Optimal Design of Sensor Networks for Monitoring of Structures

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ABSTRACT

The development of the digital twin technology for civil infrastructure, such as buildings and bridges, operating under an uncertain seismic environment is important for building data-informed computational models that are reliable over different seismic excitations expected at a site. Data collected from a monitoring system can help build a reliable digital twin that cover the various linear and nonlinear mechanisms activated under different seismic excitations (main shocks and aftershocks), monitor the state (healthy or deteriorated) of the structure, as well as reconstructing the response time histories (e.g. drifts, accelerations, strains and stress) at unmeasured locations for evaluating safety-related indices. Optimal sensor configuration design refers to the selection of the type, number and location of sensors that are most informative for building reliable digital twins. This work outlines recent developments on the methods for selecting the optimal type, location and number of sensors for building reliable digital twins and monitoring the healthy and damaged state of the components of civil infrastructure under earthquake-induced vibrations, taking into account the uncertainty in the temporal and spatial variability expected due to seismic loading.

Key Words: Information gain, Robustness, Multi-objective optimization, Structural dynamics

1 INTRODUCTION

Monitoring data collected from a sensor network can be used to inform a digital twin of a structure that operates in an uncertain seismic environment. The data are useful for selecting the appropriate models of the structural components, for estimating the model parameters, for structural health monitoring and damage identification, and for improving model-based predictions of important output quantities of interest (QoI) such as drift and strain/stress time histories using output-only vibration measurements. Using data from a monitoring system to inform a digital twin of a structure operating under different operational and environmental conditions is crucial in making data-informed decisions regarding structural performance, health, safety and maintenance.

Optimally designed experiments and sensor systems provide substantial benefits to update models and model-based predictions and to support decisions in many fields of science, health

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and engineering, as well as to reduce cost of experimentation, instrumentation, or monitoring. Optimal sensor placement (OSP) aims to maximize the quality of the data which are collected from a monitoring system. Such data should be most informative for completing different tasks from an instrumentation. Such tasks include substructure model building, model parameter estimation, identification of location and magnitude of damage, as well as reconstruction of important safety related quantities such as strains, stresses drifts, etc. that are useful to evaluate the condition of existing structures, detect damages and make decisions regarding structural health, safety and performance. A sensor configuration designed to be optimal for one of the aforementioned tasks maybe suboptimal for another task. A monitoring system should be carefully designed to be cost-effective and capable of gaining enough information to accomplish all of the aforementioned tasks.

Information theoretic measures such as mutual information, information entropy, joint information and value of information are used in this work to measure the information content in the data [1-8]. Such information content depends on location, type and number of sensors involved in the monitoring system. Cost of monitoring is also very important in the design of a sensor configuration in order to limit the cost associated with installing and maintaining the sensor network. In addition, uncertainties should also be taken into account in the information theoretic measures. Such uncertainties arise from modelling and measurement errors, as well as excitation uncertainties that are completely unknown in the experimental design phase.

The present study discusses the issues involved in designing an optimal sensor configuration for building a reliable digital twin of civil infrastructure, such as building and bridges, for the purpose of monitoring its state, performance, reliability and safety. It presents appropriate indices for measuring the information contained in a sensor system for the different monitoring tasks, the optimization strategies for estimating the optimal sensor configuration accounting for all monitoring tasks, as well as the consideration and effect of uncertainties in the OSP design. Applications of the OSP methodology for monitoring the individual tasks can be found elsewhere (e.g. [9-12]).

2 INFORMATION GAIN FROM A SENSOR NETWORK

The information content in the data collected from a sensor network is quantified using information theoretic measures such as mutual information, Kullback-Liebler divergence, information entropy, joint information and value of information [1-8]. Such measures are built using a Bayesian learning framework for parameter inference or response predictions. For this, it is assumed that physics-based models for the components of the structure are available. Such models are usually linear and nonlinear finite element models that can account for all the mechanism that are activated in a real structure during its operation. The models are usually parameterized and the objective is to use data to select models and update the model parameters and thus improve the digital twin so that it is representative under different excitation conditions expected during structural operation over the structure's lifetime. Also, the finite element models can be used for response predictions in all critical locations of the structure using output-only vibration measurements. Building a finite element model of a structure should also take into account the tests performed at material and component level to validate the models used, for example, models for the hysteretic behaviour of structural elements comprising the structure and/or for the behaviour of vibration isolation devices. A monitoring system should also be designed to monitor the state of such devices or components along with the global state of the structure.

