Seismic Risk Management

By : Kamran Vahdat

Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

The University of Leeds
School of Engineering

May 2015

The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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List of Publication

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Abstract

Seismic risk management is a problem of many dimensions, involving multiple inputs, interactions within risk factors, criteria, alternatives and stakeholders. The deployment of this process is inherently fraught with the issues of complexity, ambiguity and uncertainty, posing extra challenges in the assessment, modelling and management stages. The complexity of earthquake impacts and the uncertain nature of information necessitate the establishment of a systematic approach to address the risk of many effects of seismic events in a reliable and realistic way.

To fulfill this need, the study applies a systematic approach to the assessment and management of seismic risk and uses an integrated risk structure. The fuzzy set theory was used as a formal mathematical basis to handle uncertainties involved within risk parameters. Throughout the process, the potential impacts of an earthquake as the basic criteria for risk assessment were identified and relations between them were accommodated through a hierarchical structure. The various impacts of an earthquake are then aggregated through a composite fuzzy seismic risk index (FSRi) to screen and prioritize the retrofitting of a group of school buildings in Iran.

Given the imprecise data which is the prime challenge for development of any risk model, the proposed model demonstrates a more reliable and robust methodology to handle vague and imprecise information. The significant feature of the model is its transparency and flexibility in aggregating, tracing and monitoring the risk impacts. The novelty of this study is that it serves as the first attempt of the process of a knowledge base risk-informed system for ranking and screening the retrofitting group of school buildings. The model is capable of integrating various forms of knowledge (quantitative and qualitative information) extracted from different sources (facts, algorithms, standards and experience). The outcomes of the research collectively demonstrate that the proposed system supports seismic risk management processes effectively and efficiently.

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List of Abbreviations

AAL	Average Annual Loss
AHP	Analytic Hierarchy Process
ATC	Applied Technology Council (US)
ASCE	American Society of Civil Engineers
BHRC	Building and Housing Research Council
DSRA	Deterministic Seismic Risk Assessment
DPM	Damage Probability Matrix
FAHP	Fuzzy Analytic Hierarchy Process
FMCDM	Fuzzy Multi Criteria Decision Making
FEMA	Federal Emergency Management Agency
GIS	Geographic Information Systems
HAZUS®	Hazards U.S.
IIEEA	International Institute of Engineering Earthquake and Seismology
MAUT	Multi Attribute Utility Theory
MCDM	Multi Criteria Decision Making
MFs	Membership Functions
FSRi	Fuzzy Seismic Risk index
KBES	Knowledge Based Expert System
NRCC	National Research Council Canadian
NSI	National Statistics Institute (Iran)
PGA	Peak Ground Acceleration
PSRA	Probabilistic Seismic Risk Assessment
RM	Response Management
RVS	Rapid Visual Screening
UN-ISDR	United Nations International Strategy for Disaster Reduction
WAM	Weighted Arithmetic Mean

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Chapter 1: Introduction

1.1 Research Background

Seismic risk management can be viewed as a process of complex dynamics involving the interactions of many factors. These factors typically include the physical environment, the social and demographic characteristics of the communities that experience seismic risk, as well as the buildings, infrastructure and other facilities that are known to be vulnerable in the environment (Simonovic 2011). The purpose of seismic risk management is to mitigate the consequences of seismic events in prone areas. Thus, the system is not to predict seismic events; rather, we are looking at how to manage the adverse impacts when seismic events occur. To accomplish this, a broad range of operations, planning and decision-making needs to be performed.

Seismic risk management is characterized as having multiple dimensions, such as social, economic, political and environmental dimensions, some of which may be in conflict with each other. Several alternatives may need to be considered and evaluated in terms of the many different criteria which results in a vast body of data that are often imprecise or uncertain. Many individuals may be involved in the risk assessment process, including decision makers, planners, experts and other interest groups, from organizations and the community, all of whom may have conflicting preferences (Lahdelma et 2000).

Moreover, seismic risk assessment is a complex process due to the interactions within risk drivers. Seismic hazard is inherently uncertain, partly because it is a forecast of future situations based on previous knowledge, which may be scarce and variable in quality or not fully understood (Dowrick 2003). The scope of seismic risk management is defined in relation to balancing what these uncertain information. The multiple views and interests of individuals and organizations within the seismic risk management process cause an inherent complexity that requires a systematic reconciliation of these disparate, often conflicting factors through a structured knowledge framework (Avouris 1995).

Broadly speaking, aggregating a large number of inputs within a complex system requires a heuristic methodology that is capable of interacting with a range of information, facts, algorithms and experiences. The challenges to the existing approaches to this problem are three-fold. Firstly, there are many factors involved in seismic risk management, each with varying importance depending on the scenario; thus, the factors should adequately represent the situation and the scope of the application. Secondly, expert opinions and experiences play a major role in the assessment yet may add significant uncertainty into the process – this needs to be accounted for. Thirdly, the adopted methodology should be consistent with needs, allowing the tracking of results so that decisions can be updated.

Seismic risk management is an iterative process of decision-making described within a multifaceted process, including preparedness, prevention, response and recovery, with the eventual aim of mitigating the social and physical impacts of earthquakes. The application of decision models to risk assessment and management of critical infrastructure facilities exposed to low-probability, high-consequence seismic hazard requires a thorough understanding of the risk impacts and effective disaster management strategies. Seismic mitigation measures are an ongoing strategy to reduce the consequence of earthquakes, either structurally through retrofitting/reconstruction, or through non-structural strategies such as land use zoning and relocating development, as well as implementing and enforcing building codes.

According to Simonovic (2011), mitigation activities should address the measurement and assessment of the evolving risk environment while incorporating a comprehensive, proactive measure that enable the prioritization of mitigation investments. The mitigation process heavily relies on predictive models of risk to address disaster impacts and effectively communicate and respond prior to an event. More systematic approaches to evaluation would likely yield to the adoption of broader and efficient mitigating decisions over the long term (Ramesh et al. 2007). Thus, it is important to adopt an appropriate method to systemically project the disaster impacts and support decisions in the face of significant uncertainty. Furthermore, most strategies employed to manage seismic risk have been developed out of the structure (NRC 2011) that increases the complexity of risk management. Rational risk management should focus on comparing and prioritizing the aspects of disaster systems. The ability to compare risk across regions becomes more critical, particularly in a mitigation programme that requires rendering the state of the system less vulnerable. This also directs the resources and mitigation measures in both private and public sectors who have competing priorities for risk management investment. In some cases, those investments might compromise the mitigation measures by retarding the retrofitting process, misleading the resource development away from structural to non-structural measures, and consequently leading to costly, unreasonable and long-lasting decisions.

1.2 Research Motivation

The motivation for conducting the research was to facilitate mitigating decisions by focusing on estimating and ranking seismic risk within the portfolio of retrofitting school buildings in Iran. The national hazard map of the country indicates that a large populated portion of the country, almost 37% carrying 22% the population, are exposed to range of medium to high intensity earthquake threat (Ghafory-Ashtiany and Hosseini 2007; NSI 2010). Furthermore, much of the economic and social infrastructure in Iran is prone to medium to high degrees of seismic risk.

Reported damages and losses in recent earthquakes have highlighted the importance of school protection, occupant security and proactive safety measures prior to an earthquake. More than 90% of local educational establishments with 10,000 students were lost or destroyed in the catastrophic Bam earthquake in 2003(Ghafory-Ashtiany and Hosseini 2007). Seismic mitigation measures were initialized after the 1997 Manjil earthquake and were accelerated following the 2003 Bam event. Iran's government enacted a seismic mitigation policy entitled "The National Strategy for Earthquake Risk Reduction" to reduce the impacts of the earthquake in infrastructure and public buildings. Particular attention was devoted to the educational sector because of the vulnerability of both the buildings and students across the country, leading to launching a $4 billion Seismic Risk Mitigation Programme in 2006 for improving 126,010 vulnerable classrooms

(39% of the total) by 2011. The aim of the programme was to reduce seismic risk within public schools through several mitigation measures, including retrofitting and reconstruction. The initial task was to identify and screen the schools with potential risk to life safety during an earthquake. A survey conducted by the school rehabilitation office (Table 1.1), revealed that almost 65% of total schools (~70,000) had low to medium structural capacity to withstand a likely earthquake. A further screening phase revealed that there were almost 15,000 structurally vulnerable schools that required attention. Authorities decided that retrofitting and strengthening works to be carried out within a tight schedule (five year mitigation programme).

Table 1.1 – Status of school buildings in Iran (NSI 2010)

Schools	No.	Percentage
needs reconstruction	39353	35.86
needs retrofitting	31180	28.41
adequate strength	39201	35.72
Total	109,734	100

Practically speaking, the screening, identifying, evaluating processes are not straightforward, not to mention the difficulty of managing this large number of projects in a tight time frame. Two mitigating measures were officially adopted, namely 'retrofitting' and 'reconstructing' (demolish and rebuild). The process of evaluating vulnerable schools was 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 months. Considering the large number of participating 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 is of paramount importance, and can facilitate the mitigation decision, particularly for those in urgent need, as well as providing a roadmap for disaster planning and management.

1.3 Research Purpose

The ever-evolving and complex nature of seismic risk is a decisive contributor to disasters, intensifying the urgency to pursue a systemic risk assessment as a prerequisite to intervene in seismic risk management planning and risk mitigation, in particular. Existing models fail to effectively address the methodological perspective to undertake seismic risk management within a large group of school buildings. The non-existence of such an appropriate seismic risk assessment model has initiated this research, thereby highlighting the critical need for development of a holistic risk assessment model as a decision aid to guide school mitigation programme. A structured and systematic approach could significantly enhance seismic risk management, leveraging the capability of mitigation decisions while maintaining the quality of the process and validity of its outcomes. The systemic perspective of risk assessment and management, helps quantify the complex, multifaceted composition of the seismic risk and ultimately secures the credibility and effectiveness of decision-making.

A systems approach allows the integration of comprehensive and cross-disciplinary views of the many apparently separate facets of a complex process such as seismic risk management (Johnson et al. 2006). The system analysis framework requires subjective inputs to make a decision (Bender and Simonovic 1996). Brill (1979) asserts that system analysis tools should facilitate and provide creative decisions, avoiding the recommendation of a single, 'best' solution. This study proposes a risk management system, applying trade-off among risk parameters to improve the understanding of alternative behaviour, managing the technical complexity of the seismic risk system and facilitating the implication of choices.

In response to the emergent complexity and uncertainty involved in estimating earthquake impacts, the study builds upon the notion of combining both a theoretically well-grounded systems approach with a risk analysis to support risk management. The methodology suggests a necessary insight to the process of structuring an appropriate tactic that promotes seismic risk management. In this process a system approach to the task of identifying, analysing, aggregating, ranking and monitoring risk are applied.

This thesis includes an exploratory review, identifying the critical contributing factors for each region and examining the interactions within them. A thorough analysis of seismic risk assessment provides a comprehensive picture of school buildings by tracing and examining the above factors and linking towards effective risk mitigation measures. Furthermore, the critical literature review provides a theoretical framework for seismic risk management, which forms the basis for the model's development. Hence the study serves as a valuable tool for the public to enhance disaster planning, protection and promotion of school safety by practically reducing seismic risk.

The novelty of the research is the systemic characterization of seismic risk through a hierarchical risk structure. The proposed multi-level structure for seismic risk improves the practice of seismic risk management by integrating a broad range of information collected from multiple disciplines, in a manner that is objective (fact, algorithms) and subjective (experience, opinions). The outcomes of such a model are a greater understanding and conceptualizing the knowledge of seismic risk assessment that yield better-informed participation of the relevant stakeholders and an active mitigation process.

An added value of the research is that, apart from contributing to the general academic discussion on seismic risk management and seismic mitigation programmes, the structure of the model contextualizes the application of a systematic approach to different levels of government. The early outcome of this co-operation is assisting and encouraging the community and public officials to better understand the scope of the seismic risk management in school buildings by portraying a comprehensive picture of seismic risk, raising awareness about school safety, strengthening the related infrastructures and emergency management facilities. The effective implementation of the developed model warrants the school safety protection by prioritizing and allocating the resources for urgent retrofitting intervention.

1.4 Aims and Objectives

The aim of the research is to assess potential impacts of earthquakes and investigate the feasibility, applicability and usefulness of a system to model multidimensional aspects of seismic risk management. In pursuit of this aim, six objectives were outlined:

1. To review the background and characteristics of seismic risk management, and systematic challenges involved.
2. To investigate the feasibility of mathematical techniques for modelling seismic risk.
3. To introduce the fuzzy modelling approach in practice and review the terminology, scope, limitations and potential barriers associated with modelling the complex domain.
4. To investigate the potential impacts of earthquakes, to collect the necessary information and to establish the structure of seismic risk assessment.
5. To apply and implement the model for evaluating and ranking seismic risk within retrofitting school buildings of Iran and to review the results.
6. To investigate the effectiveness of the proposed model and to verify and validate the results.

1.5 Limitation and Scope

The thesis provides a holistic seismic risk assessment model for prioritizing large group of school buildings subjected to varying levels of earthquake hazard. It is concerned with systematic evaluation and documenting the status quo within school buildings in seismic prone areas, thereby improving recognition of those areas which are seismically vulnerable. The procedure described in this thesis has been designed for screening existing buildings, particularly low-rise projects in Iran, however it can be applied to other seismic prone regions with readjus

accepting that even though some of the principles may be suitable, it would require further work to apply to other situations and countries. This procedure is intended to serve as a national decision aid for public officials, urban planners, insurance companies, disaster managers or other international interest groups (e.g. UNDP, The Red Cross) who are implicitly involved with disaster management planning, financing or budgeting the mitigation programme or undertaking seismic rehabilitation.

Several risk assessment tools are currently in use. However, most are not effective enough to be used for a particular group of infrastructure at such a large-scale mitigation programme. The model proposed in this research is novel in that it is designed to be simple, affordable and consistent with existing screening standards. The outcome of the research focuses not only on systemic ranking of the school buildings that are potentially vulnerable, but it also highlighting the critical factors that require more attention and investigation. It is expected that most buildings recognized as vulnerable in accordance with this process conform to desired levels defined within screening standards. However, it may not guarantee compliance with the seismic performance of buildings noted in design codes since the scope of screening and design standards are different. Screening procedures aim to evaluate a large number of projects at a preliminary stage and ultimately guide decision-makers to find potentially vulnerable buildings; while design codes, particularly those verifying the performance of individual buildings and observe design rules by the means of analytical or empirical methods.

The purpose of this research is to project seismic risk impacts on buildings, offering a state-of-the-art knowledge-based system as a decision aid to address current needs for seismic risk mitigation planning. The model focuses specifically on producing a generalized estimates of expected loss and damage as a preliminary risk screening tool to identify the significance, criticality and urgency for retrofitting school buildings. However, it is beyond the scope of this thesis to estimate the loss (death and injury), structural damage or deficiencies in school inventory, the destruction of school contents and equipment, or the disruption of the school delivery services due to an earthquake. In addition, the procedure does not determine whether or not a retrofitting intervention should be undertaken for a particular school building; neither does it specify the types of retrofitting suitable for school buildings.

1.6 Thesis Outline

The content of the thesis is organized into the following chapters:

Chapter 2 - Seismic Risk Management : This chapter critically reviews the current practices of seismic risk management and analyses the general characteristics of the seismic risk system. It clarifies the 'risk' definition and its components in relation to seismic risk management. Moreover, the main methods that are currently in use in risk assessment are critically discussed. Finally, the major issues and challenges involved with the seismic risk management are highlighted.

Chapter 3 - System Modelling Techniques: This chapter introduces system perspective as an alternative concept for modelling seismic risk, and draws a picture of the prospective risk management system while focusing on the key requirements of the prospective model. In this light, the chapter provides a comparative review of potential mathematical tools that support decision-making under uncertainty. The multiple risk-based theories for classifying, evaluating and ranking alternatives with multiple criteria have been critically reviewed with their advantages and limitations. The application of fuzzy multicriteria decision making (MCDM) as a potential candidate is explored through a pilot study.

Chapter 4 - Research Methodology : This chapter establishes the theoretical framework and methodological design procedure required to achieve the aim and objectives of the research. The chapter first explains the choice of research strategy and overall design of the research. It further outlines research configurations and critically reviews the methods concerning data collection and data analysis. Several data collection methods have been examined and compared in terms of strengths and weaknesses. Finally, the chapter summarizes the strategy adopted to conduct the research.

Chapter 5 - Fuzzy Modelling : The chapter focuses on knowledge-based systems and systemic requirements for knowledge acquisition, knowledge extraction and knowledge elicitation. Under particular scrutiny are terminologies and common types of knowledge involved in risk modelling, as well as how knowledge systems can support risk-based decision-making. Moreover, the background methodology of the current study is briefly discussed through introducing fuzzy expert system and hypothetical issues for applying knowledge-based system in complex domains.

Chapter 6 - Data Collection : This chapter investigates the input factors, and collects necessary information required to undertake the case study in two parts. First the general characteristics of alternative school buildings of Iran are reviewed in terms of size, type and material. Second, the potential impacts of earthquakes are reviewed and classified in major categories consistent with the geography, seismology and typology of buildings in Iran. The major impacts of earthquakes were then decomposed through a hierarchical risk structure required for estimating the seismic risk. The information about alternatives, criteria and structure collectively forms a road map for the synthesis of various risk factors.

Chapter 7 - Case Study : This chapter develops the knowledge based expert system (KBES) based on the information collected in the previous phase. The risk structure and information are interpreted using fuzzy expert system. The entire process of risk assessment was modelled through 21 fuzzy inference engines and synchronized using MATLAB© programming language. The results of the proposed system are reviewed and discussed.

Chapter 8 - Verification and Validation : This chapter is concerned with testing and evaluation the proposed system, and discusses the obtained results in relation to research objectives. To perform this task, the chapter is organized in two parts, including verification and validation. The verification part assesses the sensitivity and uncertainty of risk parameters, using the statistical toolbox in MATLAB©. Throughout the validation process, various analytical and empirical approaches are devised to evaluate the performance of the system under three conditions, including 'best case', ‘normal case’ and ‘worst case’ scenarios.

Chapter 9 - Conclusions : This chapter provides the summary and conclusions of the research by highlighting the significant conclusions and findings. It also outlines the contributions and recommends areas for further research.

The structure of the thesis is presented in Figure 1.1 and consists of three parts. The first part (Chapters 2 and 3) is concerned with a literature review, including seismic risk management, challenges and techniques proposed to address the research problem. The second part (Chapter 4) introduces the conceptual methodology used in the research. The subsequent five chapters are the main part of the thesis that focuses on model development and implementation.

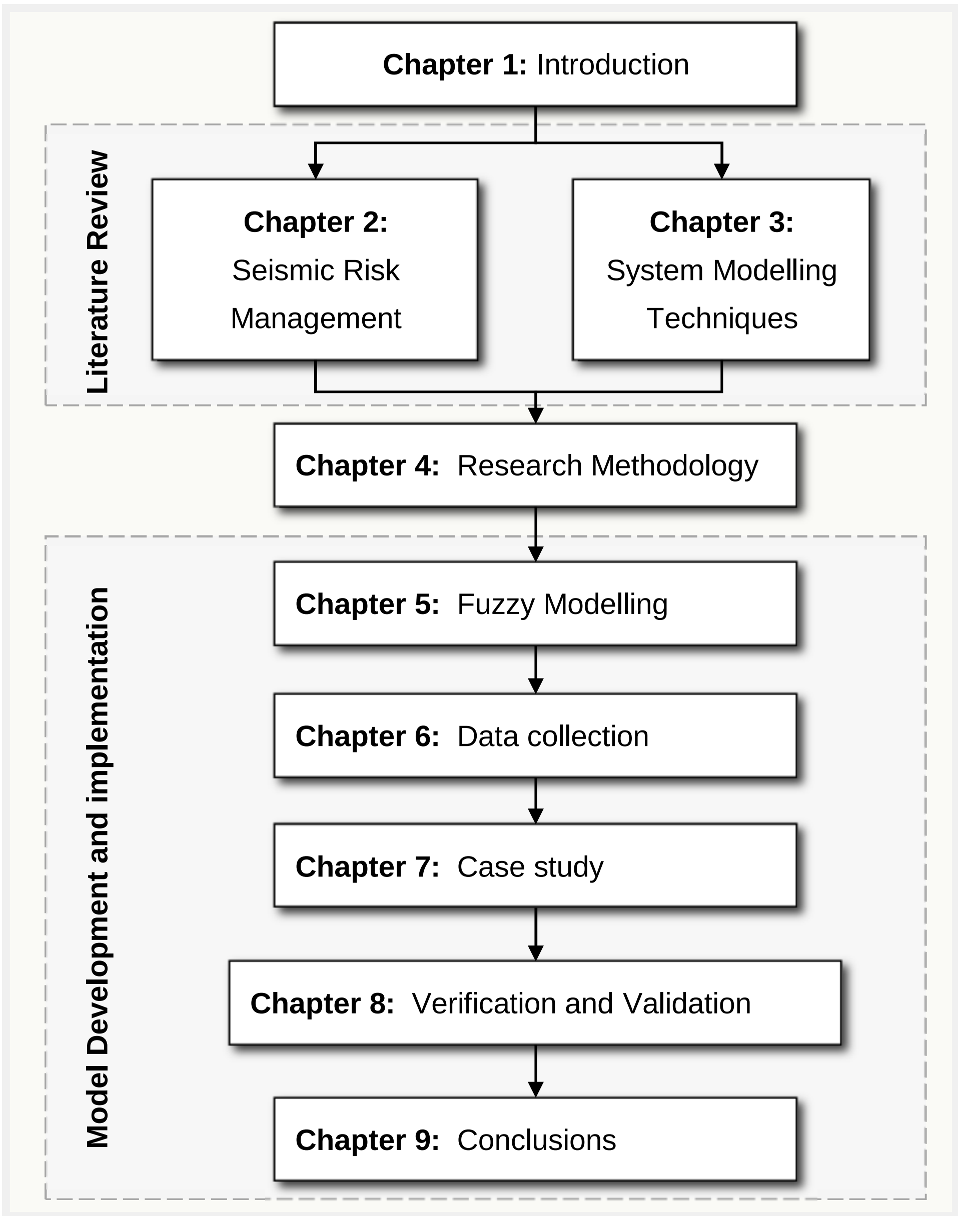


Figure 1.1 – Thesis structure

Chapter 2: Seismic Risk Management

2.1 Introduction

This chapter reviews the basic notions of seismic risk management, focusing on the general characteristics along the scope of the seismic risk from a system perspective. Major risk assessment frameworks are classified according to their application in seismic risk management. Finally, the chapter summarizes the challenges and issues involved with seismic risk management.

2.2 Basic Notions

The term 'risk' is defined in the Merriam Webster Dictionary (2003) as "possibility of loss or injury due to hazard". Rackwitz (2005) defined the risk as "the chance of an adverse outcome for human health, the quality of life, or the quality of the environment". Kofi (1998) addressed the risk as the probability or likelihood of an adverse impact or assessed threat to people and property due to some hazardous situation. Rowe (1988) defined the risk as "the potential occurrence of undesired, negative consequences of an event". Following the definitions of UN-ISDR (2004), risk was addressed as the "average expected losses" from a "given hazard" over a specified period of time, whether expressed in terms of life loss, economic loss, physical damage to facilities, properties, structures, business and activities (Mezzina et al 2007; Carreno et al 2006).

More precise definitions have been proposed in ISO-99 as "combination of the probability of an event and its consequences" or a "combination of the probability of damage and its severity". Though, the challenge of formalizing the definition of risk is to understand the risk as the effect of uncertainty; since risk is rather abstract in nature and definitions vary according to context.

From these definitions, it can be noticed that risk is closely linked to potentially uncertain consequences and severity of these consequences. For example, in insurance context, the notion of risk is highlighted with maximum consequences without taking the probability of occurrence, which is not suitable for optimal risk management. Current studies use the broader viewpoint of the 'Seismic Risk' as a complex interaction of 'Seismic Hazard', 'Vulnerability' and 'Exposure' which are defined as follows:

- Seismic Hazard (H): Probability of occurrence of any physical phenomenon (e.g. ground shaking, ground failure, etc.) associated with an earthquake which has adverse effects on people, communities and built environment.
- Vulnerability (V): Potential loss or degree of damage induced by a given hazard.
- Exposure (E): Population, properties, assets and economic activities at risk.
- Seismic Risk (R): Probability of any social or economic consequences of earthquakes (e.g. expected loss, damage, disruption to lifelines, infrastructures and business activities) caused by a particular hazard.

The elements at risk are commonly addressed as populations, communities, and built environment (i.e. buildings, infrastructure, economic activities), which are subject to disaster threat in a given area (Alexander 2000). Specifically, the elements at risk within the built environment can be classified into four main categories: buildings inventory, utility, infrastructures and critical facilities. Any element of an urban environment is considered as "at risk" when it is potentially exposed to the occurrence of sort of loss for a given hazard. Thus, risk can be quantitatively expressed as a combination of its influence factors (UN-ISDR 2004; FEMA 395 2002) which is adopted here.

$$\text{Risk} = \text{Exposure} \times \text{Hazard} \times \text{Vulnerability} \qquad (2.1)$$

The expression implies several facts regarding the seismic risk. Both seismic risk and hazard are intrinsically uncertain since they essentially forecast future situations as a product of extrapolating the past historical records (Dowrick 2003). Seismic risk can be managed by reducing the potential damage and elements exposed; while seismic hazard is constant for every region and cannot be minimised. Based on the importance and value exposed to seismic hazard, seismic risk may be amplified or reduced. Thus, historical damage records cannot solely be representative of risk without the importance of buildings, asset or elements. In addition, the risk 'expression' implicitly denotes that the risk of a particular hazard which can be exhibited in a given area if and only if all the contributing factors are present. For example, in a low-seismicity region that is potentially vulnerable in terms of structure, economy and population, the total risk would be very low or negligible. Conversely, the risk could be at an extreme level if the contributing factors are at their highest level. Accordingly, various levels of hazard and vulnerability can be developed for particular scale categories to measure the levels of seismic risk over a region (Figure 2.1).

Hazard		VL	L	M	H	VH
Very High	VH	17	21	22	**24**	**25**
High	H	14	15	16	20	**23**
Moderate	M	7	8	**12**	13	19
Low	L	3	**5**	6	11	18
Very Low	VL	**1**	2	4	9	10

Vulnerability

Zone	Risk Impact
1 - 3	Tolerable
4 - 8	Moderate
9 - 17	Strong
18 - 22	Severe
23 - 25	**Disaster**

Figure 2.1 – Risk matrix for qualitative description of risk impacts

However, the quantitative mean of seismic risk must be used carefully. This form of translation could distort the overall result since low-probability, high-consequence earthquakes are commensurate with high-probability, low-consequence events. The former clearly has more criticality in managing such extreme and catastrophic events. Hence, it is important to come to a precise understanding of risk, the scope of events and context. Moreover, true understanding of risk dimensions is critical for resource allocation, particularly in mitigation programmes where multiple competing regions are involved. One of the difficulties involved in aggregating risk factors is to represent adequately the relations between risk factors while maintaining a certain degree of precision. This could be even more challenging because several dimensions of hazard, vulnerability and exposure have to be aligned, scaled and aggregated in the presence of uncertainty. In this light, an effective integration of risk factors was set up as an ultimate aim of the research.

2.3 Seismic Risk Management

Risk management is the systematic application of policies, procedures and practices to the tasks of identifying, analysing, assessing, controlling and monitoring risk (Standards Australia/Standards New Zealand, 1995). The United Nation Strategy stipulated a generic version of this process in the disaster context for Disaster Risk Reduction (UN-ISDR, 2004):

> "The systematic process of using administrative decisions, organization, operational skills and capacities to implement policies, strategies and coping capacities of the society and communities to lessen the impacts of natural hazards and related environmental and technological disasters. This comprises all forms of activities, including structural and non-structural measures to avoid (prevention) or to limit (mitigation and preparedness) adverse effects of hazards."

The universally accepted tasks of seismic risk management were defined within the Hyogo framework (UN-ISDR 2006) in four distinct risk categories: preparedness, mitigation, response and recovery, which are performed in pre-, during and post-disaster (Table 2.1). Neal (1997) states that disaster phases are "mutually inclusive and multidimensional" as they are strongly interconnected; while each measure maintains the individual aspects of disaster to enhance the tasks of risk management.

Table 2.1 – Generic seismic risk management process (Altay and Green 2006)

Measure	**Phase**	**Activities**
Preparedness	Pre-Disaster	Emergency response plan, shelter, public information and education Evacuation plan, Earthquake training, manoeuvring, Warning system
Mitigation	Pre-Disaster	Retrofitting, rehabilitation, augmentation, reinforcing Legislation, Code enforcement, zoning/land use management, Insurance, reserve fund, site improvement
Response	During Disaster	Response strategy, critical management centre, mobilizing and medical aid service, search and rescue team, locating (GPS) and recording intensity, communication
Recovery	Post - Disaster	Medical service, rehabilitation, reconstruction, financial assistance, Restore public infrastructure, essential service and business

According to UN-ISDR (2004), preparedness refers to promoting the inherent knowledge and capacities by governments, critical emergency organizations, disaster professionals, communities and individuals in preparing a response and recovery plan for any likely event. Mitigation refers to set of strategies to reduce and limit the exposure or potential damage due to an earthquake. Mitigation strategies pay attention to preventive measures as the key intervention for seismic risk management. Response measures include sets of emergency provisions to assist the public immediately after a disaster, in order to save lives, reduce health impacts and to ensure public safety. Recovery is an unavoidable reaction performed by governments. Obviously, additional investment in preventive measures and preparedness can be more effective and economically justified compared to post-disaster actions and reduces the cost of response and recovery (Simonovic 2011). This is the reason mitigation is highlighted as a critical measure within seismic risk management.

Essentially, identifying future mitigation is the main concern of risk management, which closely links to vulnerability, thereby requiring a reliable estimation of loss and potential capacity of damage within the built environment. Risk management aims to reduce the potential loss and damage within communities by identifying and assessing the potential factors that contribute to those effects and proposing appropriate response actions. Since the seismicity and severity of earthquakes cannot be reduced or modified, the management of the risk logically focuses on reducing vulnerability as an effective measure for damage mitigation. It is impossible to predict the severity of an earthquake in a given area due to its stochastic (random) nature; however the adverse effects of an earthquake can be effectively reduced or avoided using appropriate risk assessment and management (Bostrom et al. 2006). Thus, risk assessment and management are complementary processes, while the former uses a systematic method to determine the probability of adverse effects, the latter tries to systematically decide and choose the appropriate option to manage the risk (e.g. mitigate, transfer, response, recovery).
The study focuses on the active mitigation measures that directly reduce the seismic risk within buildings through systematic retrofitting. Other mitigation strategies such as insurance that indirectly transfer the risk fall out of the scope of research.

2.3.1 Retrofitting

A broad range of mitigation activities can be conducted to limit the 'vulnerability' or 'potential damage' through active structural measures such as retrofitting and rehabilitation. The aim of retrofitting is to improve the lateral resistance of buildings against likely earthquake to desired safety performance objectives as addressed in FEMA-273. Existing buildings that suffered degradation over time might need 'rehabilitation' to regain and maintain the original strength they were initially designed for; however, if the original level of performance does not meet the safety level it may require seismic upgrading or seismic retrofitting. For this, a set of structural interventions and technical modifications are mobilized to raise the structural indices such as strength, stiffness, ductility, stability and integrity. Recent earthquake experiences indicate that inadequate lateral stiffness along the lack of integrity in load-carrying system has been the major cause of damages to masonry school buildings. Some of those have been illustrated in Figure 2.2.

Figure 2.2 – Lack of integrity in school buildings in Iran (SRO 2011)

For URM buildings, there are common retrofitting strategies such as surface reinforcement, external reinforcement, cross ties, pre-stressed-core and post-tensioning (FEMA 273 1997). Some of those including pre-stressed tendon-core masonry require particular tools (for continuous vertical drilling) and expertise, which makes it justifiable only for high importance monuments and historical buildings; while post-tensioning imposes less of a burden in operation. Surface reinforcement is the most popular technique for retrofitting masonry and concrete buildings through reinforced cement plaster (or concrete jacketing). A similar version of retro-reinforcement has been implemented for improving the tensile strength and ductility of masonry bridges in the UK (Garrity 1995). The principal objective in surface retro-reinforcement is minimizing the disturbance and intrusion in appearance, function, thereby reducing the cost of operation (Garrity 1994). The common practice of surface treatment consists of surface preparation (e.g. providing adequate roughness), installing steel connectors and surface mesh to the walls and diaphragms and applying the overlay shotcrete. Additional bracing chords might be carried out to improve the stiffness, integrity and rigidity of diaphragms as indicated in Figure 2.3.

Figure 2.3 – Shotcrete overlay (Jacketing) to enhance stiffness and integrity (SRO 2011)

For URM buildings where enhanced ductility and strength is sought, an external reinforcement can be alternatively devised by attaching steel straps and clips, making crossties to the walls around as shown in Figure 2.4. If the reinforcing straps are properly anchored to the walls, lateral in-plane and out-of-plane flexural strength and ductility of the walls will be considerably increased under truss-action behaviour. Crossties are useful to collect out-of-plane forces and distribute them to diaphragms.

Figure 2.4 – Steel strapping the masonry walls in schools (SRO 2011)

The scope of retrofitting has been extensively addressed in the literature (Elgawady et al 2004; FEMA 273); while the efficiency of a choice of system requires a detailed, case-by-case structural analysis. However, the reliability of retrofitting can be only measured where they are subjected to real earthquake loads. In general, it is indicated that retrofitting not only mitigates the seismic risk in buildings itself, but it can also improve the response, recovery service and ultimately raise safety protection in the community after a disaster.

Accessibility of school buildings as the convenient locations for public assembly makes the school buildings the first choice to serve as immediate shelters spots and a centre for the first aid service. The retrofitted schools that survived after the recent earthquake in Iran (Varzeghan, 11 Aug 2012) has shown the importance of retrofitting and the role of schools to serve a community in post disaster recovery (Figure 2.5).

Figure 2.5 – The new retrofitted schools survived and served after an earthquake (SRO 2011)

2.4 Risk Mitigation Challenge

The aim of a risk mitigation programme is to reduce levels of seismic risk for a particular group of interests which consider the scope of programme, conditions and resources. Existing groups of infrastructure, hospitals, schools, bridges and other lifeline networks are the forefront of this sort of programmes. Common characteristics of critical facilities are their strategic functions to serve in both emergency and normal conditions. Thus, there is an urgent need to identify and screen the group that may be exposed to higher risk and to take justifiable decisions to control them.

The challenge of mitigation is to effectively manage the seismic risk by directing the resources and investment to urgent public buildings and infrastructure. A great majority of infrastructures such as hospitals, highways and schools in Iran have been designed using out-dated codes of practice that do not meet modern seismic standards. Identifying the critical group and prioritizing them in order of urgency is crucial before any retrofitting measures are implemented due to cost and time restriction. Generally, several variables involved in such decisions include technical, social, economical, environmental, historical and cultural factors. Risk mitigation programmes require a structured algorithm to initially recognize which class of buildings, under what conditions and the definition of safety levels, and performance criteria that are to be included within the programme (Holmes 1996).

The scope of mitigation is important to distinguish at the very outset. For individual buildings, retrofitting is a financial decision, which is normally based on a trade-off between benefit (desired level of performance) and the cost of the strengthening operation. However, the objective of national mitigation programmes turns to a wider scope of screening and selecting those buildings and infrastructure that require urgent retrofitting. At this scale, mitigating decisions could be a highly subjective process, and therefore varies from place to place. This is because several social, economical, environmental and political constraints, as well as the level of hazard and technological development can potentially influence decision-making process. Thus, understanding the scope of application, context and constraints is crucial for risk mitigation.

According to Tesfamariam and Goda (2013): "the risk management must be capable of weighting alternatives (options) and selecting the most appropriate action". This can be achieved by integrating the results of risk assessment with engineering data as well as social/economic/political factors to reach an acceptable decision. Prioritization the mitigation strategies is also mandated by most international bodies such as UNDP, FEMA, etc. Viewed in this perspective, the study attempts to establish an informed risk-based system to sort, prioritize and screen a large group of school buildings.

2.5 Current Trends in Seismic Risk Assessment

Seismic risk assessment refers the "methodology to determine the nature and extent of risk by analysing potential hazards and evaluating existing conditions of vulnerability that could pose a potential threat or harm to people, properties, livelihoods and the environment on which they depend" (UN-ISDR 2004). This process provides a roadmap for estimating the adverse consequences of earthquakes and reducing fatalities, injuries and damage. The current practice of seismic risk assessment relies on the use of a probabilistic approach as an underlying concept, assuming the risk as "a measure of probability of adverse effects". According to this notion, the likelihood of losses is calculated based on the probability of occurrence of an earthquake hazard (Klugel 2008). There are various implications of this theory reported in literature. In probabilistic seismic risk assessment (PSRA), all possible seismic source locations and geometries are determined, the maximum magnitude (M_{max}) expected from each source is estimated and the recurrence model or frequency of earthquake events for each source is obtained (Euguchi et al 2006). In fact, this process extends the probable set of events in the past that could occur in the future, defined as the site-specific spectrum. Deterministic seismic risk assessment (DSRA) applies the largest ground motions expected at their respective sites as a worst-case scenario. This process was defined primarily by the magnitude of earthquake hazard and epicentre location (distance to fault) along previous historical events (e.g. response spectrum quantified by peak ground acceleration). DSRA accounts for the random nature of earthquake hazards based on observed data, which accommodate more realistic results (Kijko et al 2004).

A common feature of the existing models is an implication of loss estimation as an effective means for quantifying the mitigation measures. For example, PSRA establishes the annual loss distribution in various geographical regions, thereby supports insurance and disaster officials, providing a rough estimation of future losses. Using the average annual loss (AAL) translates the losses into the annual benefit that could actively support a mitigation programme (Grossi 2008).

The loss estimation approaches offer a strong, realistic view of earthquakes, but have several limitations owing mostly to data inadequacy. Although, the accuracy and quality of the estimation in these approaches directly rely on the quality and availability of the inventory databases. Furthermore, these processes require a precise investigation using professional expertise to locate geological/ seismological observations that complicate the process by increasing the degree of sophistication along the time and cost of the assessment. In addition, certain assumptions usually made for developing the loss exceedance probability distributions may not precisely address the real probability of impacts and thus are limited in some applications such as insurance schemes (Boomer et al. 2002). In this case, the probability of adverse effects should normally represent the probability for each consequence of the disaster; however, due to the diversity in the likely impacts of an earthquake, not all these consequences could clearly have the same probability distribution (Haimes 2012b). Further, the limitations of current modelling practices might potentially distort the mitigation strategies which can be deemed as a static view of the earthquake magnitude.

The scope of these models accounts for likely losses that directly affect the areas at the time of the event and ignores the secondary losses (e.g. lifeline disruption/dam breakage causing unforeseen loss). This means that existing practice supports mitigation measures by addressing the direct losses while it fails to actively link the disaster consequences to response and recovery measures. According to French (2008) the problem of current modelling effort can be referred to "poor quality/expensive inventory data; the inability to model casualties accurately; the inability to estimate length of disruptions in lifeline functions; the overestimation of losses for small events and underestimation for large events".

The alternative trend takes the impact of individual earthquakes by the mean of damage and subsequently produces the various likely damage states for different scenarios of earthquake as reflected in the literature (Meroni and Zonno, 2000; Pais 1996; Klugel 2006). This direct though computationally demanding process requires a large statistical analysis based on the inventory databases to generate separate earthquake scenarios for regional study. Hence, most of these studies have employed a GIS based platform to manage the loads of data involved with the process. HAZUS is an example of this trend that establishes its direct and indirect (physical, economical and social) loss estimation upon GIS. However, HAZUS built-in loss functions defined within a damage estimation module could be a reliable predictor of seismic impacts for the cases in the US since the inventory databases have only been validated for earthquakes in California. There are many other GIS-based models with special capabilities and scopes that target particular geographic regions such as Risk Link-DLM (Detailed Loss Module - http://www.rms.com), RADIUS - US (Risk Assessment tools for Diagnosis of Urban Areas against disastershttp://www.geohaz.org/contents/projects/radius.html), CEDIM-Germany (http://www.cedim.de/english/riskexplorer.php), PEER-USA (http://peer.berkely.edu/products/strong_ground_motion_db.html), NATECH-Europe (http://enatech.jrc.ec.europa.eu/) EPEDAT - Australia (http://www.eqe.com) and SELENA – Norway (http://www.norsar.no).

Yet the library of earthquake scenarios and building losses usually employed in such models are developed for particular types of buildings for specific geographical regions and hence are unable to effectively address the real vulnerability and hazard parameters in other countries. GIS-based systems are practically limited to be widely implemented in developing countries due to technical constraints. Lack of consistency and errors in earthquake loss databases have been identified as major shortcomings that should be considered (Kleindorfer and Serter 2001). "GIS allows for easy display of input and output providing a critical function for communication of outcomes that could be useful to emergency planners and decision-makers" (Bendimorad 2001), though such a sophisticated system requires a large amount of computational and data resource which may be unavailable or unreliable in many countries (Rodriguez et al 2012). Coppock (1995) argues about the issues of existing GIS models including the weakness of commercial GIS software in modelling socioeconomic data that represent the infrastructure of any vulnerability assessment procedure; the inability to meet the needs of intended users adequately; the lack of large volumes of appropriate data typically required in vulnerability analysis; and finally, the lack of appropriate methods that are based on a sound understanding of the phenomena under consideration.

The more recent probabilistic loss estimation trend focuses on a narrow group of facilities including RC buildings (Askan and Yucemen 2010; Tesfamariam et al 2008; Tesfamariam and Liu 2010; Modirzadeh et al 2012), infrastructure: lifelines (Pitilakis et al 2006), bridges (Padget et al 2010), and hospitals and schools (Smyth et al 2004). Such studies address certain earthquake scenarios through vulnerability assessments and microzonation maps but fail to acknowledge other determinant aspects of risk management (Anagnostopoulos et al 2008). Thus, it should be noted that a comprehensive approach that could incorporate multidimensional aspects of seismic risk management is still lacking.

2.6 Classification of Seismic Risk Models

Seismic risk management occurs from a nationwide to a regional scale. This universality disables its applicability for any given specific practice. As a consequence, customization is required according to local conditions. Klugel (2008) asserts that seismic risk assessment must be conducted in a way to minimize the effort needed to obtain the results based on the client's needs. Risk assessment should consistently address the importance of application. The form and richness of the results should also correspond with application needs and objectives. Because of the difficulties involved with evaluation of hazard and vulnerability, risk assessment models could vary considerably from well-structured analytical models to empirical heuristic approaches. In this light, several seismic risk models can be distinguished in the literature which have been designed for a particular application. Reviewing the literature, the most common variants of seismic risk assessment can be identified in four categories as indicated in Table 2.2.

Table 2.2 – Summary of seismic risk assessment classes (Vahdat et al 2015)

Class	Model	Scope of application	Parameter used	Risk analysis		Reference
				Hazard analysis	Vulnerability analysis	
I	Deterministic	Critical infrastructure	Detailed geological	Deterministic	Analytical	Klugel (2006)
		High importance facility	Seismo-tectonic data			Konakli &Kiureghia(2011)
		Specific studies	Detailed Structural	Stochastic		Berrah & Kausel (1992)
II	Probablistic	Noncritical infrastructure		Probablisitc	Empirical/ Statistical	Yakut et al (2006)
		Important building/facility	Magnitude Frequency Relation			Yucemen et al (2004)
		Infrastr. Network analysis				Kiremidjian et al (2007)
		Local and regional studies	Damage Index		Analytical	Park and Ang (1985)
			Detailed Structural			Gulkan and Sozen(1999)
			Hazard distribution			Bozorgnia & Bertero(2003)
			functions			HAZAUS (2001)
III	Heuristic	Building in large area	General technical	Heuristic	Heurisitc	Carreno et al (2006)
		Mitigation program	Inventory data			Tesfamariam & Wang(2011)
		Global/regional risk analyis	Economic Index			Karbassi & Nollet (2008)
		Urban /Mega cities studies	Social Index	Microzonation		Sucuoglu & Yazgan (2003)
		Portfolio of buildings		Maps		Davison and Shah (1997)
		Resource allocation				Miyasato et al. (1986)
		Financing/insurance				Fruta et al (1991)
IV	Screening	Regional studies	General technical	Code-based	Judgmental /	ATC-13 (1985)
		Mitigation program	Inventory data	Screening	Expert opinion	Rojhan (1986)
		Planning , management		Microzonation	Checklist	ATC-21 (2002)
		Disaster risk management		Maps		ATC-40 (1996)
		Financing/Insurance				NRCC (1992)

2.6.1 Deterministic Models

For high importance applications and critical infrastructure (e.g. dams, nuclear plants) a deterministic model (DSRA) is the most appropriate option as there is no compromise between the simplification of structural models and the efficiency of analysis (Klugel 2008). DSRA is a deterministic approach since it is based on objective data and physical models. DSRA in a broader sense can be regarded as a stochastic process (Wen 2003). Using response spectrum and time-history analysis methods, Konakli and Kiureghian (2011) applied a stochastic dynamic analysis to investigate bridges considering the spatial variability of ground motions. A deterministic approach allows detailed investigation of structural response using advanced analytical models which help give a more precise interpretation of seismic risk with respective scenarios. However, developing such complex models requires sophisticated tools and expertise that can be used for single studies of high importance infrastructure at a detailed design stage.

2.6.2 Probabilistic Models

Probabilistic seismic risk assessment (PSRA) in a broader sense focuses on the most probable earthquake by defining the frequency of events or the frequency of exceedance of ground motions (or exceedance probability). A PSRA can be implemented for less important applications such as regular infrastructure, facilities and buildings in both regional and local studies. Unlike DSRA, in PSRA all possible earthquakes that may affect the system could be considered and imported into the model. Quantification of the most probable mode of damage is challenging because different states of damage have to be distinguished objectively in terms of material, age, quality and functionality. Generally, potential losses for different classes of structures are based on prior historical damage.

Potential damage is often presented in two forms of fragility curves (or vulnerability functions) and a damage probability matrix (DPM). Intersecting the most probable earthquake with fragility curves, the most likely vulnerability level of a building can be estimated for any given earthquake magnitude. Essentially, the vulnerability function is a subjective metric for assessing and predicting the potential damage of buildings, and is developed by clustering the statistical damage records for different classes of buildings. Historical records of damages are evaluated following an earthquake by groups of experts. Hence the accuracy of the functions relies on the quality of records as well as the expert's experience. Coburn and Spence (2003) developed typical vulnerability functions for masonry buildings for different states of damage as a metric of intensity measure as shown in Figure 2.6. More complete databases for vulnerability functions were documented in ATC-13 (1985) and HAZAUS (2001) which covers the most typical classes of structure in the USA.

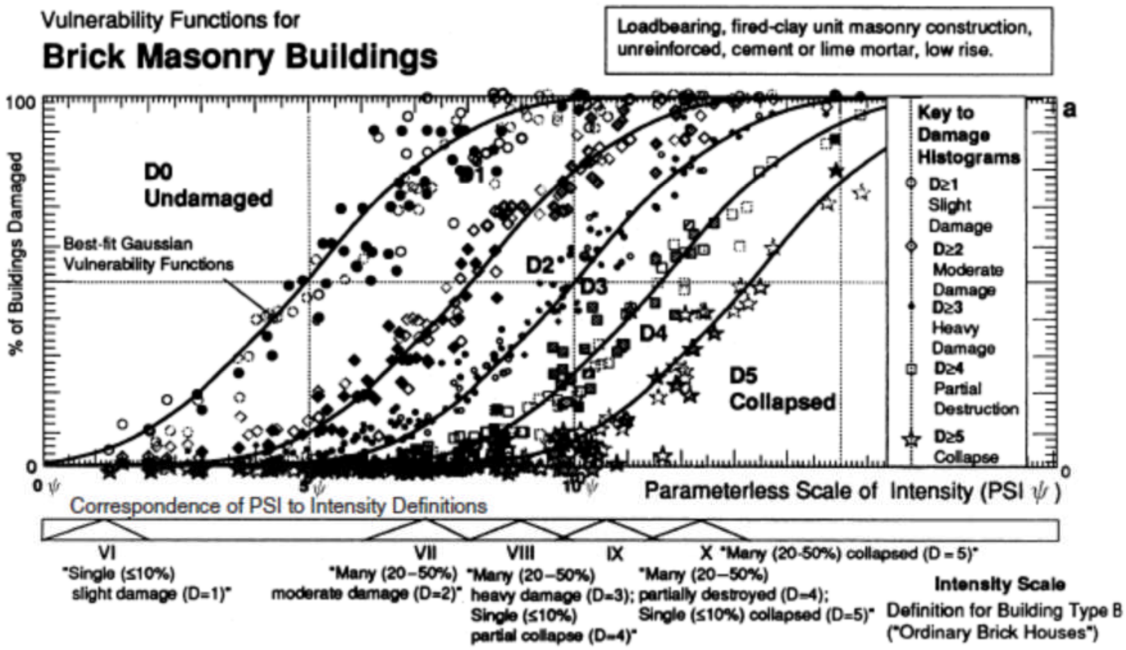


Figure 2.6 – Vulnerability functions for range of earthquake intensities (Coburn and Spence 2003)

In probabilistic approaches, macro seismic intensity scales and fragility curves establish the underlying concepts of probabilistic risk models. However, analysing the seismic risk on the basis of vulnerability functions and intensity scales raises some issues (Coburn and Spence 2003):

- Significant uncertainty due to variations in observed data can potentially be imported to the fragility curves. Normally, various states of damage are differentiated through statistical records by experts. Distinguishing the threshold among the different states of damage relies on the perception of the experts and can significantly vary among groups of surveys deriving from different places.
- Estimation of intensity is an inherently descriptive, and not a continuous, scale, which makes it difficult to use for predictive purposes.

- Intensity scales assume a relationship between the performance of typical building types with certain configuration which may not precisely match in practice.

There have been several attempts to improve the quality of vulnerability analysis using analytical and empirical methods. Yucemen et al (2004) proposed a simplified damage index to estimate the seismic vulnerability of low-rise to mid-rise reinforced concrete buildings. Yakut et al (2006) developed a scoring system for estimating the damage within low-rise buildings using different structural and seismic modifiers. Park and Ang (1985) developed an analytical damage index for estimating the vulnerability of RC buildings. The potential levels of damage were characterized as a function of seismic intensity based on two probable earthquakes, the 1971 San Fernando and 1978 Miyagiken-Oki events. Basoz and Kiremidjian (1996) used the PSRA to prioritize the risk within bridge networks that were intended for retrofitting. In this process the basic hazard and vulnerability factors (ground motion, expected structural damage) were combined to estimate the expected utility of the bridge. Temporal variations in the seismic hazard were implicitly included in the analysis by taking the maximum credible earthquake (500-year-return period intensity measure). Using a damage index as the sole criterion for estimating the risk is a reliable measure, although the threshold of structural damage can also be correlated with other indirect consequences and socioeconomic losses (e.g. human losses and casualties, costs of rehabilitation) to achieve greater performance (Coburn and Spence 2003). Nevertheless, importing such indirect effects into the existing frameworks is problematic.

2.6.3 Heuristic Models

Probabilistic models have been used extensively in regional risk assessments due to their inherent simplicity. These methods require extensive damage records from previous events which may not always available. Heuristic models are an alternative mid-range option that can be used flexibly in conjunction with analytical and empirical models to overcome existing limitations. The common feature of heuristic models is the use of a systems approach as an underlying concept.

Broadly speaking, seismic risk management requires not only the estimation of seismic risk, but also the detailed values of risk factors, in order to effectively support mitigation decisions. This involves a comprehensive systemic view that can be achieved through heuristic frameworks. A system perspective allows customizing of the structure of risk, thereby decision makers can better focus on different pieces of knowledge and clearly identify critical attributes within the risk system. A heuristic model in a broader sense can be regarded as "a transparent simulation box" while is applicable as an information system and a useful tool for higher classes of mitigation programmes, such as financial, insurance, planning and management of the disaster risk. However the scope of these models is limited to approximate risk assessment for disaster planning and management and they are not precise enough to be used in the detailed design stage, compared to deterministic and probabilistic models.

The application of major system modelling techniques such as Artificial Intelligence (AI) and Multi Criteria Decision Analysis (MCDA) to seismic risk management has not been fully appreciated yet. Miyasto et al (1986) have developed a hierarchical risk system for the preliminary evaluation of seismic risk for different types of buildings. Fruta et al (1986) proposed a knowledge-based expert system for assessing the damage status of bridge structures based on the fuzzy reasoning method. Gulkan and Yakut (1996) developed a rule-based expert system for integrating various seismic and structural attributes for estimating the damage levels of buildings. Davison and Shah (1997) introduced a linear additive model for evaluating and comparing earthquake risk between major metropolitan cities worldwide. Cardona et al (2004) developed a holistic risk system, taking to the account socioeconomic aspects of seismic risk, including physical exposure, social fragility and resilience. Using the structural damageability index as the major factor, Tesfamariam and Wang (2012) established a fuzzy-based risk assessment system for prioritizing civic infrastructure in the US. Using a weighted arithmetic mean (WAM), Sucuoglu and Yazgan (2003) have developed a two-level seismic risk assessment tool for Istanbul. The model integrates the most critical structural performance modifier using a multivariable stepwise linear regression analysis procedure. Karbassi and Nollet (2008) developed a fuzzy inference system to evaluate the risk of failure in water main pipelines in Quebec.

The common advantage of existing heuristic models is a systematic aggregation of likely impacts to evaluate the utility of interest options for certain areas that could effectively support disaster risk management. However the main challenge of existing practices is in providing a solid means to assess the accuracy and reliability of the simulation. In an attempt to address this issue, the present study will apply multiple tests to clearly investigate the effectiveness and reliability of study through verification and validation.

2.6.4 Screening Models

Screening models provide a simple method for highlighting vulnerable buildings among large groups. The process is often conducted through a rapid visual survey to identify inventory and thus classifies buildings that are potentially hazardous for safety (ATC-21 2002) by the mean of structural performance index (SPI). Hazardous buildings are identified by examining the building characteristics such as seismicity, soil condition, structure type and irregularities, as well as usage and occupancy to determine the overall SPI. Different versions of screening procedures have been suggested by ATC for evaluating potentially hazardous buildings (ATC-10 1982; ATC-13 1985; ATC-14 1987; FEMA-154 2002). ATC-13 and ATC-14 provide data and methodology that serve as the basis for Rapid Visual Screening (RVS), which was updated in FEMA-154 and developed with hazardous regions of US such as California in mind. A similar process was developed in Canada (NRCC 1992) and New Zealand (NZSEE 2009). A sample checklist for screening the buildings in high-seismic zones is shown in Figure 2.7.

OCCUPANCY	SOIL	TYPE	FALLING HAZARDS
Assembly, Govt, Office, Commercial, Historic, Residential, Emer. Services, Industrial, School	Number of Persons: 0 – 10, 11 – 100, 101-1000, 1000+	A Hard Rock, B Avg. Rock, C Dense Soil, D Stiff Soil, E Soft Soil, F Poor Soil	☐ Unreinforced Chimneys, ☐ Parapets, ☐ Cladding, ☐ Other:

BASIC SCORE, MODIFIERS, AND FINAL SCORE, *S*

BUILDING TYPE	W1	W2	S1 (MRF)	S2 (BR)	S3 (LM)	S4 (RC SW)	S5 (URM INF)	C1 (MRF)	C2 (SW)	C3 (URM INF)	PC1 (TU)	PC2	RM1 (FD)	RM2 (RD)	URM
Basic Score	4.4	3.8	2.8	3.0	3.2	2.8	2.0	2.5	2.8	1.6	2.6	2.4	2.8	2.8	1.8
Mid Rise (4 to 7 stories)	N/A	N/A	+0.2	+0.4	N/A	+0.4	+0.4	+0.4	+0.4	+0.2	N/A	+0.2	+0.4	+0.4	0.0
High Rise (> 7 stories)	N/A	N/A	+0.6	+0.8	N/A	+0.8	+0.8	+0.6	+0.8	+0.3	N/A	+0.4	N/A	+0.6	N/A
Vertical Irregularity	-2.5	-2.0	-1.0	-1.5	N/A	-1.0	-1.0	-1.5	-1.0	-1.0	N/A	-1.0	-1.0	-1.0	-1.0
Plan irregularity	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
Pre-Code	0.0	-1.0	-1.0	-0.8	-0.6	-0.8	-0.2	-1.2	-1.0	-0.2	-0.8	-0.8	-1.0	-0.8	-0.2
Post-Benchmark	+2.4	+2.4	+1.4	+1.4	N/A	+1.6	N/A	+1.4	+2.4	N/A	+2.4	N/A	+2.8	+2.6	N/A
Soil Type C	0.0	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4
Soil Type D	0.0	-0.8	-0.6	-0.6	-0.6	-0.6	-0.4	-0.6	-0.6	-0.4	-0.6	-0.6	-0.6	-0.6	-0.6
Soil Type E	0.0	-0.8	-1.2	-1.2	-1.0	-1.2	-0.8	-1.2	-0.8	-0.8	-0.4	-1.2	-0.4	-0.6	-0.8
FINAL SCORE, *S*															

COMMENTS	Detailed Evaluation Required
	YES NO

Figure 2.7 – Checklist for evaluating performance of buildings (FEMA-154 2002)

Screening models follow a simple procedure to rapidly evaluate those buildings that require urgent mitigation action. The process supports the mitigation process by addressing the public safety concerns within the community. However the scope focuses on structural damage as a direct mean of vulnerability assessment; other indirect damage induced by earthquake hazards such as ground failure (e.g. liquefaction, landslide) is not addressed in these models.

In addition, the form, quality and accuracy of scoring tactics are major concerns in screening models. The information collected from a field survey is always prone to high subjective error. As a result, great amounts of uncertainty can be imported into the model due to variability between the observed and actual data.

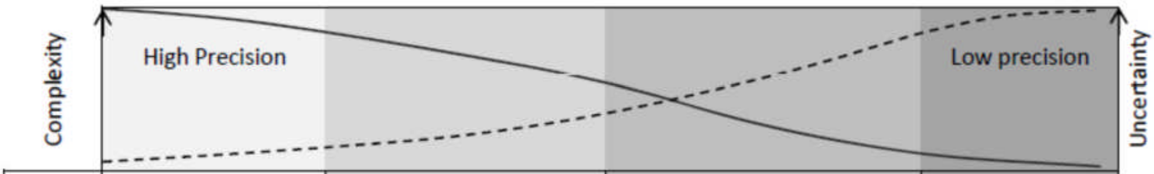
Other shortcomings of screening models are addressed in the literature (Rojhan 1986; Karbassi and Nollet 2008). The scoring model and its weight are pre-set and provided for facilities in California. The procedure uses general buildings with average conditions as representative of the whole structural group. The largest margin of uncertainty exists within the visual survey, which is still not addressed by this procedure. Further, large amounts of information are required for verification and validation of the model. In a broader sense, screening models can be regarded as a specific case of heuristic models as they use the simple additive model to score the alternative buildings according to their structural type, age, material and configurations. The scope of screening models and rigidity in using built-in criteria limits their applicability to preliminary risk assessment.

2.7 Characterising Problems

Risk assessment entails the process of quantifying the risk and essence of any disaster management process. It offers a reliable tool for making rational decisions that is often used prior to rehabilitation and developing emergency response and recovery plans. Decisions about mitigating seismic risk rely on the quality of the risk assessment and the spectrum of uncertainties in the risk parameters and processes. Some of these uncertainties can be addressed and reduced stochastically through standard procedures (i.e. ATC-14 1987). Eguchi and Seligson (2008) note the evaluation pitfalls that commonly occur in standard procedures and lead to under-prediction within large scale and over-prediction of losses in small earthquake events. They maintain that the damage functions developed for such earthquakes are mostly based on specific scenarios derived from severe earthquakes in California (1971 San Fernando and 1994 Northridge) thereby covering a narrow range of magnitude (strong to severe), and essentially ignoring the potential losses within areas experiencing lower or greater intensities (outrange earthquakes) (Eguchi et al 2008). The mitigation decisions based on these models could be valid only for a specific geographical area and may not reliable for other regions. For example, the ATC-14 method of "evaluating the seismic resistance of existing buildings" deals with regions experiencing few, but low intensity earthquakes, and this is applicable to certain regions of the US. Thus, the selection of appropriate analysis should be based on understanding the underlying concept, scope of analysis and considering its strengths and limitations to different applications.

From a systems viewpoint, various classes of application can be distinguished according to their accuracy and complexity of modelling as indicated in Table 2.3. The complexity and uncertainty of each procedure might significantly vary depending on the scope and type of problems for which they designed. For example, some deterministic models are suitable for detailed individual studies, whereas screening procedures can be useful for large group evaluation and prioritizing. Thus, to handle the problem of seismic risk management, prospective models should have adequate functionality and structure to address the multifaceted nature of risk. Risk analysis must be appropriate to the scope of application, not be overly complex (making it too expensive) yet not too simplistic, where simplicity is substituted for effectiveness. The model should also have adequate precision to handle both objective and subjective uncertainties commonly involved with different types of qualitative and quantitative information.

Table 2.3 – Complexity and uncertainty within different classes



Class	I	II	III	IV
Model	Advanced analytical	Empirical/Simple analytical	Heuristic	Screening
Method	Detailed analysis	Observed vulnerability	Expert opinion,simulating	Scoring assignment
Application	Individual building , facility or Critical infrastructure	Building stock , individual building and important infrastructure	General building stock , portfolio of building	General building stock
Cost / Expertise	High ←			Low
Data	Objective data , Fact	Mixed statistical/analytical	Mixed fact ,statistical,judgmental	Subjective data
Uncertainty type	Randomness Spacial Variability Stochastic	Randomness Temporal Variability	Mixed fuzzy , Ambiguity, Vaugness Data variability	Fuzzy knowledge-base

Existing models are largely focused on structural system performance, building capacity, layout and certain response parameters. Detailed risk analysis relying on comprehensive data collection are generally employed for the assessment of individual buildings, as they require sophisticated modelling, thereby aiming to determine whether any given building needs rehabilitation (Yakut et al 2006).

