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ROTORCRAFT FLIGHT SIMULATION TO SUPPORT AIRCRAFT CERTIFICATION: A REVIEW OF THE STATE OF THE ART WITH AN EYE TO FUTURE APPLICATIONS

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Abstract

This paper presents the approach for Rotorcraft Certification by Simulation proposed within the RoCS project. In particular, the aspects of model validation and credibility assessment through the usage of uncertainty quantification techniques are reviewed, and some lesson learned are presented. It is shown that the increase of effort required to thoroughly evaluate the capability of the simulation model is often counterbalanced by the advantages of the insight that can be obtained and possibly exploited also for design purposes. It is shown that the numerical approaches, and in some cases even the tools required to perform the necessary uncertainty analyses are publicly available and can be directly employed. This paper is one of a set presented at the 49th European Rotorcraft Forum discussing results from the EU Clean Sky 2 project, Rotorcraft Certification by Simulation (RoCS).

NOTATION

Acronyms:

AC	Advisory Circular
ACR	Applicable Certification Requirement
BA	Bare Airframe
CR	Confidence Ratio
DoE	Domain of Extrapolation
DoV	Domain of Validation
DoR	Domain of Physical Reality
eVTOL	Electric Vertical Take-off and Landing
FCS	Flight Control System
FS	Flight Simulator
FSM	Flight Simulation Model
FTMS	Flight Test Measurement System
FAA	Federal Aviation Administration
HQ	Handling Quality
HQR	Handling Quality Rating
M&S	Modelling and Simulation
MC	Monte Carlo
MoC	Mean of Compliance
QOI	Quantity of Interest
RCbS	Rotorcraft Certification by Simulation
VBD	Variance-Based Decomposition
V&V	Verification & Validation
UQ	Uncertainty Quantification

1. INTRODUCTION

To certify an aircraft means to issue, by the competent regulatory authority (e.g., EASA in Europe), a document that states that the aircraft complies with the relevant certification standards. This, in turn, means that the aircraft has been demonstrated to meet the necessary requirements to fly safely within the allowable limits. It is the applicant's responsibility to develop processes to show 'means of compliance' that typically rely on a combination of physical testing and computations through virtual models (Refs. 1,2). As an example, in the field of rotorcraft, the standards state that proof of compliance with EASA CS-27/29 Subpart B (Refs. 3, 4) (or the equivalent Federal Aviation Administration (FAA) standards) must be obtained by "tests upon a rotorcraft of the type for which certification is requested, or by calculations based on, and equal in accuracy to, the results of testing". FAA Advisory Circular AC-29.21(a) (Ref. 5), the term "calculation" includes flight simulation.

Historically, the certification evidence provided by the applicant has relied heavily on physical tests, because the level of confidence in their reliability has always been considered high. This prevalence of physical testing is certainly rooted in the fact that acceptable means of compliance, i.e. methodologies to show compliance to a certification requirement (Ref. 1), were developed in periods where simulation approaches lacked the necessary fidelity and robustness. However, paraphrasing a famous quote attributed to Albert Einstein, it is also true that "*A simulation model is something nobody believes, except the person who made it; an experiment is something everybody believes, except the person who made it*", expressing the general lack of credibility that is often associated with simulation.

However, there are several reasons that may push applicants in the direction of certification by simulation in place of performing physical tests for some requirements. Defining a flight test setup and performing the tests are expensive and may be extremely time-consuming. Physical testing, and in particular flight testing, has several limitations. Some flight test conditions for rotorcraft, or those related to engine or control systems failure, may carry significant safety risks. Additionally, the lack of repeatability and the limited capability to control the environmental conditions and the scenarios may make flight testing a suboptimal approach for certification.

FAA's AC 25-7D §3.1.2.6 defines the general principles under which flight simulation may be proposed as an acceptable alternative to flight testing for large aeroplanes (Ref. 6). With the increase in fidelity of physics-based rotorcraft flight simulation models, it is foreseeable that the usage of flight simulation to replace flight testing through a virtual-engineering process will become more dominant, as the industry pursues efficiency, low cost, increased safety, and low energy consumption (Ref. 7). The team of the European CleanSky2 funded project, Rotorcraft Certification by Simulation (RoCS), has the aim to explore the possibilities, and limitations of flight simulation for certification. With this aim guidelines for best practices have been developed to guide compliance the demonstration for the airworthiness regulations related to helicopters and tiltrotors (Refs. 8,9).

Within the framework of the RoCS project, preliminary Guidance for the application of (rotorcraft) flight modelling and simulation has been developed in support of certification for compliance with standards CS-27/29, PART B (Flight) and other flight-related aspects (e.g. CS-29, Appendix B, Airworthiness Criteria for Helicopter Instrument Flight) (Refs. 10, 11). The Guidance follows a requirements-based approach and is presented in the form of a structured process for Rotorcraft Certification by Simulation (RCbS). The process starts with the selection of 'applicable certification requirements' (ACRs) for RCbS, with judgements on a matrix of factors of Influence (how the RCbS process will be applied), Predictability (extent of interpolation/extrapolation), and Credibility (confidence in results), in line with a comprehensive description of the assembly of flight simulation requirements.

