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Optimal planning of structural performance monitoring based on reliability importance assessment

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ABSTRACT

Recently, the effective use of information from structural health monitoring (SHM) has been considered as a significant tool for rational maintenance planning of deteriorating structures. Since a realistic maintenance plan for civil infrastructure has to include uncertainty, reliable information from SHM should be used systematically. Continuous monitoring over a long-term period can increase the reliability of the assessment and prediction of structural performance. However, due to limited financial resources, cost-effective SHM should be considered. This paper provides an approach for cost-effective monitoring planning of a structural system, based on a time-dependent normalized reliability importance factor (NRIF) of structural components. The reliability of the system and the NRIFs of individual components are assessed and predicted based on monitored data. The total monitoring cost for the structural system is allocated to individual components according to the NRIF. These allocated monitoring costs of individual components are used in Pareto optimization to determine the monitoring schedules (i.e., monitoring duration and prediction duration).

1. Introduction

Structural Health Monitoring (SHM) of civil infrastructure can provide abundant information on the current condition of a structure so that an informed assessment and prediction of the structural performance can be made. Integration of SHM into maintenance management is considered as a significant tool for rational maintenance planning. In general, the objectives of SHM include (a) assessing the current structural performance to prevent structural failure; (b) predicting the remaining service life of a structure; and (c) providing a decision support tool for optimum maintenance planning [1]. The objectives of SHM are mainly related to damage detection, including the reduction of uncertainty (i.e., epistemic uncertainty) associated with the current assessment and prediction. The costs associated with SHM consist of the first installation cost, operating cost, and maintenance and renewal costs. All these monitoring costs should be compensated through reduction in the total life-cycle cost of a structure. Therefore, cost-effective monitoring planning should maximize the potential benefit of SHM.

In the last decade, research towards technical development of SHM methods has been performed actively [2]. Determination of the optimal number of corrosion sensors under uncertainty was proposed, considering the sensor spacing and the accuracy of the sensors as a bi-objective problem [3]. However, there has been little research on the establishment of effective monitoring planning of deteriorating structures. In this paper, an approach to optimal monitoring planning of deteriorating structural systems considering time-variant structural performance is proposed. The information extracted from SHM over a long-term period can be applied to make a current assessment as well as a prediction of structural performance. As the monitoring duration increases, more reliable information can be obtained, but additional cost is needed. Therefore, monitoring planning should be formulated as a bi-objective optimization problem in order to obtain well-balanced solutions.

This paper focuses on monitoring planning according to the reliability importance factor (RIF) of individual components of a structural system. In order to estimate the time-dependent reliability of each component, a time-dependent function based on monitored data is applied. For assessment of the structural system performance, a series–parallel system model is used. The total monitoring cost for the structural system is allocated to the components according to their normalized reliability importance factors (NRIFs). The allocated monitoring cost of each component determines the monitoring plan (i.e., monitoring duration and prediction duration) by using the Pareto optimal solution set of a bi-objective optimization problem which minimizes the total monitoring cost and maximizes the availability of monitoring data (i.e., strain data). An existing bridge (Bridge I-39, Northbound) in

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Wisconsin, USA, is used as an illustrative example. The approach proposed in this paper can be applied to any monitored structure and, in particular, to bridges.

2. Assessment and prediction of structural performance

SHM can be defined as the process of implementing a structural damage identification strategy, which includes the process of assessing and predicting the state of health of the structural system [4]. The output from SHM is recorded continuously until obtaining sufficient samples to accomplish successful condition and damage assessment [5]. The monitored data should serve in structural performance assessment using probabilistic and statistical methods. In this section, the approach for such a performance assessment based on monitored data is presented as the first step for effective monitoring planning.

2.1. Assessment of structural performance based on monitored data

In general, a state function is related to the difference between the resistance and the load effect (i.e., safety margin). Based on monitored data, the state function of component *i* can be formulated in terms of the physical quantity of interest (e.g., stress, strain) as

$$g_i(\mathbf{q}_i) = q_{limit,i} - q_{mon,i} \tag{1}$$

where $\mathbf{q}_i$ is a vector of variables related to the physical quantities of component *i*, $q_{limit,i}$ is the predefined upper limit of the physical quantity of component *i*, and $q_{mon,i}$ is the physical quantity obtained from the monitoring system installed on the critical location of component *i*. The predefined limit $q_{limit,i}$ and the monitored physical quantity $q_{mon,i}$ can both be treated as random variables. In this study, the probability that the monitored physical quantity does not exceed the predefined limit serves as the reliability measure.

