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# Using system-level simulation in early mechatronic design stages

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**Abstract**
Simulation has become indispensable in engineering design. That is the reason why the authors developed a framework for simulation-based design of mechatronic systems where system simulation is intended to be used already very early in the design process. Besides the benefits in early phases, there are several issues caused by unknown or vague system parameters required for simulation. Such uncertainties lead either to models which cannot be simulated or to deficient simulation results.
In this paper the different reasons for and the origins of uncertainties as well as the related deficiencies of simulations will be analyzed and discussed. Furthermore the state of the art is analyzed regarding existing methods and techniques for the improvement of reliability and results of simulation.
In order to improve the usability and reliability of simulation in early phases the analyzed techniques are integrated into the simulation-based framework and validated on a mechatronic design example.

***Keywords: Mechatronic design, simulation-based design, uncertainty, conceputal design***

## 1 Introduction

Simulation has become an indispensable part in engineering design for evaluation purposes. Although there are numerous sophisticated techniques available [1] a consistent integration of simulation into a simulation-based design framework is still missing [2]. Due to this lack the authors developed a framework [2-4] for the development of mechatronic systems which integrates simulation as the core activity for design evaluation. A simplified version of the underlying process model is depicted in Figure 1 – a more detailed description can be found in [3] and [4]. This generic version consists of three main phases which correspond to those of VDI 2206 [5] and VDI 2221 [6]. The integration of simulation is done through two parallel activity streams: design activities and analysis activities. Those are highly interlinked and build numerous analysis-synthesis-cycles as depicted in Figure 1. The management of the interactions of the two activity streams is done through several Analysis Milestones (AMS) which for example contain information about the property that is to be analyzed, the analysis technique which is used and the responsibility for the analysis. This paper is focused on the conceptual system design phase and the corresponding simulation phase. In these early stages simulation is done on system level with a lower level of detail instead of using very detailed, domain-specific simulations [7]. Those simulations are used on the one hand to determine the behavior of the system and check if this meets the requirements. In this way it is possible to compare different system concepts and choose the best one [8]. On the other hand simulation can be used to refine – or even define – requirements. This means that based on initial requirements a simulation can be run and based on the results the validity of the requirements can be analyzed.

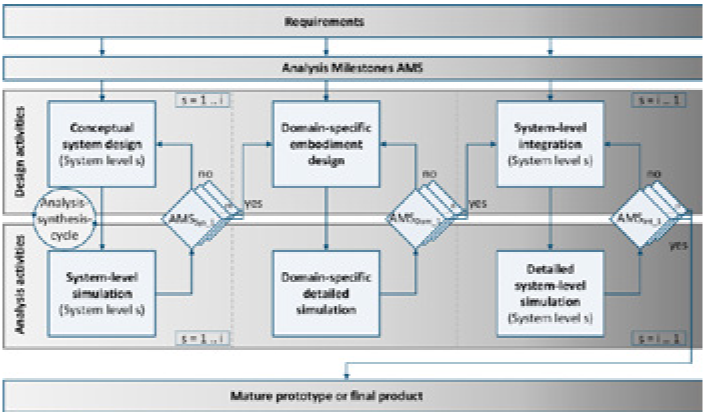

Figure 1 Simplified version of the simulation-based process model

Early stages of design are characterized by a low degree of defined characteristics [9] which makes it more difficult to parameterize and run simulations. Partially this problem is evaded by using models with lower level of detail which require fewer characteristics to be defined – at the expense of lower accuracy of the simulation results. Nevertheless, also these models need parameters to be executable which are often not fully known or still very vague – for example only intervals for the parameters are known – because knowledge about the system which is being developed is still rather low. Hence in order to receive reasonable and reliable results, guidance is needed to support in dealing with such uncertainties.

In the following sections different kinds of uncertainties as well as their origins in the development process will be discussed. Furthermore the state of the art of methods for dealing with uncertainty is analyzed. Based on those findings, the simulation-based framework for mechatronic design will be complemented with guidance for the handling of uncertainties in the early conceptual system design stages and the corresponding simulation phases.

