Robust optimization of a rudder hinge system taking into account uncertainty in Airframe parameters

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ABSTRACT

For a tier 1 supplier of aircraft components it is essential to develop components that can absorb changes in its requirements without having a negative influence on the supplier's profit margin. In order to achieve this, the effect of design changes needs to be investigated early in the design process. To realize this vision the design process must be highly automated and incorporate solution finding techniques such as Design Of Experiments (DOE's) and optimizations.
In this paper a framework is presented that estimates the weight and cost of an aircraft rudder hinge system. This framework has been researched and developed within the context of the H2020 AGILE project to support 3rd generation multidisciplinary design optimization teams .The process is fully automated and packaged in the Process Integration and Design Optimization (PIDO) tool Optimus. This packaging allows the generation of DOE data with which robustness analyses can be performed. The robustness analysis presented in this paper is the response of the rudder hinge system to a change in design loads. It is shown that the best design found in a deterministic approach, so looking at one design point only, is not the best design available from a robustness point of view. In this way the value of robustness analysis in the design process of aircraft components is demonstrated.

KEYWORDS *Multi-Level Optimization, Collaborative Design, Aircraft Rudder, Knowledge Based Engineering, Uncertainty Quantification*

NOMENCLATURE

CPACS – Common Parametric Aircraft Configuration Schema
DOE – Design of Experiments
FOSM – First Order Second Moment
HDOT – Hinge system Design and Optimisation Tool
KBE – Knowledge Based Engineering
MC – Monte Carlo
MDO – Multi-disciplinary Design Optimization
OEM – Original Equipment Manufacturer
OML – Outer Mould Line
PIDO – process integration and design optimization
RFP – Request For Proposal
UQ – uncertainty quantification
VTP – Vertical Tail Plane
UCA – User-customizable action
pdfs – probability density functions

1 INTRODUCTION

The Horizon 2020 project AGILE addresses Multi-Disciplinary Optimization (MDO) in the design process of an aircraft. Aircraft designs are often split into multiple lower level design processes often not conducted by the airframe manufacturer or Original Equipment Manufacturer (OEM) but by lower tier suppliers. Typically, the presence of multiple levels increases the level of uncertainty of the design process at the early phase before contract award. This uncertainty linked to design variables may have a significant effect on the final costs (and as a consequence, expected revenues) of a contract proposal. In this phase the aircraft definition is not fixed and the intellectual property of both supplier and OEM needs to be protected. Furthermore requirements are often only specified at the highest level.
In the phases before contract award the tier 1 supplier proposes a design concept which defines its profit margins for the whole aircraft program, which can often be as long as 25 years. It is therefore essential that his proposal is sound and provides a healthy profit margin. When the proposed design is based on uncertain design variables and requirements the risk of a sound profit margin not materializing are large. Therefore the impact of uncertainties in the design process on the design concept needs to be addressed.
When assessing the uncertainties in the design process the most important question that needs to be answered is if the design concept offered remains valid, in other words if the chosen solution remains within the design space provided by the changed requirements and design variables. To be able to answer this question quickly automated systems are needed. These systems can assess requirement changes without the need for manual rework.

Within the Agile project different use cases have been defined to further develop MDO techniques. One of these use cases is the use case of multi-level optimization. In this use case optimizations at lower levels, for example the tier 1 level, are coupled to optimizations at the complete aircraft level. By coupling the 2 optimizations the relations between the 2 optimization loops can be analysed.

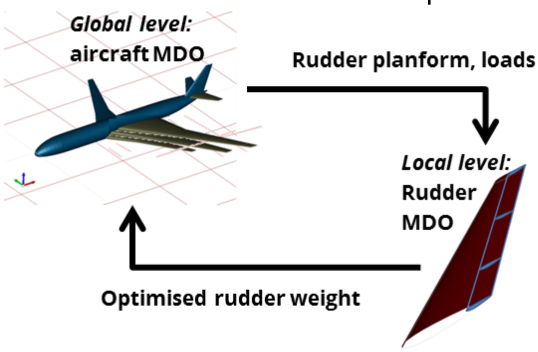

Figure 1 Global and local levels in aircraft and rudder design [1]

In this paper the application of robust design techniques to address uncertainty in the design process is presented. This paper focusses on the lower level analysis flow. Besides the application of robust design techniques the development of this lower level analysis flow is also discussed. Only limited results of the application of robust design techniques will be shown. However its impact and also the future work required will be made clear.

The paper is organized as follows:

- Section 2 focusses on the problem experienced in the design problem by tier 1 aircraft component suppliers plus proposed solution direction
- Section 3 discusses the theory of robust design techniques in MDO flows
- Section 4 addresses the multi-level flow set up developed within AGILE
- Section 5 details the implementation of the lower level analysis flow within Agile environment
- Section 6 describes the results of the lower level analysis flow
- Section 7 presents the main conclusions and discusses the impact on the design process of robustness analyses

2 PROBLEM DESCRIPTION AND SOLUTION DIRECTION

2.1 Tier 1 in design process

The development process of an aircraft component of a tier 1 supplier can be divided in the pre-contract phase and the post contract phase. The pre-contract phase has the objective to create a business case able to meet the customer requirements and provide a sound profit margin for the supplier. The post-contract phase has the objective to secure the business case in an environment in which requirements are changing and converge in time.
In the pre-contract phase the main challenge is to, based on the limited information provided and the limited lead-time given, choose the best concept design able to meet the (anticipated) requirements. As requirements will change and converge after contract award the main challenge is to choose a design concept with a robust response to these requirements without significant impact on the business case parameters, such as airworthiness, cost and weight (the overall business case is for now out of scope as financial engineering is the leading factor in this). A design concept not being able to absorb these changes in requirements will lead to a potentially uncontrolled design process with an uncertain result.

