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A risk-based system for managing the retrofitting school buildings in seismic prone areas: A case study from Iran

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Abstract

Earthquake events are inevitable but the consequences of earthquake disasters are partially controllable using an effective risk management system, since the seismic risk is the interaction of ground shaking intensity with the built environment. A systematic risk-based method is proposed for assessing the resilience capacities of school buildings exposed to varying levels of seismic risk. This approach screens and monitors the equivalent seismic performance of buildings by the means of new composite risk index (FSRi). The process of performance assessment of existing buildings is usually performed through walk-down surveys and associated with expert judgments which are often highly subjective. The pervasive nature of uncertainty within the risk assessment process often ignored or not completely reflected within the existing models. To handle the uncertainty associated with risk attributes, fuzzy set theory was used to characterize the uncertain qualitative information. The application of the model was applied to retrofitting school buildings in Iran. The screening results reveal that the composite risk index (FSRi) does not necessarily follow its factors' trends and therefore relying on sole factors such as hazard and vulnerability may mislead the decision making process . Therefore seismic mitigation decisions should be made in compliance with the multi dimensional aspects of seismic risk as an aggregated index rather , such as FSRi.

Key words: seismic risk management, fuzzy logic, uncertainty, vulnerability

1. Introduction

The resilience of infrastructure in seismic areas is one of the grand challenges for many countries particularly in facilities such as schools that carry high occupancy load. Even though the seismicity of the regions remains constant, the rapid increase in population, urbanization and economic development can significantly increase the seismic risk and trigger a disastrous event. Reported damage and losses in recent earthquakes in Iran highlights the importance of school protection and risk assessment. More than 90% of local educational establishments which catered for 10,000 students were lost or destroyed in 2003 Bam seismic event (IIEES 2003). Most of this loss could have been prevented by identification and primary screening of vulnerable schools. Educational facilities deserve special attention because of their primary role with vulnerable users. To reduce seismic induced impacts and to promote life safety, an effective risk management system is of utmost important. Thus in recent decades , risk methodologies have tried to include not only the estimated physical damage, the number and type of casualties or economic losses , but also the conditions related to social vulnerability and lack of resilience (Carreno et al 2006)

Several risk assessment systems exist which are capable of computing damage and casualties in many cities of the world based on probabilistic concept (Chen et al 2010; Davison and Shah 1997; Cardona O. D 2004; PEER 2011). The important ingredients of this loss estimation procedure is consideration of hazard related factors reflecting the losses and direct physical damages to building stock. Imprecise measurements of the damages and losses of a disaster are often the major concern in such probabilistic-based approaches. Karbassi and Nollet (2008) developed a rapid visual screening approach for existing buildings in Quebec using standard loss estimation concept. Sen (2010, 2011) applied a similar approach to estimate the seismic hazard of buildings in Turkey focusing on related hazard-related attributes to represent the overall seismic risk taking to the account magnitude and some basic structural indices such as soft storey , building height stiffness , storey , etc. However specific hazard factors would be limited to certain group of buildings in specific area only and would not be reliable to be used for use in other regions. Besides , hazard assessment requires detailed historical records and reliable structural performance indices which may not always available in many areas. In cases where historical records are missing or available information is scarce or imprecise conventional probabilistic-based approaches may not be able to generate reliable results. Limitations and imperfections in historical data, along with imprecise human perception in capturing the multi dimensional aspects of seismic risk, pose great uncertainties for the seismic risk assessment process. Moreover, evaluating and synthesizing a large amount of information from a variety of sources is acknowledged as a complex process.

Seismic risk assessment requires aggregation of numerous non-commensurable input parameters. Several methods of aggregation are reported in literature including simple aggregating operators (e.g. average , MIN , MAX) , weighted arithmetic mean (WAM) , simple multi attributes rating technique (SMART) , analytic hierarchy process (AHP) and other generic multi criteria decision analysis (MCDA). Aggregating multiple inputs of a complex system into a single output should reliably and precisely represent the whole is a synthesis as parts (Ross 2004) . According to Tesfamariam and Sediq (2008) there is a potential for loss of information in conventional aggregation methods due to exaggeration and eclipsing. Both types of errors can unacceptably generate the high score output for unimportant input and conversely, low score results for high importance parameters. These errors normally stem from ignoring the properties of input data and type of uncertainties involved , complexity of system and capacity of the aggregating methods in handling both uncertainty and complexity. For example Davidson and Shah (1997) developed an earthquake disaster risk index(EDRI) based on WAM to evaluate the seismic risk between cities. Kapes et al (2012) examined SMART Assessing physical vulnerability for multi-hazards. Cardona et al (2004) used AHP to estimate the weights of seismic risk factors . Carreno et al (2006) improved a similar approach using a fuzzy attributes capable of aggregating wide array of input. Tesfamariam and Liu (2013)conducted a comparative study using Bayesian belief network(BBN) and WAM to estimate the seismic risk over 11 Canadian cities. BBN, as with other heuristic based methods, has shown more utility and strength in aggregating and differentiating the results comparing to WAM.

Generally, aggregating the parameters associated with a complex system such as an earthquake requires a heuristic methodology capable of interacting with different range of information , fact , algorithm and experience. The great challenge of existing approaches is three folds. First there are lots of factors involved in risk assessment whose importance varies from place to place and thus the factors should be calculated so as to adequately represent the situation and the scope of the application. Second experts opinions and experiences play a major role in preliminary risk assessment imposing significant uncertainty into the process that needs to be accountable. Third the adopted methodology should be consistent with former needs and be capable of not only aggregating reliably the risk factors and expert views and experiences but also of simply reflecting the uncertainty of the results to guide decision making process. Further, there is an urgent need for a comprehensive system capable of integrating multiple risk factors effectively and efficiently since the detailed hazard assessment is a technically complex and expensive process which may not deliver precise results for some buildings (Sinha and Goyal 2004). Alternatively , the preliminary risk assessment can assist risk mitigation process by screening the schools in terms of their risk influencing factors. In this way , more detailed investigations can be focused and limited to the most critical buildings.

Therefore, the main purpose of this paper is to develop a new heuristic method for seismic risk assessment that simply characterizes and represents the seismic risk influencing factors, capable of aggregating types of information, facts and experiences. The research contributes primarily a new heuristic methodology that is systemically capable of integrating seismic risk factors and handling uncertainty through the risk assessment process. The paper determines the overall fuzzy seismic risk index (FSRi) through fuzzy based methodology. The scope of this work covers the preliminary risk assessment of large group of school buildings in high seismic zones.

