

**RISK-INFORMED DECISION FOR CIVIL INFRASTRUCTURE
EXPOSED TO NATURAL HAZARDS: SHARING RISK ACROSS
MULTIPLE GENERATIONS**

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Presented to
The Academic Faculty

by

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**RISK-INFORMED DECISION FOR CIVIL INFRASTRUCTURE
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MULTIPLE GENERATIONS**

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I dedicate this research to my family for their endless love

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SUMMARY

Civil infrastructure facilities play a central role in the economic, social and political health of modern society and their safety, integrity and functionality must be maintained at manageable cost over their service lives through design and periodic maintenance. Hurricanes and tropical cyclones, tornadoes, earthquakes and floods are paramount among the potentially devastating and costly natural disasters impacting civil infrastructure. Even larger losses may occur in the future, given the population growth and economic development accompanying urbanization in potentially hazardous areas of the world. Moreover, in recent years, the effects that global climate change might have on both the frequency and severity of extreme events from natural hazards and their effect on civil infrastructure facilities have become a major concern for decision makers. Potential influences of climate change on civil infrastructure are even greater for certain facilities with service periods of 100 years or more, which are substantially longer than those previously considered in life-cycle engineering and may extend across multiple generations. Customary risk-informed decision frameworks may not be applicable to such long-term event horizons, because they tend to devalue the importance of current decisions for future generations, causing an ethical and moral dilemma for current decision-makers. Thus, intergenerational risk-informed decision frameworks that consider facility performance over service periods well in excess of 100 years and extend across multiple generations must be developed.

This dissertation addresses risk-informed decision-making for civil infrastructure exposed to natural hazards, with a particular focus on the equitable transfer of risk across multiple generations. Risk-informed decision tools applied to extended service periods require careful modifications to current life-cycle engineering analysis methods to

account for values and decision preferences of both current and future generations and to achieve decisions that will be sustainable in the long term. The methodology for supporting equitable and socio-economical sustainable decisions regarding long-term public safety incorporates two essential ingredients of such decisions: global climate change effect on stochastic models of extreme events from natural hazards and intergenerational discounting methods for equitable risk-sharing. Several specific civil infrastructure applications are investigated: a levee situated in a flood-prone city; an existing dam built in a strong earthquake-prone area; and a special moment resisting steel frame building designed to withstand hurricanes in Miami, FL. These investigations have led to the conclusion that risks can and should be shared across multiple generations; that the proposed intergenerational decision methods can achieve goals of intergenerational equity and sustainability in engineering decision-making that are reflective of the welfare and aspirations of both current and future generations; and that intergenerational equity can be achieved at reasonable cost.

CHAPTER 1

INTRODUCTION

1.1 Statement of the Problem

Civil infrastructure facilities are susceptible to damage brought about by the effects of natural hazards and aging caused by aggressive environmental conditions, both of which may cause deterioration in performance and increase the risk of structural failure. The human and economic losses that may result from these failures or from lack of proper maintenance of infrastructure facilities can be significant. The potential exists for even larger losses in the future, given that population and infrastructure development in hazard-prone areas of the United States are increasing dramatically; for example, 39 percent of the U.S. population resides in Coastal Shoreline Counties defined by the most recent report from NOAA in 2010 and is projected to have more than 134 million people by 2020, an increase of nearly 9 percent from its 2010 level of 123 million (Crossett et al. 2013). The world's population becomes more concentrated in urban areas, making communities much more vulnerable to natural hazards (Huppert and Sparks 2006). Moreover, in recent years, there has been growing evidence that global climate change may affect both the frequency and severity of the extreme events from natural hazards. The potential effect of climate change-related hazards on civil infrastructure facilities is likely to become a major concern for regulatory authorities and other decision-makers.

Risk-informed models to predict structural resistance and extreme structural loads due to natural hazards are a critical part of life-cycle reliability assessment as well as probability-based limit states design or performance-based design codes. Aging and degradation mechanisms and the structural demands that arise from operating environments and natural and man-made hazards invariably are stochastic in nature, making the reliability of civil infrastructure facilities time-dependent. Although time-

dependent reliability analysis of aging structures has matured during past two decades (Ellingwood and Mori 1993, Mori and Ellingwood 1993, Frangopol et al. 1997, Val and Melchers 1997, Stewart and Rosowsky 1998, Petcherdchoo et al. 2008), such analyses generally have considered only the deterioration in structural capacity in time through simple semi-empirical stochastic models, and have treated the service and environmental demands as stationary in nature. The assumption of stationarity in demand is not accurate when the time-dependent reliability analysis involves demands that are the result of evolving geophysical or climatological influences due to global climate change, which may cause the extreme events which govern failure of civil facilities to occur more frequently and to increase in intensity over a long period of time (Sterl et al. 2008, Steenbergen et al. 2012). However, the implications of non-stationarity in demands on civil infrastructure systems due to climate change have been considered in only a few instances (Bjarnadottir et al. 2011, Stewart et al. 2011, Bastidas-Arteaga et al. 2013). Stochastic models to account for this non-stationarity, as such effects are understood at the present time, must be developed. Furthermore, these stochastic representations of capacity and demand must be integrated in a time-dependent reliability assessment that is used to estimate how facility performance might be affected by climate change over extended service periods.

Life-cycle performance, safety, reliability and risk have become emergent issues for civil infrastructure systems exposed to recurring natural and man-made disasters, the infrastructure crisis, sustainability issues and global warming. While civil infrastructure (at least in North America) seldom has been designed and constructed with specific service periods in mind, it is commonly understood that buildings, bridges and similar facilities should perform their intended functions for service periods of approximately 50 to 75 years (American Society of Civil Engineers [ASCE] 2010, American Association of State Highway and Transportation Officials [AASHTO] 2012). For certain civil infrastructure projects, the service period might be substantially longer than what

typically has been customary for buildings and bridges. Such considerations extend the potential consequences of life-cycle engineering decisions to future generations, far beyond the customary facility utilization horizon, budget cycles for public investment, terms of office of elected public officials, or lifetimes of responsible decision-makers. Over such extended periods, the long-term effects of structural deterioration and nonstationary occurrence rate and intensity of extreme environmental events due to climate change may play an even more significant role. Moreover, current quantitative risk-informed decision support procedures are limited to decision preferences of the current generation: current decision-makers have tended to consider costs and benefits to the present generation rather than try to achieve life-cycle objectives for extended periods, especially when the service lives extend beyond their own generation. Thus, current decision methods will require modifications to evaluate performance of essential infrastructure facilities over extended time frames and to support sustainable decisions regarding long-term public safety and economic performance (Rackwitz et al. 2005, Nishijima et al. 2007, Lee and Ellingwood 2013).

1.2 Research Objectives and Scope

The research herein aims to develop an intergenerational risk-informed decision framework for civil infrastructure exposed to natural hazards, with a particular focus on the equitable transfer of risk across multiple generations. Such decision-making processes require that current models for time-dependent reliability assessment and existing decision methods based on life-cycle cost be modified to be applicable to situations with time horizons extending to future generations. The intention is to assess long-term risks due to natural hazards and to achieve equitable and socio-economically sustainable decisions for civil infrastructure, in which the likelihood of successful future performance is maximized at a reasonable, if not a minimum, cost. To achieve these objectives, the following research tasks will be conducted:

- Review and critically appraise recent research in time-dependent reliability, life-cycle cost analysis, discounting practices and risk-informed decision methods for civil infrastructure;
- Investigate stochastic models of structural behavior that incorporate non-stationarity in actions resulting from natural hazards that may be affected by climate change, coupled with existing material aging and structural deterioration models;
- Integrate uncertainties in future demands and structural aging mechanisms in time-dependent structural reliability analysis to demonstrate compliance with reliability-based performance objectives;
- Propose an intergenerational discounting method for civil infrastructure to achieve equitable risk sharing between current and future generations;
- Develop an intergenerational risk-informed decision framework that considers facility performance over service periods extending to 100 years or more;
- Examine the feasibility and practicality of such a framework through several benchmark problems for different types of infrastructure exposed to hurricanes and earthquakes.

The research will examine a number of key issues that must be addressed in the course of life-cycle reliability assessment of civil infrastructure facilities that must remain functional for service periods of several generations.

1.3 Organization of Dissertation

The content of the dissertation is organized into the following chapters.

Chapter 2 reviews and appraises previous risk-informed decision methods, including stochastic models of deterioration and natural hazards, time-dependent reliability assessment, life-cycle cost analysis and decision-making. In addition, the last section thoroughly reviews the economics literature on discounting method, where its

concept and importance in decision-making have provided experience that is lacking in the context of civil infrastructure.

Chapter 3 reveals some of the deficiencies in current risk-informed assessment procedures through a simple example of minimum expected life-cycle cost analysis. The example shows the urgent need of decision support framework for socio-economically sustainable civil infrastructure and identifies two ingredients as intergenerational elements of a decision framework which is applicable to situations with time horizons extending to future generations: one is a time-dependent failure rate and the other is a time-varying discount rate.

Chapter 4 presents time-dependent reliability assessment of civil infrastructure under climate change, which is one of the intergenerational elements suggested in Chapter 3. This chapter examines the probabilistic structures of the stochastic process describing the structural load, which an analysis of climate change effects on civil infrastructure systems should include, and investigates stochastic models of statistically nonstationary loads, such as increasing sea surface temperature and hurricane wind speeds affected by global climate change. The impact of climate change and structural deterioration on minimum expected cost decision-making is illustrated with a simple structural model exposed to wind load.

Chapter 5 presents an intergenerational discounting method for civil infrastructure, which is another intergenerational element identified in Chapter 3. This chapter begins by exploring some of the recent developments in discounting practices in the field of economics, and next proposes a new discounting method for use in life-cycle analysis of civil infrastructure facilities expected to function over multiple generations to achieve intergenerational equity and sustainable decision-making. Finally, the proposed discounting method is compared with several approaches to discounting to show how a new approach can lead to equitable decision-making by distributing the burden of the costs fairly between generations.

In Chapter 6, the effect of the intergenerational elements on long-term sustainable decision-making is illustrated with a life-cycle analysis of a hypothetical nine-story building located in two hazard-prone areas to assess the practical feasibility of the modified decision framework developed in this dissertation. Optimal decisions regarding seismic-resistant and wind-resistant design are examined to provide an improved understanding of these elements in a refined decision framework.

Finally, Chapter 7 summarizes the major findings and conclusions of this research, and suggests future research needs.

CHAPTER 2

REVIEW AND CRITICAL APPRAISAL OF PREVIOUS RISK-INFORMED DECISION METHODS

From an engineering viewpoint, risk-informed decision-making for assurance of civil infrastructure performance and integrity has three essential ingredients: physics-based models of time-dependent environmental hazards, material aging and structural deterioration; time-dependent reliability models to capture the uncertainties in facility behavior over its projected service life; and a decision framework that synthesizes physical models and sources of uncertain time-dependent behavior for purposes of design and condition evaluation and risk management (Ellingwood 2005). Most deterioration models at present are empirical in nature rather than physics-based, are strongly dependent on experimental data, and are sensitive to the environment. In contrast, probabilistic modeling of structural demands arising from natural hazards such as snow, wind and earthquake has been customary practice in the civil engineering community for the past three decades. It should be noted, however, that the probabilistic models have been stationary in nature (implying that “the past is representative of the future”). Likewise, quantitative time-dependent reliability assessment tools have matured to the point where they can assist in establishing strategies for analyzing risk of aging infrastructure exposed to natural and man-made hazards. Similarly, life-cycle cost analysis has become an accepted tool for managing public investments in performance enhancement and risk mitigation (Frangopol and Maute 2003, Petcherdchoo et al. 2008, Kumar and Gardoni 2014). The following sections in this chapter will review and summarize previous research in the field of quantitative risk-informed decision support framework.

2.1 Structural Deterioration Mechanisms and Models

Existing civil infrastructure may deteriorate as a result of aging or degradation of construction materials from operating conditions and aggressive service environments, which is manifested by deterioration in strength and stiffness of the systems during their service periods. Such deterioration causes continuous changes to structural material or geometric properties, which may impair the safety and serviceability of structural facilities. In this context, modeling structural degradation mechanisms has been considered as a crucial step in evaluating the service life of structural components and systems, and extensive research studies have been carried out on physics-based models of material aging and structural deterioration. Aging mechanisms that cause deterioration of concrete structures may be produced by chemical or physical attack on either the cement-paste matrix or aggregates. Chemical attack may occur by efflorescence or leaching, sulfate attack, attack by acids or bases, salt crystallization and alkali-aggregate reactions. Physical attack mechanisms include freeze/thaw cycling, thermal expansion/thermal cycling, abrasion/erosion, shrinkage cracking and fatigue. Degradation in strength of mild steel shapes or steel reinforcement in concrete can occur as a result of corrosion, elevated temperature or fatigue. Pre-stressing or post-tensioning systems are susceptible, in addition to the above, to loss of pre-stressing force due to relaxation. Some deterioration mechanisms are synergistic (e.g., corrosion/fatigue); others may interact with or impair the effectiveness of protective systems such as coatings or cathodic protection (corrosion and cracking). These interactions and synergisms are poorly understood (Naus et al. 1999).

Much of the literature on structural deterioration mechanisms has been developed from small specimens tested under laboratory conditions. These tests have been conducted in different environments and at different temporal scales that would be typical for civil infrastructure facilities (Pommersheim and Clifton 1985, Liu and Weyers 1998, Naus et al. 1999), and the relevance of these data to structural engineers seeking to assess

and manage risks to aging civil infrastructure is questionable. Supporting data for measuring deterioration of structures *in situ* are limited. Accordingly, models of structural deterioration that have been used in time-dependent reliability analysis of aging infrastructure are, for the most part, rudimentary (Mori and Ellingwood 1993, Ciampoli and Ellingwood 2002, Frangopol et al. 2004), and research is in progress to better define these models (e.g., Stewart and Rosowsky 1998, Ellingwood 2005). Practically, relatively simple models have been used for this reason. Deterioration, measured in terms of penetration of damage (e.g., corrosion, loss of section and spalling), usually has been modeled for time-dependent reliability assessment using simple rate equations of the form:

$$X(t) = \alpha (t - T_i)^\beta + \varepsilon_1(t); t \geq T_i \quad (2-1)$$

or

$$X(t) = \alpha (t - T_i)^\beta \varepsilon_2(t); t \geq T_i \quad (2-2)$$

in which $X(t)$ is the deterioration parameter, t is the elapsed time, T_i is the initiation or induction period (often modeled as a random variable), α and β are the parameters determined from a regression analysis of experimental data, and $\varepsilon_1(t)$ and $\varepsilon_2(t)$ are random processes describing the uncertainty in the deterioration with time. In Eq (2-1), ε_1 customarily is assumed to be modeled at present by a normal random variable, with $E[\varepsilon_1] = 0$ and $SD[\varepsilon_1] = \sigma_1$ while in Eq (2-2), ε_2 is modeled by a lognormal random variable, in which $E[\varepsilon_2] = 1$ (assuming the model is unbiased) and $SD[\varepsilon_2] = V_2$, the coefficient of variation describing the variability in deterioration. To avoid the possibility of $X(t)$ or its derivative from becoming negative, which is inconsistent with the physics of deterioration, Bhattacharya et al. (2008) suggested the following model:

$$\frac{dX(t)}{dt} = a(t - T_i)^\beta e^{\varepsilon(t)}, t > T_i \quad (2-3)$$

in which $\varepsilon(t)$ is a zero-mean stationary process, which is given as:

$$\frac{d\varepsilon(t)}{dt} = -k\varepsilon(t) + \sqrt{D}W(t) \quad (2-4)$$

in which k and D are constants and $W(t)$ is the Gaussian white noise. This model avoids the possibility of $X(t)$ decreasing over time and permits the correlation in degradation to decrease as the time instants become more widely separated. However, this model requires additional parameters which are difficult to calibrate to experimental data, and is hard to implement in practical engineering analysis.

The stochastic model of damage penetration, $X(t)$, is necessary to determine the time-dependent resistance, $R(t)$:

$$R(t) = R_0 G(t) \quad (2-5)$$

in which R_0 is the initial strength, and $G(t)$ is a time-dependent degradation function defining the fraction of initial strength remaining at time, t . Generally, $G(t)$ is dependent on $X(t)$ and a nonlinear function of $X(t)$. Due to the uncertainty in the progressive deterioration mechanisms and their structural effects, the function $G(t)$ is stochastic rather than deterministic. A stochastic model of structural deterioration, represented by process, $G(t)$, is illustrated conceptually in Figure 2.1.

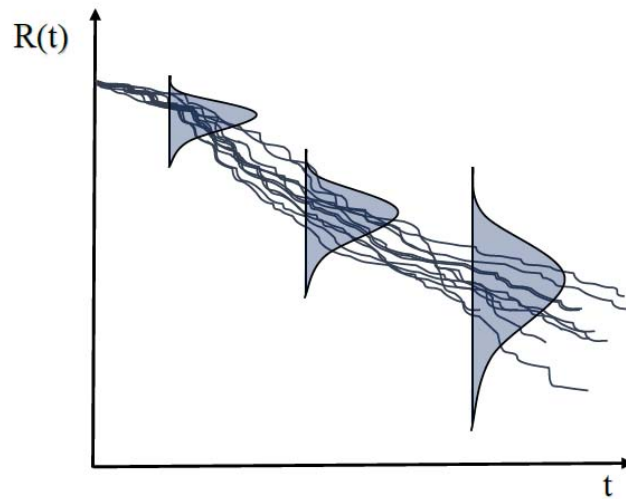


Figure 2.1 Stochastic models of aging

Models such as those in Eqs (2-1) – (2-5) and in Figure 2.1, despite their mathematical complexity, nonetheless are empirical in nature, are strongly dependent on experimental data (and thus limitations in experimental procedures), and are sensitive to the environment (temperature, atmosphere, aeration, humidity, etc.). They are difficult to generalize to environments not reflected in the database. While certain deterioration mechanisms, such as general corrosion of reinforcement in concrete, are becoming more amenable to physical modeling (Bentz et al. 1996, Peng and Stewart 2014), *in situ* service conditions are difficult to reproduce in laboratory tests and scaling to prototype conditions raises additional uncertainty which is difficult to model. Thus, it is not clear whether such modeling offers any practical improvement in the reliability assessment over the simple models reflected by Eqs (2-1) and (2-2). Furthermore, a more complete description of the deterioration in time (and better estimate of time-dependent reliability) requires, in addition to Eqs (2-1) and (2-2), the covariance function, $C[\varepsilon(t_1), \varepsilon(t_2)]$, which describes the correlation in deterioration at two points in time t_1 and t_2 . Information to describe the covariance for practical time-dependent reliability analysis does not exist, although one might expect that the covariance might be described by a simple exponential decay model:

$$C[\varepsilon(t_1), \varepsilon(t_2)] = \sigma^2 \exp\left(-\frac{|t_2 - t_1|}{T_c}\right) \quad (2-6)$$

in which $\sigma^2 = \text{Var}[\varepsilon]$ and T_c is the period of significant correlation. A recent study involving Monte Carlo simulation (Li et al. 2015) revealed that the error introduced by assuming that the deterioration process was perfectly correlated was negligible in situations where the uncertainty in load exceeded that in the resistance.

2.2 Stochastic Load Modeling

Most reliability analyses to date (time-dependent or otherwise) have modeled the load (demand) on the system as a stationary random process (Ellingwood and Mori 1993, Sanchez-Silva et al. 2011). Under this assumption, the occurrence of a discrete load event in time usually is treated as a Poisson renewal or pulse process with stationary increments; if $N(t)$ is the number of load events which occur in time $(0, t]$, $N(t)$ is described by the probability mass function:

$$P[N(t) = n] = \frac{(\lambda t)^n \exp(-\lambda t)}{n!}; n = 0, 1, 2, \dots \quad (2-7)$$

where λ is the mean rate of occurrence of the load events, and the intensity of each load is described by a probability density function that is invariant in time. Such models might be justified for periods of a few decades, but is unlikely to be adequate for modeling structural demands over longer service periods due to changes in service utilization from economic growth, global climate change or other factors.

The assumption that the loads on a structure comprise a stationary random process becomes untenable, especially when the effects of global climate change (Intergovernmental Panel on Climate Change [IPCC] 2007) are considered. Such effects may result in more frequent and increasingly severe wind storms and extremes of temperature, precipitation and flooding. The structural engineering research community is just beginning to consider the effects of such increases on structural loads (Bjarnadottir et al. 2011, Stewart et al. 2011), and only very simple models of non-stationarity (e.g., time-dependent characteristic extremes) have been postulated. Extrapolation to service periods on the order of 100 years or more, however, is highly uncertain and may be inadequate to assess the potential risks from hazards occurring in the future generations (Lee and Ellingwood 2013). Moreover, serial correlation in the stochastic load models of environmental variables has not yet been taken into account in time-dependent structural reliability analysis. Finally, models employed by scientists modeling climatology, such

as General Circulation Models (GCMs), are large in scale (greater than 10^4 km^2); local climatology of the scale of interest to structural engineers is orders of magnitude smaller (10^2 km^2). Bridging the gap between models of these scales is problematic but is essential for risk-informed decision-making on a multi-generational scale.

2.3 Time-dependent Reliability Assessment

Civil infrastructure facilities are expected to maintain their integrity and serviceability over their lifetimes. Evaluating the behavior and performance of such facilities must consider numerous uncertainties in randomness in strength, occurrence or intensity of loading and modeling (Ditlevsen and Madsen 1996, Melchers 1999). Inherent (aleatory) and knowledge-based (epistemic) uncertainties are integrated in the reliability analysis framework to evaluate current and future performance of structures.

The basic reliability problem considers the safety of a structure characterized by one load effect S and one resistance R . The probability of failure of such an element, P_f , is (Melchers 1999):

$$P_f = P(R \leq S) \quad (2-8)$$

and is the fundamental metric of performance under uncertainty. In practice, structural loads, engineering material properties and strength degradation mechanisms are random functions of time. Then, the time-dependent probability of failure becomes:

$$P_f(t) = P[R(t) \leq S(t)] \quad (2-9)$$

in which $R(t)$ is the resistance at time t and $S(t)$ is the dimensionally consistent structural action (moment, shear, etc.) from the applied loads. Eq (2-9) provides a snapshot of failure probability of a structure at an arbitrary point in time. For service life prediction and reliability assessment, however, the probability of satisfactory performance over some specified service period is a more relevant metric of performance. If, for example, n discrete loads S_1, S_2, \dots, S_n occur at times t_1, t_2, \dots, t_n during $(0, t]$, the probability that a structure survives during this interval is defined by the reliability function, $L(t)$:

$$L(t) = P[R(t_1) > S_1 \cap \dots \cap R(t_n) > S_n]; \quad (0 \leq t_1 \leq t_2 \leq \dots \leq t_n) \quad (2-10)$$

Under the simple assumption (discussed in Section 2.2) that the sequence of applied loads are discrete events occurring randomly at times, t_i , in accordance with a Poisson process with a constant mean rate of occurrence, λ , and that their intensities, $S(t_i)$, are identically distributed and statistically independent random variables described by CDF $F_S(x)$, the reliability function becomes:

$$L(t) = \prod_{i=1}^n F_S(R(t_i)) \quad (2-11)$$

If the initial resistance is random, the survival probability can be obtained by convolving Eq (2-11) with the density function describing the initial resistance. Once the reliability function is obtained, it can be related to the conditional failure rate or hazard function, $h(t)$:

$$L(t) = \exp\left[-\int h(\xi) d\xi\right] \quad (2-12)$$

in which $h(t)$ defines the (conditional) probability of failure in interval $(t, t+dt]$, given survival through $(0, t]$. If the load process is continuous (or is modeled as continuous) rather than discrete, $L(t)$ can be approximated by replacing the conditional failure rate, $h(\xi)$, with the mean down-crossing rate of level zero. The conditional failure rate can be used as a tool for maintenance planning and condition assessment of existing infrastructure that already has performed successfully for an extended period of time.

