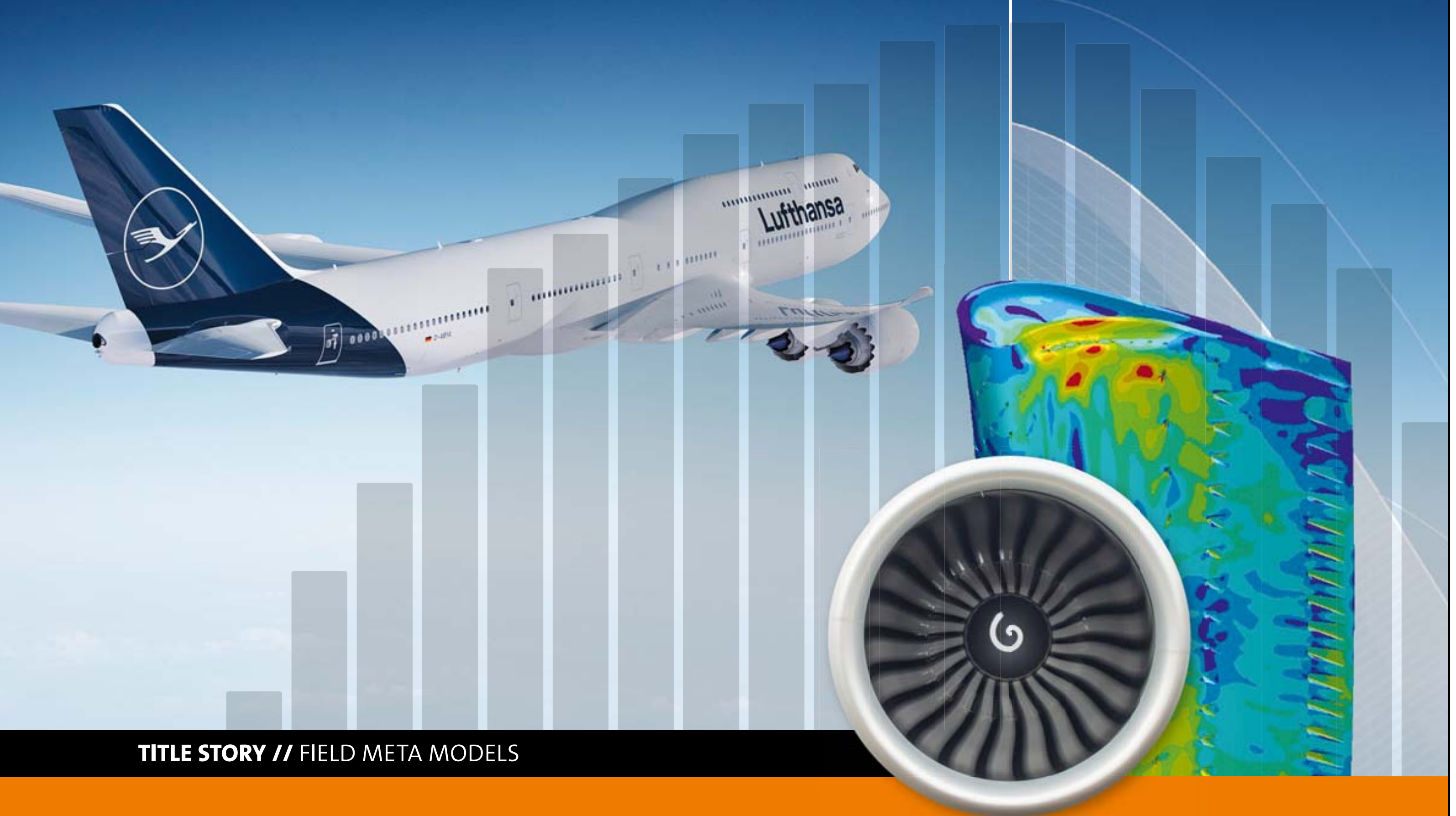

REAL-TIME PROCESSING WITH 3D META MODELS FOR PREDICTIVE MAINTENANCE OF AIRCRAFT ENGINES

At Lufthansa Technik (LHT), field meta models efficiently enable the life prediction of components, such as a turbine blade, taking into consideration the specific operating conditions.