In particular, the topic of Credibility of the modelling and simulation approach used goes beyond the classical Verification and Validation (V&V) processes when a model is developed for certification purposes. Credibility represents what is necessary to reach the level of confidence in the evidence presented based on simulation tests compared to that gained during a flight test. To build credibility it is, in fact, necessary to take into consideration a detailed assessment of errors and uncertainties, both in the areas of validation of the model and in the ranges where extrapolation is applied, as well as a certain degree of conservatism when the level of uncertainty is relatively large. In fact, as well stated by Roy and Oberkampf, "*without forthrightly estimating and clearly presenting the total uncertainty in a prediction, decision-makers are ill-advised, possibly resulting in inadequate safety, reliability and performance of the system*" (Ref. 12), suggesting that under-estimating the predictive uncertainty of a model may lead to incorrect conclusions.

The need to develop methodologies to perform certification by simulation has been considered by a broad range of technical communities. AIAA developed a recommended practice to use flight modelling to reduce flight testing supporting aircraft certification (Ref. 13). EASA issued a Certification Memorandum dedicated to the use of Modelling and Simulation for CS-25 Structural certification (Ref. 14). NASA developed its own guide on simulation credibility that provides "*an approved set of requirements, recommendations, and criteria with which models and simulations (M&S) may be developed, accepted, and used*

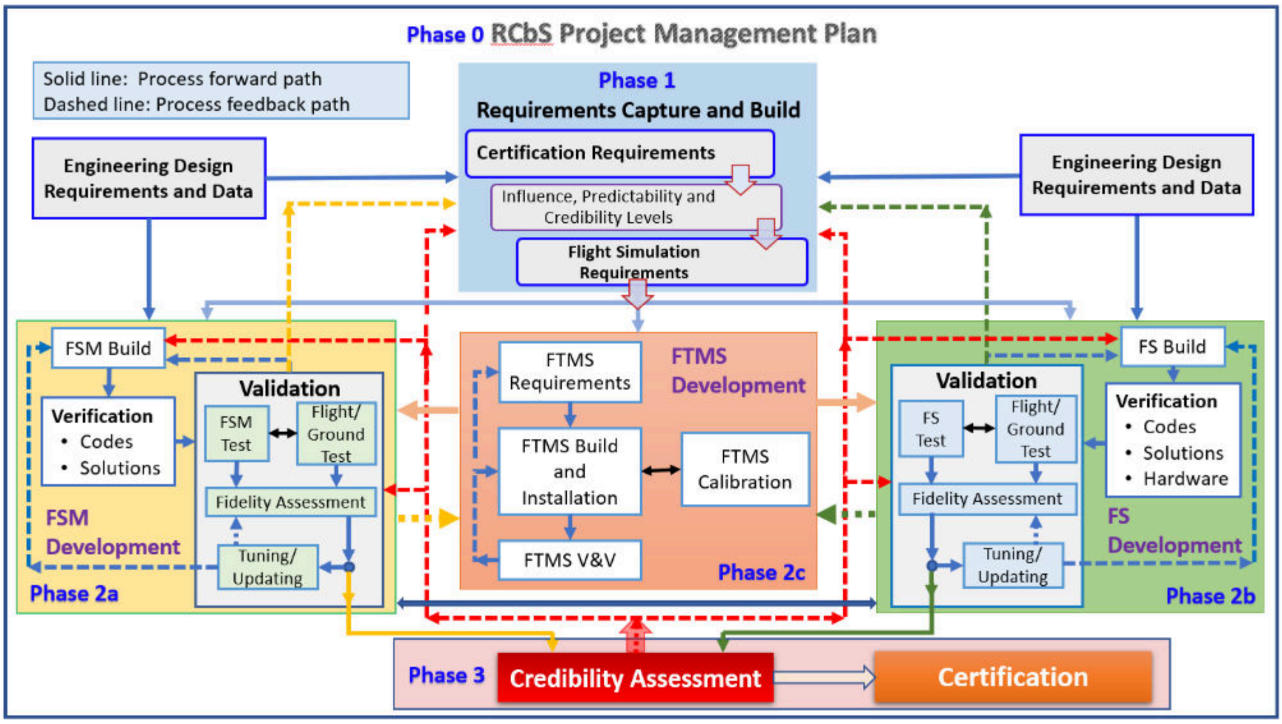

Figure 1 Rotorcraft Certification by Simulation process.

in support of NASA activities" (Ref. 15). ASME developed several standards for the V&V of numerical models [16]. Similar ideas are pursued for the certification of autonomous automotive vehicles (Ref 17). The specification for the approval of the driving system for fully automated vehicles adopted by the European Parliament contains, in part 4, the principles for credibility assessment of models for certification (Ref. 18).

