DATA UNCERTAINTY IN BRIDGE MANAGEMENT

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A candidate for the degree of Master of Science in Civil Engineering

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ABSTRACT

The effectiveness of bridge management decisions is based on the quality of data obtained regarding various processes in the bridge lifecycle. Hence, data play a crucial role in bridge management. In general, data collected has some amount of uncertainty, which may impact management decisions. In order to assess the impact of uncertainty on the decisions, the uncertainty should be quantified. This document describes a two-part procedure that has been developed for measuring the level of uncertainty in bridge condition assessment data. In the first part of the procedure, a bridge deterioration model was used to estimate the future condition of a bridge. The deterioration modeling in this research was conducted using Pontis, a commonly used bridge management software program. These deterioration models are based on Markov chains. The inputs to the deterioration model were the present condition assessment data for the bridge. In the second part of the procedure, reliability theory was applied to estimate the structural reliability of the bridge. The structural reliability of the bridge components was estimated on the basis of load carrying capacity (resistance of the structure) and the actual loads present on the structure. Finally, the reliability of the bridge after ‘x’ years was estimated and then compared to the results obtained from the deterioration model. Because results are also reported as probabilities, the results can be compared. By studying the variations between the results obtained from the two different approaches for data obtained at different times, an uncertainty scale was produced which showed the level of uncertainty of the data for that bridge, thus quantifying data uncertainty.

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1. Introduction

Management, as the word suggests, is "the act or art of managing."(Management @ 1999). It means the coordination and judicious use of means and tools, to optimize output or achieve a goal. Infrastructure management includes the systematic, coordinated planning and programming of investments or expenditures, design, construction, maintenance, operation, and in-service evaluation of physical facilities (Hudson et al. 1997). Types of infrastructure facilities or services include rail transportation, road networks, telecommunication networks, electric power grids, and water supply systems. Managing infrastructure effectively requires data. The term data refers to raw facts concerning people, objects or events as they are physically recorded and stored. All decisions about the construction, operation and maintenance of facilities are made on the basis of the data pertaining to that particular facility.

In order to extract the optimal output in the form of good management decisions with least resources, a bridge management system is maintained by most states in the United States. In bridge management, decisions regarding maintenance, repairs and rehabilitation are based on condition assessment data for the bridges. Because of the critical role of data in these decisions, the reliability and certainty of the data are important. The main purpose of this research is to study the uncertainty associated with condition assessment data and to quantify it based on mathematical and statistical principles. The validity of the bridge management decisions can be mathematically supported by a factor of certainty associated with the data.

The remaining portion of the chapter explains the problem, the objectives of this research, and the research procedure.

1.1 Problem

The effectiveness of decisions in bridge management systems is based in part on the quality of data (information) obtained regarding various processes in the systems. Hence, data play a crucial role in bridge management. In bridge management, while considering various projects or options, the decisions would be more effective if a true picture in the form of accurate data is presented for those projects. Indirectly, the accuracy and precision of the data affect all the decisions in bridge management systems. In order to know the impact of this uncertainty on the decisions, the uncertainty in data should be quantified.

1.2 Objective

The primary objective of the research was to develop a procedure to quantify the level of uncertainty in data collection for bridge management. In other words, the main purpose of this research was to develop a procedure that calculates a numerical value which can be assigned to a specific data set as a measure of its uncertainty. Specifically this research compares condition predictions for bridges or bridge components based on different models. The result of the comparison provides an indication of the level of uncertainty in the data.

1.4 Research Approach

The research proposes a procedure to quantify data uncertainty. A case study is also carried out in this research to demonstrate the procedure. Two models, a deterioration model and a reliability model, are used to obtain transition probabilities and probabilities of failure respectively, from the condition assessment data. These probabilities are then compared to find the coefficient of correlation, which represents the uncertainty in the data. This approach is applied to a small data set, which consists of condition assessment data for three bridges, and the uncertainty in this data in the form of coefficient of correlation is calculated. This procedure may be used to quantify data uncertainty for a large sample size and over a longer period of time.

1.5 Outline

Chapter 2 reviews the relevant literature pertaining to bridge management, uncertainty, condition assessment, deterioration models and reliability theory. Chapter 3 describes the models used in this research and explains the research approach. Chapter 4 discusses the case study and results while chapter 5 present the conclusions of this research. The document concludes with a list of the references cited in this research.

2. Background

Engineering problems generally are related to the design, analysis, performance, operation and maintenance of facilities. The problems are solved using data, which are based on observations at different system levels, such as the project level or the network level. The observations can be about a structural member, the interaction between structural members, the interaction of the entire system with the external environment, or the way the system reacts to the external conditions. The data collected for analysis are associated with uncertainty at every level of observation (Ayyub 1998). This uncertainty in the data should be taken into account when solving a problem, giving a higher reliability to the solution.

Solutions to and decisions about engineering problems depend on the data pertaining to that particular problem. Uncertainty in data will produce a certain amount of uncertainty in proposed solutions to the problems. Therefore, quantifying data uncertainty is important. It is one of the aspects of data quality, which in turn affects decisions based on those data.

According to Ayyub (1998), a method to increase the quality of data, known as repetitive analysis, can reduce uncertainty in data. Repetitive analysis is a process in which a particular analysis is carried out a number of times to ascertain the credibility of the result. However, this is only possible in the case of data (measurements) for which repetitive analysis is a feasible option. In infrastructure management repetitive analysis is not a feasible option as the process of data collection is time consuming and costly. A new method is needed to quantify uncertainty, because the methods available are not sufficient.

The remainder of this chapter discusses the history and state-of-the-art of bridge management in the United States, condition assessment, deterioration modeling, and reliability theory. Condition assessment, deterioration models, and reliability theory are discussed in detail, starting from their basic definitions to their application in solving the problem of data uncertainty in bridge management. Section 2.5 of this chapter defines uncertainty and discusses types of uncertainties. At the end, examples of two methods for finding uncertainty are presented.

2.1 Bridge Management

Once a bridge is completed and brought into service, it not only starts to carry traffic, but it is also exposed to the environment (wind, water, temperature changes, chemicals, etc.). As time passes, the bridge and its components deteriorate due to environmental conditions and under increased traffic loads, for which the bridge may not have designed. In order to handle these problems in a planned manner, a bridge management system is required to manage a network of bridges.

A bridge management system (BMS) is a rational and systematic approach to organizing and carrying out the activities related to planning, design, construction, maintenance, rehabilitation and replacement of bridges. A BMS should assist decision-makers in selecting the optimal cost-effective alternative needed to achieve desired levels of service within the allocated funds, and to identify future funding requirements (Hudson et al. 1997). The alternatives might be a combination of different types of maintenance actions, repairs, funding, etc. The most basic requirement for bridge management is a bridge inventory, which includes location, type, functional classification, importance within network, condition data, maintenance data and historical data. These data are important because most of the decisions in the bridge management system are based on information obtained from these data (Hachem et al. 1991). Hence, the reliability, accuracy, precision and appropriateness of the data play a vital role in the outcome of the decision making process in a bridge management system. Reliability is the state of being dependable or responsible, accuracy is the correctness of a particular reading or a value, precision is the closeness to the correct value and appropriateness is the quality of being suitable.

