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Robust lightweight design and digital twins considering manufacturing quality variation and sustainability requirements

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Summary In this paper, robustness optimization of a fatigue-critical welded structure with measured misalignments and a generic robust design procedure are presented. The motivation for considering uncertainties, robustness and multi-criteria decision making in engineering design comes from the increasing sustainability requirements. Lightweight design of vehicles can reduce CO_2 emissions and increase energy and material efficiency, but often the fatigue of welds limits the weight reduction. The manufacturing quality affects the fatigue strength of welds, and by quantifying the manufacturing quality and using robust design methodology the increasing sustainability requirements can be met, while also considering the technical and economical constraints. The surrogate model representing the relationship between the actual, measured geometry and the fatigue life can be used as the digital twin during operation.

Key words: digital twin, quality, metrology, optimization, uncertainty quantification, reliability, robust design, fatigue, sustainability

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Introduction

The climate change induced green transition motivates to consider the sustainability requirements in engineering design, such as energy and material efficiency, and the reduction of CO_2 emissions. For example, reducing the structural mass of a vehicle increases the energy and material efficiency in production and reduces the CO_2 emissions, but tends also to increase the stress levels in the vehicle structure. Therefore, the fatigue strength of welds often becomes the limiting factor in the lightweight design. The variations in manufacturing quality significantly affect the fatigue strength of welds. The increasing complexity of products and supplier chains and the growing use of recycled

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and biobased materials increase the variation and uncertainty of the design data. Thus, the uncertainty and interactions of various factors need to be handled in engineering design.

The traditional approaches such as design for X in design [12], and Six Sigma [10] in manufacturing quality management consider typically the various factors independently. Anyhow, the interactions between the various factors are not considered, and the factors are not directly related to the performance of the end-product. Sequential and partial design approaches lead to designs which are often less than optimal, as each engineering team sets their safety factors independently from others. Thus, each sequential design task narrows down the design space. In addition, the life cycle and sustainability assessments are typically done after the product development is completed. The life cycle and sustainability metrics should be predicted already in the concept design phase: the designed product should also fulfill the sustainability requirements. As the design problems are becoming increasingly complex, multi-criteria decision making should be used. Optimization is a systematic approach for handling multiple and often conflicting design criteria, requirements, and constraints. The sustainability metrics and requirements can be treated as constraints in the optimization [6] and the product reliability [16] can be evaluated instead of using the traditional safety factors. The multi-objective and reliability-based optimization methods are used increasingly, as for example in [1] and in [11]. They enable better development of competitive products that fulfill the performance and sustainability requirements at controlled operational reliability. In general, the increasing amount of available measured data, modern simulation software, and efficient computers enable the use of reliability-based approaches in engineering design.

Unlike the traditional approaches, model-based design enables the assessment of the relationships between the design parameters and the product performance as well as evaluating the interactions between the various factors. By using the reliability-based approach, instead of the various safety factors, the reliability is evaluated directly.

In this study, reliability-based design optimization (RBDO), i.e., robustness optimization, is used for the weight minimization of a welded steel structure. The robustness optimization is demonstrated using the mock-up structure. A generic robust design procedure for considering the effect of the manufacturing quality on the product reliability and the sustainability requirements is presented. Additionally, the concept of the surrogate models as digital twins is discussed.

Design of the mock-up structure

In this work, the manufacturing quality was quantified by manufacturing and measuring a series of mock-up structures. In general, mock-up structures with carefully planned geometric features and quality specification can be used early in the design cycle to quantify the deviations and defects, and to carry out weldability and fatigue tests to validate the computational model of the relationship between deviations/defects and performance measures such as fatigue life. The parametric models validated with mock-ups can then be used in the design and analysis of the actual components and structures. The weld connection models can be re-used in various implementations.

The mock-up structure was designed to represent the welded connections and geometric features of a structural detail of an industrial target structure. The mock-up structure used in the finite element analyses (FEA) is a symmetric component, which enables to use similar loading conditions as in fatigue tests. The mock-up structure used in manufacturing is unsymmetric to fit the manufactured pieces on standard pallets for transportation. The geometric features referring to fatigue test are hidden in the manufactured mock-up design to ensure normal workshop quality.

Dimensional measurements

The mock-up structures were measured using a tactile Mitutoyo Legex coordinate measuring machine (CMM) in the metrology laboratory of VTT. The CMM has very good accuracy and the $E_{0,\text{ MPE}}$ value (Maximum Permissible Error) of the CMM is (0.35 + L/1000) µm, where L is measured length in mm. Verification is done with interferometrically calibrated gauge blocks on a regular basis and by using international comparison measurements [15]. Thus, it is ensured that the measured data is reliable and can be used as reference. The purpose was to measure the misalignments to get data for FEA to evaluate effects of the misalignments on the fatigue life of the structure. The accuracy of measured data is critical and affects the reliability of fatigue life predicted by FEA. The International Institute of Welding (IIW) fatigue classes address the effect of misalignment of 5–15% of plate thickness, depending on the connection type. To get adequate data for FEA and fatigue analysis, the measurement uncertainty should be consistent with the IIW recommendations.

The dimensional parameters having the highest contribution to fatigue were defined by tolerances. As an example, the mock-up structure design, a manufactured mock-up structure and a part of the measurement plan are shown in Figure 1.