As part of the development of first-generation probability-based codes more than three decades ago, extensive reliability assessments were conducted to determine measures of reliability of acceptable performance (Ellingwood 1994). Methods for determining the survival or failure probabilities of structural components or systems as functions (or intervals) of time from stochastic process models of deterioration, residual strength and service and environmental loads using Eqs (2-8) – (2-12) are well-established (e.g., Ellingwood 2005). However, such analyses generally have been

applied to structures with service lives of 50 years or less. In order to develop a methodology for evaluating current and future reliability and performance of civil facilities over service periods extending to several generations, the non-stationarity in demands and capacity must be introduced to the above time-dependent reliability framework. Only rudimentary tools to perform such an analysis are available at the present time (Lee and Ellingwood 2013, Li et al. 2015).

2.4 Life-cycle Cost Analysis and Risk-informed Decision-making

In current risk-informed decision-making, performance goals generally are expressed in terms of probabilities, expected losses measured in monetary or human terms, or a combination of these metrics, which is generally defined as risk. There is a growing awareness, prompted by recent experience following natural disasters that, in addition to public safety assurance, the likelihood of business interruptions, social disruptions, and unacceptable economic losses also must be minimized in certain situations. In fact, the new paradigm of performance-based engineering (PBE) is built, in part, around achieving these objectives. Accordingly, during the past several decades, different types of decision models have been developed (Rosenblueth 1976, Wen and Kang 2001a, Goda and Hong 2008, Cha and Ellingwood 2012). The design intensity for a facility, as well as in-service maintenance to maintain its safety and serviceability over its service life, should be based on a systematic approach that reflects both aleatory and epistemic uncertainties embedded in demand on and capacity of civil infrastructure. In order to manage the large uncertainties associated with natural hazards, deterioration processes and facility responses, life-cycle cost analysis and risk assessment have been used to provide quantitative evidence to support design and maintenance decisions (Ellingwood and Wen 2005). In the following sections, two approaches – minimum expected life-cycle cost analysis and utility theory – will be reviewed.

2.4.1 Minimum expected life-cycle cost analysis

The life-cycle cost of a structure includes initial cost, maintenance cost, and damage or failure costs, which may include costs of disruption of facility function, life losses or injuries (Frangopol et al. 1997, Wen and Kang 2001a, Takahashi et al. 2002). The expected life-cycle cost of a structure is expressed as (Takahashi et al. 2002):

$$E[C_L] = C_0 + E[C_D^C] + C_M \quad (2-13)$$

where $E[C_L]$ = the expected life-cycle cost, C_0 = the initial cost, $E[C_D^C]$ = the expected cumulative damage cost, which is the integration of direct and indirect damage cost, and C_M = the maintenance cost. Here, C_0 is assumed to be a deterministic value while C_D^C is considered as a random variable due to uncertainties in demands and capacity. C_M can be assumed to be a deterministic value if maintenance or repair is performed regularly with a standard procedure. The expected value of the cumulative damage cost from natural hazards is obtained utilizing renewal theory for the random occurrence and intensity of extreme events, and consequently, the total life-cycle cost, C_L , becomes also a random variable which is calculated from the sum of deterministic initial and maintenance costs and random cumulative damage costs, appropriately discounted to present values. Minimum expected life-cycle cost analysis leads to a choice that minimizes Eq (2-13) while satisfying various constraints, the most important of which is the acceptable level of structural reliability in service.

One may express Eq (2-13) as a function of time, showing time-varying characteristics of life-cycle cost as a result of the stochastic nature in structural demands and capacity. Over time period $(0, t]$, the expected total cost is:

$$E[C(t, \mathbf{X})] = C_0(\mathbf{X}) + E\left[\sum_{i=1}^{N(t)} \sum_{j=1}^k \frac{C_j P_{ij}(\mathbf{X}, t_i)}{(1 + r(t_i))^{t_i}}\right] + \sum_{n=1}^{t/m} \frac{C_m(\mathbf{X})}{(1 + r(t_n))^{t_n}} \quad (2-14)$$

in which t = the service life of a new structure or the remaining life of an existing structure, \mathbf{X} = the vector of design variables, e.g., design loads and resistance, C_0 = the construction cost for a new or retrofitted structure, $N(t)$ = the total number of extreme

events in t , k = the total number of damage states, C_j = the cost of consequence of the j^{th} limit state at $t = t_i$, r = (possibility time-varying) discount rate per year, P_{ij} = the probability of the j^{th} limit state being exceeded given the i^{th} occurrence of one or multiple hazards, m = the time interval of periodic maintenance, and C_m = the operation and maintenance cost.

The optimal design vector, such as design intensity, structural dimensions or retrofit policy, can be selected from Eq (2-14) by balancing the initial cost against the expected failure and maintenance cost of the structure. The optimal design level also can be used as a target value in design (Wen and Kang 2001a). Minimum expected life-cycle cost analysis requires the occurrence probabilities and losses be evaluated objectively and implicitly assumes that the risk can be entirely monetized (Cha and Ellingwood 2012), in which circumstances, a decision maker is said to be risk neutral. If this is not the case, the maximum expected utility criterion described in the following section, where loss is transformed into utility, can be used to reflect an individual decision-maker's preference.

2.4.2 Expected utility theory

The minimum expected life-cycle cost approaches presume that the most efficient use of limited resources can be obtained when losses are evaluated objectively in monetary terms. However, monetary consequences from extreme events may not be directly proportional to a decision maker's preferences (Goda and Hong 2008). The concept of utility was introduced in decision analysis to assess a decision maker's preferences among outcomes numerically and incorporate his/her attitude towards risk. In utility theory, subjective preferences of a decision-maker are considered through a utility function which provides an internally consistent ordinal ranking of preferences and attitudes toward risk. For example, suppose that a decision maker prefers A to B and B to C. Then, the utility function for this decision must have the following property (von Neumann and Morgenstern 1944, Benjamin and Cornell 1970):

$$u(A) > u(B) > u(C) \quad (2-15)$$

There is evidence to indicate that most individual decision-makers are risk-averse towards low-probability, high-consequence events (Slovic 1987), meaning that they demand increasing payments for accepting marginally increasing risk and that function $u(\bullet)$ is nonlinear when expressed as a function of consumption level or loss (Cha and Ellingwood 2012). Conversely, government agencies or large corporations, which have very large resources, exhibit a risk-neutral attitude and the utility function becomes essentially linear in cost. When the outcomes of a decision are random, the utility is replaced by an expected utility (Benjamin and Cornell 1970):

$$E[U] = \sum_{i=1}^n u(x_i) p_i \quad (2-16)$$

in which n = the number of possible outcomes, x_i = the i^{th} loss associated with a decision, and p_i = the probability of the i^{th} loss, x_i . In this decision framework, the optimal choice is the alternative with the maximum expected utility.

2.5 Discounting Practices

The appraisal of investments in civil infrastructure, as well as government policies, projects and programs, involves trade-offs between immediate costs and longer-term future benefits. The comparison of costs and benefits that occur at different points in time is crucial in such decisions involving different or extended time frames; discounting to present worth or value allows future outcomes (damages, costs, benefits, or utility values) to be valued in present terms. The *discount factor*, $D(t)$, gives the value of an increment in consumption at a time in the future relative to the present (or at any arbitrarily selected point in time), and is used to convert flows of future costs and benefits into their present equivalents. The *discount rate*, $r(t)$, is the annual rate of decline of the discount factor, and gives the rate at which future value is discounted. The discount

factors in discrete and continuous time domains are related to the discount rates shown in Eqs (2-17) and (2-18), respectively (Hepburn 2007):

$$D(t) = \frac{1}{(1 + r(t))^t} \quad (2-17)$$

$$D(t) = \exp \left[- \int_0^t r(\tau) d\tau \right] \quad (2-18)$$

Discounting customarily has been linked in some way to market interest rates; the rates of return on corporate investments (10 percent), to individual investors after corporate taxes (7 percent), or on bonds (4 percent) are common measures of discount rate (Newell and Pizer 2003). Over time horizons of less than 30 years, future rates based on the market interest rate can be inferred from these average estimates. While no consensus exists on the appropriate rate for discounting in life-cycle engineering decision analysis, cost-benefit or life-cycle cost analysis commonly uses one rate (3 percent per year or higher), which is held constant over the time horizon relevant for the decision at hand (Wen and Kang 2001b, Goda and Hong 2008, Petcherdchoo et al. 2008). For longer time horizons, however, simply taking the market interest rate is questionable due to market imperfections or failures, the attitude of government regarding its responsibilities, if any, toward future generations, and the attitudes of individuals that current markets may not reveal (Hepburn 2006).

A constant positive discount rate implies that the discount factor declines exponentially, i.e., $D(t) = \exp(-rt)$. Valuing an increment in future consumption less than an increment in present consumption can be justified for two reasons. First, people usually prefer receiving present benefits rather than deferring gratification (in economics, that is referred to as *individual impatience*). Second, in a growing economy, people expect to be better off in the future and an extra unit of future consumption is viewed as being worth less due to given decreasing marginal utility of consumption (Stern 2007).

These two factors are reflected in the classic *Ramsey formula* for the social discount rate (Ramsey 1928):

$$r = \rho + \eta g \quad (2-19)$$

where ρ is the *utility discount rate* (or the *rate of pure time preference*) explaining impatience, η^1 is the *elasticity of marginal utility of consumption*, modeling how fast marginal utility of consumption decreases as consumption increases, and g is the *rate of growth of consumption per capita*, describing how fast consumption increases.

The utility discount rate, ρ , measures the portion of the utility that we attribute to the welfare of future generations, and the ethical implications involved in its selection have been highly controversial among economists. Some economists assert that the rate of pure time preference should be zero in order to treat the utility of present and future generations equally. Ramsey apparently agreed that a non-zero utility discount rate is ethically indefensible, arguing that “it is assumed that we do not discount later enjoyments in comparison with earlier ones, a practice which is ethically indefensible and arises merely from the weakness of the imagination” (Ramsey 1928). With a zero rate of pure time preference over multiple generations, however, one’s willingness to sacrifice one’s own consumption in the interest of future generations becomes implausibly high, leading to another ethical dilemma: “it is not morally acceptable to demand an excessively high savings rate of any one generation, or even of every generation” (Arrow 1999). Employing a low rate of pure time preference close to zero has also been proposed by some economists, who suggested that the utility of future generations should be discounted based not on one’s myopia but on catastrophe risk, the probability that future generations will not exist (Dasgupta and Heal 1979). For example, Stern (2007)

¹ η is a measure of the curvature of the utility function and is mathematically equivalent to the coefficient of relative risk aversion: $\eta = -u''(c)/u'(c)$.

used the value of 0.1 percent per annum for the utility discount rate, which was derived from the probability of human extinction given some catastrophic event.

An additional component of the Ramsey formula is growth discounting (or consumption smoothing), which is applied to discount future consumption if higher living standards are anticipated in the future. This component is represented by the product of the elasticity of marginal utility of consumption (η) and the growth rate in per capita consumption (g). η represents three concepts of aversion simultaneously: aversion to risk, aversion to intergenerational inequality, and aversion to spatial inequality (Saelen et al. 2008). While the three concepts embedded in this single parameter have led to a substantial debate about the value of η , current practices (Stern 2007, Cowell and Gardiner 1999) suggest that values for the coefficient of relative risk aversion are typically around 1, with a reasonable range from 0.5 to 4. Since the elasticity of marginal utility of consumption is constant under the assumption of a utility function with *constant relative risk aversion* (CRRA), the discount rate is a function of how consumption is expected to change over time. Increasing (or decreasing) future consumption growth implies a higher (or lower) discount rate. Even with a zero utility discount rate, if the future economic growth rate is assumed to be positive, then the discount rate may be greater than zero.

The evaluation of alternative strategies and investments is extremely sensitive to the discount rate. Moreover, the potential influence of discount rate on long-term investments is substantially greater than on those with shorter terms, because even small changes in the discount rate have a significant impact on decision-making when discounted benefits and costs continue to accrue over several generations. The importance of choosing different discount rates can be seen in Figure 2.2 which illustrates discount factors corresponding to several annual discount rates. A higher discount rate implies that we place a lower value on future gain or loss than on the same gain or loss occurring now. To illustrate, the value of \$1 million 100 years from now would be

valued at \$369,700 if the discount rate were 1 percent, while it would be \$2,947 when employing 6 percent discount rate. Exponential discounting with a constant discount rate (often corresponding to a market interest rate or the rate on long-term US government bonds) may be sensible over the short to medium term. For longer time frames however, it appears to be inconsistent with intergenerational equity and sustainable development (Weitzman 1998, Gollier 2002, Lee and Ellingwood 2015), as it unduly diminishes the consequences of present decisions to future generations in decision-making. An equitable intergenerational approach to discounting should incorporate the perspectives of both the current and future generations explicitly.

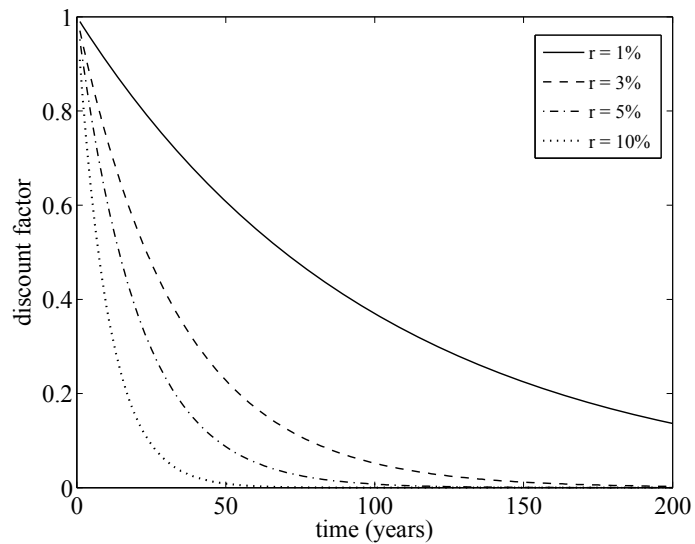


Figure 2.2 Discount factors corresponding to different annual discount rates

2.6 Closure

The review of customary time-dependent reliability assessment and decision methods has revealed a number of research issues, challenges and questions for the development of suitable methods for intergenerational life-cycle engineering and decision-making in the face of large uncertainties. How can one model changes in

structural behavior that arise from stochastic aging and deterioration brought about by normal usage and aggressive service environments? How can one deal with the non-stationarity in demands from natural hazards that arise as a consequence of climate change and extrapolate the resulting models (and their uncertainties) decades beyond the scope of available databases? How does one measure costs consistently and distribute benefits from generation to generation in an equitable fashion? How does one deal with life-cycle cost issues in civil infrastructure decision-making – discounting, decision preferences, social goals – that arise when projected service periods are extended to multiple generations? How should expected cost (or utility) analysis be modified to allocate costs and benefits equitably between the current and future generations? The following chapters will suggest answers to these questions and will offer perspectives on risk that are germane to intergenerational equity in civil infrastructure decision-making for the long-term.

CHAPTER 3

INTERGENERATIONAL RISK-INFORMED DECISION METHODS FOR CIVIL INFRASTRUCTURE

Sustainable development has become a new ethical standard for civil infrastructure design, development and maintenance. “*Our Common Future*”, also known as the Brundtland Report (United Nations World Commission on Environment and Development [UNWCED] 1987) asserts that sustainable development is the development that “meets the needs of the present without compromising the ability of future generations to meet their own needs.” Sustainability has gained special prominence in civil engineering because present decisions regarding civil infrastructure have significant effects and consequences for the future in terms of benefits and costs (Rackwitz et al. 2005, Nishijima et al. 2007). Sustainable engineering solutions strive to achieve responsible stewardship of available resources and avoid transferring the burden of costly maintenance or repair of civil infrastructure to future generations. In this light, sustainability mandates now are recognized as a key issue which must be addressed in decisions regarding civil engineering facilities.

Life-cycle engineering and life-cycle cost analysis are at the core of modern engineering decisions involving investments in performance enhancement, maintenance and rehabilitation (Rosenblueth 1976, Wen and Kang 2001a, Goda and Hong 2008, Cha and Ellingwood 2012). Most applications of such analyses have focused on decision models for service lives of 50 to 75 years. In recent years, there have been a growing number of civil infrastructure projects and policies in which the cost impact can be expected to be spread out over far longer periods of time that may extend to multiple generations. One notable example involves investments aimed at mitigating the potential impact of global climate change, which require trade-offs between the needs of the present and future generations. Moreover, service periods for certain civil infrastructure

projects (e.g., hazardous waste repositories, large dams, flood protection structures, nuclear power plants and other critical facilities) also may have design lives that span several generations. Traditional risk-informed decision methods pose significant difficulties when applied to such long-term event horizons. The ethics underlying any decision model require that a decision-maker should maximize a weighted sum of his/her utility (or monetary value) and the utilities of future generations, placing less weight on the latter by using an appropriate discounting procedure. For constant discount rates tied to market interest rates (above 3 percent per year), however, the risk to life and property in the future is trivialized with respect to present value. Thus, if traditional expected cost (or expected utility) methods are used as the basis for intergenerational decision-making and potential losses far in the future are discounted to present worth, the preferences of future generations are found to have essentially no value (Lee and Ellingwood 2015).

To illustrate some of the deficiencies in current risk-informed assessment procedures, a minimum life-cycle cost analysis is performed for a simple case when only one stochastic load and one limit state are considered; initial cost is a linear function of design parameter (e.g., safety factor), X ; the intensities of structural load variables are represented by a sequence of identically distributed and statistically independent random variables, described by an exponential distribution with mean intensity 1.0; the occurrence of discrete load events in time is modeled as a Poisson process with a mean rate of 0.2 per year; the resistance is constant and deterministic and equal to parameter, X ; the annual discount rate is constant and equal to 0.04; and periodic maintenance costs are not considered (Lee and Ellingwood 2014). The solid line in Figure 3.1 illustrates the optimal design intensities (in arbitrary units) as a function of service life. Note that the optimal decision (in the sense of present worth) becomes virtually independent of time as service life increases beyond approximately 60 years, implying that events beyond this horizon should play little role in present decision-making. This decision stance unfairly diminishes the importance of decision consequences to future generations and

demonstrates that existing decision frameworks require modification for dealing with civil infrastructure with service periods extending over several generations.

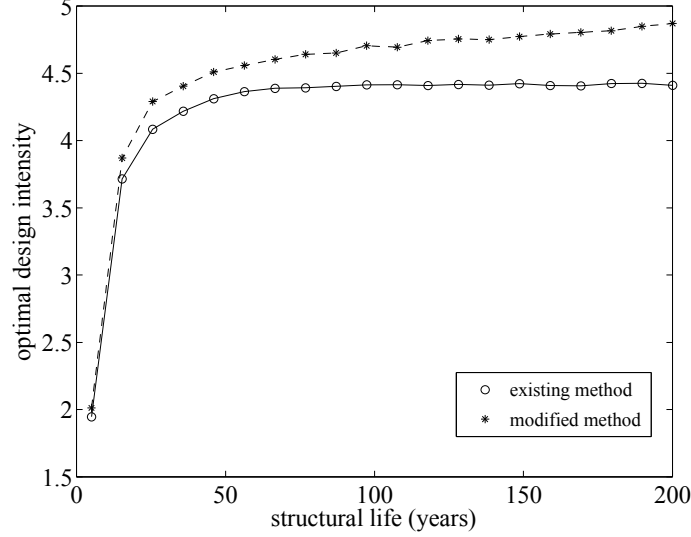


Figure 3.1 Comparison of optimal design intensities

The preferences of the present generation over those of future generations in conventional minimum expected life-cycle cost analysis can be also found from Eq (2-14). In addition to the assumptions stated in the previous example, let us assume that the probability of failure and the initial cost can be expressed in terms of a design variable, \mathbf{X} , with the equations, $P_F \approx P_0 \exp(-\mathbf{X})$ and $C_0 = a + k\mathbf{X}$, in which P_0 , a and k are constants.

Under these assumptions, Eq (2-14) can be written as:

$$E[C(t, X)] = a + kX + C_F P_0 \exp(-X) \frac{\lambda}{r} (1 - e^{-rt}) \quad (3-1)$$

The optimal design intensity, X_{opt} , corresponding to the minimum expected total cost can be expressed as:

$$X_{opt} = -\ln \left(\frac{k}{C_F P_0} \cdot \frac{r}{\lambda} \cdot \frac{1}{1 - e^{-rt}} \right) \quad (3-2)$$

and for an extended structure life, this optimal design intensity becomes:

$$\lim_{t \rightarrow \infty} X_{opt} = -\ln \left(\frac{k}{C_F P_0} \cdot \frac{r}{\lambda} \right) \quad (3-3)$$

which is independent of time, t . On the other hand, changes in λ and/or P_F as well as time-varying discount rate, r , enable the optimal solution to be a function of time. As a starting point, two ingredients can be identified as intergenerational elements of a decision framework which is applicable to situations with time horizons extending to future generations: a time-dependent failure rate considering the effects of structural aging and/or climate change, and a time-varying discount rate. To show the effect of such elements on optimal decisions, simple forms of time-dependent failure rate and time-varying discount rate are assumed and applied to the same example above (summarized in Figure 3.1) using Monte Carlo simulation. The annual discount rate is assumed to exponentially decrease from 0.04 to 0.01 over a period of 200 years with the form of $r(t) = 0.04 e^{-\alpha t}$ to avoid shifting too much risk to future generations. At the same time, the incidence of the hazards is represented by a nonhomogeneous Poisson process with a 20 percent increasing mean rate of occurrence during the design life, while the mean value of the load intensities is assumed to increase linearly by 20 percent in 200 years. Finally, structural system capacity is assumed to decrease linearly by 10 percent during 200 years. The dashed curve in Figure 3.1 indicates that the optimal design intensity clearly increases with service life when these time-dependent effects and extended service lives are considered.

This very simple example reveals that changes in the probability of failure and discount rate with time make it difficult to describe the expected life-cycle cost by an analytic solution similar to that in Eq (3-1). More complicated loading and deterioration situations must be handled through Monte Carlo simulation. Two elements that are central to intergenerational risk assessment will be addressed in further depth in Chapters 4 and 5, respectively, and will be illustrated with a nine-story steel frame building to show their effect on optimal decision in Chapter 6.