Although detailed analysis provides high-precision results, it is restricted to individual case studies and thus cannot be used for regional studies in which a large number of buildings are involved. Furthermore, these methods are based on underlying theory that could only handle the inherent variability of the hazard data (randomness) and are unable to address the uncertainties commonly involved in decision process due to modelling, parameters and modellers perception of risk. Klugel (2008) reviewed different versions of seismic risk assessment approaches and identified that the traditional probabilistic concept has insufficient understanding of modern risk analysis. This could result in the inability to present a correct definition of the true relationship, hence proposing inappropriate treatment of uncertainty. For such situations, heuristic models utilizing limited data and simple simulation are preferred because they require less expertise and allow taking into consideration more practical factors. These models have the flexibility to deal with a broad range of data and precision in practice. Hence, the research study seeks to establish a heuristic model which is able to efficiently handle a portfolio of buildings on a regional level.

Viewed from this perspective, the heuristic method was identified as the best category that fits the scope of study and thus adopted for the problem of seismic risk management for several reasons. First, the risk management process is an interdisciplinary concept that several risk parameters (expressed in various forms, accuracy and quality) from multiple sources have to be combined as an input data; while processing such a complex information system is beyond the ability of conventional methods. Second, the subjectivity involved within seismic risk management requires a flexible, well-structured methodology that could simply handle the predominant form of knowledge consistent with uncertainty theories. For example, risk analysis is concerned with estimating the potential impacts and disastrous consequences. The diagnosis of damage is a subjective process that is largely based on intuition and experience. A knowledge based system provides a consistent means of system approach that is capable of handling vague, imprecise knowledge and addressing the inherent subjectivity involved within the process. Third, decision-making in mitigation is a multidisciplinary process and requires detailed information within each category (e.g. hazard and vulnerability) along total risk. The heuristic (system) view of risk suggests a comprehensive picture of seismic risk by means of detailed knowledge, thereby supporting seismic risk management. Overall, the heuristic model can explain and clearly address the systemic interaction involved with the process of seismic risk assessment and management.

2.8 Challenges in Seismic Risk Management

Risk management strategies are concerned with an objective risk assessment that is based on evaluating the Hazard and Vulnerability. Ultimate efficacy of risk management is to provide an effective and efficient risk assessment to support decisions and policy options (Smith et al. 2006). Underestimation of risk may result in ineffective mitigation and inadequate preparedness and response measures; while over-estimation of risk could lead to costly mitigation efforts. Decisions about risk management are made upon risk assessment results, which are rarely free of the multidimensional aspects of the earthquake, including social, political, economical and strategic considerations. Thus, seismic risk management can be particularly challenging because multiple participants with different sorts of influence and behaviour are involved in the risk process (Bristow et al 2012).

The difficulties in processing risk can be referred to two major concerns and limitations. Firstly, the complexity of the disaster system is under scrutiny, due to the interactions among multiple quantitative/qualitative, linear/non-linear risk variables. Establishing the proper relationships among risk input parameters and output consequences is problematic. Secondly, the uncertainty involved within seismic risk assessment is related both to describing the level of hazard (identification of initiating events, measurements of severity of ground shaking and frequency of occurrence which is random in nature) and to the vulnerability of facilities, as estimated loss to facilities for various levels of intensity is subject to ambiguity in knowledge and lack of experience.

This implies that the characterization of uncertainties is critical in both hazard and vulnerability assessments. According to McGuire (2008), unbiased quantification of uncertainties is crucial to making rational decisions for risk mitigation. Seismic risk cannot be accurately estimated without quantifying the epistemic uncertainties in ground shaking or in building response and damage. The need to quantify uncertainty has been extensively addressed in risk applications such as NERHP, PEER and FEMA. However the reliability of these models in describing and incorporating the uncertainties within the process has not properly examined. For example HAZUS provides a standard loss estimation model through probability estimation of credible earthquakes for high seismic regions in the US. However, the inability to explicitly address the uncertainty reduces the cost-effectiveness of retrofitting options proposed by the model (Davison 2008; Durham et al 2008). The standard procedure enhanced within FEMA-154 (2002) or similar versions in Canada (NRCC 1992) serve as a rapid diagnostic tool for prescribing the decision to retrofit or not. Essentially, these approaches target a broad range of buildings through a simple field survey; while they fail to clearly provide the detailed reasoning for the proposed diagnosis and following decisions. Analytical approaches provide an in-depth investigation of earthquake hazards, although they are limited to merely providing a random picture of seismic risk. Furthermore, existing risk assessment approaches provide a prescriptive procedure that covers general types of problems. Predefined (built-in) risk parameters in such approaches can be adapted to cover a broad spectrum of facilities in terms of, for example: size, function, and occupancy load. In addition, current approaches integrate some information with pre-set weights based on the common statistical cases. The main issues in these prescriptive approaches are inability, inflexibility to add or remove new variables and options due to prescriptive concept; the inability to change the importance (or weight) of the variables for certain problems; the inability to track the operation and parameters in the model; the inability to apply for particular seismic application (i.e. critical portfolio of buildings); the inability for tuning due to the low sensitivity of model to small changes in risk input parameters (i.e. screening models).

Rational risk management should be capable of effectively comparing and prioritizing multiple alternatives. The ability to compare risk across regions becomes more critical to both private and public stakeholders who have competing priorities for urgent retrofitting action. Inadequate decisions could compromise mitigation measures by slowing the retrofitting, renovation and even reconstruction process. Moreover, there is a need for a simple but well-grounded risk management system to interplay within different levels of risk knowledge and decision makers. Therefore, a rational risk management system to address multidimensional impacts of earthquakes and support mitigation decisions is paramount.

2.8.1 Uncertainty Paradigm

Uncertainty is a critical dimension in seismic risk management as it directly influences the accuracy of the risk modelling, assessment and management. The entire process of risk assessment involved with the sort of uncertainty that can be classified in the two categories: aleatory and epistemic (Ayub and Klir 2006). Aleatory uncertainty refers to variability or randomness as an inherent feature of a disaster system. This deals with data variability in time and space which affects the overall risk management process. Epistemic uncertainty originates from the lack or deficiency in knowledge, and thus can be reduced by improving the quality of the underlying knowledge and expanding the sources of information. This kind of uncertainty is caused due to the subjectivity of the risk analysis and emerges during the survey process, thereby relying on the skills and experience of experts.

Seismic risk assessment is a product of both types of uncertainties, and thereby depends on the scope of application. Some types of uncertainties might be highlighted and considered as a major determinant. Traditionally, probabilistic expressions are used to represent the variability and randomness within seismic hazard analysis. Randomness prevails in determining the likely severity and hazard analysis of critical facilities exhibiting the temporal and spatial aspects of earthquake hazard, and therefore requires high-quality historical information to establish the probability distribution of severity and occurrence. In this case, historical records in terms of size, location and magnitude are the major sources of data to address the temporal and spatial variability of an earthquake event.

However, uncertainty captured by the classical statistical approaches (e.g. probabilistic, stochastic) is restricted to variability of risk data and thus can be applied only to estimate probabilistic model input parameters (Nilson and Aven 2003); while a great portion of risk assessment and management is fraught with imprecise vague information which cannot be fully addressed through classical probabilistic approaches. Describing the intensity of seismic hazard can be highly subjective as it relies on the subjective scale of damage (MMI scale for intensity). Most of the hazard attributes are site-specific and dependant on the quality of the field survey as well as the perception of subsurface (geology) characteristics. Exploring more precise geological surveys can improve the knowledge of underlying soil, hence reducing uncertainties in site-specific data. Different levels of uncertainty exhibited in various risk applications can be schematically shown in Figure 2.8.

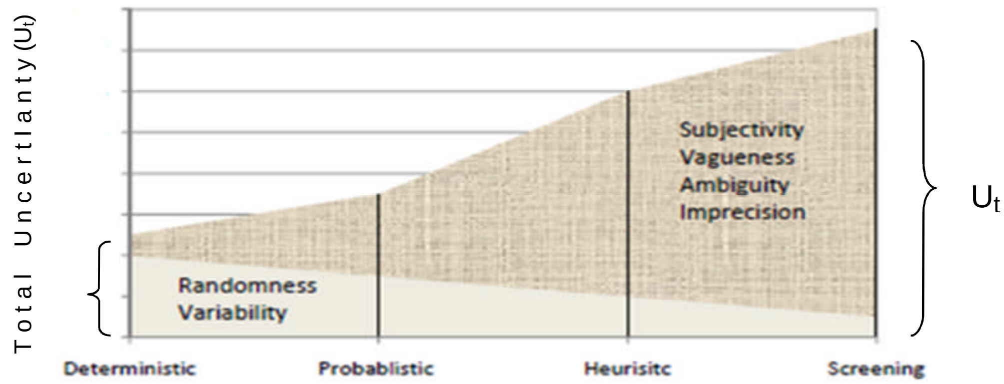


Figure 2.8 – Uncertainty in seismic risk models

Analytical and empirical models that use precise objective information are prone to subjective errors, and therefore more appropriate for detailed-design studies. In this case, the randomness in estimating seismicity is predominant in the risk assessment process, while epistemic uncertainty prevails in heuristic and screening models since the knowledge extracted from survey and expert opinion. The more human engagement in the knowledge acquisition process (i.e. perception, judgment and qualification), the more subjectivity and vagueness will be imported to the model.

Any field survey (inspection) is prone to subjective/qualitative judgments (Hadipiriono and Ross 1991) which are prone to ambiguity and imprecision. The modeller's perception can significantly influence risk modelling and assessment and management (Haimes 2012a). For example, the vulnerability of a facility is an inherent subjective factor that is commonly evaluated through observation and expert survey. The inventories of the existing buildings are imprecise in nature as it is a product of a (visual) survey of the structure, materials and engineering quality; all of which relies on the surveyor's skills and experience. In addition, the estimation of likely damage is a subjective process which might significantly vary from individuals and places involved.

Several vague and imprecise terms such as 'high performance', 'strong' and 'severe damage' are frequently used in describing both hazard intensity and likely consequences of an earthquake. For example, to determine the performance levels in buildings, some basic states such as 'life safety', 'collapse prevention', 'extent of damage' and ' severity of earthquake hazard' are commonly used. It is evident that these types of statements describe epistemic (or knowledge-based) uncertainty because it can be reduced by expanding new resources and knowledge. According to Bristow et al. (2012) the uncertainty of extreme events might be attributed to ambiguity in identifying the initiating events, perceptions of risk-causing factors and distinguishing them; lack of knowledge in developing the complete set of consequences; and impreciseness in measuring the intensity and magnitude of the consequences. Part of this uncertainty stems from a qualitative scale of perception which is full of vague overlapping terms. This type of uncertainty is also regarded as fuzziness because it stems from ambiguity or vagueness in describing knowledge, thereby reflecting the human ability to address the real world problems using statistical models (Ahmad and Simonovic 2011).

2.8.2 Complexity Paradigm

Pich et al. (2002) defines complexity as "the inability to evaluate the effects of actions because too many variables interact". Earthquake risk is the product of complex interactions between multiple disaster causing factors, disaster-prone environments and the hazard bearing bodies as an input terminal for the whole disaster system. One reason for this complexity is the interaction within and between the natural environment, human population (actions, reactions and perceptions), and surrounding built environments, all of which can create a complex challenge particularly in seismic risk context (Simonovic 2011). In addition, the complexity of a disaster risk system is the result of interaction within sub-system components including hazard and vulnerability.

The causes for seismic hazards are many and diverse, therefore the risk might exhibit a broad range of impacts on communities and infrastructure. Earthquakes are the product of highly nonlinear and very complex physical phenomena that could potentially cause varying degrees of damage to socioeconomic systems, social life and regional economy (Jiu-Ping and Yi 2009). The integration of various physical, socioeconomic impacts of such complex system requires a cross-disciplinary thinking which cannot be modelled through a simple additive model. Furthermore, nonlinear variation in natural environments (hazard attributes) and human-extracted knowledge hamper the implementation of the existing model due to large interactions. NRC (2011) asserts that:

> ". . . No theory adequately describes the basic features of dynamic rupture and seismic energy generation, nor is one available that fully explains the dynamical interactions within networks of faults. Large earthquakes cannot be reliably and skill fully predicted in terms of their location, time, and magnitude. Even in regions where we know a big earthquake will eventually strike, its impacts are difficult to anticipate."

In addition, decision-making in a disaster context is an inherently complex process as it is involved with several interrelated risk parameters that are processed through the diverse methods, with varying degree of reliability (Haimes 2009).

Seismic risk assessment consists of complex processes, such as describing the diverse characteristics of buildings on a limited scale, estimating likely damages, aggregating and ranking wide range of risk factors (Mezzina et al 2008). Furthermore, the vast majority of existing models take certain aspects of earthquakes into consideration, thereby failing to accommodate a comprehensive picture of risk impacts. For example, utility measures have been widely used as a sole determinant for evaluating mitigation options through cost-benefit analysis (Smyth et al 2004), life-cycle costing (Arikan et al 2005) or direct monetary valuing (Vanzi 2002). Moreover, an integrated perspective of seismic risk that could be applicable to the technical level of the system is still lacking. A systematic analysis of earthquake impacts is the premise for recognition, simulation, and evaluation of the system (Jiu-ping and Liu 2009). Therefore, a systematic perspective should be enhanced within the underlying concept any seismic risk management problem.

2.9 Summary

The deployment of seismic risk management is fraught with issues of complexity, ambiguity and uncertainty which pose critical challenges in assessing, modelling and management. The complexity of earthquake impacts and the uncertain nature of information necessitate the establishment of a systematic framework as a critical requirement for processing seismic risk management. A variety of applications can be used for modelling seismic risk, while most of those share a common probabilistic concept that could capture only the physical aspects of earthquakes and may be unable to effectively address the multidimensional composition of the seismic risk. The scope of existing models is restricted to particular applications in a rigid format which may not be customized or be expanded to large-scale mitigation programmes. Implementing existing methodology for managing large mitigation programmes could mislead the overall retrofitting measures because they have been essentially designed for detailed investigation within high-seismic regions; thus they are unable to process large number of buildings subjected to varying degrees of seismic hazard. Consequently, prioritizing the retrofitting of school buildings requires a holistic risk-informed system to effectively address, not only the physical impacts of an earthquake, but also to be capable of incorporating the socioeconomic effects of a disaster to support multiple stages of the seismic risk management.

Moreover, the conceptual theory of probabilistic models is unable to capture the epistemic uncertainty (e.g. vagueness, imprecision and subjective judgment) that is often involved with seismic application. The existing models share a common issue which is the pre-defined and built-in concept (i.e. criteria, scale) that does not allow any modification or customization for a new situation. As a result, this thesis adopts a heuristic model to systemically address the existing challenges within seismic risk management problems.

Chapter 3: System Modelling Techniques

3.1 Introduction

The primary aim of this research is to investigate the feasibility of a system in order to model multidimensional aspects of seismic risk. In pursuit of this aim, Chapter 3 explores the potential techniques (MCDM and AI) that might be used in system modelling.

3.2 System View of Seismic Risk Management

Risk analysis is inherently involved with a complex, multidimensional process that requires the integration of myriad sources of information to characterise seismic risk. According to Haimes (2012a): “the entire process of risk assessment, management, and communication is essentially a synthesis and an amalgamation of the empirical and the normative, the quantitative and the qualitative, and of objective and subjective evidence”. Different modes of thinking are required to address the challenges associated with defining, modelling and quantifying the risk which is often influenced by the modeller’s skills and experience. Several quantitative and qualitative tools and techniques contribute to risk analysis in order to improve understanding of risk in specific disciplines. However, the intricacy and complexity involved in risk assessment cannot be modelled, understood and addressed through ad-hoc approaches. Given the diversity in size, scope, functionality and configuration of current infrastructure, as well as the immense uncertainty associated with the risk management process, modelling should be grounded on a systemic and repeatable basis, presenting the multidimensional characteristics of seismic risk through the integration of multiple metrics.

A systems approach is appropriate to managing complex problems by dividing them into simpler sub-systems or components (Deng et al. 2011). This approach usually focuses on interactions among the myriad elements involved in risk assessments, as well as on the effects of their interactions in future decisions. System-based risk modelling can effectively address the multifaceted composition of seismic risk by incorporating levels of uncertainty and complexity due to the nonlinear nature of the states of all human and built environments (Haimes 2009). Aven (2011) argues that risk and vulnerability are the manifestation of the inherent state of the system and its environment; hence they should be dealt with and quantified through a system-based hypothetical and methodological approach. Haimes (2012b) advocates that the process of risk modelling, assessment, and management must be holistic, comprehensive and repeatable and must be handled systemically to perceive the state of the system and model the system blocks. Accordingly, the systems approach is required for complex situations to improve the understanding of the system's characteristics, including function, behaviour and interactions.

Hence, a system-based approach to risk assessment and management is of utmost importance for the credibility and effectiveness of decision-making and the ultimate quantification of the complex multidimensional aspects of seismic risk.

3.3 System Characteristics of Seismic Risk Management

Seismic risk management is characterized by carrying multiple dimensions, with typical aspects of social, economic, political, environmental which might be in conflict with each other. Several alternatives need to be considered and evaluated in terms of the many different criteria which result in a vast body of data that are often imprecise or uncertain. A large number of individuals are usually involved in the risk assessment process, including decision-makers, planners, experts and other interest groups from organizations and the community, some or all of which may have conflicting preferences (Lahdelma et al. 2000). The scope of seismic risk management involves balancing these variables, as shown in Figure 3.1.

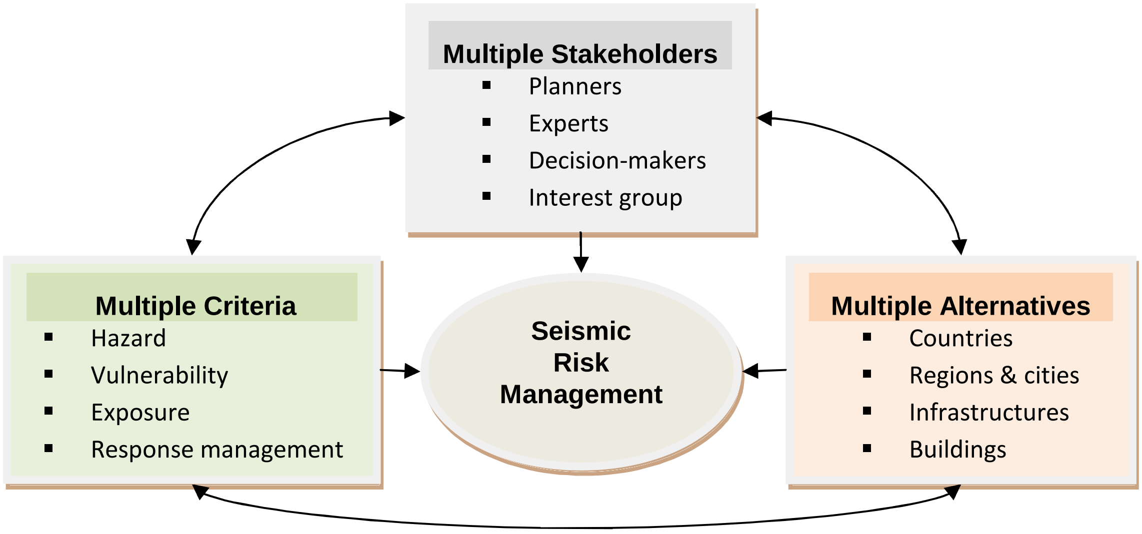


Figure 3.1 - Multifaceted aspects of seismic risk management (Vahdat et al. 2014a)

Multiple views and interactions within risk factors, alternatives, individuals and organizations cause complexities that require a systematic and structured reconciliation of these disparate factors (Avouris 1995). Clearly, there is no single or best solution for this kind of problem, and thus seismic risk mitigation decisions require a compromise to address a wide range of criteria at different levels of organization and operation among experts and local users.

Risk management is concerned with modelling and assessing risk which can refer to the inherent characteristics of the disaster risk system. According to Avouris (1995) a disaster system is multidisciplinary by nature, as it requires a continuous compromise between various demand knowledge base and problem solutions that could only achieve through an expert-based cooperative approach. Within the process various conflicts may arise due to multiplicity of views, thus requiring consensus within the decision-making process. In addition, the complexity and dynamic nature of an earthquake hampers the modelling process. Due to the subjectivity and variability of risk data, information used in the risk assessment process has been often imprecise, uncertain or even erroneous. Furthermore, spatial variation is an inherent feature of natural systems, since disasters impose a range of impacts for a given scope of the study (i.e. international, regional or local).

Therefore, aggregating a large number of inputs within a complex system requires an approach that is capable of interacting with a range of information, facts, algorithms and experiences. The questions and challenges in a seismic risk management process cannot be addressed effectively and reliably, without adhering to a systemic approach to risk modelling, assessment and management. A system-based risk analysis can effectively address the potential challenges caused by complex multidimensional aspects of seismic risk, and can handle uncertainties (due to spectrum of objective and subjective information) present in decision process. The systems approach can be viewed as a common denominator, unifier and unique integrator that acts as a bridge between the various disciplines involved in the seismic risk management, taking advantages of both system engineering and risk analysis.

3.4 System Requirements

Planning for disaster management involves not only physical and structural consequences of a natural hazard, but also considerations of different socio-economical, environmental and historical factors which might influence a population or future generation. Thus, a risk management framework should capable of integrating various perspectives of seismic risk; conducting seismic risk assessment; evaluating the mitigation strategies; and performing a risk-based trade-off among mitigation strategies (retrofitting decision). Improvement in the seismic risk prevention and mitigation process directly depends on the perception of earthquake impacts which in its most general sense relies on the surveyor's experience and quality of the assessment. This could directly affect the investment in seismic risk mitigation and preventive measures, as well as the development of legislation, standardization, and governmental regulations and control (Ahmad and Simonovic 2011). The framework developed in this research must support a broad range of decisions in disaster management context. A new holistic approach is required specifically to address the existing limits. The prospective model should be capable of handling the following characteristics (Vahdat et al. 2014a):

- Multidisciplinary processes
- Multiple sources, criteria and uncertain data
- Conflict among variables
- Multiple stakeholders
- Multiple causes and effects
- Multiple alternative comparisons and rankings

Viewed in this light, the prospective method should be able to address the following requirements:

(1) Complexity: It must be systematic, following a logical process in multiphase mitigation processes within a complex system;

(2) Nonlinearity: It should allow trade-offs between non-commensurate, often conflicting variables by capturing nonlinear interactions;

(3) Consistency: It should be consistent with rational decision-making;

(4) Flexibility and Customizability: It should flexible enough to handle multiple sources of data,(including quantitative and qualitative types) and to be customized to interact with multiple disciplines;

(5) MCDM-based: It should allow comparison and prioritizing alternatives;

(6) Uncertainty: It should explicitly address the subjectivities while it is implicitly capable of handling randomness;

(7) Transparency: It should be clearly written in order to be easily understood and to be tractable through the verification process;

(8) Communicative: It should be informative to communicate effectively between experts and stakeholders;

(9) Efficiency: It should be able to rapidly handle a great amount of information and broad range of variables, in order to produce relevant outputs at the reasonable time and cost;

(10) Trade-off: It should be full compensatory in concept, allowing for trade-offs among disparate, often conflicting risk parameters.

In addition to above requirements, Dallenbach and McNickle (2005) suggest that the decision model should be able to produce information that is appropriate in a useful form which can be used directly for decision-making without further manipulation or extensive translation. The model must also be robust enough in that reasonable changes in uncontrollable input parameters should not completely distort the results and invalidate the model. In other words, it should adequately reflect the small changes in input variables while maintaining its robustness.

The above criteria collectively define the boundary of an ideal system and can be used as a guideline to review and select the appropriate mathematical technique. The techniques that better satisfy the above requirements would be potential candidates for further investigation.

3.5 Uncertainty in Disaster Context

In seismic risk modelling, the nature of uncertainty is crucial and should be carefully considered prior to the selection of an appropriate method (Ross 2004). The challenge of selecting a method is "to formulate suitable numerical models in a quantitative manner without ignoring significant information or unwarranted assumptions; inappropriate modelling of uncertainty can undermine the purpose of an analysis. If this balance is violated or not achieved, computational results may deviate significantly from reality and associated decisions may lead to serious consequences" (Beer et al. 2013). Broadly speaking, a mathematical model can be formulated by analysing the nature of the available information. In reality, available information may appear in various forms, either objective or subjective, or due to imprecision, incompleteness or ambiguity. The appropriate model should support the type and quality of information to consistently address this problem.

Table 3.1 gives a summary of information commonly used in various seismic risk applications. Referring to various classes of risk analysis already discussed in Chapter 2 (Section 2.6); the role of vulnerability or hazard analysis might vary considerably. For example, the stochastic nature of an earthquake (or randomness) in terms of time (temporal) and location (spatial) is a core concept within DSRA and PSRA; while in heuristics and screening approaches the vulnerability assessment is highlighted. Decisions regarding risk mitigation have been highly focused on estimating the capacity of damage within existing buildings, rather than spatial or temporal considerations of an event.

The inherent ambiguity and vagueness associated with a vulnerability assessment make a compelling reason that seismic risk assessment is prevailed by subjectivities as a result of vague or imprecise terms frequently used in risk assessment, damage assessment and expert judgments. Vague, imprecise and incomplete nature of inputs of the risk parameters can be suitably handled using the fuzzy set theory.

Table 3.1 - Generic information within seismic risk application

Application	User	Purpose	Information	Category
Urban planning	Planners	Identify high risk locations for urban design and infrastructure development	Risk mapping	Risk
Building Retrofit	Owners	The best retrofitting option	Structural capacity Cost-benefit	Vulnerability Economy
Mitigation program	Disaster manager	Identify high-risk portfolio screening	Potential buildings capacity	Vulnerability
Insurers and reinsurers	Insurer company	Set insurance premium	Annualized loss exceedance probability	Hazard
Emergency planning	Civil protection agencies	Plan size and location of emergency facilities	Estimate potential fatalities, injuries, damages	Hazard Vulnerability Exposure
Building code development	Building regulators	Determine optimum resistance levels	Structural algorithm Experiments cost-benefit data	Vulnerability, Hazard Economy

Sources: Ozcan et al. (2011), Birkmann (2006), UN-ISDR (2004), NRC (2011)

Furthermore, "the level of uncertainty within a system is proportional to its complexity, which arises as a result of vaguely known relationship among various entities, and randomness in the mechanism governing the domain" (Deng et al. 2011). Zadeh (1973) asserted, "as the complexity of a system increases, our ability to make precise and yet significant statements about its behaviour diminishes until a threshold is reached beyond which precision and significance become almost mutually exclusive characteristics".

According to Blockley (2013) and Zadeh (1996) "complex systems cannot be dealt with effectively by the use of conventional approaches, largely because the description languages based on classical mathematics are not sufficiently expressive to serve as a means of characterization on input-output relations in an environment of imprecision, uncertainty, and incompleteness of information". In addition, it is difficult to precisely establish the temporal and spatial relations for earthquake events, due to the complexity and random nature of earthquakes. Application of probability theory in the large complex disaster system is compromised. As a result, an alternative heuristic model is required to address multifaceted nature of earthquakes while supporting multiple stage of seismic risk management.

3.6 Classification of Uncertainty Theories

Decision-making in the disaster risk context is a complex process due to the presence of a broad range of variables in assessment and a great deal of uncertainty involved with both parameters and modelling process. The nature of uncertainty is crucial and should be pondered prior to the selection of an appropriate method. Risk modelling should be capable of handling different types of uncertainty; while implicitly accounting for the factors that affect the input in the form of a probability distribution (Shaheen et al. 2009). Types of uncertainties in various situations can be captured through different uncertainty theories. However, classifying individual uncertainties and quantifying them into a single perceived uncertainty is extremely difficult as it still in their infancy (Philips et al. 1999). Thus, understanding and identifying each type of uncertainty within a system greatly contributes to the total uncertainty. A detailed summary of uncertainty can be found in literature (Klir 2006; Ross 2004). The former presents nine theories of uncertainty by means of their generality. The five most common theories used in the context of disaster risk assessment are potential candidates for present model.

Probability theory is the most popular way of quantifying aleatoric or natural variability by the mean of statistics of frequencies (Blockley 2013). Due to the random nature of seismic hazard, the probability theory has been effectively used to quantify uncertainties in the size, location and the rate of recurrence of earthquakes. "Because of the uncertainty of the knowledge available about earthquakes and their recurrence patterns, all loss estimates are necessarily extrapolations into the future of the observed statistical distribution of earthquakes and their effects in the past" (Coburn and Spence 2002). In reality, lack of physical data (i.e. historical records of earthquake intensity and losses), or of poor quality data to establish loss distributions, restrict the effectiveness of the probability method in objective risk modelling. Monte Carlo simulation is an alternative way to overcome the limitation of data through random sampling and stochastic modelling. Expert knowledge is another way to compensate the inadequacy or poor quality data through Bayesian and evidence theory.

Bayesian theory is another variant of probability theory that uses a probability measure, either as a frequency, or as a subjective judgment about a degree of belief which can be conditional on unknown variables. However, such an approach does not allow the decision-maker to acknowledge incompleteness explicitly (Blockley 2013). In other word, the Bayesian method allows, "updating subjective knowledge with experimental results of observations" (Singal and Kiremidjian 1998) combining the domain knowledge within multidisciplinary platform (e.g. historic data, expert opinion). The theory has the ability to analyse the observations that occur sequentially at different times and thus is useful for calculating the probability of multiple related events through conditional probability.

Singal and Kiremidjian (1996) proposed a systematic approach for estimating fragility curves and damage probability matrices in different structural systems. To obtain a more robust fragility curve they used Bayesian theory to enhance the prediction's robustness. Thus the Bayesian method takes advantage of aggregating multiple techniques for improving the robustness of the model (Li et al. 2010). Bayraktarli (2009) examined the ability of the Bayesian method for various seismic risk mitigation, including retrofitting decisions, seismic risk assessments and the updating of fragility curves with new information in consideration.

The Bayesian-based model, although accommodating a decent control in complex modelling of interdependencies within risk variables, still carries the limitations of probability theory, requiring a great amount of data to establish the distribution of events. In addition, users have to precisely define the interrelations between risk variables in advance. Nevertheless, Bayesian theory provides a sound platform for treatment of uncertainty in both forms of aleatory and epistemic (Beer et al. 2013).

Dempster-Shafer theory (DST) of evidence offers an alternative to probability theory for describing the uncertainty within intervals or due to significant ignorance. This concept is potentially valuable as it allows the combination of subjectivities with probabilities and thus can be used in situations where precise measurement is not possible. Furthermore, the rule of combination in the framework of the DST provides a compromised-platform for combining multiple pieces of evidence given by independent sources of information, regardless of what form that takes, e.g. observation, experiment or judgement (Yamada 2008). This ability is a significant privilege among alternatives as it enhances the scope of information within individual environments and from the viewpoint of consensus generation.

In other words, the DST can effectively work as a combinational rule of evidence in either probability or fuzzy sets environments. For example, Dong et al. (1987) developed a model based on the DST to incorporate fuzzy information with the current probabilistic approach for seismic hazard analysis. However, the proposed DST-based method requires extensive consensus among experts to establish belief functions. Moreover, the controversies regarding the validity of the DST and the problematic justification of polling evidence still remain since "existing formulations of the requirements for the use of Dempster's rule are not completely clear" (Voorbraak 1991). In addition, the adequacy of knowledge in representing interdependencies of evidences and defining the belief functions is questionable (Yamada 2008).

Beer et al. (2013) argue that the intervals may not reliably describe the impression of boundaries because the specification of intervals implies that "although a number's value is not known exactly, exact bounds on the number can be provided". Alternatively, the fuzzy set theory provides a more flexible basis for describing imprecision by relaxing the bounds to a smooth transition that truly support the imprecision concept. This feature makes fuzzy sets the first choice for representing the subjectivities by the means of vagueness, imprecision and ambiguity. For example, the common statement in damage assessment such as 'heavy', 'considerable', 'significant' express the fuzziness in terms of vagueness or imprecision. Many other terms used in seismic codes such as 'life safety', immediate occupancy', 'collapse prevention', 'required level of seismic performance', 'extent of damage', the 'severity of seismic hazard exposure' can be referred to epistemic uncertainty because these terms are intrinsically vague.

This is epistemic as the uncertainty is reducible by expending resources to obtain more precise information. Buckley (1983) examined the preference between

Bayesian and fuzzy set theory in risk-based decision-making. He suggested that suitably of each method should be seen, according to the problem features. The fuzzy set theory is appropriate for the case where state of system is vague, too complex or ill defined, and where statistical (Bayesian) methods have limited ability to address it effectively. If uncertainty stems from randomness, the Bayesian theory might be appropriate.

As a result, the fuzzy set theory was adopted to maintain a consistent framework for representing epistemic uncertainty along high levels of complexity, within seismic risk management. The fuzzy algorithm is beneficial for improving the high level of system (i.e. KBS) that allows interaction with other approach.

3.7 Mathematical Modelling Techniques

Mathematical models express the relationship between the various components in the form of quantitative (Dallenbach and McNickle 2005). While the relationship within simple problems might be formulated using mathematical expressions, complex systems require performance measures to evaluate how well the decision variables or alternative course of action could meet the objective under problem constraints. Thus, the modelling technique should be simple in that the relation and interactions are easily tractable and perceivable by decision-makers.

Selecting an appropriate mathematical modelling technique is of utmost importance. Several methods have been developed to support a sound decision-making process by balancing the pros and cons of alternative courses of action. However, most bear one or more shortcoming that hampers an effective aggregation and trade-off among criteria (Ohlson et al. 2006). Some methods only focus on generating detailed or precise information about a narrow set of impacts. For example, conventional risk assessments are limited to temporal or spatial impacts of earthquake; while real-world mitigation decisions always involve trade-offs among multiple risk factors under certain scales of concern (i.e. short or long term disaster planning).

A balanced representation of impacts is crucial to achieve the objectives, regardless of how precise it is, as it is "far better an approximate answer to the right question . . . than an exact answer to the wrong question" (Tukey 1962). Many methods produce a single 'best' alternative, rather than an open exploration of a range of 'feasible' alternatives. A sound modelling technique should assist decision-makers in evaluating and exploring wide range of alternatives and also support a transparent unbiased documentation on the logic and be rationale for ultimate decisions (Keeney 1992). Zanakis (1998) argues that different techniques could produce different results for a same problem, possibly with the assumptions used by the same user. This inconsistency in results is not unexpected, first because each method applies a different algorithm for selecting the best solution; and second because techniques of weighting are different depending on aggregating operators. Finally, some methods use different scaling techniques that may not necessarily be linear and thus could change the weight and in turn the final results.

In the present problem of seismic risk management, the modelling techniques should be able to aggregate several dimensions of earthquake impacts while being capable of incorporating the DM’s preference and behaviour in the presence of uncertainty within transparent and mathematically based risk management. For this purpose, 10 mathematical modelling techniques were chosen. AI and MCDM disciplines are briefly reviewed in terms of their advantages and drawbacks in the following sections.

3.7.1 AI Techniques

3.7.1.1 Genetic Algorithms

Genetic algorithms (GAs) is a heuristic search technique proposed by John Holland (1975) for optimizing relevant objective or fitness function. This evolutionary computation algorithm is inspired by biological evolution and concepts regarding chromosome, genes and inheritance, cross over. Like other optimization algorithm, GAs starts with defining objective functions and ends by testing for convergence. However, rather more complicated process follows to translate and narrow down the set of possible solutions (array of decision variable values) so called as chromosome (Rani et al. 2012).

According to Everett (2001) GAs can be useful in three distinct domains. First, in optimizing or improving the performance of real operating systems where the interactions between the parameters are not generally amenable to analytical treatment and thus the researcher has to resort to appropriate search techniques.

Second, it can be used for testing and fitting quantitative models that require searching for parameters to optimize a fitness function. Third, it maximizes the operating system's performance and minimizes the misfit between a model and observed data, which is known as system tuning.

The advantage of GAs in solving large-scale, nonlinear optimization problems involved with either discrete or continuous parameters when no compromise for simplifying the assumptions is required (Haupt and Haupt 2004) such as a water distribution systems (Nicklow 2010), traffic and scheduling (Cevallos & Zhao 2006), and allocation of funds to projects, and Space Truss Optimization (Krishnamoorthy et al. 2001).

3.7.1.2 Artificial Neural Networks

Artificial neural networks (ANNs) is self-learning optimization algorithms inspired by the basic framework of the brain, the neuron. Unlike the symbolic AI approach (expert system) where people have the problem of a "knowledge acquisition bottleneck", ANNs employ a data-driven acquisition process (machine learning) and their nonparametric ability to generalize (Bae and Kim 2011). The advantageous feature of ANNs for classical statistics is the forecasting ability where no deep reasoning is required. In other words, there is no need to know the concrete functional relationship between input and output (Wang ad Elhag 2007). This feature makes it suitable for finance applications such as business classification (Pendharkar 2005), resource allocation (Ko & Lin 2008), pattern recognition and regression.

Like GAs, ANNs are a powerful tool for solving complex nonlinear problems associated with high computation rate where no rigid assumption is required for simplifying the problem. However, ANNs have significant shortcomings; perhaps the most daunting issue is the unclear process of training that makes it seems as a "black box" and unsuitable for addressing real-world problems. Secondly, ANNs require a long time for training in order to deal with huge amounts of data of large databases. Thirdly, neural networks lack explanatory facilities for their knowledge. The knowledge of neural networks is hidden in their weights and structures. Besides, it is sometimes hard to extract rules from a trained neural network (Craven & Shavlik 1997; Bae and Kim 2011; Ko & Lin 2008).

Nevertheless, ANNs has been successfully used in engineering applications. Kim et al. (2002) applied ANNs to concrete quality assurance and concrete mix designer tools that support the decision process. Dias et al. (1996) explored ANNs for construction bidding decisions. Aiken (1997) employed ANNs to study group DSS and compared them with regression and GAs. ANNs results found to be more reliable than regression analysis.

3.7.1.3 Expert System

The expert system, more broadly known as the 'knowledge base expert system' (KBES) is a branch of AI that employs fuzzy logic as a mean of approximate reasoning. "Fuzzy reasoning approach possesses the ability to mimic the human mind to effectively employ modes of reasoning that are approximate rather than exact" (An et al. 2013). Within a KBES, the fuzzy set theory is applied or extended to handle both numeric and linguistic input/output variables in a uniform way. The knowledge base can be developed by encoding expert knowledge into linguistics (IF-THEN) rules, giving a transparent system which can be maintained, expanded and verified by experts (Roubos and Setnes 2001).

Since the knowledge base is commonly fraught with uncertain and vague information, an expert system requires high-performance domain-specific experts. In general, fuzzy logic has the ability to cover a broad range of complex problems involved with uncertain nonlinear relationships within variables.

However, fuzzy logic comes with some general limitations. Hong & Lee (1996) argued that it is a shallow concept that is unable to offer a common framework to deal with different kinds of problems; while this feature may be attributed to the flexibility in heuristic approaches that offer case-by-case answers with no formal procedure to apply to all problems. Knowledge base acquisition is another challenge in an expert system – a difficult task particularly in large multilayer systems. Experts may not always be available in specific domains, and their knowledge may hardly reach a consensus on first survey that could lead to episodic and time-varying. In addition, the validation process and refining of knowledge is episodic and time-varying, and is hardly a trivial task.

Despite these shortcomings, expert system experienced in multiple contexts including construction engineering and risk management. Kangari (1988) applied an integrated knowledge-based system for construction risk management using an expert system to calculate overall risk of a project by combining values for different on-site risks. Alim and Smith (1989) applied expert system to facilitate interpretation of seismic design codes. They have used fuzzy sets to formulate such imprecise linguistic variables and to infer conclusions about seismic design parameters. Sen (2011) applied the expert system for developing an earthquake loss estimation framework.

The model uses basic hazard and vulnerability indices to classify the buildings into different life-safety categories (building failure classes). The model provides a rapid framework that is suitable for preliminary screening, although it requires a detailed structural property (stiffness values) to establish reasoning procedures which failed to capture a picture of risk due to lack of exposure data. Tesfamariam and Modirzadeh (2009) used a hierarchical expert system to identify critical bridges which pose a significant threat to life safety, and prioritized them accordingly. Despite the sound implication of fuzzy logic for aggregating the different performance parameters in the presence of vagueness and uncertainty, the model requires a deep calibration and validation through real stakeholders.

3.7.1.4 Neuro-Fuzzy Inference Systems (ANFIS)

The neuro-fuzzy inference system (ANFIS) combines the strengths of fuzzy logic and ANNs and thus is capable of handling complexity, uncertainty, unspecificity and nonlinearity (Jang 1993). There are a number of areas in which both methods have a synergy for integration. Both expert systems and ANNs have a common origin for simulating human intelligence. They each have the ability of aggregating quantitative and qualitative information. They share a multidisciplinary scope of applications in science and engineering, though the ANNs technique is still in its infancy. Limitations of expert systems in knowledge acquisition and representation can be compensated by ANNs that can learn from typical example data. Conversely, weaknesses in user-interface and explanation capabilities of ANNs can be strengthened by using an expert system (Osyk and Vijayaraman 1995).

Sanchez-Silva and Garcia (2001) developed a seismic damage assessment model based on fuzzy logic and ANNs in order to define mitigation procedures and risk management strategies. Using ANNs and fuzzy logic, Mosely (2007) developed an integrated screening model to estimate the seismic vulnerability of buildings. The hybrid model, although exhibiting a significant potential for optimizing the rapid screening procedure, requires a great amount of damage recording for training. Zamani (2013) employed a hybrid ANNs-ANFIS to examine the spatial-temporal variations in seismicity parameters for an earthquake in Iran (Qeshm, 10th September 2008). The model presents efficient results in classification and prediction of spatial and temporal seismic pattern. However, such models fail to sufficiently provide a proof of validity in the real world context.

3.7.2 MCDM Techniques

The multicriteria decision making method (MCDM) is defined as the process of making preference decisions (e.g. evaluation, prioritization, selection) – known as best choice – among a finite set of alternatives that are characterized by multiple, often conflicting attributes (Hwang & Yoon, 1981). Best choice in single criterion problems can be simply defined as 'optimum solution', implying alternatives with maximum or minimum performance criterion among feasible alternatives. In MCDM problems where multiple criteria are involved, conflict arises within criteria. In this case, the concept of 'optimum solution' turns into 'compromise/satisfying solution' that meets or exceeds the decision-makers' minimum expected level of achievement (Ravindran 2008).

There is a broad range of MCDM techniques reported in literature that have both common origin and goals; yet some of these might differ in principle methodology, core structure and model development process. Thus, different MCDM approaches may yield varying results for exactly the same problem (Triantaphyllou, 2000).

The most popular classes of MCDM can be summarized on the basis of their methodological concept of scoring methods (Multi attribute utility theory, or MAUT), outranking methods (PROMETHEE and ELECTRE), compromising method (TOPSIS) and eigenvalue method (AHP). The main characteristics of common variants of MCDM are shown in Table 3.2. The methods are organised according to their modelling effort which defines the richness of the output. MAUT and AHP generate the most complete form of ranking for each alternative associated with its global score; while TOPSIS and PROMETHEE provide a preliminary form of ranking, including a short list of feasible solutions which may not necessarily be supported by a comparable score. High-effort modelling approaches can effectively include a hierarchical structure and interaction of the criteria in each layer to create relative a ranking score; while in low-effort approaches the performance score of each alternative are measured individually.

Table 3.2 - Comparative analysis of MCDM ranking methods

Feature	**TOPSIS**	**PROMETHEE**	**ELECTRE**	**AHP**	**MAUT**
Methodology	Order Preference Similarity to the Ideal Solution	Determining concordance indices	Determining concordance & discordance indices	Hierarchical structure & pairwise comparison	Utility performance on specific criterion
Information processing	Compensatory	Non-compensatory	Compensatory	Compensatory	Compensatory
Determining weights	Not-any linear normalization	Not specific method based on decision makers	Not specific method based on decision makers	Yes Pairwise comparison	Not specific method based on DM
Number of Pairwise comparison	1	N(N-1)	N(N-1)	N(N-1)/2	1
Consistency check	No	No	No	Yes	No
Input	Ideal and anti-ideal option	Indifference & preference thresholds	Indifference, preference on a ratio scale	Pairwise comparison on ratio scale	Utility function
Output	Complete ranking with closeness score	Partial and complete ranking (pairwise reference degrees & scores)	Partial and complete ranking (pairwise outranking degrees)	Complete ranking with scores	Complete ranking with scores
Ranking effort	Very low	Low	Medium	High	Very high

Sources: Hwang and Yoon (1981), Ozcan et al. (2011), Ishizaka and Nemery (2013), Saaty (1981)

Nevertheless, all MCDM approaches have intrinsic strengths and weaknesses. The significant benefit of MCDA is the ability to handle problems bearing complex structures. Using MCDM, a complex problem can be decomposed into multiple manageable portions. MCDM also allows implicit and explicit evaluation of both quantitative and qualitative criteria on a common scale. Among most widely used methods proposed for risk assessment, MCDM provides a realistic way for DMs to actively participate and understand the critical features and peculiarities of real world problems (Zopoundis and Doumpos 2002). This increases the productivity of MCDM in handling multidisciplinary (public-related) problems by saving time and energy, although its formalized style of working impose an extra burden for group decision-making. For example, logical rules based on certain fundamental axioms such as transitivity of preference limit the scope of MCDM to normative problems (Lootsma 1999).

In addition, MCDM has potential synergy to connect flexibly with AI approaches in areas such as knowledge based systems, fuzzy logic and data mining. However, the greatest weakness in most MCDM approaches (except AHP) is the lack of systematic control on the consistency of judgments (Belton 1986). All MCDM approaches share a common weakness in aggregating concept which is the inability to capture uncertainty within a process, restricting the application to process crisp information; while in many situations, crisp data is inadequate to model real-life problems since human judgments are often vague and may not be precisely expressed through numerical values (Vahdani and Zandieh 2010).

3.7.5.1 TOPSIS

TOPSIS was originally developed by Hwang and Yoon (1981) to rank a feasible number of alternatives based on the concept of compromise solution. The comprise solution in TOPSIS is referred to a solution that has the shortest Euclidian distance from the ideal solution and the farthest Euclidean distance from the negative ideal solution. Due to its simplicity in perception and use, TOPSIS has been adopted in different fields (i.e. location selections Ozcan et al. (2011); contractor selection (Lin et al. 2008). The advantage of TOPSIS is in being able to handling a large number of criteria as well as alternatives. However, the best performance of TOPSIS can be achieved in problems with data expressed in quantitative and objective forms. Another limitation is the lack of consistency check. Since TOPSIS measures the distance from two points, the effects of each attribute automatically doubles these results to an exaggerated domination of attribute weight in the alternative preference.

3.7.5.2 Outranking Methods

The PROMETHEE outranking method is a class of MCDM family proposed by Brans et al. (1984) based on concordance analysis. With concordance concept, a set of alternatives is compared in pairs (pairwise comparison) with respect to each criteria in order to establish the degree of dominance, using a concordance score. The main feature of outranking family is "non-compensatory", which means "no trade-off" occurs to one criterion against the other for each individual option (unlike AHP). However the scope of application is limited to generating a "short list of preferred options" for a relatively large number of alternatives, rather than a "single best option" (Rogers 2011). PROMETHEE also fails to include inconsistencies within the process and to obtain average ranking.

ELECTRE is another family of MCDM originally developed by Roy (1968) for outranking the alternatives. This method employs concordance and discordance index to establish outranking relations and generate the set of preference by forming a kernel (Hwang and Yoon 1981). The advantage of ELECTRE is a compensatory trade-off between attributes that allow all information within a decision matrix to be utilized effectively. It can also process a large number of alternatives; although as the number of alternatives increases, the amount of computation rises exponentially.

Despite the complexity, outranking methods possess multiple advantages (Rogers 2011). First, concordance techniques allow criteria on different scales to be measured on a same framework. Second, unlike AHP or MAUT, no transformation to a common scale is required before evaluating the relative performance. Third, it does not rely on direct pairwise comparisons in the case of conflict or missing information. Given the ability of processing a large number of alternatives, outranking methods might be used as a rough estimate prior to the screening stage.

3.7.5.3 MAUT

Multi-attribute utility theory (MAUT) is considered as a leading MCDM approach developed by Keeney and Raiffa (1976), providing an enhanced form of ranking within decision problems. The MAUT concept is based upon expected utility which is a synthesis of possible performance of alternatives with respect to each criterion; "The expected utility of an event is calculated as the sum of the utilities of the payoffs weighted by their probabilities" (Ananda and Herath 2005). This concept outranks MAUT to other MCDM methods by extending the scope of application to risk-based decision-making, such as the risk ranking of gas pipelines (Brito and de Almeida 2009), public risk assessment (Ananda and Herath 2005) and evaluating mitigating decision for disaster risk (Tamura et al. 2000). While MAUT incorporate imprecise information into decision preference, it can hardly deal with missing knowledge situations where the consequence or performance of alternatives is not sufficiently defined (Jimenez et al. 2009).

Unlike conventional MCDM techniques, MAUT attempts to explicitly represent multiple dimensions of a problem to a single utility function. The function can be additive, multiplicative or any other type that best fits the problem scope. Yet the main issue is to find a rational operator to establish the utility function and to aggregate all criteria in a way to adequately express the decision makers' preferences (Tzeng and Huang 2011). MAUT has the benefits of full compensatory processing that could be useful for situations where there is no means to quantify the possible interrelations between the criteria.

Without any knowledge of the decision makers' preference structure, the rank order can be established. Unlike other MCDM methods, MAUT makes the simplest assumptions for modelling, which allows decision makers to fully understand the mathematical basis of ranking. The issue of incomparability often occurs in outranking method, but could not arise in MAUT as two utility functions are always comparable due to the transitivity principle (Ishizaka and Nemery 2013). However, developing the utility function could be too complicated where many alternatives are involved. The practical use of MAUT might be limited to problems with no interdependency within criteria as utility functions are based upon the preferential interdependence axiom.

3.7.5.4 AHP

The Analytic Hierarchy Process (AHP) was proposed by Saaty (1980) and is based on subjective judgment for handling multi-attribute problems in real situations. This method employs expert opinions to establish priorities for alternatives and the criteria used to generate the alternatives ranking within a system.

The AHP methodology is based on four steps, including decomposition, pairwise comparison and priority vector generation and synthesis. First, the problem should be decomposed and set up in the form. Second, comparing the attributes in pair (pairwise comparison) and forming a reciprocal matrix. Third, combine the subjective judgments and generate the relative priority weight vector. Fourth, the relative weight vector is synthesised to reach the best alternatives.

The AHP gained a popularity in multidiscipline applications because of its ability to support complex and unstructured decision problems such as resource allocation (Tzeng and Huang 2011), group decision-making (Dyer and Forman 1992) and recycling selection (Saaty 1980). Consistency verification is regarded as one of the greatest advantages of the AHP, which is not available in other MCDM methods and guarantee that judgments are consistent. However, despite its popularity and simplicity, AHP is criticized for the strong assumption of its unbalanced ratio scale and its inability to address uncertainty associated with subjective judgment. The ambiguous scale of preference makes it difficult for decision-makers to judge the exact numerical numbers and provide a sound pairwise comparison.

3.7.5.5 Fuzzy MCDM

Fuzzy AHP or broadly known 'Fuzzy MCDM' term is an important extension of the MCDM method, and was first introduced by Laarhoven and Pedrycz (1983). Buckley (1985) extended Saaty's AHP method in which decision-makers could express their preference on the fuzzy ratio scale instead of crisp values. Fuzzy MCDM attempts to overcome previous criticisms by improving the ratio scale, allowing for a more flexible way of aggregating inherent uncertainty and imprecision associated with expert's judgment. This extension gained popularity in literature and hence been extensively used in several applications, such as: project risk assessments (Zeng, An and Smith 2007; Tuysuz and Kahraman 2006), site selections (Vahidnia et al. 2009), country risk assessments (Murtaza 2003) and post-disaster management (Opricovic and Tzeng 2003).

Despite its advantages, the Fuzzy MCDM is argued for its complex process of computation that may lead to a counterintuitive prioritization (Deng 1999). It is also criticized on several disparate methodologies developed for acquiring the fuzzy utilities and prioritizing the alternative ranking. There are multiple versions of fuzzy MCDM, each following a different way of aggregation, potentially leading to inconsistent ranking results. Chen and Hwang (1992) listed over 15 aggregation operators for handling fuzzy MCDM within which more than 25 ranking methods has been devised. Some of the examples of major ranking methods are the α-cut method (Zeng, An and Smith 2007), fuzzy extent analysis (Chang et al. 1988), the geometric mean method (Buckley 1985), and the fuzzy lambda method (Csutora and Buckley 2001).

3.7.5.5.1 Pilot Study

Given the capability of fuzzy MCDM for handling imprecise information in risk contexts, a pilot study was performed to examine its performance through an example. This example was designed to examine the capability of the fuzzy MCDM for evaluating and prioritizing seismic risk within a small group (five alternative regions of Iran). Throughout the process, the subjective weights of risk attributes were aggregated using the geometric mean method proposed by Buckley (1985). Sample weight aggregating processes for a vulnerability block is briefly reviewed here (see Vahdat et al., 2014a for more details).

According to Buckley's method, the weight of various risk factors and risk attributes were assessed using a subjective process. Experts were asked to describe the relative importance of risk variables in pairwise comparisons using linguistic terms such as 'equal', 'low', 'medium', 'high', and 'extreme', representing fuzzy numbers within the ratio scale including $\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$ respectively as defined through a triangular function (Table 3.3).

Table 3.3 – Linguistic terms and ratio scale

Fuzzy number	Linguistic term	Fuzzy scale
$\tilde{1}$	Equally important	(1,1,3)
$\tilde{3}$	Low important	(1,3,5)
$\tilde{5}$	Medium important	(3,5,7)
$\tilde{7}$	Highly important	(5,7,9)
$\tilde{9}$	Extremely important	(7,9,9)

The fuzzy judgment matrix for each expert can be then constructed as follows:

$$\begin{bmatrix} 1 & \tilde{a}_{12} \cdots & \tilde{a}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} \cdots & 1 \end{bmatrix} \quad \text{where } \tilde{a}_{ij} = \begin{cases} 1 & , \; i = j \\ \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} & , \; i \neq j \end{cases} \tag{3.1}$$

Then, a fuzzy judgment matrix can be developed to convert the linguistic terms used in the pairwise comparisons. Using a geometric mean technique, the fuzzy geometric mean and the fuzzy weight of each criterion proposed could be determined as follows:

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \ldots \otimes \tilde{a}_{in})^{\frac{1}{n}}, \quad (3.2)$$

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \ldots \oplus \tilde{r}_n)^{-1} \quad (3.3)$$

Where $\tilde{a}_{in}$ is the fuzzy comparison value of criteria i, with respect to criteria *n*. Thus, $\tilde{r}_i$ is the geometric mean of the fuzzy comparison value for criteria i to each criteria, $\tilde{w}_i$ is the fuzzy weight of the i^{th} criteria and can be denoted by a triangular fuzzy number (TFN) , $\tilde{w}_i$ = (L_{wi} ,M_{wi} , U_{wi}) where L_{wi}, M_{wi} and U_{wi} indicate the lower, middle and upper values of the fuzzy weight of the i^{th} criteria. The major advantage of using the geometric mean over the arithmetic mean is a reduction in the influence of the highest and lowest values (Max, Min).

Numerically, the geometric mean and weights can be obtained from expert judgments. For example, the summary of pairwise comparison of hazard criterion is shown in Figure 3.3 (due to matrix symmetry, only half is shown).

$$\begin{array}{cc} & \begin{array}{cccccc} C11 & C12 & C13 & C14 & C15 & C16 \end{array} \\ \begin{array}{c} C11 \\ C12 \\ C13 \\ C14 \\ C15 \\ C16 \end{array} & \begin{bmatrix} 1 & \tilde{5}^{-1} & \tilde{1}^{-1} & \tilde{7} & \tilde{5}^{-1} & \tilde{7} \\ & 1 & \tilde{5}^{-1} & \tilde{5}^{-1} & \tilde{5} & \tilde{1}^{-1} \\ & & 1 & \tilde{5}^{-1} & \tilde{3}^{-1} & \tilde{5}^{-1} \\ & & & 1 & \tilde{5}^{-1} & \tilde{1}^{-1} \\ & & & & 1 & \tilde{5}^{-1} \\ & & & & & 1 \end{bmatrix} \end{array}$$

Expert #1

$$\begin{array}{cc} & \begin{array}{cccccc} C11 & C12 & C13 & C14 & C15 & C16 \end{array} \\ \begin{array}{c} C11 \\ C12 \\ C13 \\ C14 \\ C15 \\ C16 \end{array} & \begin{bmatrix} 1 & \tilde{5}^{-1} & \tilde{1} & \tilde{5} & \tilde{5} & \tilde{1} \\ & 1 & \tilde{3} & \tilde{3} & \tilde{5}^{-1} & \tilde{5} \\ & & 1 & \tilde{1}^{-1} & \tilde{3} & \tilde{3}^{-1} \\ & & & 1 & \tilde{5}^{-1} & \tilde{1}^{-1} \\ & & & & 1 & \tilde{7} \\ & & & & & 1 \end{bmatrix} \end{array}$$

Expert#2

$$\begin{array}{cc} & \begin{array}{cccccc} C11 & C12 & C13 & C14 & C15 & C16 \end{array} \\ \begin{array}{c} C11 \\ C12 \\ C13 \\ C14 \\ C15 \\ C16 \end{array} & \begin{bmatrix} 1 & \tilde{1} & \tilde{3}^{-1} & \tilde{3}^{-1} & \tilde{3}^{-1} & \tilde{1} \\ & 1 & \tilde{5} & \tilde{7} & \tilde{9} & \tilde{5} \\ & & 1 & \tilde{5} & \tilde{1}^{-1} & \tilde{7} \\ & & & 1 & \tilde{1}^{-1} & \tilde{3} \\ & & & & 1 & \tilde{5} \\ & & & & & 1 \end{bmatrix} \end{array}$$

Expert#3

$$\begin{array}{cc} & \begin{array}{cccccc} C11 & C12 & C13 & C14 & C15 & C16 \end{array} \\ \begin{array}{c} C11 \\ C12 \\ C13 \\ C14 \\ C15 \\ C16 \end{array} & \begin{bmatrix} 1 & \tilde{5} & \tilde{9} & \tilde{1}^{-1} & \tilde{5}^{-1} & \tilde{3}^{-1} \\ & 1 & \tilde{3} & \tilde{7} & \tilde{1}^{-1} & \tilde{7} \\ & & 1 & \tilde{3}^{-1} & \tilde{5}^{-1} & \tilde{5} \\ & & & 1 & \tilde{1}^{-1} & \tilde{1} \\ & & & & 1 & \tilde{5} \\ & & & & & 1 \end{bmatrix} \end{array}$$

Expert#4

Figure 3.2 - Summary of expert judgments matrix for hazard category

Where six criteria within the hazard category are represented by C_{11} (closeness to fault), C_{12} (ground shaking index), C_{13} (population) and C_{14} (liquefaction susceptibility), C_{15} (sliding susceptibility) and C_{16} (soil class). Using the geometric mean method, a combined judgment array was computed as follows:

$$\tilde{a}_{12} = \tilde{5}^{-1} \otimes \tilde{5}^{-1} \otimes \tilde{1} \otimes \tilde{5} = \left(\left(\frac{1}{7},\frac{1}{5},\frac{1}{3}\right) \otimes \left(\frac{1}{7},\frac{1}{5},\frac{1}{3}\right) \otimes \left(\frac{1}{3},1,1\right) \otimes (3,5,7)\right)^{0.25}$$
$$= (0.378, 0.669, 0.939)$$

According to Buckley's equation (2.2), the average fuzzy weight of the judgment matrix can be obtained as follows:

$$\tilde{r}_1 = (\tilde{a}_{11} \otimes \tilde{a}_{12} \otimes \ldots \otimes \tilde{a}_{16})^{\frac{1}{6}} = (0.686, 1.004, 1.603)$$
$$\tilde{r}_2 = (1.151, 1.834, 2.475)$$
$$\tilde{r}_3 = (0.541, 0.890, 1.408)$$
$$\tilde{r}_4 = (0.410, 0.613, 0.925)$$
$$\tilde{r}_5 = (1.054, 1.469, 1.919)$$
$$\tilde{r}_6 = (0.474, 0.678, 0.959)$$

Then, using equation (3.3), the fuzzy weight of each criterion was obtained as follows:

$$\tilde{w}_1 = \tilde{r}_1 \otimes (\tilde{r}_1 \oplus \ldots \oplus \tilde{r}_6)^{-1} = (0.074, 0.155, 0.371)$$

Likewise, other arrays can be developed using the similar aggregation process as shown in Table 3.4.

Table 3.4 - Reciprocal judgment matrix for hazard attributes
(C.I = 0.09, C.R = 0.07)

	C_{11}			C_{12}			C_{13}			C_{14}			C_{15}			C_{16}			W		
C_{11}	1	1	1	0.378	0.669	0.939	0.827	1.316	2.280	1.000	1.848	2.817	0.333	0.508	0.939	1.000	1.236	3.000	0.074	0.155	0.371
C_{12}	1.065	1.495	2.646	1	1	1	0.809	1.732	2.764	1.375	2.329	3.409	1.000	1.732	2.141	1.968	3.637	4.304	0.124	0.283	0.573
C_{13}	0.439	0.760	1.210	0.362	0.577	1.236	1	1	1	0.669	1.495	2.432	0.293	0.615	1.000	0.809	1.236	2.141	0.058	0.137	0.326
C_{14}	0.355	0.541	1.000	0.293	0.429	0.727	0.411	0.669	1.495	1	1	1	0.218	0.447	0.577	0.508	0.760	1.000	0.044	0.094	0.237
C_{15}	1.065	1.968	1.000	0.467	0.577	1.000	1.000	1.627	3.409	1.732	2.236	4.583	1	1	1	1.592	2.432	3.201	0.113	0.211	0.445
C_{16}	0.333	0.809	1.000	0.232	0.275	0.508	0.467	0.809	1.236	1.000	1.316	1.968	0.312	0.411	0.628	1	1	1	0.059	0.117	0.276

A consistency test was performed to check if there is any unreasonable judgment. The calculated values of the consistency index (CI) and the consistency ratio (CR) for each judgment matrix can be found in the two last columns. Note that since all the CI and CR values were kept fairly low, the fuzzy judgment matrix should be consistent with expert views.

