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AIRCRAFT CONFIGURATION ANALYSIS USING A LOW-FIDELITY, PHYSICS BASED AEROSPACE FRAMEWORK UNDER UNCERTAINTY CONSIDERATIONS

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Abstract

During the early stages of aircraft design, limited information is available to conduct decisions that base on the quality of aircraft configurations. In the present study, information on physical and statistical models is supplemented by the uncertainty that is inherent to the applied analysis modules and propagated through the complete design workflow. Using this method, the possibility arises to make a statement on the level of certainty with which one concept is preferred above another.

1 Introduction

When analyzing the potential of novel aircraft configurations on a conceptual to preliminary design level, the often limited amount of time available to investigate physical properties of design candidates dictates both the low fidelity level and limited amount of analyses that can be conducted. The increase in computational power over the last decades has resulted in an increase in analysis capabilities to assess aircraft concepts. However, analyses based on using physical models of higher-fidelity still find their application only in the detailed design phases.

To create a proper basis for making design decisions in early design phases given the limited available information on the aircraft physics, it is necessary to supplement that information by the uncertainty of the implemented analyses. The DLR internal project “Future Enhanced Aircraft Configurations (FrEACs)” aims to extend the early design phase with uncertainty information.

The present study investigates the analysis of aircraft configurations under consideration of propagated uncertainties in early design stages. Aside from the uncertainties inherent to the individual analysis model, the study investigates the sensitivities of the physical properties of the aircraft, and the propagation of uncertainties between individual modules in analysis workflows is necessary to quantify the overall uncertainty of these properties. The base for making well-grounded design decisions in conceptual and preliminary design stages is thereby improved.

The present study shows first results of the implemented uncertainty modules within the analyses workflows. In a following paper, the capabilities which were built up will be applied to multiple aircraft configurations and larger DOEs.

2 Aircraft design system

Today's conceptual and preliminary aircraft design is usually formulated in Multi-Disciplinary Analysis and Optimization (MDAO) studies. In recent developments, these studies are often conducted in distributed and collaborative design environments rather than in monolithic codes. The design environments offer an increased flexibility to choose the analysis method appropriate to the design task at hand. Furthermore, the design environments ease the introduction of further disciplinary expertise as the analysis modules are loosely coupled. Hence, disciplinary tools can be included without major implementation overhead.

As shown in Figure 1, a distributed, collaborative design environment consists of three components:

Disciplinary analysis models, from low-fidelity empirical models to high-fidelity full-scale numerical models, form the core of the design environment. These disciplinary models are usually focused on a specific discipline and often represent either a single or a group of components of an overall aircraft model, e.g.: fuselage structures or wing aerodynamics.

A common data exchange language that is based on a central data model approach. This enables the communication between both analysis models and experts. The applied central model consists of a schema definition and the explicit model data itself. The model elements, its attributes and the connecting data structure are defined in a schema definition which is generally applicable to a large variety of aircraft models. The explicit model content is stored in a separate xml data set which conforms to the schema definition. Whereas the data set is mainly used for the exchange of information, the schema definition is utilized for documentation, model validation and model generation.

An integration framework that consists of an editor and visual environment for the creation, modification and control of analysis tool chains. This graphical user interface provides a kind of workspace and enables process designers to interact with analysis modules. This encompasses coupling modules as well as interactions with central model representations. Furthermore, a major part of the framework provides the core logic organizing data transfer between remote components, management of intermediate and resulting data sets as well as extraction and merging of partial data with the central data model. The framework also supports convergence control and optimization, in order to execute (partly) automated design studies.

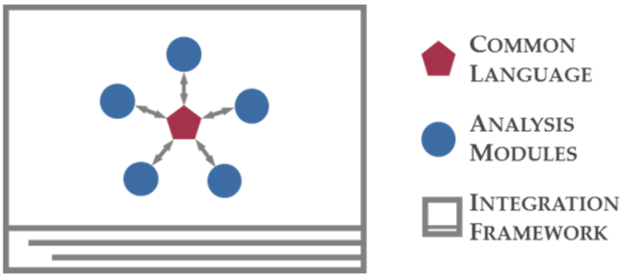


Figure 1: Three components of distributed, collaborative design environment

Several design environments that bring together these components exist in literature. Among others, CEASIOM [1] and MDOPT [2] are indicated as outstanding examples. The present study is based on the aircraft design system currently under developed at DLR. Therefore, the central model approach uses the Common Parametric Aircraft Configuration Schema (CPACS) [3] as data exchange format. The Remote Component Environment (RCE) [4] is the integration framework of choice. The disciplinary analysis models applied are the empirics-based conceptual design tool VAMPzero [5] and vortex-lattice aerodynamic analysis module Tornado [6]. Section 3 further elaborates on the characteristics of these models.

