Structural Identification: A Tool for Bridge Reliability Evaluation

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EXTENDED ABSTRACT

Cost effective infrastructure management depends on objective and systematic approaches to condition assessment. The condition states currently available for use in infrastructure management are primarily subjective often dependent on the individual inspector's experience and qualifications. Decisions about a structure's safety and maintenance needs are made based on inspection data derived from subjective judgements that typically include information on a fixed scale (i.e. 0–9 or 0–5, depending on the bridge management system adopted by the state highway department). Structural–Identification (St–Id) is the process of developing an analytical model of a structure such that for a given set of inputs the model can simulate the output response. Thus, St–Id can provide objective information for the decision making process.

An integrated approach to St–Id is presented in six general steps that involve: (1) the development of a–priori models, (2) experiment design, (3) full–scale testing, (4) data processing, (5) model calibration and parameter estimation, and (6) utilization. The quality of each step is improved by integrating experimental and analytical components. Any step may be repeated to ensure that the geometric model converges to a mathematically optimal and a physically realistic solution. The results obtained from St–Id are discussed from a reliability point of view and the need for a service reliability index is suggested.

Before the results obtained from the parameter estimation can be used to estimate service reliability, the quality of the process and the results from St–Id need to be understood. Specifically, the sources and magnitude of the uncertainty entering the St–Id process and the effect of the uncertainty on the outputs need to be evaluated. Once the uncertainty is contributions are documented, techniques to handle the uncertainty during testing, post–processing, and parameter estimation need to be developed. Issues related to the compatibility between the experimental objectives and the analytical needs for convergence to acceptable results are discussed. Uncertainty contributions at each step of the integrated process cause the error or noise on measured response to propagate. It is paramount that the final noise level in the measured response is less than the acceptable noise level for the analytical parameter estimation to
converge to structural parameters within acceptable error bounds.

A preliminary investigation is presented to identify the sources of error, their magnitude, and the effect on the output response. Results are given for a physical model tested in the laboratory. Three static tests and three dynamic tests are performed and the variability in the results is calculated. Future efforts to quantify the experimental errors are outlined.

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ABSTRACT

An integrated approach to Structural-Identification (St-Id) is presented. The results obtained from St-Id are discussed from a reliability point of view and the need for a service reliability index is suggested. Before the results obtained from the parameter estimation can be used to estimate service reliability, the quality of the process and the results from St-Id need to be understood. The process, which integrates experimental and analytical approaches, is presented in six general steps. Issues related to the compatibility between the experimental objectives and the analytical needs for convergence to acceptable results are discussed. Uncertainty contributions at each step of the integrated process cause the error or noise on measured response to propagate. It is paramount that the final noise level in the measured response is less than the acceptable noise level for the analytical parameter estimation to converge to structural parameters within acceptable error bounds. A preliminary investigation is presented to identify the sources of error, their magnitude, and the effect on the output response. Results are given for a physical model tested in the laboratory. Three static tests and three dynamic tests are performed and the variability in the results is calculated. Future efforts to quantify the experimental errors are outlined.

INTRODUCTION

Cost effective infrastructure management depends on objective and systematic approaches to condition assessment. The condition states currently available for use in infrastructure management are primarily subjective often dependent on the individual inspector’s experience and qualifications. Decisions about a structure’s safety and maintenance needs are made based on inspection data derived from subjective judgements that typically include information on a fixed scale (i.e. 0-9 or 0-5, depending on the bridge management system adopted by the state highway department). Structural-Identification (St-Id) is the process of developing an analytical model of a structure such that for a given set of inputs the model can simulate the output response. Thus, St-Id can provide objective information for the decision making process.

Structural parameter estimation, one area within the field of St-Id, uses optimization to reconcile an analytical model of a structure with full-scale test data. The result is a set of estimated parameters (modal or stiffness properties) capable of simulating “actual” structural response. Modal properties of the structural system (ϕ, ω, ζ) or stiffness properties for each element (EA, EI, GJ, Kspring) can be estimated. The theory behind parameter estimation and St-Id is not new and the reader is referred to the literature reviews prepared by Ghanem and Shinozuka (1995) and Doebbling et al. (1996). Increased computational capability has resulted in
significant progress in algorithm development and testing making St-Id and parameter estimation objective tools for determining the actual state properties, performance, and limit states of a structure. Thus, it is possible to gain an improved understanding of a structure’s mechanical characteristics and serviceability performance leading to improved knowledge of the structure’s stiffness/flexibility distribution, critical response mechanisms, and boundary and continuity conditions. This information helps to reduce the uncertainty associated with the resistance of the structure leading to an improved reliability evaluation of a structure’s vulnerability.