This example demonstrates that a systematic fuzzy MCDM can provide a meaningful way to aggregate multiple expert opinions and effectively generate weights. The major advantage of this example is that both qualitative and quantitative risk information could be aligned, scaled and aggregated with the presence of uncertainty. The model not only considers the trade-offs between both qualitative and quantitative factors involved in developing risk, but it also enables decision-makers to deal with inconsistent judgments systematically.

However, fuzzy MCDM requires a great amount of computation for evaluating fuzzy performance of alternatives. The performance values of each alternative with respect to each criterion need to be mapped to fuzzy numbers. Due to the inability of tuning the mid stages, complexity grows exponentially for medium- to large-scale problems in which large numbers of alternatives are involved. For the present study that contains more than 18 criteria (in four categories) and 50 alternatives, over 40 pairwise comparisons and more than 900 mapping calculations are required. More comparison and mapping means more likely errors can be potentially imported during the process. However, like AHP, fuzzy MCDM could be more appropriate for a simpler problem containing 4 to 8 alternatives.

3.8 Comparison of Methods

Several mathematical modelling techniques were critically reviewed and compared according to their potential for addressing the problem. There are many mathematical techniques with different perspectives that might be considered for modelling the seismic risk problem. These decision techniques range from classical methods to more complex AI methods such as GAs, ANNs and ANFIS. Mitigation decisions are often involved with risk-based decision preferences to select an appropriate solution addressing the defined levels of safety while maintaining the other socioeconomic dimensions.

The complex nature of the seismic risk with multidisciplinary aspects, in which range of imprecise information is involved, requires a heuristic framework to tackle the challenges systemically. The prospective method should also be consistent with the scope of the research to meet the problem's requirements. According to Kangari (1987), despite the popularity of the classical MCDM techniques in risk context, they are limited in their applicability to disaster management where nearly all mitigation decision problems are imprecise ill-defined and vague in nature. This imprecision tends to characterize uncertain risk knowledge which is predominantly subjective and linguistic in nature. In addition, there are many situations in seismic risk management where quantitative and detailed information to evaluate uncertainty is not available.

Considering the characteristics of the methods and scope of the problems, none of the classical MCDM methods are not appropriate for modelling risks. Conventional scoring techniques like TOPSIS and MAUT have no potential for modelling imprecise risk parameters systematically. Outranking techniques, however, have the ability to handle a large number of alternatives, but could not effectively provide an effective compromise. These methods also fail to provide a complete figure for preference and indifference relations which are basically intransitive. Although the outranking concept introduces an incomparability relation to compensate the issue that often occurs for alternatives with a major difference, its primitive form of ranking restricts it for many applications (Doumpos and Zopoundis 2002).

The optimization techniques (GAs, ANNs and ANFIS) may not be useful for seismic risk assessment because such these approaches are seeking to limit the stochastically selected domain to a finite solution space. According to McCall (2005), GAs is appropriate for the problems in which "solution sets are finite but so large that brute-force evaluation of all possible solutions is not computationally feasible". Unlike MCDM that provides a single compromised solution satisfying the constraints (criteria), optimization techniques offer an infinite set of feasible domains that adequately fit the objective function. In addition, such complex techniques could make decision-making more complicated because their process of aggregation is not clearly traceable. Some of those techniques (like ANFIS) require a great amount of information for training and testing.

Reviewing the variants of MCDM, it can be concluded that only a high-effort modelling technique might be the best candidate for such situation bearing uncertainty. AHP and MAUT can handle relatively complex situations using a quality scoring process. AHP has an extensive ability for the simple ranking of choices in real situations; however, it is criticized due to the rigidity of its ratio scale and inability to handle uncertain information.

The fuzzy MCDM, although overcoming the previous issue mentioned, still carries the systematic limitations of the AHP. The numerical example shows that the reliability of the fuzzy MCDM method directly depends on the consistency of expert judgment, which can be hardly achieved at first run. Moreover, a complex problem with large number of alternatives and criteria requires a myriad pairwise comparison, which is exhausting.

An experiment conducted by Triantaphyllou (2011) to compare common MCDM methods demonstrates that the number of alternatives in a decision problem is very critical. As the number of alternatives rises, so does the failure rate of classic MCDM techniques to fully capture the aspects of the problem. Thus, the potential MCDM approaches which may be incapable of handling a large number of alternatives would be obviously inappropriate for the present problem.

Other methods such as ELECTRE and MAUT have addressed this issue in their concept; yet both suffer from other shortcomings that limit their applications. ELECTRE generates a low-quality ranking scheme that might be appropriate only for the first round of preliminary screening of the large group of alternatives. MAUT is another popular variant of MCDM that could be useful for practical tasks that bear no uncertainty; although knowledge elicitation is a major challenge (Keeney and Raiffa 1976). Using a numerical scale for ranking can potentially limit the scope of application in processing subjective judgments, particularly for risk situations involved with in-situ surveys.

The need to prioritize a large number of retrofitting projects with multiple interactions within tangible or intangible risk criteria requires a systematic approach. Consequently, any systematic methodology for aggregating, selecting and ranking seismic risk must cater for these multiple criteria and must also give decision-makers the opportunity to simply express their own viewpoints in a transparent way. Keeping this in perspective, KBES stands far higher than classic MCDM approach and could be the best fit for this problem.

This process has potential to tackle the challenges existing within risk frameworks for a number of reasons. First, KBES can effectively address the inherent imprecision associated with seismic risk parameters using fuzzy set theory. This process allows the input parameters to be expressed qualitatively through fuzzy variables. The ability to represent seismic parameters using approximate reasoning is considered a significant feature in the light of AI development. Second, KBES is created for the broad purpose of handling complex systems. It supports rational decision-making in general and MCDM in particular, allowing complex, multidimensional aspects of seismic risk to be modelled intuitively. Third, KBES also provides a heuristic platform to integrate multiple context information concepts effectively.

Previous applications reported in the literature demonstrate the efficacy of KBES for handling uncertainty and vagueness in risk and damage assessment (Murlidharan et al. 1999; Ross 1990; Dong et al. 1990). Given the ability of expert systems for handling complexity, and enhanced capacity of fuzzy sets for addressing uncertain risk parameters, KBES was adopted as a first choice to conduct the study. The form and methodology to implement KBES will be discussed in later chapters.

3.9 Summary

Given the diversity in size, scope, functionality and configuration of existing buildings and keeping in mind the immense uncertainty associated with the risk management process, modelling should be grounded on the systemic and multcriteria basis presenting the multidimensionality characteristics of seismic risk through the integration of multiple metrics. System-based risk analysis can effectively address the potential challenges caused by complex multidimensional aspects of seismic risk, handling uncertainties present in the decision-making process due to spectrum of objective and subjective information.

The mathematical techniques that could potentially be used in modelling the seismic risk impacts were reviewed, compared and ranked according to systemic capabilities and modelling effort. Considering the ability to handle uncertainty and complexity as two determinant requirements, the KBES was adopted. KBES provides a high-effort modelling framework that allows a systemic method for handling both complexity and uncertainty. The complex process of seismic risk can be modelled using a multicriteria framework that allows various criteria to be aligned, scaled and aggregated; while the imprecision associated with risk attributes can be captured using the fuzzy set theory. In general, KBES theoretically addresses the basic concerns of complexity, uncertainty, flexibility, and MCDM consistency, among others. Nevertheless, thorough evaluation of KBES requires a structured case study to implement and test it in practice.

Chapter 4: Research Methodology

4.1 Introduction

This chapter outlines the methodology and procedures used to accomplish the research, and is presented in two main parts. It begins with an introduction to the research design concept, then reviews the potential methods of data collection. The second part identifies and justifies the research strategy adopted.

4.1.1 Definition

The term *Research* consists of two parts: *re*, meaning 'again', and *search*, which of course means to look for something. Jointly, research connotes academic activity to systemically investigate into a subject in order to discover facts. According to Webster's Dictionary (2003) research is a careful inquiry or examination in seeking facts or principles; a diligent investigation to ascertain something. This definition makes clear the fact that research is not merely a search for truth, but a prolonged, intensive, purposeful exploration.

The purpose of research is to discover answers to questions through the application of scientific procedures. Its main aim is to develop a procedure for the discovery of truth which is a method of critical thinking. It comprises defining a problem; formulating a hypothesis or suggested solutions; collecting facts or data, organizing and analysing the facts; evaluating data; reaching certain conclusions towards the concerned problem; and finally, verifying the conclusions to examine whether they fit the formulating hypotheses (Singh 2006).

Similar definitions of research have been reported in literature. According to Mouly (1970) research is "the systematic and scholarly application of the scientific method interpreted in its broader sense, to the solution of social study problems; conversely, any systematic study designed to promote the development of social studies as a science can be considered research". Kerlinger (1986) points out that "research is a systematic, controlled empirical and critical investigation of propositions about the presumed relationship about various phenomena".

Furthermore, Kumar (2006) highlights major characteristics of the research to ensure its quality. This comprises research that is controllable, rigorous, systematic, valid, verifiable, empirical and critical. From these definitions, it can be concluded that a sound research is concerned with key characteristics, including 'systematic', 'logical', 'structure', 'integrity', 'critical thinking' and 'verifiable'. These aspects ensure the quality of research. For example, a piece of research must be 'systematic' and structured in accordance with the defined set of rules and procedure. It should be logical because a rational process of reasoning is necessary to carry out the research. Creswell (2003) suggests three critical questions for designing a research:

- What knowledge claims are addressed by the researcher?
- What strategies of inquiry and reasoning are required to conduct the research?
- What methods should be used for data collection (qualitative, quantitative or mixed)?

In response to the above questions, research approaches should be accommodated to discover answers to questions by addressing the key elements of research (knowledge claims, strategies and methods required in research procedure) as indicated in Figure 4.1.

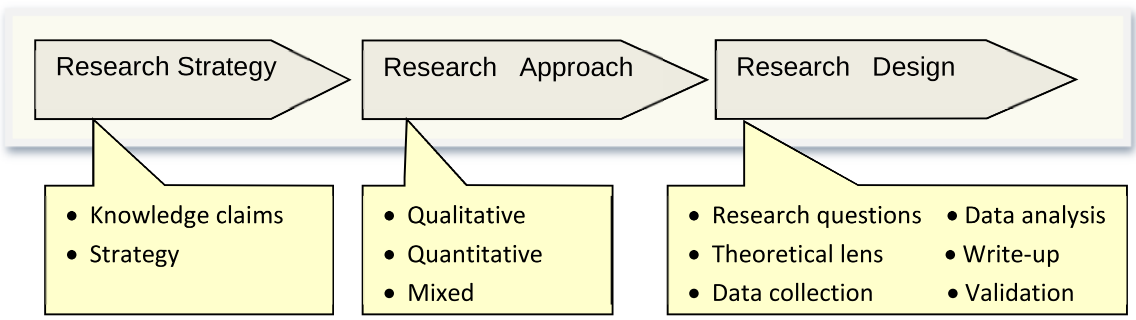


Figure 4.1 – Knowledge claims, inquiry and approaches toward research design (Creswell 2003)

4.2 Research Strategy

Research strategy refers to the general plan, structure and desired objectives of research on how research questions can be addressed (Saunders et al. 2009; Sing 2006). The research strategy is commonly based on the objective of the research, while research approach is based on the nature of the research problem. To adopt an appropriate strategy, several considerations regarding to knowledge claims and inquiry of research need to be taken. In this regard, the researcher should decide the best way to conduct knowledge claims, to develop the logic of inquiry and to adopt the appropriate methods for capturing data.

Knowledge claim refers to certain assumptions, paradigms or conceived methodologies to approach the research. A logical methodology needs to be adapted to link the data collection and methods of research to answer the main research questions being investigated. According to Fellow & Liu (2003), research strategy is related to several crucial factors, including the purpose of study and the type and availability of information involved. Creswell (2003) suggested four factors to select a particular research strategy, including implementation, priority, integration and theoretical perspective. The main priority in this thesis is to adopt the most appropriate strategy and methods to fulfil the research objectives. The strategy highlights the plan and way adapted to investigate the research and solve the research problem.

4.2.1 Reasoning

Reasoning is a scientific mode of thinking (Sing 2006). Research is guided by the rules of logical reasoning to draw conclusions from scratch. There are three logical process of reasoning: deductive, inductive and a combination of both. Deductive research is a theory-testing process that commences with an established theory or generalization, seeking to discover whether the theory applies to specific examples (Hyde, 2000). This type of argument starts with general theory and then narrows down to the more specific hypothesis that one can test through the observation. Observations provide specific data for testing and validating the hypothesis or the original theory (Figure 4.2). Common sense reasoning and syllogism are the simplest form of deduction employing fact and general premise to reach specific conclusions.

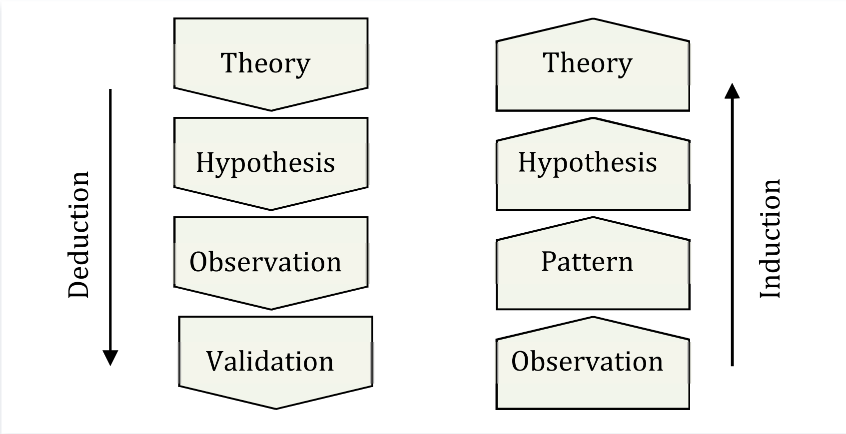


Figure 4.2 – Deductive vs. inductive reasoning process

Unlike the deductive process, inductive research is a theory-building process that moves from specific to general. It begins with specific observations of specific example seeking to discover likely pattern (correlation, variation) to formulate the tentative hypothesis. Systematic observation and exploration of the events in the real world can explain the governing rules, thereof developing the hypothesis. The process of exploring may continue until the argument leads to some general conclusions or theories.

Clearly, the concept of reasoning is different in both procedures. Deductive reasoning is more narrow and limited in nature as it can handle specific kinds of statements for testing and validating the hypothesis, while inductive reasoning is naturally an open-ended and exploratory procedure. Unlike deduction, which can be tested by observation and syllogism, induction more relies on personal experience, inference, self-evident proposition and scientific inquiry as underpinning sources of evidence (Singh 2006). These characteristics can make the induction uncontrollable, haphazard and restricted to be applied in practice (Walliman 2005). Nevertheless, induction is still a priori choice in social science, psychology and medical context of its nature, requiring empirical research to fit the data and infer a theory.

It can be untenable to rely on experience as the only source of knowledge, in contrast with a basic feature of research, which is systematic and controlled. In this regard, inductive and deductive reasoning can be combined, taking advantage of both to fit with new situations and data restrictions. This research employs an inductive reasoning as the underlying concept of research to develop the theory by exploring the literature and previous records, establishing the causal relationship between risk drivers and conceptualizing the hypothesis. The data was collected from observation and statistics (inference) and integrated with previous experiences in literature to manage the research methodology.

4.3 Research Approach

The research approach is referred to the way in which knowledge examined, collected and presented. Several classifications reported in literature (Singh 2006; Walliman 2005; Kumar 2006) address multiple perspectives of research based on various philosophical assumptions, including: scope of application (fundamental/pure research, applied research), methodology (conceptual, empirical), the purpose of research (descriptive, exploratory, interpretative) and mode of knowledge inquiry (quantitative, qualitative and mixed). The main characteristics of the approaches are further outlined below.

4.3.1 Mode of Inquiry: Quantitative or Qualitative?

A mode of inquiry defines the forms of the research process, which can take the structured or unstructured approaches. Quantitative research is structured in that everything has been already predetermined, including the objective, design, sample, for example. Qualitative inquiry is an unstructured piece of research that allows more flexibility to explore the nature of the phenomena examined (Kumar 2006).

Quantitative research focuses on measurement, the extent of variation, observation and testing. This process deals with tangible, countable characteristic focusing on standard statistical procedure presented in graphs, cross-tabulations and other statistical procedures. Creswell (2003) described quantitative research as an objective procedure for knowledge inquiry that particularly used in social science to deal with the problem based on testing a hypothesis or a theory composed of variables, measured with numbers, and analysed with statistical procedures, in order to determine whether the hypothesis or theory holds true. This method tries to understand a rational theory by examining the related literature. Qualitative research, though, is a subjective process aims to identify the characteristics and structures of phenomena and causal relations between contributing factors examined in a natural context (Jonker & Pennink 2009).

According to Creswell (2003) qualitative research is concerned with experts' perceptions, experiences and knowledge. It is a mixture of the rational, explorative and intuitive, which make it more flexible but rather an unstructured approach. In this process, data are not collected by statistical methods or other process of quantification. This kind of research is mostly suitable for doing inductive research that focuses on events, behaviours, organizational functioning, interaction and relationships (Ghauri et al. 2010). The main characteristics of those approaches are compared in Table 4.1.

Unlike qualitative research that may have no rigidity in structure and knowledge inquiry, quantitative research tends to follow a logical process to develop the hypothesis and to test it in practice. In order to improve the strength of each strategy, it is recommended that two approaches be used together (Jankowicz 1994; Esterby-Smith et al. 2001). As a result, the study applies a combination of quantitative and qualitative method of inquiry to collect information.

Table 4.1 - Comparison between qualitative and quantitative methods
(Ghauri et al. 2010; Kumar 2006)

Qualitative Research	Quantitative Research
• Unstructured/flexible/open methodology • To describe the variation nature • Emphasize on description of the variables • Inquiry focus on understanding from respondent's / informant's point of view • Interpretation and rational approach • Observations and measurements in natural settings • Subjective 'insider view' and closeness to data • Explorative orientation • Holistic perspective • Fewer cases and sample size	• Structured/rigid/predefined methodology • To quantify the extent of variation • Emphasize on classification of variables • Logical and critical approach • Controlled measurement • Objective 'outsider view' distant from data • focus on hypothesis testing and verification • Result oriented • Particularistic and analytical • Emphasize on greater sample size

4.3.2 Other Categories

Research might be conducted using many other strategies. There are types of research approaches in the literature that address different underlying concepts for various themes of research. Fellows & Liu (2008) classified the most common themes which have been used in different research applications in four major categories (Table 4.2). Marshall & Rossman (1999) explained the general research questions corresponding to each category. For example, exploratory research aims to provide an overwhelming amount of information through a cause-effect relationship in the areas containing little information (Glicken 2003). Explanatory research uses a considerable amount of information available from prior research studies and aims to provide meaningful conclusions as well as major issues raised. Understanding the scope and implication of either approach is important in designing the research.

Table 4.2 - Different type of research approach
(Fellows & Liu, 2008; Marshall & Rossman, 1999)

Type of Research	Purpose of the Study	General Research Questions
Exploratory	• To investigate little-understood phenomena • To identify or discover important categories of meaning • To generate hypotheses for further research • To test, or explore, aspects of theory • To provide a clear and precise statement of the recognized problem • To diagnose a situation, screen alternatives and to discover new ideas	• What are the most important themes, patterns, or categories of meaning for the participants? • How are these patterns linked with one another?
Explanatory	• To explain the patterns related to the phenomenon in question • To identify plausible relationships forming the phenomenon • To develop the hypotheses which the research will test • To answer a particular question	• What events, beliefs, attitudes, or policies shape this phenomenon? • How do these forces interact to result in the phenomenon?
Descriptive	• To document and describe the phenomenon of interest • To systematically identify and record (all the elements of) a phenomenon, process or system • May be undertaken as a survey (possibly of the population identified) or as case study work to enable the subject matter to be categorized	• What are the salient actions, events, beliefs, attitudes, and social structures and processes occurring in this phenomenon?
Predictive	• To predict outcomes and to forecast events and behaviours fit findings/experience to a theoretical framework or model • To use when empirical testing cannot be done	• The models used may be heuristic, in which variables are grouped according to relationships to replicate/ simulate the 'reality' as closely as possible.

4.4 Research Methodology

The research methodology of the study is designed in eight steps, as shown in Figure 4.3. The process follows a structured quantitative inquiry. It aims to heuristically explore the potential impacts of earthquakes, structure their relationships, and predict the extent of risk by aggregating the respective disaster patterns. Thus the methodology should be exploratory, while maintaining an inductive concept to establish the empirical interrelation within risk drivers.

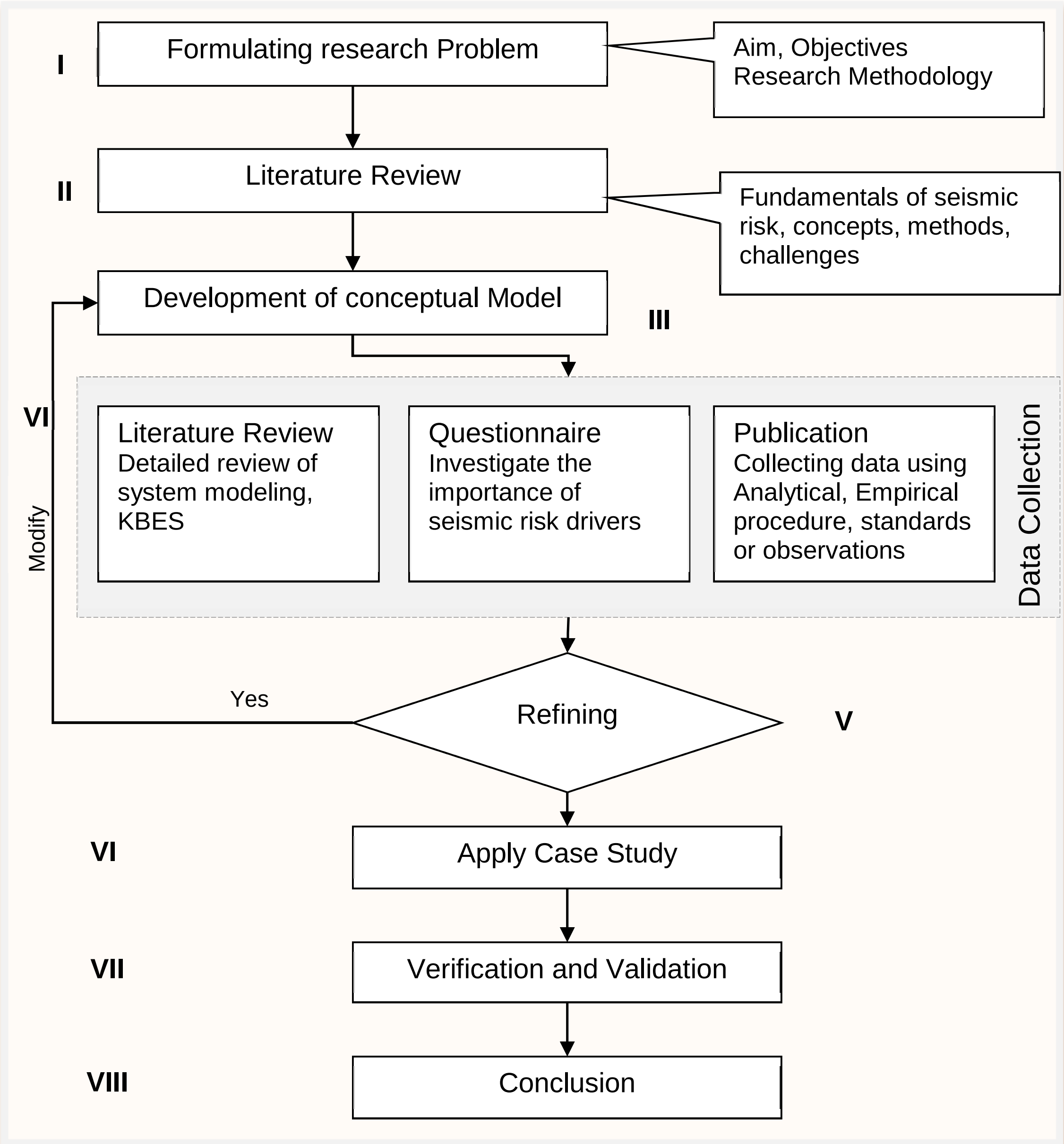


Figure 4.3 – Research stages

Step I: Formulating a research problem

The formulation of the general topic into a specific research problem is the primary step in research. This requires an extensive review of relevant disciplines contemplated in the knowledge claim. Literature review has been undertaken to improve the understanding around the field and to identify the likely challenges that have either been ignored or insufficiently addressed within the context.

The literature review was carried out in two styles: firstly conceptual literature presenting the various concepts and theories; secondly the empirical literature consisting of different case studies performed earlier. This guides the data and other materials which enabled the researcher to develop a new research problem in a similar context. In this regard, several reading materials, such as academic journals, conference proceedings, government reports, books and online database were systemically utilized.

Having defined the scope, objectives and methodology to approach the research, a detailed plan of research problem can be formulated. A transfer report is a good example of a research proposal that introduces research problems, describing the available methodologies to conduct the research, addressing potential challenges and limitations, and outlining the proposed conceptual framework to develop the model.

Step II: Literature Review

The methodological aspects of the seismic risk system have not been fully addressed in the literature. Hence, a literature review was performed in two major categories, including 'risk analysis' and 'system theory'. A risk analysis was further broken down into several subcategories relevant to the context, including risk assessment, risk management, planning and disaster management. Several studies and reports conducted by earthquake institutes and other well-known international bodies (The World Bank, UNDP) have been employed as complementary sources.

System theory, on the other hand, covers methodologies and the knowledge management part of the study consists of theoretical and methodological methods for decision-making under uncertainty. This includes conventional methods (MCDM) as well as heuristic approaches (AI). Special attention was made to numerical tools and programming software for operational research. As a result, exploring the literature, software and previous research drew potential capacities for further development and contribution to knowledge.

Step III: Development of a conceptual model

Once the research problem has been formulated in clear-cut terms, it is required to prepare a research design. According to Kerlinger (1986):

> "A research design is a plan, structure and strategy of investigation so conceived as to obtain research questions or problems. The plan is the complete scheme or program of the research; It includes an outline of what the investigator will do from writing the hypotheses and their operational implication of the final analysis of data".

The above definition implies two main aspects of research design. The first is the development of the logistical arrangement required in order to conduct the research. The second is the quality in these procedures to ensure validity, objectivity and accuracy (Kumar 1996). Accordingly, the purpose and concept of research may be addressed through exploration, description, experimentation and diagnosis.

Considering various knowledge-based systems and new AI developments in risk assessment contexts, an intelligent knowledge base expert system (KBES), which supports both human reasoning and statistical inference, was chosen as the basic modelling paradigm. A conceptual risk assessment process was established as a roadmap to bring a comprehensive insight of research and to address the problem, the kind of information involved as well as methodological and software requirements for programming, processing and integrating the knowledge. In this regard, several packages were examined when developing the system, including Expert Choice®, MATLAB®, Visual Basic and Excel® (spreadsheet).

Step IV: Data Collection

Data collection is a crucial stage toward research design. Having developed the research proposal, different aspects of data are considered. A plan and strategy for collecting and analysis of data are usually defined at the onset of the process. In this regard, researcher should decide what kind of data is required to conduct the research and how to approach it, whether it is qualitative or quantitative, how to sample it, and what sources are available.

According to Guddard and Melville (2006), reliability and validity are two fundamental criteria that must be fulfilled in any data collection. Strauss and Corbin (1990) highlight the importance of flexibility in collecting and analysing data. They point out that data collection is a crucial as it helps the researcher to improve the understanding of phenomena through a complete and comprehensive picture of the object of study. Therefore adapting the appropriate data collection methods is of utmost importance in this research. The extent and diversity of information have been the major challenges of this stage due to the multidisciplinary nature of risk. In this regard, a critical review was conducted in previous research, publications and industry data to identify the contributing risk factors, and to establish their relations, and classify them in a structured manner. This is followed by a questionnaire survey to collect the preliminary information.

Step V: Refining the conceptual model

To identify the possible flaws within the conceptual model and explore the likely challenges, real data are applied to the model. According to Gill & Johnson (2010), when refining the conceptual model, the researcher should be aware of the analytical aspects of the project when inductively generated hypotheses may need to be rigorously tested and refined through a more structured methodology. The latter works as systematic problem-solving in which researcher is urged to develop, refine, modify and maximize the potential of the theory being generated.

Step VI: Applying the case study

Once the conceptual model was refined, the prototype decision support system can be subsequently evaluated through a real (ongoing) case study. In this research, the case study of retrofitting school buildings was adopted to examine the application of KBES in seismic risk management.

Step VII: Verification and validation

Once the system has been successfully refined, verification and validation were performed through a systematic process. Gupta (1991) classified verification as white-box testing, designed to determine if the system works and accurately implements user specifications, while validation was classified as black box testing designed to determine if the system meets user requirements.

System verification involves a logical process in which consistency, robustness and completeness of the system are examined and evaluated. According to Morell (1988), a system is considered as inconsistent if it presents something that does not reflect within the modelled domain. Robustness is a characteristic that secures the system performance in worst condition where some of the input data or reasoning rules are missing, unreliable or inexact, and when data and knowledge inherently involves uncertainty (Jung and Bums, 1993).

To verify how robust the system is, a sensitivity analysis was carried out. This indicates how much a system performance can be affected due to the changes of input parameters. Samson (1988) notes that sensitivity analysis is a useful tool that should be integrated into every step of the decision process. Incompleteness refers to a system that cannot respond to all situations that may arise within the domain (Cragun and Steudel 1987).

Verification and validation are complementary process that examines the internal consistency and external credibility of the system using real-world data. This process contains checking the accuracy, consistency, usability and reliability of the model in different condition. Accuracy reflects how precise the system output is in real situation and if it is within the expected range. Consistency ensures the model is continuously consistent over its domain interval. Usability implies the degree of human involvement and user-friendliness of the system. Reliability covers essential characteristics of a system and reflects to what extent the overall system is robust, accurate, efficient and usable for the prospective application. To demonstrate validity within the study, a set of experiments was designed using benchmarking, cross-validation and Monte Carlo analysis in Chapter 8.

Step VIII: Conclusion Report

Once the model was successfully tested, verified and validated, the write-up process was launched. The report comprises the evaluation of the initial concept and the process of refinement, leading to an approved system as well as the research results.

4.5 Research Design

The research design is a procedural plan, strategy and structure that is adopted by researchers in order to address the research questions effectively, accurately and reliably. It contains the blueprint for fulfilling objectives and answering questions (Cooper and Schindler 2006). A research design is "the plan that guides the investigator in the process of collecting, analysing, and interpreting observations. It is a logical model of proof that allows the researcher to draw inferences concerning causal relations among the variables under investigation" (Nachmias and Nachmias, 1992; Yin, 2009). Fellows and Liu (2003) suggest that a casual relation between the main elements of research (data collection, research questions and methods) should be established through a logical process in order to fulfil the research objectives. In this regard, the current study aims to address four areas: identifying the research problem, proposing action; finding a methodology, acquiring data; and why this tool and methodology are selected. Constructing a design may be complicated by the availability of a large variety of methods, techniques, procedures as well as data required for applying to the research. Hence, it is necessary to follow a logical plan for the research to connect the different stages of the thesis and to meet the research objectives. This procedure is established by integrating three basic components of research, as shown in Figure 4.4.

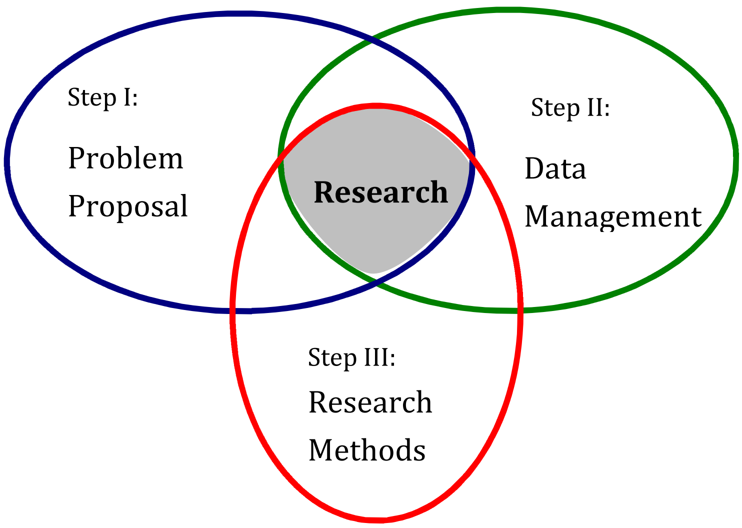


Figure 4.4 - Integrated research methodology

The research methodology begins with 'problem proposal', identifying the problem and then developing the research proposal. It is subsequently followed by 'data management' which includes collecting and analysing the data from different sources. Among various tools and techniques examined in the literature review, an appropriate research method was selected with regards to the research problem, data type and availability.

The nature of the research method employed should reflect these aims by examining the following elements of research theory: research strategy, sampling the population, data collection methods and data analysis techniques. These areas are further discussed in the following sections in order to devise an appropriate research methodology.

4.5.1 Research Proposal

The identification and analysing a research problem is the first and most crucial step of research. This stage starts with reviewing the literature and selecting a topic of research or the statement of the problem. The topic is the definition of the problem that delimits the scope of research and pinpoints the possible strategy to take. According to Singh (2006), a problem proposal involves several tasks, such as determining the field of research, reviewing recent trends and studies in the area, prioritizing the field of study, drawing an analogy and insight in identifying and locating a problem, as well as pinpointing the aspect of the problem. The process is adapted and modelled in multiple stages as shown in Figure 4.5 below.

The current research proposal starts with a literature review and examines the context related to seismic risk management. The seismic risk management approach is multidisciplinary by nature, involving multiple participants. This kind of problem requires a 'continuous compromise' between interdisciplinary breadth and depth of disciplinary knowledge demanded for understanding the problem and establishing a solution which cannot be achieved without cooperation of multiple expert (Avouris 1995). Furthermore, seismic risk management problems require a balanced feedback between stakeholder, different contexts and domains. According to Bender (1996), providing the balancing feedback and facilitating the understanding of the various relationships among participants is essentially a knowledge base problem and thus must be handled through a knowledge-based approach.

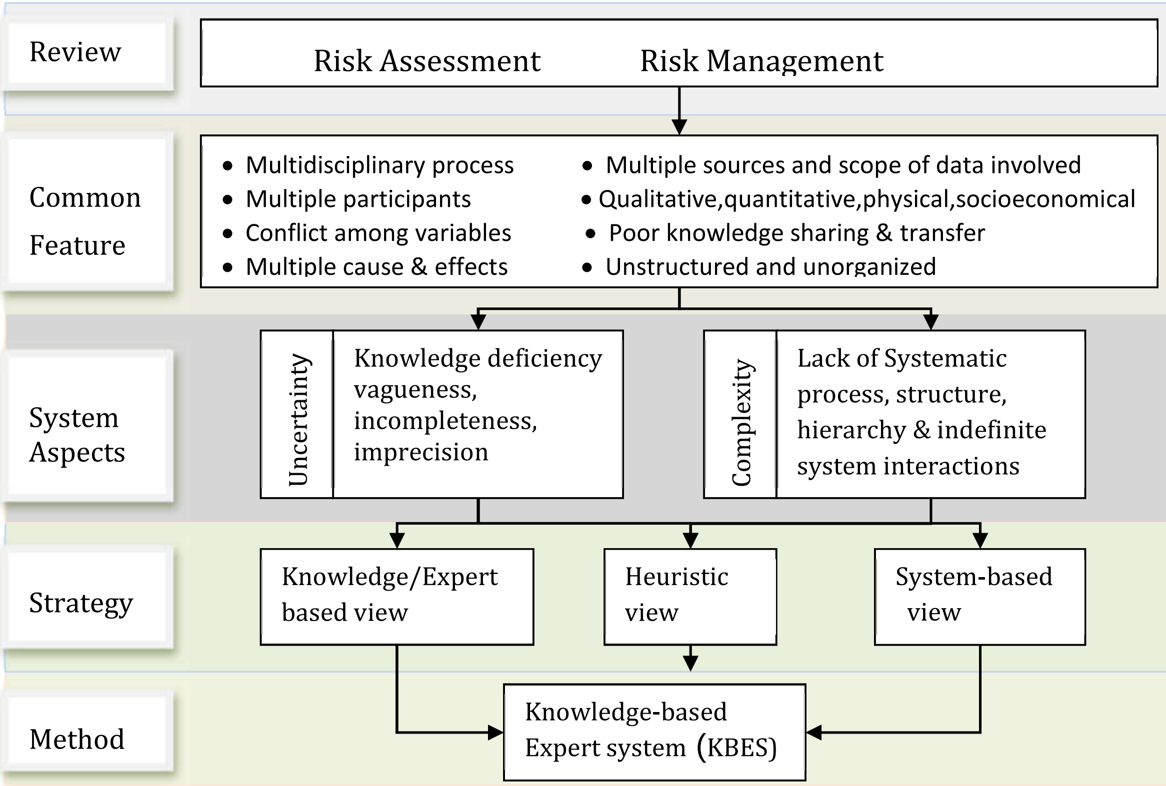


Figure 4.5 – Process of developing the research problem

In addition, earthquakes cause various sorts of impacts on society, comprising not only of primary physical damages and losses, but also social and economic impacts which remains for a considerable amount of time. While there is no single cause of earthquakes, an interaction of multiple causes directly and indirectly contribute to earthquake disasters. Unlike man-made systems that can be described through a finite number of states, predicting the consequence in a natural system is difficult due to the dynamic nature of earthquakes.

The estimation of the parameters involved in earthquake hazards process usually involves imprecise or vague data, incomplete information or lack of historical data, thus requiring an appropriate mechanism to capture, share, and process the information. Various uncertainties are present in identifying the hazard, modelling and assessing the risk, mainly stemming from knowledge deficiency. This can be even more problematic when the focus turns to regional risk management in which a large number of cases are involved. For such a situation, a heuristic structural approach is required to systematically and efficiently manage the information in different layers of systems.

However, systematic perspectives of seismic risk are either ignored or not properly addressed in the literature as already discussed in the review. Therefore, artificial intelligence (AI) is adopted as the overarching strategy to deal with such knowledge-centred problem.

The complex problem of risk assessment and management can be handled through a simple and manageable set of sub-systems. The underlying idea is to cope with the complexity of a problem by applying some kind of decomposition that makes a hierarchy of lower complexity systems (Magdanela 2002). More specifically, the subjective and uncertain nature of problem requires an approach that capable of handling multiple expert opinions. The problem can be framed in the form of computer software decision support, knowledge bases which can take the shape of expert system or some other type of AI technique. Knowledge based expert system (KBES) is a potential approach which can deal with data insufficiency and inaccuracy involved within seismic risk management. The KBES is an AI method that perfectly matches this need. It is a problem-solving approach that works as a learning machine developing the solution for new problems by searching previous knowledge and experiences. As a result, KBES is an appropriate approach for improving seismic risk modelling, assessment and management. A risk assessment model based on KBES is then defined as an objective of the research which is framed in the research proposal.

4.5.2 Data Management

Data management refers to the overall plan and procedure in order to collect, analyse and process the data within piece of research. During data management it should be decided what type of data is required, what sources are available and what method should be used for data analysis. To manage data properly, such questions should be addressed.

According to Walliman (2005), other considerations may also affect decisions about data collection and analysis, which includes: the research strategy, characteristics of the problem, and specific sources of information. Furthermore considerations include the research type (explorative, descriptive); strategy (qualitative, quantitative, mixed); available data sources included the format, scope and range of data and alternative sources; a survey of existing software and data processing methods. Two phases of data management are further explained in the following sections.

4.5.2.1 Data Collection

Data collection is essential in any piece of research, and provides its solid foundation. Type and sources of data are critical in any collecting process. Normally two kinds of data involved in the data collection process: primary and secondary. Primary data are all of the material gathered by researchers, including systematic observations, information from archives and results of case studies and surveys (i.e. questionnaire, interview, etc.). Secondary data consists of everything else derived from other research results, such as electronic records, books, journals, and reports.

Broadly speaking, primary data may not sufficiently usable and reliable enough to be applied directly in research. Jankowicz (1994) supports this viewpoint, stating that primary data are ‘raw, specific, undigested and largely meaningless’; ‘Information’, in contrast, must be used when data have been processed in such a way that uncertainty is lessened, queries resolved and questions answered. For example, data may be ‘missing’, ‘partially complete’, or ‘repetitive or presented in an incomprehensible survey’. Accordingly, it is the researcher’s responsibility to verify the primary data and subsequently decide what data should be processed, filtered or omitted from the data collection process. Therefore, everything provided in a piece of research should be directed to the collection and presentation of data, from which information can be easily extracted (Jankowicz 1994).

Several data collection methods were reported in the literature, each carrying advantages and limitations as shown in Table 4.3. An overview of the data collection methods is given in the following sections.

Table 4.3 - Various research methods, including strength and weakness (McNamara, 1999)

Method	Overall Purpose	Strength	Weakness
Questionnaires , Surveys, Checklists	when need to quickly and/or easily get lots of information from people in a non-threatening way	• can complete anonymously • inexpensive to administer • easy to compare and analyse • administer to many people • can get lots of data • many sample questionnaires already exist	• might not get careful feedback • wording can bias client's responses • are impersonal • in surveys, may need sampling expert • doesn't get full story
Interviews	when want to fully understand someone's impressions or experiences, or learn more about their answers to questionnaires	• get full range and depth of information • develops relationship with client • can be flexible with client	• can take much time • can be hard to analyse and compare • can be costly • interviewer can bias client's responses
Observation	to gather accurate information about how a program actually operates, particularly about processes	• view operations of a program as they are actually occurring • can adapt to events as they occur	• can be difficult to interpret seen behaviours • can be complex to categories observations • can influence behaviours of program participants • can be expensive
Focus Groups	explore a topic in depth through group discussion, e.g., about reactions to an experience or suggestion, understanding common complaints, etc.; useful in evaluation and marketing	• quickly and reliably get common impressions • can be efficient way to get much range and depth of information in short time • can convey key information about programs	• can be hard to analyse responses • need good facilitator for safety and closure • difficult to schedule 6-8 people together
Documentation Review	when want impression of how program operates without interrupting the program; is from review of applications, finances, memos, minutes, etc.	• get comprehensive and historical information • doesn't interrupt program or client's routine in program • information already exists • few biases about information	• often takes much time • info may be incomplete • need to be quite clear about what looking for • not flexible means to get data; data restricted to what already exists
Case Studies	to fully understand or depict client's experiences in a program, and conduct comprehensive examination through cross comparison of cases	• fully depicts client's experience in program input, process and results • powerful means to portray program to outsiders	• usually quite time consuming to collect, organise and describe • represents depth of information, rather than breadth

Questionnaire

A questionnaire is an objective means of survey that collects two types of information, facts and opinion. The questionnaire can be approached via mail, internet or simple gate survey. According to Denscombe (2007) there are three types of questionnaire in terms of the questions asked, including closed-ended questionnaires, open-ended ones, or a combination of both. Close-ended questions are those that have structured answers via certain choices while open-ended questionnaires leave the respondent to decide the answer's wording as well as the subject to be raised in the answers.

A questionnaire benefits from other survey approaches as it provides a 'standardized measurement' which is consistent across all respondents, enabling the researcher to have an unbiased response to meet research need (Fowler 2009). There are several advantages of questionnaires; they are cheap; easy to arrange; obtain a wide coverage; supply standardized answers; have pre-coded answers; and the data is accurate. However, the disadvantages of questionnaires are: poor response rate and incomplete or poorly completed answers.

Interview

Generally, interviews provide insight by probing deeply to uncover new clues, exploring new dimensions of a problem and securing vivid, accurate, inclusive accounts that are based on personal experience (Burgess, 1982). In this process, information is "extracted" from the material by using the strands of similarities of opinions, called themes or clusters. Hence, respondents may repeat similar words, opinions or clusters of information which can subsequently be processed.

Interviews are appropriate when questions are open ended, allowing for more probing for information on a particular subject to generate insights and concepts. The face-to-face interview provides an opportunity to better explain the purpose of study rather than a closed information sheet which is usually attached to a questionnaire. However the interview process takes much longer than questionnaires and thus the former is expensive if performed over a wider geographical region.

The main issue in an interview stem from biases that could distort results. Potential biased results are common pitfalls that might happen due to personal attitudes, expectations, age and other inconsistencies in setting the attributes, sequence of questions or even the places arranged (Bell 1994). Due to cost and time constraints, interviews have not been considered as a survey priority in this research. In addition, the form of close-ended surveys can be effectively undertaken using simple methods such as questionnaires.

Observation

Observation refers to a systematic field, noting and recording of events, behaviours and concrete descriptions of what has been observed (Marshal and Rossman 1999). It is highly important as it explores the complex interactions between multiple events in a natural setting. This process is often employed jointly with other survey methods for examining, probing and exploring the causal relationship of variables (Graham 2000).

Observation is generally performed in two ways. First, direct observation in which a specific subject is recorded via common audio-video recording tools. Second, participants (third-party) observation that is good for studying multiple regions, language, ethnicity and geography. Observation were used within the study to collect primary information of schools inventory. The vast majority of information collected from school buildings was already surveyed by local experts, audited by supervisors and then processed through the existing database. Use of available surveys could save a significant amount of time and effort to collect numerous school inventories across the country. This process has been routinely performed by professionally trained experts using a standard inspection procedure since the start of the mitigation program. This database was used as a source of information in this thesis.

Document review (content analysis)

Document review or content analysis deals with the systematic examination of current written (or verbal) records or documents as a source of data. A review of research in any area naturally involves the analysis of the contents of research articles that have been published (Kothary 2006). Content analysis was conducted to analyse the contents of documentary materials such as books, magazines, journals and newspapers. It has six steps: select a suitable sample of the images or text; break the text down into smaller units; develop relevant categories for data analysis; code the unit in line with the categories; count the frequency with which these units occur; and analyse the text in terms of the frequency of the units and their relationship with other units that occur in the text. According to Denscombe (2007), document analysis benefits from using documents, and include access to data, cost-effectiveness, and permanence of data, while a major issue in document analysis is the credibility of sources as the documents may not necessarily trustworthy. Consequently, documents must be reviewed critically and crosschecked with other sources for validation. This type of data collection is common in most of research as well as the present study.

Case study

"A case study is an empirical inquiry that investigates a contemporary set of events within its real life context, particularly when the boundaries between phenomenona and context are not distinguishable"(Yin 2009). Case study explores the situation qualitatively by answering "how" and "why" questions. Case studies may be used for organizing a wide range of information about a case and then analysing the contents by seeking patterns and themes in the data and by further analysis through cross-comparison with other cases. A case can be individuals, programs, or any unit, depending on what the program evaluators want to examine through in-depth analysis and comparison.

Jankowicz (1994) pointed out that the case study approach can be used when the researcher's thesis focuses on a set of issues in a single organization, individual or project and they want to identify the factors involved through an in-depth study of the organization or a single department within it. According to Yin (2009) the case study is the most comprehensive form of research that benefits from prior development of theoretical propositions to guide data collection. However, it relies on multiple sources of evidence for validating through a triangulating fashion, which takes much longer. Nevertheless, case studies are appropriate for exploring new situations (Eisehardt 1989) with low historical records in which many variables and data points are involved, such as the current study.

4.5.2.2 Data Sampling

Basically, processing a large number of the population is not practical; rather a sample of the population is selected and used instead of survey (Downing and Clark 1996). In most descriptive surveys, the researcher takes out samples to process as a basis for sample analysis. The sample design should be carefully performed to be a reliable representation of the full population. An inappropriate sampling frame could be a major source of problems since any systematic discrepancy between the research population and the sampling frame can be a source of error (Gill and Johnson 2002). Thus the sample size should be large enough to cover and represent various attributes across the population. Gill and Johnson (2002) advocate that "the larger the sample the lesser the likelihood that findings will be biased does hold, diminishing returns can quickly set in when samples get over a specific size which need to be balanced against the researcher's resources". Common sense suggests that degree of accuracy in a survey is directly proportional to the sample size. However Denscombe (2010) argued that the crucial factor in selecting the sample size is not the proportion of the population included within the survey, but the absolute size of the sample.

Sampling strategies may vary according to: the population and the purpose of the inquiry; importance and layers of data; and survey method chosen. There are two main types of sampling: probability (or random) sampling and non-probability (or purposive/judgmental). Probability sampling refers to the methods that statistically pick the sample on a random basis, such as simple random sampling, systematic sampling, and stratified random sampling. This type of sampling is useful in large populations where anonymity is a critical factor. Theoretically, there are several statistical tools and formulas for determining sample size. However, there are situations that the sampling population may not be defined precisely, or where a list of the sampling population is unavailable. In this case, non-probability or purposive sampling can be approached according to specific characteristics, criteria, behaviour or experience rather than overall population size.

4.6 Adopted Research Strategy

Broadly speaking, there is no single strategy that suites different research. At any stage of the inquiry, the researcher has to make a decision about the kind of investigation required and the certain types of problem that may arise. Some basic characteristics of a research project such as the size (e.g. large scale), time (long or short term) and cost restrictions can guide the choice of strategy (Densecomb 2007).

When choosing an appropriate strategy, certain elementary factors should be considered in terms of suitability, feasibility and ethics. Firstly, the strategy should be clear enough to answer the research questions. This was supported by Yin

(2009) stating that understanding and drawing a portrait of research questions (i.e. what, who, where, why questions) is the most critical task of selecting the suitable strategy. Suitability is required to ensure that the research produces an appropriate kind of data fit within the procedure. Secondly, the strategy must be feasible and practical to meet the project's cost, time and resource availability (Densecomb 2010). Finally, the strategy should be of such a form as to allow the researcher to work within an appropriate code of practice and to meet basic concerns such as confidentiality, not being harmful to participants and there being no conflict of interest.

This study identifies variables, seeks causal relations and builds up a theory. The data collected in this process originally comes from a combination of quantitative and qualitative process. For this, a mixed strategy was considered as a potential approach for integrating qualitative and quantitative methods of data collection and the analysis (Crooks 2011). Therefore the mixed method was adopted as an overarching research strategy to gain a full, true and clear understanding in terms of both processes within which model development takes place, and the wealth of material used within the process. Mixed methods have multiple use which has the advantage of both quantitative and qualitative approaches and presents greater consistency between the results. It provides new information and understanding of validity beyond those supplied when independently investigating the findings stemming from either qualitative or quantitative methods.

Quantitative models were used to quantify the properties of data by the use of statistical analysis. Several mathematical models have been employed in order to verify the feasibility of the model in real practice. In this research, a large sample project was taken to test and verify the model quantitatively. In contrast, the qualitative approach focuses on both process and outcomes by explaining the 'how' and 'why' of events occurring (Creswell 2003). Empirical investigations provide a real-world understanding of the phenomenon under study. Qualitative approach was adopted to describe the relationships between variables (risk drivers) and to measure their magnitude through a systematic human reasoning process. Furthermore, the qualitative process enriches the theory by grounding it with relevance and meaning, while the quantitative phase verifies and tests the model on the basis of the developed theoretical framework.

To accomplish the adopted strategy, several methods have been integrated and applied to meet the research objectives. These methods are further outlined in the following sections.

4.7 Adopted Research Method

There are a number of methods available to conduct the research, including experiment, survey and case study. Yin (2009) suggests the requirements to choose a research method include the type of research question, and the extent of control over actual behavioural events. He emphasized on classifying the research questions as a critical determinant of research method.

Essentially, ‘how’, ’what’ and ’why’ are common questions often defined at the onset of research. ‘How’ and ‘why’ are more explanatory nature and thus appropriate to the use of case studies and experiments as a preferred research method. ‘What’ might reflect the two forms of the question; ’what’ as an exploration implies the type of method that can be applied, or ‘what’ in term of ‘how many’ or ‘how much’ that favours a survey method.

Although the survey method is better answering the ‘how many’ type of question, this research also requires in-depth analysis of the seismic risk impacts within the interest group of school buildings. According to Yin (2009) the ability of the survey as a sole strategy to investigate the context is limited. Depending on the survey as a sole strategy can restrict the research on subjective sources.

Hence, the case study method was adopted as the overarching strategy to explore the research and address the research questions jointly with questionnaire survey. First, because case studies enable researchers to investigate ‘how’ and ‘why’ questions for developing specific situations. Second, they have the potential to deal with subtleties and intricacies of complex phenomena (Denscome 2007). This potential comes from a strategic decision that restricts the range of studies in focusing on specific situations.

The nature of this research is to explore and discover new activities and events and this can be only achieved through a case study approach (Creswell 2003). Furthermore, this approach is appropriate for developing a new perspective of the contemporary set of events, which have been little investigated and addressed in the literature (Yin 2009). In the present research, since the multidisciplinary impacts of earthquake have been explored for the first time, the case study approach could be the best choice to conduct the research. According to the case study method, it should be exploratory and descriptive, not explanatory or casual. This is mainly because this research aims to explore and describe a real life event in the way of managing risk and uncertainty, in order to build and expand the theory and not to test it. Figure 4.6 displays the general research process adopted in this thesis, addressing both qualitative and quantitative aspects of the study.

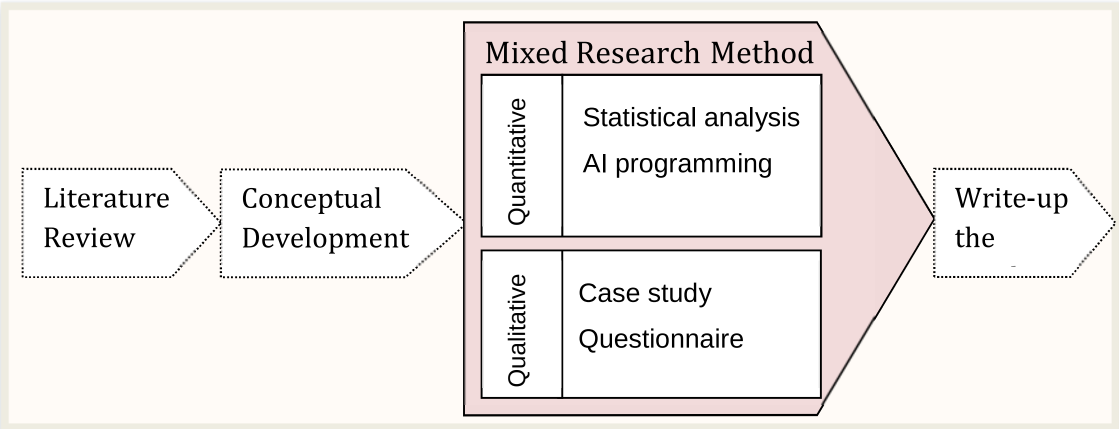


Figure 4.6 – Adopted research method procedure

4.8 Statistical Analysis

Statistics is a scientific language to describe information and communicate the research outcome in the quantifiable form of numerical information (Beins and McCarthy 2012). Statistical analysis involves a set of mathematical techniques or processes for gathering, describing, organizing and interpreting numerical data. Since research often yields such quantitative data, statistics is a basic tool of measurement of research. In this regard, various scales of measurement can be used to describe the data. Some data may be relatively raw, requiring information about categories in which observations fall. Other data are more mathematically complex, allowing for more complicated algebraic manipulation. According to Beins and McCarthy (2012), the selection of a descriptive statistics tool should be made in accordance with the underlying mathematical properties of the information that is being reported. In this case, various scales of measurement can be applied, such as nominal, ordinal, interval and ratio. However, depending on how data are described, categorized and formatted, the perceptual theory can be changed. In other words, the scale of measurement can influence the way in which statistics are used. The more meaningful reporting statistics are, the more effective research the outcome will be. Therefore, utmost care must be given to descriptive statistics as it portrays the picture of outcomes derived from research.

4.8.1 Computer Programming

One of the objectives of this research is to examine the application of AI in order to improve the process of seismic risk assessment. Computer-based analysis is a quantitative means of research that allows the researcher to process, combine, summarize and convert data into usable information. In this regard, several programming software packages were examined for the use of research. The main packages utilized in this research can be categorized as follows:

- Origin Pro®, SPSS®, Excel® were used for statistical data processing, analysis and visualizing (scientific charting).
- MATLAB® as high performance programming language was used for the automated reasoning process (inference engine) and simulating purpose.

4.9 Adopted Data Collection Method

The choice of the data collection method is primarily affected by the resources available for the research. However, other constraints such as strategy and type of data determine the selection process (Fellow & Liu 2003; Dawson 2007). A quick look at the research indicates that seismic risk management contains a mixed of qualitative and quantitative information, while the majority of this information can be processed and presented in numerical format. Hence, the research aims to develop a seismic risk evaluation system by the means of quantitative approach. Furthermore, the proposed system is essentially set up to work with the sort of information scaled, presented and stored in numerical format. Therefore, the data collection method must be quantitative in nature to fit within the overall research methodology.

In this regard, an extensive literature review of potential approaches was performed before the survey in order to obtain the required background information in the context of earthquakes. A large amount of disaster reports and case studies were examined with two aims. The first was to identify the risk factors possibly involved in the earthquake loss process in term of physical and socioeconomic effects, and to determine the range of impacts (reduce or increase) on the urban area. The second aim was to establish the causal relationship within risk factors and to classify them in different categories. In this regard, there is a relatively comprehensive stock of studies conducted in various disciplines of the earthquake context. For example, the World Bank, UNDP along with FEMA have addressed standard reports and procedures about previous and recent earthquakes which was implemented within the research.

In this light, the questionnaire format is preferred as it provides an unbiased standard measure and is consistent for all respondents. A questionnaire survey was conducted in summer 2013 from the experts involved in seismic risk management. The questionnaire form is available in Appendix A. In total, 80 experts was asked to participate from which 51 completed survey questionnaires were obtained (3 incomplete).

According to the proposed structure of seismic risk, a survey questionnaire was designed and formulated in six sections. In order to extract the knowledge from experts, a five-grades scale was used for each attribute within the questionnaire. The purpose of this questionnaire is to frame the importance of the risk factors using expert opinions as an input source for rule-base design.

4.9.1 Survey Data Processing

Elicitation of expert knowledge is critical for the judgment process, since it is associated with varying degree of belief or levels of confidence. Generally, basic statistical approaches such as mean and geometric mean have been the primary tools for aggregating expert opinions. However, theses methods have limited ability to handle the uncertainties involved within experts' aggregation process.

Bardossy et al. (1993) suggested that expert opinions should be represented through fuzzy numbers. The fuzzy aggregation method has been widely implemented in multicriteria problems that require consistency and consensus among experts. Several methods were used to aggregate various opinions based on the similarity aggregation method (Lee 1999; Hsu and Chen 1996; Deng et al.

2011); while the notion of them all based on similarity between expert opinions which can be represented by fuzzy sets. The individual opinion with the most similarity with the others is considered as a more credible judgment and thus receives higher impact factors than other inconsistent opinions in a group.

Sharing this idea, both confidence levels and similarities were taken into account for processing the survey data. The confidence levels of expert can be evaluated through skills and experience levels. More experienced experts mean more skills and receive a higher expert index. Respondents were classified in three groups based on their experience, including 14 people 5 - 10 years of experience, 26 people with 10 - 15 years of experience, and 8 individuals with over 15 years of experience. Accordingly, a confidence index was assigned to each group of experts as shown within Table 4.4.

Table 4.4 - Summary of expert confidence index based on experience

Expert Group	Expert No.	Percentile	Experience	Expert Index
EG-1	14	29	5 < E < 10	0.166
EG-2	26	54	10 < E < 15	0.333
EG-3	8	17	15 < E	0.5

Expert opinions about the seismic risk factors and the summary of the opinions aggregation process is available in Appendix B.

4.10 Adopted Research Sampling

Different sampling techniques have been discussed earlier in this chapter. A combination of random and purposive sampling was framed because the different form of data as well as mixed strategy (qualitative and quantitative) involved in this research. Statistical analysis requires a broad range of attributes to establish a ratio scale. The ratio scale provides the widest range of flexibility in terms of reporting descriptive statistics (Beins & McCarthy 2012). In this regard various attributes were selected according to criticality, intensity, geography, typology and extreme cases to develop a comprehensive representation of whole populations. Alternatively, random sampling was used to cover the domain intervals and fulfil the normality requirements of the system.

Purposive sampling is a prime choice for qualitative research, entailing a small number of samples to characterize attributes within the context. According to Graham (2000) and Denscomb (2007), choice of events or people for inclusion in the sample tends to be on the basis of small-sized purposive sampling. Thus purposive sampling was applied through a questionnaire survey. Throughout the sampling, a group of experts was chosen according to their skills, experience and knowledge around research problem.

4.11 Summary

This chapter has presented the research methodology adopted for this study. It first discussed the methodological concept of research, including the knowledge inquiry and the strategy followed by potential methods for collecting data. Seismic risk management requires consequence-based research, so inductive knowledge inquiry can better describe the overall effect of the potential impacts. The mixed method research strategy was adopted because the problem is combination of quantitative and qualitative information, and therefore required an appropriate method to consistently follow a logical process to develop the theory. The case study approach was chosen as an overarching strategy to explore the likely impacts of earthquakes and to heuristically conceptualize the causal relationship within risk drivers. The data collected from the questionnaire survey as well as observations, statistics, documents and reports from previous experiences in literature collectively build the basis for the research development.

Chapter 5: Fuzzy Modelling

5.1 Introduction

This chapter provides the necessary background, definitions and terminology of fuzzy sets, fuzzy logic and fuzzy expert systems in order to model seismic risk impacts. Fuzzy modelling techniques, such as fuzzy set theory, fuzzy logic and fuzzy expert systems are formal mathematical grounds to deal with vague and imprecise information. The fuzzy set theory is based on many valued logic that enables the handling of vague concepts.

Fuzzy logic works as a mathematical vehicle for the inference and reasoning of ambiguous statements by processing first-order linguistic uncertainties. The fuzzy expert system is an extension of fuzzy set theory, which uses experts to map sets of inputs to a set of outputs. The fuzzy expert system is a common use of fuzzy logic in a larger complex system. This chapter investigates its application in the complex domain of seismic risk management.

