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# EXPLORING PROPAGATED UNCERTAINTIES IN A MULTI-DISCIPLINARY AIRCRAFT DESIGN FRAMEWORK

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## Abstract

*This publication provides a method for understanding the propagation of uncertainties across multiple analysis tools. For each parameter the information about uncertainty and the effect on a following parameter will be analysed. This helps to understand which parameters have the most effect on the result and which parameters are driving the overall uncertainty.*

## 1 Introduction

When analysing the potential of novel aircraft configurations on conceptual and preliminary design levels, the amount of time available dictates both the fidelity level and amount of analyses that can be conducted. The increase in computational power over the last decades has resulted in an increase in analysis capabilities for assessing aircraft concepts in the same amount available time. However, considerations based on analyses using methods representing high-fidelity physics-based analysis still find their application in detailed design phases only.

The DLR project "Future Enhanced Aircraft Configurations (FrEACs)" is aimed at extending the early design phase to high fidelity physics based analysis with required uncertainty information. To create a proper basis for making design decisions in early design phases using the limited available information on the aircraft physics, it is necessary to supplement that information by the uncertainty of the implemented analyses.

The current paper investigates the analysis of aircraft configurations under consideration of propagated uncertainties in early design stages. In addition to investigating sensitivities of the physical properties of aircraft, the propagation of uncertainties between individual modules in analysis workflows allows for determination of the overall uncertainty of these properties. The base for making well-grounded design decisions in conceptual and preliminary design stages is thereby improved.

In order to propagate uncertainties across multiple analysis tools, uncertainties first have to be determined at the individual tool level. In publication [1], this uncertainty determination is described for the disciplinary analysis modules within a low-fidelity physics based aerospace toolkit [2]. According to the analysis question at hand, workflows are built up by connecting these modules in the distributed integration environment RCE [3]. In this way, an analysis process is generated for the evaluation of target functions on an Overall Aircraft Design OAD level that keeps track of uncertainty data. The aircraft geometric parameters, analysis results and uncertainty data are exchanged using the Common Parametric Aircraft Configuration Scheme (CPACS) [4].

## 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 increased flexibility to choose the analysis method appropriate to the design task of interest. 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. **A common data exchange language** that is based on a central data model approach. **An integration framework** that consists of an editor and visual environment for the creation, modification and control of analysis tool chains. [5]

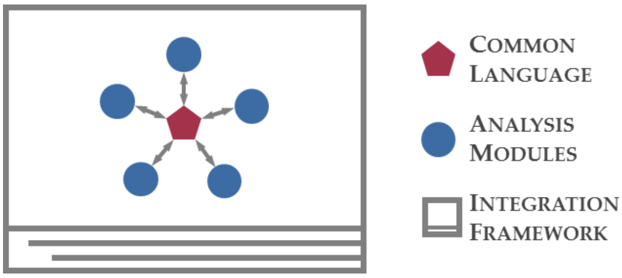



**Figure 1: Three components of distributed, collaborative design environment**

Several design environments that bring together these components exist in literature. Among others, CEASIOM [6] and MDOPT [7] 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) [8] as data exchange format. The Remote Component Environment (RCE) [9] is the integration framework of choice. The disciplinary analysis models applied are the empirics-based conceptual design tool VAMPzero [10] and physic-based for example vortex-lattice aerodynamic analysis module. Section 5 further elaborates on the characteristics of the used 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 a 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 Uncertainties in the design process

Complex natural processes can be approximated using explicit rules in model representations and applied to describe future events. By observing the real processes, conceptual models can be generated which mostly reflect a simplification of events occurring in reality. Before simulating future events using 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 modelling 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, *aleatory* 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; therefore these cannot 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 this study there are two sources relevant:

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 in 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.

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 [11], [12], [13], [14].

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, uncertainties have to be determined at the individual tool level. This uncertainty determination is described in [5] of the disciplinary analysis modules within the low-fidelity physics based aerospace toolkit.

## 4 Propagation of uncertainties in the design process

Due to the dependence of input parameters of one module on the output parameters of a preceding module, uncertainties are propagated within analysis workflows (see Figure 2). The way in which uncertainties are propagated depends on the analysis method that underlies the specific analysis model (the sensitivity of a modules' output parameter is to its input parameters).

