

IWRERM 2008

Reliability Engineering and Risk Management

**Proceedings of the International Workshop on Reliability
Engineering and Risk Management**

Editor Jie Li Yan-Gang Zhao Jianbing Chen



同济大学出版社
TONGJI UNIVERSITY PRESS

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内 容 提 要

本书是2008年8月21—23日在同济大学举行的 International Workshop on Reliability Engineering and Risk Management 特邀报告和大会报告的论文集,作者包括国际结构安全性与可靠性协会(IASSAR)创始人之一、执委会成员和前任主席、美国工程院院士 A. H-S. Ang,结构可靠度联合委员会主席 Faber,国际结构安全性与可靠性协会执委会副主席 Frangopol 等国际著名学者。该书反映了近年来国际上可靠度工程与风险管理方面的研究现状与最新进展。

本书可供土木、机械、航空航天和海洋工程等专业的教师、研究人员、研究生和高年级大学生使用或参考。

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Preface

In the past decades, natural and manmade disasters and accidental events made increasing damage to modern societies. Therefore reliability engineering and risk management have been attracting increasing attention and are of growing importance in many disciplines of engineering. The contents of structural safety and reliability are being extended broadly, simultaneously from single structure to system of structures and from pure engineering to considering involved environmental and societal effects.

Within this background and considering the recent rapid progress in society and economy in China, particularly in construction of large structures and infrastructural system, the International Workshop on Reliability Engineering and Risk Management (IWRERM'08) was organized and held in Shanghai, China on Aug. 21 – 23, 2008. Around 30 invited participants from 8 countries attended the workshop and conducted fruitful discussions and communications. Wide consensus was reached on recent advancement in reliability and risk management and future work needed to be enhanced, resulting in a memorandum of the workshop.

Included in the present book are the keynote lectures, invited lectures and supplementary lectures, totally 21 papers and a memorandum as appendix. These papers cover the state-of-the-art of the wide topics from stochastic mechanics and theory and applications of reliability to risk analysis and management. We are grateful to the contributions from the participants and authors who make the workshop successful.

Jie Li, Yan-Gang Zhao & Jianbing Chen

September, 2008.

CONTENTS

Preface	J. Li, Y. G. Zhao & J. B. Chen	i
Significance of Uncertainty in the Assessment of Reliability and Management of Risk	A. H-S. Ang	1
Risk Management of Structures Using Advanced Tools	D. M. Frangopol, T. B. Messervey	10
Risk Based Approach to the Management of Structural Robustness	M. H. Faber	20
Risk Communication on Probabilistic Seismic Safety of Buildings	J. Kanda	31
Seismic Risk Management for Existing Non-conforming Wooden Houses in Japan	Y. Mori, T. Yamaguchi, H. Idota	38
Probability Density Approach of Performance Function for Structural Systems	Y. G. Zhao, Z. H. Lu, A. H-S. Ang	47
Probability Density Evolution Equations: Recent Development and Applications	J. Li, J. B. Chen	57
The Fourth-Moment Method for the Determination of Load and Resistance Factors	Z. H. Lu, Y. G. Zhao, A. H-S. Ang	86
Probabilistic Risk Optimization Based on LQI Concept	M. Holický	94
Recent Advancements for Probabilistic Seismic Hazard Assessment	T. Takada	103
General vs. Local Reliability Based Design in Geotechnical Engineering	Y. Honjo	114
Geotechnical Reliability Analysis for Practitioners Using EXCEL	K. K. Phoon	129
The Most Likely Story Mechanisms of Column Over-designed Frames	T. Ono, Y. G. Zhao, W. C. Pu	138
Reliability of Reinforced Concrete Elements Made of Recycled Aggregates	M. Breccolotti	150
Reliability Design Study on Heat Exchanger of Ground Source Heat Pumps	C. S. Guan, Z. D. Liu & X. Y. Chen	161
Development of Artificial Vehicle Wheel Load to Analyze Dynamic Behavior of Bridges	S. H. Kim, K. I. Cho, M. S. Choi, P. B. Kwak	168
Target COF with Variation of Load and Strength Characteristics of Material	M. Sharfuddin, Y. G. Zhao & N. H. Duc	177
Reliability-based Design of Roofs Exposed to a Snow Load	M. Sykora, M. Holicky	183
Pseudo Normal Transformation and First Order Third Moment Reliability Method	Y. G. Zhao, Z. H. Lu, K. Hirai	189
Stochastic Finite Element Method Based on Non-orthogonal Polynomial Expansion	B. Huang	197
Quantitative Analysis of Structural Robustness	X. L. Liu, Y. Gao	206
Appendix A: Memorandum of the International Workshop on Reliability Engineering and Risk Management (IWRERM 2008)		214
Appendix B: List of the Keynote and Invited Lecturers		217

Significance of Uncertainty in the Assessment of Reliability and Management of Risk

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ABSTRACT: The uncertainty in the calculated reliability or in the estimated risk are as important as the reliability and risk themselves, particularly when specifying the reliability level for design and for determining risk-informed decisions in engineering. This uncertainty can be represented by the distribution (or frequency diagram) of the range of possible values of the reliability or risk, from which a risk-averse value of the reliability or risk may be specified for design or decision making. The modeling and quantification of two types of uncertainty are emphasized and their respective roles are illustrated in determining the appropriate safety index for the optimal design of infrastructure systems based on minimum life-cycle cost.

