# MODELING AND SIMULATION OF SAAB GRIPENS VEHICLE SYSTEMS, CHALLENGES IN PROCESSES AND DATA UNCERTAINTIES

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## Abstract

*In aircraft development, it is crucial to understand and evaluate behaviour, performance, safety and other aspects of subsystems before and after they are physically available for testing. Simulation models are used to gain knowledge in order to make decisions at all development stages.*

*This paper describes the development of Saab Gripen′s vehicle systems and some methods and challenges related to uncertainties in test and model data. The ability to handle uncertain information and lack of information is the key to success in early design. The vehicle systems comprise fuel, environment control system (ECS), hydraulic, auxiliary power, escape, electrical power and landing gear system.*

## 1 Introduction

The Gripen fighter aircraft (a/c), see Fig. 1, is the most complex and advanced aircraft Saab has ever built. The systems are highly integrated and optimized, which is a challenge when modifying the systems or introducing new systems or functions. It is vital to minimize the number of errors during the development, which can be achieved by e.g. adopting Model Based System Engineering (MBSE).

Complete systems (e.g. fuel, ECS, hydraulic, and auxiliary power systems), subsystems (e.g. the fuel transfer system), equipment (e.g. valves and turbines), and the control unit's hardware and software are integrated with 60 years of experience, currently from the military fighter Gripen, the civil aircraft Saab 340 and 2000, the trainer Saab 105, and UAVs.

Fig. 1. The Saab Gripen fighter aircraft.

In order to achieve cost-effectiveness, modelling and simulation have been used since 1968 to develop the most complex vehicle systems. Generally speaking, modelling and simulation within vehicle systems are among other things used for:

- Total system specification and design, e.g. functionality on the ground and in the air
- Equipment specification and design
- Software specification and design
- Various simulators
- Test rig design
- System function and performance verification
- System safety
- Fault analysis

Aircraft vehicle systems require test rigs and installation of the equipment in test aircraft. Simulation reduces the risk of detecting design faults late in the development work. Research has shown that early detection and correction of design faults cost 200-1,000 times less than at later stages [2].

The paper begins with a background that describes the modelling and simulation history of a/c vehicle systems. This is followed by a section that describes how modelling and simulation have been implemented in the design process for development of the Gripen a/c vehicle systems followed by chapters on uncertainty and sensitivity analysis. The paper ends with a summarizing section containing a discussion and some conclusions.

### 1.1 Modelling and simulation history

In the late 1970s Schlesinger [17] defined the M&S activities, such as verification and validation and their relationship, and this has been improved upon by Sargent [16] with the real-world and simulation-world relationship with its analogies.

Before the 1980s the modelling of larger vehicle systems models was often error prone due to difficulties in visualizing and modifying the model.

In the 1980s the era as we know it today began, with tools that have friendly graphical user interfaces with features like “drag and drop” of block components and the power port (based on bond graph technique) concept or at least appears to be power port to the user. Boeing's EASY5 is such example of an early M&S tool.

In the 1990s the co-simulation between tools become a common feature in commercial tools and heterogeneous simulation increased.

In 1997 the first version of the multi-domain modelling language Modelica was released [8]. The language has come to be widely used in both industry/academia and in different physical domains.

In the 2000s the possibility to generate code from models directly to product or for hosted simulation [21] together with a now mature and M&S friendly design organization drastically changed the complete fundamentals of the when, why and impact of M&S in the design process. This change resulted in a new way of working, MBSE, with a model centric development approach.

### 1.2 Modelling and simulation background

One main focus of the work presented in this paper is to support the conceptual, preliminary and detailed design phases. Ullman [22] speaks of the design paradox, where very little is known about the design problem at the beginning but we have full design freedom. When knowledge about design is enhanced at an early stage, design freedom is retained and cost committal is postponed.

By adopting MBSE already in the concept phase, the constantly increasing requirements to shorten development schedule plans and minimize project risks are managed, in contrast to development of a system in a traditional way with many prototypes and M&S mainly used to solve problem late in the development phase.

Modelling and simulation in aircraft subsystem development, is today an important part of the design process. An increasing part of the system verification relies on results from simulation models rather than expensive testing in system rigs and flight tests [1]. The next step in M&S is models with known accuracy and validity range. The need for detailed system models and validation of system models has therefore increased.

