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Robust design of aero engine structures: Transferring form error data when mapping out design spaces for new turbine components

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Abstract

In aerospace modeling and simulation, nominal geometries are norm. However, it has been shown that form error, or irregular deviations in geometry, aggravates thermal stresses, which in turn reduces product life. While form error can be measured on manufactured products using 3D laser scanners, a simulation infrastructure is needed to analyze its effects on aerodynamic, structural and thermal performance. Moreover, in early product development phases, before manufacturing has begun, form error data is not available. This paper describes a method for including form error data in mainstream simulation activities. The suggested method works by creating parametric CAD-models to accommodate form error. There are two main benefits of this method. Firstly, it enables proactive robustness simulations where substantial design changes can be tested and evaluated. Secondly, it enables the mapping of data from previous products onto new designs, which means that robustness analyses can be performed in earlier design phases. To demonstrate this capability, a case study shows how a robust optimization scheme using genetic algorithms can improve product robustness to form error. The results show that form error have effects of the same order of magnitude as key design parameter changes. This finding underlines the importance of performing form error analyses in exploratory early design phases.

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Keywords: Robust design; Genetic Algorithm; Uncertainty quantification; Form error.

1. Introduction

In the aerospace industry, probabilistic design practices have long been understood as potential game changers. They are recognized as tools that improve product quality, and reduce costs, risks and lead times. They are also understood to increase confidence in analysis tools [1].

Although probabilistic design practices hold all this promise, significant barriers remain. In a report compiled by Zang et al. [1], the lack of methods for assessing form error is declared a major barrier to implementing probabilistic methods. Form error, or irregular deviations in geometries, are often difficult to model using mainstream simulation approaches. When form error is examined, it is generally done late in the product development process for manufacturing quality control, when it generally is too late to proactively change problematic or suboptimal designs.

Different modelling approaches are preferred for different engineering applications. Whereas geometric designers generally work with NURBS-based CAD-model, finite element models are used by most mechanical analysts. When it comes to quality control and model validation, the area where 3D scanners are most commonly used, working with point cloud geometries is the standard practice. However, a well-acknowledged problem with point cloud geometries is that they generate "frozen" or killed geometries in that that are not parameterizable and difficult to modify, and they do not capture the design intent of a model [2]. This means that they do not contain the higher-level information of CAD-models, and cannot distinguish between different features, like holes, cylinders, surfaces [3]. Point clouds live in a separate ecosystem, something that is often times unfortunate since intensive interaction between geometric design, mechanical analysis and model validation is often highly desired due to the iterative nature of a typical product development process [4].

The aim of this paper is to demonstrate how including form error data into parameterized CAD models can enable new types of analyses.

Section 2 of this paper presents the theoretical framework. Section 3 describes the industrial case study, showing how to setup a simulation to assess thermal stresses on a turbine component, while transferring form error data from one

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design to another. It also outlines the genetic algorithm used for part optimization. Section 4 is the results section, and section 5 outlines the quantitative and qualitative conclusions drawn from this study.

2. Theoretical Framework

Point cloud geometries do not inherently contain any higher-level geometric information. There does, however, exist an array of methods to extract higher-level information from point cloud geometries [3,2,4], generally deriving from the field of reverse engineering. However, the capture and translation of shape information into a CAD model is a difficult and complex task [3]. As components vary among themselves, any given scanned part only represents one sample in a distributed population. Therefore, the tolerance distribution in parts have to be accounted for. One way to do this is to scan multiple part scans and calculate of the resulting data. Another practical problem is limitations on geometrical accuracy in fixturing [3].

Varady et al. [3] divides the process of extracting higher-level information from point cloud into three distinct steps:

1. **Segmentation** is the process of logically dividing the original point set into subsets, one for each natural surface, so that each subset only contains just those point sampled from a particular natural surface.

2. **Classification** is the process of determining to what kind of surface each subset of points belongs (e.g. planar, cylindrical, etc.)

3. **Fitting** is the process of finding the surface of the given type that is the best fit to the points of a given subset.