1 INTRODUCTION

The main purpose or the practical usefulness of reliability and risk analyses is to quantitatively model and resolve the significance of uncertainties in engineering and in decision-making. For this purpose, it is important to recognize that there may be two distinct types of uncertainty; one type is associated with the randomness of nature and can be represented with a random variable, and its effect can be described naturally in terms of probability. The other type is associated with the inaccuracy or error in predicting or estimating the true state of nature. In this latter case, the inaccuracy of prediction represents a real uncertainty; a practical way to model or represent this inaccuracy is by specifying a range of possibilities. Often, this range may have to be specified largely on the basis of judgments.

The above two types of uncertainty may be classified broadly as the *aleatory* and the *epistemic* types, respectively. The aleatory type represents the inherent randomness or variability of nature and is

largely data-based, whereas the epistemic type represents our inability to model or predict reality and therefore is knowledge-based. It is also important to recognize that the significances of these two types of uncertainty are distinctly different. The aleatory type can be described with a random variable and its effect can be expressed in terms of a calculated probability. Within the range of possibilities representing the epistemic uncertainty, a suitable distribution function (*e. g.*, a PDF) may be specified; then its effect may also be treated through probability, resulting in the probability distribution of the calculated probability that is associated with the aleatory variability. In other words, because of the epistemic type the calculated probability also becomes a random variable and its distribution expresses the uncertainty in its calculated value. Similarly, risk is the result of the aleatory variability and the uncertainty in the calculated risk is associated with the epistemic type.

In these terms, *i. e.*, by classifying the uncertainties into the two distinct types, the implications in engineering design and/or decision making are significant. In light of variabilities in the

design parameters, their effects may be described in terms of probability; whereas the unavoidable epistemic uncertainties will lead to the distribution of the probability (or of the risk). This distribution, in fact, also gives more complete information on the calculated probability, or risk. On the basis of this distribution, risk-averse or conservative values of the pertinent probability (or risk) may be specified.

The aleatoric and epistemic types of uncertainty may be combined to yield the total uncertainty; on this basis, the resulting probability or risk is the “best estimate” or mean value (a single value). Observe that this “best estimate” value has approximately a 50% chance of being inadequate, whereas this chance can be minimized (if the two types are treated separately) by specifying a risk-averse value from the distribution of the corresponding probability or risk.

In order to facilitate the implementation of the above concept, there must also be practical methods for modeling and estimating each of the two types of uncertainty, and for assessing the respective effects on safety or reliability.

1.1 Modeling and Quantifying Uncertainty

Methods for modeling and estimating each of the two types of uncertainty are also important and essential. The aleatory type would normally be estimated from available data. However, for the epistemic type, data should be specifically for validating the accuracy (or inaccuracy) of a particular predictive model (see Examples 1.2 and 1.3 in Ang and Tang, 2007). Data observed from structural health monitoring (SHM) of existing structures can also be useful for this validation (*e. g.* , Frangopol and Messervey, 2008). Normally, however, practical estimation of the epistemic uncertainty must often rely on judgment which may be to specify a reasonable range of possibilities, with a plausible distribution over the specified range.

As the predicted mean is of first-order importance, the epistemic uncertainty may be limited to the possible inaccuracy (error) underlying the estimated mean (or median) value. Although there

will also be error in the estimated variance as well as in the other statistical parameters, these latter errors will be of secondary importance relative to that of the mean.

Observe that the aleatory variability is not reducible as it is inherently part of the randomness of nature — additional observational data or improvement in the data collection process will increase the accuracy of the degree of variability, but may not reduce it; in fact it may even increase the degree of variability. On the other hand, the epistemic uncertainty can be reduced through the use of better or improved models for predicting reality, or through more seasoned judgments of experts.

By separating uncertainties into the two types — aleatory and epistemic, their respective significances in practical applications can be delineated as follows:

*The probability of non-performance (or failure) of a system is associated with the aleatory variability, whereas because of the epistemic uncertainty the calculated failure probability becomes also a random variable with corresponding distribution (*e. g.* , PDF).*

1.2 Significance of Epistemic Uncertainty

As mentioned above, in the presence of the epistemic uncertainty, the failure probability becomes a random variable with its distribution (PDF). This distribution clearly describes more complete information of the failure probability. Similarly, the inverse of the failure probability distribution will yield the corresponding distribution of the safety index.

The probability distribution of the safety index is of special significance in the specification of the appropriate safety level for design. For risk averseness (Ang, 2006), a high percentile value may be specified, particularly for the design of an important system, in order to minimize the effect of the epistemic uncertainty. For example, by selecting the 90% value, there is implicitly a 10% probability that the selected value may be inadequate. Observe, on the other hand, that the “best estimate” value (or mean value) of the safety index could be inadequate by a probability of around 50% .

1.3 A Simple Illustration

To illustrate the concepts expounded above, consider the failure probability of a structural component with the capacity R and load effect Q as follows;

$$R = N(70, 15)$$

$$Q = LN(15, 0.33)$$

The standard deviation in R of 15, and the c. o. v. in Q of 0.33 are variabilities which are the respective aleatory uncertainties.

