



Titre: Multimodel structural performance monitoring
Title:

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Date: 2010

Type: Article de revue / Article

Référence: Goulet, J. A., Kripakaran, P., & Smith, I. F. C. (2010). Multimodel structural performance monitoring. Journal of Structural Engineering, 136(10), 1309-1318.
Citation: <https://doi.org/10.1061/%28asce%29st.1943-541x.0000232>

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Document issued by the official publisher

Titre de la revue: Journal of Structural Engineering (vol. 136, no. 10)
Journal Title:

Maison d'édition: ASCE
Publisher:

URL officiel: <https://doi.org/10.1061/%28asce%29st.1943-541x.0000232>
Official URL:

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MULTI-MODEL STRUCTURAL PERFORMANCE MONITORING

AUTHORS

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ABSTRACT

Measurements from load tests may lead to numerical models that better reflect structural behavior. This kind of system identification is not straightforward due to important uncertainties in measurement and models. Moreover, since system identification is an inverse engineering task, many models may fit measured behavior. Traditional model updating methods may not provide the correct behavioral model due to uncertainty and parameter compensation. In this paper, a multi-model approach that explicitly incorporates uncertainties and modeling assumptions is described. The approach samples thousands of models starting from a general parameterized finite element model. The population of selected candidate models may be used to understand and predict behavior, thereby improving structural management decision making. This approach is applied to measurements from structural performance monitoring of the Langensand Bridge in Lucerne, Switzerland. Predictions from the set of candidate models are homogenous and show an average discrepancy of 4 to 7% from the displacement measurements. The tests demonstrate the applicability of the multi-model approach for the structural identification and performance monitoring of real structures. The multi-model approach reveals that the Langensand Bridge has a reserve capacity of 30 % with respect to serviceability requirements.

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KEYWORDS

Structural Identification, Bridge Behavior, Static Measurement, Multi-Model, Data Interpretation, Uncertainties, Dynamic Behavior

1. INTRODUCTION

Bridges are designed according to codes that specify conservative limits on loading and material properties. Behavioral models used in design, while leading to safe and serviceable structures, are not intended for data interpretation and long-term management. The Langensand Bridge is a good example of innovative structural engineering using composite design. During the design stage, engineers made justifiably conservative assumptions regarding behavioral aspects such as composite action and support conditions. Behavioral models using these assumptions often underestimate the load-bearing capacity of the bridge. Static load-tests may lead to numerical models that more accurately reflect real structural behavior. Such models enable owners to compare predictions with measurements of structural performance and thus take effective future management decisions. For example, when evaluating the effects of increased traffic loading in the future, predictions of a model that reflects real service behavior may indicate that no strengthening is necessary. The ability of a bridge to sustain exceptional loads may also be assessed with such models. Another benefit could involve suspected deterioration in the future. Measurements taken from a new set of static load-tests may be able to flag damage initiation phases when they are compared with predictions from an accurate behavior model. Engineers can then initiate corrective action early, thereby avoiding costly repairs when problems become more apparent. An extended list of potential applications is also reported by Brownjohn (2007).

Static and dynamic load-tests are not new. Measurements have been used for example to update parameters of bridge models (Banan and Hjelmstad 1994; Brownjohn et al. 2003; Sanayei and Saletnik 1996). The objective is generally to tune model parameters such that predictions fit measured data. However, updating may not bring out trustworthy information about the behavior of a structure. The ASME committee for verification and validation (ASME 2006) recommends that an updated

model should only be used for comparison purposes. Predictions for new load cases may be inaccurate. An updated model is also not valuable for observing the evolution of structural properties (ex: creep or structural change).

System identification (*SI*) is the science of inferring models from observations (Ljung 1999). Several system identification approaches have been applied to full-scale civil engineering structures (Brownjohn et al. 2003; He et al. 2009; Morassi and Tonon 2008; Teughels and De Roeck 2004). Most of these methods are based on dynamic testing which have their strength and weaknesses. One of the main reasons for conducting these tests is their ease of use. For example, ambient vibration may be recorded without interrupting traffic. However, dynamic measurements are sensitive to environmental changes. This reduces their potential to correctly identify the behavioral model of a structure or to detect damage. Moreover, all significant modes may not be identifiable from ambient vibration measurements. He et al. (2009) notes the advantage of several system identification methods for cross validation purposes in order to reduce the number of missing modes. Brownjohn and Xia (2000) report that when performing ambient vibration monitoring, fundamental hypothesis requiring input nonstationarity is inevitably violated. Therefore, it is difficult to distinguish between features that are related to the input excitation and those that are related to structural response. Moon and Aktan (2006) conclude that independent approaches must be employed (i.e., comparison of static and modal flexibility) to ensure that identification is reliable.

While the presence of uncertainties has been widely acknowledged in literature (Beck and Katafygiotis 1998; Brownjohn and Xia 2000; Catbas et al. 2008; Hadidi and Gucunski 2008; Raphael and Smith 1998) some approaches overlook uncertainties in the system identification process and focus on finding models such that predictions fit measurements. These approaches are susceptible to error compensation. The wrong model may be identified due to compensating measurement and modeling errors. Inverse tasks are also prone to parameter compensation. For example, in a composite girder, the effect of a large value for the Young's modulus of steel could be compensated by a smaller value for Young's modulus of concrete.

To address the challenges associated with errors and parameter compensation inherent to inverse tasks, Raphael and Smith (1998) proposed the multi-model approach. This method attempts to explicitly take into account all sources of uncertainties identified during the modeling and measurement process. The method differs from deterministic model updating approaches in that it searches for multiple candidate models that explain the measurements taken from a structure. Threshold values on model predictions determine whether or not a generated model is a candidate. Raphael and Smith (2003) used a stochastic search (PGSL) to identify potential behavioral models. Robert-Nicoud et al. (2005b) successfully applied the method on a laboratory benchmark beam. Robert-Nicoud et al. (2005b) determined threshold values by adding the estimated values for modeling and measuring uncertainties. A model is selected as a candidate model if its predictions lie below threshold values at each prediction location for each load case. This process usually leads to a population of candidate models from which further models can only be eliminated using user judgment, supplementary measurements and non-destructive testing.

