Protocol for Reliability Assessment of Structural Health Monitoring Systems Incorporating Model-assisted Probability of Detection (MAPOD) Approach

J. C. ALDRIN, E. A. MEDINA, E. A. LINDGREN, C. F. BUYNAK and J. S. KNOPP

ABSTRACT

This paper will describe the progress in the development of a methodology for reliability assessment for SHM systems. The methodology consists of the development and use of appropriate statistical metrics of reliability for SHM systems that detect, localize, and/or size damage, and a protocol designed for utilizing empirical data, models, simulations, and uncertainty analyses for statistically characterizing these systems. The protocol comprises several critical steps: a procedure for analyzing all pertinent characteristics of the SHM system to identify the critical factors that affect system performance, a multistage approach to system validation, a modeling and experimental methodology for efficiently addressing a wide range of damage and operational conditions, and effective methods for evaluating the appropriate metrics of reliability depending on the SHM system type and function. A critical aspect of the protocol is that by addressing variability in the model and minimizing unexplained error in the representation, less experimental data will be required to address the total unknowns in the evaluation. The application of these methods in the protocol will be presented in detail including several demonstrations using simulation-based case studies.

INTRODUCTION

To support effective deployment of Structural Health Monitoring (SHM) systems that effectively complement Nondestructive Evaluation (NDE) methods to enable Condition Based Maintenance (CBM) for structures, SHM systems must be the subject of verification and validation (V&V) processes congruent with the level of reliability that the system must achieve in detecting, localizing, and/or quantifying structural health degradation. Unfortunately, empirical assessment of the performance of an SHM system in its operational environment is not trivial and could easily be cost prohibitive because of the extensive testing required on

John C. Aldrin, Computational Tools, 4275 Chatham Av. Gurnee, IL 60031, USA; Enrique A. Medina, Eric A. Lindgren, Charles F. Buynak, and Jeremy S. Knopp Materials and Manufacturing Directorate, Air Force Research Laboratory, WPAFB, Ohio 45433, USA

Report Docum	Form Approved OMB No. 0704-0188			
Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.				
1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED		
SEP 2011	N/A	-		
4. TITLE AND SUBTITLE		5a. CONTRACT NUMBER		
Protocol for Reliability Assessment of				
Systems Incorporating Model-assisted	5b. GRANT NUMBER			
Approach		5c. PROGRAM ELEMENT NUMBER		
6. AUTHOR(S)		5d. PROJECT NUMBER		
		5e. TASK NUMBER		
		5f. WORK UNIT NUMBER		
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Computational Tools, 4275 Chatham Av. Gurnee, IL 60031, USA		8. PERFORMING ORGANIZATION REPORT NUMBER		
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR'S ACRONYM(S)		
		11. SPONSOR/MONITOR'S REPORT NUMBER(S)		
12. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release, distribut	ion unlimited			
13. SUPPLEMENTARY NOTES See also ADA580921. International W Maintenance to Autonomous Structur Government or Federal Purpose Righ	orkshop on Structural Health Monite es. Held in Stanford, California on S ts License.	oring: From Condition-based eptember 13-15, 2011 . U.S.		
14. ABSTRACT This paper will describe the progress is SHM systems. The methodology consi reliability for SHM systems that detece empirical data, models, simulations, and The protocol comprises several critical SHM system to identify the critical factory system validation, a modeling and experimental conditions, and reliability depending on the SHM system addressing variability in the model and experimental data will be required to the these methods in the protocol will be re-	in the development of a methodology sts of the development and use of app t, localize, and/or size damage, and a nd uncertainty analyses for statistical l steps: a procedure for analyzing all ctors that affect system performance, erimental methodology for efficiently nd effective methods for evaluating th em type and function. A critical aspe d minimizing unexplained error in th address the total unknowns in the eva- presented in detail including several d	for reliability assessment for propriate statistical metrics of protocol designed for utilizing lly characterizing these systems. pertinent characteristics of the a multistage approach to y addressing a wide range of ne appropriate metrics of ct of the protocol is that by ne representation, less aluation. The application of lemonstrations using		

simulation-based case studies.

