

Lectures

Predictive reliability with signal based meta-models

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Abstract

The development of algorithms and models to be used for prediction of the reliability and health monitoring of components and sensors is of great importance in aerospace, automotive and power generation industry. For this purpose metamodels have been developed that are based on physical simulations and that are able to quantify the impact of uncertainties on system behavior. These surrogate metamodels for time dependent signals can approximate the failure behavior and detect symptoms of aging. Furthermore, the prediction which input parameter combination can be run by the measurement setup without risk of failure or break in testing is an important application. Our approach has been validated for a high lift system in the aerospace industry.

1. Motivation and objective

The prediction of test results is especially important for very expensive tests like in aerospace industrial applications, e.g. testing high lift systems. The reduction of the amount of physical tests by virtual testing saves resources and accelerates the product development process.

Currently, physical modelling of mechanical aspects, solved by flexible multi-body simulation are used to approximate the responses of the analyzed high lift system. This process is detailed but computationally very intensive, slow and hardly feasible for stochastic analyses. Moreover, it has no real-time capability. Therefore, there is a need to reduce computational cost maintaining high fidelity modelling. At the same time, the possibility to perform robustness analysis to quantify the impact of scatter and uncertainties and the integration into real-time simulators or functional integration workbenches is necessary.

Therefore, our approach presented in this paper uses metamodels that approximate the dynamic response of the test. They are built using physical simulations that represent the test results very well but need a lot of computational power and time to be computed. Our metamodels having short response times will potentially be used to replace existing simplified models in real time simulators for hardware-in-the-loop simulations in a test environment [1, 2].

The combination of physical testing and virtual testing for test planning allows an evaluation of the test rig, enables more realistic and more complex tests, as well as the reduction of a risk of damage. Moreover, this combination will augment physical tests to gain more

insight into system behavior and to improve representativeness of the tests.

2. Methodology

For the development of metamodels for dynamic outputs we modified our existing Metamodel of Optimal Prognosis (MOP) algorithm that can be used for scalar inputs and outputs. This MOP performs an automated selection of the most suitable approximation model, searches for the best fit and verifies the models with cross validation. The MOP is selected by the highest Coefficient of Prognosis (CoP), a cross validation based quality measure for the prediction ability of the model [3].

The extension of this MOP approach is realized by the application of the random fields approach [4]. This extension leads to the Field-MOP or F-MOP. The first step is to represent spatial or time dependent variations of field responses by scalar parameters due to a decomposition of the signals into scatter shapes and amplitudes. The second step is to represent these parameters by MOP based on input samples. The full variation shape pattern of the measured signal can be described in this manner (Figure 1).

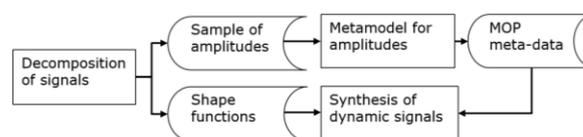


Figure 1: Overview of the developed approach for decomposing the signals to obtain metamodels that can describe dynamic systems.

Using this dynamic metamodels we obtain a simplified and reduced parametric of the dynamic signal based on a statistical metamodel. The user doesn't need to find a parametric himself.

3. Results and discussion

The application of the new metamodeling approach to the high lift system used the following parameters for the analysis:

- Given flap positions and loadings,
- Simulated rupture of 2 of the 4 actuators,

The considered uncertain parameters have been

- Stiffness of the actuators,
- Backlash of the actuators,
- Damping and

- Friction.

The observed responses were

- Actuator moments,
- Drive strut forces and
- Stations Position Pickup Unit (SPPU) angles.

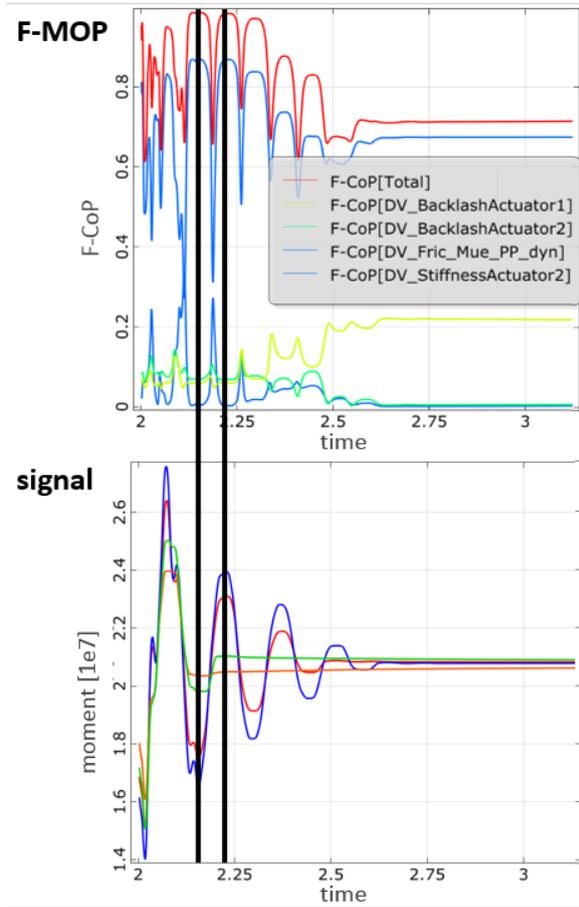


Figure 2: Prediction ability of the total model for the time dependent signal (F-CoP [Total]) and the impact of each input parameter on the total model for the signal (DV_Backlash Actuator1 and 2, DV_Fric_Mue_PP_dyn, DV_StiffnessActuator2). The signal is illustrated in the figure below and the black lines between the figures indicate that the prediction ability of the F-MOP corresponds to the time of the signal.