Saitta et al. (2009; 2005; 2006; 2008) introduced data mining techniques in order to search more effectively within the space of candidate models. For example, K-means was used to group similar models into more general behavioral classes. Saitta et al. (2008) also used results from data mining to identify subsequent locations for measurements such that a maximum number of models may be eliminated from the population of candidate models. Thus, the multi-model approach enables an iterative strategy of system identification where measurements are used to identify populations of candidate models and model populations are used to identify subsequent measurement locations. However, the approach has been illustrated using only laboratory tests and simulations. It has not been previously applied for structural identification tasks on full-scale structures. The uncertainties present during the various steps of measurement and modeling of full-scale structures have not been fully assessed.

Building on previous work done at EPFL, this paper develops and improves the multi-model approach in order to make it suitable for structural performance monitoring of full-scale structures. The goals of

this study are to investigate the applicability of the multi-model *SI* approach to full-scale structures and to evaluate the approach for condition assessment of structures. The paper presents results from static load tests performed on the newly built Langensand Bridge in Switzerland. The multi-model approach is used to identify candidate behavioral models able to predict the reserve capacity of the bridge. This paper is organized in five sections. The following section describes the multi-model framework. Next, the testing process and the results obtained from the structural performance monitoring of the Langensand Bridge are discussed. Specifically, results from data interpretation using a multi-model structural system identification methodology are given. Results from the multi-model *SI* approach are then compared with those from a traditional model-updating technique. Lastly, conclusions from the study and avenues of future work are presented.

2. SYSTEM IDENTIFICATION USING MULTI-MODEL APPROACH

Recent developments in the field of computing enable the use of computation-intensive approaches for interpreting measurements from static load-tests. Performing thousands of finite element simulations to identify a good set of candidate models is now feasible. The set of candidate behavioral models can be used to understand structural behavior and support predictions. The SI framework used in this study is presented in Figure 1. It is adapted from previous work done at EPFL (Raphael and Smith 1998; Robert-Nicoud et al. 2005a) to systematically deal with uncertainties arising in static-load tests of full-scale structures.

MODEL GENERATION

The first step in the *SI* process is the development of a general finite element model (*GM*) of the studied structure. This model is parameterized according to behavioral assumptions. Examples of model parameters are material properties, partial interaction in a composite structure and damage location. The values of model parameters are determined by probability density functions defined using a priori knowledge. The Latin Hypercube Sampling (*LHS*) method is used to generate the models. This method was first proposed by McKay et al. (1979) in order to improve the efficiency of

Monte-Carlo methods when used with direct (random) sampling methods. LHS leads to well distributed sampling in multi-dimensional spaces. In this study, LHS is used as a sampling technique and not for probability assessment. This model generation method starts with a general model (*GM*) and uses LHS to generate several potential behavioral models (*PM*) that have different sets of values for model parameters. A *GM* may include parameterization of aspects such as support conditions, loss of section and interface conditions.

LOAD TESTS

Static-load tests are performed on the structure in order to measure its behavior. Measurements are recorded at many locations (*i*) for each load case (*j*). The measurement locations and load cases may be determined on the basis of predictions from models obtained in the previous step (Robert-Nicoud et al. 2005a).

