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Computational platform for the integrated life-cycle management of highway bridges

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ABSTRACT

Throughout their service life, highway bridges are subject to progressive deterioration in performance; an issue that may render the use of these facilities unsafe at some point in time. Over the last few decades, there has been successful research towards developing procedures for establishing the various vital elements required in the life-cycle management of civil infrastructure. It is noted, however, that frameworks for integrating these elements together are lacking. The objective of this paper is to present an integrated framework for the life-cycle management of highway bridges in the form of a detailed computational platform. The elements integrated into the framework include the advanced assessment of life-cycle performance, analysis of system and component performance interaction, advanced maintenance optimization, and updating the life-cycle performance by information obtained from structural health monitoring and controlled testing.

1. Introduction

Throughout their service life, highway bridges are subject to progressive deterioration in performance; an issue that may render the use of these facilities unsafe at some point in time. The importance of predicting the changes in performance is one thing, but being able to optimally maintain this performance satisfactorily may pose a challenge. Further yet, the agreement between the prediction and the true performance is a matter shaped by uncertainties in what information is available and how representative it is. These uncertainties should be constantly put to the test, properly handled, and reduced when possible.

Over the last few decades, there has been successful research towards developing procedures for establishing the various vital elements required in the life-cycle management of highway bridges [1]. These elements include the life-cycle performance measures, maintenance optimization formulations, and reduction of epistemic uncertainty by integrating information obtained from SHM and controlled testing among others.

A multitude of life-cycle performance measures are now available [2–4]. However, the selection of the proper measures has to be made by considering their ability to be integrated in the life-cycle management framework and interact properly with all its other relevant elements. For instance, the selected performance measure should facilitate a proper maintenance optimization solution. This requires the performance measure to accurately represent the intended structural quality, and not to pose a computational burden in solving the optimization problem.

Several maintenance optimization formulations have been developed during the last two decades. However, the advances in genetic algorithms (GA) in the last decade [5] have accelerated progress in developing complex multi-objective maintenance optimization formulations. A key reason for this outcome is that GAs are capable of analyzing the optimality of a population of solutions simultaneously at each iteration (called generation in GA terminology). This eventually provides a Pareto-optimal set per a GA optimization solution, as opposed to only one optimum solution per a conventional optimization solution. Another key reason for using GAs is that their operations can be conducted on the corresponding encodings of the design variables. This encoding can be binary, simulated-binary (for continuous real variables), and integer. In fact, the GA operations are robust and flexible enough to handle any desired logical encoding. This is a significant advantage for solving complex maintenance optimization problems. Introducing mixtures of innovative encodings, and the ability of GAs to handle them, has significantly improved the state of maintenance optimization process [6–14].

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The power of structural health monitoring (SHM) in providing crucial information about the performance of structures has been exploited in several studies for drawing meaningful conclusions about the reliability of these structures [15–21]. It has been recognized that SHM can be a valuable tool in reducing the uncertainties inherent in the predicted structural performance. The established literature documents the means to determine the reliability of structures based on SHM data. However, integration of SHM in life-cycle management requires its data to be combined with the uncertainty in the framework database. In addition, the performance measures used in the framework may be different from structural reliability.

Despite the progress in developing the elements of life-cycle management, it is noted, however, that frameworks for integrating these elements together are lacking. The objective of this paper is to present a framework for the life-cycle management of highway bridges in the form of a detailed computational platform. The elements integrated include the assessment of life-cycle performance, analysis of system and component performance interaction, advanced maintenance optimization, updating the life-cycle performance by information obtained from SHM and controlled testing. It should be emphasized that the details of the framework elements have been developed and presented in [13,14,22–25]. This paper reviews these developments and establishes the means for their integration into a detailed life-cycle management process.

2. The computational platform

The computational platform of the framework proposed in this paper is an integrated procedure composed of several sequential phases that include: (a) life-cycle performance prediction; (b) maintenance optimization; and (c) updating of life-cycle performance using SHM data and controlled testing results. The steps and features involved in each of these phases are carefully selected and/or developed to be compatible with the rest of the framework. This framework is designed for management of highway bridges over their life-cycle, and thus serves as a reference for decision making from early stages until the end of their service life.

A schematic of the computational platform for the life-cycle management framework is shown in Fig. 1. As shown, the framework is designed to provide a decision support for a given bridge by performing an integrated process of interactive computations. Each of these computations is described in detail in this paper. Among these computations are the Response Surface (RS) method, the Latin Hypercube Sampling (LHS), the Genetic Algorithm (GA) optimization of maintenance which nests an Essential Maintenance Optimization (EMO2) algorithm, updating the resistance, and updating the load computation procedures. As will be shown in the rest of this paper, some of these computation procedures are interconnected such as the RS and the LHS, and updating the resistance and the LHS.

The details of the main computational platform are shown in Fig. 2. The following sections of this paper will explain this framework and walk the reader through the detailed steps and phases of its computational platform.