The present paper reviews and compares different approaches to better explain what it means to assess and improve the credibility of M&S when used for certification purposes. In particular, the aspects related to the quantification of uncertainty will be discussed to provide approaches that are in line with the guidelines whilst being feasible to execute with the current tools and within the current time frames of a certification process.

The final part of the paper is dedicated to what comes next, i.e. what course of action should be pursued to further develop the RCbS approaches for the enhancement of aviation safety and to support fast and smooth introduction of innovative systems and vehicles, with focus on eVTOL.

The paper is one of a set presented at the 49th European Rotorcraft Forum discussing results from the EU Clean Sky 2 project, Rotorcraft Certification by Simulation (RoCS). The other companion papers (Refs. 20, 31, 32, 33) present some experiences in the application of RCbS.

2. OVERVIEW OF THE RCbS PROCESS

2.1. General

The Guidance for the RCbS process is organised into three, serial but iterative, phases, as shown in Figure 1 and expanded on in Refs, [9,10].

- Phase 1; requirements-capture and build,
- Phase 2; developments of the flight simulation model (FSM, 2a), flight simulator (FS, 2b) and Flight Test Measurement System (FTMS, 2c);
- Phase 3; Credibility Assessment and Certification.

The activities in these three phases are undertaken within a governance framework defined in the Project Management Plan and created in Phase 0 of the RCbS process.

In this paper we will concentrate on Phase 2a relative to the development of the flight simulation model and the subsequent Credibility Assessment performed in Phase 3. Put simply, an FSM used for certification compliance demonstration purposes should include the physics necessary to achieve sufficient fidelity for the cases and conditions of interest, the ACRs.

The modelled physics shall describe the behaviour of the aircraft and predict the three essential aspects of flight, i.e. trim, stability and response. The assumptions that define the conceptual model focus on what physical phenomena will be included and what will be ignored. Consequently, the FSM should, therefore, be physics-based, i.e., expressed in terms of, or derived from, the physical laws applied in the creation of the mathematical model and in the operation of the numerical simulation. In this way, the model obtained will be *prognostic* as defined in (Ref. 19), i.e. "*models used to predict the behaviour of a system given a supposedly understood law*". Ideally, it should be developed following a component-based building block approach since it allows two main advantages:

- It allows for a structured uncertainty quantification assessment since it is possible to proceed for each component or building block to identify the most relevant parameters. This may lead in some cases o a global (aircraft-level) assessment only with a reduced number of parameters.
- It makes it easier to prove that the model is correctly operating within the limits of the conceptual hypothesis used to develop it.

Once a flight simulation model has been created, the next crucial step is the Verification & Validation (V&V) process. Verification is the process of determining that a computational model represents, within the required limits of accuracy, the underlying conceptual and mathematical models and their solutions. The process can be divided into two steps: code verification and solution verification. Validation is the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended use. Usually, validation is performed by comparing the results obtained by the simulation with the results of experiments.

When developing and validating a building block of the FSM it is always important to establish the limits of the input, the output and existing internal states of the building block and monitor them for exceedances, either during the simulator flight tests or during a post-processing phase. The use of phenomenological sub-models (p-models) for components is not considered to be prohibited, but they can generally not be used in extrapolation, i.e., in cases where there are no experimental data to support the validation, simply because there will be no robust way to assess the uncertainty and the associated model error.

2.2. Validation errors and uncertainty

Figure 2, derived from (Ref. 16), is used to support the description of key errors. It can be seen that both the referent (typically experimental data) *R* and the simulation result *S* have errors relative to the 'truth'. Validation looks at the difference between two values, both affected by errors: *S* and *R*, called the validation error δ_{val}.

Before going into further detail, it is important to classify the uncertainties as aleatory or epistemic, defined as

- *Aleatory*: the inherent, and also irreducible, variation associated with the physical system or the environment under consideration. It is stochastic in nature.

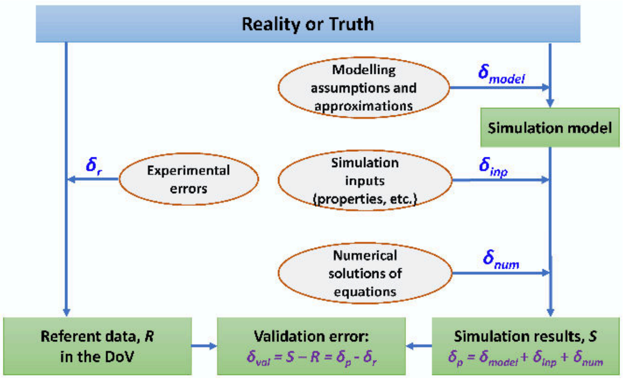

Figure 2 Overview of the derivation of the validation error.