2. Background and Motivation

Iran is known as a country prone to high levels of seismic activity and has experienced more than 130 strong earthquakes in the recent past. The national hazard map of the country indicates that a large populated portion of the country, almost 37%, is subject to frequent earthquakes (Ghafory-Ashtiany and Hosseini 2007). Furthermore, much of the economic and social infrastructure in Iran is prone to medium to high degrees of seismic risk. This is due to a combination of poor risk management and inconsistent prediction of seismic risk impacts when choosing the project sites. Having acknowledged the earthquake threat and with a desire to improve mitigation measures, Iran's government enacted a seismic mitigation policy to reduce seismic risk impacts for infrastructure and public buildings. Seismic mitigation measures were initialized after the 1997 Manjil earthquake and were accelerated following 2003 Bam seismic event. Particular attention was devoted to the educational sector because of the vulnerability of both the buildings and occupants across country. The national school inventory (NSI 2010) database shows that 22% of the total population (nearly 14 million students) is exposed to the threat of a medium to high intensity earthquake event. The latest survey, made by school rehabilitation office, reveals that about 65% of the total schools (110,000) do not have the structural capacity to withstand a likely earthquake. Within the preliminary screening phase almost 15,000 vulnerable schools were identified across country .It was agreed that retrofitting and strengthening works would be carried out within a tight schedule (five year mitigation program). Practically, evaluating and managing this large number of projects in a tight time frame is critical. Two mitigating measures have been officially adopted namely 'retrofitting' and 'reconstructing' (demolish and rebuild). The process of evaluating vulnerable schools is usually undertaken by a group of experts (Retrofit engineering consultants) through a complex structural performance analysis leading to a feasible structural reinforcing system. The conceptual study needs to be peer reviewed and approved for construction by an expert panel chosen from universities prior to tender. The process of decision making for each school building typically takes at least 6 to 12 month. Considering the large number of participant schools in the retrofitting scheme, only a small percentage of these schools will pass through the process every year. Thus developing a system of risk assessment in schools which can facilitate the decision making process, particularly for those in urgent need, and provide a roadmap for disaster planning and management is paramount.

3. Existing seismic risk system

Simnovic (2011) defined a disaster system as a set of complex dynamics involving the interaction of innumerable systems parts within three major systems: the physical environment; the social and demographic characteristics of the communities that experience them; and the buildings, infrastructures and other components of the constructed environment. Seismic risk systems facilitate the evaluation and monitoring of the hot spot locations within the network and convert this data into knowledge that would be extremely valuable to decision makers involved in seismic risk management (Chen at al 2010). Indicator based systems are in demand in policy circles in order to identify, rank (for the purpose of informing resource allocation, or targeting support programs or other interventions) (Eikin et al 2008). Theoretically, all applicable indexes need to be considered within a disaster system; however it is impractical to include all possible factors.

Several approaches have been developed with the goal of identifying indicators that could serve as proxies for commonly used attributes of risk and vulnerability. A classification of various vulnerability and risk systems can be found in Birkmann (2006). The United Nation Development Program (UNDP) has produced the Disaster Risk Index (DRI) a national level disaster risk assessment index, emphasizing the relationship between disaster risk and national development (UNDP 2004). The U.S. Federal Emergency Management Agency (FEMA) established multi hazard disaster risk assessment system using HAZUS. The HAZUS system is based on a Geographical Information System (GIS) platform for direct and indirect (physical, economical and social) loss estimation on a regional scale. HAZUS loss functions and damage estimation module could be a reliable predictor of seismic impacts for generic median cases (HAZUS 2001); however the applicability of such approaches are limited because they have been developed for a particular region and thus cannot be easily applied in another geographic area. Such sophisticated systems require large computational and information resources as well as high quality data which may be unavailable (Rodriguez et al 2012).

Some studies particularly focused on seismic risk management. Using a linear weighting system, Davison and Shah (1997) introduced an index system for evaluating earthquake risk in urban cities .Cardona et al (2004) developed a holistic risk system taking to the account socio-economic aspects of seismic risk including physical exposure, social fragility and resilience. Using the structural damageability index as major factor, Tesfamariam and Wang (2011) established a risk-based indicator system for prioritizing civic infrastructure in U.S.

With the aim of creating a comprehensive tool that provides metrics concerning the main disaster risk influencing factors with the presence of uncertainty, a new evaluation indicator system has been designed by the authors. This model uses a fuzzy based approach to handle uncertain information of risk attributes such as vulnerability that relies on field survey and engineering judgment. This model is further outlined in the following sections.

4. Underpinning methodology

A systematic fuzzy based methodology for evaluating and rating the seismic risk was proposed in four stages including risk analysis, risk assessment, verification and risk ranking as shown in Figure 1.This approach used a knowledge-based expert system to aggregate the knowledge from different sources of data, information, and multiple experts' opinions. Expert system is appropriate for evaluating seismic risk because much of the assessment involves expert opinion and knowledge from past experience.

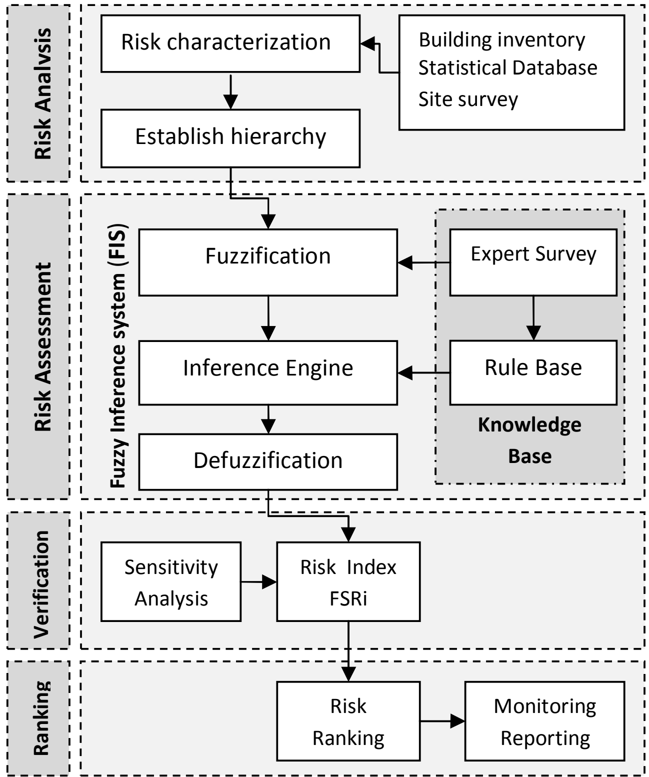


Figure 1 – Framework of fuzzy risk assessment

Initially, a project survey was conducted to collect related data and quantify into units. For instance, baseline information related to site condition, building inventory and microzonation maps are required to characterize the seismic risk factors and evaluate the carrying capacities of different sites with respect to hazard and vulnerability. Given the complexity of the interactions amongst factors and the necessity of managing the common pitfall of the fuzzy system, called the "Curse of dimensionality", a hierarchical system to be established. This issue happens in the fuzzy systems since the number of rules and hence the complexity increases exponentially with the number of variables involved in the system (Tesfamariam and Wang 2011).

