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PREDICTING THE USEFULNESS OF MONITORING FOR IDENTIFYING THE BEHAVIOR OF STRUCTURES

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Abstract

Structures can be better understood through structural identification. This is where measurement data are used to improve modeling of structural behavior. During structural identification, uncertainties may limit the extent of such understanding. The objective of this paper is to determine probabilistically to what degree measurements are useful for structural identification. The procedure is intended to be used prior to monitoring. The new methodology evaluates the probability of occurrence of two performance indices; the expected number of candidate models and the expected prediction ranges. Since it does not require intervention on the structure, the method can be used to support prioritization of decisions related to full-scale testing. These features are illustrated through the study of the Langensand Bridge (Switzerland). In this example, the methodology shows that increases in modeling uncertainties hinders the usefulness of measurements for identifying model parameter values. The predictive capability of the method proposed is verified by agreement with observations made during a recent identification exercise. Quantifying the expected identifiability is able to support infrastructure decision-making such as determining whether or not certain types of structural monitoring are useful.

Keywords: Expected identifiability, System identification, Bridge monitoring, Model-updating, Residual minimization, Errors, Uncertainties, Correlation

INTRODUCTION

With increasing availability of communication systems and the decreasing cost of sensors, more and more structures are measured. However, our capacity to analyze large amounts of data is increasing only marginally. System identification (SI) techniques have the potential to process such data. Nevertheless, important challenges

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remain. Ideally, identification should be able to decide, prior to analysis, if all unknown values for model parameters can be identified. For most full-scale structures in civil engineering, unique identification of a model is unlikely. Previous work (Goulet and Smith 2010; Goulet et al. 2010; Goulet and Smith 2011b) showed that when uncertainties are included during an identification, several hundreds (even thousands) of candidate model instances can be expected. Therefore, a new methodology is required in order to quantify to what extent a system (structure) is identifiable.

System identification (SI) is understood in this paper as the task of inferring sets of model parameters (model instances) from observations of the system studied. Several SI methodologies are available in the literature. They are mostly based on residual minimization and on parameter-domain probabilistic representations.

Residual minimization involves minimizing the discrepancy between measured and predicted value by adjusting the model parameter values (Catbas et al. 2007; Friswell 2007; Sanayei et al. 2001; Strauss et al. 2010). This approach is analogous to curve fitting and usually leads to a single answer.

Examples of parameter-domain probabilistic representations are Bayesian inference, Bayesian model-updating and Bayesian parameter identification. These approaches are now widely applied in almost every field of science. Several civil engineering applications can be found in the literature (Beck and Katafygiotis 1998; Cheung and Beck 2009; Katafygiotis and Beck 1998; Hadidi and Gucunski 2008; Tarantola 2004). These methods involve updating probability density functions (PDF) representing prior knowledge using the comparison between observations and model predictions. This leads to a joint PDF quantifying, in the parameter domain, the degree of belief that each set of parameters has a set of value. Goulet and Smith (2011b) showed that parameter-based methodologies may provide unreliable solutions because of their underlying assumption that dependencies between uncertainties are known. Such an hypothesis may not always be satisfied since correlations between uncertainties are often not quantifiable. An error-domain methodology was proposed to overcome these limitations. Section 2 summarizes the principles of this approach.

Ljung and Glad (1994) described identifiability for parameter-domain probabilistic representations as a criterion which determines if an identification procedure leads to unique values for parameters and whether or not the resulting model is the right system. Katafygiotis and Beck (1998) also applied the concepts of identifiability for structural SI. Their approach is based on the work of Bellman and Åström (1970). They proposed that a system is locally identifiable if there are minima in the posterior PDF of the difference between predictions and measurements. A system is defined to be globally identifiable if there is a single minimum. This concept of identifiability is limited to parameter-domain probabilistic representations.

This paper presents a performance indicator called expected identifiability. The objective is to determine probabilistically to what degree the initial-model-instance set (IMS) can be reduced through monitoring a structure and to what extent prediction ranges on unobserved quantities can be narrowed. This procedure is intended to be used prior to obtaining measurements from in-situ monitoring.

PREVIOUS WORK

Previous work focussed on developing a system identification methodology that is able to perform inverse tasks in presence of correlated uncertainties.

Error domain identification

The framework of error-domain identification is to generate sets of models, obtain predictions for each of them and compare predicted and observed values in order to falsify wrong models. The identification approach was proposed by Goulet and Smith (2011b) building upon a decade of research (Raphael and Smith 1998; Smith and Saitta 2008; Robert-Nicoud et al. 2005; Goulet et al. 2010). The philosophy behind the approach is based on a principle known in basic science for centuries: models cannot be validated by observations, they can only be falsified. This methodology rejects models based on the combination of uncertainty sources involved in the identification process. This is achieved by comparing observed and expected residuals. A residual is the difference between predicted and observed values. Uncertainties are combined together into a multi-dimensional probability density function (PDF) representing the possible residual outcome for each measurement location (see Figure 1). Uncertainties originate from both modeling and measurement processes.

Uncertainty combination

Uncertainties are defined as the probabilistic representation of the possible outcomes of errors. Uncertainties associated with modeling and measurements can either be evaluated using statistical methodologies or expert judgement. Even if uncertainties are evaluated separately, they have to be combined together in order to obtain the distribution of the combined error. The combination of errors leads to the probability distribution of the expected residual between predicted and observed values. The observed residual values are compared to the expected residual in order to evaluate the plausibility of each model instance. Uncertainties can be combined through a Monte-Carlo combination approach (Draper 1995; Cox and Siebert 2006) that draws samples from each uncertainty distribution and then sums them together. Details regarding uncertainty combination is provided in Goulet and Smith (2011b).