Each model consists of one or more input and output variables and may have different characteristics. The model can be deterministic or stochastic. It can be for example, a mathematical model or a table of data or various other shapes.

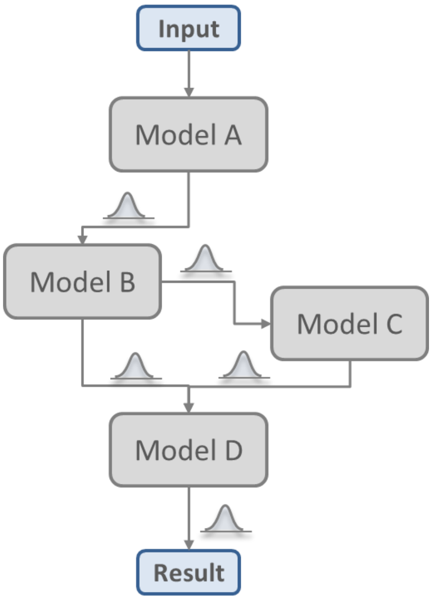



Figure 2: Propagation of Uncertainties

The input parameters can be controllable or uncontrollable (See Figure 3). The controllable parameters are set either from outside or they are deterministic output parameters from previous models. The uncontrollable parameters are those which are present as a stochastic variable. They can have different nature as described above.

To analyse the influence of uncontrollable and controllable parameters on the output parameters of a model, these parameters can be varied and the model used repeatedly. Stochastic input parameters also generally lead to stochastic output parameters and can be evaluated statistically. These in their turn, can be embedded in the multi-disciplinary design and evaluated.

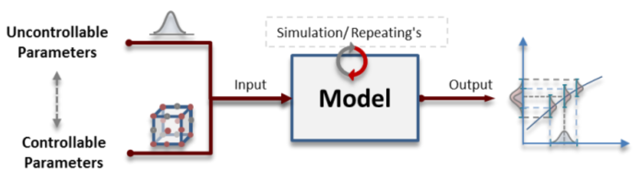



Figure 3: Influence of uncontrollable and controllable parameters on the output parameters of a model

Determining the sensitivities 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 behaviour 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 modelling, 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).

In the propagation of uncertainties should here be pointed out three main features, which serve as the basis of this:

- The **effect** of an input parameter to an output parameter,
- the **uncertainty** of input parameter itself
- as well as **confidence** in its uncertainty (uncertainty of higher order by confidence intervals).

These features are schematically shown in the Figure 4. All three affect the probability to make mistakes due to an interpretation of output parameters. If the effect of an input parameter is strong, uncertainty high and confidence in the uncertainty low, the uncertainty of the output parameter increase and thus the probability to make mistakes in interpretation.

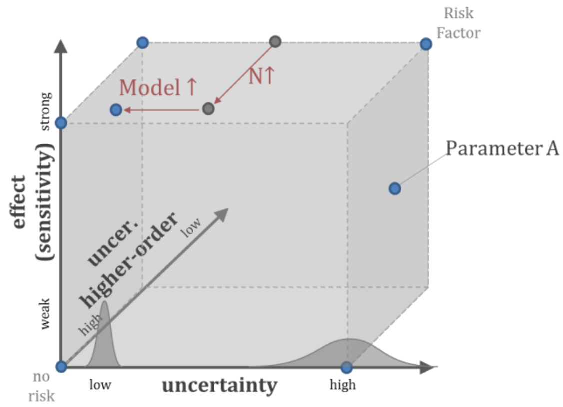



Figure 4: Features of the uncertain input parameters on one specific output parameter

*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 analyse, control, and observe its propagation behaviour. The component can handle both stochastic and deterministic models as well as intrusive and non-intrusive uncertainties. The uncertainties can be analysed using different approaches, in order to adjust the balance of time and quality of the performed analysis. The uncertainty component itself cconsists 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.

This component can be integrated into any tool chain built in RCE, provided that 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 5, this process is shown for a single module. Here, a CPACS data set is loaded and thereafter controlled by the uncertainty component. The analysis module gets the data and sends the result back to the uncertainty component. After completion of the uncertainty sampling, the results are passed to a potential 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.