Structuring the risk systems is a crucial step toward knowledge base development since the risk assessment process is accommodated using a knowledge base inference system to synthesize the knowledge from different sources of data, information, and multiple expert opinions. An expert system is appropriate for evaluating seismic risk because much of the assessment involves expert opinion and knowledge from past experience. In this stage, the risk attributes are mapped to a fuzzy scale and aggregated using knowledge base reasoning: rule base. Acquiring knowledge for rule base module can be achieved from expert survey and experimental data. Considering the impreciseness and vagueness of the knowledge acquisition process, all information should be described on the basis of a common natural linguistic scale. This process is so called as fuzzification. To quantify various linguistic terms for describing the risk attributes, the basic input parameters needs to be grouped (or clustered) into the linguistic quantifiers such as low(L), medium(M) and high (H). In the other word, the input values are converted (or fuzzified) into a homogenous scale by assigning corresponding membership functions (MFs) to the clustered data. After converting the crisp data and clustering to different MFs, the knowledge base rules can be evaluated using an Inference engine. The knowledge base rules defines the relationships among risk attributes. The outcome of the Inference engine is a fuzzy index representing the interaction of multiple attributes in each category. The aggregated fuzzy risk index encompasses a range of values and thus it must be defuzzfied to a single value. For example Center of Area (COA) is the most common method for defuzzification that develops the center of gravity of the area under membership function.

To verify the robustness of the aggregation results, sensitivity analysis is applied to ensure the variation and uncertainty of risk attributes is within the range. The inference process has to be applied for each category of seismic risk, including hazard factors, vulnerability and etc. The crisp defuzzified results of the four sub-models are then combined together through a new Inference system to generate the overall fuzzy seismic risk index (FSRi) as shown in Figure 2. Finally, schools can be prioritized in accordance with their FSRi and may be monitored for further mitigation action. The main steps of the methodology are outlined in more detail in following sections.

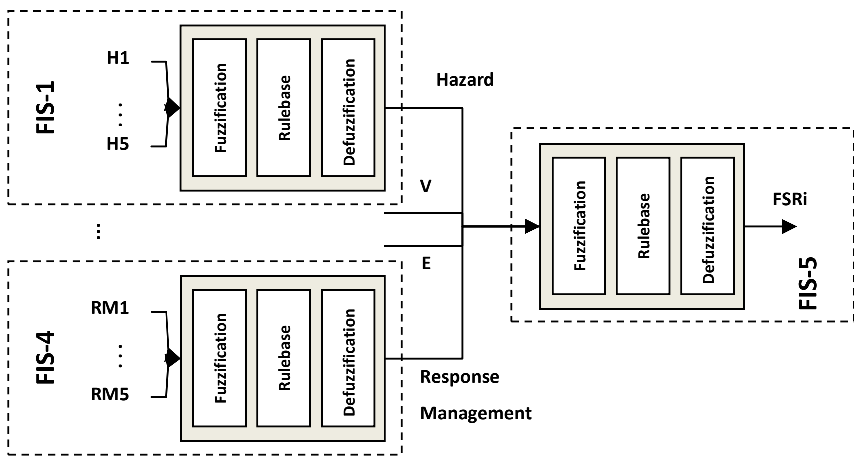


Figure 2 – Developing hierarchical fuzzy system by integrating different FIS

5. Risk characterization

According to Carreno et al (2006) risk is defined as the potential economic, social and environmental consequences of hazardous events that may occur in a specified period of time. The purpose of risk management is to assist decision makers in formulating relevant risk prevention, reduction or mitigation measures and policies. Thus the scope of risk assessment should consider not only scientific and physical aspects but also social and economic dimensions of risk need to be acknowledged (Chen et al 2010).

Selection of the underpinning methodology is very important for the process. There are two main streams in literature for characterizing the seismic risk; the probabilistic approach and the more 'mixed method' fuzzy approach. Conventional probabilistic based approaches use historical records related to damage and intensity to describe the seismic hazard and vulnerability respectively; however this methodology might be restricted due to lack of data. Alternatively, the fuzzy seismic risk index (FSRi) can be used on the basis fuzzy set theory as proposed by Zadeh (1965). Unlike previous approaches; this methodology relies on subjective information to describe the relationship of seismic risk with hazard and vulnerability.

In this paper, the risk model is developed by applying the fuzzy concept on a hierarchically-structured system using common risk factors that mostly been considered as important in literature (UNDP 2004; Davison and Shah 1997; Cardona O. D 2004; PEER 2011). Risk is characterized in this research by the fuzzy seismic risk index (FSRi) representing the multidimensional aspect various risk attributes such as hazard (H), vulnerability (V) , exposure (E) and response management (RM).Hazard refers to potential intensity or severity of a disaster event that threats the life, property and business. Earthquake hazard could cause severe damage and losses to people and building assets which can be expressed by exposure factor. Vulnerability conveys a broad range of degrees of susceptibility for people and buildings exposed to severe earthquake. In countries with both technically sound seismic codes and active regulation and enforcement, their building stocks would likely be above a certain safety threshold and thus responses capacity and recovery management could have as important as other risk factors. Areas with high density population and with sparse infrastructures would be exposed to a great amount of risk during an earthquake event. For the regions which have had an emergency response policy and critical plans for disaster management, for example early warning systems, shelters and first aid provisions, the risk of loss could be considerably reduced and managed.

5.1 Risk hierarchical structure

Based on the conceptual framework of seismic risk outlined above, a hierarchal risk breakdown structure has been established. This structure provides the basis for classification and characterization of risk factors by the means of relevant scope. The hierarchy was structured in three levels as illustrated in Figure 3. Level 1 denotes the objective of the decision problem defined as ”fuzzy seismic risk index” (FSRi). Level 2 represents a set of factors that play major role in characterizing the seismic risk context.