Suppose that (from intuitive judgments) the inaccuracies in the models for estimating the mean value of R and the median value of Q are, respectively, $\pm 20\%$ and $\pm 30\%$. This implies that the actual mean of R could range from 56 to 84; whereas the actual median of Q could range from 10.5 to 19.5. By assuming uniform distributions within the respective ranges, the safety index of the structural component becomes a random variable with the distribution shown in Fig. 1.

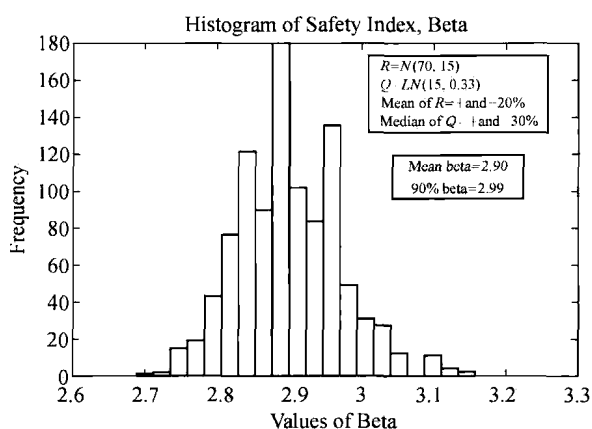


Figure 1 Distribution of Safety Index

From Fig. 1, the mean value of β is $\mu_\beta = 2.90$, whereas the 90% value of β is $\beta_{90} = 2.99$. Alternatively, the above ranges of the mean and median values correspond to equivalent c. o. v. 's of 12% and 17% for μ_R and q_m , respectively.

Therefore, alternatively, may assume normal distributions $N(1.0, 0.12)$ and $N(1.0, 0.17)$ for the inaccuracies in the mean and median values of R and Q , respectively; then the corresponding mean value of β would be $\mu_R = 2.85$ and the 90% value of β would be $\beta_{90} = 2.95$ which are close to the values

obtained above with uniform distributions.

From this example, it appears that the safety index is not very sensitive to the distributions assumed or prescribed for the respective ranges of the estimated mean and median values of R and Q . This is somewhat comforting.

Furthermore, if the above inaccuracies in the estimated mean value of R and the median value of Q were lower, the safety index can be expected to be higher. For instance, if the inaccuracy in the mean value of R is $\pm 10\%$ (instead of $\pm 20\%$) and that in the median value of Q is $\pm 20\%$ (instead of $\pm 30\%$), the corresponding results would be $\mu_\beta = 3.13$ and $\beta_{90} = 3.29$.

2 ILLUSTRATIVE APPLICATION

2.1 Reliability and Design of a Cable-Stayed Bridge

In recent years, cable-stayed bridges have become one of the most popular types of long-span modern bridges in the world, including in China. The general concepts described above is applied to examine the reliability and life-cycle cost design of a cable-stayed bridge in Korea (Han and Ang, 2008). For this purpose, several alternative designs of the bridge were considered in which the sections of the main members were increased or decreased relative to a standard design. Reliability analyses were then performed for each of the alternative designs and the corresponding expected life-cycle costs were estimated.

2.1.1 Profile and Analyses of the Cable-Stayed Bridge

Figure 2 shows the overall configuration of the cable-stayed bridge in Korea under consideration, which consisted of a steel box type girder, 2 sets of steel box type towers, and 68 sets of lock coiled type cables. Figure 2 also shows the three dimensional model of the cable-stayed bridge (Han and Shin, 2005), indicating the locations of the critical members.

According to the design specification for highway bridges in Korea (KICT, 1995), particularly for long

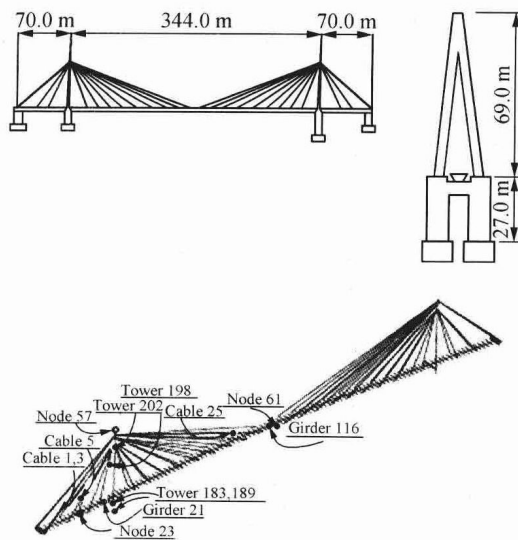


Figure 2 Profile and 3-D Model of the Cable-Stayed Bridge

span bridges, the influence of the DB load is greater than that of the DL load. Therefore, when performing static analysis, the DL load was applied to two lanes simultaneously as live load, and the impact factor of $i = 15/(40 + L) = 0.04$ was applied. The distributed live load and concentrated live load under these conditions were applied so that the maximum positive bending moment occurred at the center of the main span.