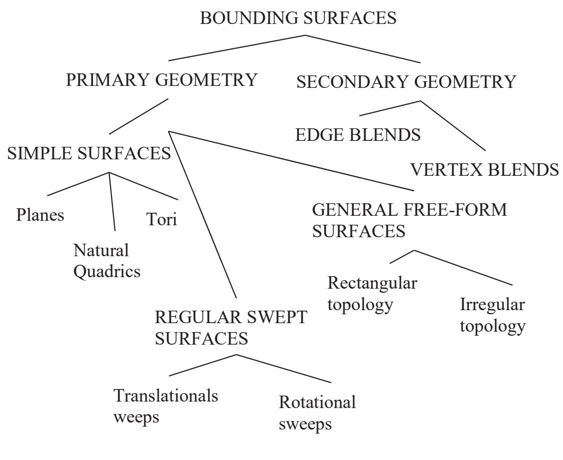

Fig. 1: Varady's hierarchy of surfaces [3]

Fig. 1 shows how, in the classification of surfaces, different surfaces types can be broken down into a hierarchy. Note, however, that these are merely tools to describe, understand and communicate surfaces. These concepts are not intrinsic in the physical world.

3. Uncertainty Quantification

If simulations are performed on geometries derived from point clouds, a verifying and validating the results is not straightforward. This is simply because in any simulation, there is a collection of phases that all add uncertainties to the simulation [5]. These phases are listed in Fig. 2.

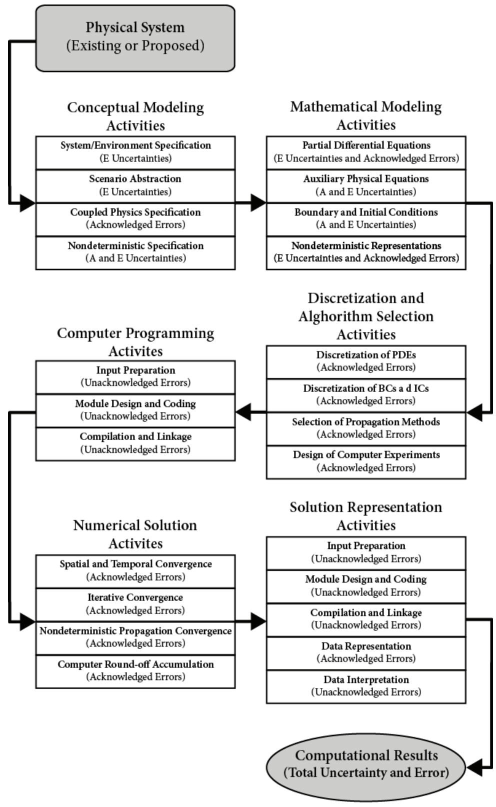

Fig. 2: Uncertainties in modeling and simulation [5].

In this context, quantifying the effects of form error belongs in the phase of mathematical modeling activities, and more specifically in the category of deterministic versus nondeterministic representation of geometry. However, to make sure that these differences are isolated, all differences created upstream when the models were created have to be identical. This gives rise to a *genesis* problem. When two models are created through different processes, these processes will leave there mark on the model. As a consequence, the resulting models will exhibit different sets of uncertainties. When representing the same physical object using different techniques, say a point cloud geometry, a CAD geometry and a FE mesh, their properties and characteristics will differ somewhat. This makes it difficult to single out effects. For instance, when a manufactured part is scanned into a point cloud and compared with a CAD geometry, differences of genesis partially occlude whether these differences accurately reflect physical differences.

4. Industrial Case Study

In this paper, a case study is performed with a Swedish manufacturer of aerospace engine components. The study examines the turbine rear structure (TRS) of a commercial turbofan engine, shown in Fig. 3. The rearmost part of an engine, the TRS attaches the engine to the aircraft pylon, while holding the low-pressure turbine bearing in place. It also redirects the hot exhaust flow from the combustion chamber [6]. Thus, the TRS has range of functionality criteria from numerous fields of engineering. It needs to be light and aerodynamic, and withstand significant thermal and structural loads [7].