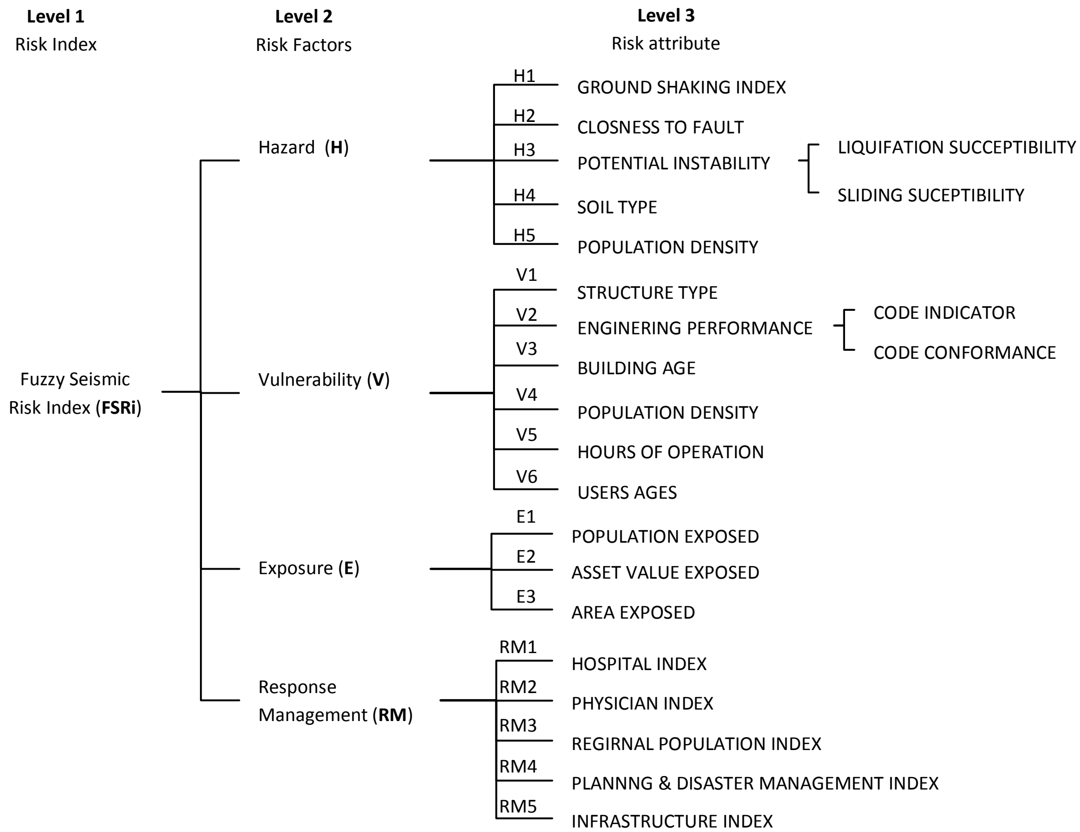


Figure 3 – Hierarchal structure for seismic risk

In Level 3 , four major factors including H, V, E and RM were further broke down into more detailed attributes to reflect more precisely the seismic risk aspects. For example, hazard was characterized by five attributes namely H1 to H5. Some attributes such as “Ground shaking index” and “Closeness to the faults” were selected to take potential intensity of earthquake hazards into the account. Potential instability refers to seismic impact capacity which could be induced by liquefaction and sliding due to ground conditions. “Liquefaction susceptibility” could amplify the hazard by reducing the bearing capacity of the soil grades during a likely earthquake event. “Sliding susceptibility” linked to the topographical impacts that may occur if the building located on slope or susceptible soil. Clearly, the population density in a school affects the potential loss of life and consequently has a direct impact on the seismic risk; likewise, other factors were broken down into more detailed attributes so as to be measured effectively.

5.2 Fuzzy representation of risk attributes (Fuzzification)

In the fuzzification step, all the qualitative and quantitative variables can be measured based on a common scale, the so called linguistic variables. The use of linguistic variables facilitates the handling imprecise qualitative information using common scale in a flexible manner (Miri Lavasani et al 2011). The use of such a scale facilitates the quantification of imprecise statements as ‘low’, ‘very low’ to ‘fairly’ (Schmucher 1984). Describing a risk attribute may vary considerably in practice due to individual understanding, situations and application oriented. Linguistic terms allow expert judgment to be consistently managed in a common language scale.

Membership functions (MFs) represent the degree to which an element of a set fits the linguistic scale. Various membership function (MFs) can be used to develop a fuzzy system including triangular, trapezoidal, Gaussian, etc (Figure 4).

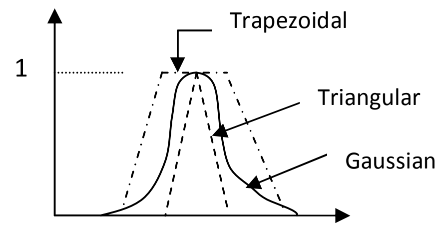


Figure 4 – Various membership functions

Triangular functions has been adopted to describe the input variables (risk attributes) at the third level of the hierarchy. Alternatively, for other risk factors in second and first level of hierarchy that require more accuracy and smooth transition in output results, a Gaussian function was implemented. Karwowski and Mital (1986) recommended using five to nine linguistic terms to get high performance results in judgment process. Having reviewed the attributes and considered the expert opinion, five levels scale was selected for linguistic variables including '*very low*' (VL) , '*low*' (L) , '*medium*' (M) , '*high*' (H) and '*very high*' (VH).

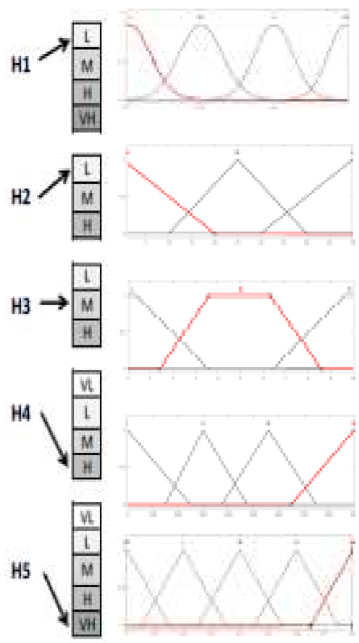
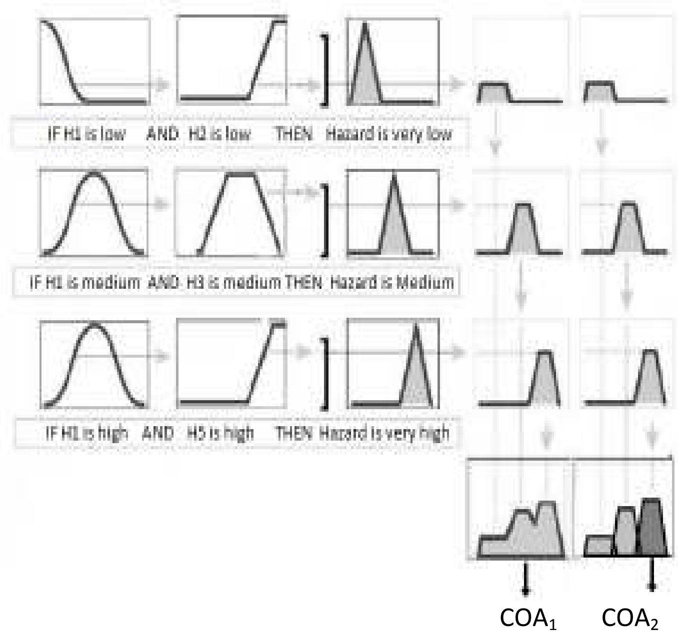
5.3 Fuzzy Inference System (FIS)

