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Advanced Modeling for Efficient Computation of Life-Cycle Performance Prediction and Service-Life Estimation of Bridges

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Abstract: The rapid progress in computational hardware and software has brought about advanced capabilities enabling more accurate modeling of structures and better understanding of their lifetime behavior. Unfortunately, research in life-cycle performance prediction and service-life estimation of bridges has not fully caught up with the impressive advances in today's technology, and has not taken enough advantage of the power offered by these advances. In this paper, a computational methodology for the life-cycle prediction and service-life estimation of bridges using advanced modeling tools and techniques is presented. The methodology employs incremental nonlinear finite element analyses, quadratic response surface modeling using design of experiments concepts, and Latin hypercube sampling, among other techniques. The methodology is illustrated on an existing bridge in the state of Wisconsin.

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Introduction

In the United States alone, the budget estimated by the ASCE to bring the state of the nation's infrastructure to a good condition has increased from \$1.6 trillion in 2005 (ASCE 2005) to \$2.2 trillion in 2009 (ASCE 2009). This alarming fact emphasizes that the reduction of the number of deficient bridges is faced with serious financial constraints. It becomes vital to asses the highway infrastructure with the highest accuracy possible. Accordingly, the optimum allocation of funds for the upkeep of highway infrastructure is ensured.

The rapid progress in computational hardware and software has brought about advanced capabilities enabling more accurate modeling of structures and better understanding of their lifetime behavior. Unfortunately, research in life-cycle performance prediction and service-life estimation of bridges has not fully caught up with the impressive advances in today's technology, and has not taken enough advantage of the power offered by these advances.

The assessment of reliability of structural systems based on component reliability leads either to a considerable waste of resources because of overconservatism in evaluation of redundant structural systems or to overestimation of the actual load-carrying capacity of nonredundant structural systems (Hendawi and Frangopol 1994). On the other hand, the true performance of a whole structure can be evaluated by accurate assessment of its structural system reliability (Estes and Frangopol 1999).

To compute the system reliability, Estes and Frangopol (1999) and Akgül and Frangopol (2004a,b, 2005) used AASHTO guidelines to formulate limit-state functions for the components of various bridge systems against different failure modes. The system reliability was then computed by establishing a series-parallel model for an assumed failure scenario for the structural systems. The shortcoming in this approach is clearly the need to assume a model for system failure. System reliability methods that provide more insight into the possible failure scenarios of the system such as the incremental method (Moses 1982; Rashedi and Moses 1983, 1988; Tang and Melchers 1988; Okasha and Frangopol 2010), the member replacement method (Hendawi and Frangopol 1994), the linear programming search, and the β-unzipped methods (Thoft-Christensen and Murotsu 1986) have not been proven to be practical enough to be implemented in complex bridge structures.

Recently, the use of incremental nonlinear finite element analyses (INL-FEA) in the computation of system reliability of bridge structures has emerged in part due to the advances attained in the finite-element (FE) field and its commercial software and the rapid increase in the speed and power of computers. Using INL-FEA accurately allows for the prediction of the resistance of the entire system, where all components are acting together under a given loading condition. In this approach, the specified loading is applied incrementally until a failure mode occurs and the resistance of the structural system is the load at which the failure mode occurs. In fact using this approach, serviceability as well as ultimate limit states can be considered accordingly.

In this paper, a methodology for the life-cycle prediction and

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service-life estimation of bridges using advanced modeling tools and techniques is presented. The methodology employs INL-FEA, quadratic response surface (RS) modeling using design of experiments concepts, and Latin hypercube sampling, among other techniques. The methodology is illustrated on an existing bridge in Wisconsin.

The steps of the presented methodology are: (1) build the FE model; (2) generate the response envelope; (3) forecast the average daily traffic (ADT); (4) perform statistics of extremes for finding the live-load multiplier; (5) perform the RS analysis; (6) perform the Latin hypercube sampling for resistance computations; (7) compute the point-in-time reliability; (8) compute the cumulative-time failure probability; and (9) compute the life-cycle performance and the service-life. The remaining sections of this paper describe the details of these steps.

Modeling of Bridge System Resistance

Assuming that the live-load applied has the configuration of the AASHTO HS-20 (AASHTO 2002) vehicle, the bridge resistance at point in time t is the HS-20 truck weight multiplied by a factor $LF(t)$, which produces the load at which the bridge collapses or large vertical deformations rendering the bridge unfit for use are reached, whichever occurs first. Accordingly, the instantaneous probability of failure can be generally represented by an equation of the form (Ghosn et al. 2010)

$$P_f(t) = P[LF(t) < LL(t)] \tag{1}$$

where $LL(t)$=expected normalized maximum live-load effect that will be applied on the superstructure within the appropriate return period until time t. The limit chosen for the vertical deformations was determined as 0.01 and 0.0075 of the span in Ghosn et al. (2010) and Czarnecki and Nowak (2008), respectively. The latter limit is conservatively used in this study.

