RISK-BASED BRIDGE MANAGEMENT

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(Reviewed by the Highway Division)

ABSTRACT: This paper outlines a methodology for bridge project selection based on reliability methods and optimization procedures, which could serve as part of a bridge management system. The Markovian model is used to decay the structural components. Then, a reliability index is determined for each element using either subjective assessment or first-order reliability methods. The overall reliability of the bridge is calculated as a system reliability by combining the individual reliability of the components in a series system. Risk is obtained from the reliability of the bridge and the consequence of closure. Repairs can be modeled in any year. The optimum set of repairs is defined as that which minimizes the total network risk in the planning horizon. Methods for finding the optimum set of repairs are discussed, and a near-optimum algorithm is selected.

INTRODUCTION

The development of a risk-based bridge project selection system requires a stochastic model of the deterioration of bridge elements, a reliability analysis of individual bridges, and an effective approach for the selection of repairs within the whole network. There are two primary constraints: First, the methodology must be relatively simple to be systematically implemented to all bridges in the network. And, second, the data needed in the reliability analysis should be contained within the bridge inspection and inventory data base.

Previous work (Cesare et al. 1992a; Jiang 1989; MacCalmont 1990) discussed the modeling of deterioration and repairs by Markov processes; therefore, it is assumed that Markovian transition matrices are available. In this paper, a procedure is described for evaluating the reliability of a bridge in any year in the future, without repair or with a particular repair done in any year. This information is then used to select the combination of repairs that minimizes the total risk for all bridges in the network.

METHODOLOGY

The proposed methodology consists of several steps symbolically outlined in Fig. 1. A brief description follows (Appendix II summarizes the notation).

Step 1: Condition Rating of an Element

In this first step, the probability distribution q for the condition rating of each element is determined for each year n; the distribution is obtained for

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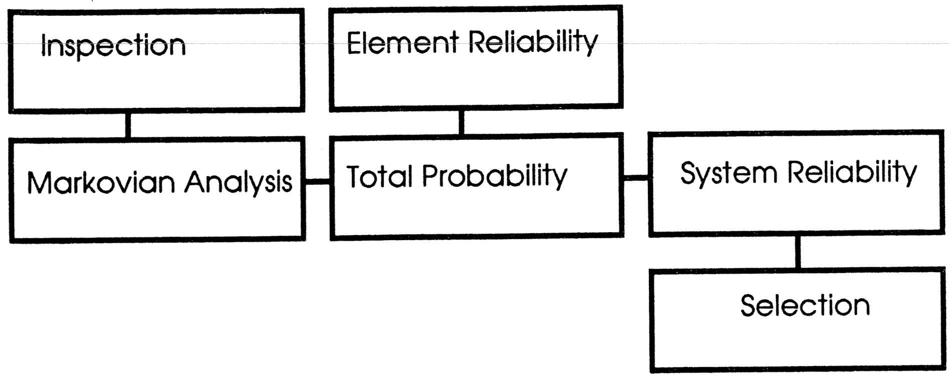

FIG. 1. Symbolic Outline of Risk-Based Management System

every year in the horizon, before and after the year r, of repairs. Appropriate Markovian transition matrices are used in this task, specifically developed for the given bridge element (e.g., foundation, structure, wearing surface):

$$q_n = q_0 T^n \qquad n < r \quad \text{(1a)}$$

$$q_n = q_0 T^r R T^{n-r} \qquad n \leq r \quad \text{(1b)}$$

The application of Markov chains to condition ratings of the various elements of a bridge provides a discrete probability distribution for the condition of each item inspected for each year in the future, within a predetermined horizon (Cesare et al. 1992).

Step 2: Probability of Failure of an Element

Given a function $F(*)$ that relates condition ratings to reliability index of an element, and assuming normal distribution Φ, the probability of failure of each element P_{En} in each year n is obtained by summing over all valid values of all condition ratings, to obtain the total probability of failure

$$P_{En} = \sum_{cr1} \sum_{cr2} \cdots \sum_{crm} q_1 q_2 \cdots q_n \Phi[F(cr_1 \cdots cr_m)] \quad \text{(2)}$$

Note that the function $F(*)$ is specific to the element being considered and cannot be expressed in a general form. The estimation of this function is discussed later in the text.