Fuzzy inference system consists of a knowledge base that defines the relationship between input and output parameters of system. The knowledge base is commonly presented as a set of IF-THEN rules expressing the expert's opinion valuation for a particular uncertain state of risk attribute. It can be simply shown as :

$$\textbf{IF} \quad x = A_1 \quad \textbf{AND} \quad y = B_1 \quad \textbf{THEN} \quad z = C_1$$

where A1 , B1 and C1 are the linguistic values defined by fuzzy sets on universe of discourse X and Y. The source of IF-THEN rules stems from the use of linguistic variables (Zadeh 1965).For simplicity ,the process of generating rule base consisting of hazard attributes is shown in Table 1.

Table 1 - Typical rule base aggregation process

Hazard attribute	Aggregation process
	 H = $\bigcup_{i=1}^{n}(H1_i \cup H2_i \ldots \cup H5_i) = \sum COA_i$

In this study combination of large number of rules was handled through fuzzy logic toolbox of MATLAB. Sample module of Hazard is indicated in Figure 5.

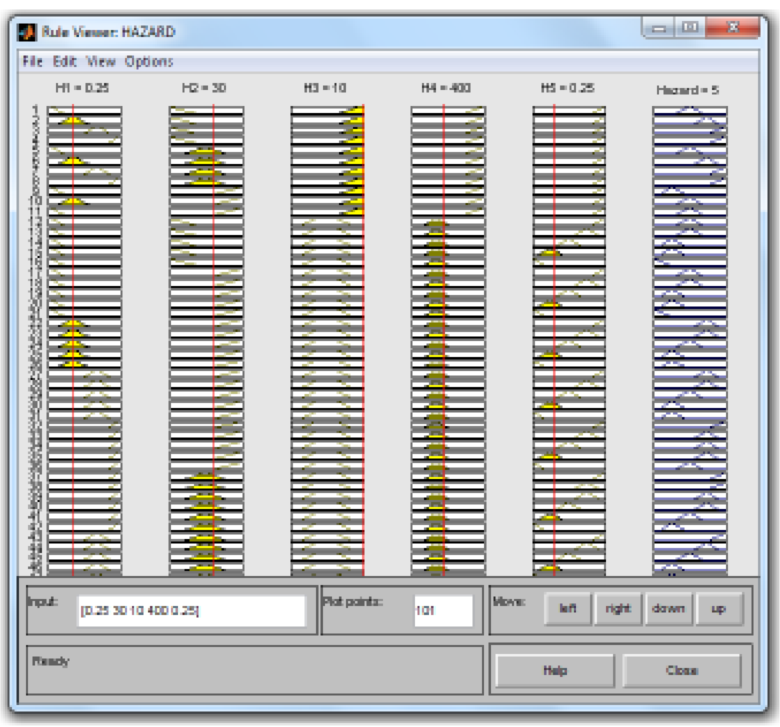


Figure 5 - Sample rule base viewer in MATLAB for Hazard attributes

6. Case study from Iran

The purpose of schools, their occupancy, their economic basis, and their role in society are features that distinguish them from other building types (FEMA 2002). A trial case example of the seismic risk system was applied to selected country schools in Iran. The initial screening of schools conducted by school rehabilitation office (SRO 2011) showed that almost 65% of total buildings required either retrofitting or reconstruction. The report also reveals that a high percentage of schools, over 68%, were built prior to 1989 when no seismic code of practice was in force.

For this research,a sample of twenty one school buildings were taken from moderate to high seismic risk regions of Iran. The schools chosen in the case study represented a variety of material types, structures, population and site conditions. The building inventory database established by the school rehabilitation office (SRO 2011) together with the national census (IIEES 2003; BHRC 2006) were taken as main sources for current study.

6.1 FIS description

Applying the five FIS's to the seismic risk framework articulated earlier, the risk factors can be integrated within the hierarchy as depicted in Figure 6. This diagram shows the integration of input-output of each risk sub-system that can be carried out in two steps. Initially, different risk attributes at level three are combined with regard to their fuzzy rules. The output variables in FIS-1 to FIS-4 represent the risk factors that are computed for each school. These data were considered as input variables for next level that to be imported to FIS-5 based on the new reasoning rules to develop the fuzzy seismic risk index (FSRi).

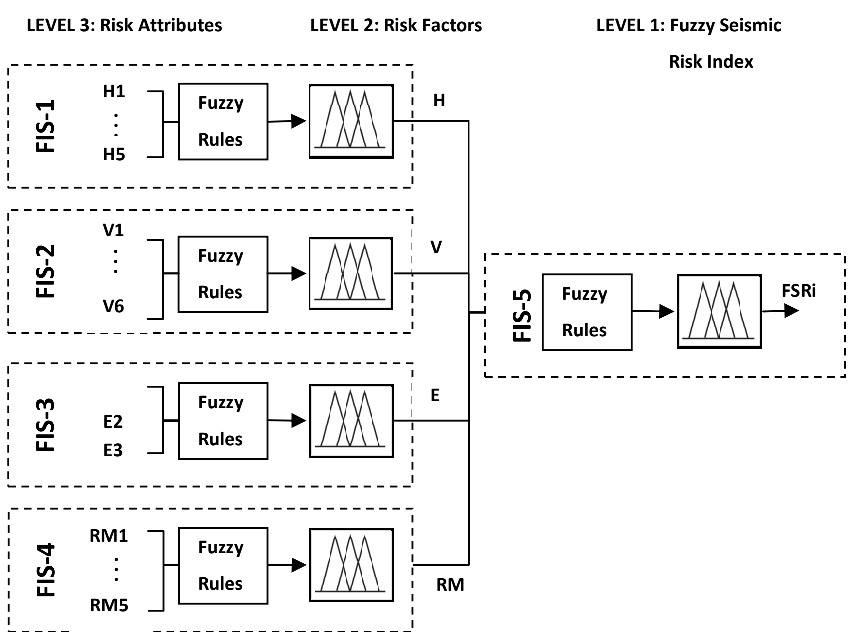


Figure 6 – Integrating FIS for seismic risk system

The fuzzy system implemented in risk model is based on a Mamdami and Assilian (1975) with the characteristics reported in Table 2.