- *Epistemic*: The potential inaccuracy in any phase or activity of the modelling process that is due to a lack of knowledge or to intentional approximations applied by the analyst. It is potentially reducible by model improvements or through an improved measuring technique employed to assess model parameters.

Referring to Figure 2, it is possible to see that the prediction error δ_p, associated with the simulation result S, is composed of,

a) the errors due to modelling assumptions δ_{model} including those generated by the choices made in the conception of the model that are, by nature, related to epistemic uncertainties,
b) the numerical errors, δ_{num}, stemming from the computational methods used to solve the

underlying equations of the FSM (generally accounted for as epistemic uncertainty),,

c) the errors, δ_{inp}, arising from the input parameters of the FSM. The input parameters may have epistemic or aleatory, or both at the same time, depending on the nature of the input parameter taken into consideration.

The prediction error can be expressed by:

(1) $$\delta_p = \delta_{model} + \delta_{num} + \delta_{inp}$$

The validation error δ_{val} refers to the comparison error observed between the referent and the simulation in the Domain of Validation (DoV), i.e. the domain that contains all test conditions used to perform the validation so that any model for intermediate values of the paprameters can be correctly defined as an interpolation of validated models[2] (Ref. 11 for more information about the modelling domains adopted in the RCbS process). Including the referent error, δ_r associated with the referent value R (usually this is the experimental error), the validation error can be written in the form:

(2) $$\delta_{val} = \left|\delta_{model} + \delta_{num} + \delta_{inp} - \delta_r\right|$$

Hence, the error due to modelling assumptions, i.e. the error an applicant needs to quantify and understand in the DoV validation process, can be written as:

(3) $$\delta_{model} = \delta_{val} - \left|\delta_{num} + \delta_{inp} - \delta_r\right|$$

The absolute-value term on the right of (3) is composed of terms that are of unknown magnitude and sign. Assuming the errors are effectively independent (see Ref.16) the associated validation uncertainty u_{val}, can be defined as:

(4) $$u_{val} = \sqrt{u_{inp}^2 + u_{num}^2 + u_r^2}$$

The simulation model error cannot be uniquely identified but falls within the range:

(5) $$\delta_{model} \in \delta_{val} \pm u_{val}$$

The measurement (referent) or experimental uncertainty u_r is determined by the measurement set-up and encompasses not only systematic and random errors in the data acquisition and instrument calibration, but also random error or variability due to atmospheric conditions and piloting technique. The numerical uncertainty u_{num} is obtained from the solution verification process. It is associated with spatial and temporal discretisation errors of the FSM, incomplete iterative convergence etc. Finally, the input uncertainty u_{inp} can be derived through uncertainty quantification methods (see Ref. 16, 13).

If the validation error is significantly larger than the validation uncertainty, the error due to modelling assumptions δ_{model} can be expected to be close to δ_{val}, and so the only way to reach a better agreement can be through an improvement/enrichment of the conceptual model and the associated modelling assumptions. Alternatively, when $|\delta_{val}| \leq u_{val}$, it can be concluded that the model is within the precision achievable given the data and software available. The uncertainty u_{val} provides a target to be reached when performing model validation in the DoV.

This approach ensures the availability of an error metric given by u_{val} that adapts naturally to the FSM chosen to satisfy the requirements. This approach represents a natural extension of the idea of sufficient fidelity introduced in the requirement capture phase. In this process, it should be stressed that characterising the uncertainty of the validation measurements u_r is equally important as characterising the modelling uncertainties.

It must be noted that characterizing the uncertainty u_{val} only in terms of the interval value, and not any other stochastic characteristic, makes the implicit assumption that all uncertainties are treated as epistemic, considering all uncertain elements as unknown, but bounded. This may appear as a rather crude approach, but it is not so different from similar approaches used in other fields. The interested reader can refer to the debate ongoing in the structural design field between non-deterministic design approaches and deterministic approaches, where safety factors are used to deal with insufficient knowledge (see Ref. 20 and references therein). There it is shown that probabilistic design and unknown-but-bounded approaches to uncertainty yield coincident results when the required reliability tends to unity. The deterministic approach is often less computationally intensive, but requires a wise selection of

[2] This domain is usually defined mathematically as the convex set of the validation points.

the intervals of the variability of the considered parameters. It is also useful to note that current approaches accepted for the certification of structures are all based on the usage of safety factors.