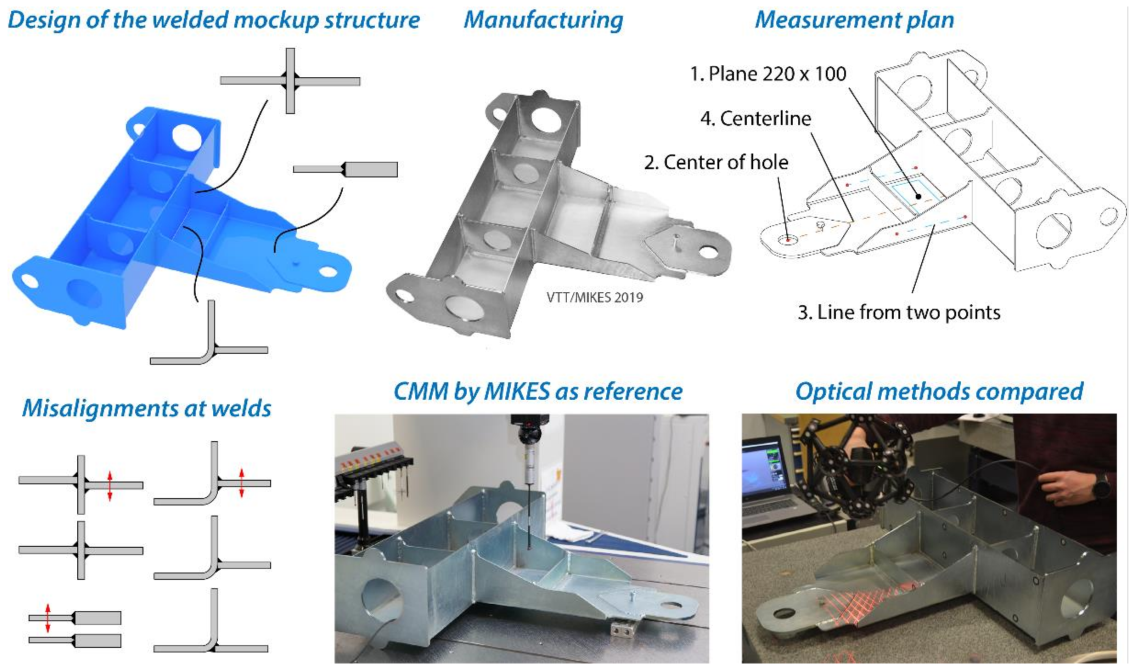


Figure 1. To study the effect of misalignments, mock-ups were designed, manufactured and measured using optical instruments. Reference measurements were made using a tactile CMM.

In industrial applications welded structures would be measured with semi-portable optical scanners rather than with tactile CMMs. Anyhow, a high accuracy CMM was used to get reference data to be used in a comparison for optical scanners. In total, a comparison study for accuracy with five optical scanners was done as a part of the study. Typically, optical scanners have measurement uncertainties in range 0.030 mm to 0.5 mm for a measurement volume of about 1 m^3. According to the performed comparison study the accuracies of the tested optical scanners were better than 0.1 mm. Thus, the comparison results indicate that the proposed measurement procedures would be suitable also in industrial applications.

Two ten-piece series of the mock-up structures were manufactured by two welding shops at quality specified according to EN ISO 3834-2 [13]. The dimensions of the mock-ups were measured, and statistical distributions were formed from the measured dimensions which were then used as input for the robustness optimization. The statistical distributions of the measured misalignments of the welds are presented in Figure 2. The two manufacturers appear as two different populations of misalignments typically in the order of 6 mm to 7 mm for one workshop and of 1 mm to 2 mm for the other (see Figure 2).

Nondestructive testing (NDT) was not done in this study, but a typical, expected range of values was used for the variation/uncertainty related to the unfused root length by ultrasonic test (UT) [5]. The uncertainty of unfused root length was defined using a Probability Of Detection (POD) curve as input for the robustness optimization. In general, NDT, Röntgen tomography, component and material tests, and inspection data can be used for the digital twin[2] models of the individual components in the manufactured series and predict their performance in the end-product assembly.

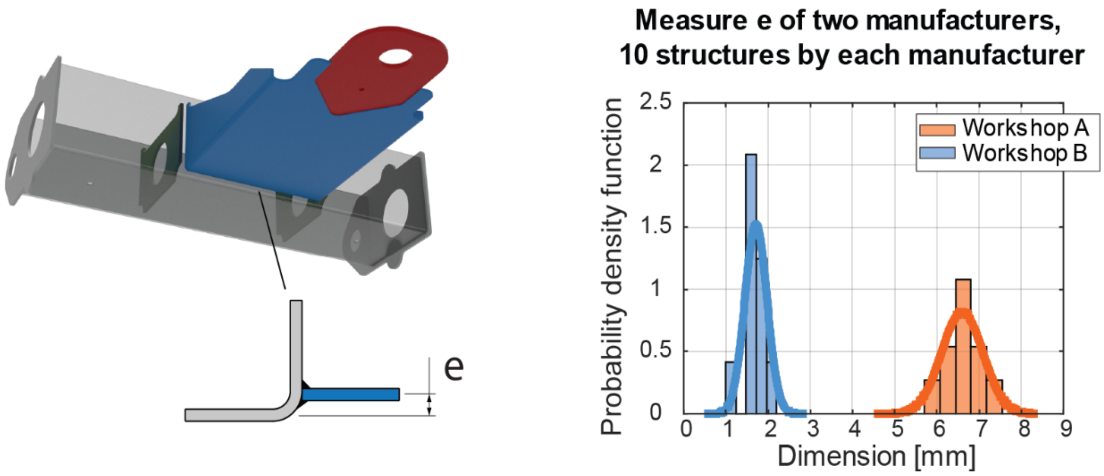


Figure 2. Two ten-piece series of mock-up structures were purchased from two welding shops at specified quality and their dimensions were measured. The difference between the two populations is due to different interpretations of the specifications in the technical drawing (epistemic uncertainty). In this work we focused on the random (aleatory) type of uncertainties.