The sensor network should be designed to be able to perform simultaneously several monitoring tasks. Such tasks along with the supporting methods to optimally design the sensor network, are next outlined. A monitoring system should be designed to cost-effectively trade-off the information gained for each of the aforementioned tasks since an optimal monitoring system for a task might not be optimal for another task.

2.1 Monitoring Task: Mode Identification (ModeID)

For a finite element model of the structure, representative of its dynamics for low amplitude vibration measurements, the information contained in the data collected from a sensor network $\underline{\delta}$ for identifying the modal properties (modal frequencies and modeshapes) is obtained using the modal expansion technique for which the response vector $g(\underline{\theta},\underline{\varphi})$ at the measured locations is expressed as a linear function of the modal coordinate vector $\underline{\xi} \equiv \underline{\theta}$ as follows: $g(\underline{\theta},\underline{\varphi}) = L(\underline{\delta})\Phi(\underline{\varphi})\underline{\theta}$, where $\Phi(\underline{\varphi})$ is the displacement and/or strain modeshape matrix corresponding to n model DOF and m contributing modes, $L(\underline{\delta}) \in R^{N_0 \times n}$ is the observation matrix that maps the displacements or accelerations at all n model DOF to the N_0 measured displacement or strain or acceleration quantities indicated by the sensor location vector $\underline{\delta}$, and the parameter set $\underline{\theta}$ is associated with the model coordinates. Using utility theory [13], the OSP is accomplished by maximizing the expected information gain over all possible data generated from the prediction error model. It can be shown that the utility function is given as [12,14]

$$U_{ModeID}(\underline{\delta},\underline{\varphi}) = \frac{1}{2}\log\frac{\det[Q_{ModeID}(\underline{\delta};\underline{\varphi}) + Q_{\pi}(\underline{\varphi})]}{\det[Q_{\pi}(\underline{\varphi})]} \tag{1}$$

where

$$Q_{ModeID}(\underline{\delta};\underline{\varphi}) = S_{ModeID}(\underline{\delta};\underline{\varphi})[L(\underline{\delta})\Sigma_e(\underline{\varphi})L^T(\underline{\delta})]^{-1} S^T_{ModeID}(\underline{\delta};\underline{\varphi}) \tag{2}$$

$S_{ModeID}(\underline{\delta};\underline{\varphi}) = L(\underline{\delta})\Phi(\underline{\varphi})$ is the sensitivity of the response predicted by the modal expansion at the measured locations with respect to the model parameters $\underline{\xi}$, $Q_{\pi}(\underline{\varphi})$ is inverse of the covariance of the Gaussian prior distribution assumed for the modal coordinates, $\Sigma_e(\underline{\varphi})$ is the covariance matrix of the error between the measurements and the model predictions at all possible sensor locations. According to the theory, the optimal location of sensors is based solely on the displacement or strain modeshape components $L(\underline{\delta})\Phi(\underline{\varphi})$ at the measured locations provided by the finite element model, the model for the covariance $\Sigma_e(\underline{\varphi})$ of the error discussed in [15,16], as well as the prior distribution of the modal coordinates assumed here for convenience to be zero-mean Gaussian with covariance matrix $Q_{\pi}^{-1}(\underline{\varphi})$. The optimal sensor design $\underline{\delta}_{opt}$ maximizes the function in (1), guaranteeing that the data collected from the sensor network will be most informative to estimate the modal coordinates using mode identification techniques.

For number of sensors less than the number of modes, the matrix $Q_{ModeID}(\underline{\delta};\underline{\varphi})$ in (2) is singular. In this case, the OSP cannot be performed unless the extra information is borrowed from the prior distribution of the model parameters (modal coordinates) through the matrix $Q_{\pi}(\underline{\varphi})$, making the overall matrix $Q_{ModeID}(\underline{\delta};\underline{\varphi})+Q_{\pi}(\underline{\varphi})$ in (2) invertible. In general, however, a reasonable constrain for the modal expansion technique is that the number of measurements required to identify the modes should be equal or greater than the number of contributing modes in order to gain substantial information from the sensor network. In principle, using the modal expansion techniques the OSP design is independent of the excitation levels.