Table 2 - Characteristic of Mamdani Model

Operation	Operator	Formula
Union (OR)	MAX	$\mu_c(x)= \max(\mu_A(x), \mu_B(x))= \mu_A(x) \vee \mu_B(x)$
Intersection (AND)	MIN	$\mu_c(x)= \min(\mu_A(x), \mu_B(x))= \mu_A(x) \wedge \mu_B(x)$
Aggregation	MIN	$\max(\min (\mu_A(x), \mu_B(x)))$
Defuzzification	COA	$COA=\int x\, \mu_C(x)dx / \int \mu_A(x)\, dx$

As an example, applying Mamdani model to FIS-5 , using MIN operator for aggregating the risk factors :

$$\mu_{FSRi}(x)= \max(\min (\mu_H(x), \mu_V(x), \mu_E(x), \mu_{RM}(x))) = \max(\mu_H(x) \wedge \mu_V(x) \wedge \mu_E(x) \wedge \mu_{RM}(x))$$

Where μ is a membership function for each variable and ∧ and ∨ are max and min operators, respectively. The process of aggregation was modeled through MATLAB® Fuzzy Logic Toolbox.

6.2 Linguistic scale

In current study, five sets of linguistic scale were taken for risk attributes as indicated in Table 3. This classification covers the whole range of data including min and max values; Though some qualitative attributes may be simply described by three or four scales such as H1 (as indicated in local seismic code) or engineering performance index V2.

Table 3 – Linguistic scale for representing the risk attributes

#	Seismic risk attribute	UNIT	VL	L	M	H	VH
H1	Ground shaking Index*	-	-	0.2g	0.25g	0.3g	0.35g
H2	Closeness to fault	Km	-	>20	10-25	<10	-
H3	Potential instability	-	-	Low	Normal	High	-
H4	Soil type*	-	I	II	III	IV	-
H5	Population density	student/area	<0.15	0.05-0.35	0.25-0.55	0.45-0.75	>0.65
V1	Structure index *	-	E	D	C	B	A
V2	Engineering performance	-	6-8	4-7	1-5	<2	-
V3	Building age	Years	<10	5-20	15-30	25-35	>30
V4	Population density	student/area	<0.15	0.5-0.35	0.25-0.55	0.45-0.75	>0.65
V5	Hours of operation	Hour	-	<4	3-6	5-8	>7
V6	Users age	Years	-	<8	6-12	10-17	>16
E1	Population exposed	student	<100	50 - 150	100 - 350	300-500	>450
E2	Asset exposed	(x$1000)	<200	100 - 300	200- 500	400-700	>600
E3	Area exposed	m^2	<200	150-350	300-750	700-1000	>900
RM1	Hospital index	Bed	<50	20-100	80-250	200-550	>450
RM2	Physician index	Per 100,000	<100	60-300	250-750	600-1600	>1400
RM3	Region population index	x 10,000	>100	70-100	25-80	5-30	<10
RM4	Planning & disaster Mng. Index	-	<4	3-6	5-8	7-10	-
RM5	Infrastructure index(accessibility)	-	-	low	medium	high	-

* Taken from local seismic code (BHRC 2006)
g = acceleration of gravity

Some attributes are broken down into more detailed factors as indicated in Table 4, 5 and 6. Clearly, a hazard index can be dramatically increased by proximity to a fault. Any school building in can be endangered by collateral hazards such as liquefaction and/or sliding phenomena that may be caused following an earthquake ,Table 3.The standard maps for liquefaction and sliding have been developed by IIEES and taken as benchmark for determining the potential instability (PI) index for each site. Soil type has also a direct impact on earthquake amplification and propagation the structural damage. Generally speaking, the deeper the soils, the more damaging the earthquake motion will be (FEMA 2002). According to the soil classification made by BHRC (2006), four types of soil were considered in the hazard assessment module.

Table 4 – Potential Instability

PI Index		Liquefaction		
		H	**M**	**L**
Sliding		5	3	1
H	5	25	15	5
M	**3**	15	9	3
L	1	5	3	1

Table 5- Structure Index

Grade	Structure Type	index
A	Masonry (No tie)	1
B	Masonry + Tie	3
C	Simple frame	5
D	Rigid Frame	7
E	Combo system	9

Table 6 – Engineering Performance

Code		Pre code	Post code
Conformance		0.4	1
H	10	4	10
M	**7**	2.8	7
L	5	2	5
VL	2	0.8	2

The engineering performance of a school building depends on the year in which building constructed (Pre-code/Post-code) and how much the building conforms to current code of practice (Table 6). Having known the year in which seismic codes were initially adopted and enforced by the local jurisdiction and the year in which significantly improved seismic codes were implemented as a benchmark, the building conformity index can be deduced. In the current case study most of the buildings were identified in pre-code period meaning that no seismic requirements were considered in design and operation.

6.3 Rule base

The development of the rules describing the relationship between linguistic variables is a critical step, because they describe the heuristic knowledge about the behavior of the physical system (Gentil e al., 2003). Initially, the lowest and most effective set of rules that describe each FIS needs to be identified. This selection requires extensive cause and effect analysis of each linguistic variable and requires also the collaboration of experts who are involved in subjective judgment.

As an example, the variables ''FSRi" has five fuzzy sets for each factor and totally 625 (5x5x5x5) rules can be developed to describe the FIS-1; although the system can be further simplified by discarding the least significant rules which has no data in input variables. The calculation of "FSRi" requires five inputs at the same time. This process was programmed in MATLAB® to reduce the human error and complexity in defining the rule base. The risk factors can be primarily modeled in pair based on common sense judgment as already discussed. For example **IF** "Hazard" is *L* **AND** 'Vulnerability' is *M* **THEN** 'FSRi' is *L*. For simplicity, the reasoning rules can be expressed in matrix format as shown in Table 7 and 8.

