Condition Prediction of Deteriorating Concrete Bridges Using Bayesian Updating

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Abstract: It is well known that the U.S. infrastructure is in need of extensive repair. To ensure that the scarce resources available for maintaining the U.S. bridge inventory are spent in an optimal manner, bridge management programs have been mandated by the Federal Highway Administration. However, these programs are mainly based on data from subjective condition assessments and do not use time-variant bridge reliability for decision making. Many nondestructive test methods exist for the detailed inspection of bridges. Predictions based solely on inspection data may be questionable, particularly if limitations and errors in the measurement methods that are used are not considered. Through the application of Bayesian techniques, information from both inspection data and engineering judgment can be combined and used in a rational manner to better predict future bridge conditions. In this study, the influence of inspection updating on time-variant bridge reliability is illustrated for an existing reinforced concrete bridge. Inspection results are combined with prior information in a Bayesian light. The approach is illustrated for a reinforced concrete bridge located near Pueblo, Colo. For this bridge the effects of corrosion initiation time and rate on time-variant strength are illustrated using simulation. Inspection results are combined with prior information using Bayesian updating. Time-variant bridge reliability computations are performed using a combined technique of adaptive importance sampling and numerical integration. The approach presented allows accounting for inspection results in the quantitative assessment of condition of bridges and shows how to incorporate quantitative information into bridge system and component condition prediction.

INTRODUCTION

As the U.S. bridge inventory continues to age, the cost of maintaining it at an acceptable safety level continues to increase. The current annual maintenance cost of all U.S. bridges has been estimated at $3 billion per year (Chase and Washer 1997). In an effort to prioritize the maintenance of existing bridges, transportation agencies have funded the development of several bridge management programs [e.g., Pontis (Thompson 1994) and BRIDGIT (Lipkus 1994)]. However, most of the bridge management strategies used by these programs are based on subjective condition assessment and empirical models of future conditions (Aktan et al. 1996) without considering bridge reliability degradation explicitly. The need for the application of time-variant reliability methods to bridge life-cycle cost management is becoming increasingly recognized in the U.S. (Chang and Sinozuka 1996; Frangopol and Hearn 1996).

Perhaps the most significant challenge to today's bridge management systems is the acquisition and interpretation of field inspection data. According to Aktan et al. (1996), subjective or inaccurate condition assessment has been identified as the most critical technical barrier to the effective management of highway bridges. Prior to the 1960s, repair and replacement decisions were based on visual observations and hammer sounding, which are highly subjective (Van Daveer 1975). In the United States, even today the data that feeds all bridge management systems are based on visual inspection and subjective condition assessment (Chase and Washer 1997). This is not limited to the United States, however. Although bridge inspection intervals vary around the world, in most countries the current bridge inspection practice is based on judgment in the form of a visual inspection. Because reliability and life-cycle cost methods depend on quantitative rather than qualitative information, the development of methods that do not rely solely on subjective data is essential.

A significant amount of research has been performed on the condition assessment of existing bridges, yet the data obtained from this research have not been incorporated into the bridge management database. Typically, due to the uncertainties in detecting damage and measuring it accurately, data from nondestructive inspections are difficult to interpret. Bayesian methods have been used extensively for strength and structural reliability predictions (Sørensen 1993; Engelund and Sørensen 1998; Geyskens et al. 1998; Zheng and Ellingwood 1998). Through the application of Bayesian techniques, information from both inspection data and engineering judgment can be combined and used in a rational manner to better predict future bridge conditions. This approach has the following advantages: (1) Measurement errors are explicitly considered; (2) prior information based on engineering judgment and/or experience can be incorporated into the prediction of future deterioration; and (3) because inspection data merely alter (rather than replace) existing subjective data, the method provides a framework for incorporation of new inspection data into the existing bridge management systems.

In this study, inspection updating for deteriorating concrete bridges is used in a Bayesian light. In this manner, the aforementioned advantages are all incorporated into the proposed approach. The effect of updating prior information on time-variant bridge system reliability is quantified. The approach is illustrated for a reinforced concrete (RC) bridge located near Pueblo, Colo. For this bridge, the effects of corrosion initiation time and rate on time-variant strength are illustrated using simulation. Inspection results are combined with prior information using Bayesian updating. Time-variant bridge reliability computations are performed using a combined technique of adaptive importance sampling and numerical integration. The results of this study allow accounting for inspection results in the quantitative assessment of the condition of bridges and show how to incorporate quantitative information into bridge system and component condition prediction.

INSPECTION UNCERTAINTY

In general, large uncertainties exist in the interpretation of inspection data for RC bridges. Probabilities of damage detec-

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tion for a particular inspection method are often unavailable. Also, the equipment must be used properly and inspections must be made in regions where damages are likely to occur. Some of the uncertainties, are due to the difficulties associated with isolating individual random variables. For example, consider the three-electrode linear polarization (3LP) method, which is used to determine the rate of corrosion of steel reinforcement in RC structures (Kay 1992). The 3LP device measures changes in electrical current in a given steel reinforcement bar under corrosion, and the results can be converted to the rate of change of metal loss due to corrosion. Because there are many steel reinforcement bars in close proximity to one another, one of the problems associated with the 3LP method is the isolation of individual bars for the identification of corrosion within a particular bar (Clear 1992). Another example of the problems associated with the isolation of random variables can be found when using the half-cell potential method for determining the presence of corrosion in RC structures. The results of this method are influenced by temperature (Babaei 1986), but corrosion is also temperature dependent. In addition, other variables such as moisture content influence the results (Clear 1992).

The condition of a structure and field data collection practices also have a significant influence on inspection results. For example, Marshall (1996) showed that the half-cell potential method may under- or overpredict the amount of damage in an RC bridge deck, depending on the percentage of deck area that is damaged. Other factors may influence the inspection data, or may cause the data to be rejected completely. For example, according to Babaei (1986), half-cell potential test data must be completely rejected when the concrete is frozen, due to the relatively high electrical resistance of ice.