CHAPTER 4

TIME-DEPENDENT RELIABILITY UNDER CLIMATE CHANGE

The review in Chapter 2 and the critical appraisal in Chapter 3 have revealed that the use of customary risk-informed decision methods raises ethical issues in terms of project risk shared between current and future generations, especially when project expectations require the facility to function over extended periods of time that may be a century or more. Current models for time-dependent reliability analysis are inadequate for making forecasts of civil infrastructure performance over service periods of this magnitude. Furthermore, traditional life-cycle cost analysis and other risk-informed decision frameworks tend to overweight the preferences of the present generation and discount the importance of such decisions to future generations. In this context, Chapter 3 has proposed two intergenerational elements – the potential impact of non-stationarity in structural capacity due to aging and in climatological features on time-dependent reliability and time-declining discount rate – to provide a refined decision support framework which accommodates future generations in current decision-making.

This chapter presents time-dependent reliability assessment in an intergenerational decision framework. Risk assessment and management in an era of climate change require modeling the effects of non-stationarity in demands on facilities that may function over extended periods. Since relatively simple models of structural deterioration are used through this dissertation due to the reasons stated in Section 2.1, this chapter investigates stochastic models of structural behavior which change over time due to statistically nonstationary loads, such as increasing sea surface temperature and hurricane wind speeds affected by global climate change. A simple structural model exposed to wind load is illustrated to examine how sustainability requirements are more

likely to be achieved if the role of climate change and structural deterioration is incorporated in time-dependent reliability assessment.

4.1 The Impact of Non-stationarity in Structural Load Modeling and Time-dependent Reliability Assessment

Most statistical analyses of climatological data (wind speeds, snow loads, temperatures and precipitation) have been based on the assumption that the extremes of interest for structural engineering form a stationary random process, described by a probability distribution and parameters that remain invariant in time. For example, the idea that (static) loads (e.g., annual extreme winds) can be modeled as a sequence of identically distributed and statistically independent random variables is embedded in first-generation probability-based limit states design (e.g., return period values of annual extreme 3-s gust wind speeds or annual extreme ground snow loads for design purposes are based on the assumption that the annual extremes can be analyzed as random samples and that “the past is representative of the future”). Under the assumption that the service load can be modeled as statistically stationary random process and aging does not occur, the conditional failure rate or hazard function becomes constant, such as $h(t) = v$ (a constant), and failures are said to occur randomly during the service life. Most studies of time-dependent reliability analysis of aging infrastructure indicate that the cumulative limit state probability or conditional failure rate increase over time by orders of magnitude, absent any rehabilitation (Ellingwood 2005). For example, if the conditional failure rate increases in accordance with $h(t) = \alpha t^\beta$, in which α and β are constants, the time to failure can be described by a Weibull distribution (Benjamin and Cornell 1970, Ang and Tang 2007).

When the demands placed on the structure are the result of climatological parameters that reflect evolving geophysical or climatological influences due to global climate change and cause the frequency and intensity of the extreme events from natural

hazards to increase in time, the assumption that the demands are stationary in time-dependent reliability analysis is not tenable. Such effects of global climate change on civil facilities have become a major concern to facility owners and to authorities responsible for managing risk in the public interest. The American Society of Civil Engineers has formed a Committee on Adaptation to a Changing Climate to consider the potential impact of climate change on civil infrastructure design. This committee's work is in the formative stage (Olsen 2015).

Recently, as a starting point, a simple statistical model for climate change and its potential impact on structures were proposed and used in a simple life-cycle assessment of civil infrastructure (Stewart and Li 2010, Bjarnadottir et al. 2011, Stewart et al. 2011). Bjarnadottir et al. (2011) assumed that the Weibull distribution is an appropriate model of the 3-s gust wind speed at a height of 10 m on open terrain for hurricanes in the US and modeled the effect of climate change by increasing the wind speed linearly over a 50-year time period and holding the coefficient of variation constant, regardless of climate change scenario. Stewart et al. (2011) forecasted the changes in the atmospheric CO₂ concentration, local temperature and relative humidity over the next 100 years in the Australian cities of Sydney and Darwin based on nine General Circulation Models (GCMs) involving three different emission scenarios. However, none of these simplified models take into account the impact of temporal correlation in successive load events, which would be suggested by the existence of an underlying common climatological cause; rather, such models presume that the stochastic nature in demand can be modeled adequately through an increase in the mean and variance of the climate variable. Climatological research has suggested more sophisticated models to characterize climate change, including Markov chains, first-order or higher-order auto-regressive processes, and auto-regressive moving average processes (Katz 1977, Katz and Skaggs 1981, Bassett 1992). All of these models include the combination of an increasing trend in the mean intensity, changes in variability and stochastic dependence in time introduced

through autocorrelation or autocovariance functions. Such advanced models have not yet to be applied in structural engineering applications.

An analysis of climate change effects on civil infrastructure systems should include the probabilistic structure of the stochastic process describing the structural load, defined by the joint or conditional distributions of its random variables at consecutive times (e.g., wind speeds, in the case of wind load) in order to explain both the probabilistic behavior in time of each climate variable (marginal distribution) and the interrelations (statistical dependence or correlation structure) existing between the variables measured at successive times due to a common underlying cause (global warming). Here, the stationary and IID assumptions in Eqs (2-7) and (2-11) which have been made for simplicity in current time-dependent reliability assessment are relaxed. Serial correlation between successive values of climatic variables is incorporated in demand variables. The intensities of load events, S_i , may have non-identical distributions, $F_{S_i}(x)$, along the time axis, and the occurrence of a series of these events in time may be represented by nonstationary point process (a nonhomogeneous Poisson process is one possibility) with a time-varying mean rate of occurrence, $\lambda(t)$. Changes in either λ or $F_{S_i}(x)$ with time would make the load process nonstationary, resulting in an extreme value distribution of the load that is vastly different from the current distribution determined under the assumption of stationarity, as shown conceptually in Figure 4.1. Moreover, the numerical analyses using Eqs (2-10) and (2-12) for realistic civil infrastructure systems can be quite complex. However, efficient computational methods for determining the time-dependent limit state probabilities of structural components or systems from stochastic process models of deterioration, residual strength and service and environmental loads have advanced considerably in recent years (Ellingwood and Lee 2015, Li et al. 2015). Computation is no longer the formidable barrier that it once was since more complicated loading and deterioration situations can be handled through simulation.

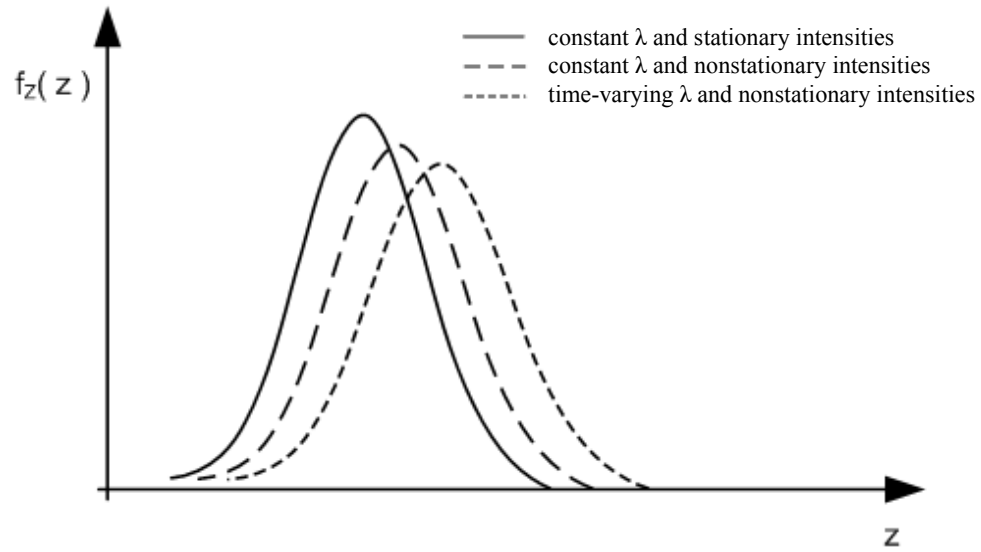


Figure 4.1 Conceptual figure of extreme value distributions under three different assumptions

The main statistical properties of a nonstationary process (e.g., hurricane wind speed) can be described by time-dependent parameters (e.g., mean, variance, coefficient of variation, etc.) in the marginal distributions and by the temporal correlations in the stochastic time series model. Figure 4.2 illustrates conceptually the non-stationarity due to climate change reflected in sample functions of a climate variable through changes in mean, standard deviation, and coefficient of variation (COV) over time. It is evident that simply changing the mean (or location parameter) may not be sufficient to explain the trend in long-term climate behavior; changes in variability (or scale parameters) as well as COV may also be important (Katz and Brown 1992). Each climate variable is described by its own distribution, such as the Weibull distribution for wind speed, normal distribution for daily temperature, or generalized extreme value (GEV) distribution for extreme values of those variables. Changes in the location and scale parameters can be assumed by considering possible scenarios or estimated from historical data. Either way,

time-varying parameters have a significant impact on the intensity and frequency of extreme events.

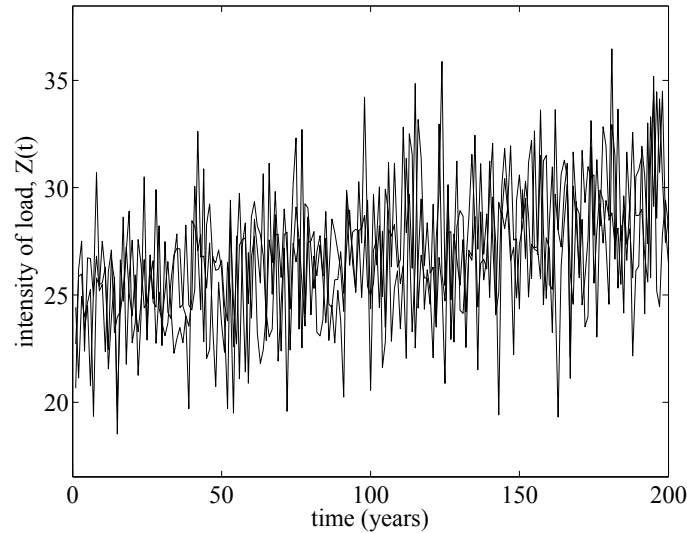


Figure 4.2 Sample functions of load intensity

Stochastic dependence in time due to the underlying physical cause is described, in a second-moment sense, by the autocorrelation or autocovariance functions of the load process, shown in Figure 4.3. These functions can be estimated from a time series model. In the example shown in Figure 4.3, the values are positively correlated over intervals of approximately 10 years, but the correlation is essentially zero (within the range of sampling error) for longer periods. Several alternatives for explaining temporal dependence and for generating correlated future values in a time series include an autoregressive (AR) model, auto-regressive moving average (ARMA) model, and auto-regressive integrated moving average (ARIMA) model, as discussed subsequently.

Auto-regressive models are widely used in climate research (Mearns et al. 1984, Colombo et al. 1999), mainly because they can reproduce the dynamics of many physical processes (von Storch and Zwiers 1999). An AR model captures temporal dependence

between consecutive random variables by regressing past values towards the mean and then adding noise. An auto-regressive process of order p , denoted an AR(p) process, is one for which the current value of a climate variable, X_t , depends on p past values. If there exist real constants α_k , $k = 1, \dots, p$, with $\alpha_p \neq 0$, then an AR(p) process X_t , is defined as:

$$X_t = \alpha_0 + \sum_{k=1}^p \alpha_k X_{t-k} + \varepsilon_t \quad (4-1)$$

in which ε_t is a white noise process that is independent of X_t . The AR model is a relatively simple way to model dependence over time, and requires only modest computational effort, especially in the case of the first-order AR model. However, since the implementation of an AR process requires an implicit assumption that the process be stationary, an additional transformation of X_t is necessary to introduce non-stationarity into the sequence. AR processes are part of a generalized class of ARMA processes, and consequently this intrinsic assumption is also applicable to ARMA models.

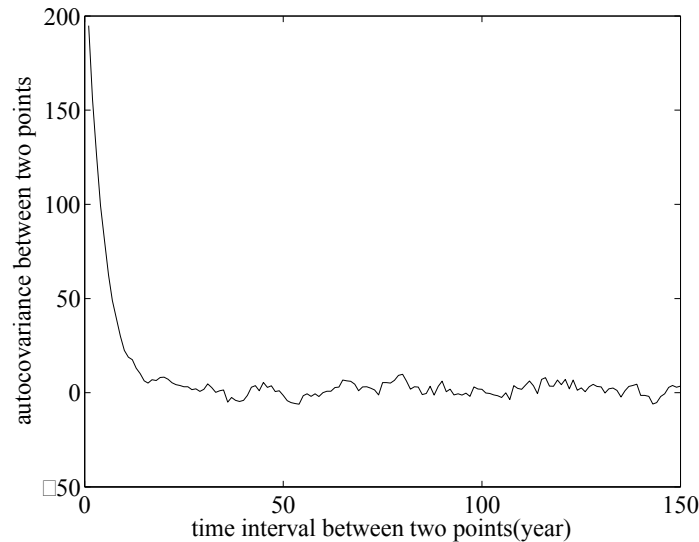


Figure 4.3 Autocovariance function of the load process

Auto-regressive moving average (ARMA) processes (Box and Jenkins 1976) are the most common models used for simulating time series for climate variables (Smith and Mehta 1993, Xie and Billinton 2009, Hill et al. 2012). An ARMA process is a mixture of auto-regressive and moving average models and consists of two parts: an auto-regressive (AR) part comprised of weighted present and past observations, and a moving average (MA) part comprised of weighted present and past random shocks (Pena et al. 2011). Thus, an ARMA model can take into account past values of the data, prediction errors and a random term. An ARMA(p, q) process of orders p and q , which are the integers defining the orders of the AR and MA components, respectively, is represented as:

$$X_t = \sum_{i=1}^p \alpha_i X_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (4-2)$$

An ARMA model is appropriate when a system is a function of a series of unobserved shocks (the MA part) as well as its own behavior. Even though there is substantial overlap between auto-regressive, moving average, and ARMA models, ARMA models can estimate the behavior of a process more accurately (measured in a mean-square sense) with fewer parameters than a pure AR or MA model can (von Storch and Zwiers 1999).

AR and ARMA models both represent weakly stationary time series. If the time series is not stationary, then it can be differenced (as explained below) until stationarity is achieved. If differencing of the data is performed to achieve stationarity in ARMA(p, q) model, the resulting model is denoted an auto-regressive integrated moving average (ARIMA) model. ARIMA models are useful when dealing with many types of nonstationary behavior such as random walks, trends, or seasonal variations. An ARIMA(p, d, q) process, where order d defines the order of differencing, is represented as (Box and Jenkins 1976, Falk et al. 2006):

$$\Delta^d X_t = \sum_{i=1}^p \alpha_i \Delta^d X_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} \quad (4-3)$$

where $\Delta^d X_t$ is a stationary process, obtained by differencing d times and eliminating its trend from X_t . Differencing of the data provides an easily applied and powerful technique for dealing with nonstationary data, which must be transformed into a stationary series prior to analysis as an autoregressive model.

4.2 Sea Surface Temperature Forecast using ARIMA model

Global sea surface temperature (SST) has risen over the past century, and is one of the primary physical impacts of climate change. This change is one of the key factors that cause a rapid rise in sea level, resulting in inundation of coastal habitats and higher storm surges. The effects of higher SST are also seen in the form of stronger and more frequent tropical storms, hurricanes and cyclones. Due to high consequences induced by this rise, changing SSTs in the future becomes a major concern not only for climatologists but also for the public. Forecasting SSTs also plays a significant role in modeling the impact of climate change on hurricane formation, which will be introduced in the next section. To illustrate the application of the ARIMA model to sea surface temperature modeling, the National Oceanographic and Atmospheric Administration's extended reconstructed sea surface temperature (ERSST) V3b are used. The newest version of ERSST, Version 3b, is derived from the International Comprehensive Ocean-Atmosphere Dataset with missing data filled in by statistical methods and is optimally tuned to exclude under-sampled regions for global average (National Climate Data Center [NCDC] 2015). The dataset provides global monthly SSTs beginning in January 1854 continuing to the present on a $2^\circ \times 2^\circ$ global grid resolution. Figure 4.4 illustrates the annual mean and 5-year moving average SSTs on the specific $2^\circ \times 2^\circ$ grid location shown in Figure 4.5, depicting the Atlantic Basin. The average SST in Figure 4.4 has increased by approximately 1°C over the past 160 years; similar increases have been observed in other grids over the entire Atlantic Basin. Numerous factors influence these local sea surface temperatures, including human-induced emissions of heat-trapping

gases, particulate pollution, and natural variability (Booth et al. 2012). The rise in SST will persist into the future, with continued large impacts on climate, ocean circulation, chemistry, and ecosystems.

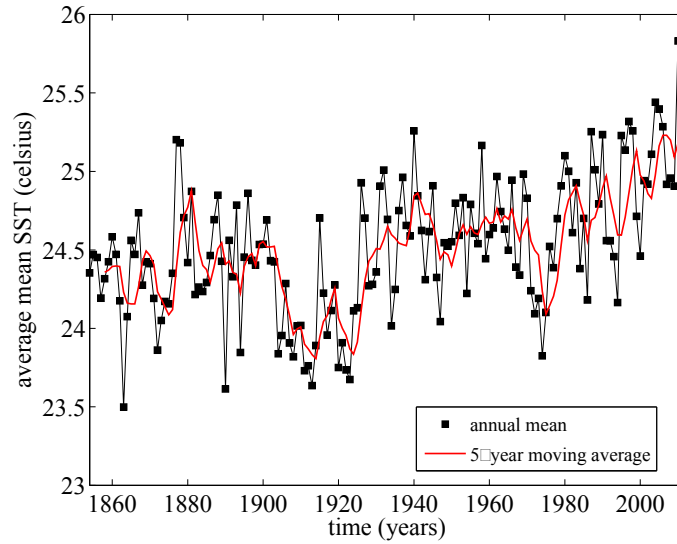


Figure 4.4 Annual mean and 5-year moving average sea surface temperature at $2^{\circ} \times 2^{\circ}$ grid location in Figure 4.5

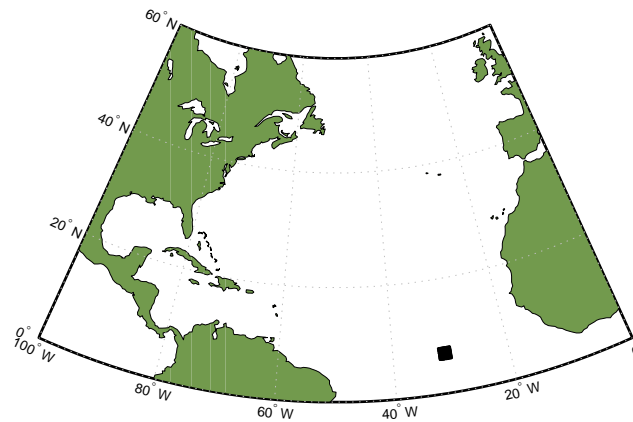


Figure 4.5 $2^{\circ} \times 2^{\circ}$ grid location corresponding to Figure 4.4

The ARIMA model described above is used to forecast future SSTs on the $2^\circ \times 2^\circ$ grid shown in Figures 4.4 and 4.5 (and in other grids in the Atlantic Basin). Monthly data is considered to take into account seasonal trends and the time series is rendered stationary by differencing once. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are examined to determine if lags of the stationarized series and/or lags of the forecast errors should be included in the forecasting equation. The ACF defines the linear dependence between time series and lags of itself over time, while the PACF represents the correlation between a variable and a lag of itself that is not explained by correlations at all lower-order-lags. Although higher orders of AR and/or MA terms provide a more accurate model measured in a mean-square sense, seasonal ARIMA(1,1,1) is selected to represent monthly forecasts of the conditional mean of the response data according to the principle of parsimony. The forecasts shown in Figure 4.6 suggests that SSTs are projected to increase by almost 1.5°C over the next 200 years. Each $2^\circ \times 2^\circ$ grid location on the Atlantic Ocean has its own grid-based terms of AR and MA as well as coefficients for forecasting future SSTs.

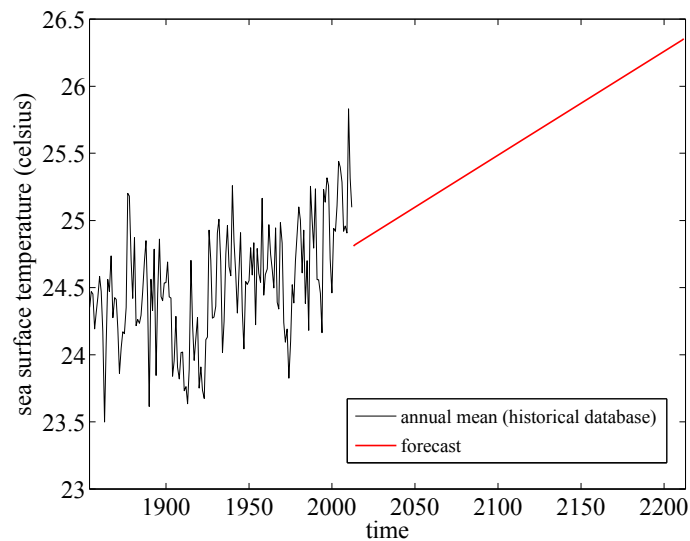


Figure 4.6 Sea surface temperature forecast in the location corresponding to Figure 4.5

4.3 Influence of Climate Change on Extreme Winds from Hurricanes

One of the most significant potential impacts of climate change on structural engineering practice is found in the hurricane wind speeds, which determine the wind forces used to design buildings and other structures (American Society of Civil Engineers [ASCE] 2010). Wind forces on structural systems are proportional to the square of the wind speeds for buildings in which aeroelastic effects are insignificant². The current design-basis wind speed in Miami, FL stipulated in *ASCE Standard 7-10* (at a return period of 700 years for Risk Category II buildings) is 170 mph; if this wind speed were to increase to 185 mph over the next century due to climate change, the design forces would increase by 18 percent and the cost of the structural system of a typical building would increase by a similar amount. In the following section, the potential impact of non-stationarity in hurricane occurrence and intensity on the design wind speed is illustrated.

Quantification of hurricane hazards is a significant first step in reducing the loss of life and damage induced by these storms. Assessing the vulnerability of civil infrastructure to such disasters is governed by the prediction of extreme wind speeds, which cannot be dealt with using the normal empirical/statistical approaches relied upon for synoptic winds due to the infrequent nature of hurricanes and the considerable uncertainties in their intensity. Furthermore, the vulnerability of surface instruments to damage may cause sampling errors and the inevitable relocation of anemometers can affect continuity and homogeneity of hurricane wind speed records (Georgiou 1985). These difficulties have created a need for alternative approaches for estimating wind speeds for the design of structures.

² If aeroelastic effects are significant, as they may be for very slender tall buildings, stacks and long-span cable-stayed or suspension bridges, the wind force is proportional to a power of the wind speed higher than two.