For condition assessment and service-life prediction, the probability of satisfactory performance over a service or interinspection period is a more relevant indicator of performance (Ellingwood 2005). For this purpose, the cumulative-time failure probability of a component during a period of time t_L can be calculated as (Mori and Ellingwood 1993)

$$F(t_L) = 1 - \int_0^{\infty} \exp\left[- \lambda t_L \left[1 - \frac{1}{t_L} \int_0^{t_L} F_s\{r \cdot g(\xi)\} d\xi \right] \right] f_{R_0}(r) dr \tag{2}$$

where R_0=initial resistance; $f_{Ro}(r)$=probability density function (PDF) of R_0; $g(t)$=mean value of the degradation function $G(t)$; λ=with mean occurrence rate of the applied load whose occurrence is described by a Poisson process; and $F_s(s)$=cumulative distribution function (CDF) of the applied load. Eq. (2) usually must be evaluated numerically by Monte Carlo simulation (MCS) for realistic deterioration mechanisms (Ciampoli and Ellingwood 2002). Even though Eq. (2) is component-oriented, it is used in this study for evaluating the cumulative-time failure probability of the system, where the resistance variables are those of the resistance of the entire system acting as a unit and the load effect is that acting on the entire system. Eq. (2) is used to estimate the service-life of structures under uncertainty.

In this paper, Eq. (1) is solved with the second-order reliability method using the program CALREL (Liu et al. 1989) and Eq. (2) is solved using the program RELTSYS (Enright and Frangopol 2000). The degradation in resistance over time is primarily caused by section loss due to uniform corrosion penetration. The degradation function is developed using regression of the INL-FEA responses under uncertainty for the bridge over time and considering the cross section losses due to corrosion.

Treatment of Uncertainties

Even though the INL-FEA is the ideal method for predicting the true system behavior, it can still be computationally expensive. Furthermore, the computational expense of using INL-FEA in reliability analyses is significantly amplified due to the need to treat the uncertainties. The INL-FEA obtained strength has been treated in various studies as an independent random variable (i.e., independent of the geometric and material properties of the system), and the system reliability is computed in the reduced random variable space using methods such as the first-order reliability method (FORM) (Ghosn et al. 2010; Ghosn and Moses 1998; Liu et al. 2000). The mean value of the system resistance is obtained from the results of INL-FEA by using of the means for all the random variables related to the geometric and material properties of the system. The coefficient of variation of the system resistance is established based on engineering judgment, experience, and statistical analyses.

The highest accuracy in evaluating the system reliability is obtained in the original or full random variable space. This can be done using a MCS of the INL-FEA. Unfortunately, the high reliability associated with practical structural engineering applications demands an enormous number of simulations to accurately compute the system reliability. Even with current day advances in computational technology, MCS of INL-FEA is too expensive and impractical. Strauss et al. (2008) implemented a hybrid approach to a bridge structure in which: (1) the probabilistic distribution of the resistance is generated through Latin hypercube sampling (Olsson et al. 2003) of the INL-FEA considering all random variables of the system and (2) the reliability is calculated using FORM. Latin hypercube sampling is an intelligent alternative to simple random sampling, and a special case of stratified random sampling, which yields a more representative distribution of model outputs (in terms of smaller sampling variability of their statistics) for the same number of input simulated realizations (Kyriakidis 2005). Alternatively, Czarnecki (2001) used the Rosenbluth $2n+1$ method to obtain the mean and standard deviation of the bridge resistance.

The RS method has also been implemented in system reliability of bridge substructures (Liu et al. 2000), superstructures (Ghosn and Moses 1998), and bridge systems (Ghosn et al. 2010, 1993a,b; Moses et al. 1993). The RS method consists of executing INL-FEA analyses at predetermined values of the random variables and uses the results of the FE analysis to generate an approximate closed-form expression of the response. Regression, interpolation or first-order Taylor series expansion is used to generate the RS expression (Ghosn et al. 2010).

Thus far, only linear RS expressions for bridge structures have been implemented. The RS expression is treated as the system resistance and the system reliability is calculated using FORM. Ghosn et al. (2010) have expanded the Taylor series around the means of the random variables considered. They also used regression to develop the RS expression and used the support points found by perturbing the random variables by one standard deviation around their means one at a time. In both cases above, clearly a small number of points are needed to generate the linear RS expression.

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Higher order RS expressions evidently provide higher accuracy to the solution. In addition, the interaction terms that are left out in the linear RS expression provide further insight into the system behavior. However, developing a higher order RS expression requires generation of many more support points. This requires additional computational expenses and tedious modifications of the input parameters and extraction of the responses for the INL-FEA. Furthermore, an informed decision to which support points (i.e., the points at which the model is analyzed) to generate has to be made.

In this paper, quadratic RS expressions with interaction terms are developed for a bridge structure. A high speed workstation is used to overcome the computational expense issues, design of experiments are used to effectively select the support points, and efficient software automatic interaction is used to overcome the need for manual user interference between the large number of analyses at the support points generated.

Design of Experiments for RS Analysis

The generation of a RS function is conducted by fitting a mathematical expression to the outcomes of an experimental or numerical model as a function of input variables to this model. The reason for this procedure stems from the high expenses associated with conducting the experiment or simulating the numerical model. Depending on the selected RS model, support points for each of the design variables (i.e., the random variables in reliability applications) have to be chosen to estimate the unknown parameters of the RS expression in a sufficient way. In general, this is done by applying predefined schemes. These predefined schemes are combinations of the input variables, each of which is a point in the n-dimensional design space. The particular arrangement of points in the design space is known as an experimental design or design of experiments. The central composite design (CCD) offers the opportunity for fitting a quadratic RS model (*VisualDOC, design optimization software version 5.1; theoretical manual* 2005). This method is used in this paper.

