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Project Title

Investigating the Applicability of Multi-Fidelity Modeling to Condition Evaluation of Transportation Infrastructure

University

Colorado State University

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Research Needs

Evaluating the condition of infrastructure assets is important to effective asset management, but at the same time resources spent on evaluating assets don't contribute to improving the assets' condition. Furthermore, careful assessment of transportation assets is often complicated by factors such as difficulty of access, the need for traffic control, significant time and resource investment in advanced inspection techniques like non-destructive evaluation (NDE), and considerations of inspector safety, experience and judgement (Mohan and Poobal 2018; Omar and Nehdi 2017; Taddesse 2011). For these reasons, techniques that can better leverage available inspection data, reducing the need for repetitive, routine inspections offer the potential to enhance our ability to evaluate and manage infrastructure assets while also saving resources for the actual repair or renewal of infrastructure.

Recently, multi-fidelity modeling has shown great promise and gained popularity in the aerodynamics field. This method is motivated by the fact that high-fidelity data is expensive in terms of cost, time and resources, while the low-fidelity data can save cost significantly but may be subjected to larger uncertainties and error sources. Multi-fidelity modeling fuses the low- and high-fidelity data, and utilizes the benefits of both to achieve more accurate but less expensive predictions. Given its many advantages, multi-fidelity modeling appears to be a technique that could be usefully extended into the field of transportation asset inspection. In this context, we

propose investigation of a multi-fidelity modelling approach as a means to leverage inspection information from available low-cost data and fewer in-depth inspections to achieve high quality condition assessment of a large number of transportation assets for better decision making. We believe that multi-fidelity models might be usefully applied to the inspection and evaluation of a variety of transportation infrastructure assets such as bridges, high mast lighting, tunnels and retaining walls and in this proposal we will investigate the feasibility/ applicability of the technique to different types of assets (we plan to focus on bridges, but will investigate other assets if bridges are not amenable to the approach).

Research Objectives

The research objectives of this study are to:

1. Use existing datasets to study means of grouping assets with similar deterioration modes allowing application of multi-fidelity modeling to a group of assets.

2. Apply the multi-fidelity modeling technique to fuse low- and high-quality inspection data for assets within groups to study how high-quality data about a few assets can be used to inform the evaluation of other assets in the group.

3. Evaluate the efficacy of multi-fidelity modeling in the context of bridges by assessing its suitability as a technique for data fusion and its impact on inspection practice and maintenance decision making.

Research Methods

We envision the application of this new data fusion approach in two steps. The initial step in the process involves grouping assets to ensure that the grouped structures are expected to deteriorate in similar ways (i.e. assets where we expect strong correlation in their condition over time). This step will reduce the dimension of the multi-fidelity modeling problem and facilitate subsequent computation. For example, bridges constructed within a given period of time (e.g. a 5-year window), using the same materials and subject to similar environmental conditions would be expected to deteriorate in a similar fashion and will be grouped together. As the first step in the process we will consider the groupings used by the Long Term Bridge Performance program[1] which has identified three common types of bridge construction: steel multi-girder, prestressed concrete multi-girder, and prestressed box girder for consideration and seven different climate zones (e.g. very cold, mixed humid, hot dry, etc.). We will also study different grouping methods (e.g. clustering methods such as k-means (Seber 1984), Gaussian mixture (McLachlan and Peel 2000) etc.) and check the correlations of the data using existing condition databases such as the National Bridge Inventory (NBI) to ensure the grouped data are well correlated.

Next, for a group of assets we will investigate the integration of inspection data from different inspection processes using multi-fidelity modeling approaches to see how high-quality condition

[1] https://highways.dot.gov/long-term-infrastructure-performance/ltbp/long-term-bridge-performance

information about a few assets in the group can be interpolated to inform our knowledge of the condition of other assets in the group. For example, for a set of bridges it might be feasible to inspect a small number of bridges using NDE techniques to obtain high-fidelity data while inspecting other structures visually in less detail than used in current bridge inspection practices to obtain low-fidelity data.

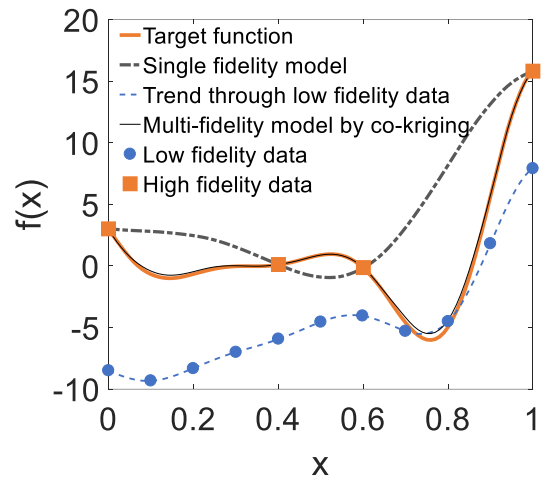

Figure 1. An example of single and multi-fidelity model (co-Kriging), adapted from (Forrester et al. 2007).