5.2 Complex System Modelling

Decision-making in real world problems is a complex human activity (Xiang et al 1992). Models are mathematical abstractions of the real world, and thereby a simulation of a problem should portray as accurate as depiction of the true situation as possible. An effective simulation requires understanding the purpose and restrictions of the prospective system. This is necessary in order to fit the appropriate tool to the problem (Shannon 1975).

Complexity and uncertainty are two important dimensions in modelling processes, as shown in Figure 5.1. A complex system is composed of multiple subsystems that are integrated through functional hierarchy. The integration of models, methods, and stakeholders’ concerns decides the complexity of the system. However, modelling a complex system requires the simplification of assumptions that could potentially import uncertainty into the simulation.

According to Shannon (1975) simulation is an "imprecise" process requiring a high calibre of perception that may not be available. Fuzzy modelling is an effective way to handle complex systems by mimicking mind reasoning. In this process, human reason approximates its behaviour, thereby maintaining only a generic understanding of the problem, as suggested in Zadeh's principle (1965) of incompatibility; complexity and ambiguity are correlated (Klir and Yuan 1995; Ross 2004).

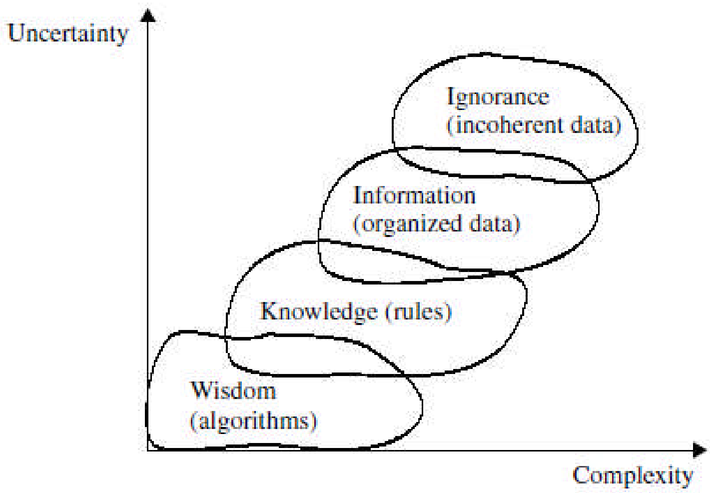


Figure 5.1 – Uncertainty and complexity dimensions in system modelling (Ross 2004)

In developing a fuzzy system, the methodology should correspond with the way uncertainty and complexity are exhibited in the problem. Klir and Yuan (1995) suggest the three characteristics of uncertainty, credibility and complexity with the aim of maximising the fuzzy model's usefulness. While uncertainty plays a crucial role in maximising a system's effectiveness, the interaction with the other two factors is also significant in constructing a fuzzy system.

Allowing more uncertainty in modelling may reduce complexity and increase the credibility of outcomes (Ross 2004). In situations with little complexity or uncertainty (where systems can be described algorithmically with a precise database), fuzzy systems are less efficient than conventional statistical approaches. However, the fuzzy systems provide a shallow understanding of a problem in the systems with a little more complexity and uncertainty; ones exhibiting imprecision and ambiguity in their process, such as nonlinear systems. For very complex systems, few imprecise numerical data are available. Fuzzy reasoning provides the most appropriate way to describe system behaviour by defining the approximate relations between observed input and output situations which are mainly based on deduction. Finally, for the most complex systems that require forms of learning due to induction, or combinations of induction and deduction, more complex approaches such as Bayesian theory and game theory may be applied (Ross 2004).

5.3 Fuzzy Set Theory

Fuzzy set theory was proposed by Zadeh (1965) and provides a concept to accommodate uncertainty and vagueness (fuzziness) as a means to model through natural language. The term "fuzzy" refers to the situation where no defined boundaries of a set exist (Chen and Hwang 1992). Fuzzy sets has the capability to express gradual transitions from membership to non-membership, as opposed to classical sets where each element can only take either 1 (completely inside) or 0 (completely outside) as indicated in Figure 5.2.

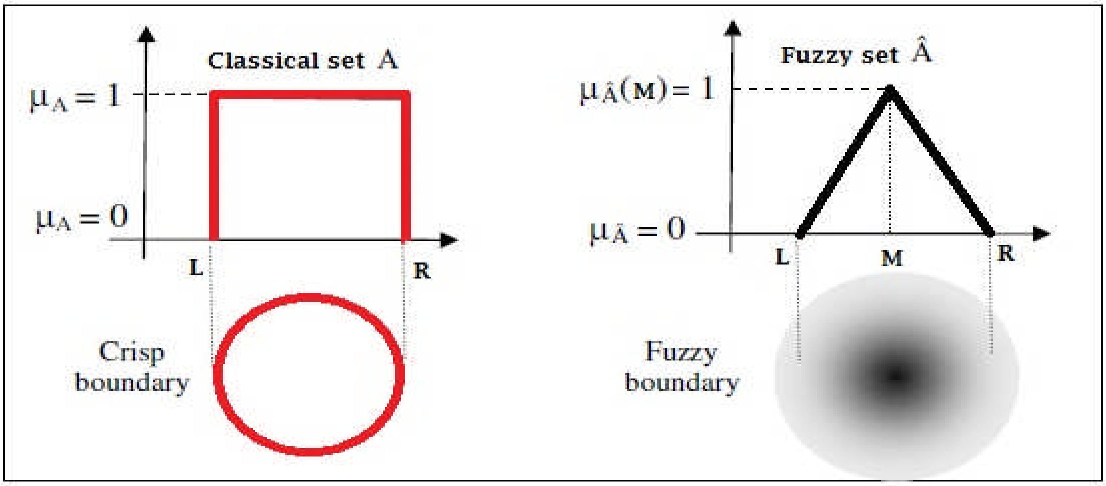
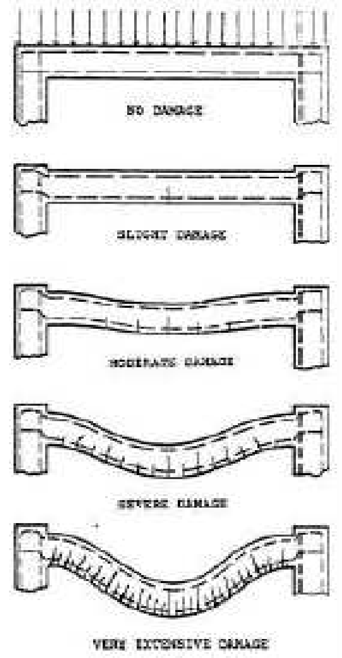
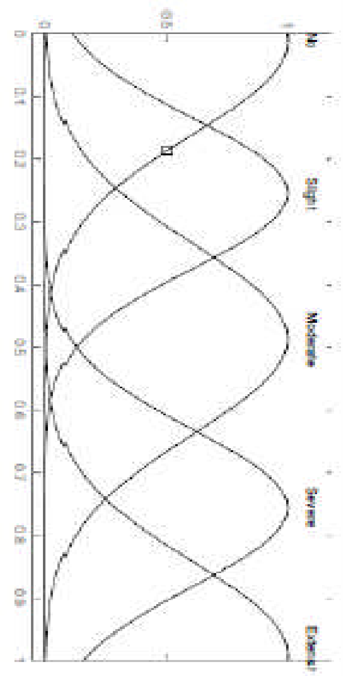
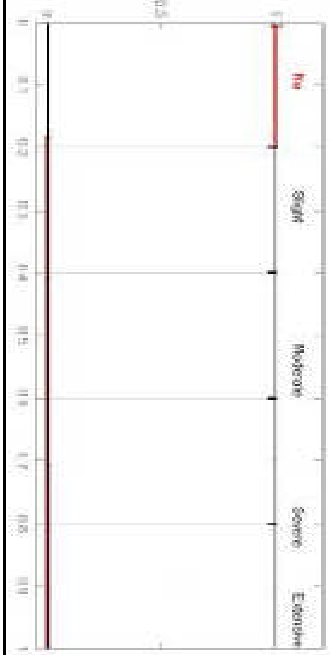


Figure 5.2 – Classical set vs. fuzzy set

Most concepts in the real world are somewhat vague and imprecise. According to Zimmerman (1991), two major issues may arise in factual modelling. First, real situations are not crisp and deterministic enough to be described precisely. Second, a thorough description of a real system is either too complex or far more detailed data than a human could ever recognize, understand and process simultaneously. A fuzzy set not only "provides a meaningful and powerful representation of measurement uncertainties, but also a meaningful representation of vague concepts expressed in natural language” (Klir and Yuan 1995). Many concepts in daily life are of this kind, such as 'class of experienced engineers', 'class of tall men’, 'class of high-speed racing cars’, and 'cold/warm/hot water’. Similarly, hot, warm and cold are vague concepts that cannot be described precisely since there is no clear boundary between each state.

More complex concepts can be found in civil engineering and disaster management. For example, the state of damage within buildings has been commonly described by two discrete values: survival or failure. Looking closer at the problem, however, more states can be distinguished. It can be also noticed that state of damage is a continuous parameter, as opposed to being discrete. This kind of problem lacks crispness (or inherent fuzziness), causing uncertainties in determining the clear levels of damage that hampers identifying the acceptable level of damage (Savage 1988; Adeli 1988). The uncertainty or vagueness in describing the states of damage can be effectively captured through fuzzy numbers. The more overlap between adjacent grades (e.g. slight, moderate), the more uncertainties in distinguishing each grade.

Table 5.1 - Linguistic descriptions of damage levels (After Savage 1988)

Damage Sate	Fuzzy Set	Classical
		

Mathematically, classical set theory (or crisp set) is based on two-valued logic. If A is a subset of the universe of discourse U ($A \subset U$) that consists of elements x ($x \in U$) then each element x is either a member of A ($x \in A$) or not ($x \notin A$).

In contrast, the fuzzy set theory is based on multi-valued logic that allows mapping of any values from the universe of discourse to a universal range of 0 to 1 according to which grade of membership they belong to. Let $\boldsymbol{A}$ be a subset of universe ($\boldsymbol{A} \subset U$) and membership function μ_A defines the partial membership function in a set. Unlike classical set that μ takes two values, in fuzzy set theory the degree of membership of an element can be any value within the interval [0, 1]. For instance, if μ = 1 then the item is definitely a member of the set. Conversely, for μ=0, the element is definitely not a member of the set.

For other membership values between 0 to 1 the values indicate partial membership (or belief) that the element is a member of the set. For example, let set A as the universe of various concrete (sample) strengths (MPa):
$\boldsymbol{A}$ = [18, 20, 22, 24, 26, 28, 30, 32]
In this case the x_i represents the values of concrete strength. Fuzzy set A can be represented in terms of its membership functions (Zadeh 1965); Dubios and Parade 1985) :

$$\boldsymbol{A} = \left[\frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots + \frac{\mu_A(x_n)}{x_n}\right] = \sum_{i=1}^{n} \frac{\mu_A(x_1)}{x_1} = \int \frac{\mu_A(x)}{x} \qquad (5.1)$$

Where '___' is a delimiter that indicates the association of the membership value $\mu_A(x_i)$ and the symbols '+' ,'Σ', '∫ ' denote the union of all elements of the fuzzy subset in the form of discrete and continuous respectively. Accordingly, a moderate concrete strength concrete may be expressed by the means of fuzzy terms as (Figure 5.3):

'Moderate Concrete' = $\left[\frac{0.0}{18} + \frac{0.0}{20} + \frac{0.2}{22} + \frac{0.8}{24} + \frac{1.0}{26} + \frac{0.5}{28} + \frac{0.0}{30} + \frac{0.0}{32}\right]$

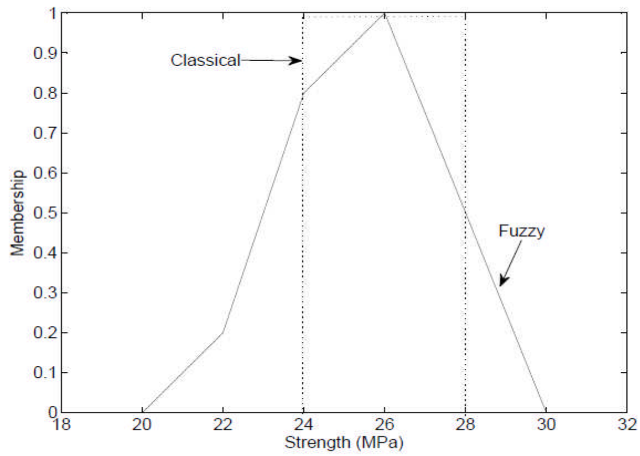


Figure 5.3 - Classical and fuzzy representation of a 'moderate strength' state

Fuzzy sets make it easier to develop solutions to problems in practice. The concept of a linguistic variable transforms linguistic terms into numeric quantities which can be used for mathematical operations within a fuzzy system. This feature allows a practitioner to model vague concepts by means of linguistic variables. Using fuzzy sets not only facilitates capturing vague concepts, but it also allows a gradual transition between states of linguistic variables, whereas in the classical set this transition occurs abruptly and discretely. This gradual transition is a result of using linear (first-order) or non-linear membership functions. Thus, fuzzy sets can effectively represent events in both continuous and discrete forms.

5.4 Fuzzy Aggregating Operators

The aggregation process in fuzzy sets is performed by a set of connectives or operators. Various aggregation operators have been reported in the literature, covering a broad range of applications, from general to specific situations. Some of the most common operators are listed following (Chen and Hwang 1995; Zimmermann 1992).

5.4.1 Intersection (t-conorms)

The intersection of two fuzzy sets A (μ_A) and B (μ_A) can be computed through different mathematical operations such as minimum and bounded difference, as well as algebraic product. Each operator measures the different degree of 'AND' in the decision space. Common operators belonging to the class of t-conorms (Upper bound is min) are categorised under intersection operators as indicated in the following.

Minimum: $\mu_{S1} = \min(\mu_A, \mu_B) = \mu_{A \cap B} = \mu_A \cap \mu_B$ (5.2)

$\mu_{S2} = \min(\mu_A, \mu_A)$ if $\max(\mu_A, \mu_A) = 1$, else $\mu_{S2} = 0$ (5.3)

Bounded difference: $\mu_{S2} = \max(0, \mu_A + \mu_B - \mu_A \cdot \mu_B)$ (5.4)

$$\mu_{S3} = \frac{\mu_A \cdot \mu_B}{2-(\mu_A + \mu_B - \mu_A \cdot \mu_B)} \quad (5.5)$$

Algebraic Product: $\mu_{S4} = \mu_A \cdot \mu_B$ (5.6)

$$\mu_{S5} = \frac{\mu_A \cdot \mu_B}{(\mu_A + \mu_B - \mu_A \cdot \mu_B)} \quad (5.7)$$

The above operators measure different degrees of 'AND' in the decision space. In this case, parametrized 'Min' operators such as Yager's and Dubios-Parad's can be used instead, as reported in Zimmermann (1992).

5.4.2 Union (t-norm)

The compensatory max operator such as the bounded sum and algebraic sum are three basic forms of union operator that allow some degree of compensation when using in the decision space. Common operators belonging to the class of t-norms (lower bound is max) are categorised under union operators as indicated following.

Maximum: $\mu_{V1} = \max(\mu_A, \mu_B) = \mu_{A \cup B} = \mu_A \cup \mu_B$ (5.8)

$\mu_{V2} = \max(\mu_A, \mu_A)$ if $\min(\mu_A, \mu_A) = 1$, else $\mu_{V2} = 0$ (5.9)

Bounded sum: $\mu_{V3} = \min(0, \mu_A + \mu_B)$ (5.10)

$$\mu_{V4} = \frac{\mu_A \cdot \mu_B}{1+(\mu_A \cdot \mu_B)} \quad (5.11)$$

Algebraic sum: $\mu_{V5} = \mu_A + \mu_B - \mu_A \cdot \mu_B$ (5.12)

$$\mu_{V6} = \frac{(\mu_A + \mu_B - 2 \cdot \mu_A \cdot \mu_B)}{(1 - \mu_A \cdot \mu_B)} \quad (5.13)$$

Likewise, the above operators measure different degrees of 'OR', and for special cases, parameterized max operators such Yager's and Dubios-Parad's may be fit better. More detail is available in Zimmermann (1992).

5.4.3 Averaging Operators

Intersection and union operators measure lower and upper bounds through 'logical AND' and 'logical OR' in the decision space. However, when some course of action requires a compromised solution between two bounds those operators are not applicable. These operators are known as 'averaging' or 'compensatory', and return the results between two bounds (greater than min and less that max). Some of the averaging operators are listed below:

$$\mu_{C1} = \frac{\mu_A + \mu_B - \mu_A \cdot \mu_B}{1 + \mu_A + \mu_B - 2 \cdot \mu_A \cdot \mu_B} \tag{5.14}$$

$$\mu_{C2} = \frac{\mu_A \cdot \mu_B}{1 + \mu_A + \mu_B + 2 \cdot \mu_A \cdot \mu_B} \tag{5.15}$$

$$\mu_{C3} = \frac{\min(\mu_A, \mu_B)}{1 - (\mu_A - \mu_B)} \tag{5.16}$$

$$\mu_{C4} = \frac{\max(\mu_A, \mu_B)}{1 + (\mu_A - \mu_B)} \tag{5.17}$$

$$\mu_{C3} = \frac{\mu_A + \mu_B}{2} \tag{5.18}$$

The family of averaging operators provides a more flexible way to combine fuzzy sets within extreme limits, within which 'Min' and 'Max' as shown in Figure 5.4.

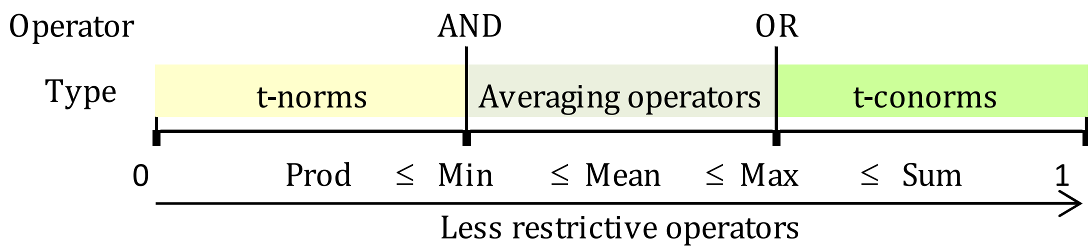


Figure 5.4 – Common aggregation operators (Larsen 2002; Zimmerman 1992)

The advantage of averaging operators is in its flexibility to encompass a range of operators bounded between 'Min' and 'Max'. Ordered weighted averaging (OWA) operators are well-known examples for averaging operators that have compensatory behaviour.

5.4.4 Selection of Aggregation Operator

The aggregation operation determines the way to approach fuzzy modelling. Since the use of operator is context sensitive, the aggregation operation reflects an attitude toward objectives. Thus, a meaningful assessment of operators requires careful adoption of an aggregation operation (Dubios and Parade 1985; Munda 1995).

Aggregation operations in fuzzy decision-making are broad, including a number of aggregation operators and connectives for the following situations: general and specific, compensatory and non-compensatory, single-level and hierarchical (Chen and Hwang 1992), and cover a wide range from totally pessimistic through totally optimistic scales. The variety of aggregation operators stems from differences in problem aims, strategies, hypotheses, opinions and relevance (Kuncheva and Krishnapuram 1996).

Selection of the aggregating operation is context-dependant. A straightforward approach for aggregating fuzzy sets is by applying the aggregating procedures frequently used in multicriteria decision theory and utility theory. According to Zimmerman (1992), the operators must primarily have the sufficient axiomatic strength to mathematically satisfy axioms and empirically represent system behaviour. In addition, compensation and rigidity are important features that account for the contribution of all criteria into the model. Since a MCDM problem seeks for general consensus among experts, the aggregation operators must be compensatory to reflect a variety of attitudes in the overall result.

The use of compensatory operators could lead to a compromised satisfactory solution. For example, 'Min' and 'Max' are non-compensatory operators biased towards extreme limits (lowest, highest), and despite having numerical efficiency; they cannot be adapted for many situations. However, the combination of Min and Max allows for better compensation within the interval [0,1]. Rigidity also restricts the range of aggregation by reducing the strength of results in higher levels, irrespective of the magnitude of input sets (Sadiq et al 2010). For example, the ‘Prod’ (Product operator) cannot be applied to a multilevel problem since each aggregation step reduces the strength of results and distorts the overall decision.

Nevertheless, there are a few number of operators that are able to model many situations. Aggregation operators are context-specific; appropriate operators should be adapted to efficiently fit particular context. In this case, some parameterised Yager’s operators can be useful, though it requires more computational and effort compared to min/max operators.

Taking the above into the consideration, this study employs a combination of compensatory 'Min' (logical AND) and 'Max' (Logical OR) that allows a trade-off between two states. The aggregation procedure is known as 'generalization' and uses the 'Implication' operator, which is based upon 'the extension principle’. This procedure offers more freedom in practice and covers more real-world applications.

5.5 Fuzzy Expert System

The fuzzy expert system is a heuristic approach with concepts and operations associated with the fuzzy set theory and fuzzy logic that mimic human reasoning (Shaheen et al. 2009; Ross 2004). Because knowledge plays a key role in various components of expert systems, including acquisition, representation, processing and verification, the expert system is also known as the knowledge-based expert system (KBES).

There are specific characteristics that distinguish the expert system from conventional approaches as indicated in Table 5.2. High quality performance is a significant feature of expert systems due to using narrow domain-specific knowledge. The speed of decision-making is an important factor particularly in critical situations such as emergency response and management (Negnevitsky 2005).

Table 5.2 - Comparison of expert system with conventional systems and human experts (Negnevitsky 2005)

Human experts	Expert systems	Conventional programs
• Use knowledge in the form of rules of thumb or heuristics to solve problems in a narrow domain. • In a human brain, knowledge exists in a compiled form. • Capable of explaining a line of reasoning and providing the details. • Use inexact reasoning and can deal with incomplete, uncertain and fuzzy information. • Can make mistakes when information is incomplete or fuzzy. • Enhance the quality of problem solving via years of learning and practical training. This process is slow, inefficient and expensive.	• Process knowledge expressed in the form of rules and use symbolic reasoning to solve problems in a narrow domain. • Provide a clear separation of knowledge from its processing. • Trace the rules fired during a problem-solving session and explain how a particular conclusion was reached and why specific data was needed. • Permit inexact reasoning and can deal with incomplete, uncertain and fuzzy data. • Can make mistakes when data is incomplete or fuzzy • Enhance the quality of problem solving by adding new rules or adjusting old • Ones in the knowledge base. When new knowledge is acquired, changes are easy to accomplish.	• Process data and use algorithms, a series of well-defined operations, to solve general numerical problems. • Do not separate knowledge from the control structure to process this knowledge • Do not explain how a particular result was obtained and why input data was needed. • Work only on problems where data is complete and exact. • Provide no solution at all, or a wrong one, when data is incomplete or fuzzy. • Enhance the quality of problem solving by changing the program code, which affects both the knowledge and its processing, making changes difficult.

The transparency feature enhances the explanatory line of reasoning that allows experts to scan and review its reasoning and explain the corresponding decision. This ability enables users to effectively trace the rules fired during the inference process. Another important feature is that the knowledge base is separated from its inference-processing unit. Mixing this knowledge could cause difficulties in reviewing and tracking the process if any change happens for either of them. This flexibility in expert system allows new knowledge to be incrementally added into the existing knowledge base (Buchanan and Duda 1982). The heuristic feature of expert systems with regards to transparency and flexibility explains and track the aggregation process, collectively making it the best choice for processing the complex problem of seismic risk management.

5.5.1 Knowledge Acquisition

The most significant task of developing a fuzzy expert system is in knowledge-base. Knowledge representation is critical in analysing and reviewing the problem and to find best possible solutions. Since the knowledge base may be obtained from a variety of domains, inconsistencies may arise among different sources, gaps in domain knowledge, none-monolithic and fragmented knowledge. Usually, various types of knowledge are involved in developing an expert system. They are:
Facts – Factual knowledge is the most primitive of all kinds of knowledge. It can commonly be found within standards, handbooks, compilations, as with any other engineering based properties established upon factual or experimental knowledge.

Heuristic (judgment) – The mind tends to use previous experience to understand, judge new situations, or find shortcuts for them. This process is often known as "rule of thumb" or "heuristic knowledge". Expert systems simulate the same procedure to guide reasoning as well as to reduce the search area for a solution (Negnevitsky 2005). Thus the quality of heuristic knowledge depends on the experience, insight, understanding, relevance and homogeneity of participants. The engineering knowledge typically used in risk management (e.g. quality inspections) is of this kind, exhibiting a wide range of variability.

Algorithmic (procedural) – Based on calculus and algebra, algorithmic or procedural knowledge uses numeric and non-numeric procedures for solving problems. Algorithms transform factual knowledge from one state to another. For example, the fundamental period is a key factor in obtaining the seismic design force and potential response of a building which is subjected to an earthquake. The algorithm commonly used in codes of practice (FEMA 273; BHRC 2006) to calculate the fundamental period (T) of a building is:

$$T = C_t \cdot H^{3/4} \tag{5.19}$$

Where 'H' refers the height of the building and C_t is a coefficient that varies according to the type of structure (e.g. 0.08 steel, 0.07 RC, 0.05 masonry; BHRC 2006). In this research, this procedure is used for developing the site response.

Control – Otherwise known as meta-knowledge, control manages the processing of previous types of knowledge in the KBES and is most commonly utilized in complex multi-layer systems. Directing the appropriate source for domain-specific problems and coordinating the priority and form of the knowledge gives KBES as a means of explanation and reasoning.

Traditionally, expert opinion has been the underlying source to construct the rule-base. However, procedure and control knowledge can be also used in certain domains of engineering such as structural optimization (Adeli 1988). Nevertheless, the use and choice of knowledge depends on many considerations, such as extent of knowledge (narrow, closed), availability of experts, problem complexity, as well as whether or not the knowledge can be specified through a conventional algorithm (Ortolano and Perman 1987).

5.5.2 Fuzzy Expert System Structure

The fuzzy modelling approach can be formulated in three separate steps (Zadeh 1973) as shown in Figure 5.5. They are: defining the fuzzy variables along numerical variables (fuzzification); characterizing the relations between variables within the inference engine using IF-THEN rules; and translating the fuzzy results back into the crisp output (defuzzification).

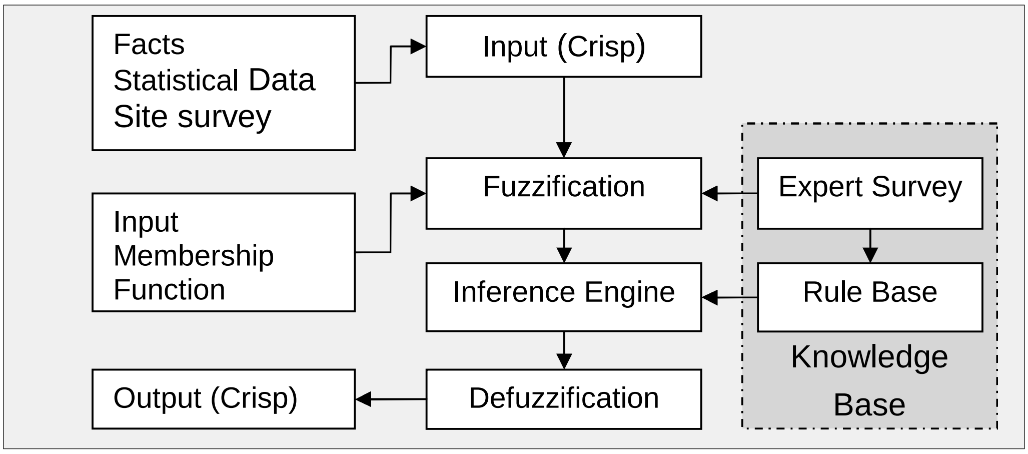


Figure 5.5 - Typical fuzzy expert system structure

The following sections briefly review the fundamentals of fuzzy logic and approximate reasoning.

5.6 Fuzzy Logic

According to Zadeh (1975), the term 'fuzzy logic' is an imprecise logical system in which truth-values are fuzzy subsets within unit intervals. Unlike the classical set which assumes that every statement is true or false, fuzzy logic propositions can be partially true or false. The knowledge base in the fuzzy expert system is developed from factual information, algorithms, rules or heuristics collected from experts. Because much human knowledge is vague and imprecise in nature, it is important to find a way to describe facts, rules and heuristics with some degree of certainty (Chang et al 1988). Fuzzy logic can be used as a mean to deal with vagueness and imprecision associated with the development of the knowledge-based expert system (KBES).

In fuzzy logic, the compositional rule is the most common way to represent human knowledge as a natural language (Ross 2004). Fuzzy logic formulates as a compositional rule of inference which is also referred to as fuzzy modes pones. The simplest form of modus pones is 'IF a THEN b', whereby ‘b’ is only true when ‘a’ is true. Fuzzy modes pones can be presented in the following syllogism (Zadeh 1965; Chang et al 1988):

Rule: IF X is A THEN Y is B

Fact: X is A*

Reasoning conclusion: Y is B*

Where X, Y are linguistic variables and A, B, A* is known, but B* is deducted from composition rule of inference. The truth-value of the statement depends on the value of fuzzy set A which is presented in linguistic terms such as ‘False’, ‘Partially False’, ‘Partially True’ or ‘True’. This truth-value of a fuzzy set A (x) is defined by the interval [0, 1] to represent uncertainty or degree of belief in predicting A. If a rule's antecedent is determined as true, and the rule is activated, the rule is fired. Thus, every rule to some degree takes part in the reasoning process.

In real world problems, most fuzzy systems contain more than one rule. Complex fuzzy rule-bases can be made up from several simple propositions. The process of aggregating rules is performed using aggregation operators or connectives, including the conjunctive ‘AND’ and disconjunctive ‘OR’ which corresponds respectively with min and max operators. In the context of risk assessment, for instance, expert and heuristic knowledge can be adjoined making rule-base such as:

IF soil-quality is LOW AND quality is LOW THEN vulnerability is HIGH

IF soil-quality is LOW AND quality is MEDIUM THEN vulnerability is MEDIUM

IF ground shaking is HIGH AND quality is MEDIUM THEN vulnerability is HIGH

IF ground shaking is V-HIGH AND quality is MEDIUM THEN vulnerability is V-HIGH

5.6.1 Fuzzification

The term “fuzzification” has two meanings: to find the fuzzy version of a crisp input, and to find grades of membership of linguistic values of a variable corresponding to a scalar or fuzzy input (Selir and Buckley 2005). This study focuses on the first sense that implies on generating membership functions (MFs). Various forms of MFs which represent linguistic concepts can be used in fuzzy set theory. Triangular, trapezoidal and Gaussian are the most common forms of linear /non-linear membership functions shown in Figure 5.6.

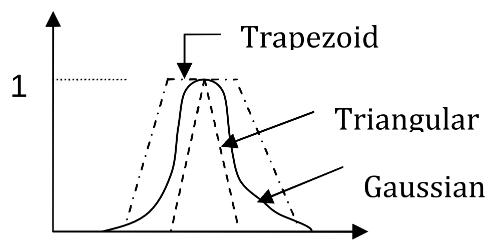


Figure 5.6 – Various membership functions

The literature presents several methods to generate MFs on the basis of numerical data. Amongst those are fuzzy clustering (Klir and Yuan 1995), parametric optimization (Pedrycz and Gomide 1998), statistical distribution (Civanlar and Trussell 1986), vertical and horizontal methods (Pedrycz and Gomide 1998), and interpolation and measurement theory (Chen and Otto 1995). The choice of MFs is context-specific and depends on the characteristics of the data.

Karkowski and Mital (1986) recommend the number of MFs should be limited between five and nine. Clearly, such low numbers of MFs may not adequately present the knowledge required for modelling. As such, too many MFs may pose extra complexity in understanding and processing the model in practice. The number and type of MFs are a context-dependant issue. To enhance modelling capability, MFs must adequately justify the physical meaning of the original data set. This can be achieved by transferring the milestone points into a scale that has significant impacts on the output variable. For example, to transfer pre-code and post-code school buildings within the range of 1965-2002, the milestone points are the dates that code was issued and enforced by the government in 1988 and 1993 as indicated within Figure 5.7.

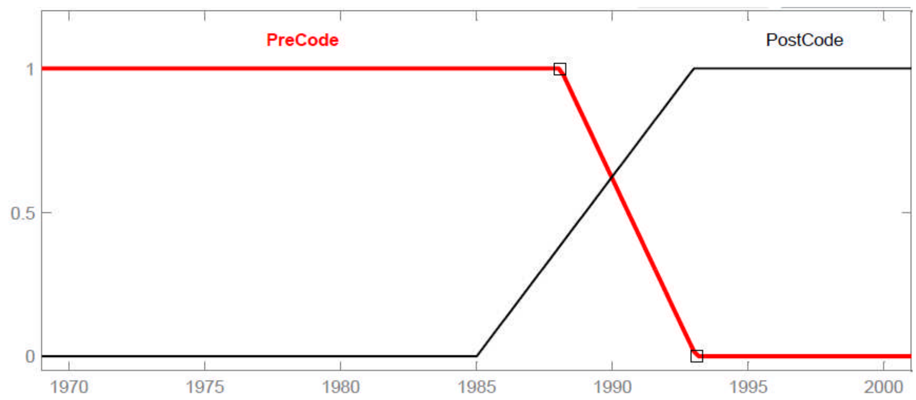


Figure 5.7 - Membership function for 'Code indicator' variable

The most powerful feature of MFs is allowing the conversion of crisp information into linguistic terms. This can be achieved by assigning the linguistic terms of the grades of membership functions. To quantify various linguistic terms for describing the risk attributes, basic input parameters need to be grouped (or clustered) into the linguistic quantifiers such as very low (VL), low (L), medium (M), high (H) and extremely high (EH) and by assigning corresponding membership functions (MFs) to the clustered data.

The same linguistic scale can have different implicit meanings in varying contexts (Fayek and Sun 2001). To deal with this issue, membership functions can be developed using different scales of measurement, such as ordinal, ratio and interval scales. Depending on the context, characteristics and relationships within the universe of discourse, the measurement scale can be arranged for risk attributes.

According to Lootsma (1997), humans can only process seven categories at most. Hence, it is often recommended that the number of linguistic terms should be in the range of five to seven (Karwowski and Mital 1986). While too few terms may not be adequate to represent the whole domain of the variable, too many terms could also cause difficulties in following steps (i.e. rule-base design). Therefore, five grades of membership were adopted in this study to express different risk attributes, unless the universe of discourse can be defined with fewer variables. For example, MFs for liquefaction susceptibility index was defined in three grades of Low, Medium and High as shown in Figure 5.8.

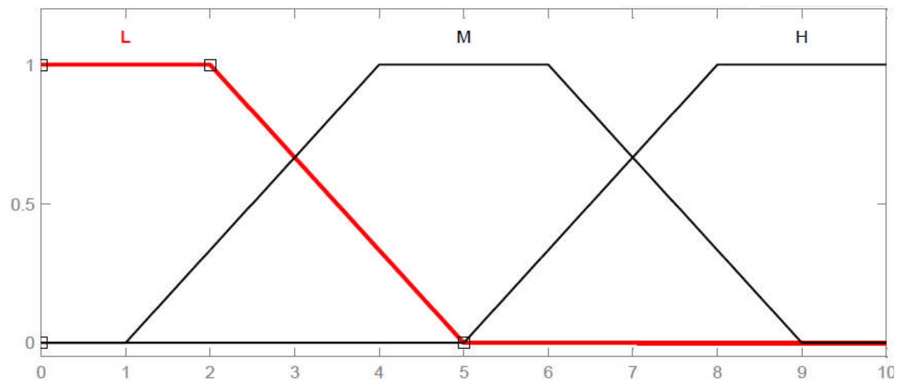


Figure 5.8 - Membership function for 'Liquefaction susceptibility' variable

Another concern in a fuzzy representation of risk data is the shape of MFs. There are several forms of MFs reported in literature (Ross 2004; Karwowski and Mital 1986). However, it is believed that the shape of MFs is not a controlling factor in engineering applications (Klir and Yuan 1995). According to the pilot study conducted by Vahdat and Smith (2014b), it was demonstrated that the form of MFs could not significantly influence the inference process and distort the results as much as the number and location of the functions. No matter what type of risk data, three of the most popular shapes (Triangular, Trapezoidal and Gaussian) functions were used for developing the MFs in the case study. Triangular and

Trapezoidal functions have been broadly used in risk assessment (Min An et al. 2006, 2007; Zeng et al. 2007) due to computational simplicity and descriptive power. Gaussian functions were also used due to flexibility in presenting the real world variation.

5.6.2 Fuzzy Inference

Inference is the process of deducting from existing data. The inference process is performed through aggregating several consequents to draw the overall conclusion. Klir and Yuan (1995) introduced various fuzzy inference methods based on linguistic rules, including the Mamdani and Sugeno systems. The former is the most common method of inference that is addressed in the literature (Mamdani and Assilian 1975; Takagi and Sugeno 1985).

A fuzzy system of multiple inputs and single output can be extended and modelled through an inference system. The Mamdani fuzzy system can be shown in the form of IF-THEN propositions:

$$IF\ x_n\ is\ A_1^i\ and\ \ x_n is\ A_1^i\ \ THEN\ y_i\ is\ B_i \qquad for\ i = 1,2,\dots,n \tag{5.20}$$

The Mamdani inference method of implication can be used for a set of disjunctive rules to aggregate output of ‘n’ rules, such as:

$$\mu_B(y) = \mathrm{Max}\ [\mathrm{Min}\ [\mu_{Ai}(x),\dots\ \mu_{An}(x),\ ]] \tag{5.21}$$

Equation 5.21, also called the implication operator, can be interpreted through a graphical example. A fuzzy inference process for the damage assessment of a concrete beam is illustrated in Figure 5.9 using two rules, where the symbols A_{11}, A_{12} and A_{21}, A_{22} refer to the first and second rule antecedent respectively. Similarly, symbols B1 and B2 represent the fuzzy consequents of the first and second rule. The minimum function in Eq. 5.21 fires the lowest value corresponding to A_{11}, A_{12} as it is connected by a logical ‘AND’ operator. The minimum inference truncates the membership function for the consequence of each rule. The truncated membership function for each rule is aggregated using ‘OR’ operator as denoted within ‘Max’ function in Eq. 5.21. Thus the result is an envelope of the truncated membership forms from each rule. If one wishes to find the equivalent crisp value for aggregated fuzzy number, defuzzification can be performed.

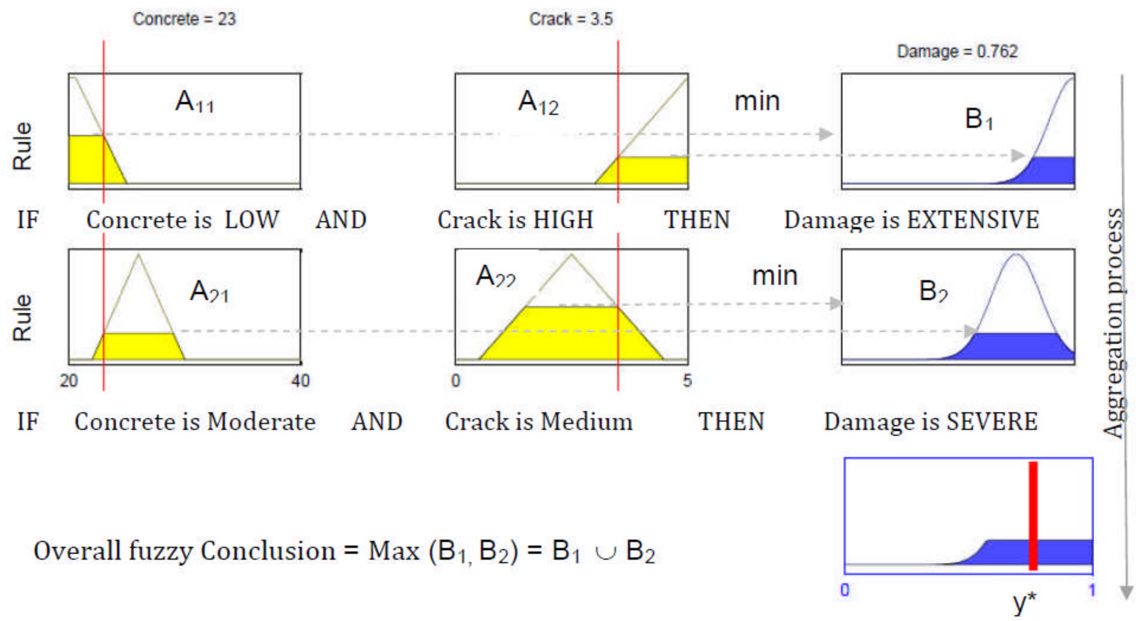


Figure 5.9 - Graphical illustration of fuzzy inference system

5.6.3 Defuzzifiation

Defuzzification is a numerical assessment of a fuzzy set. The fuzzy output extracted from the inference engine can be presented in the form of scalar or crisp number. Different methods have been reported in the literature that most of these have a common principle in terms of concept (Klir and Yuan 1995; Siler and Buckley 2005; Filev and Yager 1991). The most frequently used techniques are:

- Centre of Area (COA) or centroid. This technique calculates the centre of the area under a combined fuzzy set using the first - order moment of the area

$$COA = \frac{\int_a^b x.\mu(x)}{\int_a^b \mu(x)} \tag{5.22}$$

- Mean-of-Maxima (MOM). This technique computes the arithmetic mean of all values with maximum membership.
- Centre-of-Maxima (COM). This technique finds the arithmetic mean between the highest and lowest values for which there is support.

$$COM = \frac{\bar{x}_1.\mu_1 + \bar{x}_2.\mu_2 + \cdots .+\bar{x}_n.\mu_n}{\mu_1 + \mu_2 + \cdots + \mu_n} \tag{5.23}$$

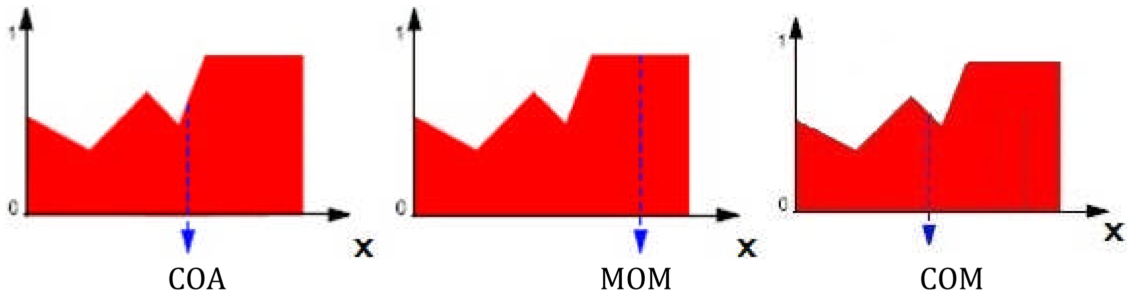


Figure 5.10 – Common defuzzification method

Applying COA algorithm in the previous graphical example (Figure 5.10) to find the centroid of the aggregated blue area, as shown in the conclusion graph by a red line (y* = 0.762).

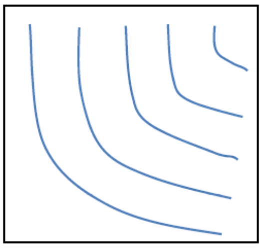
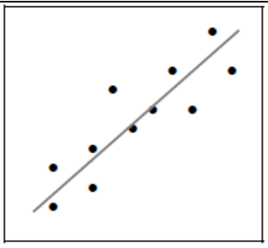
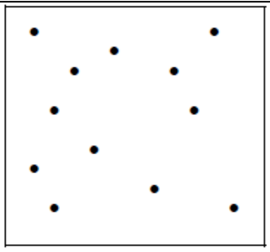
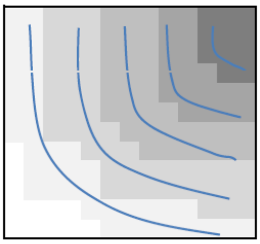
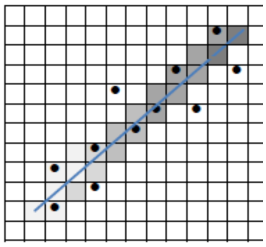
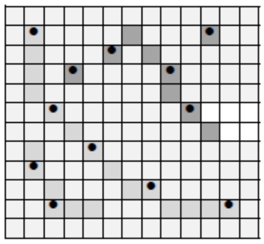
5.7 Rule construction

Rule construction or knowledge based development is a process where knowledge and data are translated or codified into rules. Since the expert system processes the reasoning based on its rules, the choice of ways to develop the rule-base is of utmost importance. There are different situations where the combination of experts and data are used to construct the rule-base (Bardossy and Duckstein 1995):

- The rule can be defined directly by the experts (known algorithm/structure)
- The rules can be evaluated by the experts, but updated using available data.
- The rules are not known explicitly, but the variables required to describe the system can be identified by the experts
- Only objective data (observation) are available, and rule-base should define the interrelations between I/O of the data set through the procedure

Theses situations define the way to simulate the data and expert knowledge into the explicit rule-base as indicated in Table 5.3.

Table 5.3 – Knowledge representation in fuzzy modelling

Model	**Case 1:** Explicit structure/Algorithmic	**Case 2:** Partially explicit knowledge/empirical data	**Case 3:** Unknown structure or knowledge
Conventional (Statistical)			
Expert system			
Supporting method	Weighted counting algorithm, clustering,	Regression – curve fitting (e.g. least square)	Experts knowledge Machine learning, clustering, artificial neural net

There is a situation that the structure of data can be explicitly defined through an algorithm (Case 1). In this case, the algorithm describes the relationship between the knowledge and information, leaving no data point outside of the domain. However, in many physical problems, the process cannot be described easily through mathematical expressions. In the other words, there is a small amount of information which exists to develop an algorithmic relation, usually relying on observable data and input-output features of the system which can be measured. For example, in estimating the 28-day strength of a concrete cube, observable data are often used to develop strength-time algorithm. Alternatively, for the situations where data cannot be measured through conventional approaches, there are two possibilities. First, the situations (Case 2) where knowledge is partially explicit by the means of empirical data and observation (e.g. damage survey, clinical test). This case might be handled through a regression and standard curve-fitting technique to establish the (empirical) algorithm which describes it best.

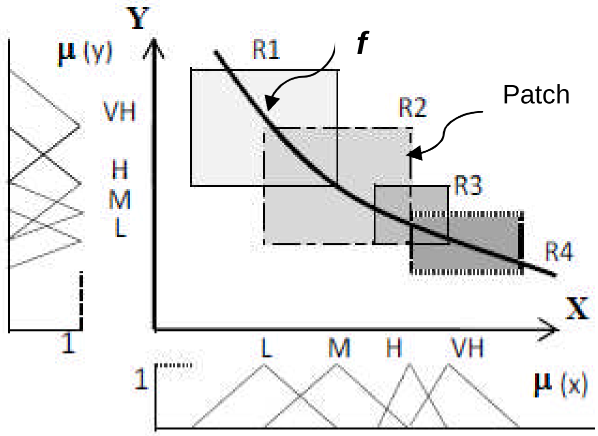
Second, there is no algorithm, structure or explicit knowledge available to guide the description of the system objectively (Case 3). In this case, a heuristic knowledge can be used which is based on expert opinions and subjective judgments. Since the data are scattered irregularly around the domain, this situation can be effectively described with the use of fuzzy modelling.

In Cases 2 and 3, a set of observed data in the universe of discourse indicated by patches (domain specific) describing the relationship between I/O variables within the models. These patches convey fuzziness and also express the I/O relation which can be modelled using the fuzzy system.

The extent of the patches represent the ambiguity and imprecision in observation or expert judgments. Expert knowledge can be used where no information and structure is available; while empirical knowledge or algorithms can only capture a pre-defined behaviour of the system. For complex situations such as seismic risk management (where kinds of information, algorithms and structures exists), a combination of data- and expert-driven knowledge types can significantly improve the quality of the system. Moreover, this combination can explicitly address specific responses to certain areas, leaving freedom for data fitting in others (Bardossy and Duckstein 1995). Clearly, fuzzy modelling can be used for all situations mentioned. Nevertheless, the best performance can be achieved in situations where no explicit knowledge, algorithms or observations are available because the more ambiguity in knowledge, the more appropriate it is to be modelled through fuzzy system. For this reason, in this study a combination of expert-driven and data-driven knowledge has been used to develop the rule-base.

5.8 Fuzzy Expert System as Rule Patches

Generally, a simple fuzzy expert system is described by the set of rules that map multiple inputs to a single output. The rules denote the fuzzy relation or patch in **X** x **Y** space as shown in Figure 5.11. Rules patches can be adjusted to cover decision space (f). Each rule relates the input-output capturing specific domain of the decision.



#	Rule base
R_1	**IF** μ(x) = L **AND** μ(y) = VH **THEN** *f*(x,y)=f_1
R_2	**IF** μ(x) = M **AND** μ(y) = H **THEN** *f*(x,y)=f_2
R_3	**IF** μ(x) = H **AND** μ(y) = M **THEN** *f*(x,y)=f_3
R_4	**IF** μ(x) = VH **AND** μ(y) = L **THEN** *f*(x,y)=f_4

Figure 5.11 – Fuzzy rule patches cover the decision function

The underlying concept of a fuzzy expert system is based on approximate reasoning and thus it can be used as universal approximator (Kosko 1994). In other words, a fuzzy system R: X→Y can be employed to map a function f: X→Y by taking appropriate rule patches.

It is obvious that the more rule patches, the more specific and accurate the domain will be. Reducing the rule patches size (selecting smaller intervals on X, Y) would lead to a more accurate approximation of '*f* ', though the number of rules would rise accordingly. Thus, when approximating a function, it is important to select an appropriate number of rules (or knowledge base), first to cover the whole domain, and second to easily define and handle the entire domain without losing any information. One way to manage this issue is to organize the rules hierarchically through the system (Pearl 1984) which is employed in this research.

5.9 Fuzzy Modelling in Complex Domains

Real world problems such as seismic risk assessment require many of variables for modelling. More variability in a system means more complexity in processing, requiring larger domain to address it. When an application moves from a simple domain to complex one, the usual procedure having flat rules becomes infeasible (Torra 2002). As the number of variables increases in expert systems, the number of rules to cover the decision space increases exponentially. For example, 10 variables with 5 terms imply a set of almost 10 million rules. The problem of dealing with such a large number of rules which grows exponentially with the number of variables is known as "rule explosion" or "curse of dimensionality".

The literature reports several ways to deal with this issue (Jamshidi 1997; Torra 2002; Magdanela 2002). Some of the most relevant techniques are emphasized in following:

- Rule hierarchy: Rules are grouped into modules according to their roles in the system. Each module computes a partial solution, and these partial solutions are thereafter used in subsequent modules to compute the final output of the system.
- Identification of functional relationship: For situations in which functional dependencies can be identified between variables (i.e. algorithm data), they can be used directly in the system instead of using rules to express them. This reduces the size of the rule base as there is a drop in the number of variables.
- Sensory fusion: This includes combining two or more variables to build a new input variable to replace the original ones. A reduction in number of variables yields a reduction of the number of rules.
- Interpolation: This method is useful for the situations where no rules available. In this case, the output of the system is interpolated from the outputs of the nearest points (Rules).

A hierarchical fuzzy system is defined as a technique to solve problems with high levels of complexity. This approach reduces the complexity of the system by structuring the knowledge (Magdalena 2002). According to Magdalena: (2002) "the underlying idea is to cope with the complexity of a problem by applying some kind of decomposition that generates a hierarchy of lower complexity systems". Three different architectures for hierarchal fuzzy systems are shown in Figure 5.12.

Combining different levels in a hierarchy is a difficult task. Usually the levels of a fuzzy system are selected based on their preference. It is a fact that the different levels of a hierarchy incorporate information which managed at different levels of intelligence, abstraction, and time scale (Saridis 1983). Machine learning, optimisation and clustering are three ways of grouping rules and information in large systems which can be referred to literature (see Sayyarrodsari et al 1997; Klir and Yuan 1995) for more details.

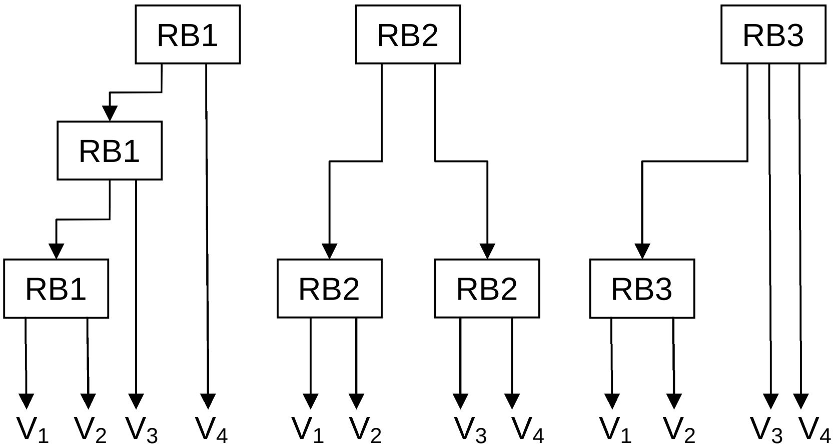


Figure 5.12 - Typical architecture for four variables (Torra 2002)

This study uses a combination of methods to build a fuzzy expert system in order to estimate seismic risk. Due to the complexity of the system and a number of factors involved in modelling, hierarchical structure of variables is initially adopted. The most influential variables are then chosen as input variables at first level, the next most important variables are chosen as input variables at second level, and so on. The output variable of each level is introduced as an input variable at the following level. For variables with an algorithm or function, the rule base will be reduced accordingly. Furthermore, an influence diagram was used to group the variables within a family into a new module. In the case of missing or unavailable information in a survey or in the factual data, an interpolation will be applied using nearest available points around unknown rules. The detail of structuring a hierarchy will be outlined in Chapter 6.

5.10 The Utility and Limitation of Fuzzy Modelling

Several benefits derive from the application of the fuzzy modelling in knowledge based context as noted below (Cox, 1999; Turban and Aronson, 2000; Ross 2004).

First, this applies to situations involved with complex systems requiring human or large computational power. Universal approximation has been addressed as a major strength of the fuzzy system for modelling a system's behaviour. Improved computational power of expert systems in performing and encoding of knowledge allow experts to understand and manage complex problem very quickly, where no analytical function or numerical relation exists. Complex systems usually involve human-related situations such as social, economical or political systems in which several input and output information may not be systematically captured and managed through conventional analytical approaches. Moreover, the relationship between multiple inputs and outputs of such systems could be difficult to understand, though it is often perceived through analysis of cause and effect.

Second, it applies for situations where an approximate but quick solution is expected. Fuzzy systems are appropriate for modelling more conventional systems where precise solutions are not warranted. According to Ross (2004):

> "An approximate, but fast solution can be useful in making preliminary design decisions or as an initial estimate in a more accurate numerical technique to save computational costs or in the myriad of situations where the inputs to a problem are vague, ambiguous, or not known at all."

Examples of approximate evaluations occur in real life where exact solutions are not necessary or are compromised by imprecise knowledge. Hence, fuzzy systems are ideal for the real-life situations where human perception plays a major role in decision-making.

Third, it is relevant for situations where a significant amount of uncertainties is involved. Having acknowledged the distinction between 'modelling the system' and 'modelling the uncertainty', a fuzzy system has great potential for undertaking both. According to Ross (2004): "the primary benefit of fuzzy systems theory is to approximate system behaviour where analytic functions or numerical relations do not exist". The systems whose outputs are not sensitive to changes in the inputs are recognized as a robust system because the uncertainties involved in both inputs and outputs are essentially employed in developing the system structure itself; while in conventional systems, models need to be developed based on the set of statistical assumptions and then uncertainties of the mathematical abstraction have to be captured accordingly. Theoretically, the mathematical modelling of such an abstract system and the subsequent uncertainty modelling may not be unreasonable, but it might carry unpredictable results and hence it could mislead the decision-making process.

Nevertheless, the fuzzy system has been criticized as a shallow concept since it follows an inductive approach for reasoning and infers theoretically from general to particular (top-down approach). Inductive reasoning might imply a shallow concept due to the use of underlying knowledge for predicting the behaviour in the models. The fuzzy approach was also criticized due to its reliance on human knowledge, linguistic expression and experience as a sources of uncertainty, whereas deductive reasoning models are developed based on the data which can be observed or generated by nature (Arciszewski et al. 2003). Moreover, fuzzy systems might be constrained to 'domain-specific knowledge' rather than 'general problem-solving' approaches. The greater knowledge base the problem has, the more possibility there is for it to be effectively modelled through a fuzzy system. Therefore, a combination of expert-driven knowledge and data-driven knowledge can significantly address and improve the intrinsic shortcomings of expert systems.

5.11 Summary

Fuzzy modelling provides an effective strategy for capturing and processing uncertain data often involved with seismic risk assessment. The use of expert system assists decision makers to overcome difficulties in risk modelling, such as the quantification of uncertainty, nonlinearity within variables and the lack of historical data. Moreover, fuzzy modelling offers a meaningful characterizing the uncertainty of input/output and draw conclusions using uncertain information. Various forms of knowledge (i.e. facts, heuristic knowledge and algorithms) can be expressed through compositional IF-THEN rules. Thus, both linguistic and numerical forms of data can be processed and reviewed on a common framework.

The advantage of fuzzy modelling is in reducing the dependency on historical data. Unlike conventional systems that rely on high quality information, a fuzzy expert system can be alternatively developed where no precise statistics are available. There are some situations in which algorithms, structures or explicit knowledge (empirical, observation) are available and thus it can be effectively simulated through classical sets. However, in complex systems where knowledge is partially explicit or not clearly definable through empirical methods, the fuzzy expert system can be more effective than conventional methods. In this case the combination of data-driven and expert-driven knowledge can be devised to achieve the best performance.

Chapter 6: Data Collection

6.1 Introduction

This chapter explores the necessary information required to develop the KBES, including risk criteria and alternative projects, which are outlined in two parts. First, the general characteristics of retrofitting school buildings in Iran were reviewed in terms of size, type and material. Second, the potential impacts of an earthquake were assessed and classified in different categories using a hierarchical risk structure (risk tree) consistent with geography, seismology and typology of buildings in Iran. The information about alternatives and criteria collectively form the prerequisite structure for developing the KBES and has been already published in detail by Vahdat and Smith (2014) and Vahdat et al. (2014a).

6.2 Characteristics of School Buildings in Iran

Developing a risk-based management model should be conducted with respect to regional characteristics since school buildings might vary greatly in size, population, resources and technical specification. A model designed for certain regions may not sufficiently valid for others. For example, a risk management model within mid-rise schools in highly populated cities like New York cannot be prescribed for seismic-prone California. Thus, developing a model requires addressing the multidimensional aspects of a school to identify the proxy of buildings carrying the most critical factors, and to design the case study accordingly.

Given the diversity of material, types and forms of school buildings in Iran, major characteristics can be selected. Understanding the general characteristics of the school of interest is crucial as it helps to figure out the dominant issues and facilitates risk identification. Building vulnerability is one of the most critical factors that vary among existing buildings in Iran. Scanning the schools database reveals those Iranian school buildings have certain features in term of seismicity, material, structure types, forms (plan), population and stories. These elements are briefly outlined in the following sections.

6.2.1 Seismic Hazard Levels in School

School buildings may be exposed to different levels of seismic hazard; though the historical records (SRO 2010) show that more than 80% of school buildings are subject to high to very high intensity earthquakes (M7 – M9) and more than 95% of the schools are exposed to earthquake with magnitude over 6 (> M6). The distribution of school buildings exposed to different degree of seismic hazard is shown within Table 6.1.

Table 6.1 - Distribution of the schools exposed to various levels of seismic hazard (NSI 2010)

Hazard Level	Intensity (PGA)	No#	Percentage
Low	0.20g	221	0.91
Moderate	0.25g	4134	16.93
High	0.30g	16483	67.52
Very high	0.35g	3573	14.64
Total		24,411	100.0

6.2.2 Building Classes

Building size and typology play significant role in evaluating the seismic performance of a building. As indicated in Figure 6.1, the overall population of the schools indicates predominantly low rise buildings with 86% with one storey and 10% with two storeys. Nevertheless, the structures and material employed in buildings varied between five categories, comprising of steel, concrete, masonry, adobe and other as shown in Figure 6.2. Masonry and steel structures are the most common type of the buildings over the country, consisting of 89% and 8% respectively. The potential susceptibility and frequency of out-dated masonry schools necessitate the urgent need for managing such a large group.

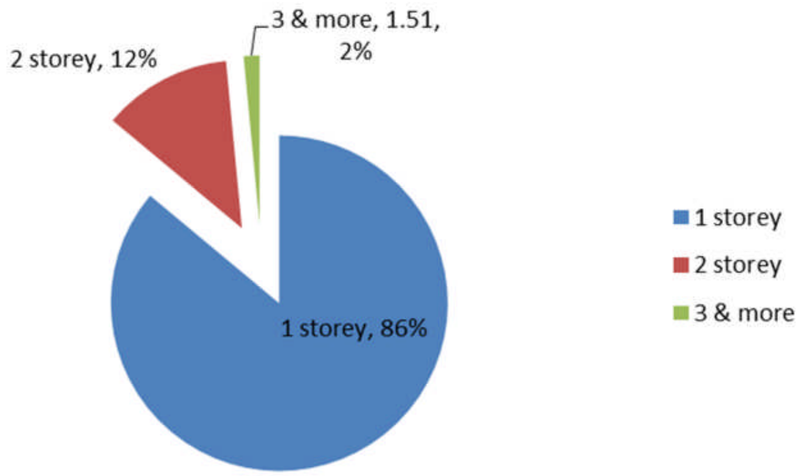


Figure 6.1 – The number of storey number among masonry schools of country (SRO 2011)

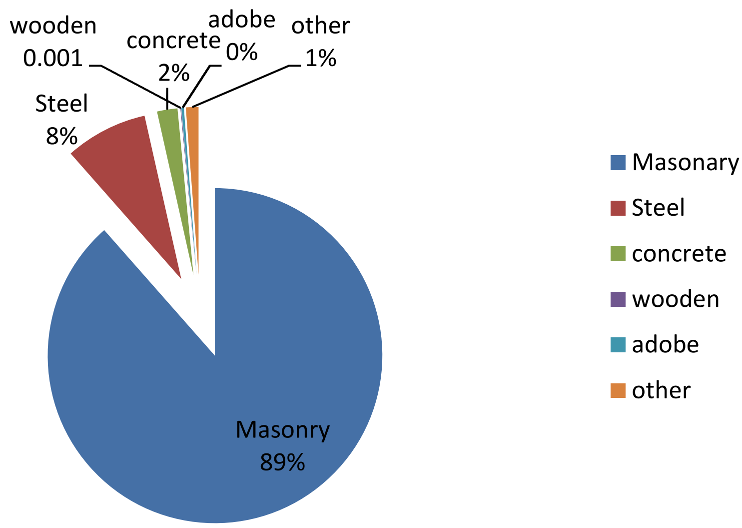


Figure 6.2 – Review of the common material (structure type) within school country (SRO 2011)

6.2.3 Construction Time

Most of public school buildings in Iran were built according to a previous seismic code, which is now out-dated. Hence, understanding the construction date is important in order to effectively estimate the seismic performance of buildings. Generally the school buildings that have been constructed before regulation and enforcement of new modern codes have a higher risk of damage.

