Uncertainty Assessment with Stochastic Simulation in Aircraft Cabin Development

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ABSTRACT

To fulfill the need for shorter development cycles in modern product development the increased use of computer-aided engineering is one possibility. While the numerical calculation of a model leads to one single solution, the behavior of systems in the real world is never exactly repeatable due to tolerances and natural scatter in the system parameters. The assessment of the resulting uncertainties is of great importance for systems requiring a high level of reliability (such as aerospace systems), therefore they should be treated with special care in the development process and in particular in computer-aided engineering.

This paper describes the execution and analysis of an uncertainty management technique with Stochastic Simulation for an LS-DYNA model of an exemplary system consisting of an overhead stowage bin and carry-on baggage excited by external acceleration. The Stochastic Simulation results are evaluated using statistical methods. It is shown which parameters are of paramount influence on system behavior and may hence result in a critical load due to carry-on baggage.

KEYWORDS:

CAE, FEA, Stochastic Simulation, Uncertainty, Risk Assessment, Reliability

INTRODUCTION

Modern product development is exceedingly influenced by the factors time, cost and quality. The increased use of computer-aided engineering (CAE) is one possibility to fulfill the need for shorter development cycles while maintaining a high product complexity.

The calculation of the space and time discretised model of a system in the solver deterministically leads to an exact solution. However, in the real world system behavior is never exactly repeatable due to tolerances and natural scatter in the system properties and its boundary conditions. Without further knowledge about the relations of uncertain parameters the influence on system behavior or a worst case scenario may not be deduced.

An approach to simulate the consequences of scatter is Stochastic Simulation of the system using the Monte Carlo Method. For this procedure the scattering system parameters are defined in a meta-data model with their specific probability density functions. From this meta-data model manifold random samples are drawn for all parameters with respect to their specific distribution function. Multiple duplicates of the deterministic model are created and every one of them is assigned with a set of drawn random samples. All models are computed with LS-DYNA on a Linux cluster and the results are extracted to a uniform database format. The system behavior of the entire population can be deduced from the analysis of the respective samples.

The assessment of uncertainties is of great importance for systems requiring a high level of reliability (such as aerospace systems), therefore they should be treated with special care in the development process and in particular in CAE.

PROBLEM DESCRIPTION

One example of uncertainties in aircraft cabin development is carry-on baggage, which is quite heterogeneous concerning its mass, stiffness, damping and density properties. In addition, it is placed nearly arbitrarily in the overhead stowage bins (Figure 1) of an aircraft. Accelerations due to turbulences or while landing can temporarily apply forces of a multiple of the carry-on baggage's own weight to the overhead stowage bin and furthermore onto the aircraft structure.

This paper shows exemplarily how to incorporate uncertainties of product usage entirely virtually by using Stochastic Simulation of Finite-Element Analysis (FEA) already in the early phases of product development. For this example the following problem description is assumed.

Figure 1: Lateral overhead stowage bin in an aircraft

The system consists of a box with approximately the dimensions and mechanical properties of a single hatch lateral overhead stowage bin. This box will further be referred to as overhead stowage bin. The bin will be mounted at five points (see figure 2), similarly to a real overhead stowage bin in an aircraft.

The overhead stowage bin is loaded with two cuboidal bodies with rounded corners. These comply with the requirements for aircraft cabin carry-on baggage of the IATA [3]. Hence the bodies have the size of typical carry-on trolley cases and will be referred to as trolleys further on.

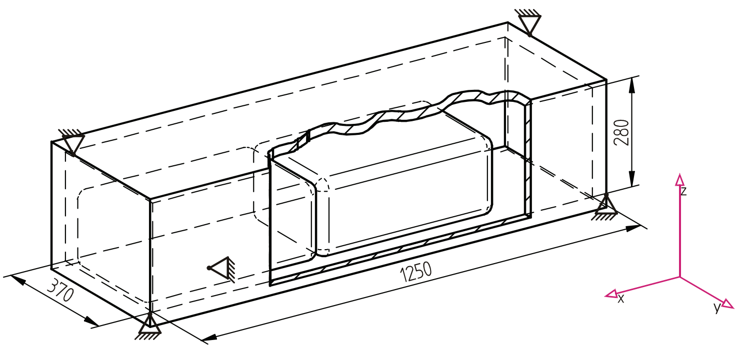

Figure 2: Overhead stowage bin with carry-on trolley cases

This system consisting of overhead stowage bin and trolleys possesses a global initial velocity v_{ini} in x-direction. The overhead stowage bin will be decelerated over time at the mounting points by a triangle impulse till zero velocity, see figure 3. The peak deceleration and the rise time are comparable with the FAR Parts 23 and 25 [10, 11] containing regulations for aircraft cabin components, and with the requirements of the SAE AS 8049 [9].

