MEASUREMENT SYSTEM DESIGN FOR DAMAGE DETECTION USING MODEL-FREE DATA INTERPRETATION METHODS

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Designing a measurement system is usually performed using only engineering judgment and experience. Thus, it may result in either a large amount of redundant data or insufficient data leading to ambiguous results. This paper presents a systematic approach to design measurement systems for damage detection using model-free data-interpretation methods. The approach provides decision support for two tasks: (1) determining the appropriate number of sensors and (2) placing these sensors in the most informative locations. These tasks correspond to two steps. The first step is to evaluate the performance of measurement systems in terms of the increasing numbers of sensors. Engineers can then determine the number of sensors to be used at the point where the improvement of the performance is modest with the addition of more sensors. The second step is to configure measurement systems in order to place the sensors at the most informative locations. This step involves evaluating the performance of measurement configurations using three criteria: minimizing the number of non-detectable scenarios, minimizing the average time to detection and maximizing the average damage detectability. The result obtained from three-objective optimization is a set of non-dominated solutions. Thus, to choose the best compromise solution, a multi-criteria decision-making strategy is employed. A railway truss bridge in Zangenberg (Germany) is used to illustrate the applicability of the approach. Measurement systems are designed to monitor the bridge where measurement data are interpreted using two model-free (non-physics-based) methods: moving-principal-component analysis and robust-regression analysis. The configurations that are found do not correspond to configurations that would be selected using engineering experience only. Results demonstrate that the proposed approach is able to provide engineers with decision support in determining the appropriate number of sensors and identifying the most informative locations that lead to more rational measurement system designs.

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ABSTRACT: This paper presents an approach for measurement system design where static measurement data are interpreted for damage detection using model-free (non-physics-based) methods. The main goal of the proposed approach is to provide decision support for two tasks: (1) determining the appropriate number of sensors to be employed and (2) placing sensors at the most informative locations. The approach involves damage-scenario generation, multi-objective optimization and multi-criteria decision-making. A railway truss bridge in Zangenberg (Germany) is used for a case study to illustrate the applicability of the proposed approach. Measurement systems are designed for situations where measurement data are continuously interpreted using two model-free methods: Moving Principal Component Analysis (MPCA) and Robust Regression Analysis (RRA). Results demonstrate that the proposed approach is able to provide engineers with decision support for rational measurement-system design.

1 INTRODUCTION

The number of structures that are continuously monitored has been increasing as sensors, measurement systems and data storage technologies have become more affordable. Many structures have been monitored using sophisticated measurement systems with a large number of sensors. For example, the cable-stayed Stonecutters bridge in Hong Kong is equipped with more than 1200 sensors (Ni et al. 2008). Due to the lack of systematic approaches for the configuration of measurement systems, many measurement systems were designed using engineering judgment only. This results in either a large amount of redundant data or insufficient data. Redundant data leads to high data-interpretation costs while insufficient data results in ambiguous interpretations. Therefore, it is important to develop a systematic approach for measurement system design.

One of the goals of structural health monitoring is to detect damage before it reaches a critical level. Damage in civil structures may be identified by continuously interpreting monitoring data. There are generally two classes of data-interpretation methods: model-based (physics-based) methods and model-free (non-physics-based) methods (ASCE 2011). Posenato et al. (2010) proposed two model-free data-interpretation methods: (1) Moving Principal Component Analysis (MPCA) and (2) Robust Regression Analysis (RRA), to detect and localize damage in civil engineering structures. Signal noise due to

traffic and temperature variations create situations where the effects of damage are not visible in the measurement data. It was demonstrated that the performance of MPCA and RRA for damage detection was superior to that of other methods when dealing with civil-engineering challenges that include high noise, missing data and outliers. Laory et al. (2011) further evaluated the performance of these methods under environmental variations and showed that they are complementary methods.