The Federal Highway Act of 1968 created the National Bridge Inspection Program (NBIP) to catalogue and track the condition of bridges in the United States (Czepiel 1995). The states collect and report the NBIP data, which is stored in the National Bridge Inventory (NBI) database. The Federal Highway Act of 1970 requires that the data from the NBI be used to determine federal funding for the Special Bridge Replacement Program (SBRP). In this scheme, the bridges are classified into three categories: non-deficient, structurally deficient or functionally obsolete (Czepiel 1995). The Surface Transportation Assistance Act of 1978 changed the eligibility of bridges for federal funding, and the Highway Bridge Replacement and Rehabilitation Program (HBRRP) replaced the SBRP.

The Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) mandated that every state department of transportation implement six different management systems to maximize resource allocation for maintenance planning (Czepiel 1995). One of the six management systems was a BMS. The mandates were later rescinded by the National Highway System Designation Act of 1995, but most states still implemented or are implementing BMS. A BMS typically estimates the least-cost maintenance, repair and rehabilitation strategies. According to Czepiel (1995), this is achieved in four steps.

1. Collect data (inspection data) and assess the condition of the bridge based on the condition of its elements.
2. Apply deterioration models to determine the future condition of the bridge.
3. Use cost models to predict the maintenance cost for activities needed to improve the condition of the bridge.
4. Use optimization models to optimize the strategies used for carrying out maintenance, repairs and rehabilitation.

Bridge management in most cases is based on a deterministic approach, and the assessment of the reliability or the safety in general is based on subjective statements (Thoft-Christensen 1996). Because of this nature of the BMS it is difficult to address the problem of uncertainty as the data is in the form of subjective statements. Diagnosis of bridges (based on inspection data) showing signs of functional or structural deterioration is the first step that has to be taken before making any decisions regarding maintenance or repair. If this diagnosis is in the form of subjective statements then the decisions regarding maintenance or repair may vary from person to person. A standardized correlation should be established between diagnostic methods and the defects detected, which can be done using stochastically based management systems (Thoft-Christensen 1996).

Bridge management systems like Pontis and Bridgit are stochastically based systems with rational assessment procedures (Thoft-Christensen 1996). These procedures set guidelines for data collection and reduce the subjective nature of data. Pontis was developed by the Federal Highway Administration (FHWA) in conjunction with six state Departments of Transportation (DOTs). The deterioration models used in predicting the future condition of the bridge are probabilistic and based on the Markov process. The optimization model in Pontis employs a top-down analytical approach by optimizing over the network before determining individual bridge projects (Czepiel 1995).

Bridgit was developed jointly by the National Cooperative Highway Research Program (NCHRP) and National Engineering Technology Corporation. Bridgit uses similar deterioration and cost models to Pontis. One of the major differences between Pontis and Bridgit is the optimization model; Bridgit uses a bottom-up approach for optimization. Also, Bridgit has the ability to define and distinguish between specific protection systems for elements when determining feasible options (Czepiel 1995).

2.2 Condition Assessment

According to an article on condition surveys of concrete bridges, “Condition assessment is defined as measuring and evaluating the state properties of a constructed facility and relating these to the performance parameters” (Busch et al. 1988). Condition assessment is a professional examination by a qualified analyst of the current condition of a facility. The condition assessment data, maintenance data, and proper operation and functioning data of the facility can be used for analyzing and modeling the condition of the facility. The data obtained by condition assessment may be objective (quantitative), showing figures and numbers, or subjective (qualitative), describing the condition of the facility.

Condition assessment of infrastructure is important because these data are used to predict the life of the facility and to forecast the maintenance schedule for that structure, which helps in managing the infrastructure in an effective manner. According to Aktan et al. (1996), “Lack of sufficient, accurate, detailed and reliable information on bridge condition adversely affects rational bridge management decisions.” Condition assessment of bridges is important for bridge management, particularly to predict deterioration and to plan maintenance strategies. Data collected during the bridge inspection are analyzed to quantify the condition of the bridges or bridge components. Hence, condition assessment is an outcome of bridge inspection.

Generally, condition assessment focuses on the overall state of a facility, which is based on the condition of regional or local aspects (components) of the facility. Condition assessment of bridges is typically based on the data obtained by carrying out routine bi-annual inspections. In-depth inspections and evaluations of the condition of bridges are performed by qualified inspectors/evaluators. The condition assessment process can be summarized into the following steps (Aktan et al. 1996).

1. Decide the range of state parameters, and set the scale of the state parameters that provide the condition of the facility as a whole.
2. Measure the extent of damage/deterioration.
3. Determine the effect of that damage/deterioration on the condition of facility.
4. Compare the existing damage/deterioration with records of previous condition assessment to establish the trend of deterioration of the structure.

Condition assessment may be used to determine a condition rating. A condition rating is a predefined set of numbers, which assigns a numerical value to a particular state of the structure. The Pontis condition ratings shown in ***Table 1*** are used in the research and are described in more detail in Scherer and Glagola (1993).

TABLE 1 CONDITION STATE DESCRIPTIONS

Condition States	Description
9	New Condition
8	Good Condition: no repairs needed.
7	Generally Good Condition: potential exists for minor maintenance.
6	Fair Condition: potential for major maintenance.
5	Generally Fair Condition: potential exists for minor rehabilitation.
4	Marginal Condition: potential exists for major rehabilitation.
3	Poor Condition: repair or rehabilitation required immediately.

2.3 Deterioration

Deterioration is a long-term, gradual degradation leading to reduction in the performance of a member, structure and the entire facility. Considering bridges specifically, deterioration can be defined as decline in bridge element condition (Czepiel 1995). One function of a BMS is to predict deterioration rates of bridge elements. Deterioration models have been developed to predict the amount of deterioration and deterioration rates of bridge members. Several factors influence deterioration. Those considered in this study include (Scherer & Glagola 1993):

- Age of the bridge,
- Type of bridge structure,
- Maintenance and rehabilitation,
- Average daily traffic, and
- Structural components and environment condition.

These factors are chosen because they represent a majority of the factors influencing deterioration and have a high degree of impact on the deterioration process in bridges.

A number of deterioration models can be used to predict the future condition of a bridge. According to DeStefano and Grivas (1998), “Deterioration models are essential components of the condition prediction algorithms in bridge management systems.” The majority of these models are based on one of two basic theories of mathematics, namely statistical regression and stochastic modeling.

Statistical regression is the relationship between the mean value of a random variable and the corresponding values of one or more independent variables. In case of the bridges the random variable is the condition of the bridge at a given time a while the independent variables are the factors affecting the condition of bridge at that time.