2.3. Credibility and Confidence Ratio

Confidence is an elusive concept, but for RCbS it must be reinforced by quantitative analysis of the uncertainties in predictions, and test data, in both the DoV and Domain of extrapolation (DoE), i.e., the domain within which extrapolation of predictions are made to achieve certification for an ACR. The Confidence Ratio (CR) concept is used in (Ref. 11) to quantify the credibility assessment relating to the prediction of a 'margin'. *M* is the margin, or the generalised 'distance', between the performance requirement (e.g. control limit, touch-down velocity or the damping of an oscillation) and the FSM prediction, i.e. the performance assessment. Credibility assessments are concerned with deriving, and ultimately ensuring, the sufficiency of the variety of margins related to an ACR. A generalised CR can then be defined as,

$$CR = M/U \quad (6)$$

where $U = u_{val}$ if the evaluation is in the DoV, or U is the extrapolation of the uncertainty if the FSM is used in the DoE. Clearly, at this point it is crucial to unambiguously define u.

An intuitive result of this simple expression is that the smaller the margin to the performance limit, then the lower should be the uncertainty. Credibility relates to the relative size of *U* and *M*, and from a safety perspective it seems appropriate (though by no means straightforward) to define a minimum acceptable CR for the credibility-safety trade-off.

The minimum requirement for the performance metric assessment is for positive confidence, i.e. CR>1. Note that CR<1 implies uncertainty larger than the margin; a situation requiring further attention in Phase 3, should certification be sought for such cases. For added assurance, values of CR in higher ranges could be used; The uncertainty is reflected in the level of confidence an applicant will have in the FSM prediction of the margin with smaller uncertainty reflecting a higher confidence level. This concept is again related to the idea of the safety factor to arbitrarily account for elements that have not been considered.

Table 1 connects the CR ranges to different cases of exploitation of RCbS. In general, moving from left to right means exploiting more and more the capability of the tuned physics-based model to be prognostic in the DoE. However, the further the application moves outside of the DoV, the higher is the risk that unknown-unknowns, not considered in the validation process, increase the simulation errors. This should be reflected in the increasing uncertainty as predictability levels increase towards P4. To counteract this tendency, a higher threshold for the CR should be required.

Table 1 Influence-Predictability Level Matrix with Confidence Ratios in the RCbS process

RCbS ACR	Influence Levels	Predictability Levels with Confidence Ratios			
		P1	P2	P3	P4
	I1	(L)	(L)	(L)	(L)
	I2	(L)	(L)	(M)	(M)
	I3	(L)	(M)	(H)	(H)
	I4	(M)	(M)	(H)	(VH)

At the same time, moving from the upper part to the lower part of the table, the higher becomes the influence of the decision taken using the results of simulations, and so a higher CR must be taken to account for the larger risk assumed. The different letters L, M, H, VH used in Table 1, refer to the ranges suggested in Table 2. The absolute values reported in the table are, at this point, purely notional and require further scrutiny in the future.

Table 2 Suggested CR levels

$1.0 \leq CR$	Minimum confidence (L)
$1.1 \leq CR$	Medium confidence (M)
$1.25 \leq CR$	High confidence (H)
$1.4 \leq CR$	Very High confidence (VH)

The cases with a sufficient level of confidence of L are those for which the uncertainty accounted for by u is already sufficient to limit the risks; so, it is sufficient to require a CR larger than 1. In the most critical cases, very high (VH) confidence should be achieved, meaning the value of CR should be around 40% higher than the L ones.[3]

[3] For structures the safety factor used to compute the ultimate loads given the limits loads is 1.5, meaning 50% more than the predicted limits. So, a maximum close to 50% should be considered sound. We propose a slightly lower value, i.e. 40% because we are proposing to keep

It should be clear at this point that it is extremely important for the application of RCbS processes to arrive at a detailed quantification of the uncertainty of the models. The following section will review the state of the art and the approaches proposed by different authors to perform this task.

3. UNCERTAINTY QUANTIFICATION

Uncertainty quantification is the process of identifying uncertainties, propagating them through the implemented FSM, and estimating statistical content for the relevant quantities of interest (QOI). The process requires the characterisation of all relevant sources of uncertainty and the quantification of their effect on the QOI. This will enable analysts to make justifiable statements about the accuracy and the degree of credibility of the prediction based on the analysis (see Refs. 12, 13). The three important elements of validation uncertainty were introduced in the previous section: the uncertainties due to numerical errors, those associated with the experimental error, and those due to uncertainty in the input parameters. Details of candidate methods for performing the identification of u_{num} can be found in Section 2 of (Ref. 16) and in parts II and III of (Ref. 13). Regarding flight test data, the experimental uncertainty u_r should be determined within the flight test measurement system development and instrument calibration, including the quantification of the data process noise. This requires a great deal of care, but should not be a novelty for the analysis of certification flight tests. Finally, uncertainty due to input parameters u_{inp} will be discussed in the following.