In this paper, the RS terms include linear, quadratic and interaction terms. Such model captures accurately the dependence of the response on each of the design variables and the effect of the interactions among the design variables on the response. However, in this case, the number of terms in the RS model can become very large. There are several strategies for selecting an appropriate subset of terms in the RS model. The most widely used methods are forward selection, backward elimination, and stepwise regression (*VisualDOC, design optimization software version 5.1; theoretical manual* 2005). The forward stepwise regression is used in this paper.

In order to obtain the PDF of the initial resistance $f_{Ro}(r)$, a simulation is performed for the RS expression to compute the descriptors of this distribution. Although MCS is possible, in this paper, Latin hypercube simulation is performed for its higher efficiency and need for a lower number of samples, leading to a less computational cost.

Modeling of Bridge Loading

The loading of the FE bridge model takes place in two steps. In the first step, the dead loads are applied. In the second step, the live-load is applied incrementally until the stopping threshold is crossed, while the loads of the first step (i.e., the dead loads) are kept constant. The live-load configuration is that of two side-by-side HS-20 trucks (Ghosn et al. 2010; Czarnecki 2001). Each of the truck dual wheels is modeled by a concentrated load. The magnitude of these concentrated loads is progressively incremented in proportion to the HS-20 truck configuration. This loading configuration is shown in Fig. 1.

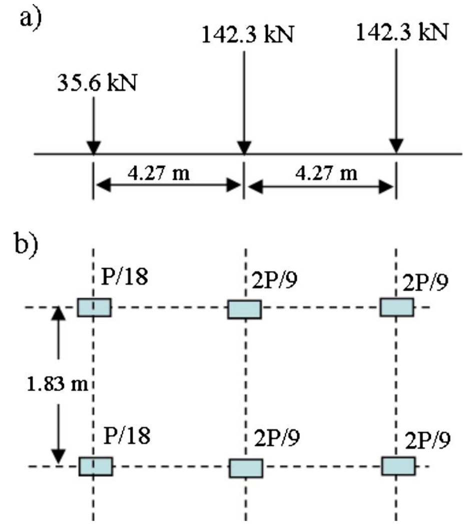

Fig. 1. Loading: (a) standard HS-20 truck loading; (b) its modeling configuration in the incremental nonlinear FE analysis

The critical position of the two trucks has to be determined. Longitudinally, they are applied in the position causing maximum bending moment. In this study, a continuous multispan bridge is investigated. The location of the truck load is determined using the girder FE model. This model is entirely composed of shell elements in ABAQUS, which does not provide influence lines or envelopes anyways. Therefore, a point load is applied at the middle of the top flange, one node at a time and at each time the maximum vertical displacement is extracted and saved. An envelope of the displacement due to a moving point load is provided by this analysis and used to longitudinally position the two trucks.

The transverse position of the trucks is also a key parameter in the analysis. Ghosn et al. (2010) positioned the two trucks such that the outermost wheels of the exterior truck are over the exterior girder. Czarnecki and Nowak (2007) treated the transverse position of the truck within the roadway (curb distance) as a random variable. The variation in transverse traffic position was based on a survey on interstate highways in southeastern Michigan. The PDF was approximated by a lognormal distribution with a coefficient of variation of 0.33 and mean one-fourth of the lane width (Czarnecki and Nowak 2007). However, the reliability analysis was conducted for a number of selected transverse positions, one at a time, and the weighted average of the reliability index was calculated based on the distribution of the curb distance (Czarnecki and Nowak 2007).

In this paper, the curb distance random variable is treated as one of the support variables used in constructing the RS model. In other words, the relationship between the bridge response and the curb distance random variable is explicitly taken into account in the RS expression. In order to do so, the point loads have to be relocated systematically for each different value of the curb distance chosen in the RS analysis. For this reason, the FE model is meshed such that nodes are available for a number of different positions of the two trucks, where the wheel loads of the truck can be applied. The nodes are grouped in node sets according to their

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location with respect to a given truck position. The nodes corresponding to the front axels are in separate sets from the nodes corresponding to the rear axels (see Fig. 1). The node sets are labeled with the value corresponding to the distance between the outermost wheels and the curb. For a given value of the curb distance, this value is entered by *VisualDOC, design optimization software version 5.1, how to manual* (2006) in the node sets where the loads are applied, inside the ABAQUS input file, and accordingly the transverse position of the two trucks is modified. In VisualDOC, the curb distance variable is treated as discrete having the set of values of truck positions decided.

In order to conduct the time-dependent reliability analyses, the changes in the live-load over time need to be predicted. The live load multiplier at a time t, $LL(t)$, is calculated using statistical theory of extremes. Details of such analysis for use in bridge time-dependent reliability can be found in Estes (1997). In this analysis, a live- load model is developed based on available truck survey data performed by the Ontario Ministry of Transportation covering about 10,000 selected trucks (Nowak 1999). The relevant data are extracted from the curves provided in Nowak (1999) and extrapolated over the period required for the reliability using extreme value statistics. In addition, the cumulative-time failure probability as calculated by Eq. (2) requires the rate of occurrence of the live-load, λ, as input. This information can be obtained from historical traffic records of the bridge. A procedure for forecasting the traffic using the historical records for the predefined service-life is outlined in National Cooperative Highway Research Program (NCHRP 2005).

System Performance and Service-Life Estimation

Once the system resistance expression and live-load model are developed, different life-cycle performance indicators can be computed. The instantaneous probability of failure can be computed by Eq. (1). The point-in-time reliability index, $\beta(t)$ can be calculated by

$$\beta(t) = \Phi^{-1}[1 - P_f(t)] \tag{3}$$

where Φ=CDF of the standard normal distribution.