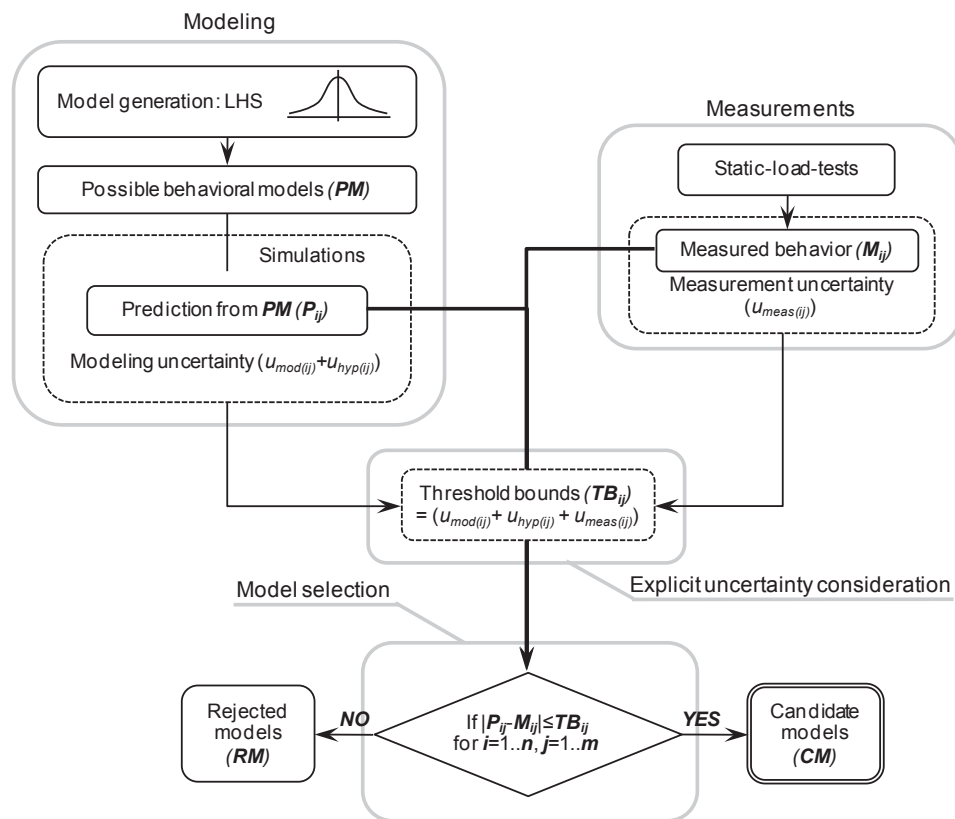


FIGURE 1 - CANDIDATE MODEL SELECTION PROCESS

UNCERTAINTIES AND THRESHOLD VALUES

Uncertainties are present in every stage of the process that is outlined in Figure 1. They may be classified into two categories: measurement uncertainties and modeling uncertainties. The latter consists of hypothesis and modeling uncertainties. Both measurement and modeling uncertainties may include aleatory and epistemic uncertainties. Oberkampf et al. (2002) reviewed several definitions of terminology for uncertainty estimation and mentioned that the term uncertainty refers to the concept of an unknown which can be characterized upon examination. Uncertainties are classified into two types: aleatory and epistemic (Oberkampf et al. 2002). Aleatory uncertainties are irreducible. They describe the inherent variation associated with physical systems (such as variation in material properties, element, geometry and several subsequent measurements of the same quantity. Epistemic uncertainties are attributed to a lack of knowledge. The values of these uncertainties may be reduced to more elementary origins (Examples of epistemic uncertainty are simplification in finite element modeling and temperature effects occurring during a load test). Most studies address only aleatory uncertainties. Epistemic uncertainties are usually assumed to be zero which for real engineering tasks is erroneous. Nevertheless, upper bounds of epistemic uncertainties can usually be quantified based on experience.

In this study, uncertainties are generally expressed as percentages since this is the most common representation of experience based uncertainty. The measurement uncertainty at a given location for a given load case is evaluated as the product of the measured value and the percentage uncertainty. Similarly, modeling uncertainties are evaluated as the product of the percentage uncertainty and predicted values. The main sources of uncertainties are identified below. The labels (A) and (E) identifies if the uncertainty is either aleatory (A) or epistemic (E).

MEASUREMENT UNCERTAINTIES ($U_{MEAS(LJ)}$)

- Sensor accuracy (A)
- Site conditions, cable and contact losses (A)
- Structure and sensor movement from ambient vibrations (A)
- Repeatability of measurements and truck positioning (A)
- Uncertainty over the truck weight (E)

- Temperature effects (E)

HYPOTHESIS AND MODELING UNCERTAINTIES ($U_{MOD(i,j)}$, $U_{HYP(i,j)}$)

- Finite element method (FEM) approximation (E)
- Mesh discretization (E)
- Uncertainties in geometry (E)
- Assumption of linear elastic structural behavior (E)
- Assumption that bearing devices and loads are acting as point loads (E)

Specific threshold bounds (TB_{ij}) are computed for each combination of location (i) and load case (j) by adding the upper bounds of uncertainty terms $u_{mod(ij)}$, $u_{hyp(ij)}$ and $u_{meas(ij)}$. Candidate behavioral models are selected by comparing the difference between predicted (P_{ij}) and measured values (M_{ij}) to the associated threshold value (TB_{ij}).

CANDIDATE MODELS

Each model in PM is analyzed for all load cases (j) and the predictions (P_{ij}) at locations i are recorded. Candidate models are those models which are able to predict the measured values to within a threshold value (TB_{ij}) at each measurement location (i) and load case (j). The selection process is schematically illustrated in Figure 1.

If the absolute value of the difference ($P_{ij}-M_{ij}$) is smaller than the threshold value (TB_{ij}) at every location and for every load case, the model is considered as a **candidate behavioral model (CM)**. Each *CM* thus represents a possible behavioral model of the bridge which may explain the measurements taken on site. The set of candidate models includes the correct behavioral model for the structure and those that have uncertainty compensation since all these models give predictions lower than the threshold value. Models presenting obvious parameter compensation may be rejected using engineering judgment and experience. Lower and higher values for each parameter must be sampled in the initial model set in order to search over the full space of possible solutions. However a candidate model having parameter values such as abnormally low Young's modulus for concrete combined with an abnormally high value for say steel Young's modulus is highly improbable. Even if unlikely, these combinations of low or high parameters must be tested in case they would result to be the only

selected candidate models. They would therefore raise a flag indicating that more candidate models must be evaluated or a more detailed evaluation of the structure is required.

3. PERFORMANCE MONITORING OF LANGENSAND BRIDGE

This section describes results from structural system identification using a multi-model approach of the Langensand bridge in Switzerland.

3.1. DESCRIPTION OF BRIDGE AND STATIC-LOAD-TESTS

The new Langensand Bridge in Lucerne (Switzerland) is a single span 80m long structure. Its slenderness ratio (L/h) varies from approximately 60 at the abutment to 30 at mid-span. Figure 2 shows the main girder profile and its boundary conditions.

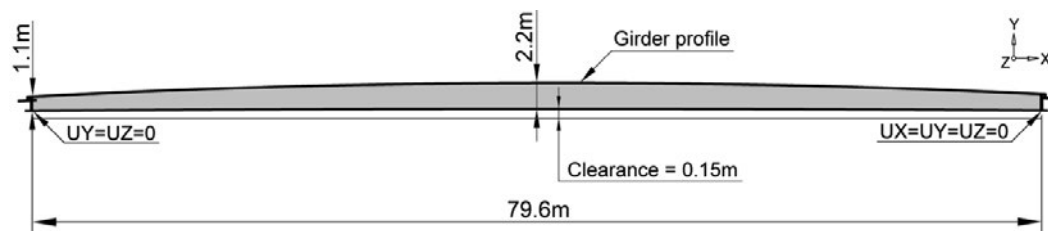


FIGURE 2 - LANGENSAND BRIDGE: MAIN GIRDER PROFILE

The structure is being built in two phases to avoid traffic interruption on the existing bridge. Load tests were performed after the completion of the first phase when only a half of the bridge was completed (see Figure 3).