Models for simulating hurricane wind speeds have emerged as the most accepted tools for quantitative understanding of design wind speeds in hurricane-prone regions. Until recently, statistical distributions were fitted to data defining key hurricane parameters (including minimum approach distance, heading angle, central pressure deficit, radius to maximum wind speeds, and translation speed) based on historical data and each parameter was sampled from such statistical distributions by a Monte Carlo simulation to estimate wind speeds at the mileposts of interest along the Gulf/Atlantic coast (Georgiou et al. 1983, Georgiou 1985, Vickery and Twisdale 1995). The track modeling approach first introduced by Vickery et al. (2000) overcame the drawback of earlier studies being limited to a single point or small regions, by making it possible to model the full track of each hurricane, from its initiation over the ocean to its final dissipation, along the coastline of the North American continent (Vickery et al. 2000, Emanuel et al. 2006, Vickery et al. 2009). The simulation models by Vickery et al. (2000, 2009), which will be used in this dissertation, also are used in the development of the basic wind speed maps in the United States (American Society of Civil Engineers [ASCE] 2005, 2010). Contours of basic wind speeds for both non-hurricane and hurricane provided in *ASCE Standard 7-10* govern the design of structures for wind loading at the present time.

4.3.1 Existing hurricane simulation model

The Vickery et al. (2000) simulation model uses statistical properties of historical hurricane initiation, tracks and intensities, as given in the HURDAT2 database (Hurricane Research Division/National Oceanic and Atmospheric Administration [HRD/NOAA] 2014). The number of storms to be simulated in any year is sampled from a negative binomial distribution with a constant mean and standard deviation determined from this historical data. Figure 4.7 shows the initial positions of hurricanes simulated for 200 years over the Atlantic Basin. The date, time, position, initial storm heading

angle and translation speed also are sampled from the HURDAT2 database. The subsequent positions of the storm are calculated from translation speed, c , and heading angle, θ , at 6-h intervals, which are modeled as linear regression functions on each $5^\circ \times 5^\circ$ grid over the entire Atlantic Basin:

$$\Delta \ln c = a_1 + a_2\psi + a_3\lambda + a_4 \ln c_i + a_5\theta_i + \varepsilon \quad (4-4)$$

$$\Delta \theta = b_1 + b_2\psi + b_3\lambda + b_4c_i + b_5\theta_i + b_6\theta_{i-1} + \varepsilon \quad (4-5)$$

where $a_1, a_2, \dots, b_1, b_2$, etc. = grid-based coefficients obtained from the HURDAT2 database and determined separately for easterly and westerly headed storms, ψ and λ = storm latitude and longitude, respectively, c_i = translation speed at time step i , θ_i = heading angle at time step i , and ε = random error. A more detailed description of this procedure can be found in the original paper (Vickery et al. 2000).

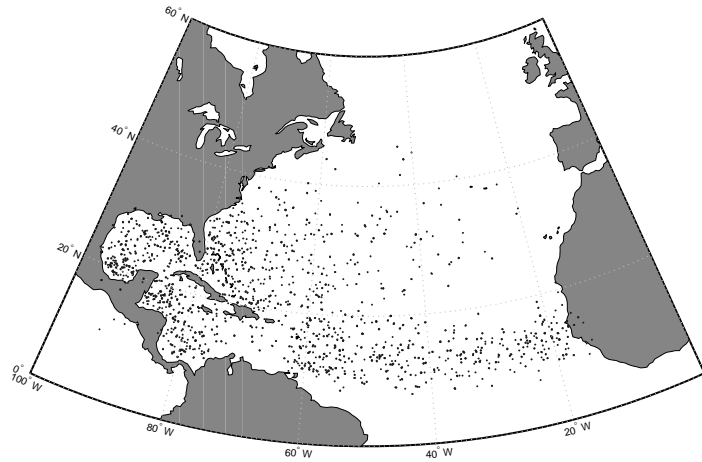


Figure 4.7 Initial locations of hurricanes simulated for 200 years

The hurricane central pressure is related to the relative intensity of the storm. The relative intensity at any point in time is the ratio of the pressure drop in the center of the hurricane to the greatest possible pressure drop, which is a dimensionless quantity with a

value normally between 0 and 1 (Darling 1991). This dissertation follows the calculation process described in Darling (1991) in converting central pressure estimates into a relative intensity using the values: relative humidity = 0.75; gas constant of water vapor = 461; temperature at the top of the stratosphere = 203°K. The relative intensity I at each time step is a function of sea surface temperature (T_s) and is calculated from the grid-based equation (Vickery et al. 2000):

$$\ln(I_{i+1}) = c_0 + c_1 \ln(I_i) + c_2 \ln(I_{i-1}) + c_3 \ln(I_{i-2}) + c_4 T_s + c_5 \Delta T_s + \varepsilon \quad (4-6)$$

where c_0, c_1 , etc. = grid-based coefficients, I_i = relative intensity at step i , T_s = sea surface temperature (in degrees Kelvin), ΔT_s = difference in sea surface temperatures (SST) between step i and $i+1$, and ε = random error. The SST at the storm center is obtained from the NOAA extended reconstructed model SST V3b, which has been introduced in Section 4.2, and accordingly, Eq (4-6) is developed on each $2^\circ \times 2^\circ$ grid over the entire Atlantic Basin. Once a hurricane makes landfall, the decay of central pressure is modeled using the hurricane filling models proposed by Vickery and Twisdale (1995). If a storm moves back over sea, Eq (4-6) is again used to model the central pressure with time.

Given key input values, an estimate of the wind speed at gradient height is obtained based on Georgiou's gradient wind field model (Georgiou et al., 1983). For the Northern Hemisphere, the gradient wind speed in polar coordinates, $V_g^2(r, \alpha)$, is defined as:

$$V_g^2(r, \alpha) = \frac{r}{\rho} \frac{\partial p}{\partial r} + V_g(r, \alpha)(V_T \sin \alpha - fr) \quad (4-7)$$

where r = radial distance from a storm center, α = angle from direction of motion (clockwise positive), ρ = air density, p = pressure at distance r , V_T = translation speed, and f = Coriolis parameter. The pressure, $p(r)$, at a distance r from the center of the storm is given as (Georgiou et al., 1983):

$$p(r) = p_c + \Delta p \exp \left[- \left(\frac{R_{\max}}{r} \right)^B \right] \quad (4-8)$$

in which p_c = central pressure, Δp = central pressure difference, R_{max} = radius to maximum wind speeds, and B = Holland parameter. The parameters R_{max} and B are given by Vickery et al. (2000):

$$\ln R_{max} = 2.636 - 0.00005086 \Delta p^2 + 0.0394899 \psi + \varepsilon \quad (4-9)$$

$$B = 1.38 + 0.00184 \Delta p - 0.00309 R_{max} \quad (4-10)$$

The error term in Eq (4-9) is assumed to be described by a normal distribution, with zero mean and standard deviations of 0.4164 and 0.3778 for storms that are south and north of 30 °N, respectively (Lee and Rosowsky, 2007).

4.3.2 Nonstationary hurricane simulation model under climate change

Although reliable mathematical models of hurricanes for wind hazard analysis and for estimating wind speeds for the design of structures under stationary conditions now are available (Vickery et al. 2000, Emanuel et al. 2006, Vickery et al. 2009), special problems are encountered when the effects of climate change on hurricane formation are considered. The non-stationarity in annual frequency and intensity of hurricanes that is induced by climate change introduces changes (and additional uncertainty) to the extreme wind loads used in time-dependent reliability assessment. Nonstationary hurricane simulation models also are essential for estimating concomitant storm surge or flooding, which are the leading causes of death and injury among natural disasters (Swiss Re 2010).

To consider the impact of climate change on hurricane wind speeds and to generate future hurricanes over extended future service periods, this dissertation utilizes a track modeling approach originally developed by Vickery et al. (2000), but modifies it to account for non-stationarity in occurrence and intensity. Figure 4.8 illustrates the annual occurrence of storms in the Atlantic Basin obtained from the HURDAT2 database, clearly revealing that the annual frequency of historical storms over the Atlantic Ocean has increased since 1851. Thus, the number of storms in any year is sampled from a

negative binomial distribution with increasing mean and standard deviation determined from historical database.

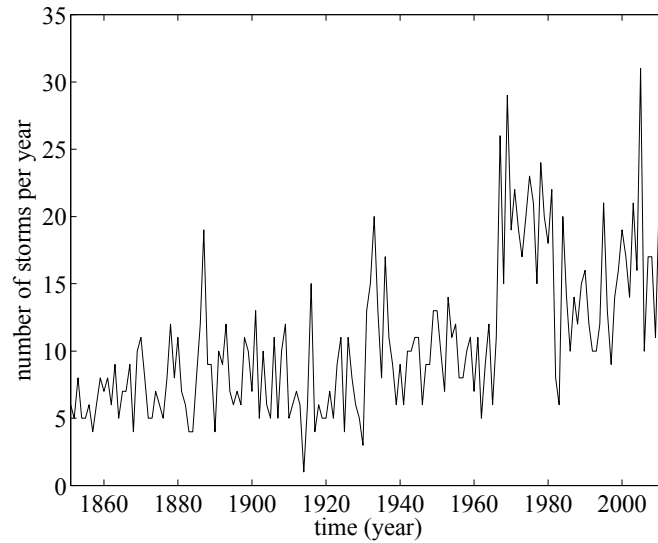


Figure 4.8 Annual number of storms in the Atlantic Basin

There has been a substantial increase in virtually every measure of hurricane activity in the Atlantic; such measures are linked to higher sea surface temperatures in the region in which Atlantic hurricanes form and translate. Moreover, a link between sea surface temperature and hurricane power dissipation (related to hurricane wind speed) recently has been noted (Emanuel 2005): small changes in ocean temperature reflect large changes in ocean heat storage. Since the relative intensity in Eq (4-6) is a function of previous intensities as well as sea surface temperature, a rising SST as a result of climate change will affect the intensity (and thus the central pressure, as previously noted) of storms in the simulation model. While the central pressure of a hurricane responds to more than just sea surface temperature, SST is widely agreed to be a prominent factor; thus, this model considers only the relationship between hurricane intensity and SST for simplicity. Future SSTs on each grid are estimated from a grid-based ARIMA model, as shown in Figure 4.6.

The probability density functions (PDFs) of maximum hurricane wind speeds in Miami during two periods (2014-2064 and 2014-2214), considering the potential effects of climate change (here, the non-stationarity in frequency and intensity), are obtained from simulations using Eqs (4-4) – (4-10). The results of these simulations are illustrated in Figure 4.9. It is clear that wind speeds (and wind loads) used in design must be increased for extended service periods to comply with performance objectives for civil infrastructure that customarily are stated in terms of uniform probability of exceedance during the projected service period (Lee and Ellingwood 2013).

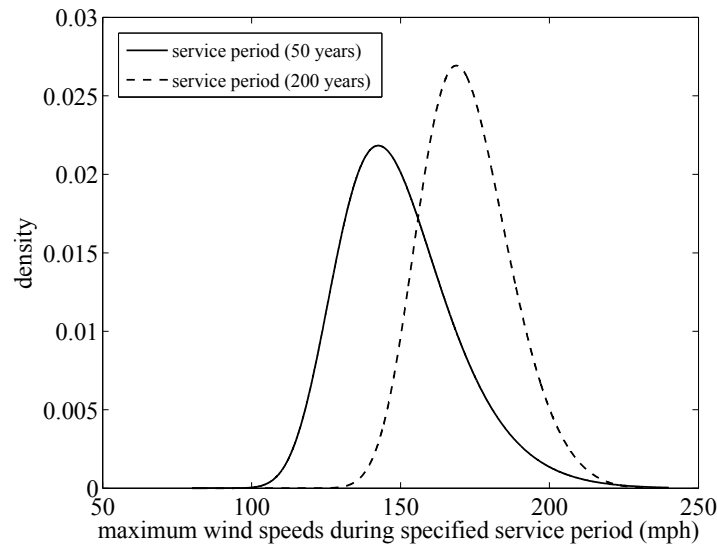


Figure 4.9 Extreme value distributions for wind speeds in Miami during different service periods under nonstationary assumption

Figure 4.10 presents the probability density functions of maximum hurricane wind speeds over a 200-year service life in Miami determined from under two different assumptions. To show the possibility of this model to simulate wind speeds in any location along the coastline of the North American continent, the 200-year maximum wind speed distribution in Charleston, SC is also shown in Figure 4.11. Both figures clearly show the difference between wind speeds obtained from stationary (or existing)

and from nonstationary hurricane models. Such nonstationary hurricane wind speeds with time should be carefully integrated in a time-dependent reliability assessment aimed at achieving more reliable forecasts of facility behavior, especially for extended service periods.

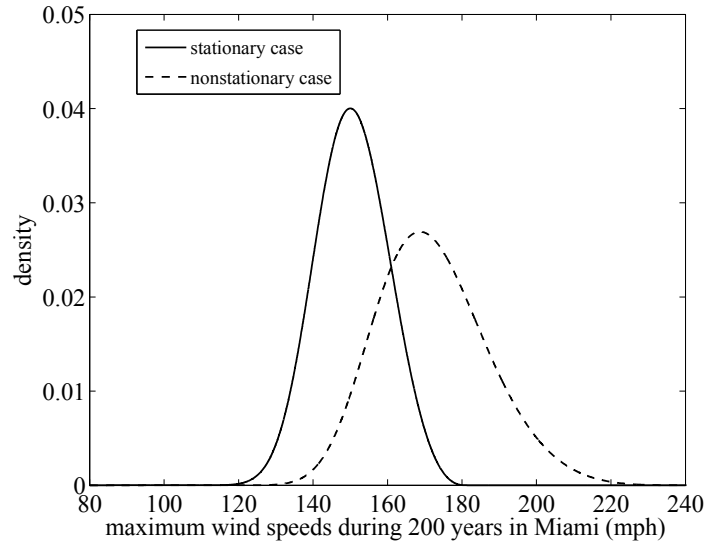


Figure 4.10 PDFs of maximum wind speeds in Miami over a 200-year service period under two different assumptions

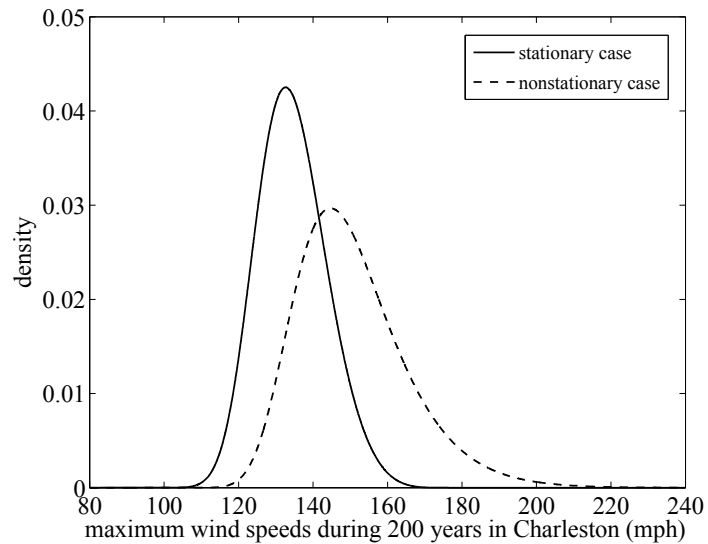


Figure 4.11 PDFs of maximum wind speeds in Charleston over a 200-year service period under two different assumptions

4.4 The Role of Climate Change in Time-dependent Reliability Assessment

To illustrate the effect of time-dependent failure rate on minimum expected cost decision-making, different loading and deterioration situations are assumed and their impacts on time-dependent reliability analysis and optimal solutions are illustrated using a simple structural model exposed to wind load. For simplicity, the structure is designed by the following equation:

$$0.9 R_n = C_n V_n^2 \quad (4-11)$$

in which R_n = nominal capacity, C_n = coefficient that transforms wind speed to structural action (including aerodynamic and exposure coefficients), and $V_n = 170$ mph (76 m/s), the nominal wind speed in Miami, FL, which corresponds to a 700-year mean recurrence interval (MRI) based on *ASCE Standard 7-10*. Table 4.1 summarizes the statistical parameters of initial resistance and aerodynamic coefficient. The hurricane simulation models described in Sections 4.3.1 and 4.3.2 are used to generate wind speeds in Miami, and the uncertainties in the wind speed are handled directly in the simulation process.

Table 4.1 Probabilistic models of initial strength and aerodynamic coefficient

	Mean	COV	PDF
Initial Strength	1.10 XR_n	0.10	Normal
Aerodynamic Coefficient	0.75 C_n	0.15	Normal

Four different cases are considered to assess the relative importance of the different causes and factors necessary to explain long-term trends. Table 4.2 summarizes characteristics and assumptions used in each time-dependent reliability model.

Case 1. In first-generation probability-based limit states design codes, the load intensities often are modeled as a sequence of independent and identically distributed (IID) random variables described by CDF $F_S(x)$, and the occurrence of these events in time is described by a Poisson process with a constant mean rate of occurrence, λ , of the events. In Case 1, the model by Vickery et al. (2000), also introduced in Section 4.3.1, is used to simulate

stationary wind speed. The structural degradation function, $G(t)$, in Eq (2-5) is 1, and accordingly, resistance, R , is random but constant over time.

Case 2. In most previous applications of time-dependent reliability of aging structures, the structural loads have been modeled in the same way as in Case 1 (Ellingwood 2005). To account for non-stationarity in resistance due to structural deterioration, structural capacity is assumed to decrease linearly by 20 percent in 200 years.

Case 3. The modified nonstationary hurricane model (cf. Figure 4.10) described in Section 4.3.2 is used to consider climate change effects on windstorms over a service period of 200 years. No structural deterioration is assumed in Case 3.

Case 4. Both the structural deterioration process and climate change effect on load intensities are considered in order to identify coupling of these effects in time-dependent reliability analysis.

Table 4.2 Different assumptions in time-dependent reliability assessment

	Resistance	Structural load
Case 1	Constant with random initial capacity	Stationary
Case 2	Decreasing with random initial capacity	Stationary
Case 3	Constant with random initial capacity	Nonstationary
Case 4	Decreasing with random initial capacity	Nonstationary

The cumulative probability of failure, $F(t) = 1 - L(t)$, which is obtained from Monte Carlo simulation, is presented in Figure 4.12. If the hazard is constant, $F(t) = 1 - \exp(-\alpha t)$, and for small values of α , this would be approximately αt . Since the hazard function for Case 1 is constant over the service life as discussed in Section 4.1, the solid line in Figure 4.12 is approximately linearly increasing for small values of constant conditional failure rate. The failure rate for an aging structure exposed to a stationary load process (cf. Case 2) generally is increasing. Note that the gap between Case 3 and Case 4 increases dramatically beyond 100 years, showing that synergistic effects of the

deterioration process and climate change on risk to winds play a significant role in time dependent reliability assessment for extended service periods.

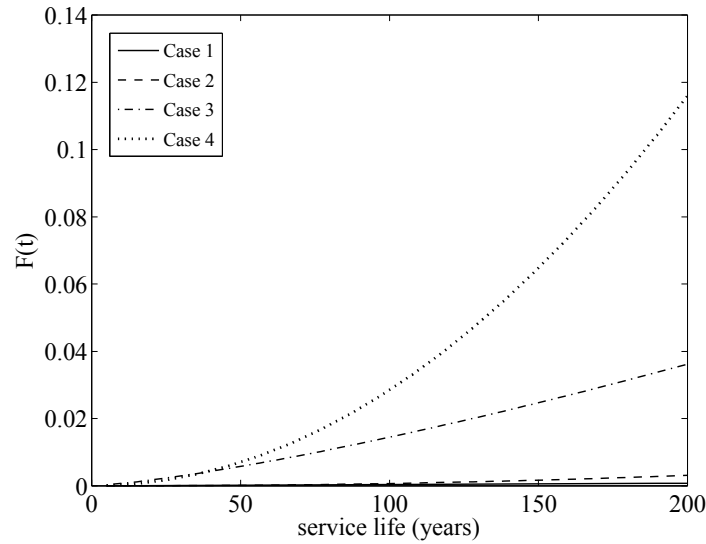


Figure 4.12 Cumulative failure probability under four different cases

To show the effect of time-dependent reliability on decision-making, the example presented above is analyzed using minimum life-cycle cost analysis, where the objective is to determine the optimal design parameter, X in Eq (2-14). The solid curve in Figure 4.13 shows the optimal design intensity (in an arbitrary unit) for Case 1 as a function of service life. Similar to the illustration presented in Chapter 3, the optimal design intensity becomes essentially constant beyond a projected service life of 60 years. The optimal design solutions taking into account the change in loading conditions and structural capacity (Case 4 in Table 4.2) are shown as the dash-dot curve in Figure 4.13, which increases slowly with service life. The difference between the optimal design intensities represented by this curve and the solid curve reflects the increasing failure rate due to the effect of climate change and structural deterioration. Intergenerational equity is more likely to be achieved if the role of climate change and time-declining discount

rate is incorporated in decision-making processes. This notion will be explored in more detail in Chapters 5 and 6.

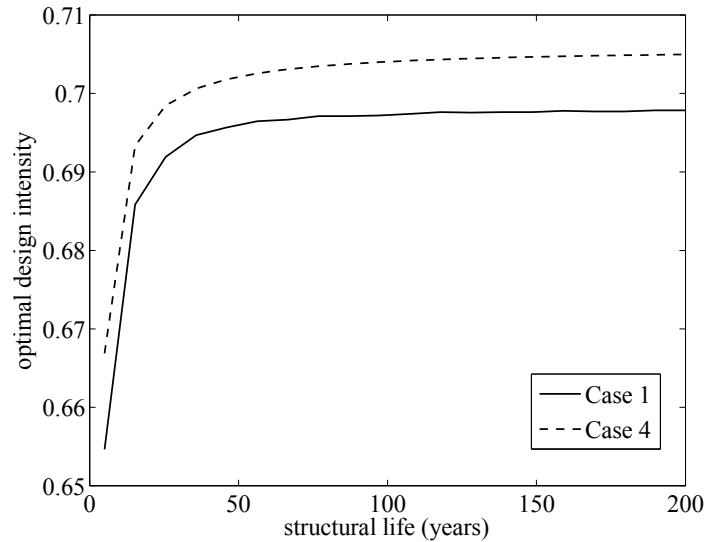


Figure 4.13 Comparison of optimal design intensities for Cases 1 and 4

4.5 Closure

This chapter has illustrated some of the significant challenges to time-dependent reliability assessment of structures under climate change and has suggested modifications of existing load and resistance models, which would enable the impact of the changes in loading conditions and deterioration processes on safety and serviceability to be better understood and to be assessed quantitatively. Stochastic models of structural loads that incorporate non-stationarity and serial correlation in actions resulting from natural hazards that may be affected by climate change have been investigated. To account for physical characteristics as well as statistical properties of hurricanes, mathematical simulation models under climate change have been carefully developed. These stochastic representations of capacity and demand have been integrated in a time-dependent structural reliability assessment to estimate how facility performance might be affected

by structural aging and climate change. The illustration of such modifications in current practices with a simple structural model exposed to wind load has shown that the non-stationarity in structural loading and deterioration plays a significant role in time-dependent failure rate. Moreover, the potential influence of climate change and aging on civil infrastructure is significant for facilities with service periods of 100 years or more, which are substantially longer than those previously considered in life-cycle engineering.