## 2 Types of uncertainty and their origins

Uncertainties can have several origins. In literature mainly two kinds of uncertainty are distinguished based on their origins: aleatory and epistemic uncertainties [10]. The first one is also referred to as irreducible, inherent and stochastic uncertainty or as variability [11]. Consequently aleatory uncertainty originates from randomness [12]. The mathematical representation for this kind of uncertainty is usually a probability distribution [11]. In the case of simulation of mechatronic systems this can be for example a stochastic variation of input parameters due to production tolerances or the signal noise of a sensor. According to the definition of Oberkampf et al. [11], aleatory uncertainties describe the inherent variation associated with the physical system or the environment under consideration. Those will not be of particular interest in this paper. Their handling is well established through traditional probability theory [13].

Epistemic uncertainty is also referred to as reducible, subjective or cognitive uncertainty [11]. According to the definition of Oberkampf et al. [11], this kind of uncertainty is a potential inaccuracy in any phase or activity of the modeling process that is due to lack of knowledge or incomplete information. Incomplete information can be caused by vagueness, nonspecificity, or dissonance [14]. Corresponding to [13], the models which are used for simulation in the context of this paper are considered as deterministic. Hence the handling of aleatory uncertainties is of minor interest but rather epistemic uncertainties are focused on in this paper since they describe the uncertainties due to a lack of knowledge about the system and its parameters in early conceptual phases which affect system simulation.

Kiureghian and Ditlevsen [15] define sources of uncertainty in modeling ranging from uncertainty of the input variables to uncertainty in the selection or definition of probalistic and physical submodels to uncertainty due to computational errors or numerical approximations. According to the different sources of uncertainty, Oberkampf et al. [13] further distinguish for the modeling of physical systems between parametric uncertainty – corresponding to uncertainty of input parameters – and model form uncertainty – corresponding to the other uncertainties. The first one can be either aleatoric or epistemic while the last one is always epistemic [13].

Besides uncertainty, errors are also important in modeling and simulation. Error is defined as a "recognizable deficiency in any phase or activity of modeling and simulation that is not due to lack of knowledge" [14]. Furthermore Oberkampf et al. [14] distinguish between acknowledge errors – for example conscious simplifications of models – and unacknowledged errors – for example due to human mistakes during modeling. Particularly acknowledge errors occur in early system simulation stages because simplified models are used to improve simulation runtime and to improve model parameterization because of model parameters which are not know yet.

## 3 Methods for dealing with uncertainty

In this section the state of the art is briefly analyzed regarding methods and techniques which are used in order to handle uncertainties in engineering design, particularly in combination with modeling and simulation. At first the problems of simulation in early phases are discussed. As already stated before, the early stages – which in the context of this paper means "Conceptual system design" and "System-level simulation" as depicted in Figure 1 – are characterized by many unknown or vague system parameters which will only become clear with increasing knowledge during the design process [16]. One approach for dealing with this problem is the use of simplified models. This means that the physical behavior is not modeled in detail in order to reduce the number of required input parameters and to reduce the runtime of simulations. In general such simplifications are accepted in early phases where simulation is mainly used to compare concepts [7]. Hence according to the definition in the previous section, such simplifications are acknowledged errors. Apart from simplified models the issue in early stages is that input parameters for models are not totally clear, but rather an interval in which they will fit in is known or can be estimated. Another possibility is that simulation is used to generate input parameters based on desired output parameters of simulation. Since simulations cannot be simply inverted, a first set of input parameters has to be estimated and those parameters have to be iteratively refined. Doing this in an unstructured way can be very time-consuming. Those issues can be categorized as epistemic uncertainty according to the definition in the previous section. In the following, several methods and techniques are analyzed which can support in dealing with unacknowledged errors and epistemic uncertainties. In Figure 2 the different methods for uncertainty handling, which are discussed in the following, are assigned to the different applications and issues of simulation.