Previous studies (Kang et al. 2008; Li et al. 2007; Li et al. 2004; Meo and Zumpano 2005; Papadimitriou 2004) have focused on the configuration of measurement systems for dynamic tests where measurement data are interpreted using model-based methods. Papadimitriou et al. (2000) proposed an entropy-based sensor placement approach for structural model updating. For multiple-model methods using static measurements, Robert-Nicoud et al. (2005) proposed an iterative greedy algorithm to design a measurement system that gives maximum separation between predictions of candidate models. Few studies have used damage-scenario generation as a starting point for measurement system configuration. Although many studies have been conducted to design measurement systems for structural identification, none have developed a measurement system configuration where static measurements are continuously interpreted using model-free methods

The number of measurement configurations is exponentially increased with respect to the number of sensors and their possible locations. Hence, the task of configuring measurement systems is best carried out using stochastic search algorithms. Several studies (Kripakaran and Smith 2009; Liu et al. 2008; Rakesh and et al. 2008; Rao and Ganesh 2007; Tongpadungrod et al. 2003) have employed stochastic search algorithms for measurement system design. The evaluation of the potential configurations should include several criteria (objectives). Thus, the solution is either a set of non-dominated solutions (Pareto-optimal solutions), or a compromise solution according to engineers' preferences. The task of selecting a compromise solution falls into the field of multi-criteria-decision-making (MCDM). The best compromise solution can be determined by ranking each solution in the Pareto set using Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) (Behzadian et al. 2010; Brans and Mareschal 2005). The ranking is based on the utilization of a preference index to compute a net flow for each Pareto optimal solution. Other studies have identified PROMETHEE as an effective strategy for MCDM (Bel Hadj Ali and Smith 2010).

This paper presents a systematic approach to design measurement systems where quasi-static measurement data are continuously interpreted using model-free methods. The approach involves damage-scenario generation, multi-objective optimization and multi-criteria decision-making. It consists of two steps. The first step is to provide decision support for engineers to determine the appropriate number of sensors to be employed. The second step is to configure sensor locations based on three criteria: minimizing the number of non-detectable scenarios, minimizing the average time to detection and maximizing damage detectability. A multi-objective optimization using a genetic algorithm (Sastry 2007) is employed to evaluate potential configurations and search for optimum solutions. Then, a multi-criteria decision-making method, PROMETHEE, is applied to provide support for identifying the best compromise configuration. To illustrate the applicability of the proposed approach, measurement systems are configured for the Zangenberg railway bridge (Germany) where the measurement data

are interpreted using Moving Principal Component Analysis and Robust Regression Analysis.

2 MODEL-FREE DATA-INTERPRETATION METHODS

2.1 Moving principal component analysis (MPCA)

The idea behind MPCA for damage detection is that the correlation between measurements at several locations on structures may change when damage occurs (Posenato et al. 2010). The aim is to enhance the discrimination between features of undamaged and damaged structures so that damage which is not directly visible from measurements can be detected. It also requires less computational time in comparison with that of a normal principal-component analysis (PCA). MPCA applies principal-component analysis (Hubert et al. 2005) to a moving constant-sized window of measurements instead of the whole dataset. MPCA works by first constructing a matrix that contains the history of all the measurements. Then, it sequentially extracts datasets corresponding to a moving window to compute the principal components using PCA. Damage is detected when the time histories of eigenvectors corresponding to the first several principle components (or eigenvalues) are larger than a specified confidence interval.

2.2 Robust regression analysis (RRA)

RRA is applied for continuous monitoring of structures by observing sensor pairs that are strongly correlated. These pairs are identified using correlation coefficients. All sensor pairs having a correlation coefficient greater than the threshold are selected in order to formulate the robust regression models. Measurement data are then evaluated by observing the discrepancy between measurement and prediction using the regression models. Damage is detected when the difference is larger than a specified confidence interval.

3 MEASUREMENT SYSTEM DESIGN

The aim of measurement system design is to determine an appropriate number of sensors and to place them at the most informative locations so that the measured data can be meaningfully interpreted. In order to reduce computational time, these two tasks are conducted in two steps (Figure 1). The first step is a preliminary exploration of the solution space based on the performance of measurement configurations with respect to the increasing number of sensors. Each configuration is evaluated using a criterion of minimizing the number of non-detectable scenarios when using MPCA and RRA to interpret measurements for damage detection. Evaluating all the combination of i sensors among n possible locations has the following computational complexity

$$\sum_{i=1}^{n} C_n^i = 2^n - 1 \tag{1}$$

This equation indicates that the task of placing i sensors among n possible locations is combinatorial and the total complexity is exponential. A deterministic optimization method is useful only for a small number of possible sensor locations. In civil engineering applications, however, this number is often large which makes the evaluation of all possible configurations infeasible. Furthermore there may be many

