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A comparison of optimal measurement-system design with engineering judgement for bridge load testing

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ABSTRACT: Due to conservative approaches in construction design and practice, infrastructure often has hidden reserve capacity. When quantified, this reserve has potential to improve decisions related to asset management. Field measurements, collected through load testing, may help in the identification of unknown model-parameter values and this task is called structural identification. Then, the reserve capacity is assessed using the updated behaviour model. The quality of model updating depends on the choice of the measurement system, including sensor types and locations. In most practical applications, these sensor systems are designed using engineering judgement based on experience and signal-to-noise ratios. However, finding the optimal design is difficult due to redundancies in information gained from sensors. The information gain of each possible sensor location can be quantitatively evaluated using our hierarchical algorithm in order to select the best location. When multiple sensors are involved in the configuration, this algorithm explicitly accounts for the mutual information between sensors, thus avoiding redundancy in information gain. In this study, near-optimal measurement systems, given by the hierarchical algorithm, are compared with measurement systems that were configured by engineers in terms an information-gain metric: joint entropy. For this comparison, three full-scale case studies are used: The Singapore Flyover Bridge (Singapore), the Exeter Bascule Bridge (United Kingdom) and the Rockingham Bridge (Australia). For all case studies, measurement systems provided by the hierarchical algorithm have outperformed sensor configurations chosen by engineers. Using a quantitative methodology to design measurement systems thus leads to a potentially higher information gain compared with engineering judgement alone. This is expected to improve the quality structural identification and subsequent management decisions.

KEY WORDS: Structural Identification, Optimal Sensor Placement, Error-Domain Model Falsification, Joint Entropy.

1 INTRODUCTION

In developed countries, the management of existing civil infrastructure is challenging due to evolving functional requirements, code changes, aging and climate change. As economic, environmental and material resources become increasingly scarce, more sustainable solutions for asset management are required. Due to conservative approaches in construction design and practice, infrastructure often has hidden reserve capacity and when quantified, this reserve has potential to improve decisions related to asset management [1]. Field measurements, collected through load testing, may help in the identification of unknown parameter values and this process is called structural identification [2].

As effects (behavior) rather than causes (parameter values) are typically measured, structural identification is an ambiguous task. This challenge is particularly difficult in civil engineering due to the large systematic-uncertainty levels present in finite-element models of complex structural systems such as bridges [3]. For this reason, several approaches to structural identification have been proposed [4].

Typically, structural identification challenges are met using a residual-minimization approach due to its simple formulation [5]. Although calibrated parameter values may provide acceptable results for interpolation tasks, this methodology has been shown to provided weak support for extrapolation tasks [6]. Researchers have developed a structural-identification framework based on Bayesian model updating (BMU) such as [7], [8] among others. While these methodologies have often involved the assumption of zero-mean Gaussian distributions for uncertainties, this assumption is not plausible for civil-engineering-system models [9]. Although BMU can be used with more realistic uncertainty distributions, these modifications lead to complex formulations that are beyond traditional engineers statistical background [10]. Understandably, practitioners do not want to use black-box tools due to the high consequences of their decisions. For these reasons, BMU has seldom been used in practical applications of structural identification.

Error-domain model falsification (EDMF) is a structural-identification methodology that is easy to use for engineers [11]. This methodology is based on the concept of falsification by Popper [12], where scientific hypotheses cannot be verified with data; they can only be refuted. In EDMF, a set of model-instances is first generated, where each instance is a numerical model with a unique combination of parameter values. Then, by comparing these model-instance predictions with field measurements, non-plausible models are falsified. By falsifying models, initial ranges of possible parameter values can be reduced, leading to an information gain. In the presence of systematic model bias, EDMF has been shown to provide more accurate model-parameter identification than traditional BMU [13].

The performance of structural identification directly depends on the choice of the sensor configuration [14]. Measurement-system design is usually carried out by engineers using only qualitative rules of thumb and estimations of signal-to-noise ratios. This choice involves deciding sensor types and locations as well as the excitations such as static or dynamic tests. However, finding the optimal design is difficult due to redundancies in information gained from sensors and load tests [15]. Often, suboptimal sensor configurations are thus selected by engineers.