Reported accuracies can be completely obscured by field data collection techniques. As an example, consider the chloride ion measurement method (Clear 1992). The equipment used in the field collection phase is very primitive compared with that of the laboratory testing phase. Although the accuracy of the wet chemical (laboratory) chloride ions analysis method has been reported to be within 0.5% of the chloride ion present (Berman 1972), this accuracy can be completely lost due to field collection methods and practices.

BAYESIAN UPDATING

Inspection results must often be supplemented with engineering and/or subjective judgment, particularly when the observed data are limited. Bayes theorem provides a rational method for incorporating the prior information or judgment into prediction of future outcomes. Bayesian methods are becoming increasingly popular for parameter updating and have also been applied to multiple events in the form of Bayesian networks (Normand and Tritchler 1992).

The uncertainty associated with some of the methods commonly used for acquiring bridge inspection data can be significant, particularly when the number of samples is relatively small. On the other hand, deterioration predictions based solely on data from historical records of similar bridges can be misleading, because the extent of damage to a bridge is often site-specific. One approach to the prediction of deterioration of RC bridges is to develop a baseline deterioration rate that can be updated as inspection data become available. Suppose that, historically, the rate of strength degradation of a particular class of bridges can be described by a random variable Θ. If no inspection data are available, then bridge reliability estimates could be obtained at any time t, based on degradation rate Θ. If an inspection is performed on the bridge, and the degradation rate from inspection measurements is described by a random variable X, a conditional probability density function (PDF) for the new degradation rate can be identified based on the previously assumed degradation rate and on the inspection data, $g(\underline{\theta}|\underline{x})$. The PDF represents the predicted degradation rate based on one set of inspection evidence, and can be updated each time that new inspection data become available. An expression for the updated distribution, $g(\underline{\theta}|\underline{x})$, can be defined in a Bayesian manner as follows (Martz and Waller 1982):

$$g(\underline{\theta}|\underline{x}) = \frac{f(\underline{x}|\underline{\theta})\cdot g(\underline{\theta})}{\int f(\underline{x}|\underline{\theta})g(\underline{\theta})\,d\underline{\theta}} \tag{1}$$

where $f(\underline{x}|\underline{\theta})$ = conditional PDF of $\underline{X}$ given $\underline{\theta}$ (sampling distribution); $g(\underline{\theta})$ = PDF of $\underline{\Theta}$ (prior distribution); $g(\underline{\theta}|\underline{x})$ = posterior PDF of $\underline{\Theta}$ given $\underline{x}$ (posterior distribution); $\underline{\boldsymbol{\theta}}$ = continuous parameter vector; and $\underline{x}$ = sample data.

Eq. (1) can be applied to predict a posterior distribution of degradation rate based on the previous data (prior distribution) and current inspection data (sampling distribution), and can also be applied to updating of other random variables (e.g., corrosion rate, corrosion initiation time).

TIME-VARIANT RESISTANCE AND SYSTEM RELIABILITY

In recent years, the use of time-variant methods for predicting reliability of structures has increased (Mori and Ellingwood 1994; Thoft-Christensen et al. 1997; Stewart and Rosowsky 1998a,b; Enright and Frangopol 1998b, 1999). The time-variant resistance of a structural member with respect to a given failure mode can be expressed as the product of the initial resistance and a resistance degradation function

$$R(t) = R_0 \cdot g(t) \tag{2}$$

where $R(t)$ = time-variant resistance; R_0 = initial resistance; and $g(t)$ = resistance degradation function (i.e., fraction of initial resistance of member remaining at time t). Depending on the material and environment of the structure, many degradation functions are possible (Mori and Ellingwood 1993). The resistance degradation function of an RC member can be expressed in terms of two random variables k_1 and k_2 (Enright and Frangopol 1998)

$$g(t) = 1 - k_1 \cdot t + k_2 \cdot t^2 \tag{3}$$

where t = elapsed time since corrosion initiation (years).

The cumulative-time failure probability (i.e., probability of failure over the duration (0, t_L]) of a first-failure system (also called weakest-link system because the system fails if any of its components fail) of m deteriorating members subjected to a Poisson live load process with intensity S_1 can be expressed as (Mori and Ellingwood 1993)

$$P_f(t_L)_{ser} = \underbrace{\int_0^\infty \cdots \int_0^\infty}_{m-fold} \left[1 - \exp\left(-\lambda_{S_1} t_L \cdot \left\{1 - \frac{1}{t_L}\int_0^{t_L} F_{S_1}\left[\min_{i=1}^m \left(\frac{r_i \cdot g_i(t)}{c_i}\right)\right] dt\right\}\right)\right] \cdot f_{\underline{R_0}}(\underline{r})\, d\underline{r} \tag{4}$$

where S_1 = time-variant (live) load; λ_{S_1} and F_{S_1} = mean load occurrence rate and the cumulative distribution function of S_1, respectively; $g_i(t)$ = resistance degradation function for element i; c_i = structural action coefficient for element i, and $f_{\underline{R_0}}(\underline{r})$ = joint PDF of the initial strength of the elements in the system.

COMPUTER IMPLEMENTATION

As previously mentioned, inspection data may contain a number of errors due to improper data collection methods and

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inherent uncertainties associated with a particular inspection method. The primary benefit of Bayesian updating is that all of these uncertainties can be addressed and adjusted using experience and/or prior knowledge, provided that the experience-based knowledge can be expressed numerically. To illustrate the Bayesian updating procedure, it is assumed that distributions for corrosion random variables (e.g., corrosion rate, chloride ion concentration, or corrosion initiation time) are known for a set of inspection data. The procedure for computing the main descriptors (mean, coefficient of variation) and PDF of the posterior distribution is as follows:

1. Evaluate the denominator of (1), $\int f(\underline{x}|\underline{\theta})g(\underline{\theta})\, d\underline{\theta}$, by numerical integration.
2. Compute the mean value of the posterior PDF, $E[g(\underline{\theta}|\underline{x})]$, by numerical integration.
3. Compute the coefficient of variation of the posterior PDF, $V[g(\underline{\theta}|\underline{x})]$, by numerical integration.
4. Plot $g(\underline{\theta}|\underline{x})$ versus $\underline{\theta}$ over the interval $E[g(\underline{\theta}|\underline{x})] \pm 5\sigma[g(\underline{\theta}|\underline{x})]$, where σ means standard deviation.