Stochastic modeling uses a probabilistic approach based on theories like the Weibull distribution, normal distribution, or Markovian concepts. Deterioration models based on Markovian concepts are more effective in predicting deterioration than other methods because the Markovian chains predict bridge deterioration based on the age of the bridge using current condition of bridge (Sinha & Jiang 1989). Markov process is a stochastic process in which the future distribution of a variable depends only on the variable’s current value. In this case the variable is the condition of a bridge. The Bridgit and Pontis deterioration models are based on Markovian concepts.

2.4 Reliability Theory

A structure should perform the function for which it is designed in an adequate manner. According to Gertsbakh (1989), “The word ‘reliability’ refers to the ability of a system to perform its stated purposes adequately for a specified period of time under the operational conditions encountered.” A system is said to be reliable if the system does not fail for the desired period of time. Failure of a system is generally caused by the combined effect of many unpredictable, random processes. Hence, any failure has a random (stochastic) nature.

The reliability of a system is based on the probability of failure of the system, comprised of the combined effects of the system components. The effect of aging is seen through a decline in performance characteristics in almost all systems, increasing the probability of failure. This effect of aging is accounted for in reliability analysis of a system (DeStefano & Grivas 1998). For example, reliability theory is used for the reliability of highway bridges under the effect of reinforcement corrosion (Thoft-Christensen 1996). In this method, non-linear finite element structural models and probabilistic models for traffic loads are used to find corrosion propagation, bond characteristics, material properties, element dimensions and reinforcement placement. Reliability is estimated in terms of the reliability index.

2.5 Uncertainty

A significant body of research on uncertainty of data exists, and most of the work has classified types of uncertainties and proposed models to express the level of uncertainty. However, a gap exists in applying these techniques to civil engineering problems. A significant amount of the research in this area relates to industrial engineering.

As most work in industry can be checked for precision and accuracy, guidelines to identify and reduce uncertainties can be set. The accuracy and precision in manufacturing, testing and maintenance is high in industry (industrial engineering) as compared to construction (civil engineering). This is so because the above mentioned processes often are carried out by computers or other machines in industry, thus reducing errors due to factors such as environmental and other unknown conditions, and human factors which are very much present in construction. Hence, it is easier to set guidelines to account for uncertainties in industry than for structures like buildings and bridges. Researchers typically have proposed methods either to account for uncertainty in a process or to express uncertainty in a numerical form.

As explained and defined by Ayyub (1998), uncertainties in data can be grouped and accounted for depending on their type. Uncertainties in engineering systems mainly can be attributed to ambiguity and vagueness in defining the architecture, parameters and governing prediction models for the systems. The ambiguity component is generally attributed to non-cognitive sources. These sources include (1) physical randomness; (2) statistical uncertainty due to the use of limited information in estimating the characteristics of these variables; and (3) model uncertainties, which are due to simplifying assumptions in analytical and predictive models, simplified methods, and idealized representations of real performances. Vagueness related uncertainty is due to cognitive sources, which include (1) variables such as structural performance, deterioration, and quality; (2) human error and other human factors; and (3) interrelationships among variables of a problem, especially for a complex system.

According to Kikuchi and Parsula (1998), different models are used to analyze uncertainty depending on the application or type of data. In one method for analyzing uncertainty related to transportation engineering data, uncertainty is broadly classified into two types, cognitive and non-cognitive. Cognitive uncertainty is subjective and cannot be easily quantified. The non-cognitive type is the uncertainty in predicting the behavior and design of structural systems. Fuzzy analysis applies to cases with the non-cognitive type of uncertainty. In this type of analysis, fuzzy sets are defined, and these sets are analyzed using methods such as fuzzy arithmetic or permutation. Fuzzy random analysis is generally used to identify and quantify the cognitive type of uncertainty. Generally, fuzzy set theory and random analysis are combined to determine the uncertainty (Kikuchi and Parsula 1998).

The National Institute of Standards and Technology (NIST) has developed guidelines for evaluating and expressing uncertainty related to data in industrial engineering. According to Taylor and Kuyatt (1994), uncertainty is divided into two components, random uncertainty and systematic uncertainty. The component of uncertainty arising from random effects gives rise to possible random uncertainty. The component of uncertainty arising from systematic effects gives rise to possible systematic uncertainty. Random effects have no specific pattern, purpose or objective and are completely unpredictable, while systematic effects are the opposite. Random uncertainties are generally evaluated using reliability theory, and systematic uncertainties are evaluated based on scientific judgement of series of observations. NIST deals with standards for and accuracy of data rather than any particular type of data. The uncertainty of data collected consists of several components, which are evaluated according to the classification by using statistical methods.

As summarized in the above discussion, authors have classified uncertainty broadly into two types and have proposed models either to account for uncertainty in a particular problem or numerically quantify the uncertainties. According to Ayyub (1998), uncertainty is mainly attributed to ambiguity and vagueness, and according to Kikuchi and Parsula (1998), uncertainty is either cognitive or non-cognitive. All the authors have classified uncertainty in two forms on the same lines, but Kikuchi and Parsula have gone further to propose a model to formulate uncertainty using fuzzy logic.

3. Research Approach

This research proposes a procedure to quantify data uncertainty in bridge management. A deterioration model and a reliability model are used to obtain probabilities from the condition assessment data. These probabilities are then compared to find the coefficient of correlation, which represents the uncertainty in the data.

This procedure was applied to a data set of three bridges to obtain a numerical value of uncertainty. Condition assessment data for these three bridges were used by the models to predict the future condition of bridges. This chapter explains the procedure developed, including the condition assessment framework, deterioration model, reliability model and coefficient of variance.

3.1 Condition Assessment Framework

Bridges of a particular structural type, such as reinforced concrete slab, steel stringer, prestressed concrete, or box-reinforced concrete slab, have similar response and loading mechanisms. However, no two bridges are similar in all respects, especially in their deterioration and aging characteristics, and it is difficult to assess all types of bridges in the same condition analysis framework. A bridge type specific condition assessment for concrete bridges is used in this research. It has a condition assessment framework specifically for concrete bridges, for selecting a bridge component and analyzing its condition. Concrete bridges are considered because the data for this procedure was easily available/accessible.

A bridge comprises of three components, the superstructure, substructure, and foundation. The deck is the load-carrying component of the superstructure. Abutments are part of the substructure, which support the end spans of the bridge and retain the soil on the approaches. Piers, which transfer the load from the deck to the foundation, are the part of the substructure. The bridge is basically divided into three main components for condition assessment, which are deck, abutments, and piers. These are further classified into predefined elements such as slabs, girders, railings, etc. (Ang & Tang 1984). Bridge inspection data pertaining to these elements are collected, and, based on these data, the condition of the bridge elements is assessed. The elements are assessed for the following indicators of deterioration: cracking, scaling, spalling, delamination, leaching, stains, deformations and hollow or dead sounds (Aktan et al. 1996).

3.2 Deterioration Models

There are many uncertain factors responsible for the deterioration in bridge condition, such as traffic volume, environmental condition, quality of construction, age of the bridge, and maintenance. Although statistical regression theory, which is a deterministic process, has been used to model deterioration, it cannot be applied to bridges in order to replicate the deterioration process in a true sense. On the other hand, stochastic modeling takes these uncertain factors takes into consideration, yielding a more realistic solution for replicating the deterioration process.