[2] https://www.digitaltwinconsortium.org/glossary/glossary/#digital-twin

The robustness optimization of the welded structure

The robustness optimization, or RBDO, is typically a sequential optimization run using Monte Carlo simulation after a deterministic design optimization (DDO) run. The robustness optimization with two design parameters is illustrated in Figure 3.

Surrogate modelling is used for efficient calculus of the large number of sampling points generated in the Monte Carlo simulation. In this work the surrogate modelling was done by Kriging based procedure in the RAMDO software[3]. In robustness optimization the design parameters are assigned distributions that describe the variation and uncertainty of the design parameters. Parametric modelling of the system is used with Monte Carlo simulation to determine the variations in the input and output parameters. The reliability of the performance measures can then be determined by comparing the output distributions to the constraints.

The parametric surrogate model prepared during the design process and used in the robustness optimization covers the expected variation in quality and loading conditions. The surrogate model is also well suited for fast calculus of fatigue lives. The parametric surrogate model can therefore be used in the operation phase as a digital twin for monitoring the remaining useful life (RUL) of the fatigue critical welds at actual, measured misalignments and other measured deviations and defects. In this work, the digital twins of each manufactured mock-up structure were generated using the parametric model and the measured misalignments.

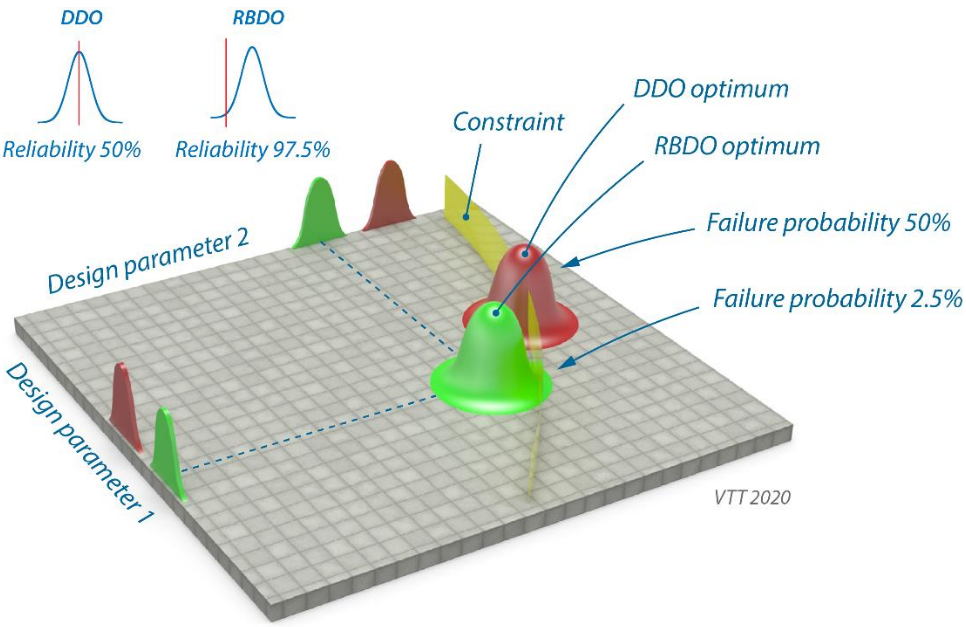


Figure 3. Illustration of the robustness optimization with two design parameters. The DDO is run first, and RBDO continues from the deterministic optimum with Monte Carlo simulation, to find the optimum considering the variation of design parameters and the target reliability.

[3] https://ramdosolutions.com/

In general, the digital twins can be used in the robust design procedure for model-based design and treating the variation and uncertainty along the product development phases. In addition, the models can be verified and validated based on measured data. The digital twin concept is further discussed e.g., in references [9] and [14].

Fatigue analysis methods

Hierarchical modelling is used in the fatigue analysis. It enables the selection of suitable accuracy in comparison to the modelling effort and according to the implementation. Fast and simplified methods can be used in the early concept design phases while more accurate methods are used in subsequent implementation phases with the gained design information.

The effective notch stress (ENS) method was used here in the early design phase for the parametric studies. The optimization of the weld dimensions and the weld quality parameters were investigated also with the ENS. Linear elastic fracture mechanics (LEFM) can be used for predicting the crack lengths during monitoring, and for decision of inspection intervals.

As the calculus of the fatigue life is one step in the analysis chain of the surrogate modelling, both methods are applicable for the surrogate modelling and either method can be used according to the case specific needs.