Step 3: Probability of Failure of Bridge

The probability of failure of the N_e elements of a given bridge are combined by system reliability to obtain the probability of failure of that bridge P_s^n in each year n:

$$P_S^n = 1 - \prod_{i=1}^{N_e} (1 - P_{Ei}) \quad \text{(3)}$$

A series system is assumed, in this calculation of the reliability of a bridge, because most elements that are important enough to have their own condition rating will also cause closure of the bridge if they are found likely to fail (the exception being joints and railing).

Step 4: Risk due to Bridge Failure

The probability of failure, taken as the need for closure, of a bridge P_n in year n, and the consequences K of a failure define the risk Q_n due to "failure" in year n:

$$Q_n = P_n K \quad \text{for each bridge} \qquad (4)$$

In a first approximation, consequences K can be evaluated as the product of the average daily traffic ADT_b, and the detour around the bridge, DT_b (in units of time, distance or cost). This can be interpreted as the expected number of kilometers (miles), hours, or dollars of inconvenience to the public.

Then, the total risk that bridge b presents within the N_y years of the planning horizon is computed taking into consideration the probability of failure $P(b, n, j_b, n_{rb})$ in each year n, and the repair j_b done in year nr_b

$$Q(b, j_b, tr_b) = \sum_{n=1}^{N_y} P(b, n, j_b, nr_b)\mathrm{ADT}_b DT_b \qquad (5)$$

Note that if no repair is done, $j_b = 0$ and tr_b is irrelevant.

A more comprehensive form of consequences K incorporates additional terms to account for other costs. For example, lane width and clearance deficiencies, accidents (traffic safety) and construction delays (Erickson et al. 1989). In order to incorporate these other costs, they must be converted to the same units before summing.

Step 5: Total Network Risk

Finally, the total risk Q for the whole network, throughout the planning horizon is found by summing the individual total risks $Q(b)$ for all N_b bridges

$$Q = \sum_{b=1}^{N_b} Q(b) \qquad (6)$$

Observations

Risk in step 4 could be computed by associating a cost function to each element probability of failure (step 2) and summing to obtain the total risk. However, this requires the subjective assignment of weights or detailed replacement cost data.

Within the context of the proposed approach, the total risk Q is the most meaningful parameter to assess the soundness of a repair option. Two problems remain: (1) The definition of functions $F(*)$ that relate condition rating of elements to their reliability index; and (2) the generation of optimal repair options. These two problems are addressed next.

CONDITION RATING AND RELIABILITY

The proposed methodology attempts to maximize the usage of available inspection information; however, it requires a correlation function $F_{Ei}(*)$ to transform condition ratings to the reliability index of a given element. This function can be found using either subjective estimates or first-order reliability methods (FORM) (Thoft-Christensen 1982; Moses 1987). This time independent function is based only on the condition rating of the given element; therefore, deterioration and safety are both accounted for, but kept separate.

In some cases there will be only one relevant condition rating; in other cases two or more condition ratings are involved. Because $F(*)$ does not have generic form, specific cases are presented.

One Condition Rating—No Detailed Information

Two extreme points and a linear relationship are assumed. Elements are designed for a β of about 4 (Moses 1987), which by definition corresponds to condition rating 7 ("new": 1–7 scale), hence the point ($\beta = 4$, $CR = 7$) is known. The lowest condition rating, 1, defined as "hazardous" is associated with a low value of the reliability index, $\beta = 1.5$. It follows that the linear relationship $\beta = a, + b\ CR$, becomes $\beta = 1.08 + 0.42\ CR$.

Two Condition Ratings—No Detailed Information

A similar approach may be used if two condition ratings contribute to the reliability of an element and detailed information is not available. This case may apply to pier footings where the risk depends on the footing rating itself and the erosion control rating. A simple model is proposed as

$$F_{Ei}(CR_1, CR_2) = a + bCR_1 + cCR_2 \quad (7)$$

Three points are needed: (1) If both condition ratings are good, $CR_A = CR_B = 7$, then the reliability will be high, $\beta = 4$; (2) if both are low, $CR_A = CR_B = 1$, the reliability will be low, $\beta = 1$; and (3) for $CR_A = 7$ and $CR_B = 1$ a moderate level of reliability may be expected, $\beta = 2.5$. If more points are "known," surfaces with curvature can be developed.