A general-purpose Monte Carlo simulation program developed at the University of Colorado for corrosion studies, Monte Carlo simulation for corrosion (MCSC) (Enright 1998) is used to determine the corrosion initiation time, and resistance loss function $(R_0 - R(t))/R_0$. The mean values of the degradation parameters k_1 and k_2 in (3) are determined by regression analysis using Monte Carlo simulation results with a sample size of 50,000.

The reliability of time-variant systems (RELTSYS) computer program (Enright 1998) is used to determine the cumulative-time failure probability of both individual components and systems. It is assumed that load and resistance are uncorrelated random variables. The distribution of the initial strengths of components is defined by the joint PDF $f_{\underline{R}_0}(\underline{r})$, in which the correlation among initial strengths is described by an initial resistance correlation coefficient ρ_R. The mean resistance degradation function for each element is defined using the mean values of the degradation parameters k_1 and k_2 obtained independently from MCSC. Using a combined technique of numerical integration and adaptive importance sampling, the number of simulations can be reduced by two to three orders of magnitude compared with Monte Carlo simulation. System failure probability estimates are obtained with a maximum of 10,000 simulations and 40 adaptations. The number of simulations is selected such that the computational error in the cumulative-time failure probability estimate is relatively small {i.e., $V[P_f(t_L)] < 0.02$, where V denotes coefficient of variation}.

RELTSYS uses a failure probability estimator of the form (Melchers 1987)

$$\hat{P}_f = \frac{1}{n} \sum_{k=1}^{n} \left\{ I[\ ]\, \frac{f_{\underline{X}}(\hat{\underline{\mathbf{v}}}_k)}{h_{\underline{V}}(\hat{\underline{\mathbf{v}}}_k)} \right\} \tag{5}$$

where $n = n_{\text{monte}}$ = number of trials (i.e., number of samples used for Monte Carlo simulation); $I[\ ]$ = indicator function; $f_{\underline{X}}(\ )$ = PDF in $\underline{X}$; and $\hat{\underline{\mathbf{v}}}_k$ = vector of sample values taken from the importance sampling function $h_{\underline{V}}(\ )$. The main descriptors of the importance sampling function are computed using intermediate failure probability estimates obtained during the simulation procedure, based on an adaptive scheme suggested by Mori and Ellingwood (1993).

APPLICATION TO EXISTING HIGHWAY BRIDGE

Consider the RC T-beam highway bridge shown in Fig. 1. It is located near Pueblo, Colo., and is designated as Colorado Highway Bridge L-18-BG. The bridge consists of three 9.1-m simply supported spans, and each span has five girders equally spaced 2.6 m apart. The cross section of one of these girders is shown in Fig. 2 (Frangopol and Enright 1998b).

The main descriptors for the initial resistance and load effects are indicated in Table 1. The mean and coefficient of variation of the resistance and dead load effect are based on site-specific data and information presented in MacGregor et al. (1983) and Nowak et al. (1994). However, the main descriptors of shear resistance were computed using Monte Carlo simulation based on AASHTO specifications (*LRFD* 1994). The mean and coefficient of variation of the initial (at time t = 0) live load effect are obtained from the linear regression analysis of load effects due to heavily loaded trucks (Nowak 1993) for a single lane of traffic.

The live load carried by the bridge can be determined based on the location and occurrence rate of trucks crossing the bridge. Several load cases were considered for the bridge (Enright 1998). The critical load event for the bridge is associated with two trucks with fully correlated weights placed side-by-side in lanes 1 and 2 (Enright and Frangopol 1999). It is assumed that the mean occurrence rate of this event is 1,000 times per year. The live load process is modeled as a Poisson point process, and (4) is valid for time-variant bridge system reliability analysis. Load distribution to girders is computed using the grillage method. Girder distribution factors (GDFs) were computed using the SAP computer program (*SAP* 1989).

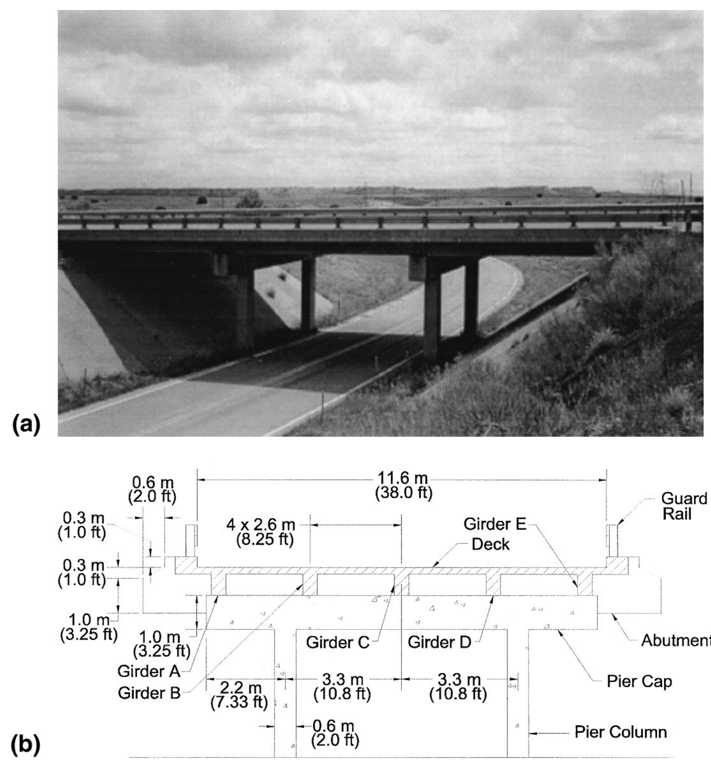

FIG. 1. Colorado Highway Bridge L-18-BG: (a) Photograph; (b) Bridge Cross Section