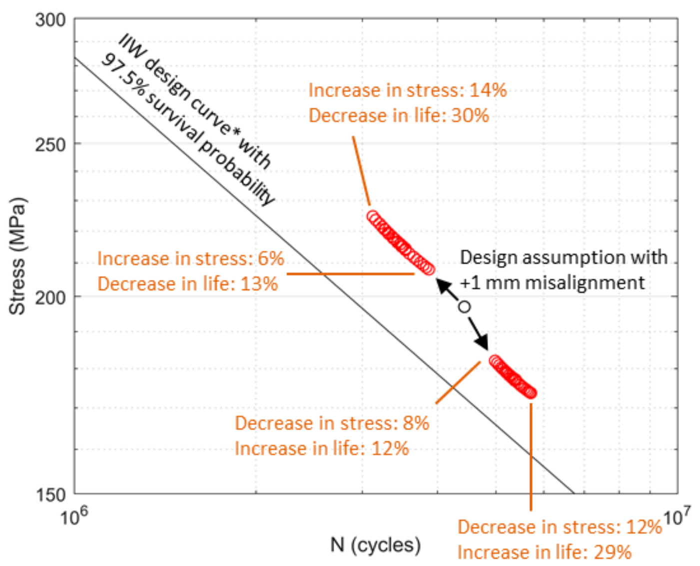
Calculation of fatigue crack growth life with assumed initial crack size

LEFM was used to estimate the fatigue crack growth life of the structural detail with varying level of misalignment and varying weld characteristics. The result is an estimation of variation in fatigue life in relation to the manufacturing quality. In this study, by manufacturing quality is referred to the deviations in the weld angle and size and in the misalignment.

The LEFM-calculation is based on the work of Goyal and Glinka [7] and done according to the IIW recommendations [8] [15][15][15]for welded joints. The assumed initial crack size a was 0.05 mm. The crack size was not varied and there was no information on the actual initial defects, such as inclusions or porosity, in the specimens. The 0.05 mm initial crack size was considered to represent normal welding quality with initial defects, in which case, the fatigue crack initiation life can be ignored.

The crack growth path and the stress distributions along it were determined using the parametric FE-model. Both the stress distributions and the crack growth paths varied depending on the misalignment, and the weld size and angle. The misalignments were measured from the mock-up specimens, whereas the weld sizes were assumed. Both were varied artificially in the ENS-analysis.

Figure 4 shows how the variation in local geometry impacts the fatigue life. The black curve shows the IIW design curve for the detail with 97.5% survival probability. The black circle gives the fatigue life for the detail with assumed 1 mm misalignment. The red circles represent the fatigue life with 2 mm misalignment and varying weld angle and size (see Figure 4 for definitions). In both groups (of red circles), the fatigue life increases with increasing weld size. For the lower group, with an increase in fatigue life up to 29%, the weld angle is 15 degrees. For the upper group, with a decrease in the fatigue life up to 30%, the weld angle is 30 degrees.



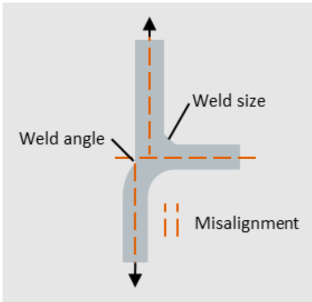


Figure 4. Effect of misalignment and notch or weld angle on stress and fatigue life.

Demonstration of the robustness optimization workflow

The FE-modeling techniques are presented in Figure 5:

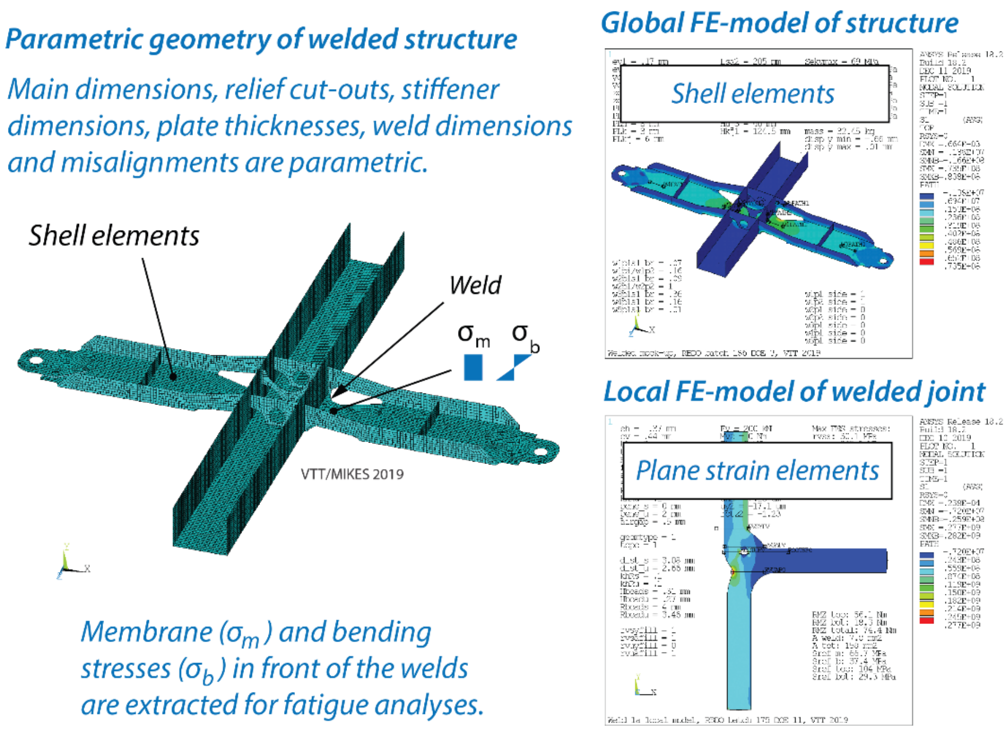


Figure 5. The robustness optimization uses sequential and hierarchical FEA of global and local models. The global structure and the local weld models are linked together using the bending and membrane stresses in the vicinity of the weld.