Introduction

LHT, as a part of the Lufthansa Group, is an independent provider of maintenance, repair and overhaul (MRO) services in the world's airline business. Organized in different product divisions, LHT offers aircraft services for line and base maintenance including overhaul, component services, landing gear services, VIP & special mission aircraft services, as well as engine services. In the product division of engine services, different offerings are made to different types of customers. Other MRO providers may procure only individual engine part repairs, while engine manufacturers may contract individual engine overhauls to be performed in an LHT engine shop. Airlines, however, will usually require MRO coverage for their whole fleet, including engineering tasks, such as maintenance planning and workcope definition. In addition to engine maintenance performed in the shop, LHT also offers Mobile Engine Services, which are carried out while the engine is still on-wing, often with the aim of avoiding an imminent engine removal.

Motivation for the use of prognostic methods for predictive maintenance

The engine is one of the most complex and technologically challenging components of an aircraft. They usually account for a significant portion of any airline's total operating cost. Furthermore, as shown in Fig. 1 for the engine type CF6-80C2, the largest portion of the total cost, produced during an engine's life cycle, does not stem from the engine's purchase, but from the MRO expenses. In the last 30 years, this has led to a very competitive market for engine MRO, with engine manufacturers stepping into the aftermarket besides the established independent MRO providers. As in all competitive markets, the margin for error in assessing the risks involved with a certain contract tends to be low.

Contracts for the MRO coverage of a whole engine fleet are usually rather long-term (10 – 15 years run-time are no exception). These types of contracts are very complex. They increasingly tend to contain fixed price elements, price caps or they can be right-out flat-rate contracts. Either way, the contract structure has two significant implications for the MRO provider:

1. Because of the price caps and/or fixed price elements, the maintenance provider carries a significant portion of the risk involved in the prediction of the total maintenance cost.

2. Because of the long run-time, predictions for expected total maintenance cost have to be made far into the future and, at the same time, they have to be very accurate in order to produce a competitive offer.

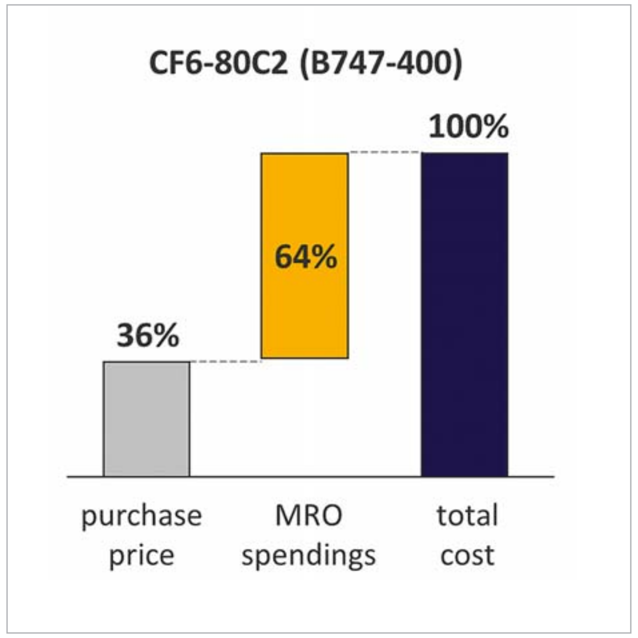

Fig. 1: Engine lifetime cost

The different factors mentioned above make it necessary for MRO providers to develop methods capable of accurately predicting the expected maintenance cost as a function of a customer's specific operating conditions in order to be competitive. It is no longer sufficient to disassemble and assemble engines efficiently in a shop, nor to perform any number of engine part repairs. In addition to this, it is increasingly important to perform proper fleet management throughout the operation. This involves removal and maintenance planning in a manner that allows constant monitoring. Once a plan was made, it has to be compared to the actual performance of an engine fleet, and the predictions for further development have to be constantly updated. If done properly, this will allow risk management through the early detection of problems, and will thus reduce the engine maintenance cost per flight hour.