CHAPTER 5

INTERGENERATIONAL DISCOUNTING

Allocation of financial resources is essential for decision-making when demands on and response of a civil infrastructure facility are random, the effects of policies are expected to stretch out over a long period of time, and costs and benefits accrue at random or non-uniform points in time. Estimated expected costs generally are discounted to present value, but in customary discounting practices,³ future impacts are severely discounted as measured by present value. As discussed in Section 2.5 and Chapter 3, discounting of long-term effects presents a dilemma for decision-makers, in that people's values and preferences are treated differently because they live at different times. Many believe that this is contrary to moral or ethical standards that should underlie public policy. Ethical arguments on discounting will play an even more significant role in such projects with service periods that extend to multiple generations. The choice of the discounting method is critical in assessing the trade-offs between investments in design and planning by today's generation and the cost and burden of maintenance or replacement of civil facilities for future generations. When the period of interest is a century or more, even slight differences in discount rate and its method can lead to vastly different inferences and decisions (Bayer 2003).

To address these issues, this chapter begins by exploring recent developments in intergenerational discounting practices in the field of economics, and next proposes a new way of incorporating sustainability mandates into discounting in the context of civil

³ As noted in the review in Chapter 2, current discounting practices in life-cycle engineering have been tied to practices in the financial service industry. Often, the rate on the 30-year US Government Treasury Bond is used as a benchmark. Returns on investment for periods of substantially more than 30 years seldom have been of interest in the financial industry, and thus there has been little motivation to explore discounting practices for extended periods of time.

infrastructure. Finally, the proposed discounting method is illustrated with a benchmark problem to show how it can lead to sustainable decision-making while maximizing the likelihood of successful future infrastructure performance.

5.1 Recent Developments in Intergenerational Discounting Practices

To consider the preferences and needs of future generations in current decision-making, on the surface, the simplest approach might be to employ very low discount rates in the decision analysis. For instance, the Stern review on the Economics of Climate Change (Stern 2007), which is one of the most comprehensive surveys of the topic, employs a relatively low discount rate of 1.4 percent. This review suggests more rapid reduction in greenhouse gas emissions, which should be paid by current generation for the well-being of future generations, than had been suggested in previous reports. But this suggestion solves one problem by creating another: with a discount rate this low, the current generation may sacrifice too much to reduce risks faced by future (and presumably wealthier) generations. Rather, the intergenerational approach to discounting should explicitly incorporate the perspectives of both the current and future generations.

In evaluating public projects with the effects of which extend to future generations, the United States Office of Management and Budget (OMB 2003) recommends a constant rate of 3 percent, in addition to the 7 percent as a sensitivity. In contrast, France and the United Kingdom use declining discount rates over time; the rates used to discount costs incurred in the near future (near-market rates) are higher than rates for costs in the distant future. Figure 5.1 shows the schedules of such rates used in France (Lebegue 2005) and the UK (HM Treasury 2003). France has recommended a time-declining discount rate that starts at 4% for below 30 years (the initial rate consistent with the Ramsey formula with $\rho = 1.0$, $\eta = 2.0$ and $E[g_0] = 1.5\%$) and decreases to 2% for longer horizons, which corresponds with discount factors of $(1.04)^{-t}$ for time horizons less than 30 years and $(1.04)^{-30} (1.02)^{-(t-30)}$ for horizons longer than 30 years. The

government of the UK uses a stepwise declining discount rate: 3.5% for 0-30 years (the initial rate set by the Ramsey formula with $\rho = 1.5$, $\eta = 1.0$ and $g_0 = 2\%$), 3% for 31-75 years, 2.5% for 76-125 years, 2% for 126-200 years, 1.5% for 201-300 years, and 1% for longer periods. The constant discount rate used in both approaches for periods less than 30 years is consistent with current practices in financial markets, in which the time horizon should exceed that value.

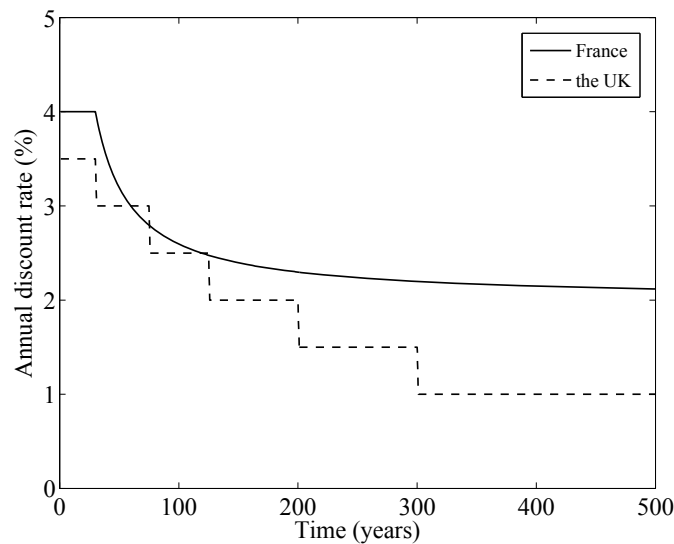


Figure 5.1 Declining discount rates in France and the UK

Thus, in recent years, the basic notion of a discount rate that decreases with time has been widely accepted by governments as a method to achieve dynamic efficiency in the economy and intergeneration equity. This notion can be justified based on at least two perspectives: preferences and behavior of individuals or the uncertainty incorporated in the discount rate.

As for the first, empirical evidence suggests that the form of discount rate used by individuals on inter-temporal decisions is hyperbolic and declines over time (Henderson and Bateman 1995). Hyperbolic discounting reconciles the exponential rate (the normal

rate; cf. Chapter 2) in the near term with lower rates in the distant future. However, the individual preferences reflected by hyperbolic discounting should not be basis for the public policy and investment decisions. Moreover, a time-varying discount rate can cause problems of time inconsistency, which arises when a project considered worth an investment at present is no longer considered worth the investment in the future. This dependence of the worthiness of a project on the period in which it is evaluated can lead to continuous revisions of a project.

As to the second, the more convincing argument for a declining discount rate is its implications regarding future uncertainties and lack of confidence in both economic and noneconomic forecasts (such as the rate of economic growth, the amount of capital that will be accumulated, the level and pace of technological progress, the stability of the political system, the state of the environment, etc.) in the distant future. Weitzman (1998, 2001) deals with the uncertainty by using an averaging procedure, denoted the *certainty-equivalent discount rate*, which postulates that the variable that should be averaged over various uncertain states of the world is not the discount rate, but the discount factor. The average discount factor over time is the *certainty-equivalent discount factor*; knowing this factor, the certainty-equivalent discount rate can be calculated from Eq (2-17) or (2-18). A numerical example of certainty-equivalent discount factors and rates is given in Table 5.1. In Figure 5.2, the certainty-equivalent discount rate decreases over time, approaching the minimum discount rate having any positive probability (1% in this example) as time goes to infinity. Thus, incorporating uncertainty in discounting practices suggests a theoretical rationale for the declining certainty-equivalent discount rate over time and, at the same time, overcomes the ethical issues of traditional discounting in achieving intergenerational equity.

Future discount rate scenarios and probabilities assigned to them play an important role in determining the particular shape of the decrease in certainty-equivalent discount rates. Two approaches, which address uncertainty about the discount rate itself

and uncertainty about the future growth of the economy, have been considered over the last decade.

Table 5.1 Certainty-equivalent discount factors and rates based on ten equally probable discount rate scenarios from 1% to 10% per year

Time (years)	10	50	100	200	300	500
Certainty-equivalent discount factor	0.6097	0.1567	0.0592	0.0159	0.0053	0.0007
Certainty-equivalent discount rate	5.0722	3.7763	2.8672	2.0926	1.7600	1.4647

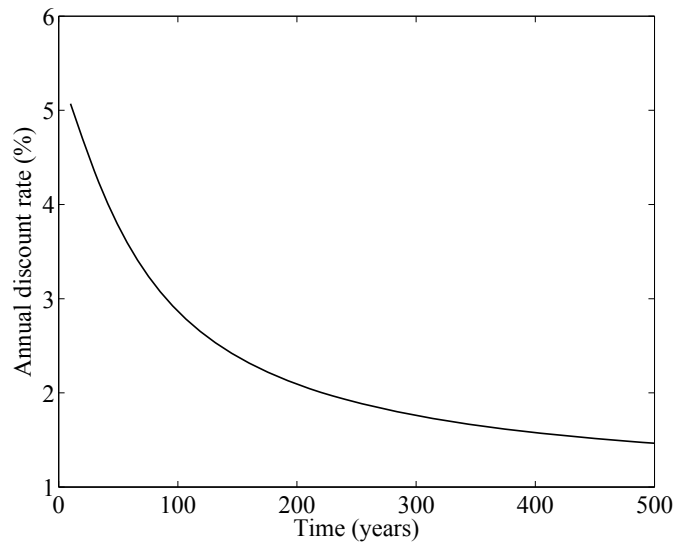


Figure 5.2 Certainty-equivalent discount rate

The first approach assumes that the most fundamental uncertainty is about the discount rate itself. Weitzman (1998) initially developed this approach, showing that the uncertainty reflected in future discount rates results in a decline in certainty-equivalent discount rate as illustrated in Table 5.1 and Figure 5.2. In his work on *gamma discounting* (Weitzman 2001), a probability distribution of the discount rate was constructed from the results of a survey of opinions of 2,160 experts concerning what future discount rates will be. Even if every individual expects a constant discount rate,

the gamma probability distribution of opinions leads to a decreasing certainty-equivalent discount rate. Weitzman's concept has been applied to develop intergenerational discounting procedures by Newell and Pizer (2003) and Groom et al. (2007). Under the assumption that historical real interest rates from the recent past are informative about the future, Newell and Pizer (2003) used long-term government bond rates in the United States to forecast future interest rates, and to create simulations of future certainty-equivalent discount rates by using random walk, mean-reverting, and simple unlogged models. They demonstrated that uncertainty about future rates can lead to a higher valuation of future benefits over long horizons regardless of the initial rate. Groom et al. (2007) developed five models – random walk, mean-reverting, AR-IGARCH (Auto Regressive - Integrated Generalized Autoregressive Conditional Heteroskedasticity), regime-switching and state space models⁴ – for UK and US interest rate data, and suggested that either a regime-switching or state-space model is most appropriate for forecasting the future and determining the path of certainty-equivalent discount rates.

The second approach addresses the uncertainty in the rate of growth in consumption, g_t , rather than the uncertainty in the discount rate (see Eq (2-19)). Estimating the rate of growth in consumption for the next 30 years is difficult; beyond three decades, the estimation is even more uncertain due to incomplete knowledge of future technological progress, political choices, and the accumulation of capital which will impact the long-term consumption growth. Intuitively, incorporation of the uncertainty in growth in consumption should reduce the discount rates for long-term

⁴ For regime-switching, Groom et al. (2007) estimated a two-regime model with each regime being an AR(2) process, which has the same diffusion and drift functions but different parameter values. In their paper, each regime means the state that the interest rate process goes through. In addition to this characteristic, the state-space model can consider the evolution of the level and variance of the process over time.

horizons. The classical Ramsey Formula (Eq 2-19) can be modified to consider this source of uncertainty and to account for an additional *prudent effect* (Gollier 2002):

$$r = \rho + \eta \frac{E(G_t)}{t} - 0.5\eta^2 \frac{Var(G_t)}{t} \quad (5-1)$$

in which random variable $G_t = \log$ consumption growth (to be explained in Section 5.2).

The last term in Eq (5-1) is referred to as the *prudent (or precautionary) effect* and represents the fact that a prudent decision-maker is willing to accept a greater financial burden for the future by lowering the discount rate. If economic growth is subject to a series of perturbations (shocks) that are identically distributed and statistically independent, the precautionary term in the extended Ramsey formula is constant. If shocks to growth are positively correlated over time, however, this term becomes sizeable for long horizons, leading to a decreasing discount rate. Such uncertainty in future consumption growth rates should be based on historical observations, whenever possible. Weitzman (2004) found the fourth term in the extended Ramsey formula, which represents a *statistical forecasting effects*, by investigating the uncertainty in technological progress. This term also reduces the discount rate in the far-distant future.

As noted previously, time inconsistency may be a problem when the utility discount rate is time-varying, but does not arise from the discount rate which is declining due to time-varying growth rate of consumption under the assumption of constant utility discount rate, ρ . Accordingly, in the next section, a new intergenerational discounting method for civil infrastructure, which considers the uncertainty in the rate of growth in consumption in developing declining discount rates over time, will be suggested based on this approach.

Lind (2007) suggested a different approach to support sustainable decision-making, using the notion of a *financing horizon*. The financing horizon is the duration for which the project is to be financed. It is project-specific: the financing horizon for some civil facilities may equal the design life, while for others, including bridges,

tunnels, toll highways, etc., it may correspond to the amortization period of the initial investment. Lind (2007) postulated that the financing horizon for public infrastructure projects should equal the remaining mean life expectancy of the current population in order to avoid imposing risk on future generations. Once a specific discount rate is selected for a project, it is applied only during the financing horizon. No further discounting is applied subsequent to the end of the financing horizon, which implies that risk incurred beyond the financing horizon should be valued as if it occurred at the end of the financing horizon. This principle yields an effective discount rate, which is constant over the financing horizon and decreases hyperbolically with time after the financing horizon (Lind 2007). Figure 5.3 illustrates the effective discount rates when different lengths of financing horizons are assumed. Shorter financing horizons induce more dramatic decrease in discount rates, and at the end of a 200-year service period, lead to much lower discount rates.

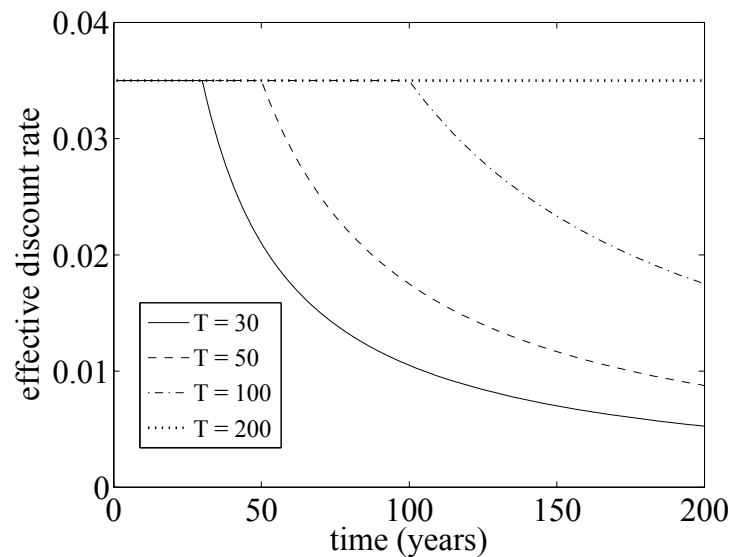


Figure 5.3 Sensitivity analysis of effective discount rate to financing horizon

5.2 Intergenerational Discounting for Civil Infrastructure Decision-making

5.2.1 The role of future economic volatility in intergenerational discounting

Two sources of uncertainty – embedded in the discount rate itself and in the state of the economy – that lead to a declining discount rate were discussed in Section 5.1. For both sources, the stochastic process generating future discount rates in the former and economic growth rates in the latter plays an important role in determining the declining structure of discount rate. Forecasting future discount rates based on past market interest rates relies on the assumption of efficient financial markets, which may not be appropriate for multi-generational time frames due to the factors discussed in Section 2.5. Moreover, few markets exist for assets with maturities exceeding 30 years, making the interest rate beyond that horizon even more uncertain. To develop a new method for intergenerational discounting for civil infrastructure, we will focus on uncertainty that is inherent in economic growth rates and will examine the implication of this source of uncertainty on discount rates.

The impact of uncertainty in the rate of growth in consumption on the discount rate has been examined by Gollier (2007, 2008, 2012). With the large uncertainty about the economic growth, the social discount rate that satisfies the capital asset pricing model for a risk-free rate can be written as (Gollier 2008):

$$r_t = \rho - \frac{1}{t} \ln \frac{E[u'(c_t)]}{u'(c_0)} \quad (5-2)$$

where $u(.)$ = utility function on consumption, which is assumed to be three times differentiable, increasing and concave, c_t = consumption at date t , and c_0 = consumption at date 0. Under the assumption that $u'(c) = c^{-\eta}$, where η represents a constant relative risk aversion and that $G_t = \ln(c_t) - \ln(c_0)$, the log consumption growth between date 0 and

date t , is normally distributed, Eq (5-2) can be shown to be equivalent to Eq (5-1) (Gollier 2007).

Different models of stochastic process G_t determine the shape and extent of decline in discount rates over time. The simplest model is that log consumption, $\ln(c_t)$, follows a Brownian motion with trend μ and volatility σ . This implies that G_t is normally distributed with mean $E(G_t) = \mu t$ and variance $Var(G_t) = \sigma^2 t$. Eq (5-1) then can be written as (Gollier 2008):

$$r_t = \rho + \eta\mu - 0.5\eta^2\sigma^2 \quad (5-3)$$

Due to the proportional increase in the mean and variance of G_t with time, the discount rate is independent of time horizon. The inclusion of the uncertainty of G_t reduces the discount rate by subtracting a third term from the standard Ramsey equation, but cannot lead to a declining discount rate.

Shocks to growth in real world generally are positively correlated over time because the current political and economic situations depend on the previous state due to the nature and stability of their system. Gollier (2008) proved that positively correlated shocks to the growth rate of the economy can justify using a decreasing discount rate. To illustrate the effect of correlation in shocks on aggregate consumption, the change in log consumption is assumed to follow an autoregressive process (Bansal and Yaron 2004, Gollier 2012):

$$\begin{aligned} \ln(c_{t+1}/c_t) &= x_t \\ x_t &= \mu + y_t + \sigma\eta_t \\ y_t &= \phi y_{t-1} + \rho_e \sigma e_t \end{aligned} \quad (5-4)$$

where η_t and e_t are statistically independent and normally distributed variables, with zero mean and variance 1. When $0 < \phi < 1$, $Var(G_t)/t$ increases over time and converges to $\rho_e^2\sigma^2/(1-\phi)^2 + \sigma^2$ as t goes to infinity. The precautionary term becomes sizeable for a long horizon, leading to a declining discount rate. For growth in consumption that is

positively correlated, risk and uncertainty accumulate over time, leading to a smaller discount rate at a longer horizon (cf. Eq (5-1)).

The discount rate based on the extended Ramsey formula (Eq (5-1)), with positively correlated shocks to the growth rate of the economy as in Eq (5-4), will be used in developing an intergenerational discounting method for civil infrastructure. The parameters of this uncertain process can be based on statistical inference drawn from past values, assuming that the past is informative about the future. Bansal and Yaron (2004) suggested the following parameters in Eq (5-4): $\mu = 0.0015$, $\sigma = 0.0078$, $\phi = 0.979$, and $\rho_e = 0.044$, where the time unit is months, using annual observations in the United States from 1929 to 1998. The discount rate obtained from Eq (5-4) with these parameters starts at 3.5% and approaches to 2.8% over 200 years, as shown in Figure 5.4. Although positive correlation in consumption growth permits the model to reflect the increase in uncertainty as consequences further in the future are considered, it is questionable whether decision-making based on such a discount rate supports an equitable weighting of the preferences for present and future generations due to the relatively high discount rates applied to future generations; the discount factor at 200 years using the above model would be approximately 0.004 and the future consequences would have a negligible impact on present decisions (Lee and Ellingwood 2015).

In order to ensure inter-temporal equity in engineering decisions, the additional increase in uncertainty due to the factors affecting the economic growth (introduced in Section 5.1) should be incorporated in Eq (5-4). Similar to the model with time-varying volatility of consumption growth suggested by Bansal and Yaron (2004), the change in log consumption affected by time-increasing volatility, σ_t , is assumed to be:

$$\begin{aligned} \ln(c_{t+1} / c_t) &= x_t \\ x_t &= \mu + y_t + \sigma_t \eta_t \\ y_t &= \phi y_{t-1} + \rho_e \sigma_t e_t \end{aligned} \tag{5-5}$$

where σ_t represents the time-varying economic uncertainty incorporated in consumption growth rate. Quantification of reduction in the discount rate also depends on specification of the form of uncertainty (Stern 2007). Models of increasing volatility summarized in Table 5.2 were selected to examine the sensitivity of the discount rate to the type of uncertainties over time.

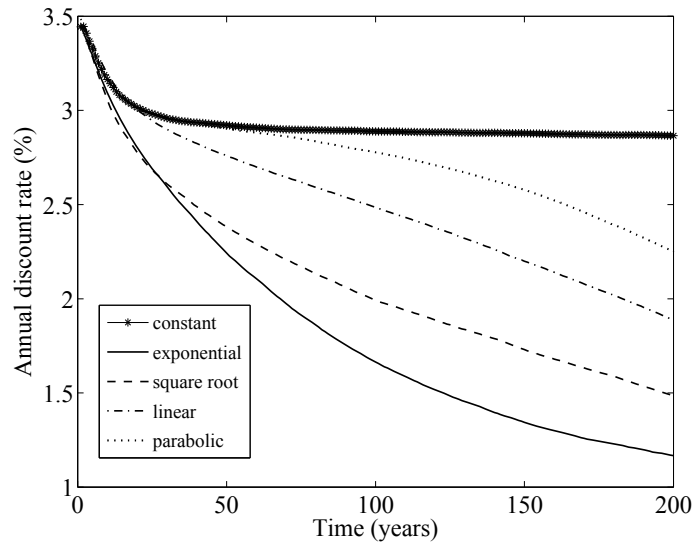


Figure 5.4 Dependence of discount rates on the shape of time-varying volatility
for $\rho = 0$ and $\eta = 2$

In Table 5.2, σ is the initial volatility and α is the annual increment rate in volatility. For comparison, models in Table 5.2 are normalized and illustrated in Figure 5.5: for all models, volatility increase from its initial value at year 0 to approximately twice its initial value at year 200. The time-declining discount rates obtained from these different models of volatility are shown in Figure 5-4. The additional increases in uncertainty introduced through Eq (5-5) lead to lower discount rates than are implied by Eq (5-4). Moreover, the time-varying nature of the volatility affects the shape and extent of the decline in discount rates over time. Models of time-varying volatility and/or its

parameter α can be determined by decision-maker to reflect his/her level of risk aversion toward possible risk posed to future generations.