The introduction of uncertainties into the aircraft design system affects most of its components. First of all, the analysis models with inherent uncertainties need to explicitly provide uncertainty information in their output. Hence, the central model needs to provide means to describe and store this uncertainty information in a structured manner. The integration framework needs to be extended to propagate information on uncertainties in a design process consisting of several analysis models. Given the fact, that significant computational cost may arise from this uncertainty propagation, it may be beneficial to extend the design environment with surrogate modeling techniques.

3 Quantification of uncertainties in the analysis modules

Complex natural processes can be approximated using explicit rules in model representations and applied to describe future events. By observing the real processes, these conceptual models can be generated which mostly reflect a simplification of events occurring in reality. Before simulating future events using the conceptual models, a computer model representation is created and again compared to or validated with reality. The approximations contained in the computer models typically result from incomplete knowledge, errors in modeling or by deliberate reduction of complexity. As a consequence, the representation power of the models is subject to uncertainties.

Types of uncertainties

In literature there are different ways to define uncertainty. In the present study, *aleatoric* and *epistemic* uncertainties are discerned. Uncertainties due to random numbers or chaotic processes are referred as aleatory. Designers have by definition no significant influence on this kind of uncertainties; these can therefore not be avoided or reduced. Uncertainties caused by the ignorance of matter are referred as epistemic. By additional information, these uncertainties can be reduced.

Sources of uncertainty

There are various sources of uncertainty; in the literature a distinction is made between the following sources of uncertainty:

Uncertainties through **physical model assumptions**: A physical model bases on data and logic derived from observation of real processes. By neglecting physical effects, e.g., not incorporating transonic effects in an aerodynamic simulation, uncertainties are introduced in the model. Model simplification might be required due to the complex nature of the physics to be represented, e.g., weather, not knowing or understanding reality well enough or since simple model representations often require less computational power and represent reality sufficiently enough. The description of uncertainties can be defined either within the model or subsequently be imprint on the output parameters of a model.

Uncertainties occurring on the **input parameters** of the design study: Input parameters or assumed constants within analysis models can be fraught with uncertainty. Input parameters can be subject to a dependent uncertainty, e.g., function, or constant. In the course of the present study a distinction is made between time-dependent and time-independent input parameters. For time-dependent parameters, the uncertainty is a function of the prediction time point, e.g.: the oil price in 2030 or 2050. These parameters and their corresponding uncertainty band can be derived from future scenarios. Time independent parameters are those that do not change over time, such as slightly differing material properties of certain composite materials due to uncertainties in the production process.

Uncertainties due to **statistics**: Statistics usually include a finite number of samples from a data population. Since the number of samples is limited, the population is not covered completely and thereby data uncertainty occurs. From statistics only the correlations follow only from the observed data points, an explicit description of the physics behind the model is not present. Consequently, the parameter space is limited to the range in which the monitoring took place. Outside this range, the model should not be evaluated, and furthermore, the uncertainty can not be quantified.

Other sources of uncertainty are: *application errors*, *higher-order uncertainties* (uncertainty in the uncertainty modelling), *numerical representations and discretization* and *convergence* assumptions within analysis modules and the overall design workflow. The present study focuses on the uncertainties that arise from physical modeling, uncertain input parameters and statistics. It is our goal to include further sources of uncertainty in future research.

Regardless of the source of uncertainties, the information on the uncertainty may either be integrated intrusively or non-intrusively. By integrating uncertainties within the model, an intrusive approach is chosen. If the information is subsequently imprinted to the models analysis results then a non-intrusive approach is used.

Uncertainty analysis using probability distribution functions

Uncertainties can be described differently depending on the source causing the uncertainty. In literature numerous theories and methods are described, see for example [7], [8], [9], [10].
In the present study, uncertainties are described by probability theory and inductive statistics. In inductive statistics, the properties of a population are derived from the data of a sample. Through the application of probability theory, uncertainties can be handled using probability distribution functions. Expressed as a probability function or random function, the specific parameters of the uncertainty function are set dependent on the source causing the uncertainty.

