ROBUST AND RELIABLE FATIGUE DESIGN

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Abstract: While durability simulation methods allow improving nominal product design using virtual prototypes, uncertainty and variability in properties and manufacturing processes lead to large scatter in actual performances. Especially in fatigue the influence of the scatter in material, and manufacturing is important. Uncertainty must hence be incorporated in the durability simulation process to guarantee the robustness and reliability of the design. This paper presents application of both cases – material influence and manufacturing influence using applications from automotive and aerospace fields.

1 INTRODUCTION

Product designers worldwide are confronted with highly competitive though conflicting demands to deliver more complex products with increased quality in ever shorter development cycles. Refining and optimizing design performance with purely test-based approaches is no longer an option and numerical simulation methods are widely used to model, assess and improve the product design based on virtual prototypes. Functional performance attributes as durability can already be optimized before entering the expensive test phase.

The use of the Finite Element (FE) method is widely established for the virtual prototyping phase. A major issue is the presence of uncertainty and variability in the material and geometrical properties and manufacturing processes; their effect on the performance cannot be predicted from a single durability analysis. A traditional solution is to apply safety factors on the system parameters, but this typically leads to oversized, too heavy structures. A more promising approach is to include uncertainty in the mechanical simulation process, guaranteeing the robustness and reliability of the design.

2 UNCERTAINTY & VARIABILITY METHODS

2.1 Uncertainty and variability

In real-life structures, it is typically not possible to assign an exact value to all parameters. Oberkampf [1] distinguishes two classes of non-determinism in parameter values. Variability refers to the variation inherent to the physical system or the environment under consideration, while uncertainty is a potential deficiency in any phase or activity of the modelling process that is due to lack of knowledge. Note that other definitions may be agreed upon, but the above definitions are used throughout this paper.

2.2 Reliability analysis and Reliability based design optimization (RBDO)

After quantifying the variability of input parameters with statistical distributions, design criteria can be assigned and well-established Reliability Analysis [2] approaches can be applied to compute the system reliability and improve it with a reliability-based design optimization (RBDO) procedure. For practical purposes, reliability estimations are often expressed in multiples of the standard deviation Sigma: the larger the Sigma-value, the higher the system reliability. Nowadays, the Design for Six Sigma (DFSS) paradigm is often heard: this aims at creating highly reliable 6σ designs (i.e. with a very small failure probability in the order of 10^{-10}).

A more detailed description and discussion of the methodologies is given in [3]. This paper focuses on the feasibility to include RBDO in fatigue performance problems.

2.3 Uncertainty and variability in durability performance

In analysing the fatigue behaviour there are many sources of variability and uncertainty. Clearly there is variability in

- Geometry, from manufacturing
- Material quality
- Usage (loading)

In the analyses described in this paper, the geometry and material influences are considered. Further on it is assumed throughout the application cases that only variability is considered and that enough information is available about the scatter of the input variables. Clearly there are many more influencing factors from manufacturing like pre-stresses, that could be also taken into account. Especially the analysis of the loading situation is not considered in this paper. Here both the analysis of the external system loads, e.g. in the automotive industry how the car, bus, truck is used in different regions and the load transfer, e.g. the influence of hard point placement, bushing stiffness etc. are not considered even though they have substantial influence on the final durability behaviour.

3 KEY ENABLERS

3.1 Process Capturing

To align with modelling and solver standards, industrial processes for uncertainty-based design and multi-disciplinary design optimization are typically built on top of a (nominal) deterministic case, which must then be iterated numerous times to achieve the desired result.

3.2 Design Space Exploration

Design Of Experiments (DOE) [4] is a general approach to investigate complex correlations between input parameters and output response quantities. The experiments are set up in such a way that a maximum amount of information is obtained in a minimum amount of computation time. It is often combined with Response Surface Methodology (RSM) [5]: a meta-model of certain order is estimated from the experimental data, which yields insight in the functional relationship between the input parameters and the true response and output quantities.

3.3 Mesh Morphing and mesh-based design

Fully automated finite element meshers for complex structures (vehicles, aircraft, ...) have not yet become a reality. Therefore, when a new CAD design is realized, substantial manual operation is typically needed before an accurate CAE mesh is realized. After a design update, this refinement step is needed for each performance attribute. In the case that a vehicle is designed as design variant (or incremental improvement of a legacy vehicle model) one can apply mesh morphing [6] technique to shortcut the tedious CAD-to-CAE iteration.

