RISK-INFORMED DECISION MODELS FOR LOW-PROBABILITY, HIGH-CONSEQUENCE HAZARDS

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RISK-INFORMED DECISION MODELS FOR LOW-PROBABILITY, HIGH-CONSEQUENCE HAZARDS

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I dedicate this dissertation to my mother and father for their endless support.

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CHAPTER 1

INTRODUCTION

1.1 Motivation

The essential components of risk to civil infrastructure are the probability of occurrence of a potentially damaging event and the consequence of that damage if it occurs. In recent years, the analysis and assessment of risk have become important considerations in rehabilitation of existing structures or in the design of new structures, especially in situations in which the consequences of structural failure are severe in human or economic terms. In first-generation probability-based limit states design codes (e.g., AISC LRFD 1986), the limit state probability (or reliability index) has served as a satisfactory measure of risk. Reliability-based design criteria such as LRFD provide essentially uniform reliability under specified combinations of loads. However, advances in risk-based design and evaluation beyond this initial stage will need to include, in addition to limit state probability, consideration of the consequence of failure [Benjamin and Cornell, 1970; Wen and Kang, 2001; Tversky and Kahneman, 1992; Nathwani, Lind, and Pandey, 2008; Murphy and Gardoni, 2010]. Risk-informed design and decision-making thus should incorporate probability of occurrence and cost and other consequences of failure together over the service life of the facility. Some decision models in the literature that incorporate these ingredients in various degrees include reliability-based design, minimum expected cost analysis (MECA), utility theory (UT), prospect theory (PT), cumulative prospect theory (CPT), life quality index analysis (LQIA), and the capability-based approach (CBA).[1] Each of these models has been advocated as a decision-aiding tool for design or rehabilitation of certain civil infrastructure facilities. While the first three models have been applied, in varying degrees, to practical problems, the remaining four are relatively new and have been applied only in idealized and theoretical academic studies.

The application of such decision models to risk assessment and management of civil infrastructure facilities subjected to low-probability, high-consequence hazards requires a fundamental understanding of the role played by the perceptions of risk by the responsible decision makers and how those perceptions affect choices. Those attitudes govern the decision-maker's willingness to accept or transfer (or socialize) risk, and affect the manner in which he/she evaluates the limit state probability as well as the consequence of the hazardous event. The importance of risk attitude in the decision-making process has been noted in the literature [Keeney and Raiffa, 1976; Quiggin, 1982; Tversky and Kahneman, 1992]. Risk-averse decision-makers tend to overestimate possible losses and limit state probabilities, especially for low-probability events that are outside the realm of their experiences. They may resist choosing a decision alternative which a traditional quantitative risk assessment (e.g. minimum expected cost analysis) suggests is near-optimal, and are likely to pay excessive premiums to reduce the risk, especially when the possibility of personal injury is involved. There is substantial evidence of risk-averse behavior in decision-making, manifested by such phenomena as

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[1] These decision models will be discussed in detail in Section 2.

probability neglect [Sunstein, 2003] and the precautionary principle [Lofstedt, 2003]. Although it seems clear that overestimation of risk and apparently irrational behavior (at least from the stance of classical MECA) tend to increase as the consequences of the event increase or become less certain, the roots of risk aversion and how it affects irrationality in decision processes are not fully understood. Achieving such an understanding is essential for advancing the basis for decisions regarding performance and safety of buildings and other civil infrastructure, which typically involve events with low probability and severe but uncertain consequences and where such risk-averse behavior may play a prominent role.

1.2 Objectives and Scope

The research in this dissertation is aimed at examination of risk-informed decision-making frameworks incorporating risk-attitudes of individuals and group decision makers for situations involving natural low-probability, high-consequence (LPHC) events affecting civil infrastructure. To achieve this objective, the following research tasks are required:

- Critically evaluate the advantages and limitations of risk-informed decision methods proposed recently for addressing risks from LPHC hazards;
- Identify the major factors affecting attitudes of decision-makers toward risks from LPHC hazards in risk assessment and risk-informed decision making;
- Through a set of carefully selected decision problems, investigate the nature of risk attitudes in various decision contexts, as affected by these factors identified;
- Evaluate the role of risk attitudes in decisions regarding civil infrastructure exposed to LPHC hazards.

The research will scrutinize decision models with flexibility to incorporate the risk attitudes through several decision problems to enhance our understandings on the role of risk attitudes in decision making. Each decision problem involves a somewhat different decision context, including structural configuration (including building type, height), loss characteristics (magnitude of possible economic losses or extent of casualties), the decision-maker's role as a public or private entity, resources available to the decision-maker, and societal impact, whether direct or indirect.

1.3 Organization of Dissertation

The remainder of this dissertation consists of five chapters, followed by a list of references.

Chapter 2 reviews the state-of-the art of current research and practice on risk-informed decision making in structural engineering. In Chapter 3, a principal implication on subjective consequence evaluation is introduced using an analysis of risk pricing technique in reinsurance business as an example, and a retrospective methodology for encapsulating a risk attitude from a decision is suggested in the framework of CPT. The insights drawn from this analysis form the basis for the following two chapters in which the nature of risk attitudes in decision making in different contexts is investigated. In Chapter 3, the variation of risk attitude as resources of decision-makers and magnitude of possible losses changes is then investigated with the example of reinsurance underwriting. In Chapter 4, the attitude of a decision-maker toward seismic risks is examined and role of the risk attitude is evaluated with a decision concerning seismic retrofit of a unreinforced masonry building and seismic design of a steel moment frame utilizing characteristics of risk attitudes observed earlier in Chapter 3. In Chapter 5, the risk attitude of a building code committee confronted with risk from hurricane wind hazards is explored, and is compared with attitudes toward seismic risk. Finally, Chapter 6 summarizes the major contributions of this research and suggests future lines of inquiry.

CHAPTER 2

REVIEW OF PREVIOUS WORK

2.1 Decision-making in the presence of uncertainty

Until about 30 years ago, the traditional approach to assessing uncertainties and risk was to identify scenarios that were worst-case (or nearly so) and to apply deterministic factors of safety to the structural actions arising from those scenarios. The approach rested on the idea that absolute safety could be achieved with sufficiently conservative design. Those factors of safety were determined by judgment and experience.

Modern risk assessment methods that have been developed in the past three decades recognize that absolute safety is an illusion, and address uncertainty (measured through event probabilities or annual frequencies) and consequences (direct and/or indirect economic losses, injuries, deaths) quantitatively. The fundamental differences in these methods are most apparent in the way that they model the uncertainty and consequence aspect of risk, particularly consequences that reflect human perception and tolerance of rare, adverse events. These differences will be clarified by the review of the various decision paradigms in this chapter.

2.1.1 Structural Reliability Analysis

Structural failure due to natural or man-made causes is a random event. In other words, the exact path through which a structure reaches various damage states, ranging from local damage to general collapse, cannot be predicted with certainty. Uncertainties are embedded in the mechanical properties of materials, dimensions, loads, and even in the choice of mathematical model used in analyzing a structure [Thoft-Christensen and Baker, 1982; Melchers, 1999]. Taking these uncertainties into account, structural reliability analysis provides a better understanding of the possible behavior of a structure subjected to random demands. Structural reliability is measured by the probability that the structure will not reach a specified limit state during a specified reference period [Thoft-Christensen and Baker, 1982]. The survival probability is evaluated from the probability of failure:

$$\Re = 1 - P_F \tag{2-1}$$

$$P_F = P(R - S \leq 0) \tag{2-2}$$

where R = resistance of the structure and S = load (demand) on the structure, dimensionally consistent with R. The reliability index, which is defined as [Melchers, 1999]

$$\beta = -\Phi^{-1}(P_F) \tag{2-3}$$

is an alternative means for conveying the survival probability.

The reliability index and probability of failure derived from reliability analysis have become relatively mature concepts in the past three decades. These measures of performance can be used directly in problems involving uncertainties to define benchmarks of performance that guide design requirements and decision options. ASCE Standard 7, Minimum Design loads for Buildings and Other Structures [ASCE, 2010], the LRFD Specification for Steel Buildings (2010) and the LRFD Bridge Design Specifications issued by the American Association of State Highway and Transportation Officials (2007) are well-known examples of the successful implementation of reliability principles in practice. The reliability index and probability of failure also may play a role in the other decision models that will be introduced later.

2.1.2 Minimum Expected Cost Analysis (MECA)

One of the first risk assessment models to introduce the role of consequences in decision was the minimum expected cost model [Moses, 1969]. The life-cycle cost for a structure consists of initial cost (C_I), inspection and maintenance cost (C_M) and failure cost (C_F), in which failure cost includes economic losses from loss of life as well as structural and nonstructural damage and repair, and loss of service [Wen and Ang, 1991; Wen and Kang, 2001; Ellingwood and Wen, 2005]. In its simplest form, the expected cost is expressed as:

$$E[C_T] = C_I + C_M + E[C_F] = C_I + C_M + C_F \cdot P_F \tag{2-4}$$

The initial cost and failure probability are functions of the design or decision variables. Generally as the design level increases (or design becomes more conservative), the expected failure cost decreases (due to the decrease in P_F) whereas initial cost increases. The opposite behavior of the expected failure and the initial cost functions yields a concave-shaped total cost function, usually one with a distinct minimum, as shown in Figure 2-1. The fundamental idea of minimum expected cost analysis is to identify this minimum point over the feasible region defined for the decision at hand, which is interpreted as the optimal point of design.

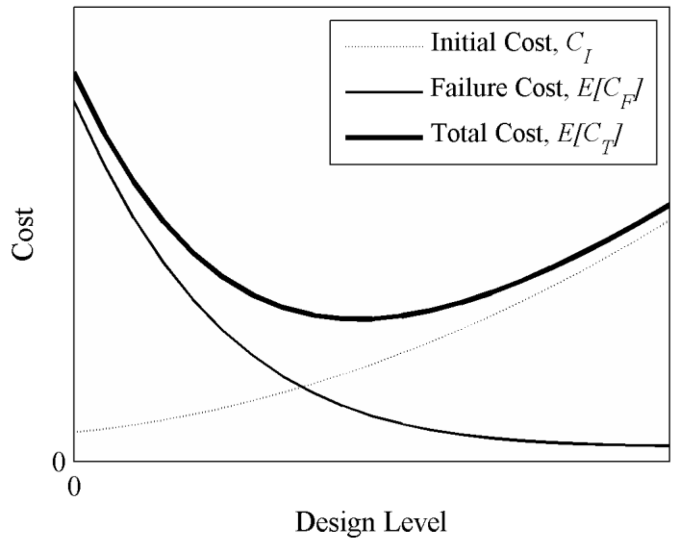

Figure 2-1. Expected life cycle cost and cost components

Extending this idea to periods of service, during which the demand and capacity both may be uncertain time-dependent functions, yields the following form of the expected life-cycle cost for a civil infrastructure facility (Estes and Frangopol, 1999; Ellingwood and Wen, 2005)

$$E(C_T(t,\boldsymbol{Z})) = C_I(\boldsymbol{Z}) + E\left[\sum_i \sum_j C_{F\,j} \cdot e^{-\lambda t_j} \cdot P_{F\,ij}(t_i,\boldsymbol{Z})\right] + \int_0^t C_M(\boldsymbol{Z}) \cdot e^{-\lambda \tau} d\tau \qquad (2\text{-}5)$$

in which t = time period of interest in the decision analysis, $\boldsymbol{Z}$ is a vector of engineering design parameters, i = extreme loading occurrence number, t_i = loading occurrence time, j = limit state number, and λ = discount rate. The analysis of minimum life-cycle cost often requires information on the occurrence rate, intensity and multiple limit states associated with competing hazards, time-dependent structural capacity, discount rate and lifetime of a structure [Frangopol, Lin, and Estes, 1997; Estes and Frangopol, 1999].

The minimum expected cost approach seeks the most cost-efficient way of using resources in the face of uncertainty. A key underlying assumption of the MECA model is that the decision-maker has a risk-neutral attitude[2]. This fundamental assumption has been criticized on several counts [von Neumann and Morgenstern, 1944; Tversky and Kahneman, 1986, 1992]. For one, it does not account for individual attitudes toward risk, which can differ among decision-makers. Studies of risk attitudes in the fields of behavioral economics and cognitive psychology have pointed out that most individuals are not risk-neutral when confronting a hazard or threat. Furthermore, risk attitudes of decision-makers concerned with large projects influencing public safety often are not risk-neutral, and may be based on political as well as purely technical or economic grounds. It is essential that a decision model maintain the flexibility to incorporate these different attitudes toward risk. For another, the minimum expected cost approach requires evaluation of life loss in calculating failure costs; such methods are controversial and are distasteful to some decision-makers. FEMA 228 (1992) summarizes several approaches to this difficult problem, including the human capital approach, the court awards method, the risk-cost method, and willingness-to pay. In the FEMA guidelines for Benefit-Cost Analysis (2009), the social value of a life is estimated at approximately $5,800,000 in 2008 dollars. Although one can deal with this difficult but essential component in cost evaluation, there is no guarantee that an appropriate value will be

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[2] A decision-maker's attitude toward risk can be classified, in general, as risk-seeking, risk-averse, and risk-neutral. To illustrate the difference between these three, suppose that a person has the choice between receiving $100 and a 10 % chance of winning $1000. A risk-seeking person chooses 10% chance of winning $1000 while a risk-averse person chooses the certainty of receiving $100. If a person is a risk-neutral, he/she assesses each option equally and shows no preference between them.

selected, and some decisions are very sensitive to which value is chosen. Such selections are outside the domain of civil engineering and may be difficult to rationalize on technical grounds.

2.1.3 Utility Theory (UT)

The concept of utility was introduced by von Neumann and Morgenstern (1944) in their classic study of games and economic behavior as a means for incorporating a decision-maker's attitude toward risk. In UT, each individual's attitude toward risk can be encapsulated in a utility function. An individual's utility function for a particular decision problem can be chosen through an interrogatory process involving simple preference statements. Suppose that a person is confronted with a decision having two alternatives, a1 and a2. Alternative a1 has certain outcome B, and alternative a2 has outcome A with probability p and outcome C with probability $(1-p)$. The person prefers A to B and B to C. Then, a utility function, $u(.)$, is defined such that the function satisfies the following [Raiffa and Schlaifer, 1961; Pratt, Raiffa, and Schlaiffer, 1965; Benjamin and Cornell, 1970]:

$$u(A) > u(B) > u(C) \tag{2-6}$$

Then, if the decision-maker chooses a1 rather than a2, the utility function is defined such that

$$u(B) > u(A) \cdot p + u(C) \cdot (1 - p) \tag{2-7}$$

The utility function chosen from simple preference tests represents the subjective evaluation of outcomes. The value of the utility function associated with the given outcomes replaces the cost of outcomes in evaluating expected utility and the optimal decision is obtained by maximizing the utility. Most individual decision-makers choose a convex shaped function, which reflects diminishing sensitivity of utility as wealth increases and a risk-averse attitude. In contrast, the utility function for large institutions or governmental agencies, which are self-insured, typically is linear (or nearly so); a linear utility yields exactly same preference and optimal decision point as a minimum cost analysis. A general utility function which representing risk aversion of individual decision-makers is shown in Figure 2-2.

As a normative model[3] of decision, utility theory (UT) is based on two essential assumptions [Arrow, 1982]: invariance and dominance. Invariance implies that the preferences in a decision problem are not affected by the representation of the problem; dominance implies that the option with most favorable outcome in each state should be chosen. As a descriptive[3] model of decision, UT shows some inconsistencies with observed economic behaviors [Kahneman and Tversky, 1979, 1986, 1992] that are too widespread and systematic to be ignored. For example, evidence shows that variations in framing of outcomes of alternatives (e.g. loss or gain) results in different preferences, contrary to the assumption of invariance [Fishburn and Kochenberger, 1979; Hershey and Schoemaker, 1980; McNeil et al., 1982; Tversky and Kahneman, 1986]. In addition, the limitations on the descriptive capability of UT to account for how the decision is affected by the problem representation, distortions in an individual's perception of relative likelihood of extreme events, and people's willingness to accept risk can be considered to be a lack of flexibility of the theory; in turn, this restricts its application. This can be an

[3] A normative model prescribes what rational decision makers should do whereas a descriptive model explains what is observed in decision-making. [Tversky and Kahneman, 1986]

obstacle to dealing with a decision problem including low-probability, high-consequence events appropriately.

2.1.4 Cumulative Prospect Theory (CPT)

Prospect theory (PT) originally was developed by Kahneman and Tversky (1979), based on a series of controlled experiments, to cope with the descriptive inconsistencies observed in UT. (Cumulative Prospect Theory (CPT) is a later modification, as described subsequently.) Prospect theory characterizes the decision process as having two phases: (1) framing and editing, and (2) evaluation [Tversky and Kahneman, 1986; Kahneman and Tversky, 1979].

In the first phase, the decision problem is defined appropriately to reflect the decision maker's preferences. A reference point is chosen; then an outcome higher than that point is considered as a gain and an outcome lower than that point is considered as a loss. An interesting example introduced by Tversky and Kahneman (1986) shows that the preference can be changed as the reference point moves to another point even when the newly framed problem is fundamentally identical to the previous one. Editing processes follow, such as cancelling common factors in each prospect [4] for simplicity and eliminating the dominant prospect. If any single prospect dominates others, it is chosen and no further evaluation is performed.

In the second phase, the value, *V(.)*, of each prospect is calculated in a manner similar to the way in which an expected life-cycle cost or utility is calculated. This

[4] Prospect refers to a lottery [Kahneman and Tversky, 1979]

process involves a summation of the values assigned to each uncertain outcome, multiplied by decision weights. The value function is the counterpart to the cost and utility functions in MECA and UT, respectively. As a function of outcomes, the value function is an S- shaped curve, as shown in Figure 2-1, which is convex above the reference point and concave below the reference point. This convexity and concavity reflects the principle of diminishing sensitivity[5], which was identified in controlled psychological experiments [Kahneman and Tversky, 1979]. The slope of the value function in the loss region is steeper than in the gain region, which reflects loss aversion. The decision weight, $\pi(p)$, is the counterpart of probability in MECA and UT and in fact is a convex function of probability, p. For $p = 0, \pi(0) = 0$ and $p = 1, \pi(1) = 1$, similar to a probability. However, low probability is exaggerated and high probability is underweighted by the assignment of the weights, and the amount of offsets is larger in underweighting than in overweighting. That is, $\pi(p) + \pi(1\text{-}p) < 1$. Using appropriately chosen value and decision weight functions, the value of each prospect is assessed and the one having the highest expected value is chosen. Once the value and decision weighting functions are determined, the mathematics of the solution process is similar to that used for obtaining solutions in MECA or UT.

Cumulative Prospect Theory is a modified version of prospect theory, in which the major difference is in the way that probability is transformed into decision weight. In prospect theory, decision weight is transformed directly from its associated probability, where it can be considered as a function of probability. In CPT, the transformation occurs

[5] In PT and in CPT, to be described shortly, the principle of diminishing sensitivity states that the impact of a change diminishes with the distance from the reference point. [Tversky and Kahneman, 1992]

through a non additive set function, referred to as a "capacity" [Tversky and Kahneman, 1992]. Capacity, w, is a monotonically increasing set function [Choquet, 1954], i.e. $w(\Phi) = 0$ and $w(\Omega) = 1$ and $w(A) \le w(B)$ for all A ⊂ B ⊂ Ω. If there exist n distinct states of nature with the associated probabilities p_1, p_2, through p_n and each of states has positive outcomes, x_1, x_2, through x_n, then, the decision weight for i^th outcome is defined as

$$\pi^+{}_i = w(p_i + \cdots + p_n) - w(p_{i+1} + \cdots + p_n) \quad ; \quad 0 \le i \le (n-1) \tag{2-8}$$

Similarly, for the i^th outcome in m negative outcomes, the decision weight becomes

$$\pi^-{}_i = w(p_{-m} + \cdots + p_i) - w(p_{-m} + \cdots + p_{i-1}) \ ; \ (1-m) \le i \le 0 \tag{2-9}$$

Note that the original formulation included a term p_0, intended to account for probability of zero outcome as a separation of gain and loss.

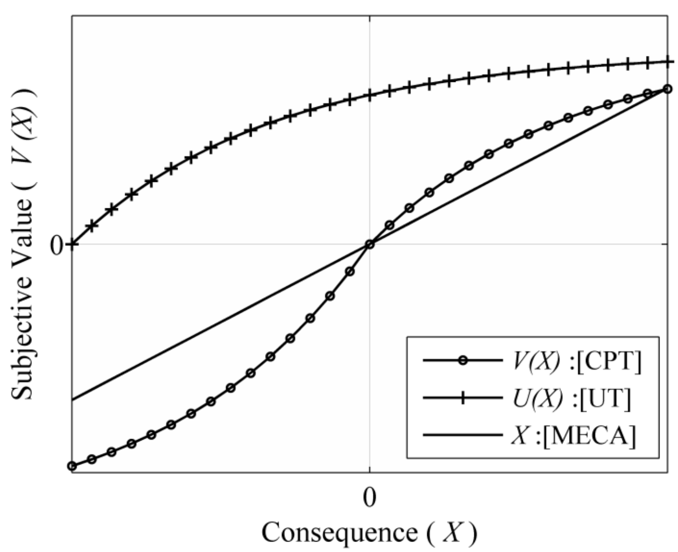

Figure 2-2. Subjective evaluation of consequence

Since function $\pi(p)$ satisfies the axioms of probability, it can be regarded as probability measure or, more precisely, a subjectively weighted probability. A general format of the capacity, *w(p)*, was derived empirically by Tversky and Kahneman (1992) and was later studied theoretically in depth by Prelec (1998). Prelec observed that *w(p)* has four properties[6] - regressive, asymmetric, inverse-s shape, and reflective – each of which explains a different risk attitude. The capacity functions in Eqs. (2-10) and (2-11) describe, respectively, situations involving gain and loss [Prelec, 1998]:

$$w^{+}\left(\sum_{a=k}^{n^{+}} p_a\right) = \exp\left[-\alpha^{+}\cdot\left(-\ln\left(\sum_{a=k}^{n^{+}} p_a\right)\right)^{\varphi^{+}}\right] \tag{2-10}$$

$$w^{-}\left(\sum_{a=1}^{k} p_a\right) = \exp\left[-\alpha^{-}\cdot\left(-\ln\left(\sum_{a=1}^{k} p_a\right)\right)^{\varphi^{-}}\right] \tag{2-11}$$

in which p_a is probability for the rank-ordered and one-sided consequence, and α^-, α^+ and φ^-, φ^+ are shape parameters which govern the convexity of the inverse-s shaped weighting function, as illustrated in Figure 2-3. The probability weighting function determined by parameters, α and φ, are convex with α <1, concave with α >1, inverse-s shape with φ <1, and s-shape with φ >1. If both parameters are equal to 1, the probability weighting function is linear and decision weights are equivalent to the original probabilities. In general, inverse-s and convex *w(p)* indicates risk-aversion, and s-shape and concave *w(p)* indicates risk-acceptance.

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[6] Regressivity refers to w(p) intersecting the diagonal from above; inverse s-shape refers to its convexity on an initial interval and concavity beyond that; asymmetry refers to that the point of the transition from convexity to concavity occurs at about 1/3; reflectivity refers to assigning equal weight to given loss and gain probabilities.

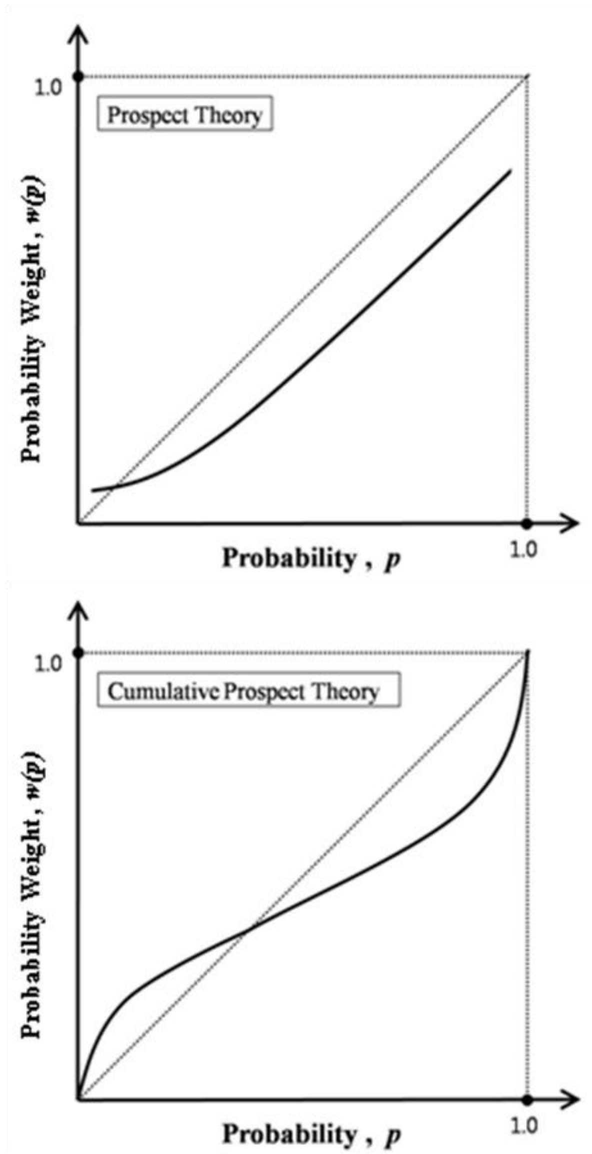

Figure 2-3 Decision Weights of Prospect Theory and Cumulative Prospect Theory

This modified treatment of the decision weights enhances the potential applications of CPT over MECA and UT in several respects. First, the scope of problems to which the theory can be applied extends to include those involving continuous probability distributions, which is essential for the completeness of the theory. Second, irregular behavior of decision weights near the boundaries is refined, which is needed for application of the theory in problems involving LPHC events. Finally, the use of different decision weights for the negative and the positive outcomes generalizes the theory. In fact, it has been suggested [Goda and Hong, 2008a, 2008b] that CPT is a general model that encompasses both UT and PT.