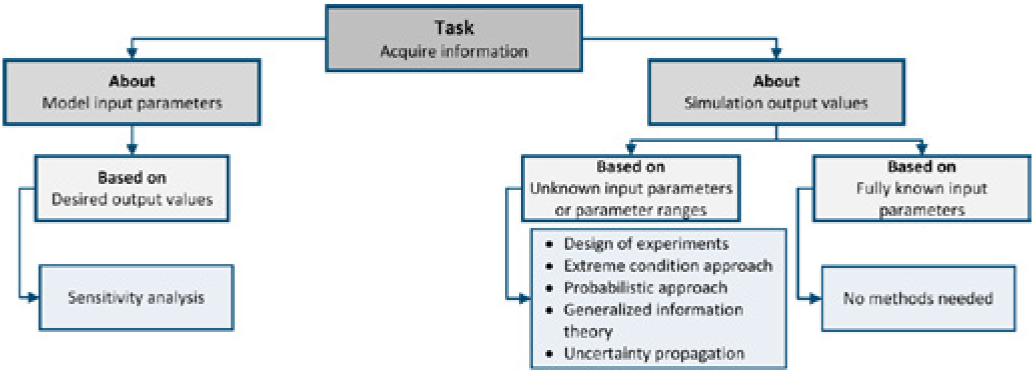


Figure 2 Overview of methods and their application

### 3.1 Design of experiments (DOE)

Design of experiments is a statistics-based method which is used to analyze the relations between the input and the output of a system under consideration with a minimum of experiments. Although this method was originally developed for physical experiments, it can also be used for simulation. In traditional approaches input parameters are alternated “one factor at a time”. This means that for every factor that is changed a new experiment has to be run. Consequently a large effort is associated with this method and furthermore interrelations of parameters cannot be examined. These issues can be addressed by the use of design of experiments, which refers to the process of planning, designing and analyzing experiments so that valid and objective conclusions can be drawn effectively and efficiently [17].

In general full or fractional factorial designs at two- or three-levels are used in DOE [17]. Full factorial means that all input parameters of the simulation model are varied whereas in fractional factorial design, parameters of lower relevance or interest are kept constant. Two-level design means that the range of a parameter is only considered by the two boundary values. In a three-level design an additional value in the middle of the range is used. The benefit of a full factorial design is that all parameter combinations are tested which allows drawing conclusions regarding interactions and mutual influences of parameters. However, for a model with k input parameters a two-level design would require $2^k$ experiments. Depending on the complexity of a model and the related simulation runtime this can be very time consuming. But generally this is still easier for simulation compared to physical tests. Such experimental designs and the simulations can also be easily automated. In order to reduce the effort of a full factorial design, fractional factorial designs can be used. In this case higher-order interactions are neglected [17] which requires the engineer to decide if this acknowledged error is acceptable for the current task.

For more information regarding design of experiments, see the large amount of contributions in literature, for example [17].

### 3.2 Extreme condition approach

The extreme condition approach is used to determine the range of the output of a simulation based on a given range of input parameters [18]. This approach is very effective regarding time and resources spent for simulation. However it does only provide the possible minimum and maximum values of a simulation result. Information regarding the distribution of the results cannot be determined. It is similar to two-level design in design of experiments.

### 3.3 Probability methods

Besides the extreme condition approach, statistical methods are common in order to analyze uncertainty. Among those methods Monte Carlo simulation is often used. It considers a statistical distribution of the input parameters of a simulation model. This means that those input parameters do not have a fixed value but are rather described by a statistical distribution, for example a Gaussian distribution. Based on this assumption a simulation is run with randomly taken values from the distribution for each parameter which are called samples. Accordingly such techniques are called sampling-based methods. In order to obtain a probability distribution for the simulation results, this procedure is repeated several times with different, randomly taken input values, ideally until a converged value for the standard deviation of the result-distribution can be estimated [19]. Certainly a Monte Carlo simulation can result in an enormous effort regarding time and resources, depending on the distributions of the input parameters and the complexity of the simulation model itself. In this case, the number of required simulations can be reduced through the use of different sampling methods. Among those, particularly Latin Hypercube Sampling (LHS) is often used for complex simulations [20]. For more information regarding Monte Carlo simulation and sampling methods including the mathematical formulation, literature offers a huge amount of contributions, for example [19] for Monte Carlo simulation and [20], [21] for sampling methods.