Seismic response analysis (Nazmy and Abdel-Ghaffar, 1990) was performed by applying the acceleration time history to the elastic supporting points of all piers and abutments in the horizontal, lateral and vertical directions simultaneously. The applied force component in the horizontal direction is identical to those in the lateral direction, and the component in the vertical direction was assumed to be 2/3 of the component in the horizontal and lateral directions.

A reliability analysis was performed of the cable-stayed bridge under the lifetime maximum load; i. e., under the combined dead, live and earthquake loads. The reliability analysis was conducted with cable tensions, axial forces of girders and towers, and bending moments using first-order reliability method (FORM). The factors containing uncertainties include the ultimate stress, cable tensions, area, member forces and moment

of inertia. Normal or lognormal distributions were assumed. The ultimate capacity of the cables was assumed to be 1,160.0 MPa, whereas for the girders and towers, the material was SM400 steel with an ultimate stress of 240.0 MPa. The coefficient of variation (c. o. v.) for the ultimate stress, δ_c , was assumed to be 12%; whereas the c. o. v.'s of the area and moment of inertia, δ_s , δ_I , were assumed to be 10%. The c. o. v. of the member forces by the dead load, δ_D , was assumed to be 10%; and the c. o. v.'s of the member forces induced by the live load and acceleration time history, δ_L , δ_E , were assumed to be 15%. These c. o. v.'s represent the respective aleatory uncertainties.

2. 1. 2 Results of Reliability Analysis

Reliability analysis was performed for the standard design of the bridge; similar analyses were also performed for the designs with increased and decreased sections of the members as shown in Fig. 2. Figure 3 shows the safety indices and failure probabilities of the critical members (Girder 21, Tower 189 and Cable 5) for the different designs. The values on the left axis in Fig. 3 show the safety indices and those on the right axis represent the corresponding failure probabilities.

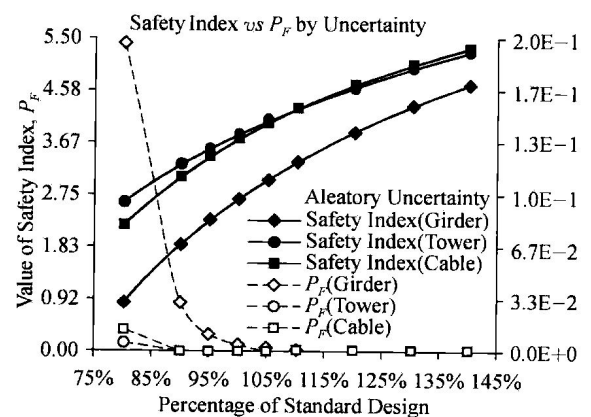


Figure 3 Failure Probabilities and Safety Indices Associated with Aleatory Uncertainties

For the standard design, the failure probabilities of the critical members are as follows:

$$\text{Girder: } P_{F1} = 3.647\text{E} - 03,$$

$$\text{Tower: } P_{F2} = 6.664\text{E} - 05,$$

$$\text{Cable: } P_{F3} = 9.425\text{E} - 05$$

The failure probability of the bridge system is the union of the failure probabilities of the critical members, yielding therefore the system failure probability of $P_{FS} = 3.807E - 03$. The corresponding safety index would be $\beta = 2.669$.

The above results assume that there are no errors (or epistemic uncertainties) in the estimation of the properties, such as ultimate capacities of the critical members, and of the dead load, lifetime maximum live load and seismic load. Clearly, there will be inaccuracies in these estimations, and thus epistemic uncertainties in the estimated mean (or median) values. Assuming no biases in these estimations, the epistemic uncertainties may be expressed in terms of the respective c. o. v. 's as $\Delta_C = 0.09$, $\Delta_S = \Delta_I = \Delta_D = 0.10$, and $\Delta_L = \Delta_E = 0.20$.

2.2 Determination of Optimal Design

In order to determine the optimal design based on minimum expected life-cycle cost, nine alternative designs were considered, including the standard one (based on current code), by increasing and decreasing the member sections relative to the standard design. On this basis, the initial costs corresponding to each of the alternative designs can be determined as summarized in Table 1.

Table 1 Initial Costs of Alternative Designs (in million USD)

Design	Initial Cost, C_I
80% of Standard Design	809.90 million USD
90% of Standard Design	845.50
95% of Standard Design	867.91
Standard Design	890.00
105% of Standard Design	934.50
110% of Standard Design	934.50
120% of Standard Design	1 112.50
130% of Standard Design	1 219.30
140% of Standard Design	1 334.67

2.2.1 Initial Cost of Bridge

The initial cost for each of the alternative designs includes the design costs, construction costs and eventual load testing costs before use (Ang & De Leon, 2005). The initial cost for the standard design

of the bridge is based on information from construction reports. All of the initial costs for the standard design and those of the different alternative designs are shown in Table 1 (in million US dollars).