The procedure of combining uncertainties is performed independently for every measurement location. If N measurement locations are used, the outcome is a multi-dimensional PDF where each dimension represents the expected residual value for a measurement location based on uncertainty evaluation. A graphical representation of a multidimensional PDF is presented in Figure 1. Due to the central limit theorem, the combined PDF may be approximated by a normal distribution. However this is not a requirement for the approach to be valid. Note that due to systematic errors the combined PDF is often not centered on zero. This means that in presence of systematic errors, the most probable expected residual is often not zero. This is in part why curve-fitting methodologies are unreliable.

Model rejection

If a single measurement location is used during identification, the observed residual between the measured value and the prediction of a model must be within the upper and lower bounds of the coverage interval (defined in the error domain (i.e. the expected residual PDF)). The coverage interval (or region) is the PDF bounded interval that contains a target probability φ. Coverage intervals are defined by lower and upper bounds (for a given φ) at each measurement location within which observed residuals should lie. If this condition is not met for a model instance, the instance is discarded. Figure 1 shows the expected residual probability density function along with its coverage region.

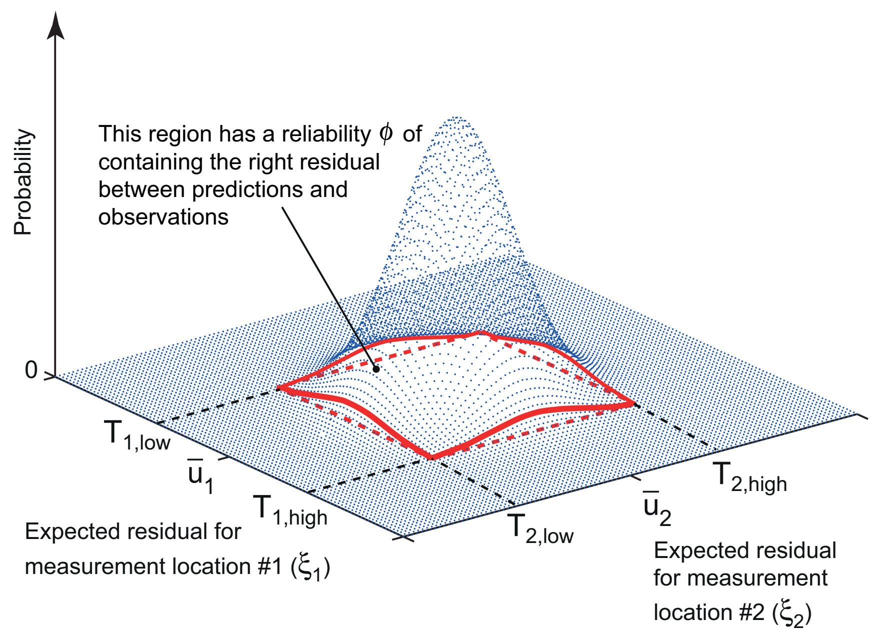

Figure 1. Expected residual probability density function along with its square coverage region having a reliability φ of including the right residual between observations and predictions

Mathematically, this principle is translated into the relation presented in Equation 1. $T_{i,Low}$ and $T_{i,High}$ represent the coverage bounds for each measurement location ($i = 1..N$). The probability function $p(\xi_1, \ldots, \xi_N)$ is derived from Equation 2 where the distance between the observed residual (ξ_i) (i.e. the difference between predicted (r_i)

and observed value y_i, see Equation 3) and the most probable value ($\bar{u}_i$, see Equation 4) of the expected residual PDF are compared. Σ is the covariance matrix associated with the expected residual PDF.

The shape of the coverage region is taken to be an n-dimensional hypercube. This shape provideds robustness with respect to misevaluation of uncertainty correlations between measurement locations. Defining coverage intervals independently for each measurement location provides conservative coverage regions for any level of correlation between uncertainties.

$$\forall i = 1, \ldots, N : \varphi = \int_{T_{i,Low}}^{T_{i,High}} p(\xi_1, \ldots, \xi_N) d\xi_i \tag{1}$$

$$p(\xi_1, \ldots, \xi_N) = \frac{1}{(2\pi)^{N/2}\sqrt{\det \Sigma}} \cdot \ldots$$
$$\ldots \exp\left(-\frac{1}{2}[\xi_1 - \bar{u}_1, \ldots, \xi_N - \bar{u}_N]\Sigma^{-1}[\xi_1 - \bar{u}_1, \ldots, \xi_N - \bar{u}_N]^T\right) \tag{2}$$

$$\xi_i = r_i - y_i \tag{3}$$

$$\bar{u}_i = E[u_i] \tag{4}$$

Generation of the initial set of model instances

In order to initialize the sets of model parameters requiring identification, ranges of possible parameter values are defined for the n parameters. The discretization interval is the parameter interval size that is considered as non-differentiable. A n-dimension grid is generated using the discretization intervals provided for each parameter to identify ($i = 1..n$). This leads to a representation of the space of possible solutions that a-priori are able to explain observed behavior. The set is named the Initial Model Set (IMS). Model instances are obtained by passing parameter sets $[\theta_1, \ldots, \theta_n]$ as arguments to a template model $f(\theta_1, \ldots, \theta_n)$. For this purpose, template models used are most of the time issued from the finite element methodology. The goal of the identification is to discard some model instances from the set in order to reduce the prediction range.