3. Life-cycle performance prediction

The computational platform begins with the prediction of the life-cycle performance. All information regarding the bridge geometry, section details, material properties and loading statistics are gathered. As previously mentioned, a selection of the proper performance measures for use in the management framework has to be made. The performance indicators are established mainly for conducting the maintenance optimization which provides the

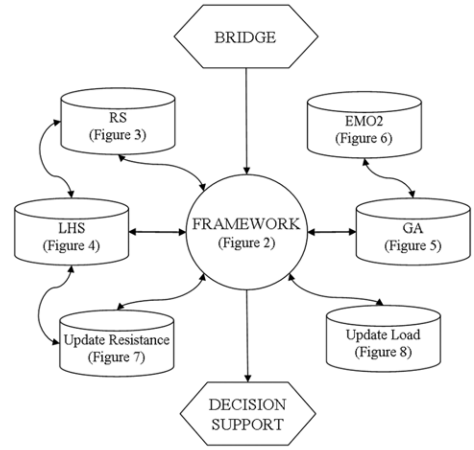

Fig. 1. Schematic of computational platform for the life-cycle management framework.

decision making space. Hence, the selection of these performance indicators needs to take into consideration the maintenance optimization formulation and solution strategy. On one hand, a study by Frangopol and Okasha [13] revealed that the lifetime functions are the most computationally efficient performance measures for advanced maintenance optimization schemes. On the other hand, the lifetime functions are the least amenable to updating by SHM data or controlled testing results and the least representative of the load and resistance of the specific bridge under consideration. This is because lifetime functions are traditionally generated from statistical analyses of lifetimes of similar bridges [2] and not the particular one considered.

In order to overcome this dilemma, Okasha and Frangopol [22] used the finite element (FE) model of a highway bridge in a Latin hypercube sampling simulation to compute the cumulative-time failure probability and used the results with nonlinear regression to generate the lifetime functions of the bridge. Thus, the details of the specific structure are taken into account and by using these powerful computational tools with these details, the generated lifetime functions are representative of the performance of the structure. Furthermore, Okasha et al. [24] used the FE model of the bridge to update its resistance parameters using the results of a crawl test and updated the live load models using the SHM data. Therefore, the gap between the information obtained from SHM and controlled testing was bridged using this approach. This enabled a proper and powerful integration among the features of the developed management framework.

Conducting the maintenance optimization requires knowledge of the performance of the structural components such that the effects of applying maintenance to these components are identified. However, the maintenance decisions are preferably based on the system performance. Understanding the contributions of components to the overall system performance is no easy task. Traditionally, the relationship between component and system performance is established by assuming reasonable series–parallel models [26–29]. Unfortunately, the results have been found to be quite sensitive to the series–parallel model assumed [21]. Okasha and Frangopol [23] used FE models, LHS simulations, cumulative-time failure probability analysis, and statistical estimation for both the components and the entire structure of a highway bridge to generate their lifetime functions and used them to determine the component-system relationship using nonlinear regression. Therefore, the life-cycle performance prediction in this computational platform is conducted first for the system then for the components of the highway bridge in consideration.