2.1.5 Life Quality Index Analysis (LQIA)

The use of social indicators in place of cost, utility or value functions in decision problems involving risk addresses the controversial question: *How can loss of human life be dealt with?* As one of several compound social indicators, the Life Quality Index was first introduced by Nathwani, Lind and Pandey (1997), and a number of applications of the LQI in decision problems have been published in the past decade. The fundamental concept of risk management using the LQI is similar to that of other decision theories previously introduced. The net benefit to the public should be positive; otherwise the option, which can be a risk-preventing measure or design safety level, is invalid. A positive change in the LQI implies positive net benefit and the option that produces the most positive change in the LQI is chosen.

The LQI is a function of two social indicators - Gross Domestic Product per person and Life Expectancy - which are assumed to provide the foundation for describing enrichment of life (UNDP, 1990). The LQI is defined as follows (Nathwani et al., 1997):

$$L = G^q E^{(1-q)} \tag{2-10}$$

where G = Gross Domestic Product per person , E = Life Expectancy at birth, and q = fraction of time spent in productive work during an average life expectancy per year.

Since changes in the LQI are of particular interest in applications to decision problems, the following measure is useful:

$$\frac{dL}{L} = q \cdot \frac{dG}{G} + (1 - q) \cdot \frac{dE}{E} \tag{2-11}$$

In a decision scenario involving risk-mitigating measures, a negative dG reflects cost for each measure and a positive dE reflects safety earned from the measure. Similarly, in a decision scenario involving increasing risk, positive dG reflects monetary benefits produced from the project and negative dE reflects increased risk. A variety of applications using LQI, including Implied Cost of Averting Fatality (ICAF) and Societal Willingness To Pay (SWTP) have been studied [Rackwitz, 2002; Ditlevsen, 2003; Pandey and Nathewani, 2004]. Such applications can be integrated into a MECA by recognizing that that the ICAF is a number which society should be willing to pay for saving lives according to its ethical principles and which it can afford, i.e. for safety-relevant regulations in cost-benefit calculations [Rackwitz, 2002], or that the ICAF is the money-equivalent of an anonymous person killed in an accident, which should enter the public decision process [Ditlevsen, 2003]. The LQI approach has been applied to a decision problem concerning retrofit of a 50-year old (hypothetical) existing gravity dam by Nathwani, Lind and Pandey (2007).

2.1.6 Capability Based Approach (CBA)

A more recent application of social indicators in risk management is denoted the capability based approach. In this approach, “capabilities” are dimensions of well-being with respect to achievability of specific functionings[7], such as being alive, being healthy, and being sheltered [Sen and Nussbaum, 1989, 1993, 1999a, 1999b, 2001a, 2001b; Murphy and Gardoni, 2007]. Introducing the concept of "capability," Murphy and Gardoni constructed compound indicators such as the Hazard Risk Index (HRI) and Disaster Impact Index (DII) [Murphy and Gardoni, 2010].

$$HRI = \sum_{j} C_j \tag{2-12}$$

$$DII = \frac{1}{n_T} \cdot \left\{ \frac{1}{n} \cdot \sum_{j=1}^{n} II_j^{\,a_j} \right\}^{1/a_j} \tag{2-13}$$

where C_j = the expected value of the indicator for the jth capability over the considered population, II_j = Normalized indicator index for the jth capability over the considered population, n = number of capabilities considered, n_T = population affected, and a_j = discounting factor. The derivation of these indices follows the general procedure as the derivation of the Human Development Index, which is the measure of development of society presented in the Human Development Report of the United Nations (UNDP, 2008). The construction of the DII begins with the identification of the relevant capabilities, selection of the associated indicators, normalization of each indicator and combination of normalized indicators, and finally dividing that combination by the population affected by the hazard. Murphy and Gardoni suggest that these indices can be used as decision criteria by examining the cost efficiency of each risk mitigation measure or by using them to derive thresholds of risk such as acceptable or tolerable risk. These

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[7] Functionings represent parts of the state of a person in particular, the various things that he or she manages to do or be in leading a life. (Sen, 1993).

capability-based indices have not been applied to civil engineering decision problems. However, comprehensive information provided by the capability-based indices can enhance decision of policy-makers to allocate resources to mitigate risk of civil infrastructure from natural and manmade disasters.

2.2 Critical appraisal

The foregoing review of existing decision models suggests that decision-aiding tools for dealing with low-probability, high-consequence hazards should satisfy four criteria: flexibility, practicality, acceptability, and integrity. An approach must be sufficiently flexible that it can accommodate the preferences of decision makers with diverse attitudes toward risk. It must be practical so that a decision can be reached within a reasonable time and with available resources. The decision process should be transparent, acceptable and easily defended, considering the potential consequences of LPHC hazards to the public. Finally, the decision process must be founded on explicit and firm principles (decision integrity) which are unlikely to be misinterpreted or misused and where different decision-makers with the same data and value systems are likely to arrive at the same conclusions. Each of the above-mentioned approaches meets these four criteria to some degree but not perfectly.

2.2.1 Flexibility

The major contributor to flexibility of a decision model is how it encodes a decision-maker's attitudes toward risk. Risk perception of high-consequence hazards is a challenge to model in a reasonable way. As the potential consequence of the hazard increases, the level of risk that people perceive also increases, but not proportionally. If, in addition, the hazards have very low probability, accounting for risk perception becomes more complicated since people tend to overestimate the likelihoods of low probability events. Combining these two extreme cases together leads to some apparently irrational behaviors such as probability neglect [Sunstein, 2003; Stewart, 2008] which, nonetheless must be addressed if the decision model is to be reflective of actual risk attitudes. In other words, dealing with the multiple dimensions of risk perception requires flexibility in risk-attitude; this flexibility is essential when dealing with LPHC hazards.

Whether irrational behavior is taken into account and how it is dealt with in risk assessment under uncertainty is still an open issue in minimum expected cost analysis, utility theory and cumulative prospect theory. Each model has a different method of accounting for irrational behavior by using nonlinear functions to map the subjective evaluations of consequence and likelihood. Issues related to whether and how much irrational behavior should be accounted for in decision problems are central to the criticism of MECA and UT. However; there exists no systematic comparison of the optimal decisions chosen from these models in which levels of irrationality are treated differently.

2.2.2 Practicality

An approach must not be too complex to be used in practice. At one extreme, minimum expected cost analysis is relatively simple, which partially explains why it is most commonly used. In a sense, it is self-contained (assuming that cost is the sole basis for decision), whereas the other decision models require further information as part of the decision process; UT and CPT require subjective information on risk attitudes, and LQIA and CBA require information on social indicators. Flexibility generally is accompanied by complexity, which may be a barrier to practical implementation, particularly by relatively unsophisticated decision-makers. Additional effort is needed to utilize this additional information and the complexity of a method may present a formidable barrier to its practical implementation.

2.2.3 Acceptability

An issue related to acceptability comes from dealing with life loss and injury in the decision model, which often are critical components in risk-informed decision problems. For example, Kang and Wen (2000) optimized building design yield strength (expressed in terms of the ratio of base shear to weight of structure) of 9 story steel moment resisting frames in office buildings located in LA and Charleston and subjected to earthquake and wind using MECA. They found that the inclusion of life loss and injury increased the optimal design yield strength up to by 50%. The value assigned to life loss and injury is obviously important and there is no definitive value for decision-making, even though FEMA Guidelines (2006, 2009) provide some suggestions[8]. Use of UT or CPT may solve the problem to some degree but assigning a utility or value function to life loss and injury also can be controversial. Alternative decision models that are not dependent on the answer to this difficult question would make the problem easier; in large measure, these difficulties motivated the development of the LQI and capability

[8] FEMA Guidelines for Benefit-Cost Analysis (2006) suggested $2,710,000 in 2001 dollars, which was updated to $5,800,000 in 2008 dollars in FEMA Benefit-Cost Analysis Reengineering (2009).

metrics. The LQIA and CBA use objective indicators, such as reduced life expectancy, to reflect life loss and injury as components in the decision process.

2.2.4 Integrity

Finally, a decision model should be founded on explicit, clearly defined and easily understood principles. Such a model is unlikely to be misinterpreted or mis-applied when it is used and would lead to essentially the same optimal solution (risk mitigation strategy) when the analysis is performed by different individuals who have similar value systems and risk preferences and are supported by the same databases. Deficiencies in supporting databases to account for risk attitude affect the integrity of decision models. CPT relies on the value function and probability weighting function to take risk attitude into account in risk assessment. In the initial development of the theory, the functions were based on experiments on hypothetical decision which did not relate to engineering systems nor low-probability, high-consequence event. However, a framework which explicitly addresses how to use these functions to account for diverse risk attitudes has yet to be established. UT has the same drawback. Although general methods for deriving utility functions are well-defined in literature, there exists no framework to connect the utility function to diverse risk attitudes appropriately.

2.3 Closure

This review has identified some of the research issues associated with the use of each decision model in civil engineering decision-making in the presence of LPHC hazards. The following chapters will address some of these issues in further depth, focusing on flexibility and integrity of the decision models in incorporating attitudes of individual and group decision-makers towards risk from LPHC hazards. A framework for investigating the nature of risk attitude is suggested in Chapter 3, which is followed by an examination of the role played by risk attitude in various decision contexts. These studies are aimed at enhancing our understanding of a decision-maker's perception and aversion to risk, and will allow flexible decision models such as UT and CPT to be used in practical risk-mitigation decisions regarding civil infrastructure exposed to LPHC hazards.

CHAPTER 3

RISK ATTITUDES AND THEIR IMPORTANCE IN DECISION-MAKING

As shown in the review in the previous chapter, the importance of a decision-maker's attitude toward risk has been well recognized. Although it has been noted that complete rationality is hard to achieve in decision-making and irrationality in risk assessment tends to intensify for rare events with extreme consequences, the roots of risk perception and how it affects irrationality in decision processes still need to be thoroughly investigated. Civil infrastructure facilities are exposed to rare and catastrophic natural and man-made hazards in nature, and thus achieving such an understanding is fundamental to enhance integrity of decision regarding performance and safety of civil infrastructure.

This chapter explores the nature of risk attitude on the part of decision-makers, focusing on risk aversion embedded in decisions regarding safety of civil infrastructure subjected to low-probability, high-consequence natural hazards such as earthquakes, and hurricanes. We begin with a brief review of indices introduced for measuring risk aversion in utility theory. Because quantitative data pertaining to risk aversion in civil infrastructure decision-making for rare events is unavailable, we next examine how risk aversion has influenced the pricing of risk due to extreme natural hazards in the insurance industry, where the underwriting process has provided experience that is lacking in the context of civil infrastructure. Finally, a methodology of quantitative and retrospective analysis of risk attitude is introduced by utilizing the value function derived from these examinations.

3.1 Value Systems in Reinsurance Practices

3.1.1 Risk Aversion Index

Measuring risk aversion uses the concept of a *risk premium*, a notion that is common to all decision models that reflect risk aversion. The risk premium is defined as the margin between the expected value of a lottery and its certainty equivalent [Keeney and Raiffa, 1976]. A positive sign to the risk premium indicates a risk-averse attitude on the part of the decision maker; furthermore, if his attitude toward the lottery is more risk-averse than the attitude of others, his risk premium is larger than others. The risk premium is a complex function of the initial wealth of the decision maker and the magnitude and uncertainty in the risk, and relatively simple quantitative measures of risk aversion have been introduced in the literature [Pratt, 1964; Menezes and Hanson 1970; Arrow, 1971].

If a utility function for wealth, W, is denoted $u(W)$, the sign of its second derivative, $u''(W)$, determines the behavior of the risk premium with initial wealth and risk magnitude and reflects the decision-maker's attitude towards risk [Arrow, 1971]. By definition, a convex-shaped increasing utility function is characteristic of a risk-averse decision maker; a positive or negative sign of $u''(W)$ implies risk-taking and risk-averse attitudes, respectively. However, the numerical value of $u''(W)$ does not have significance as an absolute measure of risk aversion because multiplying $u(W)$ by a positive constant multiplies $u''(W)$ by the same constant, even when the risk premium is invariant.

Several investigators have suggested that the ratio $u''(W)/u'(W)$ provides an improved measure of risk aversion. Three alternative methods for measuring risk aversion are represented by the following risk aversion indices [Arrow, 1971; Pratt, 1964; Menezes and Hanson 1970]:

$$A(W) = -\frac{\partial^2 u(W)/\partial W^2}{\partial u(W)/\partial W} \tag{3-1}$$

$$R(W) = -W \cdot \frac{\partial^2 u(W)/\partial W^2}{\partial u(W)/\partial W} \tag{3-2}$$

$$P(\lambda; W_0) = -|\lambda| \cdot \frac{\partial^2 u(W_0 + \lambda)/\partial \lambda^2}{\partial u(W_0 + \lambda)/\partial \lambda} \tag{3-3}$$

in which W = wealth, calculated as the sum $W_0 + \lambda$, in which W_0 = initial wealth, and λ = economic consequence (gain or loss). Each risk aversion index has been shown to model the behavior of the risk premium (and thus the behavior of risk aversion) mathematically in different decision contexts [Menezes and Hanson 1970]. Absolute risk aversion, defined by Eq. (3-1), is an appropriate measure when the risk is fixed and the wealth is varied. Relative risk aversion, defined by Eq. (3-2), is relevant when both risk and wealth are varied proportionally. Finally, partial relative risk aversion, defined by Eq. (3-3), appears appropriate when the wealth is fixed and the risk is varied. These functions are defined in such a way that for positive wealth (W) and a possible consequence (λ), a positive value of each function indicates a risk-averse attitude while a negative value indicates a risk-taking attitude. In the present study, we investigate the characteristics of risk aversion when the consequence (λ) changes for a given initial wealth or fixed resources to mitigate risk (W_0), which is the typical stance of a civil engineering decision maker. Thus only the partial relative risk aversion measure (Eq. (3-3)) will be considered in this section.

3.1.2 Analysis of Risk Premium

As noted previously, quantitative information on risk aversion in the context of civil infrastructure decision-making is lacking. To gain further insight into this phenomenon, we turn to the insurance industry. More than any other industry, the insurance industry has developed objective ways of pricing risk [Walker, 2008], making it useful as a starting point to gain insight into the nature of risk aversion. An insurance premium (which is tantamount to the certainty equivalent, defined in decision theory [Keeney and Raiffa, 1976] as the point of indifference between two alternatives, one of which has a deterministic outcome and the other where the outcome is uncertain) is determined from a dynamic financial analysis that considers average annual losses, targeted average annual return on initial capital, probability of insolvency, and business expenses. The insurance premium reflects the willingness of the insurance company to accept the risks that are being underwritten or, in other words, how risk-averse the insurance company is in underwriting risks from damages due to natural hazards and other catastrophic events. Thus, the nature of risk-aversion (at least as it is viewed by a relatively large corporate entity) can be inferred from the process by which an insurance premium is determined. In turn, this can be utilized to inform the development of possible value systems for other large civil infrastructure-related decisions.

Our examination of mathematical models of risk aversion in insurance underwriting practices is conducted in four phases: generation of loss data, determination of risk premium, derivation of general partial relative risk aversion functions, and implication for the choice of value/utility functions. Losses have been generated based on a study by Walker (2003) of data from a Swiss Re report (2002). This report tabulates the most costly individual insurance losses from 1970 to 2002. These losses have been used to derive the probability plot of individual losses shown in Figure 3-1, which indicates that instances of losses exceeding \$200 million average approximately 14 per year.

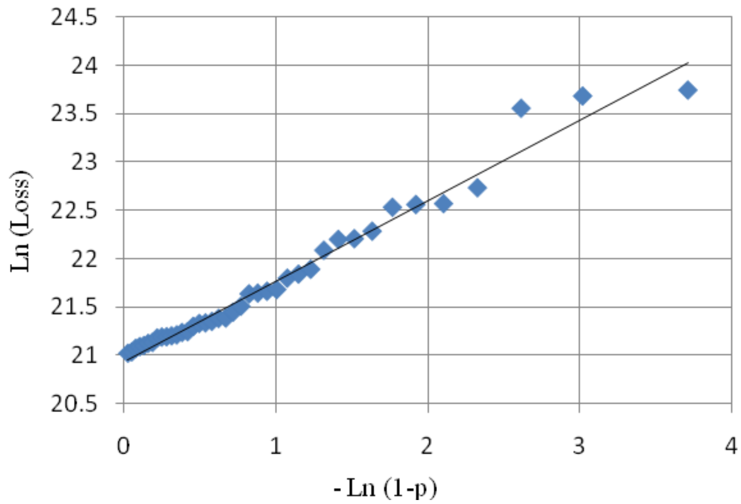

Figure 3-1 Probability plot of largest natural catastrophe insured losses 1970 - 2002

The occurrence of such losses (event losses) each year is simulated from the cumulative distribution function of individual losses derived above, noting that the number of losses in a given period can be modeled as a Poisson process with a mean occurrence rate equal to 14/yr. Individual losses for each year then have been used to estimate annual losses with 40 different maximum loss levels to investigate the effect of size of possible loss on risk aversion. The simulation has been performed over a period of 10 years using 10,000 replications. The determination of the risk premium also requires the investors' expectation of return on investment, which depends on the annual rate of return and the probability of insolvency [Kaufmann et al., 2001]. In this example, it is assumed that the expectation of the investors is that the maximum probability of loss of investment over 10 years is 10%. The average return on investment of funds is assumed to be 5%, while business expenses, including taxes, as a proportion of premium income are assumed to be 30% [Walker, 2003].

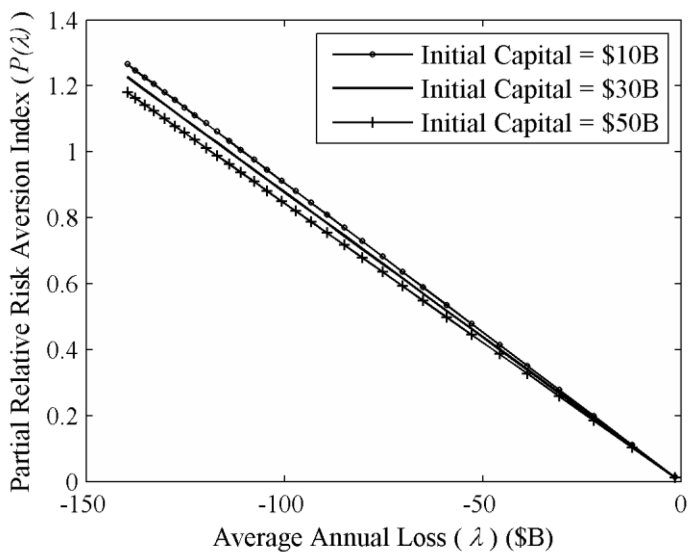

Figure 3-2. Risk aversion embedded in insurance industry premium decisions

The minimum insurance premium required to meet the stipulated maximum probability of loss of investment over 10 years has been calculated for initial capital amounts varying from $1 to $50 billion. If this minimum insurance premium is assumed to equal the certainty equivalent, it represents the expected change in value/utility corresponding to the expected annual loss. The partial relative risk aversion function for the annual loss then can be determined using Eq. (3-3). Figure 3-2 shows partial relative risk aversion functions for the annual losses when the initial capital equals $10, 20, 30, 40, and 50 billion, suggesting that corporate risk aversion tends to increase almost linearly as the average annual loss increases, regardless of the amount of the initial capital. Aversion to a specific high-consequence risk is slightly larger when the initial capital is small than when it is large, which implies that levels of risk aversion of entities with different resources, when confronting a specific catastrophic risk to civil infrastructure, might differ. However, the difference does not appear to be sufficient to affect decision preferences in this particular example, possibly because it considers on decision-making of a large corporate entity which is assumed to take near risk-neutral attitude.

3.1.3 Implications for Value Function

A value function for loss, V^-, which is consistent with Figure 3-2, is:

$$V^-(\lambda;W_0) = -a \cdot e^{-b\cdot(\lambda + C(W_0))} \tag{3-4}$$

in which $a > 0$ and $b > 0$ are constants and $C(W_0)$ depends upon the initial capital. Note that negative values of λ correspond to loss. The value of b represents how rapidly a decision maker becomes risk-averse with respect to the consequences; in other words, b corresponds to the slope of the partial relative risk aversion function in Figure 3-2. For this reason, b will be termed as the *risk sensitivity* factor in the following discussion. If b is large (small), then the value function represents a decision maker whose risk aversion is sensitive (insensitive) to a change in the risk consequence. Practical limits on b, however, depend on the resources of the decision-maker. In the present analysis, b was found to range from 0.046 (for W_0 = \$50 billion) to 0.051 (for W_0 = \$1 billion) when a is fixed. For the analysis performed in the following section, a will be held constant because the numerical value of a does not affect the preference ordering nor optimality in general. The value of b, however, will be varied from 0.01 to 1.0 to model risk perspectives that may be broader than those represented by the insurance industry.

3.2 Methodology for Quantifying Risk Attitude

3.2.1 Normalized Value Function

This section examines the risk attitude on which a specific decision rests and the severity of each risk attitude. The quantitative approach is based on a normalized value function which is inferred from the value system in section 3.1.

We begin by normalizing the value function suggested from the examination of reinsurance underwriting practices to eliminate effect of differences between size of possible consequences faced in reinsurance underwriting and in practical structural engineering decisions. In this section, all decision problems are framed to have only losses and a normalized exponential value/utility function for one-sided consequences as shown in Eq. (3-5) is adopted [Stewart et al., 2010]:.

$$V(x) = \frac{1}{1-e^{-\gamma}}\left(1-e^{-\gamma\left(\frac{x_{\max}-x}{x_{\max}}\right)}\right), \quad \gamma \geq 0, \quad x \geq 0 \tag{3-5}$$

in which x = loss, and γ = risk aversion parameter (assumed constant in this illustration), which reflects the degree of risk aversion (cf. Figure 2-2). Eq. (3-5) is consistent with the increasing trend of risk sensitivity factor with consequences (cf. Figure 3-2) and is dimensionless, which gives it flexibility for applications to other decision problems. In Eq. (3-5), γ is the only parameter that represents risk aversion; a positive value of γ indicates a risk-averse attitude while a negative value indicates a risk-taking attitude. The absolute value of γ represents the severity of each risk attitude.

3.2.2 Qualitative analysis of risk attitude

Each decision is categorized in the framework of CPT by the normalized value function and probability weighting function. We consider two different decision contexts, the first involving two alternatives and the second involving three or more alternatives.

Two Alternatives

If a decision involves two alternatives, a_1 and a_2, the risk attitude of the individual or group responsible for that decision can be identified by the following approach. Suppose that a_2 is safer or more conservative than a_1. Sets of possible outcomes for a_1 and a_2 are (C_{11}, C_{12}, … , C_{1m}) and (C_{21}, C_{22}, … , C_{2n}), respectively, where m and n are the total number of possible outcomes for a_1 and a_2. Then, four possible combinations of chosen options and optimal options based on MECA are possible.

(1) a_1 is optimum and a_1 is chosen.

(2) a_1 is optimum; however a_2 is chosen.

(3) a_2 is optimum; however a_1 is chosen.

(4) a_2 is optimum and a_2 is chosen.

If a_2 is chosen [Cases (2) and (4)], it is possible that the decision might have been affected by a risk-averse stance on the part of the decision maker. Conversely, if a_1 is chosen [Cases (1) and (3)], the decision maker might have adopted a risk-accepting stance. In other words, choosing a_2 is a necessary condition for a decision to reflect risk-averse behavior on the part of a decision maker, while choosing a_1 is a necessary condition for a risk-accepting decision. If a decision is categorized by case (2), the effect of risk-aversion clearly is reflected in the decision because a_2 is chosen, even though the additional safety realized by a_2 is not sufficient to compensate for the additional cost associated with a_1. However, a decision categorized by case (4) generally does not provide as much knowledge about risk attitude as the one in case (2). It only implies that a risk-accepting attitude did not affect the decision. A decision categorized by case (3) indicates that the decision maker is risk-accepting because a_1 is chosen even though a_2 provides additional safety at reasonable additional cost. Decisions categorized by Case (1) do not yield any more information than that risk-aversion did not affect the decision.