Once models are filtered from the IMS, a Candidate Model Set (CMS) is obtained. These models are able to explain the observed behavior while including uncertainties. The filtering process is expressed in Equation 5. The CMS is made from the model instances of the initial model set for which $\Omega_{\Xi}(\theta) = 1$.

$$\begin{aligned} &\Omega_{\Xi}(\theta) = 1 \quad \forall i = 1, \ldots, N : T_{i,Low} \leq \xi_i \leq T_{i,High} \\ &\Omega_{\Xi}(\theta) = 0 \quad \text{Otherwise} \end{aligned} \tag{5}$$

PREDICTING IDENTIFIABILITY OF SYSTEMS

Predicting the efficiency of observations for discarding model instances can be achieved prior to measuring the structure by generating several sets of simulated measurements (SM). SM are taken to be measurements that help predict probabilistically the expected number of candidate models and prediction ranges.

Generation of simulated measurements

Simulated measurements (SM_i) can be obtained from the combination of model predictions (r_i) and uncertainties (U_i). This process is illustrated in Figure 2. Since prior performing observations on a structure any model instance can be the adequate explanation of its behavior, any model can be randomly chosen as a the right model. Each model instance in the initial model set is made from a combination of parameter ($[\theta_1, \theta_2, \ldots, \theta_n]$) used in a template model $f(\theta_1, \theta_2, \ldots, \theta_n)$. Even if a right parameter set would turn out to be the true value, the predicted values from the template model ($[r_1, r_2, \ldots, r_N]$) would never exactly correspond to those measured on the true system ($[y_1, y_2, \ldots, y_n]$) since errors are present in both model predictions and measurements. Errors are thus added to predicted values obtained from the right parameter sets. In most situations, uncertainties are not adequately represented by gaussian random white noise. Several systematic and aleatory uncertainties sources need to be represented. For each simulated measurement instance, errors (u_i) are generated for each measurement location ($i = 1 \ldots N$) from the expected residual distribution (U_i). The uncertainty correlation (ρ) from different measurement locations is evaluated and included in the process of error generation in order to obtain "realistic" simulated measurements.

Simulated measurements instances (SM_i) are obtained through the summation of model predictions (r_i) and correlated error instances (u_i) taken from the expected residual distributions (U_i).

Correlations between uncertainties

In the case of the expected identifiability evaluation, the goal is to provide a quantitative metric to support the decision of whether or not a structure should be measured. Assuming that there are no dependencies between measurement location and measurement type would lead to simulated measurements that does not represent observations. As shown by Goulet and Smith (2011b), in full scale structures, uncertainties are likely to be correlated. If uncertainties are wrongfully assumed to be independent, results may be unconservative. An alternative approach is to provide realistic evaluations of uncertainty correlations.

Evaluating uncertainty correlations between sensor types and locations remains a cumbersome task since little quantitative information is available. For the purpose of generating simulated measurements, a method based on qualitative reasoning is proposed to estimate uncertainty correlations in a stochastic process. Qualitative Reasoning (QR) (Williams and Kleer 1991) uses common sense reasoning to support complex

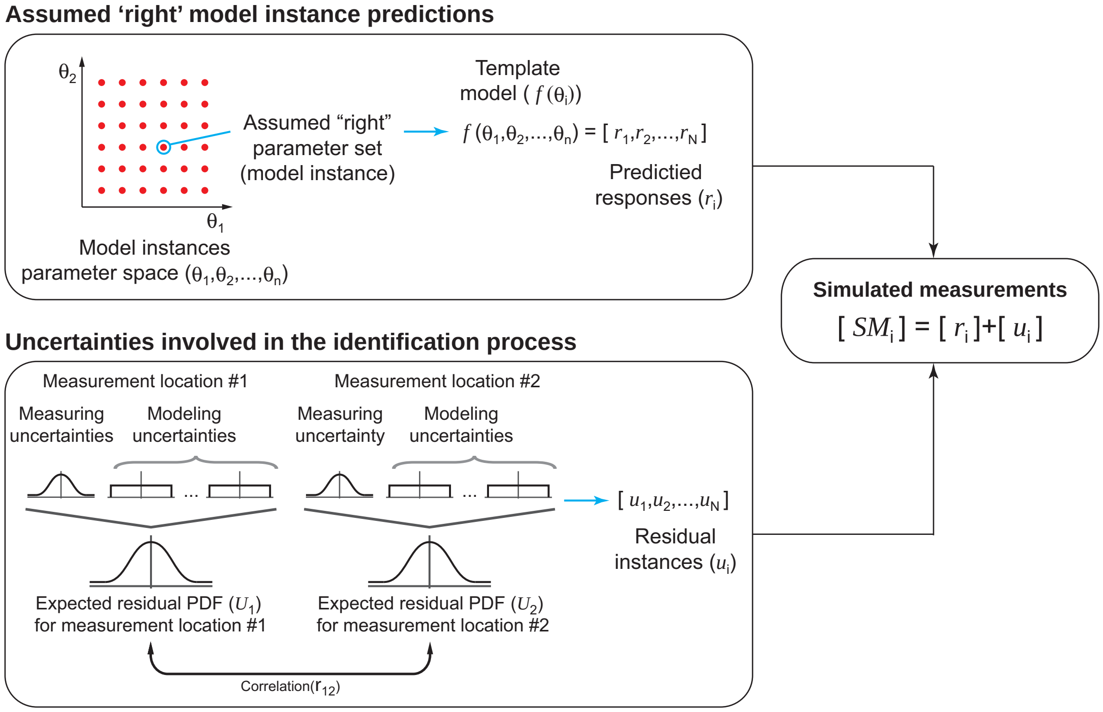

Figure 2. Illustration of the process of simulating measurements based on the prediction of an assumed "right" model instance and on uncertainties

decisions. QR is often used in the field of modeling, control and to support decision when limited information is available. Figure 3 shows the qualitative reasoning scheme proposed by Goulet and Smith (2011c) to qualify uncertainty correlation between sensor type and locations. In this figure, the correlation value is presented on the horizontal axis. The vertical axis corresponds to the probability of given correlation value depending on its qualitative description. It is hard for users to provide accurate correlation values. Indicating whether the correlation between uncertainties is low, moderate or high and whether the correlation is positive or negative is easier than providing numerical values. Note that this proposal should not be confused with fuzzy logic, since in this situation there is no causal link. Qualitative reasoning methods are used only to represent incomplete knowledge.