With regard to Iran, the first seismic code was released and issued for construction in 1991 following the previous year's Gilan-Manjil destructive earthquake in the north of Iran. The newer versions of the seismic code were released in 2000 and

2006 respectively. Hence, there are still some newly-built schools that fail to conform to new versions or to which the standards were not enforced during construction. The overall distribution of key construction dates reveal that more than 95% of public schools have been constructed before 1991 and probably need appropriate actions to confront earthquake risk (Figure 6.3).

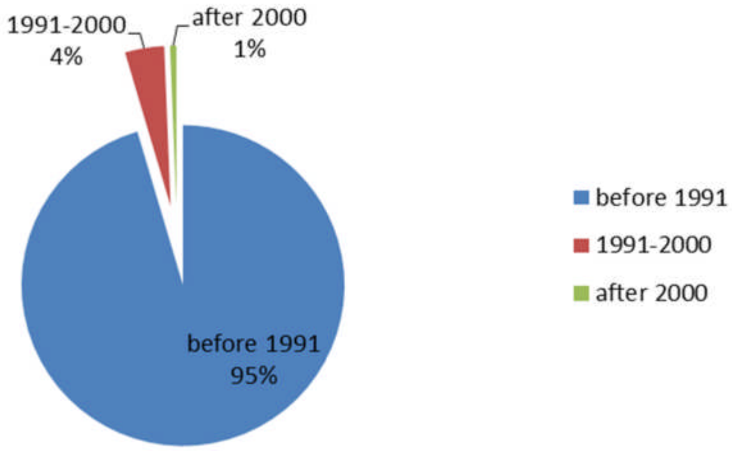


Figure 6.3 – Distribution of school buildings according to construction time (SRO 2011)

6.2.4 Building Forms and Irregularities

Irregularities in the building's plan and height can significantly affect the seismic vulnerability of a building. Setbacks in the plan or the height are common irregularities that affect the performance of existing buildings. Buildings with decent lateral-load resistance in only one direction, as well as buildings with major stiffness eccentricities in the lateral force-resisting system, for instance, can be severely damaged as a consequence of torsion around the vertical axis (FEMA154 2002).

Reviewing the typical plans of school buildings indicates the fact that most of the schools had been built based on two or three template plans. One possible sort of damage that occurs in such buildings can be caused due to vertical discontinuities, pounding effects and irregular configurations. While the major issue in school building has been identified as the lack of integrity in load carrying system (URM, RM), no major irregularities were observed in the schools in rural areas. Furthermore, most of the schools have been located independently, thus there being no need to compare the potential for pounding effects. The vast majority of schools were constructed in the form of low-rise style from one to three floors. Typical sample forms of school buildings are illustrated in Figure 6.4.

1 Storey school (4 - 8 Classrooms)

2 Storey school (10 - 16 Classrooms)

3 Storey school (18 - 24 Classrooms)

Figure 6.4 – Typical forms of school buildings in Iran

6.3 Selection of Alternatives

Having identified the major characteristics of the schools, alternative projects can be now selected. These retrofitting projects are as part of live 'School Rehabilitation Programme' ongoing in 24 provinces of Iran by Ministry of Education. Primary information regarding the schools (material, forms, structure, age) was collected through surveys, which have been conducted in the local group of experts in each province and documented through the online repository database. The initial data were then verified and processed in rehabilitation office. Potential vulnerable schools are then identified and approved for further detailed investigation by nominating consultants who are qualified and accredited for retrofitting studies. A total of 66 retrofitting school projects was selected out of the 185 available projects. This group of projects covers 15 provinces of the country and technically covers more than 90% of the variation in building forms, material, seismicity, structure and population. Sample distribution of the selected projects has been illustrated in Figure 6.5. Detailed characteristics of schools inventory are available within Appendix C.

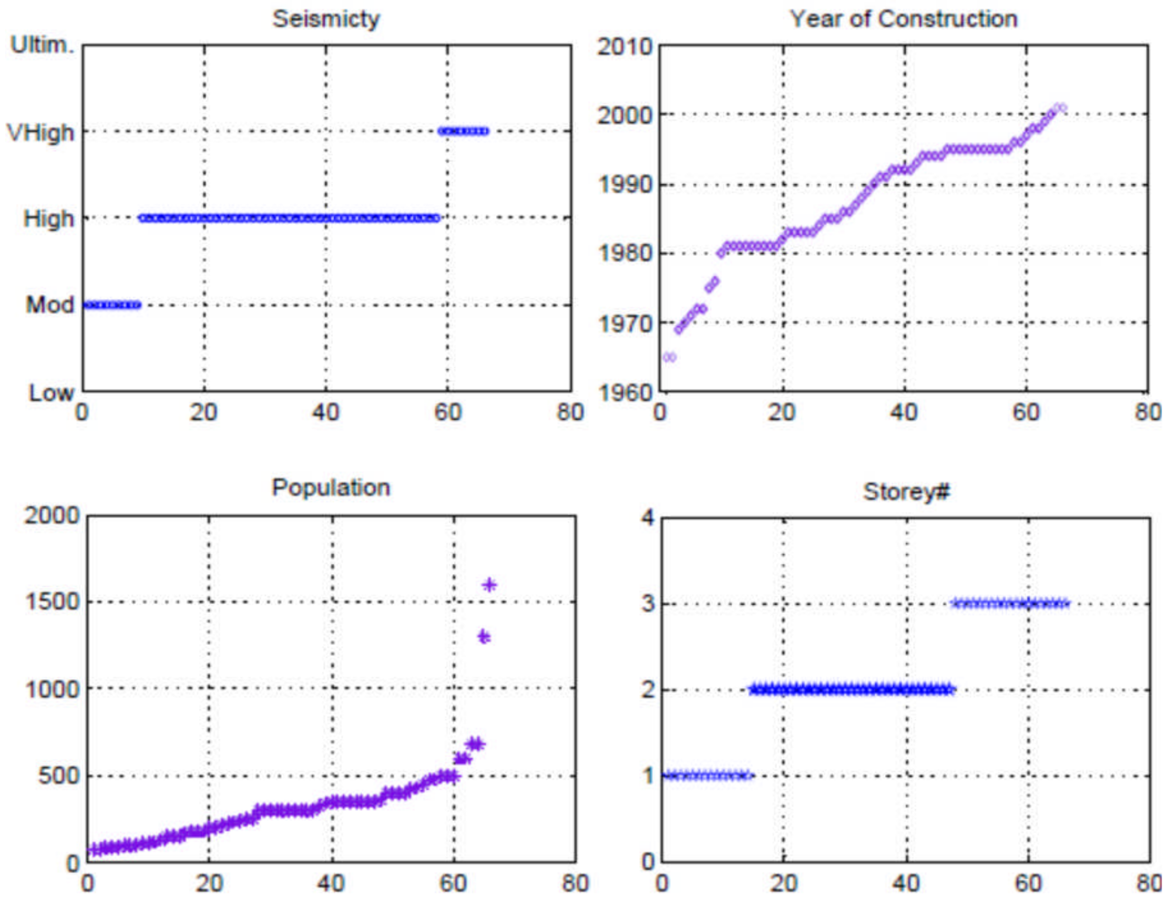


Figure 6.5 - Characteristics status of the selected schools

6.4 Risk Identification

Identifying, quantifying and analysing the impacts of earthquakes are all crucial in developing a case study. Earthquakes can potentially cause various impacts on population, communities, the built environment (infrastructure, utilities, and lifeline), as well as economic activities and services. Based on these effects, the elements at risk can be classified in different categories as shown in Figure 6.6. Regardless of the direct effects that might occur following an earthquake, there are many other indirect impacts that are the product of interaction between the disaster system, the socioeconomic system and the built environment.

This thesis focuses on the major quantifiable impacts that might affect the public network of schools. Other intangible impacts such as cultural, historical and political impacts were disregarded. The framework of impacts considered a way to reflect the major concerns that are prevalent in the geography, topography and typology of schools in Iran. For example, a hazard may cause specific impacts on prone coastal cities (i.e. as tsunami, seiches) and mountainous cities (i.e. rock fall, avalanches) but these may not be applicable to the geography of Iran. The following sections will address the most relevant impacts of earthquakes that could possibly interact with the schools of Iran.

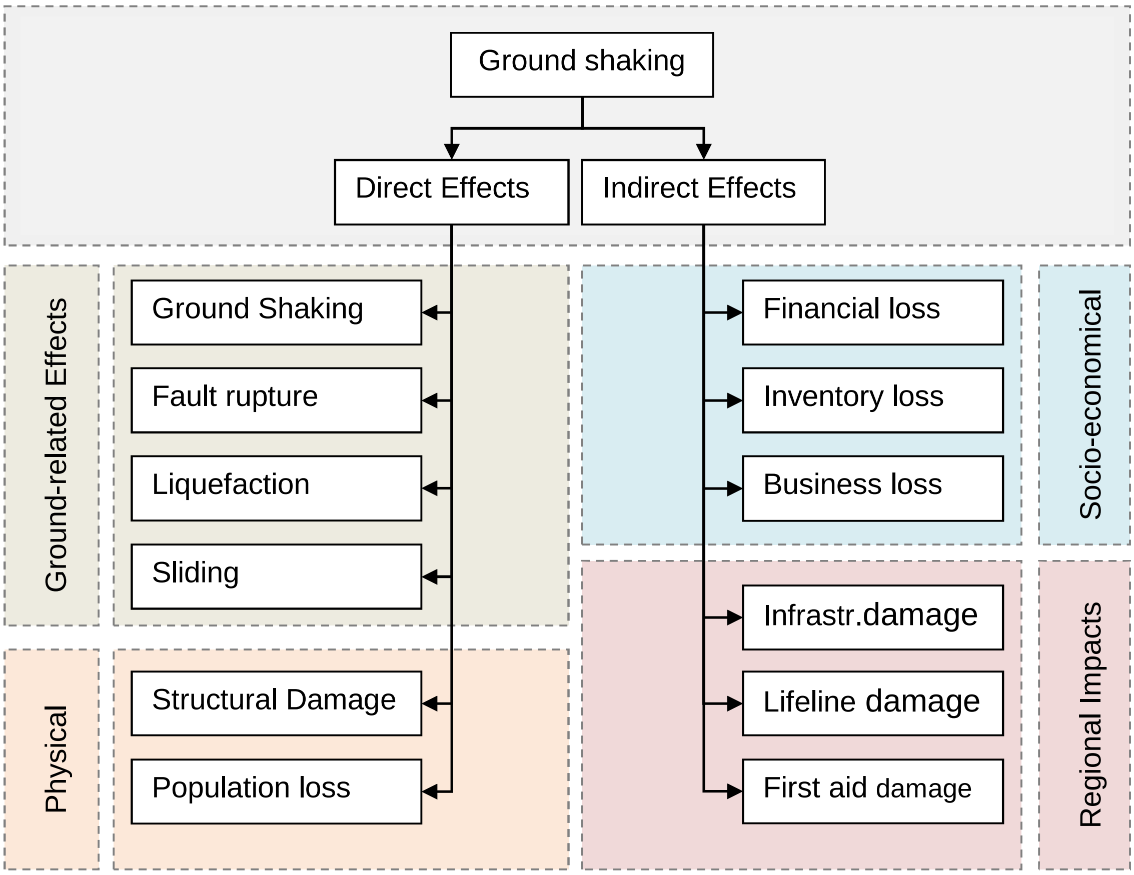


Figure 6.6 - Classification of earthquake general Impacts

6.5 Seismic Hazard

A seismic hazard can be exhibited by the various impacts on an urban area that may vary based on geological and geographical conditions as shown in Figure 6.7. Earthquake hazard might be exhibited in different forms including ground shaking, fault rupture, ground failure due to liquefaction and landslide, collateral or secondary hazards such as fire, avalanche, flood due to dam failure, unequal settlements, pipeline explosions and environmental pollution.

Alternatively, seismic hazards on coastal cities, seashores and islands can result in tsunamis and seiches. Primary damage to structural and non-structural elements can be the result of fault rupture and ground shaking. Loss of life, injury, cost of rehabilitation and reconstruction are the primary losses that might occur immediately after an earthquake. Long-term socioeconomic loss of earthquake can be experienced in cities through business interruption, unemployment, loss of market, etc.

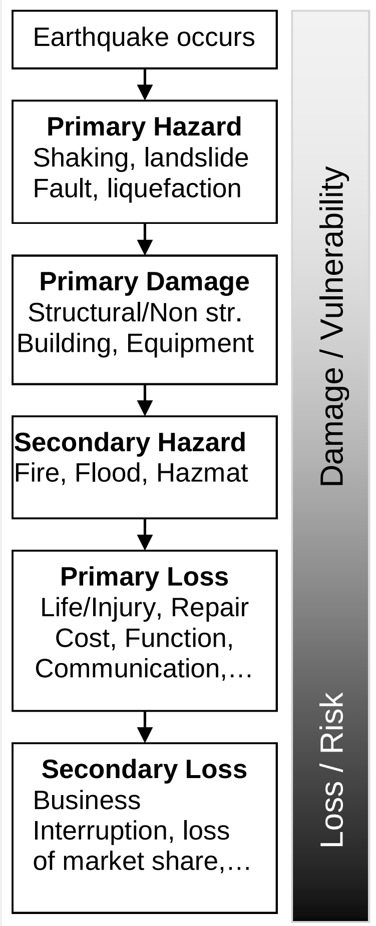


Figure 6.7 - Earthquake Loss Process, SSC(1999)

Every region may potentially be exposed to specific kinds of hazard according to its site characteristics and topographical situation, among other factors. The most common seismic-induced hazards are briefly addressed in the following sections.

6.5.1 Ground Shaking Hazard

Generally, for a given site and distance from an earthquake source, ground shaking severity is directly proportional to the magnitude of the earthquake (Rojhan 1994). Thus the greater magnitude of an earthquake, the more severe ground shaking will be.

Technically, seismologists address an earthquake with its ground motion characteristics, including amplitude, frequency content and duration. Ground shaking amplitude is normally expressed in terms of peak ground acceleration

(PGA), velocity (PGV) and, in some cases, displacement using seismic accelerograms. Miyakoshi et al. (1997) calculated the distribution of PGV of strong motions during the Kobe earthquake (1995) and developed a damage ratio of low-rise buildings as functions of PGV.

Seismic hazard is often expressed in terms of PGA through hazard map representing the annual exceedance probabilities for the full range of damaging ground motions (Kiremidjan et al. 1997). PGA refers to the maximum horizontal acceleration while in some cases it can also denote the vertical accelerations. For example, a PGA 0.3g means that maximum horizontal acceleration is 30% of the earth's gravity. Records of past PGA are a major source for developing seismic hazard maps.

6.5.2 Seismic Intensity Scale

Apart from instrumental methods to measure the PGA, there are many intensity scales in which earthquake damage can be measured subjectively. For example, the European Macro-seismic-Scale (EMS) (formerly known as MSK scale), as well as the Mercalli Modified Intensity (MMI) scale, is the most widely used measurements in many countries. While descriptive scales are a useful metric for earthquake effects, the conversion between scales has been a great concern. In general, intensity scales based on observed damage or perceptions could potentially associate with great uncertainty that could not be effectively addressed through a common probabilistic approach. The main issue is that there is no distinction between grades, and instead of a clear number, a range of damage often refers to each grade. Empirically, there is a correlation between intensity scales and PGA, which has been often described on a logarithmic scale. An update in observed damage could change the correlation, and subsequently the conversion scale might vary temporally and spatially. A sample conversion scale between PGA and MMI scale is shown in Table 6.2. (see Appendix E for more details)

Table 6.2 - Conversion between intensity scales (Fahmi and Malkawi 1998)

PGA	MMI	Magnitude(M)	Damage state
0.005 - 0.01	IV-V	3.4 - 4	Negligible
0.011 - 0.05	V-VI	4.0 - 4.6	Minor
0.051 - 0.15	VI-VII	4.6 - 5.3	Moderate
0.151 - 0.30	VII-VIII	5.3 - 5.8	Strong
0.301 - 0.50	VIII-IX	5.8 - 7.0	Major
> 0.5	> X	> 7	Extreme

6.5.3 Earthquake Magnitude

Magnitude is an objective attribute that indicates the relative size of earthquakes. Magnitude is defined based on the maximum ground shaking and can be recorded by seismographs. Unlike intensity scales, which vary spatially from the earthquake source, magnitude is an inherent characteristic of an earthquake. Ground shaking can be very strong if it is close to the fault while it attenuates or decreases with distance from the fault.

Attenuation of the earthquakes depends on the magnitude and geology of the region (SSC 1999). The most commonly-used measure of local magnitude (ML) is commonly referred as the "Richter scale". In this study, all earthquake magnitudes are reported as an "M" followed by a value (e.g. M7, M5.5). Since earthquake magnitude is measured using a logarithmic scale, the intervals between each number can vary exponentially. For example, the difference between earthquake magnitude of seven to eight is much more severe than the earthquake magnitude between two and three. Statistically, the average occurrence of earthquakes per year follows a logarithmic scale of magnitude (Table 6.3). It follows that earthquakes with higher magnitudes rarely occur compared to medium and low magnitude earthquakes.

Table 6.3 – Annual number of earthquakes worldwide (After Broth and Key 1998)

Magnitude (Ms)	Average Occurrence N per year >Ms	Log (occurrence)
M8	2	0.3
M7	20	1.3
M6	200	2.3
M5	3000	3.5
M4	15000	4.2
M3	>100000	5.0

Considering the above graph, there is a correlation between PGA and earthquake probability, which can be developed, based on historical data analysis (Ghosh 2000). The empirical relation for earthquake recurrence was proposed by Gutenburg and Richter (1954), which has been used as the underlying algorithm for estimating earthquake occurrence in probabilistic risk assessment:

$$\text{Log } N = a - b.M \tag{6.1}$$

Where a, b are constant and N is number of earthquakes of a given magnitude M or larger per unit time.

6.5.4 Closeness to Active Fault

According to EuroCode-8 (2012), "peak values of the ground motion parameters (PGA) are not good descriptors of the severity of an earthquake and of its possible consequences on construction". Hence, a more realistic strategy is to describe seismic hazards based on the extent of proximity with fault ruptures. Fault ruptures can cause damage to the buildings and infrastructure located immediately over simple fault breaks, and also to structures situated in alluvial surficial deposits (ATC-13 1985). The severity of ground shaking generally reduces with distance from the ruptured fault; however, other factors contribute to local variations in ground shaking, such as soil condition, which can amplitude the ground shaking even more strongly than the epicentre. Sample attenuation curves suggested by EuroCode-8 (2012) are illustrated in Figure 6.8.

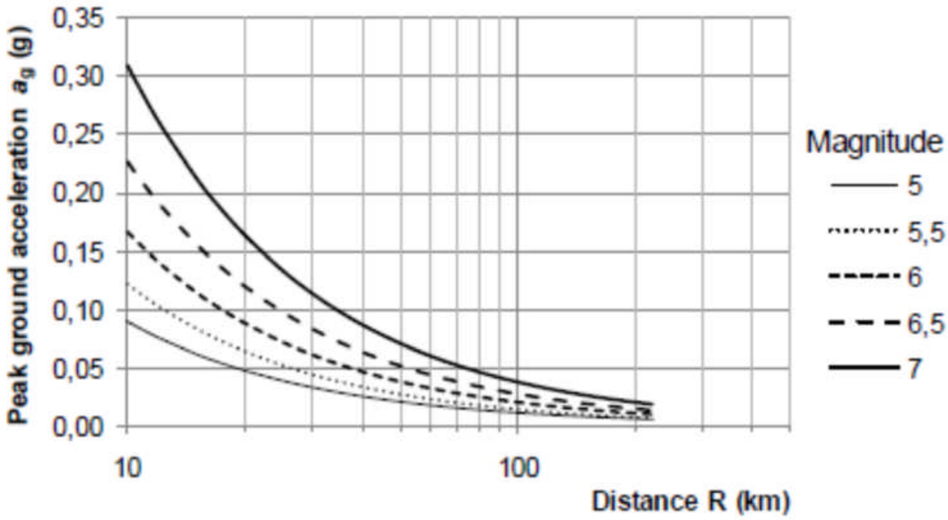


Figure 6.8 - Attenuation curves suggested by EuroCode-8

Empirically, since attenuation patterns vary from place to place, the geological characteristics along historical records should be accommodated to develop a relation for a region of interest. Chandra et al. (1979) analysed twelve earthquakes in different parts of Iran and accordingly proposed an empirical relation which have been used in the case study to estimate the intensity:

$$I(R) = I_0 + 6.453 - 0.00121\,R - 4.96 \log (R+ 20) \qquad (R<120\text{ Km}) \qquad (6.2)$$

Where I(R) is the intensity at the distance R from the epicentre. This relation shows that attenuation is quite sensitive to the selection of epicentral intensities, I_0. The graphical form of relation is shown in Figure 6.9.

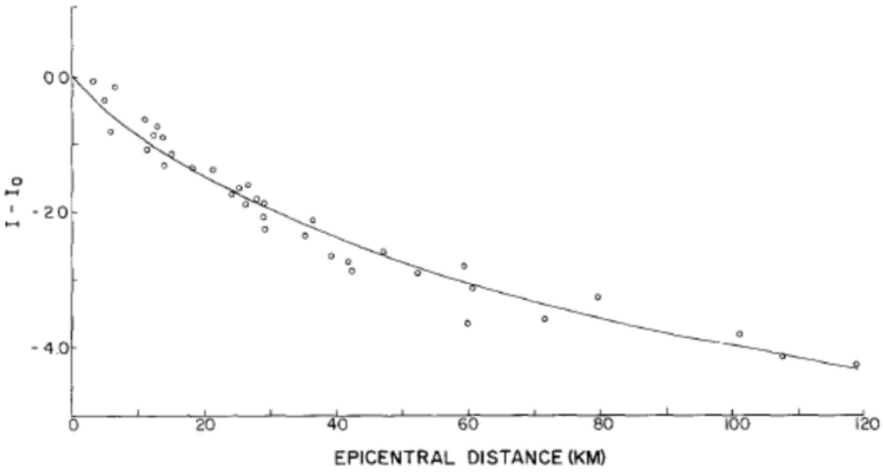


Figure 6.9 - Attenuation curve for Iran based on 12 earthquakes (Chandra 1979)

Depends on how far a building is from a fault (as a source of energy), different ranges of intensity may be felt and measured, implying the subjectivity inherent in this concept. Therefore, a factor that accounts for the close proximity of a structure to a fault should be accommodated within a risk assessment framework.

6.5.5 Soil Condition (Site response)

Soil condition includes poor ground such as loose sands, sensitive clays, and some lightly cemented sands, all of which can be a major source of damage during an earthquake and can significantly amplify its magnitude. Following the 1989 Loma Prieta earthquake, damage patterns occurred in the San Francisco region where the PGA amplified 2-4 times over adjacent rock sites. Similar site amplification occurred in Mexico City earthquake (Michoacan, 1985), which exhibited an extreme damage pattern due to the local soil condition. Input PGA, which is less than 0.4g in the rock, was amplified almost five times on the soft clay, causing disastrous effects on structures close to the site (Finn et al. 1988).

Site amplification has been commonly addressed in most seismic codes as a function of shear wave velocity. Codes in the US (UBC 2003) and Iran (BHRC 2007) use four site categories based on soil profile and shear wave velocity. According to Tucker et al. (1998), the response of soil sites subject to ground motion is essentially elastic, and therefore controlled by site period. When the fundamental period of a site coincides with the dominant period of buildings, the motion in buildings can be amplified by two or more times (Rojhan 1993). Microzonation maps for different soil categories can build a distinct pattern of site response. Typical (normalized) spectral responses to different soil classes have been addressed in several codes such as US (UBC 2007), EuroCode-8 (2012) and Iran (BHRC 2006). It can be noticed that the response factor between in weakest soil (grade IV: soft moisture deposit) could propagate the earthquake more than twice the extent of stiff soil (grade I) in any seismicity conditions. This confirms the importance of soil layers in calculating the seismic hazard of a building.

6.5.6 Potential Soil Instabilities (geological hazards)

Earthquakes can induce potential instabilities due to geotechnical and topographical conditions. Previous experience shows that seismic induced liquefaction and landslides could occur in the zones with unfavourable soil conditions or areas exhibiting slope instabilities. Hence, unstable areas are often mapped according to their susceptibilities. While sandy soil areas with high ground water table along rivers and lakes are a primary target for liquefaction, mountainous and hilltop areas could be exposed to potential sliding and overall instability or collapse. Sample soil instabilities that experienced in Turkey (Kacoli 1999) and Mexico (Loma Prieta 1989) are shown in Figure 6.10.

Figure 6.10 - Liquefaction and sliding hazard in Kocaeli, (Turkey 1999) and Loma Prieta, (Mexico 1989)

6.5.7 Liquefaction

Since liquefaction-induced ground failure is a major cause of damage during earthquakes, recognition of this hazard is critical in seismic risk management (Youd 1988). Several damages reported as a result of liquefaction during the 1999 Kocaeli earthquake (Turkey) and 1964 Alaska (Saatcioglu et al. 2001). Since liquefaction occurs for a specific range of grain size, the potential ground failure due to liquefaction can be assessed accordingly. Theoretically, soil is recognized with a potential hazard to liquefaction if the soil curve lies inside the critical range as indicated in Figure 6.11. According to the grain size, weight, texture and zone depth, an appropriate stabilization scheme is usually prescribed in geotechnical reports.

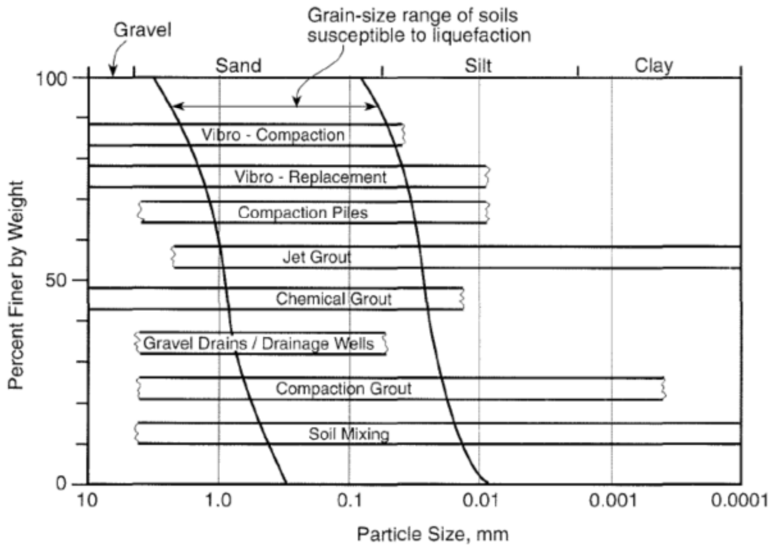


Figure 6.11 - Critical zone within the grain size susceptible to liquefaction (Finn 1972)

For rapid assessment of liquefaction hazard, susceptibility maps can be alternatively used for assessing seismic prone areas. Liquefaction susceptibility map of Iran was provided by the IIEES (2006) and was used for this case study. The information clearly exhibits the zones with greatest liquefaction potential to range of earthquake occurrences (Tucker et al. 1994). The maps were compiled using both geological, seismological and water table criteria. Although these maps seem to be conservative in detailed procedure, they are precise enough for such screening and rapid risk assessment application.

6.5.8 Landslide

Landslides can potentially trigger catastrophic damage, particularly for structures located on a hillside slope where down slope movements occur. The slope of surface on which a landslide occurs might vary significantly from somewhat steep to almost horizontal. In addition, rainy seasons are a potential time for landslides because the increase in moisture content of soils could reduce the stability in weak soils. DRM (2004) defined a practical indicator to measure landslides and topographical effects within a site. The sliding susceptibility of a building is measured based on its safety factor. Normally, for the site with slope of more than 15%, the overall stability and safety factor (SF) needs to be checked. ATC-13 (1985) suggests the correlation between slope and PGA for the range of soil characteristics (e.g. c, φ , γ) that could potentially fail when subjected to critical acceleration, as indicated in Figure 6.12.

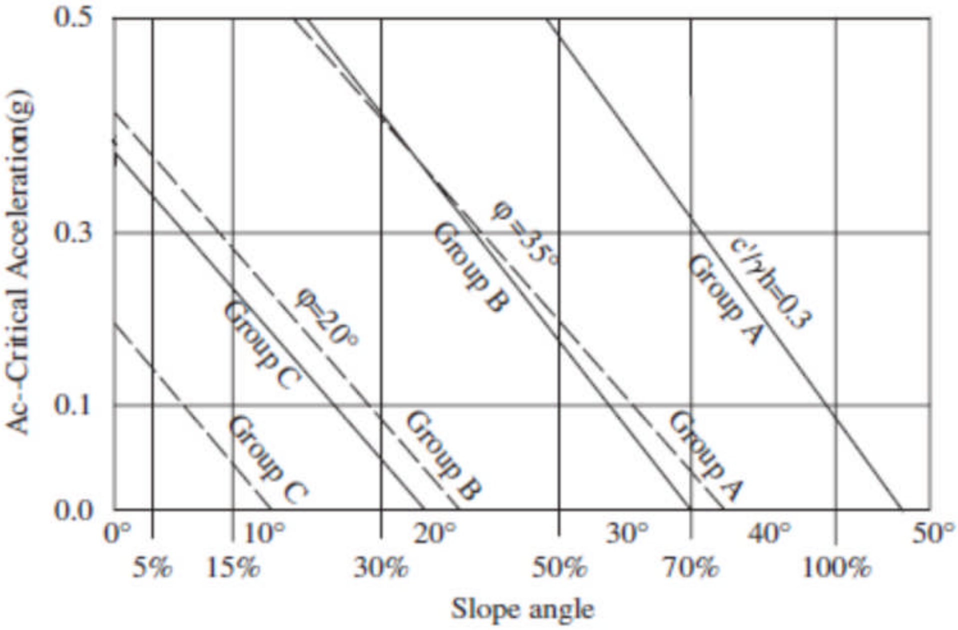


Figure 6.12 - Correlation between slope angle and PGA (ATC-13 1985)

This kind of ground failure can be exacerbated if the building foundation was laid on different levels. In the zone with complex geotechnical situations, particularly with loose cohesiveness layers and high ground water table, a detailed geotechnical investigation might be necessary.

6.6 Vulnerability

Vulnerability assessments are crucial to manage and to minimize seismic risk. Planning for disaster management and retrofitting programmes require quantifying the potential impacts on built environments, such as information about the extent of damage in past earthquakes. Decisions regarding the seismic retrofitting of existing schools require consideration of both physical and socioeconomic damage that buildings may suffer due to an earthquake. Estimating the physical damage of buildings can be performed by evaluating the seismic performance of building components, hence they could vary based on structural characteristics of buildings such as types, material, class and typology. A selection of major vulnerability factors that been addressed in the code are listed in Table 6.4.

Table 6.4 - Major vulnerability factors used in different codes of practice

Type	Factor description	Proposed	Screening Codes				Detailed design Codes	
			FEMA 154	NRC	NZS	HAZUS	EuroCode8	FEMA 310/SSC
Structural	Structural type	Y	Y	Y	Y	Y	Y	Y
	Building Height	Y	N	Y	N	Y	N	Y
	Diaphragm Integrity	-	-	-	Y	-	N	N
	Weak /Soft Storey	*	-	-	-	-	Y	Y
	Redundancy/Stability	-	-	-	-	-	Y	Y
	Irregularities/Torsion	*	-	-	-	-	Y	Y
	Short Column/Spandrel	*	-	-	-	-	Y	Y
	Occupancy Load/Population	Y	Y	Y	Y	Y	Y	Y
	Building use/Importance	Y	Y	Y	Y	Y	Y	Y
	Visible crack/Settlement	N	-	Y	Y	-	N	-
Scio-economical	Occupancy Load/Population	Y	Y	Y	Y	Y	Y	Y
	Deterioration/Mat. Quality	N	-	-	-	-	Y	-
	Pounding/Adjacent Building	*	N	N	Y	Y	Y	N
	Inventory /Asset loss	Y	.	-	-	Y	-	Y
	Area of building	Y	Y	-	Y	Y	Y	Y
	Year of Construction	Y	Y	Y	Y	Y	Y	Y
	Financial cost	-	-	-	-	Y	-	-

Y: Considered, N: not clearly considered, - : Not considered, * : Not applicable in present portfolio

NRC: National Research Canada, NZS: New Zealand Standard, SSC: Seismic Safety Commission California

The choice of factors depends on the application, precision and purpose of risk analysis. Common factors addressed within screening codes (i.e. FEMA 154, NRC, NZS) emphasises on the overall safety of buildings, and this can be useful for prioritizing vulnerable buildings.

Detailed structural factors focus deeply on building demand and performance that is appropriate for detailed design phase. For example, FEMA 310 captures a greater extent of characteristics required within a detailed vulnerability assessment, though their application is limited to the availability and applicability of the information to the group of alternatives to be studied.

With the aim to enhancing the safety protection of schools, this study uses critical social indices (i.e. population load and density) along structural factors that are commonly utilized within seismic codes. Most of these schools were either masonry or steel structures with infilled walls and no major quantifiable irregularities in a plan and height that could potentially distort the results. Generally, the factors described within the codes include median typologies of buildings for a generic condition and functionality. For specific buildings with likely socioeconomic impacts, such as schools, particular attention should be regarded in the choice of factors. For example, schools with high occupancy loads and larger areas are obviously more vulnerable to a disaster than a simple residential building.

6.6.1 Vulnerability Scale

Vulnerability analysis is based on observation and statistics of past earthquake damage. The effectiveness of application and reliability of observational damage data relies on the scale implemented. The vulnerability scale reflects how different types of buildings respond to likely earthquakes and present the extent of damage they would probably suffer. Several scales of damage have been addressed by the codes of practice covering ‘general’ and ‘standard' typologies of buildings for a given area. A summary of major scales of damage is compared in Table 6.5.

There is a noticeable difference between scales in screening codes and detailed codes of practice. While FEMA 310, ATC-13 and SEAOC-95 suggest a greater five-grade scale of damage, screening codes like FEAM 154, NRC and HAZUS provide a simplified two or three points scale to measure the extent of damage. Obviously, the more grades in damage scale, the lower uncertainty that will be imported into the process.

Table 6.5 - Comparison between damage scales of different codes

<table>
<tr><td rowspan="4">Proposed Scale</td><td>Damage State</td><td>D0</td><td>D1</td><td colspan="2">D2</td><td colspan="3">D3</td><td colspan="3">D4</td><td colspan="4">D5</td><td>D6</td></tr>
<tr><td>Description</td><td>None</td><td>Slight</td><td colspan="2">Light</td><td colspan="3">Moderate</td><td colspan="3">Strong</td><td colspan="4">Severe</td><td>Collapse</td></tr>
<tr><td>Damage Range%</td><td>0</td><td>0 - 1</td><td colspan="2">1 - 10</td><td colspan="3">10 - 30</td><td colspan="3">30 - 60</td><td colspan="4">60 - 100</td><td>100</td></tr>
<tr><td>Central Damage%</td><td>0</td><td>0.5</td><td colspan="2">5</td><td colspan="3">20</td><td colspan="3">45</td><td colspan="4">80</td><td>100</td></tr>
<tr><td rowspan="8">Code -Based Scale</td><td>EMS 98</td><td rowspan="8">No - Damage limit sate
None-Structural Damage</td><td colspan="4">Grade 1</td><td colspan="3">Grade 2</td><td colspan="3">Grade 3</td><td colspan="3">Grade 4</td><td rowspan="8">Collapse limit state</td></tr>
<tr><td>MSK 69</td><td colspan="4">D1</td><td colspan="3">D2</td><td colspan="3">D3</td><td colspan="3">D4</td></tr>
<tr><td>HAZUS 1999</td><td colspan="7">Slight damage</td><td colspan="4">Moderate</td><td colspan="2">Extensive</td></tr>
<tr><td>FEMA 310</td><td colspan="6">Immediate Occupancy</td><td colspan="2">damage control</td><td colspan="2">Life safe</td><td colspan="2">Limited Safety</td><td>Collapse prevention</td></tr>
<tr><td>FEMA 154 (ATC-21)</td><td colspan="3">Safe</td><td colspan="10">require detailed investigation</td></tr>
<tr><td>NRC</td><td colspan="2">Safe</td><td colspan="3">Low priority</td><td colspan="8">medium to high priority
(require detailed investigation)</td></tr>
<tr><td>ATC-13</td><td colspan="3">Slight</td><td colspan="3">Light</td><td colspan="2">Moderate</td><td colspan="3">Heavy</td><td colspan="2">Major</td></tr>
<tr><td>SEOAC 95</td><td colspan="4">Fully operational</td><td colspan="4">Operational</td><td colspan="2">Life safe</td><td colspan="2">Near Collapse</td><td>Collapse</td></tr>
</table>

Among these scales EMS-98 describes the vulnerability of buildings through a simple and straightforward process. The important difference between EMS-98 and other scales of intensity lies in detailed commentaries which clearly address types of buildings, degree of damage and quantitative characteristics of the expression for various impacts of the earthquake (Sidorin 2010). This feature provides a significant source of information that facilitates the process of reasoning and increases the precision of the obtained results. The advantage of EMS-98 to its predecessor MSK-67 is that it was developed based on a grade that varies continuously between typologies of buildings. Secondly, it suggests two bounds of possibility for each grade of vulnerability instead of presenting results deterministically. A similar damage scale was used in this study for measuring the vulnerability as indicated in Appendix E.

Other damage scales were specifically made for certain structural typologies or specific procedures. For example, a seismic damage index was developed by Park and Ange (1985) through an analytical procedure that was repeatedly used in the literature to estimate the seismic demand of structures. Rosseto and Elnashai (2003) also proposed an empirical scale (HRC scale) that was homogenized for the RC structure using a rich database of 340000 RC structure and 99 post-earthquake damage distributions observed in 19 earthquakes. Specific scales of damage were avoided in this study as they either cover limited ranges or require detailed performance analysis of structures. As a result, a five-grade scale of damage within the study was selected in such a way as to be consistent with existing codes of practice while it captures whole typologies and variations in extents of damage that might occur for the environment of school buildings in Iran (Appendix D).

6.6.2 Vulnerability Classification System

The classification system is a major concern in estimating the vulnerability of existing buildings. Practically, a large-scale (macroseismic) analysis of a region with a great number of buildings is a difficult task. Buildings behave differently when they subject to a likely earthquake. This is due to the diversity in building characteristics (i.e. typologies and material) that could cause different responses.

A range of damage could possibly occur in a certain type of structure with the same material. For example, two identical types of buildings with the same material could possibly suffer disparate ranges of damage that vary based on location, usage, construction and engineering quality. Thus, in order to assign a unique range of damage for each type of structure, it is necessary to identify and distinguish certain classes and categories of buildings that suffer similar damage patterns.

Various buildings can be classified according to their size and height (i.e. low-rise, mid-rise, high-rise), material (i.e. masonry, steel, concrete), age, engineering design (i.e. non-engineered, engineered) and construction quality. Record of damages in past earthquakes is a major source for creating the damage pattern.

Different buildings with the same observed vulnerability have been classified in terms of likely damage and grouped into certain categories. For example, ATC-13

(1985), developed 78 facility classes in terms of earthquake characteristics and social functions. For each class, a damage probability matrix (DPM) was addressed that relates damage state to ground motion intensity (MMI). An updated classification version with reduced classes was used in HAZUS for estimating the loss within built environment and facilities in the US. While this method developed based on ’standard‘ construction with ’simplified rules‘ (or modifier) for adjoining different DPM with engineering design and construction quality (Anagnos et al. 1995), both reflecting US construction environments and may not be a truly representative of built environment in other countries.

Table 6.6 - Building classes proposed by the code of practice

Category	Proposed	EMS-98	HAZUS 99	FEMA 154	NRCC 93
Masonry	URM	Adobe Simple stone massive stone URM + stone URM + concrete	Unreinforced Masonry (URM)	Unreinforced Masonry (URM)	Unreinforced Masonry (URM)
	RM	Reinforced Masonry (RM)	RM+ S Deck RM + PC Deck	RM+ S Deck RM+ C Deck	RM + S Deck RM + C Deck
Reinforced Concrete	FRM + mod ERD	FRM (NO ERD) FRM + mod ERD FRM + high ERD	MRF SW FRM+ INF W	MRF SW FRM+ INF W	MRF SW FRM+ INF W
	N/A	W (No ERD) W + mod ERD W + high ERD			Precast FRM Precast Wall
Steel	MRF SBF	Steel structures	MRF SBF Light FRM FRM + SW FRM+ INF W	MRF SBF Light Metal FRM+SW FRM+ INF W	MRF SBF Light FRM FRM+SW FRM+ INF W
	N/A				
	FRM + INF W				
Other	N/A	Timber Structures	Wood/Precast	Tilt-up / Wood	Wood

ERD : Earthquake Resistance Design W + mod ERD : Wall + moderate FRM + INF W : Frame with Infilled wall ERD MRF: Moment Resistance Frame PC Deck: Precast Concrete Deck SBF: Steel Braced Frame SW: Shear wall

On the other hand, the European Macroseismic Scale Ed-98 (Grünthal 1998) characterises vulnerability of 17 classes of buildings in 4 categories, focusing mainly on masonry classes. EMS-98 promoted its predecessor MSK-64 in terms of expert experiences and consistency with other intensity scales like MMI. EMS-98 provides more diversity in building types and less complete in material, simplicity, consistency and robustness of approach which makes it suitable for general application. Since the majority of buildings within the current research contains masonry classes, this approach was adopted. Furthermore, the linguistic damage scale used within EMS-98 is completely consistent with build environment of case study (Iran) which predominated by masonry classes and can be effectively modelled through a fuzzy framework. EMS-98 classifies 14 typology of buildings in four categories in terms of material, type and construction quality. Screening approaches also employ certain typology of building in their procedures. FEMA 154 and NRCC classify 15 typologies of the building in 5 and 4 categories respectively. A summary of different building classes is indicated within Table 6.6.

Each class of building represents a certain range of damage and hence corresponds with the specific damage function or fragility curve. In order to compare the vulnerability of each class of building, it is required to have unique damage index representing the range of damage in past earthquakes.

6.6.3 Date of Construction & Quality

The year of construction is important for assessing the vulnerability of existing buildings in two aspects. First, structural conditions changes over time due to material degradation, weather changes and long term settlement effects. Second, the quality of construction and engineering design has been improved over time. Hence, it is important to have an approximate year of construction to estimate the quality of engineering design and the technology of construction. Even some buildings that were constructed in the early stages of the seismic code may not adequately conform to more recent codes. According to the survey conducted on a group of buildings in New Zealand (by Dowrick and Rhoades 1997), the damage ratio of more recent buildings (1970-1987) were found to be significantly better than those built in the pre-code era (pre 1970) as shown in Figure 6.13. The similar results were obtained from a survey conducted in Armenia by Markaryan and Davidian (2000).

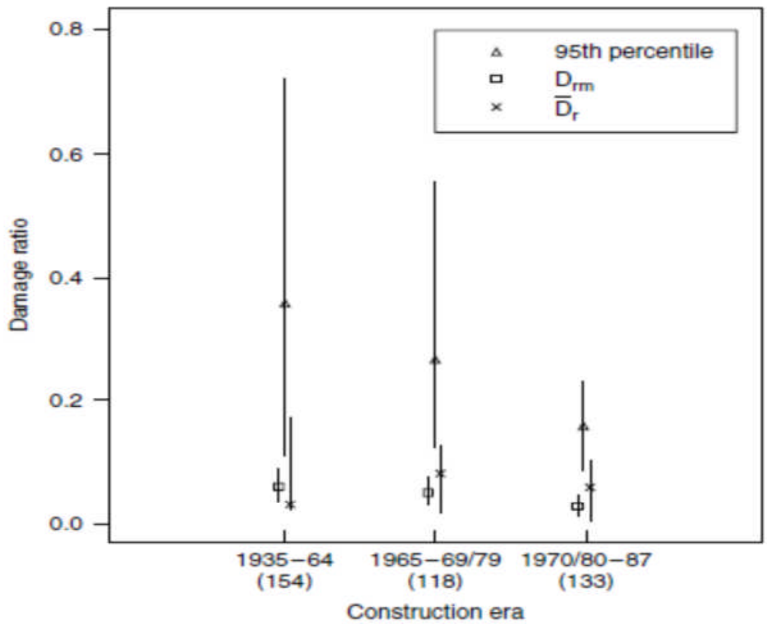


Figure 6.13 - Variation of damage ratio in different construction era (Dowrick & Rhoades 1997)

Therefore, the year of construction was also considered as a contributing indicator of vulnerability as already addressed in both screening and detailed codes of practice (FEMA-154, FEMa 273 and CNRC).

6.6.4 Engineering Performance

Engineering performance is a significant factor that contributes to the vulnerability assessment. Buildings with similar types, plans and materials could suffer a different range of damage based on the quality of construction and engineering design. Engineering performance is a site-specific characteristic that requires subjective field-based survey conducted by experts. The engineering performance could also reflect the overall quality, integrity, stability and other on-site issues that may not be explicitly modelled along the other factors.

In this study, engineering performance was determined by integrating both construction and design quality. Design quality is can be addressed by the year of construction and degree of conformity with the corresponding code. Even the newly-built schools with low conformity to design codes may not reliably resist an earthquake. Conversely, the old schools that conform to its construction time design-code may behave better than the newly-built low-quality ones.

6.6.5 Social Vulnerability

Social vulnerability refers to groups of people exposed to earthquake risk. This factor might be alternatively addressed through exposure. Due to vulnerability of users (students) and potential exposure (high occupancy load) in school buildings, social characteristics of schools have been highlighted separately through both vulnerability and exposure factors. To address social vulnerability within schools, it is necessary to understand the distribution of users (e.g. age ranges) and how these quantities vary within a day. This can also help to identify which groups of schools are potentially more vulnerable. The operational hour is also a concern that could increase social vulnerability since various educational institutions might be used in multiple purposes. Many institutions in Iran have an extra programme in their after-school hours, presenting additional courses and skills courses. Some of these might have been designated as earthquake shelters or could be used as summer accommodation for tourists. The generic operational hours of country schools of Iran have been listed in Table 6.7.

Table 6.7 - Comparison of educational institutions in Iran (NSI 2010)

Educational institution	User age	Normal service Hours	Extra service Hours	Boarding School Hours	Private(chartered) School Hours
Primary School	6 - 11	6 - 8	0 - 2	24	8 - 10
Middle school	11 - 14	6 - 8	0 - 2	24	8 - 10
High school	14 - 19	8 - 10	2 - 6	24	10 - 12
Pre-college school	17 - 19	8 - 10	2 - 6	-	10 - 12
Vocational School	16 - 20	8 - 12	-	-	-
Instructional college	18 - 22	8 - 12	2 - 4	-	-

6.7 Exposure

Exposure describes the socioeconomic capacity and extent of damage that a building, region or city potentially suffers following an earthquake. Social exposure is crucial as it represents the life safety concern in schools. No matter how severe an earthquake, without a social exposure, there would be nothing to be damaged and thus there would be no risk. Socioeconomic exposure is important in selecting seismic mitigation measures. Schools with higher population or higher occupancy load obviously require more attention as they have a higher expected loss. This also true for the size of buildings as examined through a number of cases (Dowrick and Rhoades, 1997, 2002) as shown in Figure 6.14.

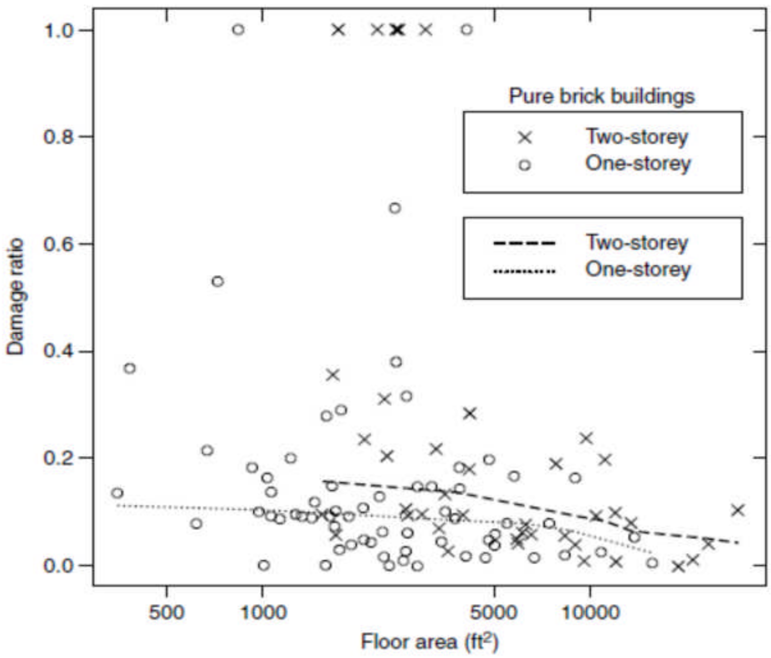


Figure 6.14 - Correlation between damage state and building area/storey for MMI-8 intensity in Wairarapa (NZ) earthquake (Dowrick & Rhoades 1997)

Another feature that could influence exposure is asset and inventory value. It has been found that the damage ratio is sometimes related to property value (Rhoades and Dowrick, 1999). The potential economical exposure is a concern for an insurance company to estimate the insurance premium and also important for disaster planners when evaluating the cost of mitigation measures. Higher exposures mean higher asset values at risk, leading to higher insurance premiums that could considerably exceed expected loss or decisions to not offer coverage (Kovacs and Kunreuther 2001).

This study considers the exposure of school buildings from a socioeconomic perspective. The size and distribution of people within buildings are major factors and highlight the importance of schools. The time, budget and workforce required for retrofitting measures depend on the size, area and location of the schools. Clearly, the greater area of the school, the more costly mitigation measures will be. For example, considering two schools with the same population, should the one with the greater area be prioritised as more important for mitigation measures? To resolve this issue, a new index called "occupancy load" (or population density) is proposed, indicating that social exposure has to be considered along with population index. In the present work, potential economic loss was addressed through "asset value at risk (VaR)" and "area exposed". Four groups of economic loss were considered in estimating the VaR including: displacement costs, rental cost, supply cost and new construction costs. Displacement costs defined as the extra costs of moving, rental and other operations costs to find a temporary place during retrofitting operations.

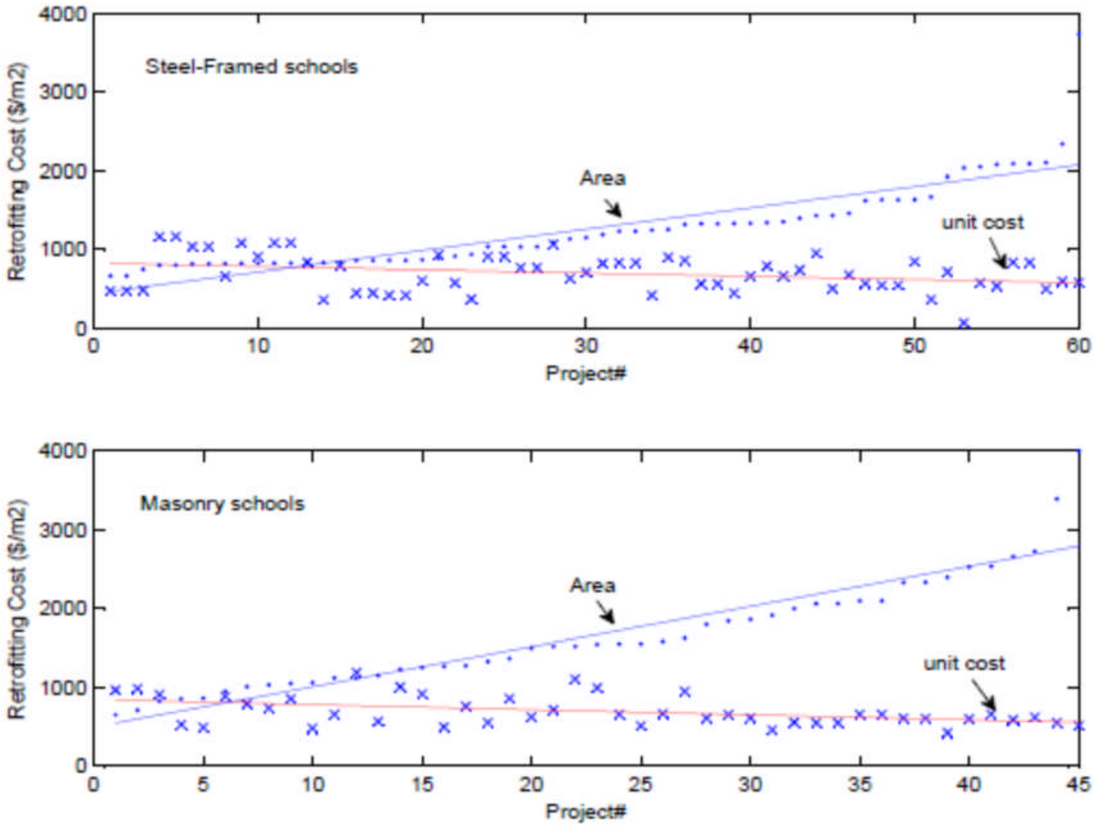


Figure 6.15 – Avergae retrofitting cost (US$) of school buildings of Iran

In order to analyse the average retrofitting cost of school buildings in Iran, a survey was conducted, using final approved bills of 105 contracts, including 60 steel and 45 masonry retrofitting projects undertaken between 2009-2010. The variety of cost was indicated in Figure 6.15 for different school areas. These graphs reveal that the total cost of retrofitting reduces when the area of buildings increase. There is a slight variation of retrofitting cost in both masonry and steel-structured buildings that might affect projects with unforeseen design situations. It can be also noticed that the unit cost of masonry buildings is much less than steel structure buildings. This means that using a fixed-budget, the greater number of masonry schools (greater area/more classrooms) can be retrofitted. This result demonstrates how useful the economical aspects could be in planning and prioritizing the mitigation measures.

6.8 Response Management (RM)

In a general sense, response capability and disaster management relate to the resilience of a community and region. 'Resilience' refers to the capacity of a system, community or region that is potentially exposed to earthquake hazard, to adapt and maintain an acceptable level of functioning and structure (UN-ISDR, 2004). In this study, RM factors describe how effectively a region can systematically respond and recover earthquake impacts, representing the resilience of a city against earthquakes.

'Response capability' refers to fundamental hardware and resources mobilised through a community in order recover during after an earthquake. Critical infrastructure plays an integral role in public health and safety during an event. Identifying and evaluating the performance of those critical facilities could improve the ability of regions to respond prior to an event. The major attributes that were used for the RM module are addressed within Table 6.8. These attributes can be organized into three major categories: pre-earthquake measures (preparedness and planning), resources for post-earthquake response (emergency shelters, first aid response facilities and rescue bodies, hospitals and physicians), and infrastructure for post-earthquake response and recovery (access road, airport, railway, lifeline). Some schools can be used for multifunctional purposes, such as shelters for post-event refugees. Fire stations, along other rescue bodies, provide the sources for emergency response. Lifelines and utility networks are also required for the post-disaster response, maintaining basic needs and securing public health.

However, RM was considered as background factor which can indirectly influence the total risk index. Compiling a baseline inventory of infrastructure, lifelines, shelters, emergency facilities, planning and resource capacity of alternative regions can draw a picture of response capability in a city. Clearly, schools located in areas containing poorly-constructed (emergency) facilities are more susceptible to great loss in the event of an earthquake than similar schools in major resilient cities. Thus, schools located within low resilient cities require more attention and have to be prioritized in mitigation programmes.

Table 6.8 - Response capability and disaster management indicators

RM Phase	Attribute	Sub-attribute	Description
Pre-event Preparedness	Disaster Management & resource	Financial resource	Dedicated emergency budget (yearly)
		Human resource	Trained manpower and experts within region
		Critical plans	Active integrated plan (real-time response plan)
Infrastructure & lifelines (Post-event response)	Mobility Access	Roads	Road network & transpiration quality
		Railway	Railway network & terminals
		Airport	Airway network & terminals
	Telecom	Communication	Landlines & wireless (Mobile) communications
		Broadcasting	TV & radio & emergency alarming system
	Lifelines	Water	Water treatment plant & Potable water lines
		Sewage	Sewage treatment plant & transfer systems
		Gas	Earthquake resilient Gas line for householders
		Electricity	Power plant & substations & power line
Post-event Recovery	First-aid Facilities	Hospitals	Number of hospitals per 100,000
		Physicians	Number of physicians per 1000
		Shelters	Designated places in cities for a disaster event
		Firefighting	Firefighting stations & manpower

6.9 Hierarchical Risk Breakdown Structure (HRBS)

The risk information described in the previous sections hampers the analysis and measurement of the total risk, because of the interactions within risk factors. By analogy to the WBS concept, a hierarchical structure can be an effective way to handle multidimensional characteristics within such a complex system. According to Hillson (2002), WBS provides the multiple aspects of a project in a hierarchy that makes it more accountable and manageable for planning, reporting and communication. Likewise, risk breakdown structure (RBS) describes the risk data, and organizes them on the sources from which risk arises. An example of RBS can be found in project risk assessments (Zeng et al. 2007; Chapman 2001), railway risk assessments (An 2006, 2007), food and supply risk assessments (Chan and Wang 2013), and environmental risk assessments in offshore constructions (Yang et al. 2010; Mirilavasani 2011). Categorising risk using the HRBS provides a greater insight into the seismic risk management phases in several ways:

- Risk identification: Using HRBS ensures that all common sources of seismic risk have been explored. The upper levels within HRBS can be used to identify and to highlight sources of risk.
- Risk assessment: building seismic risk taxonomy improves the understanding of risk exposure, focusing on the areas within the HRBS which have the most significant concentrations of risk that requires the development of risk response plans. Using the HRBS also helps to identify any dependency or correlation between various sources of risk.
- Risk ranking and comparison: Using HRBS, multiple retrofitting projects can be compared and ranked according to their risk severity. High risk projects can be further allocated for detailed analysis, budgeting or future risk mitigation measures.
- Risk monitoring and reporting: The HRBS can be used to gather risk information within single or multiple retrofitting projects for different levels of clients and decision-makers.

In the present research, the risk information was summarized classified using a hierarchical risk breakdown structure (HRBS) as shown in Figure 6.16. Similar HRBS was developed by Vahdat and Smith (2014a) and Vahdat et al. (2014b) for seismic risk assessment. The risk taxonomy contains four major risk categories that are organized in a multilevel structure to describe the sources of seismic risk. Each category of risk was further expanded into more detailed sub-factors so as to be precisely measured. The process of risk break-down can be continued until all risk attributes are defined explicitly. The risk factors selected in this study were identified from the most relevant factors that have significant measurable impacts, specifically on school buildings. The main idea behind the choice of risk factors is that their physical significance in terms of objective interpretation is based on physical consequences and potential human loss.

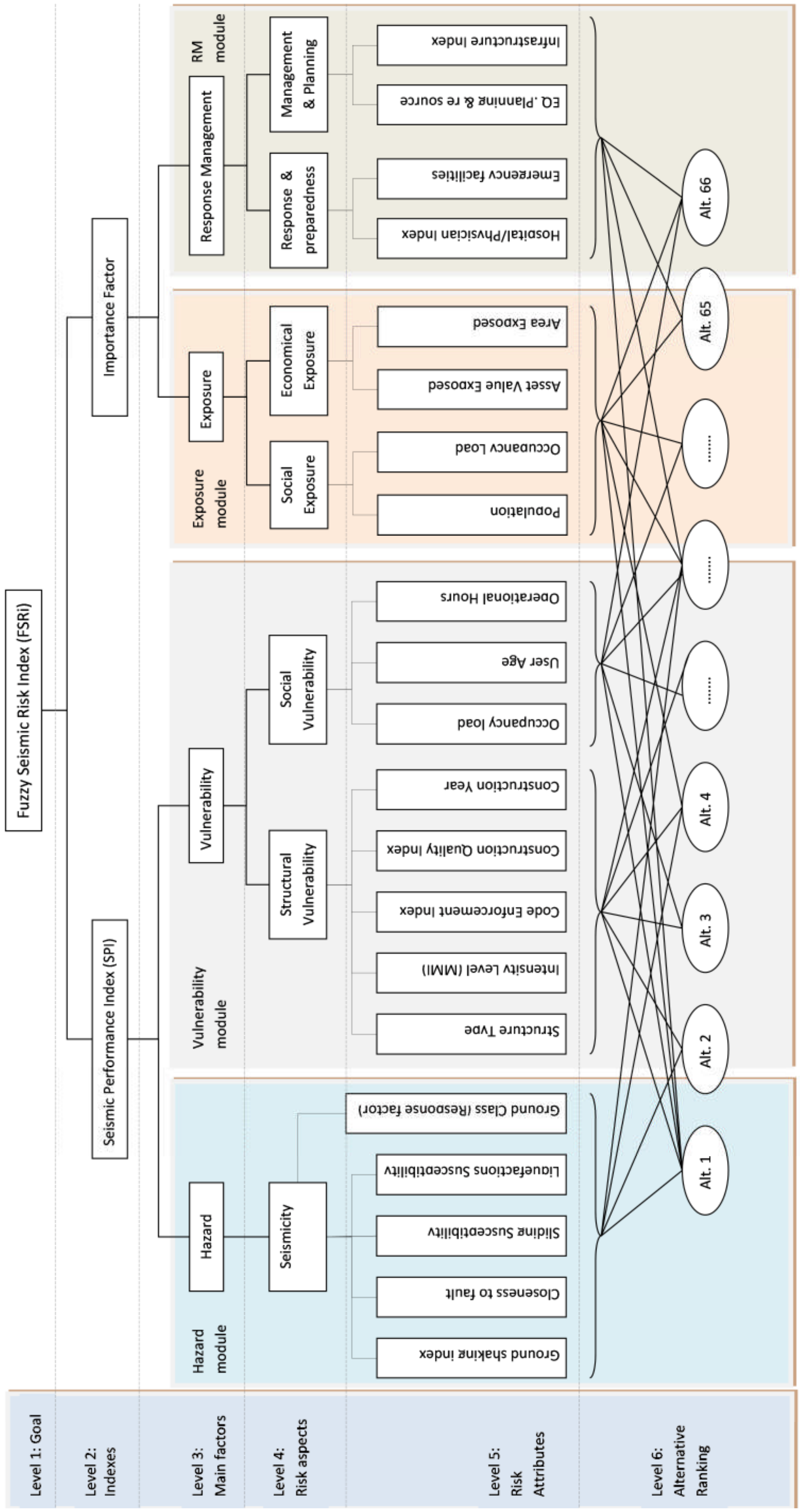


Figure 6.16 – Hierarchal risk breakdown structure for seismic risk

Having outlined the structure of the seismic risk, the KBEs can now be developed accordingly. The risk factors, criteria and alternatives discussed here plot the road map for determining the composite seismic risk index.