To obtain a robust design concept choice able to absorb requirement changes multiple concepts have to be traded and their responsiveness/robustness to requirement changes have to be checked. However available time is limited as the lead time between Request For Proposal (RFP) and final proposal is limited. Furthermore OEM input is limited and most importantly in the current design process the tasks and analyses to be performed have a high manual labour content and are mono-disciplinary oriented. As a result of this only a few design points can be examined to a limited extent.

A solution to overcome this is found in shifting large part of the process upfront by creating a database of standardized product solutions, which can be instantiated by means of a highly automated design system. The behaviour and applicable design spaces of these standard solutions can be explored upfront and in such a way deduce the driving requirements and design parameters as well as their sensitivities to changes of these. By the time the OEM submits a RFP the optimal design concept can be deduced much faster and with far less effort. This is called the frontloaded design process. Front loading was described by Thomke[2] as "a strategy that seeks to increase development performance by shifting the identification and solving of design problems to earlier phases of a product development process".

Fokker, as a tier 1 supplier, proposes to take the problem identification and problem solving even further forward by using front loading. This means developing engineering knowledge before the earliest phases, i.e. before the actual design process starts. This is achieved by capturing product knowledge from earlier projects, and re-use and standardize this engineering knowledge and design process to rapidly evaluate many design variants covering different requirements sets. With the front loading principle, improved overall maturity, compliancy, change integration and controllability is achieved. This is described in detail by van den Berg[3].

The process can be summarized as follows. The objective of the frontloading process is to fill the database with standard solutions. This includes: design definition, knowledge rules, tools, applicable design spaces and behaviour. The process begins with declaring a design solution as a standard solution. Based on this the associated knowledge rules are formalized. The knowledge rules are represented in automation tools. First a toolset containing the full set of parameters is created. These tools are linked using a Process Integration and Design Optimization (PIDO) tool into a multi-disciplinary workflow. With this PIDO workflow Design Of Experiments (DOE's) are run to acquire knowledge about parameters/requirements etc. that drive the main business case objective being airworthiness/weight/cost. Based on this knowledge higher level tools are/can be created e.g. design curves/surrogate models best suited for application in MDO (pre-contract phase). With these tools design spaces are explored, which provide the boundaries of applicability of a standard solution with respect to a given bill of requirements (space) and its response (bill of features). Based on the foreseen business development trigger this will show if the set of standard solutions in the database is sufficient, if not this will trigger the required creation of a new standard solution.

The solution approach as developed in AGILE links tools from OEM and lower tier suppliers. This solves potential inconsistencies in data transfer and provides the possibility to link the design drivers through the different levels. As such this framework has the ability to perform the studies as discussed above; this AGILE framework is discussed further in chapter 4

2.2 Uncertainty in design process

The described frontloaded design process has 2 major constituents; one based on standardized product solutions based on a design system of linked multi-disciplinary tools/services in a workflow, second performing design space exploration and design point optimization including robustness analysis. The first one is not dealt with in this paper, projects like ITEA2 IDEaliSM[4] thoroughly explain the creation of such systems. The second one, analysis of the robustness of a product design is relevant, and is discussed further in the next chapters.

The aim of this analysis is to obtain design responsiveness curves as figure 1. (note: this is a very simple representation of the principle goal)

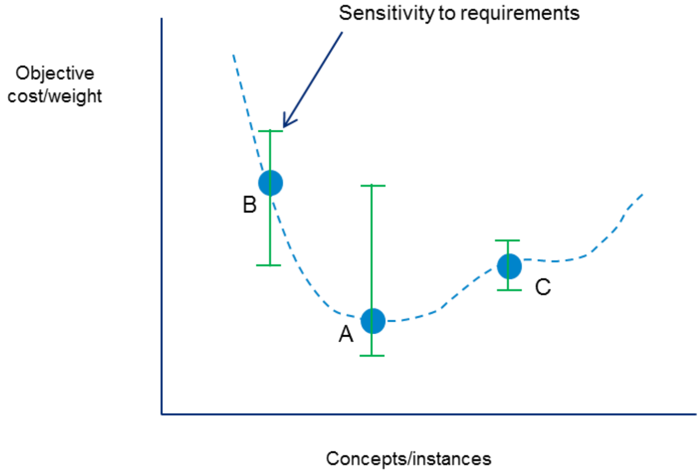

Figure 2 Sensitivity of a design to changing requirements

Three different design concepts are traded of which concept A shows the lowest weight/cost potential, however it has a very high sensitivity to requirements changes. So for robustness and therefore a predictable result of the business case concept C is the better one.

