ROBUST MODEL CALIBRATION OF A WIND TURBINE POWER TRAIN WITH LOAD UNCERTAINTIES

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ABSTRACT

The goal of this work is to explore a model calibration strategy for an industrial problem consisting in a MW class geared wind turbine power train subjected to uncertain loads. Lack of knowledge is commonplace in this kind of engineering system and a realistic model calibration cannot be performed without taking into account this type of uncertainty. The question at stake in this study is how to perform a more robust model of a dynamic system given that the excitations are poorly known. The uncertainty in the latter will be represented with an info-gap model. This methodology is illustrated on a Megawat class wind turbine power train torsional model.

1 INTRODUCTION

Validating structural dynamic numerical models is a common engineering task. Confidence in simulation results is critical for product development and risk management, and the preferred framework to quantify this confidence is model verification and validation (V&V) [1]. The confrontation between numerical simulations and experimental observations often indicates that the model is unsatisfactory. Four different paradigms have been developed over the years to improve fidelity to data based on model calibration strategies, namely: Reference basis methods [2], Local deterministic methods [3],Local stochastic methods [4] and Local robust methods [5].

The first three paradigms have been studied extensively on both academic and industrial examples. As different as these approaches are, they share the same fundamental hypothesis, namely that the best solution to the calibration problem is the one that minimizes the defined test-analysis metric. While this assumption is commonplace, it fails to recognize that most real world problems are plagued by various sources of lack of knowledge due to poorly understood physics.

The present work is based on the concepts presented in [5] (the fourth paradigm) and serves to illustrate the relevance of robust parameter calibration under load uncertainties. The focus in this paper will be on the tradeoff between fidelity to data and robustness to uncertainty and the strategy is applied on a simple but realistic wind turbine power train model which is calibrated with respect to a simulated transient response. Wind turbine power trains are a good example to illustrate both the problem faced and the approach. This type of device is suitable to illustrate the approach because in the authors opinion the robust parameter calibration strategy presented here can be a step forward on the process of assessing models prediction credibility

2 ROBUST PARAMETER CALIBRATION

A numerical model can be denoted by:

$$y = \mathcal{M}\left(q\right) \tag{1}$$

The model $\mathcal{M}$ defines a relationship between y, the response feature of interest and q, model input parameters or decision variables. The impact of lack of knowledge on model responses will be studied using info-gap models of uncertainty [6]. The uncertain variable is denoted by u, and the info gap model of uncertainty is defined as $U(u_0;\alpha)$, hence:

$$y = \mathcal{M}\left(q;u\right),\ u \in U\left(u_0;\alpha\right) \tag{2}$$

where the parameter α is known as the horizon of uncertainty, while u_0 is the nominal value of the uncertain variable. The objective here is to study the robustness of the model fidelity to experimental data given uncertainty loads. The discrepancy between reference and simulation data can be assessed with a metric $D(q;u)$ defined as the norm of the difference between the test data y^{Test} with the results obtained from the model y:

$$D\left(q;u\right) = \left\|y^{Test} - y\right\|_2 \tag{3}$$

where y^{Test} ; y will be assumed here to be real vectors. Furthermore, let D_c denote the greatest level of discrepancy that can be tolerated:

$$D\left(q;u\right) \leq D_c \tag{4}$$

The robustness of the discrepancy with respect to uncertainty can now be formally defined as:

$$\hat{\alpha} = \underset{\alpha \geq 0}{Argmax} \underset{U(u;\alpha)}{max} \{D(q;u)/D(q;u) \leq D_c\} \quad (5)$$

The robustness function assesses the immunity of the discrepancy to uncertainty in u. Large $\hat{\alpha}$ means that discrepancy is relatively insensitive to variations in the uncertain quantities u, while small $\hat{\alpha}$ means that small variations in the uncertain quantities lead to large discrepancy.