Three or more Alternatives

The general conclusions above can be extended to decision problems with three or more alternatives. Assume that a decision problem has alternatives, a_1, a_2… a_k, in which the alternatives are rank-ordered in increasing levels of safety. Let a_i and a_j represent the chosen alternative and the optimal alternative based on MECA, respectively. If $a_i \neq a_j$, either a risk-averse or risk-accepting attitude is indicated for the decision. Specifically, if a_i is a safer alternative than a_j (or, $i > j$), a decision is a resultant of risk-averse attitude of a decision entity while if a_i is a less safe alternative than a_j (or, $i < j$), the decision implies a risk-accepting attitude of the decision entity.

3.2.3 Quantitative analysis of risk attitude

For a decision with known preferences, the risk attitude now can be evaluated in terms of severity of risk attitude reflected in the decision. The evaluation requires a consequence-based decision model with flexibility of accounting for risk attitude in risk assessment. Attitude toward risk affects evaluation of consequence and probability in risk assessment. To account for both influences, the suggested quantification methodology is based on CPT.

Risk Attitude reflected in Value System

First, the investigation of level of risk-aversion or risk-acceptance is performed on the assumption that only subjective value system is sufficient to accommodate risk attitude; utility theory is formulated similarly. Utilizing the normalized value function introduced in 3.4.1, the level of risk attitude is represented by the value of risk-aversion parameter, γ. To study a decision reflecting the risk-averse attitude of a decision entity, a value function with a positive γ allows the chosen alternative to be the optimum based on expected value (or utility).

Considering the two-alternative decision problem identified as risk-averse (Case (2)) introduced in 3.2.1, the expected value of the chosen alternative ($E[V_2]$) becomes larger than the expected value of the original optimal alternative ($E[V_1]$) as values of positive γ exceeds a threshold. The value of that threshold represents how risk-averse the decision is and the value is denoted as the tipping point $\gamma_{tipping}$. Similarly, for a risk-accepting decision (Case (3)), the expected value of the chosen alternative ($E[V_1]$) becomes larger than the expected value of the original optimal alternative ($E[V_2]$) for values of negative γ below a threshold. Then, the value of tipping point $\gamma_{tipping}$ implies how risk-accepting the decision is. A similar approach is used for decisions with a larger pool of alternatives; in other words, the value of γ is increased/decreased until the chosen alternative becomes the optimum based on highest expected value.

Risk Attitude Reflected in Probability Weighting System

Next, the role of probability weighting system in reflecting risk attitude is recognized by decomposing the portions of risk attitude into value and weighting systems. Consideration of this additional source of reflecting risk attitude allows us to have sets of value and weighting systems which represent a risk attitude reflected in a decision problem while a unique tipping point $\gamma_{tipping}$ is obtained only when risk attitude is reflected in the value system. An example of sets of value and weighting systems are shown in Figures 3-3 (a) and (b), in which use of ($V_i(X)$, $w_i(p)$) will result in the same decision analyzed. Each curve in Figures 3-3 represents five pairs of value and probability weighting functions obtained from the above approach. Each value function (from the most to least convex) is paired with a probability weighting function (from the most to the least linear). The first pair (V_1 and w_1) in Figures 3-3(a) and 3-3(b) corresponds to utility theory-based decisions in that probability is not weighted. The amount of risk aversion reflected in the probability weighting function increases as the value function becomes less and less convex. Finally, in the fifth pair (V_5 and w_5), all the risk aversion is reflected in the probability weighting function.

For a risk-averse decision, an inverse-s shaped probability weighting function (or capacity function) is adopted to represent severity of overestimation of low-probability of high consequence event. Risk-aversion parameter φ, which characterizes an inverse-s shape of the probability weighting function, represents how severely the low-probability region is overestimated. The sets of pairs of risk-aversion parameters $(\gamma, \varphi)_{tipping}$ are then denoted as *risk-equivalent (or risk-averse equivalent)* in that use of each pair results in same preference ordering (and thus same optimum). A similar approach to develop *risk-equivalent* is adopted for a risk-accepting decision except that a concave probability weighting function is adopted to represent underestimation of the low-probability region. Using risk-accepting parameter α, which characterizes a concave shape of probability weighting function, *risk-equivalent* is determined. Search process of risk-equivalent is performed by changing risk parameter φ (or α) and determining the value of γ corresponding to each φ (or α).

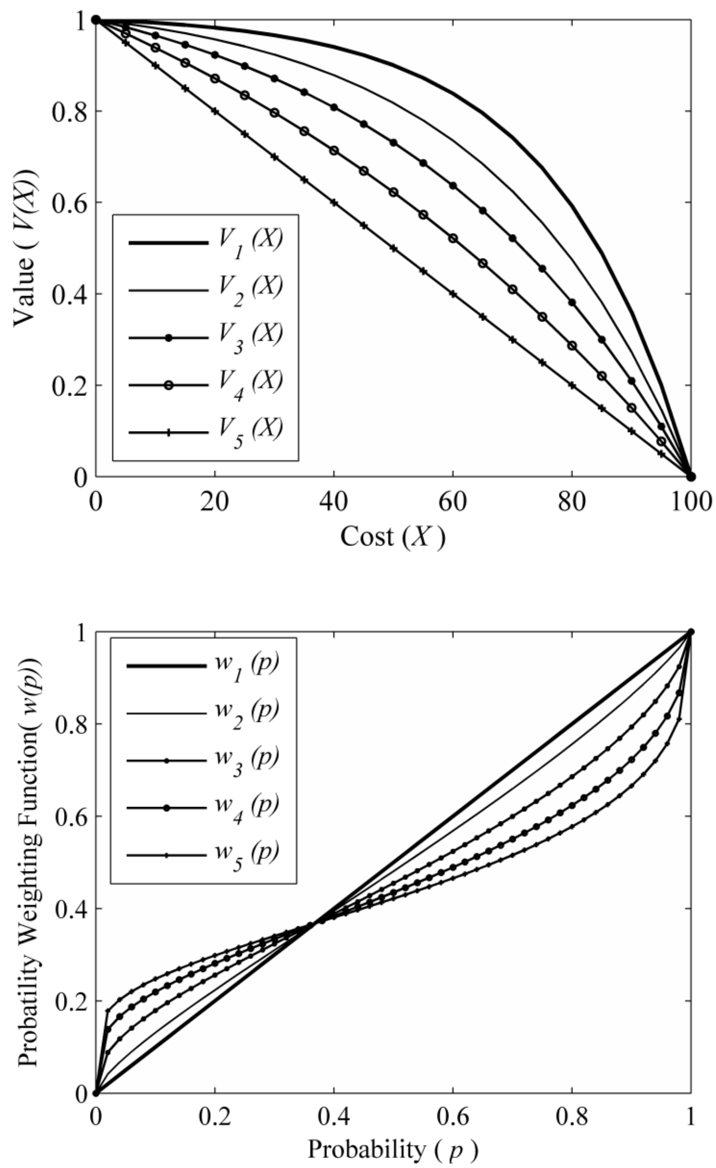

Figure 3-3. Illustration of equivalent (in terms of total risk aversion) pairs of (a) value and (b) probability weighting functions

3.3 Risk Aversion Embedded in Insurance Rate-Setting

The advantages of CPT in modeling risk aversion come at the expense of requiring more descriptive information about the decision-maker's preferences – not only the relation between value and monetary cost but also his/her perceptions of the likelihood of events. Such information may be difficult to acquire for decisions regarding safety of buildings, bridges and civil infrastructure exposed to rare natural or man-made hazards. To better understand the nature of risk aversion from another context where it has been recognized and informs decision-making, a risk pricing methodology used in the insurance industry, which was introduced in section 3.1, was revisited and investigated in depth by utilizing the retrospective methodology proposed in section 3.2. In the current section, we examine how risk-aversion of a corporate entity changes with size of resources and/or size of risk (in terms of maximum possible consequences) by analyzing insurance premiums considered in section 3.1.

An insurance premium reflects aversion of risk on the part of the insurance company's management and the stockholders toward potential business failures, including insolvency or non-profitability. The source of such risk is the uncertainty in the consequence of future hazardous events which are covered by the insurance policy. The phenomenon of risk-aversion of a re-insurer can be studied by analyzing the required premium income for the company that underwrites the re-insurance. Each of the required insurance premiums obtained from dynamic financial analysis in section 3.1 represents a judgment associated with a specific decision context consisting of the size of the anticipated consequences and the company's state of wealth. Thus, analysis of these insurance premiums explains, in large measure, the relation between risk attitude and the considered decision context.

3.3.1 Modeling Decision of Reinsurer

Analyzing the nature of risk aversion through the process of pricing an insurance premium begins with a consideration of the following two decisions:

(1) If the insurance premium (p) ≥ minimum insurance premium (p_{min}), underwriting is preferable.

(2) If $p < p_{min}$, declining to underwrite is preferable.

Each decision consists of two alternatives, underwriting (less safe option between the two, denoted as a_1, as in section 3.4) and declining to underwrite (safer option between the two, denoted as a_2). If a_1 is chosen and the optimum is based on MECA, further information on risk attitude is not provided, other than that the decision is not affected by a risk-accepting attitude. Conversely, if a_2 is chosen while a_1 is optimum based on MECA, the safer option is selected despite the fact that it is not cost-efficient, and the decision, by definitione, is risk-averse. Thus, this decision provides fundamental insight into the attitude toward risk on which the insurance premium decision rests.

The risk-aversion parameter, γ, leading to the optimal decision by the reinsurer is determined for each pair of initial capital and maximum loss limit and the corresponding insurance premium is determined by dynamic financial analysis, as described in section 3.1. The search for the parameter is performed by the following steps:

- For a value of insurance premium $p < p_{min}$, change/increase the value of risk-aversion parameter, γ, from 0 incrementally to allow the effect of risk-aversion in the decision to be considered.
- Find the tipping point of γ, the point at which "declining to underwrite" becomes preferable to "underwriting" based on the maximum expected utility.

Alternatively, the search can be performed by using $p = p_{min}$ as follows:

- For a value of insurance premium $p = p_{min}$, change/decrease the value of risk-aversion parameter, γ, incrementally from a reasonable maximum to approach the tipping point from above.
- Find the tipping point of γ, the point at which "underwriting" becomes preferable to "declining to underwrite" based on the maximum expected utility.

The two approaches should yield estimates of the tipping point $\gamma_{tipping}$ in a close range if feasible values of insurance premium are discretized, which was done for computational efficiency in this study. The estimate given by the first approach represents the lower bound of $\gamma_{tipping}$ while the estimate given by the second approach represents the upper bound of $\gamma_{tipping}$ which satisfies the condition that "declining to underwrite" is preferred to "underwriting" for $p < p_{min}$. Since the upper bound provides a closer estimate of γ on the conservative side, it is used to establish the trends of risk-aversion in various decision contexts (combination of initial capital and maximum loss limit).

As noted in chapter 2, cumulative prospect theory embodies a decision-maker's risk aversion in the functions describing both consequence and probability of the anticipated risk. To allow the effect of the probability weighting system to be reflected in the decision, the search for risk parameter γ, which represents the subjective evaluation of the consequences of underwriting the insurance policy, is extended to a search of risk parameters representing a subjective evaluation of probability as well as consequence. While the degree of risk aversion that is reflected in both value function and probability weights is required to fully assess the role of risk aversion in decision-making, a lack of data at present precludes disaggregating the degree of risk aversion into these components. Accordingly, a set of discrete pairs of value and probability-weighting components was evaluated to provide possible disaggregated solutions that describe the degree of risk-aversion. Since risk-aversion is implied for this decision, an inverse-s shaped probability weighting function was adopted, so that risk parameter φ (cf. Eqs. (2-10) and (2-11)) is the only parameter required to convey information on the overestimation of event probabilities in the low-probability region. The disaggregation analysis is performed for each pair of initial capital and maximum loss limit, repeating the search process introduced in the previous section. The following steps were taken:

- Fix the value of φ equal to 1.
- For a value of insurance premium $p = p_{min}$, change/decrease the value of risk-aversion parameter, γ, incrementally from a reasonable maximum to approach the tipping point from above.
- Find the tipping point of γ, the point at which "underwriting" becomes preferable to "declining to underwrite" based on the maximum value principle.
- Change/decrease φ incrementally and repeat the process until $\gamma_{tipping}$ reaches 0, since that value corresponds to the point where risk aversion is no longer reflected in the value function.

The pairs $(\gamma, \varphi)_{tipping}$ obtained in this analysis characterize the risk-aversion to underwriting of an reinsurance company with a certain amount of initial capital and maximum loss limit.

3.3.2 Risk-Aversion Reflected in Reinsurer's Insurance Premium Income

Risk-Aversion Represented by Value Risk Aversion Parameter (γ)

How the preference of a reinsurer for not underwriting (with insurance premium, $p = p_{min}$) changes to a preference for underwriting is shown in Figure 3-4 as risk parameter γ decreases. Figures 3-5 and 3-6 show $\gamma_{tipping}$ as the initial capital and the maximum event loss limit change. As the initial capital of the company increases, $\gamma_{tipping}$ decreases significantly. The decreasing trend of $\gamma_{tipping}$ represents decreasing risk aversion, which agrees with the results in section 3.1. It is also found that above and beyond a certain value of initial capital, $\gamma_{tipping}$ becomes zero, which represents a risk-neutral attitude in risk pricing. The point at which $\gamma_{tipping}$ becomes zero is found to increase as the maximum loss limit increases: \$29B, \$35B, and \$38B for maximum loss limit equal to \$3B, \$4B, and \$5B, respectively. As the maximum loss limit increases, γ_{LB} increases as well. If the initial capital is very small, $\gamma_{tipping}$ is found to be relatively higher than in other cases, as noted from Figure 3-6, but the increasing trend, representing increasing risk aversion, does not appear to be significant. The fact that $\gamma_{tipping}$ is virtually constant suggests that risk aversion tends to be constant if the relative consequence of the risk to initial wealth of a decision maker is high. However, for a very large initial capital, $\gamma_{tipping}$ is found to equal zero, regardless of the size of expected loss, as indicated from Figure 3-5, representing risk neutrality of a decision maker.

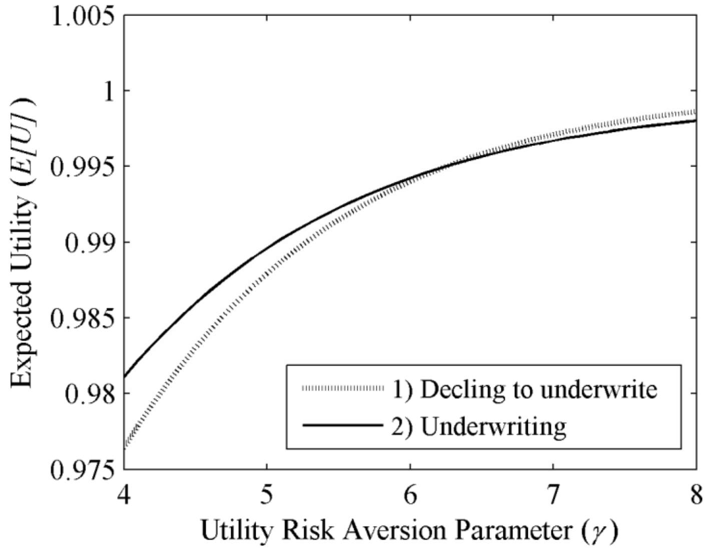

Figure 3-4. Expected utility for (1) Declining to underwrite and (2) Underwriting as risk aversion increases (as γ decreases) when (initial capital, maximum loss limit) = $B(20, 5)

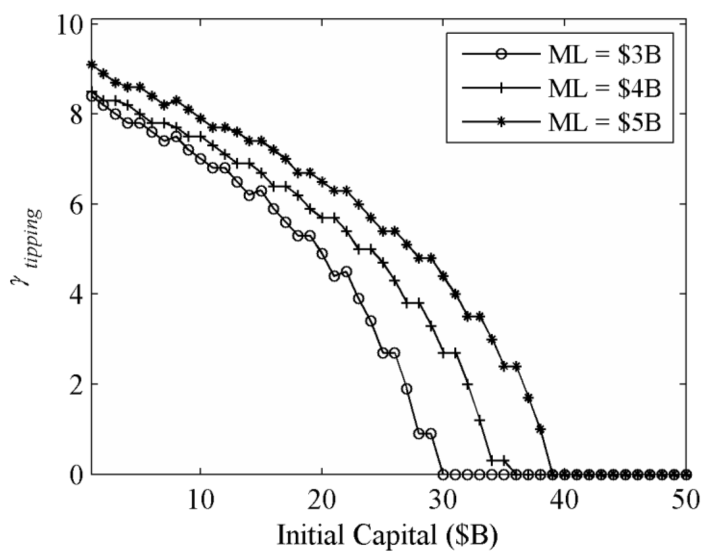

Figure 3-5. Risk aversion embedded in insurance industry premium decisions (in terms of risk aversion parameter, $\gamma_{tipping}$) as initial capital changes

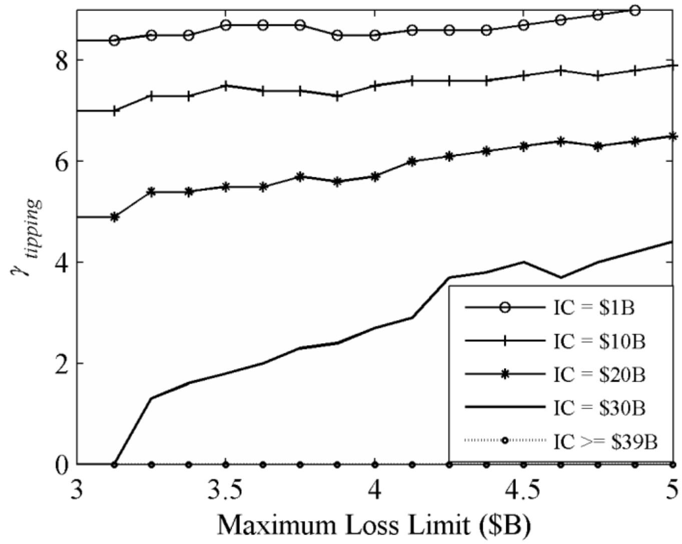

Figure 3-6. Risk aversion embedded in insurance industry premium decisions (in terms of risk aversion parameter, $\gamma_{tipping}$) as maximum loss limit changes

<u>Risk-Aversion Represented by Risk-Averse Equivalent Pairs</u>

Figure 3-7 shows the $(\varphi, \gamma)_{tipping}$ pairs obtained for (Initial capital, Maximum loss limit) = $B (1, 5), (1, 3), (20, 5), (20, 3), and (38, 5). Since $(\varphi, \gamma)_{tipping}$ forms a line and each pair equivalently leads to the same insurance premium decision, we denote this line the *equivalent preference line*. The value of $\gamma_{tipping}$ at $\varphi = 1$, represents the case when risk aversion is reflected solely in the value function and corresponds to the value of $\gamma_{tipping}$ determined in the previous section. As φ decreases from 1, the convexity of the probability weighting function in the low-probability region increases, which represents a more risk-averse attitude. Thus as φ becomes smaller, the corresponding $\gamma_{tipping}$ becomes smaller as well. In other words, as additional risk aversion is reflected in the probability weighting function, the portion of risk aversion reflected in the value function becomes smaller. Note that φ decreases (and thus risk aversion increases) as the initial capital decreases and as the maximum loss limit increases at any assumed value of $\gamma_{tipping}$, a result similar to that noted previously. Moreover, the use of each point on the equivalent preference line yields the minimum required insurance premium. Finally, when the initial capital is lower and maximum loss limit is higher, the risk aversion parameters cover a broader range.

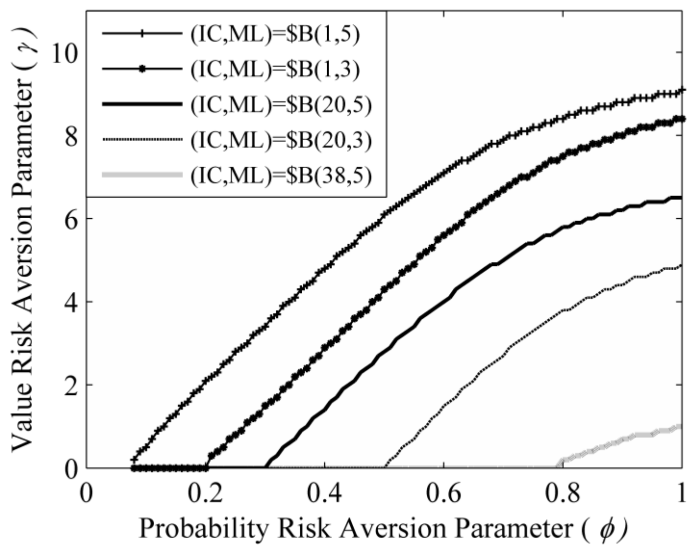

Figure 3-7. Risk aversion embedded in insurance industry premium decisions represented by sets of risk aversion parameters, $(\varphi, \gamma)_{tipping}$

3.4 Closure

The nature of a decision-maker's attitude toward risk was examined in terms of a quantitative risk aversion index by analyzing risk-pricing practices in reinsurance. As a first effort to understand the nature of risk aversion and to quantify it, a corporate risk-averse attitude was analyzed for various levels of initial capital and size of potential consequence. A value function was inferred from the general trend of the risk aversion index, which was validated by comparison with an existing model. Adopting the suggested subjective value system, a retrospective approach to identify phenomenon of risk attitude reflected in a specific decision was developed, which is quantitative as well as qualitative. The approach was applied to identify risk aversion of a reinsurer in underwriting. This investigation of risk-pricing in reinsurance underwriting revealed that the reinsurer's level of risk-aversion when faced with low-probability high-consequence natural hazards depends on its initial capital and the size of the anticipated consequences. By exploring values of risk parameters, it is observed that a reinsurer becomes more and more risk-averse toward underwriting a policy with a higher maximum loss limit as its initial capital decreases. The insights derived from this analysis of insurance underwriting will be adopted to explore characteristics of attitude toward risks from low-probability high-consequence hazards in various decision contexts in the following chapters.

CHAPTER 4

RISK AVERSION IN EARTHQUAKE ENGINEERING

The phenomenon of risk aversion in structural engineering decision-making is explored further in this chapter by analyzing a decision by a local building authority involving seismic retrofit of unreinforced masonry buildings located in the San Francisco Bay area following the Loma Prieta Earthquake of 1989. Adopting the general relationship between risk aversion and the potential consequence of risk in section 3.3, the relation of this decision to the structural configuration (in terms of number of stories in the building) and building occupancy is investigated. Comparative analyses are performed using minimum expected cost analysis, utility theory, and cumulative prospect theory, but the emphasis is on cumulative prospect theory due to its generality and flexibility in modeling characteristics of risk aversion quantitatively. The characteristics of risk-aversion are also investigated for a decision involving a 9-story steel moment-resisting frame building. These case studies allow the suggested value system, which is incorporated as the value function in CPT, to be validated with an existing model and the role of risk aversion to be examined in the context of practical structural engineering decision problems.

4.1 Quantification of Risk Aversion

The nature of risk aversion has been recognized in utility theory and cumulative prospect theory [Tversky and Kahneman, 1992; von Neumann and Morgenstern, 1953; Ang and Tang, 1984; Keeney and Raiffa, 1976], The degree of risk aversion is reflected in the parameters that are part of each model. Thus, providing information on the reasonable ranges of these parameters is a necessary first step toward quantifying and understanding risk aversion in engineering decision-making. In this section, the ranges of the risk parameters are assessed.

Suppose, for example, that a decision involves building retrofit and the owner of the building can choose to either (0) maintain the building in its present condition or (1) implement the retrofit option. If the owner wishes to make the decision based on the minimum expected cost, the expected cost for each option is

$$E[X_0] = X_{LS,0} \cdot p_{LS,0} + X_{I,0} = X_{LS,0} \cdot p_{LS,0} \tag{4-1}$$

$$E[X_1] = X_{LS,1} \cdot p_{LS,1} + X_{I,1} \tag{4-2}$$

where X_{LS} is the cost caused by an occurrence of a specified limit state, P_{LS} is the probability of the occurrence of the limit state, X_I is the cost of implementing the option, and subscripts 0,1 denote options (0) and (1). $X_{I,0}$ is zero because maintaining the building in its present condition does not involve any retrofit cost. The retrofit option will be implemented only if $E[X_1]$ is smaller than $E[X_0]$.