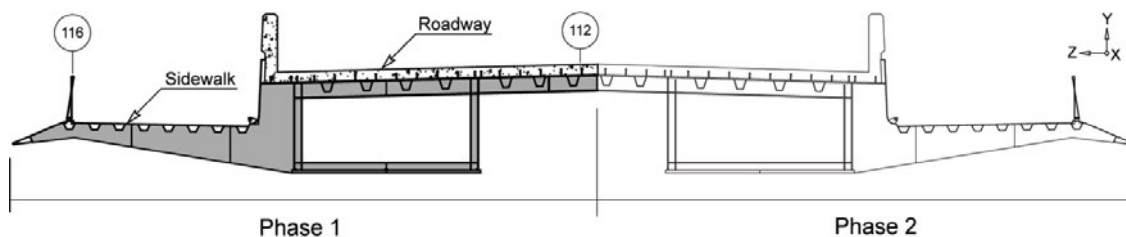


FIGURE 3 – CONSTRUCTION PHASES OF LANGENSAND BRIDGE

Understanding the structural behavior of this bridge is not straightforward due to the following aspects. First, the structure has an unusually high slenderness ratio ($>L/30$). Moreover, the cross section of the bridge is non-uniform, and the geometry of the structure is also slightly arched in elevation along its length. This particular geometry makes the free end of the structure move farther from the fixed end when subject to loading. Furthermore, this structure has a skew of seventeen degrees at abutments.

The behaviour of the bridge is measured when subjected to five load cases. Figure 4 shows load cases *LP-1* and *LP-2*, and reference axes that are used to illustrate measurement locations. For the third load case *LP-3*, the truck *T1* is placed at the same position as in *LP-2* and the second truck *T2* is positioned right behind it. For load cases *LP-4* and *LP-5*, the two trucks are placed alone on the bridge in their same respective positions as in *LP-2*. Load cases *LP-2*, *LP-3* and *LP-5* are used to verify the assumption of linear structural response.

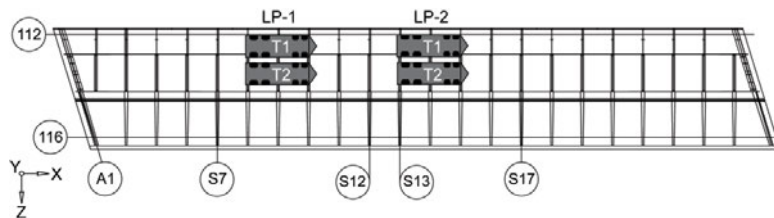


FIGURE 4 – TOP VIEW OF LANGENSAND BRIDGE WITH REFERENCE AXES FOR MEASUREMENT LOCATIONS

The following types of measurements are taken during the static-load tests:

- Displacement measurements are taken at six locations (at the intersections of the axes: S7-112, S7-116, S12-112, S12-116, S17-112 and S17-116) with optical devices
- Rotations about the Z-axis are measured using two inclinometers placed near the abutment (at the intersection of the axes: A1-112 and S7-112).
- Strains are measured at three locations on the bridge along the section S13 using SOFO Michelson-type fiber-optic sensors. Two sensors are placed along the X-direction over the centre of the main steel box girder such that one is embedded near the top of the concrete deck

and the other near the bottom of the concrete deck. The third sensor is placed on the top side of the bottom chord of the steel girder.

Figure 5 shows a detailed cross-section of the finite element representation from which possible behavioral models are generated. The structure consists of a steel girder plus a concrete slab and barrier. Shear connectors are provided on the top chord of the steel girder in order to allow for composite interaction between the steel and concrete components. A finite element model of the bridge is created using ANSYS (2007). The girder elements (steel plates and concrete deck) are made of 8-nodes shells (SHELL281). The stiffener flanges are modeled as 3-node beam elements (BEAM189). The concrete barrier is represented as tri-dimensional 20-node solid elements (SOLID186). The reinforcement is modeled by 2D smeared reinforcement (REINF265). Fixed boundary conditions are specified by requiring zero displacement at appropriate degree of freedom. A partial restriction in the longitudinal movement of the bridge is imposed with one-dimensional spring elements (COMBIN14). This restriction is applied at the intersection of the concrete slab, the barrier (Figure 5) and the axis A1 (Figure 4). The model has approximately 24000 elements and 335000 degrees of freedom and requires 1.6 Gb of RAM in order to be solved in-core using ANSYS (2007). Each resolution of the model takes between 15 to 30 seconds depending on CPU properties. The post-processing of the models is completely automated using the APDL programming language (ANSYS 2007) and therefore, the solving time include post-processing.

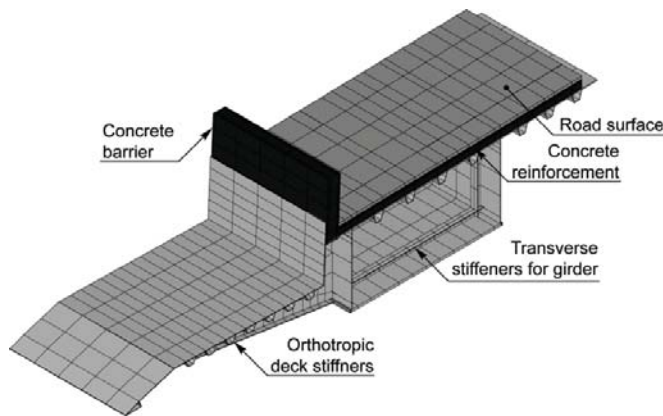


FIGURE 5 - LANGENSAND BRIDGE CROSS-SECTION OF FINITE ELEMENT MODEL

Researchers (Broquet et al. 2004; Chung et al. 2006; Conner and Huo 2006; Eamon and Nowak 2002; Eamon and Nowak 2004; Hassan 1994; Mabsout et al. 1997) have already shown that sidewalks and barriers may significantly affect the load and stress distribution in a structure. These results are also corroborated by a study conducted by the authors (Goulet et al. 2009), which showed that factors such as deck inclination, steel reinforcement and road surface should not be neglected when conducting a system identification study. Therefore an attempt is made to model all elements of the bridge that may contribute significantly to the stiffness of the structure including secondary structural elements such as stiffeners, concrete reinforcement, and road surface.

3.2. CANDIDATE MODEL SELECTION PROCESS

MODEL GENERATION

Several parameters are initially included in the general finite element model. However, the influence of uncertainties in parameters such as element thickness, rebar position and Young's modulus of pavement on predicted response is observed to be very small (i.e. <1%). The values for these parameters cannot therefore be accurately estimated using the measurements from the load-tests. The main parameters of interest are found to be the Young's modulus of steel, the Young's modulus of concrete and the stiffness of the bearing device restriction. For sampling purposes, these parameters follow a Gaussian distribution with means and standard deviations given in Table 1. If a negative value is sampled for the stiffness of the bearing device movement restriction, the parameter value is taken to be zero.