Quantification of uncertainties

In order to propagate uncertainties across multiple analysis tools, at first uncertainties have to be determined at the individual tool level. This uncertainty determination is described below for two of the disciplinary analysis modules within the low-fidelity physics based aerospace toolkit [11].

Uncertainty quantification of module 1: VAMPzero

Based on top level aircraft requirements, an initial configuration is generated in the design environment, which is improved by further more detailed analyses.
As initial model generator for aircraft configurations, the conceptual design tool VAMPzero is used. VAMPzero is developed within DLR for CPACS based applications. The calculation of the aircrafts physical parameters is based on handbook equations, which itself are based on statistical aircraft data. The basis of these equations is data of existing aircraft configurations, due to

which the equations have limited applicability. As an extension of VAMPzero, the consideration of uncertainties originating from the involved statistical formulas is introduced. This VAMPzero version therefore features intrusive uncertainty considerations. Each equation that involves uncertainty information incorporates a standard deviation which originates from the underlying statistics (see Table 1). The probability distribution function is assumed to be normally distributed. The calculated parameter values will be extended by information from a random distribution function, taking the corresponding standard deviation into account. This feature can be turned on or off, such that the analysis can be performed either deterministically or stochastically.

Parameter in VAMPzero		Equation in VAMPzero	Standard deviation [%]	Samples
aircraft.mLM	Landing mass	$m_{LM} = \left(0.2 + 0.9 \cdot e^{\left(\frac{-desRange}{1854}\right)}\right) \cdot (m_{TOM} - m_{ZFW}) + m_{ZFW}$ (1)	3.9	38
aircraft.mTOM	Take off mass	$m_{TOM} = m_{FM} + oEM + m_{Payload}$	4.75	36
aircraft.mZFW	Zero fuel mass	$m_{ZFW} = oEM + m_{Payload}$ (2)	13.17	36
aircraft.oEM	Operation empty mass	$oEM = m_{Wing} + m_{Htp} + m_{Vtp} + m_{Engine} + m_{Fuselage} + oIM + m_{LandingGear} + m_{Pylon} + m_{Systems}$ (3)	3.6	-
…	…	…	…	…
Equation sources	(1): Synthesis of Subsonic Airplance Design, E. Torenbeek, Delft University Press, 1982, p. 275, Eq. 8-2 (2): Luftfahrttechnisches Handbuch, N.N., 2004, MA 212 00-02 p.4 (3): Luftfahrttechnisches Handbuch UL-442.0(T)			

Table 1: Standard deviation of VAMPzero statistical formulas

Uncertainty quantification of module 2: Tornado

The analysis code Tornado calculates aerodynamic forces and moments of an aircraft configuration in several flight conditions. Tornado is a vortex-lattice module which applies thin airfoil theory, small angle approximations and assumes incompressible, inviscid, irrotational flow conditions. The flow velocity and force distribution is calculated using a lattice of horseshoe vortices that represent the actual geometrical model. The method offers high flexibility in the calculation of the flow around thin geometries and requires a limited amount of lifting surface geometrical data to be able to generate physical model representations. Therefore it is suitable for applications in preliminary aircraft design, where the amount and detail of model information is limited. The uncertainties for Tornado have been calculated from the database provided in [12]. In the database, the results of several aerodynamic analysis modules were compared to data from wind tunnel tests for six different aircraft configurations. The quantified errors and standard deviation of error of the lift (CL) and drag coefficient (CD) are listed in Table 2. The error is used to calibrate the parameters and the standard deviation used for uncertainty implementation.

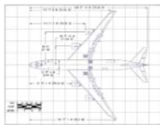
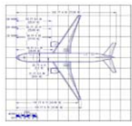
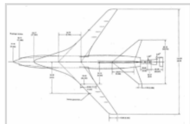
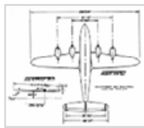
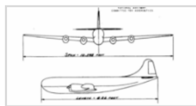
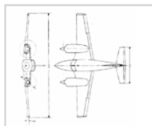
Geometry		Mean error [%]		σ of error [%]	
		CL	CD	CL	CD
B747-100		4.6	4.5	2.8	4.2
B777-300		6	6.7		
TF- 8A		6	11		
Lockheed C-69		1	13		
Boeing Strato-cruiser		11	2		
Command er 680 Super		4	14		