Lifetime functions have been used in bridge life-cycle management and maintenance optimization problems (Yang et al. 2004, 2006a,b). Using lifetime function representations, several life-cycle properties can be quantified. Thus far, lifetime functions have been derived based on historical data of failure or defect occurrence in stocks of bridges and/or bridge components (Maunsell Ltd. 1999; van Noortwijk and Klatter 2004). For instance, an appropriate distribution function is fitted to the database of the times to failure of bridges from the same type. This provides the first lifetime functions representation, PDF of the time-to-failure $f(t)$. Even though this derivation provides a useful probabilistic indication of the overall performance of a given structure with reference to other similar structures, it may not explicitly take into account the unique properties of this structure. In this study, a different approach is proposed. One of the representations of the lifetime functions is the cumulative-time failure probability. It is the probability that a component or structure will fail before time t_f and is calculated by integrating the PDF of the time-to-failure as

$$F(t_f) = P(T \le t_f) = \int_0^{t_f} f(u)du \tag{4}$$

The cumulative-time failure probability can also be calculated using Eq. (2). This is justified since both Eqs. (2) and (4) have the same failure definition (i.e., they provide the probability of failure during a period of time). However, unlike Eq. (4), Eq. (2) does take into account the unique properties of the component or structure, since it makes use of information regarding the resistance and load effects for the structure itself. The cumulative-time failure probability at many points-in-time is first generated using the RELTSYS program (Enright and Frangopol 2000). This program uses a combined technique of adaptive importance sampling, numerical integration, and fault tree analysis to compute time-dependent reliabilities of individual components and systems. Time-invariant quantities are generated using MCS, whereas time-dependent quantities are evaluated using numerical integration (Enright and Frangopol 2000). Having the cumulative-time failure probability results from RELTSYS, an appropriate CDF is fitted to these values using the method of least-squares, where the parameters of the distribution are determined by solving the following optimization problem (Bucher 2009)

$$\text{Find:parameters vector } \boldsymbol{p} = \{p_1, p_2, \ldots p_n\} \tag{5a}$$

$$\text{To minimize:} s = \sum_{i=1}^{l} [F(t_i) - F^*(t_i, p)]^2 \tag{5b}$$

where $t_i = 1, 2, \ldots, l$=times at which the cumulative-time failure probability are calculated; $F^*(t_i, p)$=fitted CDF at time t_i with parameters p; and $F(t_i)$=cumulative-time failure probability computed by RELTSYS. Eq. (5) is solved for several distributions. The goodness of fit is determined using the coefficient of determination R^2 statistic (Bucher 2009)

$$R^2 = 1 - \frac{s}{\sum_{i=1}^{m} [F(t_i)]^2} \tag{6}$$

The R^2 statistic takes values between 0 and 1, where the closer to 1, the better the fit. The distribution with the highest R^2 value is the one chosen for fitting the cumulative-time failure probability. The most common distribution to be fitted for components of decaying resistance is the Weibull distribution (Ramakumar 1993; Leemis 1995; Hoyland and Rausand 1994). The CDF of the Weibull distribution is calculated as

$$F^*(t) = \begin{cases} 1 - e^{-(\lambda_s t)^\kappa} & \text{for } t > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where λ_s=scale parameter and κ=shape parameter (i.e., $p_1 = \lambda_s$ and $p_2 = \kappa$).

Using the obtained CDF, the other lifetime representations can be obtained. For instance, the survivor function up to time t_f, $S(t_f)$, is defined as the probability that a component or system survives up to time t_f and is calculated as (Leemis 1995)

$$S(t_f) = P(T > t_f) = 1 - F(t_f) \tag{8}$$

The time-to-failure PDF is calculated as

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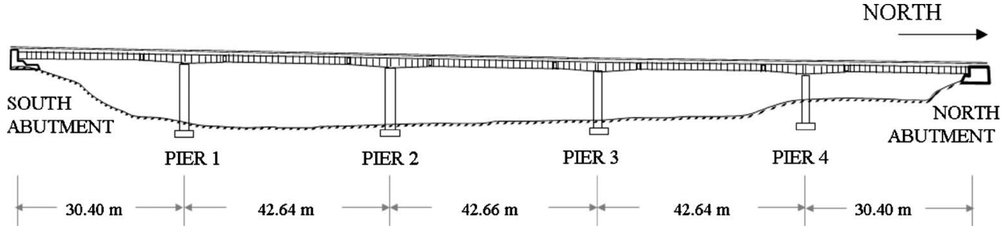

Fig. 2. Elevation of the north bound bridge over the Wisconsin River

$$f(t) = \frac{d}{dt}F(t) \tag{9}$$

The hazard function provides a measure of the instantaneous failure rate. It is defined as the conditional probability that given a component, or structure, has survived until time t it will fail in the time interval $t+dt$ (Ramakumar 1993) and is calculated as (Leemis 1995)

$$h(t) = \frac{f(t)}{S(t)} = -\frac{dS(t)}{dt}\frac{1}{S(t)} \tag{10}$$

The cumulative failure rate from the time the component is put in service until the time t can be estimated by the cumulative hazard function, which is calculated as (Leemis 1995)