### 3.4 Generalized information theory

The probability-based techniques discussed in the previous section have several drawbacks. For example the definition of an appropriate probability distribution for the input parameters is often very difficult. Additionally the number of required experiments is rather high and thus time consuming. Hence besides the probability-based techniques, there are also methods which are based on generalized information theory (GIT) [13]. Examples for those are possibility theory, evidence theory and fuzzy set theory. Fuzzy sets for example offer the possibility to take into account the gradual or flexible nature of specifications or are able to represent incomplete information [22]. This means that if the boundaries of an interval of input parameters is not clearly known, this uncertainty is expressed by a characteristic function taking values in the interval from 0 to 1 [22]. For further information, see for example [23], [24].

### 3.5 Uncertainty propagation

The methods described above are intentionally used for single models. However, particularly in mechatronic design where several domains have to interact [25] and in early stages where simulation is done on system level, system models consist of several submodels. These can be either part of an enclosed system model which is run in a single software environment – for example a system model in Modelica – or each submodel is simulated on its own and the results of the simulation are used as an input for the next submodel. Each of those submodels can be affected by uncertainty. At the end of the simulation model chain this leads to an accumulated effect of the individual uncertainties of the submodels [18]. According to [18], the uncertainty of the vector of input parameters x is taken into account by a certain kind of distribution. The output vector y of model 1 – which corresponds to the simulation result – can then be expressed by:

$$y = F_1(x_1) + \varepsilon_1(x_1) \tag{1}$$

The internal uncertainty $\varepsilon(x)$ is used to express the uncertainty which is caused by and within the model itself. Consequently, the output vector z of model 2 is expressed by:

$$z = F_2(x_2, y) + \varepsilon_2(x_2, y) \tag{2}$$

This procedure can also be applied for every simulation model chain consisting of more than two models. The approach also applies to both the extreme condition approach and the statistical approaches.

### 3.6 Sensitivity analysis and parameter screening

Sensitivity analysis refers to the determination of the contribution of individual uncertain analysis inputs to the uncertainty in analysis results [20]. In this way the individual parameters are screened regarding their importance on the simulation output. Based on an importance ranking, the number of required simulations can be reduced since only the most important parameters have to be varied across their entire range. The less important parameters only have to be simulated with few values or can even be fixed. In this way the number of simulation runs can be drastically reduced.

Sensitivity analysis and parameter screening are mainly based on the techniques described earlier in this section. For example design of experiments is used with fractional factorial design to determine the individual influences of the input parameters with a minimum of experiments. Among these designs, Plackett-Burman designs are widely used for parameter screening [17]. The results can be depicted in Pareto diagrams or effect plots. However it should be taken into consideration that influences between parameters can hardly be identified with those designs. Apart from DOE-based methods, sampling-based or statistical methods can also be used for sensitivity analysis. Typically sampling methods like Latin Hypercube sampling are chosen because they require less experiments then for example traditional Monte Carlo simulation. The results can then be analyzed through several techniques like scatterplots or regression analysis [20]. For more information regarding sensitivity analysis with sampling-based methods, see for example [26].

## 4 Integration of uncertainty handling into a simulation-based design framework

In this section the methods described in the previous section are being integrated into the described framework for simulation-based design. The individual steps which are described in the following are exemplified on the simulation-based development of an active suspension system for bicycles. This system – a typical example of a mechatronic system – is used as a validation project for the overall development framework. More information about this system and its simulation-based development are provided in [27].

Particularly early phases, as already mentioned, are characterized by a high degree of uncertainty. This is caused by unclear requirements, unclear design concepts or unclear characteristics which serve as input parameters for the simulation model. This section is structured according to the application of methods as depicted in Figure 2. The first application scenario corresponds to the right arm of Figure 2 which is used to gain information about the system behavior, represented through the output of the simulation. The case that all input parameters for the model are known is very hardly probable and hence not further considered. More likely is the opposite case that input parameters are unknown or only parameter ranges are known. This is a typical issue for original design where there is limited knowledge about the system to be developed. For variant or adaptive design, information and experience have been gathered from the predecessor and hence system parameters are more clearly or can be better estimated resulting for example in a smaller range for parameters.