One Condition Rating—Objective Analysis

Based on the methods used for determining load capacity of bridges (Moses 1987), a simple analytical method is proposed to determine reliability index from condition rating. Let's assume a short concrete pier (buckling not considered) for which the original design load and the current usage are known from the inventory data, but detailed dimensions are not. The original capacity can be approximated from the design equation. This original capacity, R_0, is reduced by a factor Δ, which is a function of the condition rating. The coefficient of variation for Δ is considered 0.0% at $CR = 7$ and 20% at $CR = 1$ (Moses 1987).

A limit-state function of the form $g = R - S$ is used with the first-order reliability method (FORM) to find the reliability as a function of the condition rating, assuming all variables are lognormally distributed. FORM is run for all condition ratings. No structural analysis is needed because the influence coefficient for the loading will not have changed from the original

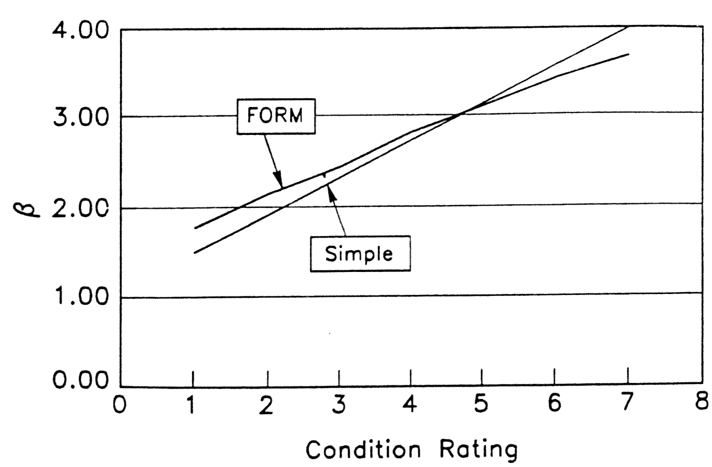

FIG. 2. Relationship between Condition Rating and Reliability

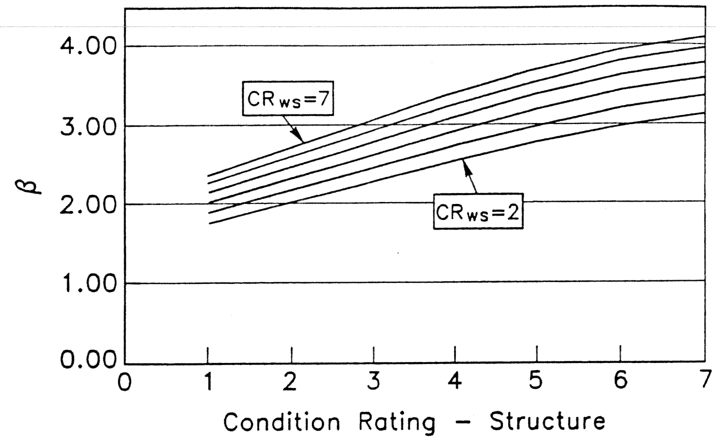

FIG. 3. Relatonship between Multiple Condition Rating and Reliability

design. Fig. 2 is a plot of β-versus-*CR* for this example. The relation found by the simplified method (case 1) is also shown.

Two Condition Ratings—Objective Analysis

The final case for determining $F(*)$ examines a situation where the failure probability of an element depends on two condition ratings. Let us consider the case of the primary structure and the wearing surface. $F(*)$ for the "primary-structure element" combines the condition rating of the primary structure CR_{prime}, and the wearing surface CR_{WS}. These values are based on a linear mapping of the condition rating into the various structural parameters.

The case was simulated through a FORM, where CR_{prime} was varied giving an indication of the loss in carrying capacity, and CR_{ws} modeled the change in dynamic impact factor. Results are presented in Fig. 3. Note that is not a mapping of condition rating into β as in the simplified case, but the result of considering the actual physical characteristics of the elements. A more detailed analysis is not warranted given the verbal and qualitative definitions of condition ratings (*Bridge inspection* 1982b).

