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META-MAPOD: OPEN-SOURCE FRAMEWORK FOR METAMODEL-ASSISTED PROBABILITY OF DETECTION

EXTENDED ABSTRACT

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ABSTRACT

Model-assisted probability of detection (MAPOD) is key for the reliability analysis of nondestructive testing (NDT) systems. This work presents an open-source framework of efficient metamodel-based MAPOD analysis as an integrated platform of the current state-of-the-art metamodeling methods and MAPOD analysis. In this paper, the application scope, structure, and capabilities of this framework are described. The framework is demonstrated on analytical function and NDT data.

Keywords: nondestructive testing, open-source framework, model-assisted probability of detection, metamodeling methods.

1. INTRODUCTION

Reliability analysis due to the variabilities existing in nondestructive testing (NDT) systems is important. Probability of detection (POD) [1] was originally proposed for this task, purely depending on repeated experimental data. With the development of physics-based NDT simulation models, model-assisted POD (MAPOD) [1, 2] advances the early POD conception by reducing the experimental budgets, and supports NDT reliability analysis.

Metamodeling [3] refers to the process of constructing an efficient model representing the physics information in lieu of computationally costly physics-based models. Metamodeling techniques can be used to accelerate the MAPOD analysis, thereby, enabling the MAPOD-based design or further analysis within limited computational budgets. The metamodel-based MAPOD (Meta-MAPOD) analysis is becoming an important tool for the assessment of the detection reliability of NDT systems.

This paper presents the open-source Meta-MAPOD framework as an integration platform of the current state-of-the-art metamodels and MAPOD analysis. These two main elements, i.e. metamodeling and MAPOD, can be implemented separately. In particular, the MAPOD component can be used directly on existing data or computationally efficient physics-based models, and the metamodeling methods can also be applied to other engineering problems.

The remainder of this paper is organized as follows. Details about the Meta-MAPOD framework are discussed in Section 2. Section 3 shows simple applications on analytical function and NDT systems. The paper ends with conclusion.

2. THE META-MAPOD FRAMEWORK

This section discusses the open-source Meta-MAPOD framework in detail. Specifically, the objective scope, structure and capabilities are described.

2.1 Objective Scope

The Meta-MAPOD is developed for fast MAPOD analysis using metamodeling methods. In terms of MAPOD analysis, Meta-MAPOD makes it an independent module capable of working with the following modalities and data sources:

(1) direct MAPOD on any NDT systems, such as ultrasonic testing, eddy current testing, and radiography,

(2) direct MAPOD on computationally efficient NDT physics-based models,

(3) direct MAPOD on sufficient existing experimental / simulated data,

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(4) metamodel-based MAPOD on limited amount of representative data.

In terms of metamodeling, Meta-MAPOD incorporates the current state-of-the-art metamodeling methods as a separate component, for the convenience of using or not using it in MAPOD analysis and other engineering applications.

2.2 Structure

The flowchart of the Meta-MAPOD framework is given in Fig. 1. Five main modules are contained: pyMAPOD, func_data, sparse_md, ahat_vs_a, and the POD_gen. Descriptions of each are given as follows.

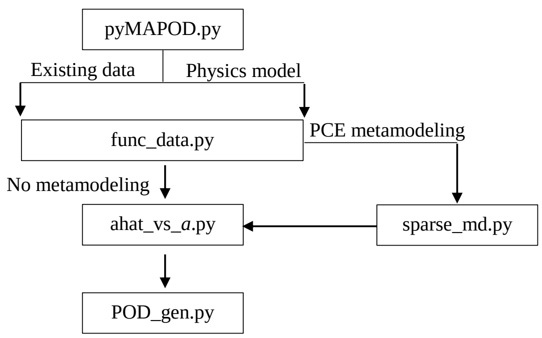

FIGURE 1: FLOWCHART OF THE META-MAPOD FRAMEWORK.

pyMAPOD is the main function of Meta-MAPOD, used as a configuration file for the POD calculation. All related parameters, including data source, use or not use metamodel, detection threshold, need to be provided here.

func_data is used for reading, reviewing and returning data to pyMAPOD from user-provided data files before starting MAPOD analysis.

sparse_md constructs the default sparse grid-based multi-dimensional polynomial chaos expansions (PCE) metamodel [4] if selecting to use metamodel, and ordinary least-squares (OLS) and least-angle regression (LARS) [5] are two methods that can be used to solve for PCE coefficients.

ahat_vs_a completes the linear regression on log-log scale between model responses and defect sizes, and shows the regression line together with data points, then returns line coefficients to pyMAPOD.