Recently, quantitative methodologies for optimal sensor placement has attracted much research interest, for example

[16], [17]. Model-based strategies used for measurement-system design are decomposed in two parts: i) an objective function to assess sensor types and locations and ii) an optimization strategy to reduce the computational time of brute-force search.

Typical optimization schemes involves finding either the global optimum [18] or a near-optimal solution (local search) in a reasonable computational time [19]. Since the general problem has an exponential computational complexity with respect of the number of sensor types and locations, most researchers have used greedy algorithms to reduce the computational effort [20].

Regarding the objective function, recent studies have used an information-entropy criterion that either minimizes the information entropy in model-parameter posterior distributions [21] or maximizes information entropy in model predictions [22]. However, these methodologies often do not account for the redundancy of the information collected when multiple sensors are included in the configuration, leading to unnecessary sensor clustering [16].

Recently, a novel strategy has been introduced using joint entropy as an objective function for wind predictions around buildings [23]. This metric explicitly accounts for the mutual information within sensor-data sets. To avoid high computational time, a sequential (greedy) search using the joint entropy has been implemented in a hierarchical algorithm. This methodology has then been adapted to structural-identification contexts such as multiple static tests [24], static and dynamic excitations [25] and multiple criteria in measurement-system design [26]. Although the hierarchical algorithm has been validated using field measurements [27], a comparison with engineering practice is currently missing.

This paper presents a comparison of sensor configurations that have been i) designed by engineers without advanced computing support and ii) obtained through the hierarchical algorithm. For this comparison, three-full scale bridges are used: the Singapore Flyover (Singapore), The Exeter Bascule Bridge (UK) and the Rockingham Bridge (Australia). This comparison is performed in terms of expected information gain. The study is organized as follows. Section 2 is a presentation of the error-domain model falsification framework and Section 3 describes the hierarchical algorithm. Section 4 contains a description of three case studies and sensor configurations according to engineering judgement and obtained through the hierarchical algorithm. Results are then discussed in Section 5.

2 BACKGROUND

Error-domain model falsification (EDMF) is a structural-identification methodology that [11] helps identify plausible model-parameter values using field measurements given uncertainty estimations. An initial population of model instances (IMS) is generated through assigning a unique set of parameter values using a sampling technique. Then, by comparing model-instance predictions with sensor data, models that cannot explain field measurements given the uncertainty level are falsified (refuted). Information is gained by reducing initial model-parameter ranges through falsifying model instances.

Let n_y be the number of measurement locations. For each location $i \in \{1, \dots, n_y\}$, R_i denotes the true structural response (unknown in practice) and y_i corresponds to the sensor data that is compared to model-instance predictions $g_i(\boldsymbol{\theta})$. As both predictions and field measurements are not perfect Model-prediction $U_{i,g}$ and measurement uncertainties $U_{i,y}$ should be taken into account. $U_{i,y}$ is typically estimated by conducting multiple series of tests under site conditions and manufacturer specifications, while $U_{i,g}$ is estimated using values taken from the literature, stochastic methods and engineering judgment. Equation (1) expresses the link between R_i, y_i, and $g_i(\boldsymbol{\theta})$.

$$g_i(\boldsymbol{\theta}) + U_{i,g} = R_i = y_i + U_{i,y} \forall i \in \{1, \dots, n_y\} \quad (1)$$

Equation (2) is obtained by rearranging the terms in (1) and merging the two sources of uncertainty $U_{i,g}$ and $U_{i,y}$ in the combined uncertainty $U_{i,c}$.

$$g_i(\boldsymbol{\theta}) - y_i = U_{i,c} = r_i \ \forall i \in \{1, \dots, n_y\} \quad (2)$$

The left-hand side of (2) expresses the discrepancy between a model-instance prediction and the field measurement at location i and is called the residual r_i.