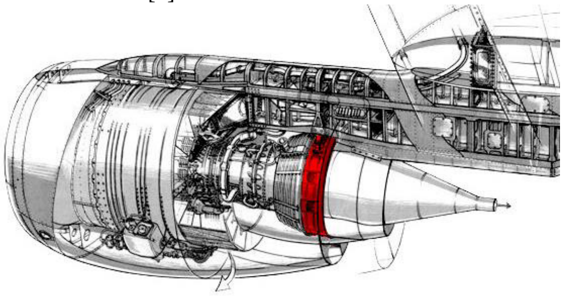

Fig. 3: Turbine Rear Structure

This paper focuses on one problem. With each flight, the TRS heats up to about 600°C. The resulting thermal expansion of the material puts significant stress on the structure [8]. The constant heating and cooling of the structure in between flights creates low-cycle fatigue. This material fatigue is a limiting factor on the number of flights one component can safety withstand.

Fig. 4: Turbine Rear Structures on different size engines

As illustrated by Fig. 4, TRSs are found in all sizes of turbofan engines, and thus come in all shapes and sizes. Although sizes differ, the general design element are the same. As such, product knowledge and technology platforms can be easily transferred between different products.

The TRS is a fabricated assembly consisting of a number of cast parts welded to sheet metal flanges. Each one of these cast parts has some degree of form variation. By using a 3D scanner, these errors can be quantified.

4.1. Part model generation

The part geometries for the vane-shroud T-sections of the geometries were based on 30 individual manufactured parts, which were scanned using a laser 3D scanner [9]. Fig. 5 shows a color-coding of the variation of one scan.

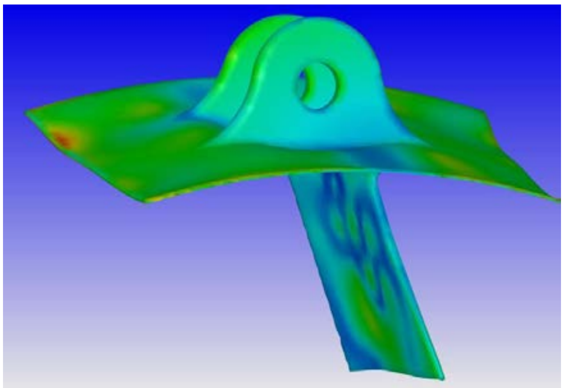

Fig. 5: Color-coding of scanned geometry

Fig. 6 shows the sequence with which a part CAD-geometries generated from the point cloud data. In step 1 there is merely point cloud data. Step 2 segments the points and classifies them into three categories: vane (red) and shroud (blue), and auxiliary (green). The green auxiliary points are merely there to ensure continuity and tangentiality conditions. They are thus not measurement points, but created by the software, and will be part of the final solid geometry. Step 3 uses B-spline curves to connect points, while keeping color classification. In step 4, the spines are combined into NURBS surfaces through a sweep operation. These surface geometries are converted into solids in step 5, using a thicken operation. The thickening operation introduces an error, as manufacturing does not guarantee uniform thickness. However, this error does not effect the aero surfaces. Step 6 trims the geometries to their final shape, and step 7 unites the segments into one solid. In Step 8, the secondary geometry, i.e. the shroud-vane blend, is created. In step 9, all intermediate geometry is hidden, and only the solid part is active.

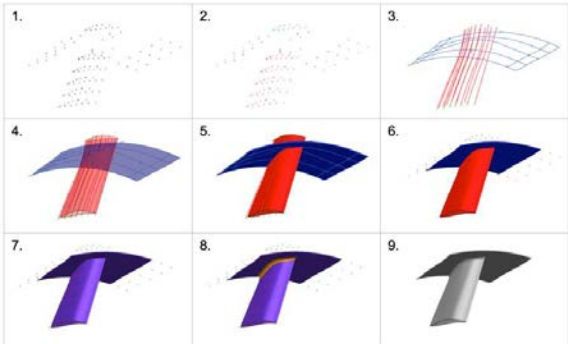

Fig. 6: Generating a feature-based CAD model from point cloud data

4.2. Assembly generation

Part geometries are placed in fixtures, where they are welded together. In the simulation, fixturing is done through 3-point referencing. In reality, parts interfaces are machined to fit together. The ingoing cast geometries have over-dimensioned interfaces, so that excess material can be removed. In doing so, surface continuity can be obtained even when geometries have deviations. For the simulation, this step is mimicked by continuous sweeps between interfaces. This method is more thoroughly described in Forslund et al. [10].