3.1. Identification of input uncertainty

All potential sources of input parameter uncertainty should be considered, since that can ba significant contributors of u_{val} The distinction between u_{num}, and u_r and the model form uncertainty, i.e, δ_{model}, is straightforward. Instead the distinction between u_{inp} and δ_{model}, can be less clear-cut (Ref. 16), because sometimes we may hide as input variability the choice to not include some detailed mathematical models. However, they both contribute to validation uncertainty, as shown by Eq. (2), so the distinction seems a matter of low importance in the DoV. However, this is not the case when we move to the evaluation of the predictive uncertainty into the DoE. Here, the extrapolation of u_{inp} is based on the knowledge of the mathematical structure of the physics-based model andso is more solid. Instead, the extrapolation of is not based on physics and so less reliable (see Ref. 20 for applications). For this reason, it is important in the validation phase of the model to reach a condition where $|\delta_{val}| \leq u_{val}$, because this means that the effect of model form uncertainty has been reduced appropriately in the DoV.

To reach this validation goal it is perfectly reasonable to perform a model tuning and updating phase (Ref. 11), with care taken to keep all parameters within physically meaningful bounds and to ensure that the aircraft-level tuning does not deteriorate the correlation against component-level test data. In case of doubt, it may be necessary to explore the limits of validity of a given parameter by comparison against a higher fidelity simulation approach. If a system-level p-model is used, then a range of model-updating techniques could be applied, keeping always in mind that such a model can be used only for P1 predictability levels, i.e. interpolation only, since its domain of physical reality DoR cannot extend, by definition, beyond the DoV. Therefore, also the model tuning phase could provide good indication that the choice of the inpu parameters to be used to assess uncertainty is appropriate. Difficulties in model tuning may often hide problems in the model forms.

Consequently, the general philosophy should be, as suggested in (Ref. 12), to consider an aspect/parameter as uncertain unless there is a strong and convincing argument that the uncertainty assessment will result in minimal effects. However, this may easily lead to a situation where the more variables we promote to the rank of input and allow to vary, the greater could be the variance to be expected in the model prediction; potentially arriving at a situation where the model predictions vary so much as to be of no practical use. However, as suggested in (Ref. 19), practice has shown that often only a few factors create a significant amount of the uncertainty with the majority having a negligible impact if there are only a few key elements, i.e., the QOI, on which the effects of uncertainty are evaluated. Consequently, it is essential that the QOIs are “judiciously chosen”. The addition of a

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into account in a more rigorouse way the extrapolation of uncertainties.

few, less relevant, parameters adds completeness and defensibility to the uncertainty analysis without necessarily affecting the variance of the output. So, a crucial role in this identification phase is played by subject matter experts that for every component or building block of the model can identify the relevant parameters, but more importantly, the range of variability of these parameters.

To simplify the approach, and allow for possible repeated use of the same analysis for different models, it is suggested that the analysis is initially conducted at the level of the building blocks (e.g. main rotor or even rotorblade), identifying for each one of them the relevant parameters and using this analysis to perform the selection of parameters at the level of higher model tiers. Support for this parameter selection process could be provided using sensitivity analysis, as described in section 3.3.

Another aspect to consider is the computational burden that may become too large to make analysis feasible. So, it is important to identify simpler and less demanding approaches to be used for a first screening that can be followed by more precise approaches applied to a limited number of parameters. as a rule of thumb it is suggested to have a number of parameters lower than 10 (see Refs. 19,24).

3.2. Characterisation

Characterisation is concerned with definiing a mathematical structure for the uncertainty analysis and the assignment of associated numerical values. The first choice to be made is to distinguish between aleatory or epistemic uncertainties. While the employment of aleatory uncertainty seems very elegant and gives the opportunity to provide detailed information about the reliability of the output, it often requires a characterisation of the input that may be challenging to be obtained. Additionally, conveying the correct interpretation of the output to stakeholders not accustomed to stochastic analysis may be difficult (see Ref 21). So, it is suggested to consider, in the simpler cases, all uncertainties, also for input parameters, as epistemic, reducing also the computational burden required for the propagation of the uncertainties. More sophisticate approaches to combine aleatory and epistemic uncertainties can be found in (Ref. 12).

For the quantification of ranges of variability, it is always a good idea to resort to expert opinion, as suggested in (Ref. 16).

Alternatively, in cases where the derivation of the uncertainty range may be difficult it is possible to use a Bayesian Calibration to identify the posterior probability distribution of the related parameters that caused the experimentally measured statistical uncertainty (see Ref. 22). Swiler et.al 23 developed a method to match the mean and variance of the output identifying the variability of a set of selected parameters characterised by a Gaussian probability distribution. This algorithm has been implemented in Dakota (Ref. 26) and applied to a multibody model of rotorcraft in (Ref. 24) used to validate the a model of a rotorcraft loads in ground effect.

3.3. Sensitivity

Sensitivity analysis can be used to rank the relevance of several parameters and so to help identify the most relevant for the selection of input uncertainty. It may be also used in some cases to perform a model simplification, allowing the engineer to discard or simplify parts of a complex model that do not contribute significantly to the QOI. In some cases, it may also be used to support the experimental setup for the validation Flight Tests, allowing the prioritisation of quantities that need to be measured or the selection of the precision required (Ref. 19).