At each sensor location, falsification thresholds are defined in the uncertainty domain according to a level of confidence. This confidence level is a tradeoff between accepting incorrect models and falsifying the correct model. It is typically set at 95% [11], similarly to characteristic values for material properties in civil engineering.

If the residual exceeds thresholds at one location, the model instance is falsified, meaning that this combination of model-parameter values is not plausible. Model instances for which residuals are within threshold bounds for sensor locations are included in the candidate-model set (CMS). Using the CMS, parameter-value ranges are updated. Uniform distributions of parameter values are usually assumed between bounds as more accurate information of true distributions is rarely known. Once all measurement data is compared with predictions, engineers use new model-parameter ranges for extrapolation tasks such as predictions using asset-management scenarios. Asset management scenarios can include retrofit strategies, revised fatigue life predictions and no-action possibilities such as replacement avoidance. Such activities are not supported by data-only model-free methods.

3 MEASUREMENT-SYSTEM DESIGN

The two measurement-system-design strategies that are compared in this paper are introduced in this section. The first strategy is traditionally used by engineers based on experience and qualitative metrics, while the second strategy is a quantitative sensor-placement algorithm called the hierarchical algorithm.

3.1 Engineering judgement

In practice, measurement systems are typically designed using engineering judgement and occasionally, basic quantitative metrics such as the signal-to-noise ratio. When the signal-to-noise ratio (SNR) is used, sensor locations are evaluated using the quotient between the predicted quantity $g_i(\boldsymbol{\theta})$ over the measurement uncertainty $U_{i,y}$at location i (Eq. 3).

$$SNR = \frac{Signal}{Noise} = \frac{Mean\ (g_i(\boldsymbol{\theta}))}{U_{i,y}} \quad (3)$$

A large value of SNR means that field measurements at this sensor location will be significant compared with the sensor precision. When a population of model instances is used, the

SNR can be defined as the mean value of predictions divided by the measurement uncertainty at this location. Additionally, engineers have also distributed sensors on the structure through, for example, installing devices on several beams [28]. Such decisions are typically made without quantitative metrics.

3.2 Hierarchical algorithm

In this section, a quantitative strategy to design measurement systems, called the hierarchical algorithm, is introduced. This model-based methodology employs estimates of the prediction variability at sensor locations and the potential redundancy of information gain between locations to select the optimal sensor configuration.

The flowchart of the hierarchical algorithm is presented in Figure 1. Optimal measurement systems depend on the goal of monitoring, such as either structural identification or damage detection. Especially when the goal is structural identification, a behavior model, usually a finite-element model, is built. Then, the model class is defined, including the most important parameters, plausible ranges of their values and non-parametric uncertainty estimations. In parallel, available sensors and possible locations as well as the excitations (load tests in Figure 1) are then defined. Next, a population of model predictions is generated. These instances correspond to the IMS used in EDMF (Section 2) that are also used here in the sensor-placement strategy..

Next, an optimization strategy to select sensor configurations is chosen and this involves an objective function and an optimization algorithm. The hierarchical algorithm utilizes the joint entropy to discriminate between possible sensor locations and a sequential search to reduce the computational time. Both choices are described below.

In a sequential search, once a sensor location is selected, this choice is not re-evaluated for subsequent sensor-placement decisions. When a greedy search is used, a ranking of possible sensor locations associated with its sensor type is obtained as well as objective-function evaluations of measurement systems with respect to the number of sensors. This strategy reduces the computational time and was shown to provide high-quality sensor configurations for structural identification [24]. Joint entropy evaluations are then used to compare measurement systems to select the most appropriate sensor configuration. The optimal measurement system is the combination of the optimal sensor configuration involving several sensor types and the optimal set of static load tests.

Sensor placement is thus defined as an optimization task, where an objective function and optimization algorithm must be defined. The information entropy was introduced by Papadimitriou [21] as an objective function for the task of sensor placement. Locations were evaluated through their ability to reduce the entropy in posterior distributions of model parameter. In the hierarchical algorithm, information- and joint-entropy values are evaluated in the prediction domain. In this approach, locations are thus evaluated through their variability in model-instance predictions. Therefore, locations that maximized these metrics are selected.