Within vehicle systems development, a switch is now made from a sequential document driven development to a model centric development approach, (MBSE), to produce a more efficient process supported by development environment and tools.

One of the cornerstones in MBSE is that M&S results in early system knowledge compared to older system development where system knowledge is gained late from physical test rigs and prototypes. With MBSE many different concepts and design variants can be evaluated, thereby gradually increasing the system model detail and system knowledge during the design process as the system develops [23].

The main purpose of simulations is to support decisions. Early in the design phase decisions are based on simulation/analysis and experience. Measurements that can support the model validation, and increase the simulation confidence, will always be in short of supply, independent of design phase, that is, the model will always have parts that are not validated against test data. For these parts, model and parameter uncertainty descriptions can be used to gain knowledge about the model.

The need for more complete validation methods that complement the traditional validation, knowledge of a model's maturity and simulation result accuracy, has emerged due to the intensity of M&S that MBSE has in early design phases. A solution for this need is important to succeed in system development where early design decisions have to be made supported by simulation only.

## 2 MBSE for the Gripen´s vehicle systems

The vehicle systems comprise fuel, ECS, hydraulic, auxiliary power, escape, electrical power and landing gear system. Vehicle systems have several modelling challenges such as different combinations of compressible fluids (air) and heavy incompressible fluids (fuel, oil) where acceleration vector matters, nonlinear effects such as turbulent flow cavitation and saturation and controlling software, add to the complexity.

### 2.1 Vehicle systems design process.

The vehicle systems design process can be schematically described as in Fig. 2 [20].

*First loop, desk top simulations.*

The first loop consists of two phases: with and without a complete software model. First, a simple control logic is developed in the same tool as the physical system in order to assess the closed loop behaviour [1].

In the loop without a complete software model, the physical system performance (e.g. cooling effect, flow and maximum temperature/pressure), and dimensions, (e.g. pipe diameter and heat exchanger size), is specified for system components and to confirm the design choices in the concept phase.

When complete control and monitoring software is available, a closed loop verification (software and hardware models simulated together) can be done by co-simulation or by hosted simulation [21]. The major development of the software takes place in this phase and much of the purchased system components and airframe structure design has already been frozen. In the remaining loops the major focus is on tuning, verification, and validation.

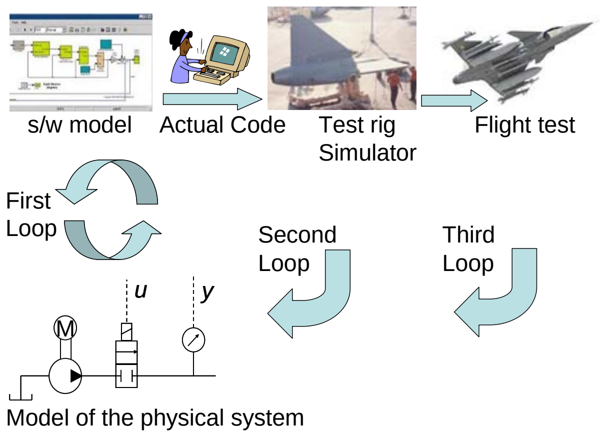


Fig. 2. The vehicle systems design process.

*Second loop, simulator and rig tests*

One purpose of the test rig and simulator activities is to verify the control software and its interface with other systems. Typical errors concern units and interfaces that are difficult to cover in the first loop. A first partial validation can be done in the test rig, where the influence of e.g. wiring and detailed fluid dynamics, can be analyzed. An important part of the rig test activity is to feed the models with measurement data to improve the model's accuracy.

*Third loop, flight tests*

If all modified software functions are non-critical, flight tests are not considered mandatory for opening up the flight envelope. If modified software functions are critical, flight tests are considered mandatory in order to secure airworthiness. The flight test should also provide the models with measurement data.

## 3 Uncertainties

Mastering model uncertainties in system development is a key factor for success. The main sources of deviation between the simulation result and the real object's behaviour, [7], can be categorized as:

- parameter uncertainties
- model structure uncertainties
- model validation data uncertainties
- numerical simulation error
- model inputs

The list has been extended with model inputs. Other examples that lead to deviation between the simulation result and the real object's behaviour are model, data and configuration management errors (illegitimate errors) and simulation tool bugs [11]. These kinds of sources will not be further discussed in this paper.