If the decision-maker instead uses utility as his decision basis, the expected utility for each option is

$$E[U_0] = U(X_{LS,0} + X_{I,0}) \cdot p_{LS,0} + U(X_{I,0}) \cdot (1 - p_{LS,0}) \tag{4-3}$$

$$E[U_1] = U(X_{LS,1} + X_{I,1}) \cdot p_{LS,1} + U(X_{I,1}) \cdot (1 - p_{LS,1}) = E[U_0] + \Delta U \tag{4-4}$$

where the utility, U, is a function of cost, and is a monotonically decreasing convex function. For simplicity, it is assumed that $U(X_{I,0})=U(0)=1$, and $U(X_{max})=U(X_{LS,0})=0$. Then, the retrofit option will be implemented only if $E[U_1]$ is larger than $E[U_0]$ or, in other words, if ΔU is positive. The increment ΔU is affected by the convexity of the utility function as well as the cost and effectiveness of the retrofit option. Thus, the retrofit option may be chosen if the decision-maker is risk-averse, even if its cost is relatively large and the mitigating effect of seismic retrofit on risk is small. This characteristic of utility theory allows us to examine the degree of risk aversion that is embedded in each decision, as described in the following.

Assume that the owner has made a decision to retrofit the building. If his decision has been based solely on minimum expected cost analysis, the decision would be termed risk-neutral. Conversely, if the decision is based on other than minimum expected cost, then an element of risk aversion has been introduced into the decision process. The degree of risk aversion embedded in the decision can be determined in the following way [Stewart et al, 2010]:

- Perform a minimum expected cost analysis of the options of building retrofit *vs* maintaining the building in its current condition;
- If the option chosen is not based on minimum expected cost for some reason, perform the analysis based on utility theory while increasing the risk aversion parameter, γ, in the utility function incrementally;
- Find the tipping point of the risk aversion parameter, γ, the point at which the retrofit option becomes preferable to maintaining the status quo based on maximum expected utility approach.

The tipping point quantifies the minimum degree of risk aversion required for the retrofit option to be preferable to the status quo and therefore implies the amount of risk aversion embedded in the decision.

Finally, in cumulative prospect theory, the notion of a utility is extended further to determine the amount of risk aversion by introducing the probability weighting function in conjunction with the value function (which serves much the same purpose as a utility). The expected value for each option then is

$$E[V_0] = V(X_{LS,0} + X_{I,0}) \cdot \pi(p_{LS,0}) + V(X_{/I,0}) \cdot (1 - \pi(p_{LS,0})) \tag{4-5}$$

$$E[V_1] = V(X_{LS,1}) \cdot \pi(p_{LS,1} + X_{I,1}) + V(X_{I,1}) \cdot (1 - \pi(p_{LS,1})) = E[V_0] + \Delta V \tag{4-6}$$

where the value function, V, is a function of cost and π is a function of limit state probability which has properties introduced in chapter 2. If the limit state is assumed to be characteristic of a low-probability, high-consequence event, $\pi(p_{LS})$ is exaggerated and results in more risk-averse decisions. To determine the unique contribution of V and π to a decision is not possible unless an additional condition[9] is imposed; unfortunately, data are currently unavailable to determine the appropriate independent conditions for typical civil infrastructure decision contexts. Accordingly, in this study, pairs of the value function and probability weighting function are obtained in the following way:

- Fix the risk aversion parameter, φ, in the probability weighting function
- Find the tipping point of parameter γ in the value function using the same approach as in utility theory.
- Change/decrease φ incrementally and repeat the process for each φ.

This process leads to relationships between value and cost (Figure 3-3(a)) and probability weighting function and probability (Figure 3-3(b)). Each pair of curves [(V_i, w_i), i=1,…,5] represents a possible set of value and probability weighting functions,

---

[9] Analysis of two independent decisions made by a decision-maker is required to determine a unique set of value and probability weighting functions which represents the stance of the decision-maker. Risk-averse equivalent pairs of γ and φ are obtained for each decision, which form a curve in the space of γ and φ; an intersection point of the two curves will represent the unique combination of value and probability functions.

which result in the same decision, and are said to be *risk-averse equivalent*. For this reason, all pairs associated with the same decision will be regarded to represent the same amount of risk aversion.

If we consider multiple limit states in the risk analysis, the expected value for each option is

$$E[V_0] = \left[\sum_{i=1}^{n} V\left(X_{LS,0_i}\right)\cdot \pi\left(p_{LS,0_i}\right)\right] + V(0)\cdot\left(1-\sum_{i=1}^{n}\pi\left(p_{LS,0_i}\right)\right) + V\left(X_{I,0}\right) \tag{4-7}$$

$$E[V_1] = \left[\sum_{i=1}^{n} V\left(X_{LS,1_i}\right)\cdot \pi\left(p_{LS,1_i}\right)\right] + V(0)\cdot\left(1-\sum_{i-1}^{n} w\left(p_{LS,1_i}\right)\right) + V\left(X_{I,1}\right) \tag{4-8}$$

where n is the total number of limit states considered in the analysis, $X_{LS,0/1_i}$ is the cost corresponding to each limit state in descending order, and $\pi\left(p_{LS,0/1_i}\right)$ are decision weights determined according to Eqs. (2-8) and (2-9). All steps to model risk aversion in pairs of value function and probability weighting function are the same as before, using Eqs. (4-7) and (4-8) for expected value. The evaluation of these equations usually must be performed numerically.

4.2 Risk Aversion in Seismic Retrofit of Unreinforced Masonry Buildings in San Francisco

4.2.1 Statement of the Problem

In 1990, San Francisco's Department of City Planning (DCP) prepared an Environmental Impact Report on a possible ordinance to require mandatory seismic strengthening of 2,007 privately-owned unreinforced masonry (URM) buildings in San Francisco. A portion of this report, prepared by Rutherford and Chekene (1990), deals with damage reduction and the cost of three seismic retrofit alternatives:

(1) Out-of-plane wall strengthening;

(2) Proposed Uniform Code for Building Conservation (UCBC), Appendix Chapter 1;

(3) San Francisco Building Code (SFBC), Section 104(f)

Retrofit alternative (1) is not related to design standards but the associated guidelines, which require tension anchors to tie the roof and floors (diaphragms) to the walls, interfloor wall supports, and anchor non-parapet falling hazards, are given in the report [Rutherford and Chekene, 1990]. Alternative (2) is based on the wood diaphragm procedure of Section A107(i) which was proposed to the 1991 Uniform Code for Building Conservation (UCBC) developed by the Structural Engineers Association of Southern California (SEAOSC). The third retrofit alternative requires compliance with Section 104(f) of San Francisco Building Code, which specifies lateral force design requirements for existing buildings.

This seismic retrofit situation will serve as a first test for developing some of the ideas introduced previously. We assume that a decision has been made to strengthen an URM building with one of these retrofit alternatives – (3) SFBC, Section 104(f) - and analyze the degree of risk aversion reflected in this hypothetical decision.[10]

4.2.2 Life Cycle Cost Analysis

The building of interest is an URM office and commercial building 3-stories in height, with a total leasable floor area of 4181 m^2 and plan dimension of 20 by 40 m. The

[10] Information is not available to determine whether the building analyzed was actually retrofitted in accordance with the SFBC.

building is located in San Francisco (37.7793 N, 122.4192 W). The required service period is 30 years from the time of retrofit.

Simulation of Seismic Demand

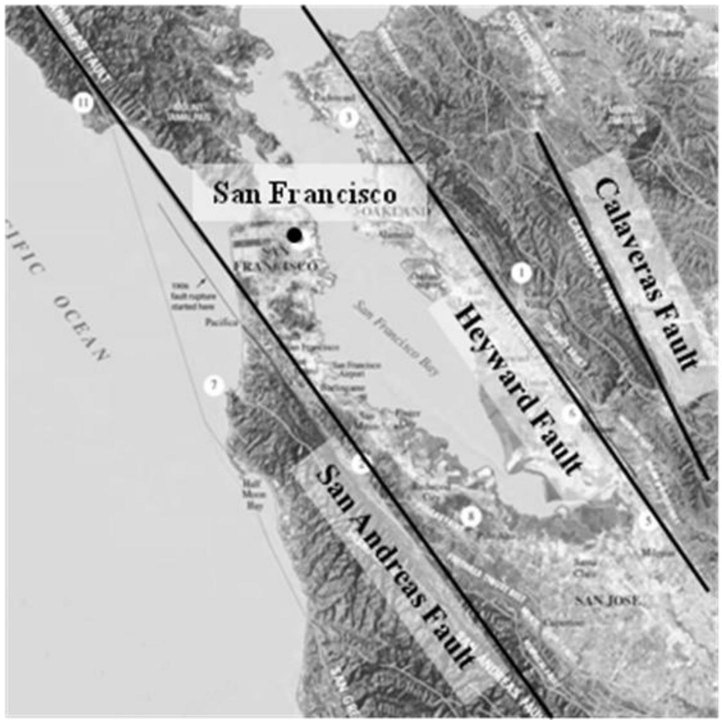

Figure 4-1 Fault systems around San Francisco, CA [Graymer et al., 2006]

Five seismic source (fault systems), shown in Figure 4-1, have been used to generate seismic demands on this URM building: San Andreas faults (North Coast, Peninsula, and Santa Cruz), Hayward fault (Northern East Bay), and Calaveras fault (Southern East Bay). Seismic demands are simulated in terms of Peak Ground Acceleration (PGA) using a seismic ground motion model that starts with the generation of a seismic event at a fault and a standard attenuation relationship[11] based on magnitude and epicentral distance, and local soil conditions at the building site [Joyner and Boore, 1981; ABAG, 1987; Peterson et al., 1996; Graymer et al, 2006]. Then, PGA is converted to the corresponding Modified Mercalli Intensity (MMI) in order to establish the building damage. All data necessary for the analysis were provided in the Rutherford and Chekene report [Rutherford and Chekene, 1990].

Modeling of Structural Response

Based on the local MMI, the building structural damage is obtained in terms of damage ratio, which is defined by the structural repair cost divided by the replacement cost. Intensity-damage relationships for the study building (and fourteen other building prototypes) are provided in [Rutherford and Chekene, 1990]. It is assumed that when subjected to the simulated seismic demands, the performance of the study building is consistent with that of the average URM building designated as prototype J [Rutherford and Chekene, 1990] (office and commercial buildings over 3 stories in height, with large areas). Table 4-1 summarizes the relationship between damage (measured in terms of a proportion of replacement cost) and seismic demand for (1) no strengthening, and (2) strengthening in accordance with the SFBC: Section 104(f). Loss of life due to the structural damage or failure is initially determined in terms of fatality ratio, which is obtained using a relationship between damage ratio and fatality rate. Then, the fatality ratio is multiplied by occupancies of the building and street, which are assumed 4 per

[11] In the analysis by Rutherford and Chekene, the attenuation relationship of Joyner and Boore (1981) was adopted, in which aleatory uncertainty associated with attenuation was not considered; the same relationship is adopted in this analysis.

1000 sq ft and 65 per 1000 linear feet, respectively [Rutherford and Chekene, 1990]. The relationship between damage ratio and fatality rates for the building considered is listed in Table 4-2.

Table 4-1. Damage for various shaking intensities, expressed as a ratio of replacement cost (office and commercial buildings over 3 stories in height, with large areas) [Rutherford and Chekene, 1990]

PGA(g)	0.05	0.11	0.22	0.45	0.7	0.9	--
MMI	VI	VII	VIII	IX	X	XI	XII
Unstrengthened	0.01	0.08	0.26	0.42	0.55	0.7	0.8
SFBC: Section 104(f)	0.005	0.02	0.08	0.17	0.28	0.41	0.55

Table 4-2. Fatality rates for street and building occupants [Rutherford and Chekene, 1990]

Damage ratio		0	0.05	0.2	0.45	0.8	1.0
Unstrengthened	Building	0	0.00001	0.00035	0.0035	0.035	0.2
	Street	0	0.0002	0.003	0.07	0.12	0.15
SFBC: Section 104(f)	Building	0	0.000008	0.0003	0.0032	0.035	0.7
	Street	0	0.0000016	0.0027	0.06	0.2	0.15

Expected Life Cycle Cost

The replacement cost for this building is \$4.44M and retrofit cost for the strengthening option is \$0.56M. The calculation of life cycle cost (LCC) considers structural damage costs, retrofit/replacement costs, and fatalities. Fatalities were monetized at \$2M [12] [Viscusi, 1992]. The expected life-cycle costs are obtained by

[12] If this valuation on fatality is updated to the recent value \$5.8M proposed by FEMA (2009), E[LCC] for each option becomes (1) \$0.66M and (2) \$ 0.74M, which suggests a possible change of decision preference when a higher value on fatality is used.

simulation using 10,000 replications of seismic demand, assuming that building response is defined as in Tables 4.1 and 4.2 [Rutherford and Chekene, 1990]. The calculated *E[LCC]* for each option is (1) \$0.36M and (2) \$0.66M, which suggests that a decision to strengthen the structure in accordance with SFBC Section 104(f) would reflect some degree of risk aversion.

4.2.3 Risk Aversion Reflected in Seismic Retrofit Requirements of San Francisco Building Code: Section 104(f)

<u>Risk Aversion Represented by Value Risk Aversion Parameter, γ</u>

Table 4-3 illustrates the utility calculation in an abbreviated form using utility risk parameter, γ, set equal to 0, 2.0, and 3.9. The simulated LCCs for options (1) and (2) are listed in the 2^{nd} and 6^{th} column in descending order of LCC ($\gamma = 0$). For the no-strengthening option, the maximum and minimum LCC in this analysis are \$7M and \$0, respectively, for which the utility is set equal to 0 and 1, respectively; in other words, $U[\$7M] = 0$ and $U[0] = 1$. One thing to note from Table 4-3 is that the utility of each LCC of the no-strengthening option covers the full range from 0 to 1, whereas the LCC of the strengthening option has a much smaller range in U. The difference between each range of utility grows as γ increases because risk aversion is characterized by a fear of extreme losses. This results in the decreasing gap between the expected utility of each option, which is shown more obviously in Figure 4-2. Accordingly, for any value of γ larger than or equal to 3.9, preference for each option is reversed and the strengthening option is selected based on $E[U_2] > E[U_1]$. Therefore, $\gamma_{tipping} = 3.9$, which is denoted the utility risk aversion tipping point.

Table 4-3. Expected utility calculation for (1) Unstrengthened and (2) SFBC: Section (f)

	(1) Unstrengthened				(2) SFBC: Section (f)			
γ	LCC($M)	0	2.0	3.9	LCC($M)	0	2.0	3.9
$U[LCC_i]$	7.00	0	0	0	4.03	0.425	0.662	0.826
	6.59	0.060	0.131	0.213	3.91	0.442	0.679	0.838
	6.59	0.060	0.131	0.213	3.91	0.442	0.679	0.838
	--	--	--	--	--	--	--	--
	0	1	1	1	0.56	0.920	0.973	0.992
$E[U]$	0.40	0.948	0.985	0.990	0.69	0.905	0.980	0.990

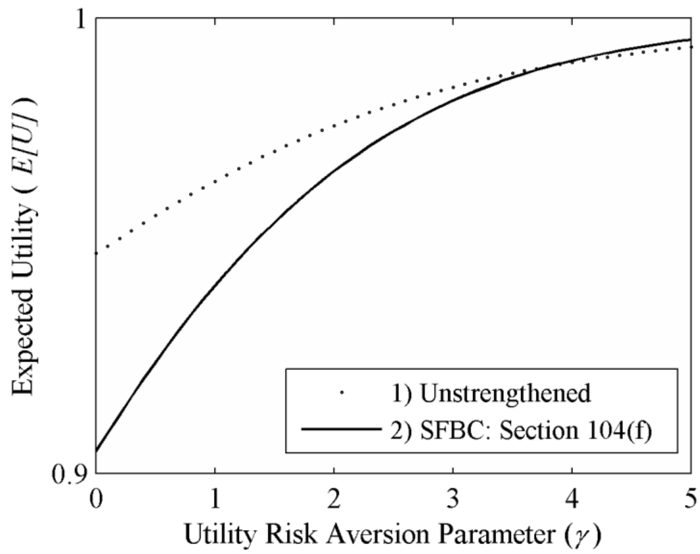

Figure 4-2. Expected utility for (1) Unstrengthened and (2) SFBC: Section 104(f) as risk aversion increases (as γ increases)

Risk Aversion Represented by Risk-Averse Equivalent Pair (γ, φ)

In the next step, the degree of risk aversion (measured by $\gamma_{tipping}$) in utility theory will be decomposed into the value function and probability weighting function of cumulative prospect theory. The tipping point of pairs, $(\gamma, \varphi)_{tipping}$, has been determined by finding $\gamma_{tipping}$ for each fixed $\varphi_{tipping}$ as described in the previous section. The value of $\varphi_{tipping}$ was decreased from 1 by 0.01 so that the probability weighting function reflects an increasing level of risk aversion. The expected value calculation for $(\gamma,\ \varphi)_{tipping}$ = (0, 0.54), (2, 0.82), (3.9, 1) is summarized in Table 4-4. Each element in Table 4-4 represents the properly weighted value for LCC of each replication and should be compared to the corresponding element in Table 4-3. For example, when $\gamma = 0$ for the unstrengthened option in the second replication, $V[LCC_2]\cdot\pi_2 = 0.0003$ compared to $U[LCC_2]\cdot p_2 = 0.000006$. This shows how the effect of the extreme event is overestimated when risk aversion is reflected in the probability weighting function; the use of π_2 gives rise to a 5000% increase in the product of value and probability weight. As a result, the option with more extreme consequences (option (1)) becomes less preferable in comparison to option (2) because $E[V_1]$ is reduced more than $E[V_2]$.

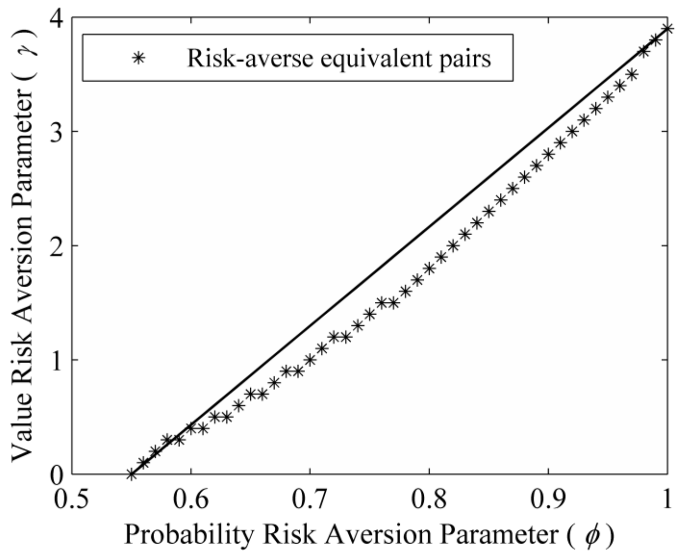

Figure 4-3 Risk aversion defined by parameters $(\gamma,\ \varphi)_{tipping}$ encapsulated in a URM building retrofit decision in accordance with the SFBC

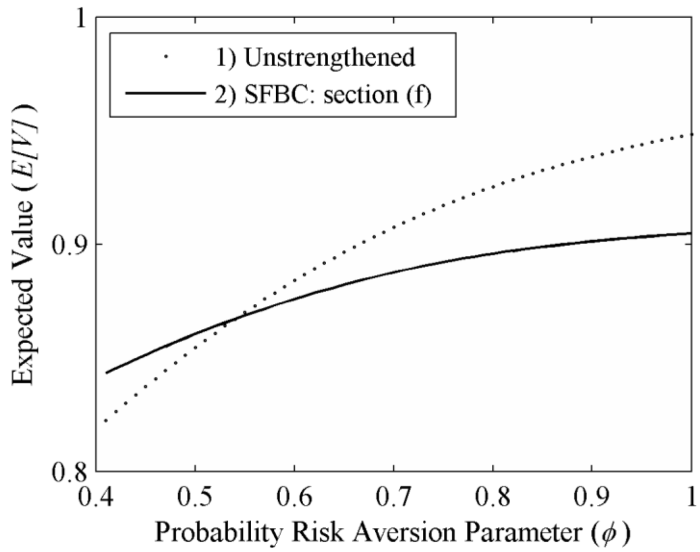

Figure 4-4 Expected value for (1) Unstrengthened and (2) SFBC: Section 104(f) as risk aversion changes

All possible pairs of tipping points are plotted in Figure 4-3. The search process is stopped at $(\gamma, \varphi)_{tipping}$ = (0, 0.54) because γ = 0 corresponds to a linear utility function and negative values of γ do not represent a risk averse attitude. The minimum of φ also can be found by decreasing φ with fixing γ = 0 as shown in Figure 4-4. The pairs in Figure 4-3 are *risk-averse equivalent*, making the strengthening option preferable to the unstrengthening option. The boundary formed by these pairs can be approximated by a line which connects the point of the lower bound of probability risk aversion parameter and the point of the upper bound of value risk aversion parameter. Note that this fit provides a safe boundary considering that the higher value of γ and the lower value of φ represent more risk aversion and any pair that lies above the boundary will lead to the same decision.

Table 4-4. Expected value calculation for (1) Unstrengthened and (2) SFBC: Section 104(f)

	(1) Unstrengthened				(2) SFBC: Section 104(f)			
$(\gamma, \varphi)_{tipping}$	LCC ($M)	(0,0.54)	(2.,0.82)	(3.9,1)	LCC ($M)	(0,0.54)	(2,0.82)	(3.9,1)
$V[LCC_i]\cdot\pi_i$	7.00	0	0	0	4.03	0.0154	0.0014	0.00008
	6.59	0.0003	0.0001	0.00002	3.91	0.0024	0.0007	0.00008
	6.59	0.0002	0.0001	0.00002	3.91	0.0016	0.0005	0.00008
	--	--	--	--	--	--	--	--
	0.00	0.0069	0.0005	0.00010	0.56	0.0063	0.0005	0.00010
$E[V]$	0.40	0.8670	0.9616	0.99013	0.69	0.8672	0.9617	0.99016

4.2.4 Extensions to Other Unreinforced Masonry Buildings

The analysis determining the risk aversion parameters that define the boundary in Figure 4-4 was extended to other prototype URM buildings. Building occupancy, planar configurations, and retrofit or replacement costs are summarized in Table 4-5; the relationships between simulated seismic demand and damage for these buildings are adopted from [Rutherford and Chekene, 1990] similarly as for building prototype J.

Table 4-5. Building configurations, and costs used in the analysis

Building type (# of stories, use)	Prototype [R & C]	Total Area (m^2)	Planar Dimension	Retrofit Cost ($\$/m^2$)	Replacement Cost ($\$/m^2$)
4+ Residential	N	3252	18 x 37	152.09	883
2,3 Residential	L	1208	15 x 27	109.36	721
1 Residential, Office and Commercial	B	929	21 x 43	95.05	635
4+ Office and Commercial	J	4281	20 x 40	134.55	1055
2,3 Office and Commercial	H	1951	18 x 37	103.23	969
2,3 Industrial	F	3345	24 x 49	89.56	667

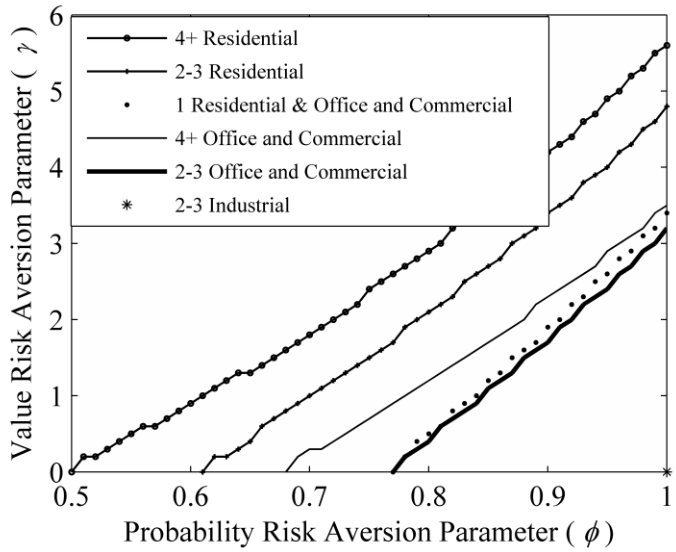

Figure 4-5. Risk aversion defined by risk aversion parameters $(\gamma, \varphi)_{tipping}$ implied by a retrofit policy for URM buildings in accordance with the SFBC

Figure 4-5 shows the boundary of pairs, $(\gamma, \varphi)_{tipping}$, obtained for the different buildings. Analyses for all buildings confirmed an increasing relationship between γ and φ; the increasing trend becomes nonlinear for the residential buildings, which appears to be mainly due to a relatively higher level of risk aversion for this building occupancy than for others. The boundaries obtained for the different building uses are distinct from each other, which imply a significant difference in the degree of risk aversion for the different building occupancies. The boundaries for the residential buildings are plotted at the top and to the left, followed by those of office and commercial buildings and industrial buildings. Noting that the pair with high γ and low φ represents high risk aversion, the trend in Figure 4-5 suggests the level of risk aversion embedded in the seismic retrofitting option is highest for the residential buildings, somewhat less for office and commercial buildings, and negligible for the industrial buildings. Another factor which affects the degree of the risk aversion is the number of building stories.

From Figure 4-5, it is observed that the degree of risk aversion increases as the number of stories of building increases for both of the residential buildings and the office and commercial buildings.