Removal and maintenance planning requires the ability to predict how the engines will behave when exposed to certain operating conditions over several years. The engine behavior in this context consists of both the overall performance deterioration, as usually measured through the exhaust gas temperature margin (EGT Margin), and the damage to critical components, such as turbine blades, which may tend to suffer cracks at certain locations. In Fig. 2, a CFM56-5C high pressure turbine blade is shown as an example. This blade usually develops cracks at the root trailing edge (marked location). An engine removal is required if these cracks reach a critical length. The number of flights or cycles to reach this point and, thus, the achievable time on wing, varies from airline to airline. It is depending on the specific operating conditions that the engines are exposed to. The major aim of the research presented here is to develop a method for predicting the useful life of components, such as a turbine blade, taking into consideration the specific operating conditions.

Big data reaching its limits

How can such a matter best be approached? The issue is complex and highly non-linear, and there are many parameters involved. The current "state-of-the-art" would likely call for a big data analysis based on all available fleet and operational data, with statistical methods identifying sensitivities that can be used as surrogate models to predict loading and resulting life for critical engine components.

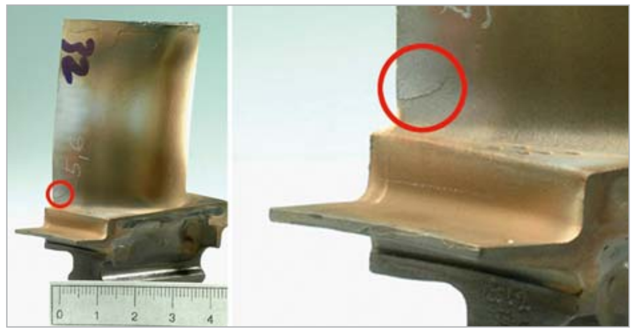

Fig. 2: Engine blade with crack on trailing edge (red circle)

LHT experience shows that a high amount of parameters influencing the results makes it all but impossible to derive meaningful results from such an analysis unless the data is filtered properly. However, then the amount of comparable data points is usually insufficient for a meaningful statistical analysis. Furthermore, while statistical methods or neuronal networks may provide a result, they usually work as black boxes and do not provide any understanding of the sensitivities. Consequently, this makes it impossible to assess if the model is working properly or not, especially when being used for extrapolations. Therefore, LHT investigates the approach of combining available fleet and operational data to extract statistical models for engine component loading. In this step, filtering and decomposition strategies become crucial to derive meaningful results. In addition, LHT uses high fidelity CAE models to predict the engine part loading and life.

A detailed CAE-based model as base to predict loading and life

LHT has been engaged for several years in the development of physics-based engine models. These include thermodynamic cycle models of the engine as a whole, as well as models for numerical simulation (CFD, FEM) of individual modules and components. Physics-based models usually

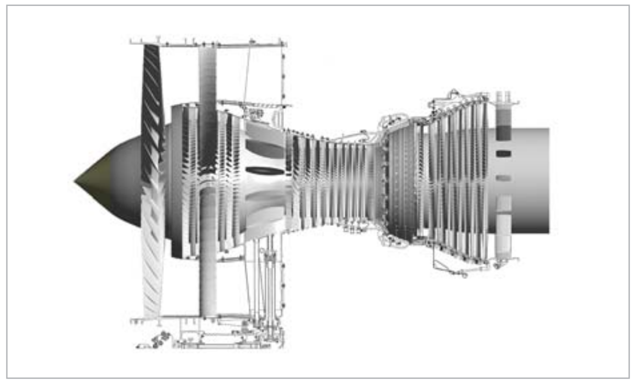

Fig. 3: Geometry of a CFM56-5C engine

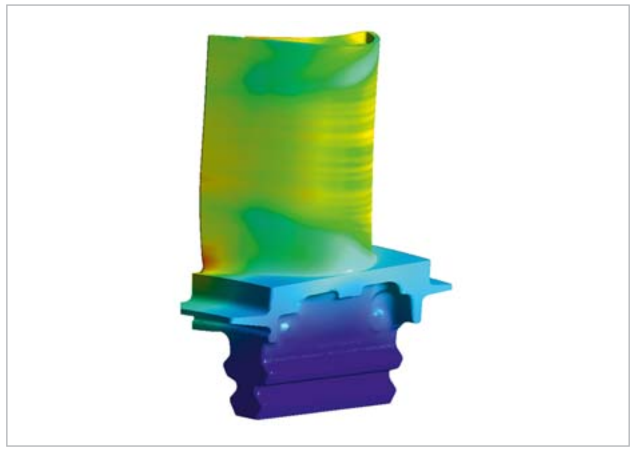

Fig. 4: Temperatures on a high-pressure turbine blade

include an accurate representation of the engine's geometry (Fig. 3 shows the geometry model of the CFM56-5C) and the engine's behavior. They also make it possible to determine the loads in a certain component under actual operating conditions. As an example, Fig. 4 shows a temperature distribution at take-off for the same turbine blade as shown in Fig. 2. With this information, useful predictions about life of critical components become possible.