## 3.1 Parameter uncertainties

A common way of classifying parameter uncertainties is in aleatory and epistemic uncertainties.

Uncertainties due to statistical variations in parameters, are termed aleatory uncertainties (also referred to in the literature as variability, irreducible uncertainties, inherent uncertainties or stochastic uncertainties [13]), and result in a variance in the simulation results. Typical model parameters with aleatory uncertainties are fluid properties and pressure drop coefficients that are dependent on manufacturing tolerances.

Uncertainties due to lack of information about parameters, are termed epistemic uncertainties (also referred to in the literature as reducible uncertainties and subjective uncertainties [13]), and also generate uncertainty in the simulation result. "*Engineering design is concerned with gathering knowledge through experiments and studies that quantify and reduce the impact of epistemic uncertainty*" [3].

Early in the concept phase, there are more epistemic uncertainties than aleatory uncertainties. During the refinement of the model, most epistemic uncertainties decrease and some epistemic uncertainties transform into aleatory uncertainties.

## 3.2 Model structure uncertainties

Epistemic uncertainties can also be related to the model structure, i.e. the system model and its equations do not describe the physical reality with sufficient fidelity. While parameter uncertainty is related to the physical parameters themselves, model structure uncertainty refers to lack of knowledge about the relationships between parameters and the underlying physical phenomena [3].

## 3.3 Model validation data uncertainties

Direct comparison between parameter values, model outputs and real object cannot be made. The real object's behaviour is always measured, and hence the comparison suffers from uncertainties such as non-ideal sensors and measurement system, natural variation due to wear and friction, and discrepancy between the tested object in its testing environment and the real object. An example of sources of uncertainties in a typical vehicle system rig, Fig. 3, is presented in Table 1. In Fig. 3 the surrounding represents both the surrounding subsystems and the ambient environment.

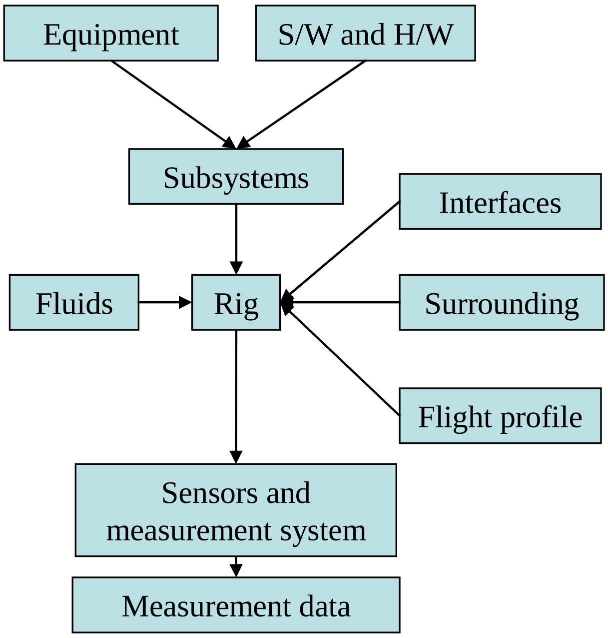


Fig. 3. Schema of a vehicle system rig.

Some uncertainties can be categorized as both epistemic and aleatory. For the fuel system, for example, it is hard to predict if soluble air will be a problem and if it occurs the probability is hard to predict and measure.

| Rig part | Example | Epistemic | Aleatory |
|---|---|---|---|
| Equipment | Pump, valve, turbine | Prototype status, valve area | Wear, manufacturing tolerances |
| Electronic Control S/W | S/W models, control code, | Prototype status | - |
| Electronic Control H/W | Computers, I/O electronics | Prototype status | Manufacturing tolerances, influence of temperature |
| Interfaces | Pipe, wiring | Simplification in interfaces between equipments and/or subsystems. Different installation geometry. | Wear, manufacturing tolerances |
| Fluid | Fuel or fuel substitute | The solubility of air in fuel | The solubility of air in fuel and fluid density |
| Surrounding, subsystems and environment | Pressure source, ambient temperature | Often lumped/discretized and with less correct or no dynamics | Wear, manufacturing tolerances |
| Mission profile | Altitude, speed, thrust | Often crudely simulated | Repeatability of mission |
| Sensors and measurement system | Flow, pressure, temperature | Disadvantageous location, low dynamic response capability, noise, sampling rate, calibration | Drift, influence of temperature, wear, manufacturing tolerance |

Table 1 Example of sources of uncertainties in a typical vehicle system rig for a fuel system.