15. SUBJECT TERMS					
16. SECURITY CLASSIFICATION OF:		17. LIMITATION OF	18. NUMBER	19a. NAME OF RESPONSIBLE PERSON	
a. REPORT unclassified	b. ABSTRACT unclassified	c. THIS PAGE unclassified	SAR	8	KESI ONSIBLE I EKSON

Standard Form 298 (Rev. 8-98) Prescribed by ANSI Std Z39-18 representative structures, expensive testing equipment, and custom made test fixtures to establish statistically significant performance metrics. The assessment of nondestructive damage detection systems typically requires a formal probability of detection (POD) study as prescribed in MIL HDBK 1823A [1]. To help mitigate the extensive amount of empirical data often required according to MIL HDBK 1823A, a process for model-assisted probability of detection (MAPOD) evaluation has recently been developed and incorporated into the latest revision of the handbook [4]. MAPOD evaluation leverages both computer models and transfer functions to enable the determination of the sensitivity of damage detection systems while minimizing the need for empirical data.

Recently, the authors have developed a draft protocol for a new model-assisted probabilistic reliability assessment (MAPRA) methodology for SHM [5]. Leveraging the MAPOD approach, this methodology incorporates empirical data, models, and simulations for characterizing SHM methods in terms of the proposed statistical metrics of reliability for damage detection, localization, and sizing. This model-based methodology attempts to minimize the number of samples that must be prepared with representative damage and testing to be performed to obtain the data required to achieve statistically meaningful characterization results. This paper describes progress on the development of a protocol and presents an initial demonstration study on the MAPRA methodology. A discussion is first presented on the need and general approach for an SHM reliability protocol, including insight into mitigating testing requirements. The design and progress of an experimental demonstration study is presented highlighting protocol feasibility and remaining challenges. A simulation-based study for an SHM system incorporating vibration methods is also introduced to demonstrate the protocol process. Probability of detection and probability of correct characterization curves were generated for different transducer locations providing key insight on sensor placement and expected detection and characterization performance.

PROTOCOL

Overview of Approach

To address these challenges for SHM implementation concerning extreme operation conditions, sensor degradation, critical damage observability, and eliminating false calls due to varying non-damage conditions, a protocol to validate SHM damage detection capability is being developed [5]. An outline of the MAPRA protocol is given in Figure 1. The MIL HDBK 1823A for USAF NDE certification based on POD is the foundation of the protocol. In addition, modelassisted approaches must be applied to address limits of experimentation, facilitate proper uncertainty analysis for damage detection cases and expand the assessment to quality of localization/characterization estimates. This protocol includes four critical components: (1) a procedure to identify the critical factors impacting SHM system performance; (2) a multistage or hierarchical approach to SHM system validation; (3) a model-assisted evaluation process to address the wide range of expected damage conditions that cannot be experimentally tested; and (4) POD, probability of false call (POFC) and probability of random missed call (POMC) evaluations with confidence bounds estimation and uncertainty analysis for damage



Figure 1. Outline of protocol for SHM validation.

detection SHM systems, and evaluation of appropriate probabilistic metrics to characterize the quality of damage localization and damage characterization for SHM systems that include such capabilities. The multistage validation approach is designed to incrementally test SHM systems with structures of increasing complexity. The multistage approach includes (a) laboratory testing of relevant flaws, (b) laboratory sub-component testing including environmental and loading conditions, (c) a system level life-testing (full-scale fatigue testing if feasible), (d) on-structure demonstration, and (e) final system verification. More information on the protocol can be found in prior work [5].