In the case that the input parameters can be narrowed down to a certain range, the extreme condition approach can be used to determine the range of the system output. For example if the input voltage for the actuator can be limited to a certain range based on the used battery technology, the minimum and maximum reaction speed and force can be determined. This procedure can also be iteratively applied to define the required input range more precisely based on a desired system behavior. This method is particularly useful for the definition or refinement of requirements in a very early stage. If there are many input parameters which affect each other and an optimal combination of these parameters is targeted, the extreme condition approach is not expedient. Here the use of design of experiments might be useful. It offers a structured procedure for the management of the simulation process and furthermore the mutual influences of parameters can be estimated. Depending on the desired accuracy and the complexity of the model – that means number of input parameters, required time and resources for simulation – the design of the experiments has to be determined. For example if a simulation is very time consuming, the number of required simulation runs should be tried to be reduced. In this case two-level and fractional factorial designs are beneficial. But the related simplifications have to be individually ponded by the analyst or engineer.

If the range of input parameters cannot be clearly determined, the use of probabilistic approaches such as Monte Carlo simulation can be used. For this, the engineer has to estimate – based on experience or technical intuition – a distribution for the input parameter, for example a Gaussian distribution where the mean is the estimated optimal parameter and the standard deviation the estimated range of plausible values. Of course this procedure contains many sources of errors, but through iterative refinement of the distributions an optimal set of parameters can be approximated. In order to reduce the number of required simulations, particularly for complex models, the previously mentioned sampling-based methods like Latin Hypercube sampling may be useful. In particular if there is no experience for the system under consideration, it can be difficult to find an appropriate distribution for the input parameters. In this case general information techniques, such as Fuzzy set theory, may be easier to handle. Fuzzy sets might be easier to define since their definition, which is based on the membership of a parameter value, is not that strict as the mathematical definition of a distribution. In the validation example, e.g. the surface profile has been simplified through a sine wave. Since the amplitude has not been exactly known and also underlies statistical variations, it has been expressed through a Gaussian distribution with estimated mean value and standard deviation as depicted in Figure 3. In this way the distribution of the resulting actuator forces have been determined which can be used to search for suitable actuators.

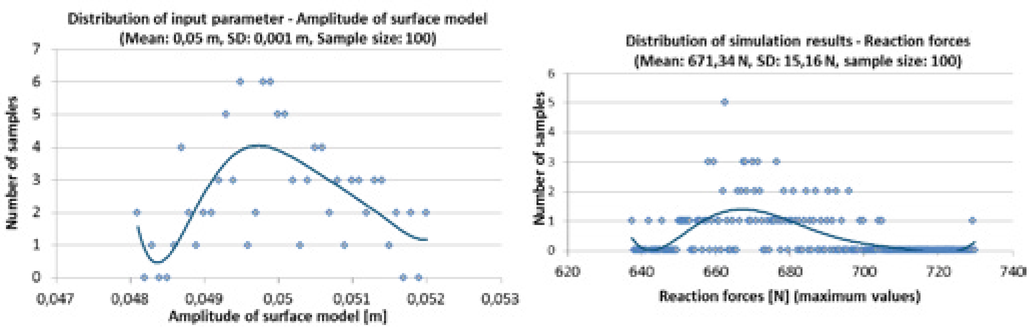

Figure 3 Monte Carlo simulation for actuator force

Typically mechatronic systems are composed of many interacting subsystems which are generally under the responsibility of different domains or departments. For a complex mechatronic system this leads to large simulation model chains, as exemplified in Figure 4 for system-level simulation of the active suspension. Even for such a rather simple example there are many circular references between the submodels, inevitably leading to an iterative procedure to consider all uncertainties. Assuming that all of these submodels have uncertain input parameters, uncertainty propagation becomes highly important but also complex. For system-level simulation within a single tool, like the Modelica-based tool used here, the individual submodels are connected to an overall system model. Hence uncertainty propagation is more or less done by the simulation environment itself – except for internal uncertainties but which are not considered here as earlier mentioned. In this case the problem lies rather in the required number of simulation runs to cover all possible input parameters. However, by using DOE and appropriate input scripts for the simulation tool, the simulation runs can be structured and automated. But if co-simulation with individual software tools is applied instead of using a single tool, uncertainty propagation has to be done by the engineer or analyst himself. This case is not considered in the present example.