A shape transformation is applied directly to the predecessor mesh, in order to re-shape the predecessor vehicle model according to new styling lines. Two approaches are distinguished: Free form and control based morphing. In this paper, the free form morphing approach is used, where the concept of control nodes, deformable nodes and fixed nodes is considered. Fixed nodes determine the boundary of the area of the deformable zone of the mesh. Deformable nodes correspond to the nodes that will be morphed. The actual displacement of the deformable nodes is determined by the displacement of the control nodes. To move the control nodes, several transformations can be applied including projection (to surfaces or lines), translation, rotation, alignment and scaling.

3.4 Multi-disciplinary design optimization

In the industrial design process, different attributes will sometimes have conflicting requirements. For example in vehicle design, pedestrian safety may call for a softer cowl top design, while a stiffer design is favourable to reduce the front windscreen vibrations. Therefore, final choices about body modifications have to be made in a multi-attribute context. A first step is to perform the optimization per attribute, and to exchange systematic information on the impact of all proposed changes at each design review. Engineers can then make design decisions based on design trade-offs.

Process Integration & Design Optimization (PIDO) tools like OPTIMUS [7] not only take care of the efficiency of the optimization process itself, but can also make optimal use of the available computer power by an efficient parallelization of all necessary calculation jobs and this in a fully automated way without any user interaction. This concerns the parallelization of jobs within a workflow (workflow-level parallelization) as well as the parallelization of individual experiments (method-level parallelization). These tools have to take into account not only the limitations about available CPUs and software licenses, but also interdependencies between different calculations as the output from one simulation very often serves as input for the next one.

4 EXAMPLES AND APPLICATIONS

4.1 Vehicle Knuckle Durability Analysis

To demonstrate the advantages of the probabilistic methodology applied to fatigue cases, a typical automotive analysis case is considered. The vehicle lifetime is highly determined by the fatigue life of its components; in turn, variability in material properties may affect the fatigue life. This is demonstrated for the vehicle knuckle structure FE model [9, 10], which is shown in Figure 1. The structure is made of grey cast iron, and has material and geometrical variability.

The fatigue analysis uses some fatigue material data. The strain-life approach has been used for the analysis to be more independent from the actual geometry. As input for the strain-life approach, a strain-life curve and a cyclic stress-strain curve is needed. Since the parameters of these curves are highly correlated, the formula from uniform material laws [11] has been selected. In this case we can directly work with easier to assess data (Young's modulus and tensile strength). The variability of these "basic" material data is shown in Table I.

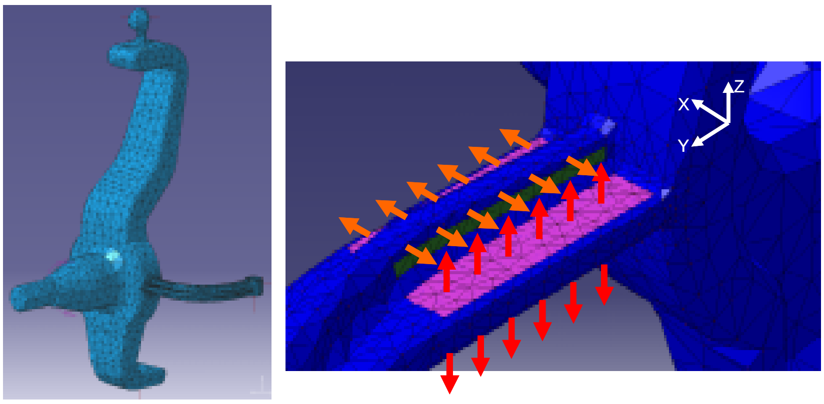


Figure 1 – Vehicle Knuckle FE model, with detail on mesh morphing parameters on the arm.

The geometrical variability has been taken into account by using a mesh morphing technology (see Section 3.3). In this case, mesh morphing is used to make a transformation of the mesh, i.e. to turn the nominal mesh into a morphed mesh that corresponds with different geometric input parameters. The morphed mesh can better represent the actual product sample, without the necessity of re-meshing from the CAD geometry.

Table I – Material and geometrical variability for the vehicle knuckle.

Property	Distribution	Mean	Standard deviation
Young's Modulus	normal	$1.8 \cdot 10^5$ MPa	$1.8 \cdot 10^4$ MPa
Tensile Strength	normal	245 MPa	24.5 MPa
Arm Morph X	Normal	0.5mm	0.06mm
Arm Morph Z	Normal	0.5mm	0.06mm

For this vehicle knuckle, a simple but typical fatigue analysis case has been applied. The loads applied on the structure (wheel loads, steering loads and upper/lower chassis connection loads [9]) have been obtained from a multi-body simulation of a quarter suspension. The load event consists of driving through a pothole.