3 ROBUST DESIGN THEORY AND HOW TO APPLY

Traditionally, design process optimizations are developed under the assumption that the system variables are not affected by uncertainties. This is typically not true, as randomness impacts the characterization of the design variables in many ways. This is due to our inability to accurately predict the ambient conditions under which the target system will operate, the imperfections affecting the manufacturing process and also the financial trends that will influence the cost models. Under these circumstances, the adoption of a probabilistic approach allows re-formulating the design process in such a way that the uncertainty associated with the input design variables is described in terms of probability density functions (pdfs). These pdfs must be defined by the user on the basis of the available experimental data, historical records or subjective descriptions [5].
The adoption of such an approach implies that also the system outputs are associated with an unknown probability density function, the characterization of which is the subject of an uncertainty quantification (UQ) analysis. Different techniques are available in order to propagate the uncertainty from the design inputs to the system outputs. A robust technique to perform UQ is the Monte Carlo (MC) method, which requires generating a huge number of random samples of the input variables distributed according to the input pdfs. A system evaluation is then performed for each of these samples, and the output population can be used to estimate the key statistical characteristics of the system output pdfs such as mean, variance, quantile values of interest and (possibly) probabilities of failure. The advantage of a MC approach consists on the possibility to characterize the entire output

pdfs. On the other hand, MC works well only when the computational cost of the system evaluation is very efficient, independently of the number of dimensions of the problem, and the failure probability is high enough (in the order of 10^{-2}). A valid alternative to MC is the First Order Second Moment (FOSM) approach, which approximates the system dynamics through a first-order Taylor expansion centred at the mean of the input variables and allows estimating analytically the variance associated with system outputs. This approach is exact in case of independent Gaussian variables.
The adoption of an uncertainty quantification framework allows formulating a robust design optimization strategy where the constraints associated with the system outputs can include additional probabilistic metrics, for example the variance or a quantile of a quantity of interest.

4 SOLUTION APPROACH IN AGILE

In AGILE an environment is developed for Multi-Disciplinary Optimization of an aircraft. This environment works on the principle that partners involved in a design process supply their specialist knowledge as a service to the whole system. From the different services a selection can be made to be used in an optimization flow which will then produce the optimal aircraft design [6]. The different services in the system communicate with each other through advanced connectivity tools such as BRICS [7].
In case of a multi-level flow the services to be used will be split between different analysis flows which communicate with each other. This works fine when there are no limitations on communication between different networks and no IP issues. Unfortunately in an industrial setting these limitations often arise. Especially in the early design phases there is no smooth connection between OEM and supplier networks and IP of the different partners needs to be guarded.
In the multi-level flow developed here this issue has been overcome by wrapping the results from the analyses flows at different levels in surrogate models. These surrogate models mimic the response to changes in design variables not by re-running the analysis flow but by looking and or interpolating between results previously calculated by the analysis flow. In this way IP is protected and the required connection between OEM and supplier simplified.

The low level flow is used to create data for the surrogate model for the higher level optimization flow. The lower level flow wraps a hinge rudder sizing tool (Hinge system Design and Optimisation Tool, HDOT [8]) within Optimus[9], which is a Process Integration and Design Optimization (PIDO) platform. To generate the data required for the surrogate model the Design Of Experiment (DOE) capability of Optimus is used. For the surrogate model data the rudder hinge weight response to the changes in rudder forces and rudder size is determined. Therefore valid ranges of inputs for the rudder forces and rudder sizes must be set.
For the rudder forces range the loads definition tool AMLOAD[10] is used. This tool determines typical rudder force and other loads based on an aircraft configuration and typical load cases. Within the AGILE project Common Parametric Aircraft Configuration Schema (CPACS) [11] is used as definition of aircraft configurations. To fit within the AGILE project a wrapper has been developed for AMLOAD that understands aircraft configurations stored in CPACS. Typical aircraft configurations have been analysed resulting in a typical rudder force range.
The rudder size is determined in CPACS by the location of the rudder hinge line and the start and end of the rudder in span wise direction. To limit the number of input parameters only changes in hinge line definitions have been considered in the lower level flow.

The DOE data from the lower level flow is stored in tables that are used to create surrogate models. The data is also used to analyse the behaviour of the rudder sizing tool packaged in the design tool. This analysis of data can give insight into the behaviour of the rudder hinge weight with respect to the chosen input ranges. Based on this analysis the robustness of the chosen design solution can also be determined. How this can be done is explained in the next sections.

5 LOW LEVEL FLOW DEFINITION

The lower level flow is used to determine the weight and cost of a rudder hinge system. In the lower level flow the existing HDOT flow is packaged in Optimus, this is necessary to run DOE's. The lower level flow must also fit in the overall AGILE framework. This means that it must use the AGILE communication protocols and other AGILE agreements must be implemented.

5.1 Fitting the existing tools in a AGILE capable framework

The main element of the lower level flow is HDOT[8]. HDOT is a tool developed in a python based Knowledge Based Engineering (KBE) platform called Parapy[12]. This tool determines the optimal hinge configurations for a given rudder under a given load. The given rudder consists of the outer shape of the vertical tail, the position and size of the rudder and the position of the rudder hinges. Within the tool the total rudder force is translated into individual hinge loads using a Finite Element (FE) model. Using these individual hinge loads and a bisection algorithm the individual hinges are optimized. As outputs the tool provides the hinge system cost and weight. Furthermore the details of the optimized hinge system such as standard parts and materials used can be reported.