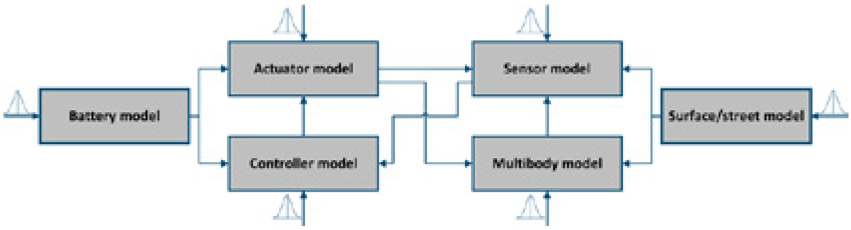


Figure 4 Simulation model chain with uncertain input parameters for the active suspension

Apart from the typical application of simulation in order to gain information about the system output, it can also be important and useful to gather information about the required inputs based on more or less defined properties as depicted in the left arm in Figure 2. One way to do this is an iterative approach of continuously refining the interval for the input parameters through a comparison of the simulation results with a desired system behavior. In this way the simulation can also be used to refine requirements. Another possibility is sensitivity analysis. As already discussed, mechatronic system models in general consist of several submodels, each of them with a set of input parameters. At the same time several concepts are simulated in order to find the best concept [7], [8]. Hence the number of parameters that have to be considered is considerable, quickly leading to an enormous number of required simulation runs. For complex models this implies large efforts, regarding both time and resources. Reducing the number of simulation runs can be most effectively achieved through a reduction of the required changes of input parameters, which sensitivity analysis can be used for. In this way parameters can be determined that have only limited influence on the overall system behavior and thus can be fixed. In the specific case of the active suspension, sensitivity analysis has been performed through the use of Plackett-Burmann design. As depicted in Figure 5 seven parameters have been analyzed with only eight simulation runs, only using maximum and minimum values for each parameter. Based on the effect plots, parameters with less influence on the simulation result can be identified. In the specific case, the rotational stiffness, the tire pressure and the friction have only minor influence, identifiable through the low slope of the effect plots. Hence for further investigation those three parameters can be fixed to a mean value. In this way the number of required simulation runs for the investigation of the remaining parameters can be considerably reduced.

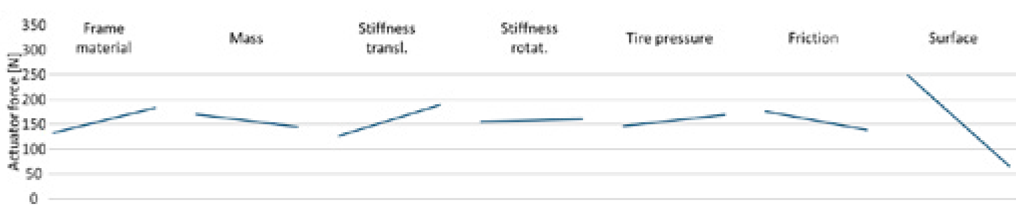


Figure 5 Effect plot of the model parameter for actuator force simulation

## 5 Conclusion

Uncertainty is ubiquitous in product development projects, particularly in early phases. The reasons are manifold and have been tried to be sorted in this paper. Furthermore the state of the art regarding methods and techniques for dealing with uncertainty has been tried to be summarized. However, since a large amount of techniques exists and countless fields like mathematics, physics, and engineering contribute to this, there is no demand for completeness and consistency of this summary. Instead the authors tried to filter the most important techniques for product development in a first attempt, particularly for simulation-based mechatronic design.

In order to make those techniques applicable in simulation-based design, these analyzed methods and techniques have been integrated into the authors design framework. This attempt is still rather generic giving advice on when to use the individual techniques and what for. The application has been illustrated on simplified examples from a mechatronic design project. Since this paper only represents a first attempt for the integration of uncertainty handling in early phases of simulation-based design, further efforts are necessary. For this purpose the state of the art from different scientific areas will have to be addressed more comprehensively. Based on the identified broader set of methods and techniques more concrete guidance for engineers dealing with simulation-based design has to be derived. This would for example mean to support the choice of suitable techniques including guidance for required information and reliability of results. The developed support should also be validated and exemplified, ideally on a case study which is dealing with more complex simulation models than the example in this paper. Eventually the development of a software tool for the support of engineers and analysts might be expedient. Such a tool could be used as a metamodel for simulation which is used to manage and control uncertainty and simulation runs providing the relevant inputs for the individual simulation environments.

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