Averaged Condition Rating and Bridge Reliability

Instead of developed $F(*)$ functions at the element level, condition ratings could be averaged for the bridge, following approaches used by most state agencies. Then, the weighted average condition rating (WAC) could be related to the bridge reliability index by a global function F_{global} (WAC). While this approach would be simpler than performing Step 2, there was concern about its validity because condition ratings for different elements may reflect different levels of reliability, and averaging formulas may not properly characterize the elemental contributions to the system.

A preliminary study was conducted to compare the reliability method with the New York weighted-average condition formula (WAC), (*Bridge inspection* 1982a, 1982b). The WAC is based on 13 structural and non-structural condition ratings. The reliability portion of this study was done using the method presented as case 1 for the determination of the elemental β, using appropriate parameters for each element. Table 1 shows the state weights and the parameters used for the reliability method. The results of both methods for 500 synthetically generated bridges are compared by plotting the WAC and reliability in Fig. 4.

Results indicate that while there is some relation between the parameters,

TABLE 1. Weights and Reliability Indices (for Fig. 4)

Element (1)	Weight (2)	β at $CR = 3$ (3)	β at $CR = 7$ (4)
Main members	10	2	4
Abutments	8	2	4
Piers	8	2	4
Seats	6	2	4
Backwall	5	3	4

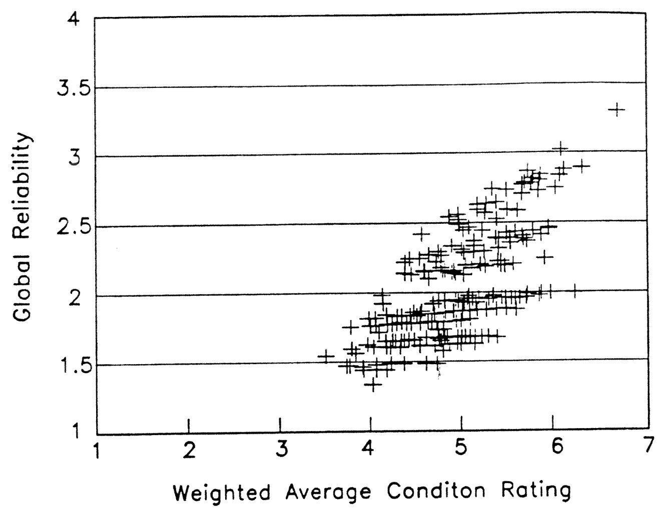

FIG. 4. Comparison of Global Reliability and Weighted Average Condition Rating

for the same WAC the reliability of the bridge can vary by an order of magnitude. Therefore, when using risk as a criterion for project selection the results may vary greatly from a system that uses the weighted average model, because the set of repairs that yields a minimum risk may not have the highest average condition rating.

SELECTION OF OPTIMIZATION ALGORITHM: PROBLEM SIZE

The problem of bridge management by risk minimization can be formulated to be solved by many available methods. Unfortunately, risk assessment procedures provide a three-dimensional array of risks for a population of bridges, $Q(b, j_b, nr_b)$ where b is the bridge number, j_b is the repair for the bridge, and nr_b is the year to repair bridge b. Then, a major consideration in the selection of an optimization algorithm becomes the size of the problem. Comments based on the writers' experiences with different algorithms follow.

Mathematical Programming

The sum of the risk on all bridges can be minimized by mathematical programming or other optimization methods. Along with the yearly budget constraint, this can be written as:

$$\min \sum_{b=1}^{N_b} Q(b, j_b, nr_b) \quad \text{(8)}$$

such that

$$\sum_{b=1}^{N_b} C(b, j_b, nr_b) < B(n) \qquad \text{for each } n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

In this equation, nr_b is in the set of possible years for repair, j_b is in the set of possible repairs, $C(b, j_b, nr_b)$ is the cost of repair j_b on bridge b in year nr_b, and $B(t)$ is the budget constraint for year t.