The distribution of model-instance predictions at each sensor location i is divided in intervals based on the combined uncertainty $U_{i,c}$ (2). The probability that a model instance output $g_{i,j}$ falls inside the j^{th} interval among $N_{I,i}$ intervals is equal to $P(g_{i,j}) = m_{i,j}/\sum_{l=1}^{N_{I,i}} m_{i,l}$, where $m_{i,j}$ is the number of model instances in the j^{th} interval. In the hierarchical algorithm, the information entropy $H(g_i)$ is evaluated for a sensor location i according to (4).

$$H(g_i) = -\sum_{j=1}^{N_{I,i}} P(g_{i,j}) \log_2 P(g_{i,j}) \qquad (3)$$

Using the information entropy, locations that provide the largest variability in predictions, thus maximizing the falsification is found. However, locations with large information-entropy values may provide redundant information.

To explicitly account for the mutual information between sensor locations, joint entropy was proposed as a new sensor-placement objective function [23]. This metric evaluates the information entropy between sets of predictions while taking into account the redundant information between them. For a set of two sensors i and i+1, the joint entropy $H(g_{i,i+1})$ is defined following (5), where $P(g_{i,j}, g_{i+1,k})$ is the probability that a model instance falls in both intervals j and k and $k \in \{1, \dots, N_{I,i+1}\}$, $N_{I,i+1}$ is the maximum number of prediction intervals at location i+1, $i+1 \in \{1, \dots, n_s\}$, and n_s is the number of potential sensor locations.

$$H(g_{i,i+1}) = -\sum_{k=1}^{N_{I,i+1}} \sum_{j=1}^{N_{I,i}} P(g_{i,j}, g_{i+1,k}) \log_2 P(g_{i,j}, g_{i+1,k}) \qquad (4)$$

The joint entropy is less than or equal to the sum of the individual information entropies of sets of predictions. Eq. (6) presents the joint entropy of two sensors, where I is the mutual information between sensor i and i+1.

$$H(g_{i,i+1}) = H(g_i) + H(g_{i+1}) - I(g_{i,i+1}) \qquad (5)$$

Joint entropy enables the simultaneous consideration of prediction variability and redundancy of information between sensor locations to define the optimal measurement system.

4 CASE STUDIES

Table 1 presents characteristics of the Singapore Flyover (Singapore) [25], [29], Exeter Bascule Bridge (UK) [26], [30] and Rockingham Bridge (Australia) [31] where monitoring has been performed in 2016, 2017 and 2014 respectively. The goal of monitoring is to reduce the range of possible model-parameter values to provide more accurate predictions of structural behavior.

Initial intervals of model parameters that must be identified during monitoring are presented in Table 1. These intervals are estimated based on engineering judgement of plausible parameter values for existing bridges. For each bridge, 1000 model instances are generated, where each instance has a unique set of parameter values within initial ranges. These populations are inputs for the hierarchical algorithm to define optimal measurement systems. In EDMF context, the aim of monitoring is to reduce as much as possible these initial ranges by falsifying model instances

4.1 Comparison in terms of chosen sensor configurations

In this section, sensor configurations chosen by engineers are compared with configurations selected by the hierarchical algorithm. For each bridge, configurations are selected using the same sensors and the same load tests. Therefore, these configurations differ only in terms of sensor locations. They are compared using information gain in Section 4.2.