The established workflow included the process integration of the Adams/Flex simulation model in order to generate the inputs, read the outputs in an automated manner and to automate the variation analysis using the simulation process. The generation of the Design of Experiments (DoE) is the basis for the variation analysis – no matter if a sensitivity or robustness analysis is performed. Subsequently, the F-MOP is built using the Adams/Flex responses corresponding to the inputs of the DoE. This step includes the signal decomposition, generation of the MOP for amplitudes and the computation of the F-CoP (Figure 1). Afterwards, new signals as a response of a particular input parameter

combination that have not been computed before by physical simulation, can be approximated using the amplitudes and shape functions within the F-MOP approach.

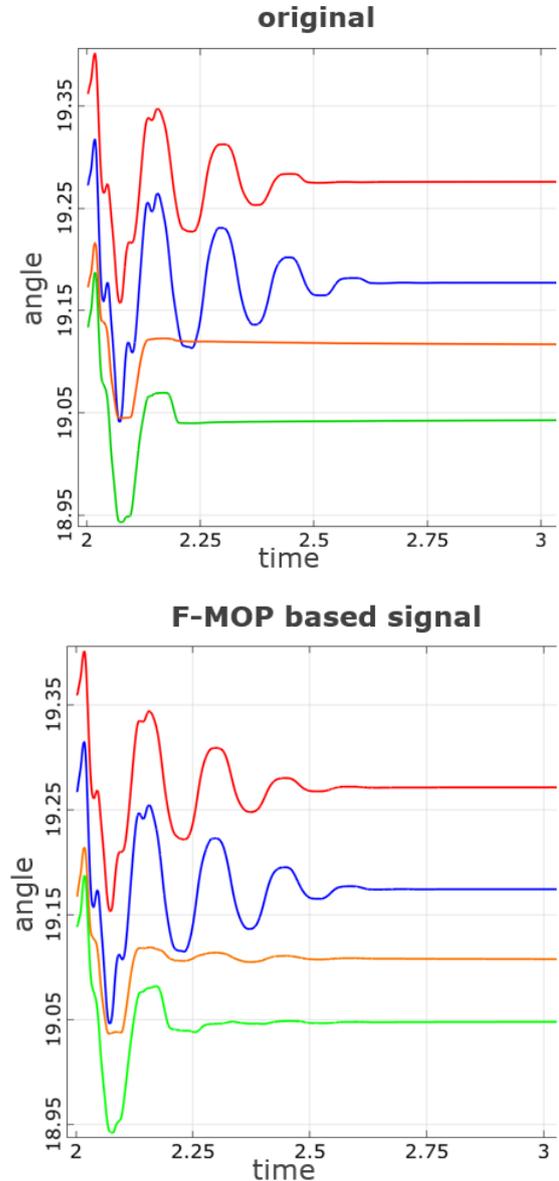


Figure 3: Comparison of original (above) and by metamodeling approximated signals of the SPPU angle (below). 4 designs have been picked and generated by metamodeling with the same inputs as the original signal.

As proof of concept the time dependent variation of an actuator moment of the high lift system was used Figure 2 (panel below, “signal”). The variation occurs due to the DoE and the varying inputs as described above. The results of the approximation are shown in Figure 2 (panel above, “F-MOP”). The F-CoP is illustrated versus time and it is ranging between 0 and 1. The figure shows very high total F-CoP values at the peaks and less near the zeroes. That means, the signal can be very well approximated at the peaks. The relative influence of the

input variables can be monitored over time by the other channels: The stiffness has dominant influence. Furthermore, the influence of the backlash of actuator 1 and 2 as well as the friction can be detected. The damping has no significant impact on the signal and is therefore illuminated from the model.

The decomposition of the signal can not only be used to explain the impact of the input parameters over time. Moreover, it can be used for “reassembling” (approximating) a new signal for an input parameter combination within the examined variation range that has not been computed before. To show this capability the time dependent variation of the SPPU angle was approximated for 4 independent designs with 4 different input parameter combinations (Figure 3). The signal can be predicted with a very high precision. Especially where the peaks of the signal occurs, the prediction ability of the model is very high (as shown in Figure 2). This approach has been also applied to approximate the actuator moments and the drive strut forces which gave very similar and promising results.

4. Conclusions

We successfully developed and proved a new approach for metamodeling of time dependent signals based on a decomposition in scatter shapes and amplitudes. These models have been applied to a high lift system. This illustrated that they can assess their prediction ability over the time dependent signal. Furthermore, these metamodels explain the impact of the input parameters over time and can be used for approximating a new signal for an input parameter combination that has not been computed before.

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