Mitigating Samples and Testing through Model-assisted Evaluation

A model-assisted strategy for the design and execution of POD studies for NDE has been developed and demonstrated to help mitigate validation costs and to improve POD evaluation quality by addressing a wider array of inspection variables. By including greater sophistication in the models, there should be less error present between the model and available experimental data. By addressing variability in the model and minimizing unexplained error in the representation, less experimental data will be required to address the unknowns in the evaluation. The following opportunities in the POD model evaluation and application steps have the potential to impact sample and testing requirements: (a) careful model factor selection addressing system variation, (b) physics-based model calibration including uncertainty bounds assessment for the specific inspections of interest, (c) controlled *physics-based model validation* to ensure the model is valid over desired range of application, (d) evaluation of POD using two-level analysis to address input parameter variability with uncertainty bounds, (e) integration of experimental data generated from a designed experiment using a Bayesian framework to revise the prior distributions of inputs and achieve new posterior distributions, and (f) inverse methods to ideally address all uncontrolled parameter variations in the measurement.

To address the challenge of performing a quality evaluation with limited data, a model-based assessment must be extended, beyond a simple deterministic representation of an NDE or SHM measurement, to incorporate the variations of the most significant input factors. Hoppe [8] has recently indicated the potential for reducing POD sample number by better managing experimental variation using more accurate statistical models and appropriately designing experiments based on prior experience and data. Developing a validated stochastic model that includes all significant sources of variation on the measurement response is key to sample and experimental test reduction. Simultaneously, less costly studies could be performed

to quantify precisely the probability density functions (with confidence bounds) for the key controlling factors *a priori*.

Before models can be directly applied in POD evaluations, two steps are needed to ensure their performance. First, model calibration involves model adjustments to variables in a way that mimics the NDE technique procedure. In many cases, gains and thresholds are set based on the desired response to a known calibration standard. Parameters of the model are essentially fit to obtain the best match with a limited set of empirical data acquired according to a calibration procedure. Second, model validation ensures that models are in agreement with well controlled studies for the appropriate range of conditions expected in the field. Note, uncertainty bounds on the measurements and numerical model error must be tracked and extended to any model-assisted evaluation.

Stochastic models are a means to efficiently represent stochastic systems and address uncertainty propagation without excessive computational overhead. Monte Carlo methods have been previously applied to MAPOD evaluation [9]. New efficient methods such as polynomial chaos theory and probabilistic collocation methods (PCM) will enable the greater application of stochastic models [10,11]. Fundamentally, this evaluation of uncertainty bounds becomes a two-level analysis. Parameter variability is associated with the inherent variability or randomness of a factor. For SHM, environmental conditions, material properties, and part geometry will all exhibit some degree of variation for each instance of monitoring. Alternatively, uncertainty in input parameters is associated with imperfect knowledge, often requiring the need for more or better quality data. In practice, parameter variability and uncertainty can be represented by the random variables of a statistical distribution and their associated confidence intervals. Several methods including second order probability, maximum likelihood estimation, and bootstrapping can be used to evaluate statistical distributions with uncertainty. Evaluation of the input parameter distributions with uncertainty can be achieved using designed experiments (ideally), validated inverse methods (see below), or possibly eliciting expert opinion.

In prior work on model validation and verification, work has explored the propagation of variability and uncertainty in computer models and demonstrated agreement with limited experimental data. Although MAPRA evaluation is similar in many respects, the goal here is to leverage mixed simulated and experimentalbased trends to formulate a complete picture of SHM reliability. Bayesian methods are necessary to incorporate empirical data with NDE models that include prior information / distributions (with uncertainty bounds) about the input conditions. A generic example of applying Bayesian methods is to evaluate the posterior distribution of an input parameter based on the prior distribution and the likelihood function propagating empirical data through the model. Through the application of empirical data, the posterior distribution can be evaluated, providing a refinement to the original prior distribution. Numerical methods such as Markov Chain Monte Carlo (MCMC) methods and Bayes factors can be applied to perform this evaluation [12]. Care must be taken to ensure that all assumptions applied are valid.

Lastly, there is an additional benefit to be achieved by implementing SHM techniques that use inverse methods to estimate any uncontrolled conditions in the measurement. One case is having an eddy current system to determine liftoff over the part. By doing so, the NDE technique can be better controlled. This should

greatly impact the performance of the technique during a validation study, as well as lead to less uncertainty in the POD result if this estimate is used in the modelbased evaluation. NDE techniques that incorporate inverse methods as process controls should naturally be easier to validate.