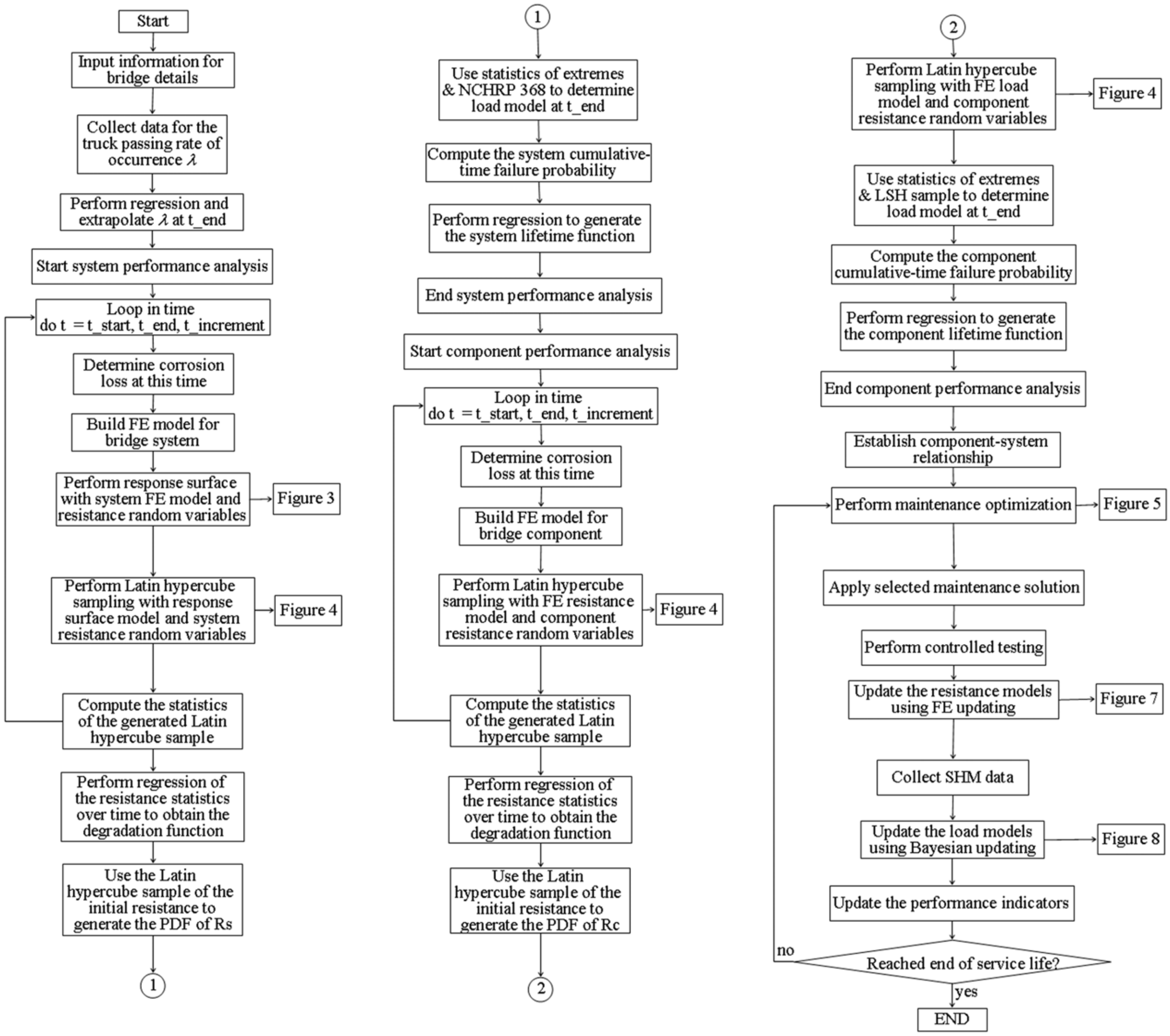

Fig. 2. Detailed flowchart of the computational platform for the life-cycle management framework.

3.1. *Live load frequency*

One of the advantages of using the cumulative-time failure probability is that this performance indicator considers the occurrence of the live load as a Poisson process. Therefore, the effect of the frequency of live load occurrence λ is taken into account. For a given highway bridge, λ can be obtained from logs of the pertinent Department of Transportation (DoT) in the United States. The data obtained from the DoT is then extrapolated to forecast the future values of λ using a regression procedure provided in NCHRP 538 [30]. Conservatively, the value of λ at the end of the projected service life is used in the computation of the cumulative-time failure probability for both the system and component.

3.2. *System performance prediction*

The analyses leading to the prediction of the system performance of a bridge over its life-cycle are conducted at several increments of time, t_increment, starting at time, t_start and ending at the end of service life, t_end. These analyses aim to establish the resistance of the system over time. At each increment, the section losses due to corrosion are determined using well established corrosion models. Accordingly, a FE model representing the corroded bridge at this time increment is built. This FE model is then used in a RS analysis to construct a RS model for the system resistance at this time increment. This step is resorted to because of the high computational cost of conducting FE analysis to obtain the resistance of complex bridge structures. Such analysis is incremental and nonlinear. The loading is incremented until the bridge collapses or a serviceability criterion is reached, whichever comes first. The high computational cost of the incremental nonlinear FE analysis prevents its direct use in a simulation for generating the probability distribution of the system resistance. Thus, a closed form RS function is rather used with the Latin hypercube sampling and the statistics of the generated sample are computed.

The RS analyses require repetitive FE analysis of the bridge system model, where different input values are used each time the FE program is run to analyze the structure, and the output value of the Load Factor at this time (LF_j) is extracted and then used in regression schemes to obtain the RS model. This is shown in Fig. 3. Commercial softwares that are able to perform the RS analysis and properly interact with another

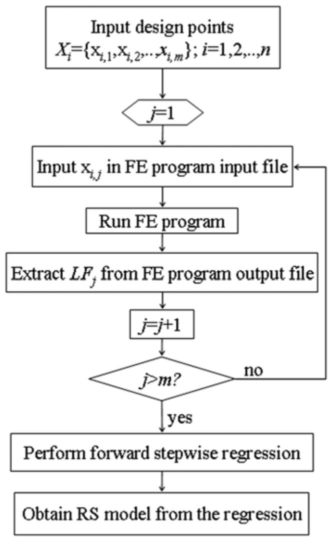

Fig. 3. Response surface procedure.

commercial FE analysis software are available such as a software package called VisualDOC [31]. The VisualDOC package includes a software component, VisualScript [32], which enables the linking of VisualDOC to any analyses softwares, such as ABAQUS [33] for FE analysis.

The algorithm for the Latin hypercube sampling is shown in Fig. 4. The goal of the algorithm is to intelligently generate a Latin hypercube sample of values for each of the random variables considered x_j and is based on Olsson et al. [34]. Then, these samples are used to evaluate the available model at each set. In Fig. 4, two types of models are considered for evaluation. The first are the explicit models that have a closed form such as the RS models. The second are non-explicit models such as the FE element models.