Notice that measurement uncertainties presented in measurement reports often only present the uncertainty due to uncertainties in sensors and measurement system. The complete picture of the measurement data uncertainty versus the true system value, not the rig value, demands an estimation of the other uncertainties and its effects. It is the authors’ experience that for the major part of the vehicle systems development phase, the epistemic uncertainties dominate the data uncertainty. Tools and methods for simulation result uncertainty assessment must therefore be able to handle epistemic parameter uncertainties that initially in the design process can be large compared to nominal parameter values.

### 3.4 Numerical simulation error

Normally, numerical simulation error is very small compared to other uncertainties independent of the maturity of the system model. In some cases, if the model stiffness is severe, the numerical simulation error can be the dominating source of uncertainty. It is, however, rather trivial to assess compared to the other sources of error. Numerical simulation error estimation will not be further discussed in this paper. The relationship between numerical simulation error and uncertainties is discussed in [14].

### 3.5 Model inputs

So far, the discussion has been concerned with a single model. Of course, the simulation result uncertainties are also dependent on the uncertainty in the model input. In a simulator environment, which typically includes some few to hundreds of models, the sources of the input uncertainty are numerous. The models in a simulator are often side effects of other modelling efforts and might have different purposes, fidelity, dynamics range, accuracy and validation. Simulator uncertainty management is a prerequisite for e.g. using simulation results for certification support. Uncertainty management needs to take into account both the information for each model and how it relates and connects to the surrounding models.

In theory two means are necessary to manage the uncertainty of the result from a simulator: some classifications of the model accuracy (meta model attribute) and a meta model of the model relationships in the simulator.

The model accuracy classification, e.g. dynamics and validation, could be in terms of a rough scale from 1 to 5 where 1 represents low and 5 high. A model with dynamics 1 and validation 5 is a model unable to cover the system dynamics but stationary validated by intense test measurements. A model with dynamics 5 and validation 1 is highly dynamic model but not validated. The meta simulator model describes the signal flow connections between models and the influence of a model's input on its outputs.

With this two means it would be possible to predict a rough simulation result quality, even before a simulation by propagation of the information. Unfortunately, the real world is a little more complicated. It is almost impossible to put a validation figure on a large model. The validation measure can be divided into several aspects. The data used at the validation comparison can have different credibility, e.g. measurement data from rig vs. flight test, and the model can be both temporally and spatially validated. The temporal aspect concerns stationary vs. dynamic while the spatial aspect can be subdivided into both model and flight envelope. For example, a subsystem in a model can be dynamically validated at low altitude but not at high altitude and the opposite for another subsystem. Furthermore, validation of a model is not automatically conducted with high accuracy, only with more knowledge about the accuracy.

A possible starting point for uncertainty management is to add rules that describe e.g. how the validation is done in a figure as a function of e.g. flight envelope parameters altitude and speed and model input on every potential output. A script can then point out where and when during a simulation outputs have been produced below a desired validation level. A manual action then remains to get insight of how indicated model outputs affect outputs of interest. This suggestion can functionally be increased with more measures and automatically with the model's inputs' influence on its outputs, e.g. sensitivity analysis (SA), to minimize manual activities. One significant drawback is that the complexity, overhead administration efforts and the required completeness in signals' and models' validation and accuracy status information required to build and maintain such an uncertainty management system, is today beyond the capabilities of available development processes, methods and tools. This must nonetheless be resolved in the near future and is an area of challenging research.

For some non-CPU-intensive simulator simulations, probabilistic design can be a part of the uncertainty management [6].

Some work in uncertainty management can be found in reference [12] where a broader aspect and on a higher level has been taken concerning M&S result credibility. Eight factors have been defined with a five-level assessment of credibility for each factor.