4.3. Sample problem – thermal stresses

A benefit of the method described above is that it can be applied to a parameterized CAD model. This means that dimensions such as inner and outer radius, features such as vane count and lean angle, and others properties can be altered, without the need for new scan data.

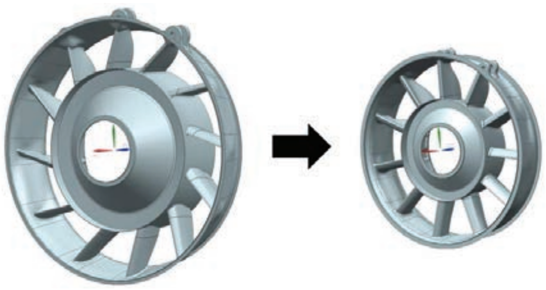

Fig. 7: Scan data obtained from a larger TRS can be mapped to a new design

In the sample problem presented here, this capability was tested by transferring scanned variation data from one product to another. Fig. 7 shows the geometry from which the data was gathered on the left side, and the geometry to which the data was mapped to the right.

To further showcase the method, one design variable of the structure was allowed to vary. Fig. 8 shows the selected design variable – the blend between vane and shroud.

Fig. 8: Blend radius set to vary between 2.5mm and 10mm

The radius of this blend was constrained between 2.5mm and 10mm. As previous work [11] have shown that thermal stresses tend to concentrate in this blend, particularly in the trailing edge, this is a region of interest in TRS design.

4.4. Simulation

With each flight cycle, the TRS is subjected to significant thermal loads as the hot exhaust flow from the combustor is led though the rear of the engine. Temperatures on aero surfaces reach 600° C. This heating leads to material expansion, which in turn results in substantial thermal stresses in the structure. Fig. 9 shows how these stresses are simulated.

Although the structure can handle these stresses, the constant heating and cooling of the structure in and between flight cycle will eventually cause material fatigue. This is a limiting factor of expected product service life.

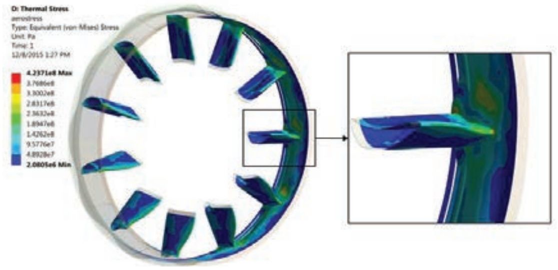

Fig. 9: Thermal stresses is a limiting factor of product life

For a nominal geometry, setting up a simulation to examine these stresses is relatively straightforward. Since the eleven vane-shroud T-sections are nominally identical, the problem is rotationally periodic, and only has one configuration. However, when form error is taken into account, each T-section is different. As a consequence, they will handle stresses and distribute loads differently. As they are connected, the properties of each T-section cannot be isolated from the next one. Hence, a simulation of the entire assembly needs to be performed for each simulation. Fig. 10 illustrates this problem, using different colors to represent different geometry variation.

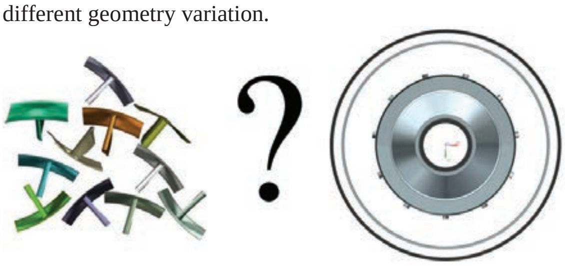

Fig. 10: A combinatorial explosion of T-section assembly

If the scope is limited to the assembly of one TRS, the problem becomes the following: What is the optimal configuration of eleven different parts, in order to minimize thermal stresses, and maximize fatigue life?