TABLE 1 - PARAMETERS ENTERING IN MODEL COMPOSITION

	Average (μ)	Std. Deviation (σ)
Young's modulus of steel	206 GPa	6 GPa
Young's modulus of concrete	37 GPa	2 GPa
Bearing device mvt. restriction	300 kN/mm	100 kN/mm

Starting from a general finite element model as presented in previous sections, potential behavioral models (*PM*) having a range of values for parameters and representing multiple models of structural behavior are generated. The Latin Hypercube sampling method (*LHS*) is used to generate more than 1000 models. Each model is analyzed for the three load cases and the predictions at 11 locations for each case are recorded (i.e. six displacement points, two rotation and three strains). The total time required to obtain the initial model set is approximately a few hours for current desktop computers.

UNCERTAINTIES

Measurement and modeling uncertainties arising from the sources listed in Section 2 are systematically assessed as follows.

MEASUREMENT UNCERTAINTIES

- Sensor accuracies are partially defined by resolution specifications from the manufacturer. In the case of electrical devices the sensor accuracy is taken as twice the specified resolution to take into account cable and contact losses as well as site conditions.
- The movement from ambient vibrations of the bridge and the sensors are filtered out by taking an average value over multiple samples. Since the noise recorded is assumed to be random, the average value tends toward the true measurand. The upper bound for uncertainty is computed as three times the standard deviation of the recorded samples. Moreover, in-between each measurement and the application or removal of loads on the bridge, there is a one minute period without activity on the bridge to allow for the attenuation of vibrations.
- The upper bound for the uncertainties associated with truck positioning and repeatability of measurements is evaluated by repeating each load case three times. A factor of three times the standard deviation obtained from the measurements of a given load case provides a confidence level of approximately 97% (for three samples).
- The effects of uncertainties in truck weights are evaluated according to engineering judgment.
- Temperature effects are eliminated by taking measurements over a short period of time for each load case.

HYPOTHESIS AND MODELING UNCERTAINTIES

- Modeling experience and judgment are used to reduce and quantify uncertainties that originate from using the finite element method (FEM).
- Mesh discretization accuracy is estimated using mesh refinement studies. The values chosen are corroborated with those found in the literature (Topkaya et al. 2008).
- Uncertainties in geometry are eliminated by using a numerical model that uses dimensions taken from the “as-built” structure.
- A fundamental hypothesis in the simulations is that the structure behaves linearly with respect to the loading. This aspect implies linear material properties, and geometric linearity. To verify this hypothesis, measurements from load cases *LP-4* and *LP-5* are algebraically summed and compared with those from *LP-2*. The structural behavior is assumed to be linear if the difference between the two quantities is less than the respective measurement uncertainties. Otherwise, the uncertainty in model predictions is appropriately increased to account for the violation of this assumption.
- Bearing devices and loads are assumed to be concentrated loads. This simplification of the real structure is valid if the results are used for understanding the global behavior of the bridge.

Table 2 summarizes uncertainty sources and quantifies the extent of uncertainties from each of them for this structural identification task.

TABLE 2- UNCERTAINTY SOURCES

Uncertainty sources	Quantification method	Uncertainty according to the type of measurement				
		PDF	Displacements	Rotations	Strains	
Measurement uncertainties	Sensor accuracy	Manufacturer specified resolution	Uniform	±0.1 mm	±1×10 ⁻⁶ rad	±2 με
	Sensor noise from ambient vibration of the bridge	Average taken over multiple samples	Gaussian	±3σ	±3σ	±3σ
	Repeatability & Truck positioning	Use value from multiple samples to determine a maximum uncertainty	Gaussian	±3σ	±3σ	±3σ
	Truck weight	Truck weight variations have a linear response on the structure	Uniform	≈±1.5%	≈±1.5%	≈±1.5%
	Temperature effects	Measurements for each load case taken over a short period of time	Uniform	≈0%	≈0%	≈0%
Hypothesis and modeling uncertainties	Finite element method	Approximate value based on experience	Uniform	≈±5%	≈±5%	≈±5%
	Mesh discretization	Upper bound based on a mesh refinement study	Uniform	≈0%	≈0%	≈±5%
	Model exactitude	Model "as built"	Uniform	≈0%	≈0%	≈0%
	Linear elastic behavior	Superposition of load cases	Uniform	≈0%	≈1%	≈0%
	Bearing devices represented as point loads	Negligible effect on the global behavior of the structure	Uniform	≈0%	≈0%	≈0%
	Truck wheels considered as point loads	Negligible effect on the global behavior of the structure	Uniform	≈0%	≈0%	≈0%

The differences between results from superposition (Δ_{linear}) of load cases *LP-4* and *LP-5* and those from *LP-2* are much lower than the corresponding measurement uncertainty in strains and displacements and the contrary for rotations. Thus the assumption of linear elastic behavior is verified from all measurements except rotations. The discrepancy with respect to rotations is attributed to the additional uncertainty in rotation predictions. To account for this aspect, the uncertainty in rotation predictions is increased by 1%.

Figure 6 shows the contributions of uncertainty sources for each measurement type. Factors that are the most important with respect to identifying the correct behavioral model are identified by high percentage values. Uncertainties related to finite element model accuracy and repeatability of the experiment are the most significant. Sensor accuracy is usually not significant source of uncertainty. Thus, choosing more accurate sensors will not necessarily help in identifying the correct behavior model. However, reducing modeling uncertainties may help identify a smaller set of candidate models.

Repeating the measurements many times may also reduce uncertainties and thus improve the quality of system identification.