## 4 Sensitivity analysis

One way to achieve model simulation result quality measures is to use sensitivity analysis. This is applicable at all relevant engineering life cycle stages, as well as in the modelling and simulation process in Fig. 2. Sensitivity analysis is the study of how the variation in the output of a model can be apportioned to different sources of variation, and how the given model depends upon the information fed into it [15]. Put another way, sensitivity analysis is the assessment of the impact of changes in input values on model outputs [5]. Sensitivity analysis has been found useful at Saab to:

- provide an overview of which inputs are of importance for the desired behaviour of a system model and thereby require additional research to increase knowledge of model parameters' behaviour in order to reduce output uncertainty
- study the influence of disturbances and uncertainties in parameters and constants
- study the degree of robustness in a system
- provide support during the model verification/validation process
- provide support in planning rig/flight tests

The local sensitivity method is useful for large models with many parameters and simulation models that involve computationally expensive simulations and where the underlying equation is not accessible for manipulation. The number of simulations required to calculate the local sensitivity matrix will be equal to the number of inputs + 1 if the one-side difference approach is used and 2*inputs + 1 if the central difference approach is used.

By changing one parameter at a time and rerunning the model, the elements of the sensitivity matrix can be obtained by linearization of the non-linear model, *f* equation (1) where the system characteristics *y* are computed from the system parameters *x*, around a nominal point, equation (2) where *J* is the Jacobian.

$$y = f(x) \tag{1}$$

$$y_0 + \Delta y = f(x_0) + J\Delta x \tag{2}$$

$$J_{ij} = \frac{\partial f_i(x)}{\partial x_j} = k_{ij} \tag{3}$$

For small variations the sensitivity matrix, equation (3), is identical to the Jacobian matrix, hence:

$$\Delta y = J\Delta x \tag{4}$$

The global sensitivity [15], however, accounts for the global variability of the output over the entire range of the input variables and hence provides an overall view of the influence of inputs on the output. Using this variance-based SA the analysis of variance can be decomposed into increasing order terms, i.e. first-order terms (main effects) depending on a single variable and higher-order terms (interaction effects) depending on two or more variables [18]. Global sensitivity analysis has the drawback that the required number of simulations increases exponentially with the number of inputs and is therefore not always suitable for computationally expensive simulations. Furthermore, if a benign nominal design point is used, the interaction effects are small.

## 4.1 Sensitivity analysis process

Benefits are achieved by separating the modelling and simulation tool from the sensitivity analysis tool. One is that the model configuration management is not affected and that the sensitivity analysis tool is forced to be more generic to be able to perform sensitivity analyses on models from different domains. A generic sensitivity analysis process, implementable in a simulator environment, is presented in Fig. 4 with some descriptions of tasks and data objects.

The task “Determine model parameters and states to be analysed” has the input: “Purpose of analysis” that identifies necessary models to be able to perform the sensitivity analysis. With the help of the input “Model description”, necessary model states and parameter names, are identified. “Model description” should also identify a necessary model to achieve a complete simulator environment, e.g. the atmosphere model that is a model connected to many others.

The task ”Determine model parameters uncertainties” selects model states and model parameter uncertainties that will be used in the sensitivity analysis. The input “Model parameter uncertainties description” is a parameter uncertainty list for each model. The output “Model state and parameter uncertainty list” is a reduced list of “Model parameter uncertainties description” with the model states and parameters from “Model, parameter and state list”.

The task “Prepare sensitivity analysis tool” prepares a batch simulation instruction for the task “Execute sensitivity analysis”. The input “Requested sensitivity method, measures and target criteria” identifies the sensitivity analysis method and measures that will be included in “Model parameter influence on model states”.

The task “Execute sensitivity analysis” calls “Initiate models” and “Execute model” until all simulations are finished and calculates the sensitivity analysis measures.

The task “Evaluation” evaluates the “Model parameter influence on model states” and summarizes it in a report.