Table 7 – Rule matrix for **H** and **V**

FSRi		Hazard (H)				
		VL	*L*	*M*	*H*	*VH*
Vulnerability (V)	*VL*	**VL**	VL	L	L	M
	L	VL	**L**	L	M	M
	M	L	L	**M**	M	H
	H	L	M	M	**H**	VH
	VH	M	M	H	VH	**VH**

Table 8 – Rule matrix for **H** and **E**

FSRi		Hazard (H)				
		VL	*L*	*M*	*H*	*VH*
Exposure (E)	*VL*	**VL**	VL	L	L	L
	L	VL	**L**	L	L	M
	M	VL	L	**M**	M	H
	H	VL	L	M	**H**	H
	VH	VL	L	H	H	**VH**

Similarly, the fuzzy rule base applied to different levels of hierarchy including risk attributes, factors as described within fuzzy risk framework. The output variable range of 1–10 is selected by the experts as being the most convenient language to discuss the consequent variable of each rule set. For seismic risk interpretation, the linguistic terms of '*VL*', '*L*', '*M*', '*H*' and '*VH*' corresponds with 'Light', 'Moderate', 'Critical', 'Disaster' and 'Catastrophic' situations respectively .

7. Risk ranking results

Setting up the MFs and rule bases using MATLAB®, the regional and site-specific data for each school were imported to Inference system to obtain the aggregated risk index. The output results for risk factors and overall FSRi are presented in Table 9. The risk ranking results highlight those schools needing retrofitting to minimize loss and casualties. The overall fuzzy risk index can be described by the means of linguistic terms. This measurement provides a more meaningful way to communicate the current status of risk and vulnerability for a large group of schools.

Table 9 – Fuzzy seismic risk Index (FSRi) for different school buildings

Project #	Type	Area (m^2)	Year	Population	Province	Hazard (H)	V	Exposure	Respnse Mng.	FSRi	Linguistic term
1	S	690	1982	420	KHs	7.28	8.93	6.44	6.1	9.05	Catastrophic
2	S	1875	1993	1300	ZN	7.8	4.54	6.3	6.3	7.67	Disaster
3	S	3635	1976	1600	AZw	5	4.28	9.08	5	7.49	Disaster
4	M	350	1981	80	MZ	5	6.23	4	5	7.49	Disaster
5	S	1296	1971	300	LO	7.28	3.00	4.02	4.4	7.4	Disaster
6	M	980	1991	350	GL	5	2.82	4	6.3	7.4	Disaster
7	M	1080	1985	350	HM	4	2.64	3.97	2.5	7.22	Disaster
8	M	824	1970	340	AZw	5	4.29	3.82	4.4	7.06	Disaster
9	S	1432	1981	215	KB	5	6.80	3.4	5	6.94	Critical
10	M	1507	1997	300	GZ	5	1.85	3.56	5.3	6.64	Critical
11	M	620	1990	90	AK	4.82	2.26	2.08	6	6.32	Critical
12	M	2176	1972	600	AZw	3.51	3.98	6.75	4.9	6.17	Critical
13	M	745	1980	300	ZN	5.15	4.13	3.55	6.2	6.11	Critical
14	C	2051	1995	600	QM	3.97	2.97	6.73	4.7	5.49	Critical
15	S	1839	1992	475	QM	3.22	2.89	5	4.6	5.49	Critical
16	S	980	1992	320	SM	6.45	3.06	3.66	6.6	5.24	Critical
17	S	2063	1995	400	SB	2.72	2.26	4	3.5	5	Critical
18	C	1550	2001	350	MZ	2.72	3.90	3.8	4.69	4.63	Critical
19	S	1551	1986	150	GL	5	2.16	2.23	3.5	4.51	Critical
20	S	1255	1998	300	SM	2.7	1.84	3.8	4.6	3.45	Moderate
21	M	317	1984	80	AK	2.68	3.41	1.8	6.2	3.39	Moderate

The FSRi can be also expressed in linguistic terms as indicated in the last column. Schools with an FSRi of more than 7 would face a disastrous loss if a seismic event occured and therefore require urgent retrofitting measures. For a seismic risk of less than 7 but more than 4, the school buildings are considered as 'critical' and would need to be managed as a priority compared with the rest of the school buildings. The fuzzy risk index can be also represented as function of different variables like 'hazard' and 'vulnerability' in the form of 2D and 3D surface view as shown in Figure 7. The graphs demonstrate the interaction of the risk parameters indicated in decision matrix, thus the trend and interactions of the risk parameters can easily be verified. Clearly, hazard or vulnerability can individually impact the seismic risk variation; although vulnerability indicates more influence particularly in 'VH' state which is reasonable. In the situation where both hazard and vulnerability have high values, the results present an extreme seismic risk irrespective of other factors.

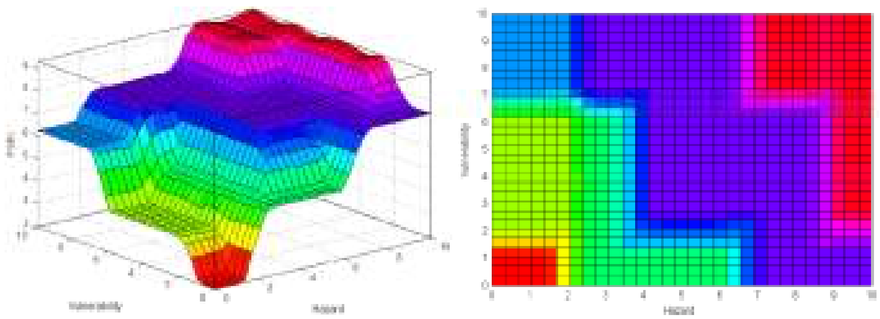


Figure 7 – 3D and 2D Surface view of FSRI with respect to hazard and vulnerability

8. Model verification

Model verification comprises the checking of the consistency and completeness of the system (Botten et al. 1989). According to Gupta (1991) model verification should be performed first to determine if the system completely and accurately implements the user specifications and second to ensure if the system asserts something that is not truly in the modeled domain. This process focused on how variations in risk parameters such as hazard and vulnerability factor affect the overall seismic risk index. Previous seismic risk results in literature were taken as benchmark to verify the robustness and reliability of the model.