$$H(t) = \int_0^t h(u)du \tag{11}$$

The estimation of the service life of a structure is a process fraught with many uncertainties. It is impossible to provide a solid deterministic answer to when the structure will fail. At best, the probability that the structure will live for t_f number of years can be calculated. This can be achieved using Eq. (8). Alternatively, by drawing a profile for the cumulative-time failure probability using Eq. (2) or Eq. (4), the service-life of the structure can be read from this figure for a given cumulative-time failure probability. Also, the mean time to failure (MTTF) can be calculated. For a structure with time-to-failure modeled by a Weibull distribution, the MTTF can be calculated as (Hoyland and Rausand 1994)

$$\mathrm{MTTF} = \int_0^\infty S(t)dt = \frac{1}{\lambda_s}\cdot\Gamma\left(\frac{1}{\kappa}+1\right) \tag{12}$$

where Γ=gamma function which is calculated as

$$\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt \tag{13}$$

and the standard deviation of the time to failure (SDTTF) is (Hoyland and Rausand 1994)

$$\mathrm{SDTTF} = \frac{1}{\lambda_s^2}\cdot\left(\Gamma\left(\frac{2}{\kappa}+1\right)-\Gamma^2\left(\frac{1}{\kappa}+1\right)\right) \tag{14}$$

Case Study: I-39 Bridge over the Wisconsin River

The I-39 Bridge is located near Wausau, Wisconsin, and carries US-51 and I-39 north bound over the Wisconsin River. It is a five-span continuous steel girder bridge and was opened to traffic in 1961. It crosses the Wisconsin River from the Village of Rothschild on the southeast side, to the town of Weston, Marathon County on the northwest side. The bridge is symmetrical about the midpoint of the third span and has a total length of 196 m. Fig. 2 shows an elevation of the north bound bridge over the Wisconsin River. The superstructure of the bridge is composed of four composite steel plate I-section girders carrying a reinforced concrete slab and the girders are tapered over the piers.

A nonlinear FE model was first built in ABAQUS. Material and geometric nonlinearities are both considered. All elements in this model are eight-node doubly curved thick shell elements with reduced integration, S8R (ABAQUS 2005). The model assumes a complete connection between girders and concrete slab with no slip. The reinforcement is represented by uniformly distributed layers of steel. A mesh convergence study was performed to determine an appropriate mesh configuration. However, the transverse node distribution of the deck was dictated by the arrangement of the HS-20 wheel loads at the various loading positions chosen. Accordingly, a 0.45 m (18 in.) spacing was used in the node distribution for the deck in the transverse distribution. Fig. 3 shows the mesh of the FE model of the south half of the bridge. Even though the entire bridge is modeled, only the south-half is shown in the figure for visual clarity. Next, the displacement envelope is generated as previously described using only one girder and passing a point load of 4.45 kN (1 kip) over the top flange. Fig. 4 shows this displacement envelope. Based on this envelope, the second span is considered for loading the two trucks at positions determined by the displacement envelope. Additional nodes are added to the model at the longitudinal positions of the wheel loads. A total of 10,894 shell elements are generated for the superstructure. However, a run time of less than 4 min was needed for analyzing the FE model of the superstructure to failure using the DELL Precision T7400 workstation. The reduction in computation time is achieved using the parallel processing capa-

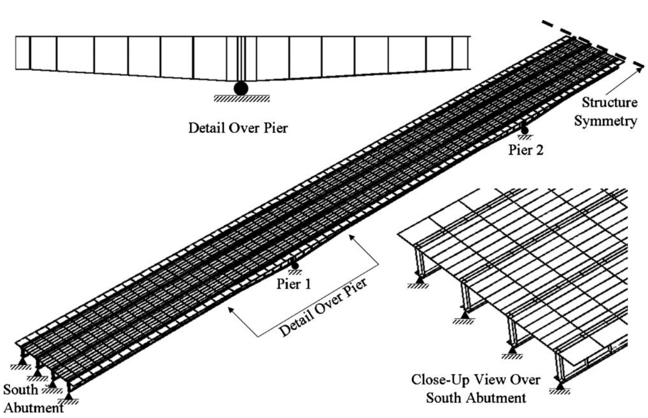

Fig. 3. Mesh of the FE model of the south half of the bridge over the Wisconsin River

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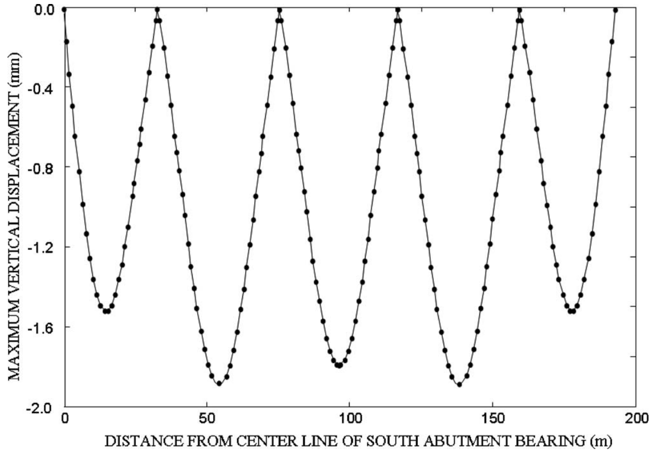

Fig. 4. Vertical displacement envelope of a girder from the bridge over the Wisconsin River under a moving unit load