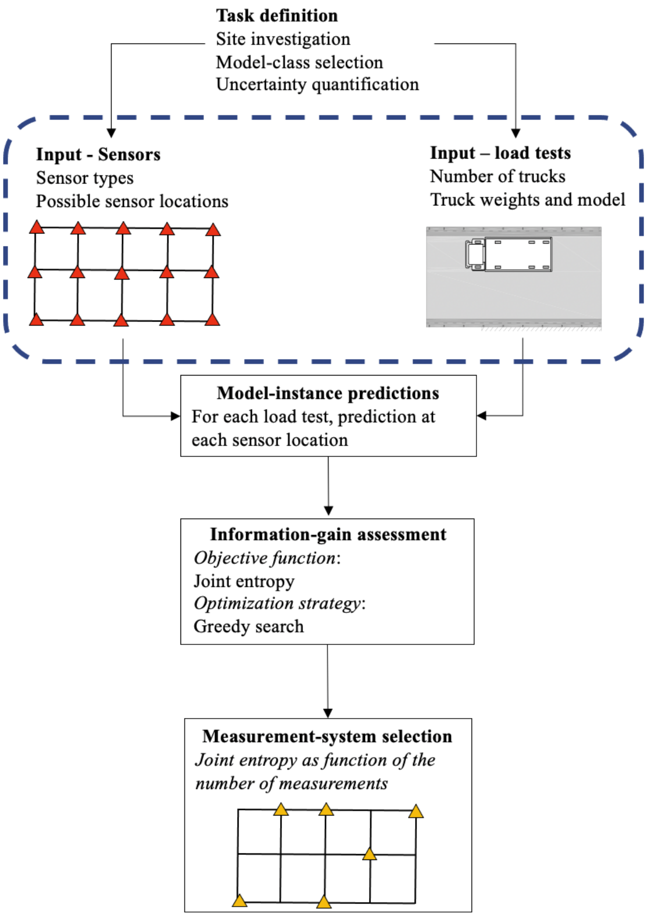

Figure 1. Flowchart of the hierarchical algorithm to design measurement systems for bridge load testing.

Table 1. Case-study description.

Name	Characteristics	Measurement system and model parameters
Singapore Flyover 	4 precast prestressed concrete beams Poured-concrete deck Built in 1985 Single span of 32.0m	4 deflection, 2 inclination and 7 strain measurements Value ranges of model parameters to reduce: Concrete-deck Young's modulus $\theta_{1,1}$ $[GPa] \in [20-35]$ Concrete-barrier Young's modulus $\theta_{1,2}$ $[GPa] \in [3-40]$ Precast-beam Young's modulus $\theta_{1,3}$ $[GPa] \in [25-50]$ Rot. stiffness of bearing devices $\theta_{1,4}$ [log(Nmm/rad)]$\in [8-11]$ Vertical stiffness of bearing devices $\theta_{1,5}$[log(N/mm)]$\in [9-13]$
Exeter Bascule Bridge 	2 steel girders Aluminium deck Built in 1972 Single span of 17.3m	1 deflection and 5 strain measurements Value ranges of model parameters to reduce: Equivalent deck Young's modulus $\theta_{2,1}$ $[GPa] \in [20-35]$ Rot. stiffness of bearing devices $\theta_{2,2}$ [log(Nmm/rad)] $\in [8-12]$ Axial stiffness of hydraulic jacks $\theta_{2,3}$ [log(N/mm)]$\in [3-5]$
Rockingham bridge 	8 precast prestressed concrete beams Poured-concrete deck Built in 1970 Spans of 13.7, 24.3 and 13.2m.	5 strain measurements Value ranges of model parameters to reduce: Beam concrete Young's modulus $\theta_{3,1}$ $[GPa] \in [25-45]$ Deck concrete Young's modulus $\theta_{3,2}$ $[GPa] \in [30-50]$