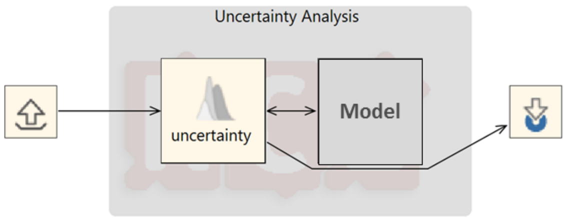



**Figure 5: Integration of the uncertainty module**

*Dependency of input to output parameters due to regression*

The information about which input parameter has what influence to output parameters is important for the traceability of the results. Input and output parameters are in this case almost random numbers. Using regression, 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.

## 5 Application of the uncertainty propagation process within the analysis workflow

Figure 6 shows the workflows for aircraft analysis, including UACs. This workflow and a design study was discussed in [5] which include the follow analyses modules:

- VAMPzero – initial model generator for aircraft configurations
- LCGplus – generates the load cases
- Tornado – calculates aerodynamic forces and moments
- AEE – calculates the primary wing structure mass
- PESTsewi – estimate the secondary wing masses
- CMU – checks the consistency of the mass breakdown
- TrimFlight – analyse the aircraft performance

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.

Based on this workflow, a new analysis workflow was constructed to analyse the propagation for the uncertainties and the sensitivities of the parameters more in detail. The constructed workflow is shown in Figure 7. For this, the same analysis tools in the same order was used.

To reduce the complexity, the analyses workflow is divided into groups. The initialization group includes VAMPzero and the structural analysis group includes the load generator (LCGplus), Tornado, AEE and PESTsevi. The mass analysis group consists of CMU and mission analysis group of TrimFlight.

## 6 Example of exploring propagated uncertainties

As an example demonstration, a reference configuration was analysed in [5] with the aid of the workflow shown in Figure 7. Selected reference configuration – named D150 – was applied as a use case.

For this analysis, the configuration is used, which has been pointed out as optimal of a previews optimization in [5]. Thus, the analysis of the reproductions is at the optimum point, which is crucial to review the configuration. The reproductions of uncertainty may also change with a change of design parameters. However, this is here also neglected.

*Parameter uncertainty propagation quantification*

When uncertainties are propagated, the number of stochastic parameters can increase. In the current analysis, there are more than 300 input parameters which exhibited a stochastic behaviour.

If the dependencies of the parameters should be found by sensitivity analysis, the number of samples would be more than 1800 (if for example formula (1) is taken into account [15]). This would entail a high computational time.

$$N_{sim} \approx k \cdot (N_{EP} + 1)\,;\ \ k = 6 \ldots\ 10 \qquad (1)$$

To skip this problem, a parameter significance test (PSU) (Parameter signifier screening) is performed before each group analysis. Here, each input parameter is changed once and the effect on each output parameter is examined. All the input parameters which have none or only a slight effect on the output parameter can be excluded from further analyses. With the reduced number of input parameters the analysis can be done.