The application of Markov chains to bridge deterioration is based on the concept of defining states in terms of bridge condition ratings (that is, to convert bridge inspection data to condition assessment data) and obtaining the probabilities of bridge condition transitioning from one state to another. These probabilities are called transition probabilities and are represented in a matrix form, called a transition matrix. The future condition after a certain time or the time needed to change the condition from one rating to another can be predicted through multiplication of the initial state vector and the transition matrix (Sinha & Jiang 1989).

The Markov chain is developed based on the condition assessment data and probability theory. Let $p_{ij}(a)$ be defined as probability that a bridge element changes its state from *i* to *j* in a given time interval for a given action *a*.

Let $s(k) \in s = (1,2,\ldots\ldots,M)$ and Eq. 1.

$a(k) \in A[s(k)]$ Eq. 2.

be the state and control (or decision) respectively at decision epoch *k*. Here M is the maximum number of states or condition that a bridge can be in (M=7), and k is the decision taken in a given period of time.

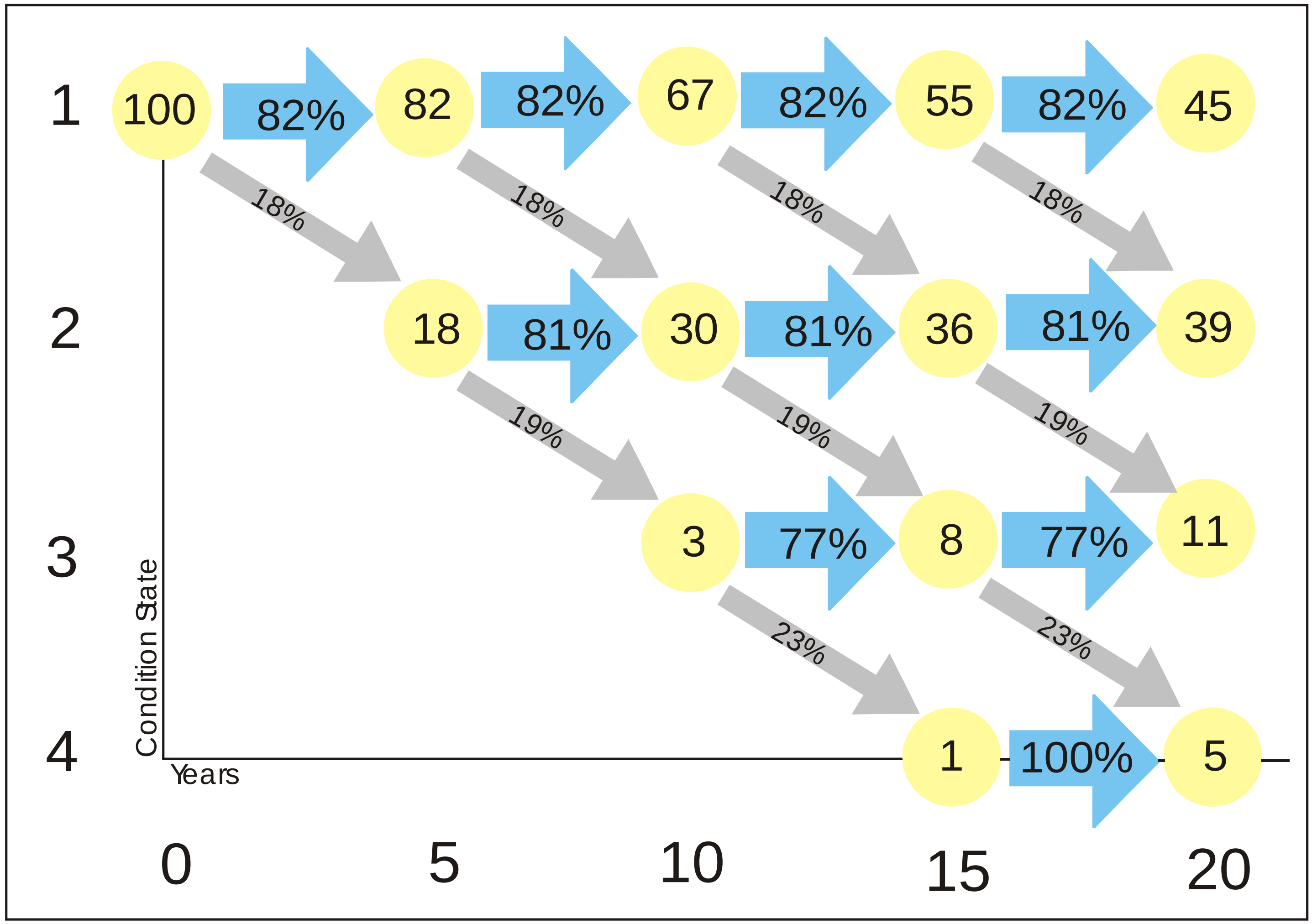
Hence, the transition matrix is

$P = [P_{ij}(a)] = \{ p[s(k+1) = j / s(k) = i, a(k) = a]\}$. Eq. 3.

There are restrictions on the transition matrix as the process is stochastic; the row must sum to 1 (Scherer & Glagola. 1993). Hence, the transition probabilities can be evaluated using the above equation, which is illustrated using numerical values in ***Figure 1***. ***Figure 1*** shows an example of a Markovian prediction over a 20-year period. The circles indicate state probabilities which can be interpreted as the percentage of the inventory predicted to be in each state. The arrows represent transition probabilities (Thompson et al. 1998).

Pontis deterioration models consist of transition probabilities, which predict that in a given environment and for a given action/no action (maintenance), the condition state will remain the same or change to another in the given period of time. The probability of

FIGURE 1: EXAMPLE OF MARKOVIAN MODEL DETERIORATION



Source: Thompson et al. 1998

deterioration depends only on the current condition data and external factors such as the environment and actions taken, not on any previous conditions or actions. The transition probability model cannot be run before a statistically significant amount of historical data are accumulated. Where sufficient data are not available, transition probabilities are based on elicitation estimates, which are values generated by simulation using the same logic as in deterioration models.

Pontis includes a preservation model, which is formulated using a top-down analytical framework. The bridge elements are characterized by discrete condition states, which describe the type and severity of element deterioration in visual terms. Pontis includes a translator function to convert the element inspection results into the older 0-9 rating scale for deck, superstructure, and substructure (Thompson et al. 1998). Since the number of condition states is limited to five for each element, the transition probability matrix is very small. Markov models assume that the condition states themselves incorporate all the information necessary to predict future deterioration. Thus, condition predictions for any future year can be made simply by matrix multiplication (Sinha & Jiang 1989).