Computation of expected identifiability

In the process of computing the expected identifiability, several simulated measurement instances are generated. These simulated measurements can be used as real observations in order to discard model instances from the initial model set using the methodology presented earlier. The study of simulated identification outcomes pro-

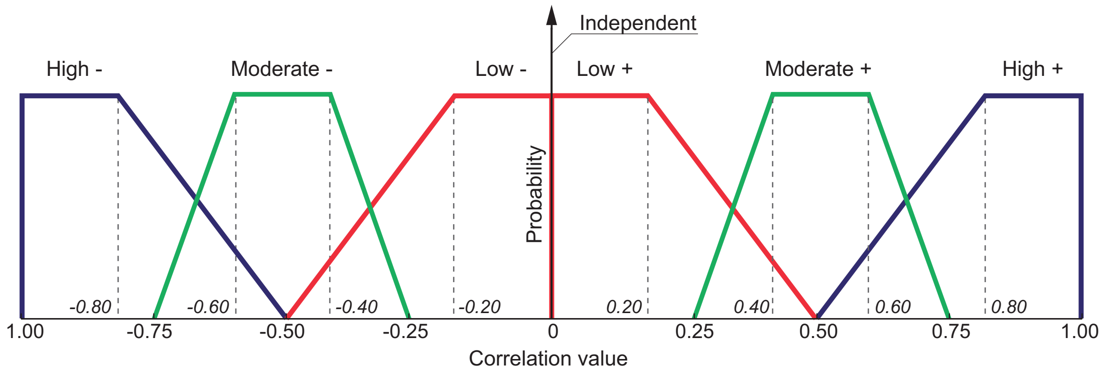

Figure 3. Graphical representation of the qualitative reasoning used to define the correlation between uncertainties.

vide information that indicate whether or not observations are likely to be useful for reducing the number of candidate models and prediction ranges of parameters.

Expected reduction in the number of candidate models

The first quantity of interest is the number of expected candidate models. The number of candidate models obtained from each instance of simulated measurements is presented as a cumulative distribution function (CDF). This CDF shows the probability of obtaining any number of expected candidate model (eCM) if measurements are taken on the structure. Examples of cumulative distribution functions are presented in Figures 8-11. The two quantities extracted from the CDF are the number of expected candidate models that should be obtained with a 95% (eCM(95%)) and 50% (eCM(50%)) certainty. The first represents, for example, a minimal expectation and the second, a maximal one.

Expected reduction in the predictions ranges

The goal of structural identification, aside from damage detection, is to be able to perform predictions related to behavior. Therefore, the second quantity of interest is the prediction ranges of unobserved quantities. The number of candidate models varies for each instance of simulated measurements. The range of predictions obtained from candidate model sets also varies. The prediction ranges are stored and then presented as a CDF showing the probability of obtaining any prediction range (ePR) if measurements are taken on the structure. ePR's are extracted from the CDF for a 95% (ePR(95%)) and 50% (ePR(50%)) certainty.

These two quantities of interest are indicators of the usefulness of measurements. For instance, if the uncertainties on a model are too large in comparison with model prediction variability, monitoring the structure is unlikely to provide useful decision support. The new metrics proposed enable, prior to performing tests on a structure, determination of whether or not instrumenting it would be useful.

Combined identifiability indicator

For practical applications, working with several performance metrics may be cumbersome. Therefore, the two indicators presented above are merged into a single Combined Expected Identifiability (CEI). CEI is computed using the relationship presented in Equation 6, where IMS is the number of models in the initial model set, N is the number of predictions and PR_i is the initial range for prediction i.

$$CEI = \left(\left(1 - \frac{eCM(95\%)}{IMS}\right) + \left(1 - \frac{1}{N} \sum_{i=1}^{N} \frac{ePR_i(95\%)}{PR_i}\right) \right)^{\frac{1}{2}} \quad (6)$$

A CEI value near 0 indicates that the measurements are unlikely to provide useful results and a value near 1 means that there is a high probability that measurements will significantly reduce the number of candidate models and prediction ranges.

APPLIED EXAMPLE

In this section, the approach proposed is used to predict the expected identifiability of a full-scale structure. The goal is to determine whether performing static-load tests would be useful to reduce the number of model instances that are able to explain the measurements and to reduce the prediction ranges of natural vibration frequencies.

Structure description

Static-load tests were performed on the Langensand Bridge built in Lucerne (Switzerland). This structure was under construction (half of width launched) when tested. Therefore, only one half of it is in the scope of the study. This bridge is approximately 80m long and has a slender profile ($\geq$1:30) see Figure 4.

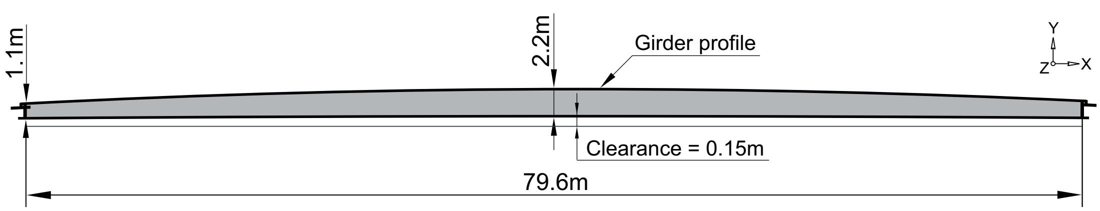

Figure 4. Langensand Bridge elevation representation. Reprinted from Goulet et al. (2010) with permission from ASCE

The shaded area in Figure 5 represents the part of the bridge in place during load testing. It consists of a concrete deck poured on a steel girder. The central part of the bridge is used as roadway and the external parts are sidewalks.