Using the obtained statistics of the generated Latin hypercube samples over the time increments, a regression is conducted to obtain the degradation function for the system resistance. Also, the Latin hypercube sample of the system resistance Rs at the initial time t_start is used to generate its probability density function (PDF). Next, the live load model is established using statistics of extremes and the procedure in [35]. Having the resistance and load models now, the cumulative-time failure probability is computed. The cumulative-time failure probabilities at many points in time are generated using the RELTSYS program [36]. This program uses a combined technique of adaptive importance sampling, numerical integration, and fault tree analysis to compute time-variant reliabilities of individual components and systems. Time-invariant quantities are generated using Monte Carlo simulation, whereas time-variant quantities are evaluated using numerical integration [36]. Having the cumulative-time failure probability results from RELTSYS, an appropriate cumulative distribution function (CDF) is fitted to these values using the method of least squares. This CDF is the base for the lifetime functions of the highway bridge.

3.3. Component performance prediction

The computations conducted for obtaining the component life-cycle performance, namely the component cumulative-time failure probability, are similar to those of the system life-cycle performance presented above. However, the FE analyses are computationally less expensive because the analyzed models are smaller and thus they can be directly implemented with the Latin hypercube sampling simulation to generate the probabilistic distribution of the component resistance. Avoiding the RS intermediate step also provides more accuracy by avoiding the approximations necessary for building the RS model. Accordingly, the Latin hypercube simulation is performed for the predefined number of samples where each time the inputs of the FE model are replaced by values of a different sample, the FE analysis is conducted, the load factors (i.e., the resistance) LF_j are extracted from the output files of the FE program, and at the end, the statistics of the sample are computed. A very large number of samples is required for an accurate simulation outcome. Also, the simulation has to be repeated at the number of time increments considered. At each increment, the section loss due to corrosion is determined and the FE model is modified to represent the corroded bridge. Therefore, the process of changing the FE input file, running the FE program, and reading the FE output file needs to be automated. This can be done by establishing an interface between the FE analysis program and another program or programming engine such as MATLAB.

Similar to the system performance computations, the obtained statistics of the generated Latin hypercube samples over the time increments are used to conduct a regression in order to obtain the degradation function of the component resistance; the Latin hypercube sample of the component resistance at the initial time t_start is used to generate its PDF. Next, the live load model is established also using Latin hypercube sampling with the FE model but the load in this case is incremented only until a code specified loading, such as the load of the HS-20 AASHTO truck load [37], is reached to determine the load effect. The generated sample is used with statistics of extremes to obtain the live load model. Having the resistance and load distributions now, the cumulative-time failure probability is computed using the RELTSYS program and an appropriate CDF is fitted to the results to be the base for the lifetime functions of the components of the highway bridge.

3.4. System-component relationship

Using the lifetime functions of both the system and components of the bridge considered, the component-system performance relationship is established using multiple nonlinear regression [25]. Accordingly, the lifetime functions of the components can now be used in the maintenance optimization and the rest of the computational platform and the obtained component-system relationship equation can be used to calculate the system performance at any time.

4. Maintenance optimization

Maintenance interventions are scheduled to either delay the occurrence of reaching a pre-defined threshold of a performance indicator or to improve the state of the performance indicator if its pre-defined threshold is reached. Thus, maintenance types may be categorized into two general groups: preventive (PM) and essential (EM) [38]. PMs are usually time-based, that is, they are applied at pre-specified time instants over the life-cycle of the structure. In contrast, EMs are performance-based in that they are applied when a performance indicator reaches a pre-defined threshold [7]. The fundamental difference between the PM and EM types prohibits the mixture of both in one homogenous optimization problem. However, the maintenance optimization approach considered herein, developed by Okasha and Frangopol [14], effectively includes both EM and PM types.

The combined EM and PM maintenance optimization is formulated as a nested optimization problem and is shown in Fig. 5. On the global level, the design variables include those of the PM optimization. Each time the global design variables are provided, a local nested optimization takes place to find the optimum set of EM applications using the algorithm EMO2 (see Fig. 6) given the presence of the PM applications and satisfying

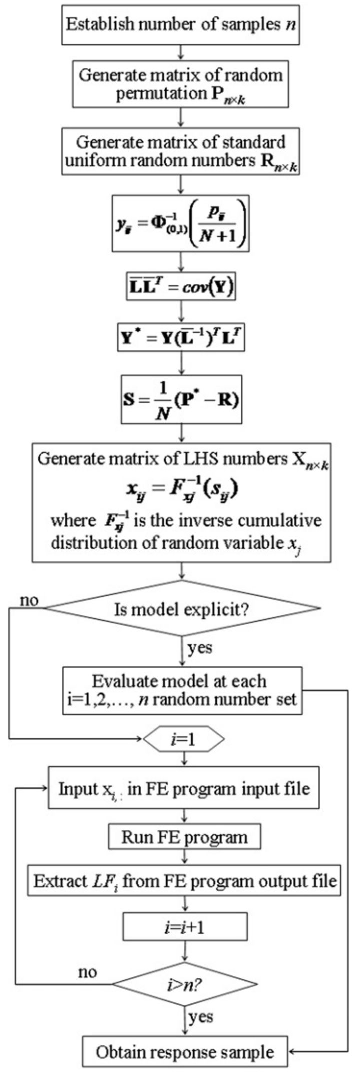

Fig. 4. Latin hypercube sampling algorithm.