POD_gen calculates corresponding POD parameters based on the results from *ahat_vs_a* module, gives the key metrics (a_{50}, a_{90}, and $a_{90/95}$), and generates the 95% lower confidence bounds with respective to defect sizes.

2.3 Capabilities

Meta-MAPOD has enable the following current capabilities:

(1) "ahat vs. *a*" log-log linear regression between model responses and defect sizes,

(2) MAPOD analysis on simulated / experimental data of various NDT systems using or not using metamodeling method,

(3) OLS- or LARS-based PCE metamodeling for NDT and other engineering systems,

(4) PCE-based statistics calculation and Sobol' indices [6] for sensitivity analysis without using Monte Carlo method.

Moreover, several other modules are already coded up, and expected to be added into Meta-MAPOD as separate module in future work. The capabilities to be added soon include:

(1) MC-based direct calculation of Sobol' indices for global sensitivity analysis,

(2) Kriging interpolation [7] as one more metamodeling option for efficient MAPOD analysis,

(3) polynomial chaos-based Kriging (PCK) metamodeling method [8], combining PCE and Kriging metamodels.

3. NUMERICAL EXAMPLES

This section demonstrates the proposed Meta-MAPOD open-source framework on an analytical function and metamodel-based MAPOD analysis on an NDT system.

3.1 Analytical Function

The objective analytical function considered in this work is

$$y = e^{k\cdot\ln(a)+b}, \tag{1}$$

where k has the distribution of $U(3, 4)$, b has the distribution of $N(5, 0.5)$, a is taken at five discrete points [0.1, 0.2, 0.3, 0.4, 0.5].

Results are given in Figs. 2 and 3. The key parameters of linear regression have the values of 5.0 and 3.5, both of which match well with the analytical results.

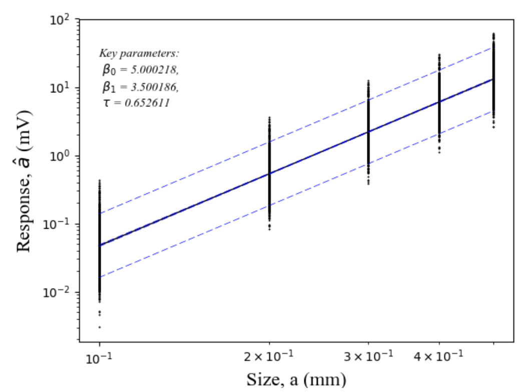

FIGURE 2: "ahat vs. a" PLOTS, ANALYTICAL FUNCTION.

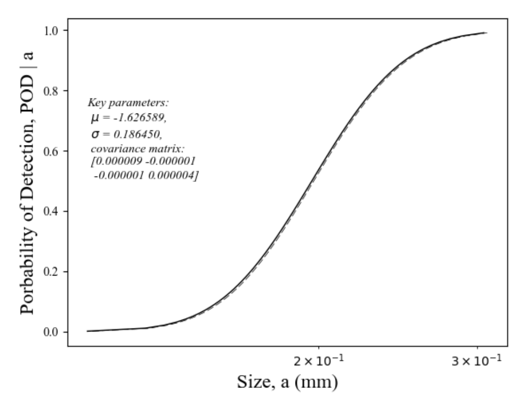

FIGURE 3: POD CURVES, ANALYTICAL FUNCTION.

3.2 Ultrasonic Testing Benchmark Case

The setup of the ultrasonic benchmark case is given in Fig. 4. In this work, the probe angle, θ, the probe F-number, F, and the probe x location, x, are considered as uncertain, with normal $N(0, 1)$ deg, uniform $U(13, 15)$ and uniform $U(0, 1)$ mm distributions, respectively.

The LARS-based PCE metamodels are constructed using 455 Latin Hypercube sampling training points at each defect size (totally five defect sizes considered). MC method is applied on the constructed PCE metamodels at all defect sizes for the predictions of totally 5,000 sampling points for the generation of POD curves. Plots of "ahat vs. *a*" and POD curves are given in Figs. 5 and 6.