Two load cases are presented in Figure 6. The measurement system used during the identification is composed of three displacements (at the intersection of axis S7-112,

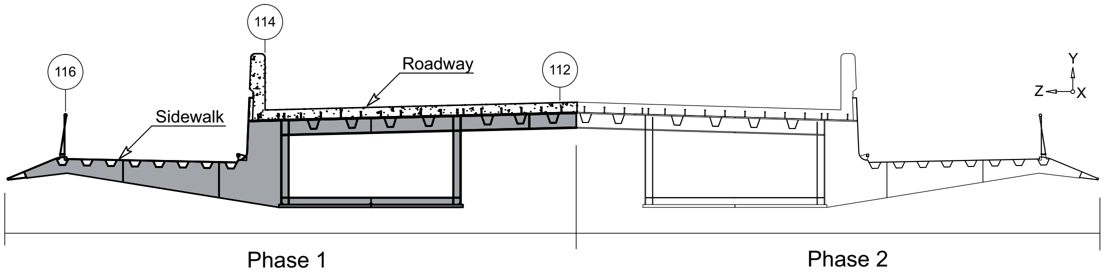

Figure 5. Langensand Bridge cross section. Reprinted from Goulet et al. (2010) with permission from ASCE

S12-112 and S17-112), two rotations (at the axis A1 and S7) and two strain measurements (in the top and bottom chord of the concrete slab at the section S13) recorded for five load cases. Complete information regarding loading, sensor layout and details are presented by (Goulet et al. 2010).

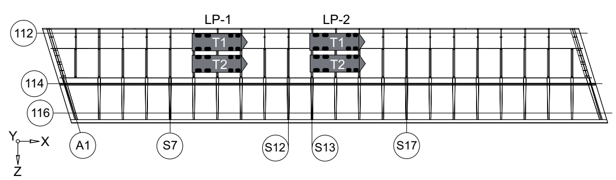

Figure 6. Test truck layout (Phase 1). Reprinted from Goulet et al. (2010) with permission from ASCE

The finite-element (FE) model cross-section is presented in Figure 7. In order to restrict the number of modeling uncertainties, secondary structural elements such as deck stiffeners, concrete reinforcement, road surface and barriers are also modeled.

Initial model set

The template model has four parameters to be identified: steel girder Young's modulus [200, 212]GPa, concrete Young's modulus [20, 32]GPa , pavement Young's modulus [2, 20]GPa and the stiffness of the horizontal support created by the bearing devices [0, 1000]kN/m. The Young's modulus range includes possible values over the whole structure. The initial model set contain 10010 model instances (combinations of the four parameters to identify).

Uncertainties and correlations

Uncertainties are separated in two categories: model-dependent and other uncertainties. Both classes are reported in the following section as described by (Goulet and Smith 2010; Goulet and Smith 2011b).

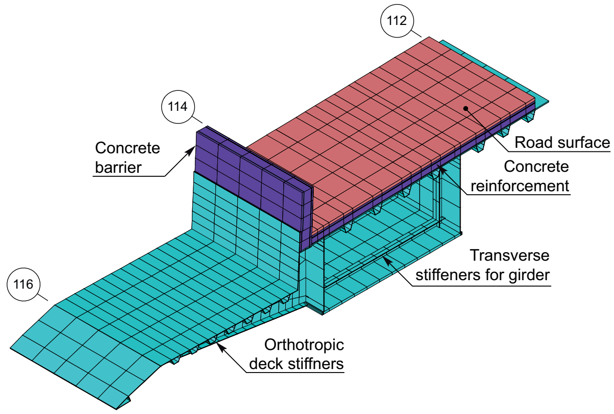

Figure 7. Langensand Bridge template finite element model (Phase 1). Reprinted from Goulet et al. (2010) with permission from ASCE

Model-dependent uncertainties

Uncertainties related to the geometry of the structure (variation in the thickness of the elements), Poisson's coefficient for concrete, truck weight and the variation of strain-sensor positioning are represented as normal distributions. The details regarding each distribution are summarized in Table 1. The variation of the temperature during the test affected the properties of concrete and pavement materials. The uncertainty on the change in ambient temperature during the tests is taken as a uniform distribution varying between 0 and 5 degrees Celsius. The uncertainty associated with temperature represents the maximal variation of temperature measured during the tests. Based on the relationship proposed by Bangash and England (2001) the variation in percentage of the concrete elastic modulus is equal to the variation of temperature divided by -137. For the road surface, this relationship is taken as the temperature variation divided by -30. This last relationship is based on the experimental work conducted by Perret (2003) on similar materials.

Table 1. Model-dependent uncertainties.

Uncertainty source	Unit	Mean	STD
Δv concrete	-	0	0.025
Δt steel plates	%	0	1
Δt pavement	%	0	5
Δt concrete	%	0	2.5
Truck weight	Ton	35	0.125
Strain sensor positioning	mm	0	5

Other uncertainty sources

For other uncertainty sources (except for sensor resolution), no quantitative information other than engineering judgement is available. Therefore, these values represent the authors' perception of the minimal and maximal bounds within which the true residual (i.e. error) should lie. Uncertainty values are presented in Table 2. For any cross section of the bridge, the effect of these simplifications combined with finite-element-method approximations are assumed to be at most seven percent for rotation and displacement predictions. Since strains are interpolated from the DOFs and are more sensitive to local imperfections (such as the presence of welds) the maximal error could be up to 20%. The Extended Uniform Distribution (EUD) (Goulet and Smith 2011a) is used for describing inexactly known uncertainty sources. It minimizes the impact of uncertain positions for uncertainty bounds. In this case, EUD reflects the fact that each uncertainty bound could be either over or underestimated by 30% (50% for strains).