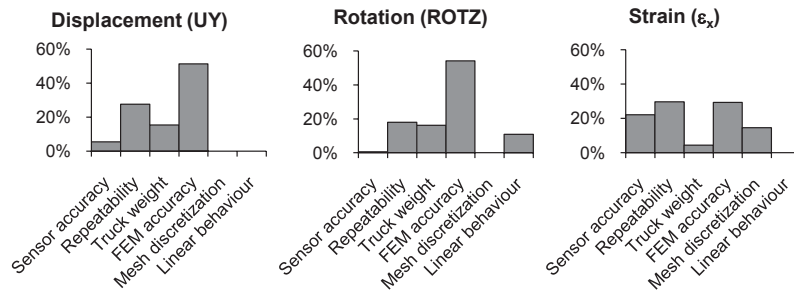


FIGURE 6 - UNCERTAINTY CONTRIBUTION BY SOURCE FOR EACH SENSOR TYPE

Figure 7 presents the percentage of uncertainties for each measurement type that are aleatory and epistemic (bias). In this case, aleatory uncertainties are smaller than the epistemic ones.

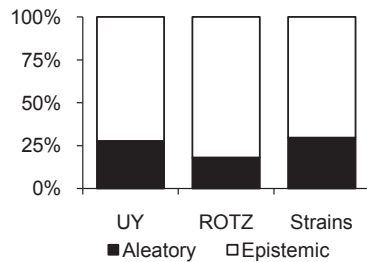


FIGURE 7 – ALEATORY AND EPISTEMIC UNCERTAINTIES FOR EACH MEASUREMENT TYPE

3.3. RESULTS

The multi-model candidate selection approach described in section 2 is applied to the set of potential behavioral models (1'000 models). The process and the resulting set of candidate models are summarized in Figure 8. This figure shows that the candidate models which are representative of the structure's measured behavior are not those that minimize the discrepancy between measured and predicted values. Moreover, it exhibits the epistemic (biased) character of uncertainties in finite element simulations.

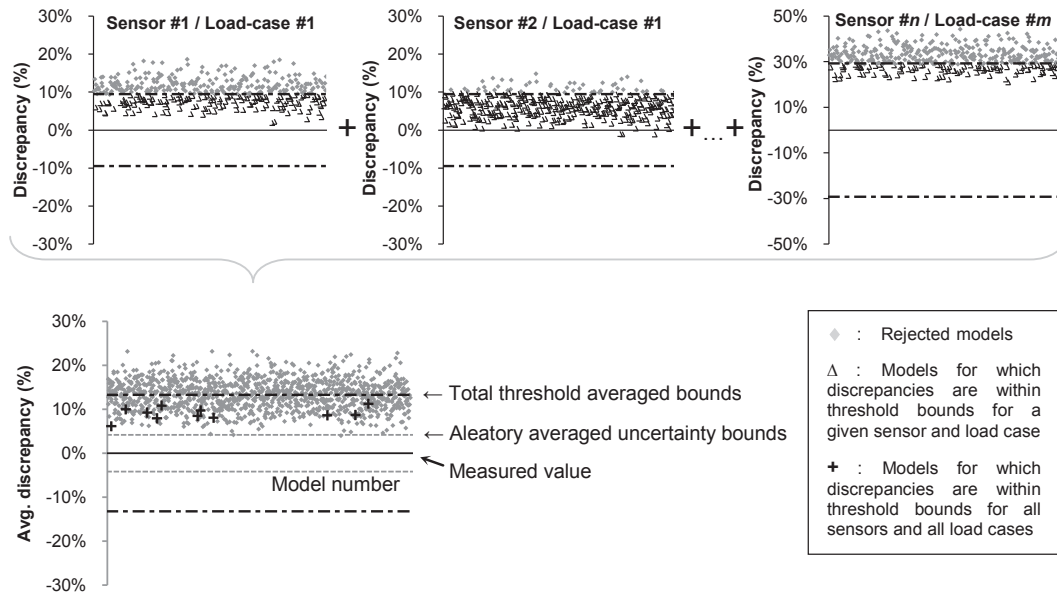


FIGURE 8 – CANDIDATE MODEL SELECTION PROCESS USING THRESHOLD

IDENTIFIED BEHAVIORAL CHARACTERISTICS

The methodology for candidate model selection identifies 152 models which are equally likely to predict measured behavior accounting for uncertainties. Next, models that have unrealistic values for model parameters are filtered. This results in eleven candidate models. Main characteristics of candidate models and the bounds used as plausible values are presented in Table 3. These results indicate that the *CM* set is able to predict the measured displacements and rotations of the structure to an accuracy of 4 to 7 %. Strains are more difficult to assess. Deviations range from 15 to 23% compared to the measurements. Model characteristics are discussed in detail in the following section.

TABLE 3 - CANDIDATE MODEL PROPERTIES

Model number	Bearing device stiffness (kN/mm) [0-325]	Young's modulus (GPa)		Averaged prediction/measurement ratio	
		Steel [200-212]	Concrete [29-45]	ROTZ & UY	ϵ_y
1	300	210.2	36.8	1.06	1.20
2	320	206.6	39.2	1.05	1.18
3	300	210.7	36.5	1.07	1.22
4	270	208.3	37.9	1.05	1.19
5	270	211.9	35.8	1.07	1.23
6	250	211.9	38.7	1.05	1.17
7	260	210.5	37.9	1.05	1.19
8	280	211.7	38.6	1.04	1.18
9	300	211.2	41.7	1.04	1.15
10	210	211.7	36.9	1.06	1.20
11	310	211.5	38.4	1.05	1.18

BEARING DEVICES WITH RESTRAINED DISPLACEMENT

After interpretation of measurements from the static-load tests, many candidate models with constrained longitudinal movement were identified to be candidate models. Visual inspection of the bearing device shows no symptoms of malfunction. Additional inspections of the expansion junction device revealed that the extremity of the bridge where the longitudinal movement is intended to be free was restrained. Two wooden blocks were left in place between the abutment and the concrete barrier of the bridge. The location and dimension in millimeters of these blocks is shown in Figure 9. A closer inspection revealed that the blocks were prestressed by the weight of the structure (i.e. they were impossible to remove manually) and they showed an elastic behavior under the passage of trucks on the bridge. From calculations using wood material proprieties (DOA 1999) the stiffness of the restraint is estimated to be 300kN/mm.