We plan to make use of existing data, including data available through the Long Term Bridge Program's: InfoBridge Database[2] and bridge inspection data obtained from local transportation agencies. The high- and low-fidelity data from high- and low-quality inspections will be fused through multi-fidelity modeling. Specifically, one of the most popular multi-fidelity methods, co-kriging, will be adopted due to its flexibility and the provision of a useful error metric (Kennedy and O'Hagan 2000). Before constructing the co-kriging model, an appropriate parameterization is needed to provide the model input. All the important control parameters that relate to/or govern the structural condition of the grouped assets should be included; while at the same time the number of the control parameters should be maintained as low as possible to the avoid computational challenge of high dimension problems. Once the control parameters are defined (e.g. traffic levels, maintenance practices), the relationship between condition measures of a structure (model outputs) and the controlling parameters (model inputs) will be described by a target function (solid orange line in Fig. 1). Firstly, the low-fidelity data (obtained from low-quality inspection) will be used to build a low-fidelity kriging model, which is comprised of a base term and a Gaussian process to predict the trend of the target function (dashed blue line in Fig. 1). Then the high-fidelity condition measures will be approximated as the low-fidelity kriging model multiplied by a scaling factor plus a difference term modeled as a Gaussian process. The parameters of low-fidelity kriging model will be determined by maximizing the likelihood function of low-fidelity data (blue dots in Fig. 1). Then the rest of model parameters, such as the scale factor and parameters for the Gaussian process, will be estimated by maximizing the likelihood function of the difference between the high-fidelity data (orange squares in Fig. 1) and the approximation given by low-fidelity kriging model (dashed blue line in Fig. 1). With the estimated parameters of the co-kriging meta-model, the condition measures for a new set of control parameters will be predicted. The feasibility and efficacy of the co-kriging method in fusing multi-fidelity data is clearly demonstrated by a simple example from Forrester et al. (2007) (Fig. 1). The single fidelity model based on four high-fidelity sample points (grey dash-dotted line) significantly deviated from the true target function. However, the integration of four high-fidelity points and an additional 11 low-fidelity points through multi-fidelity co-kriging modeling resulted in a much more accurate prediction (black solid line). The outputs of the meta-model may include various condition measures of

[2] https://infobridge.fhwa.dot.gov/Home

interest, such as component wise rating, remaining service life, or particular levels of damage (e.g. % delamination on a deck), therefore constructing a single meta-model for all outputs will compromise the accuracy for each. To achieve a higher prediction accuracy for all outputs, multiple meta-models can be constructed. In the case of particular large dimension of outputs, where building meta-models for every output may become inefficient, the principal component analysis (PCA) will be adopted to reduce the dimension of the outputs through exploiting their correlation (Jia and Taflanidis 2013).

The suitability of the multi-fidelity modeling approach as the data fusion technique will be evaluated by comparing the model-predicted condition measures with those obtained from high-quality inspections (including results from destructive testing if/when possible). Furthermore, the feasibility of applying this data fusion technique in conjunction with the modified inspection processes will be assessed by considering how the available information contributes to the quality and efficiency of inspection and maintenance planning. In addition, a simple lifecycle cost analysis will be conducted to investigate the potential savings in inspection costs.

Expected Outcomes

The results of this study are expected to help enhance bridge asset management practices by demonstrating an approach to 1) effectively fuse a variety of different data types to evaluate structural assets and 2) extend the detailed findings about a few assets to help inform knowledge of other assets where detailed data are not available. This study is preliminary in nature and the results are primarily expected to inform further study in the area of multi-fidelity modeling for transportation asset assessment. Specifically, the expected outcomes of this feasibility study are:

1. A set of statistical criteria for defining similarity and grouping bridges (or other transportation assets) to allow for effective multi-fidelity modeling of a group.
2. A demonstration of the multi-fidelity modeling approach applied to transportation assets.
3. An assessment of the strengths and weakness of the multi-fidelity modeling approach for application to asset management of bridges (and other transportation structures) and identification of areas for further study.

If successful, the proposed data fusion technique not only has the potential to disrupt the inspection process for better resource allocation, but can also be readily used to integrate various sources of existing inspection data (e.g. traditional visual inspection, NDE) from the national database (e.g. Long Term Bridge Performance program) to provide more accurate and consistent condition assessment.

Relevance to Strategic Goals

This study is most closely related to the strategic goal: State of Good Repair. The research conducted by this MPC project is intended to provide asset managers with a resource efficient method to provide understanding of existing asset condition so they can better plan for maintenance and renewal activities.

Educational Benefits

One graduate student will participate in the project including writing several papers and a report, which will result in part of his/her dissertation. They will gain valuable experience in the field of asset management and infrastructure inspection/evaluation.

Technology Transfer

As this study is preliminary in nature, it is most important that the findings are transferred to other researchers working in the field of transportation asset management. We will present the findings of the project at TRB and prepare journal article(s) about the findings and methods. Furthermore, as part of the work plan we anticipate collecting data sets from local transportation agencies (CDOT, Larimer County, local municipalities). Through this process we will continue to build relationships with engineers at these agencies and keep them informed of the multi-fidelity modeling strategy and how it could be applied in the context of their agency.

Work Plan

The work plan includes four major tasks, each with an interim deliverable/milestone:

<u>Task 1: Data collection</u>
This task identifies and collects the existing inspection data (e.g. traditional inspection, NDE and UAV-based inspection) that are publicly accessible and suitable for the methodology development (1st-4th months).

<u>Task 2: Assets grouping</u>
This task first identifies relevant asset parameters and then explores the efficacy of various clustering techniques for classifying the assets into appropriate groups (5th-6th months).

<u>Task 3: Data fusion</u>
This task develops the multi-fidelity model for data fusion. Firstly, the model parameterization will be studied. Secondly, co-kriging model will be established (7th-20th months).

<u>Task 4: Evaluation of multi-fidelity modeling for transportation assets</u>
This task evaluates the suitability of the proposed multi-fidelity modeling approach as a technique for data fusion and its impact of on inspection practice and maintenance decision making using lifecycle cost analysis (19th-24th months).

Project Cost

Total Project Costs:	$123,000
MPC Funds Requested:	$ 63,000
Matching Funds:	$ 60,000
Source of Matching Funds:	Colorado State University, in-kind support

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