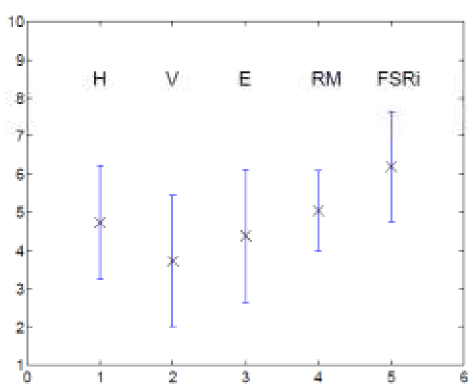


Figure 8 – Uncertainty of risk factor indices

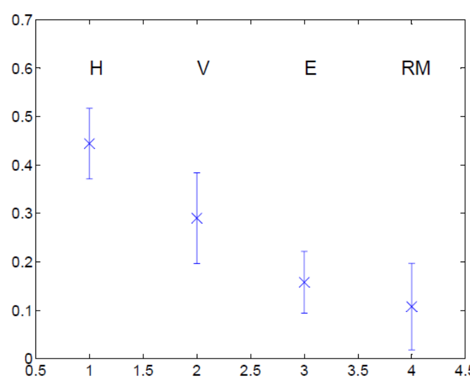


Figure 9 – Uncertainty of risk factors' weights

Sensitivity analysis was performed to evaluate the uncertainty of the risk factors indices and risk factors' weights. According to Figure 8, the highest variation (30%-35%) in three most important factors (H, V, E) and least variation in RM with 22%.The overall risk composite factor (FSRi) with almost 30% variation follows its components trend. Due to the uncertainties associated with the judgment process, the weighting of the indicators might vary significantly among various risk states. Thus, the average variation in risk factors was considered as single index for verification as indicated in Figure 9. Clearly, this chart indicates the weights of each factor in different fuzzy situations comprising VL to VH. The average weights of seismic risk factors comprising H, V, E, and RM are 30%, 35%, 15% and 10% respectively. The variation of the weights reveals that RM with 22% is the most sensitive factor in the process and the others varies between 5% to 12% and demonstrates less uncertainty comparing to past studies. In contrast with the sensitivity results obtained from previous studies (Davison and Shah 1997; Marulanda et al 2008; Vahdat and Smith 2010), the research results represent the least uncertainty, and thus more reliability, in term of overall seismic risk factors. The weighting sum method (WSM) and Analytic Hierarch Process (AHP) expresses greater uncertainty with 35% and 29% respectively. It also shows that the ranking results are sensitive to extreme changes over most important risk factors such as hazard and vulnerability.

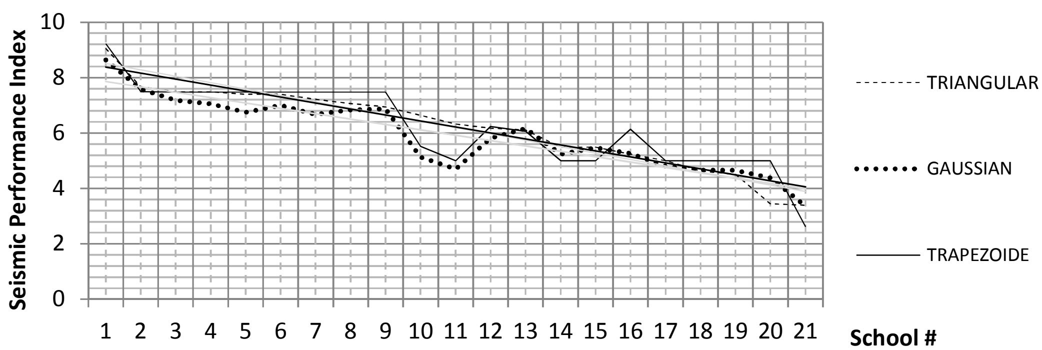


Figure 10 –Sensitivity of ranking results for different MFs

"Robustness is related to the stability and reliability of the method to deal with the uncertainty of input data and the modeling parameters" (Marulanda et al 2008). The robustness of the proposed model has been demonstrated by examining different MFs. Three types of MFs were applied to verify the uncertainty of risk attributes as shown in Figure 10. This experiment revealed how well a membership function can represent the corresponding data range. In general, all three MFs follow the same descending trend from highest to lowest performance; however there are some perturbations observed in less than 30% of dataset that related to the Gaussian and Trapezoidal MFs. Triangular MFs demonstrate less variation and thus represent more stability in output. Various defuzzification methods including COA, MOM and LOM were also applied to the model. The results indicate no significant changes in performance index and thus the overall ranking results maintained minor sensitivity to change in defuzzification operator.

9. Conclusion

To satisfy the urgent need to address and classify those school buildings having the largest potential threat to life, safety and the built environment, a risk-based ranking system has been developed using the fuzzy concept of seismic risk. The vague and complex interactions between seismic risk factors such as hazard and vulnerability were represented through linguistic variables. A fuzzy inference system was implemented to aggregate the risk factors within the hierarchy and to obtain the overall fuzzy seismic risk index (FSRi) for prioritization. The applicability of the model was tested on a real case study based on a sample of schools in Iran. It was demonstrated that prioritizing the retrofitting of schools is significantly affected by seismic risk variation. Thus retrofitting decisions in seismic prone areas should be made in conformance with the multi dimensional aspects of seismic risk.

Managing uncertainty was highlighted as a major concern in this model because much of the information in the knowledge base is derived from expert opinion which is often imprecise and incomplete. Knowledge base uncertainty has been acknowledged as prevalent in current disaster management systems dealing with imprecise qualitative information. The results of verification process for this model have shown less uncertainty in both performance indices and weightings comparing with similar risk studies that conducted using AHP and WSM. Vulnerability as key element of risk assessment is associated with the most uncertainty (35%) since it relies on both the building inventory and a checklist procedure that requires engineering judgment. Hazard demonstrated less uncertainty (less than 30%) as it based on more objective information. Response management factor has indicated the least uncertainty due to its indirect effects on seismic impacts.

Given the imprecise data, which is the prime challenge for development of any risk model, the proposed model demonstrated more reliable and robust methodology than the existing screening approach. The proposed model also presents more transparency and flexibility in using risk factors and tracking the components individually. In general, the ranking results conveys that the composite seismic performance index (FSRi) although reasonably depends on its main components (H and V) , FSRi does not necessarily follows its factors' trends. This trial reveals the importance of using multi-disciplinary risk index rather than relying on hazard and vulnerability factors alone.

Unlike previous studies, the current model allows the handling of large numbers of school buildings within the screening process. The findings from this research are beneficial to both researchers and professionals involved in seismic mitigation planning and pre/post disaster management. The results of this study contribute to body of literature examining the socio-economic aspects of earthquakes. The conceptual framework gives a new insight for seismic risk assessment in disaster management context. The potential exists for further research to be developed to extend this risk concept to other infrastructure.

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