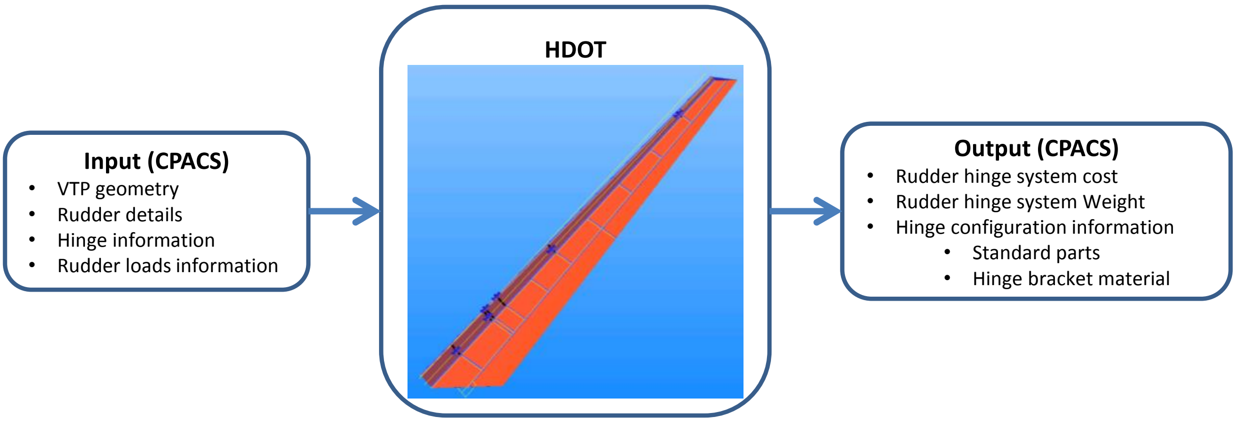

Figure 3 HDOT tool with in and outputs

In order to fit in the AGILE framework HDOT must be adjusted in such a way that it accepts CPACS file as input and also produces CPACS files as output.
In the original HDOT version the geometry of the Vertical Tail Plane (VTP) was provided to HDOT as a STEP file. Within the AGILE platform the geometry must be created based on inputs in the CPACS file. In CPACS the VTP geometry is stored as a set of airfoil points with positions and scaling. To create the VTP geometry these airfoil curves need to be created in Parapy and a surface needs to be lofted between them. This was achieved by adding a software module to HDOT, which extracts the required data from CPACS. In this module libraries dedicated for CPACS data extraction, TIXI[13] and TIGL[14], are used to extract points on the VTP Outer Mould Line (OML). These points are then used to create an OML surface in Parapy.

Besides the OML additional information must also be loaded from the CPACS file. This additional information consists of rudder data, data describing the hinge locations and loads data. This data is spread throughout the CPACS file either in CPACS entries describing the vertical or rudder or in other CPACS entries especially tool specific ones.
The rudder data consists of the hinge line location and information about the start and end of the rudder in chord and span wise directions.
For hinge locations the ribs of the VTP are used as reference because the rudder hinges must connect to hard points in the VTP. From the available ribs a selection must be made which will be used as hinge supports. This selection is stored in the HDOT tool specific part of the input CPACS file.
The final input required from CPACS is the total force on the rudder. In the lower level flow the force on the rudder is determined by AMLOAD. Therefore the rudder force is retrieved from the AMLOAD tool specific part of the input CPACS file.

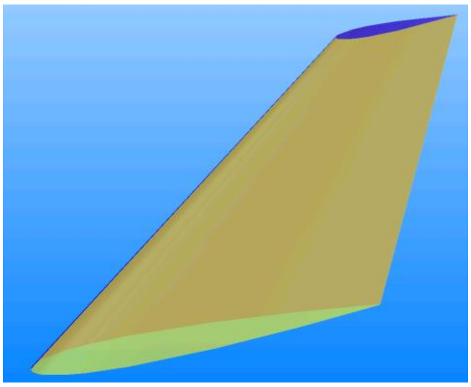

Figure 4 VTP OML based on CPACS

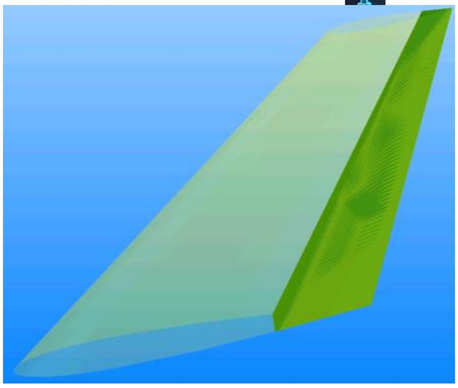

Figure 5 Rudder definition

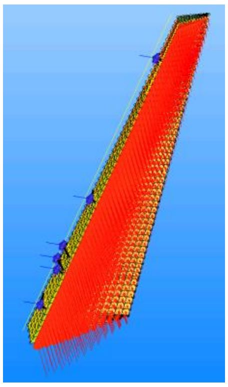

Figure 6 HDOT rudder representation

The outputs from HDOT must also be stored in CPACS format. The outputs required by the higher level flow are cost and weight. Therefore initially only cost and weight of the complete hinge system were stored in the CPACS file. However later in the development process is became apparent that this limited output set hindered tool debugging and also made understanding the tool result difficult. Therefore the output set has been expanded with all hinge system details. This set contains a description of all standard parts such as bolts bushes and bearings used in the hinges plus the material used for the hinge brackets.
The extended output has helped explain the discrepancies in the cost output of the tool. These are due to the limited content of the standard part library used and also due to material cost values being unreliable. Therefore cost figures will not be considered in the optimization process.