3.3 Reliability Model

Any system can be broadly categorized as either renewable or non-renewable. A renewable system, such as a bridge, can be repaired, maintained and reused, while a non-renewable system, such as a missile or rocket designed to carry out a single mission, cannot. Several indices of reliability can be used to quantify the reliability of a particular component of a renewable system, or the entire system. The indices are:

- Time to the first system failure.
- Instantaneous availability – the probability that the system will be operational at given time instant.
- Limiting availability – the probability that the system will be operational at time *t*, where *t* is infinitely large.

It is important that the probability of failure be low for important complex systems. According to current reliability theories, “In many cases high reliability can be guaranteed not only by building the system from highly reliable components, but also by introducing redundancy in the system or into its less reliable parts” (DeStefano & Grivas 1989). Reliability analysis is carried out during the structural design of a component in order to predict the approximate life and the probability of failure of that component. Reliability theory is also applicable for management and maintenance of infrastructure. In the case of bridges, reliability theory can be applied at the component level as well as at the bridge level.

The probability of failure in reliability theory depends on the reasonableness of the assumptions made in the reliability theory. The probability of failure is based on empirical models and relies on observational data (Ang & Tang 1984). The reliability of a structural system (Ang & Tang 1984) is defined as

$$R = 1 - P_f \qquad \text{Eq. 4.}$$

where P_f is the probability of failure. Then, for discrete variables,

$$P_f = P(A<B) = \Sigma\, P(A<B/B=b)P(B=b) \qquad \text{Eq. 5.}$$

where, A is the Capacity (Supply),

B is the Resistance (Demand), and

b is the Resistance at a given instant.

Generally, the variables whose functions are discussed above are normal random variables, and the distribution is normal. For calculating the reliability of a particular variable, the two moments, namely mean and variance, are estimated. Only these two moments of the random variables are considered practical, as large amounts of data are required to evaluate for further moments.

For a complex system, the Capacity (Supply) and Resistance (Demand) may each be functions of several other variables. Hence, the problem of calculating the reliability becomes complex, as the selected variable depends on other random variables. Further, the complexity of the problem increases when the correlation between the variables is considered. To simplify the problem, for this work only the two moments mentioned above are considered in

the form of the total load effect (capacity) and the strength (resistance).

The total load effect (S) is

$$S = D + L + I \qquad \text{Eq. 6.}$$

where D is dead load,

L is live load, and

I is impact load.

All three loads are considered to be random variables, as the loads over time are not constant. Failure for a particular component will occur when S, the total load, exceeds the strength or resistance, R.

Hence,

$$P_f = P[R<S] \qquad \text{Eq. 7.}$$

For this model

Mean: $g = R\text{-}S$ Eq. 8.

Variance: $(\sigma_g)^2 = (\sigma_R)^2 - (\sigma_S)^2$ Eq. 9.

where g is the difference between resistance and capacity,

$(\sigma_{g)}^2$ is the difference between the variance of resistance and capacity, and

$(\sigma_{R)}^2$ is the variance of resistance and $(\sigma_{S)}^2$ is the variance of load.

The failure probability is the region where $g<0$, and in a discrete form the equation for failure probability is:

$P_f = \Sigma P [g = g_i]$ for all values where $g<0$ Eq. 10.

where g_i is the difference between resistance and capacity at any given instance (i).

Safety Index:

The safety index (β) is defined as the ratio of difference between resistance and capacity (g) and the standard deviation (σ_g), which is the difference between the variance of resistance and capacity. Hence, the failure probability is the sum of probabilities over the range where the safety index obtained is negative (Ang & Tang 1984). The probability of failure can be expressed as a logarithmic function of the ratio of the difference between the loads and the difference between variances.

$P_f = \Phi\ (g/\sigma_g)$ Eq. 11.

If $\beta = g/\sigma_g$, Eq.12.

then $P_f = \Phi\ (\ \beta\ )$ Eq.13.

Here β is the safety index, and the quantitative relation between the safety index and the probability, which follows normal distribution is shown in ***Table 2***,. (Ang & Tang 1984):

$$\beta = \frac{\mu_R - \mu_S}{\sqrt{\sigma_R^2 + \sigma_S^2}} \qquad \text{Eq.15.}$$

Where μ_R is capacity of components

μ_S is load on the components

σ_R is variance of capacity

σ_S is variance of load

After finding the safety index by using data from ***Table 2***, the probability of failure is calculated.

3.4 Coefficient of Variance

Correlation techniques are used to study relationships (associations) between variables. Correlation is calculated as the level and direction of a relationship between two variables, X and Y. The range of values of a correlation coefficient is from “-1” to “+1”. The closer the value is to “+1”, the stronger the positive correlation, and the closer the value is to “–1”, the stronger the negative correlation.

The Pearson product moment correlation (r) is the most common “Correlation Coefficient.” The strength of the correlation is measured from 0 to 1, and the sign indicates whether the condition is positive or negative. The correlation coefficient reflects the degree of linear relationship between two variables. (Pearson’s Correlation @ August 1999)

A number of assumptions are for made for the Pearson r:

1. Normal distribution for both X and Y.
2. Sample representative of the population.

3. Interval level of measurement for data for both X and Y. This means that the data are measured after specific time interval. For this research, the data used are collected after every year.

The data used in the research satisfies the above requirements, wherein it is assumed that the relationship between the probabilities (transition probability and probability of failure) is normally distributed.

The Coefficient of Correlation is calculated as

$$r = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sqrt{(\sum X^2 - \frac{(\sum X)^2}{n})(\sum Y^2 - \frac{(\sum Y)^2}{n})}} \qquad \text{Eq.16.}$$

where ‘n’ is the sample size.