St-Id is an appropriate tool for the evaluation of a structure's current state. The quantifiable results obtained from St-Id provide more accurate structural models with well-defined error bounds that leads to improved information for decision making pertaining to rehabilitation or maintenance scheduling. Reliability is defined as the probability that a system will perform its intended function for a specified period of time under a given set of operating conditions. The reliability measure or reliability index is an engineering factor (the probability that a performance requirement will be exceeded) expressing the current knowledge/information about a structure's ability to meet pre-set requirements and is based on estimates of structural demands and performance (Ang and Cornell, 1974). More recently, reliability techniques have been applied to in-service structures to consider errors in design or construction and in the development of evaluation codes (Ellingwood, 1987; Verma and Moses, 1989). Vanik and Beck (1996) developed a Bayesian approach to structural health monitoring for studying the variation in time of a probabilistic damage. Two reliability indices are of interest in the case of civil infrastructure systems: (1) an index that measures the failure probability for a structure when subjected to a damaging event; and (2) an index that measures serviceability probability. Since St-Id involves field-testing, the reliability indices are based on measured structural performance.

At this time, there is no accepted standard for the use of St-Id in structural condition assessment. The combination of experimental and analytical issues, decision-making, heuristics, and information technology make the development of a standard difficult (Aktan et al., 1997). Before St-Id can be used to determine the reliability of a structural system an understanding of the reliability of the St-Id process is needed. The purpose of this paper is to introduce a six-step approach developed by the authors to integrate both the experimental and analytical components of St-Id. The application of parameter estimation reduces the uncertainty in the structural model leading to an improved estimate of the probability density function used in reliability evaluation. The preliminary study presented here is an essential first step towards using St-Id for reliability evaluation of in-service bridge structures.

**ST-ID: AN INTEGRATIVE PROCESS**

A six-step approach proposed for St-Id is shown in Figure 1. The quality of each step is improved by integrating experimental and analytical components. Any step may be repeated to ensure that the geometric model converges to a mathematically optimal and a physically realistic solution.

**A-priori models** (Step 1) are developed at the beginning of the process to represent the best knowledge about the structure/connections/foundation/soil systems construction. The finite element (FE) model must be capable of simulating the system's true behavior while being adaptable to the optimization procedure used in parameter estimation.

**Experiment design** (Step 2) requires selecting the inputs (loads, excitation, and temperature) and sensors (used to record input and response measurements) with consideration of hardware, software, and information technology constraints. The load and sensor locations and data acquisition systems are selected to obtain a set of data meeting optimality criteria considering both required bounds of confidence for parameter estimation and test feasibility. Sensors have different installation, durability/ruggedness, signal conditioning, rate, range, linearity, sensitivity, resolution, precision, and accuracy attributes. In addition, the information technology requirements of different experiment designs are a significant issue and may vary greatly. Therefore, matching each sensor to the measurement that is needed, and designing the corresponding information technology for an optimal experiment is an art that requires extensive experience. Thorough analytical evaluations are needed for each design scenario to determine if the finite element model and parameter estimation technique can support the experimental limitations such as expected noise level on the
measurements. Error sensitivity analyses are required to determine the required confidence bounds for the structural parameter estimates. Sanayei and Salcicnik (1996) developed a heuristic method for design of NDTs to reduce the error in the geometric parameter estimates caused by noisy measurements.

Full-scale tests (Step 3) include both instrumented monitoring (IM) for static tests and multi-reference impact tests (MRIT) for modal tests. The tests are performed with different sets of reference sensors, impact loads, forced excitations, and static loads. IM yields results usable for geometric parameter estimation. MRIT results are used to verify global system behavior, localized mechanisms, and critical mechanisms of a structure. The results from both static and modal tests can be used to verify the different testing methods. MRIT and IM are both emerging arts in the context of field testing of civil engineered constructed facilities (Raghavendrarach and Aktan, 1992; Shelley et al., 1995).