4.3 Role of Risk Aversion in Earthquake-Resistant Design of a Steel Moment Frame

4.3.1 Introduction

To illustrate the concept of risk aversion for a typical civil infrastructure design problem and to validate the suggested value function, we consider the seismic design level of a moment-resisting steel frame located in Vancouver, BC, Canada. A similar structure has been analyzed by Wen and Kang (2001) using life cycle cost analysis and by Goda and Hong (2008) using cumulative prospect theory but with different value functions than in this study. This particular example allows us to benchmark the methods proposed in the current study against previously published work.

Simulation of Seismic Demand

The seismicity for Vancouver is described in Adams and Halchuk (2003) and shown in Tables 4-6 and 4-7 [13] and in Figure 4-6. Twelve source zones within approximately 400 km of Vancouver, including the Cascadia subduction zone, have been considered to generate seismic demands on this frame. The occurrence of seismic events in each source zone has been modeled as a Poisson process.

[13] In contrast to the earlier study of URM buildings in San Francisco, the aleatory uncertainty in attenuation is included here through the ε - terms in Table 4-7.

Table 4-6 Seismic information [Adams and Halchuk, 2003]

Source zone	β, N_0 *			M_U		
	Best (p = 0.68)	Lower (p = 0.16)	Upper (p = 0.16)	Best (p = 0.68)	Lower (p = 0.16)	Upper (p = 0.16)
BRO	1.19, 13	1.46, 17	0.93, 8	7	6.7	7.3
CASR	0.85, 14	1.88, 1335	0.85, 14	7.7	7.7	7.7
CST	1.50, 266	1.7, 459	1.29, 153	7.5	7.4	7.6
EXP	1.30, 103	1.45, 160	1.15, 85	7	6.7	7.3
GSP	1.13, 28	1.26, 35	0.99, 24	7.1	6.9	7.3
JDFF	1.87, 91	2.26, 175	1.48, 42	7	6.7	7.3
JDFN	2.07, 109	2.58, 264	1.56, 39	7.1	6.7	7.3
NBC	2.00, 169	2.2, 203	1.8, 135	7	6	7
NOFR	1.57, 270	1.69, 360	1.45, 247	7	6.7	7.3
OFS	2.10, 46683	2.22, 73246	1.98, 30343	7.1	6.9	7.3
SBC	2.21, 1384	2.49, 2787	1.92, 673	7	6.7	7.3
Cascadia	--	--	--	8.2	--	--

* Parameters for the cumulative distribution function of moment magnitude M, $F(M) = \left(e^{-\beta M_L} - e^{-\beta M}\right) / \left(e^{-\beta M_L} - e^{-\beta M_U}\right)$ where N_0 is the total number of events per year.

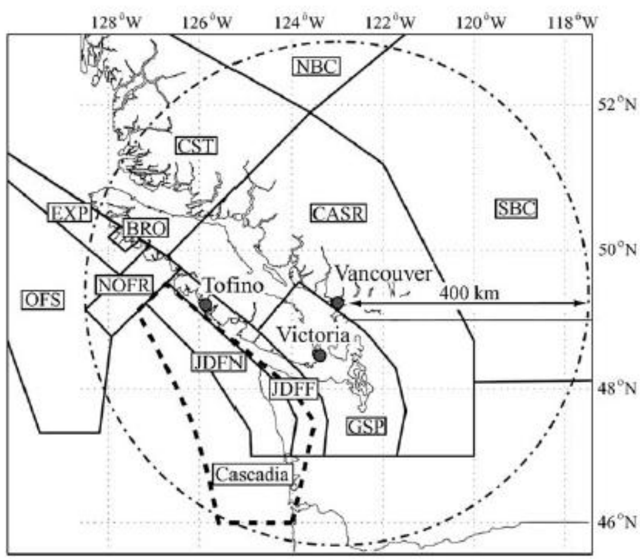

Figure 4-6 Seismic source zones around Vancouver, Canada [Adams and Halchuk, 2003]

Table 4-7 Attenuation relations [Adams and Halchuk, 2003; Boore et al, 1993, 1997]

Shallow events	Boore et al. attenuation model (for $5 \le M \le 7.7$ and $r_{epi} < 100$ (km)) $log_{10}S_{AE}(T_n; \xi = 0.05) = b_1 + b_2(M-6) + b_3(M-6)^2 + b_4r + b_5 \log r + b_6G_B + b_7G_C + \varepsilon_r + \varepsilon_\varepsilon$ where $r = (r_{epi}^2 + h^2)^{0.5}$, r_{epi}(km) is the epicentral distance, h (km) is a fictitious depth, G_B and G_C are the coefficients for site classification, b_i, $i = 1,...,7$, are regression coefficients that depend on T_n, and $\varepsilon_r + \varepsilon_\varepsilon$ is normally distributed with zero mean and standard deviation σ_ε which is a regression coefficient and depends on T_n.
Subduction events for rock sites	Youngs et al. attenuation model (for $M > 5$ and $10 \le r_{rup} \le 500$(km)) $lnS_{AE}(T_n; \xi = 0.05) = 0.2418 + 1.414M + c_1 + c_2(10-M)^3 + c_3 \ln(r_{rup} + 1.7818e^{0.554M}) + 0.00607H + 0.3846Z_T + \varepsilon$ where $r_{rup} = (r_{epi}^2 + H^2)^{0.5}$, H (km) is the focal depth, ε is normally distributed with zero mean and standard deviation of $c_4 + c_5 min(M,8)$, c_j, $j = 1,...,5$, are regression coefficients that depend on T_n, and Z_T equals zero and one for interface and intraslab events, respectively.

Modeling Structural Capacity

The structure of interest is a steel frame in a 9-story office building with a total floor area of 9,406 m^2. The required service period is 50 years. Fifteen different seismic design levels corresponding to return periods from 250 to 20,000 years have been analyzed. Design spectral accelerations S_{AEf} and the corresponding design return period T_R are listed in Table 4-8. For simplicity, each structure is modeled as a single degree of freedom system. Damage factors have been calculated from the bilinear hysteretic approach proposed by Prelec (1998) and Goda and Hong (2008) and the uncertainty in frame capacities, expressed in terms of ductility capacity, is taken from the same references.

Table 4-8 Seismic design configurations and expected life cycle cost

	T_R (years)	S_{AEf} (g)	$E[LCC]$ (Canadian dollars in 2003 value, \$M)
S1	250	0.178	10.6408
S2	500	0.252	10.0020
S3	750	0.303	9.7785
S4	1,000	0.343	9.7195
S5	1,500	0.405	9.6922
S6	2,000	0.452	9.6985
S7	2,500	0.490	9.6977
S8	3,000	0.526	9.6970
S9	3,500	0.553	9.7451
S10	4,000	0.583	9.7833
S11	5,000	0.635	9.8579
S12	6,000	0.681	9.9294
S13	7,500	0.736	10.0254
S14	10,000	0.829	10.2022
S15	20,000	1.032	10.6258

Table 4-9 Structural capacity and cost information [Goda and Hong, 2008]

Type	Description
Structural capacity and design information	Moderately ductile steel moment-resisting frame at a reference ground condition; Total floor area, A_F, is 101,250 ft^2. T_n = 1.0 (s), ξ = 0.05, and α = 0.0; $\mu_R \in$ LN(3.5,0.5)(1) and $R_N \in$ LN(2.5,0.15); and R_d = 3.5, R_o = 1.5, and $I_E = M_v = F_a = F_b$ = 1.0 -[NBCC, 2005].
Damage cost information	γ = 0.05; $C_0(C_s) = (C_{00}(C_s) + C_{RN}(C_{s,475})) \cdot A_F$; $C_{00}(C_s) = 16.97 \cdot \max(1,1 + 8.054(C_s - 0.0082)^{1.08})$ (CAD/ft^2); $C_D(C_s\|\delta) = 206.12 \cdot A_F \cdot \delta^{1.099}$(CAD); and $C_R(C_s\|\delta) = (C_{00}(C_s) + C_{RN}(C_{s,475})) \cdot A_F \cdot \delta^{0.912}$(CAD), where the nonstructural cost $C_{RN}(C_{s,475})$ per unit area equals $C_{00}(C_{s,475})/\kappa$, in which $C_{s,475}$ is the design base shear coefficient corresponding to the return period of 475 years, and κ is the ratio of the cost of structural components to that of nonstructural components, κ = 0.33.

Life Cycle Cost Analysis

It is assumed that the maintenance cost (C_M) is the same for each structure in computing the life cycle cost (LCC). Thus, the reference point of the value function in the CPT analysis is set equal to C_M so that its specific value is not required for the analysis. The calculated values of *E[LCC]* (not including C_M) obtained from simulating 30,000 samples of seismic demand and capacity (in terms of ductility) are listed in Table 4-8 and are plotted in Figure 4-7. The seismic design level (S_{AE_opt}) for minimizing *E[LCC]* equals 0.42g. We remark that each *E[LCC]* plots at a slightly lower position than reported by Goda & Hong [Goda and Hong, 2008] because of slight differences in the seismic design levels and the seismic source zone modeling between the two studies. As a result, the simulated risk in our study is slightly lower and the value of S_{AE_opt} is slightly lower than the 0.46g reported in the previous study.

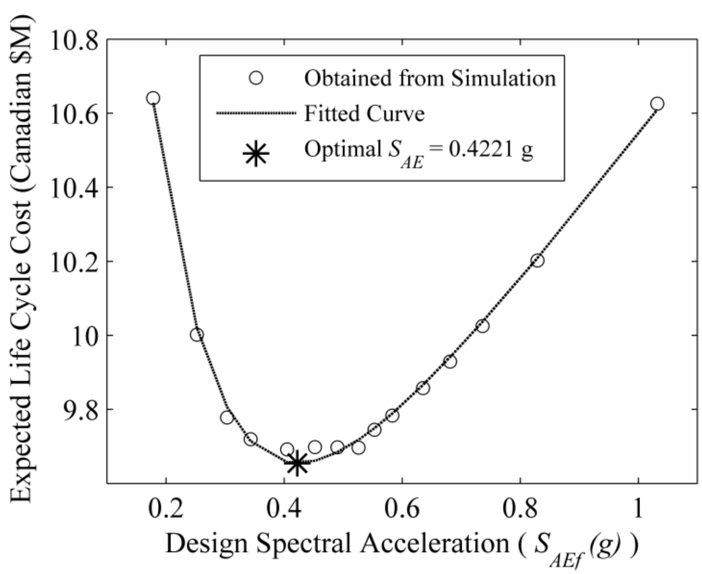

Figure 4-7. Expected LCC vs spectral acceleration

4.3.2 Risk-Aversion Represented by Risk Sensitivity Factor and Model Validation

Two cases are considered in the following comparison of optimal seismic design levels for different degrees of risk aversion. In Case 1, the probabilities are not weighted, which yields results equivalent to those from UT because the consequences all lie in the loss region. In Case 2, a nonlinear inverse S-shaped probability weighting function is utilized to show how these nonlinearities in the value and probability weighting functions affect the optimal seismic design level. In both cases, $V(\lambda;W_0)$ is defined as in Eq. (3-4). Each simulated LCC is mapped into the assumed value functions; optimization based on CPT yields the sets of spectral accelerations, S_{AE_opt}.

<u>Case 1: w(p) = p</u>

The sensitivity of the optimal seismic design level obtained from CPT to the risk sensitivity factor, *b*, is assessed by varying *b* from 0.01 to 1 (cf. Section 3.2). Figure 4-8 shows that the increase in the optimal seismic design level as *b* increases is marginal unless *b* is increased to values substantially in excess of 1.0, which is the upper limit suggested by our evaluation of risk insurance premiums. The optimal seismic design level of 0.432g (spectral acceleration), is insensitive to *b* and is only 2% higher than when MECA is used. We emphasize that the above range of the risk sensitivity factor, *b*, assumed in this analysis has been inferred from insurance industry practices and may be substantially lower than the factor for a more risk-averse individual or group with limited financial resources. If the decision maker is extremely risk-intolerant (*b* is increased to, say, 100), the optimal seismic design level is increased to 0.51g, or 21 % higher than that obtained by MECA.

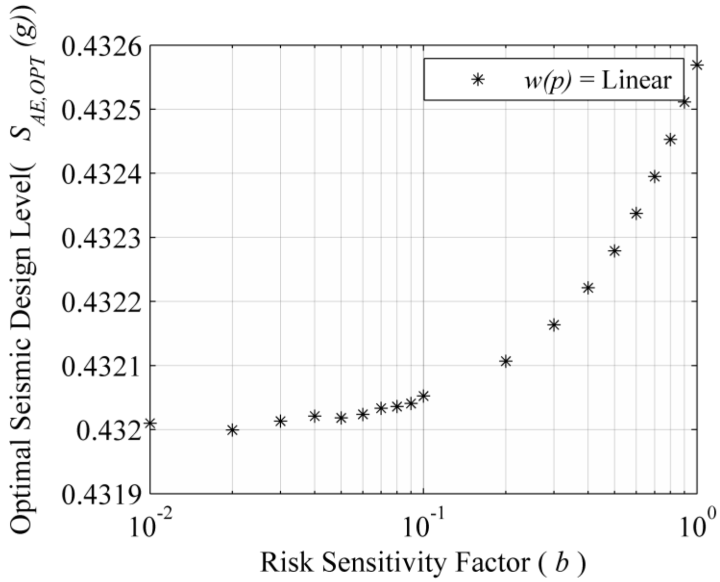

Figure 4-8. Sensitivity of optimal seismic design level to the risk sensitivity parameter, *b* (linear probability weighting function)

Case 2: w(p) = $w^-(p)$, as defined as in Equation (2-11)

To assess the effect of introducing a nonlinear probability weighting function on the optimal seismic design level, we assume that parameters [γ^-, φ^-] in Eq. (2-11) equal [1.0, 0.8]. Figure 4-9 shows the optimal seismic design level as a function of *b* for this case. Setting *b* equal to 1, the optimal seismic design level is 0.494 g (spectral acceleration), which is 14% larger than when probability is not weighted. As in Case 1, however, the optimal seismic design level is insensitive to the risk sensitivity factor, *b*, over the range of *b* considered. This insensitivity can be explained by the fact that the range of *b* used in the analysis represents the stance of a reinsurer which would take a nearly risk-neutral attitude.

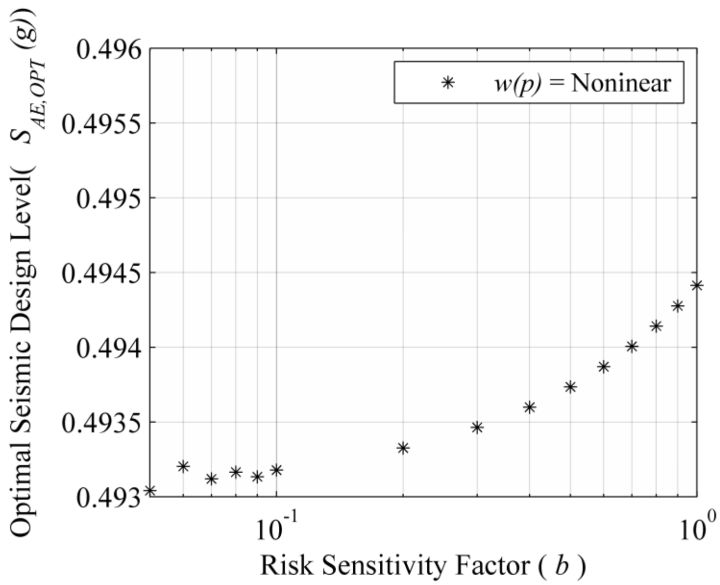

Figure 4-9. Optimal seismic design level vs risk sensitivity parameter, *b* (nonlinear probability weighting function)

Comparison with an Existing Model

Case 2 above indicated that the optimal seismic design level is increased when risk aversion is embedded in both value function and probability weighting function. A similar study has been performed by Goda & Hong (2008), but with a different value function. The values of S_{AE_opt} in both studies are compared in Table 4-10. Because the simulated risk values are different in the two studies, the optimal seismic design levels determined using the Goda/Hong value function (reported in Table 3-5) are slightly lower than in their paper. The value functions used in this study (V_1) and by Goda & Hong (V_2) each explain the nonlinearity associated with risk aversion observed in consequence evaluation with different assumptions and how this affects decision preferences. Value function V_2 covers both risk-averse and risk-acceptance stances, which can be seen in the first value 0.38g corresponding to k = 0.8, which is lower than the value obtained by MECA and implies that the decision maker has adopted a risk-taking attitude in this case.

In contrast, the value function derived in this study (V_1) cannot assume a concave shape and thus only models risk-averse attitudes. Thus, if b is reduced, the optimal spectral acceleration will approach the value obtained by MECA, but will never be less than that value. Moreover, V_1 reflects the observation that risk aversion of the decision-maker increases as the size of risk increases and the increasing rate increases as wealth decreases. In contrast, V_2, does not recognize that risk aversion increases with consequences; rather, it presumes that the degree of risk aversion is constant for any size of risk.

Table 4-10 Comparison of optimal seismic design levels obtained from this study with Goda and Hong (2008)

Optimal seismic design level (g)					
$V_1^-(\lambda) = -exp(-b\lambda)$			$V_2^-(\lambda) = -(-\lambda)^k$		
b	$w(p) = p$	$w(p) = w^-(p)$	k	$w(p) = p$	$w(p)=w^-(p)$
0.05	0.432	0.493	0.8	0.383	0.423
0.1	0.432	0.493	0.9	0.406	0.455
1	0.433	0.494	1.0	0.428	0.488
100	0.509	n.a.	1.1	0.450	0.522

* V_1 is the value function used in this study and V_2 is the value function used by Goda & Hong.

** $w^-(p)$ is probability weighting function defined as Eq. 2-11 with $[\gamma^-, \varphi^-] = [1.0, 0.8]$

4.3.3 Sensitivity Analysis – Use of Normalized Value Function

To further clarify the role of risk aversion in design, the 9-story moment-resisting steel frame for earthquake, we adopt the normalized value function (Eq. (3-5)) and probability weighting function which model risk aversion and were proposed in section 3.2 and 3.3. The optimal design spectral acceleration (0.42g) based on minimum life cycle cost basis will be compared with the optimal design spectral accelerations determined from maximizing expected utility and value.

Sets of φ and γ determined in Section 3.3 were used to determine the optimal seismic design level using the value functions (defined in Eq. (3-5)) and probability weighting functions (defined in Eqs. (2-10) and (2-11). Two cases are considered. In Case 1, risk aversion is vested entirely in γ and φ is set equal to 1.0; this corresponds to utility theory. The sets of γ shown in Figures 3-4, 3-5 and 3-6 are used for the sensitivity analysis of the optimal seismic design. In Case 2, risk aversion is assumed to be reflected in both φ and γ, which corresponds to cumulative prospect theory. The sets of φ and γ shown in Figure 3-7 are used to investigate the role of the probability weighting function in the decision model.

Sensitivity of Optimal Design Level to Value Risk Aversion Parameter γ

The sensitivity of the optimal design level of spectral acceleration to γ is first assessed by increasing γ from 0 to 10 which is slightly larger than the maximum value of γ identified in Figure 3-5 and 3-6. The increase in optimal seismic design level as γ increases, shown in Figure 4-10, is fairly linear over most of its range. A sharp increase is observed at very low γ, which suggests that even a small degree of risk aversion might impact the decision. The increase in slope that occurs when γ exceeds 8 is associated with an extremely risk-averse attitude which implies that none of the risk mitigation options will be sufficient to satisfy the preferences of the decision-maker. Figure 4-11 shows the optimal seismic design levels as a function of the ratio of the initial capital to loss size. The optimal seismic design level is related to the initial capital utilizing Figures 3-5 and 4-10. The linear relationship between γ and the optimal seismic design level results in shapes of the relationship between γ and the initial capital that are similar to those observed in Figure 3-5.

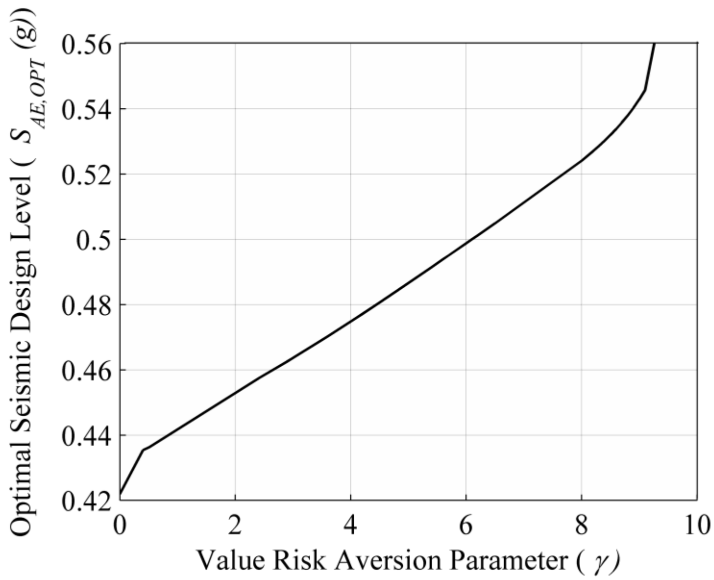

Figure 4-10. Optimal seismic design level vs risk aversion parameter, γ (φ = 1.0)

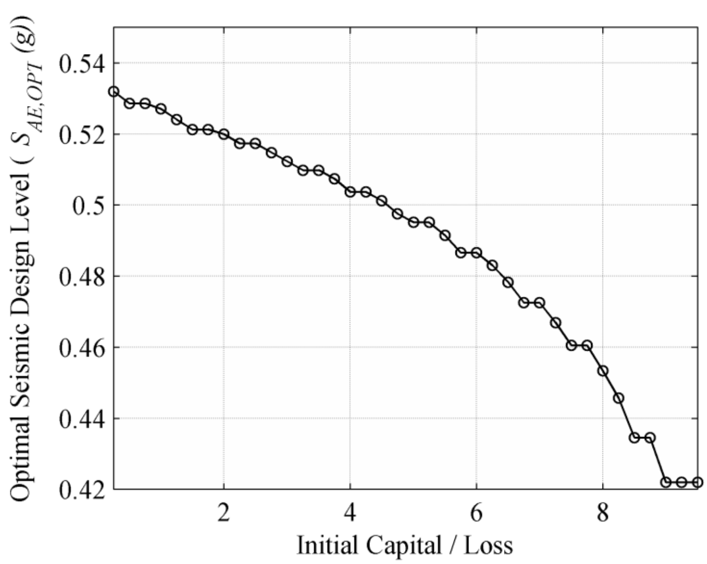

Figure 4-11. Sensitivity of optimal seismic design level to ratio of initial capital to loss size

Sensitivity of Optimal Design Level to Risk Aversion Parameters (γ, φ)

The dependence of the optimal seismic design level on the degree of risk aversion, represented by parameters (γ, φ) in Figure 3-7, is shown in Figure 4-12 (a) for five combinations of decision contexts with different loss ratios.

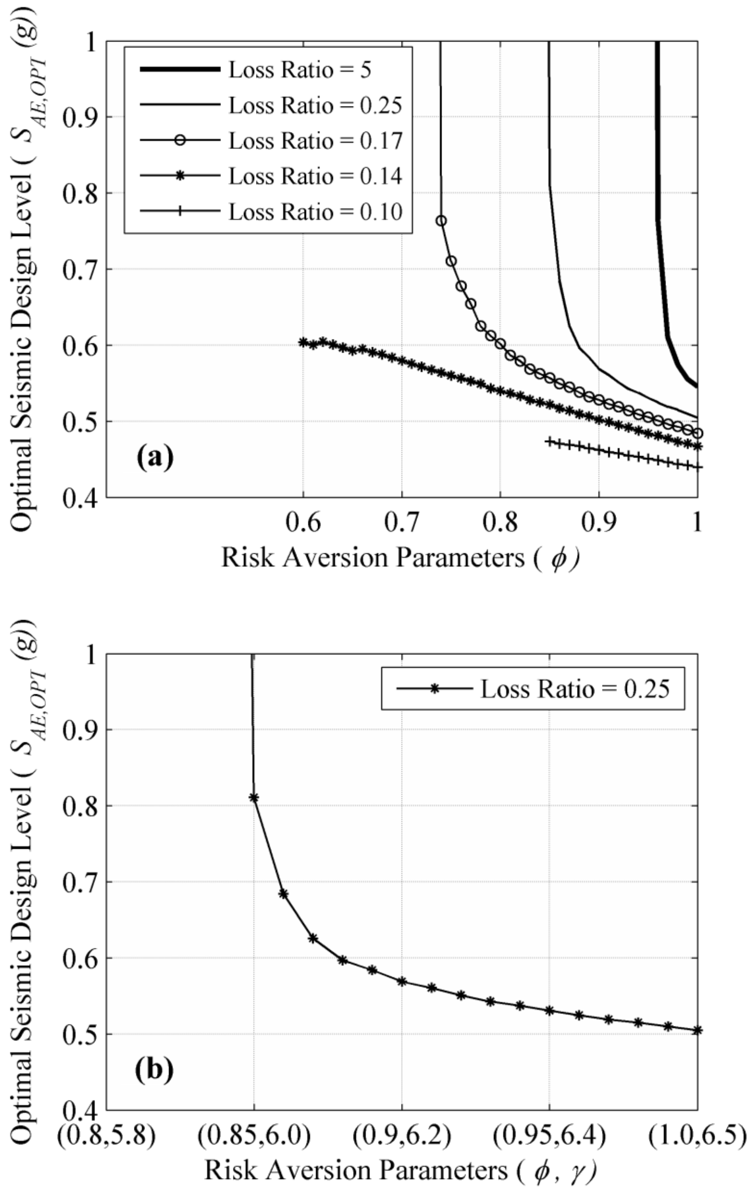

Figure 4-12. Sensitivity of optimal seismic design level to both φ *and* γ when risk-averse equivalents used

The x-axis in Figure 4-12 represents the points on the "equivalent preference line" in Figure 3-7, which are labeled with only φ (since the corresponding value of γ changes across the different loss ratios) for Figure 4-12 (a) and pairs (γ, φ) associated with loss ratio = 0.25 for Figure 4-12 (b). In part (b) of Figure 4-12, the optimal seismic design level is found to increase as risk aversion is encapsulated more by probability weighting function (lower φ) and less by value function (lower γ). Furthermore, this increase accelerates as φ and γ decreases. The part (a) of Figure 4-12 shows this same trend of optimal seismic design level as φ changes for other sets of initial capital and maximum loss limit. The increase at low values of φ tends to be more significant for smaller initial capital and larger maximum loss limits, and results in a significant increase in the optimal seismic design level.