The most classical approach to sensitivity is based on the computation of partial derivatives of the output of interest *y* with respect to the input parameters θ_i. The advantage is that the computation is typically fast. There are several techniques that could be used:

- Analytical differentiation
- Finite difference approximation
- Software automatic differentiation
- Adjoint method

A typical disadvantage is that the approach is local, i.e., limited to the small neighbourhood of the nominal parameter set. To provide the correct scaling that will allow ranking the effect of input uncertainty, it is necessary to weight the partial derivatives of each parameter with the corresponding standard uncertainty range of each input parameter, as suggested in (Refs. 16, 19):

$$u_{inp}^2 \sum_{i=1}^{n}\left(\frac{\partial y}{\partial \theta_i} u_{\theta_i}\right)^2 \qquad (6)$$

Most reliable sensitivity information when dealing with nonlinear systems can be gained by using global sensitivity approaches such as the Variance-Based Decomposition (VBD) or Sobol's method (Ref. 19). The method allows for decomposing the variance of the output of a model *y* to several input $\theta_i, i = 1, \dots, n$, into fractions which can be attributed to each input, allowing the measurement of the sensitivity across the whole input space. In the end, the variance of *y* is decomposed as,

$$Var(y) = \sum_{i=0}^{n} V_i + \sum_{i<j}^{n} V_{ij} + \cdots + V_{12\dots n} \tag{7}$$

The above variance decomposition shows how the variance of the model output can be decomposed into terms attributable to each input, as well as the interaction effects between them. Together, all terms sum to the total variance of the model output. So, scaling all $V_i, V_{ij}, \dots$ with the $Var(y)$ it is possible to obtain a measure of the sensitivity of the variable alone, or of the combination of variables. The fact that the sum of all these sensitivities is equal to 1 allows the engineer to rank them and define a threshold above witch all other variables (or higher-order interactions) could be neglected as less relevant. It is also possible to evaluate the total contribution to the output variance of θ_i, including all variance caused by its interactions, of any order, with any other input variables using the total effect indexed; (see Ref. 19) for more details.

To perform the estimation of these sensitivity indices it is required to use Monte Carlo (MC) method (Ref. 25), that involves generating a sequence of randomly distributed sampling points inside the domain on the input parameters of size *n* and then compute the QOI for each element of the sequence. The accuracy of the method depends on the number of sampling points considered *N*, and the convergence can be very slow (of the order of $N^{-\frac{1}{n}}$); unless appropriate methods to accelerate convergence are used (Ref. 25), a very large number of points may be required (of the order of thousands or of hundreds of thousands of runs). However, there are several techniques that could be used to estimate the sensitivity indices at a fraction of the computational cost required for the V_i coefficients of the VBD technique (Eq. 7). Additionally, the large number of iterations required to derive reliable statistical quantities makes impractical the adoption of the exact model evaluations. For this reason, the usage of surrogate models to approximate responses is often recommended especially for models that are time-consuming to obtain each solution. This is the approach employed for instance in Dakota (Ref. 26).

3.4. Propagation

Propagation refers to establishing the relationship that exists between the input and the output uncertainty. If the relationship between the output *y* and input parameters θ_i is nonlinear, as is typically the case, this is done again using MC approaches (Refs. 25, 26). If the computation of sensitivity through VBD has been adopted, this computation is also an outcome of the analysis, because the variance of the output will be the sum of V_i coefficients taken into consideration after the sensitivity analysis, at least if limited to the computation of the variance of the output.

In the cases where simpler local sensitivities have been employed and only epistemic uncertainties are considered, it may be possible to adopt simpler approaches for the evaluation of the output uncertainty. One is based on the possibility to employ interval analysis or an MC method, specifically designed for interval analysis, that can be much faster (Ref. 27).

Other possibilities are based on the usage methods specifically designed to propagate epistemic uncertainties, such as the Dempster-Shafer theory of evidence (Ref. 28, 26).

3.5. Extrapolation

Several validation experiments can be necessary to obtaina thorough validation of the model in the entire DoV. However, the interest in using RCbS lies mostly in the possibility to apply the developed physics-based models outside the DoV.

Consequently, a way needs to be developed to assess the effect of uncertainty outside the DoV, in the DoE. If a model has been validated up to the point where the model error has been limited to a very small amount, i.e. when $|\delta_{val}| \leq u_{val}$, then a good estimate of the extrapolation error could be given by the propagation of the input uncertainty to estimate u_{inp}. Of course, it will be important to corroborate that the extrapolation has been performed within the DoR of the model considered. In some cases, it may be reasonable to perform new sensitivity analyses in the DoE, to verify if different parameters become more relevant than those initially considered in the DoV. Additionally, it should be considered that the increase of the minimum CR threshold required to take account of the possible rise of phenomena generated by 'unknown unknowns'.