3.5 Methodology

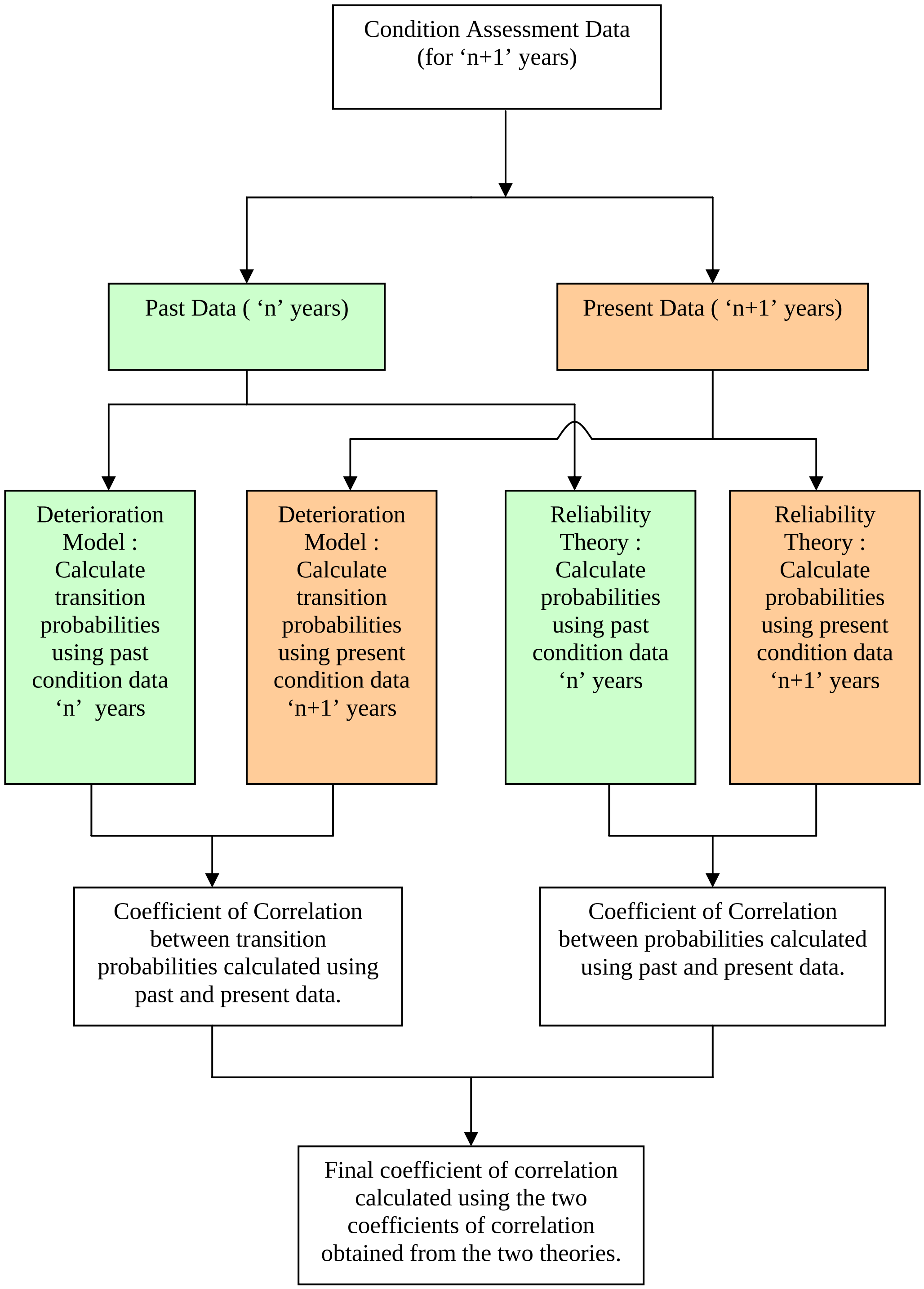
This research addresses non-cognitive, random uncertainty in bridge condition data. The methodology combines a comparison of predicted with actual data of both component condition and reliability of a bridge. A correlation coefficient is then used to quantify the level of agreement between the two, which is subsequently used to obtain an overall estimation of “accuracy.”

Typical elements of the bridge, which represent the overall condition of the bridge are selected and condition assessment data for these components are used in creating a database. This database is used as an input file for the Pontis software. Based on the Markovian principle, the deterioration model in Pontis calculates the transition probabilities for each component using past and present data. The past data represents condition assessment data for the previous ‘n’ years, and the present data represents the condition assessment data for ‘n+1’ years. The reliability model is used to calculate the probability of failure, using equation 4 through equation 15 mentioned earlier in ***section 3.3*** on reliability.

The procedure can be explained using a diagrammatic representation of the procedure as shown in ***Figure 2***. Using the condition assessment data for a period of ‘n’ years the transition probabilities for the components of bridge are calculated. Then, the transition probabilities for the same components of the bridge are calculated using condition assessment data for the period of ‘n+1’ years. Further, these transition probabilities are compared and a coefficient of correlation for the transition probabilities for a particular bridge is calculated. Similarly, in the reliability model, probability of failure is calculated using the condition assessment data at time T = n years and time T = n+1 years. The probabilities of failure are then compared, and the coefficient of correlation between both the probabilities (at T = n years and at T = n+1 years) for the same bridge are calculated. These coefficients of correlation are then compared and the final coefficient of correlation is calculated. The uncertainty is quantified in terms of this coefficient of correlation.

In this procedure the deterioration model predicts the transition probability for the future (after 1 year). Hence, when t=n years, a transition probability based on the past (n years) data is obtained. At t=n+1 years this deterioration model predicts the present transition probability where it also considers the condition assessment data for the present year.

FIGURE 2: SCHEMATIC REPRESENTATION OF THE PROCEDURE



4. Case Study

4.1 Application of Methodology

In order to quantify uncertainty of data, condition assessment data for bridges were used in the deterioration model and the reliability model to predict the future probabilities of failure. Then a coefficient of correlation between these probabilities, which represents uncertainty in data, can be calculated.

This method was applied to a set of three bridges whose condition assessment data were obtained from Missouri Department of Transportation (MoDOT) for bridges **A814**, **H198** and **H199**. A ten-year condition assessment data set for all three bridges obtained from MoDOT for this research is shown in ***Table 3***. Typical elements of the bridge, which represent the overall condition of the bridge, as shown in ***Table 3*** were selected and condition assessment data for these components were used in creating a database. The database, which was created using ten years of condition assessment data for each element, was used as an input file for the Pontis software. Based on the Markovian principle, the deterioration model in Pontis calculated the transition probabilities for each component using past and present data, as shown in ***Table 4*** and ***Table 5***. In this case study the past data represents condition assessment data for the previous 9 years (n=9), and the present data represents the condition assessment data for 10 years (n+1=10). The transition probabilities in ***Table 4*** and ***Table 5*** are quite high, suggesting that all the bridge components will most probably remain in the same condition state between past (9years) and present (10years). These transition probabilities obtained from Pontis, for past and present scenarios are compared and a

TABLE 4: TRANSITION PROBABILITIES USING DETERIORATION MODELS FOR PAST DATA

Bridge Component	A814	H198	H199
Deck	94.25	93.28	96.48
Slab	95.92	95.86	94.34
Girder	96.95	94.77	96.98
Columns	97.47	96.82	97.47
Railings	97.98	97.52	96.29
Abutment	94.34	95.47	96.11

TABLE 5: TRANSITION PROBABILITIES USING DETERIORATION MODELS FOR PRESENT DATA

Bridge Component	A814	H198	H199
Deck	95.22	92.42	94.88
Slab	93.77	93.71	93.47
Girder	95.98	92.18	96.22
Columns	96.35	95.67	95.65
Railings	96.13	97.81	94.54
Abutment	92.18	93.25	95.08

TABLE 6:COEFFICIENT OF CORRELATION BETWEEN TRANSITION PROBABILITIES

Bridge Components	Bridge A814		Bridge H198		Bridge H199	
	Transition Probabilities using past data	Transition Probabilities using present data	Transition Probabilities using past data	Transition Probabilities using present data	Transition Probabilities using past data	Transition Probabilities using present data
Deck	94.25	93.22	93.28	92.42	96.48	94.88
Slab	95.92	93.77	95.86	93.71	94.34	93.47
Girder	96.95	95.98	94.77	92.18	96.98	96.22
Column	97.47	96.35	96.82	95.67	97.47	95.65
Railing	97.98	96.13	97.52	97.81	96.29	94.54
Abutment	94.34	93.18	95.47	93.25	96.11	95.08
Coefficient of correlation	0.95069567		0.88902714		0.89800344	

coefficient of correlation for these past and present transition probabilities for a particular bridge is calculated as shown in ***Table 6***