Table 2: Quantified error and error deviation of transport aircraft in Tornado

4 Propagation of uncertainties in the design process

Due to the dependence of input parameters of one module on the output parameters of a predecessing module, uncertainties are propagated within analysis workflows. The way in which uncertainties are propagated depends on the analysis method that underlies the specific module (the sensitivity of a modules' output parameter is to its input parameters). Determining the correlation of input and output parameters proves to be a reasonable method to provide information on how a parameter and its uncertainty behave and influences other parameters. The propagation behavior of a variable can be shown by varying parameter values (within a fixed range), using Monte-Carlo simulations. When using very complex and time-consuming models, it is attractive to use surrogate modeling, e.g., response surfaces, to reduce overall analysis time. After the overall analysis is completed, the sum of all uncertainties of each individual model provides the overall system uncertainty (on overall output parameters).

Description of the uncertainty component

For the analysis of propagated uncertainties in MDO systems, an uncertainty analysis component is developed in the integration framework RCE. This component allows the inclusion of uncertainties and provides a GUI to analyze, control, and observe its propagation behavior. The component can handle both stochastic and deterministic models as well as intrusive and non-intrusive uncertainties. The uncertainties can be analyzed using different approaches, in order to adjust the balance of time and quality of the performed analysis. The uncertainty component itself consists of four parts: the processing of input parameters, sampling, storage of results, and the evaluation of results to propagate these among subsequent analysis modules. The derived uncertainty data is exchanged as extra information in addition to the aircraft geometrical parameters and analysis results, using the CPACS data exchange format.

The component can be flexibly integrated into any tool chain, provided the applied modules include uncertainty information. It can be applied to control inputs and outputs of individual system modules, groups of modules and of the overall design system. In Figure 2, this process is shown for a single module. Here, a CPACS data set is loaded and thereafter controlled by the uncertainty component. A helper component is used after the analysis module and controls whether the uncertainty component is finished processing or not. After completion of the uncertainty sampling, the results are passed to a following analysis module. This analysis structure can be used multiple times in subsequent analyses, such that concatenation of uncertainty information, and thereby the propagation of this information is realized.

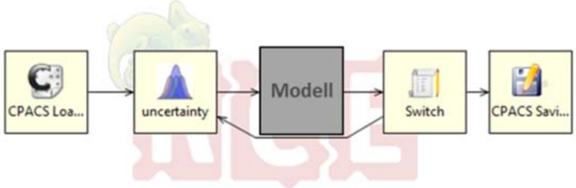


Figure 2: Integration of the uncertainty module

Application of the uncertainty propagation process within the analysis workflow

Figure 3 shows the workflow for aircraft analysis, including uncertainty propagation components in the non-iterative part of the simulation. For the current simulation, the uncertainty module is not included in the iterative part of the simulation, since this would drastically increase required computational effort. The analysis modules are repeatedly called to investigate the sensitivities of output parameters to the variable input parameters under consideration. Thereby, the corresponding uncertainty band on its output parameters is determined.

The uncertainty component is integrated twice in the workflow. The first component investigates the uncertainties of VAMPzero and the effect on the subsequent Tornado analyses. The second uncertainty component determines the effects of the uncertainties on the subsequent mission simulation module FSMS. The mission simulation mainly bases on mass parameters generated by VAMPzero and aerodynamic coefficients determined by multiple Tornado runs (in dependence on the angle of attack, Mach number and Reynolds number). Thereby, the uncertainties that occur in the input of FSMS are a result of individual uncertainties associated with geometry, mass items and aerodynamics.

Dependency of input to output parameters due to correlation

The information which input parameter has which influence to output parameters is important for the traceability of the results. Input and output parameters are in this case almost random numbers. Using correlation, the occurring dependencies can be detected. With this information, it becomes clear which parameters have major (linear) effects on the overall result and thereby drive the system uncertainty value.

Statistical dependency of input parameters due to correlation

Normally, when using multi-dimensional input parameters which contain random numbers, the statistical dependency among themselves should not be neglected. By determining the correlation between the input parameters, the occurring dependencies can be detected. By using Cholesky decompensation and a correlation matrix, new random numbers are generated, which are stochastically dependent [13][14]. These numbers should thereafter be used as input variables for subsequent analyses. This will however be included in a future extension of the uncertainty component and is therefore not included in the current investigation.