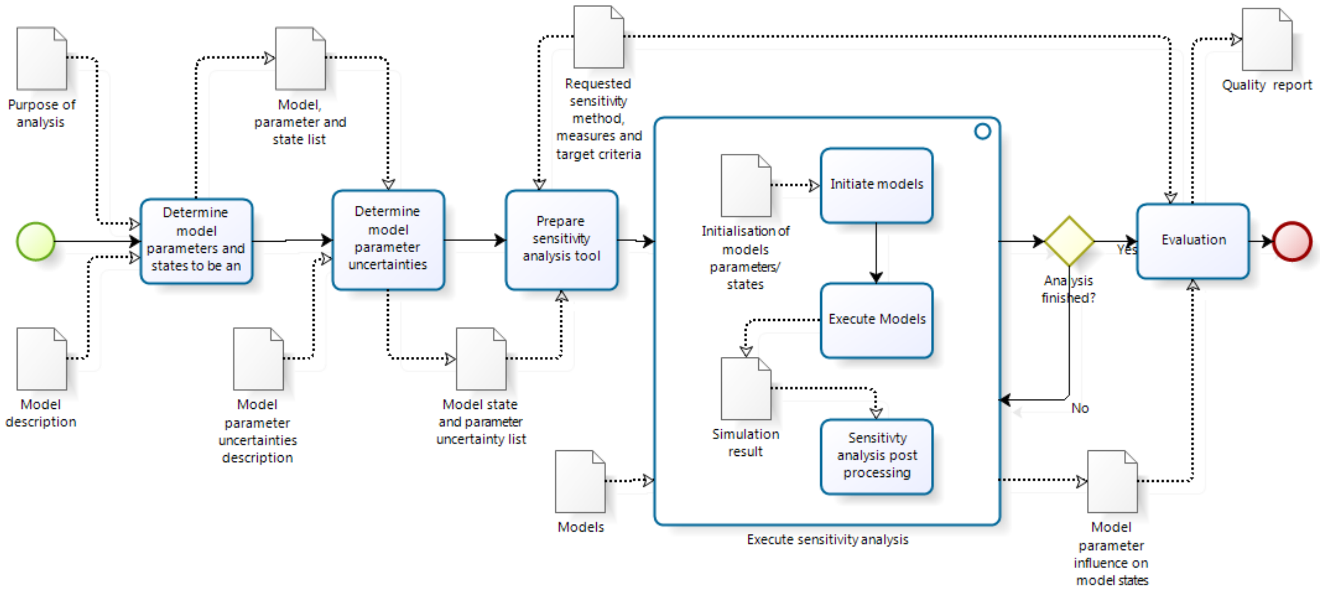


Fig. 4. Sensitivity analysis process.

## 4. 2 Sensitivity analysis in the development process

Model result uncertainty measures can serve as stop criteria for the loop iterations [19] and as support for iteration planning in Fig. 2. The vehicle systems development process in Fig. 2 can be redrawn, see Fig. 5, where some of the uses of sensitivity analysis have been explicitly marked out.

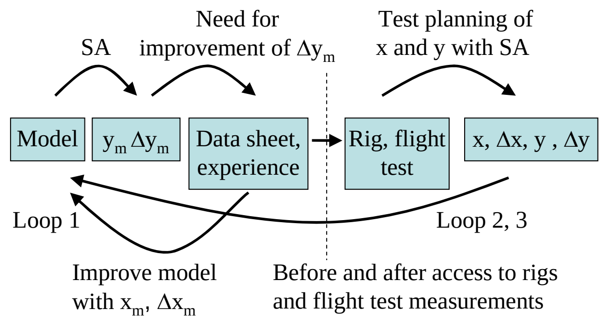


Fig. 5. Sensitivity analysis in the vehicle systems design process. Subscript m stands for model, Δ for uncertainty, x represents system parameters and y system characteristics.

Before access to rigs or flight test measurements, the focus is on system parameters because this is what can be controlled and the system characteristics are a function of these. After access the focus moves to system characteristics as a consequence of the system parameters being more or less frozen.

Sensitivity analysis is suitable for both stages, before access to measurements, by pointing out system model parameters that need to be improved, to achieve a certain level of system characteristics accuracy, and after access as test planning support.

## 4. 3 Measures

In order to make it possible to get an overview of the sensitivities, some kind of normalized dimensionless sensitivity measures is needed. The first approach to normalize the sensitivities is to employ the following definition of relative sensitivity:

$$k_{ij}^{0} = \frac{x_j \partial y_i}{y_i \partial x_j} \tag{5}$$

In this way, a non-dimensional value is obtained that indicates by how many per cent a certain system characteristic, *i*, changes when a system parameter, *j*, is changed by one per cent. Using this method, it is much easier to assess the relative importance of the different system parameters. Furthermore, it can be presented in a hierarchical fashion, so that influence at an aggregated level, e.g. the influence of uncertainty on a whole subsystem, can be assessed.