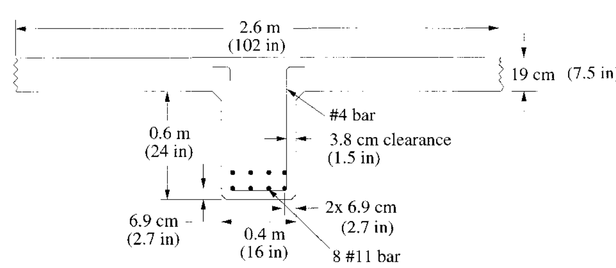

FIG. 2. Girder Cross Section of Colorado Highway Bridge L-18-BG

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TABLE 1. Initial Resistance and Load Effects

Variable (1)	Mean (kN) (2)	Coefficient of variation (3)	Distribution (4)
Initial shear resistance	776.3	0.10	Lognormal
Dead shear (bridge)[a]	498.6	0.10	Normal
Initial shear live + impact (shear per lane)[b]	158.8	0.23	Normal

[a]Dead load effect for entire bridge.
[b]Live load effect for single lane of traffic.

TABLE 2. Resistance and Corrosion Random Variables for Example Bridge

Variable (1)	Mean (2)	Coefficient of variation (3)
Steel reinforcement yield strength, f_y	310.5 MPa	0.12
Concrete compressive strength, f'_c	19.0 MPa	0.18
Initial diameter of shear reinforcement, D_{j0}	12.7 mm	0.02
Effective depth of shear reinforcement, d_v	66.30 cm	0.03
Cover depth, X	3.81 cm	0.05
Diffusion coefficient, D_c	1.29 cm^2/year	0.10
Surface chloride concentration, C_0	0.20% by weight concrete	0.10
Critical chloride concentration, C_{cr}	0.025% by weight concrete	0.10
Corrosion rate,[a] r_{corr}	0.15 mm/year	0.30

Note: All variables are assumed to have lognormal probability distributions. Short notation for this distribution $LN(\mu; \sigma)$ is used in Figs. 3–6, where μ and σ are mean and coefficient of variation, respectively.
[a]Change in diameter of steel reinforcement subjected to constant uniform corrosion.

GDFs for live shear are 0.26, 0.60, 0.64, 0.40, and 0.10 for the five bridge girders A, B, C, D, and E, respectively, shown in Fig. 1(b). GDFs for dead shear are approximately 0.20 for each of the five girders. To determine the total load effect on an individual girder, the dead and live shear GDFs are applied to the load values indicated in Table 1.

The bridge is subjected to salt spray from traffic passing under the bridge. Under this aggressive environment, strength loss is primarily due to reduction in the cross-sectional area of the reinforcement. Chloride ions enter the bridge girders at the exterior surfaces and penetrate into the concrete. The time at which corrosion begins in the shear steel reinforcement T_I can be predicted using Fick's law of diffusion [see Enright and Frangopol (1998a) for details]. Corrosion studies of concrete bridges indicate that bridge members suffer the most corrosion damage in the regions near deck joints (Novokshchenov 1989; Whiting et al. 1993). The deck joints of Colorado Highway Bridge L-18-BG are located at the abutments and at each of the three piers. Shear reinforcement begins to corrode much sooner than flexure reinforcement due to its lower depth of concrete cover. Corrosion damage occurs near the ends of the girders, where the shear demand is high. Consequently, shear is the dominant failure mode for the bridge (Enright 1998).

Resistance and corrosion random variables for the bridge are indicated in Table 2. The mean and coefficient of variation of resistance random variables were obtained from site-specific data and from data presented in the literature [Nowak et al. (1994), among others]. Values for corrosion random variables (i.e., X, D_c, C_0, C_{cr}, and r_{corr}) are based on the range of values reported for concrete bridges under corrosion (Novokshchenov 1989; Funahashi 1990; Clear 1992; Whiting et al. 1993), and are used as initial estimates for reliability analysis.

The MCSC computer program (Enright and Frangopol 1998a) is used to identify the mean values of the degradation parameters k_1 and k_2 in (3), based on AASHTO specification (*LRFD* 1994) and on the time-variant cross-sectional area of steel reinforcement. As shown in Fig. 3(a), the expected value of resistance loss $(R_0 - R(t)/R_0$ increases at a nonlinear rate. The mean values of k_1 and k_2 are 0.017 and 0.00011, respectively, as determined from regression analysis. It is interesting