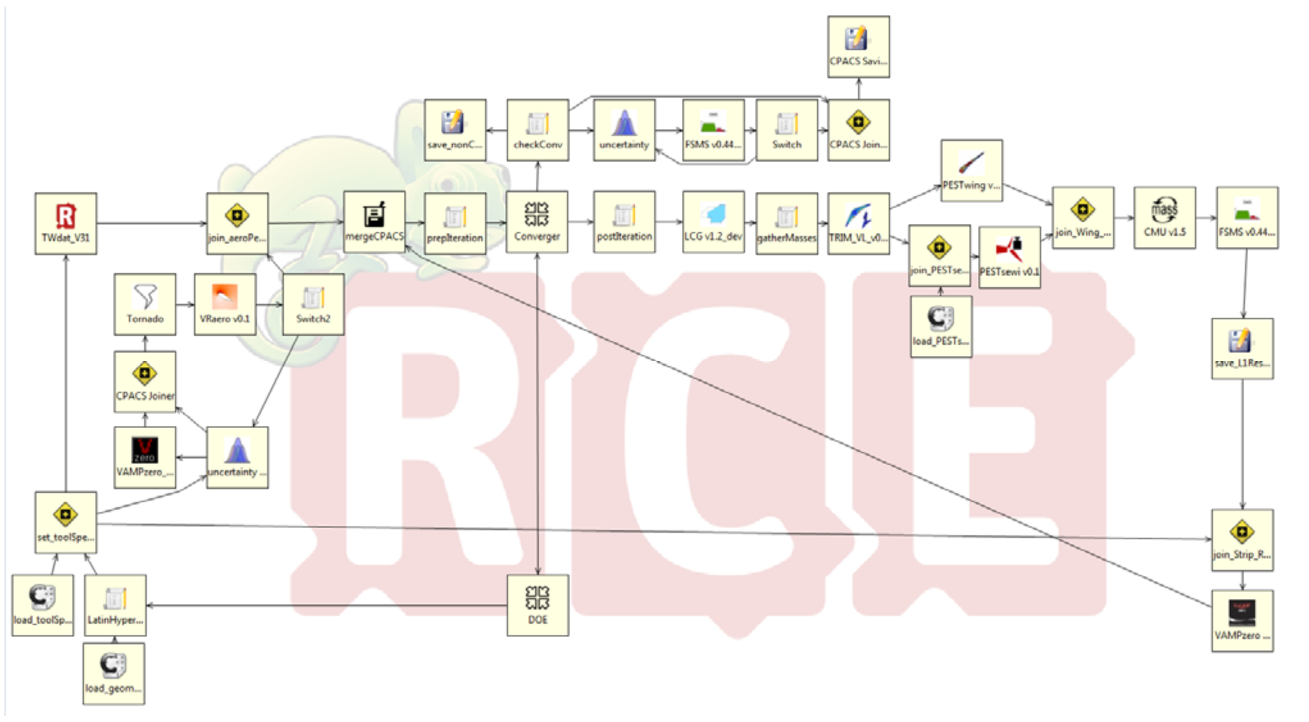


Figure 3: Analysis workflow in RCE with integrated uncertainty module

5 Example result of design variable variation under propagated uncertainties

As an example demonstration, a reference configuration is analyzed with the aid of the workflow shown in Figure 3. A parameter study is performed that varies both the wing area and the wing aspect ratio. The design of experiments is listed in Table 3. Selected parameters of the reference configuration – named D250 – are listed in Table 4. The top-level aircraft requirements are close to those of the long range aircraft A330-200.

Description of the analysis

Within the design space, a full-factorial sampling with 5 steps for each parameter is chosen. Both the individual and coupled effect of the parameter variations is investigated. Each parameter is modified linearly within the defined range. For each sampling point within the design space, 20 samples are incorporated to determine the uncertainty of the system outcome. The overall mission fuel at the

Parameter	Range
Wing Area	340 – 380 m²
Aspect Ratio	9 – 15

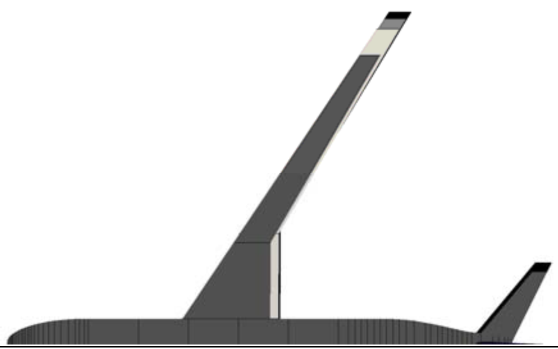


Table 3: Parameters and ranges of DOE

design range is used as accumulated uncertainty parameter, i.e., all propagated uncertainty information occurs in the quantification of the overall requirements on mission fuel.