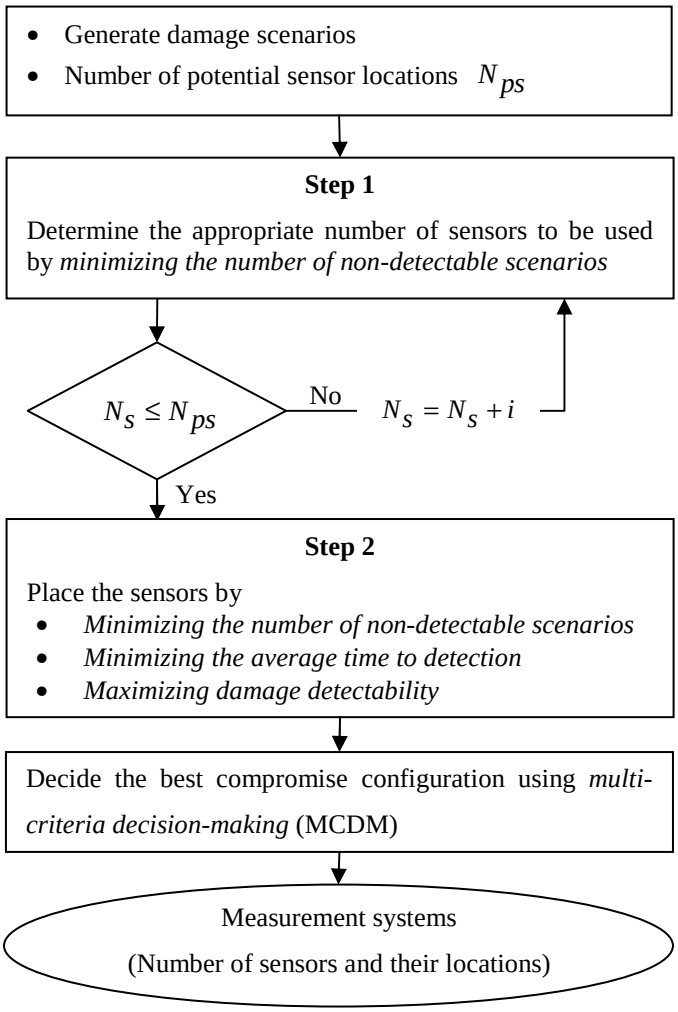

Figure 1. A procedure to design measurement systems for a structure that are continuously monitored using model-free (non-physics- based) data interpretation methods.

local minima. Thus, stochastic search is suitable for such situation. A single-objective optimization using genetic algorithm as a stochastic search is employed to find the configuration that has the smallest number of non-detectable scenarios. The results obtained from this step provide support for engineers to determine the appropriate number of sensors at the point where the improvement of the performance of measurement configurations is modest when adding more sensors.

The second step is to configure measurement systems by placing sensors at the most informative locations. Given the chosen number of sensors, this step can be seen as an intensive exploration into the solution space for measurement configurations. The performance of configurations is evaluated using three criteria: (1) minimize the number of non-detectable scenarios, (2) minimize the average time to detection and (3) maximize damage detectability. In this paper, damage detectability is defined based on the average minimum damage level that can be detected. Multi-objective optimization using genetic algorithm is carried out to identify sensor locations so that the measurement systems give good performance based on all criteria. The results obtained

from this step are a set of Pareto-optimal solutions. In order to select the "best" compromise measurement configuration from this set, a multi-criteria decision-making method is employed as a decision support tool. Incorporating preferences is also able used to help to handle conflicting objectives (Fleming et al. 2005). In this study, the PROMETHEE method (Brans and Mareschal 2005) is adopted to identify the best compromise measurement system configuration among the set of Pareto-optimal solutions.