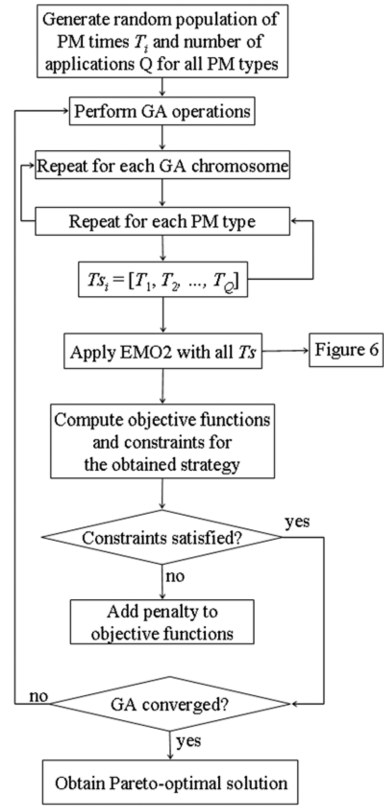

Fig. 5. Maintenance optimization procedure using GA.

the given thresholds. Thus, a set of performance thresholds is required as an input to this process. These thresholds are treated as design variables. Although each threshold set is associated with an optimal solution, the goal of treating them as design variables in the optimization is to find a well distributed set of optimal solutions [11].

The optimization of maintenance considering only EM consists of finding the optimum type of EM to apply once a performance threshold is reached. Hence, finding the optimum solution is a combinatorial optimization problem that can be complex and computationally expensive [7]. An algorithm denoted as EMO2 was developed in [14] for the EM optimization and is shown in Fig. 6. The algorithm compares the total cost of all potential EM scenarios required to provide a prespecified service life from start to end by an event-tree analysis. The resulting large number of branches (i.e., EM scenarios) to analyze can become a computational burden for solving the problem even for a limited number of EM options. The difficulty in programming this method stems from the fact that neither the number of branches nor the length of each branch is known before the end of the analysis. The EMO2 algorithm identifies the IDs and times of applications of the EM options in all scenarios $M(i, j)$ and $T(i, j)$, respectively, where $M(i, j)$ represents the ID of the maintenance option to use at the jth application in the ith maintenance scenario and $T(i, j)$ represents its time of application. Hence, the optimum maintenance scenario M_{opt} and its associated optimum life-cycle maintenance cost LCC_{opt} are identified. The method is supported with checkpoints that predict and terminate the continuation of non-optimum branches and prevent creating new branches known a priori to be non-optimum. The first checkpoint compares the partial life-cycle cost (LCC) up to the jth application of the ith maintenance scenario, $LCC(i, j)$, with the minimum (optimum) LCC value found up to that point in the optimization process, LCC_{opt}.

Including the PM in the optimization introduces the continuous design variables that represent the times of application of these PMs into the problem. Furthermore, the number of PM applications is not known and thus the number of time-of-application design variables to be used is unknown. However, the PM optimization can be performed by using continuous design variables that represent the times-of-application of PM, and integer design variables that represent the optimum number applications of each PM type. An advantage of doing this is to allow non-uniform time-interval maintenance strategies, as well as uniform ones if they are optimum, to be provided.

5. Updating the life-cycle performance

Owing to the uncertainties, the predicted life-cycle performance, despite how accurate or advanced the tools used to obtain this performance were, may deviate from the actual performance exhibited by the structure over time. Keeping the prediction and its built upon decisions on track requires a frequent updating of the life-cycle performance as new information becomes available. The two pillars of the life-cycle performance are the resistance and load models. In this framework, SHM is the tool used for gathering new information about the structural performance. However, the collected data is used to update the