Parameter	Value
Design range	7860 km
Mach number	0.82
Passengers	253
Fuel burn @ design range	57 tons
OEM	120.5 tons
TOM	233 tons
Wing loading	642 kg/m²
Wing area	363 m²
Aspect ratio	10.5

Table 4: Table of Reference Aircraft D250

Global result of the parameter study, including uncertainties

The effect of wing area and aspect ratio on mission fuel including uncertainties is shown in Figure 4. Alongside the resulting fuel mass estimations of the 20 samples per DOE point, a regression method is applied to determine the overall calculation result according to the 5x5x20 = 500 analysis results. The result of this regression is shown in the corresponding response surface (colored blue in the figure), which closely resembles the separately determined deterministic results of the DOE analysis (the bold black dots in the figure). The reference design is represented by a bold red dot in the figure.

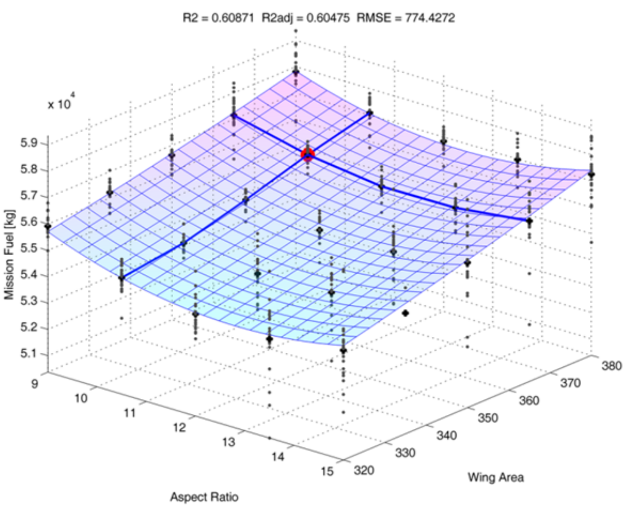


Figure 4: Mission fuel vs. aspect ratio and wing area

Figure 5 and Figure 6 show the analysis results for 2D cross-sections along the response surface centered on the reference point (aspect ratio = 10.5, wing area = 360 m²). The blue line indicates the result of the obtained regression model, whereas the colored band around the blue line indicates the 95% prediction interval of the regression. The latter implies: if the parameters are independent, normally distributed and have a constant variance, than there is a 95% probability that all future results are inside the interval. This is thereby related to the regression model, and indicates the possible error due to building the regression model. The black bars show the standard deviation of the random number simulations, i.e., the propagated uncertainty of the analysis modules itself; for one standard deviation of the mean (i.e.: 68.3% of the calculated fuel masses lie within this confidence interval). It can be seen that this uncertainty increases when deviating more from the reference result point. At the boundaries of the design range, the calculation uncertainty is the highest.

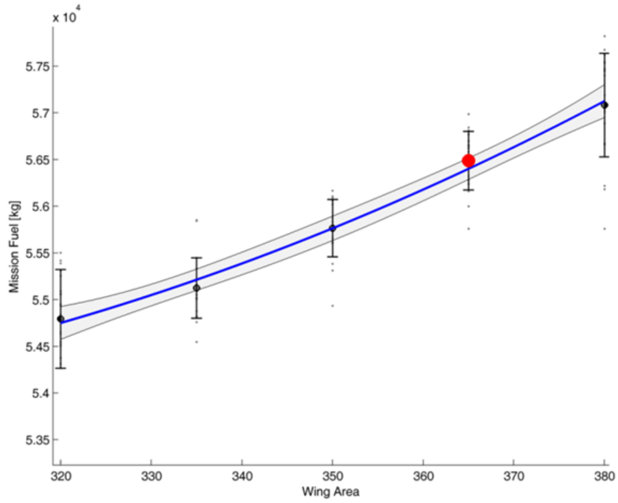


Figure 5: Mission fuel versus wing area (AR = 10) including uncertainty band of the regression model (colored blue) and standard deviation of the simulation results