A parametric FE-model was prepared using Ansys Parametric Design Language (APDL) macros. The coarse linear shell element mesh was used in the FE-model of the structure, and the dense plane strain element mesh for the welded details in separate models. The global structure and local weld models were linked together using the bending and membrane stresses in the vicinity of the weld.

The main steps of the robustness optimization are presented in Figure 6. In Figure 6, first the input distributions are defined based on the measurements or the estimated values, then the surrogate model is formed by using the parametric FEA. The uncertainty quantification (UQ) is usually studied before the optimization to help in the definition of the most important design parameters. Finally, the robustness optimization is run.

The RBDO-problem is formulated as follows:

Minimize the mass, while it is subjected to following constraints:

– fatigue life ≥ 5 million cycles, and target reliability of 95%,
– maximum stress ≤ the limit value,
– maximum displacement ≤ the limit value.

Use random parameters:

– misalignments in range ± 0.5 mm … ± 1.0 mm,
– lack of weld penetration (unfused root face length) in range 0 … 1.0 mm, defined as POD-curve.

Use random design (control) parameters:

– main dimensions, dimensions of features and details,
– plate thicknesses,
– minimum allowed transition angle at weld toe (weld quality class),
– weld throat thickness.

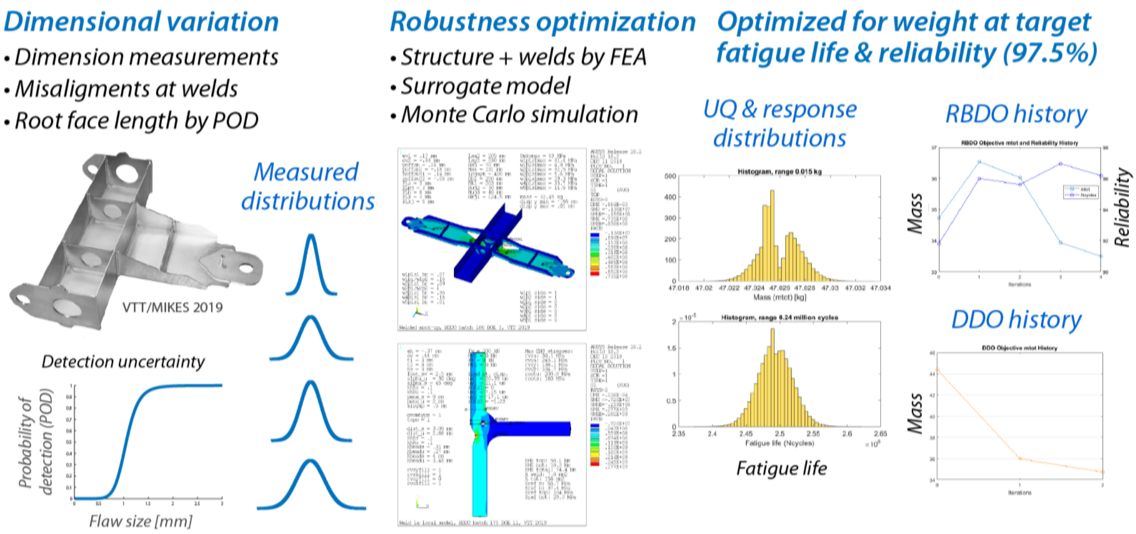


Figure 6. The main steps of the robustness optimization.

The optimization history of the welded mock-up structure is shown in Figure 7. The mass of the initial design, 44 kg, is reduced to 33 kg after the DDO, resulting to reliability of 55%. Then, after the RBDO-run, the optimum with a mass of 35 kg at 95% reliability is found. Comparison of the robustness optimization results with abrupt and smooth transitions at the outside weld toe is presented in Figure 8.

Limiting the constraint of transition angle to smooth values in optimization leads to a lighter structure. Controlling the local weld geometry serves as the control factor in the robustness optimization, and enables significant weight reduction in fatigue critical welded structures. In engineering practise limiting the constraint of transition angle equals to specification of a higher weld class at the weld.