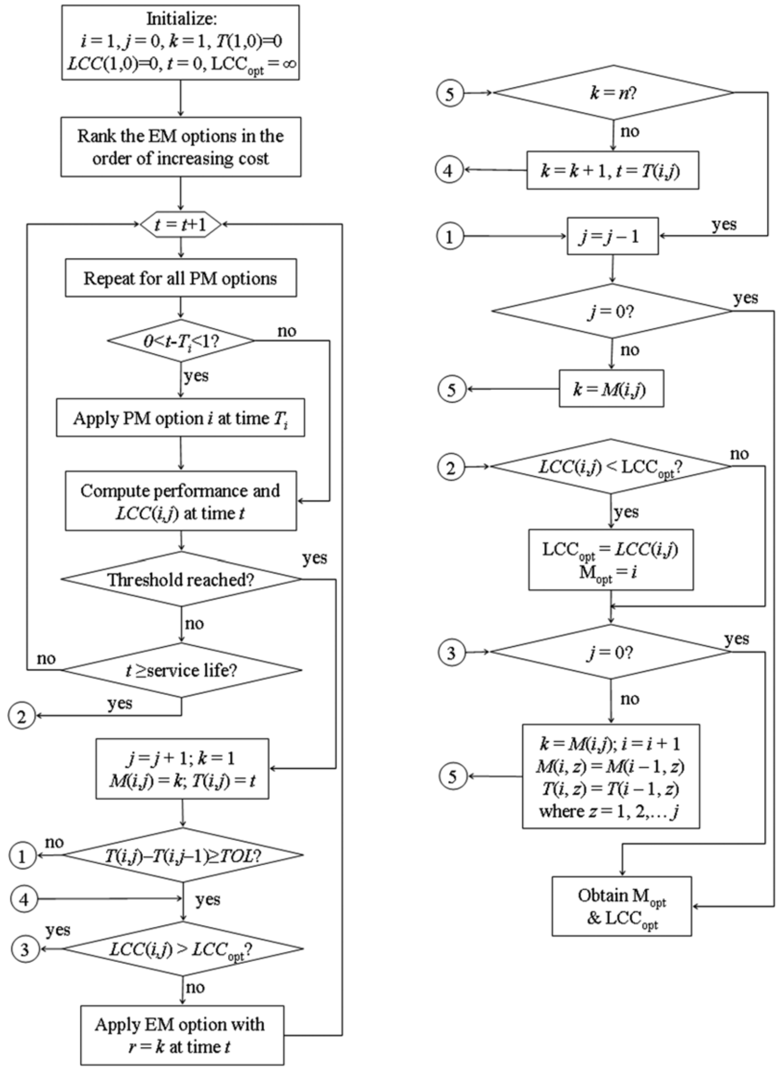

Fig. 6. Algorithm EMO2 for essential maintenance optimization.

resistance and load models differently. Once these models are updated, the life-cycle performance, in turn, is updated by using these new resistance and load models.

5.1. Updating the resistance models

The need for a controlled test in updating the resistance models stems from the fact that both the load effect and the response of the structure to this load effect is needed to create a mathematical model that captures the behavior of the structure and/or the properties of its materials. Controlled test methods can either be non-destructive in nature (rebound hammers, ultrasonic pulse velocity measurements) or may involve local damage to the structure (tensile coupons, drilled cores, pull-out tests) [39]. These tests, however, are only concerned with one aspect of the structure, typically a specific material property. In this framework, combined with SHM and FE modeling, controlled tests are used to simultaneously incur information about most of the parameters of the structure. In essence, the properties of a mathematical model of the structure that globally responds to a load effect in a manner similar to the global response of the actual structure to the same load effect are properties that are in agreement with those of the actual structure.

Herein, results from controlled tests are used to update the FE model and, in turn, update the lifetime reliability of the structure [24]. The process is shown in Fig. 7. FE model updating is a process in which the input parameters of the FE model are tuned such that the responses obtained from the FE analysis become in agreement with those provided by SHM. In general, the FE model updating is conducted for the sake of using the updated model. The objective in this framework, however, is different. The updated FE model will not be used any further. What will be used are the updated parameters. In other words, the objective is to calibrate the parameters of a structure by updating its FE model. Ultimately, these updated parameters are used to compute a new updated lifetime reliability for the structure.

In order to have a well-conditioned updating problem, and bearing in mind the limitation of the measurements, it is necessary to select those updating parameters that will be most effective in producing a genuine improvement in the modeling of the structure [40]. A good way for selecting parameters for the updating process is to conduct a sensitivity analysis. A sensitivity analysis is conducted by computing the sensitivity coefficient, defined as the rate of change of a particular response quantity with respect to a change in a structural parameter [40]. Accordingly, the structural parameters P_j are systematically perturbed and each time they are modified, the FE input file is edited, the analysis is conducted and the responses R_i are extracted from the FE

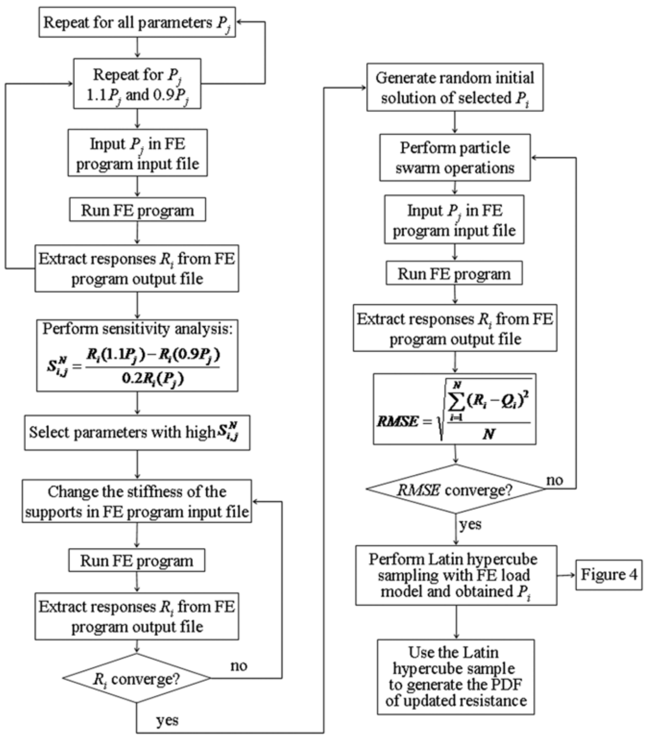

Fig. 7. Updating the resistance models procedure.

output file. Then, the sensitivity coefficient is computed and the parameters with higher sensitivity coefficients are selected for the FE updating.

