_1 is 1	and	ρ_s/ρ_{sm} is average	and	SH is low-medium	Then	$\mu_{\Delta p}$ is excessive
…	…	…	…	…	…	…	…	…	…	…	…
1728	IF H is 600	and	L is 9	and	ρ_1 is 4	and	ρ_s/ρ_{sm} is high	and	SH is very high	Then	$\mu_{\Delta p}$ is excessive

Table 5 Structural parameters considered in application of FBRAM

Section dimension H (mm)	Building elevation (m)	Longitudinal reinforcement ratio (ρ_l)	Confinement ratio (ρ_s/ρ_{sm})
350	6	1%	Poor ($\rho_s/\rho_{sm} \leq 35\%$)
400	7	2%	Average ($35\% < \rho_s/\rho_{sm} < 75\%$)
450	8	3%	Good ($\rho_s/\rho_{sm} \geq 75\%$)
500	9	4%	
550			
600			

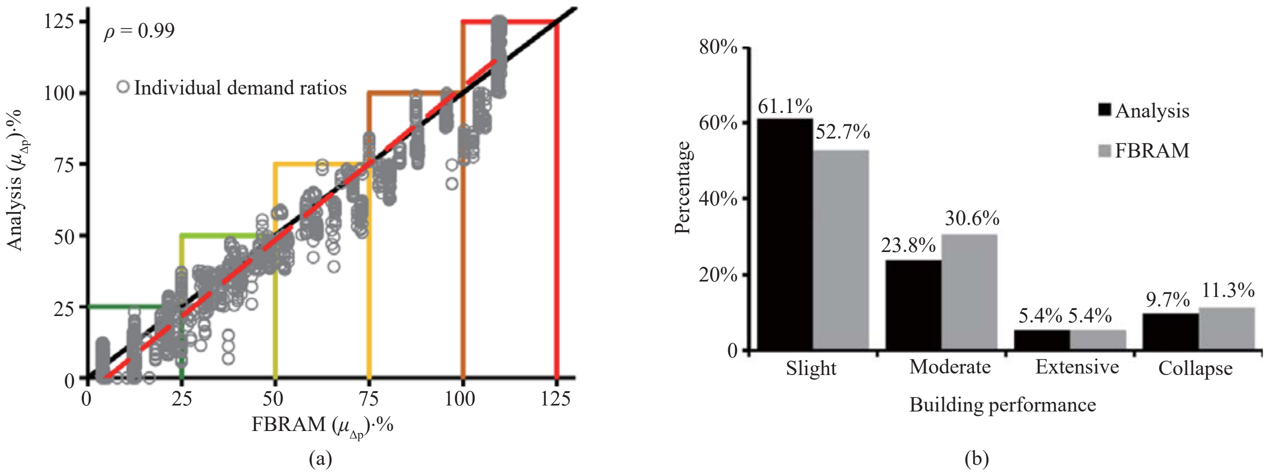


Fig. 17 Comparison of FBRAM and analytical model results

the reliability of method. Palanci (2010) evaluated the performance of two existing one-story precast industrial buildings in the Denizli Organized Industrial Zone (DOIZ). The performance of the buildings was assessed for different soil conditions: T_C = 0.46 s and T_C = 0.66 s. These scenarios are referred as “Scenario #1” and “Scenario #2” in this study.

Some salient characteristics of the first precast building are given in Table 6. As seen from the table, columns have square and identical section dimensions, longitudinal and transverse reinforcement ratios. Confinement ratio of columns indicates that they can be treated as “poor” (ρ_s/ρ_{sm} < 35%) according to the FBRAM fuzzy set. In Table 7, the capacity, demand, performance of building and hence, FBRAM results are also represented. According to the analysis results, the performance of the building is collapse and its plastic deformation ratio is higher than 100% in both scenarios. The plastic deformation predictions of the fuzzy rule based model are 90.7% and 109.4%,