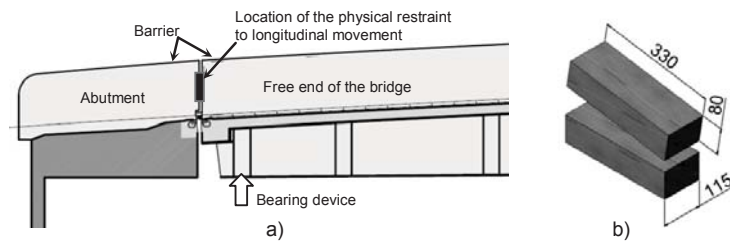


FIGURE 9 – A) REPRESENTATION AND POSITION OF THE DISPLACEMENT RESTRICTION B) DIMENSIONS OF THE WOODEN BLOCKS (MM)

Candidate models have values for bearing device stiffness between 200 and 320 kN/mm. Even if the nominal value of the stiffness of the restraint is large, its effect on the structure remains small (\approx 1-3% for displacement predictions). Therefore, identifying the exact value for this parameter is difficult.

MATERIAL PROPRIETIES

Candidate models having values for material proprieties that are within plausible values are identified. It confirms that the behavior of the structure conforms to expectations. The values for Young's modulus of steel and concrete range from 206 GPa to 212 GPa and from 36 GPa to 42 GPa respectively.

COMPOSITE INTERACTION

The design hypothesis related to composite interaction between the concrete and steel deck is verified by the candidate models. Results from measurements show no sign of partial interaction between the concrete deck and the steel girder under service loads. Candidate models having partial composite interaction also have unrealistic values for material proprieties to compensate for the additional flexibility introduced by this feature. Therefore, if the effect is present, it is not significant enough to be distinguished from fully composite interaction and it would not significantly alter the in-service behavior of the structure.

4. IMPROVEMENT OVER TRADITIONAL MODEL UPDATING

A traditional model updating results are compared with results from the multi-model approach. A simple example demonstrates that finding a model by fitting predicted values and measurements can lead to a biased solution. Advanced model-updating methods may also be unreliable if the approach involves obtaining the best agreement between predicted and measured values. In this case, an analytical formulation for beam displacement is used for traditional model-updating. Using vertical displacement predictions from the design model (provided by the engineer in charge of the design), values obtained from model updating and from the multi-model approach are compared for a critical limit state (E_d) prescribed in Swiss SIA design codes (SIA 2003). In equation 1, E_d represents the

displacement in millimeters under the combination of 75% of the lane load plus the concentrated forces and 40% of the sidewalk load.

$$E_d = 0.75 \cdot L_{Lane} + 0.40 \cdot L_{Sidewalk} \quad (1)$$

This load distribution is shown in Figure 10.

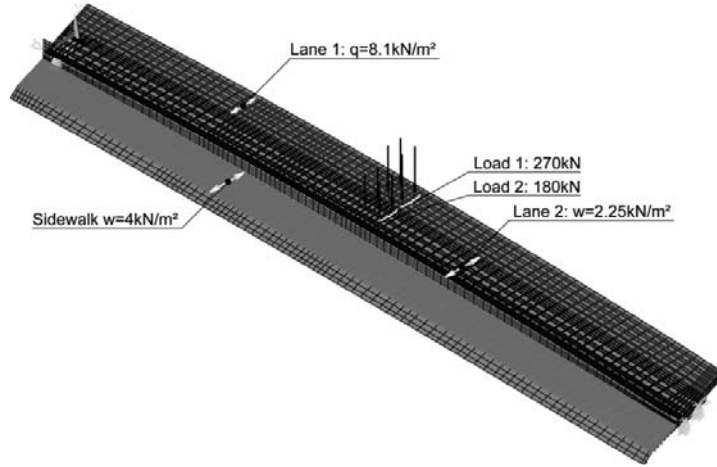


FIGURE 10 - LOADS FOR LIMIT STATE E_d APPLIED TO THE COMPLETE MODEL

4.1. SINGLE MODEL UPDATING

Bernoulli beam theory is used to determine the equivalent flexural stiffness of the bridge from the measurements. The relations for displacement and rotation measurements are presented in equations 2 and 3. A representation of the updated model is presented in Figure 11.

$$EI_{eq} = \frac{Px}{48 \cdot (UY)_{meas}} (3L^2 - 4x^2) \quad 0 \leq x \leq \frac{L}{2} \quad (2)$$

$$EI_{eq} = \frac{P}{16 \cdot (ROTZ)_{meas}} (L^2 - 4x^2) \quad 0 \leq x \leq \frac{L}{2} \quad (3)$$

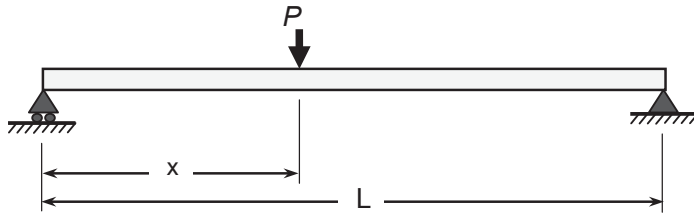


FIGURE 11- BEAM-BASED UPDATED MODEL

Measurements from one load case are used to compute the equivalent flexural stiffness of the bridge. Using the four measurements and equations (2) and (3), the average flexural stiffness is evaluated. One of the results are presented in Table 4.

TABLE 4 - EQUIVALENT RIGIDITY FOUND WITH AN UPDATING METHOD

Measurement		EI_{eq} ($\times 10^{17}$ N.mm ²)
Displacement	S07-112	2.74
UY	S12-112	2.63
Rotation	A0-112	2.64
ROTZ	A7-112	3.02
Average		2.75

This approach evaluates an equation that implicitly includes the stiffness of every element of the bridge. Therefore, it is not possible to determine the capacity of the structure without the barrier or the capacity without the abutment restriction that was present during the load tests. In the case of the multi-model approach, the abutment restriction has been removed in order to obtain the response of the structure in service.