4.3.4 A Comparative Analysis of Risk-Aversion Reflected in Seismic Retrofit Decisions

For further analysis using CPT, each simulated LCC is mapped into the assumed value function and weighted using its matching probability weighting function which reflects risk perception that was implied by the seismic retrofit decision for unreinforced masonry buildings considered previously in section 4.2 (cf. Figure 4-5). In the following, the optimal seismic spectral acceleration is determined for risk-averse equivalent pairs of value and probability weighting functions, which are identified in Figure 4-5. Once the optimal seismic spectral acceleration is determined, its sensitivity to each risk aversion parameter is identified and the importance of including the probability weighting function in the decision process is demonstrated.

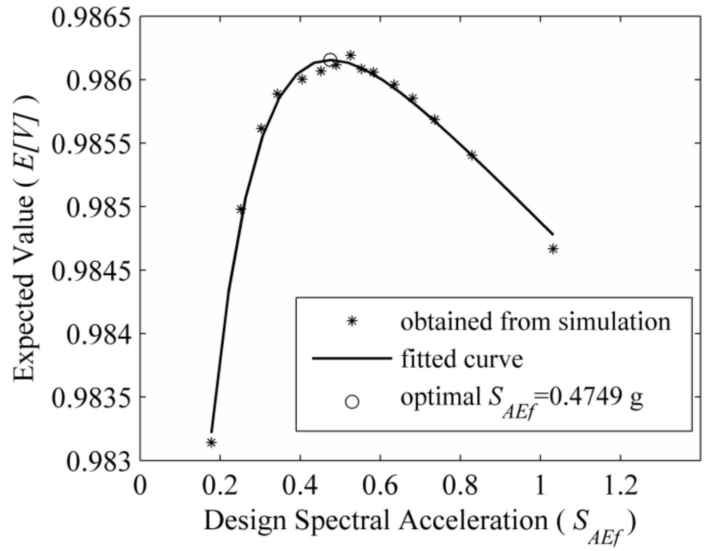

Figure 4-13. Expected value for each design level and the optimal seismic design level for *(γ, φ)* $_{tipping}$ = (3.9, 1.0)

<u>Optimal Design Level Considering Subjective Consequence Evaluation (UT)</u>

As a first step, optimization of the seismic design level is performed for the case in which all the risk aversion is reflected in the value function. Since the probability is not weighted, this case is equivalent to optimizing on maximum expected utility. From the risk-averse equivalent pairs of parameters, $(\gamma, \varphi)_{tipping}$ = (3.9, 1) is found in Figure 4-3 to correspond to this case. Using this pair, *E[V]* (equal to *E[U]* in this case) is calculated for each design level and is plotted in Figure 4-13. The plot of *E[V]* indicates that the optimal seismic design spectral acceleration (S_{AE_opt}) equals 0.47g, approximately a 12% increase over the design level based on minimum expected cost analysis. However, a closer inspection of the ordinal scale of Figure 4-13 reveals that *E[V]* of each design level is virtually the same for spectral accelerations between 0.2g and 1.0g, indicating that the expected value is insensitive to the design spectral acceleration for this nine-story moment frame. This insensitivity suggests that utility theory may not provide adequate decision support for such problems due to its limited flexibility in incorporating high levels of risk aversion.

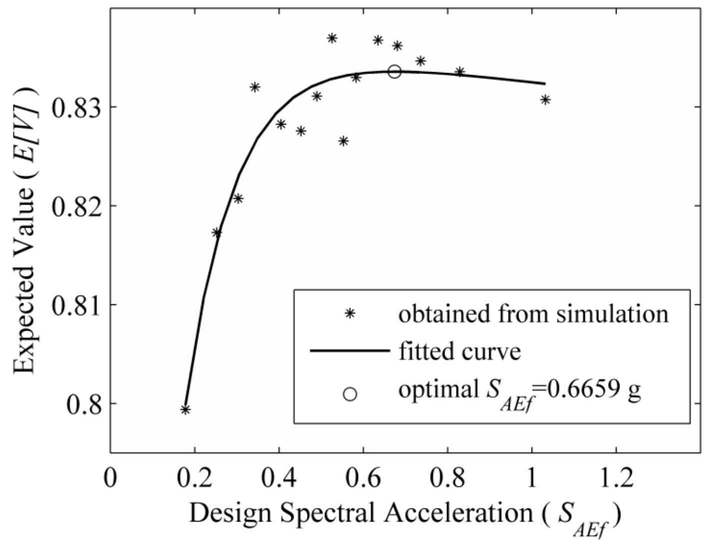

Figure 4-14. Expected value for each design level and the optimal seismic design level for $(\gamma, \varphi)_{tipping}$ = (0, 0.54)

<u>Optimal Design Level Considering Subjective Evaluation of Probability (CPT)</u>

At the other extreme, the optimal seismic design level is determined when risk aversion is assumed to be reflected solely in the probability weighting function, which corresponds to the lowest point $(\gamma, \varphi)_{tipping}$ =(0, 0.54) in Figure 4-3. In this case, the extreme LCC is not overestimated and is mapped into a linearly decreasing value function (similarly as V_5 in Figure 3-3). The calculated $E[V]$ and the optimal design spectral acceleration are shown in Figure 4-14. The scatter in that figure is due to the sample size used in the simulation and could be reduced, but at considerable computational expense. In comparison with Figure 4-13, the region of near-optimality shifts toward higher seismic design levels and is narrower than when a utility-based model is used. The optimal design spectral acceleration in this case is found to be 0.67g, which is 59% and 40% higher than when LCC analysis and utility theory, respectively, are used. When one accounts for the difference in the scale on which *E[V]* is plotted, the region of optimality is more clearly defined in Figure 4-14 than in Figure 4-13 and provides a larger range of the expected values for each design level than in Figure 4-13, where the probability weighting function is not considered.

Optimal Design Level Based on CPT

To better understand the effect of the probability weighting function on the optimal value, the maximum value is obtained for every risk-averse equivalent pair from Figure 4-3. These pairs range from $(\gamma, \varphi)_{tipping}$ = (3.9, 1) to (0, 0.54), with decreasing values of parameters, γ and φ. Since the smaller φ represents higher risk aversion, it implies that the role of the probability weighting function in encapsulating the degree of risk aversion is increasing as φ decreases from 1 to 0.54. This increasing importance of the probability weighting function is paired with the decreasing role of the value function. The optimal seismic design spectral acceleration for each of these pairs is plotted in Figure 4-15. Figure 4-15 shows an obvious increasing trend of optimal design level as more risk aversion is vested in the probability weighting function and less is vested in the value function. The total increment of optimal seismic design spectral acceleration reflected in Figure 4-15 is 0.20g, which is comparable to the 40% increase in optimal design acceleration from Figure 4-13 to Figure 4-14. It is interesting to note that the increasing trend in the optimal acceleration becomes increasingly nonlinear as φ approaches its lower end. This implies that the increasing trend will intensify for the risk averse-equivalent pairs with higher total risk aversion, which generally leads to larger ranges in the risk parameters. In turn, this will make the minimum value of the probability risk aversion parameter decrease further and increase the optimal design level, expressed in terms of spectral acceleration, further.

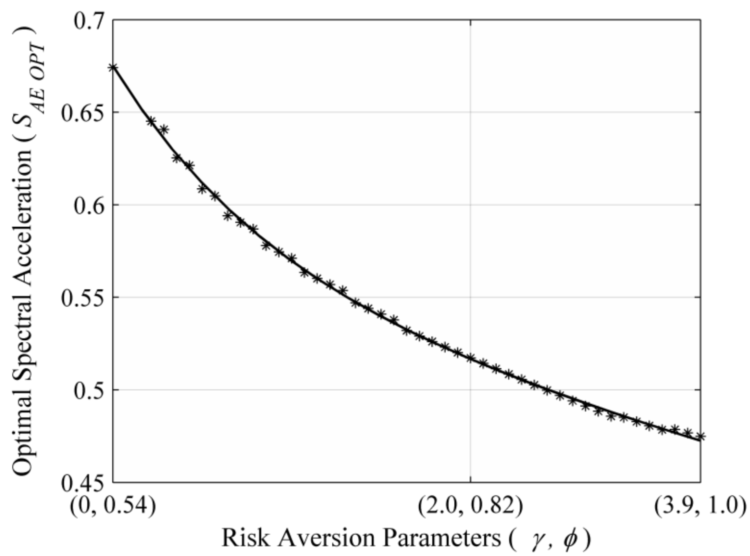

Figure 4-15. Sensitivity of optimal design level to risk aversion parameters γ and φ

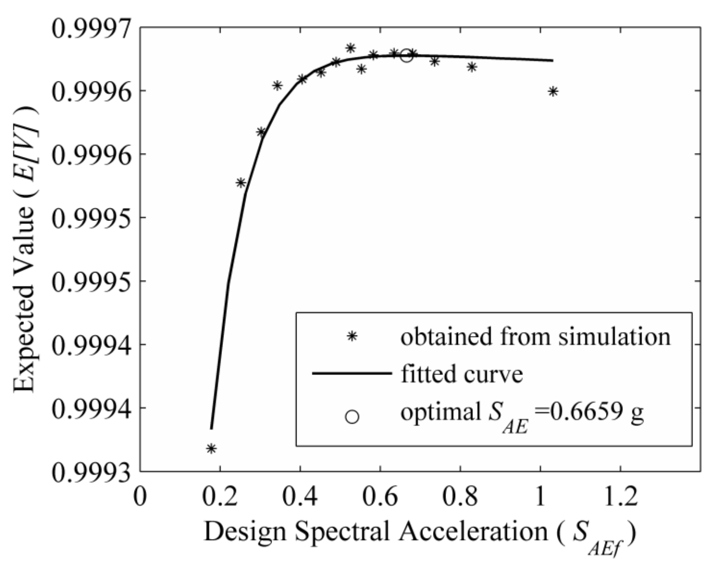

Figure 4-16. Expected value for each design level and the optimal seismic design level for (γ, φ) = (8.925, 1.0)

Significance of Using Probability Weighting Function

To see how the optimal design level changes when *only* the value risk aversion parameter is varied, γ is increased until it yields the same optimal seismic design spectral acceleration observed in Figure 4.14 (0.67g) when risk aversion has vested in the probability weighting. It is found that γ must be increased to approximately 8.925, more than twice the original utility risk aversion parameter (3.9). The expected values for each design level are shown in Figure 4-16. Compared to the plot when $(\gamma, \varphi) = (0, 0.54)$, Figure 4-14 indicates a smaller range of expected values and more clustering around the fitted curve, which flattens the curve of *E[V]* vs spectral acceleration and makes it difficult to identify the point of optimality.

4.4 Closure

This chapter has utilized CPT to explore how civil infrastructure decision-making in earthquake engineering might be affected by risk aversion, which is a major source of conservatism in structural safety-related decisions especially when confronting rare and catastrophic hazards. The characteristics of risk aversion have been explored with a hypothetical seismic retrofit decision for an unreinforced masonry building located in the San Francisco bay area. The investigation revealed that the degree of risk aversion is affected by the use of the building (residential, office and commercial, and industrial) and the number of building stories. Risk aversion tends to be highest for residential buildings, somewhat less for office and commercial buildings, and least for industrial buildings.

The risk aversion represented by the parameters identified in the study of seismic retrofit, along with those identified in sections 3.1 and 3.3, was employed to investigate optimal seismic design levels for a steel moment resisting frame that had previously been studied by other investigators. By assuming that the nature of a corporate risk attitude can offer insight into attitudes of other decision entities such as building owners, code officials and regulatory authorities, the value and probability functions proposed in chapter 3 were extended to aseismic design of this 9-story building frame. This benchmark analysis revealed that risk aversion, as encapsulated in value/utility functions similar to those in underwriting, had a notable strengthening effect on the optimal design of the frame. When the probability weighting function in CPT was allowed to reflect risk-aversion as well as the value/utility functions, the strengthening effect on optimal seismic design became even more pronounced. Characteristics of risk aversion suggested from the seismic retrofit decision were also extended to a seismic design situation. It was found that the inclusion of risk aversion in the decision model increases the optimal seismic design level. This increase becomes especially significant when low-probability, high-consequence hazards are considered, suggesting that minimum expected cost analysis might not be adequate as a decision basis in such situations.

CHAPTER 5

RISK AVERSION IN ENGINEERING FOR EXTREME WINDS

The risk to civil infrastructure from extreme winds has been increasing in recent decades due to rapid population growth and urbanization in windstorm-prone coastal areas [Berz, 1994; Rosowsky et al. 2001]. Recent hurricanes - Hugo (1989), Andrew and Iniki (1992), and Katrina (2005) - caused economic losses of up to $80 billion [Knabb et al., 2005]. Efforts to manage risk to the built environment from such catastrophic events have been made by amending building design standards and introducing requirements for retrofit of existing buildings. In this chapter, we explore attitudes toward risk when individuals or group decision-makers (such as code bodies) are confronted with extreme wind hazards. As a case study, decisions made by the North and South Carolina Building Code Councils in 2001, which placed a moratorium on enforcement of sections of the International Residential Code that would have required additional protection against wind-borne debris, are analyzed within the framework of cumulative prospect theory. Risk attitudes reflected in such decisions are investigated qualitatively and quantitatively for a range of building economic values, building size (stories) and locations. Following this case study, we will examine the wind-resistant designs of nine story steel moment-resisting frames located in Los Angeles, CA, Charleston, SC, and Boston, MA, and will compare attitudes toward wind hazards suggested by these examinations to attitudes toward seismic hazards studied in Chapter 4.

5.1 Risk-Acceptance in Wind-Resistant Design of Wood Frame Residential Buildings

5.1.1 Code Proposal to Retrofit Residential Buildings

To understand risk acceptance attitudes toward wind hazards using the methodology introduced in the previous section, we investigate the decision made by the North and South Carolina Building Code Councils in 2001 as to whether to require additional protection to glazed openings in building located in regions susceptible to windborne debris (WBD) from hurricanes. These Code Councils placed a moratorium on the adoption and enforcement of the protections against wind-borne debris (WBD) required by sections IRC Section R301.2.1.2 and IBC Section 1609.1.2 in the process of adopting the International Residential Code (IRC) and International Building Code (IBC) for their jurisdictions. As part of the decision to implement this moratorium, Applied Research Associates (ARA) performed cost benefit analyses for practical options for mitigating the effects of WBD under the IRC and IBC. The ARA study found that (a) those sections that had been placed under moratorium were, in fact, cost-effective and that (b) protecting all glazed openings with commercial panel shutters was the least costly among the options considered, and provided the maximum net present value[14] [ARA, 2002a, 2002b].

Hence, the decision alternatives examined in the present study are to;

[14] The net present value is defined as the present discounted value of the net benefit (loss reduction benefit minus cost increase), considering an annual discount rate of 5% [ARA, 2002a, 2002b].

1) Continue the moratorium on enforcing the opening protection provisions in wind-borne debris regions (WBDR) (no opening protection);

2) Adopt and enforce the more restrictive opening protection provisions in IBC/IRC in WBDR (commercial panel shutter);

The risk acceptance attitude reflected in the decision to select alternative 1) is analyzed in this section.

5.1.2 Study Buildings and Locations

Five low-rise, wood-frame residential buildings comprising a range of building values and number of stories are considered. The relevant information for these buildings is summarized in Table 5-1. The buildings are assumed to be located along the coastlines of North and South Carolina for purposes of wind hazard simulation, as shown in Figure 5-1. A total of eleven study locations were selected: seven in NC and four in SC. Table 5-2 lists the terrain exposure, design wind speed, latitude, and longitude of the locations. A modification of Georgiou’s hurricane model [Georgiou et al., 1983; Rosowsky et al., 2001] was used to simulate the gradient level wind field. The simulation of the hurricane wind fields initiates from landfall using the statistics provided in [Rosowsky et al., 2001; Huang et al., 2001a, 2001b], which are listed in Table 5-3. Coastlines are modeled with line segments for simplicity. The hurricanes generated are assumed to move along straight tracks with radii of maximum wind speed that are assumed to be constant along the track until they strike the study location of interest [Neuman et al, 1997; Elsner et al.

2010; Powell et al., 2005]. The simulated gradient balance speed[15] is converted to the effective mean surface wind speed (at 10 m elevation) averaged over 10 minutes using a conversion factor provided by [Rosowsky et al., 2001; Sparks et al, 1994].

Table 5-1. Summary data of the study buildings [ARA, 2002a]

Building No.	No. of stories	Fenestration* (%)	Glazing* (%)	Floor area (m^2)**	Building value ($)
1	1	19	12	199	140,500
2	1	21	19	134	105,500
3	3	15	13	112	165,000
4	3	25	21	167	694,000
5	3	26	24	236	545,000

*Percentage of wall area.
**100 ft^2 = 9.3 m^2

Table 5-2 Summary data of study locations [ARA, 2002a, 2002b]

Location	Terrain exposure	Design wind speed (m/s)*	Latitude (°)	Longitude (°)
Myrtle Beach, SC	C	58	33.69	-78.91
Georgetown, SC	C	58	33.36	-79.30
Goose Creek, SC	C	54	33.02	-80.11
Hilton Head, SC	C	58	32.19	-80.75
Carolina Beach, NC	C	58	34.04	-77.90
Atlantic Beach, NC	C	58	34.70	-76.74
Buxton, NC	C	58	35.27	-75.54
Swan Quarter, NC	C	58	35.42	-76.35
Nags Head, NC	C	58	35.94	-75.63
Corolla, NC	C	54	36.38	-75.83
Elizabeth City, NC	C	50	36.27	-76.18

* 1 m/s = 2.24 mph

[15] The gradient balance wind speed is determined by considering balance between the forces generated by the horizontal pressure gradient, Coriolis acceleration and centrifugal acceleration, in the presence of general storm translation [Georgiou, 1983].

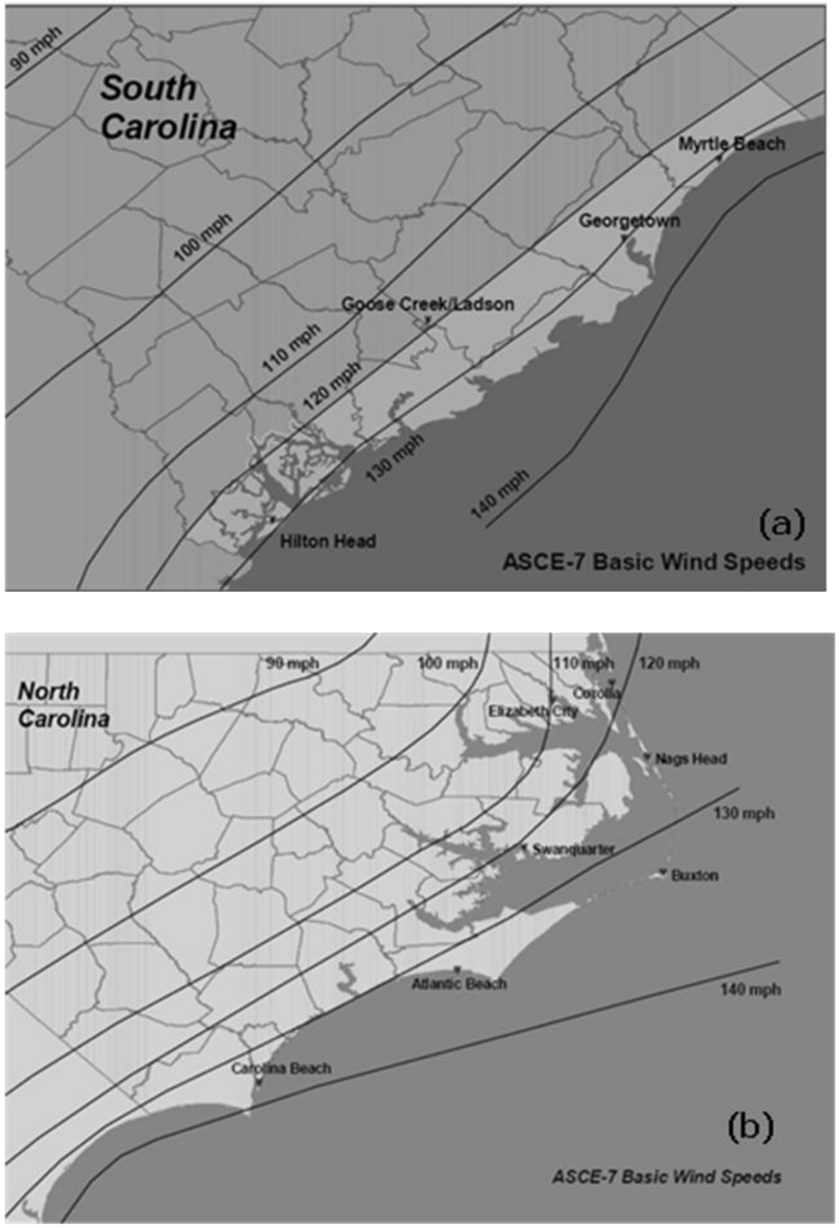

Figure 5-1 Study locations (a) South Carolina, (b) North Carolina

Table 5-3 Statistics of Hurricane Model Parameters [Rosowsky et al., 2001]

Parameter	Distribution	Distribution Parameters	
		North Carolina	South Carolina
Annual Occurrence Rate	Poisson	$\lambda = 0.277$	$\lambda = 0.306$
Approach Angle (degrees)	Normal	$\mu = 2.19$ $\sigma = 42.77$	$\mu = -20.88$ $\sigma = 44.41$
Central Pressure Difference, Δp (mb)	Weibull	u = 51.120 k = 3.155	u = 50.094 k = 2.304
Radius of Maximum Wind Speed (km)	Lognormal	$\lambda = 3.995$ $\varsigma = 0.275$	$\lambda = \ln(260/\Delta p)$ $\varsigma = 0.461$
Translation Velocity (m/s)	Lognormal	$\lambda = 1.787$ $\varsigma = 0.513$	$\lambda = 1.805$ $\varsigma = 0.456$
Decay Constant	Normal	$\mu = 0.032$ $\sigma = 0.025$	$\mu = 0.042$ $\sigma = 0.016$

5.1.3 Damage and Loss Assessment of Residential Buildings

Structural Vulnerability Model

The individual losses from the simulated hurricanes are determined using the structural vulnerability model proposed by [Stewart et al., 2000, 2003], in which the structural vulnerability (in terms of damage ratio) is defined as a function of the 10-minute surface wind speed:

$$\begin{aligned}
F_{DR}(V) &= e^{0.252(V-\Delta_D)-5.8231} && \Delta_D < V \leq (35+\Delta_D) \quad m/s \\
F_{DR}(V) &= 20+11.43\cdot(V-\Delta_D-35) && (35+\Delta_D) < V \leq (42+\Delta_D) \quad m/s \\
F_{DR}(V) &= 100 && (42+\Delta_D) < V \quad m/s
\end{aligned} \tag{5-1}$$

where F_{DR} = damage cost, expressed as a percentage of insured value and Δ_D = shift in the vulnerability curve, which is dependent on the decision alternative chosen. The shifts in the vulnerability curves were obtained for each decision alternative for each building and each location to fit the loss reductions reported by ARA (2002a, 2002b). For the five houses considered, the values of Δ_D were found to range from 8.65 m/s to 16.04 m/s for alternative (1) and from 9.98 m/s to 16.28 m/s for alternative (2). Figure 5-2 shows the vulnerability curve obtained for study building 5 located at Myrtle Beach, SC. The corresponding values of Δ_D are 12.5 m/s and 13.8 m/s for alternative (1) and alternative (2), respectively.