The FE updating is preceded with structural identification in order to determine the best model for the bridge from among a group of candidate models that differ in their boundary conditions. The candidate model that provided responses at the locations of the sensors closest to the values obtained from those sensors is selected. The boundary conditions of these models at their degree of freedom at the supports range from full restraint, partial restraint, to free. The partial restraints are modeled using springs with rotational/translational stiffnesses. The stiffnesses of these springs can be interpreted as representing the real stiffnesses provided by the piers at the supports. The boundary conditions are systematically changed by changing the stiffnesses of these springs and each time they are modified, the FE input file is edited, the analysis is conducted and the responses R_i are extracted from the FE output file. This is repeated until the responses R_i converge to those of the sensors and the model obtained is hence selected for FE updating.

Now, the FE updating begins. In iterative parametric updating methods, the model updating problem is posed as an optimization problem that is solved iteratively [41]. An objective function is formulated as a function of the difference between the analytical and experimental results. In this framework, the objective function is formulated as the root mean square error (RMSE) between the analytical and sensor responses. The solution is achieved by iteratively and systematically modifying the parameters of the model using an optimization algorithm. Herein, the direct non-gradient optimization technique particle swarm is used [42]. The general purpose optimization program VisualDOC [31] with particle swarm optimization capabilities can be used, providing the advantage of using the software component VisualScript [32], which enables the linking of VisualDOC to any analysis software, such as the FE analysis program ABAQUS [33]. In this process, the analysis proceeds in iterations until the RMSE is minimized. In each iteration, the particle swarm operations are performed to obtain new parameters P_j. These P_js are inserted in the FE input file, the analysis is conducted, the responses R_i are extracted from the FE output file, and RMSE is calculated. Once the optimum R_is are obtained, they are used in a Latin hypercube sampling simulation to obtain the probability distributions of the updated resistance.

5.2. Updating the load models

SHM provides information about various quantities of interest from bridge structures, such as strains, accelerations, and temperatures. These quantities can be related to the load effects through simple mechanical expressions. For instance, the strain collected from strain gages are related to the stresses at the gage location through Hooke's low, provided that they are not larger than the yield strain. Stresses are in turn related to the applied moment (i.e., load effect) if multiplied by the section modulus. Over a time period (i.e., long term monitoring), a huge volume of observational data is obtained from SHM. The obtained data has to be used as observational outcomes from the load effect random variable. Hence, estimation methods are needed to obtain accurate parameters of the load effect PDF using the SHM data.

Existing structures were designed based on prior engineering knowledge of the expected loads these structures would encounter throughout their service life. Monitoring a structure during its service life provides information about the same expected loads. However, this information may or may not agree with the original 'prior' believe that was used at the design stage. In other words, inclusion of the monitoring data in structural performance evaluation requires combining this data with the prior existing information. A Bayesian approach is most suited for this situation.

In engineering applications, treatment of monitoring data is associated with monitoring of extreme events. Extreme value distributions do not lend themselves easily to Bayesian updating; the main problem is that there is no conjugate distribution; the Weibull distribution does not belong to the exponential family [43]. Hence, a simulation procedure is the best way to determine the posterior distribution [44]. The slice sampling technique is a recently developed technique [45] that can also be used in difficult Bayesian problems and is available in MATLAB [46] and is used in this framework.

The load model updating procedure is shown in Fig. 8. The process is driven by obtaining a posterior distribution for the parameter of the load effects (e.g. the parameter u_n of the extreme value distribution) that combines the prior information with the SHM data. This posterior is then used to obtain the CDF of the updated load model. The posterior is obtained from the slice sampler as discrete sample points. At each sample point, a function $\pi(u_n)$ that is proportional to the posterior is computed by multiplying the prior function $f'(u_n)$ to the likelihood function $L(u_n)$. The posterior function is computed by first assuming it is unity and then multiplying itself with the extreme value distribution in a loop over the SHM data points, where each time the parameter u_n is replaced with the SHM data point. Next, a new slice sample for the parameter u_n is generated and the process is repeated until all slice samples are generated and their functions $\pi(u_n)$ are computed. These values of the function $\pi(u_n)$ are then used with numerical integration to obtain the updated load effect CDF $F'_X(x)$ at a number of values y_i. Finally, these $F'_X(y_i)$ values are used in nonlinear regression (i.e., using the method of least squares) to find a closed form of the CDF of the load effect [23].