4 CASE STUDY

The approach is applied to design measurement systems for a railway truss bridge in Zangenberg (Germany). This 80-m steel bridge is composed of two parallel trusses each having 77 members (Figure 2). The truss members are made of steel having an elastic modulus of 200 GPa and a density of 7870 kg/m^3. A finite element analysis for one truss under traffic loading and temperature variation provides simulated responses (strains). These responses are used as measurements from continuous monitoring. Supports of the truss are restrained in vertical and horizontal directions. Although this is not the boundary conditions that were designed for this bridge, these supports represent an upper-bound worst case when the supports have deteriorated with age. Traffic loading is simulated by applying a randomly generated vertical load (0-19 tones) at each node in the bottom chords. A load of 19 tones is equivalent to an axle load of a railway locomotive. Daily and seasonal temperature variations are simulated as thermal loads. Temperature differences between top and bottom chords due to solar radiation are also taken into account in the simulations. In this example, damage is represented to be a loss of member axial stiffness. Seventy-seven damage scenarios associated with the number of truss members were generated where each scenario represents 50% axial stiffness reduction of a member. Damage is detected by continuously interpreting measurement data using MPCA and RRA.

Figure 3 shows the reduction in the number of non-detectable damage scenarios with respect to the increasing number of sensors used when using MPCA and RRA. It is observed that the number of non-detectable damage scenarios reduces rapidly when the number of sensors increases from 0 to 24 sensors. For example, for MPCA this number reduces from 77 to 15. When using more than 24 sensors, the improvement of the measurement-system performance becomes marginal; that is, adding more sensors leads to only a small improvement. Therefore, 24 sensors are chosen for the design of this measurement system. Figure 3 also indicates that using the same number of sensors, MPCA detects more damage scenarios than RRA. Even when every member has a sensor, there are damage scenarios that are not detected using RRA. This illustrates the inferior damage detectability of RRA compared with MPCA.

Given the chosen number of sensors above, measurement systems are designed using a multi-objective optimization and a MCDM approach. The objectives are minimizing the number of non-detectable scenarios, minimizing average time to detection and maximizing damage detectability. To select the best compromise solution obtained from multi-objective optimization, all the solutions in the Pareto-optimal set are ranked using PROMETHEE. Figure 4 shows the Pareto-optimal solutions for both MPCA and RRA. Time to detection for RRA is smaller than that of MPCA. On the other hand, MPCA has higher detectability than RRA and detects more damage scenarios. These results indicate that RRA is able to detect damage faster than MPCA but MPCA is better in terms of damage detectability.

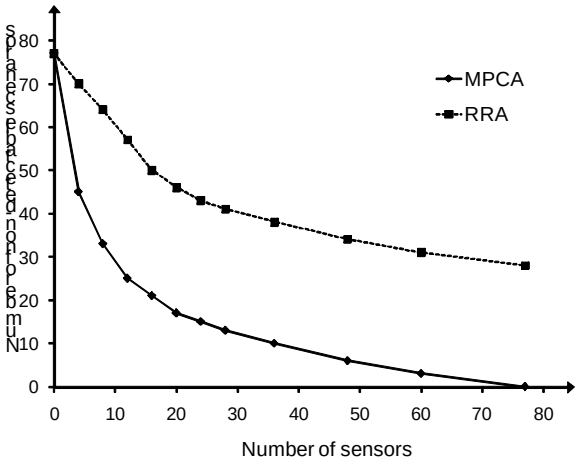

Figure 3. The number of non-detectable scenarios corresponding to the number of sensors when using moving principal component analysis and robust regression analysis for continuous monitoring of the bridge

Results obtained from Step 1 using a single objective (minimize the number of non-

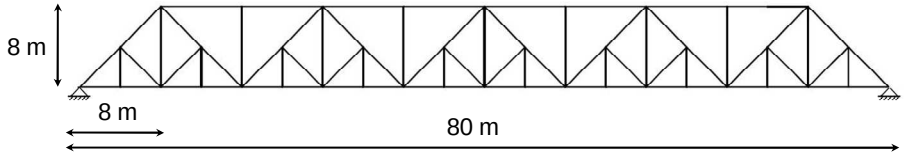

Figure 2. A truss structure inspired by a 80-m railway steel bridge in Zangenberg (Germany)