The parameter set $\underline{\varphi}$ is introduced to account for the uncertainties in the model parameters such as stiffness and mass properties of the underlining linear finite element model of the structure. Such properties are often uncertain during the experimental design phase. Also, during damage from a severe earthquake excitation, the stiffness/mass properties might also be uncertain due to damage. Probability distributions are used to quantify the uncertainty in the values of these model parameters and then the OSP methodology is designed to account for such uncertainty as described in Section 2.5.

2.2 Monitoring Task: Structural Identification (ParID)

Let $\underline{g}(k;\underline{\theta},\underline{\varphi}) \in R^n$ be the model predicted time histories of n response QoI given the values of the parameter set $\underline{\theta}$ and the input time history $\underline{u}(k;\underline{\varphi}) \in R^{n_u}$ assumed to be measured by the sensor network, where k denotes the time index at time $t = k\Delta t$, $k = 1,\ldots,n_d$, and Δt is the sampling period. Here n denotes all possible locations or DOF that sensors can be placed. The predictions depend also on a parameter set $\underline{\varphi}$ that includes the uncertain variables associated with the temporal and spatial variability of the excitation, and the nuisance parameters associated with non-updatable parameters of the structural and/or prediction error model.

Structural identification refers to methods used for selecting the most appropriate parameterized models of structural elements and inferring the parameters of these models. Laboratory experiments at isolated components as well as monitoring data at the field during ambient vibrations as well as earthquake excitation (main shock and aftershocks) can be used to select models and infer the model parameters. The sensor configuration (type, number and location of sensors) should be selected such that the data collected form the sensor network are most informative about the values of the model parameters. The information gained from data for estimating the model parameters contained in the set $\underline{\theta}$ is given by the utility function [16]

$$U_{ParID}(\underline{\delta},\underline{\varphi}) = \frac{1}{2}\int \log \frac{\det[Q_{ParID}(\underline{\delta};\underline{\theta},\underline{\varphi}) + Q_{\pi}(\underline{\varphi})]}{\det[Q_{\pi}(\underline{\varphi})]} \pi(\underline{\theta}) d\underline{\theta} \tag{3}$$

where $Q(\underline{\delta};\underline{\theta},\underline{\varphi})$ is the Fisher information matrix given by

$$Q_{ParID}(\underline{\delta};\underline{\theta},\underline{\varphi}) = \sum_{k=1}^{n_d} S_{ParID}(\underline{\delta};k,\underline{\theta},\underline{\varphi})[L(\underline{\delta})\Sigma_e(\underline{\theta},\underline{\varphi})L^T(\underline{\delta})]^{-1} S_{ParID}^T(\underline{\delta};k,\underline{\theta},\underline{\varphi}) \tag{4}$$

and

$$S_{ParID}(\underline{\delta};k,\underline{\theta},\underline{\varphi})=\underline{\nabla}_{\theta}[L(\underline{\delta})\underline{g}(k;\underline{\theta},\underline{\varphi})]^{T} \tag{5}$$

is a sensitivity matrix that accounts for the sensitivity of the response quantities at the measured DOF with respect to the model parameters, $\underline{\nabla}_{\theta}$ is the gradient operation with respect to the set $\underline{\theta}$, $L(\underline{\delta})\in R^{n_y\times n}$ is a matrix that selects from the response vector $\underline{g}(k;\underline{\theta},\underline{\varphi})$ the DOF that correspond to the sensor configuration $\underline{\delta}$, and $\Sigma_e(\underline{\theta},\underline{\varphi})\in R^{n\times n}$ is the covariance of the zero-mean Gaussian model prediction error assumed in the Bayesian inference process to build the posterior PDF of the model parameters. Maximizing the utility function (3) is equivalent to maximizing a scalar measure (the logarithm of the determinant) of the response sensitivity at the measured locations with respect to the model parameters. The sensors are preferred to be placed to locations where the measured response is most sensitive to changes in the model parameters. Placing sensors at a location where the response is insensitive to changes in the model parameters does not give any information about the value of the model parameter. The covariance matrix $\Sigma_e(\underline{\theta},\underline{\varphi})$ is selected following the approach used in [15,16]. It should be noted that the utility function (3) is a generalization of the utility function (1) for response QoI that depend nonlinearly on the parameters $\underline{\theta}$. In particular, for the case that the response QoI $\underline{g}(k;\underline{\theta},\underline{\varphi})$ depends linearly on the set $\underline{\theta}$, the $Q_{ParID}(\underline{\delta};\underline{\theta},\underline{\varphi})$ is independent of $\underline{\theta}$ and the utility function (3) reduces to (1).