4. APPLICATION OF RCbS TO eVTOL AIRCRAFT

Over the next few years, it is expected that advanced air mobility will thrive as a safe, quiet and clean (and hence publicly acceptable) alternative means of transport, particularly in urban areas. At the time of writing, several electric Vertical Take-off and Landing (eVTOL) configurations are progressing towards certification. However, for various reasons this class of vehicle was not considered under the umbrella of the RoCS project. Principally, because RoCS was focused on EASA's certification standards CS-27/29 and, during the life of RoCS, it has become clear that such eVTOLs will not be certified using these standards, but rather using their own 'Special Conditions', the so-called SC-VTOL (Ref. 29) developed by EASA. The RoCS team suggest that the RCbS process be considered as the preferred option for the certification of this future class of aircraft in Europe. The wide variety of configurations, coupled with the lack of experimental experience, may lead to long negotiations for the setup of specific ad-hoc means of compliance for each aircraft which can significantly slow down the introduction of these innovative systems.

For these vehicles, the SC-VTOL proposes the use of approaches inspired by the design standard ADS-33E-PRF (Ref. 30), as a means of compliance to assess if the aircraft handling qualities are suitable for the operational needs. In this context, the suitability of handling qualities (HQs) is expressed in terms of both performance and safety margins. The characterisation of HQs has both a predictive dimension and pilot-assigned dimension; the former derived from open-loop testing, the latter from pilots flying tasks with performance standards. Use of the Cooper-Harper Handling Qualities Rating (HQR) scale ensures that the pilots take account of workload as well as performance in their assignments. Flight safety and operational safety are closely linked by this dualism, aircraft being deemed safe if they can perform operational tasks with the pilot applying low to moderate levels of compensation. In effect, the HQR scale enables test pilots to quantify effectively how much spare capacity they have for other duties, a very important consideration for single pilot operations.

The RCbS process, flowing from the selection of the applicable requirements (e.g. stability, controllability and manoeuvrability), through the construction of simulation fidelity and credibility requirements, to the Phase 2 developments fits naturally with the innovations outlined in the SC-VTOL. A potential departure from the process lies in the need for fidelity assessments of the so-called bare airframe (BA) configuration. The typical eVTOL features a full-authority, digital flight control system (FCS), allowing novel response types such as translational-rate-command, position-hold. Flight in unaugmented bare-airframe 'mode' may never be envisaged. Yet a key aspect of the FSM fidelity assessment lies in establishing physics-based understandings and updates for the BA model. To facilitate this, a method for extracting the behaviour of the BA from measurements with the integrated BA+FCS will be required. This might seem straightforward, but the strong correlations between control inputs and aircraft motions risk important physics being 'masked' in the closed-loop behaviour. Addressing such RCbS challenges head-on will open the way for robust practices to be developed early in the life of eVTOL configurations.

The use of 'flight test manoeuvres' and 'specific flights' within the SC-VTOL means-of-compliance form natural stepping stones towards certification when exercised in ground-based flight simulators, providing the context for pilot assessment and commentary on control compensation and task performance. They also provide a sound basis for flight simulator fidelity assessment, that forms a key aspect in RCbS Phase 2b.

5. CONCLUDING REMARKS AND FUTURE DEVELOPMENTS

The material presented in this paper has highlighted how the developed 'Guidelines for Certification by Simulation', developed within the RoCS project, represent a robust and practical approach to setting up a flight model and simulator for providing appropriate 'credibility' evidence to the certification authorities. This approach should be considered particularly viable when new configurations or new technologies are introduced, because it may support the understanding of potential problems and consequently minimise the time required to develop appropriate MoC for certification.

The methodologies and the tools necessary to perform the validation and credibility assessment through uncertainty quantification (UQ) are currently available in the public domain. The standard adoption of UQ and sensitivity analyses proposed here may appear formidable, but it is likely that such processes already exist within Industry, to facilitate trade-off studies in support of design and development. It is considered a small step to build these into a robust RCbS process.

While the challenges of UQ are fully acknowledged, the authors consider that the amount of additional work required to prove the credibility of models should not hinder the application of RCbS. While it is anticipated that early adoption will occur in well-established rotorcraft industries, the opportunities for adaptation to application in the eVTOL industry, as certification programmes progress, seem significant.

The theoretical framework for UQ and credibility an analysis presented in this paper is complemented by the four RoCS 'case-study' papers presented at this 49th European Rotorcraft Forum. These studies exercise the RCbS process in a variety of ways as illustrations for potential adopters to learn from. What is now required is for Industry to take the process forward, to build RCbS capabilities, around existing flight-physics, simulation and certification skills and experience, but, as the authors emphasise, with sufficient autonomy and authority that new practices can be established efficiently and with strong governance.

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Rotorcraft flight simulation to support aircraft certification: a review of the state of the art with an eye to future applications

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