All these contributions have been simulated over a time period of 630 sample points and then applied on the different interface points of the knuckle. Subsequently the fatigue effect of the cyclic application of the load histories has been evaluated ([9]). In the analysis case in this paper, the fatigue performance measure of interest is the Maximum Damage sustained by the structure. For the nominal model (at the mean parameter values given in Table I), the maximum damage is equal to -1.5 (in $\log_{10}$ scale).

In this sample we assume that the target for this misuse case would be 10 times running through this scenario. As we analyse the $\log_{10}$ value of the maximum damage the failure criterion of -1 is defined.

With respect to the selected failure criterion, the nominal design is a safe design; the aim is now to attain a six-sigma design with a reliability index of $\beta = 6$ (i.e. a very small failure probability in the order of 10^{-10}). For this purpose, a Design-of-Experiments approach (see Section 3.2) has been used to alleviate the computational effort required for each fatigue life evaluation. More specifically, 3 DOE plans have been used (Box-Behnken, Latin Hypercube and Central Composite Inscribed) to explore the maximum damage response in the design space in the input range $[-6\sigma; +6\sigma]$ for each input parameter. From the results, a least squares quadratic Taylor Response Surface (RS) model has been computed, which is shown in Figure 2.

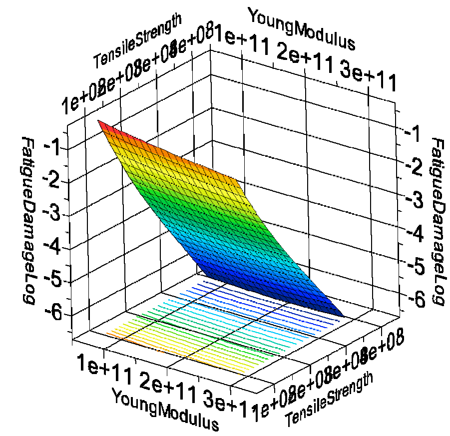


Figure 2 – Response surface of the Maximum Fatigue Damage ($\log_{10}$ scale) as a function of the Elastic modulus and Tensile Strength.

The accuracy and prediction quality of this model have been assessed; it has been shown that the error is negligible for this particular case. Therefore, with sufficient confidence, this model can be used as meta-model to assess the functional performance and the model reliability.

The small-sized response model has first been used to assess the reliability of the nominal design. Table II shows a summary of reliability analysis results. The methods differ in efficiency, but all confirm that the nominal model has a reliability index of $\beta = 5.37$, which is not sufficiently reliable in design-for-six-sigma terms.

Table II – Reliability Analysis results for the nominal Vehicle Knuckle.

Reliability Analysis	Number of Samples	Beta Index	Prob. of Failure
FORM	29	5.37	3.937·10-8
FORM + Importance Sampling	529	5.36	4.161·10-8
Line Sampling	604	5.37	3.937·10-8

As a next step, a reliability-based design optimization (see Section 2.2) case has been worked out with the aim to increase the fatigue life in the presence of the input variability. The RBDO process uses a Performance Measure Approach (PMA) methodology [12]. Design variables in this optimization process are the mean values of the material parameters and the geometrical mesh morphing parameters of the arm; the standard deviations are kept constant (same values as shown in Table I). This means that an improved material design is sought for the given variability in the material definition and geometrical parameters, in order to reduce the probability that the maximum damage exceeds its limit value. A gradient-based optimization algorithm (namely SQP) has been used in the optimization; it required 10 iterations to converge to an optimized design in terms of reliability. Figure 3 shows the key result of the RBDO analysis: the initial design (with mean material variables as given in Table I, and a reliability of $\beta = 5.3$) has been improved into a design with a sufficient reliability of $\beta = 6$.

This RBDO procedure only required a CPU time of 26s as it has been based on the small-sized Response Surface model. In the paper [9], the result has been verified with a FORM analysis on the optimized design, based on FE calculations. This confirmed the results (however at a CPU cost of about 22 hours). In this way, one can use reliability and RBDO methods to assess and then improve the durability performance of a vehicle component model. The presented procedures are generally applicable and not limited to a specific performance attribute or engineering field. To underline this, another application case from aerospace industry is presented in the next section.