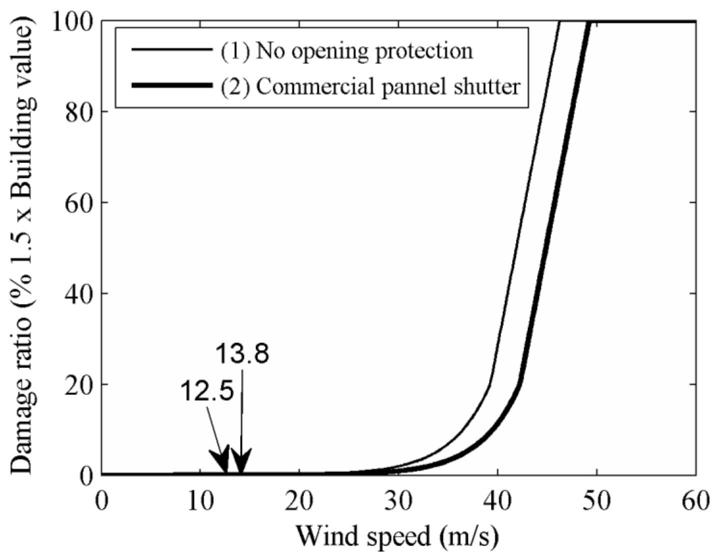

Figure 5-2. Structural vulnerability curve in terms of damage ratio (Building 5 at Myrtle Beach)

<u>Expected Life Cycle Cost</u>

Minimum expected cost analyses are based on initial cost increases and the projected 30-year loss reduction of alternative (2) (Opening protection with commercial panel shutter) relative to alternative (1) (No opening protection). The cost increase and the loss reduction for each of the study buildings located in each of the study locations were provided in the ARA reports (2002a, 2002b), where losses are assumed to occur when the buildings are damaged by wind pressure, windborne debris, or penetration of the building envelope by water. As in the ARA study, the discount rate was assumed to equal 5%. The 30-yr losses, including damage to the building, contents, and additional living expenses due to loss of building use, are obtained by simulation of hurricane wind speed using 30,000 replications.

The calculated expected life cycle cost suggested that alternative (2) (opening protection) is preferable to alternative (1) (doing nothing) in most cases. Furthermore, the gap between the life cycle costs of each alternative tends to be higher for the 3-story buildings than for the 1-story buildings, and higher in NC than in SC. Figure 5-3 shows the life cycle costs calculated for the five buildings located at Myrtle Beach. These results imply that the decision to place a moratorium on requiring additional protection against WBD for openings is characteristic of an attitude of risk acceptance on the part of the code councils.

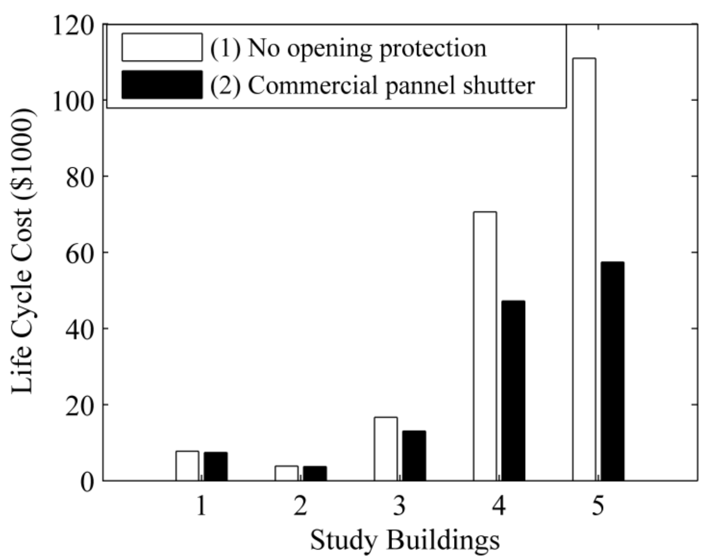

Figure 5-3. 30-yr Life cycle cost for the study buildings at Myrtle Beach

5.1.4 Risk Attitude of North/South Carolina Code Councils

Methodology

If an option chosen (alternative 1) is found to be less conservative when compared to the option based on minimum expected cost analysis (alternative 2), then the decision is characteristic of a risk-accepting attitude. The analysis to quantify the degree of risk-acceptance from a past decision is performed by decreasing the value of parameter γ in the value function (Eq. 3-5) from 0, searching for the *tipping point* of γ, at which point alternative 1 becomes preferable to alternative 2 based on maximum expected value.
The value of the tipping point, $\gamma_{tipping}$, identified in this manner indicates the minimum degree of risk-acceptance required for alternative 1 (known to be the chosen option) to become preferable to alternative 2 (option based on life cycle cost). The degree of risk-acceptance (or risk aversion) reflected in the decision, therefore, is suggested by the magnitude (in absolute value) of the tipping point.

Quantification of risk-acceptance now can be extended to both risk-acceptance parameters in value and probability weighting functions, γ and α[16]. For a two-parameter search process, α is varied from 1 to 10 by 0.01. For each value of α, a search process to identify $\gamma_{tipping}$ is performed following the above steps. The set of tipping point pairs, $(\gamma,\ \alpha)_{tipping}$ allows the sensitivity of each risk acceptance parameter to the preferred decision to be investigated. The tipping point pairs form a boundary in the risk acceptance parameter space; as noted previously, points on this boundary are denoted

[16] Note that risk parameter α is used instead of φ to represent a risk acceptance governed by a concave shape to the probability weighting function.

risk-equivalent, in the sense that they yield exactly the same preference ordering for a particular decision.

Risk-Acceptance Represented by Value Function

To better assess the attitudes toward hurricane wind risk reflected in the NC/SC Code Councils' decision on the WBD provisions, the analysis described in Section 3.2 is performed by changing the parameters that reflect risk acceptance attitude associated with value function. The parameter (γ) is considered as non-positive in the analysis because the decision made by the Code Councils typified a risk-acceptance attitude; while the minimum expected cost analysis indicated that additional protection should be provided, the actual decision was to not provide additional protection. Thus, γ is decreased from 0. The analysis is terminated once $E[V(LCC)]$ of alternative (1) becomes higher than $E[V(LCC)]$ of alternative (2); in other words, $\gamma_{tipping}$ and the corresponding value function represent the decision point of the NC/SC Code Councils regarding the WBD provisions. Figure 5-4 shows $E[V(LCC)]$ obtained for building 5 located at Myrtle Beach as an illustration. The $E[V(LCC)]$ of alternative (1) decreases sharply around the origin and becomes preferable to alternative (2) at $\gamma_{tipping}$ = - 463.22. Only for buildings 1 and 2 located at Georgetown Goose Creek and Hilton Head, SC, is alternative (1) preferable to alternative (2) based on expected life cycle cost. For those cases, $\gamma_{tipping}$ equals 0, suggesting that the Code Council stances are essentially risk-neutral. For the remaining cases, the values of $\gamma_{tipping}$ are listed in Table 5-4.

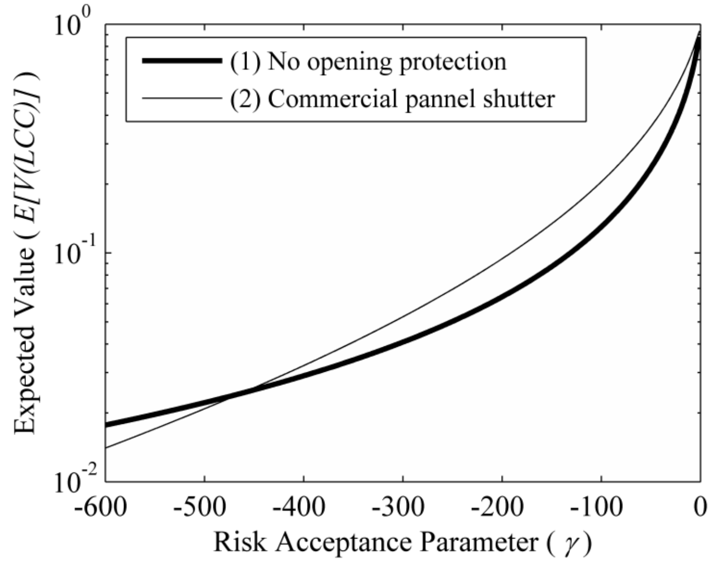

Figure 5-4. Expected value as risk-acceptance increases for building 5 located at Myrtle Beach

Table 5-4. Tipping point of risk acceptance parameter ($\gamma_{tipping}$) for 5 study buildings at 11 study locations

Buildings / Locations	1	2	3	4	5
Myrtle Beach, SC	-6.90	-5.49	-90.01	-377.52	-463.22
Georgetown, SC	0	0	-64.89	-330.61	-560.38
Goose Creek, SC	0	0	-35.69	-211.47	-317.24
Hilton Head, SC	0	0	-27.99	-151.75	-268.01
Carolina Beach, NC	-36.96	-43.08	-161.80	--*	--
Atlantic Beach, NC	-33.62	-37.51	-159.63	-481.97	--
Buxton, NC	-33.52	-42.18	-175.78	-534.58	--
Swan Quarter, NC	-5.42	-5.91	-101.51	-342.82	-594.6
Nags Head, NC	-18.83	-20.39	-127.68	-400.42	-548.95
Corolla, NC	-31.85	-22.12	-137.95	-421.31	-459.61
Elizabeth City, NC	-4.51	0	-93.79	-374.40	-382.74

*(--) indicates unlimited risk-acceptance. The corresponding value is beyond the limit of the CPT analysis, which is -710.

The value of $\gamma_{tipping}$ was found to range from 0 to -594, which suggests that the NC/ SC Code Councils adopted a risk-acceptance attitude in their decision to place a moratorium on the adoption of the windborne debris protections in the IRC. The values for the 1-story buildings are in the range of 0 to -43.08, but increase (in absolute value) dramatically for high-value buildings. The slope of *E[V(LCC)]* associated with alternative (1) decreases more slowly as $|\gamma|$ increases for these cases than for the other cases with less risk- accepting attitude and the gap between the *E[V(LCC)]* of the two alternatives is still increasing at γ = -710. For the cases examined herein, then, any consideration of the ramifications of high consequence events with low probability appears to have been ignored (by the Code Councils) in the decision process. From this analysis, one would infer that the decision made on the WBD provisions is characteristic of a risk-accepting attitude for most of the cases considered in this analysis, particularly for high-value residential buildings located in hurricane-prone regions.

<u>Risk-Acceptance Represented by Value and Probability Weighting Functions</u>

The degree of risk-acceptance is examined next by deconstructing the analysis into its consequence (value) and probability (probability weighting) components. The tipping point of risk acceptance parameters, $(\gamma,\alpha)_{tipping}$, is determined by fixing the probability risk acceptance parameter, α, and finding $\gamma_{tipping}$ similar to the aforementioned search process. Then, the value of α is varied from 1 to 10, implying that the probability of high-consequence events is increasingly underestimated (risk-accepting)[17] while the

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[17] Recall that when the decision-maker is risk-averse, he/she tends to overestimate the probability of rare events. The opposite is true when the decision-maker is risk-accepting.

probabilities of moderate or low-consequence events are given undue additional weight. For all cases considered, as more of the risk-accepting attitude is reflected in the probability weighting function, less is reflected in the value function. This results in $\gamma_{tipping}$ decreasing in absolute magnitude as $\alpha_{tipping}$ increases. Figure 5-5 shows the *E[V(LCC)]* for building 5 at Myrtle Beach as the risk acceptance parameter γ changes when the probability risk acceptance parameter α is set to 10. The *E[V(LCC)]* curves for the two alternatives cross at a lower value of $|\gamma|$ than in Figure 5; thus, $\gamma_{tipping}$ = -236.08 is found to be smaller (in absolute value) compared to $\gamma_{tipping}$ = -463.22 when the risk-acceptance attitude is reflected only in the value function. The general relationship between the two parameters, γ and α was found to be nearly linear for all cases. The pairs of tipping points separate the region of risk parameters into two sections; risk parameters lying below the boundary indicate a preference for alternative (1) while the parameters lying above the boundary yield a preference for alternative (2) regarding the WBD provisions. These *risk-equivalent* pairs of parameters, $(\gamma,\alpha)_{tipping,}$ for each study building at Myrtle Beach are shown in Figure 5-6. Note that the slopes of the boundaries are similar for each building and thus the maximum of $\alpha_{tipping}$ is larger for the higher risk-acceptance case than for the lower risk-acceptance case. Extending the range of the analysis beyond that shown in Figure 5-6, the maximum of $\alpha_{tipping}$ was found to be 21.9 for building 5.

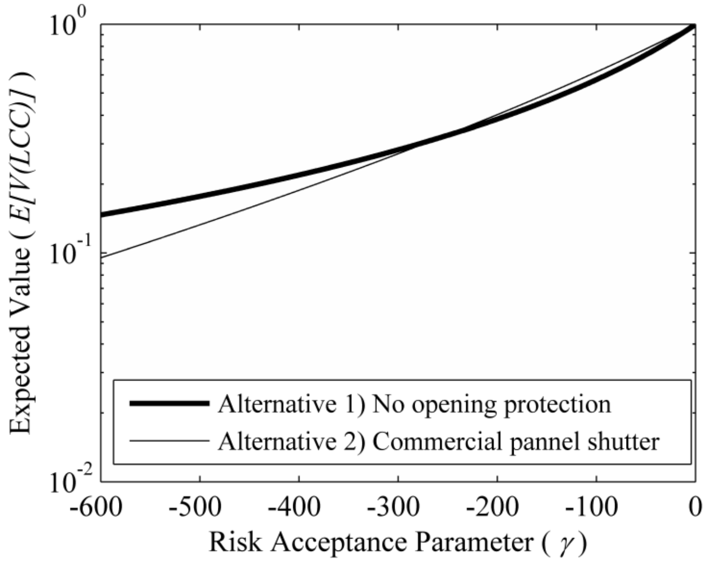

Figure 5-5. Expected value as risk-acceptance increases for building 5 at Myrtle Beach (α = 10)

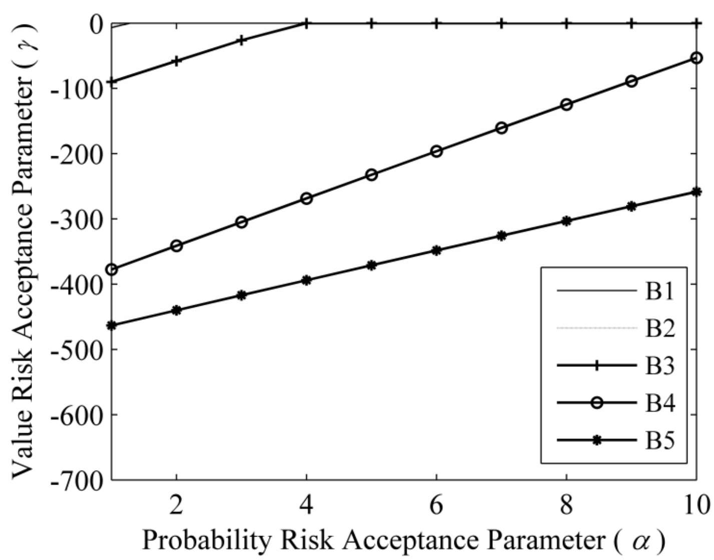

Figure 5-6. Risk-acceptance attitude defined by parameters $(\gamma, \alpha)_{tipping}$ reflected in the decision regarding WBD provisions (at Myrtle Beach)

5.2 Risk Acceptance in Wind-Resistant Design of Steel Moment Resisting Frames

To better understand attitudes towards wind risks for other building construction, the wind-resistant design of steel moment frames is examined. The frame of interest is a 9-story office building, 23 m by 46 m in plan, with a height of 36 m. The buildings are 3 bays by 6 bays in plan; the moment frame considered in this study is in the 3-bay direction, as shown in Figure 5-7. Three study locations for this building frame - Charleston, SC, Los Angeles, CA, and Boston, MA – and eight levels of wind hazard (Table 5-5) are considered. These frames previously were studied using minimum life cycle cost analysis [Kang and Wen, 2000; Wen and Kang, 2001]. Two general failure categories are considered; failure of the building envelope (12 cases) and structural limit states (10 cases). In this section, the design of the building envelope is considered; the structural limit states are considered in the following section. The 50-year life cycle cost is determined using the cost data and the associated hazard level and limit states provided by Kang and Wen (2000). The discount rate is assumed to be 5%.

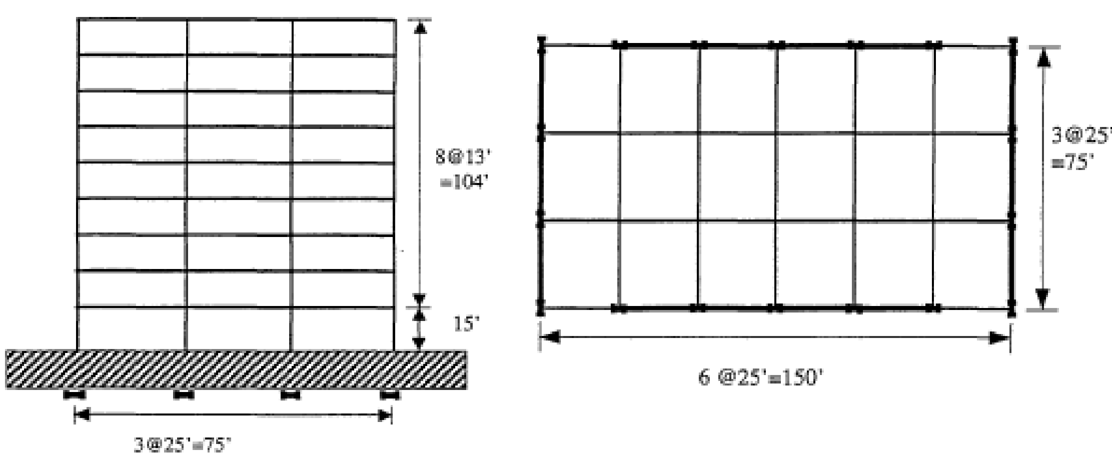

Figure 5-7 Elevation and plan of the study building

The building envelope for all frames is a curtain wall system consisting of window glass and stone panels, as shown in Figure 5-8 (for each story), of which the total glass area is 2,001 m^2 or 46.2 % of the wall. The glass thickness is the decision variable of concern. The required glass thicknesses are taken from the Pittsburgh Plate Glass (PPG) glass design chart. Since glass cladding is an architectural feature, the risk perspective is that of the building owner.

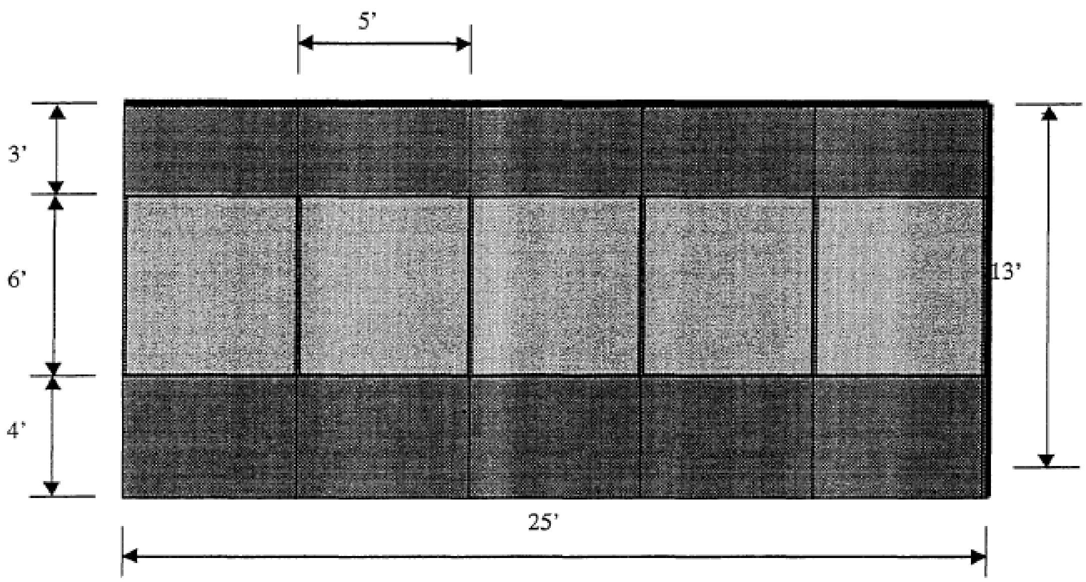

Figure 5-8 Envelope system per story consisting of stone panels and glass

5.2.1 Life Cycle Cost Analysis of Building Envelope Design

Simulation of Wind Hazard and Structural Response

Eight wind hazard levels at each location are considered, defined by mean recurrence intervals ranging from 5 (Level I) to 500 (Level VIII) years. The wind speeds for these return periods are summarized in Table 5-5. Wind hazard Level I corresponds to a serviceability condition, while wind hazard Level VIII represents approximately the wind speed that would be used in a safety check for ultimate limit states. The fragility of glass panels considers two glass failure mechanisms, wind pressure and wind-borne debris, and is provided for 12 levels of thickness and for 3 locations in [Kang and Wen, 2000; Li and Ellingwood, 2006]. The structural vulnerability curve relating damage ratio to wind velocity, which was introduced in section 5.3, is adopted to simplify the damage cost calculation.

Table 5-5. Wind speeds for each wind hazard level [Kang and Wen, 2000]

Wind Hazard Level	Wind Speed (mph)		
	Charleston, SC	Los Angeles, CA	Boston, MA
I	74.1	59.1	63.8
II	91.0	68.9	77.0
III	105.3	75.2	89.1
IV	122.2	82.0	103.4
V	134.6	88.0	113.9
VI	143.7	93.9	121.6
VII	154.1	100.7	130.4
VIII	164.5	107.5	139.2

Expected Life Cycle Cost Analysis of Building Envelope Failure

In calculating life cycle cost, both initial cost and damage cost must be included. Initial cost includes glass cost, cladding cost, and aluminum frame cost and installation [Kang and Wen, 2000]; these costs are based on unit costs suggested by Building Construction Cost Data (BCCD) and are summarized in Table 5-6. Total damage cost includes direct structural damage cost, loss of contents, relocation cost, and economic loss. Each loss is calculated based on FEMA 227 and 228 and the corresponding unit costs are \$85/sqft, \$28.9/sqft, \$1.5/month/sqft, \$0.58/month/sqft, \$8.58/month/sqft, respectively. The calculated expected life cycle costs for Charleston, Los Angeles and

Boston are shown in Table 5-6; the optimal glass thicknesses for these three locations are 1.9 cm (3/4″), 1.3 cm (1/2″) and 1.6 cm (5/8″), respectively. Since the commonly used glass thickness based on the PPG glass design chart for Charleston is 0.8 cm (5/16″), which is only 42% of the optimal thickness indicated by the minimum life cycle cost analysis, the PPG glass design chart reflects a risk-accepting attitude on the part of building owner. For Los Angeles and Boston, the optimal thicknesses are again lower than the commonly used thicknesses, 0.5 cm (3/16″) and 0.6 cm (1/4″), respectively, implying a risk-accepting attitude toward damage to the building envelope for those two locations as well.

Table 5-6. Envelope system and expected life cycle cost of Steel Frames

Thickness (cm)	Initial Cost* ($)	Total Expected Life Cycle Cost ($)		
		Charleston	Los Angeles	Boston
0.32	647,166	2,999,548	3,130,779	3,871,053
0.40	653,032	2,967,323	2,910,366	3,816,545
0.48	658,899	2,916,042	2,766,230	3,598,615
0.64	734,140	2,829,390	2,297,778	3,348,947
0.80	801,129	2,658,301	2,114,114	3,098,216
0.95	868,120	2,515741	1,981,300	2,870,165
1.27	1,010,116	2219,641	1,871,215	2,596,187
1.59	1,152,111	2,009,254	1,905,201	2,356,204
1.90	1,335,331	1,973,425	2,091,482	2,507,026
2.54	1,678,869	2,059,823	2,532,921	2,796,907
3.18	2,051,035	2,298,654	3,032,334	3,277,227
3.81	2,451,829	2,661,349	3,598,200	3,834,620

*Initial costs are listed for Charleston. For other locations, initial costs are calculated by multiplying by a location factor equal to 1.43 and 1.50 for Los Angeles and Boston, respectively.
**1 in. = 2.54 cm

5.2.2 Risk Acceptance Reflected in Choice of Building Envelope System

Risk Acceptance represented by Value Function

The attitude toward risk reflected in the above decisions regarding a suitable glass thickness for the building envelope is evaluated from the risk acceptance parameter, γ, in the value function implied by that decision, as in section 5-1. Parameter γ is decreased from 0 until it reaches the tipping point at which the commonly used glass thickness becomes preferable based on the maximum expected value. The values of $\gamma_{tipping}$ for Charleston, Boston and LA are found as -3.702, -7.194, and -331.80 from the analysis, which are relatively small compared to the comparable values for low-rise residential construction presented earlier in section 5.1. We emphasize that the risk-acceptance attitude in this section pertains to the usage of glass in the building envelope, which makes the building owner the responsible decision maker. In contrast, the risk-acceptance attitude for residential building construction apparent from the analysis in section 5.1 is reflective of the attitude of a code council. This suggests that group decision-makers may neglect risk more readily than an individual decision-maker, especially when they are not directly affected by the consequences of the risk.