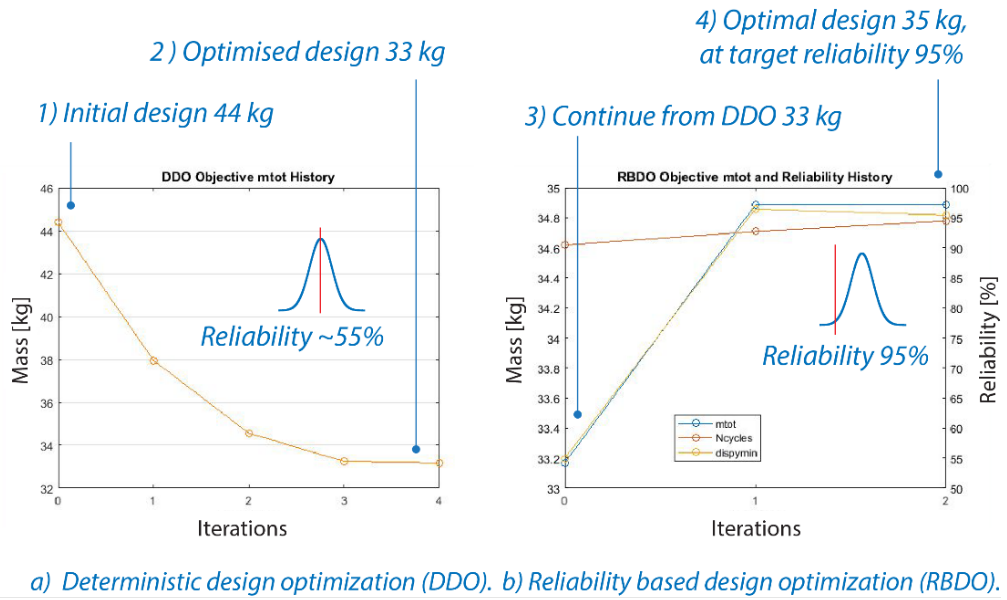


Figure 7. The optimization history of the welded mock-up structure.

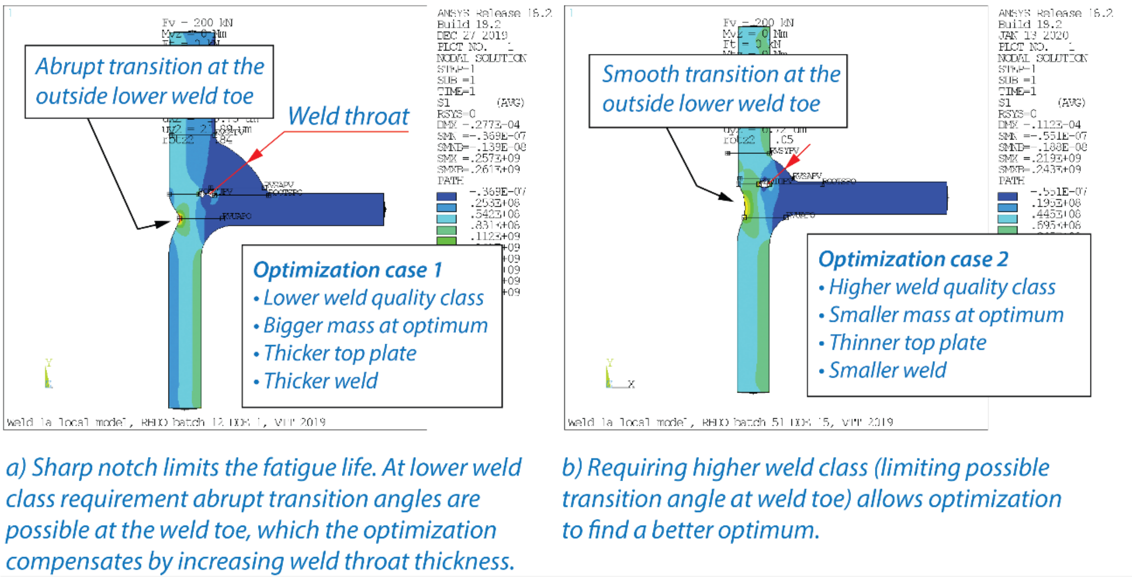


Figure 8. Comparison of the robustness optimization results with a) abrupt and b) smooth transitions at the outside weld toe.

The generic robust design process

After the workflow study of robustness optimization of the welded structure, the workflow was generalized as a robust design process, which is presented in Figure 9 and Figure 10. The robust design methodology is discussed for example in references [2], [3] and [4]. As the surrogate models are parametric and hierarchical, they can represent the behavior of the product being designed, be updated to match each phase of the implementation, and used to transfer the data between different phases and the engineering teams. Propagation of the simulation models enables the use of digital thread[4] in simulation and design. Thus, it enables the information flow between the engineering teams and towards the customer.

The robust design approach uses statistical distributions to represent the variation and uncertainty of the measured design parameters. The variation and uncertainty are compensated in the robust design approach by the control parameters, such as dimensions defining the component shape that affect the stresses of the component. In addition, the definition of the quality levels for the geometric features and defects can be used as the control parameters for welds, castings, and AM components. The robust design approach allows the definition of quality levels and thereby the allocation of high quality only where it is most needed. Thus, the approach allows to use lower quality at e.g., low risk locations. In practice, in-house quality classes can therefore be used.