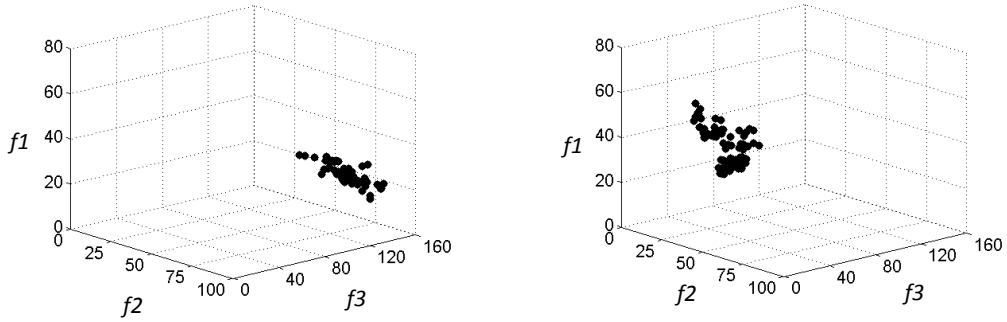

Figure 4. Pareto-optimal solutions for MPCA (left) and RRA (right). F1 is the number of non-detectable damage scenarios; f2 is the damage detectability (%); and f3 is the average time to detection (days)

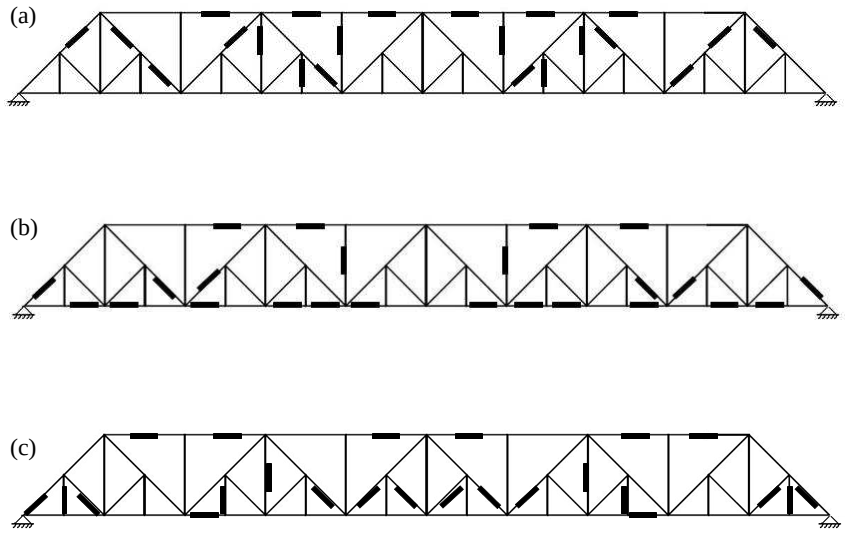

Figure 5. Measurement system configurations for situations when using a) MPCA and b) RRA for continuous monitoring of the bridge; c) the measurement configuration of 24 sensors obtained from Step 1 for MPCA.

detectable scenarios) are shown in Figure 5c. The number of non-detectable scenario is 15 after Step 1 for MPCA and 43 for RRA. After Step 2 these values changes to 17 and 45. This is due to tradeoffs with other criteria. Figure 5a and Figure 5b shows respectively the best compromise configurations for MPCA and RRA. Intuitively, engineers would place sensors at mid-span, bottom chord, for example see Laory et al. (2011). As shown in Figure 5, there is no sensor placed at these locations. It demonstrates that engineering judgment may lead to non-optimal configurations. For MPCA, no sensor is placed at bottom chord while sensors are mainly distributed at the bottom chord for RRA. Only 8 sensors out of 24 are placed at the same position.

These results show that different data-interpretation methods require different measurement configurations. For situations where information about the preference is available, PROMETHEE is a good approach for providing decision support for selecting the best compromise system configuration. Results in this case study demonstrate that the proposed approach is applicable to various model-free data-interpretation methods for damage detection.

5 CONCLUSIONS

This paper presents an approach to design measurement systems for continuous monitoring of structures where measured data are interpreted using model-free (non-physics-based) methods. The approach is able to provide support for measurement system design and applicable to various model-free data interpretation methods. The number of non-detectable scenarios, the average time to detection and the damage detectability are important metrics for the design of measurement systems. A multi-criteria decision-making (MCDM) method, Preference ranking organization method for enrichment evaluation (PROMETHEE), successfully selects compromise measurement-systems. These configurations do not correspond to configurations that would be selected using only engineering experience. Therefore, computational support for

measurement-system design provides engineers with solutions that would not have otherwise been found.

Future studies will investigate the applicability of the proposed approach for situations where multiple model-free methods are simultaneously employed for data interpretation and compare several MCDM methods for decision support.

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