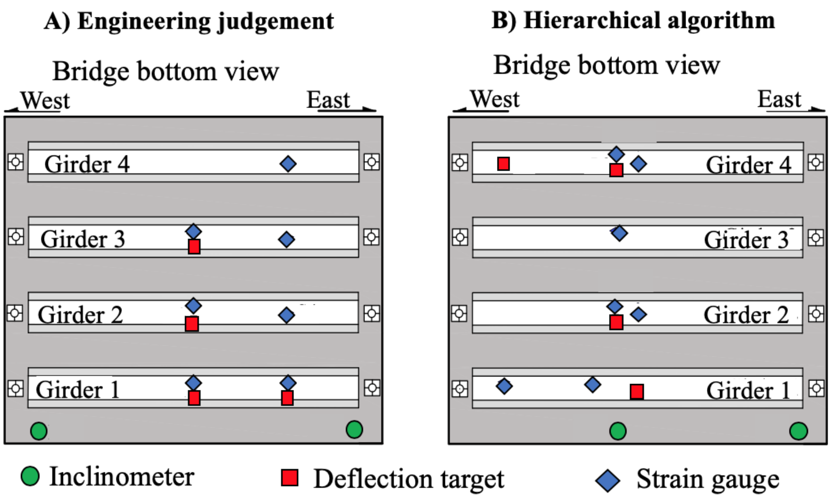

Figure 2. Comparison of sensor configurations for the Singapore Flyover (bottom view). A) Chosen based on engineering practice. B) Selected by the hierarchcial algorithm.

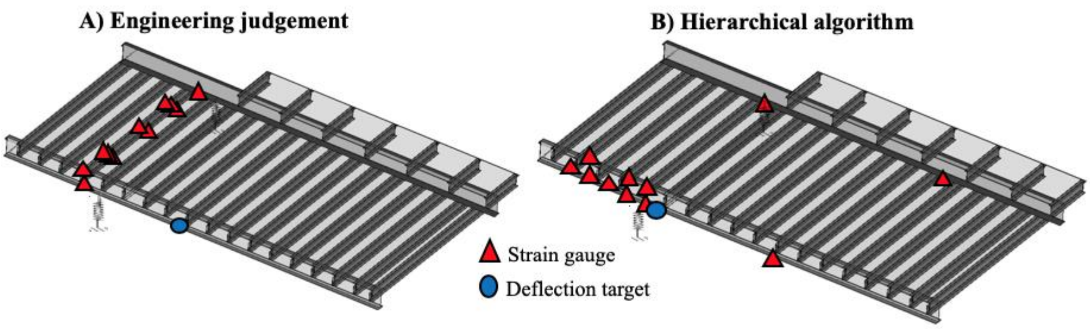

Figure 3. Comparison of sensor configurations for the Exeter Bascule Bridge (bottom view). A) Chosen based on engineering practice. B) Selected by the hierarchical algorithm.

4.1.1 Singapore Flyover

Figure 2 presents sensor configurations chosen using engineering judgement (A) and the hierarchical algorithm (B). Each sensor configuration involves the same sensors: two inclinometers on the parapet; four deflections target and seven strain gauges on the four main girders.

Engineers have chosen sensor locations on the four girders but only at quarter-span and mid-span, while inclinometers are installed on the closest locations to the support on both sides (Figure 2A). Locations with high SNR are selected, such as at midspan, and also, the engineers have qualitatively decided to spread sensors over the bridge to reduce the mutual information between them.

The hierarchical algorithm resulted in strain-gauge and deflection-target locations on the four main girders (Figure 2B). Most sensors are placed near mid-span, and some sensors are installed next to the supports. The first inclinometer is installed at the support, while the second location is selected near to the mid-span. Some sensor locations may be non-intuitive for engineers as these locations present small SNRs. A minimum SNR value, used as a constraint, ensured that useful measurements are possible. Selecting sensor locations that maximize the information gain is thus a non-trivial task.

4.1.2 Exeter Bascule Bridge

Figure 3 presents the installed sensor network by the engineers and the optimal configuration obtained using the hierarchical algorithm. Both solutions involve the same sensors, 1 deflection measurement and 11 strain gauges. The deflection measurement is made using a camera on the side of the bridge and a target on the structure, while gauges were glued directly on the beams.

The engineers selected locations with high signal-to-noise ratios (SNR), such as the deflection at midspan and locations on the secondary beams. However, they omitted consideration of the mutual information between sensors as most sensors are located near to each other. A second omission was made by engineers: they did not take into account the variability of predictions. In this case study, three parameters were involved in the analysis (Table 1). Studies [26], [30] show that the vertical stiffness value provided by the hydraulic jacks has the greatest influence on model-instance predictions. By precisely identifying this parameter value, most model instances can be falsified. The locations that are the mostly influenced the by hydraulic-jack stiffness value have thus been selected by the hierarchical algorithm. They correspond to locations next to the jack on the two main girders. Although most sensors are clustered in a very specific area, this configuration is justified to identify as precisely as possible this parameter value to maximize the information gain and thus reduce the model-prediction range for the Exeter Bascule Bridge.