SIMULATED DEMONSTRATION STUDY

A simplified numerical model was used to demonstrate and explore SHM reliability evaluation for the case of a vibration based SHM technique for detecting large cracks in a basic structural joint. Of particular interest, this study investigates robustness to varying temperature and fastener stiffness over prescribed distributions and provides output sensor metrics as a function of flaw size. A simplified parameterized FEM model was created to represent an aircraft joint subject to fatigue cracking damage with varying temperature and fastener stiffness / contact conditions present (Figure 2). Parameter values and conditions for the study are given in Table 1. The simplified aluminum plate structure was fixed to an 'infinitely-stiff' structure on the ends and attached via steel fasteners with a prescribed stiffness to a second 'infinitely-stiff' structure at mid length. Distributions for the varying temperature and fastener conditions are given in Figures 3(a) and 3(b) respectively. An excitation force was applied near the right side for damage detection [Figure 3(c)]. A through-thickness crack of variable length was located at the mid length. Four sensor locations as shown in Figure 3(c) were considered in this study. At each location, a feature vector was evaluated containing the difference between the frequency response function (FRF) for the current condition and a baseline condition over the frequency range of 40 Hz to 10 kHz. The baseline condition was defined as the 'no-crack case' with a median temperature of 55 °F and the fastener stiffness set at 100%. The damage metric was defined as the root mean square (RMS) of the feature vector.

To perform the stochastic numerical model evaluation, the PCM was used to efficiently sample the numerical model and propagate input parameter variability. A 2^{nd} order PCM model was solved requiring the solution of 6 collocation points for each crack length. Simulated results were evaluated for 6 different crack lengths,



Figure 2. Simplified geometry for representative SHM case study for global vibration-based method.

Parameter	Properties
Frequency range	• 40 Hz to 10 kHz
Source Excitation	• single source location [See Figure 2 for position]
Sensor(s)	• four sensors in study [See Figure 3(c) for positions]
Crack (notch) length	• varying crack length studied from 0 to 5 inches
Temperature	• Gaussian distribution [See Figure 3(a)]
	Elastic properties a function of temperature
Boundary conditions	• Fastener stiffness varied over uniform range from 100% [See Figure 3(b)]
	• Fastener contact (sides fixed to ground) remained constant in study
	End stiffness conditions were fixed in study

 Table 1. Parameters and conditions for simulated study.

thus requiring a total of 36 numerical runs for the study. Figure 5(a) presents output results for all of the collocation points and the damage metric 'distributions' as a function of transducer location and varying crack length. From these distributions, a typical *a-hat* (damage measure) versus *a* (crack length) relationship including confidence bounds can be calculated. The final step is evaluating the POD curves for each transducer as shown in Figure 4(b). The results indicate that for this case the sensors positioned in close proximity to the crack (in particular, the sensor located between the crack and input source) were most sensitive to the growing flaw. All in all, this case study provides a nice demonstration of the process where POD for an SHM technique in the presence of varying conditions can be estimated.

The simplified numerical model was also used to demonstrate and explore SHM reliability for characterizing cracks. The characterization 'model' tested here is presented in Figure 5(a) relating the damage metrics for select transducer locations to flaw size. The characterization model is based on a straightforward 3rd order polynomial fit to the FEM numerical data for mean temperature and fastener stiffness conditions. Probability of correct characterization was defined here as the ability to correctly classify the size of a defect within an acceptable level of uncertainty defined by δ . Results for the probability of correct characterization for the case of bounds on crack size accuracy set at $\delta = 0.49$ inches is presented in Figure 5(b). As with the detection problem, the sensor located directly between the



Figure 3. Input parameter distributions for (a) temperature and (b) change in fastener stiffness (from 100% of steel). (c) Map of locations for 4 transducers (accelerometers), input excitation and location for crack.

crack and input source (transducer 3) was found to be most accurate for these prescribed characterization 'accuracy' bounds. Due to the proximity of transducer 2 to the crack initiation location, it has more sensitivity to the smaller crack growth and thus is exhibits better sizing accuracy for smaller cracks less than 2 inches.