The model updating approach has also been applied to the complete finite element model presented in Figure 10. The model has been manually calibrated to fit displacement or strain measurements. Possible values for Young's modulus of steel and for concrete are 235 GPa and 43 GPa respectively when the model is calibrated using strain measurements and 211 GPa and 47 GPa when the model is

calibrated using displacements. This simple example shows that using two different sets of measurements from the same load tests can lead to two different results which are not realistic. Filtering unrealistic results obtained through model updating is feasible. However, difficulties occur when wrong plausible parameters are found. The values obtained from traditional model updating are questionable since parameter values may have been compensated for epistemic uncertainties that are present either in measurements or in the model.

4.2. COMPARISON OF APPROACHES

The stiffness estimated with model updating is used to predict the maximal displacement of the bridge under the limit state E_d . This result using beam model (Figure 11) is shown in Table 5. The table includes the predictions of the model obtained by calibrating the finite element model (Figure 10) and the candidate models from the multi-model approach (Table 3). The table also gives the predictions from the model used by the designer. Note that the design model does not consider the concrete barrier as per the owner's requirement.

TABLE 5 - VERTICAL DISPLACEMENT UNDER SIA (SIA 2003) RISK SITUATION E_d

Approach	Maximum vertical displacement for risk situation E_d (mm)
Beam model (Figure 11) Updated using UY&ROTZ	73.0
Updated model Complete model (Figure 10) Updated using UY	78.1
Complete model (Figure 10) Updated using strains	76.5
Multi-models	82.1 - 84.5
Design-model	117.8

The results in Table 5 show that traditional model updating may not be reliable since it underestimates the vertical displacement. However, the design-model provides safe and conservative predictions as expected. Evaluating the real displacement of the structure for the loading E_d requires conducting an equivalent load test on the structure.

This case study illustrates that models which exactly fit measurements may not be the correct model. Even when sophisticated FEM calculations are made, there are always uncertainties associated with results (in addition to the uncertainties from sources such as measurements). Uncertainties associated with civil engineering structures cannot all be represented as aleatory and independent at each measured DOF. For example, the uncertainty associated with the finite element method is epistemic making every prediction biased compared with reality. The same reasoning is also applicable for other model updating techniques. Whenever the goal is to fit model predictions to measured data exactly, the result will be biased by errors (modeling and measurement). As mentioned by Tarantola (2006) using observations to infer one model of the system (the ‘best model’ or the ‘mean model’ or whatever) is not advisable. For different sets of measurements, model updating leads to different models. In their guide for validation in solid mechanics an ASME committee (ASME 2006) noted that parametric model calibration (traditional model-updating) determines only the model’s fitting ability not its predictive capacity. In the case of the multi-model approach, the uncertainties are assessed explicitly thereby increasing the confidence in results. Results presented in Table 5 indicate that the traditional model updating approach provides a less conservative solution than what is obtained from the range of multiple model results. Table 5 also shows that the bridge has a reserve deflection capacity of 30 % for service loads when compared with the value predicted by the design model.

5. DISCUSSION

Predictions resulting from the set of candidate models are homogenous. Even if uncertainties concerning material properties are present, their effects on predictions are limited. The discrepancy between the predictions of the set of candidate models and the measurements reflects the approximate nature of the finite element method and the importance of epistemic uncertainties. Models are always an approximation of reality. Therefore minimizing discrepancies between predicted and measured values through adjusting parameter values inevitably leads to biased solutions. The parameter sets that exactly match the measured value are not representative of the real structure. The set of candidate models may be used to assess the displacement behavior of the full bridge prior to its construction to

an accuracy of 7%. This study also illustrates that as in other inverse engineering tasks, multiple solutions are likely to be found in structural identification tasks.

The quantification of modeling uncertainties used in this study is based on preliminary studies and experience. If uncertainties are not adequately estimated, results may be unreliable. Furthermore, if uncertainty values decrease due to new information such as that obtained from additional measurements, a smaller number of candidate models is likely to be identified, and vice versa.

Confidence in the solutions may be increased by quantifying uncertainties on the basis of well-designed experiments. Comparing simple (beam-based) with advance (shell & solid based) models may only give a lower bound for the uncertainties associated with simple models. In this case, the most advanced model (which is reasonably possible to solve) is used to represent the structure. Therefore, no information is available in order to quantify the uncertainty associated with the model other than engineering judgment. Moreover, the quality of the results may also be improved by using a systematic approach for measurement system design prior to the load tests. For the case study presented in this paper, such improvement are the subject of current research.

6. CONCLUSION

The conclusions of this research are:

- The multi-model approach described in this paper is applicable to structural identification and performance monitoring of real structures. Including uncertainties explicitly during the identification process is feasible. Neglecting them may lead to a biased identification.
- A major component of uncertainty is epistemic. Therefore, assuming that uncertainties are exclusively aleatory and independent at each measured DOF is inappropriate for bridge identification tasks.
- The set of candidate models that are identified for the Langensand Bridge improve understanding of structural behavior. Models are able to predict the response of the structure to within 7% of measurements.

- Results have enabled the verification of the design hypothesis that assumed the bridge to behave in a fully composite manner.

A continuation of this study is currently under way in order to further validate these results and obtain better estimates of uncertainties. Ambient vibration recording from dynamic testing of the bridge will be used to crosscheck results. Future work will also focus on assessing the uncertainties when using finite element analyses to model bridge behavior. In addition, studies using new statistical approaches are underway to develop a systematic methodology to include uncertainties in the determination of threshold values. Finally, new developments are currently being implemented for measurement system design (Kripakaran and Smith 2009) in order to increase the robustness and efficiency of structural system identification tasks.

7. ACKNOWLEDGEMENTS

Collaboration with the designers of the Langensand Bridge - Gabriele Guscetti and Claudio Pirazzi (Guscetti & Tournier), was important for successful completion of the load tests. The authors also acknowledge input from Dr. R. Cantieni and the help we received from his team when taking the measurements. Finally the authors would like to thank – I. Laory and P. Gallay for their help during load testing. The city of Lucerne provided logistics support, the trucks for the load tests and the deformation sensors. This research is funded by the Swiss National Science Foundation under contract no. 200020-117670/1.

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