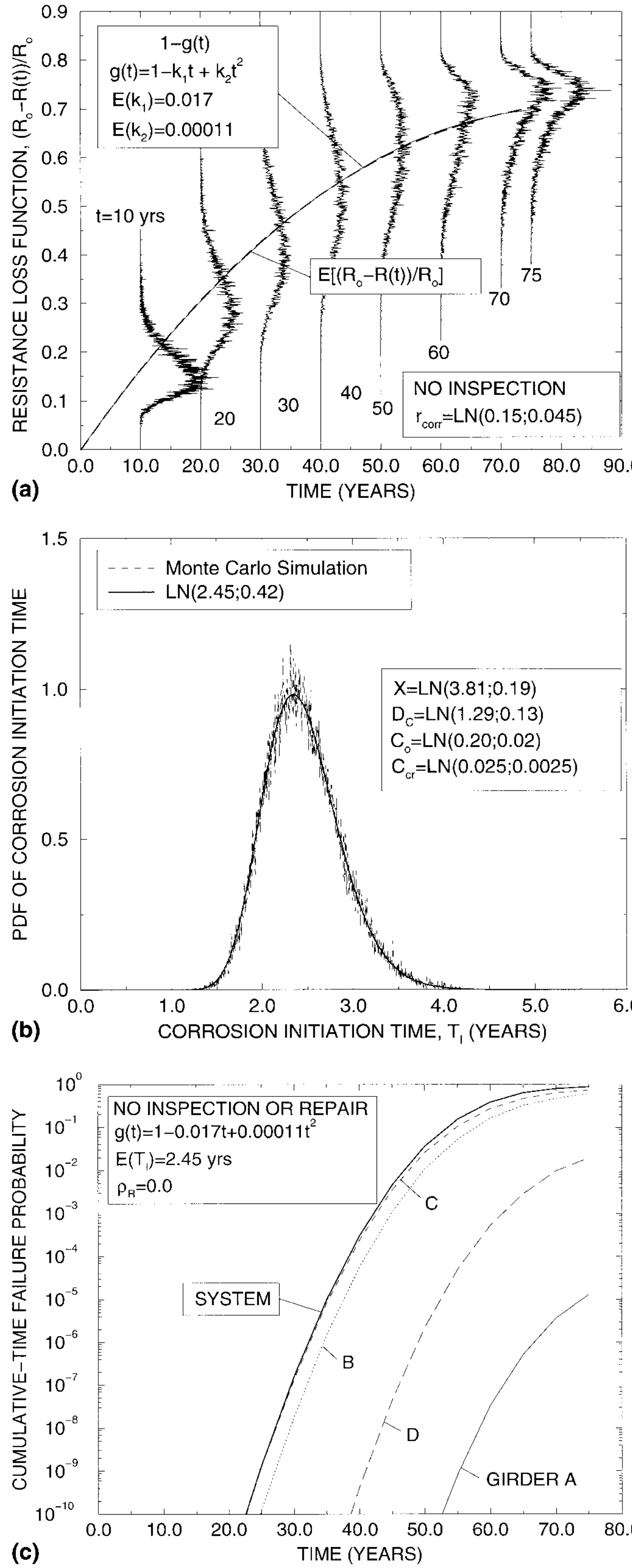

FIG. 3. Prior Data: (a) Resistance Loss; (b) Corrosion Initiation Time; (c) Time-Variant Reliability

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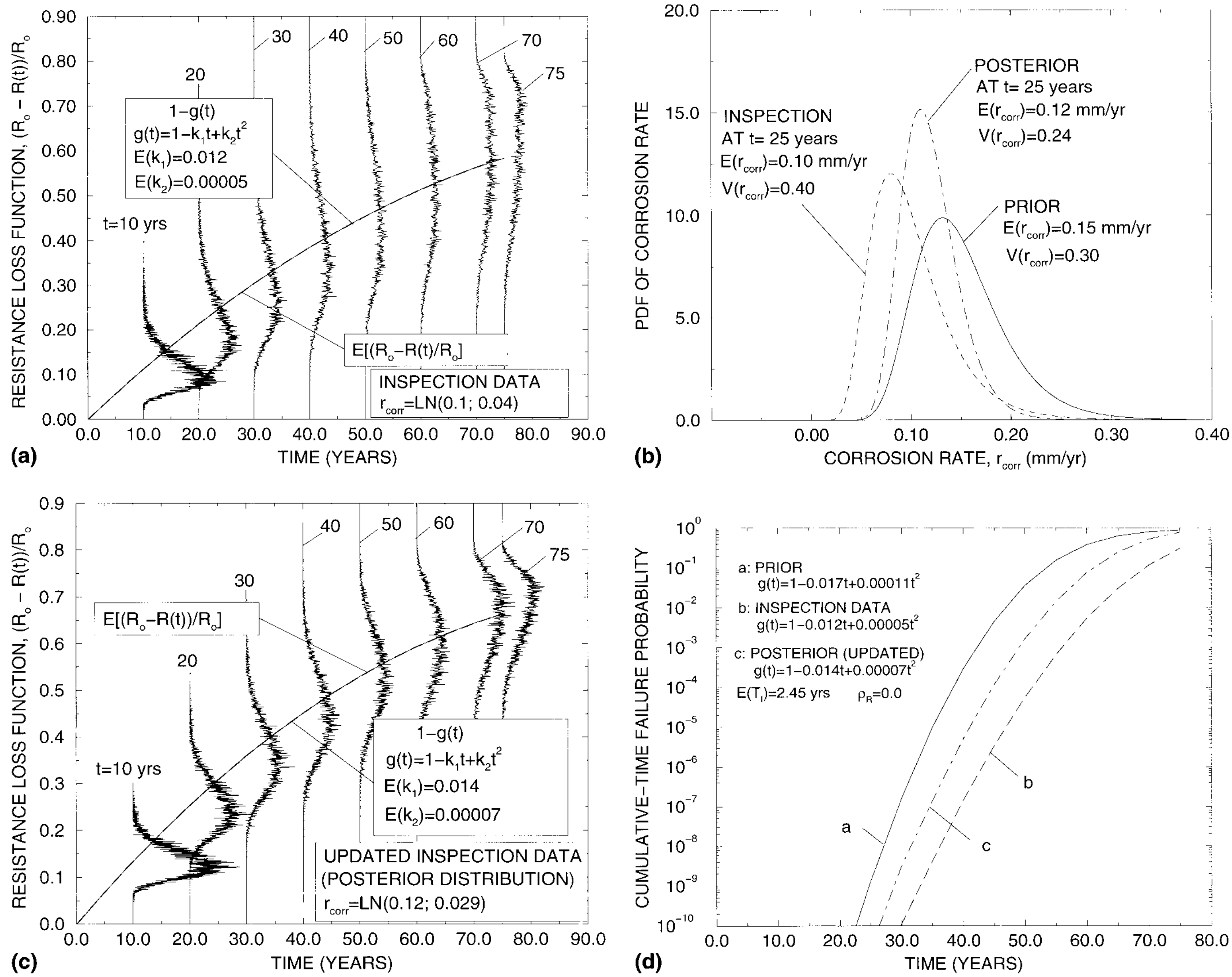