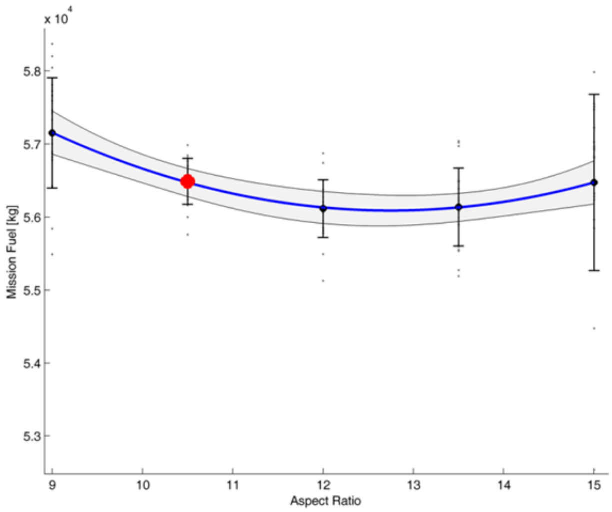


Figure 6: Mission fuel versus wing area (wing area = 360 m²) including uncertainty band of the regression model (colored blue) and standard deviation of the simulation results

Single-point result of the parameter study, including uncertainties

Observing the analysis results for a single point in the DOE provides a more clear view on the uncertainty distribution. As example we again use the mission fuel at the reference design point (aspect ratio = 10.5, wing area = 360 m²). From the performed DOE with 20 uncertainty determination samples, a mean value of 56.4 tons and standard deviation of 0.31 tons is obtained.

For this single point, the number of uncertainty calculation samples is increased to 500 in order to attain more certain simulation result. By comparing the result to a multitude of probability distribution functions, it is concluded that for this single point the results closely resemble that of a normal distribution, since this distribution results in the lowest root mean square error. As can be seen in Figure 7, this normal distribution has a mean value of 57 tons and a standard deviation of 1.1 tons, differing from the earlier obtained DOE results. The reason for this difference is found in the too low number of samples in the DOE analysis.

It is concluded that for attaining confidence in the uncertainty analysis, uncertainty convergence studies need to be performed. The goal of these studies is to obtain the minimum number of samples for which the end result in the form of a probability distribution like the one in Figure 7 does not change significantly anymore.

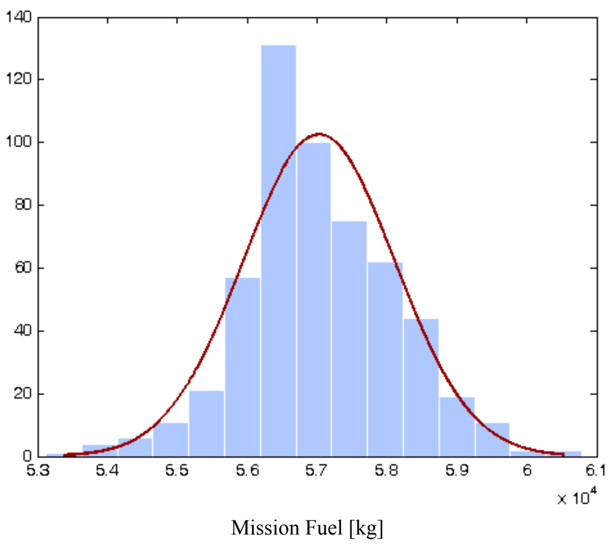


Figure 7: Distribution of the mission fuel at aspect ratio = 10 and wing area = 360 m², Mean value = 57 tons, standard deviation = 1.1 tons, Number of samples = 500

Replicability of Propagated Uncertainties

When aiming to reduce the uncertainties of the analyses results, it is necessary to identify which parameters drive the final result as well as the certainty of the underlying analysis. The parameter correlation coefficient can be used to identify the amount of dependency of output to input parameters.

In the example calculation, the correlation coefficients of the mission fuel on the (change in) input parameter values are shown in Table 5. The mission fuel correlates quite strongly with operating empty mass (OEM-mass) and takeoff mass (TOM-mass); implying a strong dependency on these input parameters. The other parameters have a lower correlation coefficient and are of lesser interest in this case.

Input Parameter	Correlation Coefficient
OEM-mass	0.99
TOM-mass	0.88
HTP-length	-0.58
TOM-x	-0.56
MLM-mass	0.54
ZFM-mass	0.46
VTP-length	-0.20
Wing-translationz	-0.19
Engine z-z	0.18
HTP-sweepAngle	-0.14
Engine x-x	0.14
Reference length	-0.12
Wing Total Length	0.08
Wing-scaling-z	0.08
Wing-scaling-x	0.08
Wing-sweepAngle	0.08
VTP-sweepAngle	0.04
Reference Point-x	-0.02

Table 5: Correlation of the selected input parameter with mission fuel

In the simplified example, only the effects of geometry and masses on the overall mission fuel requirements are investigated. For more complete analysis studies, many more parameters introducing uncertainties in the analysis process have to be observed. A reduction of overall uncertainty can be obtained by using analysis modules of higher fidelity and consequently larger computational requirements, assuming that these provide results with higher confidence.