The drawback of this modeling approach is the high computational cost caused by high fidelity simulations. A faster solution is needed in a fleet management framework with the requirement of constant updates of removal planning based on actual performance data. Therefore, surrogate models were established, which operate quickly and keep a high quality in terms of the result accuracy. The challenge for these surrogate models is that not only scalar non-linear responses need to be taken into account. The surrogate models need to forecast field responses, like stress distribution throughout the blade.

Field surrogate modeling approach (FMOP)

Based on this need for accurate field surrogate models, Lufthansa Technik, ITB and Dynardo teamed up for the development of a highly adaptive workflow providing the utmost possible automatized generation of field surrogate models. For generating the field surrogate models, the Dynardo technology to identify Field Metamodels of Optimal Prognosis (FMOP) was used. This was done for the HPT-Blade mentioned before and aims to be applied on a vast amount of engine components.

The core idea of this project is to combine all the existing data and knowledge about the engine fatigue into one workflow. This includes the flight data, as well as joining existing simulation models in a one-way fluid-structure interaction (FSI). Here, an optiSLang setup manages the process, feeding a representative set of the gathered flight data into the simulation models and providing the environment for the automated execution of the set of simulations. When all design points are calculated, the workflow is finished with an instance of Statistics on Structures, which automatically generates and exports field surrogate models for the results of the FSI simulation. This surrogate model may then be used to rapidly approximate the responses of the structure for an infinite amount of operation points or can be used for further investigations.

Numerical challenges

While the setup in optiSLang is easily accessible (see Fig. 5), a big part of the challenge in this collaboration was the efficient management and connection of the fluid-structure interaction and its highly detailed numerical models. To put this into perspective, some metrics of the numerical models have to be brought to mind. Even though the mechanical utilization is what shall be approximated by the surrogate model, the variable loads used as input data consist of flight operation parameters, i.e. in detail measured values from the engine. This includes values, such as temperatures, pressures and number of revolutions. Consequently, the loads (pressures and temperatures) for the final mechanical simulations have to be derived from the results of the fluid simulation.

The model of the high pressure part of the engine contains more than just the high-pressure blade of interest. Additional stages and their respective vanes have to be considered in order to obtain a precise answer of the system for any given operation point. Fig. 5 shows the solid domains (blue) used in the fluid simulation, which are surrounded by the fluid itself. Inner cooling channels of the HPT blade are also considered.

This results in a tremendous mesh with about 80 million nodes. These mesh sizes cause a great need for computational power in order to calculate the necessary number of design points to generate the field surrogate models in an acceptable amount of time. While this of course can be solved by simply using simultaneous design execution on powerful hardware, the additional cost for hardware and software licensing limits the achievable speed-up. Additional initial engineering effort on the setup quickly pays off and scales by each design point. For example, the fluid simulation was speeded up only by a tight definition of convergence criteria for the temperatures and pressures