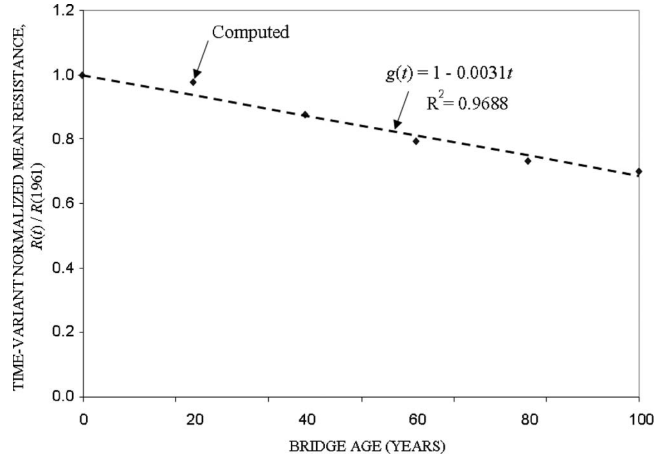

Fig. 5. Mean resistance of the bridge and its regression line over time

bilities of the workstation and the ability of ABAQUS to efficiently exploit these parallel processing capabilities. In fact, the elements of the model were distributed among the eight processers of the workstation and the analysis was performed in parallel.

The input and output files of the ABAQUS model are then integrated into the RS analysis using the VisualScript software component (*VisualScript, design integration toolkit, version 5.2, getting started manual* 2006) and a MATLAB code for postprocessing. Six random variables are considered, namely the resistances of the four girders R_1, R_2, R_3, R_4, the resistance of the slab, R_5, and the transverse loading position (i.e., the curb distance), LP. These lead to the number of 77 simulations required to conduct the CCD analysis and generate the second order RS expression. The randomness in the component resistances stems from the variability in the material property while the section dimensions are assumed deterministic. The component resistances are modeled as lognormal random variables with bias 1.05 and coefficient of variation 7.5% and the live-load factor is modeled as extreme type I random variable with bias 1.0 and coefficient of variation 19% (Ghosn et al. 2010). A coefficient of correlation of 0.8 is considered between the girder resistances.

The deterioration in the resistance is considered due to uniform corrosion penetration leading to section loss in the steel members. In this paper, a model proposed by Park and Nowak (1997) is used. In this model, three curves for determining corrosion rates are provided. The high corrosion rate exemplifies marine environments or heavy industrial conditions, or areas where deicing agents are used. This curve is used in this paper. Accordingly, the RS analysis is repeated at 20-year increments to account for the loss in the section due to corrosion. At each time increment, the areas of the steel members are modified in the ABAQUS input file and a new RS model is generated. For example, the RS expression at the 40th year (i.e., 2001) is

$$\begin{aligned}R_{40\ \text{years}} = {} & 0.63518 + 4.5184 \times 10^{-5}R_1 + 7.1393 \times 10^{-6}R_2 \\ & + 2.4476 \times 10^{-5}R_3 + 2.357 \times 10^{-5}R_4 + 6.9525 \\ & \times 10^{-5}R_5 + 0.019317 \times LP + 1.306 \times 10^{-9}R_1R_5 \\ & + 3.0572 \times 10^{-7}R_{g1}LP + 1.921 \times 10^{-7}R_{g2}LP - 1.13 \\ & \times 10^{-7}R_{g3}LP - 3.3097 \times 10^{-7}R_{g4}LP - 5.7996 \\ & \times 10^{-10}R_1^2 - 0.000\,211\,89LP^2 \qquad (15)\end{aligned}$$

It is clear from this equation that the loading transverse position has a high impact on the resistance of the bridge (the first order coefficient of LP is higher than the other variables in the equation). Therefore, treating the transverse loading position explicitly as one of the variables in the RS analysis provides better modeling of the bridge behavior. The total analysis time for generating an RS expression using the VisualDOC, MATLAB, and ABAQUS programs on the DELL Precision T7400 workstation at each time increment ranged between 223 to 331 min.

Using Latin hypercube sampling, the descriptors of the PDF of the initial resistance are determined for use in calculation of Eq. (2). In addition, the Latin hypercube sampling is performed at each of the time increments considered. The variation of the mean resistance over time is normalized with respect to its initial value (i.e., at 1961) and is shown in Fig. 5. A linear equation is fit to this profile to generate the resistance degradation function, $g(t)$, also for use in calculation of the cumulative-time failure probability [see Eq. (2)]. This equation and its R^2 statistic are also shown in Fig. 5.

Eq. (2) additionally requires the rate of occurrence of the live load. This is obtained from actual logs of traffic data that were obtained from the Wisconsin DOT and provided in Mahmoud et al. (2005). The ADT data are shown in Table 1. As assumed in Mahmoud et al.(2005), the average daily truck traffic (ADTT) is 12% of that of the ADT. In addition, it is assumed that about every 15th truck is simultaneously passing with another truck side-by-side. A linear regression is performed to forecast the future ADTT (NCHRP 2005). This is shown in Fig. 6. Accordingly, the annual rate of two trucks passing side-by-side on this bridge, λ, is calculated and also shown in Table 1. Conservatively, the value of λ after 100 years of construction (i.e., at 2061) is used for calculation of the cumulative-time failure probability [see Eq. (2)].