These sensors are placed to maximize the information gain, but this does not mean that the increase of information gain when placing new sensors is significant.

4.1.3 Rockingham Bridge

Figure 4 presents the sensor configurations selected by the engineers (red squares) and obtained using the hierarchical algorithm (green circles). Each configuration involves 5 strain gauges among the 186 possible locations on the three spans of the eight beams. The engineers have placed the sensors only at midspan of the bridge, due to the large SNR of these locations; However, for a multiple-span bridge, the highest SNR for strain gauges are close to the second and third supports. Additionally, by placing all sensors close to each other, engineers have not considered the mutual information between sensors in the measurement-system design.

Locations close to the supports as well as close to midspan have been selected by the hierarchical algorithm as these locations show high information gain. As sensors are spread over the bridge, less redundancy in the information gain between sensors is expected for the hierarchical-algorithm configuration. These configurations are compared in terms of expected information gain with respect to the number of sensors in Section 4.2

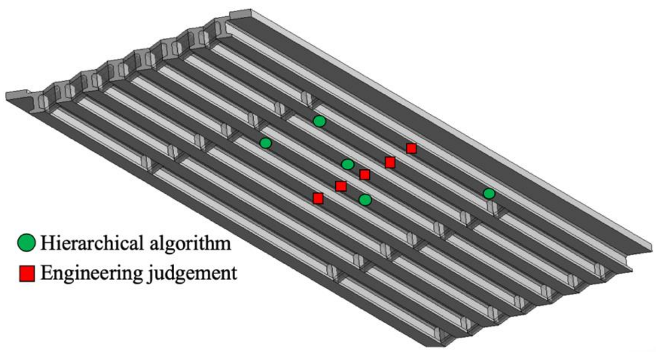

Figure 4. Comparison of sensor configurations (5 strain gauges) chosen by engineers and selected by the hierarchical algorithm –Bottom view of Rockingham Bridge.

4.2 Information-gain comparison

In this section, the information gain for both engineer and hierarchical-algorithm sensor configurations is presented. Results are shown in terms of joint entropy (information-gain metric) as a function of number of sensors.

Figure 5 presents the comparison between sensor-configuration information gain with respect to the number of sensors for each bridge independently. For engineer-selected configurations, sensors have been ranked according to their opinion on the most informative sensors. These results are compared with the optimal sensor configuration obtained using the hierarchical algorithm.

For each bridge, engineer-selected solutions are outperformed by the hierarchical-algorithm configurations for any number of sensors. This result shows that using a quantitative methodology for measurement-system design leads to a more important information gain using the same number of sensors. Additionally, this methodology helps find a configuration that involves less sensors, thus reducing significantly the cost of monitoring, without compromising the information gain.

As the hierarchical algorithm requires several simulations, in some situations, information gain may not be justified by the computational cost. A cost-benefit analysis is performed in the following section.