Table 6 General characteristics of building#1 in DOIZ

Structural geometry				Sectional properties				
Span num.	Span length	Purlin length	Elevation	Column num.	B	H	r_l	ρ_s/ρ_{sm}
-	(m)	(m)	(m)	-	(m)	(m)	%	%
1	13	7.5	6.2	1	0.35	0.35	1.2%	23.6%
2	20	7.5		2	0.35	0.35	1.2%	23.6%
3	20	7.5		3	0.35	0.35	1.2%	23.6%
4	20	7.5		4	0.35	0.35	1.2%	23.6%
5	13	7.5		5	0.35	0.35	1.2%	23.6%
				6	0.35	0.35	1.2%	23.6%

Table 7 Capacity and performance of building#1 and comparison with FBRAM

Analysis										FBRAM	
Capacity related				Demand related							
V_t (kN)	Δ_y / L (%)	Δ_u / L (%)	T_1 (s)	Scenario	a_g (g)	T_C (s)	S_{dil} / L (%)	%Δ_p (%)	Damage	$\mu_{\Delta p}$ (%)	Damage
108.63	2.32%	4.05%	2.26	#1	0.4	0.46	4.16%	106.39%	Collapse	90.7%	Extensive
				#2	0.4	0.66	5.97%	211.11%	Collapse	109.4%	Collapse

respectively. This situation implies that FBRAM makes appropriate predictions with analytical model results for the second scenario. On the other hand, FBRAM slightly underestimates the plastic demand ratio for the first scenario, but it clearly identifies that the building is potentially under the risk of collapse as the demand ratio is very close to 100% (difference 9%) and the proposed model gives very important hints about the performance of the building. Furthermore, even this conclusion is adequate for preliminary performance decision stages as the performance of the building is not fulfilling the required performance. Since the building should at least satisfy the "Life Safety" performance level, in another saying moderate damage performance, it can be concluded that the assessment model is successful as it reveals the inadequacy of the building.

Structural features of the second building are given in Table 8. Apart from the first building, dimensions, longitudinal and transverse reinforcement ratios of the precast columns in the frame are not identical, but note that all columns have square sections. Although the transverse reinforcement ratio of columns is different, it is rather high and can be accepted as "Good" according to the confinement ratio fuzzy set. In the proposed FBRAM, the difference between column dimensions and longitudinal reinforcement ratios are neglected. In other words, it assumed that all columns have similar features in the frame. Nevertheless, it is apparent that the slenderness member will control the structural behavior as it may lead to a partial collapse or severe damage due to hinge connections between components of the building. On the other hand, the occurrence of partial damage can be crucial and may cause operational and functional problems in precast industrial buildings as observed in recent earthquakes (Decanini *et al.*, 2012; Ozden *et al.*, 2014). Regarding the slenderness of the one-story precast industrial buildings, the precast column with lower dimensions (350×350 mm) and lower confinement level is used to display performance of the second building and the results are shown in Table 9.

It can be seen from the table that the proposed model predicts slightly higher plastic demands. In the first scenario, plastic demand ratio is 6.67%, but detailed analysis performed by Palanci (2010) manifests that the performance of the building is "Moderate". Outcomes of FBRAM also reveal a similar damage type. By this way, it can be deduced that the fuzzy model has good agreement with the analysis results.

In the second scenario, building damage is determined as "Extensive" by FBRAM. Note that the difference between demand (S_{dil}/L) and ultimate displacement drift ratio (D_u/L) is around 2% according to the analytical analysis results. This situation emphasizes that the structure is under potential risk of extensive damage, and if the intermediate damage levels of precast columns were considered, this situation would be more evident. Thus, Palanci (2010) determined that the difference between displacement demand and moderate damage level is less than 0.8%. In the preliminary evaluation stage, this building would be stated as under risk