5.2 The lower level Optimus flow

The HDOT tool has input and output files in CPACS format and is run with a command line expression. This facilitated automatically running the HDOT tool as is required for executing DOE's. This was implemented in an Optimus workflow as shown in figure 7.

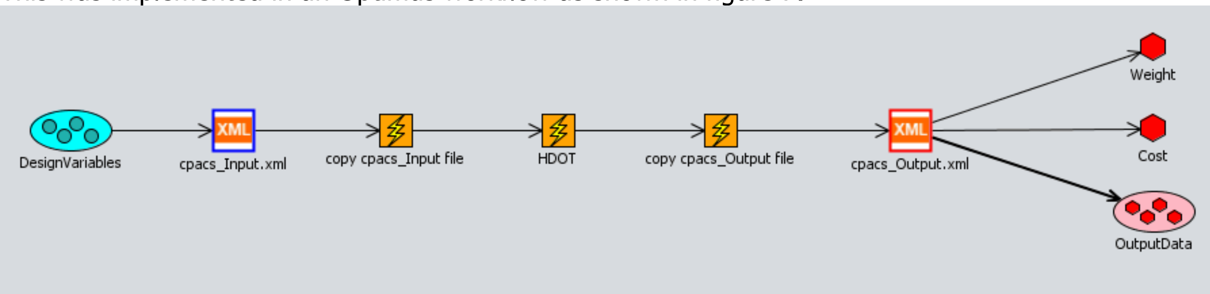

Figure 7 Optimus lower level HDOT workflow

In the DesignVariables item the variables which are required to be varied in the DOE to be run are specified. These variables are then linked with the CPACS input XML by means of the Optimus XML UCA (User Customizable Action), UCA's are dedicated XML-based templates that wrap all knowledge required to launch engineering simulations.
The next action is to copy the XML input file to the working directory of HDOT. Next HDOT can be run via a command line expression. The resulting XML output file is copied from the HDOT working directory to the current Optimus analysis directory. Finally the requested output parameters in Optimus are linked via the XML UCA with the CPACS output file.
Based on this workflow several combinations of design variables can be analysed using DOE techniques. Different DOE algorithms can be used in these analyses.

6 LOW LEVEL FLOW DOE RESULTS

First several DOE's were run to examine which HDOT input variables had the most influence on the objectives cost and weight. Then it was examined if and how these local HDOT input variables could

be linked to the aircraft design parameters. Subsequently based on these linked variables a DOE was run as the basis for surrogate model input.
Due to runtime restrictions, 1 experiment takes 1hr 50 min primarily due to the build in optimization algorithm in HDOT, the sets of variables per DOE were limited. Nevertheless a good overview of variables of influence for HDOT has been found. These are: external load, hinge line position, nr and position of hinges, actuator load working line and moment arm. The results plots used were the correlation values (example in Figure 8) and bubble plots (example in Figure 9 and Figure 10). The correlation values in Figure 8 (left) show that the external loading drives the weight to a very high extent; the position of hinge 2 also has an influence on the weight whereas the position of hinge 3 has not.
Linking of the HDOT variables of influence to the aircraft level parameters appeared only possible for the external loading (AMloadsFy) and hinge line position (innerHingeXsi and outerHingeXsi). Figure 8 (right) shows the correlation values of these variables and shows that the influence of the hinge line position is far less as compared to the external loading. Final results as input for the surrogate model are shown in Figure 9, weight is plotted against external load for two hinge line positions. As stated in paragraph 5.1 the cost module in HDOT is still not mature enough to provide reliable results, as is shown in Figure 10. Therefore results from the cost analysis will not be used for any robustness analysis.

Pearson (Spearman	AMloadsFy	Hinge2	Hinge3	Weight	Cost
AMloadsFy	1.000 (1.000)	0.000 (0.000)	0.000 (0.000)	0.935 (0.922)	0.243 (0.303)
Hinge2	0.000 (0.000)	1.000 (1.000)	0.000 (0.000)	0.236 (0.271)	0.150 (0.027)
Hinge3	0.000 (0.000)	0.000 (0.000)	1.000 (1.000)	0.002 (-0.027)	0.222 (0.054)
Weight	0.935 (0.922)	0.236 (0.271)	0.002 (-0.027)	1.000 (1.000)	0.388 (0.335)
Cost	0.243 (0.303)	0.150 (0.027)	0.222 (0.054)	0.388 (0.335)	1.000 (1.000)