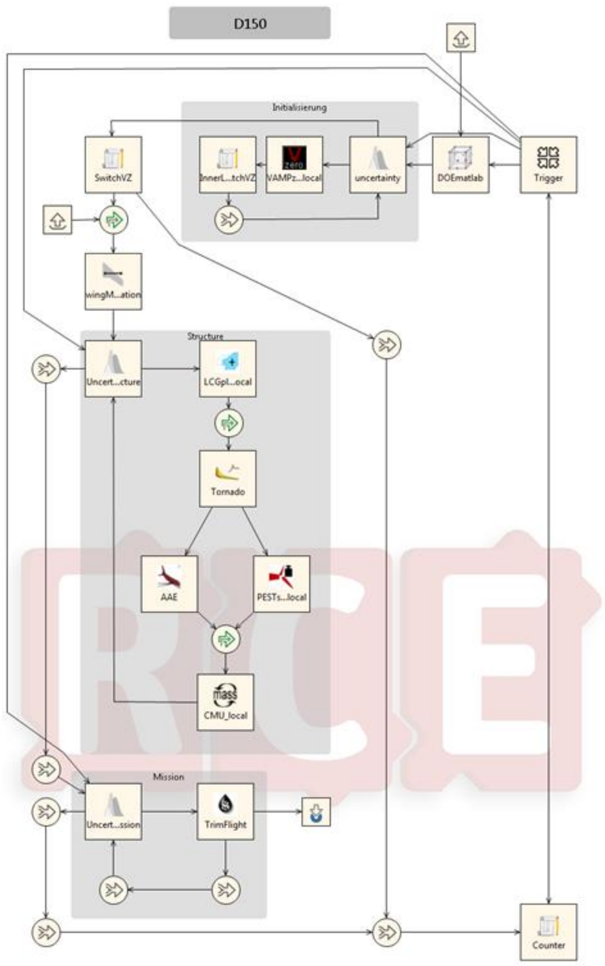



**Figure 6: Example of a workflow including uncertainty propagation components**

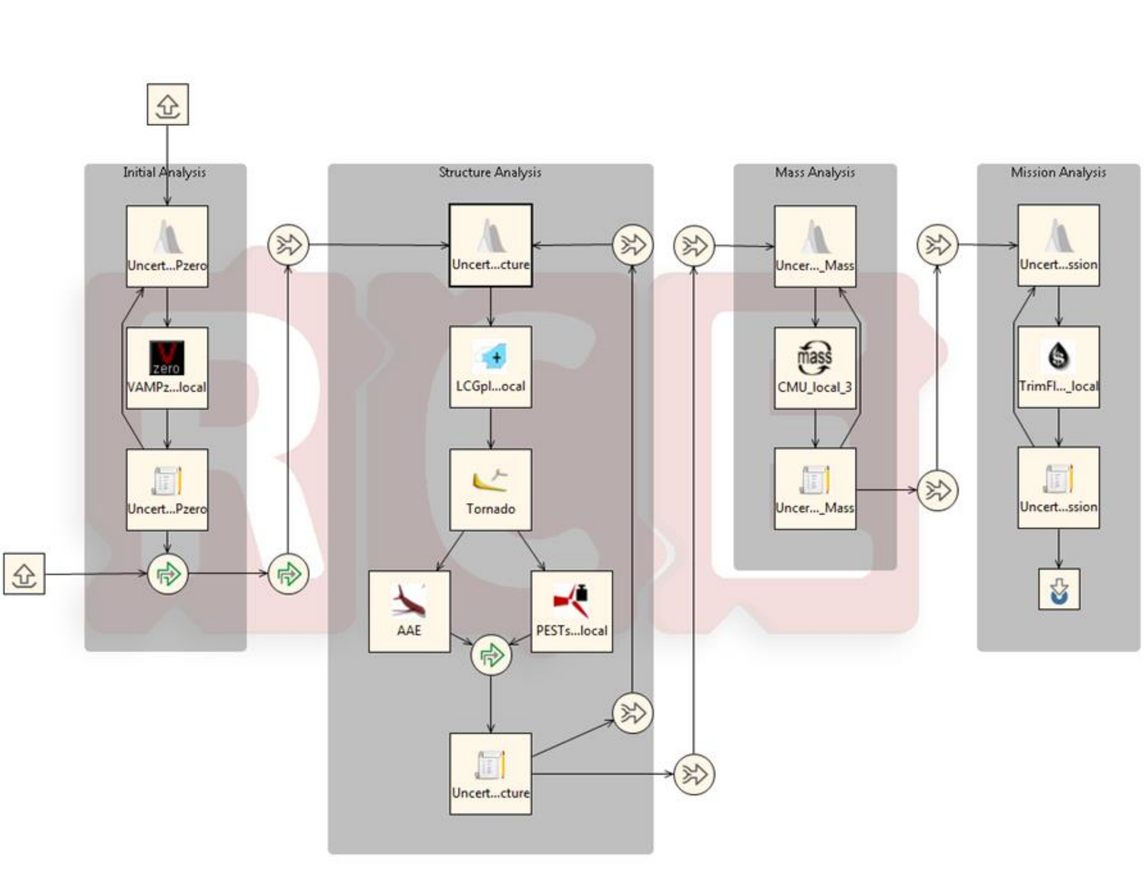



Figure 7: Reconstructed workflow for detail uncertainty propagation analysis

The number of samples is crucial for the correct conclusion of the dependencies. If the number of samples is too low, this can lead to false interpretations of reproduction. It can be detected parameters that have only a small effect, falsely have a large effect. Due to this, the formula (1) is used for estimate the number of required simulations.