The aggregated normalized sensitivity matrix therefore seems to be an excellent tool to ensure that design efforts are properly balanced in the ensuring design steps, by identifying critical areas at an early stage of the design [9], [10].

Provided that the uncertainties are small compared to the nominal values, the variance in the system characteristics can be calculated as:

$$V_{y,j} = \sum_{j=1}^{n} \left( k_{ij}^{2} V_{x,j} \right) = \qquad (6)$$
$$\sigma_{y,j}^{2} = \sum_{j=1}^{n} \left( k_{ij}^{2} \sigma_{x,j}^{2} \right)$$

Here $V_{x,j}$ is the variance in the system parameters and $V_{y,j}$ is the variance in the system characteristics and analogous to the standard deviation $\sigma_{y,j}$.

An approach that provides valuable insight is to look at the influence of the actual uncertainties in parameters on the uncertainties in system characteristics. The effect of removing an uncertainty altogether can then be calculated, Effective Influence Matrix (EIM) [10].

The Main Sensitivity Index (MSI) is another measure of uncertainties' influence. It is defined as the ratio between the total variance in a system characteristic and the contribution to that by an uncertain parameter. The difference is that in the MSI matrix the values are normalized so the row sum is always one. The EIM and MSI only provides the first-order interaction effects, but there is also a sensitivity index closely linked to the MSI, the Total Sensitivity Index, TSI [4].

Fig. 6 to Fig. 8 show a regulator and some of its system characteristics sensitivity results, e.g the parameter "Area" is the main uncertainty contributor to the characteristic time_ramp_up.

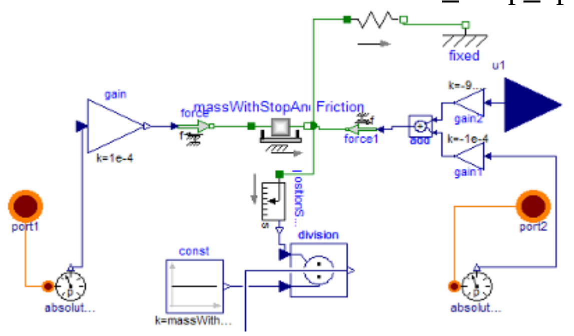


Fig. 6. A part of a pressure valve regulator modeled in Modelica.

| System characteristics | Units | Deviation | Normalized deviation | F_Coulomb | m | Pressure source | Area |
|---|---|---|---|---|---|---|---|
| | | | | 0.50 | 0.05 | 0.10 | 0.05 |
| time_ramp_up | s | 0.01 | 0.039 | 0.00 | 0.19 | 0.00 | 0.81 |
| Volume.p_kPa_g | kPa | 0.04 | 0.003 | 0.01 | 0.69 | 0.02 | 0.29 |

Fig. 7. MSI. System characteristics' deviations and the main sensitivity index of uncertainty parameters.

| System characteristics | Units | Deviation | Normalized deviation | F_Coulomb | m | Pressure source | Area |
|---|---|---|---|---|---|---|---|
| | | | | 0.50 | 0.05 | 0.10 | 0.05 |
| time_ramp_up | s | 0.01 | 0.039 | 0.000 | 0.004 | 0.000 | 0.022 |
| Volume.p_kPa_g | kPa | 0.04 | 0.003 | 0.000 | 0.001 | 0.000 | 0.000 |

Fig. 8. EIM. System characteristics' deviations and the influence of the uncertainty parameters.

## 5 Discussion and conclusion

The need for uncertainty management and more complete validation methods that complement the traditional validation, knowledge of a model's maturity and simulation result accuracy, has emerged due to the intensity of M&S that MBSE has in early vehicle systems development phases. A solution for this need is important to succeed in system development where early design decisions have to be made supported by simulation only. The ability to handle uncertain information and lack of information is the key to success in early design.

Further, the local sensitivity method has been shown useful for large models with many parameters and simulation models that involve computationally expensive simulations.

One side benefit of using sensitivity analysis is that the unexpected absence of sensitivity in parameters, might indicate modelling error, and it is therefore also a valuable debugging tool for models.

Substantial challenges remain, both for the user and the method and process developer, before uncertainties can be used in system simulators, such as the difficulty to achieve required completeness in models' validation status and signals uncertainties description and suitable validation and accuracy measures.

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