Interpretation of the results

If the implemented uncertainty calculations are trusted (by ignoring the error of the too low number of samples as indicated in the previous section), mission fuel for the reference aircraft is in the best case 55.9 tons and in the worst case 57.1 tons (within two standard deviations, implying a probability of 95.5%).

The decision to adjust the configuration by using only the knowledge of mean values corresponding to the deterministic analysis results can be an error. As indicated in Figure 8, if the configuration is adjusted by changing the wing aspect ratio (for constant wing area), the standard deviation changes as well. When the aspect ratio changes to 13.5, the mean value of mission fuel will decrease to 56.1 tons. In this point the best case of mission fuel is 55.1 tons and in worse case 57.2 tons. The adjusted configuration shows an improvement in mean value, however within the confidence interval of two standard deviations, also a deterioration of fuel mass is possible. Comparing the best case of the reference D250 with the worst case of the improved high-aspect ratio D250 implies a deterioration of 2.3 percent in mission fuel.

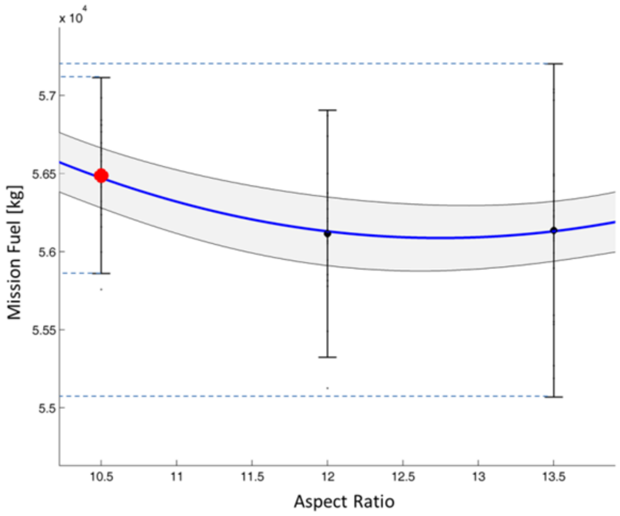


Figure 8: Optimizing the Mission fuel by changing the aspect ratio with constant reference area

The current assessment aids in making decisions in which geometry changes more effort should be invested and with which level of confidence such a statement can be made. Using the current investigation, no elaborate design decision can be made. This is mainly since only a single objective function is used, without stringent requirements on other influential factors such as takeoff field lengths. Furthermore, the lack of knowledge of other parameters driving the costs of redesigning a new aircraft dictates more extensive analyses are required before relevant design decisions are made. Finally, all included analysis modules should provide uncertainty information for propagation to subsequent modules, corresponding to its level of fidelity.

6 Summary and Conclusion

This paper provides indicative results of the implementation of uncertainty considerations within aircraft design analyses. A straightforward parameter variation of a conventional aircraft including specific uncertainties was shown and the results were compared to a reference configuration. With the assumption that the uncertainties are sufficiently covered to support design decisions, the inclusion of uncertainty data helps to make better founded decisions on the applicability of aircraft configurations to design requirements and missions. Especially when applied to the analysis of aircraft derivatives or even for unconventional aircraft configurations, the consideration of uncertainties becomes increasingly important.

The integration of uncertainty however cannot be interpreted as the final solution to cover all possible risks. Uncertainties underlie uncertainties of higher order too. A quantification of all occurring uncertainties seems to be near to impossible; nevertheless a plausible derivation of these makes sense and is useful for increasing the level of confidence in analysis result interpretation.

The integration of more sources of uncertainty of different disciplines covering major physical effects is foreseen in future work. By performing optimization including these uncertainties within the target function, a robust optimisation framework will be established. The occurring workflow will be applied to less conventional aircraft, for which uncertainty information becomes increasingly important. A larger amount of geometrical design parameters will be varied during full-scale DOE studies, the uncertainty component automatically selects the most relevant ones (based on high sensitivity to the output function or due to large uncertainty) for detailed calculations. For this a more detailed analysis of the dependencies of parameters during iterative calculations is required.

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