Furthermore, the cumulative rate of occurrence of two trucks passing side-by-side n is shown in Table 1 and is used to develop the extreme value distribution of live-load factor $LL(t)$. The values of n in the table are reduced by 0.85 (Nowak 1999) and they are representative of the gross weight of one truck for consistency (since the resistance multiplier LF is also obtained with respect to the gross weight of one truck). The profile of the live-load multiplier is shown in Fig. 7. For the instantaneous failure probability [see Eq. (1) or, conversely, the instantaneous reliability index [see Eq. (3)], the live-load factor $LL(t)$ at the analyzed point in time t is used. However, the value of $LL(t)$ after 100 years of construc-

Table 1. ADT, ADTT, Annual Rate of Occurrence of Two Trucks Side-by-Side λ, and Cumulative Rate of Occurrence of Two Trucks Side-by-Side *n*

Year	ADT	ADTT	Predicted ADTT	λ	*n*
1964	2,165	260	—	—	—
1968	3,510	421	226	5,492	18,107
1973	2,300	276	432	10,522	60,657
1978	2,620	314	639	15,552	128,358
1984	6,040	725	887	21,588	242,796
1987	8,390	1,007	1,011	24,606	313,596
1991	10,920	1,310	1,177	28,630	422,080
1994	10,000	1,200	1,301	31,648	514,005
1998	12,800	1,536	1,466	35,672	650,657
2001	14,500	1,740	1,590	38,690	763,708
2061	—	—	4,071	99,049	4,926,056

tion (i.e., at year 2061) is conservatively used for calculation of Eq. (2).

Fig. 8 shows the reliability index of the bridge over time obtained using CALREL (Liu et al. 1989). It is clear from the figure that even though the bridge was adequately designed with sufficient initial reliability, this reliability is quickly deteriorating with time. Based on results provided by RELTSYS (Enright and Frangopol 2000), Fig. 9 shows the cumulative-time failure probability of the bridge at various points in time over 100 years from construction. A probability distribution was fit using the method of least squares [see Eq. (5)] to the points shown. It was found that the Weibull distribution was the best fit. The parameters of the Weibull distribution are found to be as $\lambda_s = 1/109.58$ and $\kappa = 16.20$ and it is also plotted in Fig. 9. It is clear from the figure that despite the low order of magnitudes of the probabilities, a very good fit between the results and the Weibull distribution is achieved after about 40 years. Before that age, the probabilities decrease significantly toward the construction year and the Weibull distribution deviates from these values. However, the