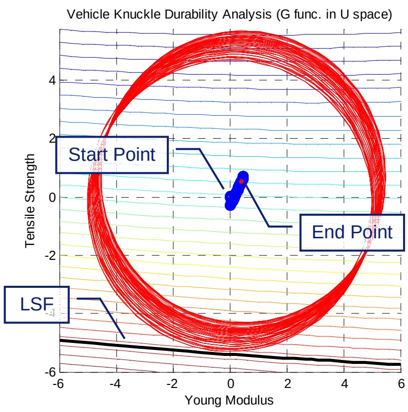
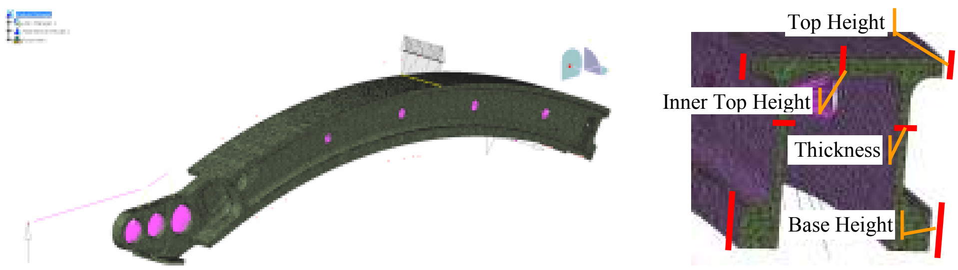


Figure 3 – Using RBDO, an optimized vehicle knuckle design has been found, which has a reliability index of $\beta = 6$.

4.2 Slat Track durability and reliability

As second application, the probabilistic methodology has been applied to a fatigue life simulation of a slat track. The FE core model (see Figure 4a) consists of 236630 tetrahedral elements; beam elements have been added to correctly represent the rack in the inner section of the slat track profile and to model the rod-leading edge assembly, connected by ball bearings. The slat track is made of a 18% nickel-cobalt-molybdenum maraging steel, which has an ultimate tensile strength equal to 1800 MPa and a Young's Modulus of 240000 MPa. For the slat track, 4 independent geometric parameters have been selected for the probabilistic characterization (see 4b).



(a) (b)

Figure 4 – Slat Track FE model with loads and constraints (a) and uncertain parameters (b)

The interesting fact on this example is that measurements are available on both sides of the slat track for all the four parameters during the manufacturing process for all slat tracks manufactured. Particularly, the difference between the nominal (design) value and the real value has been considered. This data set has been used to statistically model the input parameters with random variables, in agreement with what observed from the measurements; refer to the overview in Table III.

Table III – Statistical characterization of the input parameters, based on measured data.

Variable	Design Value	Distribution	Mean of difference from nominal	Standard Deviation of difference from nominal
Base Height	Undisclosed	Normal	0.15181 mm	0.05918 mm
Thickness	Undisclosed	Normal	0.14722 mm	0.04942 mm
Top Height	Undisclosed	Normal	0.02503 mm	0.07012 mm
Inner Top Height	Undisclosed	Normal	0.10272 mm	0.06084 mm

In addition, a check on the statistical correlation of the design parameters has been carried out using the data acquired during the manufacturing process. This check needs to be performed in order to avoid that a possible assumption of statistical independency affects the simulation results. Thus, the estimation $\hat{\rho}_{XY}$ of the linear correlation coefficient ρ_{XY} has been carried out for the input parameters considered in this case. The coefficients are reported in Table IV.

Table IV: Statistical correlation between the input parameters, based on measured data

	Base Height	Thickness	Top Height	Inner Top Height
Base Height	1	0.0944	-0.4679	-0.1123
Thickness	0.0944	1	-0.1774	0.0563
Top Height	-0.4679	-0.1774	1	0.1694
Inner Top Height	-0.1123	0.0563	0.1694	1

The fatigue analysis of the slat track requires the integration of different procedures. In fact, the slat track mesh first needs to be modified to reflect the new input parameter configuration and then analyzed with unit loads using an FE solver. As in the previous example, mesh morphing technology (see Section 3.3) has been used to make a transformation of the mesh. The results of the structural analysis are then used for the durability simulation. The outcome of the fatigue analysis, in terms of safety factor, can finally be used as the performance function for the slat track. The safety factor is always defined as the factor that can be applied to the loads in order to reach the endurance limit with respect to the amplitude of the largest stress cycle.

For the slat track, in-flight measured data has been used for the fatigue analysis [13]. An aircraft has been instrumented as for the normal qualification test campaign, where a number of different measurements were acquired in a wide variety of flight conditions. From this large database, a subset of measuring channels has been selected to retrieve the measurements of interest for the fatigue assessment on the slat-track in the worst case condition. This represents a reliable base for the fatigue life prediction. Extensive load data analysis has been used to create a damage equivalent uni-axial loading.

Since the computational effort for the whole process can still be considerable, a Design of Experiments (DOE) [4] approach has been selected to limit the required calculation time. A Latin Hypercube DOE in the range of $[-15\sigma; +15\sigma]$ has been used to compute the performance of the structure in 80 points. Subsequently, a least squares second order Response Surface [5] with interaction terms has been created to approximate and predict the response of the structure without requiring a full analysis. Also for this case, the quality of the RS model has been verified and the error is negligible. The meta-model can thus be used to assess the functional performance and the model reliability.