Other uncertainties related to the identification are described in Table 2. Model simplifications, mesh refinement and additional uncertainties are represented using the EUD. Sensor resolution uncertainties are represented by a uniform distribution and are taken as twice the manufacturer specifications to account for site conditions. The instruments used are not sensible to cable losses. The strain sensors use optical fibers to transmit signal and inclinometer signals are numerically converted directly at sensor locations. Therefore the uncertainties associated with cable losses are taken to be zero. A mesh refinement analysis has been conducted in order to determine the maximal plausible discretization error for each type of prediction. Measurement repeatability uncertainty is obtained for each measurement location from the standard deviation of three measurement repetitions during the load tests.

Table 2. Other uncertainty sources

Uncertainty source	Displacement		Rotation		Strains	
	min	max	min	max	min	max
Sensor resolution	-0.2mm	0.2mm	-4μrad	4μrad	-4μ□	4μ□
Model simplifications & FEM	0 %	7%	0%	7%	0%	20%
Mesh refinement	-1%	0%	-1%	0%	-2%	0%
Additional uncertainties	-1%	1%	-1%	1%	-1%	1%

Correlation between uncertainties for simulating measurements

For the purpose of generating simulated measurements correlations are evaluated using the qualitative reasoning approach presented previously. The qualitative evaluation of the dependency between each quantity type (displacement, rotation, strains) are presented in Table 3 for each uncertainty source. Since matrices are symmetric, only half the values are necessary. The uncertainty correlation between load cases is assumed to be highly and positively correlated.

Table 3. Qualitative evaluation of uncertainty correlation between comparison points for a each uncertainty source.

Comparison point type	Displacement	Rotation	Strain	Uncertainty source
Displacement	High +	-	-	Model
Rotation	High +	High +	-	simplification
Strain	High +	High +	High +	& FEM
Displacement	High +	-	-	Mesh
Rotation	High +	High +	-	refinement
Strain	High +	High +	High +	
Displacement	Moderate +	-	-	Additional
Rotation	Moderate +	Moderate +	-	uncertainties
Strain	Moderate +	Moderate +	Moderate +	
Displacement	Low +	-	-	Sensor
Rotation	Low +	Low +	-	resolution
Strain	Low +	Low +	Low +	

Computation of expected identifiability

Over 1000 simulated measurements are generated in order to capture the expected performance of observations at filtering model instances.

Expected reduction in the number of candidate models

The cumulative distribution function showing the expected reduction in the number of candidate models is presented in Figure 8. In this figure, the horizontal axis presents the candidate model set expected size in percentage of the initial model set. The horizontal axis shows the cumulative probability that any given percentage of reduction in the candidate model set is obtained. In this case, there is a 95% chance to reduce the initial model set by 65% (eCM(95%)≈35%) and a 50% chance to reduce the initial model set by 80% (eCM(50%)≈20%). These results represent either the 50% or 95% probability of obtaining at least the corresponding reduction in the size of the initial model set.

The probability density function (PDF) is the derivative of the cumulative density function (CDF). Therefore the high probability content of the domain is contained where the CDF slope is steep. The polygonal sign represents the actual candidate model set size that is obtained using real observations on the structure. The predicted expected number of candidate models is in good agreement with the observations. In this situation a significant reduction in the number of candidate models ($\geq$ 65%) is expected with a high certainty (95%). Therefore, if the objective is to reduce the number of possible models that explain the measurements, proceeding with the monitoring

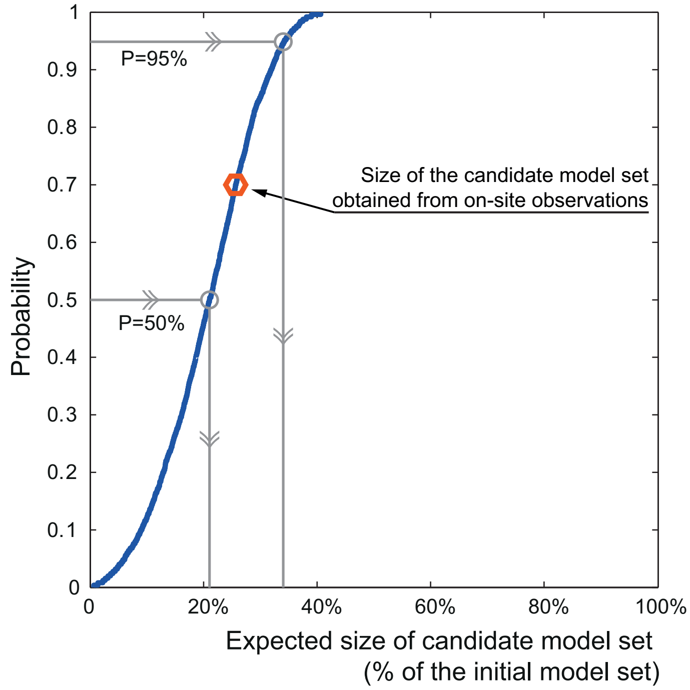

Figure 8. Cumulative distribution function of the candidate model set expected size

phase can be justified by the expected identifiability of a 95% certainty that greater than 65% of the models will be filtered.