Data processing (Step 4) of the experimental data is a critical step for error mitigation and quality assurance. As a result, the data obtained from the experiment must be processed for use in the parameter estimation module such that the quality of the data is maintained. Issues that need to be considered are: (1) Data must be validated to ensure that it originated from a reliable sensor; (2) Channels should be separated so that parameter estimation and verification can be performed in a clear checks and balances system; and (3) To ensure consistent conclusions, the results of different tests must be comparable. Quality assessment of measurements is an extremely important factor in the data processing step. Confidence factors for each sensor or data channel can be calculated using probabilistic methods, physical behavior, structural principles, and engineering judgment.

Model calibration and parameter estimation (Step 5) involve identifying critical geometric parameters using the processed static (Sanayei et al., 1997) and modal (Sanayei et al., 1998a) data from Step 4. The calibration procedures refine the global and local characteristics of geometric FE models. The refined model must be unique and represent a realistic physical structure. Model reduction and expansion techniques can facilitate the estimation procedure. Transformations that can convert a global model to a local model and vice versa need to be considered. Finally, the calibrated model must be confirmed and validated.

Utilization (Step 6) of the calibrated FE models includes obtaining interpretations in a form that are useful to other researchers and practitioners for bridge management. Once established for a specific bridge, calibrated models will consider design and/or construction defects and can be used as a baseline in the future for damage diagnoses and deterioration monitoring. Here, a motivation is provided to use St-Id for the development of reliability indices descriptive of structural performance. Additionally, when performed intermittently relative to a baseline, the updated geometric models should be able to identify, locate, and quantify damage making it possible to evaluate the impact of damage on global health.

There are a number of challenging issues within each step of the above-mentioned process that need to be considered. These challenges include (1) the design and implementation of the experiment, (2) errors in the mathematical model used for parameter estimation, and (3) errors within parameter estimation. Sanayei et al. (1998b) address these challenges in the context of a literature review.
Experimental and Analytical Compatibility

Before the results from St-Id can be used for the reliability evaluation of a single or group of structures the quality or goodness of the estimated parameters must be addressed. Parameter estimation techniques are dependent on the accuracy and completeness of the analytical FE model. The model must consider 3D geometry, displacement kinematics at critical locations (especially continuity and boundary conditions), element stiffness values and their distribution throughout the structure, and nonlinearities (material and mathematical). The optimization procedure used to estimate parameters is inherently sensitive to the error entering the system and its polluting effect propagates as the number of measured responses increase. Integrating the experimental and analytical aspects throughout the process is not sufficient to guarantee convergence. The results obtained from the experiment must be compatible with the analytical needs for parameter estimation. Specifically, error (or noise) on the measurements increases at each step of the experimental process. The final error at the completion of the experimental process must be within the acceptable noise limitation for the parameter estimation (see Figure 2). If the response error is not within the error bounds pre-specified during the experiment design, the St-Id procedure will result in large (unacceptable) confidence intervals of the parameter estimates or may diverge. Factors that may control the ability to estimate modal parameters are the availability of confidence factors, sensitivity to random and/or bias errors in the measured data, and operator expertise (Allemang and Brown, 1985). Thus, without ensuring that the two processes are compatible, it is more than likely that geometric parameter estimation will be impossible. Careful experimental testing and analytical processing is a first step in generating this compatibility. The next step involves investigating the uncertainties throughout the process.

The steps leading to the control of uncertainties that affect the integrated St-Id process follow:

(a) Identify all major sources of uncertainty in the St-Id process.
   The entire St-Id process and the possible sources of uncertainty at each step need to be documented. Technology, analytical algorithms, and the expertise of the individuals performing St-Id all contribute to the uncertainties.

(b) Quantify the added magnitude of the uncertainty at each step.
   Experiments need to be designed and analytical simulations performed to quantify the magnitude of error contribution at each step.