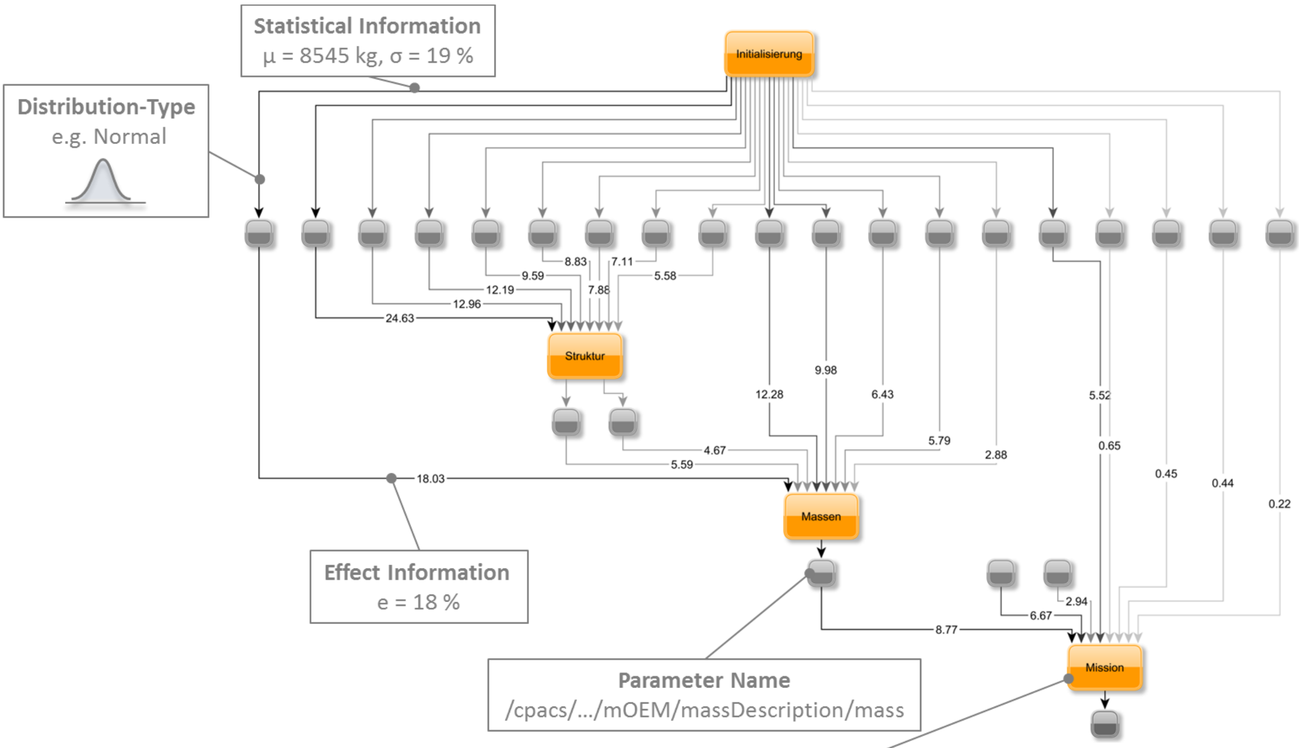
For example, 354 parameters come from the initialization part, which have an uncertainty (see Table 1). These are reduced by the PSU at 39 input parameters in the structural part. This reduces the number of samples after the application of the formula (k = 6) of 2130 to 594.

The results of a propagation analysis are shown in the Figure 8. They include the disciplinary groups as modelled in the workflow, together with the most relevant in- and output parameters.

| Group | Input Parameter | | Output Parameter |
|---|---|---|---|
| | before PSU | after PSU | |
| Initialization | - | - | 354 |
| Structure | *354* | 39 | 104 |
| Masses | *458* | 25 | 1 |
| Mission | 459 | 8 | 2 |