Title Story // Field Meta Models

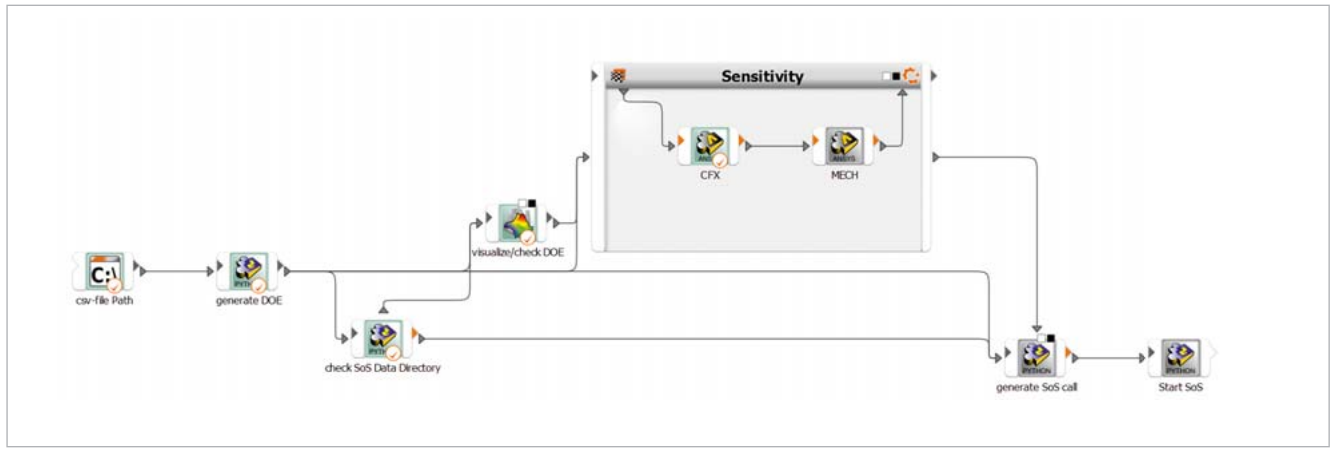

Fig. 5: optiSLang workflow

around the HPT-Blade. Furthermore, with an automatized selection of the most appropriate initial solution for each design point, the solution time was reduced to about 15 hours per design point on a 128 core cluster.

Only about one hour of computation time was used for the mechanical simulation. The involved geometries are approximated by a rather small node number of 6 million as shown in Fig. 6.

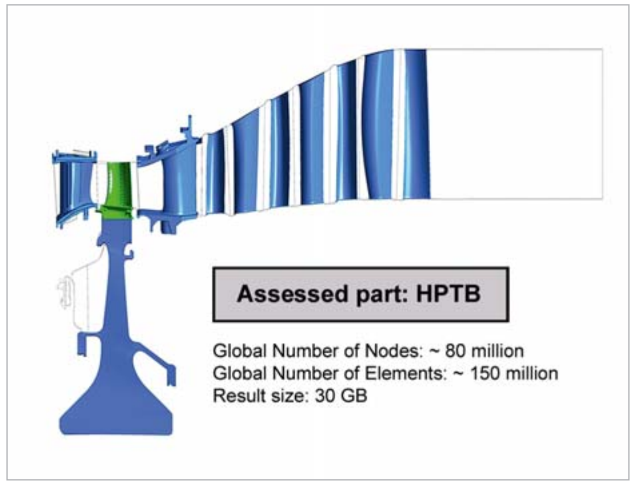

Fig. 6: Scope of the fluid simulation

Fig. 7: FE model of the blade

Validating the results

In the end, for 50 design points the total runtime of the FSI added up to about a month of computation time and approximately 2 TB of data. This data was then fed into Statistics on Structures by the workflow, creating two output files. One containing just the field surrogate model for further use and the other containing additional result sets of validation design points. These validation design points were not used for the generation of the surrogate model but can be directly compared with the values approximated by the surrogate model in SoS. A comparison of FE-results, the results from the surrogate model (also referred to as Field Metamodel of Optimal prognosis – FMOP) and their relative deviation (result accuracy) is presented in Fig. 7.

Fig. 8 (see next page) shows a screenshot directly taken from SoS. As a highlight, the F-CoP [Total] (a measurement of the quality of prediction taking into account all input variability) of the temperatures reaches a value of 99 %, while responses like the principle stresses, which are highly sensible to meshing, and boundary conditions maintain a value of 91 % at worst.

Furthermore, sensitivities can directly be derived from the data, which allow quick identification of the most important input parameters. In this case, for most responses, variation of the boundary condition parameter T4soll shows the largest quantitative impact to most response variation (refer to F-COP [T4soll] at Fig.9, see next page).