FIG. 4. Updating Corrosion Rate: (a) Resistance Loss from Inspection Data; (b) Bayesian Updating of Corrosion Rate; (c) Resistance Loss Based on Updating; (d) Prior-, Inspection-, and Posterior-Based Time-Variant System Reliability

to note that the skew of the PDF changes with time, due to the change in the area of steel reinforcement. The PDF of the corrosion initiation time identified using the MCSC program is shown in Fig. 3(b). For the values indicated in Table 2, the mean corrosion initiation time is 2.45 years, and its standard deviation is 0.42 years. The corrosion initiation time appears to be lognormally distributed, which is consistent with previously reported results (Enright and Frangopol 1998a).

Using the RELTSYS computer program (Enright 1998), the cumulative-time failure probabilities are computed for the girders as shown in Fig. 3(c) (note: The failure probability of girder E is less than 10^{-10} over the life of the structure and is not shown). The girder failure probabilities shown in Fig. 3(c) are based solely on estimates for the parameters identified in Figs. 3(a and b) (i.e., the influences of site-specific inspection data are not included). Girder C has the highest probability of failure. The failure probability of the first-failure system [(4)] is also shown in Fig. 3(c), and is slightly higher than that of the critical girder due to the assumption that girder strengths are independent.

INSPECTION UPDATING

When inspection data are available, bridge condition can be predicted based on these data only. For example, suppose that a single inspection of the girders is performed sometime during the lifetime of the bridge (say, t = 25 years). For illustrative purposes, suppose that a corrosion rate inspection is performed, and it is found that the corrosion rate is lognormally distributed with a mean corrosion rate $E(r_{corr})$ of 0.10 mm/year and a coefficient of variation $V(r_{corr})$ of 0.40. Assuming that no other information is available, the corrosion is defined to be uniform and constant with time. Using the MCSC program and regression analysis, the mean values of the degradation parameters k_1 and k_2 are computed to be 0.012 and 0.00005, respectively, as shown in Fig. 4(a). Using these strength degradation parameters, cumulative-time failure probability estimates of the bridge system (4) can be computed as shown in Fig. 4(d).

Suppose that, in addition to the inspection data, additional corrosion rate information is available (e.g., data from similar nearby bridges, previous experience). An estimate of the posterior corrosion rate can be obtained using Bayesian updating. In Fig. 4(b), distributions are shown for corrosion rates based on inspection data [Fig. 4(a)] and prior information (based on data indicated in Table 2). The posterior corrosion rate shown in Fig. 4(b) is computed using (1). Both the inspection and the prior distributions can have a dominant influence on the posterior distribution, depending on the value of the corrosion rate. For example, in the region where r_{corr} is less than 0.05 mm/year, the density of the prior distribution has relatively small values. The density of the posterior distribution is also relatively small in this region, due to the influence of the prior distribution on the final outcome.

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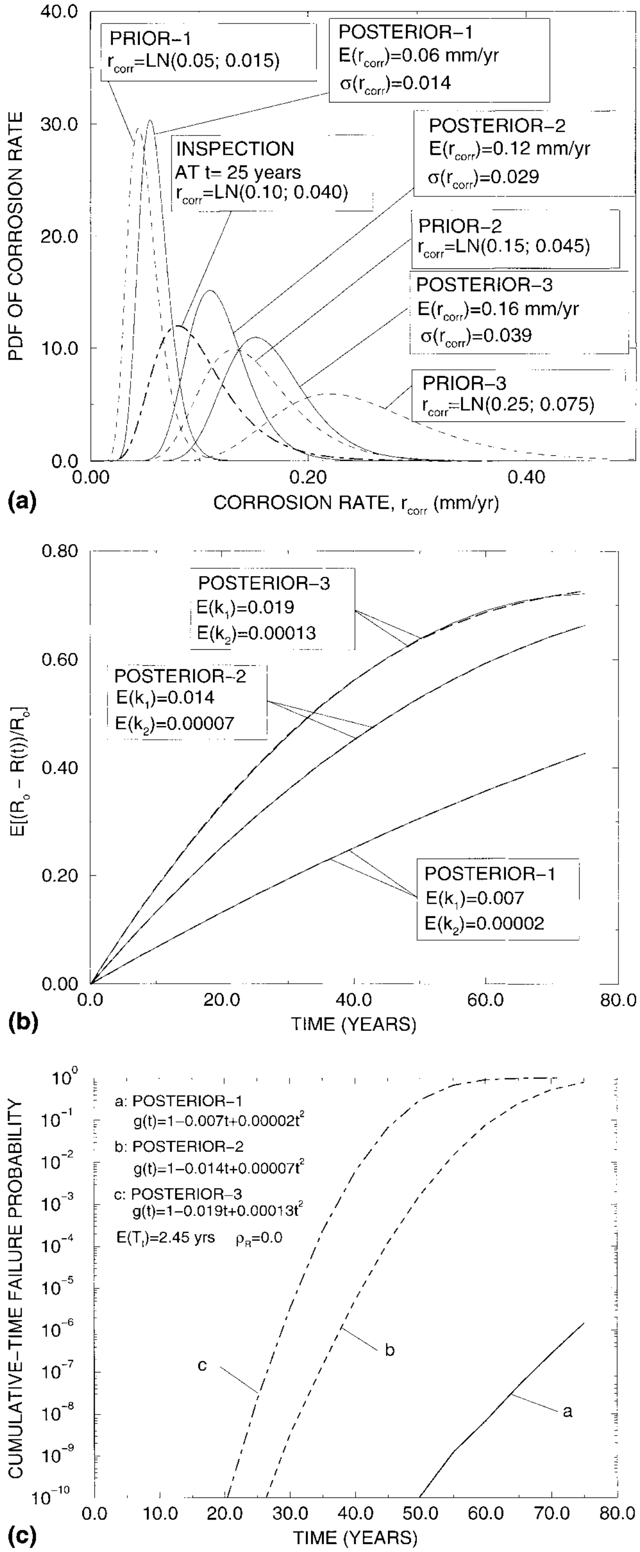