6.10 Summary

This chapter explores the important characteristics of risk input factors and potential impacts, as well as their necessary configuration prior to simulating. The information required for developing the KBES has been collected, reviewed and classified in a multilayer hierarchical structure (HRBS) containing four major categories: hazard, vulnerability, exposure and response management.

Potential impacts of risk attributes were reviewed in each category using analytical and empirical procedures described in previous research and standards. Accommodating the relations within risk factors explains the structure of the risk system in these respective categories, establishing a foundation for developing the knowledge base and the criteria to measure risk. In addition, the impact analysis determines the extent to which an attribute can potentially influence seismic risk. For example, according to international codes (UBC-97) the impact of soil conditions can rapidly increase the risk more than two-fold in soft deposits. The factors, structure, and measurement scales described in this chapter collectively comprise an underlying body required for developing the KBES.

Chapter 7: Case Study (Review & Results)

7.1 Introduction

This chapter outlines the descriptions of the developed KBES and analyses the results in two parts. First, the characteristics and types of knowledges utilised within the model is elaborated. The second part tracks the case study results and demonstrates the contributions of the seismic risk factors within the system through multiple statistical analyses.

7.2 Inference Engine Description

The important step in fuzzy modelling is to address the relationship of variables within inference engines. This research study applies Mamdani algorithm for fuzzy modelling as it works with IF-THEN rules that are based on fuzzy numbers and expressed though linguistic variables. The Mamdani model is more convenient to TSK because both antecedent and consequent part of the rules are described through fuzzy sets, instead of linear functions. Fuzzy sets are preferred for the current problem because they can express a linguistic form of variables and are easier to interpret and track. Fuzzy sets provide a transparent process that allows visualizing, interpreting and tracking variables and makes it easier to understand. The Mamdani inference system was adopted, because it provides more effective strategies to define the relationship between classified input and output variables using Min, Max and operators as shown in Table 7.1.

Table 7.1 - Characteristics of Mamdani Model

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

Where μ is a membership function for each variable and $\wedge$ and $\vee$ are Max and Min operators, respectively. The linguistic variables combined within Mamdani model are not modified by weights since all the linguistic variables have been implicitly assumed to be of the same importance.

The proposed inference process was developed according to the definition of the logical operators AND (conjunction) and OR (disconjunction) that is technically based on Min and Max operation. The Min operator represents the fuzzy intersection and returns the lowest degree of membership involved in the intersection that controls the result of the operation. The general idea behind this operation is similar to the expression that a chain is as strong as its weakest point. On the other hand, the Max operator that represents the fuzzy union returns the highest degree of membership among values. The implication operator was used in the inference engine based on Mamdani model for aggregating risk factors. The centre of the area (COA) was chosen for defuzzification process. As an example, the Mamdani model to FIS-S1 can be applied using the implication operator for aggregating the risk factors, and can be written as follows:

$$\mu_{SFI}(x)= \max(\min(\mu_H(x), \mu_V(x))) = \max(\mu_H(x) \wedge \mu_V(x)) \tag{7.1}$$

When the MFs, fuzzy engines and operators are defined, then the last step is to establish the rule-base.

7.2.1 Rule Base Design

The rule base is a fundamental part in a fuzzy expert system that describes the behaviour of the system. It maps the combination of fuzzy input sets to the specific range of outputs through IF-THEN rules. Thus the rule base should be complete enough to correspond and cover both the variations in input and output factors. According to An et al. (2006, 2007) in developing the rule base, some important factors should be accounted to meet completeness and consistency within the rule base. Completeness ensures the matches between inputs and outputs, as well as the thorough coverage of the whole system domain. To maintain consistency of the rule base, the same antecedent cannot correspond with different conclusions. Inconsistency can be avoided by eliminating contradictory rules from the rule-base.

Several approaches can be used to derive the fuzzy rules where by most are based on either numerical data analysis (or prior knowledge) or linguistic knowledge from domain experts (Ding 2001). Expert judgment is a direct way of generating the rules; yet it is a subjective process and hence the rules strength relies on the perception of experts over the context. Experts usually find fuzzy rules to be a convenient way to express their knowledge because the rules often presented in the form of natural language (linguistic scale). Data analysis methods seek any interactive or synergetic relationship among data (An et al. 2000).

Various pattern classification methods can be used to classify and establish the relation among data sets. Correlation analysis is a straightforward process in which users may be used to determine both directions and logical relationships of rule antecedents and consequences (Fayek and Sun 2001). There are other classification methods for automatically deriving fuzzy rules, such as machine learning and clustering (Hong and Lee 1996; Hong and Chen 1999) that are only viable when dealing with a limited number of variables. The complexity of clustering method and limited data makes it unsuitable for the present research.

In order to obtain the most effective way of developing the rule base in the case of seismic risk assessment, a combination of expert knowledge and numerical data analysis were used. In situations where there has been a pattern or correlation to establish the logical relation between input and output, data analysis is preferred. For the other cases where there exists no clear relation or supporting facts, expert judgment was chosen. Each method has been explained in detail through following sections.

7.2.1.1 Expert-driven Knowledge

Expert knowledge is primary source of information in risk assessment. Fuzzy rule based systems were traditionally designed from the linguistic knowledge of human experts. Generating fuzzy rules based on expert judgment can be conducted in many ways. The consideration of two risk factors has to be combined within a rule, then experts can be asked to score the strength of consequence impacts. This direct weighting method can be effective way only for limited variables and impact states. The higher number of variables, the more fuzzy rules and questions will entail. For example, when three variables with 5 impact grades, there will be 125 fuzzy rules (5 x 5 x 5) to be judged, which is practically impossible.

Indirect expert knowledge elicitation combines the impacts of risk factors through the weighted average method (WAM). Ramakrishnan (1992) suggested the WAM method to aggregate the criteria impacts of multiple alternatives with weights being obtained by using experts' opinion. Shaheen et al. (2005) used this method to enhance the input modelling process in discrete event simulation and to integrate them through fuzzy expert system. Fares (2010) also applied WAM to aggregate the impacts of deterioration factors in order to evaluate the risk of water pipeline failure. The WAM can be used in many applications, providing that the factors are independent. Applying WAM to the seismic risk factors

$$Combined\ Impact(f_1, f_2, \ldots, f_n) = \frac{w_{f1}.P_{f1} + w_{f2}.P_{f2} + \cdots + w_{fn}.P_{fn}}{w_{f1} + w_{f2} + \cdots + w_{fn}} = \frac{\sum w_{fi} P_{fi}}{\sum w_{fi}} \tag{7.2}$$

Where f_n represents the risk factors, w_f and P_f indicating the weight and performance of risk factors respectively.

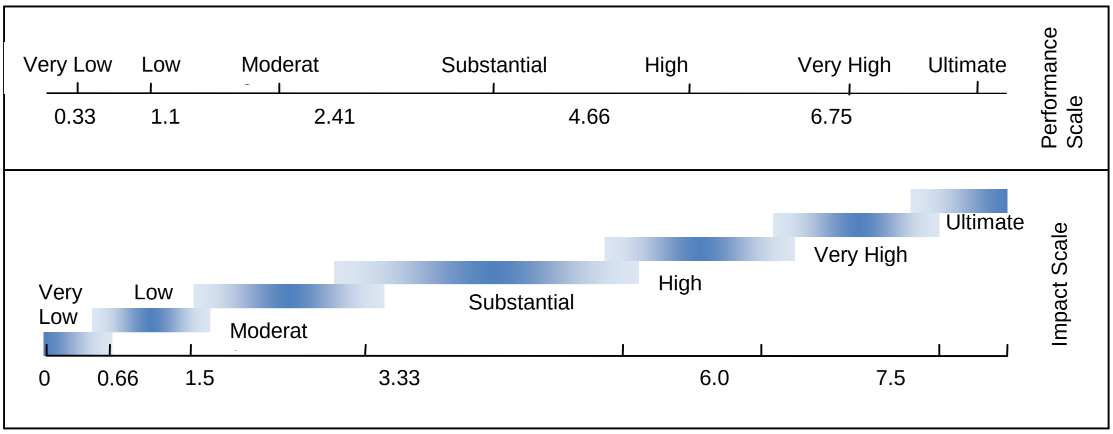


Figure 7.1- Generic scale of measurement for risk factors' performance and consequence Impact

To interpret the performance of risk factors and consequence impacts into quantifiable numerical values, a generic scale of measurement was proposed, as shown in Figure 7.1. A scale was set up for maximum seven states of impacts, including Very Low (VL), Low (L), Moderate (M), Substantial (S), High (H) , Very High (VH), and Ultimate (UL). While the metric for measurement is arbitrary and any ordinal scale may be chosen; the scale of 0 - 10 was adopted for simplicity and easier tracking. Using the weights extracted from the survey, the combined performance impacts of hazard and vulnerability can be obtained. For example, consider a rule describing two states of hazard and vulnerability:

IF Hazard is Low AND Vulnerability is High THEN SPI is?

$$\left.\begin{array}{l}\text{Hazard} \rightarrow W_H = 50.94 \\ \text{Low} \rightarrow P_H = 6.75\end{array}\right\} \text{Impact}_H = W_H \, . \, P_H$$

$$\left.\begin{array}{l}\text{Vulnerability} \rightarrow W_V = 50.23 \\ \text{High} \rightarrow P_V = 6.75\end{array}\right\} \text{Impact}_V = W_V \, . \, P_V$$

$$\text{Combined Impact}_{SPI} = \frac{W_H \, . \, P_H + W_V \, . \, P_V}{W_H + W_V}$$

$$\therefore \text{Combined Impact}_{SPI} = 3.905$$

From generic Impact scale $\therefore$ Equivalent Linguistic term = 'Substantial'

Having determined the consequent impact, the rule can be rewritten in complete form as follows:

IF Hazard is 'Low' AND Vulnerability is 'High' THEN SPI is 'Substantial'

Likewise, other rules within other risk blocks can be generated in the same manner as summarized in Table 7.2. The fuzzy rules should sweep all the possible combinations of the risk factors' performance. For example, for two risk factors, each of those described by six performance state (or linguistic variables), the rule base consists of 36 fuzzy rules. A sample block of fuzzy rule matrix is shown in Figure 7.2. The top left corner array within FIS-S1 (Blue cell) matrix represents a rule that expresses the following logical statement:

IF Hazard is 'Very Low' and Vulnerability is 'Very High' THEN SPI is 'Substantial'

Table 7.2 - Sample rules base generating for various states of risk factors using expert-derived weights

Rule #	Vulnerability (V)			Hazard (H)			Seismic Performance Index (SPI)	
	Linguistic Term	Equivalent Impact	Factor weight	Linguistic Term	Equivalent Impact	Factor weight	Equivalent Impact	Linguistic Term
1	VERY LOW	→ 0.33	50.94	VERY LOW	→ 0.33	50.23	0.330 →	VERY LOW
2	VERY LOW	→ 0.33	50.94	LOW	→ 1.1	50.23	0.712→	LOW
3	VERY LOW	→ 0.33	50.94	MEDIUM	→ 2.41	50.23	1.363→	LOW
4	VERY LOW	→ 0.33	50.94	SUBSTANTIAL	→ 4.66	50.23	2.480 →	MEDIUM
5	VERY LOW	→ 0.33	50.94	HIGH	→ 6.75	50.23	3.517 →	SUBSTANTIAL
6	VERY LOW	→ 0.33	50.94	VERY HIGH	→ 8.4	50.23	4.337→	SUBSTANTIAL
7	LOW	→ 1.1	50.94	VERY LOW	→ 0.33	50.23	0.718→	LOW
8	LOW	→ 1.1	50.94	LOW	→ 1.1	50.23	1.100→	LOW
9	LOW	→ 1.1	50.94	MEDIUM	→ 2.41	50.23	1.750→	MEDIUM
10	LOW	→ 1.1	50.94	SUBSTANTIAL	→ 4.66	50.23	2.868→	MEDIUM
11	LOW	→ 1.1	50.94	HIGH	→ 6.75	50.23	3.905→	SUBSTANTIAL
12	LOW	→ 1.1	50.94	VERY HIGH	→ 8.4	50.23	4.724→	SUBSTANTIAL
13	MEDIUM	→ 2.41	50.94	VERY LOW	→ 0.33	50.23	1.377→	LOW
14	MEDIUM	→ 2.41	50.94	LOW	→ 1.1	50.23	1.760→	MEDIUM
15	MEDIUM	→ 2.41	50.94	MEDIUM	→ 2.41	50.23	2.410→	MEDIUM
16	MEDIUM	→ 2.41	50.94	SUBSTANTIAL	→ 4.66	50.23	3.527→	MEDIUM
17	MEDIUM	→ 2.41	50.94	HIGH	→ 6.75	50.23	4.565→	SUBSTANTIAL
18	MEDIUM	→ 2.41	50.94	VERY HIGH	→ 8.4	50.23	5.384→	SUBSTANTIAL
19	SUBSTANTIAL	→ 4.66	50.94	VERY LOW	→ 0.33	50.23	2.510→	MEDIUM
20	SUBSTANTIAL	→ 4.66	50.94	LOW	→ 1.1	50.23	2.892→	MEDIUM
21	SUBSTANTIAL	→ 4.66	50.94	MEDIUM	→ 2.41	50.23	3.543→	SUBSTANTIAL
22	SUBSTANTIAL	→ 4.66	50.94	SUBSTANTIAL	→ 4.66	50.23	4.660→	SUBSTANTIAL
23	SUBSTANTIAL	→ 4.66	50.94	HIGH	→ 6.75	50.23	5.698→	SUBSTANTIAL
24	SUBSTANTIAL	→ 4.66	50.94	VERY HIGH	→ 8.4	50.23	6.517→	HIGH
25	HIGH	→ 6.75	50.94	VERY LOW	→ 0.33	50.23	3.563→	SUBSTANTIAL
26	HIGH	→ 6.75	50.94	LOW	→ 1.1	50.23	3.945→	SUBSTANTIAL
27	HIGH	→6.75	50.94	MEDIUM	→ 2.41	50.23	4.595→	SUBSTANTIAL
28	HIGH	→ 6.75	50.94	SUBSTANTIAL	→ 4.66	50.23	5.712→	SUBSTANTIAL
29	HIGH	→ 6.75	50.94	HIGH	→ 6.75	50.23	6.750→	HIGH
30	HIGH	→ 6.75	50.94	VERY HIGH	→ 8.4	50.23	7.569→	VERY HIGH
31	VERY HIGH	→ 8.4	50.94	VERY LOW	→ 0.33	50.23	4.393→	SUBSTANTIAL
32	VERY HIGH	→ 8.4	50.94	LOW	→ 1.1	50.23	4.776→	SUBSTANTIAL
33	VERY HIGH	→ 8.4	50.94	MEDIUM	→ 2.41	50.23	5.426→	SUBSTANTIAL
34	VERY HIGH	→ 8.4	50.94	SUBSTANTIAL	→ 4.66	50.23	6.543→	HIGH
35	VERY HIGH	→ 8.4	50.94	HIGH	→ 6.75	50.23	7.581→	VERY HIGH
36	VERY HIGH	→ 8.4	50.94	VERY HIGH	→ 8.4	50.23	8.400→	VERY HIGH

FIS S1		Seismic Hazard (H)					
		VL	L	M	S	H	VH
Vulnerability (V)	VH	S	S	S	H	VH	VH
	H	S	S	S	S	H	VH
	S	M	M	M	S	S	H
	M	L	M	M	S	S	S
	L	L	L	M	M	S	S
	VL	VL	L	L	M	S	S

FIS S2		Seismic Exposure (E)				
		VL	L	M	H	VH
Response Management (RM)	VH	M	H	H	VH	VH
	H	M	M	H	H	VH
	M	L	M	M	H	H
	L	L	L	M	M	H
	VL	VL	L	L	M	M

Figure 7.2 – Rule-base matrixes for risk module

The rule base matrix may be alternatively presented through 2D or 3D surface views in MATLAB as shown in Figure 7.3 and Figure 7.4 respectively. The grade of risk factors and consequent impacts are presented on a colour-coded scale according to their severity. The graphs implicitly represent the relation between risk factors, and hence can be a fast method of verifying variation in the rule base. The low resolution 2D view mimics the rule base matrix graphically; while the 3D views graphically present the state of relationship between I/O risk factors. The higher the number of performance grades, the higher resolution (precision) picture of risk variation and the more effective it is in capturing nonlinear relations between risk players.

At the limit state, the transition between grades of risk impacts would be very smooth and gradual representing the fuzzy concept that happens in the real world. Another noticeable aspect of the 3D view is that vulnerability and hazard varies on the same pattern. This was expected as the rule base was symmetric. It can thereby be concluded that:

- The variation in output risk factors depends on the strength of the input data, which is represented by aggregated nonfuzzy weights.
- In the case where aggregated weights are identical, the variation of both factors would be expected as the same, hence risk factors follow the same trend.
- Higher weights mean greater strength in variation of output risk factors.
- The number of graded risk impacts represents the flexibility of the rule base to capture the nonlinear relationship among the players.

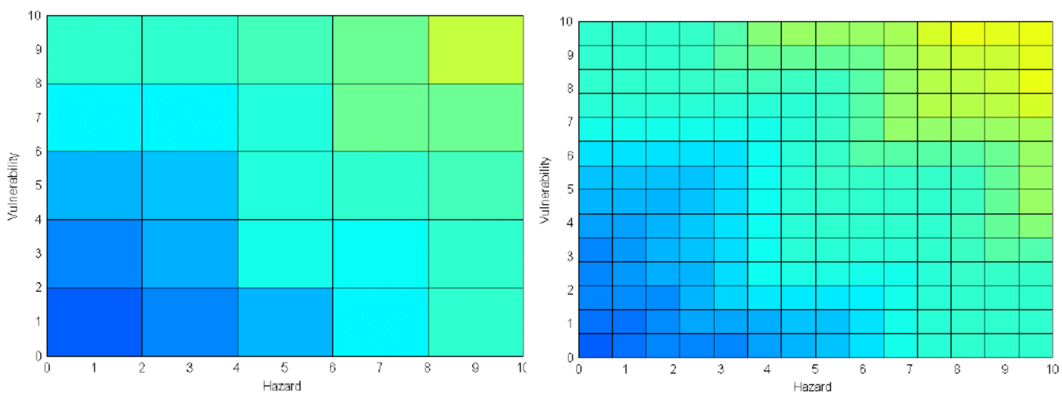


Figure 7.3 - 2D surface view of risk rule-base for two resolutions: low (5grades) and high (15 grades)

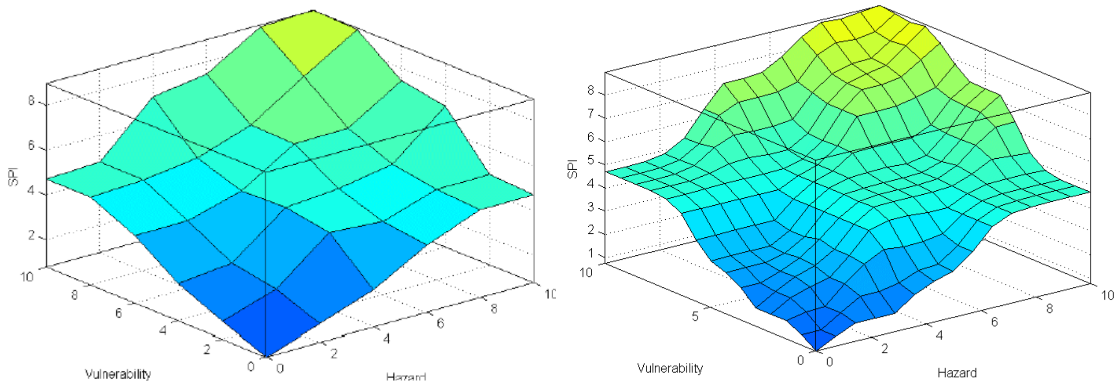


Figure 7.4 - 3D surface view of risk rule-base for two resolutions: low (5 grades) and high (15 grades)

7.2.1.2 Data-driven Rule-base

Data-driven rule-bases are an alternative way to extract rules from prior knowledge and experience. This method looks for a pattern, algorithm and correlation predominating within the data. In this case, for instance, the earthquake response action was empirically formulated in the codes through a certain procedure.

The algorithm addressed in the local seismic code of practice can be used for developing the relationship between hazard factors. According to BHRC (2010), the seismic response of a building is represented by an elastic ground acceleration response spectrum (or elastic response spectrum that was developed for two ranges of seismicity (low - medium and high - very high). The response factor is a function of ground type and building period. The building period can be obtained through a simple algorithm (Eq 5.19), suggested by codes of practice. To avoid detailed structural calculation, the period values for generic types of low-rise school buildings were calculated upon a standard algorithm as summarized in Table 7.3.

Table 7.3 - Period values for generic types of school buildings

Store	H (m)	Building Type		
		Steel	Concrete	Masonry
1	3.5	0.205	0.179	0.128
2	7.0	0.344	0.301	0.215
3	10.5	0.467	0.408	0.292

Using the period values and reference, PGA is defined within seismic zoning maps. The site response factor can be derived as shown in Table 7.4.

Table 7.4 - Response factor for different soil classes

Response factor (FIS H4)		Soil class			
		I	II	III	IV
Seismicity : Reference PGA	L	2.5	2.5	2.75	3.25
	M	2.5	2.5	2.75	3.25
	H	2.5	2.5	2.75	2.75
	VH	2.5	2.5	2.75	2.75

Since the table presents the numerical relation between seismicity (H_{41}) and soil class (H_{42}) it can implicitly represent a crisp form of rule base. Converting the crisp values in linguistic terms, the fuzzy rule base can be derived. Likewise, the other hazard rule base can be calculated based on either a code-based algorithm or empirical correlation as defined in the literature. For example, the rule base for FIS-H1 can be placed using the empirical relation (Eq. 6.2) between fault distance and seismic intensity (see Section 6.6.4 for more detail). Sample hazard rule-base matrixes are presented in Table 7.5.

Table 7.5 - Generic hazard rule base matrixes

FIS H1		Fault Rupture Distance (H_{12})					
		VL	L	M	H	VH	UL
Intensity(H_{11})	L	L	L	L	L	L	L
	M	M	M	M	L	L	L
	H	H	H	M	M	M	L
	VH	VH	H	H	M	M	M

FIS H2		Liquefaction (H_{21})		
		L	M	H
Sliding(H_{22})	L	L	M	H
	M	M	H	VH
	H	H	VH	VH

FIS H3		Propagated Intensity (H_{31})			
		L	M	H	VH
Ground Failure (H_{32})	L	L	M	H	VH
	M	M	H	VH	UL
	H	M	H	VH	UL
	VH	H	VH	UL	UL

FIS H4		Soil class (H_{42})			
		I	II	III	IV
Seismicity (H_{41})	L	L	L	M	VH
	M	L	L	M	VH
	H	L	L	M	M
	VH	L	L	M	M

7.3 Software

The risk causative factors and information regarding alternative school buildings was scaled and interpreted by means of fuzzy sets. Due to the size and extent of information, the whole structure, MFs and rule base was modelled through 21 fuzzy inference engines and was synchronized using MATLAB programming language. The fuzzy logic toolbox (enhanced within MATLAB), was used to model the whole operation based on the Mamdani algorithm. The key feature of MATLAB is an advanced programming concept that supports a systematic approach. This feature allows the use of the MATLAB language through script files which are supported by the extensive library of standard-built-in (or user-defined) fuzzy functions. The graphical user interface provides an effective tool that allows visualising, tracking and demonstrating the process of fuzzy modelling.

The potential capability of MATLAB has been improved by integrating with Excel spreadsheets. While the proposed model components (FIS engine, MFs, integrator scripts) were written in MATLAB, the I/O files were set to be called from and to Excel spreadsheets for convenience. The combination of these two software types provides the strong ability in pre-/post- processing of I/O data that is required for such a complex system.

7.4 Analysis and Interpretation of Results

Analysis and interpretation of the results are crucial to ensuring that the knowledge extracted from risk information is clear and simply understandable by related decision makers. The potential use of results disseminates the present state of knowledge by raising awareness and preparedness. In the present case, this task has been undertaken using set statistical indicators to measure the frequency, severity and tendency of samples. Different forms of charts, figures and tables were used to display and to compare the impacts of risk attributes graphically among school buildings. This form of presentation has potential to capture required attention and facilitate interpreting the results for any audience.

7.4.1 Results and Discussion

The analysis of results might be performed in several ways. The primary results of the model can be extracted through priority assessment of risk attributes. Prioritising the schools based on their critical risk factors highlights the issues that might be involved within separately in various dimensions. The ranking results can be expressed in different forms depending on the resolution required for decision. For example, high resolution results can be sorted numerically or categorically to distinguish the school buildings in term of a specific attribute. Expressing the risk values in the high precision decimal format appears effective for post-processing calculations such as distinguishing buildings and allocating resources, yet it may appear too complicated for users to interpret and to understand. Thus it is required to be normalized or rescaled in a new metric. Lower resolution (qualitative) form of results could be more appropriate for general interpretation. This form of presentation addresses the overall risk ranking through linguistic terms such as 'Extreme', 'Strong', 'Moderate' and 'Low'. Following the examples, analyse and comparison of the overall seismic risk index (FSRi) in different categories of age, origin (region) and seismicity source is required.

7.4.1.1 Seismic Risk vs. Seismicity

Figure 7.5 illustrates the seismicity (in blue ∇) along seismic risk (red O) of school buildings in 15 regions of Iran. For simplicity, the seismicity of regions is also shown on the same axis; although these concepts have fundamentally various impacts and may take different scales according to risk perceptions, risk dimensions and presumptions.

At first glance, the chart simply indicates that risk and seismicity have different values and does not follow the same trend. For example, in regions with low seismicity such as 'ILM' and 'AZW', the schools have taken high values of seismic risk. Conversely, schools in some high seismicity regions like 'BHK', 'LOR' and 'HAM' demonstrated low to moderate degrees of seismic risk. It is also noticeable that many other regions with moderate levels of seismicity could take various levels of risk, regardless. This perception explains why seismicity and risk do not follow the same trend while both are closely interrelated.

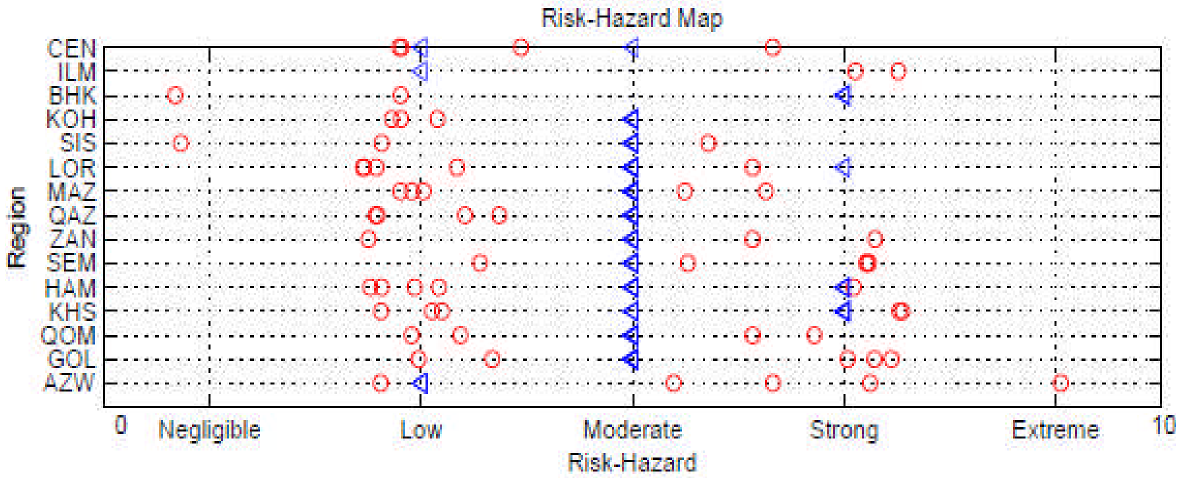


Figure 7.5 - Regional classification of school buildings using risk-hazard map

Therefore, the risk - hazard map should be jointly taken into consideration and be used in disaster planning; however, in some applications either of those might be exaggerated or disregarded depending on the context and purpose of the programme. Most mitigation programmes such as global risk management, seismic performance and multidisciplinary seismic risk reduction of lifelines require concepts to be evaluated and to be considered alongside each other.

7.4.1.2 Seismic Risk vs. Year of Construction

The overall seismic risk index (FSRi) can be compared to the group of buildings with similar characteristics. The insight gained from this comparison initially suggests a useful feedback that could support mitigation decisions as well as highlight the controlling factors at school buildings. For example, the seismic risk of school buildings can be reviewed according to their year of construction, as shown in Figure 7.6. The risk of damage usually increases as buildings get older due to material deterioration, construction quality, lack of maintenance and specifically new updates in seismic code. Nevertheless, even newly-built structures require upgrading; Conversely some old building may not require urgent consideration as is seen in the Risk - Year map.

Another noticeable scenario emerges from the graph; buildings with varying years of construction could exhibit different degrees of risk. Hence, for mitigation practice, year of construction should be taken into consideration jointly with the field survey and comprehensive quality inspections (i.e. in-situ tests).

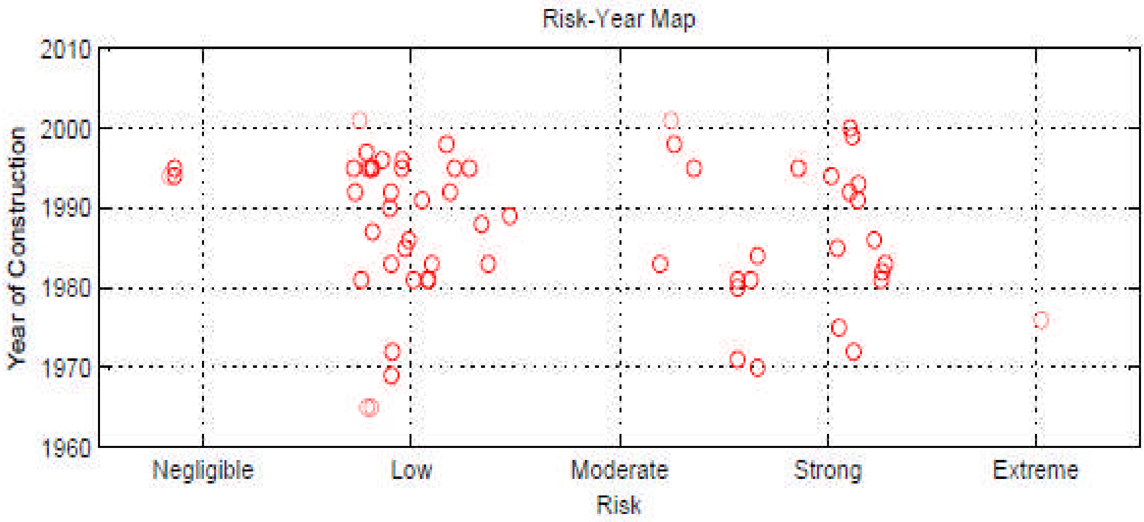


Figure 7.6 - Seismic risk within schools according to their year of construction

7.4.2 Post Processing Result

In order to review the relative contribution of risk factors, the knowledge extracted from different layers were further processed, compared and presented using advanced statistical tools. Relative contributions and trends in main risk factors are shown in Figure 7.7.

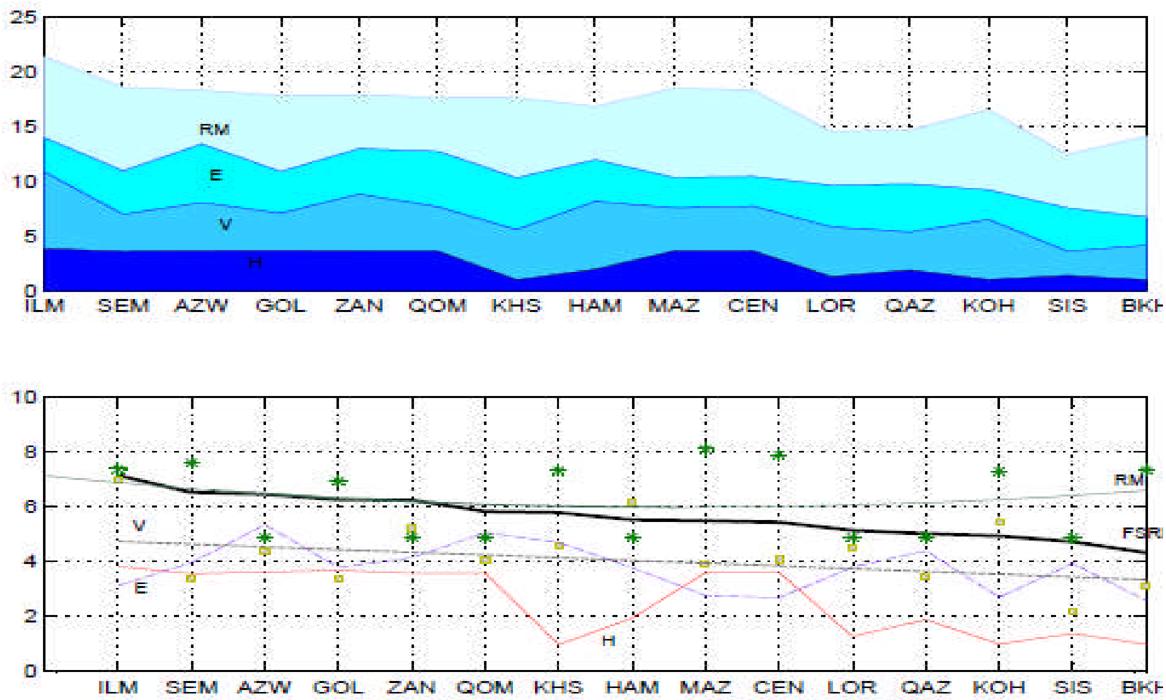


Figure 7.7 - Relative contribution and trends of risk factors within regions

Initially, some observations can be made from the graphs. First, all four main factors contribute effectively within seismic risk content, though hazard in last three regions (KOH, SIS, BKH) exhibits the lowest influence of 5% compared to the other factors. Second, the relative contribution is uneven in most regions. Even in the first six regions where hazard contribution almost identical, the overall risk index (FSRi) varies considerably due to variation in other risk factors such as V, E and RM. Third, the trends in risk factors are not identical, though some of those might follow each others' trends.

The bottom graph reveals that both seismic risk (FSRi) and vulnerability share a descending trend; while response management (RM) demonstrates a relatively steady trend. Reviewing the hazard index conveys the fact that seismic risk does not necessarily follow the hazard trend. Despite having a partially flat variation in hazard, the seismic risk follows a relatively low descending slope.

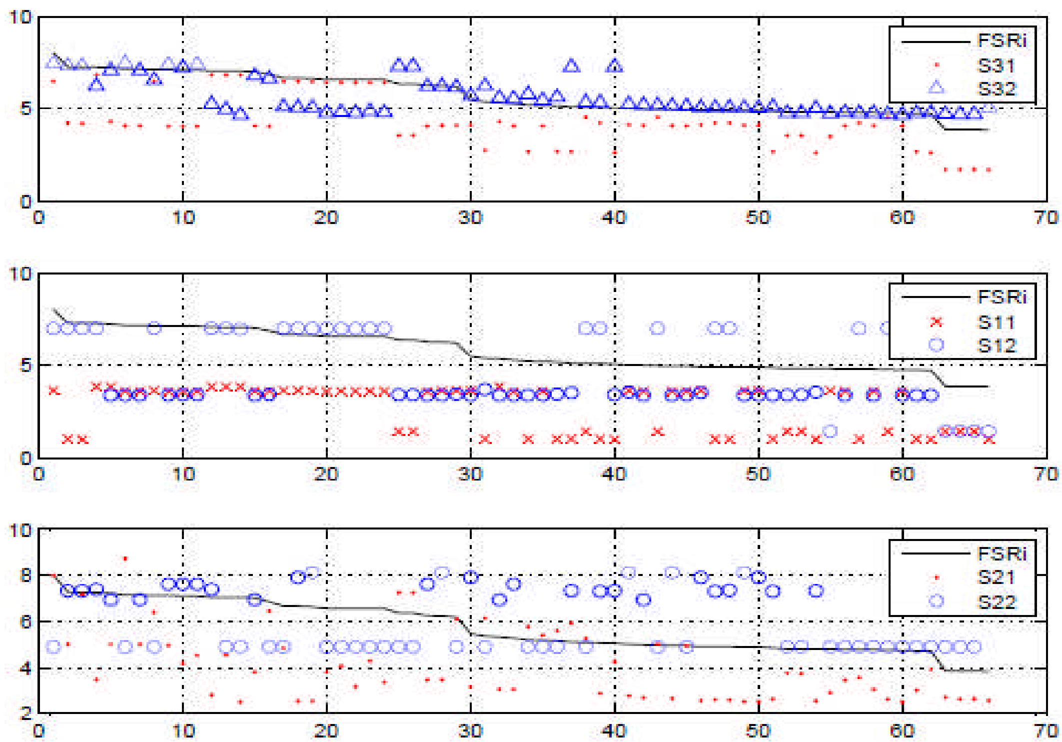


Figure 7.8 - Comparing the variation of major seismic risk factors

The other risk factor results can be also investigated in several forms. Some major pairs of risk factors that are sorted with respect to FSRi can be found in Figure 7.8. There is one figure for each pair of factors (S_{31}→SPI, S_{32}→IF), (S_{11}→H, S_{12}→V) and (S_{21}→E, S_{22}→RM). The risk results (solid line) in top figure show a gradual, steady slope in school buildings comparing to the other factors. Importance factor closely follows the risk trend for the length of the seismic performance Index. This point reveals that indirect background factors (E, RM) could have a considerable effect on overall risk ranking along direct risk drivers, since public buildings such as schools have greater demands in population, density and area compared to regular residential ones. More details can be extracted from the mid and bottom figures. Reviewing the dispersion in S_{11}(H) and S_{12}(V) reveals that seismic hazard and vulnerability cannot solely influence the risk content, and a combination of factors could potentially increase or reduce the overall seismic risk.

Furthermore, other risk factors might be compared inside their categories, as shown in Figure 7.9. It can be noticed that the soil response factor value (H_{42}) has a very smooth perturbation; while interim seismicity (H_{41}) exhibits a considerable fluctuation within its group. A similar scenario can be found in other categories including vulnerability and exposure. Unlike V_{62} (building quality) that scatter all over the risk values, V_{61} (structural damageability) demonstrates a relatively flat rate. Social and economical exposure (E_{31}, E_{32}) reflect a low fluctuation in values, though they both follow a descending trend along seismic risk (FSRi). In contrast, response management (RM) follows a higher fluctuation in RM_{31} and RM_{32} and both factor follow independent variation in values.

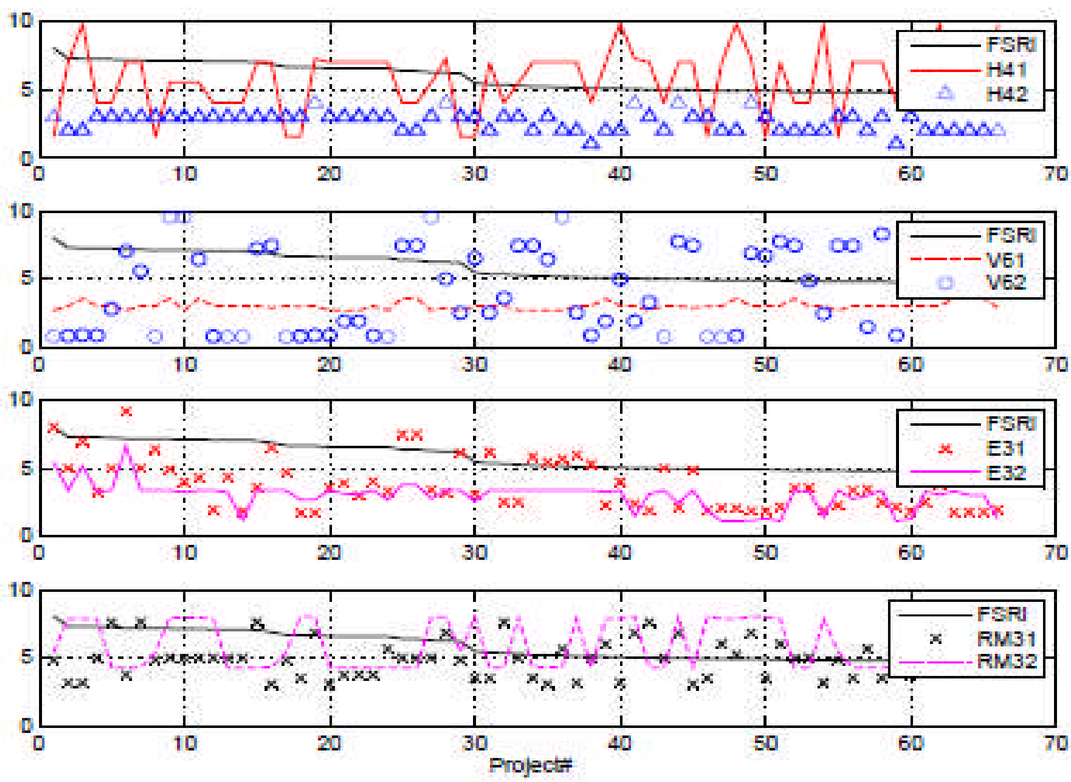


Figure 7.9 - Comparing the variation of seismic risk sub-factors

7.4.2.1 Correlation Analysis

In order to highlight the similarities and differences between experimental/ judgmental data, a correlation analysis was performed. In the present case, correlation analysis in the present case is important as it implicitly reflects the robustness of the risk structure and provides useful feedback from the proposed model. In correlation analysis, a correlation coefficient is defined as:

$$r = \frac{Cov(x,y)}{STD(x) \times STD(y)} = \frac{Cov(x,y)}{S_x \cdot S_y} \quad (7.6)$$

Where Cov (x,y) represents the covariance between two variable and Sx, Sy are standard deviation of two vectors. The coefficient '*r*' normally represents how close the two vectors are in terms of 'strength' and 'direction'. The '*r*' value range normally varies from 0 (no correlation) to 1 for complete similarities in trends and 0 to -1 for opposite trend direction.

The correlational analysis in this thesis aims to verify inter-categorical correlations and to reveal how strong the risk attributes are (within the same category) and finally to what extent each factor contributes within overall risk index. Hence cross-categorical correlation is not intended since the risk attributes have presumably been considered as a mutually exclusive system. A summary of correlation analysis of seismic risk attributes is illustrated through a risk tree in Figure 7.10.

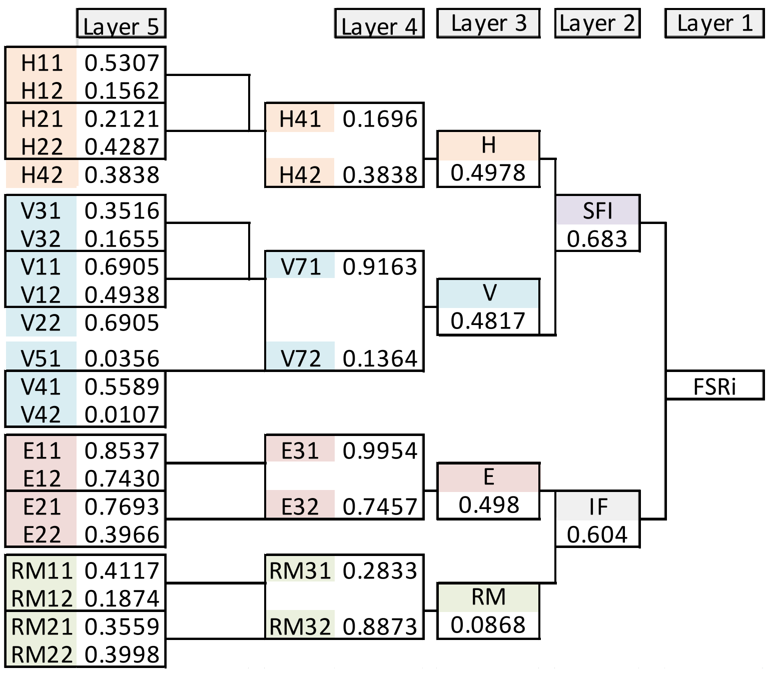


Figure 7.10 - Correlation coefficient in seismic risk factors

Evaluating the coefficients within the risk tree leads to some observations. The chart initially highlights the relation between seismic risk attributes, simply by reflecting the contribution of individual variables within composite risk. For example 'Construction Year' (V_{22}), 'Code Conformance'(V_{11}), 'Population' (E_{11}) and 'Occupancy Load' (E_{12}) demonstrate a good correlation with overall risk as previously expected. Furthermore, the chart also locates the branch or category of risk tree that has the most (or the least) influence on overall risk content. For example, social exposure (E_{31} with 0.9954) and structural vulnerability (V_{71} with 0.9163) demonstrate two strongest categories with the most conformity with the composite risk vector (FSRi); while social vulnerability (V_{72} with 0.1364) exhibits the least correlation with FSRi, confirming that social aspects are vital in disaster planning. Economical considerations should be the last factors to be accounted for within school mitigation decisions.

The idea that mid-layer factors presumably weaken the influence of risk results (in higher layers) does not seem to be valid according to the result. Having looked at the chart, it reveals that all layers (including 44 variables) within risk trees contribute effectively within overall risk content; though few of those (10 out of 44 variables) represent the low correlation (less than 0.2) that are scattered in different layers. Thus, the correlational analysis of risk vectors can improve the understanding of risk structures, and emphasises categorical explanatory risk variables that could better describe seismic risk in reality.

7.4.2.2 Multivariate Analysis

Multivariate analysis refers to set of advanced statistical techniques for examining the relationship among multiple variables at the same time. Investigating cross-variations in multiple risk factors is important since seismic risk management is a multicriteria problem. The multivariate analysis is an enhanced tool that provides deeper insight into the model by visualizing the high-dimensional data analysis; while a simple scatter plot cannot. Bivariate (2D) and trivariate (3D) analysis, for instance, allows users to analyse system behaviour and draw out the relationship between two variables regardless of others; yet there may be important patterns in higher dimensions which may not easily recognisable from this plot as well. The analysis can also be used to illustrate the distribution of the data set (I/O).

The current model involves more than 40 variables that contribute both directly and indirectly within the total risk content. A bivariate analysis was conducted between selected pairs of variables which are expected to be a major influence on overall risk. Of course, the multivariate analysis gives a better presentation and communication with users rather than correlation analysis. Sample multivariate distribution patterns (MDP) of risk factors are presented through scatter plot charts between major risk variables in Figures 7.11 and 7.12. The points in each scatter plot are colour-coded by means of the overall seismic risk (FSRi) and construction age for a given pair of variables. The pattern legend is defined in Table 7.6 representing strong colours for high disastrous risk content as well as older buildings.

Table 7.6 - Pattern scale defined for multivariate visualizing

Risk Index	Risk Descriptor	Scale of pattern			
		Low	Moderate	Strong	Disaster
FSRi	Overall risk	0 -2	2- 5	5 - 7	7 - 10
2010 - V_{22}	Construction age	Age < 15	15<Age<25	Age >25	-

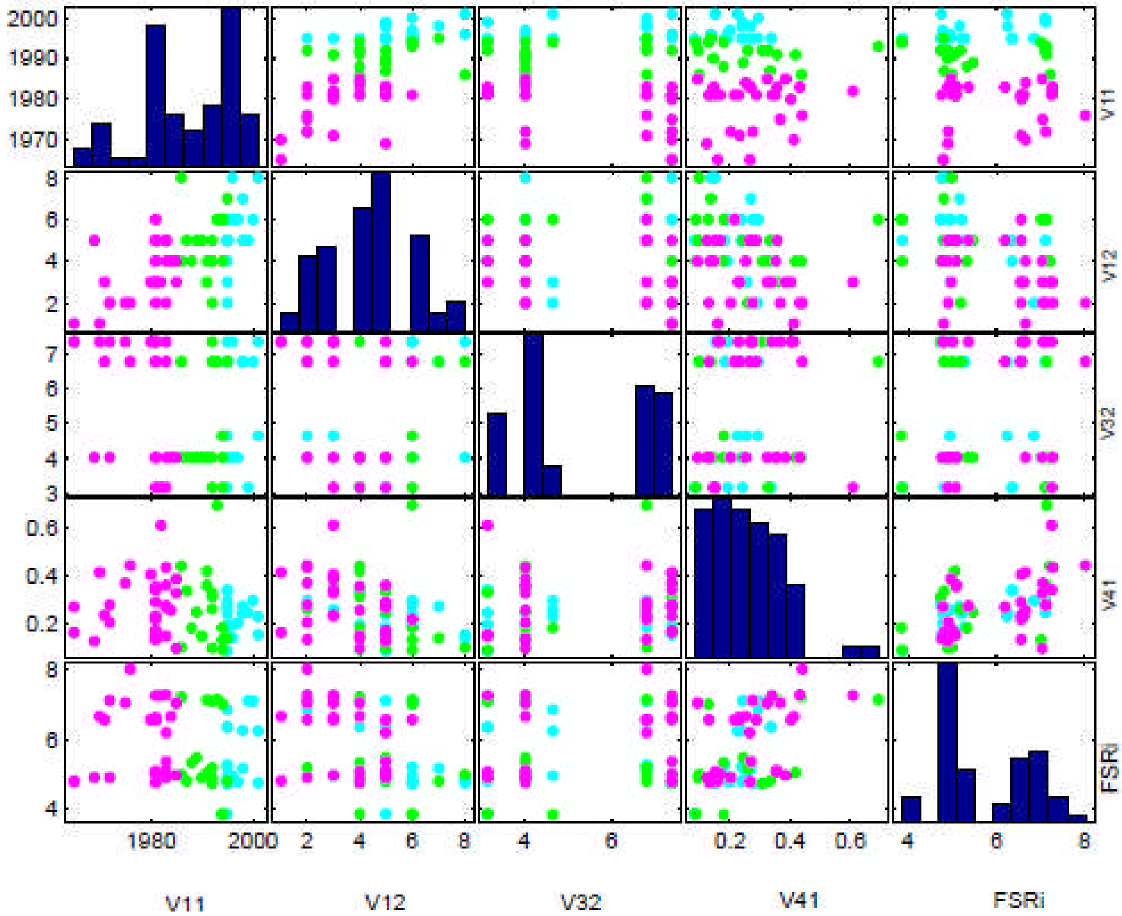


Figure 7.11 - MDP in vulnerability module with respect to construction year

The 'construction year' pattern within school buildings is illustrated in Figure 7.11 through bivariate analysis for a set of vulnerability factors. The graph reveals the following points:

- The univariate histograms (shown diagonally) demonstrate the distribution of I/O variables. This is an effective measure of testing the domains' coverage and identifying the gap. The above histograms exhibit relatively rich sampling sets that cover a wide range of domain in both input (V_{11} to V_{41}) and output (FSRi) variables.
- The first column of graphs reflects the variation of the V_{11} (code conformance) within respect to other vulnerability variables. The pattern can be clearly distinguished in three colours confirming this observation that older school buildings (>25) have less code conformance index (V_{11}) and exhibits a lower quality index (V_{12}) for a certain group of buildings with specific damage patterns (V_{32}). Some variables such as V_{42} (occupancy load) demonstrate a scattered (vague) pattern, while the other variables confirm the independency axiom assumed at early stages of the model's design.

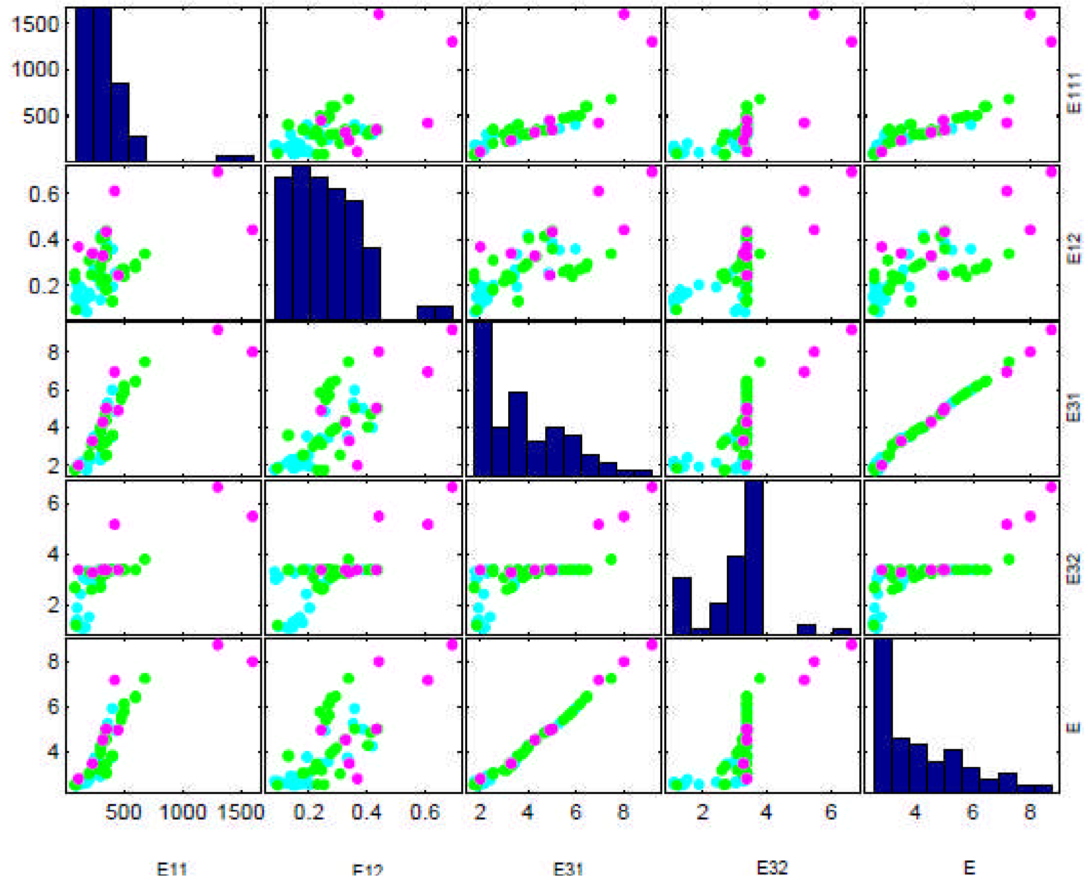


Figure 7.12 - MDP in exposure with respect to FSRi

The pattern of the fuzzy seismic risk index (FSRi) was also investigated through bivariate analysis for a set of vulnerability factors as shown in Figure 7.12. The graph indicates the following points:

- Univariate histograms show a relatively rich domain of I/O. In histogram 'E' (exposure) for example, the data range covers over 80% of domain which addresses a sound base integration and good strength in the dispersion of output data.
- Bivariate graphs exhibit a diagonal pattern arising in both variables. The E31-E and E_{11}-E graphs, for example, indicate that an increase in either of the variables can raise the overall risk (FSRi). Moreover, the social index (E_{31}) demonstrates a diagonal convergence that addresses the direct impact; while the flat pattern in the economic index (E_{32}) represents a relatively steady effect on the overall risk.
- No matter the variables, and even though the parameters and sample sizes are different, the approximate linear pattern (relationship) suggests that the two samples may derive from the same category and bear certain interrelations.

7.4.2.3 Bivariate Analysis of Risk

In order to verify the reliability of the risk results, a bivariate analysis of risk function was conducted. Considering the risk as a function of Hazard and Vulnerability $\mathbf{R} = \mathbf{f}(\mathrm{H}, \mathrm{V})$, a bivariate analysis using cumulative Gaussian mixture distribution function, generates the nearest estimate for risk values. A continuous approximation of vector H and V was undertaken using normal sampling distributions, as shown in Figure 7.13.

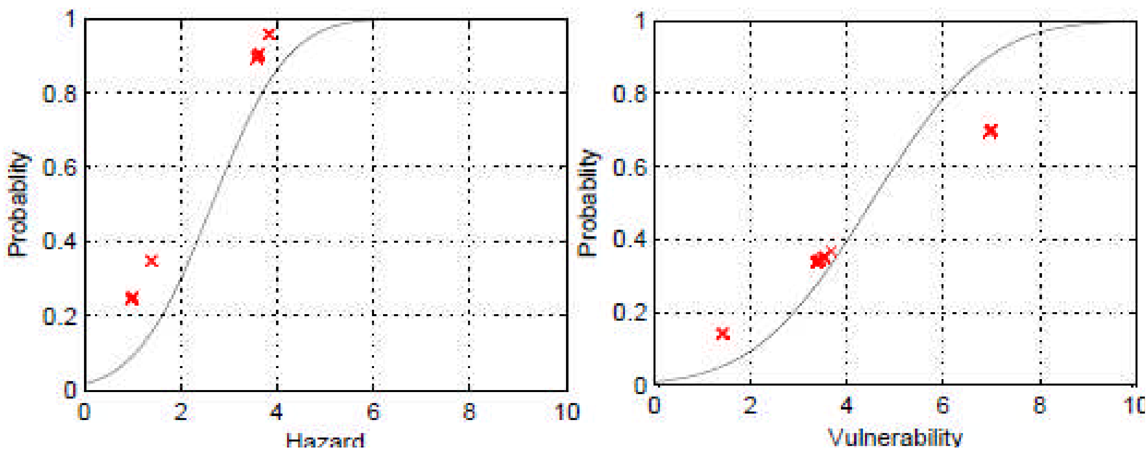


Figure 7.13 - Cumulative Probability distribution of Hazard and Vulnerability

Gaussian mixture model of risk can be formed by combining multivariate normal densities of each component as shown in Figure 7.14.

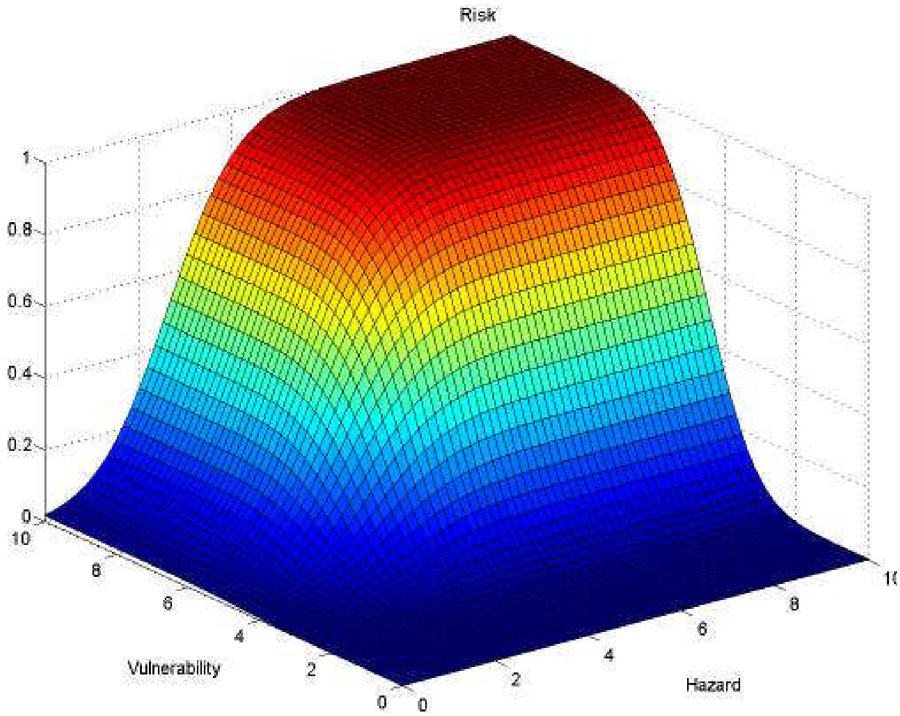


Figure 7.14 - Bivariate cumulative distribution of hazard and vulnerability samples

The graph provides a useful metric that can be used for verifying the system's performance. The rule base development (Figure 7.4) displays a close resemblance can be found with 3D surface view of risk module (H, V) in the rule-base matrix. This resemblance can be interpreted mathematically since probability and fuzzy set theories are, broadly speaking, two alternative ways of approximation with different degree of precision.

In problems with adequate samples when the frequency of observation (sample size) increases, the probability distributions gives more precise results, whereas fuzzy set theory is capable of dealing with any situation no matter the sampling is rich or weak which is an advantages. Therefore, fuzzy logic as an approximate reasoning method can be alternatively used in many risk assessment problems with data restriction.