2.2.2 Expected Damage Cost

The expected damage cost includes all the tangible and intangible losses resulting from a structural damage or failure of the cable-stayed bridge (including the cost associated with the closing of the bridge to traffic). Even though collapse of the bridge is highly unlikely under normal circumstances, the damage cost must include this as well as the insurance cost (Frangopol & Lin, 1997). Therefore, the expected damage cost, C_D , may consist of several components C_i as follows:

$$C_D = C_{FR} + C_{FL} + C_{FH} + C_{FD} + C_{FEN};$$

where

- C_{FR} = bridge replacement cost;
- C_{FL} = loss of lives and equipment costs;
- C_{FH} = culture and historical costs;
- C_{FD} = functional disruption costs; and
- C_{FEN} = environment and social costs

Specifically, in estimating the life-cycle cost of the cable-stayed bridge, the initial cost items, plus the maintenance cost and damage cost items as percentage of the initial cost can be summarized as shown in Table 2. All the above future damage cost items must be expressed in present worth. For this purpose, each potential future damage cost item must be multiplied by the Present Value Factor, PVF , as follows (Ang, Pires & Lee, 2004),

$$PVF = [1 - \exp(-\alpha L)] / (\alpha L)$$

where,

- $\alpha = \ln(1 + q)$
- q = annual discount rate; and
- L = lifetime of structure

This study assumes that the lifetime of the cable-stayed bridge in question is $L = 50$ years and the annual discount rate is $q = 4.0\%$.

Table 2

Estimates of Cost Items

Cost Items	Classification of Cost Items	% of Initial Cost
Initial Cost (C_I)	Design Costs	7% C_I
	Construction Costs	90% C_I
	Load Testing Costs	3% C_I
Maintenance Cost (C_M)	Inspections Costs (every 1 year)	10% C_I
	Detailed Inspections Costs (every 5 year)	
	Repair Costs	
Damage Cost (C_D)	Structural Failure Costs	—
	— Bridge Replacement Costs	150% C_I
	— Loss of Lives and Cost of Injuries	500% C_I
	— Cultural and Historical Costs	10% C_I
	Functional Disruption Costs	50% C_I
	— Traffic Delayed Costs	—
	— Traffic Detour Costs	
	— Heavy Traffic Costs	
	Environmental and Social Costs	15% C_I

2.2.3 Epistemic Uncertainties in Cost Estimates

The estimates of the initial and maintenance costs, C_I , C_M , for each of the alternative designs may contain some uncertainty (epistemic type). It may be reasonable to assume that the actual initial and maintenance costs could vary by $\pm 20\%$; or expressed in terms of c. o. v. 's $\Delta_{C_I} = \Delta_{C_M} = 0.12$, representing the respective epistemic uncertainties in C_I and C_M . Moreover, for each of the damage cost components, the c. o. v. 's representing the respective epistemic uncertainties may be assumed to those shown below in Table 3.

Table 3 Epistemic Uncertainties in Damage Cost Items

Damage Cost Items	C_{FR}	C_{FL}	C_{FH}	C_{FD}	C_{FEN}
C. O. V. Δ_{C_i}	0.20	0.40	0.40	0.40	0.80

Based on the information assumed in Table 2 and Table 3, the expected damage cost would be

$$\bar{C}_D = \bar{C}_{FR} + \bar{C}_{FL} + \bar{C}_{FH} + \bar{C}_{FD} + \bar{C}_{FEN} = 7.25 \bar{C}_I$$

and the variance of C_D will be,

$$\begin{aligned} \text{Var}(C_D) &= [0.2(1.5 \bar{C}_I)]^2 + [0.4(5.0 \bar{C}_I)]^2 \\ &\quad + [0.4(0.1 \bar{C}_I)]^2 + [0.4(0.5 \bar{C}_I)]^2 \\ &\quad + [0.8(0.15 \bar{C}_I)]^2 \end{aligned}$$

$$= 4.16 \bar{C}_I^2$$

Therefore,

$$\sigma_{C_D} = 2.04 \bar{C}_I;$$

hence, the c. o. v. of C_D would be,

$$\Delta_{C_D} = 2.04 \bar{C}_I / (7.25 \bar{C}_I) = 0.28,$$

from which the mean and variance of the expected life-cycle cost (LCC), C_T , becomes,

$$E(C_T) = \bar{C}_I + \bar{C}_M + \bar{C}_D \quad \text{and}$$

$$\begin{aligned} \text{Var}(C_T) &= (0.20 \bar{C}_I)^2 + (0.20 \bar{C}_M)^2 \\ &\quad + (0.28 \bar{C}_D)^2 \end{aligned}$$

2.2.4 Minimum Life-Cycle Cost Designs

With the information summarized above, the LCC for all the nine alternative designs were evaluated; the results can then be plotted between the mean β and the expected LCC considering aleatory uncertainties only as shown in Fig. 4. Similarly, the mean β may be plotted versus the 75% LCC and the 90% LCC. These results are also summarized graphically in Fig. 4 which shows that, irrespective of the percentile LCC used in the optimization process, the same optimal design is obtained at a mean safety index of $E(\beta) = 2.284$.