Table 5.2 Models of time-varying volatility

Exponential: $\sigma_t = \sigma(2 - \exp(-\alpha_1 t))$
Square root: $\sigma_t = \sigma(1 + \alpha_2 t^{1/2})$
Linear: $\sigma_t = \sigma(1 + \alpha_3 t)$
Parabolic: $\sigma_t = \sigma(1 + \alpha_4 t^2)$

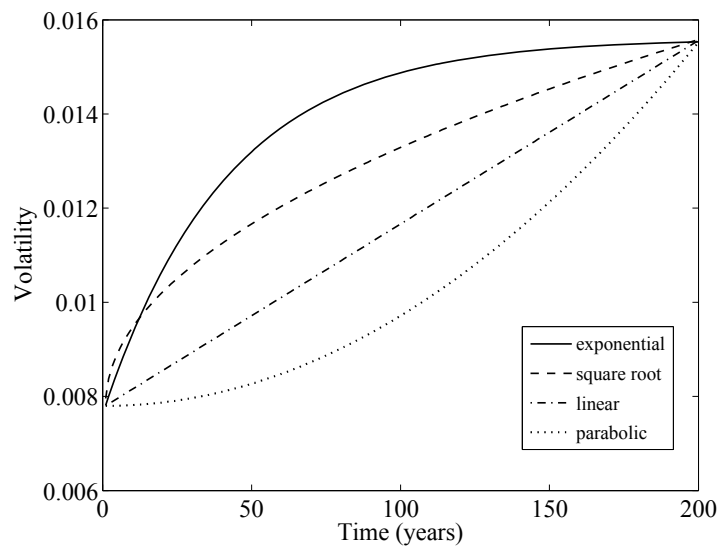


Figure 5.5 Models of time-varying volatility

Life losses, injuries and damage to individual civil facilities can be estimated relatively easily compared to potential losses to society at large (e.g., global climate change, radioactive waste disposal, loss in biodiversity, etc.). Moreover, loss of life or personal injury in future generations may play a significant role in total life-cycle cost. In accordance with the principle of life-value invariance (Nishijima et al. 2007), lives in present and future generations should be treated equally; in contrast, in at least one survey (Cropper et al. 1992), the majority of people in the current generation tended to give lower priority to lives saved in the future. Two different rates of pure time

preference, which characterize the decision-maker's attitude towards future generations, will be applied herein to human losses and to economic losses, respectively: a low rate of pure time preference (ρ) close to zero, 0.1 percent per annum (corresponding to Stern's recommendation) will be applied to discount for human losses, while ρ for economic losses will be determined from the decision-maker's preference (Lee and Ellingwood 2015). The same growth discounting (cf. Eq (5-5)) will be used for both discount rates. A simple application of the newly developed intergenerational discount rate to civil infrastructure decision-making will be shown in the next section.

5.2.2 Application of proposed intergenerational discounting method

The same simple example of minimum life-cycle cost analysis presented in Chapter 3 is considered. Suppose that no injury or loss of life occurs upon structural failure. Under the condition that the annual pure time preference rate for economic losses is 0.1 percent and that the elasticity of marginal utility of consumption is 2 (Lebegue 2005), intergenerational discount rates with the different volatilities shown in Figure 5.4 are incorporated in the example using Monte Carlo simulation. The optimal design intensities obtained for these four volatilities are compared in Figure 5.6 to the optimal design intensity using a single discount rate of 0.035 (represented by circles). The optimal design solutions increase with service life with all forms of declining discount rates. This very simple demonstration shows clearly that declining discount rates are an essential ingredient of sustainable solutions, ensuring that the current generation takes into account the well-being of future generations while making it possible to measure costs consistently over multiple generations. Of course, the issues of how much preference should be given to future generations or how costs (or benefits) should be distributed from generation to generation depend on the decision-maker's ethical viewpoint and on whether/how investments in risk reduction are balanced against available resources. A decision-maker's view on the value that should be assigned to

future generations can be reflected by the shape of declining discount rates, which determines the degree to which the optimal design intensity increases with time. In general, discount rates with exponentially increasing volatility increase the optimal design intensity more dramatically as the decision time frame increases; conversely, optimal design solutions tend to increase more slowly (placing less value on needs of far-distant generations) when the volatility increases parabolically.

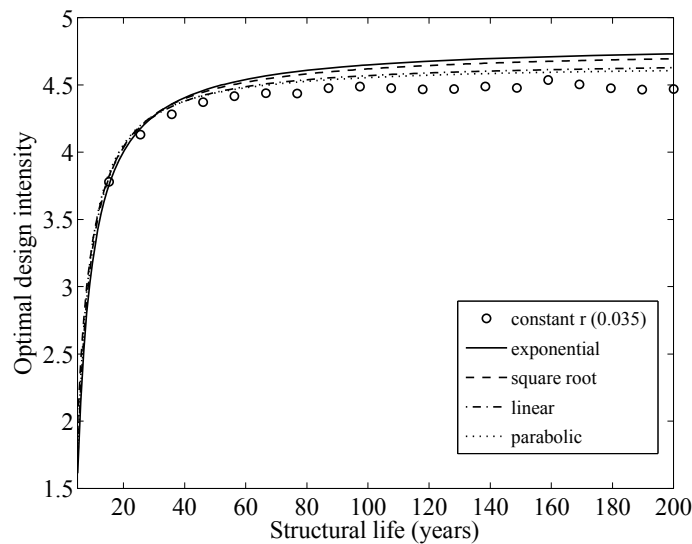


Figure 5.6 Comparison of optimal design intensities as a function of design life obtained from various types of discount rates, holding other conditions the same; hazard occurrence rate = 0.2/year and initial cost per unit design intensity = 5

If a decision-maker allocates costs and benefits between the current and future generations in such a way as to strongly favor future generations, he/she may choose to use a discount rate in which the change in the natural logarithm of consumption growth is modeled as an autoregressive process with exponentially increasing volatility over time. Government agencies or policy makers can be one example of decision-makers who adopt a more risk-averse stance towards possible risk posed to future generations than most individuals and small groups do. Such a discount rate will be used in the case study

and benchmark problems involving civil infrastructure systems in the following two sections.

5.3 Comparison of Several Approaches to Discounting with the Proposed Discounting

As discussed in Section 5.1, several approaches to discounting have been suggested recently that aimed at sharing risk equitably between generations. In Section 5.2, this dissertation proposed a new way of achieving long-term sustainable solutions in the context of civil infrastructure. This section examines how different discounting methods might affect the optimal decision and how a new approach can lead to more equitable decision-making by distributing the burden of the costs fairly between generations. A levee situated in a flood-prone zone is used for illustration.

Flooding accounts for the majority of natural catastrophic losses in the developed world and is the leading cause of death and injury among natural disasters. Moreover, flood control facilities have service periods of 100 years or more, which are substantially longer than those typically considered in life-cycle engineering of buildings or bridges and may extend across several generations. Intergenerational risk sharing in risk-informed decision-making for flood control facilities thus is an important and timely research challenge.

To compare different intergenerational discounting methods in the context of equitable transfer of risk across multiple generations, a newly constructed levee situated in a flood-prone city is considered. The city has 100,000 inhabitants and has been severely damaged by flooding at least twice since 1900. A similar structure has been considered previously for the purpose of studying the *societal capacity to commit resources* to sustainable risk reduction (Lind et al. 2009). Five alternative discounting methods considered in this section are summarized in Table 5.3 and Figure 5.7. The service period of the levee is 200 years and the design alternatives are determined by the

crest elevation H (m) of the levee. The demand on the levee structure is based on 98 years of flood data; it was found that the Gumbel distribution provided the best fit to these data, with parameters $\alpha = 0.549\text{m}^{-1}$ and $u = 5.939\text{m}$ estimated using the method of moments (Lind et al. 2009). However, this fitted distribution is overly influenced by low and central values of data. In order to refine the upper tail of the distribution, which governs the failure probability of the levee, the cross-entropy method was used to estimate the upper tail of the cumulative distribution function describing flood elevation (see Lind et al. 1989):

$$G(x) = 1 - c[1 - F(x)] = 1 - c\left(1 - \exp\{-\exp[-\alpha(x - u)]\}\right) \quad (5-6)$$

Table 5.3 Five methods of discounting

	Type
Method 1	Proposed discount rate with additional uncertainty (Section 5.2)
Method 2	Discount rate used in France
Method 3	Discount rate used in UK
Method 4	Low constant discount rate of 0.01
Method 5	Effective discount rate with a financing horizon = 30 years (Lind, 2007)

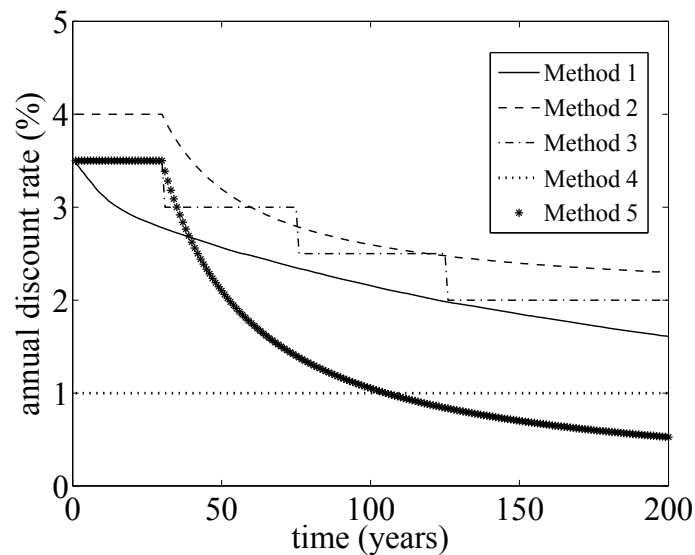


Figure 5.7 Different types of discount rates (each method corresponds to Table 5.3)

For each alternative structure with crest elevation H , the conditional annual probability that the flood exceeds level H is $p = 1 - G(H)$. The initial cost for each alternative is also approximated as a function of H . The construction cost is estimated as $C = C(H) = a (H^3 - b^3)$, where $a = \$100,000/\text{m}^3$ and $b = 13\text{m}$ are constants. Economic losses upon failure (including reconstruction cost) are assumed to be $\$400\text{M} + C$. It is assumed that levee failure is equally likely to occur in any year during the design life and to cause a loss of 300 lives. The probability of more than one levee failure during the design life of 200 years is assumed to be negligible. Assigning an economic value to human life is controversial, and recent research has suggested a way to evaluate loss of life in risk analysis (the life quality index, or LQI) that avoids monetizing the value of life (Nathwani et al. 1997). However, the LQI cannot be used in decision-making processes extending to multiple generations because it fails to account for the effect of time on the decision process. The current study, therefore, considers risk trade-offs that people make with regard to their safety, which can be represented as the value of a statistical life. The estimates of life value in the US are in the range of $\$4\text{M}$ to $\$9\text{M}$ (Viscusi and Aldy 2003), and in this illustration, $\$4\text{M}$ is allocated to the value of one human life.

The calculated values of total expected life-cycle cost for the five discounting methods in Table 5.3 are illustrated in Figure 5.8. For comparison, total expected life-cycle costs with a single discount rate of 0.035 are also shown in Figure 5.8. This value of 0.035 corresponds to an average market interest rate and is commonly used in cost-benefit analyses involving time horizons of less than 50 years. The optimal design heights using this constant rate of 0.035 and the discount rates currently recommended in France are virtually the same, even though discount rates used in France give slightly higher costs than those using the constant discount rate. This result implies that discounting procedure used in France does not address the preferences of future generations very well, at least in this example. On the other hand, a very low discount rate of 0.01 and effective discount rates with a financing horizon of 30 years (methods 4

and 5 in Figure 5.8) yield much higher optimal crest elevations compared to the elevation obtained using the constant (0.035) annual discount rate. It should be noted that a high value of optimal design does not always guarantee equitable risk-sharing over generations. Rather, it could impose an excessive burden on the current generation, which is apparent from Figure 5.9.

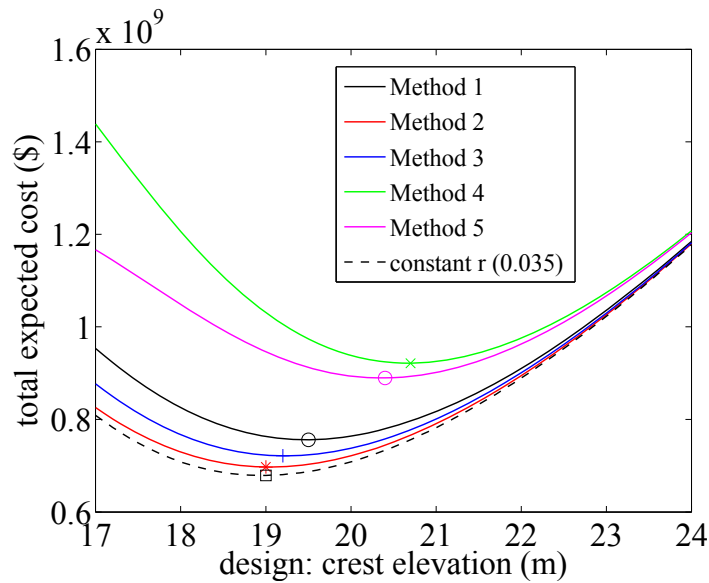


Figure 5.8 Sensitivity of total expected LCC and the optimal design level to different discounting methods

Figure 5.9 illustrates the optimal crest elevations as a function of design life obtained from the five discounting methods. All forms of discount rate indicate an increase in optimal design with service life, which means that all methods (except that used in France) consider, in some way, future generations in decision-making. Little difference in optimal levels exists for service lives less than 100 years, except when the discount rate is very low. Beyond 100 years, however, the optimal design levels do not approach an asymptotic value, but increase dramatically when employing effective discount rates with a 30-year financing horizon. This implies that the current generation places too much value on the preferences of future generations; in particular, the use of a

financing horizon of 30 years, as suggested by Lind (2007), cannot support an equitable distribution of resources between generations. The use of the intergenerational discount rates accounting for additional uncertainty developed in Section 5.2.1 lead to optimal crest elevations that increase modestly and asymptotically after 100 years, and appear to allocate costs and benefits between the current and future generations in more equitable fashion.

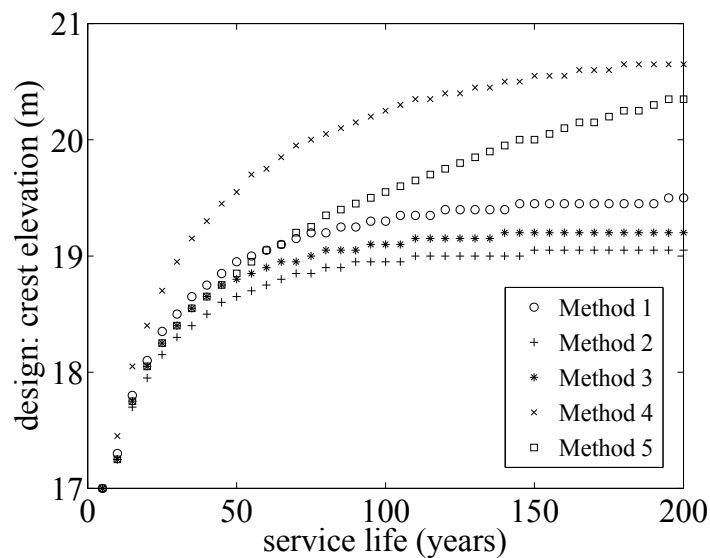


Figure 5.9 Comparison of optimal crest elevations as a function of design life obtained from five discounting methods

5.4 Case Study: Intergenerational Discounting used in Seismic Retrofit of a Dam

In Section 5.3, while all discounting practices take into account future generations in decision-making in some fashion, some practices tend to impose too much responsibility on the current generation. The newly suggested discount rate in Section 5.2.1, where uncertainty about future economic growth is incorporated, overcomes the ethical issues of conventional discounting methods and achieves a goal of socio-economically sustainable solutions. In order to illustrate the effect of the proposed

intergenerational discounting method on long-term risk to civil infrastructure facilities more clearly, a hypothetical dam built in the 1950s in a strong earthquake-prone area is considered in this section. Downstream risk involves major losses of life as well as infrastructure damage, and the dam is being considered for rehabilitation. Nathwani et al. (2008) have analyzed the same structure using the Life Quality Index (LQI) approach in their risk analysis. Their paper dealt with the cost and benefit of four seismic retrofit alternatives upon its failure: (1) do nothing (status quo); (2) drawdown of the reservoir by 5m; (3) drawdown of the reservoir by 10m; and (4) reinforcement of the dam. Investment cost, losses and probabilities of failure associated with the four alternatives are listed in Table 5.4. The land use and demography in the vicinity of the dam might change significantly with time and the dam itself could become obsolete. Even though these changes will introduce large uncertainty on failure loss estimation, losses upon failure are assumed to be constant over its service period in order to show the effect of the intergenerational discounting practice on the optimal design solution more clearly.

Table 5.4 Risk posed by four alternatives

Alternative	1	2	3	4
Relative retrofit cost	0	5	10	6
Annual P_f	0.01	0.006	0.0015	0.0004
Economic loss upon failure	\$105M	\$90M	\$65M	\$105M
Loss of life upon failure	350	140	30	350

Risk is defined as a combination of the probability of extreme events, the occurrence of life loss or injuries, and economic losses including direct or indirect losses associated with loss of function, repair or replacement of damaged structures, and loss of time and profit due to business interruptions. Once a loss mitigation policy is implemented, seismic retrofit cost at time 0 can be obtained from the product of unit retrofit cost, C_I (\$M), and relative retrofit cost (unitless). Unit retrofit cost is the same for all alternatives while relative retrofit cost depends on the methods of seismic retrofit as

shown in Table 5.4. Thus, seismic retrofit cost is proportional to the relative retrofit cost. It is assumed in this illustration that the risk can be entirely monetized and should be minimized to achieve the optimal design solution.

Two discounting approaches discussed in Section 5.2.2 – the traditional and the proposed intergenerational discounting method – are compared. The traditional discount rate is constant with a value of 5.5 percent per year. The intergenerational discount rate has two parts, one for economic losses, which can be applied to ‘economic loss upon failure’, and the other for life losses. The former has an annual 2 percent pure time preference rate, while the latter treats a pure time preference rate as 0.1 percent. The unit retrofit cost of the dam is \$70M. The required service period is 150 years from the time of retrofit. In this illustration, \$6.3M is allocated to the value of a human life in accordance with the most recent recommendations of the Federal Emergency Management Agency (FEMA 2015).

The expected life-cycle costs are obtained by simulation using one million replications of seismic demand, assuming that the failure probability of the dam is stationary over time. The results are given in Table 5.5. Alternative 1 (status quo) is optimal when the traditional (constant) discount rate is used, while alternative 4 (strengthening the dam) is optimal when the proposed intergenerational discount rate is used. This example shows why a decision-maker might be reluctant to undertake a retrofit with uncertain benefits for future generations based on a current life-cycle cost analysis with a constant discount rate. The current method favors the alternative that does not require the retrofit cost which the current generation would bear, and shifts the expected failure costs to future generations. In contrast, the use of the proposed intergenerational discounting method encourages the decision-maker to consider future generations as well as the current generation, where the expected failure costs play a significant role in determining the optimal design solution.

The bias of traditional life-cycle cost analysis toward the present generation can be seen clearly in a sensitivity analysis of unit retrofit cost, C_I , which is increased from \$5M to \$150M by increments of \$5M. The sensitivity of LCC to C_I in both traditional and intergenerational decision-making is shown in Figures 5.10(a) and 5.10(b), respectively. Using the traditional discounting method, the tipping point from alternative 4 to alternative 1 is at \$65M; for the intergenerational discounting method, it is at \$145M. In other words, seismic retrofit cost, which must be paid at the time of rehabilitation by the current generation, tends to govern the total expected life-cycle cost when using the traditional discounting method.

Table 5.5 Expected life-cycle cost for each alternative using two different discounting approaches

Discounting	Alternatives			
	1	2	3	4
Traditional	419.207*	456.059*	706.957*	436.991*
Intergenerational	907.388*	574.473*	713.468*	456.576*

*Unit: US dollars in 2013 value, \$M

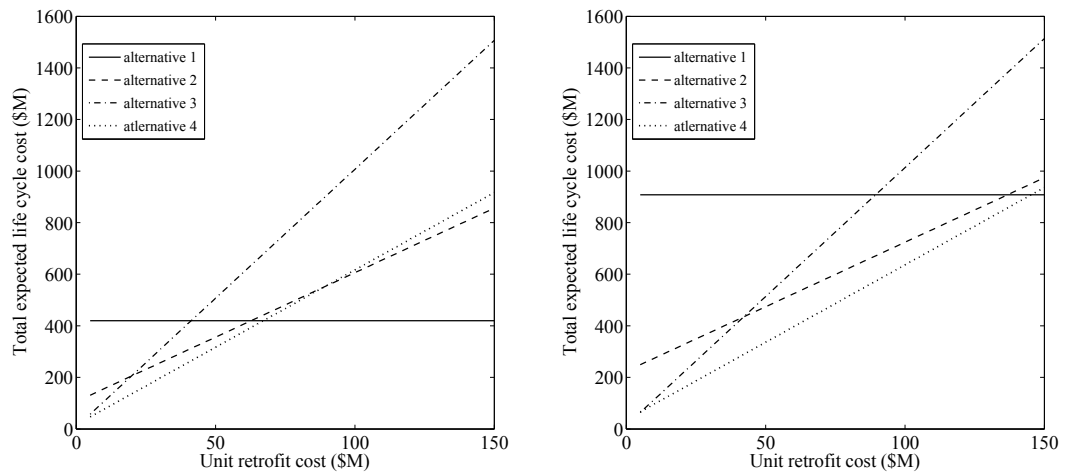


Figure 5.10 Sensitivity of total expected LCC to unit retrofit cost when using: (a) traditional discount rate and (b) intergenerational discount rate; remaining service life = 150 years, value of life = \$6.3M

The effect of intergenerational discounting on equitable decision-making can be better understood through a sensitivity analysis involving service period. Suppose that the required remaining life of the dam varies between two extreme points: 10 years and 500 years. The expected life-cycle costs of each alternative using two different discounting methods are illustrated in Figures 5.11(a) and 5.11(b) for traditional and intergenerational discounting, respectively. Traditional discounting leads to the same conclusion: that the total expected life-cycle costs for all alternatives become constant beyond 50 years and that ‘doing nothing’ is the optimum over all service periods. On the other hand, when intergenerational discounting is applied, the option of ‘doing nothing’ has the minimum LCC for remaining service periods less than 30 years due to its zero retrofit cost, while ‘strengthening’ becomes the optimal solution for all service periods greater than 30 years, mainly because of its low probability of dam failure, implying that events in the distant future have more impact on present decision-making. Moreover, the total expected LCC for all alternatives increases over time; modest increases in alternatives 3 and 4 result from the smaller losses upon failure and their relatively low probability of dam failure, given that failure occurs.