(c) Evaluate the effect of the uncertainty on all outputs.
   Even the most powerful techniques are only as accurate as the data that is analyzed (Soucy and Deering, 1989). In some cases, the process may be more sensitive to the errors. For example, stiffness is more sensitive to higher modes than flexibility and as a result is more sensitive to errors in the higher modes.

(d) Develop techniques to handle the uncertainty.
   When the uncertainty cannot be further reduced, methods (algorithms or procedures) need to be developed to reduce the effect of uncertainty making it possible to successfully identify parameters and obtain meaningful result.

The four steps listed above must be performed for both the experimental and analytical components of St-Id. The mismatch between the experimental output and analytical input is addressed in Step (d). The sources of uncertainties from the experimental components and their effect on preliminary post-processing efforts are presented in the following section.

APPLICATION TO A PHYSICAL MODEL

Before implementation to actual constructed facilities, the St-Id process is applied to a physical model system (Figure 3) and analyzed by the authors at multiple institutions. Experimental procedures and modal parameter estimation is performed at the University of Cincinnati (UC). Parameter estimation is performed at Tufts University (TU). An investigation into the sources of uncertainty and its impact in the overall St-Id result is performed at Northeastern University (NU). The physical model is a grid (3.66 m x 1.83 m) comprised of structural tubing, and designed to represent some of the structural mechanisms of a bridge superstructure with sufficient detailing to capture the complexity of an actual bridge (UCII, 1997). All connections are designed and constructed so that their rigidity is controlled. In the experiments, the joints are rendered fully rigid. The
grid is simply supported along longitudinal lines A and M and rests on four neoprene pads located at A1, A5, M1, and M5. The neoprene pads were cut from the same material that is used for fabricating bridge bearings.

The steps used by the authors to apply instrumentation and perform parameter estimation on the physical system are shown in Figure 4. This flow chart depicts the steps in Figure 2 as a linear process. If the results at any step are unacceptable, previous steps can be repeated. There are two objectives in this presentation: (1) to present the complete process from the selection of a physical model to parameter estimation and ultimately the applicability of the final results; and (2) to identify and quantify the uncertainties inherent in the experimental process. A similar study for the analytical component is not within the scope of this paper.

Step 1 is the development of a FE model of the physical structure for use at all institutions. First, a FE model is developed in SAP2000 for predictive analyses for experiment design. Subsequently, a FE model is developed for parameter estimation with PARIS, a structural PARameter identification System (Sanayei, 1997). Two independent finite element models are developed such that the two models can be used to check each other. The SAP2000 model is used primarily for experiment design (Step 2). Sixteen slide wire potentiometers (SWP), 4 tilt meters, and 21 strain gages are applied to the structure for on-demand static IM (Step 3). Static loads are applied incrementally and independently at each node with respect to a loading program, incorporating multiple loading and unloading steps at each node. Deflection, strain, and tilt measurements are taken from each instrumented point for each incremented load case applied at each of the 21 nodes. Typically, the duration of these tests may be two or more hours. Although the tests are static, they may record some time variant behavior due to the long duration of test implementation. Twenty-one accelerometers are used to simultaneously measure out-of-plane acceleration at the node points of the grid (Step 3). Impacts are applied successively at each node point for the MRIT. Five separate frequency response functions (FRF) are obtained and averaged as each node is impacted. The resulting order of the MRIT FRF matrix is 21 x 21 where each matrix element is based on the average of 5 impacts tests.

In this case, the test objectives are to obtain response data so that the reliability and limitations of either type of experiment (IM or MRIT) are clearly demonstrated. Additionally, the sources of uncertainty in each step/decision of each experimental approach are to be evaluated collaboratively by UC and NU (Step 4). Parameter estimation is to be performed at TU to demonstrate the feasibility using experimental results to estimate element stiffness properties (out-of-plane bending and torsional rigidities) and boundary conditions (the stiffness of the neoprene pads).

PARIS uses the measured responses (modal and static) to obtain parameter estimates (Step 5). First, initial guess values for the structural parameters are used to develop the FE model prepared in Step 1 and the test data are simulated based on the initial guess. An objective error function is selected to coincide with measured test data: displacements, strains, or mode shapes. The unknown parameters are then estimated such that the objective function is minimized using the appropriate constraints. Solution strategies such as grouping and condensation can be used to reduce the number of unknown parameters sought (McClain, 1996). The new parameter estimates are compared to the initial guesses and the process is repeated until convergence.