The choice of the performance function *G* for the reliability analysis and optimization is related to the desired Safety Factor minimum. For the slat track, a Safety Factor minimum value of 2.5 has been selected. The performance function *G* can thus be written as

$$G = SafetyFactor - 2.5 > 0 \quad (1)$$

With this selection, the *G* function is positive where the Safety Factor is larger than 2.5. The threshold value of 2.5 for the Safety Factor has been selected because it is close to the minimum value observed on the response surface model, within the range of validity of the RS. In the case of a wider sampling interval for the DOE, the threshold for the Safety Factor can be further improved. The results of the reliability analysis are shown in Figure 5 and reported in Table V. The initial reliability index β equals 14.398. This design is likely conservative (as β is larger than 6σ), so that potentially weight can be saved.

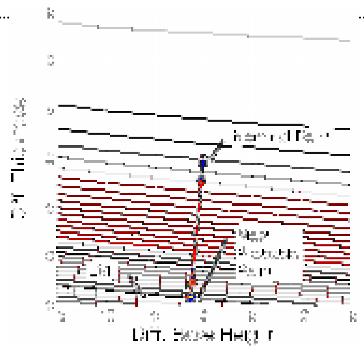


Figure 5 – Reliability Analysis results for the slat track – Location of the MPP in the standard normal space.

Table V – Location of the Most Probable Point in the standard normal space (σ -coordinate).

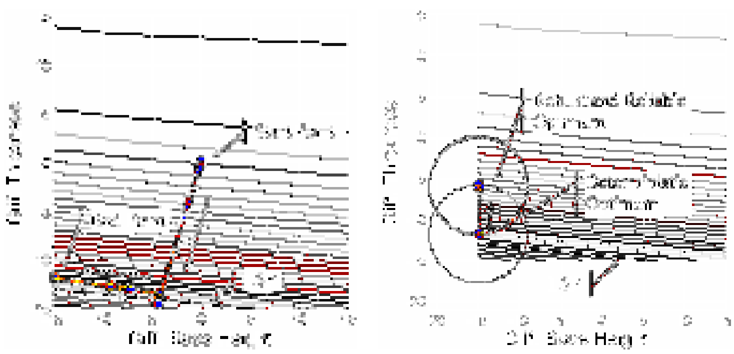
Base Height	Thickness	Top Height	Inner Top Height
-1.3586 σ	-14.324 σ	-0.3000 σ	-0.4330 σ
0.0714mm	-0.5639mm	0.1856mm	0.0250mm

Based on the results of the reliability analysis, a deterministic optimization and a RBDO process can be carried out. The target of the optimization is to reduce the total mass, while keeping a distance of 6σ from the region of the event space where the Safety Factor has a value equal or smaller than 2.5. This means that the newly found design will have a probability of $9.86{\cdot}10^{-10}$ to violate the performance function requirement in Eq. (1), given the scatter in the input parameters. The results of the optimization are reported in Table and are shown in Figure 6a for the deterministic optimization and Figure 6b for the RBDO part.

The design found with the RBDO (placed at 6σ) shows a mass reduction of nearly 8% w.r.t. the nominal design. This mass reduction constitutes the main result of the optimization and is particularly significant when one considers the very small standard deviations observed in the measured tolerance data.

Table VI – Results of the deterministic and reliability-based optimization procedures.

	Base Height	Thickness	Top Height	Inner Top Height	Total Mass
Initial Configuration	0.151813mm	0.147218mm	0.025027mm	0.102719mm	3.9327 kg
Deterministic Optimum	-0.735908mm	-0.504368mm	-1.026730mm	-0.809875mm	3.5446 kg
RBDO Optimum	-0.735908mm	-0.207602mm	-1.02673mm	-0.809875mm	3.6236 kg



(a) (b)

Figure 6 – Deterministic Optimization (a) and RBDO results (b) for the slat track, visualized in standard normal space.

5 CONCLUSIONS

Variability is an important issue in the physical design environment, and it clearly manifests itself in the experimental testing process. Incorporating the non-determinism (in the manufacturing process, design specification ...) into the modelling process is thus necessary to understand all the physical phenomena. A number of CAE application cases have been presented to underline the benefits and feasibility of the new reliability-based design paradigm in automotive and aerospace industry. Reliability-Based Design Optimization methods have been used to improve the durability performance of a vehicle knuckle in the presence of material variability and of a slat track component with geometrical variability

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