Risk Acceptance represented by Value and Probability Weighting Functions

Risk-equivalent pairs of parameters $(\gamma,\alpha)_{tipping}$ are determined by decomposing the degree of risk-acceptance into the portion reflected by the value function and the portion reflected by the probability weighting function, as before. The boundary formed by this decomposition is plotted in Figure 5-9. If plotted on an arithmetic scale, the boundary is found to be linear as implied in section 3; however those pairs are plotted in log scale of

γ, and the curve for Los Angeles is nearly constant. This suggests that the characteristics of risk attitude depend on the design or decision context, even for the same source of risk.

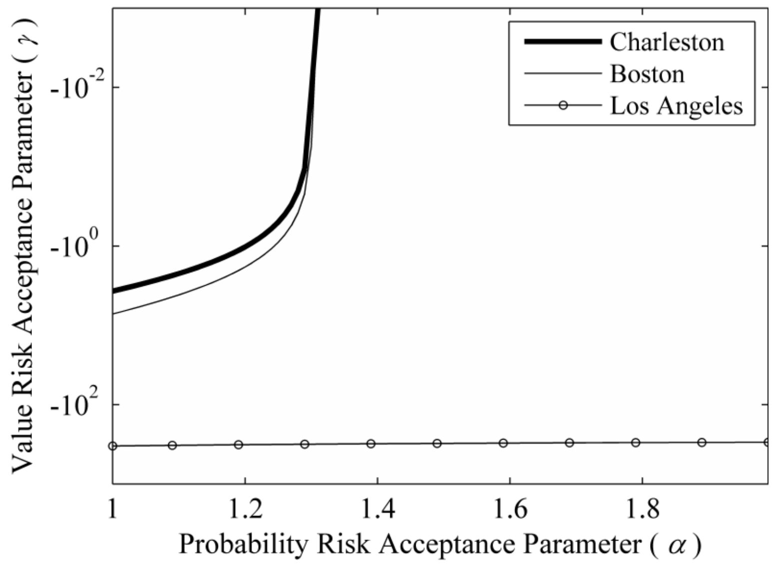

Figure 5-9. Risk-acceptance attitude defined by parameters $(\gamma, \alpha)_{tipping}$ reflected in commonly used glass thickness

5.3 Risk Attitude for Competing Natural Hazards

A decision-maker's attitude toward risk depends on various factors, including hazard characteristics, structure type and occupancy, and resources that are available to mitigate the risk. Among these factors, hazard characteristics are among the most significant factors affecting attitudes toward risk. Attitudes toward wind risk were typical of risk-accepting while the attitude toward seismic risk apparently is more risk-averse [Cha and Ellingwood, 2011]. To shed more light on this subject, risk attitudes for competing wind and seismic hazards are explored with the same structural frames considered in section 5.2. These ten frames originally were designed for earthquake according to the NEHRP 1997 *Tentative regulations for seismic-resistant design of buildings* [Kang and Wen, 2000; Wen and Kang, 2001]. The fundamental periods of these frames ranged from 1.50s to 4.34 s and the system yield force coefficient, defined by the ratio of system yield force (expressed in terms of resultant base shear) to weight, ranged from 0.033 to 0.245. To provide a consistent basis for comparison between wind and earthquake hazards, the design wind and seismic intensities for these frames are compared in this section in terms of system yield force. By comparing those design levels for wind and seismic hazards with current design recommendations, attitudes of code authorities toward risks from both wind and earthquake hazards can be examined.

5.3.1 Life Cycle Cost Analysis

Damage due to Extreme Winds

In order to determine structural damage, seven limit states, described in terms of drift ratio according to FEMA 227, are considered. Limit state probabilities for each design level, obtained from equivalent single-degree-of-freedom system analysis, are provided in [Kang and Wen, 2000]. Damage cost is calculated using limit state and damage factor relationship provided by FEMA 227 and the same unit cost considered in section 5.2. Data for the life cycle cost portion of the analysis are provided in [Kang and Wen, 2000].

Damage due to Earthquakes

Damage cost is determined considering the same limit states but with the added dimension of loss of life and injury. Loss of life and injury does not play a key role in loss due to hurricane wind hazards since such hazards can be forecast, allowing time for evacuation. However, the sudden occurrence of earthquakes precludes evacuation. The occupancy of the nine-story building is assumed to be 434 people based on the same occupancy rate used in section 4.2. Human life loss and injury rates for the limit states and mortality costs are suggested in FEMA 227.

Table 5-7. Limit states defined in terms of drift ratio [Kang and Wen, 2000]

Limit State	Damage State	Permissible Drift Ratio (%)	Damage Factor Range (%) by FEMA 227
I	None	0.2	0
II	Slight	0.5	0-1
III	Light	0.7	1-10
IV	Moderate	1.5	10-30
V	Heavy	2.5	30-60
VI	Major	5.0	60-100
VII	Destroyed	--	100

Optimal Wind Design Level

Initial costs and expected life cycle costs for wind hazards are listed for Charleston, Los Angeles, Boston in Tables 5-8, 5-9, 5-10. Column 4 of those tables shows that the optimal system yield force coefficients obtained from the minimum expected life cycle cost analysis are 0.115, 0.061, and 0.093 for Charleston, LA and Boston, respectively. These values all are larger than what was stipulated for design according to ASCE 7-98 (between 0.061 and 0.093 at Charleston and Boston, and between 0.033 and 0.061 at Los Angeles).[18] Thus, a risk-accepting attitude is apparent in the wind-resistant design criteria for this building structure.

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[18] The frames were designed by codes of practice in the mid-1990's, and the comparison is made on that basis, rather than more recent codes.

Table 5-8. Expected life cycle cost considering seismic and wind hazards (Charleston)

System Yield Force Coefficient	Period (s)	Initial Cost ($)	Expected Life Cycle Cost ($)	
			Wind	Seismic
0.033	4.335	1,182,217	5,891,359	2,266,878
0.061	3.159	1,247,258	1,990,054	1,915,903
0.093	2.542	1,321,040	1,502,703	1,801,512
0.115	2.323	1,388,844	1,490,635	1,761,860
0.140	2.062	1,451,130	1,492,382	1,773,175
0.169	1.883	1,516,234	1,531,136	1,801,331
0.188	1.772	1,582,304	1,587,713	1,843,451
0.213	1.664	1,647,512	1,648,640	1,873,880
0.230	1.572	1,723,808	1,723,994	1,927,734
0.245	1.500	1,798,785	1,798,802	1,991,740

Table 5-9. Expected life cycle cost considering seismic and wind hazards (Los Angeles)

System Yield Force Coefficient	Period (s)	Initial Cost ($)	Expected Life Cycle Cost ($)	
			Wind	Seismic
0.033	4.335	1,694,101	2,843,037	13,899,291
0.061	3.159	1,787,307	1,853,709	6,909,429
0.093	2.542	1,893,037	1,896,379	4,643,665
0.115	2.323	1,990,199	1,990,741	4,463,419
0.140	2.062	2,079,455	2,079,465	3,805,461
0.169	1.883	2,172,747	2,172,747	3,486,017
0.188	1.772	2,267,425	2,267,425	3,411,857
0.213	1.664	2,360,868	2,360,868	3,471,981
0.230	1.572	2,470,200	2,470,200	3,438,084
0.245	1.500	2,577,641	2,577,641	3,415,196

Table 5-10. Expected life cycle cost considering seismic and wind hazards (Boston)

System Yield Force Coefficient	Period (s)	Initial Cost ($)	Expected Life Cycle Cost ($)	
			Wind	Seismic
0.033	4.335	1,777,895	4,663,150	1,806,532
0.061	3.159	1,875,708	2,264,654	1,900,974
0.093	2.542	1,986,667	2,079,821	2,008,697
0.115	2.323	2,088,635	2,128,695	2,101,849
0.140	2.062	2,182,306	2,189,606	2,188,251
0.169	1.883	2,280,213	2,280,881	2,282,453
0.188	1.772	2,379,573	2,379,642	2,380,433
0.213	1.664	2,477,638	2,477,640	2,477,889
0.230	1.572	2,592,377	2,592,377	2,592,479
0.245	1.500	2,705,132	2,705,132	2,705,138

Optimal Seismic Design Level

Data needed for the life cycle cost analysis are given in [Kang and Wen, 2000]. Initial costs and expected life cycle costs for seismic hazards are listed for Charleston, Los Angeles, Boston in Tables 5-8, 5-9, 5-10. Column 5 of these tables shows that the optimal system yield force coefficients considering only seismic hazard are 0.115, 0.188, and 0.033 for Charleston, Los Angeles, and Boston. The current design level of the frame is close to 0.08 and 0.140 for Charleston and Los Angeles. Boston has relatively low seismicity and the optimal value is smaller than the design level provided by the standard. For both Charleston and Los Angeles, a risk-acceptance attitude toward earthquakes is observed for this frame and thus a further analysis of the degree of risk-acceptance is conducted, as before.

5.3.2 Risk of Structural Damage From Competing Hazards

For risk from extreme winds, an examination of the risk acceptance embodied by the above differences is conducted by searching for the tipping point of the risk acceptance parameter γ which makes the optimal system yield force coefficients become 0.61 for Charleston and Boston, and 0.33 for Los Angeles. This search process yields $\gamma_{tipping}$ = -492.4 and -286.7 for Charleston and Boston, while for Los Angeles the value of $\gamma_{tipping}$ is beyond the limit of computation. These values are much higher (in absolute value) than the values obtained for the building envelope system and are similar to those in section 5.3 for residential buildings. Since the decision of interest in this analysis involves structural design according to a building code or standard, the results again suggest that decision-makers tend to downplay risks when the consequences of those risks are indirect. Moreover, people tend to be more aware of risk if the consequence of the event is fairly well-known, such as a broken window or water damage to building contents, rather than rare, such as a structural failure. A search for the tipping point of the risk acceptance parameter when considering seismic hazards, which represents the level of risk-accepting attitude inherent in current design codes, yields $\gamma_{tipping}$ = -22.9 and -6.7 for Los Angeles and Charleston when the probability weighting parameter, α, is set to equal 1.

A further analysis of the *risk-equivalent* pairs for wind risk shows the convex shaped boundary illustrated in Figure 5-10, which is similar to that observed for envelope system design. It is interesting to note that Los Angeles tends to have a distinctly higher risk-acceptance attitude toward wind than the other two locations for both structural and nonstructural damage. When more risk-acceptance is reflected by the probability weighting function (as α increases), less is reflected in the value function (value of $\gamma_{tipping}$ decreases), as in the previous cases considered.

Comparison of Risk Attitude toward Competing Hazards

Differences between the attitudes toward wind and seismic risks are evident when comparing the risk acceptance parameters shown in Figures 5-10 and 5-11. The values of parameters, $(\gamma, \alpha)_{tipping}$ for seismic risk are much smaller (in absolute value) than those for wind hazards at all study locations, which implies much less risk acceptance for earthquake than for wind risks. These differences perhaps are not surprising, in view of the differences in the loss characteristics associated with wind and seismic hazards. Losses induced by extreme wind events tend to be more economic in nature, while losses due to large earthquakes often are accompanied by human casualties. Decision-makers usually are more risk-averse when human life loss and injury are involved. It is interesting to note that current design practices surveyed in this paper imply a degree of risk acceptance toward building performance under both wind and earthquake hazards, at least for the nine-story steel moment frame considered. Conversely, risk-averse attitudes were evident in a previous assessment of building department decisions regarding the seismic retrofit of unreinforced masonry (URM) buildings in San Francisco [Cha and Ellingwood, 2011]. These differences suggest that risk attitude is affected by not only hazard characteristics but also other factors, such as building type (SMRF or URM), decision alternatives (design or retrofit), and the possibility of secondary losses to society such as loss of a building with historical or symbolic asset value.

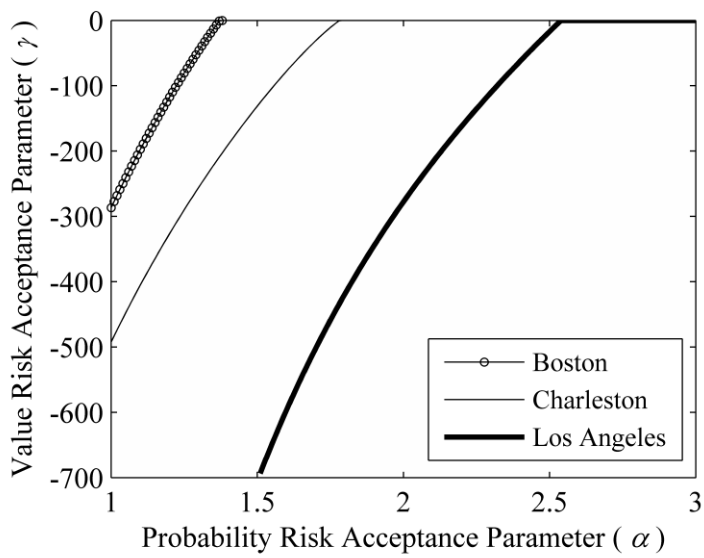

Figure 5-10. Risk-acceptance reflected in the design wind intensity in 1990

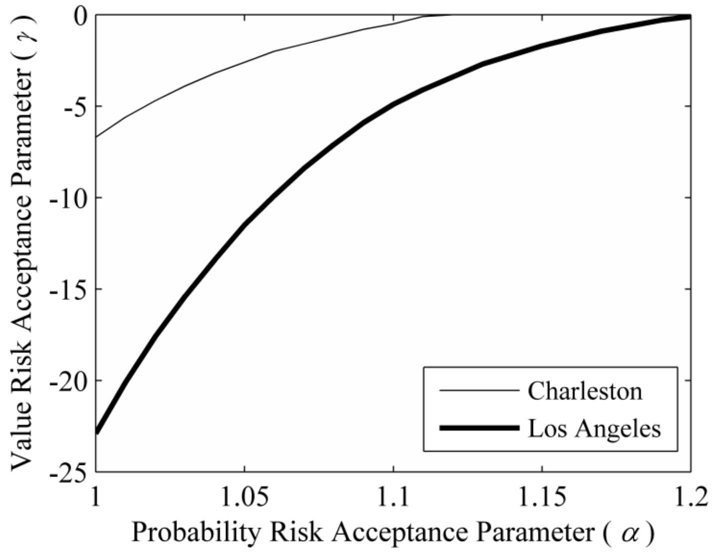

Figure 5-11. Risk acceptance reflected in the seismic design in 1990

5.4 Closure

Decisions regarding wind-resistant design or retrofit for wood-frame residential buildings and steel moment-resisting frame buildings exposed to wind or earthquake hazards have been examined in this Chapter using cumulative prospect theory to provide an improved understanding of the role of risk attitudes in structural engineering decisions in the presence of uncertainty. An attitude of risk acceptance was evident in decisions related to protection of residences against hurricane-produced wind borne debris. The degree of risk-acceptance reflected in the decisions regarding wood-frame buildings appears to be higher for 3-story buildings than for 1-story buildings and depends on the local building code authority. The reason for this is not entirely clear, but it may be because the building authority did not distinguish between wood frame buildings with different size or value in arriving at proposals for wind-borne debris. A comparison of the risk acceptance attitudes toward building protection and glass cladding design revealed that a (building code) group of decision-makers confronted with a risk to public safety tends to be more risk-accepting than an individual building owner dealing with direct consequence of the risk. A subsequent analysis of risk attitudes toward competing wind and earthquake hazards suggested less risk-acceptance toward seismic hazards than toward wind hazards. Considering these results, along with perspectives drawn from the study on risk-averse attitudes reflected in seismic retrofit of unreinforced masonry building located at San Francisco, it is clear that attitudes toward risk are governed by diverse factors and are difficult to generalize. It seems clear, however, that characteristics of low-probability events and their consequences play a dominant role.

CHAPTER 6

SUMMARY, CONCLUSION AND FUTURE WORK

6.1 Summary

Civil infrastructure, by its nature, may be exposed to natural and man-made hazards, such as earthquakes, hurricanes, floods, and terrorist attack. When individuals or groups are confronted with such events with low probability and potentially severe consequences, their perception of risk, which is an essential component of risk analysis and risk-informed decision-making, can be systematically distorted by the phenomenon of risk aversion. While this phenomenon is well-recognized, its role in practical civil engineering decision-making has not yet been investigated. A better understanding of the risk perception of responsible decision makers, including federal agencies, regulatory bodies, professional societies, individual building owners, and others, is required to develop and apply improved quantitative decision models for managing risk to civil infrastructure facilities subjected to low-probability, high-consequence hazards. Research in cognitive psychology and behavioral science has suggested that risk perception in various decision contexts is influenced by numerous factors, which range from societal impact of the risk to personal knowledge or experience of the risk.

In this study, the nature of risk perception has been investigated in relation to those decision contexts within the framework of cumulative prospect theory (CPT). We began our study of value systems which account for various risk perceptions and attitudes - risk aversion, risk neutrality, and risk acceptance - by analyzing risk pricing practices in reinsurance. The risk aversion of a reinsurer is reflected in the process by which he/she decides to underwrite policies. It was observed that risk aversion tends to increase as the size of potential loss relative to the available resources or initial capital increases A general value system which is consistent with the observed trend was proposed in the form of a value function. Based on that value function and by utilizing a probability weighting function to account for erroneous (and often excessively conservative) estimates of likelihoods of extreme events, a general methodology to analyze a past decision in which the preference is known and to identify the risk attitude reflected in that decision was been developed and tested, first for a two-alternative decision case and then for a multiple-alternative decision case. The analysis began with qualitative identification of risk attitude by comparing the known preference ordering of the considered alternatives with that based on minimum expected life cycle cost, which represents a risk-neutral stance. Once risk averse or risk accepting attitudes was identified, the relative severity of these attitudes was quantified by introducing metrics (in the form of tipping points and risk-averse equivalent pairs) to represent threshold values of risk parameters in value and probability weighting functions at which preference ordering changes to make the known preferred alternative optimum based on maximum expected value.

With the insights gained from the examination of reinsurance premium-setting as a guide, two investigations of attitudes toward risk of buildings and civil infrastructures from low-probability, high-consequence events were performed: one concerning seismic hazard and the other concerning hurricane wind hazard. First, a seismic retrofit decision of an unreinforced masonry office and commercial building complying San Francisco Building Code (SFBC) was analyzed to define specific parameters in the value and probability weighting functions identified above and to suggest a range of tipping points that define the transition between attitudes of risk-neutrality and risk-aversion. The investigation was extended to other building occupancies, including residential and industrial, and different numbers of building stories. The implied range of risk parameters representing risk aversion reflected in the regarding section in SFBC was used for a sensitivity analysis of risk aversion to aseismic design of the same steel frame introduced before.

Second, a decision by the North and South Carolina Building Code Councils to place a moratorium on the enforcement of a section in the International Residential Code concerning protection of residences against wind-borne debris was analyzed. Residences represented by different real estate values and locations were considered to provide a broad perspective on the nature of these risk attitudes. Life cycle costs of current building envelope designs were compared to costs of designing with additional protection. In contrast to the seismic retrofit decision considered previously, this decision clearly indicated a risk acceptance attitude toward residential buildings exposed to hurricane extreme winds. Risk perception on the part of building owners toward nonstructural damage due to winds was investigated further by considering design levels for glass cladding (in terms of glass thickness) on steel moment-resisting frame buildings located at Los Angeles, CA, Boston, MA and Charleston, SC. This analysis also indicated similar risk-accepting attitudes, but on the part of the building owner, since the cladding is an architectural feature rather than a building safety consideration. By comparing ranges of risk parameters obtained for building owners with those of North/Couth Code Councils, it was noted that risk perception depends on whether the decision is the responsibility of a private or a public entity. To better understand how risk attitude depends on the nature of the hazard, structural design levels of the same steel frames were examined for earthquakes and for extreme winds to provide sets of risk parameters which represent severity of risk attitudes reflected in design practices (USGS for earthquakes and ASCE 7-98 for extreme winds). In general, it was found that decision-makers are more risk-averse concerning earthquake risks than for hurricane wind risks.

6.2 Conclusions

The quantitative and qualitative assessment of risk attitude reflected in the decisions considered in this study provide some important observations on the nature of risk attitude in specific decision contexts related to civil infrastructure. While these observations are not absolutely definitive due to the limited data and number of case studies that could be performed, they nonetheless are suggestive and form the basis for further inquiry. Specifically:

1. The attitude of a large corporate decision-maker toward risk from low-probability, high-consequence hazards appears to be risk-averse. The level of risk aversion tends to increase as the financial resources of the corporation decreases and potential size of loss increases.
2. Attitudes on the part of a code council toward seismic risk to unreinforced masonry buildings, and the desirability of seismic retrofit, also appear to be risk-averse, with the severity of the risk aversion depending upon building occupancy and number of stories. Risk-aversion is most pronounced for residential buildings, followed by office and commercial buildings, and least for industrial buildings. For all building uses, risk aversion increases as the number of building stories increases.

3. When risk aversion is considered in the life cycle analysis of a steel moment resisting frame exposed to earthquake hazards, the optimal seismic design level of the frame increases noticeably compared to that obtained on the basis of minimum expected cost.
4. The effect of overestimation of low probabilities of seismic events on the optimal design level (through the nonlinear probability weighting function component of CPT) is significant, which suggests that both probability weighting function and value function may be necessary to account for risk aversion in structural engineering and other civil infrastructure decisions.
5. An investigation of attitudes toward risk to wood frame residential buildings from wind-borne debris caused by hurricanes reveals a risk-acceptance attitude on the part of the North and South Carolina code councils. Surprisingly, the level of the risk-acceptance tends to increase as building value increases, and also depends on the local building code authority.
6. The risk attitudes of individual building owners confronted with extreme hurricane wind hazards appears to be one of risk-acceptance as well, but less accepting than that of the code councils, which implies that risk attitudes of decision makers depend upon whether or not the decision maker deals directly with the potential consequences of the hazard.
7. A comparative assessment of risk attitudes toward competing wind and earthquake hazards revealed less risk acceptance toward seismic hazards than toward hurricane wind hazards. Since severe earthquakes endanger human lives, while hurricanes

cause primarily property damage, the difference in risk aversion is likely to be due to differences in loss characteristics of the two hazards.

6.3 Recommendations for future research

Our current understanding of the fundamental characteristics of risk attitudes toward civil infrastructure decision-making remains limited. Data to support the use of cumulative prospect theory and other advanced decision methods are limited, and this study could consider only a few decision contexts in which risk attitude could be identified. Additional research is necessary to investigate the nature of risk aversion embedded in general civil engineering practices and to eventually establish a more comprehensive framework for incorporating quantitative risk aversion analysis in civil infrastructure decisions. Further investigations would be desirable in the following areas:

- The current study concluded that hazard characteristics play a key role in a decision maker's perception of risk due to the different potential consequences associated with each hazard and the degree of his/her involvement in those consequences. This was apparent in the difference in the way that the Carolinas Building Code Council and individual building owners viewed hurricane wind risk. A thorough analysis is required on how the perception changes for other hazards, such as flooding, tornado, fire, and terrorist attack, to further understand the sensitivity of risk perception and tolerance to hazard type or loss characteristics.

- The influence of the general characteristics of the civil infrastructure facility – e.g., building structural system, occupancy, building size, property value - on risk attitudes must be understood further with more diverse contexts, Certain types of buildings may be especially vulnerable to damage from some hazards and such loss characteristics affect risk perception.

- A preliminary investigation of risk attitude embedded in regulatory decisions made by federal regulatory agencies such as the NRC, OSHA and EPA, revealed noticeable discrepancies in risk aversion culture in these agencies, manifested by vast differences in dollars expended on regulation per life saved. A recent study on DHS expenditures for counterterrorism [Stewart et al., 2011] also has raised questions regarding the allocation of resources for maintaining national security. The basis for these discrepancies currently is unknown and must be understood to develop and implement rational public policies for mitigating risks from different hazards and threats in the future.

- There is evidence of variation in risk attitudes across and within design codes in terms of the safety margins, importance factors, etc, stipulated in these codes. These variations must be understood to fully capture the nature of the risk attitudes of code writers and practicing engineers. The code development process is evolutionary in nature, and the safety margins embedded in codes, including the new generation of performance-based standards, have never been properly rationalized [Ellingwood, 2008] .

- Selective attention to risk and preferences among different types of risk are cross-cultural in nature. Individual and group perceptions of threats depend on their wealth and social standing, cultural biases, political orientation, and previous experience. These societal factors vary from country to country. Little research appears to have been done to address such issues. An understanding of the international variation of risk aversion in individual and public decision-making is crucial to decision-making in an increasingly global economy.

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