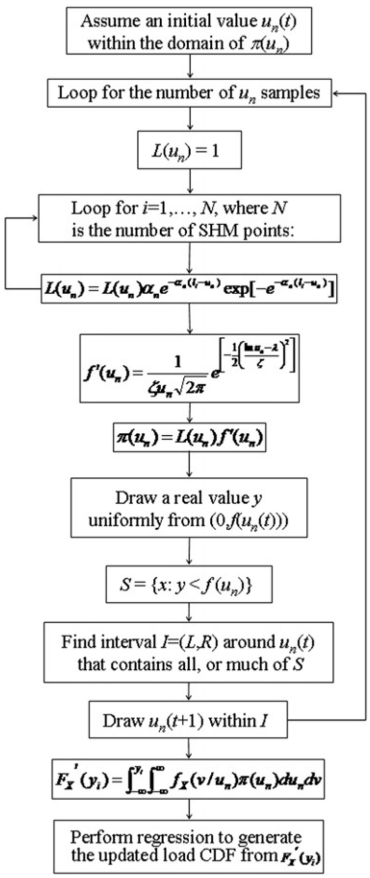

Fig. 8. Updating the load models procedure.

6. Framework ending

The outlined computational framework serves as a reference for bridge managers throughout the entire life-cycle of the bridge. Each time the SHM data is collected and/or controlled testing is conducted, the life-cycle performance is updated. Based on the amount of change in the predicted life-cycle performance before and after updating, it may be decided to conduct a new optimization to select an updated maintenance strategy. Again, the new SHM data can be collected and/or controlled testing may be conducted, the life-cycle performance is updated and a new maintenance optimization is performed. This can be repeated as long as the bridge can be safely used and its upkeep is economically feasible. Otherwise, the bridge is considered to have reached the end of its service life and should be decommissioned.

7. Examples

The details and computations associated with the platform for integrated life-cycle management of highway bridges described in this paper have been conducted on two existing bridges and the results can be found in [3,4,13,14,22–25]. These examples clearly demonstrate how the proposed computational platform works.

The Wisconsin bridge I-39

The I-39 Northbound bridge, over the Wisconsin river, located near Wausau, WI, USA (denoted herein as the I-39 bridge), was constructed in 1961. A controlled testing and long-term monitoring program were conducted on the bridge by the Engineering Research Center for Advanced Technology for Large Structural Systems (ATLSS), at Lehigh University, Bethlehem, Pennsylvania. Weldable resistance strain gages were instrumented at key locations both to understand the response of the bridge to controlled load tests (crawl tests and dynamic tests) and quantify the stress-range histograms at critical details (long-term monitoring) (see [47] for further details).

In [22], the FE model of this bridge was built and used with RS and LHS to compute the system cumulative-time probability of failure and the results were used in nonlinear regression to generate the system lifetime functions of the bridge.

Okasha et al. [24] used the results from the ATLSS controlled testing to update the resistance of the bridge and accordingly its system lifetime function. In addition, FE element models of the components of the bridge were used with LHS to compute the component cumulative-time probability of failure and the corresponding lifetime functions.

Okasha and Frangopol [23] used the previously obtained lifetime functions of the system and components to develop a component-system relationship. Also, they used the ATLSS long term monitoring data with Bayesian updating to update the load effect, and accordingly the lifetime functions.

The Colorado bridge E-17-AH

The bridge has three simple spans of equal length. The east-west bridge has two lanes of traffic in each direction. The slab is supported by nine standard-rolled, compact, noncomposite steel girders. A detailed description of this bridge can be found in [26].

Okasha and Frangopol [14] illustrated the novel maintenance optimization approach, presented previously, on this bridge using its lifetime functions. In fact, separate and combined EM and PM optimizations were performed and the efficiency of the approach was confirmed by the obtained results.

8. Conclusions

Throughout the lifespan of a structure, gradual deterioration of its performance and sudden occurrence of hazards inflict risks that may seriously compromise the integrity of this structure and make its use no longer safe. Well managed structures are those with predicted performance and planned maintenance interventions so that their safety is sustained over their intended lifespan. The proper management of structures is a process that follows the rules of an interdisciplinary framework.

In this paper, a framework for the life-cycle management of highway bridges was presented in the form of a detailed computational platform. The elements integrated include the assessment of life-cycle performance, analysis of system and component performance interaction, advanced maintenance optimization, updating the life-cycle performance by information obtained from SHM and controlled testing. It should be emphasized that the details of the framework elements have been developed and presented in [13,14,22–24,35]. This paper reviews these developments and establishes the means for their integration into a detailed life-cycle management process.

Given all the uncertainties inherent in the material properties, prediction of applied loads, and degradation of the resistance, this framework is formulated probabilistically. The performance prediction is one that takes into account the interaction among the structural components and evaluates the overall system performance. For enhancement of the efficiency of this framework and reduction in the uncertainty of its outcomes, data from SHM and controlled testing is integrated. The planning of maintenance interventions is executed based on a state-of-the-art optimization formulation and solved using advanced tools. The target of this framework is highway bridges. However, this framework can be modified to become applicable to other structures such as buildings, offshore platforms, nuclear power plants and naval ships.

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