Pearson (Spearman)	AMloadsFy	innerHingeXsi	outerHingeXsi	Weight	Cost
AMloadsFy	1.000 (1.000)	0.000 (0.000)	0.000 (0.000)	0.987 (0.993)	0.109 (0.167)
innerHingeXsi	0.000 (0.000)	1.000 (1.000)	1.000 (1.000)	-0.052 (-0.076)	-0.007 (-0.002)
outerHingeXsi	0.000 (0.000)	1.000 (1.000)	1.000 (1.000)	-0.052 (-0.076)	-0.007 (-0.002)
Weight	0.987 (0.993)	-0.052 (-0.076)	-0.052 (-0.076)	1.000 (1.000)	0.103 (0.181)
Cost	0.109 (0.167)	-0.007 (-0.002)	-0.007 (-0.002)	0.103 (0.181)	1.000 (1.000)

Figure 8 Correlation values, load and hinge position (left), and hinge line position (right). In this plot a high value means a high correlation

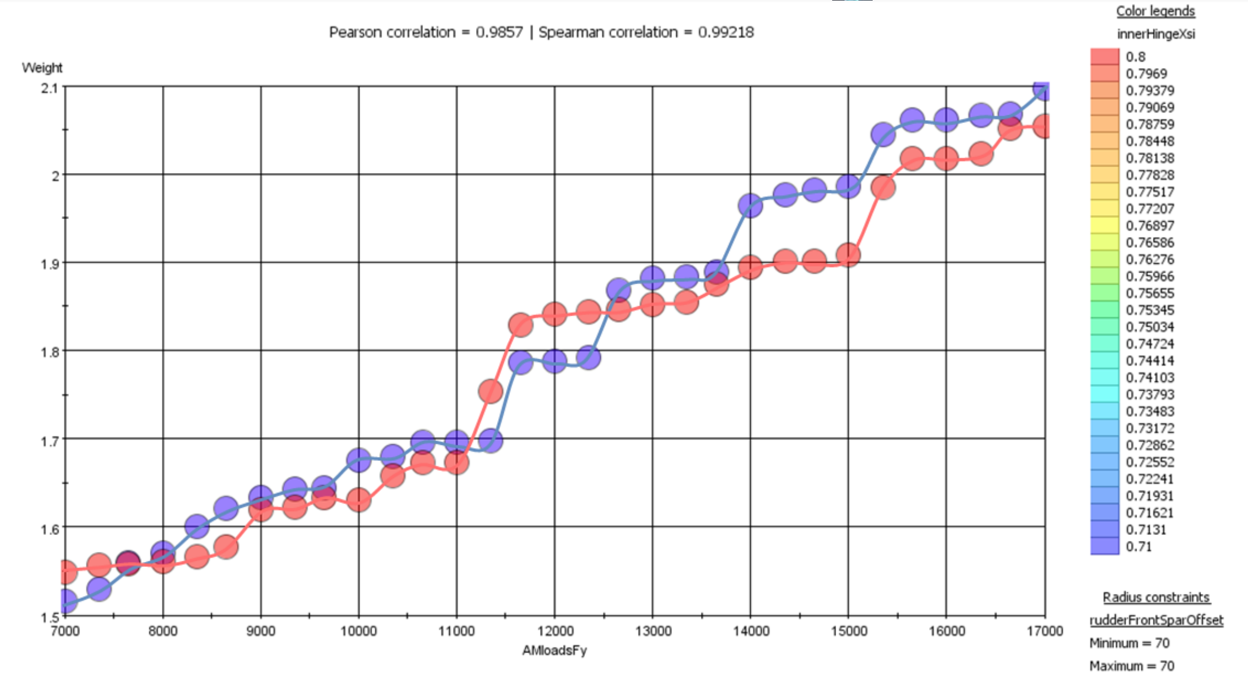

Figure 9 Bubble plot of weight versus external load for 2 hinge line positions

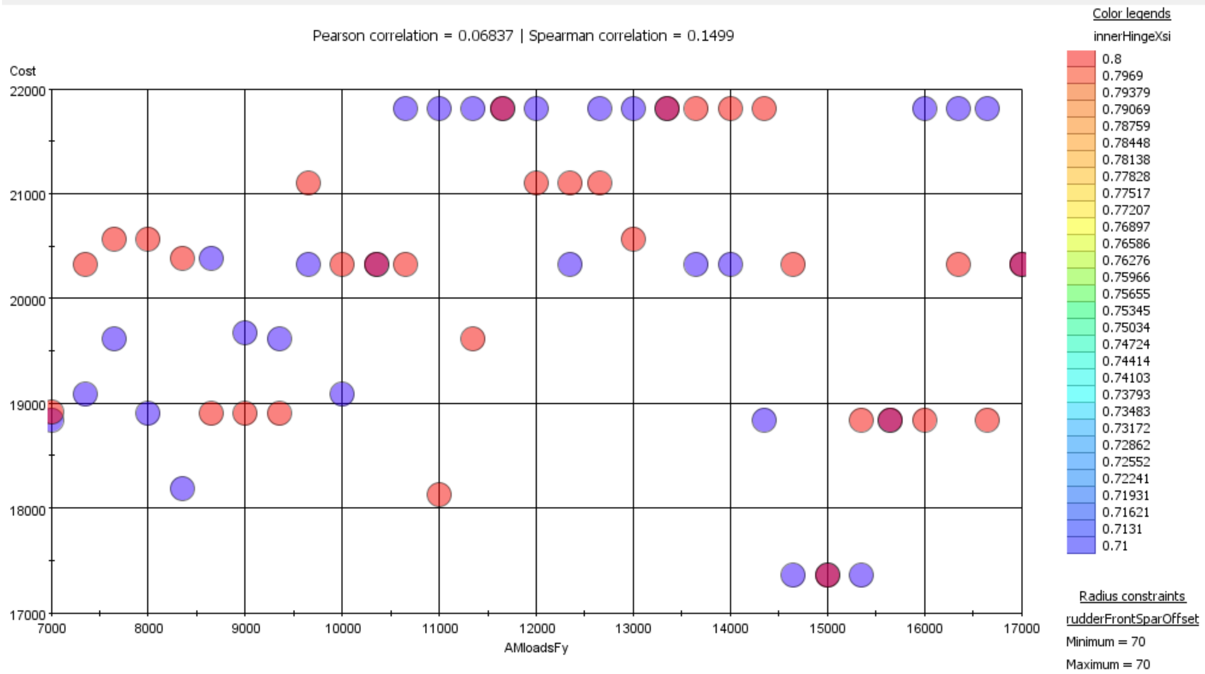

Figure 10 Bubble plot of cost versus external loading for 2 hinge line positions

The uncertainty quantification analysis is performed by adopting a Monte Carlo (MC) approach where the system evaluations are executed with a surrogate model. The feasibility and accuracy of MC in this context is ensured by the availability of an accurate surrogate model that is obtained on the basis of a large number of DOE experiments (in relation to the dimensionality of the design space, as shown