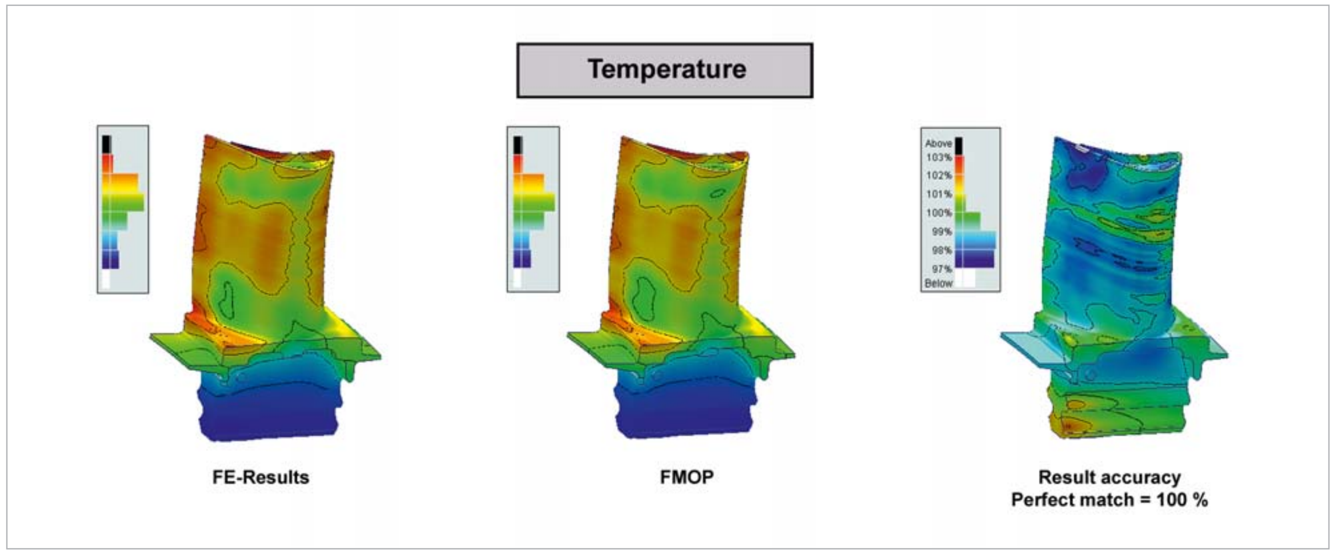

Fig. 8: Comparison of the calculated temperatures (left), the predicted temperatures (middle) and their accuracy (right)

		S1	S2	S3	SX	SXY	SXZ	SY	SYZ	SZ	TEMP
	Capped_dif50_data										
	F-CoP[Input_N1]	0.52 %	0.65 %	0.63 %	0.04 %	0.12 %	0.11 %	0.09 %	0.13 %	0.07 %	
	F-CoP[Input_N2]	5.29 %	3.75 %	3.84 %	6.53 %	5.53 %	4.35 %	3.81 %	4.00 %	3.56 %	0.03 %
	F-CoP[P25]	0.72 %	1.01 %	0.95 %	0.13 %	0.24 %	0.24 %	0.25 %	0.30 %	0.20 %	
	F-CoP[P3]	1.53 %	2.89 %	2.28 %	5.46 %	5.48 %	5.40 %	5.41 %	5.51 %	4.86 %	0.20 %
#2	F-CoP[P4soll]	18.02 %	17.26 %	14.49 %	16.67 %	14.70 %	17.62 %	14.32 %	17.52 %	18.33 %	
	F-CoP[P5Vorgabe]	1.65 %	1.58 %	1.43 %	0.06 %	0.19 %	0.20 %	0.17 %	0.18 %	0.15 %	
	F-CoP[T25]	0.66 %	1.64 %	1.07 %	0.50 %	0.99 %	0.93 %	1.94 %	1.21 %	0.79 %	0.02 %
	F-CoP[T3]	1.88 %	5.66 %	4.59 %	1.68 %	3.57 %	2.26 %	11.31 %	4.87 %	2.60 %	49.88 %
#1	F-CoP[T4soll]	82.83 %	64.32 %	62.67 %	78.36 %	70.11 %	72.26 %	56.74 %	63.67 %	64.44 %	49.02 %
	F-CoP[Total]	95.37 %	91.52 %	91.96 %	96.49 %	92.38 %	93.27 %	92.00 %	92.08 %	95.01 %	99.21 %
	mean[FMOP]										
	sigma[FMOP]										