Table 1: Number of uncertain in and output parameters, before and after PSU

For each parameter, the information of uncertainty and the effect on a following parameter is given. The path with the strongest effect on the selected overall result in this case, the mission fuel consumption) is highlighted. In this way, it can be displayed quickly and easily which are the main parameters and how they develop during the simulation. The number of parameters is limited in this illustration so that the clarity is maintained. Each group creates a table in which the information of all input and output parameters are listed. Mission fuel consumption at the end of the evaluation in the mentioned representation has the largest effects, on aircraft empty weight (OEM) and maximum payload (payload). A standard deviation change in aircraft empty weight for example, causes a 8.8% change in the fuel composition. The aircraft empty weight is most influenced by the fuselage mass. This here has a standard deviation of 19%. A change of the average mass to 19%, caused in the aircraft empty weight a change of 18%.




| | fuel mass |
|---|---|
| IN/mOEM/massDescription/mass | 8.77 |
| IN/aeroPerformanceMap/cfz | 6.67 |
| IN/payload/massDescription/mass | 5.52 |
| IN/aeroPerformanceMap/cfx | 2.94 |
| IN/wings/wing[@uID='wing']/positionings/positioning[@uID='wing_Pos2']/length | 0.65 |
| IN/mTOM/mass | 0.45 |
| IN/wings/wing[@uID='wing']/positionings/positioning[@uID='wing_Pos3']/length | 0.44 |
| IN/wings/wing[@uID='wing']/positionings/positioning[@uID='wing_Pos3']/sweepAngle | 0.22 |
| IN/wings/wing[@uID='wing']/positionings/positioning[@uID='wing_Pos4']/length | 0.12 |
| IN/wings/wing[@uID='wing']/positionings/positioning[@uID='wing_Pos4']/sweepAngle | 0.01 |

**Figure 8: Uncertainty propagation analysis of the example workflow**

Another illustration shows more closely, which input parameters affect with which sensitivity and uncertainty of a selected output parameter (see Figure 9). Sensitivity in this illustration means, a 10% change of the input parameter. It can be seen that the aircraft empty weight, the lift coefficient and the payload have the greatest effect on the mission fuel consumption. These factors may also be referred to as risk factors, because these affect the interpretation of the result the most.

This information could then be used to reduce the uncertainty of the main influencing factors and thus uncertainty in the overall level. A first step could be that the uncertainty of the aircraft empty weight is reduced. This is strongly influenced by the fuselage mass. The uncertainty of these comes from the initialization part rather from VAMPzero. The fuselage mass is determined by statistical formulas responsible for this particular uncertainty. By using a more trusting model, which determines the fuselage mass, the uncertainty could be reduced here. A reduction in the overall uncertainty can be achieved through the use of analysis modules with a higher accuracy, but only on the assumption that these results are more truthful.

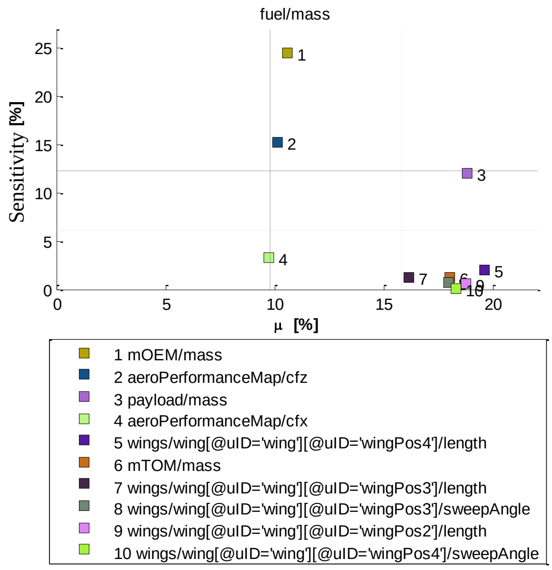



**Figure 9: Sensitivity of selected input parameter on the mission fuel over standard derivation μ of each parameter**

## 7 Summary and conclusion

This paper provides indicative results of the implementation and propagation of uncertainty considerations within aircraft design analyses. An example was shown of the propagation analysis of an aircraft design process. It was shown how the relevant parameters are selected and visualised. This helps to understand the complexity of the workflow and how the uncertainties are propagated though the process. Additional understanding about which parameters have the most effect on the result and which parameters drive the overall uncertain is also acquired.

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.

However, the integration of uncertainty 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.

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