FIG. 5. Influence of Prior Information on Corrosion Rate Updating: (a) Bayesian Updating; (b) Degradation Parameters k_1 and k_2 for Posterior Distributions; (c) Posterior-Based Time-Variant System Reliability

Using the main descriptors for corrosion rate from the posterior distribution, new values can be computed for the degradation parameters k_1 and k_2 in (3). In Fig. 4(c), the mean values for k_1 and k_2 are shown to be 0.014 and 0.00007, respectively, for the updated (posterior) distribution. The effects of inspection and inspection updating on the cumulative-time failure probability of the bridge system [(4)] are shown in Fig. 4(d). For this example, use of the prior distribution tends to predict failure probabilities that are higher than those predicted using only the inspection data. It is interesting to note that the influence of the difference in corrosion rates is less significant for the more heavily loaded girders (i.e., B and C) than for the other girders in the system (see Enright 1998 for details).

TABLE 3. Main Descriptors of Corrosion Rate for Inspection Updating

Prior distribution (1)	Mean (mm/year) (2)	Standard deviation (mm/year) (3)
PRIOR-1	0.05	0.015
PRIOR-2	0.15	0.045
PRIOR-3	0.25	0.075

The influence of the prior information on updated inspection outcomes is illustrated in Fig. 5 for the three prior lognormal distributions indicated in Table 3. As shown in Fig. 5(a), the prior distribution can have a significant effect on the shape of the updated (posterior) distribution, particularly if the prior distribution has a relatively low standard deviation (e.g., PRIOR-1 distribution). The expected values of the degradation parameters k_1 and k_2 are shown in Fig. 5(b) for the three posterior distributions considered. System failure probabilities associated with the three degradation functions based on posterior distributions 1, 2, and 3 in Fig. 5(a) are shown in Fig. 5(c). As indicated, the selection of the prior distribution has a significant influence on the system failure probability.

In Fig. 6, the effect of updating the corrosion initiation time is shown for chloride ion concentration measurements for two separate sets of inspections (Inspection A and Inspection B). The main descriptors for the equilibrium chloride concentration at the concrete surface C_0 are indicated for each of these inspections in Fig. 6(a). The main descriptors for the diffusion related variables (e.g., depth of cover X, diffusion coefficient D_c, critical chloride concentration C_{cr}) are also shown in Fig. 6(a). Using the MCSC program, the mean corrosion initiation times $E(T_I)$ are found to be 3.66 and 5.91 years for inspections A and B, respectively. In Fig. 6(b), the two inspections are updated using numerical integration, based on the prior distribution for corrosion initiation [Fig. 3(b)]. For this example, the prior distribution has a large influence on the posterior distribution, particularly for inspection B. For this inspection, the effects of the initial and updated corrosion initiation times on the cumulative-time failure probabilities of the system are shown in Fig. 6(c). Differences between failure probabilities associated with the prior, inspection B, and the posterior distributions are relatively small for all cases considered.

A comparison of the degradation functions and failure probabilities associated with the inspection updating scenarios is shown in Fig. 7. As shown in Fig. 7(a), the mean value of the degradation function $E[g(t)]$ is influenced more by updating the corrosion rate than by updating the corrosion initiation time. Also, if both the corrosion initiation time and corrosion rate are updated, $E[g(t)]$ is not significantly different as compared with the case where only the corrosion rate is updated. A comparison of the influences of inspection updating on failure probability is shown in Fig. 7(b). Similar to Fig. 7(a), updating the corrosion rate has much more influence on the failure probability than updating the corrosion initiation time.

CONCLUSIONS

The following conclusions can be drawn from this study:

1. When no inspection data are available, engineers must often resort to empirical models or predictive equations to estimate the remaining strength of deteriorating bridges. When inspection data are available, predictions