Step 7, the final step, involves using the estimated geometric parameters. Here, the generation of a reliability-index for serviceability is suggested. Before service reliability can be generated and used in a rational decision process, it is necessary to assess the quality of the result from St-Id including the experiment, modal extraction, and parameter estimation (Sanayei et al., 1996).

**CONTRIBUTING UNCERTAINTIES IN ST-Id AND CONDITION ASSESSMENT**

The uncertainties entering the St-Id process at each step are due to both known-unknowns and unknown-unknowns. For example, any mechanical or electrical measuring device has a resolution range that defines the minimum remaining bias after calibration and is considered a known-unknown. Other examples include transducer installation errors, improper affixation of strain gauges, wire and solder resistance, improper balancing and zeroing of circuitry. However, when unknown inputs affect the measured output measurement an unknown-unknown uncertainty is introduced. It is important to recognize and at least try to gain insight about unknown-unknowns and their impact on experimental results and interpretation (Aktan et al., 1997). There will always be some amount of noise present in the data. Thus, enough measurements have to be utilized to improve the estimates to some acceptable levels (Karsen and Allemang, 1984). In this study, three
IM static tests and three MRIT are performed on the same structure with the same sensors to assess the relative variability in the results (UCII, 1997). Following is a brief description of the observed difference in measured response.

In the case of IM, each SWP sensor has an initial resolution of ±0.127 mm (0.005 in) which corresponds to 5.4% to 38.8% of the measured response from the different SWP under maximum loading conditions. In addition to sensor resolution, element error sources include sensor calibration and placement, human errors in test execution, and time-variant behavior of the structure (creep). Significant variability in the measured responses is observed at the completion of three tests performed with the same physical model and sensor configuration. In many cases, the percent difference between the maximum and minimum responses from the same sensor and loading pattern is greater than 10%. Further investigation is needed to ensure that the 10% (or greater) variability between maximum and minimum responses is well within the acceptable tolerances for analytical parameter estimation. Additionally, the responses from 7 SWP fell within the resolution of the sensor and can be considered as noise. For MRIT, the resolution of the accelerometers is ±0.0001g (≈0.01-0.02% of the maximum acceleration). The elemental errors affecting measurement response are the same as in IM. Here, post-processing also affects the variability in the final experimental result (dynamic mode shapes and frequencies). The resulting variability is 4.4% and 8.8% between the maximum and minimum frequencies and mode-shapes, respectively. This variation is highly dependent on the modal extraction algorithm used.

The relationship between the elemental error contributions at the beginning and end of the IM and MRIT tests is unknown. It is reasonable to assume that the error is additive only in extreme cases when responses have the same sign and always experience worst-case errors. Estimates of total error contributions based on the root sum square, RSS, is more common (Coleman and Steel, 1989). Through investigation of the contributing errors and incremental experimental results, the authors intend to quantify more explicitly the error and the relationship between the contributing element sources on the experimental results.

DISCUSSION

A six-step procedure for the application of St-Id to full-scale civil infrastructure systems is proposed, which integrates state-of-the-art experimental and analytical approaches to parameter estimation. The proposed procedure is implemented on a structural grid and the experiments are performed in the laboratory. A series of static and dynamic experiments are designed and performed on the test grid with the objective to assess variability of measurements taken from a single structure subjected to repeated tests. The results show that the variability at the end of the experimental process can be more than 10% for displacements and 4.4% and 8.8% for frequency and mode shape measurements, respectively.

Future work in this area includes (1) Further study of error proration through the experiment. (2) An investigation of error proration and error tolerance on parameter estimates. (3) The development of methods to compensate for the mismatch error between expected experimental results and parameter estimation error requirements. (4) The development of a service reliability index based on the expected variability and quality of the identified results. (5) Implementing the procedure on a full-scale in-service structure.

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Figure 2: Potential experimental and analytical error mismatch

Figure 3: Physical model used in laboratory study

Figure 4: St-1d applied to a physical model