2.3 Monitoring Task: Structural Health Monitoring (DamID)

Damage is associated with changes in the structural elements or structural connections, usually isolated in substructures comprising the structure. Considering that the structure consists of a large number of substructures, damage may occur in one or more of the large numbers of these substructures. To design a sensor network to monitor for damage is thus a very formidable task since the requirements is to simultaneously monitor for damage a large number of substructures.

For the case where a parameterized model is used to describe the damage in a substructure (e.g. crack related parameters in steel connections [17,18]), the problem of estimating damage given that damage occurs in one of the substructures is equivalent to the structural identification problem outlined in Section 2.2. So, the optimal design of the sensor network is obtained by maximizing the information gain (3) for the particular damage scenario, denoted here by

$$U_{DamID}^{(i)}(\underline{\delta},\underline{\varphi})=\frac{1}{2}\int\log\frac{\det[Q_{DamID}^{(i)}(\underline{\delta};\underline{\theta}_i,\underline{\varphi})+Q_{\pi}(\underline{\varphi})]}{\det[Q_{\pi}(\underline{\varphi})]}\pi(\underline{\theta}_i)d\underline{\theta}_i \tag{6}$$

where i refers to a potentially damage substructure, and $\underline{\theta}_i$ refer to the parameters of the model introduced for the substructure i. For $i=1,\ldots,\mu$ potential locations of damage to be simultaneously monitored, one has to solve the problem of optimally designing the sensor network so that all information gain objectives $U_{DamID}^{(i)}(\underline{\delta},\underline{\varphi})$, $i=1,\ldots,\mu$, are optimized simultaneously. This is obviously a challenging task. One way to solve the problem is to weight the individual objectives into a single objective and optimize the single objective

$$U_{DamID}(\underline{\delta},\underline{\varphi})=\sum_{i=1}^{\mu}p_i\frac{U_{DamID}^{(i)}(\underline{\delta},\underline{\varphi})}{U_{DamID}^{(i,\max)}} \tag{7}$$

where $U_{DamID}^{(i,\max)}$ is the maximum information gain obtained by placing sensors at all available sensor locations, p_i is the prior probability assign for damage scenario i, and $\sum_{i=1}^{\mu} p_i = 1$.

2.4 Monitoring Task: Virtual Sensing - Response Reconstruction (VS)

An interesting task is also to monitor the vibration of the structure and reconstruct responses related to important QoI such as safety-related quantities (e.g. story drifts, strains and stresses). This virtual sensing can be achieved by a limited number of physical sensors placed in the structure. Model expansion [19] and filtering (e.g. [20-22]) techniques are the two types of methods developed recently and used to reconstruct responses under unknown input excitations such as wind loads and earthquake loads. The sensor locations affect the accuracy of the estimates provided by these virtual sensing methods. The optimal sensor placement is designed to guarantee the highest accuracy in the response reconstruction. Formulations for the utility function $U_{VS}(\underline{\delta},\underline{\varphi})$ quantifying the information contained in the measured data for reliable virtual sensing (response reconstruction) can be found in [12] using modal expansion technique for virtual sensing and in [23] using filtering techniques for reliable response and input reconstruction. For the case of linear models of structures, the utility function $U_{VS}(\underline{\delta},\underline{\varphi})$ depends on an uncertain parameter set $\underline{\varphi}$. The parameter set $\underline{\varphi}$ is related to stiffness and mass parameters that could be uncertain and it is treated the same way as described in Section 2.1.