CLOSING REMARKS

A general methodology for validation of SHM systems has been described and a protocol for damage detection SHM methods was defined. The next steps will be to verify the damage detection validation protocol using an SHM system of interest to AFRL, and to extend the methodology to validate SHM systems that localize and characterize damage, based on the probabilistic approach outlined here.



Figure 4. Results for (a) damage metric (including distributions generated by PCM for varying temperature and fastener stiffness) and (b) POD as a function of crack length for the four transducer locations.



Figure 5. (a) Model relating damage metric to crack length and (b) results for probability of correct characterization for prescribed bounds on crack size accuracy of $\delta = 0.49$ in. for transducer locations 2 and 3.

ACKNOWLEDGEMENTS

This work was supported by the NDE Branch, the U.S. Air Force Research Laboratory (contract FA8650-09-C-5204 with Radiance Technologies, Inc). The authors would like to thank Hank Rinehart, Wes Tharp, Louie Elliot, and Michael Pearson of Radiance Technologies for support and manufacture of the test fixture.

REFERENCES

- Medina, E. A. and Aldrin, J. C., "Value Assessment Approaches for Structural Life Management through SHM", Encyclopedia of Structural Health Monitoring, John Wiley & Sons, Ltd. (2009).
- Lindgren, E. A., Buynak, C. F., Aldrin, J. C., Median, E. A., Derriso, M. M., "Modelassisted Methods for Validation of Structural Health Monitoring Systems" Proceedings of the 7th International Workshop on Structural Health Monitoring, Ed. F.-K. Chang, Stanford, CA (September 9-11, 2009).
- 3. U.S. Department of Defense, MIL-HDBK-1823A Nondestructive Evaluation System Reliability Assessment, (August 2010).
- 4. Thompson, R. B., "A unified approach to the model-assisted determination of probability of detection", *Materials Evaluation*, Vol. 66, pp. 667-673, (2008).
- Aldrin, J. C., Medina, E. A., Lindgren, E. A., Buynak, C. F., Steffes, G., Derriso, M., "Model-assisted Probabilistic Reliability Assessment for Structural Health Monitoring Systems," *Review of Progress in QNDE*, Vol. 29, AIP, pp. 1965-1972, (2010).
- 6. Babish, C. A., "Requirements Associated with Transition of ISHM in USAF Aircraft," *Integrated Systems Health Management (ISHM) Conference Proceedings*, Covington, KY, (August 2009).
- Lindgren. E. and Walbusser. R., "Experience/Lessons Learned using Flight Parameter Sensors on US Department of Navy C-130 Aircraft", Aircraft Airworthiness and Sustainment, (Austin, TX, 2010).
- 8. Hoppe, W. C., "Parametric probability of detection (POD) estimation for eddy current crack detection," *Electromagnetic Nondestructive Evaluation*, Dayton OH, (July 21-23, 2009).
- Aldrin, J.C., Knopp, J. S., Lindgren E. A., and Jata, K. V., "Model-assisted Probability of Detection (MAPOD) Evaluation for Eddy Current Inspection of Fastener Sites", *Review of Progress in QNDE*, Vol. 28, AIP, pp 1784-1791, (2009).
- Webster, M., Tatang, M. A., and McRae, G. J., "Application of the probabilistic collocation method for an uncertainty analysis of a simple ocean model," Joint Program on the Science and Policy of Global Change, (MIT, Cambridge, MA, Tech. Rep. 4, Jan. 1996).
- 11. Aldrin, J. C., Knopp, J. S., Blodgett, M. P., and Sabbagh, H. A., "Uncertainty propagation in eddy current NDE inverse problems," *Review of Progress in QNDE*, Vol. 30, AIP, (to be published, 2011).
- 12. Mahadevan, S., and Rebba, R., "Validation of reliability computational models using Bayes networks," *Reliability Engineering and Systems Safety*, Vol. 87, pp. 223-232, (2005).