Table 8 General features of building#2 in DOIZ

Structural geometry				Sectional properties				
Span num.	Span length	Purlin length	Elevation	Column num.	B	H	r_l	ρ_s/ρ_{sm}
-	(m)	(m)	(m)	-	(m)	(m)	%	%
1	16	7	6.8	1	0.40	0.40	1.8%	127.9%
				2	0.40	0.40	1.8%	127.9%
2	16	7						
				3	0.40	0.40	1.8%	127.9%
3	16	7						
				4	0.35	0.35	3.1%	90.2%
4	16	7						
				5	0.35	0.35	3.1%	90.2%
5	16	7						
				6	0.35	0.35	3.1%	90.2%

Table 9 Performance of building#2 and comparison with FBRAM

Analysis										FBRAM	
Capacity related				Demand related							
V_t (kN)	Δ_y / L (%)	Δ_u / L (%)	T_1 (s)	Scenario	a_g (g)	T_C (s)	S_{dil} / L (%)	$\%\Delta_p$ (%)	Damage	$\mu_{\Delta p}$ (%)	Damage
205.62	2.58%	6.03%	1.67	#1	0.4	0.46	2.81%	6.67%	Moderate	49.05%	Moderate
				#2	0.4	0.66	4.03%	42.11%	Moderate	88.97%	Extensive

according to FBRAM, but if the detailed analysis was performed, it would be marked as potentially under risk. In consequence, an analyst would rather consider this building as under severe damage when the assumptions in behavior and uncertainties associated with the seismic hazard, geotechnical and modeling issues were considered.

5 Conclusions

This study proposes a fuzzy logic based risk assessment model for one-story precast industrial buildings. Input parameters and membership function of fuzzy sets in the assessment model are determined by using the reference precast buildings generated by the Monte Carlo simulation method. In this way, uncertainties associated with structural characteristics are taken into consideration. Section dimension parallel to earthquake direction, longitudinal reinforcement ratio, confinement ratio and seismic hazard that combine the severity of earthquake and the effect of soil type were used as input fuzzy sets. Plastic demand ratio was considered as the major output parameter and the performance of precast industrial buildings was determined. Note that beam-column connection failure and cladding panel effect on dynamic response are not taken into account. Some important implications of the study are given as follows:

(1) The use of the equal displacement approach has increased the simplicity of relation determination between capacity and demand related parameters. These parameters can easily be adapted to other structure types for fuzzy based performance evaluation purposes.

(2) As a result of mathematical operations, it is shown that the design ground acceleration and the characteristic periods can be used to express demand related parameters. This finding provides two crucial advantages: 1) code based applications in representing seismic hazard can easily be implemented, 2) eliminates the necessity of using the ground motion parameters to describe the seismic hazard.

(3) The Monte Carlo method is an effective tool to simulate uncertainties associated with structural parameters. Furthermore, this method made available the mapping of relation between inputs and output. Moreover, fuzzy rules of the assessment model are obtained through the results of this method.

(4) By mapping of inputs and output, the membership function of seismic hazard is determined by the supervised learning method. Although the method requires a training process until the desired level of accuracy is reached, it converges quickly if the categorization is well defined. According to the problem faced, the other machine learning methods such as association rule learning or artificial neural network algorithms can also be used.

(5) Comparisons have shown that fuzzy rule based risk assessment model has a good agreement with reference buildings results. In addition, damage indices of FBRAM and reference buildings are very similar.

(6) The assessment model is also inspected by two different existing precast industrial buildings constructed in the Denizli Organized Industrial Zone in the Aegean region of Turkey. The outcomes of these comparisons once again confirm the validity and reliability of FBRAM.

The overall results of the study have revealed that fuzzy logic is promising for seismic assessment of structures and it can be used as an effective instrument in rapid performance screening of buildings. In addition, conclusions of this study substantially encourage the application of fuzzy logic to other types of structures. In this regard, it should be expressed that several attempts are in progress for analytical performance assessment of multi-story reinforced concrete buildings.

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