It can be shown analytically that as the number of sensors increase, the information contained in the data for response reconstruction increases. Often the use of as many sensors as the number of contributing modes is adequate for response reconstruction. For large model and measurement errors, more sensors placed at their optimal locations can increase the accuracy of reconstructed responses. Optimizing $U_{VS}(\underline{\delta},\underline{\varphi})$ with respect to the sensor locations guaranties that the physical sensors are not placed at locations with low signal to noise ratio.

The modal expansion method has limitations. It can deal with reconstructing responses which are of the same type as the physical sensor. For example, acceleration sensor can be used to reconstruct acceleration at all DOF but the accuracy in reconstructing drifts or strains is not good due to the inaccuracies from the double integration involved in obtaining drifts or strains from accelerations. Filtering techniques can be used to fuse multi-type sensors and reconstruct response of dissimilar type. In addition, in contrast to modal expansion techniques, filtering techniques can also be used to reconstruct the input such as the modal forces in wind excited structures or the actual earthquake base acceleration. Details of virtual sensing techniques based on filtering methods can be found in [20] with optimal sensor location techniques found in [23]. One limitation of the existing methods is that they assume that the finite element model is linear. In principle, filtering techniques can be further developed to reconstruct input and response (virtual sensing) for nonlinear models.

2.5 Robust Information Gain Measure

Next, the definition of the utility function is extended to account for the uncertainty in the parameter vector $\underline{\varphi}$ so that the optimal design is robust to model and input uncertainties involved in $\underline{\varphi}$. For this, the uncertain parameter vector $\underline{\varphi}$ is modelled by a prior probability distribution

$\pi(\underline{\varphi})$. The information contained in a sensor configuration is defined to be the expected information gain given by

$$U_{MonTask}(\underline{\delta}) = \int U_{MonTask}(\underline{\delta}, \underline{\varphi}) \pi(\underline{\varphi}) d\underline{\varphi} \quad (8)$$

over all possible values of the parameter set $\underline{\varphi}$. The sources of uncertainties in the parameter set $\underline{\varphi}$ vary from excitation uncertainties to structural model and prediction error model uncertainties.

In particular, the excitation uncertainties are associated with loads that are usually modelled by stochastic processes. Specifically, at the experimental design phase the seismic excitation is unknown. To proceed with the OSP, a model for the excitation has to be assumed. Stochastic models, generated by introducing parameterized spectra, are used to model the earthquake excitation. An example is the well-known Kanai-Tajimi model [24,25] represented by a filtered white noise excitation with the form of the filter selected to account for the main frequency components at a site. Probabilistic seismological models can also be used with parameters that are connected to source, source-to-site and site properties [26,27]. For both models, the stochastic variability of the earthquake response time history is modelled by a discrete white noise sequence, involving a large number of Gaussian random variables. Specific realizations of the white noise sequence are used to obtain the stochastic representations of the earthquake response time histories. The OSP has to be designed to account for all possible realizations. This is achieved by extended the information gain to the expected information gain over all possible realizations of the earthquake ground motion. In addition, the uncertainty in the parameters defining the average ground motion characteristics such as the Kanai-Tajimi filter parameters or the source, source-to-site and site parameters in seismological models can also be quantified in the analysis by assigning prior distributions to these. These uncertain parameters and the random variables associated with the white noise sequence are contained in the parameter set $\underline{\varphi}$ and the robust optimal OSP design is obtained by maximizing the robust measure given in (8). As a result, the OSP is thus designed to cover all possible realizations of the stochastic process. The integral in (8) is simplified by a Monte Carlo estimate.

3 DESIGN OF OPTIMAL SENSOR CONFIGURATION

3.1 OSP Based on Information Gain Considerations

The design of a sensor network has to trade-off information provided for different monitoring tasks such as modal identification, virtual sensing, structural identification and structural health monitoring, as well as virtual sensing. Thus, the optimal sensor configuration $\underline{\delta}_{opt}$ is obtained by maximizing the utility functions associated with the information gain for each monitoring task. Specifically, the design of the optimal sensor configuration is formulating as a multi-objective optimization problem of finding the optimal type and location of sensors that simultaneously maximizes the objectives

$$\underline{U}(\underline{\delta}) = \{U_{ModeID}(\underline{\delta}), U_{ParID}(\underline{\delta}), U_{DamID}(\underline{\delta}), U_{VS}(\underline{\delta})\} \quad (9)$$