Because of axial symmetry of the loads, the orientation of the assembly is irrelevant. Hence, the problem can be reduced by locking one T-section in place, having that act as "ground", and positioning the other ten parts with respect to it. Even so, the problem suffers from a combinatory explosion. There are 10! = 3,628,800 different configurations of this one product. Analyzing everyone with a ten-minute simulation takes approximately seven years. In addition, a design variable, the vane-shroud blend, is included. As this variable can be set anywhere between 2.5mm and 10mm, the computational time grows by additional orders of magnitude.

4.5. Genetic Algorithm

To find the optimal configuration without millions of simulations, some optimization scheme is needed. Since the respective form error of each component is irregular, and consist of hundreds of measuring points for each part, using any regressive analysis is difficult. Instead, a genetic permutation algorithm is used, that also includes the discrete vane-shroud blend dimensions.

The simulation starts by generating 100 random samples. Although this is just a fraction of the 10! or 3628800 possible combinations, it gives some knowledge of how life and stress is distributed. From there on, it generates 50 new samples for each generation, using a mutation probability of 0.3 and a crossover probability of 0.4. The simulation ends after the result converges, which means that there are fifty samples within some epsilon of each other.

5. Results

Fig. 11 shows the results over 9 generations of genetic simulation. Note that on the first generations, only the 50 lowest results are shown. Already on the fourth generation, a minimum stress value of 349.5 MPa is recorded.

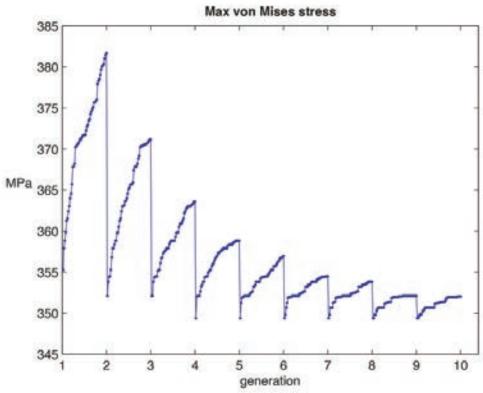

Fig. 11: MOGA iterations

Fig. 12 shows a scatterplot of all 500 design points. The maximal stress recorded is 462.3 MPa, a 32% increase over the optimal value. Within the first few generations, the algorithm converges on a blend value around 8 mm. In the vicinity of this value, stresses vary around 8%.

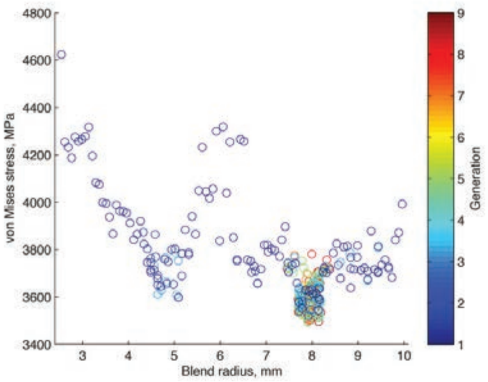

Fig. 12: Thermal stress as a function of blend radius

6. Conclusions

The method described in this paper shows how 3D scanned form error data can be transferred from a manufactured product to a different product in early stages of product development.

Although the measured variation in one product is not necessarily transferrable to a different product, as they will vary with geometry and manufacturing techniques, and material differences. However, the more similar the products, the more transferrable are variation data. However, as more products are manufactured and scan data becomes available for more geometries, a regressive model based on data from different geometries would provide a more reliable prediction for future products. This remains to be done.

Applying variations in geometry has an additional benefit. As digital representations such as FE meshes suffer for discretization and truncation errors, inflicting small variations in geometries and performing multiple simulations can be seen as a form of dithering, as it mitigates risk of computational error, and improves reliability of results.

The method for including form error data into parameterized CAD models enables new types of analyses. For instance, genetic algorithms can now be used for optimization when input parameters include both measurement data and design parameters. In the case study, the results shows that, although the stress effects of changing the design variable, which amounted to 32%, is larger than the 8% variation when keeping the design variable around 8mm, this is hardly an order of magnitude difference. This finding underlines the importance of considering form error when mapping out the design space in early design phases.

7. Acknowledgements

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