As mentioned in the previous section (3.5) the reliability model calculates probability of failure using the condition assessment data at time T = 9 years (past data) and time T = 10 years (present data). ***Table 7*** and ***Table 8*** show the reliability calculations for Bridge **A814** for past and present data respectively. ***Table 9*** and ***Table 10*** show the reliability calculations for Bridge **H198** for past and present data respectively. ***Table 11*** and ***Table 12*** show the reliability calculations for Bridge **H199** for past and present data respectively. The coefficient of correlation between both the probabilities past and present (at T = 9 years and at T = 10 years) for the same bridge is calculated as shown in ***Table 13***. These coefficients of variance as shown in ***Table 6*** and ***Table 13*** are then compared and the final coefficient of variance is calculated as shown in ***Table 14***. The uncertainty is quantified in terms of this coefficient of variance.

4.2 Results

In this research, the value assigned to the uncertainty associated with the data is in the form of a coefficient of correlation. In ***Table 6***, the coefficient of correlation is calculated for each bridge, using the probability of failure in the reliability model and the transition probabilities in the deterioration model. The coefficient of correlation for each of these bridges is very close to 1, showing that the data uncertainty is very low for the considered data set.

As discussed further in the conclusions only one coefficient of correlation could be calculated using the data for three bridges. The coefficient obtained for the three bridges for reliability model and for the transition probabilities in the deterioration model are shown in ***Table 14***. From the coefficient of correlation obtained for these bridges, it is clear that the uncertainty in the data for the bridges considered in this research is 0.892, which is very low. This is based on the fact that as the coefficient of correlation is closer to '1,' the stronger the correlation. In other words, the results obtained from two different data sets for the same bridge in the reliability model as well as in the transition model are very close, which suggests that the uncertainty in data is very low.

TABLE 7: CALCULATION OF RELIABILITY OF COMPONENTS USING PAST DATA FOR BRIDGE A814

A814	Dead Load (lbs)	Live Load (lbs)	Impact Load (lbs)	Impact Load factor	Total load carrying capacity (lbs)	Capacity reduction factor	Capacity at time t=x (yrs) 'R' (lbs)	Load on the structure at time t=x (yrs)'S' (lbs)	σ_R (lbs)	σ_S (lbs)	Reliability index β	Reliability
Deck	566658.5	70000	20860	0.298	657518.5	0.94	618067.4	580947.9	0	23642.99	1.57	93.7
Slab	566658.5	70000	20860	0.298	657518.5	0.94	618067.4	580947.9	0	23642.99	1.57	93.7
Girder	1841851	70000	20860	0.298	1932711	0.84	1623477	1514511	0	67807.13	1.607	94.42
Column	1920945	70000	20860	0.298	2011805	0.84	1689916	1580643	0	65906.59	1.658	95.14
Railings					10000	0.94	9400	7889.5	0	987.2549	1.53	93.38
Abutment					42260.63	0.84	35498.93	33259.65	0	1348.94	1.66	94.57

TABLE 8: CALCULATION OF RELIABILITY OF COMPONENTS USING PRESENT DATA FOR BRIDGE A814

A814	Dead Load (lbs)	Live Load (lbs)	Impact Load (lbs)	Impact Load factor	Total load carrying capacity (lbs)	Capacity reduction factor	Capacity at time t=x(yrs) 'R' (lbs)	Load on the structure at time t=x(yrs) 'S' (lbs)	σ_R (lbs)	σ_S (lbs)	Reliability index β	Reliability
Deck	566658.5	70000	20860	0.298	657518.5	0.84	552315.5	549849.72	0	1754.1	1.4058	91.7
Slab	566658.5	70000	20860	0.298	657518.5	0.84	552315.5	549849.72	0	1754.12	1.4058	91.7
Girder	1841851	70000	20860	0.298	1932710.8	0.76	1468860	1463419.24	0	3587.11	1.5168	93.2
Column	1920945	70000	20860	0.298	2011804.5	0.76	1528971	1522490.8	0	4036.32	1.6056	94.4
Railings					10000	0.84	8400	7139.8	0	869.01	1.4502	92.3
Abutment					42260.625	0.76	32118.08	30247.3	0	1204.2	1.5538	93.7

TABLE 9: CALCULATION OF RELIABILITY OF COMPONENTS USING PAST DATA FOR BRIDGE H198

H198	Dead Load (lbs)	Live Load (lbs)	Impact Load (lbs)	Impact Load factor	Total Load carrying capacity (lbs)	Capacity reduction factor	Capacity at time t=x(yrs) 'R' (lbs)	Load on the structure at time t=x(yrs) 'S' (lbs)	σ_R (lbs)	σ_S (lbs)	Reliability index β	Reliability
Deck	202749.3	70000	16100	0.23	288849.3	0.94	271518.3	252648.35	0	14662	1.287	90.1
Slab	202749.3	70000	16100	0.23	288849.3	0.94	271518.3	252648.35	0	14662	1.287	90.1
Girder	659049.3	70000	16100	0.23	745149.3	0.84	625925.4	565418.45	0	40685.15	1.4872	92.8
Column	683207.8	70000	16100	0.23	769307.8	0.84	646218.6	595248.97	0	33603.36	1.5168	93.2
Railings					10000	0.94	9400	7927.96	0	1015.2	1.45	92.3
Abutment					16537.26	0.84	13891.3	12870.05	0	666.78	1.5316	93.4

TABLE 10: CALCULATION OF RELIABILITY OF COMPONENT USING PRESENT DATA FOR BRIDGE H198

H198	Dead Load (lbs)	Live Load (lbs)	Impact Load (lbs)	Impact Load factor	Total Load carrying capacity (lbs)	Capacity reduction factor	Capacity at time t=x(yrs) 'R' (lbs)	Load on the structure at time t=x(yrs) 'S' (lbs)	σ_R (lbs)	σ_S (lbs)	Reliability index β	Reliability
Deck	202749.3	70000	16100	0.23	288849.3	0.84	242633.4	223067.45	0	15528.5	1.26	88.27
Slab	202749.3	70000	16100	0.23	288849.3	0.84	242633.4	223067.45	0	15528.5	1.26	88.27
Girder	659049.3	70000	16100	0.23	745149.3	0.76	566313.5	504554.15	0	48136.6	1.283	90.42
Column	683207.8	70000	16100	0.23	769307.8	0.76	584673.9	522242.44	0	44435.2	1.405	91.78
Railings					10000	0.84	8400	7349.83	0	789.6	1.33	90.89
Abutment					16537.26	0.76	12568.32	11319.53	0	904.92	1.38	91.21