Finally, to better illustrate the effect of the two distinct components of intergenerational discounting – economic losses and human losses – a sensitivity analysis involving value of life is performed in which the value of life is increased from \$1M to \$15M. The unit retrofit cost is estimated at \$10M to show the impact of a very low pure time preference rate applied to life losses more clearly. The results are plotted in Figures 5.12(a) and 5.12(b) for traditional and intergenerational discounting, respectively. Alternative 4 is the dominant retrofit solution for all values of life when the traditional discounting is employed because the advantage of alternative 1 is decreased as the relative ratio of seismic retrofit cost to failure cost is decreased. It is interesting to note that, for intergenerational discounting, the optimal solution changes from alternative 4 to alternative 3 at \$11M of life value, mainly because intergenerational discounting applies

a lower value of discount rate to loss of life than to economic losses. Since alternative 3 has smaller expected value of life losses per year, it becomes dominant after the effect of life losses on total expected life-cycle cost increases.

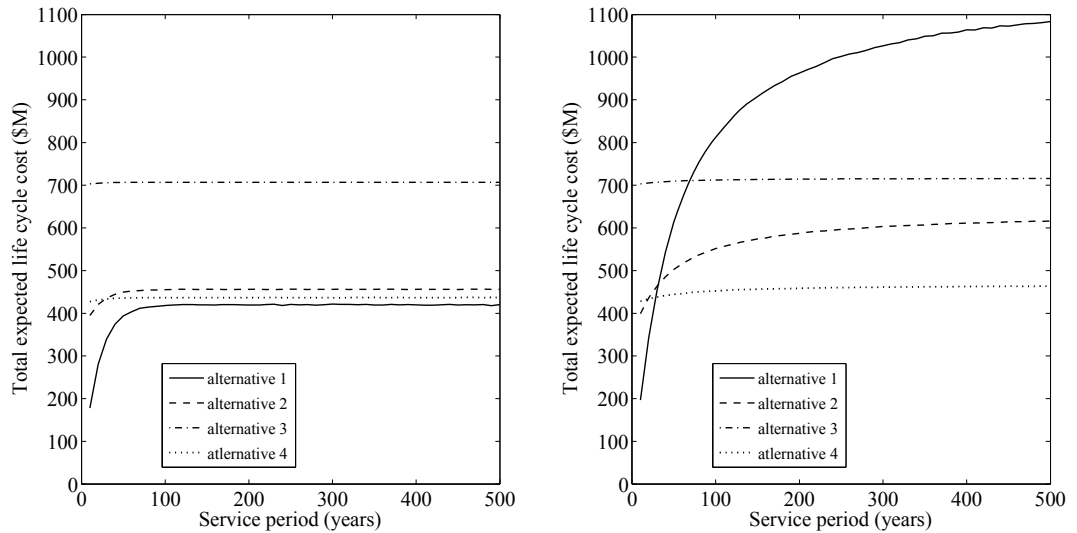


Figure 5.11 Sensitivity of total expected LCC to service period when using: (a) traditional discount rate and (b) intergenerational discount rate; unit retrofit cost = \$70M, value of life = \$6.3M

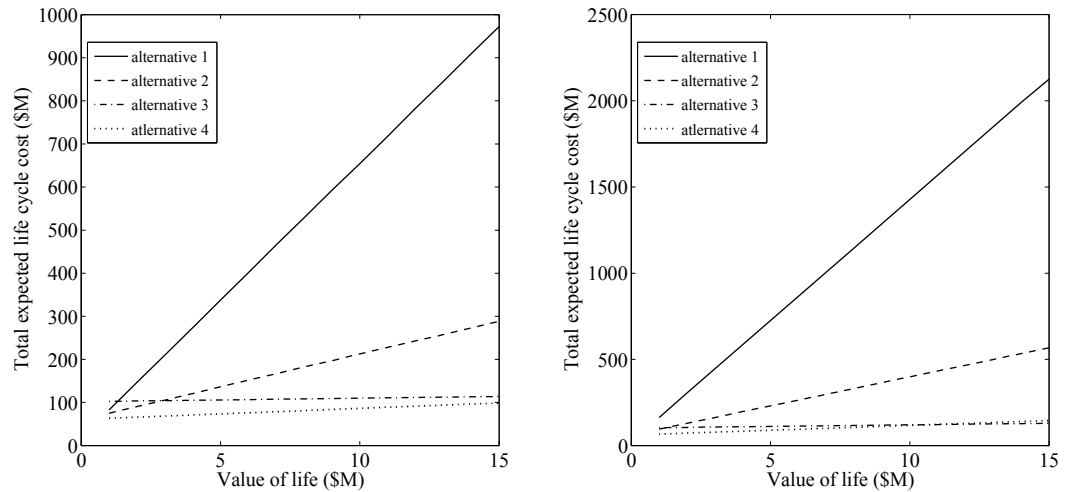


Figure 5.12 Sensitivity of total expected LCC to value of life when using: (a) traditional discount rate and (b) intergenerational discount rate; unit retrofit cost = \$10M, remaining service life = 150 years

5.5 Closure

This chapter has explored some of the recent developments in discounting methods that promote intergenerational equity in risk-informed decisions, and has proposed a new discounting method for use in life-cycle analysis of civil infrastructure facilities expected to function over extended time frames to facilitate an equitable weighting of the preferences of present and future generations and to achieve intergenerational equity in engineering decision-making. The proposed discounting has three characteristics: (1) the discount rate decreases as the time period under consideration increases; (2) the discount rate approaches a finite non-zero limit as time goes to infinity; and (3) the discount rate includes uncertainty about future prospects, expectations and economic growth patterns. Based on these characteristics, various declining discount rates with different time-varying factors to model uncertainty in future growth were postulated to investigate their effect on minimum expected life-cycle cost decision-making. The investigation revealed that the shape of the decreasing discount rate can reflect a decision-maker's attitudes toward the risk faced by future generations.

The proposed discounting method has been illustrated and compared with several existing methods in evaluating a new levee by minimum life-cycle cost analysis. This example shows that among the alternatives, the new method can reflect equitable allocations of risk between generations and incorporate sustainability into discounting in the context of risk-informed decision for civil infrastructure. To better understand the effect of the proposed discounting method on the optimal decision, civil infrastructure decision scenarios involving seismic retrofit of a dam was examined. These examinations revealed that as the service life increased, more conservative retrofit strategies were required to reflect the welfare and aspirations of future generations. However, the additional investments required to achieve intergenerational equity do not appear to be unreasonable.

CHAPTER 6

BENCHMARK PROBLEMS: INTERGENERATIONAL LIFE-CYCLE RISK ASSESSMENT ON CIVIL INFRASTRUCTURE EXPOSED TO NATURAL HAZARDS

Civil infrastructure facilities play a central role in the economic, social and political health of modern society. Their safety, integrity and functionality must be maintained at manageable cost over their service lives through design and periodic maintenance. Hurricanes and tropical cyclones, tornadoes, earthquakes and floods are paramount among the potentially devastating and costly natural disasters affecting the well-being of modern society and impacting civil infrastructure. Population growth and economic development accompanying urbanization are projected to intensify in potentially hazardous areas of the world during the future. Notwithstanding recent advances in building and construction practices, the impacts in recent years of major windstorms and earthquakes have highlighted deficiencies in our scientific and engineering knowledge concerning major natural disasters and their socio-economic impact on urban populations, and have provided an impetus for significant advances in engineering practices for design of buildings, bridges, lifelines and other civil infrastructure.

Previous chapters have introduced fundamental notions and requirements for achieving intergenerational equity in a risk-informed decision process for civil infrastructure projects with extended lifespans, and have suggested elements that are central to intergenerational risk assessment. In particular, the potential impact of non-stationarity in climatological features and intergenerational discounting practices provide a refined decision support framework to accommodate possible changes in current decision-making process. In this chapter, the effects of the intergenerational elements on long-term sustainable decision-making will be illustrated with a life-cycle analysis of a

nine-story building located in two hazard-prone areas (one for seismic hazards and the other for hurricane hazards) to assess the practical feasibility of the modified decision framework developed in this dissertation.

6.1 Statement of the Problem

The structure of interest is a nine-story special moment resisting steel frame for an office building. This building has a floor plan 23m by 55m and a height of 36m. The same structure was analyzed by Wen and Kang (2001b) using minimum life-cycle cost analysis, but under more restrictive assumptions that wind intensities and frequencies are stationary, the structure does not deteriorate over time, and the annual discount rate is constant at 5 percent. Such constraints could be justified for the relatively short service life of 50 years or less assumed in the original study. However, since the service life of the structure in this chapter is assumed to extend for 200 years and to encompass multiple generations, the proposed intergenerational discounting method developed in Chapter 5 will be utilized in the decision processes.

In the original study, twelve building frames were designed for different levels of lateral seismic ground motion demand (expressed in terms of system yield force coefficient) according to the NEHRP 97⁵ provisions with increasing lateral force resistance, and were subsequently checked for wind resistance. The characteristics of these frames are summarized in Wen and Kang (2001b). Seven limit states corresponding to interstory drift ratios from 0.2% to 5.0% are considered and are shown in Table 6.1. If the interstory drift ratio of the frame reaches 5.0% or higher, the frame is assumed to be irreparably damaged, and no effort would be made to repair it.

⁵ The 1997 NEHRP provisions have been superseded by later editions. This dissertation uses the 1997 provisions to compare the results to those obtained by Wen and Kang.

Initial cost and failure costs, including those due to structural damage, loss of contents, relocation cost, economic loss, cost of injury and cost of human fatality were estimated by Wen and Kang (2001b). All costs were stated in 1998 US dollars, and must be adjusted to 2013 US dollars at each site by using the city cost index (CCI) as well as historical cost index (HCI). The HCI in July 1998 and July 2013 are 115.1 and 201.2, respectively. The adjustments can be made as (Mubarak and Means 2012, Means 2013):

$$(Index\ for\ Year\ A) \times (Cost\ in\ Year\ B) = (Index\ for\ Year\ B) \times (Cost\ in\ Year\ A) \quad (6-1)$$

$$(Cost\ in\ City\ A) = (National\ average\ cost) \times (Location\ factor) / 100 \quad (6-2)$$

Each structure will be checked for seismic and hurricane hazards and the optimal earthquake-resistant design and wind-resistant design will be selected in the following sections.

Table 6.1. Performance and damage level in terms of drift ratio (after Wen and Kang 2001b)

Performance level	Damage state	Permissible drift ratio (%)
I	None	$\Delta < 0.2$
II	Slight	$0.2 < \Delta < 0.5$
III	Light	$0.5 < \Delta < 0.7$
IV	Moderate	$0.7 < \Delta < 1.5$
V	Heavy	$1.5 < \Delta < 2.5$
VI	Major	$2.5 < \Delta < 5.0$
VII	Destroyed	$\Delta > 5.0$

6.2 Optimal Seismic Design of a 9-story Steel Moment Frame

The structure of interest is assumed to be located in downtown Los Angeles, and the optimal seismic-resistant design is considered in this section. The seismic demand on this frame is determined by the maps of spectral acceleration provided by the United States Geological Survey (USGS). The frequency of earthquake events is modeled by homogeneous Poisson process. While updating probability-based seismic hazard models considering plate tectonics might be possible, research on the potential impact of non-

stationarity in seismological features has yet to be explored in any depth. Thus, the earthquake occurrences can be modeled as a stationary process in this example, and only the effect of the intergenerational discounting method on long-term equitable decision-making will be shown. Figure 6.1 shows the discount rates used in this example. The proposed discounting method developed in Chapter 5 considers the uncertainty embedded in the economic growth, in which the change in the natural logarithm of consumption growth is modeled as an autoregressive process with exponentially increasing volatility over time: an annual 1 percent pure time preference rate is applied to economic losses while an annual 0.1 percent pure time preference rate is for life losses. The conventional discount rate is assumed to be 4.5 percent per year, which corresponds to the initial value of intergenerational discount rate for economic losses.

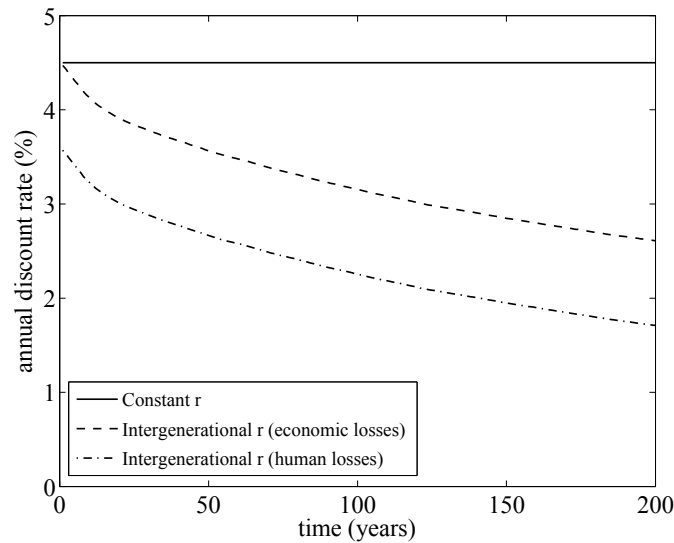


Figure 6.1 Comparison of conventional and intergenerational discount rates

The calculated expected life-cycle cost at each design level, expressed in terms of system yield force coefficient, using either traditional or intergenerational discounting method is shown in Table 6.2. The total life-cycle cost using the intergenerational

discounting method is higher for all building frames than those with constant discount rate. The optimal design solutions with (1) a constant annual discount rate of 0.045 and (2) intergenerational discount rate are plotted in Figure 6.2. In order to obtain the optimal design intensity, a polynomial is fitted to total expected cost functions around the optimal position (S4 – S10 in this example) because expected cost is relatively flat near the minimum point. The intergenerational decision framework leads to a higher optimal seismic design intensity (approximately 5% higher for the frame considered) because the higher design level results in a lower value of future losses, which the proposed time-declining discount rate prevents from being unduly discounted. As in previous illustrations in Chapter 5, intergenerational discounting makes it possible to allocate costs and benefits more equitably between the current and future generations than is possible using current discounting methods.

Table 6.2. Characteristics and expected cost calculations of twelve structures using (1) traditional discounting method and (2) intergenerational discounting method (after Wen and Kang 2001b)

Structure	Period (T) (sec)	Weight (W) (kips)	System yield force coefficient (Sy)	(1) LCC (\$M)	(2) LCC (\$M)
S1	4.335	5,046.0	0.033	19.2511	23.9168
S2	3.159	5,089.1	0.061	9.3879	11.1751
S3	2.542	5,137.6	0.093	6.5624	7.4896
S4	2.323	5,183.0	0.115	5.5617	6.1551
S5	2.062	5,223.8	0.140	4.9013	5.2621
S6	1.883	5,267.4	0.169	4.7037	4.9617
S7	1.772	5,311.8	0.188	4.5378	4.7013
S8	1.664	5,356.1	0.213	4.5483	4.6684
S9	1.572	5,398.7	0.230	4.6233	4.7103
S10	1.500	5,440.3	0.245	4.7505	4.8202
S11	1.343	5,572.3	0.321	5.1370	5.1662
S12	1.200	5,730.4	0.408	5.7084	5.7237

Figure 6.3 shows that the constant discount rate leads to the same conclusion that was reached in the previous case study of the dam in Section 5.4: that the optimal design intensity becomes essentially constant beyond 50 years of service life. The declining

discount rate makes the optimal decision (in the sense of present worth) dependent on time, and better reflects the consequences of the decision to future generations in present decision-making.

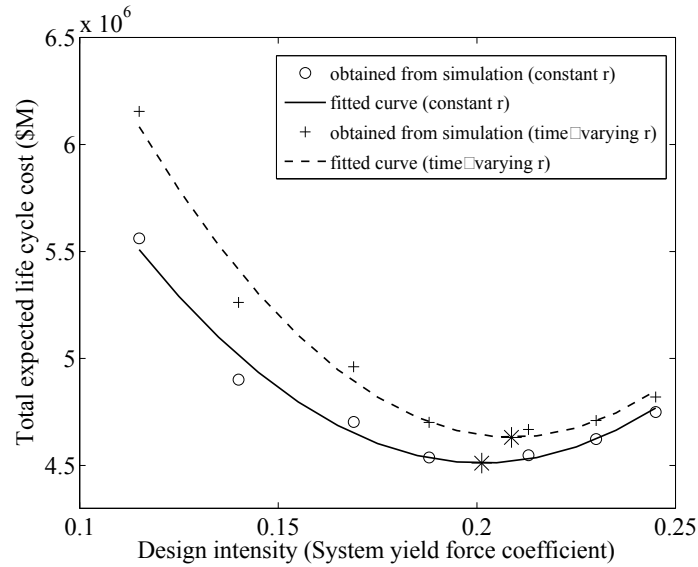


Figure 6.2 Optimal seismic design intensities when using traditional and intergenerational discount rates

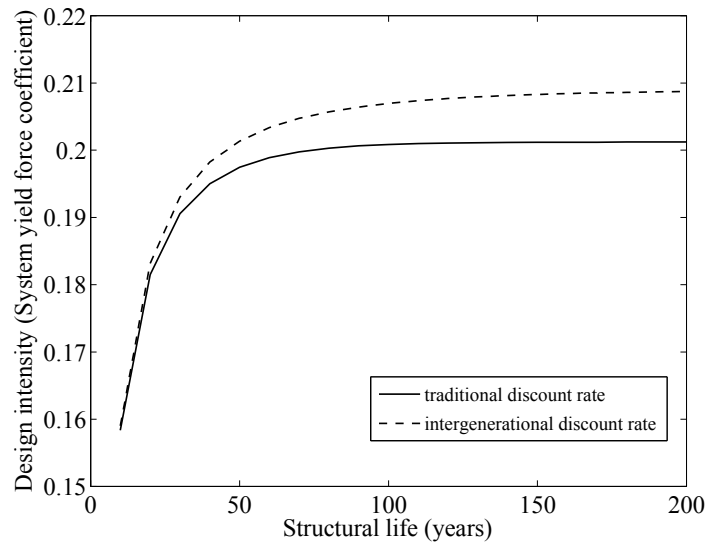


Figure 6.3 Sensitivity of the optimal seismic design intensity to service period when using traditional and intergenerational discount rates

The sensitivity of the optimal design intensity to the pure time preference rate (ρ) component of discount rate for economic losses (see Eq (2-19)) is assessed by varying the annual pure time preference rate for economic losses from 0 percent to 3 percent, while ρ for life losses is set equal to 0.1 percent. Figure 6.4 shows that the optimal seismic design level increases by 13.55 percent as ρ decreases, implying, as before, that the lower discount rate places more weight on the well-being of future generations.

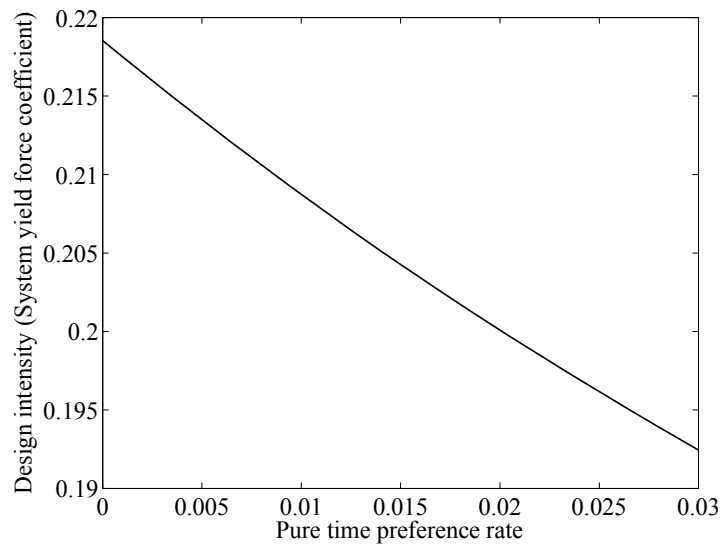


Figure 6.4 Sensitivity of the optimal seismic design intensity to pure time preference rate

6.3 Optimal Wind-resistant Design of a 9-story Steel Moment Frame

The 9-story steel frame structure is now placed in Miami, FL (25.46N, 80.11W), which is one of the most wind hazard-prone urban areas in the United States to illustrate the impact of climate change on long-term risk to the structure exposed to hurricanes. The building is situated in open-country Exposure C (*ASCE Standard 7-10*). There is growing evidence that the incidence of strong (Category 4 and 5) hurricanes in the North Atlantic and their overall intensities have been trending upward since the early 1980s; these trends are likely to continue in response to the higher sea surface temperatures

associated with global warming (see Chapter 4). To account for time-dependent reliability due to climate change and structural deterioration (one of the intergenerational elements suggested in Chapter 3), four different cases of loading and capacity are considered in this section, as summarized in Table 4.2 and Section 4.4. The hurricane simulation model described in Section 4.3 is used to generate wind speeds at Miami, FL. The approach described by Vickery et al. (2000) can be directly used for Cases 1 and 2 (see Table 4.2), while the modified nonstationary hurricane model (cf. Figure 4.10) must be used for Cases 3 and 4 to consider the non-stationarity in annual frequency and intensity of hurricanes induced by climate change.

Drift ratios due to wind load are calculated from the equation for maximum along-wind displacement in *ASCE Standard 7-10* (Eq. C26.9.1, P. 519):

$$X_{\max}(z) = \frac{\phi(z) \rho B h C_{fx} \hat{V}_{\bar{z}}^2}{2 m_1 (2 \pi n_1)^2} K G \quad (6-3)$$

in which $\phi(z)$ = the fundamental model shape $\phi(z) = (z/h)^\xi$, ξ = the mode exponent; ρ = air density, C_{fx} = mean along-wind force coefficient, m_1 = modal mass = $\int_0^h \mu(z) \phi^2(z) dz$, $\mu(z)$ = mass per unit height, $K = (1.65)^{\hat{a}} / (\hat{a} + \xi + 1)$, and $\hat{V}_{\bar{z}} = \hat{b}(\bar{z} / 33)^{\hat{a}} V$, where V is the 3-sec gust speed in Exposure C at the reference height. The fundamental mode shape is assumed to be linear: $\phi(z) = (z/h)$, where z = height above the ground surface and building height, $h = 36\text{m}$ (119ft). The fundamental natural frequency, weight, and system yield force, which are needed for the drift ratio calculations, are shown in Table 6.2. In Eq (6-1), the only factor related to structural capacity is the fundamental natural frequency, n_1 , and accordingly, structural deterioration must be expressed as a reduction in n_1 . In steel structures, cracks or corrosion due to aging reduce component cross-section properties, eventually affecting the structural stiffness and natural frequency (Hearn and Testa 1991, Chen et al. 1995). The degradation due to cracks or corrosion in steel structure is highly dependent on the structure and potential deterioration over 200

years is poorly understood. For simplicity, the change in natural frequency with time is assumed to be modeled by $n_1(t) = (n_1)_0 (1-at)$, where $(n_1)_0$ = initial natural frequency modeled as a normally distributed random variable with $\mu = 1$ and $\text{COV} = 0.08$ and a = a random variable which is uniformly distributed between 0.00025 and 0.00075, yielding degradations ranging from 0.05 to 0.15 after 200 years.

The optimal design intensities for this frame subjected to hurricane wind forces are shown in Figure 6.5 for four cases based on minimum expected life-cycle cost analysis, assuming a constant annual discount rate of 0.05. Although the impact of climate change appears to be greater than the impact of aging in this particular problem, it would be unwise to state this as a general conclusion. The optimal design intensity clearly increases when the effect of aging and/or climate change during the building service life is considered, mainly because these effects cause the conditional probability of failure to increase in time.