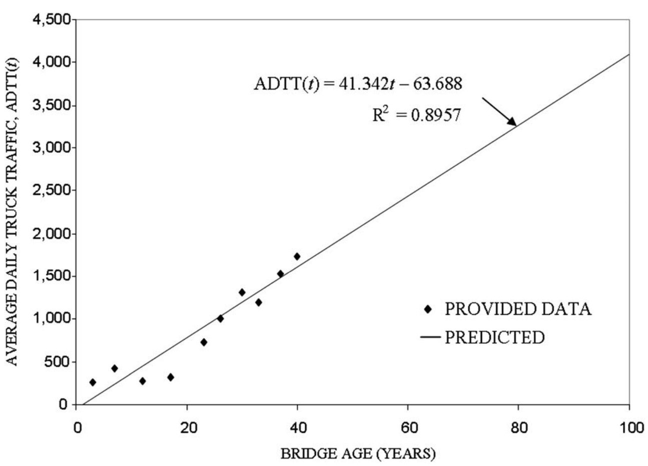

Fig. 6. Forecasting the ADTT

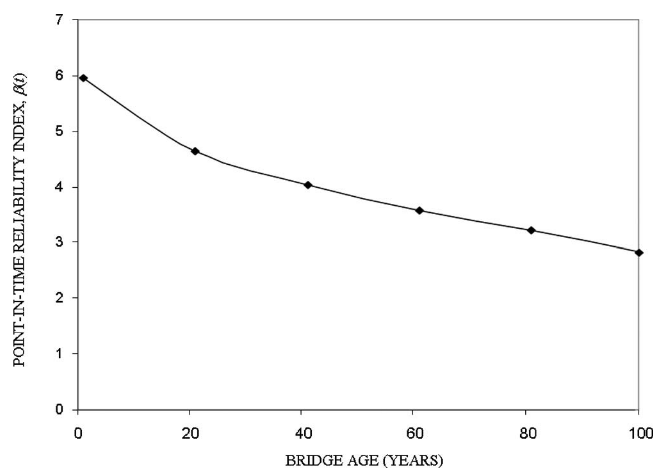

Fig. 8. Point-in-time reliability index of the bridge

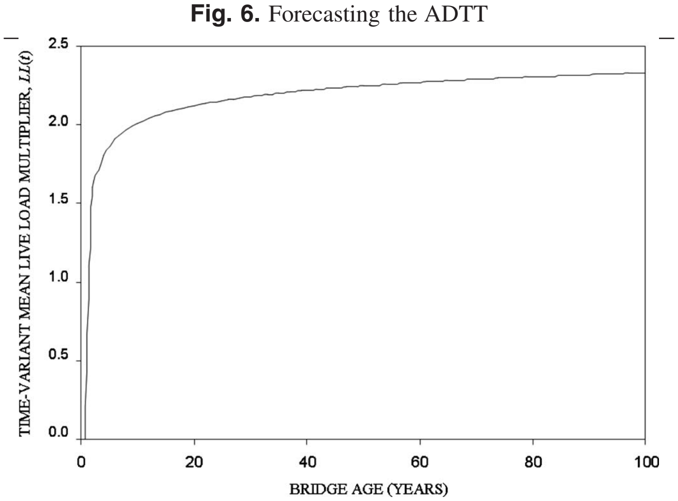

Fig. 7. Variation of the mean live load multiplier over time

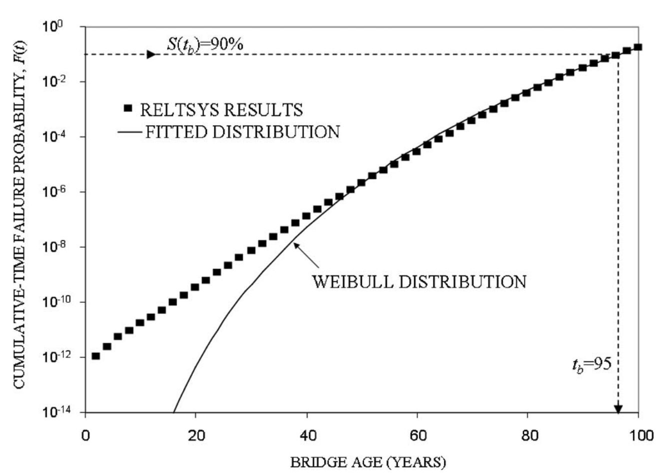

Fig. 9. Cumulative-time failure probability of failure of the bridge

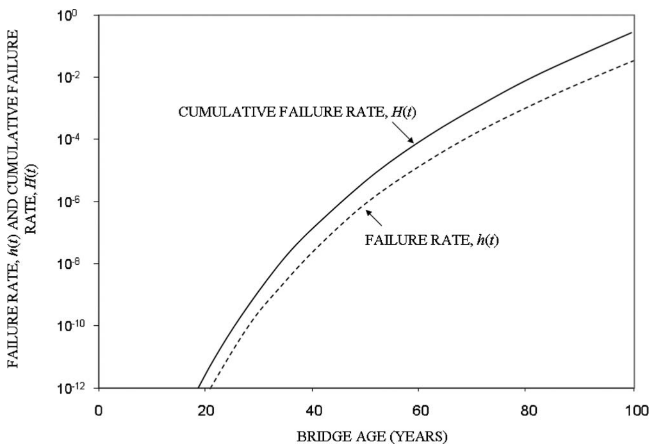

Fig. 10. Hazard and cumulative hazard function of the bridge

conservative considerations taken for the live-load may very well justify using this distribution to represent the lifetime of the structure. In addition, the R^2 obtained for this regression is 0.9996 which implies an excellent fit. Furthermore, other expressions may fit the data at all points more closely, but these expressions do not satisfy the conditions of a bona fide CDF (Ang and Tang 2007).

Using Fig. 9, the service-life of the bridge can be estimated. For a probability of 90%, the end of the service-life estimated for the bridge t_b can be read as the time corresponding to the $F(t_b) = 10^{-1}$. This gives $t_b = 95$ years. In addition, the MTTF for this bridge is found using Eq. (12) to be MTTF=107 years and its standard deviation is found from Eq. (14) to be SDTTF =8.06 years. Therefore, minor and/or major maintenance and repair actions need to be taken well prior to that date in order to keep this bridge in an acceptable safety state and operable. Finally, the hazard and cumulative hazard function curves are plotted in Fig. 10.

Conclusions

The uncertainties involved in predicting the life-cycle performance of complex structures create many difficulties in accurately assessing this performance. Understanding the sources of correlation and interaction among the structural components contributing to the overall system performance also poses a challenge. Treatment of uncertainty in modeling the system performance over the life-cycle requires special considerations. Exploiting the power of computers and the capabilities of today's software can be significantly beneficial in providing more accurate assessment of the life-cycle performance and estimating the service-life of complex structures.

In this paper, an approach for using advanced modeling techniques in predicting the life-cycle performance and estimating the service-life of bridges is presented. A case study of a five-span continuous bridge is considered. A DELL Precision T7400 workstation with two quad core Intel Xeon processors and 8 GB of RAM is used for conducting the computations required. Software used include ABAQUS for FE modeling, VisualDOC for RS analysis, MATLAB for regression, post processing of ABAQUS results and Latin hypercube sampling, CALREL for instantaneous reliability computations, and RELTSYS for computing the cumulative-time failure probability. Establishing proper interaction among these softwares is vital for time saving and overcoming the cumbersome and tedious manual interference.

In this paper, design of experiments concepts are used to generate a second order RS model including interaction terms. The transverse position of the two side-by-side trucks is treated as a random variable and explicitly considered in the RS model. A systematic method for accomplishing this is presented. It was in fact shown that the transverse position has high impact on the overall system strength of the bridge.

Several performance indicators representing different types of behavior for the bridge are presented. These performance indicators were generated for the bridge case study considered. Also, the service-life of the bridge was estimated.

The results of the case study have shown that the bridge was designed with sufficient reliability but this reliability is rapidly decaying. Clearly, a strategy for maintenance of the bridge has to be investigated. Generally, maintenance optimization problems are iterative in nature. It is not computationally feasible to perform the RS analysis for estimating the life-cycle performance during the iterations of the maintenance optimization. Therefore, a suitable alternative is to use a probability distribution that is generated by regression of the cumulative-time failure probability results. For the case study in this paper, a Weibull distribution was fitted. The life-cycle performance can be computed in closed-form using this distribution. Accordingly, the maintenance optimization can be quickly and efficiently conducted. Therefore, an efficient link is provided between the advanced life-cycle performance prediction as indicated in this paper and maintenance optimization as indicated in Frangopol (2010) and Frangopol and Liu (2007).

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