TABLE 11 CALCULATION OF RELIABILITY OF COMPONENT USING PAST DATA FOR BRIDGE H199

H199	Dead Load (lbs)	Live Load (lbs)	Impact Load (lbs)	Impact Load factor	Total Load carrying capacity (lbs)	Capacity reduction factor	Capacity at time t=x(yrs) 'R'(lbs)	Load on the structure at time t=x(yrs) 'S' (lbs)	σ_R (lbs)	σ_S (lbs)	Reliability index β	Reliability
Deck	142025	70000	21000	0.3	233025	0.94	219043.5	209536.4	0	7648.5	1.243	89.2
Slab	142025	70000	21000	0.3	233025	0.94	219043.5	209536.4	0	7648.5	1.243	89.2
Girder	411125	70000	21000	0.3	502125	0.84	421785	394522.2	0	20245.68	1.3466	90.9
Column	414963.3	70000	21000	0.3	505963.3	0.84	425009.2	392147.9	0	23375.5	1.4058	91.7
Railings					10000	0.94	9400	8622.98	0	535.8	1.4502	92.3
Abutment					17576	0.84	14763.84	1434.72	0	974.41	1.4724	92.6

TABLE 12 CALCULATION OF RELIABILITY OF COMPONENT USING PRESENT DATA FOR BRIDGE H199

H199	Dead Load (lbs)	Live Load (lbs)	Impact Load (lbs)	Impact Load factor	Total Load carrying capacity (lbs)	Capacity reduction factor	Capacity at time t=x(yrs) 'R' (lbs)	Load on the structure at time t=x(yrs) 'S' (lbs)	σR (lbs)	σS (lbs)	Reliability index β	Reliability
Deck	142025	70000	21000	0.3	233025	0.84	195741	180696.4	0	11940.2	1.26	87.28
Slab	142025	70000	21000	0.3	233025	0.84	195741	180696.4	0	11940.2	1.26	87.28
Girder	411125	70000	21000	0.3	502125	0.76	381615	346235.5	0	27857.9	1.27	88.91
Column	414963.3	70000	21000	0.3	505963.3	0.76	384532.1	344850.7	0	31147.1	1.274	89.04
Railings					10000	0.84	8400	7368.6	0	806.4	1.279	89.88
Abutment					17576	0.76	13357.76	12208.62	0	894.97	1.284	90.46

TABLE 13 COEFFICIENT OF CORRELATION BETWEEN RELIABILITIES

Bridge Components	Bridge A814		Bridge H198		Bridge H199	
	Reliability based on past data	Reliability based on present data	Reliability based on past data	Reliability based on present data	Reliability based on past data	Reliability based on present data
Deck	93.70	91.70	90.10	88.27	89.20	87.28
Slab	93.70	91.70	90.10	88.27	89.20	87.28
Girder	94.42	93.20	92.80	90.42	90.90	88.91
Column	95.14	94.40	93.20	91.78	91.70	89.04
Railing	93.38	92.30	92.30	90.89	92.30	89.88
Abutment	94.57	93.70	93.40	91.21	92.60	90.46
Coefficient of correlation	0.92746438		0.96602507		0.98538182	

TABLE 14 FINAL COEFFICIENT OF CORRELATION

Coefficients of correlation using the Reliability theory	Coefficients of correlation using the Deterioration models
0.92746438	0.95069567
0.96602507	0.88902714
0.98538182	0.89800344
Final coefficient of correlation using the data obtained for three bridges	
0.891760796	

5. Conclusions

The uncertainty in data is quantified in the form of coefficients of correlation, which may be positive or negative, and the strength of the correlation defines the extent of uncertainty in the data. The coefficient of correlation varies from 0 to 1, and the closer the value of the coefficient to 1, the higher the correlation between the predicted and present probabilities. These values can be attached to the bridge data, and weights can be assigned to different data used in bridge management based on the coefficients of correlation. This would enhance decision making in bridge management. The data used in this example is for three bridges. If data for a whole network of bridges were available, the procedure would be more efficient and effective, as uncertainty in any problem (solution) cannot be completely eliminated but only can be reduced. Hence, as the number of iterations increases, the uncertainty in the result decreases.

5.1 Evaluation of Methodology

The procedure is evaluated and the strengths and weaknesses of the procedure are discussed in the following paragraphs.

Strengths of methodology include:

- Two different models are used for every bridge to calculate data uncertainty. By doing so, we are discarding the possibility of verifying the validity of either the deterioration model or the reliability model.
- The coefficients of correlation have no units. Therefore, they can be compared to obtain a numerical value (coefficient of variance) for the condition assessment data.

- As the amount of data increases, the uncertainty in the procedure decreases. Hence the procedure may be effective at network level bridge management.

  Weaknesses of methodology include:

- A certain amount of uncertainty is present in the procedure, which is due to the assumptions made in simplifying the models.
- The methodology requires large amounts of historical data of bridges in the network to give good results.

The procedure is applied to the data for three bridges, and the results are obtained for each bridge. As a shortcoming of this research, it is not possible to obtain more than one coefficient of correlation for each bridge, for each model. This is because of the amount of data used in the research. If more data sets were available, it would be possible to calculate a greater number of coefficients of correlation between data sets, which in turn results in calculating a coefficient of correlation between the reliability and deterioration model for each bridge. For example, if 50 years of condition assessment data for each bridge was available it could have been broken down into 10 year data sets. The methodology in discussion would then be applied to each 10 year data set and coefficients of correlation would be calculated. Further the coefficient of correlation between the reliability and deterioration model for each 10 year data set would have been calculated. Finally the coefficient of correlation between these 10 year data sets (five in this case) would have been calculated to obtain a single coefficient of correlation for the bridge based on 50 years condition assessment data. Due to the above-mentioned shortcoming, the final step of this research is modified and a final coefficient of correlation is calculated between individual coefficients of correlations for the three bridges.

5.2 Future Work

This research proposes a procedure and uses a data set to show its functioning. Many questions still remain unanswered after completing this research. Hence, in this field of bridge management, the following topics related to this research still remain uninvestigated:

- Extend the approach (procedure) to a network of bridges and other types of infrastructure. Data collected through condition assessment are a common basis for decision making in bridge management as well as management of other types of infrastructure. As this approach deals with uncertainty of data it is logical to extend this approach to other types of infrastructures. Note that the deterioration and reliability models may differ depending on the type of infrastructure.
- Once the uncertainty is quantified, the effect of this uncertainty on decision making in management systems remains to be investigated. The tradeoffs between degree of accuracy and precision and cost can be further studied and investigated.

5.3 Contribution

This research has looked into the base of bridge management, which is data. As all decisions are based on data, its certainty needs to be investigated. This research has developed a procedure to quantify uncertainty in bridge data. By quantifying uncertainty of bridge data, it is possible to make a distinction between bridges based on the certainty of data. This methodology gives a parameter in the form of data uncertainty, which may be used as one of the bases of decisions in bridge management.

This methodology quantifies uncertainty of data in the form of a coefficient, which can be used as a measure of reliability of data. But in this research the amount of uncertainty due to model and reliability theory is not taken into account. This procedure may be modified to take into account changes due to these uncertainties.

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