7.4.2.4 Uncertainty Analysis

Quantification of the uncertainty is a concern of any knowledge base system because much of the information is collected from different sources. Uncertainties can be imposed in different forms, such as statistical variation, linguistic imprecision, approximation and conflict in expert judgment. The variability in risk results has been investigated in two dimensions, including performance and weight, as illustrated in Figure 7.15. Reviewing the risk factors indicates that vulnerability is the highest variation with almost 35%; while the other risk factors, including hazard, exposure and response management display far lower variations of around 25%. This was expected because the source of information utilized in developing the vulnerability module was collected from expert surveys, compared to other risk factors of more objective sources, such as hazard.

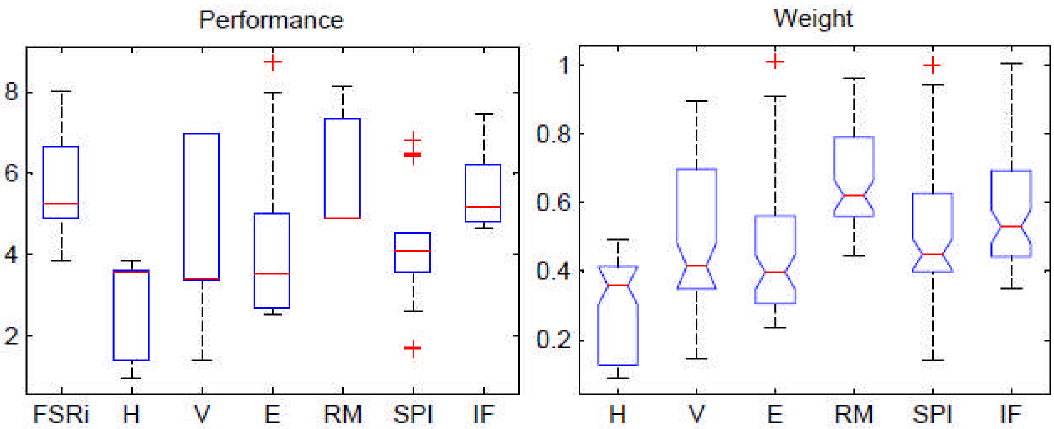


Figure 7.15 - Variation of performance and weight in major risk factors

The variation of risk factor weight conveys different story. Vulnerability and hazard exhibit the greatest variation with 30% and 35% respectively; while the other risk factors remain as low as 25% and less. The variation in vulnerability results was expected since the majority of the data regarding the buildings' quality is derived from expert surveys and relies on expert knowledge. This point can be also seen in mid-layer risk factors as shown in Figure 7.16. For instance, V_{62} (engineering performance) dominated the variation among risk factors.

Hazard and exposure indicates the lowest variation. Despite some outlying points, H_{31} (propagated seismicity), H_{32} (potential ground failure) and E_{32} (economical exposure) hold the least variation with less than 10%. The response management values have a mid range variation starting from 22% in RM, 25% in RM_{31} (response & preparedness) and the highest value occurs in RM_{32} (critical planning and management). The V_{61} (structural damageability) scenario displays almost 5% variation confirming that the vast majority of schools were selected from vulnerable classes of buildings. Surprisingly, the integration of minimum variation of potential damageability (V_{61}→%5) and maximum variation in engineering performance (V_{62}→%55) balanced the results in structural vulnerability (V_{71}) with 33%. This confirms the principle that every building class, no matter when they were built, has a basic range of damageability which might be propagated according to their engineering performance and construction quality.

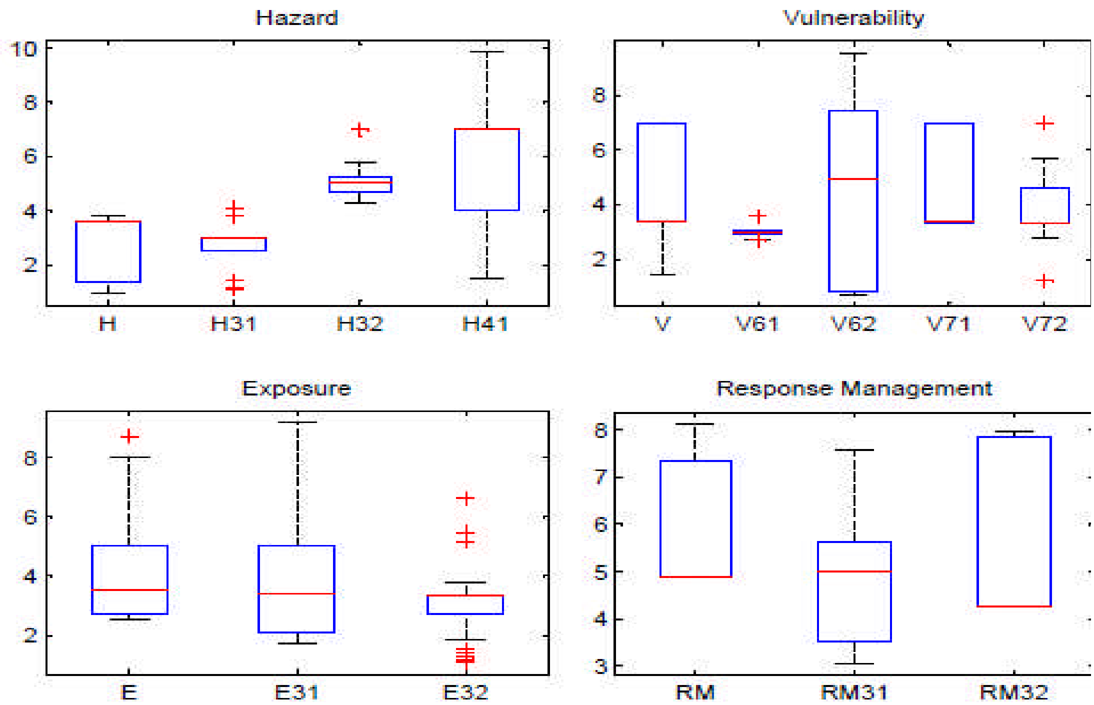


Figure 7.16 - Variation of categorical risk factors

7.5 Discussion

Analysing the case study results reveals some important points about contribution and the interactions of seismic risk impacts. The findings suggest that the composite risk index (FSRi) does not necessarily follow its factors' trends (Vahdat and Smith 2014). This implies the importance of using a comprehensive risk index for retrofitting decisions rather than relying on single impacts (i.e. hazard and vulnerability factors) because it could mislead the whole mitigation decisions. Furthermore, it was demonstrated that the risk index in medium seismicity could be as high as high seismic areas and vice-versa. Classifying the buildings based on a single factor such as vulnerability or hazard could be either too conservative or disastrous, particularly when a paramount response measure (retrofitting) is necessary. Therefore seismic mitigation decisions should be made in compliance with the multi-dimensional aspects of seismic risk instead of mere reliance on individual hazard and the vulnerability index.

Further investigation reveals some significant facts regarding the determinant criteria within the mitigation programme. The finding indicates a strong relationship between the composite risk index (FSRi) and exposure in both normal and extreme states of analysis. It also shows a strong correlation (67%) with the 'year of construction' as expected. One interpretation of this result is that both population and year of construction should actively engage within retrofitting decisions. Currently the structural vulnerability index is the major controlling factor in retrofitting decisions; while this has been scarcely incorporated within existing models as risk criteria. This test demonstrates the importance and influence of general factors to the task of risk mitigation.

The case study results were also tracked and analysed using different statistical tools. Correlation analysis of risk factors in different layers confirmed that the selected risk factors are mutually exclusive, while maintaining a strong interrelationship inside the categories. Seismic exposure was exhibited as a strong contribution to structural vulnerability and seismic hazard, and conformed with the aggregated weight results that were extracted from expert opinions. Bivariate analysis of major risk factors (e.g. hazard and vulnerability) was also tested to evaluate the consistency in the proposed model with the conventional probabilistic method. The test, although demonstrating relatively conservative results, shows a sound agreement with probabilistic approach.

Surprisingly, response management factors exhibited the lowest contributions among all criteria. This can be explained by this fact that 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 the variation of RM index is not strong enough to change the ranking results.

The outcomes of the research collectively confirm the applicability, suitability and capability of the proposed model to meet research aim and objectives. The main purpose of the research was to examine the feasibility of the KBES to support different stages of seismic risk management. The objective was met by exploring the case study of school buildings in Iran. Reviewing the results, it was demonstrated that the proposed model can operate and navigate the seismic risk management process by addressing specifically the mitigation concerns and modelling requirements.

The applicability of the model was examined in the case of retrofitting schools in Iran. This methodology provided a greater insight to the seismic risk by using the latest scientific understanding, engineering knowledge, modelling experience and expert judgment. The results indicate a clear resolution for previous concerns and issues raised in traditional probabilistic methods, taking advantage of both probabilistic-fuzzy concepts, while meeting the initial requirements of the model, client needs and data constraints.

Having met the objectives of the research, the findings collectively provide contributions both in theory and practice in several ways. Theoretically, the research merged the literature from two main areas. First, the mitigating decisions as defined in seismic risk management context (Chapter 2), and second, the risk-based ranking approach (Chapters 3 and 7). By merging the concepts and theories of the subject areas, the current research offers a deeper insight of system approach to effectively manage the school buildings exposed to varying degree of seismic risk. The major areas of theoretical contributions are the system perspective as a core concept of seismic risk management to process mitigating decisions and classification of seismic risk assessment approaches. The research also establishes a rational strategy for identifying the risk impacts and implementing the appropriate methodology to aggregate the impacts efficiently using KBES. From a practical perspective, the proposed model provides effective tools that allow decision-makers to use it in real-world mitigating decisions, finance and budgeting, insurance and disaster planning and preparation. Major areas of contribution have been implemented practically in the mitigation of city exposure to seismic risk and ranking of the school building retrofitting.

7.6 Characteristics of the Developed Model

The model proposed in the thesis has demonstrated the benefits of an integrated framework, combining conventional algorithmic methods with heuristic capabilities of expert systems in multiple aspects:

Handling complexity – The use of an expert system for modelling the complex nature of seismic risk management has been shown to be feasible. The research proposes a new method for handling the complexity of multidisciplinary contexts within seismic risk management, using a 'synchronized hierarchical framework'.

This concept provides a comprehensive view of risk in the system, allowing for the integration of multiple sources of risk data to be easily used by different users. In addition, a hierarchical structure can explicitly represent the cause-effect relationship within risk factors.

Customizability – The proposed model is developed by integrating blocks of risk impacts, according to experience and client need. The customized view of risk allows users to better control model assumptions; a complete view of seismic risk can be gained by tailoring specifically for mitigation measures while being consistent with certain organizational levels. Novice users can easily customize the structure and model components, or replace them with external data and experience. The framework used in this thesis can be simply reused in a different situation as it offers a new form of modelling and organizing risk information. The open modelling concept allows users to customize the model by adjusting or overriding model components. New data, experience and methods in the other environment can be simply interpreted and be used within a customized model. The open modelling capability makes the model more defensible and auditable in practice.

Criticality analysis – Planning for disasters and mitigation decisions requires a comprehensive picture of seismic risk within a region or group of alternatives. This picture can be only achieved through critical analysis of the contributing factors, examining the variation, dispersion or concentration of critical factors over a region. Such analysis offers the advantage of ranking different risk causes and supports mitigating measures by directing experts to the most contributing factors during an earthquake event.

Nonlinearity – Fuzzy logic is an alternative way to capture the concept of seismic risk management through nonlinear approximating functions. Because risk factors follow a nonlinear variation in reality, it is apparent that nonlinear functions can better represent the interactions among risk variables, weights and performance factors. This point has been demonstrated through bivariate analysis of risk (Chapter 7). Comparing to conventional probability approach, the present results prove that fuzzy MFs are sufficiently precise to capture the nonlinearity of seismic risk. Due to strength of fuzzy logic in systemic modelling, the benefit of simplicity of application in mitigation programmes outweighs its cost.

Transparent tracking – The proposed fuzzy system accommodates a transparent approach to track and to review risk factors in different layers of hierarchy. This feature is important, particularly for complex systems where a large number of variables involved. Using AI helps to track the myriad details involved in different stages of seismic risk management. Decision-making for mitigation programmes is a complex process that numerous factors have to be accounted for. In addition, most socioeconomic factors and school characteristics normally vary over time; hence the seismic risk should be updated from on occasion. The tracking capability of the proposed model allows a clear tracking and updating the seismic risk values automatically whenever needed.

Flexibility in communication – Seismic risk management as a complex system deals with numerous input/output that has to be managed, updated and processed effectively. The utilization of fuzzy logic allows experts and end users to communicate information about seismic risk and possible impacts of risk factors within a school building in a particular or wider group of schools within a region. Because all risk factors and school characteristics were set up as vectors and processed through matrix operations, the inputs can be simply updated, no matter how many alternatives are involved. The results can be further processed or be described in any form of presentation, while in the conventional approach, there is no such flexibility in communication to be found.

Handling Uncertainty – Seismic risk management is characterised by deep uncertainty, and dominated mostly by imperfection, imprecision and vagueness in knowledge. The fuzzy-based approach used in this research can effectively address the uncertainties as opposed to probabilistic-based methods. Using linguistic variables for representing the risk data can incorporate as much uncertainty as possible to the model. The implication of the fuzzy set theory provides a more comprehensive view of risk by addressing a wider range of uncertainties and facilitating the contribution of multiple experts within the process of decision-making.

Robustness – The proposed model is able to determine the state of risk and its components in a large-scale portfolio of school buildings. Verification results indicate that the model is much more robust than conventional approaches. The performance of the composite risk Index (FSRi) appears to be low in sensitivity with respect to risk criteria. The model also indicates that it is unaffected by missing values or outliers; consequently the model works with various levels of imperfection, imprecision and incompleteness in the state of knowledge. The implication of fuzzy logic improves the ability to deal with vagueness systemically in the early stages of the modelling. The simplicity of fuzzy logic in modelling expert knowledge makes it a robust system, one that is capable of handling complex multicriteria problems.

7.7 Summary

The systematic procedure implemented within the case study demonstrates the application of the KBES to critically analyse risk factors and their influence on the overall composite risk index (FSRi). Critical assessment of seismic risk impacts is a significant feature of the developed system. In this case, the KBES has indicated an effective way to address these challenges by integrating expert knowledge with mathematical models in a systematic way. Using expert systems, it offers a simple way of human reasoning whilst reducing the field of expertise, minimizing the variations and cost of decision-making by providing a faster response. The combination of data- and export-driven knowledge provides complementary sources of information for this case study. The knowledge base utilised within the risk system has potential to be increased incrementally while it can be updated dynamically over time. This allows the mitigating measures to be modified, changed from time to time or applied in new forms to other regions.

Chapter 8: Verification and Validation

8.1 Introduction

This chapter reports the process of verification and validation (V&V) of the study and outlines the methods to assure a sufficient level of confidence. The first part of the chapter discusses the importance of V&V as key part of the model development cycle and describes the potential techniques to verify and validate the model. In the second part, the model was debugged statically and verified dynamically using sensitivity analysis to explore the behaviour of the model. In the last part, once the system had been verified, a set of validation tests was applied to externally evaluate the effectiveness and usability of the model in practice.

8.2 Model Verification and Validation

V&V plays an important role in the development and implementation of a KBES. Model verification is defined as "ensuring that the computer program of the computerized model and its implementation are correct. Model validation means "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Schlesinger et al. 1970). Both definitions are adopted in this thesis. Suen et al. (1990) addressed the verification as glass-box testing to determine if each component of the system completely and accurately meets the user specifications; while validation was classified as black-box testing to observe the response, and if the overall system implements the user need as planned. "In essence, verification determines if the system was built right and validation determines if the right system was built" (Ng and Smith 1998). In other word, verification determines whether the system is built correctly according to its specifications; while validation determines the system actually fulfils the purpose of what it was designed for. Sargent (2013) suggested a straightforward paradigm for V&V in relation to the model development cycle as shown in Figure 8.1 and used here.

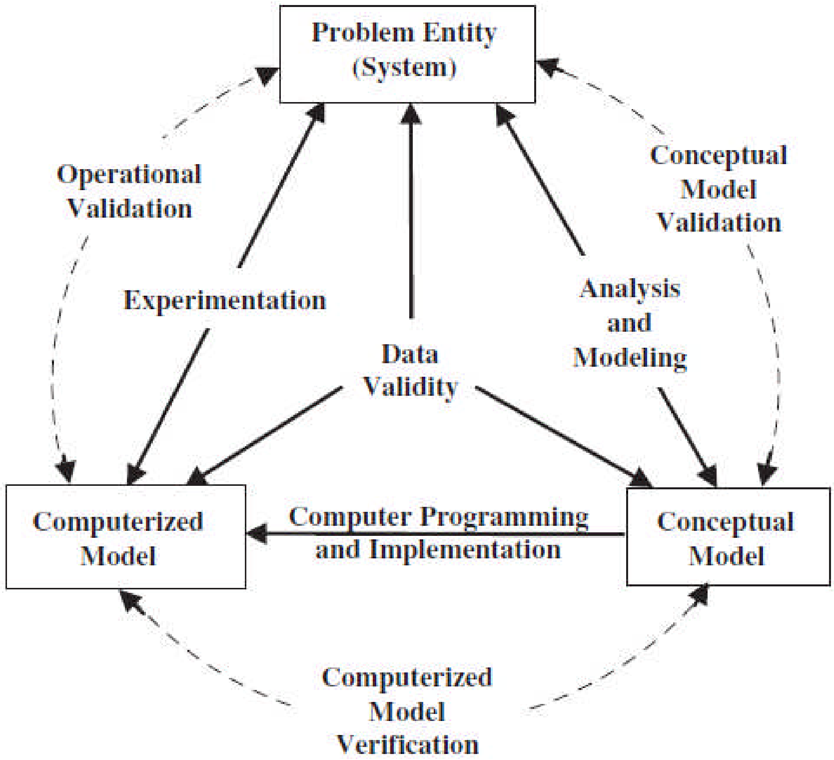


Figure 8.1 – V&V as part of model development cycle (Sargent 2013)

Accordingly, the process of V&V adopted in this thesis was based on four concepts; computerized model verification, data validity, conceptual model validation and operational validation. The computerized model verification ensures the computer programming and implementation of the conceptual model is correct, complete and consistent. Data validity determines that the required data for model development, implementation and testing are correct and sufficient. Conceptual model validation implies the theories, structure and assumptions underlying the conceptual model truly and reasonably represent the problem, event or phenomena in reality. Operational validation addresses the adequacy of the model's output to accurately meet the client's intended purpose over a specific domain of application.

The data used in this thesis were obtained from a live seismic mitigation program in Iran, which was undergone an audit process both locally and through the central rehabilitation office. The underlying structure, theories and assumptions used within the model were conceptually based on the globally accepted perspective of risk, hazard, vulnerability and resilience which are currently in use by the UN-ISDR (2004). Therefore, data validity and conceptual validity have been already achieved and the rest of the chapter will focus on computerized model verification and operational validity.

8.3 Computerized Model Verification

Simulation model verification is concerned with the correct and accurate transformation of information into a simulated model. This process aims to show that the computer program performs as expected. Whitner and Balci (1989) classify the verification process into six distinct perspectives, including informal, static, dynamic, symbolic, constraint and formal analysis as indicated in Table 8.1.

The taxonomy contains a broad range that varies from very informal (left) to very formal (right). As the formality increases, so does effectiveness and complexity. The informal analysis relates to human reasoning and subjective assessment (e.g. Delphi) which is more appropriate for conceptual qualitative studies (interview, focus group). Formal analysis is based on a formal mathematical perspective and is thus considered the most effective way to provide the proof of correctness. However, it is restricted to particular applications that predicates calculus or follows a logical deduction in its concept.

Constraint analysis verifies the model conformance to the model's assumption, ensuring that model is functioning within the desired domain. Symbolic analysis verifies the input-output transformation by symbolic tracing. Both methods are effective to be used as an auxiliary verification process; however, due to the high human resource cost and difficulties in the generalisation of input data (interpretation), symbolic and constraint analysis should not be used in its standalone form. Static analysis verifies the basic characteristics of the model in terms of deficiency and redundancy, ensuring the model is complete and consistent with presumed assumptions. Dynamic analysis evaluates the model during system execution by tracing and monitoring the input-output, and treating with the model as a black-box or white–box. This method not only provides conclusive evidence of a model's functioning, it also paves a systematic way for debugging and error detection. However, the performance of dynamic analysis relies directly on the modellers' skill and experience, as well as requiring a relatively long time to process for complex systems. Furthermore, it cannot be used as a system correctness indicator.

Table 8.1 – Model verification techniques (Whitner and Balci 1989)

	Informal Analysis	Static Analysis	Dynamic Analysis	Symbolic Analysis	Constraint Analysis	Formal Analysis
Category Definition	Analyzing through the employment of informal design and development activities	Analyzing characteristics of the static source code	Analyzing results gathered during model execution	Analyzing the transformation of symbolic inputs to outputs along model execution paths	Comparison of actual model execution state with assumptions	Formal mathematical proof of correctness
Level of Formality	Very Informal	Informal to Formal	Informal to Formal	Formal	Formal to Very Formal	Very Formal
Complexity	Low	Moderate	Moderate to High	High	High to Very High	Very High
Human Resource	Very High	Low to Moderate	Moderate to High	High	High	Very High
Computer Resource Cost	Very Low	Moderate to High	Very High	Moderate	High	Very Low
Effectiveness	Limited	Moderate to High	Moderate to High	High to Very High	Very High	Highest, if Attainable
Instrumentation Based	No	No	Yes	No	Yes	No

Considering the complexity, scope and effectiveness of the methods mentioned, and due to the fact that the model is operational nature, a combination of static and dynamic analysis was jointly devised for the study's verification. Combining the static and dynamic analyses improves the issues associated with the individual approach.

8.4 Verification of the Developed Model

The developed model has undergone a verification process to detect anomalies within the system both statically and dynamically. In static analysis, the inference engine and knowledge bases were examined without running the expert system; while the dynamic analysis was performed to verify the system in terms of functioning and behaviour. For this, a set of sensitivity analysis was conducted in two forms of black-box and white-box to reflect the external and the internal functioning of the system.

The sensitivity analysis is considered an important task since it can detect a larger class of errors. This analysis helps users to investigate the effects of changes of input data on output results of the model. Interpreting the sensitivity highlights extreme values, as well as determining the possible risk factors that have adverse effects on overall risk. The analysis therefore suggests potential measures to prevent or remove the worst action (Jovanovic 1999). However, sensitivity analysis requires complex calculating procedures, making the performance of calculations without a computer time-consuming. The situation is made worse for such a complex system with over 20 inference engines. To handle this issue in this study, a set of virtual tests was used to systematically trace and monitor the input-output variations. Since a complete dynamic testing is theoretically impossible due to input size constraint, a virtually randomized set of numbers was programmed in MATLAB to test the various aspects of the model.

8.4.1 Static Verification

Static verification is the process to ensure that the knowledge base of an expert system is free from internal errors such as redundant, conflicting or missing knowledge (An 2006 & 2007). This process can be carried out by some form of automatic knowledge base checking tool (Landauer, 1990). For this study, static test was conducted in order to verify completeness, consistency and correctness as outlined in following:

Completeness

Completeness refers the situations in which the rule base covers all possible combinations of variables that can arise within the domain. Deficiency in the knowledge base can be caused by missing rules or incomplete set of inputs inferring no conclusion. A system is complete if there is no valid conclusion which it cannot reach (Suen et al. 1992).

Consistency

A system is consistent if it cannot reach an invalid conclusion. There are many techniques for verifying the consistency of a rule base (Nguyen 1985). Various tests can be applied during the verification process, including the following (Preece et al. 1992):

Redundancy (or duplication in the knowledge base) – A situation where there are unnecessary expressions inferring any conclusions by an expert system.

IF X AND Y THEN A;
IF Y AND X THEN A;

Inconsistency (or contradiction knowledge) – Inconsistency could be raised if there is any contradiction within rule base. For example, if the same antecedent links to opposite conclusions as shown in following:

IF X THEN A;
IF X THEN not A,

Circularity (or cyclic dependencies) – This error occurs when there is a cyclic inference chain in the knowledge base that causes an endless loop. This can be simply shown as:

IF X THEN Y;
IF Y THEN Z;
IF Z THEN X;

Static verification can be performed in early stages of a model's development phase, or incrementally throughout model implementation. To avoid possible inconsistency in developing a large number of input rules in the present work, it was endeavoured to keep the model as simple as possible. Nevertheless, the expert system underwent an audit process to verify any sort of anomaly within the knowledge base.

In terms of incompleteness and inconsistency, there is no such error found within the rule base. This was expected because both antecedents and conclusions were designed independently for each FIS. Each category of the proposed system was developed by integrating a set of simpler 2D rules within an open branch, rather than closed loop. Hence there is no possibility for cyclic dependencies and contradictory rules within the knowledge base.

8.4.2 Dynamic Verification

Dynamic verification includes a series of parametric tests that explore the behaviour of the model by the means of variation. To analyse the range of sensitivity within which a model has reasonable variations in parameter values, a sensitivity analysis is recommended. This process provides useful information where the conditions of uncertainty exist within one or multiple parameters.

Thus the results of sensitivity analysis can be used for managing uncertainty in several ways. First, it helps to identify the parameters with high sensitivity that requires additional study and measurement. Second, it increases the robustness of modelling by determining the weak branches within each category. As a result, the sensitivity analysis increases the confidence in the results and ultimately improves the robustness of the model. However, sensitivity analysis could be time-consuming, thus requiring a computerised model to conduct processes as well as to monitor the results effectively. In addition, because an infinite number of test cases can be applied, the complete testing could be theoretically difficult. Another issue is the adequate test coverage, as the scope of coverage grows exponentially as the model size increase (Whitner and Balci 1989).

For this thesis, a set of parametric sensitivity tests was approached for three reasons. First, to verify the most significant risk factors in developing priorities for risk mitigation. Second, to explore the response of the model to the specific inputs, and to study their impacts on overall mitigation decisions. Third, for debugging the system, identifying the likely failure points and suggesting its possible refinement.

8.4.3 Parametric Sensitivity Tests

Due to uncertainty exists within seismic risk parameters, a sensitivity analysis was performed to identify potentially uncertain variables and to measure the extent of uncertainty affecting the risk factors. The behaviour of a KBES is notoriously difficult to predict (Wood and Frankowski 1990). Due to nonlinearity and complexity, the behaviour of the model may not be consistent in different states of risk inputs. Thus, the uncertainty within risk factors must be presented by the mean of a range in which all possible variations have been accounted for. As a result, sensitivity analysis was performed for three scenarios named as extreme limits (lower, upper) and mid-range scenarios. Simulating the most common conditions that a model might encounter, three scenarios together ensure that the possible variations in the whole range of risk data are truly captured. The result of sensitivity analysis was set up in three parts: first the sensitivity of the overall composite risk index (FSRi) is reviewed, and secondly sensitivity of major risk factors is recorded, and finally the sensitivity of risk ranking results. Each part is outlined in the following sections.

8.4.3.1 Sensitivity of FSRi

A respective procedure was systemically performed to examine the effectiveness of input parameters. To investigate the effects of uncertainties on the overall seismic risk Index (FSRi), a set of stochastically generated input was generated using random sampling distributions. The response of the system was then measured in terms of minimum, maximum and mean values. This procedure was performed three times (for three scenarios) for all 21 risk input parameters. The results of sensitivity analysis are illustrated within Figure 8.2.

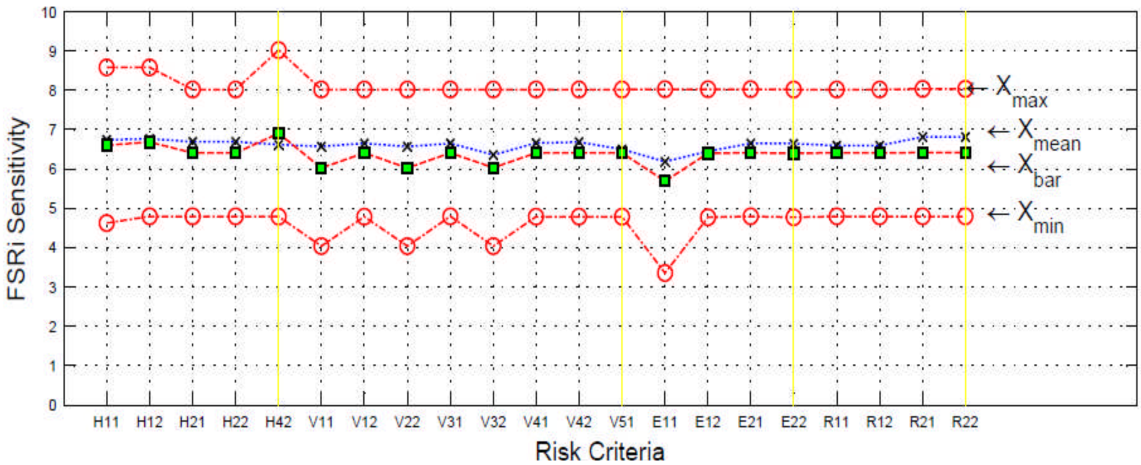


Figure 8.2 - Sensitivity results of FSRi

In general, the graph indicates a consistent variation in three states (max, min and mean) that was limited to 35% in most of the risk criteria; although some deviations can be found especially when representing the extreme limits. As it can be seen, ground shaking (E_{11}) and soil class (H_{42}) are by far the most uncertain variables with 45% variation in three scenarios. The uncertainty in structural vulnerability indices (i.e. V_{11}, V_{22}, V_{32}) as well as hazard (i.e. H_{11}, H_{12}) come second, with 40%.

The response management inputs along social vulnerability (V_{41}, V_{42} and V_{51}). Ground failure attributes (H_{21} and H_{22}) exhibit the least contribution with 35% as expected. The variation in mid-range values also represents a consistency between average sensitivities as indicated by X_{bar} ($X_{bar} = \frac{X_{min}+X_{max}}{2}$) and mid-range sensitivity results indicated with X_{mean}. This reveals that the sensitivity in the mid-range scenario consistently follows all of the trends in general; while it has less perturbation than those results corresponding in extreme limits. From a modelling perspective, the variation in extreme limits (upper and lower bounds) is often expected to be more uncertain than those in normal states. The sensitivity results confirm that FSRi are prone to higher uncertainty in more subjective factors such as structural vulnerability and soil conditions. Therefore, any efforts should be arranged to reduce the subjectivity of the input variables.

8.4.3.2 Sensitivity of Main Risk Factors

To investigate the variation of the main risk factors (H, V, E and RM), a similar procedure was set up using random sampling. The response of risk factors was measured for three scenarios as depicted in Figure 8.3. In general, the graph indicates that the main risk factors are prone to a wide range of variation in different categories. Unlike FSRi which was consistently limited to a range of 35% to 45%, the main risk factors exhibit significant ranges, varying from 20% to 80%.

It is noticeable that the 'hazard' and 'response management' categories have a great influence of 70% and 80%, while both demonstrate a steady impact of 35% on the FSRi. The 'hazard' criterion show more variation in the different states of testing with almost 80%, which is normal due to the stochastic nature of seismicity. The 'vulnerability' criterion exhibits a medium variation in its factors and is limited to 35% in general; while the 'damage' probability (V_{32}) stands at the peak in its category with 55%. The 'exposure' factor also indicates the varying degree of sensitivity in which population index (E11) plays the greatest contribution with 70%. All RM criteria show a relatively constant contribution of around 70%, implying the same strength in their category.

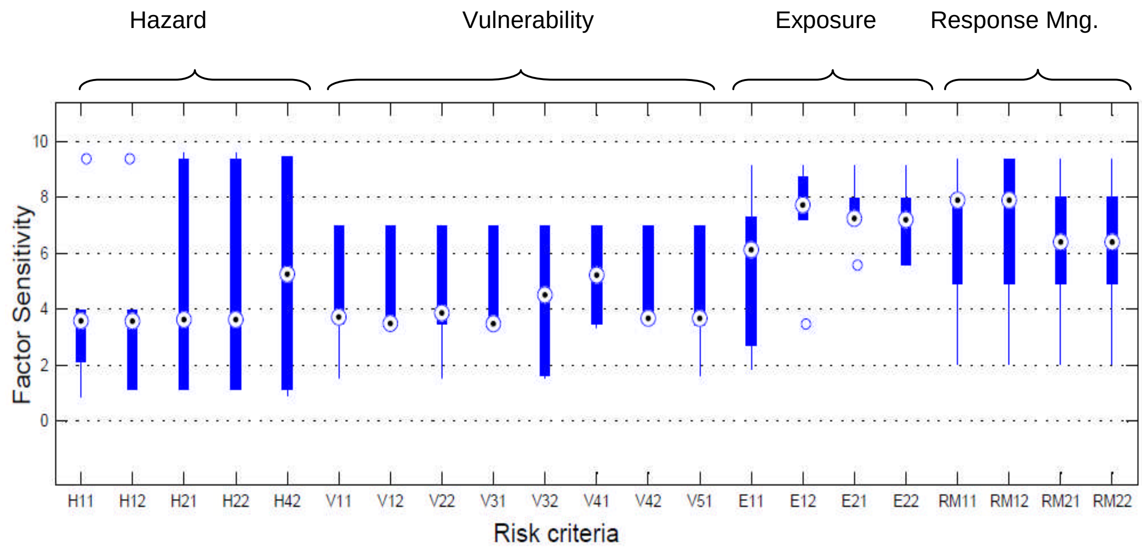


Figure 8.3 - Sensitivity results of main risk criteria

The sensitivity analysis of the FSRi and risk factors together highlights some important points. The empirical results indicate that some risk criteria (V_{41} , V_{42} , E_{12} , E_{21} and E_{22}) have the least influence on both FSRi or risk factors. In addition, the 'hazard' criterion appears critical and can be thought of as the most significant source of uncertainty within the model.

Sensitivity of Ranking

Another area of sensitivity analysis is to determine how critical each criterion is. In other words, this regards how sensitive the actual ranking of the alternatives is to changes in the risk inputs. The purpose of this analysis is to explore two closely-related issues that often influence the ranking results. The first issue is to measure how critical each criterion is due to small changes. Using sensitivity analysis, it can be determined to what extent the risk criterion are sensitive and could significantly disturb the ranking results. The second issue is to determine how critical the various performance measures of a risk criterion are in the overall ranking. This test is intended to pinpoint the critical criterion and to measure the extent they could possibly influence the FSRi results.

To investigate the criticality of ranking, an incremental sensitivity analysis was applied. During this procedure, the priorities and performance of FSRi were measured by incremental changes in input data. A procedure was formulated in four steps using 10%, 20%, 30% and 40% increase of respective risk criterion. The performance of alternative ranking was then calculated and compared using statistical tools.

Because each criterion has various influences on the overall FSRi index, it was expected that each should exhibit different performances on alternative ranking. Even a slight change in FSRi could change the priorities of alternatives and consequently change the mitigation decision. As the sensitivity shows the change in priorities of alternatives numerically or pictorially, a quantitative measurement is required to compare different alternatives and to determine how sensitive each criterion is. A ranking index is proposed to measure the sensitivity of the alternatives group by using the weighted average method.

Considering a decision problem with M alternatives and N criteria: If alternatives ranking denoted as R_i (for i= 1,2,3, . . . , M) and criterion performance denoted as Pj (J=1,2,3,. . . , N), the sumproduct index is defined as:

$$I_{SP} = \sum_{j=1}^{N} \sum_{i=1}^{M} (R_i . P_j) \tag{8.1}$$

Comparing I_{sp} with original product index, the ranking sensitivity index can be determined as the following:

$$I_{RS} = 1 - \frac{I_{sp}}{I_0} = 1 - \frac{\sum_{j=1}^{N} \sum_{i=1}^{M} (R_i . P_j)}{\sum_{i=1}^{M} (R_i . P_i)} \tag{8.2}$$

The sensitivity index could take maximum value when the new ranking of alternatives are reversed. Conversely, when there is no change in FSRi results, both numerator and denominator will be the same and thus the I_{RS} = 1. Using this concept, the value and direction of sensitivity for each criterion can be determined in terms of group ranking values. The performance sensitivity of alternatives has been analysed for 21 risk criterion for each increment. The results are then classified in four categories as displayed in Figures 8.4 and Figure 8.5. The graphs illustrate the change to each increment by a set of colours, dark green for the 10% increment and yellow for 40% increment.

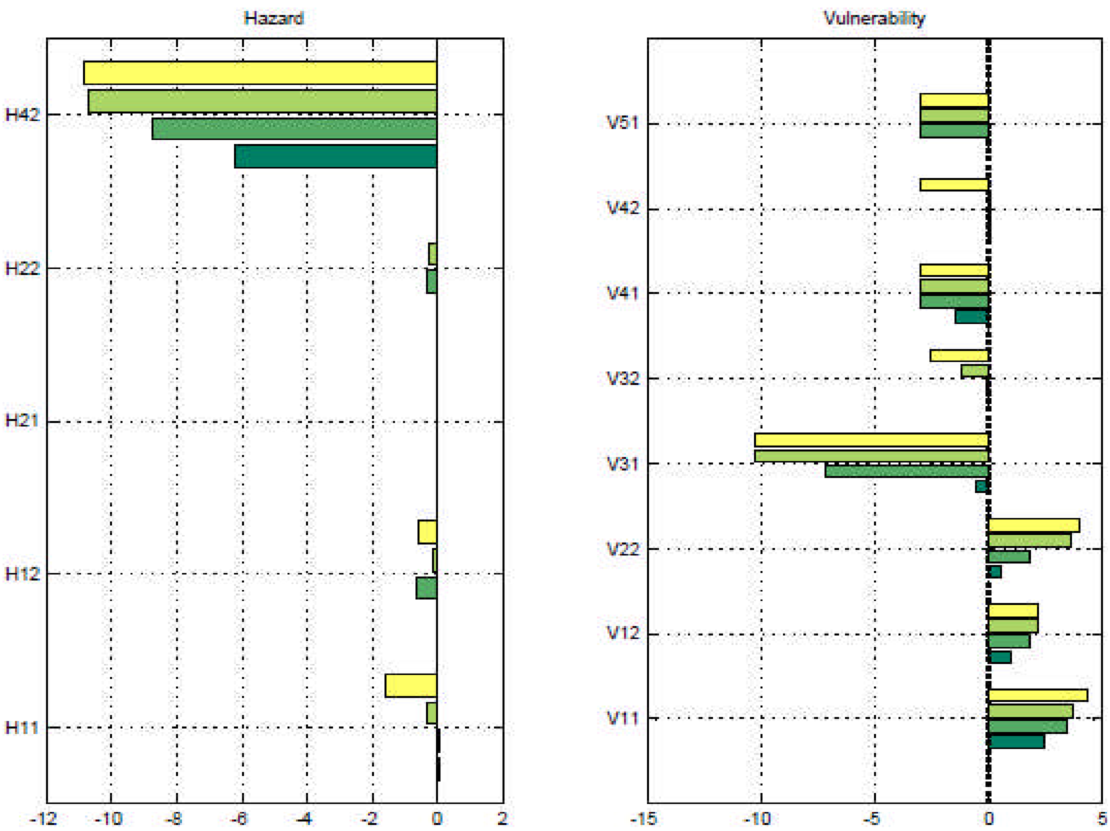


Figure 8.4 - Ranking sensitivity Index for Hazard and Vulnerability criteria

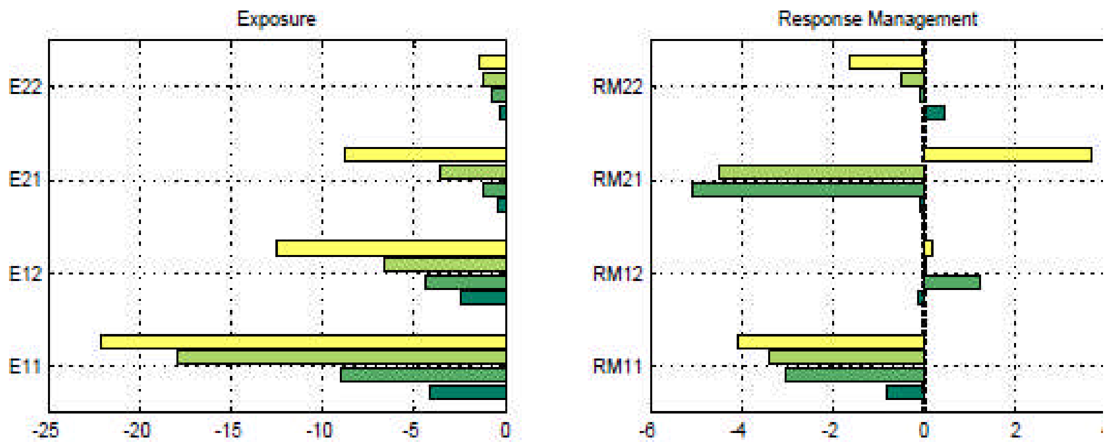


Figure 8.5 - Ranking sensitivity for Exposure and Response Management criteria

The graphs reveals that final priorities of alternatives are sensitive in limited ways to the performance of risk criteria. Small changes in the releative performance of a few criteria can cause a varying degree of changes in the final ranking. Depending on the extent of changes, the criteria can be classified in three groups. The first group includes the most critical criterion E_{11} as it has the greatest influence, with over 20% on final ranking. The second group consists of criteria that are less sensitive (5% to 10%) to small changes such as H_{42} and V_{31} and E_{12}. The third group includes very low sensitivity criteria contributing less than 5% in overall performance, comprising vulnerability and response management criteria along with E_{21}, E_{22}, H_{11} and H_{12}. However, there are some criteria that show either no sensitivity or partial sensitive to significant changes. For example the incremental increase in H_{21} and H_{22} could not change the final ranking. Other criteria such as V_{32}, V_{42} and H_{11} are only sensitive to larger increments (30% to 40% at least). In other words, the threshold of changes in some criteria is much higher than normal criteria.

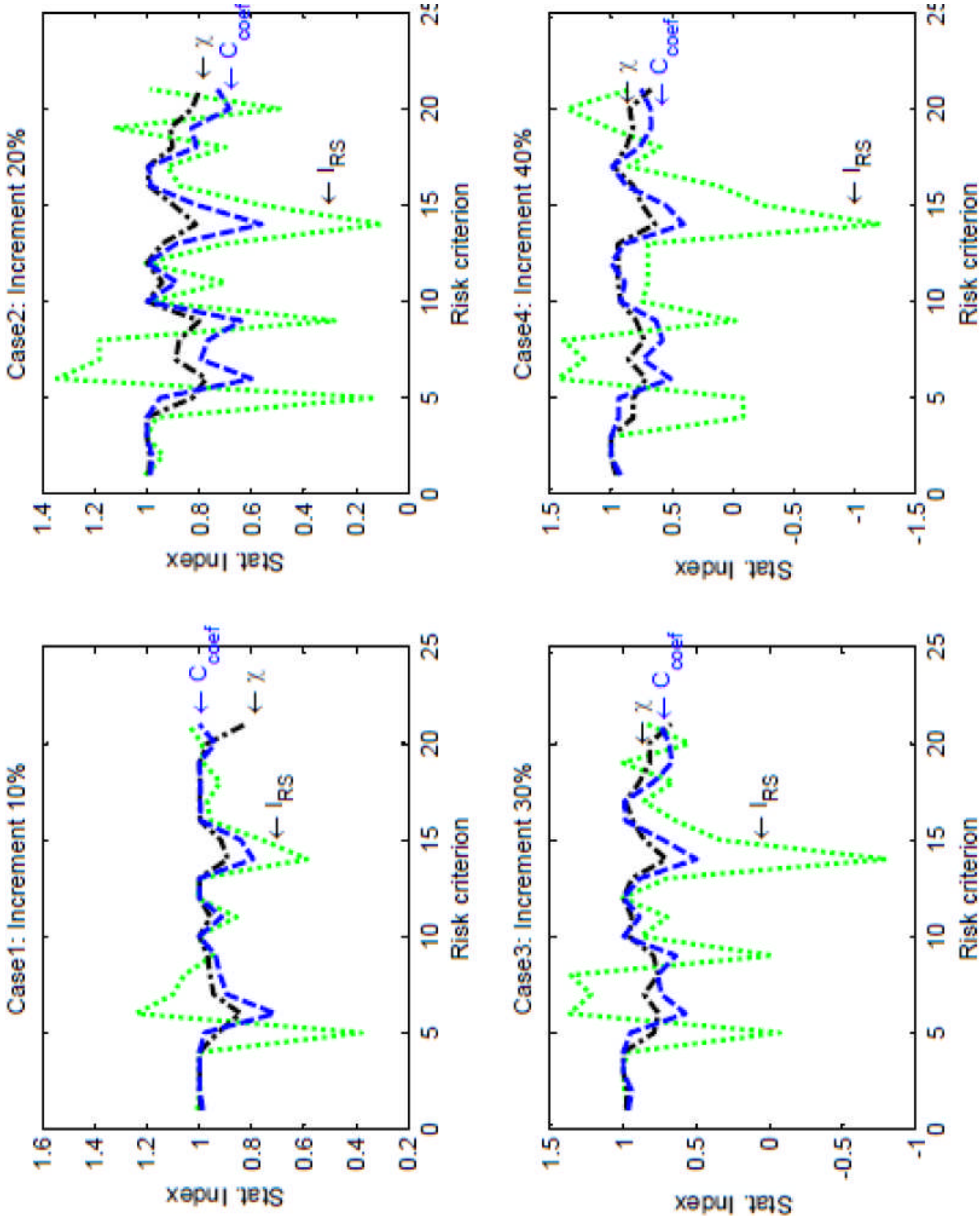


Figure 8.6 - Ranking sensitivity for Exposure and Response Management criterion

Other statistical tests were also employed to verify the initial sensitivity results. Considering the performance of overall risk (FSRi) at each increment, four vectors can be derived from each criterion. To measure the relations and discrepancies between new vectors and original performance vectors, a comparative analysis was carried out using correlation test (C_{coef}) and Chi-square test (χ^2). Figure 8.6 displays comparatively the variation of statistical indices along the proposed sensitivity rank index (I_{RS}) that has been set up for different cases (increment 1: 10% to increment 4: 40%).

In general, the comparison confirms that the IRS follows the same trend as χ^2 and C_{coef} in most criteria with over 70% confidence. The discrepancy can be addressed by the number of inconsistent criteria that start from 4 (80% match) and increases in the third case to 5 (76%) and 6 in the last increment (71%). Having low discrepancy in sensitivity results and statistical index implies that initial sensitivity results are reliable. However, it should be noted that the results derived from the sensitivity analysis are only valid for the present model, particularly with the geography of Iran in mind. Expanding the results to other regions with different criteria might generate inconsistent results and mislead the mitigation decisions. Therefore, efforts should be made to define the appropriate settings consistently with new environments.

8.5 Operational Validation

Validation is referred to the correctness of knowledge structure, the credibility of a description, generality of conclusion, explanation, interpretation, or any other sort of account (Maxwell 1996). Since the absolute validation of a model over its application domain can be costly or time-consuming, the credibility of a model can be claimed for an intended use and prescribed condition (DMSO 1996). Consequently, validation relates to the degree of confidence of a domain under which the model has been tested with sufficient accuracy. The greater accuracy and confidence in a hypothesis test, the more credibility and validity is expected to achieve.

Table 8.2 – Operational validity classification (Sargent 2013)

Approach	Observable system	Non-observable system
Subjective	• Comparison using graphical display • Explore model behaviour	• Explore model behaviour • Comparison to other models
Objective	• Comparison using statistical tests and procedures	• Comparison to other models • Using statistical test

According to Sargent (2013), the framework of validation can be classified in two distinct categories: subjective and objective (Table 8.2). Depending on whether a system is observable or non-observable, various objective tests can be applied such as benchmarking (comparison to other models), Event validity (a simulated model compared to real event), internal validity (stochastic consistency of a model), hypothesis test (tests of significance) and graphical comparison.

Having the historical records of previous cases, the correctness of the results can be tested against benchmarking results. For example, in disaster management models, comparisons are often made using historical event losses (or damage survey), industry average annual loss (AAL), and the exceedance probability curves (RMS 2012). Alternatively, in the absence of objective test cases, a validation can be performed subjectively through a multiple-round expert panel (i.e. Delphi) to judge about the correctness of the results and compare them against their predictions.

However, Linstone (1978) argues that the expert panel should be invoked as a method of “last resort”, because it is particularly suitable for highly subjective situations that require a group consensus, and cannot be objectively handled through either analytical or empirical paradigms. Finally, they cannot be managed due to cost or time constraints, or other concerns such as bias, prejudice and parochialism. In addition, subjective validation may not be practical due to time and lack of professional experts in the area of interest. For these reasons, it is quite difficult to validate the results subjectively since the model is composed of both objective and subjective information. Rather, empirical techniques would apparently generate faster and more reliable results in disaster modelling as it relies on objective facts. Therefore, the validation of this thesis is focused on well-known objective-based techniques which are outlined in following.

8.5.1 Investigate Model Behaviour

In validation, one attempts to demonstrate if the model fully reflects the behaviour of the real system. In an expert system for instance, a set of test cases can be used to compare performance with the reference or standard (O'Keefe, Balci & Smith, 1987). The performance of the model has to be reliable, accurate and expandable to the similar situations while it sufficiently meets client needs. A model is accurate if the predictions it makes fit closely to the observed (measured) data. Furthermore, the model can be considered reliable if the parameters of the model vary minimally with the predicted samples used to fit the model changes. The model accuracy and reliability can be estimated through cross validation, benchmarking and parametric sensitivity tests.

8.5.2 Comparison (Benchmarking) Techniques

Comparison is an apparent method of validation that compares the output of an existing system to the real system's output. In a narrower context, benchmarking can be used to compare numerical and analytical solutions, reference or accepted standards (Oreskes et al. 1994). A model is considered valid if one can demonstrate the agreement between prediction and observation. Using statistical tests, it can be ascertained whether two samples are taken from the same or from different populations. To evaluate the "goodness of fit" within two samples, mathematical techniques such correlation and regression analysis might be used. While regression proposes a statistical relationship between two samples (e.g. linear/nonlinear functions), correlation addresses the goodness of fit, ultimately implying the contiguity of two samples. However, unlike correlation, regression analysis is restricted due to the assumption that there is cause-and-effect relation within dependant and independent parameters (Shannon 1975). There are many other statistical tests to evaluate the goodness of relationship. Most of those can be jointly used to compare the model's behaviour graphically, hypothetically or theoretically; some of these are briefly outlined in following.

8.5.2.1 Graphical Display

Alternatively, the behaviour of a model can be monitored graphically for various sets of conditions to monitor the accuracy of the model's output over an intended domain. Usually, types of histograms, boxplots, scatter plots and bivariate/multivariate plots can be devised to measure major behaviour indices such as mean, variances, extreme values, for example. A sample graphical analysis of the study was undertaken within Chapter 7. However, to obtain the best performance, a graphical test can be employed as a complementary method of validation jointly with other methods such as face of validity (expert survey), Turing test and independent V&V. Unlike statistical distributions, the graphs do not require satisfying either with regards to independency or the normality of the data (Sargent 2013).

8.5.2.2 Hypothesis Test

A hypothesis test statistically determines if two or more samples derive from the same population within an acceptable range of accuracy (Sargent 2013). There are relatively large numbers of parametric tests (e.g. F, t, Z test) and each aim to explore and compare the behaviour of a model in relation with another (e.g. a reference system) by means of probability distribution parameters such as means and variance.

The hypothesis test is based on the predication of a null hypothesis (H_0), assuming it is correct, and is compared to an alternative hypothesis (H_1). The result can be either "failed to reject H_0" or "reject H_0 in favor of H_1". For example, a null hypothesis can be "a positive influence of building age on overall seismic risk". The null hypothesis can be a result of sampling, observations (e.g. historical damage record) or previous research. If the results of an experiment are statistically consistent with the prediction (i.e. fails to reject H_0), the hypothesis is retained; otherwise it is considered that the hypothesis is likely to be wrong and will be rejected.

However, it should be noted that "not to reject H_0" does not necessarily mean that the null hypothesis is true, as rejecting H_0 might suggest, but it does not prove that H_1 is true (Sornett et al. 2007). According to Mckillup (2012), no hypothesis or theory can be experimentally proven since it might be new evidence to reject and suggest a new hypothesis. Thus, further experiments are required to strongly uphold the widespread generality of the initial hypothesis or theory.

Furthermore, Barlas (1994) points out the potential issues associated with the hypothesis tests. Statistical tests of significance are based on normality and independency of variables; thus the test might not be valid for correlated systems. To satisfy this condition, all significance tests require a vast model simplification and data transformation which might be difficult to achieve in complex systems. Therefore, the effectiveness of hypothesis testing is provided for reasonable sample sizes, normalities and independent aspects of the system.

8.5.2.3 Confidence Interval

Unlike significance tests which provide "either-or" outcomes, confidence intervals provide a range that addresses how close the estimated values are to the actual population (Hinton 2008). It is presumed that 95% confidence is a generally accepted limit within which 95% of sample indices (e.g. μ, σ) lie around the larger population. However, 90% represents a narrower range of samples, and is consistent with an actual population. Conversely, 99% requires a wider range of samples to cover extra range. As the number of samples increases, the standard error (SE) reduces ($SE = \sigma/\sqrt{n}$) and the breadth of confidence becomes smaller, as shown in Figure 8.7. Therefore, the larger the sample size, the narrower the distribution and the greater the reliability of an estimate for a population.

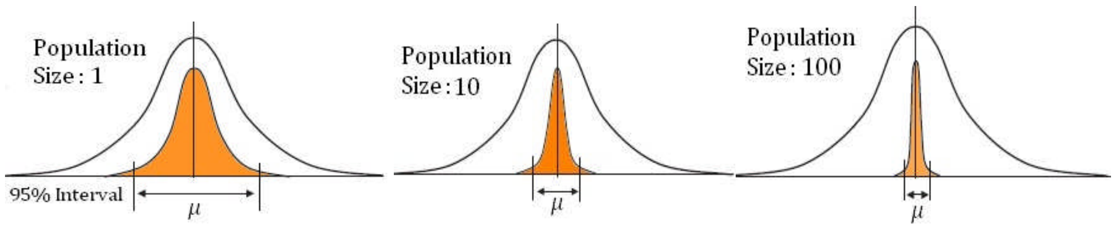


Figure 8.7 – Typical breadth of confidence interval in three sample sizes (Hinton 2008)

8.6 Validation of the Developed Model

Validation of this thesis was conceptually developed in two ways to prove both external (e.g. credibility, reliability) and internal dimensions (e.g. consistency, continuity, robustness). Externally, the model must be generalisable beyond the study environment and must also demonstrate a broader extent in the results. Internal validity, on the other hand, signifies that a model contains no detectable flaws and is consistent over its domain (Oreskes et al. 1994). Theoretically, if a computerised simulation model maintains both external and internal aspects, it is expected to be valid under the specific domain.

This process can be straightforward for precise deterministic systems. However, since the absolute validation of a natural system is impossible, the validation of an imprecise numerical model can be often accommodated through a 'range of validity' or 'validity interval' (Shannon 1975; Oreskes et al. 1994). Defining the bounds of validity (or range of the confidence interval) can effectively address to what extent the model might be valid. In other words, one may not be able to precisely (or absolutely) addresses whether a model is reliable or not, but one is able to evaluate the model over a 'range of validation' or ‘conditional validation’.

Following this concept, a boundary of validation must be defined upon which the model can be tested. Three hypotheses were proposed to conceptually address the external and internal aspects of validity, upon which three sets of scenarios were designed to test the model at "best case", "normal case" and "worst case" conditions in practice. The scenarios were developed upon three underlying hypotheses that collectively address all aspects of validation within the study. The conceptual order of validation is shown within Table 8.3

Hypothesis I: “If the fundamental components of the model are statistically valid within the defined confidence interval, the overall model can be practically valid within the same interval."

Hypothesis II: “The model is internally valid if it is consistent, continual and robust under any combination of the dataset within domain interval."

Hypothesis III: “The heuristic model results must be competitively comparable with formal screening results."

Table 8.3 – Operational validity concept, scenario and hypotheses

Hypothesis	Validity Concept	Aim	Experiment	Scenario
I	External	Comparison to observed samples	Correlation/ Chi-squared test	BCS: Best case
II	Internal	Explore model behaviour	Monte Carlo Simulation	NCS: Normal case
III	External	Cross validation with other standard	Hypothesis test	WCS: Worst case

Since the model's validity is accommodated upon these hypotheses, three scenarios represent multiple faces of validation at different conditions, implying generality and breadth of validation. The best-case scenario (BCS) examines the estimated results against an actual test case extracted from the Bingol earthquake survey. The normal case scenario (NCS) examines the overall validity of the model through Monte Carlo simulations. Finally, the worst-case scenario (WCS) ensures that the results are externally consistent with formal screening standards (i.e. NRCC or FEMA 154).

These three scenarios jointly address the model validity at various states. The extent of satisfaction with each scenario addresses the degree of validity within the corresponding hypothesis. Thus, the more satisfactory scenario outcomes, the greater validity is expected over the interval domain.

Given the extent to which above hypotheses are met, the model validity can be measured accordingly. The model can be improved by examination under different situations, adding to its results credibility and clearly drawing the boundaries of model validity. The component or algorithm which requires more attention can be highlighted by possible flaws, both in consistencies and any significant gaps between estimated and actual results. The testing scenarios are outlined in the following sections.

8.6.1 BCS: Bingol Earthquake Test Case

The first scenario examines the validity of main components using an observed damage survey. It aims to ensure that model components generate reasonable results for a given specific risk data by comparing the output with comparable benchmarks, taking care to compare "apples-to-apples" (RMS 2012). Suen et al. (1990) suggest five criteria for selecting test cases, which must be: "based on an actual situation; cover a range of difficulty; be generated by unbiased experts; test as many aspects of the system as possible; be carried in the field".

Theoretically, decision models behave variably in real situations as they use different scales of measurement. Thus, every model generates unique results which may have no similarity to be compared against. Broadly speaking, there is a limited number of databases that contain a detailed, specific damage survey along a site-specific hazard. In the present case, for example, the database does not include sufficient information to compute building importance/exposure, thus the evaluation is focused on the level of seismic damage index (SDI) instead of seismic risk.

Reviewing the literature, a test case (§) is chosen from Bingol city earthquake because it covers a wide range of detailed damage surveys that specifically is focused on school buildings, along with similar conditions in the present study (plan, size, tear, seismicity, for example.); yet the database is restricted to RC buildings.

The Bingol earthquake occurred on May 1, 2003 with a magnitude of M = 6.4, resulting 168 casualties, 520 injuries and extensive range of damages. The major damage observed in school buildings was caused due to poor construction and engineering performance (i.e. soft storey, shear failure in columns, short columns and weaknesses in detailing) as illustrated within Figure 8.8. The level of damage was classified in five categories and described through qualitative descriptors, including: none (N), light (L), moderate (M), severe (S) and collapse (C).

§ SERU, Middle East Technical University, Ankara, Turkey; Archival Material from Bingol Database located at website http://www.seru.metu.edu.tr.

The earthquake engineering reports (Ozbec et al. 2003) indicate two potential faults near the city, with distances from 5 to 15 km. The reports also confirm some earthquake-triggered landslides in the region that caused a range of damage types within buildings. Geological investigation shows that the area struck by the earthquake was mainly covered by sedimentary weathered alluvial deposits.

(a) Collapse due to soft storey (b) Shear wall failure (c) Brittle column failure

Figure 8.8 - School buildings'damage in Bingol Earthquake (Ozbez et al. 2003)

The summary of Bingol damage survey contains 28 state buildings (e.g. schools, libraries) that are available in Table 8.4. The Bingol database was imported into the model to measure the levels of damage within buildings. The estimated results indicate varying degrees of seismic damage index (SDI) from low (L) to medium (M). About 70% of buildings (19 out of 28 cases) show a high level of alliance (over 80%) with the observation, which is satisfactory. 14% of cases shows a medium degree of matching (60%-80%). The rest of the cases exhibit the lowest match between estimated and observed damage values.

There is a case of collapse that could not be truly estimated by the model. Despite having desirable characteristics (material, type and year of construction) the damage index of this case is lower than expected. With regards to the two buildings (BNG-6-3-4 and BNG-6-4-3) which were built in the same year, the former underwent a light degree of damage and the latter collapsed during the Bingol earthquake, The estimated results indicate the low and medium range of damage respectively. This implies that even a reasonable result may not necessarily match with the observation. A thorough prediction of the earthquake’s impacts are very difficult due to the random nature of earthquakes.