in Figure 9). The probability distribution assigned to the uncertain input variable (AMloadsFy) is a triangular distribution with minimum and maximum values equal to 11000N and 14000N respectively, while the mode is set to 12000N The results of the uncertainty quantification analysis are displayed in Figure 11 and Table 1 while their impact on the robust optimization strategy is discussed in the next section.

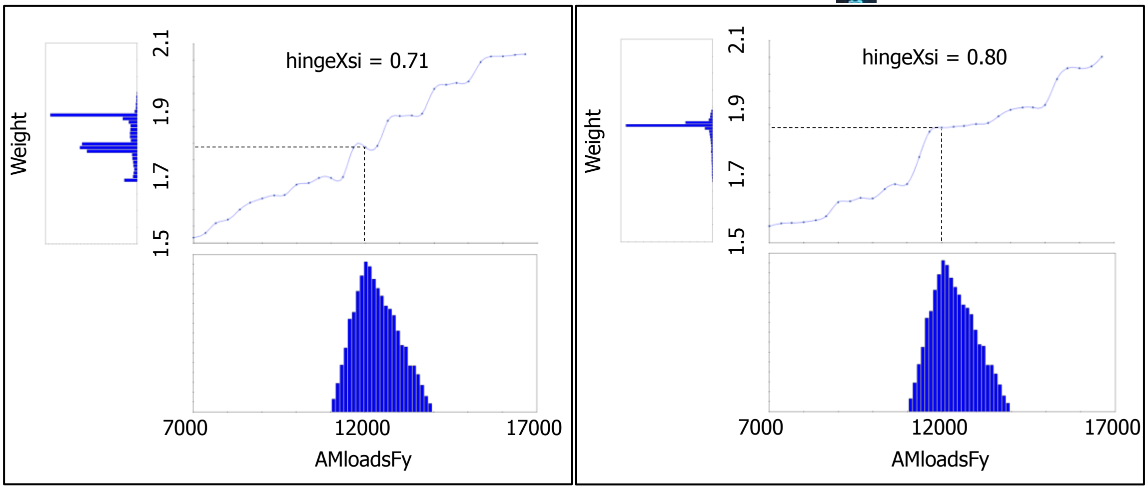

Figure 11 Sample distributions approximating the pdfs of the input variable AMloadsFy and of the output Weight for innerHingeXsi = 0.71 (left) and innerHingeXsi = 0.8 (right). The corresponding surrogate models (continuous lines) and the DOE experiment results (dots) are also shown.

Table 1 Statistical analysis of weight for Fy is 12000 based on DOE results

	innerHingeXsi = 0.71	***innerHingeXsi = 0.8***
Deterministic	**Weight: 1.788 kg**	**Weight = 1.841 kg**
Stochastic	**AMloadsFy:** triangular distribution with [lower; upper; mode] = [11000; 14000; 12000] **Weight:** [lower; upper] = [1.69; 1.96] SIGMA = 0.056 95% quantile = **1.88 kg**	**AMloadsFy:** triangular distribution with [lower; upper; mode] = [11000; 14000; 12000] **Weight:** [lower; upper] = [1.68; 1.89] SIGMA = 0.029 95% quantile = **1.86 kg**