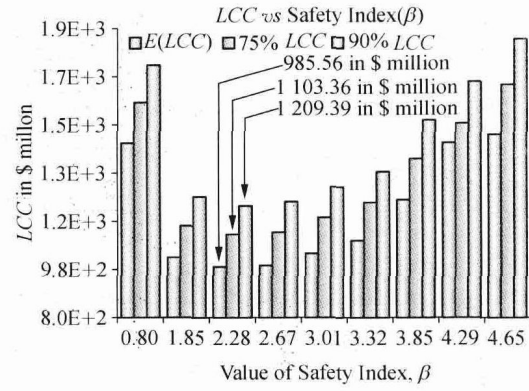
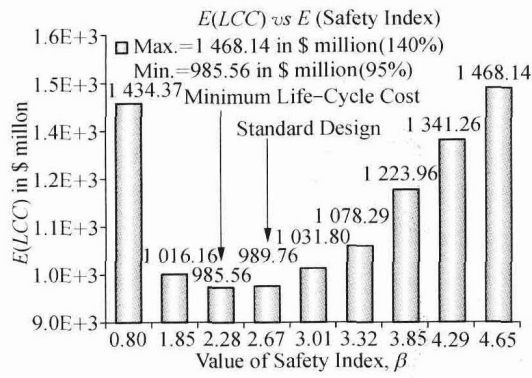


Figure 4 Mean or % LCC versus $E(\beta)$ with Epistemic Uncertainties $\Delta_{c_I} = \Delta_{c_M} = 0.20$ and $\Delta_{c_D} = 0.28$

Table 4 Failure Probabilities and Safety Indices

Percentile	Mean	25% P_F ; 75% β	10% P_F ; 90% β
P_F ; β	1.112E - 2; 2.281	8.600E - 3; 2.835	6.149E - 3; 3.324

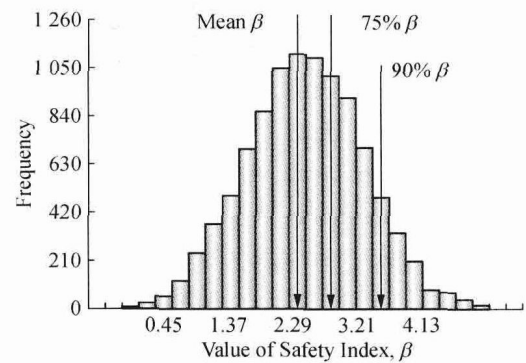
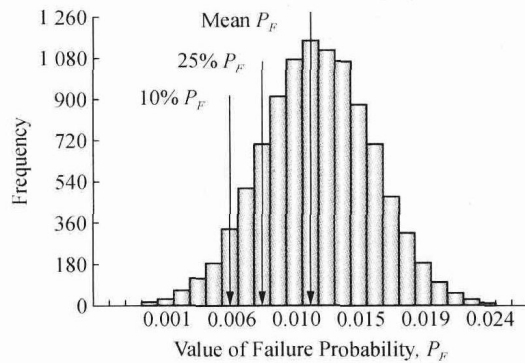


Figure 5 Frequency Diagram of P_F and β for Optimal Design due to Epistemic Uncertainties

Finally, because of the epistemic uncertainties described earlier in Sect. 2.2.3 and in Table 3, the true failure probabilities, corresponding safety indices, and LCC will, respectively, be random variables. In particular, the histograms of the system failure probability and safety index generated through Monte Carlo simulation with a sample size of 10,000 are portrayed respectively in the two parts of Fig. 5. From this set of figures, the mean value, the 75% value, and the 90% values of P_F and corresponding β 's are determined as summarized in Table 4 for the optimal design of the cable-stayed bridge in Jindo, Korea.

The main results for the bridge can be summarized as follows:

Failure probabilities,

$$\text{Mean } P_F = 1.112E - 2,$$

$$75\% P_F = 1.394E - 2,$$

$$90\% P_F = 1.627E - 2.$$

The corresponding safety indices are,

$$\text{Mean } \beta = 2.281,$$

$$75\% \beta = 2.835,$$

$$90\% \beta = 3.324.$$

It may also be of interest to observe the frequency diagram of the expected LCC for the optimal design as shown Fig. 6. As expected, the LCC will increase with higher percentile level (the price for additional confidence). From Fig. 6, the mean value, as well as the 75% and 90% values of the LCC for the optimal design are obtained as follows (in million USD):

$$\text{Mean } LCC = 988.23,$$

$$75\% LCC = 1104.81,$$

$$90\% LCC = 1207.42.$$

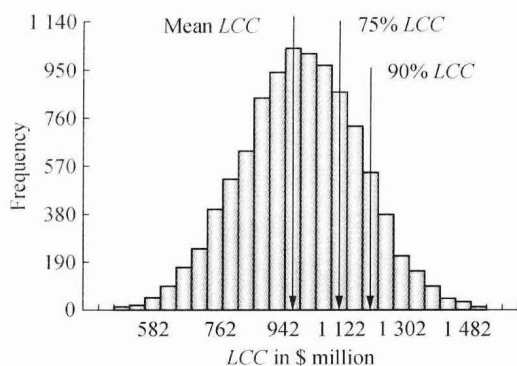


Figure 6 Frequency Histogram of LCC of Optimal Design with $\Delta_{c_l} = \Delta_{c_M} = 0.20$ and $\Delta_{c_D} = 0.28$

2.2.5 Summary of Results

This study performed the reliability analysis and determined the minimum life-cycle cost design of a cable-stayed bridge by considering separately the two types of uncertainties; namely the aleatory type and the epistemic type. The systematic procedures involved were illustrated for a cable-stayed bridge in Jindo, Korea under dead, live and earthquake loadings. Based on estimates of the aleatory uncertainties and reasonably realistic assumptions of epistemic uncertainties, complete information (*i. e.*, distributions) of the failure probability and safety index, as well as of the LCC, were obtained for the optimal design of the bridge. This allows the specification of prescribed percentile values of the pertinent results. In this regard, for the cable-stayed bridge in Jindo, Korea, the results indicated that the 90% value of the safety index for the optimal design is 3.324 and the corresponding 90% value of the LCC was estimated to be US \$1,207.42 million. The results of the study show that the current design of cable-stayed bridges in Korea is close to optimal from the standpoint of minimum life-cycle cost.