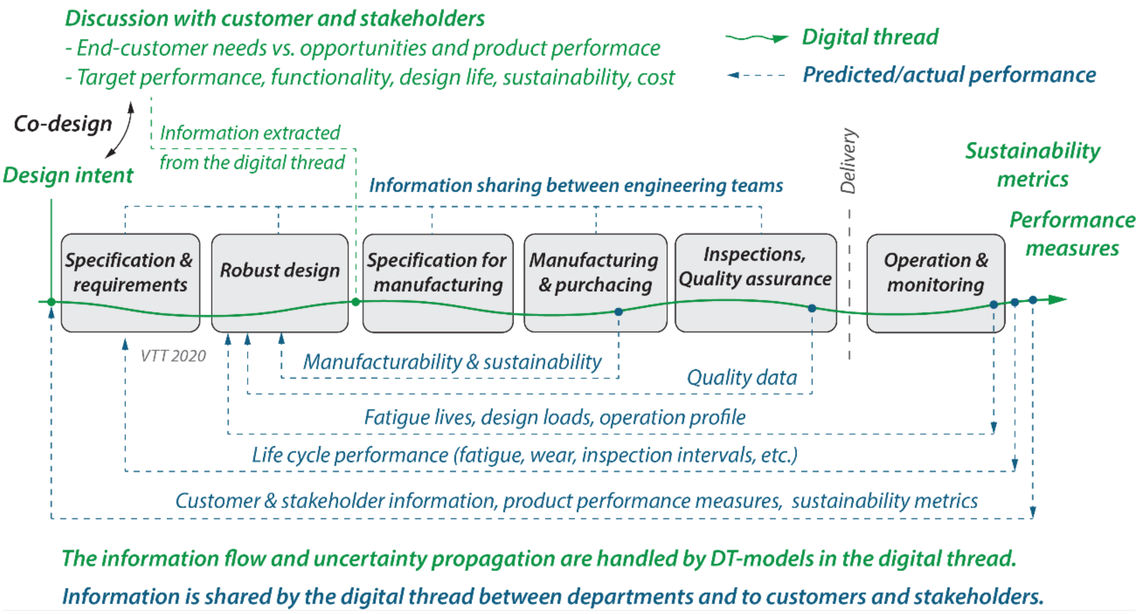


Figure 9. Illustration of the robust design process enabling performance-based design, as the product performance and constraints are predicted over the product life span considering the uncertainties. The engineering process generates information that the customers and stakeholders can use in their decision making.

The statistical distributions, POD curves, and geometric tolerances serve as interfaces between the engineering teams in the robust design process information flow. The

[4] https://www.digitaltwinconsortium.org/glossary/glossary/#digital-thread

statistical distributions of the measured geometrical deviations and the POD curves defining the inspection data are used as inputs in RBDO and UQ. The geometric tolerances are planned based on the quantified uncertainties and predicted effect of the uncertainties on the product performance. This leads to robust product that is insensitive to the quantified variation of manufacturing quality. The results of simulations using randomly generated misalignments will help designers to find more detailed tolerance specifications which are relevant for fatigue life. The manufacturing quality, design, and random parameters in structural optimization, and the dimensional measurements are planned, analyzed, evaluated, and defined using geometric tolerances and multi-criteria decision making considering the quantified uncertainties and the variation of manufacturing quality, and its effects on the product performance. The tolerances are used to pass the target quality information from design to manufacturing. The measured geometrical deviations and the analyzed distributions are fed back from manufacturing and quality assurance to design and model verification and validation (V&V). The model V&V can be based on component and mock-up tests in the design phase. By using the model and the UQ the tests can be planned to provide relevant data for decreasing the highest uncertainties affecting the key performance indicators (KPI) relevant to the product development. As the surrogate model is validated during the product development, the surrogate model can be used as the digital twin in the fatigue life monitoring during operation. The use of digital twin in the robust design process is illustrated in Figure 10.