A valid restriction to the solution space would be the number of repairs per bridge per horizon. Artificial constraints such as not considering bridges in good condition for repairs are not valid because bridges decay at different rates. Similarly, constraints of "acceptable-minimum" type are not applicable as they can lead to unfeasibility at a given budget level. Should these artificial constraints be applicable, they they will naturally manifest themselves in the optimum solution.

Search Strategies

"Full search" and even "branch-and-bound" are inapplicable to large problems of this type. On the other hand, heuristic methods require extensive past experience and careful selection of parameters.

The problem could be reduced by preselecting bridges according to thresholds on an overall rating scale: e.g., one above, which no projects are done; or another below, which projects must be done (acceptable and minimum levels of service). Such acceptable levels could be set in the risk-based method. For example never do a repair above $\beta = 3$ and always do a repair below $\beta = 2$. However, with bridges deteriorating at different rates, the use of only the current condition alone, may result in nonoptimal allocations throughout the planning horizon.

Near-Optimum Solutions

In the context of this research the solution of the risk based bridge project selection problem has been solved by a class of optimization procedures known as "genetic algorithms" (Goldberg 1989). These methods evolve a population of solutions toward the optimal by recombining and mutating existing solutions to form new ones, and discarding those with higher total risk (Cesare 1991). The solution evolves rapidly in the earlier iterations, finally becoming increasingly close to the optimal solution. The user may monitor the evolution of the solution and decide when a sufficiently acceptable result has been reached. Results obtained with this approach are presented in the following section.

PARAMETRIC STUDY—CASE HISTORY

A problem with 50 bridges was run using the methods proposed and the genetic algorithm-based optimization. Each bridge was considered for one of six possible repairs in the next eight years. The results for several different cases are shown in Table 2 (risk is in units of distance, expected value of autokilometers [car miles]). The first two cases bound the possible solutions, and correspond to no budget and unlimited budget.

The third case presented the total risk if repair decisions are based on condition rating. The fourth case is based on risk minimization without consideration of deterioration. The last case is also based on risk minimization, but deterioration is taken into consideration.

TABLE 2. Optimization—Parametric Study

Case description (1)	Total risk (2)
Large budget: all repairs can be done if needed (minimum risk)	75,313
Projects selected based on condition rating, and fixed budget	191,561
Projects selected by risk minimization without accounting for deterioration, and fixed budget	180,023
Projects selected by risk minimization, accounting for deterioration, and with fixed budget	170,767

It is observed that the lowest total risk is obtained when decisions are based on risk minimization, taking into consideration deterioration of the bridge components within the planning horizon.

ANALYSIS

The proposed approach is more cumbersome to implement than most standard management methodologies. It requires more information, and awareness of the uncertainty of such information. For example, a significant historical database, discriminated by element and materials is needed to develop significant Markovian transition matrices, and to assess the stationarity of the deterioration process.

The final optimization is complicated by the size of the solution space that expands in the time dimension. Therefore solution algorithms are computation intensive. Shortcuts such as the use of the weighted average condition rating and artificial constraints are discouraged, but could be used to start the genetic algorithm. Near-optimum solutions may be preferred in solving this problem.

The risk-based approach can also be used for a more appropriate planning scheduling of inspections.

The implementation of the proposed methodology still needs better definitions of limit states for each element, adequate data bases and the comparative evaluation of more comprehensive cost functions.

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APPENDIX II. NOTATION

The following symbols are used in this paper:

ADT_b = average daily traffic bridge b;
$B(n)$ = budget in year n;
$C(\ )$ = cost of repairs;
CR = condition rating;
$cr1, cr2, \cdots$ = condition ratings of specific elements;
DT_b = detour—bridge b;
$F(*)$ = reliability index as function of condition rating;
g = limit state function;
j_b = repair—bridge b;
K = consequences of closure;
m = number of condition ratings;
Nb = number of bridges;
Ne = number of elements;
Ny = number of years;
n = year number;
nr_b = year of repair—bridge b;
P_{Ei} = probability of failure of element i;
P_S^n = system failure probability in year n;
Q = total network risk for planning horizon;
Q_n = risk in year n of bridge;
q = distribution of condition rating;
R = resistance;
r = number of years before repair;
S = load;
T = Markovian transition matrix for deterioration;
β = reliability index; and
Φ = unit normal distribution.