7 DISCUSION AND CONCLUSIONS

7.1 Discussion

Looking at the results of the analysis in Figure 9 the difference in weight response for 2 different hinge line values can clearly be seen. The values for a innerHingeXsi=0.71 clearly show a stepped response meaning that it is unstable or not robust around certain values of Fy. The values for innerHingeXsi=0.8 appear to be more stable and therefor more robust.
This difference in stability can also be substantiated with a statistical analysis as presented in Table 1. Around Fy=12000 the deterministic weight value for innerHingeXsi=0.71 is better than the one for innnerHingeXsi=0.8. However when taking into account a triangular distribution leaning towards a higher load the 95 quantile weight value is better for innerHingeXsi=0.8.
What does this mean for a real life situation? When there is no DOE capability available and the tier 1 supplier can only do one or a few analysis he might be tempted to offer the innerHingeXsi=0.71 solution in a proposal, because this has a better weight. However when the DOE data is available it becomes clear that the innerHingeXsi=0.8 solution responds better to changing requirements and therefore is more robust.

In the analysis discussed above only innerHingeXsi or the location of the hinge line is taken into account, however Figure 8 (left) shows that the position of hinge2 has a much larger influence on the hinge system weight then the innerHingeXsi. Therefore the position of hinge 2 should also be taken into account in the surrogate model for higher level flows. However in this case the higher level flow did not define the hinge positions and therefore inclusion in the surrogate model for the higher level flow would have been useless.

For more effective use of surrogate models at the higher level it is therefore essential to understand the sensitivity of the lower level flows. The in- and outputs of the higher level flow should match these sensitivities and they should be included in the lower level surrogate models.

The analyses performed up till now are relatively simple, only a few design variables are analysed. In this case the robustness can be evaluated by looking at plots such as Figure 9. However as was shown in the previous paragraph for a realistic analysis of the problem more design variables must be taken into account. At a certain moment plots don't suffice any more and more advanced statistical methodologies, as presented in Figure 11 and Table 1 are required to analyse the data.

7.2 Conclusions

A rudder hinge system analysis framework has been presented. This framework is used to create DOE's, which are used to create surrogate models for higher level analysis flows and also to investigate the behaviour of the rudder hinge system design itself. For this investigation the robustness of the design has been analysed. It was shown that the best design from a deterministic point of view is not necessarily the best design if changes in requirements, such as loads increases, are taken into account. For a tier1 supplier this is essential information as requirements often shift during the design process of an aircraft component.

The proposed front loaded design process for a tier1 aircraft component supplier has also been presented. In this design process designs are created without a fixed requirement set. Therefore it is essential to understand the response of a design to requirement changes. As a result such a design process will only work if robust design techniques are implemented.
Additionally in the front loaded design process many design concepts are evaluated. This is only possible if the designs can be generated automatically and can be packaged in PIDO tools for running DOE's and optimisation. This automation and packaging has been shown in this paper using the rudder hinge system as use case.

8 ACKNOWLEDGMENT

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REFERENCES

[1] W. Lamme, B. de Wit, J. Vankan, H Timmermans, T. van der Laan, 2017, " Collaborative Design of Aircraft Systems - Multi-Level Optimization of an Aircraft Rudder", submitted to Aerospace Europe 6th CEAS Conference,, October 2017, paper no. 898
[2] S. Thomke, T. Fujimoto,2000, "The effect of "Front-Loading" Problem solving on product development performance", J PROD INNOV MANAG 2000:17:128-142"
[3] T. van der Berg, T. van der Laan, Martijn van Rij, 2015, "Aerospace solution optimization through front loading techniques", 2105 SC Aerospace Conference and Exhibition, Columbia, USA.
[4] https://itea3.org/project/idealism.html [Cited 03-08-17]
[5] R. E. Melchers, "Structural Reliability Analysis and Prediction", 2nd Edition, Wiley, 1999
[6] https://www.agile-project.eu/ [Cited 04-08-17]
[7] E. Baalbergen, E. Moerland, W. Lammen, P.D. Ciampa, "Methods to Support Efficient Collaboration for Competitive Aircraft Design", submitted to Aerospace Europe 6th CEAS Conference,, October 2017, paper no. 844
[8] A.R. Kulkarni, R.E.C. van Dijk, T. van den Berg, G. La Rocca, 2017," A Knowledge based engineering tool to support front-loading and multi-disciplinary design optimization of the fin-rudder interface" ", submitted to Aerospace Europe 6th CEAS Conference,, October 2017, paper no. TBD
[9] Noesis Solutions; 2017; "Optimus Rev 10.19 - User's Manual"; Technical Report

[10] H. Timmermans and B. Prananta; 2016; "Aeroelastic Challenges in the Aircraft Design Process"; READ & SCAD conference; Warsaw; September 2016
[11] B. Nagel; D. Böhnke, V. Gollnick, P. Schmollgruber, A. Rizzi, G. La Rocca; J. J. Alonso, 2012,"Communication in aircraft design: Can we establish a common language?", 28th Congress of the International Council of the Aeronautical Sciences (ICAS), Brisbane, Australia
[12] https://www.parapy.com/ [Cited 01-08-17]
[13] Various Authors. TiXI, description and API Documentation. url: https://github.com/DLR-SC/tixi
[14] Various Authors. TiGL, description and API Documentation. url: https://github.com/DLR-SC/tigl