Expected reduction in the prediction range

In a second case the expected reduction in the prediction range is studied. The results are summarized for the first five natural frequencies of the structure in the CDF presented in Figure 9. In this figure the horizontal axes represent the frequency range for each mode. The full horizontal scale of each plot corresponds to the frequency range of the initial model set.

For every mode, a significant reduction (50%-70%) is expected with a high confidence (95%). The combined expected identifiability indicator has a value of 0.88. This would justify performing the load tests on the structure in order to reduce the variability of predictions and the number of candidate models. The polygonal symbols on Figure 9 represent the prediction range computed from the real candidate model set (obtained from on-site observations). For every mode, the results obtained from observations do not lie in the distribution tail. This confirms that the expected identifiability algorithm supports infrastructure management decisions. For example, if several structures have to be monitored under a constrained budget, prioritization of actions can be made using this methodology.

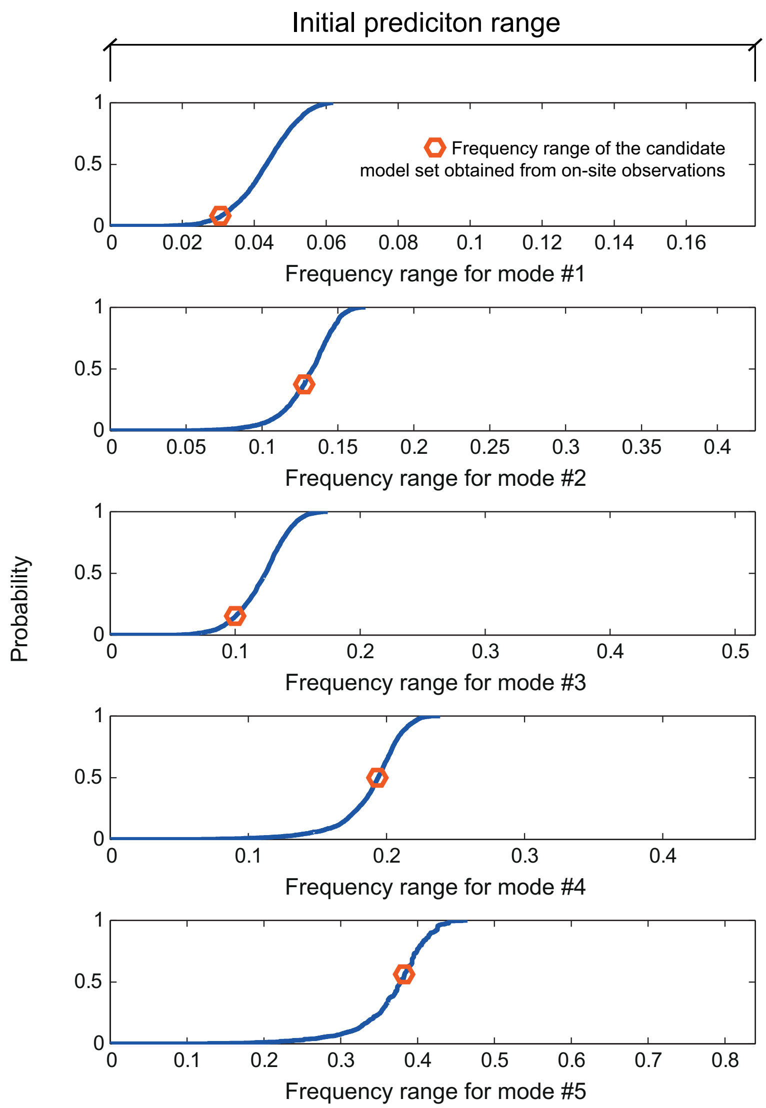

Figure 9. Cumulative distribution function of the candidate model set expected prediction range for the first five natural frequencies of the structure

THE INFLUENCE OF MODEL SIMPLIFICATIONS

Goulet et al. (2010) showed that the dominant uncertainty source is often associated with model simplifications. Furthermore, results obtained in the previous section are intrinsically dependent upon the choice of template model and on its level of refinement. Greater accuracy of the template model, reduces the uncertainties associated with model simplifications. This explains the high level of refinement used in the Langensand Bridge model. If an overly-simplified model is used, users would have to define larger uncertainty bounds. For simple-beam representations, errors on displacements of 50% and more than 100% for strains may occur (see (Goulet et al. 2009)).

Computation of expected identifiability

In this section, the uncertainties related to the model simplifications have been voluntarily increased to represent the case where overly simplified models are used. The model is assumed to be able to predict the displacements and rotations of the structure within 0 and 20% of the true behavior and within 0 and 40% for strains. The change in expected identifiability in comparison with the results obtained in the previous section is presented here.

Expected identifiability

The cumulative distribution function showing the expected reduction in the number of candidate models is presented in Figure 10. For these uncertainties, there is now a 95% chance to reduce the initial model set by 30% (eCM(95%) $\approx$ 70%) and a 50% chance to reduce the initial model set by 60% (eCM(50%) $\approx$ 40%).

Figure 11 presents the expected frequency range for the first five modes. The expected prediction ranges have significantly increased in comparison with the results obtained with a lower level of uncertainty. It is now only possible to expect (with a high certainty (95%)) a 30% to 40% reduction in the prediction ranges. The spread of the tail region has also increased, indicating an increase in the variability of the expected solution.

With the increases in the expected identifiability indicators have decreased by almost 50% according to the number of expected candidate models and prediction ranges. The combined expected identifiability indicator has a value of 0.47. Under these conditions, the potential gain of monitoring is marginal. It shows that using an over-simplified model hinders identification capability. Therefore, the best template model possible should be selected in order to obtain meaningful identification results.