Fig. 9: Screenshot from Statistics on Structures showing the correlation between input and output parameters

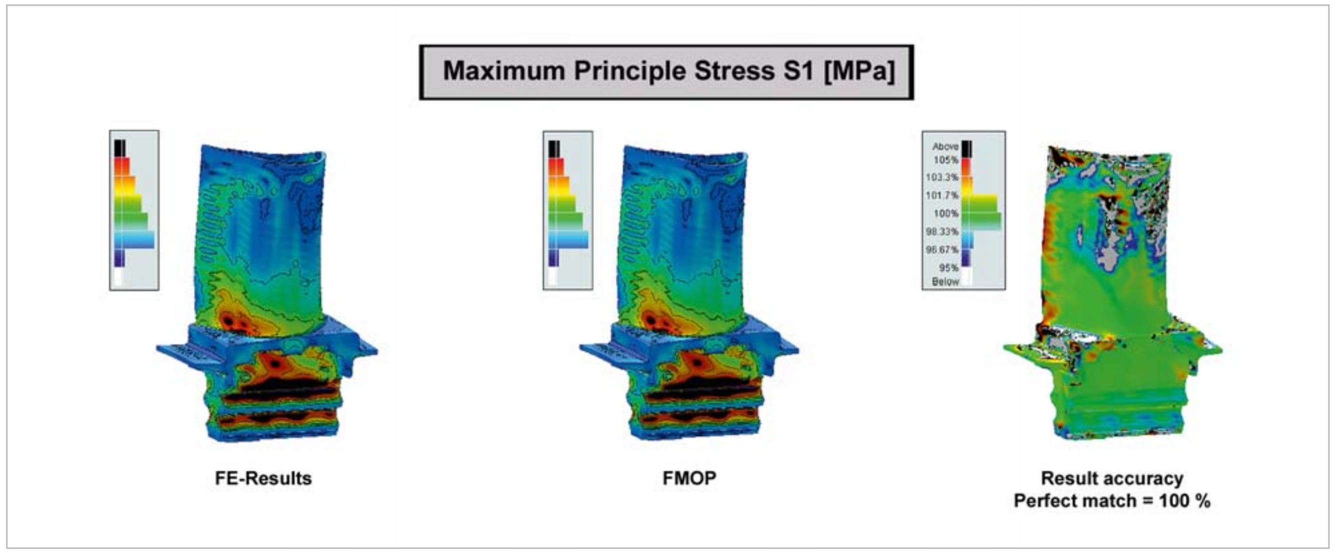

Fig. 10: Comparison of the calculated maximum principle stresses S1 (left), the predicted S1 (middle) and their accuracy (right)

Similar to the temperature results shown in Fig. 7, the maximum principle stress is compared in Fig. 9.

Since finally the behavior of the blade regarding fatigue is of interest, the percental result accuracy of the stresses is not directly correlated with the accuracy of the fatigue and the derived prediction of lifetime.

As shown in Fig. 10, the local accuracy for predicting the principle stress may be off by 5 % and more. However, if the total stress level is considered, the areas of high stresses from the FE-result as well as from the FMOP do not overlap with the less accurate regions from the accuracy plot. Vice versa, the regions with an interesting high stress level show a satisfying high accuracy. For example, the stresses of the root trailing edge from Fig. 2, which tends to crack, is predicted with a rather small inaccuracy of about 3 %.

An evaluation of the generated field surrogate models quality considering the predicted lifetime yet has to be conducted. However, the workflow itself proves to be working and the initial comparisons using the validation points show promising results.

Applied on further engine components, this process leads to field surrogate models which will give very important information to digital twins for the critical parts in engine operation and may be the cutting-edge technology making precise predictive maintenance predictions possible.

Summary

This article presented a new approach for building field surrogate models for a real-time digital twin for predictive maintenance of aircraft engines. The simulation model is generated with ANSYS, the workflow is organized by optiSLang and the meta modeling is managed by SoS. The numerical models are very complex and require an HPC cluster for half a day for each single design calculation. The resulting field surrogate model is sufficiently accurate for predicting temperatures, stresses and strains and reduces the computing time to a few seconds.

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