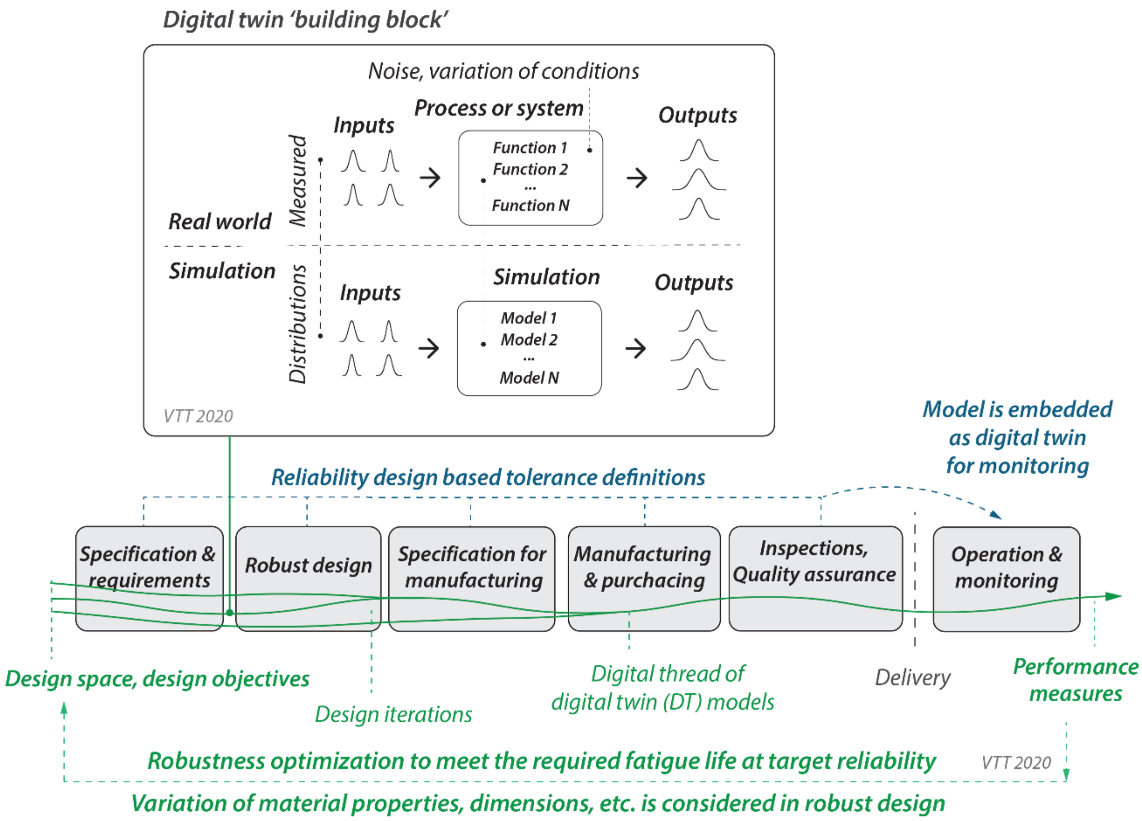


Figure 10. Illustration of the robust design process. The basic parametric digital twin block propagates through the project phases and collects the relevant data and information.

The product performance vs. variation of design parameters can be studied by RBDO using the various design, sustainability, etc. requirements as optimization constraints. The variability and uncertainty of the design parameters and factors contributing the most to the overall product performance can be determined by UQ. Condensed information of product performance vs. various scenarios can be extracted from the robust design process for customers and stakeholders for the basis of their decision making already in the concept design phase, enabling co-design in the product development projects. The robust design process provides predictions of complex interdisciplinary effects on performance, sustainability, and cost with reliability estimates, thus enabling multi-criteria decision making under uncertainty.

The monitored manufacturing quality data and the simulated loading events serve as the statistical design data in the robustness optimization. The actual, realized manufacturing quality and the configuration of each individual product can be used in the model-based monitoring of remaining fatigue life during operation. The individual load histories and models representing the deviations are the digital twins of the individual products of the fleet. The digital twin representation is used already in the design phase for evaluating the uncertainties and allocating additional tests and measurements to the factors with the highest contribution to the product performance, to decrease the uncertainty in a controlled way. As the RBDO uses Monte Carlo simulation and parametric surrogate modeling, the surrogate models representing the products with the measured manufacturing deviations can be used as the digital twins for fatigue life monitoring in the operation phase. The digital twin models will contain the manufacturing quality deviation information and they thus enable the prediction of the individual remaining fatigue lives of the individual products in the fleet with a high accuracy.

Discussion

The idea of tolerancing is to define the target manufacturing quality. In addition, the tolerances affect the manufacturing costs, and can be used as design parameters with model-based relationship to the end-product reliability. By measuring the part with either a tactile CMM or optical scanner it can be inspected how the actual misalignments compare with the tolerances. In addition, the effect of the measured dimensional variation on the end-product performance and reliability can be predicted by the reliability-based analysis using parametric surrogate modelling.

According to the performed comparison study the measurement uncertainties of the tested optical scanners were smaller than 0.1 mm which is satisfactory for the analysis presented in this paper. In general, UQ and reliability-based FEA can be used for determining the required measurement uncertainty to achieve the target reliability in predicted performance of the end-product.

The computational procedure presented in this paper enables the use of the relationships between the tolerance values and the performance measures of the end-product, such as the fatigue life. About 25% decrease in mass was achieved by robustness optimization of the example structure, and the required reliability of 95% was met for the fatigue life, while considering the measured variation in the manufacturing quality. The two RBDO-cases show that a lighter structure is achieved by using higher manufacturing quality (higher weld class), which agrees with the engineering judgement.

The optimization results are also in agreement with the engineering judgement: e.g., in the two optimization cases shown in Figure 8 the optimization compensates the stress concentration at weld toe by increasing the weld throat thickness. Also, after defining higher weld quality and thus limiting the local stress concentration, the optimization finds a better overall optimum.

Conclusions

Weld quality criteria and definitions can be linked to fatigue life in reliability-based design and optimization. The hierarchical FE-modelling of the structure and the welds, and the use of surrogate modelling allow efficient reliability-based design and optimization of fatigue critical welded structures.

The robustness optimization enables engineers to increase the energy efficiency and decreasing the CO_2 emissions of vehicles and to study the relationship between the manufacturing quality variation and the fatigue strength in lightweight design.

The dimensional measurement and inspection equipment suitable for a certain need, typically considered versus cost and effort, can be chosen based on the uncertainty quantification and the target reliability, and by using the model-based prediction of end-product performance. In this study the accuracies of the optical scanners were adequate for this purpose.

The digital twins of the fatigue critical welds can be created readily from the parametric models used in the model-based design and robustness optimization during the design phase, by using case specific measured data as the design parameter values. The digital twin can also be used for collecting and passing information between the engineering teams, and for continuous verification and validation of the models used in the model-based robust design process.

The variation and uncertainty can be compensated in design by using the reliability based, robust design methods. The resulting product is then said to be robust, or insensitive, to the expected variation and uncertainty. The variation and uncertainty need to be quantified, that requires either extensive measurements, tests, and prototypes, or combining the simulation-based data with measurements. With simulation-based approach the measurements, tests, mock-ups, and prototypes can be planned and designed to provide data. This will decrease the critical uncertainties and allows to allocate the resources where they are the most useful for achieving the required product performance at the target reliability within the target costs.

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