DISCUSSION

Even if good identifiability is predicted and confirmed by observations, future increases in computing power could further reduce the degree of simplification made for predictions (for example by using solid elements instead of shells). Improvements in sensor technologies and their increased availability could reduce other sources of uncertainty. The new methodology proposed is also able to quantify the level of uncertainty required in order to reach a given target expected identifiability. It enables,

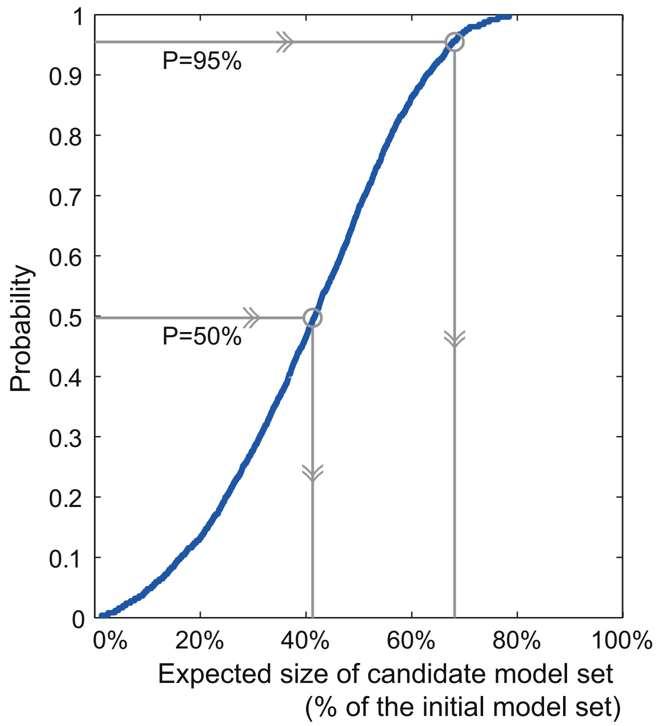

Figure 10. Cumulative distribution function of the candidate model set expected size under increased modeling uncertainties

prior to taking measurements, a prioritization of interventions by addressing first the structures where measurements are most likely to improve understanding of structural behavior. Characteristics of the measurement system, for example sensor locations, types and the load configurations chosen for measurement are also closely related to the expected identifiability of a structure. This topic is the subject of current research.

CONCLUSIONS

It is possible to study the usefulness of monitoring a structure. The methodology proposed evaluates the probability of occurrence of three performance indices; the expected number of candidate models and more importantly, the expected prediction range and the combination of these two indicators (combined expected identifiability (CEI)). It allows users to determine, prior to taking measurements, whether or not performing tests is likely to be useful for understanding the structure behavior and making accurate predictions.

1. The expected identifiability methodology proposed can predict the usefulness of measuring structures. The approach is based upon the generation of realistic

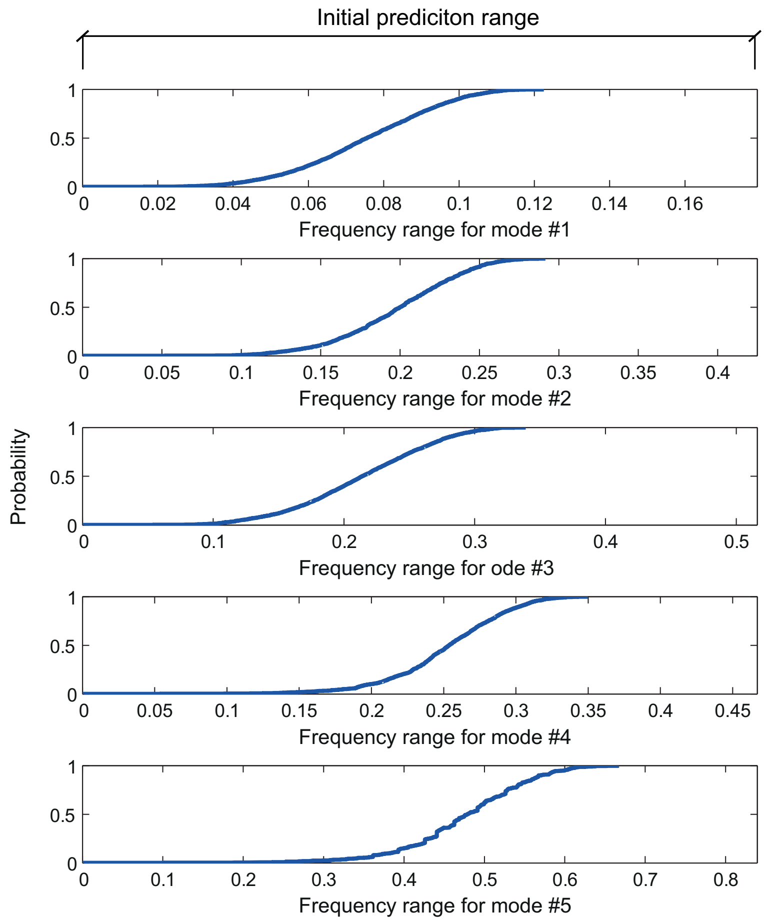

Figure 11. Cumulative distribution function of the candidate model set expected prediction range for the first five natural frequencies of the structure under increased modeling uncertainties

simulated measurements that include correlated uncertainties.

2. For Langensand Bridge, reductions in the model and measurement uncertainties can lead to significant reductions in the number of expected candidate models and prediction ranges. The predictions performed for the Langensand Bridge are confirmed by observations made during the identification of the structure.
3. Since the methodology does not require intervention on the structure, the expected identifiability can be determined prior to measuring a structure for a fraction of the cost required for full-scale testing.
4. Over-simplified structural models may hinder the identification capability. The methodology is able to quantify what level of uncertainty is acceptable in order

to reach a given target expected identifiability.

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