In order to compute the system reliability, the first step is to define a model that realistically describes the behavior of the system using series–parallel modeling [6]. For a series system, the reliability of the system requires that none of its components fail. In contrast, for a parallel system, system failure requires failure of all its components. The probabilities of failure for a component, series system, and parallel system are defined, respectively, as follows:

- for component *i*: $p_{F,i} = p(g_i(\mathbf{q}_i) \le 0)$ (2a)
- for a series system: $p_{F,S\text{-}system} = p\left(\bigcup_{i=1}^{N}(g_i(\mathbf{q}_i) \le 0)\right)$ (2b)
- for a parallel system: $p_{F,P\text{-}system} = p\left(\bigcap_{i=1}^{N}(g_i(\mathbf{q}_i) \le 0)\right)$ (2c)

where *N* is the total number of components. In this study, the system reliability is computed using the software RELSYS (RELiability of SYStems) developed by Estes and Frangopol [7].

2.2. Prediction of structural performance based on monitored data

In order to predict the structural performance, a probabilistic approach based on monitored data is applied [8]. If the predefined limit is assumed to be constant over time, $g_i(\mathbf{q}_i, t)$ can be formulated as follows:

$$g_i(\mathbf{q}_i, t) = q_{limit,i} - \zeta_i(t) \times q_{mon,i} \tag{3}$$

where $\zeta_i(t)$ is defined as the ratio of the predicted largest value during future time period *T* to the largest value obtained during the monitored period [8]; $\zeta_i(t)$ can be derived using monitored data. If the monitored stress (the monitored strain multiplied by Young's modulus is called the monitored stress herein) is considered as the physical quantity of interest, the random stress induced by all vehicles crossing a bridge can be assumed, for example, as Gaussian. In this case, the largest stress $\sigma_{\max}$, induced by only heavy vehicles, is asymptotically approaching a Gumbel distribution (i.e., double exponential distribution). The CDF of $\sigma_{\max}$ is [9]

$$F(\sigma_{\max}) = \exp\left(-\exp\left(-\frac{\sigma_{\max} - \delta}{\rho}\right)\right) \tag{4}$$

where δ is a location parameter; and ρ a scale parameter. The largest stress $\sigma_{\max}(N_T)$ among the stresses induced by the expected number of heavy vehicles N_T during future time period *T* can be predicted from $F(\sigma_{\max}(N_T)) = 1 - (1/N_T)$ [10]. Therefore,

$$\sigma_{\max}(N_T) = \delta - \rho \cdot \ln\left[-\ln\left(1 - \frac{1}{N_T}\right)\right]. \tag{5}$$

Consequently, the time-dependent function $\zeta_i(t)$ can be obtained as [8]

$$\zeta_i(t = T) = \max\left\{\frac{\delta - \rho \cdot \ln(-\ln(1 - 1/N_T))}{\max(\sigma_{\max,1}, \sigma_{\max,2}, \ldots, \sigma_{\max,j}, \ldots, \sigma_{\max,No})}; 1.0\right\} \tag{6}$$

where $\sigma_{max,j}$ is the monitored maximum stress induced by the *j*th heavy vehicle on the bridge; and N_o is the number of heavy trucks crossing the bridge during the given monitored period T_o. However, there is no guarantee that the largest stress $\sigma_{\max}$ will asymptotically approach a Gumbel distribution. For this reason, in order to select the most appropriate PDF of the largest stress $\sigma_{\max}$, the relative goodness of fit tests have to be performed with several candidate distributions.

3. Reliability importance factor (RIF)

A structural system is composed of various components with different limit states. In general, the system performance can be assessed by using a series–parallel model. In order to establish effective monitoring planning, it is necessary to rank the structural components based on their reliability importance factors [11,12]. For instance, an individual component having the highest probability of failure in a series system has the highest impact on the system reliability. To quantify the impact of reliability of an individual component on the system reliability, the reliability importance factor (RIF) is used. The RIF of component *i* can be defined as the gradient of the system reliability with respect to reliability of component *i* as [13]

$$RIF_i = \frac{\partial p_{S,system}}{\partial p_{S,i}} \tag{7}$$

where $p_{S,system}$ is the system reliability and $p_{S,i}$ is the reliability of component *i*. The associated normalized reliability importance factor (NRIF) of component *i* is defined as [11]

$$NRIF_i = \frac{RIF_i}{\sum_{j=1}^{N} RIF_j} \tag{8}$$

where *N* is the number of components in the system, and $0 \le NRIF_i \le 1.0$. For example, the reliability $p_{S,series}$ of a series system consisting of two statistically independent components is $p_{S,1} \times p_{S,2}$, where $p_{S,1}$ is the reliability of component 1, and $p_{S,2}$ is the reliability of component 2. From Eq. (7), the RIFs of components 1 and 2 become $p_{S,2}$ and $p_{S,1}$, respectively. Therefore,