Another illustrative application of the same concept to the optimal design of offshore oil platforms is described in De Leon and Ang (2008).

3 CONCLUSIONS

In reliability-based engineering, it is important to distinguish the difference between two broad types of uncertainty; the aleatory type which is part of the randomness of natural phenomena whose significance

can be expressed in terms of the probability of occurrence, and the epistemic type which is associated with imperfections in modeling and estimation of reality and leads to uncertainty (lack of complete confidence) in the calculated probability of occurrence.

For practical applications, epistemic uncertainty may be limited to the imperfections in the estimation or predication of the mean (or median) value of a variable or parameter.

Because of these epistemic uncertainties the calculated results, such as failure probability, safety index, risk, and expected life-cycle cost, become random variables with respective distributions (or histograms). For decision-making purposes, the distributions represent complete information of the respective calculated results, and allow the specifications of high percentile values of the essential design parameters (such as safety index) to ensure sufficient risk averseness. For example, the 90% value, or the 75% value, of the safety index may be appropriate, leading to sufficiently conservative designs (particularly important) for long span bridges or other critical engineering systems.

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Risk Management of Structures Using Advanced Tools

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ABSTRACT: This paper uses recent technological advances in structural health monitoring (SHM) as the motivating factor to discuss the next generation of civil infrastructure management programs with special emphasis on highway bridges. After reviewing the need for such programs and the current state of the art, the desirable characteristics of infrastructure management programs and the advanced tools and concepts available to support these characteristics are discussed. In specific, several reliability approaches to include their advantages and disadvantages, uncertainty, time effects, and the inclusion of risk are detailed within a life-cycle context. Additionally, how to include, leverage, and facilitate the use of SHM in such models is presented. Monitoring topics include macro-level adoptions in concert, the top-down design of monitoring systems, accounting for monitoring costs in a life-cycle context, optimal design concepts, and long-term data collection efforts.

1 INTRODUCTION

Over the past two decades, the challenges associated with the maintenance, safety, and condition of civil infrastructure worldwide have passed from an issue handled and discussed amongst a relatively small group of engineering professionals, to one that has essentially become common public knowledge. Disasters such as Hurricane Katrina and the subsequent failure of over 50 levees in the greater New Orleans area (Wikipedia, 2005), the Laval Overpass collapse in 2006 near Quebec, Canada (CTVNews, 2006), the 2007 collapse of the I35W Minneapolis Bridge in Minnesota, USA (Cho & Van Hampton, 2008), and the 2003 blackout of the Northeast power grid that left over 50 million people without power shutting down transportation networks, airports, and nuclear facilities (Wikipedia, 2003) have brought public at-

tention on questions engineers face daily. How safe is safe enough? How robust should civil infrastructure be? How should such structures and systems be inspected and maintained? In the United States, reports on the subject are readily available. Examples include the ASCE Infrastructure Report Card which states an estimated US \$1.6 trillion (as of 2005) of investment is needed to bring the Nation's infrastructure up to good condition (ASCE, 2005), the Texas Transportation Institute Urban Mobility Report which estimates the cost associated with traffic congestion at US \$78 billion (TTI, 2007), or one of many available news reports online that outline and track deficient US bridges and the problems associated with their upkeep (Dedman, 2008a).

The current emphasis on civil infrastructure is appropriate and necessary. With respect to safety, much of the civil infrastructure worldwide is at or near the end of its planned service life and it is unclear if

current rehabilitation and replacement programs are keeping up with the rate of new deficiencies. With respect to societal importance, it has been noted that the safe and reliable performance of civil infrastructure directly impacts the economic growth and social development of a modern society (Frangopol & Liu, 2007). In terms of magnitude, new civil engineering construction is the largest industry in the world representing approximately 10% of annual world Gross Domestic Product (GDP). Of this 10% of GDP spending, an estimated 5% – 10% is the result of the failure (not necessarily collapse) of existing structures (Bijen, 2003). For most countries, existing structures are their most valuable asset and their upkeep represents one of their most significant investments. Unfortunately, these assets are deteriorating at an alarming rate due to overuse, overloading, aging or damage (Frangopol & Messervey, 2007a). It has also become recognized that maintenance and repair costs over the life of a structure are typically much greater than the initial construction costs. Despite this realization and although such concepts are gaining momentum, warranty periods, maintenance plans, and other life-cycle costs are not yet a part of the current design bid-selection process (minimum safe design).