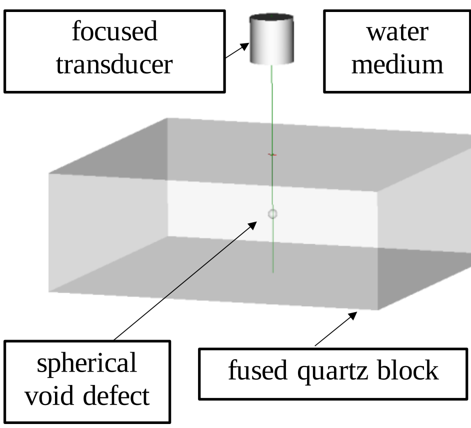

FIGURE 4: UT BENCHMARK CASE SETUP.

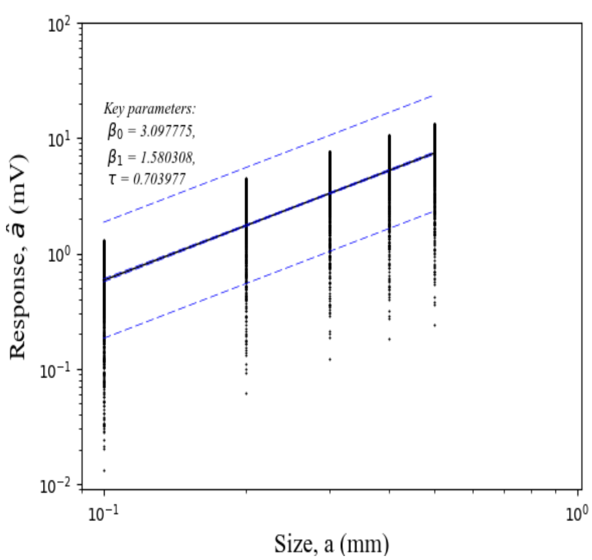

FIGURE 5: "ahat vs. a" PLOTS, NDT BENCHMARK CASE.

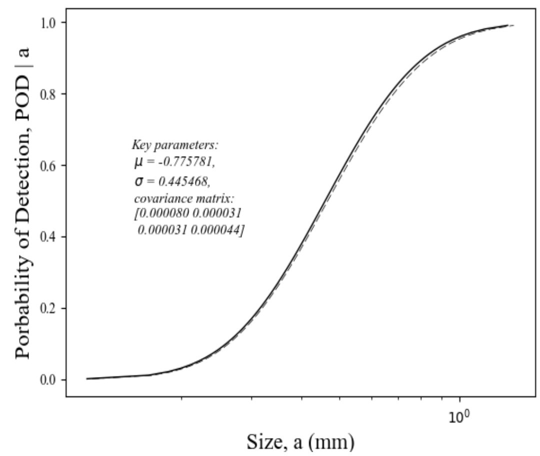

FIGURE 6: POD CURVES, NDT BENCHMARK CASE

4. CONCLUSION

This works describes the open-source Meta-MAPOD framework for efficient MAPOD analysis using metamodeling methods. Details including the scope, structure and current capabilities of Meta-MAPOD are provided. Demonstration on numerical examples shows promising results compared to state of the art methods. The full paper will show several more NDT cases.

ACKNOWLEDGEMENTS

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REFERENCES

[1] Annis, C., "MIL-HDBK-1823 - Nondestructive Evaluation System Reliability Assessment", Department of Defense Handbook, 1999.

[2] Annis, C., "MIL-HDBK-1823A - Nondestructive Evaluation System Reliability Assessment", Department of Defense Handbook, 2009.

[3] Slawomire, K. and L. Leifsson, "Surrogate-Based Modeling and Optimization, Applications in Engineering," Springer, New York.

[4] Wiener, N., "The Homogeneous Chaos," American Journal of Mathematics, Vol. 60, 1938, pp. 897-936.

[5] Blatman, G., "Adaptive Sparse Polynomial Chaos Expansions for Uncertainty Propagation and Sensitivity Analysis," PhD. Thesis, Blaise Pascal University, 2009.

[6] Blatman, G. and Sudret. B., "Adaptive sparse polynomial chaos expansion based on Least Angle Regression". Journal of Computational. Physics. Vol. 230, 2011, pp. 2345–2367.

[7] Forrester, A., Sobester, A. and Keane, A., "Engineering Design via Surrogate Modelling: A Practical Guide," *Wiley*, 2008.

[8] Schobi, R., Sudret, B. and Wiart, J., "Polynomial-Chaos-based Kriging," International Journal of Uncertainty Quantification, Vol. 5, 2015, pp. 193-206.