over all possible sensor configurations $\underline{\delta}$. Alternatively, a single utility function can be introduced to measure the total information gain for all tasks, defined as the weighted average of the normalized information gains as follows:

$$U(\underline{\delta}) = w_1 \frac{U_{ModeID}(\underline{\delta})}{U_{ModeID}^{\max}} + w_2 \frac{U_{ParID}(\underline{\delta})}{U_{ParID}^{\max}} + w_3 \frac{U_{DamID}(\underline{\delta})}{U_{DamID}^{\max}} + w_4 \frac{U_{VS}(\underline{\delta})}{U_{VS}^{\max}} \tag{10}$$

where $U_{MonTask}^{\max}$ it the maximum information gain for each monitoring task that is achieved by placing sensors at all possible sensors locations, and the weights w_i, $i = 1, 2, 3, 4$ measure the contribution of each monitoring task on the optimal sensor configuration, with $\sum_{i=1}^{4} w_i = 1$. The normalized information gain for each monitoring task guarantees that each term $U_{MonTask}(\underline{\delta}) / U_{MonTask}^{\max}$ in Equation (10) varies from 0 (no information gain) to 1 (maximum information gain).

For a system with small number of possible sensor locations, an exhaustive search method [2] is used to exactly solve the multi-objective optimization problem (9) or the alternative single objective optimization problem (10). For large number of possible sensor locations, genetic algorithms [28] or heuristic algorithms (e.g. [3,7]), including forward and backward sequential sensor placement (FSSP/BSSP) algorithms [3,23] are employed to solve the optimization problem.

Due to the large number of objectives, to obtain a solution that is informative for all tasks is not a straightforward subject. Likely for each task there is a large number of near optimal solutions and one hopes that a fraction of these near optimal solutions for each task contain solutions that are near optimal for all tasks. However, this has to be confirmed in practical applications. The methods proposed in the work can be used to design a reasonable sensor configuration that is near optimum for all monitoring task considered.

3.2 OSP Accounting for Cost Considerations

It has been shown analytically [2,12] that as the number of sensors increase the information gain increases. In addition, after a number of sensors is optimally placed in the structure, as one keeps adding sensors in the structure the extra information gain is insignificant. The optimal number of sensors should be a trade-off between the information that one gains with extra sensors versus the cost of instrumentation as well as the cost of maintenance of the sensor network system. In addition, such cost should also take into account the high cost of placing sensors in less accessible or difficult to access areas in the structure that are most informative versus the cost of placing multiple sensors in easy to access areas that all together provide higher information with less cost. Cost issues have been considered in a number of studies [29-32]. The optimal number and location of sensors is obtained as the one that maximizes the information gain and minimizes the cost. This is setup as a two-objective optimization problem that can be readily solved (e.g. [32]) to find the Pareto optimal solutions. Alternatively, given cost constrains (a fixed budget available for designing a monitoring system) one can solve a cost constrained optimization problem to estimate the type, number and location of sensors.

4 CONCLUSIONS

This work outlines the issues arising in optimally designing a sensor configuration for structural monitoring purposes. It focuses on civil engineering structures such as building and bridges with the monitoring information to be extracted during earthquake excitations or low intensity ambient loads. The challenges associated with the design of the sensor network to gain information from different competing monitoring tasks is investigated. Such monitoring tasks include modal identification, finite element model selection and parameter estimation, damage identification and virtual sensing. Using information theoretic measures, an optimal sensor network methodology was presented which can be used for building reliable digital twins of the structure. The optimal design of the sensor configuration is formulated as a multi-objective optimization problem with each objective associated with the information gain from each monitoring task. The sensor network design depends on the information provided by a digital twin built to account for all operational states, including linear response to low amplitude excitations, nonlinear responses to strong earthquake excitations, expected damage scenarios and damage mechanisms, as well as virtual sensing. The optimal design also accounts for the modelling, measurement and input uncertainties that are present at the experimental phase of designing the sensor system to monitor a structure. Methodologies are also discussed to trade-off information provided from a monitoring system versus the cost of installing and maintaining the sensor network. The proposed framework is applicable to a variety of civil infrastructure components subjected to earthquake excitations.

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