Against this backdrop and offering great potential to help address these challenges, SHM technologies have become practical for civil structure applications due to reductions in size, wireless capabilities, improved energy performance, and reductions in cost. Although monitoring devices have existed for some time, they have typically required a controlled environment, hard wired cables, and immense effort to obtain data making their application to civil structures difficult. Recent improvements in these devices are making it feasible to obtain site-specific response data cost effectively and offer great potential with respect to the design, assessment, and management of civil infrastructure (Frangopol & Messervey, 2008a). Moreover, SHM is likely the enabling technology that will lead to the next significant evolution of the design, assessment, and management of civil infrastructure. Similar to the impact brought about by

computers and structural analysis programs, access to site-specific data across a variety of measurements provides the capability to implement several advanced tools, concepts, methods, and ideas that have existed for some time, but have not yet matured in practical applications. These include, among others, the smart system concept, multifunctional materials, performance and durability based design, life-cycle design, reliability-based structural assessment, and damage detection capabilities (Frangopol & Messervey, 2008b).

Although SHM offers great potential, such technologies will likely not be adopted unless they are proven cost-effective due to competing resource demands. In addition, appropriate methods, metrics, and policy decisions must be adopted in order to enable and facilitate the development and employment of monitoring solutions. In order to quantify the cost-benefit of increased information, reduced uncertainty, and the corresponding increased level of safety provided by real-time in-service data, the consideration of risk and use of the reliability index is required. If the process is considered over time, a life-cycle cost analysis is necessary. For an existing structure, this implies a reliability-based life-cycle management approach with the inclusion of risk. For a new structure, this implies performance-based and durability-based design. Although such methods are not new, they have yet to be widely adopted in practice. However, these methods are the ones that are appropriate to evaluate and communicate the utility of monitoring technologies (Frangopol & Messervey, 2008c).

2 DESIRABLE CHARACTERISTICS OF INFRASTRUCTURE MANAGEMENT PROGRAMS AND THE MODELS THAT SUPPORT THEM

2.1 State of the art

Several bridge failures in the 1960s focused national attention on bridge safety resulting in the initiation and standardization of federally mandated bridge in-

spections established with the Federal Highway Act of 1968. Since this time, the Federal Highway Administration (FHWA) has revised national bridge inspection standards (NBIS) almost yearly as methods and the base of knowledge in the field have improved. Currently and almost exclusively, bridge management programs are based on visual inspections. In special cases, non-destructive evaluation (NDE) tests are performed to investigate a specific area or problem of interest. Although relatively few, there is a growing number of monitoring applications.

Condition state models such as Pontis (Pontis, 2007) are currently the most widely adopted bridge management programs in service. Based primarily on visual inspection data, the main advantage of these models is that they are relatively simple to implement. The primary limitation of condition-state models is that safety is not adequately addressed as visual appearance does not always correlate to structural performance and accuracy is lost due to a limited number of discrete condition states (Frangopol & Liu, 2007). Human error is also a consideration. One recent study reported that in some cases more than 50% of bridges are being classified incorrectly via visual inspections (Catbas et al., 2007). Although certainly not the norm, a separate recent article highlighted the falsification of bridge inspections by contractors to keep up with timelines for reporting purposes (Dedman, 2008b). In response to these limitations and concerns, reliability-based models were developed that specifically assess structural safety (Watanabe et al. 2004, Casas et al. 2002). Such models seek to simulate or calculate all parameters affecting structural performance and are well suited to account for structural redundancy through system analysis. However, due to the amount of input parameters required and the sensitivity of the results to the accuracy of the input, these models have been limited in implementation. In the foreseeable future, it is likely that monitoring technologies will provide the mechanism to make reliability-based models more practical for implementation.

A further improvement on reliability-based models is possible by combining the advantages of the

condition-state and reliability-based models. As condition-state models do not directly address safety, reliability-based models do not directly address condition where repairs may be required to improve trafficability despite a high level of structural safety. This has led to the development of hybrid-type models that account for both condition and safety (Frangopol, 2003, Neves et al. 2006, Bucher & Frangopol, 2006, Neves & Frangopol, 2004). Such models provide a more holistic treatment of the problem but also imply a greater degree of complexity and increased cost.

2.2 Desirable characteristics of infrastructure management programs

Provided the deteriorating condition of existing structures, the current state of the art of infrastructure management programs, and the emergence of new enabling technologies (SHM), it is worth developing an unconstrained listing of the desirable characteristics of an infrastructure/bridge management program. Although not conclusive or exhaustive, several of the most important characteristics are:

- Safety is accounted for
- Adequate condition is assured
- Cost is minimized
- System effects are considered
- Site-specific data is utilized
- Existing National Bridge Inventory (NBI) data is leveraged
- Model is flexible / easy to update
- Uncertainty is taken into account
- Past performance is considered

To account for safety requires some measure of structural performance v. s. demand that is not based upon condition. For this purpose, reliability concepts are appropriate. However, it is not desirable to abandon condition-based approaches as condition also needs to be considered for serviceability and aesthetic reasons, to leverage the 40 years of data available in the NBI, and because the value of human judgment when conducting visual-based inspections cannot be replaced. To make use of site specific data for safety assessment either nondestructive evaluation (NDE)