Table 8.4 - Summary of Bingol earthquake test case

ID	Region	PGA	TYPE	CY	Floor	f_{ck}	CQ	Observed Damage	SDI	Estimated Damage	Satisfaction (match)
BNG-10-3-10	Inonu	0.4	RCF	-	3	16.5	L	M	3.32	M	High
BNG-10-3-3	Inonu	0.4	RCF	1975	3	18.5	L	M	3.32	M	High
BNG-10-4-4	Inonu	0.4	RCF	1998	4	19.0	M	M	2.59	L	Medium
BNG-10-4-6	Inonu	0.4	RCF	1976	4	36.0	H	L	3.32	M	Medium
BNG-10-4-7	Inonu	0.4	RCF	1988	4	22.3	M	L	2.59	L	High
BNG-10-4-9	Inonu	0.4	RCF+SW	2002	4	21.5	M	N	2.59	L	High
BNG-10-5-1	Inonu	0.4	RCF+SW	1990	5	25.2	M	M	2.54	L	Medium
BNG-10-5-11	Inonu	0.4	RCF	1988	5	33.0	H	L	2.59	L	High
BNG-10-5-2	Inonu	0.4	RCF+SW	1990	5	15.0	L	L	2.54	L	High
BNG-11-2-3	Yesilyurt	0.4	RCF	1970	2	-	L	M	3.32	M	High
BNG-11-4-1	Yesilyurt	0.4	RCF+SW	1998	4	20.3	M	S	4.12	M	Low
BNG-11-4-2	Yesilyurt	0.4	RCF	1989	4	22.8	M	S	4.12	M	Low
BNG-11-4-4	Yesilyurt	0.4	RCF	2000	4	18.0	M	M	4.12	M	High
BNG-11-4-5	Yesilyurt	0.4	RCF	1997	4	-	L	L	4.12	M	High
BNG-3-4-1	Karsiyaka	0.4	RCF	1998	4	18.0	M	L	2.59	L	High
BNG-3-4-2	Karsiyaka	0.4	RCF+SW	1996	4	-	L	N	2.54	L	High
BNG-3-4-4	Karsiyaka	0.4	RCF+SW	1970	4	26.0	M	N	2.99	L	High
BNG-5-5-1	Yenisehir	0.4	RCF	1990	5	21.6	M	L	2.59	L	High
BNG-6-2-8	Yeni Mahal	0.4	RCF	1992	2	12.1	L	S	4.12	M	Low
BNG-6-3-1	Yeni Mahal	0.4	RCF	1991	3	20.8	M	M	4.12	M	High
BNG-6-3-10	Yeni Mahal	0.4	RCF	1995	3		L	N	2.59	L	High
BNG-6-3-11	Yeni Mahal	0.4	RCF	-	3	13.9	L	N	2.62	L	High
BNG-6-3-12	Yeni Mahal	0.4	RCF	-	3		L	L	2.62	L	High
BNG-6-3-4	Yeni Mahal	0.4	RCF	2003	3	19.1	M	L	2.59	L	High
BNG-6-4-2	Yeni Mahal	0.4	RCF	2001	4	19.8	M	S	4.12	M	Low
BNG-6-4-3	Yeni Mahal	0.4	RCF	2003	4	30.0	H	C	4.12	M	Unsatisfactory
BNG-6-4-5	Yeni Mahal	0.4	RCF	1996	4		L	N	2.59	L	High
BNG-6-4-7	Yeni Mahal	0.4	RCF+SW	1996	4	20.3	M	S	4.12	M	Low

CY: Construction Year CQ: Concrete Quality RCF:Reinforced Concrete SW: Shear Wall

8.6.2 NCS: Monte Carlo Simulation

Monte Carlo (MC) generates a sample distribution of input values to evaluate the performance of output values by virtually simulating a real condition. In this case, MC analysis was performed: to examine the robustness of the proposed model, to obtain an estimate for an expected value of the overall risk index (FSRi), as finally, to obtain an estimate of stochastic uncertainty. The aim of this analysis is to ensure that the model is expandable for any risk data within a specified domain interval.

The overall seismic risk index (FSRi) is influenced by a sort of uncertainty that is mainly rooted in the subjectivity of weights and membership functions. The application of the MC simulation allows analysis of uncertainty propagation, examining the pattern of variation within risk factors by means of randomness as well as determining the levels that might affect the performance and reliability of the model (Barbat et al. 2010).

The value of FSRi was calculated 100,000 times, using a random vector of risk input. The stochastic results of the MC simulation were then collected and displayed through probability density function (PDF) and cumulative density function (CDF) graphs. The statistical analysis of PDF and CDF reveals a crucial result in terms of distribution shape, peak, spread and any gap or concentration within domain intervals.

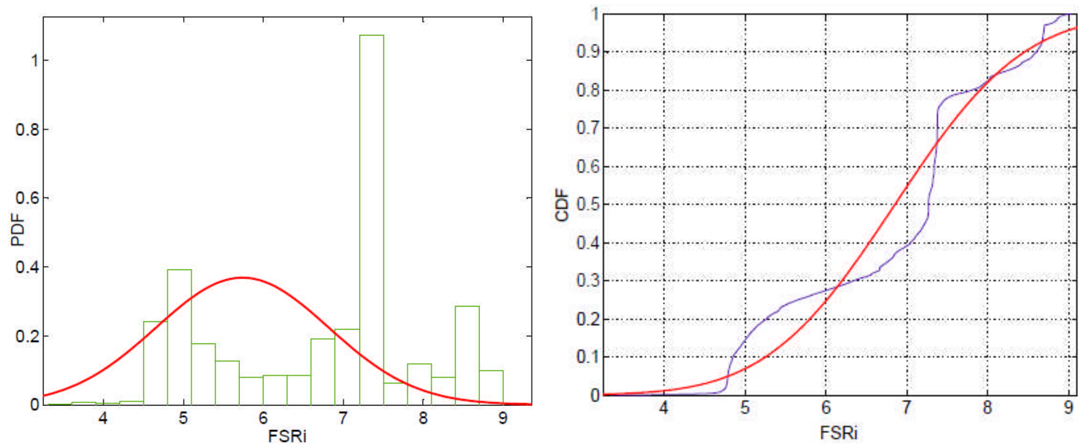


Figure 8.9 - PDF and CDF for expected seismic risk values

Figure 8.9 illustrates the histogram of PDF and CDF of the FSRi performance. The histogram has three peaks, implying that three probable ranges of values that FSRi could take. In other word, three dominant groups of school buildings can be discerned that carry ranges of risk from moderate to extreme. The expected values are consistent with the generic scale of risk that is initially presumed for knowledge elicitation.

Table 8.5 - Statistical parameters for Monte Carlo simulation

Risk Factor	Domain Interval			Distribution shape	Distribution Parameters		Confidence Interval		Confidence Level
	Min	Max	Coverage		μ	σ	$\mu - 2\sigma$	$\mu + 2\sigma$	
Hazard	0.846	9.571	87%	Normal	3.395	2.012	-0.629	7.419	95%
Vulnerability	1.076	8.326	72%	Normal	5.994	1.708	2.578	9.410	95%
Exposure	1.832	9.107	73%	Normal	5.482	1.963	1.555	9.408	95%
Response Mng.	2.016	9.346	73%	Normal	6.537	1.568	3.400	9.674	95%
FSRi	2.747	9.034	63%	Normal	6.853	1.248	4.356	9.349	95%

Statistical parameters of the Monte Carlo simulation are summarized in Table 8.5 including mean (μ) and standard deviation (σ). Extreme values (Min, Max) of risk factors indicate a considerable coverage in domain interval. While FSRi maintains the lowest coverage by 63% , it is still satisfactory as it comes with 95% confidence interval. Due to low deviation in the results, 95% of the values fall between $\mu - 2\sigma$ and $\mu + 2\sigma$, no matter the domain interval. However, it should be noted that the proposed model could only cover the range of risk from moderate to very high (extreme), while missing the FSRi values beyond this limit (values <2.74 and values > 9.03) representing the lowest and the ultimate states of seismic risk.

8.6.3 WCS: Screening Test

The last validation test is to compare the estimated risk results with the scores obtained from the standard screening method. The Canadian screening manual (NRCC 1992) and American version (FEMA-154 2002) are two common screening procedures which have been widely used in industry to identify and classify vulnerable buildings. Although both approaches follow an identical scoring procedure, the method as defined by NRCC uses more detailed factors (as discussed Chapter 6) for evaluating performances and that is why it was adopted here.

The seismic performance Index (SPI) as derived from NRCC procedure generates a set of benchmarks which can be used for cross-validation under the third scenario. Theoretically, if an identical set of data is imported to either of screening methods, the results may not necessarily be the same (since the scale of measurement is different); while the distribution of each one can be expected to have a similar trend, tendency and overall distribution shape as noted within the hypothesis (III).

To verify the similarities between estimated risk results (called as observed FSRi results) and observed SPI, a parametric analysis was performed correlation test (Chi-Squared). It should be noted that the experiment does not intend to show how close those results are individually. Rather, parametric tests are sought after the display of sufficient evidence, first to prove the validity of the model as a whole entity, and second if the observed sample is derived from the same population.

At the first step, one may wish to test the assumption if the FSRi vector is a random sample from a normal distribution. The statistical test is based on a normal probability plot gives a quick idea, as shown in Figure 8.10. The graph simply illustrates the goodness of the observed FSRi to fit the expected SPI values based on normal distribution. If the samples do derive from the same distribution, the plot will be linear (at ideal situations).

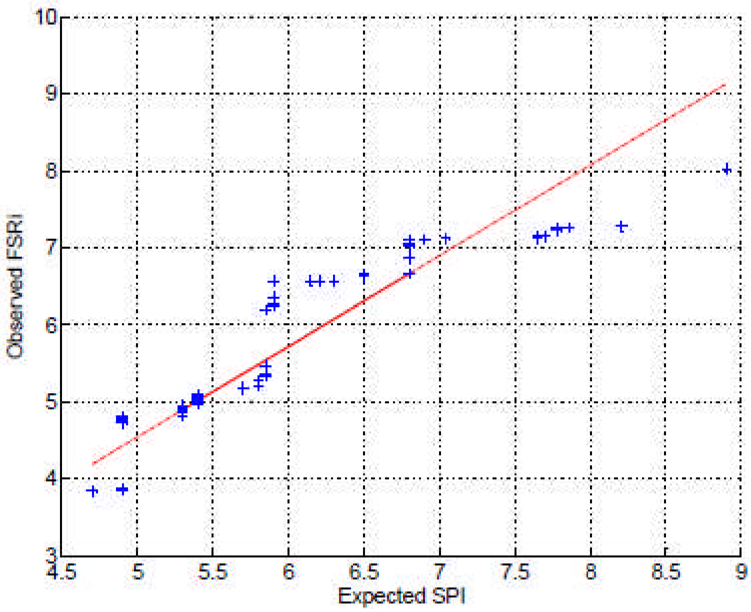


Figure 8.10 - Accuracy plot of observed FSRi against expected SPI

The other statistical test can be performed to validate the initial (null) hypothesis, which states that the observed FSRi is derived from from the SPI population. Table 8.6 provides a summary of the statistic tests carried out. These tests assess the evidence against the null hypothesis in term of probability. The P-value is a probability indicator used to reject or to accept the null hypothesis, explaining the distance the samples are relative to the individual observations.

Table 8.6 - Statistical tests of hypothesis (III): worst case scenario

Statistic test	Descriptive index		Inference Parameter			Confidence Level	Remark
	μ	σ	P-value	Confidence Interval			
t	5.9457	0.98425	0.180	-0.518	0.0991	95%	Satisfactory
z	5.9457	0.98425	0.0839	5.4988	5.9738	95%	Satisfactory
F	5.9457	0.98425	0.4492	0.7394	1.9721	95%	Satisfactory
Chi-square	5.9457	0.98425	0.2839	0.8527	1.7048	95%	Satisfactory

A P-value less than 0.05 means that there is enough evidence to conclude that the observed and the expected (target) population are significantly different and do not come from the same distribution. Since all the P-values are by far more than 0.05, it fails to reject the null hypothesis at 95% confidence interval. Consequently, the tests reveal that the observed FSRi and expected SPI are strongly related.

Overall, the parametric tests demonstrate the statistical agreement between observed and predicted risk results, confirming that results can be fit to a subset of total standard measured data accurately and reliably. In other words, it can be concluded that the proposed model could generate a range of valid risk results (FSRi) that very closely follow the standard screening distribution. Therefore, the generated results have satisfactory passed the minimum controlling requirements noted within the worst-case scenario, implying that the presumed hypothesis (III) is valid.

8.7 Summary

This chapter described the development of a systematic V&V process for application of seismic risk management. Initially, the system underwent the verification process. At this stage, the knowledge base was statically debugged and subsequently verified using a set of parametric sensitivity tests. The sensitivity results indicated that social exposure, for instance, is the most significant variation with over 20%. The verification process was successfully accomplished through different tests, implying the model's robustness.

Next, the validation process was devised using three tests that conceptually linked three underlying hypotheses. These address multiple faces of validation both internally and externally. A higher level of achievement on each test results in more reliable results. The consistency of the model was evaluated through the Monte Carlo simulation. The internal test indicated a high degree of coverage in the output domain interval with 95% confidence. In addition, the credibility of the model was also examined using two experiments. The test statistically revealed a close agreement between estimated and predicted risk performances that occurred within 95% confidence interval.

Given that the model was successfully verified and validated at different conditions, it can be assumed that the model is reliable. Therefore the proposed risk-informed system can be implemented in prioritising the retrofitting of school buildings.

Chapter 9: Conclusions

9.1 Introduction

This chapter provides the main findings of the research. The context of the thesis is summarized and major contribution to knowledge is discussed. It also outlines some recommendations for future research.

9.2 Context Summary

Seismic risk management is a knowledge-intensive process which deals with a great amount of information from different sources. The risk databases are very large and are associated with uncertain information containing a mixture of heterogeneous incommensurate information that need to be scaled, aligned and measured on a common platform. The uncertainties in the seismic risk context are significant and may not be effectively captured through conventional probabilistic methods. In addition, the complex nature of earthquakes poses an extra challenge suggests the need for a systematic process to handle the intricate characteristics of seismic risk management involved with:

- Multiple sources, criteria and alternatives
- Multidisciplinary processes
- Conflict/interaction among risk variables
- Multiple stakeholders, clients and interest group
- Multiple causes and effects

Keeping this in perspective, multidimensional aspects of risk are at the core concept of seismic risk management and lie beyond the practical reach of conventional models.

Deterministic models are too complex and require sophisticated tools and expertise to achieve the intended levels of accuracy for critical infrastructure. The probabilistic method requires a great amount of information to establish the correlation between seismicity and damage records to extrapolate the results for future damage prediction. In addition, conventional models are application specific and fail to support problems in heterogeneous environments (e.g. various forms of data). They are thus restricted to regions with richness of data.

The existing frameworks suffer from a lack of power in structuring the knowledge in a way that is simply interpreted and reused by experts. Therefore, the research focuses on the development of a heuristic system to effectively integrate kinds of knowledge about risk with existing constraints. The significance of this concept stems from the fact that risk can be viewed as common denominator that allows considering non-commensurate characteristics in single measures. However, implementation of pure holistic systems relies strongly on expert intuition and experience, without the straightforward way of incorporating knowledge contained in numerical data (i.e. data driven rules). Therefore, the formulation of the scope of seismic risk management must be arranged according to the application and potential decisions to be made.

9.3 Objectives

9.3.1 Objective 1

The first objective was to review the background and characteristics of seismic risk management and systematic challenges involved. The literature review identified four distinct categories of risk analysis (deterministic, probabilistic, heuristic and screening) in terms of accuracy, complexity and uncertainty. The review revealed that the scope of each procedure can vary significantly according to the application and may not fit for large mitigation programmes where numerous retrofitting projects are involved. The review concluded that prioritizing the retrofitting of schools requires a holistic risk-informed system to effectively address not only physical impacts of the earthquake, but also to incorporate the socioeconomic characteristics of the disaster to support multiple stages of seismic risk management.

Achieving the first objective improves the understanding of seismic risk management by providing an insight into how important background characteristics are, what the potential challenges involved from the system perspective are, and has given the basis which going to built a model later on the thesis. It also helps users to compare systems and choose the appropriate risk assessment approaches according to the scope, size, accuracy and complexity of the application, which would be desirable for any system.

9.3.2 Objective 2

The second objective was to investigate the feasibility of mathematical techniques for modelling seismic risk. This objective was pursued through a review of existing mathematical modelling techniques. Given the diversity in the criteria, alternatives and participants, the problem describes multicriteria characteristics. A Multi Criteria Decision Making (MCDM) approach was then defined as a target to be explored.

The review revealed that MCDM could be used as a unique integrator that acts as a bridge between the various disciplines involved in seismic risk management. However, exploring the MCDM methods indicated that there is no single technique that could uniquely address the multiple requirements simultaneously. The utility of MCDM varies depending on the problem size, data type and technique used for handling criteria trade-off. Classic MCDM is not considered to be capable of handling uncertainty. For example, Analytic Hierarchy Process (AHP) as a crisp version of MCDM could not essentially address the subjectivity and vagueness. Moreover, this technique is highly dependent for its validity on the comparative judgment of every pair of criteria, which is not practically possible for current problems involving a large number of criteria and alternatives.

Several methods from MCDM and Artificial Intelligence (AI) were reviewed and compared in respect of two parameters that significantly affect the selecting process. The first of these is the systemic ability of processing large numbers of alternatives. There are few candidates from MCDM and AI-based methods, which can systemically handle large amounts of information, criteria and alternatives. Secondly, the modelling effort is also a critical parameter that determines the level of richness in the ranking scores. AI methods carry the most desirable characteristics required for handling such complex problems.

However, some of the above, such as Genetic Algorithms (Gas) and Artificial Neural Networks (ANNs), are either too complex or require a great amount of information for training the model. Among AI methods, Knowledge Based Expert System (KBES) was adopted due to its potential to effectively address the challenges caused by complex multidimensional aspects of seismic risk while also being capable of handling the subjectivities exist in the decision processes due to the broad spectrum of objective and subjective information. A comparative study undertaken in Chapter 3 reveals the appropriateness of the proposed ranking knowledge base system for seismic risk application, demonstrating that the heuristic fuzzy modelling outranks the other methods in all perspectives.

This objective was achieved by categorising the mathematical techniques by means of system perspectives, taking into consideration complexity, trade-offs, input-output requirements and modelling efforts. This classification allows the modeller to provide evidence from a broad range of perspectives that ultimately improves the understanding of the model's restriction and capabilities. As a result of the critical analysis of these mathematical techniques, it has been possible to develop a taxonomy that improves the credibility and functionality of the model by accommodating an organized, effective format for assessing the simulation results.

9.3.3 Objective 3

The third objective was to introduce the fuzzy modelling approach in practice and review the terminology, scope, limitations and potential barriers associated with modelling the complex domain. This objective was achieved by exploring the significant characteristics and necessary operations required for fuzzy modelling. Knowledge acquisition was identified as a critical stage in establishing the KBES. The process of knowledge acquisition and representation requires extracting the useful knowledge from different sources (fact, algorithm, experience, and control knowledge) and formalizing it into a set of rules that constitute the knowledge base. The knowledge base sources include building codes, earthquake reconnaissance reports and expert opinions (questionnaire feedback) on the various impacts of seismic risk.

This research is practical and unique in that it integrates a large number of fuzzy inference systems (FIS) in a comprehensive framework allowing multidimensional analysis of seismic risk in regional scale which has not been attempted before. The proposed system provides a powerful modelling tool to aggregate a large amount of information over multiple regions both effectively and efficiently. The major advantage of this study is that both qualitative and quantitative risk information could be aligned, scaled and aggregated with the presence of uncertainty. The model not only considers the trade-offs between both qualitative and quantitative factors involved in developing risk, but it also enables decision-makers to deal with inconsistent judgments systematically. However, the proposed KBES relies on the expert knowledge to develop the knowledge base. The identification and co-operation of relevant experts could be a great challenge if they have not been chosen wisely or they could not reach a consensus.

The proposed KBES improves the existing framework, allowing as many factors as possible to be integrated, and yet is capable of being specifically tailored for certain interests. The KBES offers a new, systematic and structured reconciliation of numerous risk factors through a multi-layered hierarchy, which is capable of interacting with a range of information, facts, algorithms and experiences.

9.3.4 Objective 4

The fourth objective was to investigate the potential impacts of earthquakes to collect necessary information and to establish the structure of seismic risk assessment. This objective was pursued by investigating the multidimensional effects of earthquakes in four major categories, including the hazard (ground-related effects), vulnerability (physical and structural effects), exposure (social and economic effects) and response management capability (regional background effects) and classifying them hierarchically into a structured system. The critical challenge of this phase was to adopt a right 'scale of damage' that could adequately represent the size and typologies of buildings in Iran while being measurable and consistent with existing standards.

The available scale of damages as defined within seismic codes is either too conservative to truly represent the spectrum of buildings or not clearly expressed in a way to be simply transformed into fuzzy language. Moreover, the types of structures defined in some US codes may not fully cover the typologies of buildings in Iran. To address this issue the thesis proposes a new damage index based on the probabilistic concept of damage and consistent with EMS-98. EMS-98 presents a subjective way for defining the state of damage in buildings that makes it coherent to be modelled through fuzzy modelling. However a damage survey used in this study for developing the fragility functions is limited to a specific range of damage covering the most common classes of school buildings in Iran. Further works can be focused on upgrading the framework by extending the database to cover a wider range of earthquake damage, building types and importance. The factors, structure, and measurement scale described in this chapter collectively make an underlying body required for developing the KBES.

The outcome of this task contributes to knowledge three fold. First, it identifies the potential impacts of earthquake on school buildings in multiple aspects. Second, the new model offers a systematic method of aggregating risk factors and to study the characters of seismic risk assessment of school safety. While conventional screening models can handle a limited number of retrofitting projects manually (which is costly, time-consuming and may require a great amount of information and experience), the new models offer a systematic method which is capable of handling a large number of cases. Third, it demonstrates the importance of a multi-level hierarchy for structuring seismic risk. The advantage of this structured knowledge is providing a deeper insight into the seismic risk and its relevant impacts in different categories in a systematic manner. Unlike previous frameworks which focus only on physical aspects of seismic risk, the proposed model improves existing models and provides a comprehensive picture of seismic risk that incorporates multidimensional aspects such as socioeconomic criteria in the decision process. As a result, this objective has demonstrated that earlier models have underestimated the significance of social damage and thus allows the new model to extend risk assessment, taking into consideration more features of seismic risk management.

9.3.5 Objective 5

The fifth objective was to apply and implement the model for evaluating and ranking seismic risk within retrofitted school buildings in Iran and to review the results. This objective aimed to complete the case study by processing the feedback from practising engineers by the means of fuzzy aggregation.

A comprehensive seismic risk management methodology was implemented using a KBES. The complexity issue was addressed through a synchronized hierarchy and operated using an integrated programming in MATLAB®. The nonlinearity and ambiguity within the risk data were handled by examining different grades of risk impact. It is apparent that the higher number of grades in risk factors, the greater precision and effectiveness in capturing nonlinearity and uncertainty.

The application of the proposed model demonstrates the benefits of the KBES in handling complex problems in the seismic risk context. A significant outcome of the study has been the development of a versatile system that is capable of processing sorts of information at various levels of accuracy, form (qualitative and quantitative), measurement scales (ratio, interval) and algorithms (code based functions). Throughout the task, a simple, impartial algorithm for aggregating the expert opinion was established. The process employed a fuzzy-based algorithm for aggregating a large number of expert's opinions by identifying consensus amongst the individual experts, sorting and aggregating a based on common agreement in a hierarchy.

Implementing the KBES brings several benefits to the decision class, such as increased speed and access to knowledge, reduced cost, errors, and increased retention of expertise. A significant feature of the new system is the flexibility in reporting and communicating with decision-makers. The model facilitates the process of decision-making by allowing a transparent analysis of the risk contributing factors at any stage of risk management. Unlike similar models that process the risk inputs in a "black-box", the new approach provides a rich form of risk output in subsequent levels of hierarchy to support the final risk ranking results. The model not only produces a composite risk index (FSRi) that collectively represents the general position of an alternative within the whole group, it also offers a comprehensive reasoning tool that supports each index explaining why a building is at higher risk than the others and which categories and dimensions could be critical for mitigation. For example, some densely populated post-code school buildings could be quite more vulnerable to those pre-code buildings with a lower population. The form of reasoning is unprecedented in the disaster risk context which cannot be achieved through other rival approaches (FEAM 154 and NRCC).

The proposed methodology is the first systematic management of retrofitting school buildings subjected to seismic risk on a large scale. It contributes primarily to a new heuristic method that is capable of integrating seismic risk factors in the presence of uncertainty.

This research has produced a unique procedure for capturing a multifaceted picture of earthquake risk for school buildings. The process specifically offers a new rapid screening tool that adapts to geological, structural and social demands in Iran. The methodology is based on aggregating the key determinant factors that impose a dominant threat to school safety. Therefore, the method improves the previous frameworks by interactively addressing the seismic risk impacts to decision-makers.

9.3.6 Objective 6

The sixth objective was to investigate the effectiveness of the proposed model and to verify and validate its results. The objective was pursued by performing a set of analytical and empirical tests to ensure the success of the model's implementation in real situations.

This task was carried out in two stages of computerised verification and operational validation. In the model verification the knowledge base was statically verified in terms of correctness and consistency, and then passed a black-box test using a sensitivity analysis. The model was operationally validated in three ways to test the simulation model externally by comparing it to other models (benchmarking) using a statistical test of significance (hypothesis test), and internally by exploring the model behaviour using a stochastically generated inputs (Monte Carlo simulation). Finally, the model was cross-validated with a standard screening result. The tests together confirm the reliability and credibility of the results within the specific domain of school buildings in Iran. This process served to demonstrate the validity of the method and suitability of the field of seismic risk management as a domain for expert system development. However, further subjective-oriented tests might be performed to establish the model's validity in the industry.

The significant contribution of the research serves as an investigation into the applicability and usefulness of the KBES to the domain of risk mitigation planning. The versatility and power of the expert system in processing complex systems outweighs its conceptual limitations in the context of disaster management. Essentially, seismic risk management is tightly linked to the mitigation programme. The key challenge was to effectively project the potential impacts of earthquakes on school buildings.

The main objective of this research has been to investigate whether the knowledge base system for such a problem is feasible, possible, justified and appropriate. The potential application of such system was examined through the case study of school buildings in Iran. Throughout the process, it was demonstrated that meaningful results could be obtained regarding the feasibility and applicability of the KBES in seismic risk management.

The application of the KBES for prioritizing a large number of retrofitting projects in Iran makes it possible to improve the ongoing mitigation programme in several ways. Firstly, it increases the quality of mitigation decisions, bringing a more controllable tool that enables users to easily add or remove risk attributes and track and monitor the output at any stage. Secondly, it includes multiple groups' concerns (weight and preference) in the decision process in various dimensions (physical, social and economical). Thirdly, the model offers a high performance decision support system that facilitates the planning and management of vulnerable school buildings in less time, cost and expertise, increasing school safety by expediting mitigation measures. For the first time, it is possible to identify the hazardous school buildings and to prioritize them in terms of retrofitting urgency. In this instance, the application of the developed screening method not only fulfils the direct needs of mitigation programme, but it will also have a significant impact on the whole of the disaster management cycle, including preparedness, mitigation, response and recovery.

The outcomes of the research collectively confirm that the proposed model fulfils the objectives of the study for the intended application of seismic risk management necessary to protect school safety.

9.4 Recommendations for Future Research

Following the study, the model can be further extended and enhanced by recommendations to direct future research. The possible research areas for such extensions and enhancements can be outlined in three major areas.

First, the methodology can be expanded and adapted to other sectors such transportation, healthcare and emergency facilities by adjusting the model's configuration and structure.

Second, the proposed model estimates the seismic risk of school buildings on a standalone platform. Future research could focus on integrating this model with local knowledge and maps systemically through a Geographic Information System (GIS). Currently, there are no detailed hazard and vulnerability maps available in cities because of the lack of an integrated knowledge base platform. The GIS based platform is a powerful resource to improve the quality of the database within the process of seismic risk management. This platform could effectively help individuals to strengthen the capacity of local communities in identifying the detailed zoning maps and developing the appropriate response plan.

Finally, the system developed in this research is the first attempt to assess the likely impacts of seismic risk on retrofitting buildings. Due to enrichment of database of retrofitted buildings over the time, an extensive corroboration process should be performed to calibrate the values and weights consistent with actual experience. This is important to determine what level of accuracy is required for a risk parameter to make the model adequately valid and useful in future mitigation programme.

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Appendix

Appendix A. Questionnaire Survey

Dear Expert

UNIVERSITY OF LEEDS

Data sheet: General Information and definition

Seismic risk is defined as the combination of several factors and commonly expressed in terms on lives loss and damages to properties , facilities , business and activities. Any element of urban environment such as population at risk (PaR) , asset or value at risk (VaR) is considered 'at risk' when they exposed to likely occurrence of the sort of losses for a given hazard (here is seismic hazard) and thus can potentially propagate the seismic risk. Accordingly, three basic components can be distinguished from the above definition to characterize the seismic risk including:

- Seismic Hazard (H): the probability of occurrence of earthquake hazard for a given area or level of ground shaking within a specified period of time
- Vulnerability (V): potential susceptibility or degree of loss to a given element(s) at risk resulting from the occurrence of a seismic hazard with a given magnitude
- Exposure (E): Population, properties, asset and economic activities at risk in a given area
- Seismic risk (R): is referred as the expected number of lives lost, or degree of damage and disruption to properties, infrastructures and economic activities caused by a seismic hazard

These factors are abstract and thus needs to be classified into more detailed sub-factors and attributes to precisely address each category. The identification of the weights and the effects of these factors is crucial to aggregate and combine risk factors, identify the most riskiest set of facilities/buildings and finally to take the suitable measures to mitigate their risk.

The expert opinion collected through the questionnaire will be used in building a knowledge based expert system (KBES) to predict the seismic risk of the building of interest. As the expert system mainly relies on the expert's judgment and experience, a questionnaire is prepared for integrating your valuable judgment using the proposed KBES.

This questionnaire consists of two parts. In the first part, the expert is required to give weights to the main factors that seismic risk defined upon. In the second part, the expert is asked to evaluate the contribution (performance) of sub-factors with respect to each risk factor.

Your cooperation with us will increase public safety by improving the seismic risk mitigation measures. Thus, your contribution is valuable for us and highly appreciated.

Lead researcher

K.Vahdat

Questionnaire Form

Part 1 : Seismic risk factors

1. Rate the overall weight (importance) of risk factors on a scale of 1 - 10 in which 1 represents lowest and 10 represents highest contributing factor (most important) in seismic risk. (The sum of the weights is unimportant.)

i	Seismic risk Factor	weight w_i	1	2	3	4	5	6	7	8	9	10
1	Hazard											
2	Vulnerability											
3	Exposure											
4	Response management (preparation , planning and emergency facilities: hospital)											

Part 2: Risk sub-factors

2**. Hazard category** : Rate the importance of hazard sub-factors on scale 1 - 10 :

i	Hazard sub-Factor	weight w_{ih}	1	2	3	4	5	6	7	8	9	10
1	Ground Shaking (seismic amplitude/intensity)											
2	Closeness to fault											
3	Potential soil instability (Liquefaction / Sliding)											
4	Site factor (soil condition)											

3**. Exposure category** : Rate the importance of exposure sub-factors on scale 1 - 10 . For simplicity you may think how much an building/school/hospital can be potentially exposed to an earthquake threat with respect to following sub-factors.

i	Exposure sub-Factor	weight w_{ie}	1	2	3	4	5	6	7	8	9	10
1	Population exposed											
2	Population per area											
3	Asset/ Value exposed											
4	Area exposed											

4. **Vulnerability category** : Rate the importance of vulnerability sub-factors on scale 1 - 10 :

As an example , consider a risk comparison between group of school buildings (similar function) limited to 3 storey (height) , no major irregularities and architecturally comply with basic safety measures (entrance design , stair case , opening and equipped with primary fire distinguisher).

i	**Vulnerability sub-Factor**	weight w_{iv}	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	Structure type (simple/rigid steel/concrete frame , reinforced/simple masonry											
2	Engineering performance (Construction quality and code conformity : Pre-code/post-code buildings)											
3	Building age (material quality , corrosion , defects)											
4	Hours of operation (8 hr, 12 hr , 24hr)											
5	Users age (kid, adult ,senior)											
6	Population load (density)											

5. **Response capability and disaster management category** : Rate the importance of response management sub-factors on scale 1 - 10 . For simplicity you may consider the pre or post-disaster measures which can reduce the disaster loss and impacts and thus influence the risk.

i	**Exposure sub-Factor**	weight w_{id}	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	Hospital , physicians											
2	Emergency facilities of city: shelter , first aid , blanket,...											
3	Regional Planning , resource and management index											
4	Infrastructure index (access roads /airport)											

6. You may add any other factor you think important in determining seismic risk but has not been addressed in this survey .

Appendix B. Survey Data Processing

B.1 - Fuzzy Aggregation Of Expert Opinions

Experts were asked to provide a value on a scale of 1 to 100 corresponding the linguistic terms of VL (1-20), L (21-40), M (41-6), H (61-80), VH (81-100) for each risk factor. To aggregate different state of impacts, a set of triangular membership functions was assigned to each that is shown in Figure B.1.

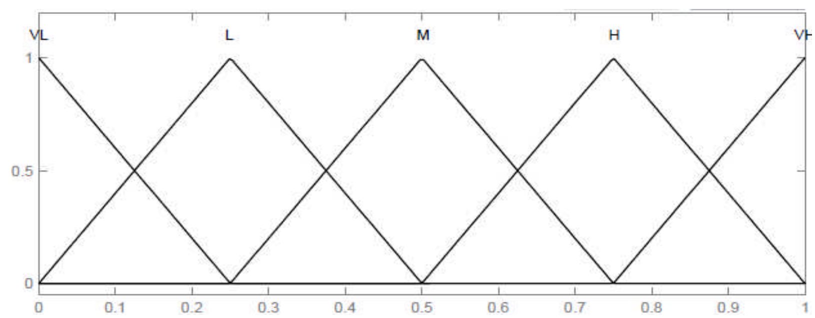


Figure B.1 - Triangular membership functions for different impacts

In order to measure the prevalence impacts within survey data, a frequency distribution algorithm was used. Opinions with higher frequency considered as a higher impact on overall results and consequently received a higher rating factor. The algorithm combines both expert Index (EI) and Impact rating (IR) corresponding with each opinion $\tilde{r}_{ij}$ of each individual expert (i =1, 2, . . . , 48) for a range of risk factors (j =1, 2,....18) formulated as:

$$\tilde{R}_j = \sum_{i=1}^{48} EI_{ij} . IR_{ij} . \tilde{r}_{ij} \qquad \text{(B.1)}$$

The mean non fuzzy values of opinions can be calculated as follows (Chou 2003):

$$R_j = \frac{1}{6} (\tilde{R}_j^l + 4 . \tilde{R}_j^m + \tilde{R}_j^u) \qquad \text{(B.2)}$$

Where *l* , *m* and *u* represents the lower , middle and upper bounds of fuzzy numbers. The sample aggregation process of expert opinions is explained through an example. Considering the opinions collected for hazard factor (H), and frequency, number of impacts (N), the aggregated fuzzy result ($\tilde{R}_1$) can be obtained as follows:

$\tilde{R}_1 = \tilde{r}_{VH}\ .IR_{VH}.(N^{VH}_{EG-1}\ .EI_{EG-1} + N^{VH}_{EG-2}.EI_{EG-2} + N^{VH}_{EG-3}\ .EI_{EG-3}) + \tilde{r}_{VL}\ .IR_{VL}) + \tilde{r}_{H}\ .IR_{H}.\ (N^{H}_{EG-1}\ .EI_{EG-1} + N^{H}_{EG-2}.EI_{EG-2} + N^{H}_{EG-3}\ .EI_{EG-3}) + \tilde{r}_{M}\ .IR_{M}.(N^{M}_{EG-1}\ .EI_{EG-1} + N^{M}_{EG-2}.EI_{EG-2} + N^{M}_{EG-3}\ .EI_{EG-3}) + \tilde{r}_{L}.IR_{L}.\ (N^{L}_{EG-1}\ .EI_{EG-1} + N^{L}_{EG-2}.EI_{EG-2} + N^{L}_{EG-3}\ .EI_{EG-3}) + \tilde{r}_{VL}\ .IR_{VL}.\ (.EI_{EG-1} + N^{VL}_{EG-2}.EI_{EG-2} + N^{VL}_{EG-3}\ .EI_{EG-3}) = (0.75,1,1)\odot(1x0.166 + 12x0.333 + 5x0.5) + (0.5,0.75,1)\odot(5x0.166 + 12x0.333 + 3x0.5) + (0.25,0.5,0.75) \odot (3x0.166 + 1x0.333 + 0x0.5) + (0,0.25,0.5)\odot(3x0.166 + 1x0.333 + 0x0.5) + (0,0,0.25) \odot (2x0.166 + 0x0.333 + 0x0.5) = (36.42,52.03,61.06)$

The equivalent aggregated Nonfuzzy opinion can be calculated using Eq. (B.2):

$R_1 = (36.42 + 4 \times 42.03 + 61.06) / 6 = 50.94$

Alternatively, the process of aggregation is briefly summarized in Table B.1.

Table B.1 - Summary of expert opinion aggregation for hazard block (H)

Impact	Linguistic Values			rating	Frequency			H			Mean Nonfuzzy Value
					EG-1	EG-2	EG-3	Combined Fuzzy Impact			
					0.166	0.333	0.50				
VH	0.75	1.00	1.00	4.00	1	12	5	19.99	26.65	26.65	25.54
H	0.50	0.75	1.00	5.00	5	12	3	15.82	23.72	31.63	23.72
M	0.25	0.50	0.75	3.00	3	1	0	0.623	1.247	1.87	1.25
L	0.00	0.25	0.50	2.00	3	1	0	0	0.416	0.831	0.42
VL	0.00	0.00	0.25	1.00	2	0	0	0	0	0.083	0.01
Aggregated Fuzzy Opinions ($\tilde{R}_H$):								36.42	52.03	61.06	50.94
Total Mean NonFuzzy Opinion values:											50.94

The result derived from the above algorithm represents the individual local weights of risk factors in each block. The global weights of risk factors can be obtained by integrating the global share of each block with local opinions. For example the global weight of the ground shaking factor can be calculated as follows:

$\tilde{w}_{H_{11}} = \tilde{R}_H \odot \tilde{R}_{H_{11}} = (36.42, 52.03 , 61.06) \odot (39.05, 54.53, 60.69) = (1422,2837,3706)$

Accordingly the aggregated Nonfuzzy weight (ANW) can be obtained using fuzzy arithmetic (Hsieh et al 2004):

$$R_j = \frac{1}{3}\left(\tilde{R}_j^u - \tilde{R}_j^l + \tilde{R}_j^m \right) \qquad \text{(B.3)}$$

Using Eq. (B.3), the ANW for H_{11} will be: $w_{H_{11}} = \frac{3706 - 1422 + 2837}{3} = 1701$

Likewise, the other global weights of risk factors can be calculated as shown within Table B.2.

Table B.2 - Summary of aggregated weights of seismic risk data

ID	Criteria	Local weights			Global weights			ANW	Scaled ANW
H	Hazard	36.42	52.03	61.06					
H_{11}	Ground shaking	39.05	54.53	60.69	1422	2837	3706	1707	82
H_{12}	Closeness to fault	37.33	53.61	63.72	1360	2789	3891	1773	85
H_{32}	Potential Instability	35.42	52.11	65.14	1290	2711	3977	1800	86
H_{42}	Soil class	24.73	39.46	53.36	900.6	2053	3258	1470	71
V	Vulnerability	35.01	51.03	62.27					
V_{31}	Building type	42.16	57.85	62.39	1476	2952	3885	1787	86
V_{21}	Engineering Performance	35.59	52.2	65.6	1246	2664	4085	1834	88
V_{22}	Building Age	29.51	45.16	58.82	1033	2305	3662	1645	79
V_{51}	Operation hour	24.6	39.42	53.74	861.3	2012	3346	1499	72
V_{42}	User Age	20.95	34.39	47.46	733.2	1755	2955	1326	64
V_{41}	Occupancy Load	20.1	33.55	47.12	703.8	1712	2934	1314	63
E	Exposure	35.88	52.44	64.68					
E_{11}	Population	41	56.52	61.6	1471	2964	3984	1826	88
E_{12}	Population density	36.67	53.31	65.3	1316	2796	4223	1901	91
E_{21}	Asset/Value exposed	37	54.35	68.55	1327	2850	4433	1985	95
E_{22}	Area Exposed	25.73	41.13	55.53	923.1	2157	3592	1609	77
RM	Response Management	33.5	49.53	61.56					
RM_{11}	Hospital, Physician Index	36.84	52.32	60.36	1234	2591	3715	1691	81
RM_{12}	Emergency facilities	35.63	52.11	64.26	1194	2581	3956	1781	85
RM_{21}	Planning & resource Index	34.05	50.36	63.02	1141	2494	3879	1744	84
RM_{22}	Infrastructure Index	29.76	45.12	57.86	997.2	2235	3561	1600	77

The scaled ANW draw a global picture of criteria's weight. According to ANW values, most hazard factors, building type and performance as well as response management factors exhibit a relatively high strength in general. It can be also noticed that, the population load and density have the most influence on overall risk; while the other socioeconomic factors such as user age, operation hours indicate less importance.

Appendix C. School Inventory Data

#	School ID	Region	City	Sch. Type	Class Room	User Age	Op. Hour	Area (m2)	Cons. Time	Age	Pop.	Oc. Load	Hazard Index	Fault dist.	Sliding	Liqu	Soil Class	Floor
1	BS-AZ1	AZW	Urmieh	H	30	15	12	3635	1976	34	1600	0.44	M	VH	L	M	III	3
2	BS-AZ2		Urmieh	Ex.	11	10	8	2200	1995	16	300	0.136	M	VH	L	M	III	2
3	BS-AZ3		Urmieh	P	15	7	8	1880	1983	17	500	0.266	M	VH	L	M	III	3
4	BS-AZ4		Urmieh	P	11	7	8	824	1970	40	340	0.413	M	VH	L	M	III	2
5	BS-AZ5		Urmieh	M	16	13	12	2176	1972	38	600	0.276	M	VH	L	M	III	3
6	BS-GL1	GOL	Gonbad	Hw	5	18	16	1551	1986	24	150	0.097	H	VL	L	H	III	3
7	BS-GL2		Gonbad	Hw	17	18	16	3110	1994	16	400	0.129	H	VL	L	H	III	3
8	BS-GL3		Aliabad	Hw	10	18	16	800	1986	24	350	0.438	H	M	L	H	III	2
9	BS-GL4		Minudash	M	10	13	12	1962	1988	22	350	0.178	H	H	L	H	III	2
10	BS-GL5		Kordkoy	M	10	13	12	980	1991	19	350	0.357	H	VL	L	H	III	2
11	BS-QM1	QOM	QOM	H	20	18	12	1839	1992	18	475	0.258	H	VL	L	L	III	3
12	BS-QM2		QOM	W	16	18	12	1690	1995	15	430	0.254	H	VL	L	L	III	3
13	BS-QM3		QOM	W	24	18	12	2051	1995	15	600	0.293	H	VL	L	L	III	3
14	BS-QM4		QOM	H	16	18	12	3080	1981	29	400	0.13	H	VL	L	L	III	2
15	BS-KH1	KHS	Gaen	Hw	11	18	16	690	1982	28	420	0.609	VH	VL	L	L	II	1
16	BS-KH2		Birjand	M	10	13	8	810	1983	27	350	0.432	H	VL	L	M	II	1
17	BS-KH3		Birjand	H	11	18	12	1120	1983	27	400	0.357	H	VL	L	M	II	2
18	BS-KH4		Sarayan	H	9	18	12	720	1991	29	300	0.417	VH	VL	L	L	II	1
19	BS-KH5		Sarayan	H	5	18	12	625	1965	45	100	0.16	VH	VL	L	L	II	1
20	BS-HM1	HAM	Nahavan	H	12	18	12	1124	1981	29	150	0.133	VH	VH	L	L	I	2
21	BS-HM2		Tuserka	Hw	10	18	16	910	1985	25	350	0.385	H	VH	L	L	II	2
22	BS-HM3		Malayer	M	10	13	8	1080	1985	25	350	0.324	H	VH	L	L	III	2
23	BS-HM4		Malayer	M	12	13	8	972	1985	25	90	0.093	H	VH	L	L	III	2
24	BS-HM5		Asadabd	H	6	18	12	750	1987	23	250	0.333	H	VH	L	M	II	2
25	BS-HM6		Hamdan	M	11	13	8	1020	1981	29	360	0.353	H	VH	L	M	I	2
26	BS-SM1	SEM	Semnan	H	10	18	12	1020	2000	10	300	0.294	H	M	L	L	III	2
27	BS-SM2		Semnan	H	16	18	12	1255	1998	12	300	0.239	H	M	L	L	III	2
28	BS-SM3		Semnan	H	16	18	12	1915	1995	15	350	0.183	H	M	L	L	III	2
29	BS-SM4		Garmsar	H	14	18	12	980	1992	18	320	0.327	H	M	L	L	III	2
30	BS-SM5		Shahrud	H	16	18	12	1860	1999	11	450	0.242	H	M	L	L	III	3
31	BS-ZN1	ZAN	Zanjan	CI	11	22	16	1875	1993	17	1300	0.693	H	VL	L	M	III	3
32	BS-ZN2		Zanjan	D	6	18	24	600	2001	9	90	0.15	H	VL	L	M	III	1
33	BS-ZN3		Zanjan	M	6	13	8	1045	1981	29	300	0.287	H	VL	L	M	III	2
34	BS-ZN4		Zanjan	Tech	11	18	16	1395	1981	29	300	0.215	H	VL	L	M	III	2
35	BS-ZN5		Zanjan	P	11	7	8	745	1980	30	300	0.403	H	VL	L	M	III	2
36	BS-CS1	QAZ	Caspian	H	14	18	12	1850	1983	27	500	0.27	VH	L	L	L	II	2
37	BS-CS2		Caspian	H	16	18	12	2100	1995	15	500	0.238	VH	L	L	L	II	3
38	BS-CS3		Takstan	D	10	18	24	1052	1995	15	250	0.238	VH	VL	L	M	III	3
39	BS-CS4		Caspian	H	12	18	12	1507	1997	13	300	0.199	VH	L	L	M	III	2
40	BS-MZ1	MAZ	Noor	I	6	25	16	678	1996	14	130	0.192	H	VL	M	H	IV	1
41	BS-MZ2		Amol	P	10	7	8	1192	1981	29	200	0.168	H	L	H	H	IV	2
42	BS-MZ3		Noshar	M	10	13	8	1064	1992	18	100	0.094	H	VL	H	H	IV	2
43	BS-MZ4		Sari	M	6	13	8	350	1981	29	80	0.229	H	VL	H	H	IV	1
44	BS-MZ5		Amol	H	12	18	12	1550	2001	9	350	0.226	H	L	H	H	IV	3
45	BS-LR1	LOR	Brojerd	M	10	13	8	1090	1995	15	300	0.275	VH	L	L	L	II	2
46	BS-LR2		Khorma	P	6	7	8	650	1992	18	200	0.308	H	VL	L	L	II	2
47	BS-LR3		Khorma	H	18	18	12	1780	1998	12	480	0.27	H	VL	L	L	II	2
48	BS-LR4		Koodash	M	11	13	8	1296	1971	39	300	0.231	H	VL	L	L	III	2
49	BS-LR5		Alashtar	H	8	18	12	900	N/A	8	240	0.267	H	VL	L	L	II	2
50	BS-ZH1	SIS	Zahedan	H	20	18	12	2025	1995	15	680	0.336	H	H	L	L	II	3
51	BS-ZH2		Zahedan	H	21	18	12	2063	1995	15	400	0.194	H	H	L	L	II	3
52	BS-ZH3		Zahedan	H	20	18	12	2025	1995	15	680	0.336	H	H	L	L	II	3
53	BS-ZH4		Zahedan	P	17	7	8	2100	1994	16	180	0.086	H	H	L	L	II	3
54	BS-ZH5		Zahedan	P	17	7	8	2200	1995	15	180	0.082	H	H	L	L	II	3
55	BS-ZH6		Zahedan	P	17	7	8	2100	1994	16	180	0.086	H	H	L	L	II	3
56	BS-KH1	KOH	Gachsar	HW	10	18	16	1432	1981	29	215	0.15	H	L	L	L	II	2
57	BS-KH2		Dehdash	M	9	13	8	1221	1969	41	150	0.123	H	L	L	L	II	1
58	BS-KH3		Dehdash	M	11	13	8	1242	1996	14	170	0.137	H	L	L	L	II	2
59	BS-BK1	BKH	Yasuj	M	6	13	8	825	1983	27	120	0.145	VH	VL	L	L	II	2
60	BS-BK2		Faradnb	P	6	7	8	615	1994	16	110	0.179	VH	VL	L	L	II	1
61	BS-IL1	ILM	Ilam	M	6	13	8	300	1975	35	110	0.367	M	VL	L	L	III	1
62	BS-IL2		Ilam	M	16	13	8	680	1981	29	230	0.338	M	VL	L	L	III	1
63	BS-CN1	CEN	Tafresh	M	10	13	8	900	1989	21	220	0.244	H	VH	L	L	III	2
64	BS-CN2		Delijan	M	4	13	8	620	1990	20	90	0.145	H	VH	L	L	III	1
65	BS-CN3		Komijan	P	4	7	8	495	1972	38	100	0.202	M	VH	L	L	III	1
66	BS-CN4		Khondab	P	4	7	8	317	1984	26	80	0.252	M	VH	L	L	III	1

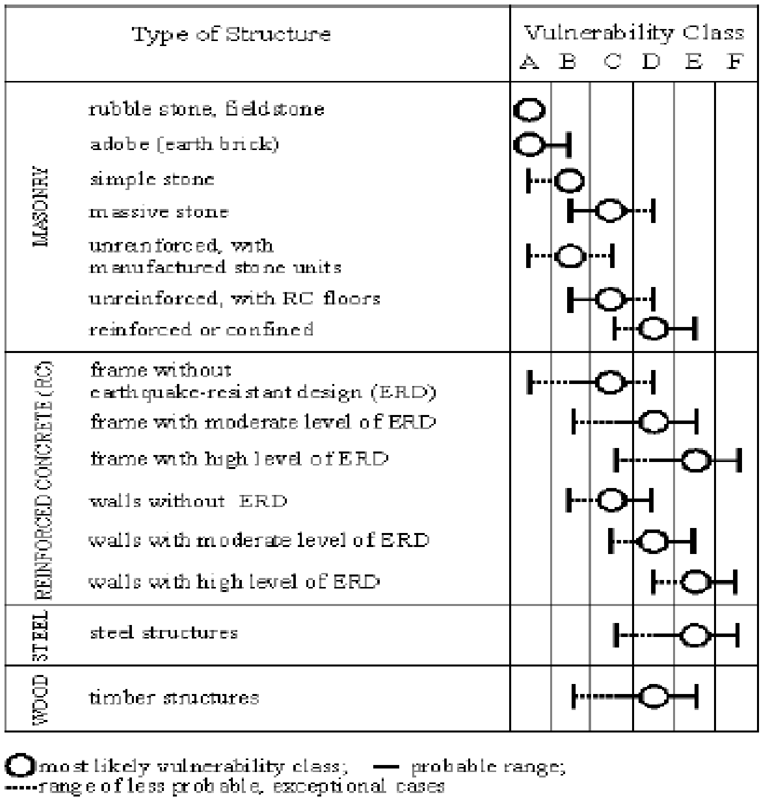
Appendix D. Developing Damage Index Based on EMS-98

D.1 Developing Damage Index

Once the scale of vulnerability has been defined and building typology classes analysed, it is necessary to derive the fragility curve (functions) for each class of building. Fragility functions are smoothed push-over of the damage record in a certain typology for a specific range of seismicity. Alternatively, fragility curve can be presented in a form of damage probability matrix (DPM) to describe the state of damage in each class of building for a given range of earthquake intensity. The DPM matrix can be developed either empirically by correlating the past damage records with corresponding intensity (Yucemen et al 2004; Rossetto and Elnashai 2003) or analytically using a nonlinear (push-over analysis) structural damage thresholds (Park and Ang 1985; Singhal and Kiremidjian 1996). Empirical methods rely on the wealth of observed damage data available from past earthquakes, and the correlation of those with construction materials and types in different geographical and seismic regions (Tesfamariam and Goda, 2013). Analytical approaches require a complex nonlinear structural performance analysis. This kind of approach can be a useful tool for detailed investigation; it, however may not appropriate for analysing large number of school buildings due to expertise, time and cost restriction. In the absence of observational damage database and the lack of standardized fragility curves that specifically defined for building typologies in Iran, standard fragility curves defined in the code of practice was used as a major source for developing the equivalent fuzzy fragility functions. The study applies this concept within the proposed model by simulating the existing DPM data points into equivalent membership functions to infer the damage state within school buildings. Alternatively, damage probability matrixes can be also presented using fragility curves in the graphical form.

In order to develop damage index for different classes of school buildings, EMS-98 damage scale has been adopted. EMS-98 suggests a subjective way for defining the damage state of buildings (Table D.1) which make it coherent to be modelled through fuzzy modelling.

Table D.1 - Classification of vulnerability classes based on EMS 98



EMS-98 defines the vulnerability class of buildings in terms of linguistic terms "Most" (most likely), "Many" (likely/possible) and "few" (unlikely) as shown in Table D.2. Analogous to probability concept, damage state can be obtained by integrating the most probable states of damage for a given intensity. The probability of damage has been commonly estimated through lognormal distributions requiring the mean (A) and standard deviation (B) of damage data set as below:

$P_{total} = \Sigma P[\text{damage} \geq ds|MMI] = P_{D|MMI}\,[d|MMI] =$

$$= \int_0^{MMI} \frac{1}{yB\sqrt{2\pi}} . exp\left[-\frac{1}{2}\left(\frac{\ln(MMI)-A}{B}\right)^2\right] dMMI \qquad \text{(D.1)}$$

Hence, the state of damage can be alternatively expressed by using A and B. This clearly shows the fact that richer data set generates more precise fragility curve. While the data set is itself generated empirically from expert opinion, the precision relies on the wealth of sampling characteristics including size, shape and dispersion.

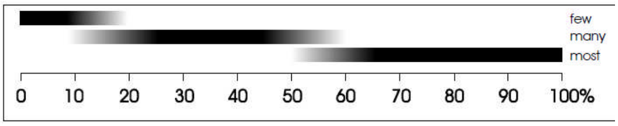
Table D.2 - Vulnerability Class of common buildings based on EMS-98 scale

Building #	Building Class	A	B	C	D	E	F	Damage level Fuzzy Interpretation	MDI*
M1	URM							$0.2(\mu_A) + \mu_B + 0.2(\mu_C)$	7.37
M2	RM							$0.2(\mu_C) + \mu_D + 0.6(\mu_E)$	4.02
C1	FRM + ERD							$0.2(\mu_B) + 0.6(\mu_C) + \mu_D + 0.6(\mu_E)$	4.65
S1	FRM - ERD							$0.2(\mu_A) + 0.6(\mu_B) + \mu_C$	6.79
S2	SBF							$0.2(\mu_C) + 0.6(\mu_D) + \mu_E + 0.6(\mu_F)$	3.15

Most likely : $50\% < P < 100\%$

Possible(many): $10\% < P < 60\%$

Few(Unlikely) : $0 < P < 20\%$



* MDI: Mean Damage Index

Probability scale

Similarly, the damage state can be interpreted in the form of fuzzy set by combining sets of damage membership functions for different building classes. For example mean damage index (MDI) in a common reinforced masonry can be computed by adding the probability of corresponding classes (noted within EMS-98) as following:

$$\mathrm{MDI}_{RM} = \sum_0^{MMI} f(RM) = f^{p=0.2}_{C(RM)} + f^{p=1}_{D(RM)} + f^{p=0.6}_{E(RM)} \equiv 0.2(\mu_C) + \mu_D + 0.6(\mu_E)$$

Where MDIRM is a fuzzy number representing mean damage Index and μ_C, μ_D, μ_E are membership functions for vulnerability classes C, D and E respectively. Alternatively, the fuzzy processing of damage state may be demonstrated graphically by adding the individual fuzzy numbers corresponding the vulnerability classes C to D. Presumably, the vulnerability classes of EMS-98 can be presented on a scale of 1 to 10 through six trapezoidal membership functions shown in Figure D.1.

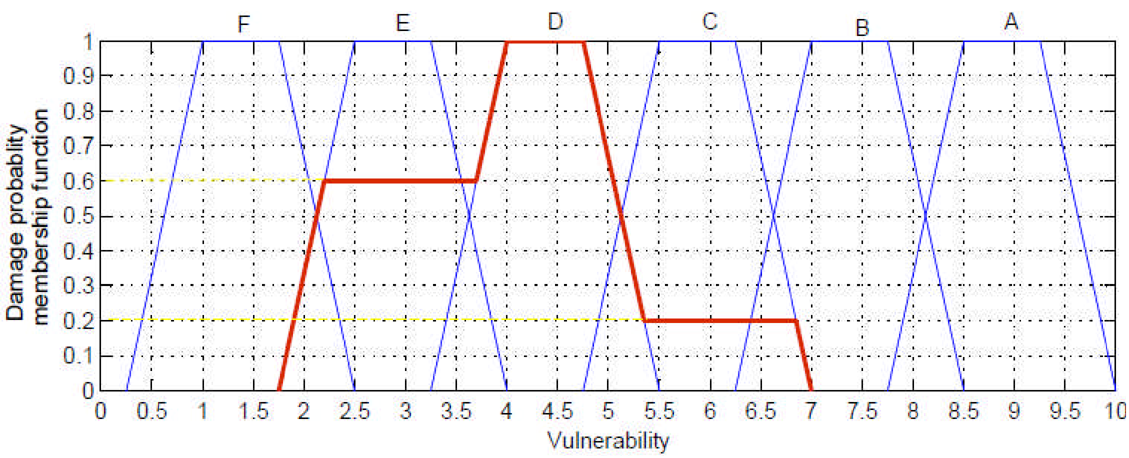


Figure D.1 - Developing Mean Damage Index (MDI) for building type M2 (RM)

Equation (D.1) can be interpreted by using a union aggregating operator:

MDI$_{RM}$ = $f_{c(RM)}^{p=0.2} + f_{D(RM)}^{p=1} + f_{E(RM)}^{p=0.6} \equiv \cup \mu_{RM} = \mu_C^{0.2} \cup \mu_D^{1} \cup \mu_E^{0.6}$

Which is a new aggregated fuzzy number shown in red line. Defuzzifying the fuzzy number using COA (centre of the area), an equivalent crisp value of MDI can be obtained. For precision, the computing process was modelled in MATLAB© as shown in Figure D.2.

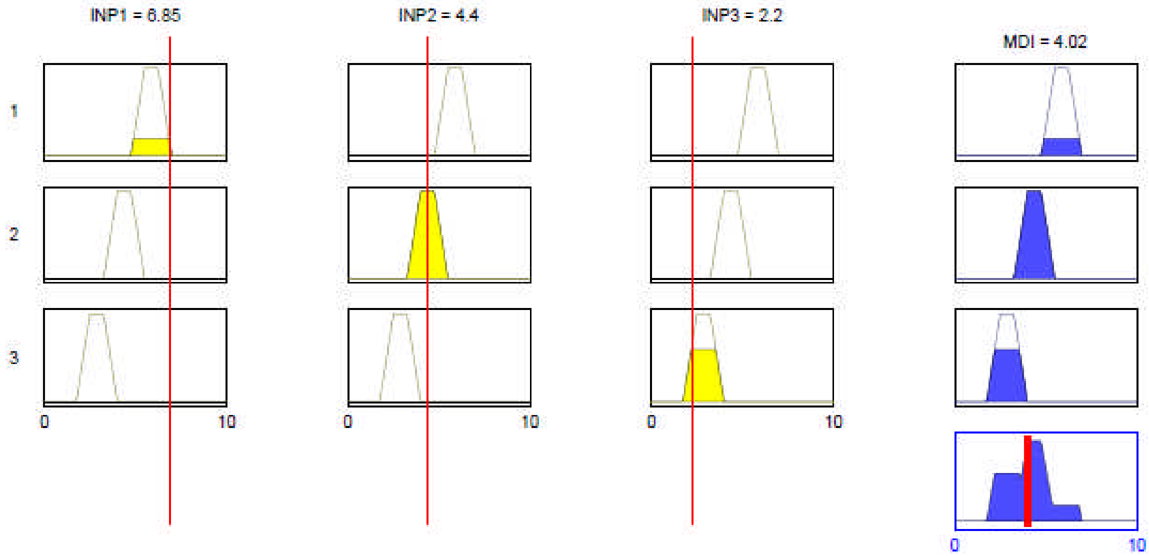


Figure D.2 - MDI aggregation process modelled in MATLAB©

Hence, Mean Damage Index (MDI) for class M2 (RM) would be 4.02. Similarly MDI for other classes of buildings can be obtained.

Appendix E. Appendix E: Scale of measurement in Hazard & Vulnerability

E.1 Seismic Hazard Levels

Seismic hazard levels are closely linked with the earthquake magnitude trends and thus it has a correlation with earthquake occurrence. The extent in which these hazards might influence a facility performance relies on many factors such as earthquake magnitude, distance and direction of fault rupture propagation and site geology (Fajfar and kraw 1997). Considering the full spectrum of potential seismic induced events may occur ranging from small to large magnitude, there is high probability that a site experience low hazards events within life cycle of building and conversely, low probability to occur high hazard events in a long time. In practice, this point allows discretion of potential earthquake events and clustering to certain level of hazards. Thus the seismic hazard levels may represent the range of seismic severity for which a building performance is desired. Consequently, the levels of hazard adopted for this study is shown in Table E.1 which is based on the earthquake magnitude and seismicity defined in local code of practice.

Table E.2 – Seismic hazard levels adopted for the study

Hazard Level	PGA	50 years Probability of Exceedance	MMI	Earthquake Magnitude
Very Low	0.005 - 0.01	50%	**IV-V**	**3.4 - 4**
Low	0.011 - 0.05	25%	**V-VI**	**4.0 - 4.6**
Medium	0.051 - 0.15	20%	**VI-VII**	**4.6 - 5.3**
Substantial	0.151 - 0.30	10%	**VII-VIII**	**5.3 - 5.8**
High	0.301 - 0.50	2%	**VIII-IX**	**5.8 - 7.0**
Very high	> 0.5	1%	**> X**	**> 7**

The PGA and MMI scale jointly address the objective and subjective aspects of seismic hazards.

E.2 Seismic Vulnerability Levels

The concept of vulnerability is multidimensional and often contains tangible and intangible characteristics. The scope of vulnerability directly linked to the research objective and target mitigation programme. The evaluation of the effects of earthquake damage on structures requires the selection of a measurement parameter. Procedures adopted in current study use the anticipated performance of the building during future earthquakes as the measurement parameter. The likely impacts of earthquake damage on basic structural properties control the seismic performance of a building. Thus, the vulnerability scale adopted for this study is based on the potential damages that a building could suffer following an earthquake (Table E.2). This scale is consistent with international standards (FEMA 273; EMS 98; ATC 13) as discussed in Chapter 6.

Table E.2 – Seismic vulnerability levels adopted for the study

Vulnerability linguistic term	Damage State	Damage Scale%	Remark
Very Low	D0- None	0 - 1	Not any damage
Low	D1- light	1 - 10	Negligible damage in non-structural elements – No damage in structural elements
Medium	D2- Moderate	10 - 30	Slight structural damage, moderate non-structural damage
Substantial	D3 - Strong	30 - 60	Considerable damage in structural and heavy non-structural elements
High	D4 - Severe	60 - 80	Severe damage and partial collapse of structural elements – (failure in load carrying systems)
Very High	D5 - Collapse	80 - 100	Destruction