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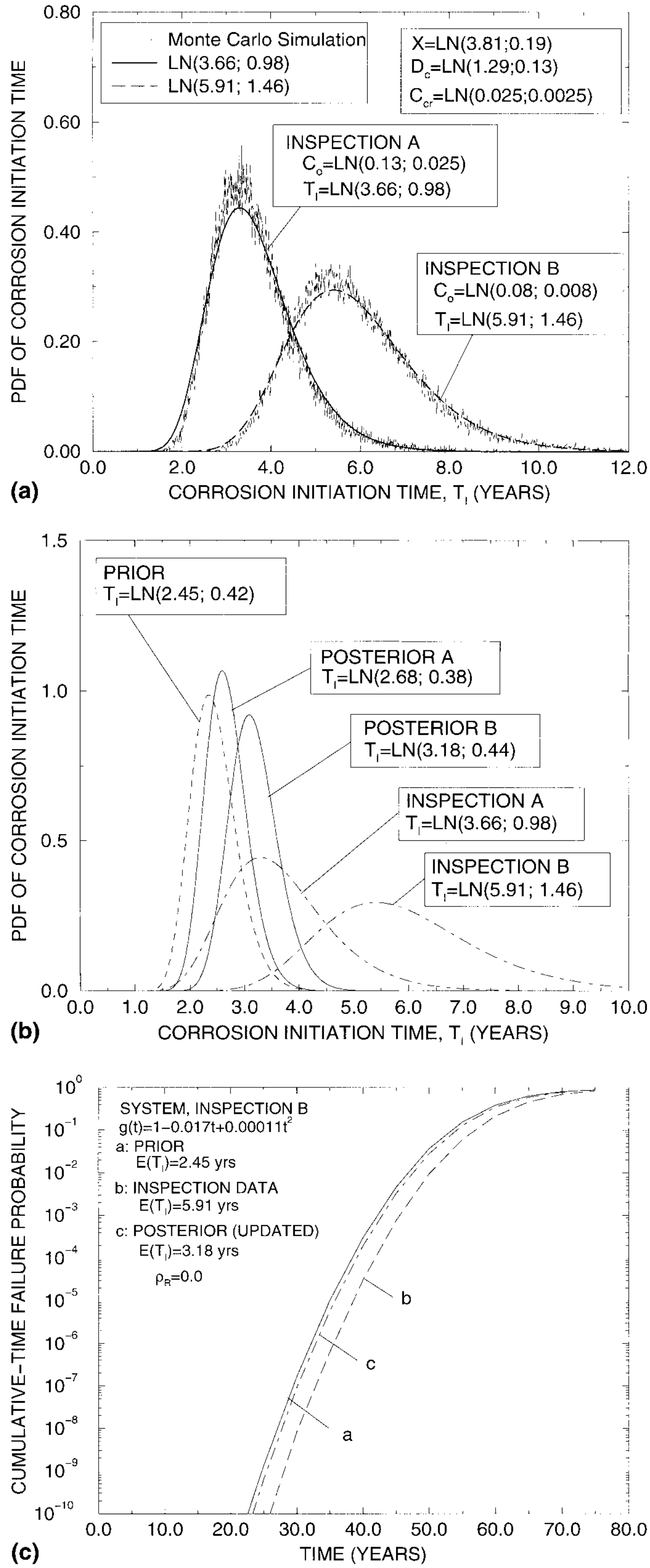

FIG. 6. Updating Corrosion Initiation Time: (a) Corrosion Initiation Time; (b) Bayesian Updating of Corrosion Initiation Time; (c) Prior-, Inspection-, and Posterior-Based Time-Variant System Reliability

based solely on these data may be unrealistic, particularly if uncertainties, including model uncertainties, are not considered. A method was shown for incorporating prior information into probabilistic strength loss predictions and time-variant reliability estimates of deteriorating bridges using Monte Carlo simulation, regression analysis, numerical integration, and adaptive importance sampling. The approach presented allows accounting for inspection results in the quantitative assessment of condition of bridges and shows how to incorporate quantitative information into bridge component and system condition prediction.

2. Several examples were presented that illustrate the inspection updating procedure for parameters that are obtained using traditional bridge inspection methods. The results can be used for the development of sensitivity studies with the objective of identifying inspection methods that provide the best balance between inspection uncertainty and inspection cost.
3. The inspection updating approach shown in this study is not tied to a specific inspection technique, and is applicable to a wide range of nondestructive evaluation methods. However, this approach relies on the availability of both sampling and prior distributions. Further research is necessary to develop these distributions so that they can be used in practice by State Transportation Departments. Quantitative assessments based on these distributions can be updated as new data become available.
4. The results presented are only valid in the context of the stated assumptions. They can be used as a guide for lifetime maintenance planning efforts for RC bridges subjected to strength degradation using inspection updating. This study illustrates a method for computing strength degradation using a probabilistic approach, and for up-

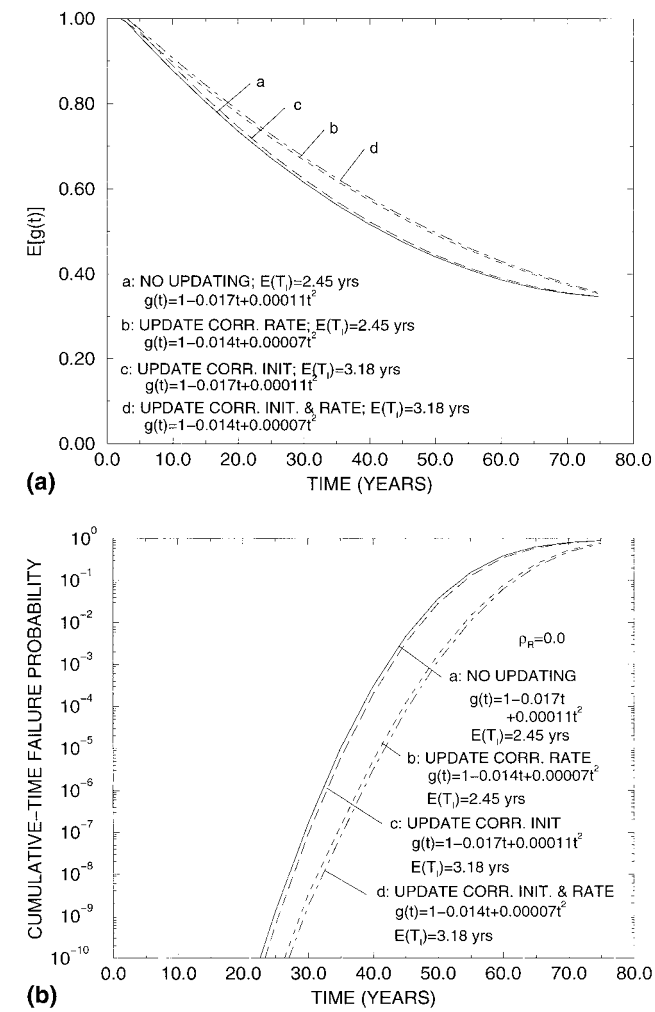

FIG. 7. Summary of Inspection Updating: (a) Resistance Degradation Function; (b) Time-Variant System Reliability

dating strength degradation predictions using Bayesian methods. The influence of updating on time-variant system failure probability is illustrated for an existing RC highway bridge. The updating methods illustrated may be applied to other bridge types, and may be particularly useful when inspection data are scarce.

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