Robust parameter calibration searches for a model design q which maximizes the robustness of the discrepancy for a given horizon of uncertainty:

$$\hat{\alpha}(D_c, q) = max(\alpha : \left\{ (\underset{u \in U(\alpha)}{max} D(q;u)) \leq D_c \right\}) \quad (6)$$

According to equation 6 the robust calibrated parameter can be defined as:

$$\hat{q}(D_c) = \underset{q}{argmax} \left(\hat{\alpha}(D_c, q) \right) \quad (7)$$

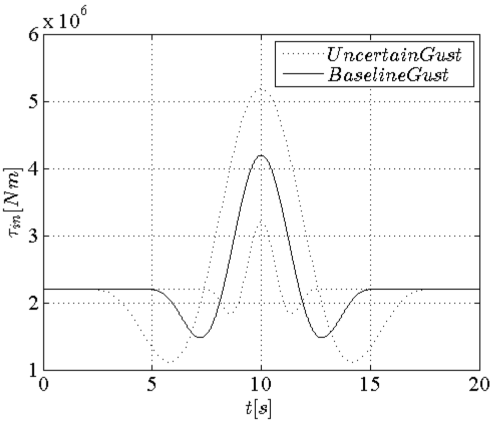
3 APPLICATION

The robust calibration strategy is applied to a MW class wind turbine power train model. This case study focuses on a wind gust as it is defined for certification purposes [7], the wind gust shape is translated as a torque input. A simulated Gearbox housing deflection is used to formulate the discrepancy function.

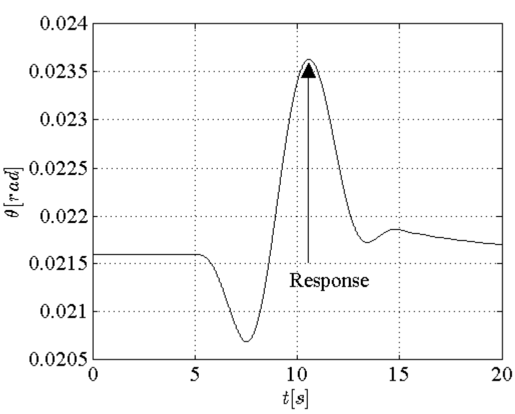
For this application, a discrete model is adopted consisting in a one degree of freedom per body rotational model. The gearbox support stiffness is modeled as a non linear spring. Such a model is widely used to represent this kind of rotating devices [8]. The dynamic system to solve can thus be written as:

$$[I] \cdot \left\{ \ddot{\theta} \right\} + [C] \cdot \left\{ \dot{\theta} \right\} + [K] \cdot \{\theta\} = \{T\} \quad (8)$$

The mathematical model is implemented in the Dymola software. The performance criteria is defined as the fractional error between the maximum displacement values during the wind gust (Figure 1b) for both reference and simulated responses in the gearbox housing θ_{HOU}.



(a) Envelope bound uncertainty model



(b) Response feature of interest

Figure 1

The mexican hat wind gust type shape is set to be uncertain (Figure 1a). To model the uncertainty an envelope info-gap model [6] is used. The performance requirement is defined as the fractional error of the system response maximum difference between nominal and maximum gearbox housing displacement amplitude during the wind gust. This fractional error is not greater than a specified critical discrepancy D_c. Before the robustness curve is calculated a deterministic parameter calibration is conducted. The error for each point is calculated using the performance criteria defined. A robustness analysis is conducted for both the baseline model (before calibration) and the deterministic calibrated model. The robustness curves are calculated and compared. A robust parameter calibration strategy is conducted for the power train model (equation 8) and the uncertain wind gust. The calibrated robustness curves are obtained and commented.

4 CONCLUSION

Model calibration is an important phase in the overall model validation process and serves to improve fidelity to data. Model calibration methods generally seek to optimize fidelity. Meanwhile, the presence of lack of knowledge in the modeled physics renders fidelity-based approaches suspect given that the purported calibrated performance can no longer be guaranteed. A new robust calibration paradigm was proposed in [5] and forms the basis of ideas explored in this study which focused on the tradeoff between fidelity to data and robustness to uncertainty. It was shown that the best deterministic model does not necessarily provide the most robust predictions under lack of knowledge.

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