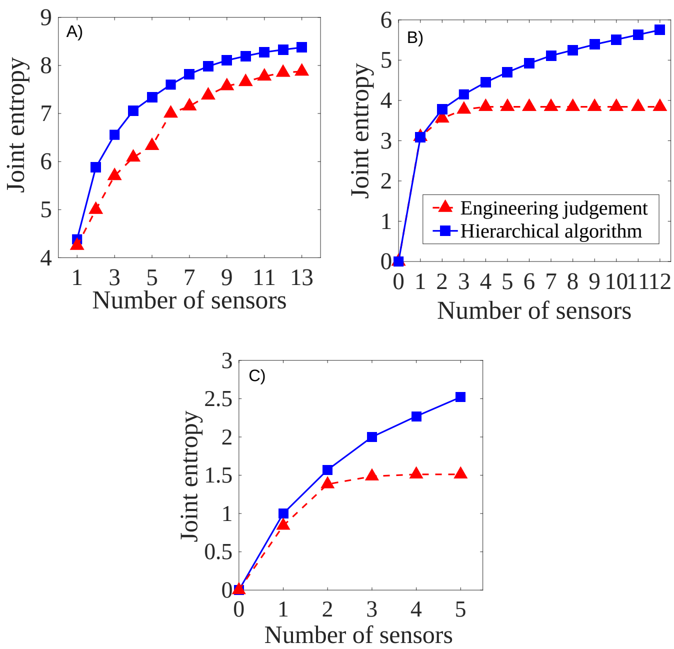

Figure 5. Comparison of information gain (joint entropy) of sensor configuratjions as function of the number of sensors. A) Singapore Flyover; B) Exeter Bascule Bridge; C) Rockingham Bridge.

5 DISCUSSION

Engineers traditionally design sensor configurations based on their experience and signal-to-noise-ratio estimations. This strategy presents the advantage of finding a solution quickly without numerical simulation. However, finding the optimal sensor configuration is a non-trivial task since uncovering truly informative locations is difficult. For this reason, advanced computing methodologies that require several numerical simulations may enable selection of optimal measurement-system designs, thus increasing the potential performance of the structural-identification process.

The hierarchical algorithm uses the same input as EDMF (Section 2) and therefore does not require additional simulations using the finite-element model provided that tests and measurements will be carried out and that data is interpreted using EDMF. Typically, a sensor-placement run needs one hour using MATLAB on a laptop.

Tables 2 and 3 show the benefits of using the hierarchical algorithm instead of traditional engineering decision making for measurement-system design. For each case study, these benefits are quantified in terms of increase of information gain for the same number of sensors (Table 2) and number of sensors "saved" to reach the same information gain as the engineering solutions (Table 3). In all three cases, the hierarchical algorithm leads to significant improvement of the sensor network. As this quantitative methodology does not require significant additional computational time than the structural-identification (EDMF), it is thus recommended for measurement-system design.

The main drawback of using a quantitative methodology is that it must be made prior to monitoring. In this situation, the selection of the appropriate model class (model with parameters of which values are modified to generate model instances of the IMS) is not trivial, and several iterations are sometimes necessary [32]. As the optimal measurement system depends on the model class, the hierarchical algorithm may not provide a good sensor design when the model class is incorrect. Nevertheless, a modification of the hierarchical algorithm has been proposed to include several plausible model classes in the design to ensure high information gain regardless of the model class [33].

Table 2. Comparison of information gain using sensor configurations selected by the hierarchical algorithm and chosen by engineers.

Name	Info. gain hierarchical algorithm	Info. gain engineering judgement	Increase of information gain
Singapore Flyover	8.4	7.9	6.3 (%)
Exeter Bascule Bridge	5.8	3.8	53 (%)
Rockingham Bridge	2.5	1.5	67 (%)

Table 3. Potential number of sensors not deployed to reach the same information gain as engineering designs using the hierarchical algorithm.

Name	Total number of sensors	Sensors needed to meet engineer solution	Sensors not needed
Singapore Flyover	13	7	6 (46%)
Exeter Bascule Bridge	12	3	9 (75%)
Rockingham Bridge	5	2	3 (60%)

6 CONCLUSIONS

A quantitative strategy for measurement-system design, called the hierarchical algorithm, is compared with engineering designs that use experience and the signal-to-noise ratio for three full-scale bridges. These case studies show that an advanced methodology leads to better sensor configurations in terms of expected information gain. The following specific conclusions can be drawn:

- A quantitative informatics methodology to design measurement systems increases the potential performance of structural identification when compared with traditional engineering designs using only qualitative rules of thumb and the signal-to-noise ratio.
- Use of the joint-entropy metric to estimate the variability of model predictions, is a more rational means of evaluating the potential information gain of sensor locations.
- By accounting for the redundancy of information gain between sensor locations, the hierarchical algorithm avoids unnecessary sensor clustering, leading to better sensor configurations than proposed by other entropy-based approaches.

Future work includes development of a sensor-placement methodology that requires fewer model-instance predictions without reducing the effectiveness of the measurement-system design.

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