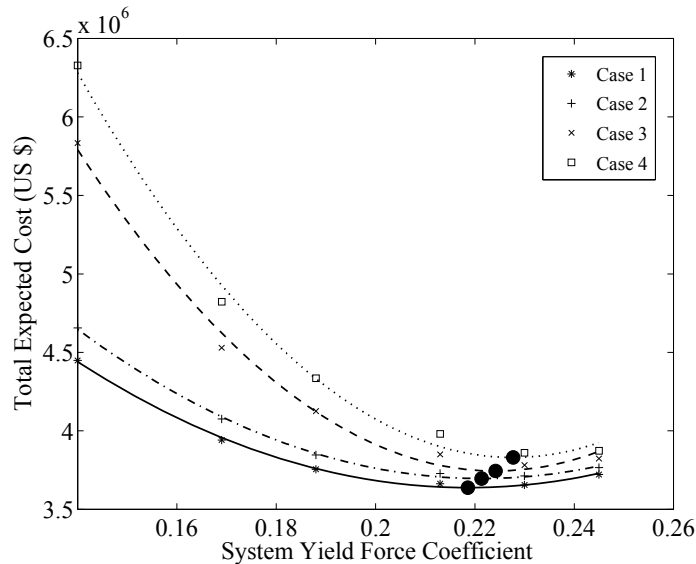


Figure 6.5 Optimal design intensities of four cases in Miami

The hazard functions (conditional failure rates) for four cases are illustrated in Figure 6.6 for the weakest frame in the ensemble (S1 is assumed here). Synergistic effects of deterioration and non-stationarity in wind force clearly play a significant role in both time-dependent reliability assessment and the optimal design level, especially for extended service periods.

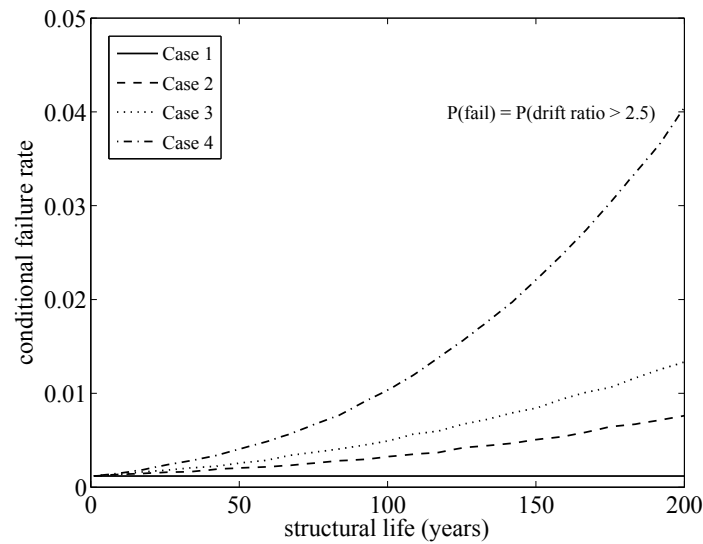


Figure 6.6 Hazard functions of four cases as a function of service life in Miami (S1 is assumed)

The role played by intergenerational discounting (cf. Figure 5.4) in decision-making over extended service periods will be assessed in more detail using Case 4 in Table 4.2, in which it is assumed that the structure deteriorates over time and that underlying climatology in hurricanes is nonstationary. As discussed in Chapter 5, the intergenerational discount rate has two parts, one for economic losses and the other for life losses. The utility discount rate, ρ , measures the portion of the utility attributed to the welfare of future generations. To better understand the effect of the pure time preference rate, the sensitivity of the optimal design intensity to ρ is assessed by varying the annual

pure time preference rate for economic losses from 0 percent to 5 percent, while ρ for life losses is set equal to 0.1 percent per annum. Figure 6.7 shows that the optimal design level increases by 14.56 percent as ρ decreases, showing that the lower discount rate encourages the decision-maker to consider the welfare and aspirations of future generations. It is interesting to note that the increasing trend in the optimal design becomes less apparent as ρ on economic losses increases and that the effect of climate change on decisions in the distant future is negligible. It implies that the attitude of a decision-maker towards socio-economic sustainability plays a significant role in decision-making even when an intergenerational discount rate and climate change are considered.

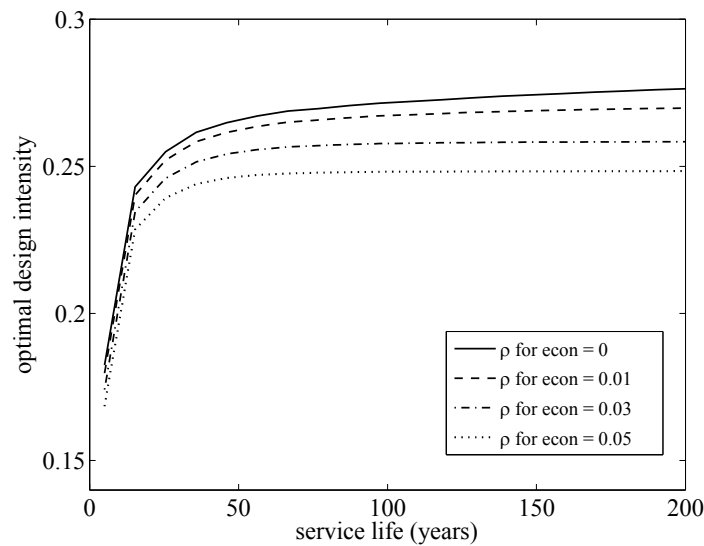


Figure 6.7 Sensitivity of the optimal design intensity to pure time preference rate (Case 4 is assumed)

The effect of the model of time-varying volatility summarized in Table 5.2 on the optimal design intensity is shown in Figure 6.8. The pure time preference rate is assumed to be 0.1 percent per annum for both life and economic losses to show the impact of the model of volatility more clearly. The optimal design solutions increase with service life

with all forms of time-varying volatility. The rate of increase in optimal design intensities over time depends on the form selected; an intergenerational discount rate with exponentially increasing volatility makes the optimal design intensity increase more rapidly due to its higher rate of declining discount rate over time, suggesting 2.18 percent higher optimal design at 200 years of service life than a discount rate with parabolically increasing volatility.

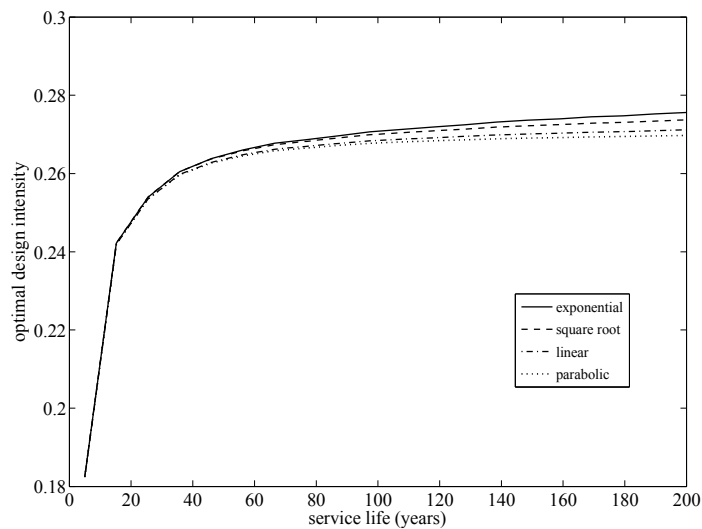


Figure 6.8 Sensitivity of the optimal design intensity to the model of time-varying volatility, holding other conditions the same: pure time preference rate = 0.001; the elasticity of marginal utility of consumption = 2; and Case 4 is assumed

The rate of increasing volatility (the parameter α in Table 5.2) also reflects the preference of the decision-maker and the value he/she assigns to the burden of the current decision on future generations. Figure 6.9 depicts the sensitivity of the optimal design intensity to the parameter α of exponentially increasing volatility. Parameter α affects the rate of decline in the discount rate, and accordingly, determines the rate of increase in optimal design intensity with time; higher α leads to a 2.31 percent higher optimal solution in this specific example. The issues of how much preference should be given to future generations or how costs (or benefits) should be distributed from generation to

generation depend on the decision-maker's ethical viewpoint and on whether/how investments in risk reduction are balanced against available resources. As shown in the three sensitivity analyses above, pure time preference rate, models, and rates of time-varying volatility can be stipulated by the decision-maker to reflect his/her level of risk aversion when considering future generations. In this particular problem, the impact of the pure time preference rate on the optimal design solution appears to be greater than the impact of the other factors in the discounting methods.

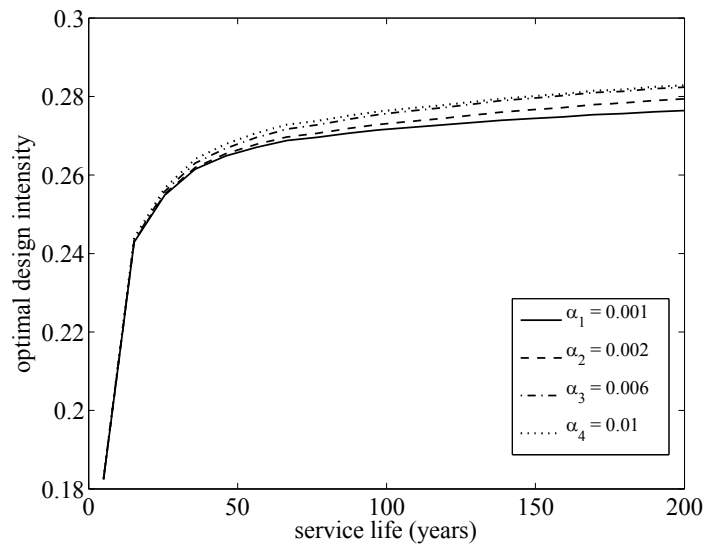


Figure 6.9 Sensitivity of the optimal design intensity to the increasing rate of time-varying volatility, holding other conditions the same: pure time preference rate = 0.001; the elasticity of marginal utility of consumption = 2; discount rates with exponentially increasing volatility is considered; and Case 4 is assumed

Figure 6.10 compares the optimal design solutions of Cases 1-4 (Table 4.2) as a function of service period, holding other conditions the same (as shown in the solid curve in Figure 5.4): $\rho = 0.001$; the elasticity of marginal utility of consumption, $\eta = 2$; and exponentially increasing volatility assumed to increase from its initial value at year 0 to approximately twice its initial value at year 200. In all cases, the intergenerational discounting method leads to the conclusion that the optimal design levels increase with

increasing required service period. Coupling effects of the two intergenerational elements – climate change and intergenerational discounting – should be noted. The optimal design intensities obtained from current practice, where neither climate change nor aging are considered (Case 1), and a constant discount rate of 3.5% per year is used, are also shown in Figure 6.10. The optimal design intensity obtained from a refined decision framework involving both intergenerational elements suggests a 8.75% higher design solution for a service life of 200 years. Clearly, the refined decision framework is better able to reflect the preferences of both current and future generations than current practice.

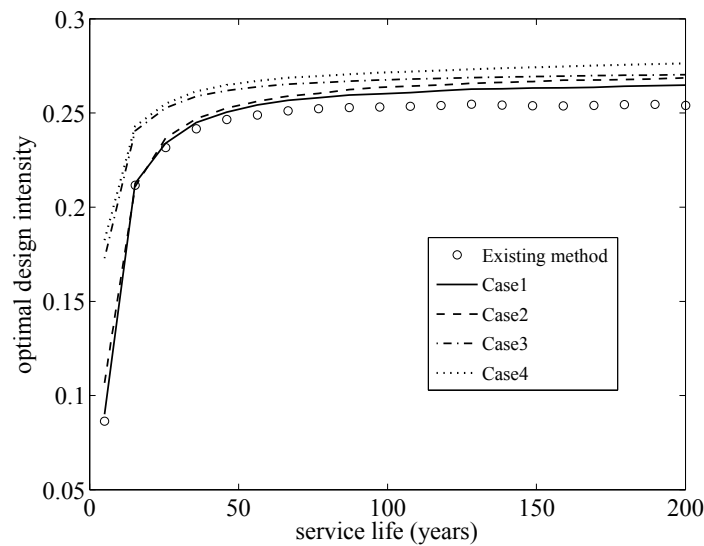


Figure 6.10 Optimal design intensities of four cases as a function of time when considering an intergenerational discount rate with exponentially increasing volatility; volatility is assumed to increase from its initial value at year 0 to approximately twice its initial value at year 200

6.4 Closure

This chapter has examined decisions regarding seismic-resistant and wind-resistant design for a hypothetical nine-story building to provide an improved understanding of two intergenerational elements in a refined decision framework. Non-

stationarities in both/either capacity and/or demand caused the probability of failure and the optimal design level to increase. Current decision models appear to overestimate the time-dependent reliability of civil infrastructure, which can result in underestimations in catastrophic losses due to extreme events from natural hazards. Moreover, intergenerational discounting led to further increases in the optimal design intensity as the service life became longer. Risk attitudes of present-day decision-makers can be reflected in the intergenerational discounting method through their choice of pure time preference rate and volatility function.

The application of such factors in minimum expected cost decision-making can be extended to other types of decision models such as utility theory or cumulative prospect theory. Such extensions will be the topic of future research.

CHAPTER 7

SUMMARY, CONCLUSIONS AND FUTURE WORK

7.1 Summary

Safe and serviceable civil infrastructure performance is essential for the social, political and economic well-being of a society. Civil infrastructure in the United States and in other industrialized countries is subjected to continually increasing operational and social demands at a time when diminished budgets cause essential maintenance and repair to infrastructure to be deferred or eliminated. Decisions aimed at ensuring performance or maintaining integrity of civil infrastructure systems affected by natural or man-made disasters, such as floods, hurricanes, earthquakes, fire, industrial accidents or terrorist acts, can entail billions of dollars and expose thousands of people to the possibility of injury, death or financial ruin. Significant knowledge gaps exist between capabilities for analysis and prediction of infrastructure performance during or following low-probability, high-consequence events, and public policy and decision-making in the public interest. Quantitative risk-informed methods are required to assess engineering strategies – design, maintenance and rehabilitation – for their effectiveness in mitigating risk to civil infrastructure over extended service periods and to establish investment priorities within financial constraints. Sustainable decision-making for periods extending over multiple generations requires new ways of thinking about life-cycle engineering. Such decisions involve ethical decisions that heretofore have not been considered.

This dissertation has proposed a risk-informed framework that is applicable to intergenerational decision-making aimed at assessing long-term risks of natural hazards and achieving socio-economically sustainable decisions for civil infrastructure. Sustainable decisions for civil infrastructure, as defined herein, are those that avoid transfer of excessive burdens to future generations and that advocate responsible

stewardship of constrained resources. Current life-cycle assessment procedures require modifications to support sustainable and equitable decisions regarding long-term public safety. This study has addressed two significant intergenerational elements – the potential impact of non-stationarity in hazard due to climate change and deficiencies in traditional discounting practices – that are essential to provide an improved decision support framework that accommodates the needs and values of future generations.

The first element for equitable intergenerational decisions is time-dependent reliability assessment which considers the non-stationarity in demands and capacity. Many civil infrastructure facilities are susceptible to aging, where deterioration in performance may occur as a result of natural internal processes, aggressive service or environmental conditions, or improper construction or usage. The challenges to civil infrastructure posed by aging have prompted numerous research programs that address risk management issues for buildings and bridges, offshore and inland riverine navigation facilities, port and harbor facilities, and nuclear plants and other critical facilities. Despite the advances in facility risk assessment and management made possible by this research, significant challenges to risk assessment for infrastructure with expected service periods of a century or more remain due to its high uncertainty. Moreover, there is compelling evidence that our climate will evolve over such intervals. Thus, current natural hazard and risk assessment models, which are based on a presumption of stationarity in hazard occurrence and intensity, may not be adequate to assess the potential risks from hazards occurring in the distant future. The stochastic process describing the structural loads affected by climate change should permit serial correlation in successive load events as well as the non-stationarity in frequency and intensity of extreme events from natural hazards. This study utilized an ARIMA model for explaining temporal dependence and for generating nonstationary correlated future values of local (or micro-scale) meteorology, and applied this model to mean sea temperatures, which are believed to be correlated to the increasing frequency and intensity of hurricane

wind storms in the Atlantic Basin. To reduce the anomalies introduced by the normal empirical/statistical approaches in the prediction of extreme wind speeds, a track modeling approach (Vickery et al. 2000) was utilized as stochastic demand models resulting from hurricanes. Hurricane wind speeds were simulated under two different assumptions – stationary and nonstationary –, showing that the non-stationarity in annual frequency and intensity of hurricanes induced by climate change introduces changes (and additional uncertainty) to the extreme wind loads used in time-dependent reliability analysis.

The second element that conventional methods fail to address is discounting for extended service periods. The use of conventional discounting methods for projects spanning multiple generations conflicts with our moral intuitions with regard to an equitable transfer of risk between generations. A high degree of uncertainty about future prospects exists when outcomes at some distant time in the future are considered, and this uncertainty plays a significant role in discounting practices. For such horizons, the discount rate should decrease with time. In order to reflect such characteristics of declining discount rate, this study has proposed an intergenerational discounting method for civil infrastructure that reflects the uncertainties in future economic growth and consumption. This method has a range of flexibility, in that the shape of the decreasing discount rate can reflect a decision-maker's attitudes toward the values and perspectives of future generations. The example of seismic retrofit of a dam revealed that the proposed discounting method can achieve intergenerational equity in risk-informed decision for civil infrastructure.

The effect of the proposed intergenerational elements on decision consequences was highlighted through a benchmark problem involving optimal seismic design and wind-resistant design of a nine-story steel moment frame located in two hazard-prone areas. The inclusion of non-stationarity in capacity and/or demand caused the probability of failure and the optimal design level to increase for the building system considered

herein. Moreover, when a declining discount rate was employed, the optimal design intensity increased as service life became longer, suggesting how events far in the future might affect present decision-making.

As a final observation, it should be noted that some investigators have argued against the use of optimization in setting structural safety targets (Proske et al. 2008). Optimization has some ethical implications and the potential to damage trust; the Ford Pinto case revealed how disturbed the public can be about corporate decisions that balance life safety and cost (Schwartz 1990). One simply cannot state, following a disaster, that the decision leading to that disaster was an acceptable one, based on minimum cost and justify that decision solely on that ground. Designing for robustness – achieving an engineered system that is insensitive to perturbations in the design envelope or events outside that envelope – is an alternative approach that is only beginning to be explored in the structural reliability community.

7.2 Conclusions

This dissertation has touched upon a number of possible answers to the key questions that must be addressed to achieve sustainable solutions to many pressing infrastructure problems: common structural degradation mechanisms, demand models accounting for climate change effect, practical time-dependent reliability analysis tools and methods for assessing life-cycle performance, and discounting that is relevant to intergenerational equity in civil infrastructure decision-making. The investigations of several specific civil infrastructure applications (a levee situated in a flood-prone city; an existing dam built in a strong earthquake-prone area; and a special moment resisting steel frame building designed to withstand earthquakes or hurricanes) have led to the following conclusions:

- Climate change effects increase structural demand on civil infrastructure systems;

- Non-stationarity in structural system capacity and/or demand causes the limit state probability, conditional failure rate, and the optimal design level to increase;
- Current decision models tend to overestimate the time-dependent reliability of civil infrastructure, which can result in underestimations in catastrophic losses due to extreme events from future natural hazards;
- A time-dependent discounting method is an essential ingredient of sustainable solutions, ensuring that the current generation takes into account the well-being of future generations while making it possible to measure costs consistently over multiple generations. Such a method was proposed and tested herein;
- A decision-maker's view on the value that should be assigned to future generations can be reflected by the shape and volatility of intergenerational discount rates: in general, discount rates with exponentially increasing volatility place more value on the needs of far-distant generations than other volatilities. Similarly, a higher volatility implies a decision-maker with higher risk aversion toward possible risk posed to future generations;
- The two intergenerational elements suggested in this study have a wide range of applicability, in that they can be easily and broadly used in various decision scenarios, replacing conventional time-dependent reliability assessment and discounting procedures used in life-cycle structural engineering;
- The coupling effects of two intergenerational elements are significant, especially for extended service periods;
- The issues of how much preference should be given to future generations or how costs (or benefits) should be allocated between generations depend on the decision-maker's ethical viewpoint and on whether/how investments in risk reduction are balanced against available resources;

- Intergenerational equity can be achieved at a reasonable cost.

7.3 Recommendations for Future Work

The research conducted in this dissertation has identified several topics worthy of further investigation:

- The current study's approach to incorporating intergenerational transfers of risk in decision frameworks has focused on discounting practices. To achieve intergenerational equity and efficiency, alternative solutions might be possible. Aversion to intergenerational inequality can be reflected in the utility or value function, by presenting a decision-maker with a range of different functions, or by adjusting the weights placed on consumption flows at each point in time. Also, while the Life Quality Index (LQI) can be an alternative measure as a basis for risk-informed decision, additional research is necessary to find a way of accounting for the effect of time on a decision process involving the LQI.
- The expectations of the public toward the performance of buildings and other civil infrastructure have evolved in recent years, and if the framework for decision-making involves a horizon of a century or more, it is virtually certain that those expectations will evolve further. Moreover, possible changes in technology in the future may affect the presumed discount rate unpredictably, given that technology development may be unimaginable for a period of 100 years. The ethical standards of future generations may evolve in the face of this advanced technology. How this evolution in expectation and technology development can be addressed in risk-informed decision economically is unclear. Clearly, facilities should be designed for maximum future adaptability to changing performance requirements. Such solutions are likely

to require a mode of thinking at the conceptual stages of design that is foreign to what is typical at present.

- Sustainability and resilience have become key issues to be addressed in the design, construction, and maintenance of civil infrastructure, as well as in community development. Despite the growing concern for sustainable and resilient development, the investigation of such issues is still in its infancy partly due to the complexity of dealing with a broad range of economic, ecological, and social needs. To incorporate two seemingly different goals into decision support frameworks, the well-defined performance goals and tools/indices to support quantitative assessment combining the two concepts must be prioritized. In this process, the mutual interaction/interdependence and conflicts between these two goals should be carefully investigated.
- This study has focused on a risk-informed decision framework for civil infrastructure exposed to natural hazards. However, a facility may be challenged by a number of hazards at the same time due to the natural environment or social/political circumstances. In such cases, investments in risk reduction must be balanced against competing demands for finite resources and other constraints. There is a clear need to develop multi-hazard risk assessment and management, but there are few concrete examples to date where this has been done successfully. Multi-hazard design is inherently multi-disciplinary in nature; these disciplines often approach the quantitative assessment of uncertainty and related reliability analysis differently, view the dimensions in loss from different perspectives, and adopt different design philosophies. The diverse risk attitudes of decision-makers toward different types of potential disasters further complicate the problem. Risk-informed decision frameworks for civil infrastructure exposed to multiple hazards must

balance mitigation strategies for single and multiple hazards for competing risks.

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