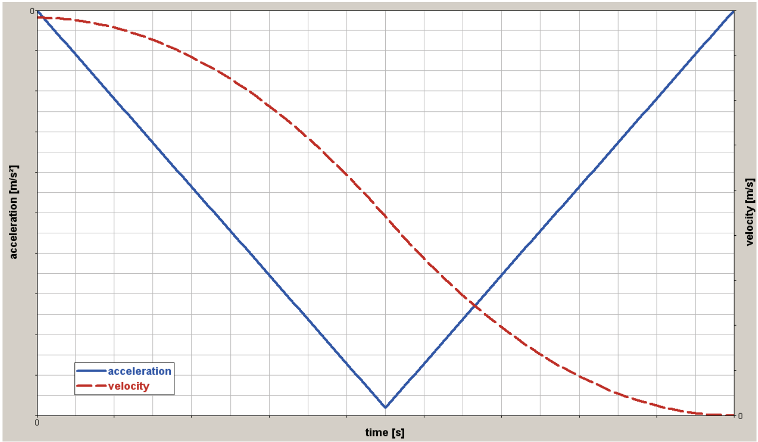

Figure 3: Velocity decrease during deceleration impulse

STOCHASTIC MODELLING AND SIMULATION

Based upon this specification an LS-DYNA model for explicit calculation is developed with Altair HyperMesh. The structure of the overhead stowage bin is built with Belytschko-Tsay type quad shell elements, the trolleys are built with hexahedron and prismatic constant stress solid elements. The mounting points of the overhead stowage bin are defined as single point constraints at the respective nodes (see figure 4). The prescribed acceleration in x-direction, causing the deceleration of the overhead stowage bin during the simulation time, is applied to the same nodes. The *INITIAL_VELOCITY v_{ini} is derived from the deceleration impulse by integration, in order to stop the movement of the overhead stowage bin at the end of the simulation.

Two contacts are defined to calculate the interaction between the trolleys and the overhead stowage bin. The *CONTACT_SURFACE_TO_SURFACE covers the interaction between the leading trolley and the front wall of the overhead stowage bin, which is highlighted blue in figure 4. This contact definition is ancillarily used to measure the forces applied to the overhead stowage bin by the carry-on baggage during deceleration. The *CONTACT_SINGLE_SURFACE is used to calculate the interaction among the trolleys as well as the interaction with the five remaining walls of the overhead stowage bin. The coefficients for static- and dynamic friction of both contact definitions are assumed according to the investigations in [13].

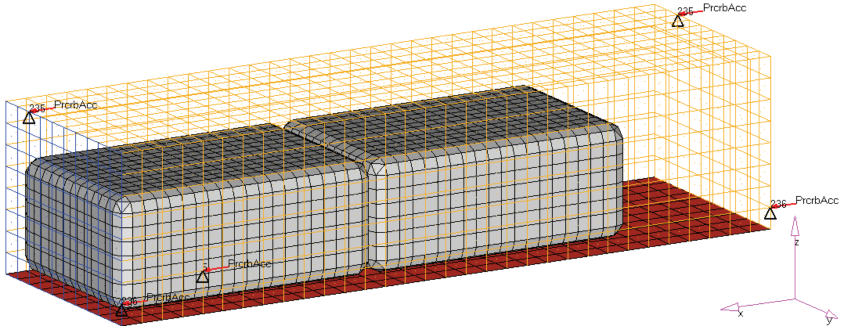

Figure 4: FEA model of the overhead stowage bin with trolleys

STOCHASTIC META-DATA MODEL

The meta-data model is based upon the deterministic FEA model of the overhead stowage bin with the trolleys described above. To incorporate the uncertainties of the system additional parameterizations have to be conducted. For the preparation of the meta-data model the deterministic model is loaded into Altair HyperStudy, which is used for the stochastic parameterization and management of the Stochastic Simulation. The following system uncertainties are defined in the meta-data model:

- Peak deceleration and duration of the deceleration impulse
- Static and dynamic friction
- Gap between trolley1 and front wall of the overhead stowage bin
- Gap between trolleys
- Mass and stiffness of each trolley respectively

Each uncertainty parameter is created in the meta-data model using a specific probability density function (PDF) and the particular characterizing parameters of the function. Figure 5 displays two commonly used probability density functions that are relevant for this paper.

It is assumed that the scatter in peak deceleration and duration of the impulse are uniformly distributed. The upper and lower limits of the uniform distribution function are defined 10% above respectively below the nominal value of the uncertain parameter. This is a proposed assumption for unknown scatter of uncertainties in literature [4] that can be confirmed by experience. The static and dynamic friction coefficients are modelled analogously with a uniform distribution and 10% variation.

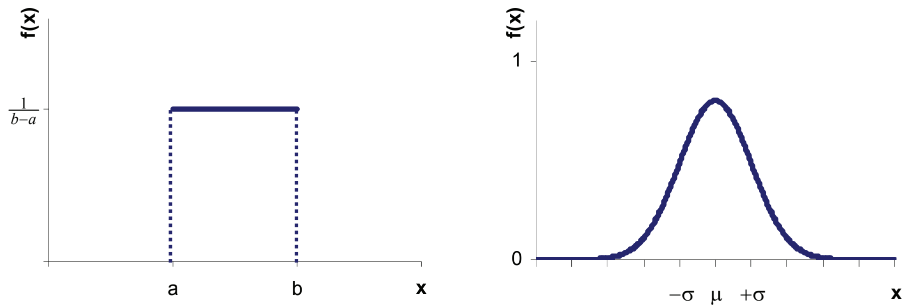

Figure 5: Density functions of a uniform distribution (left) and a normal distribution (right)

To analyze the effects of different trolley positions the two gap parameters are modeled with a uniform distribution. The lower limit is zero for both parameters, this means that no gaps exist. The upper limit is restricted by the free space in the overhead stowage bin. The gap parameters are realized in the FEA model code with the parametric mesh morphing tool Altair HyperMorph, enabling the trolleys to be positioned nearly arbitrarily in x-direction within the overhead stowage bin. Furthermore, this tool prohibits the trolleys from changing their sequence and from initially penetrating each other or the stowage bin.

The masses of the trolleys are modeled independently from each other with a normal distribution, hence the probability density function is a Gaussian curve. The distribution function and the necessary parameters for mean and standard deviation are selected and defined by means of several surveys [2, 5, 6, 8, 12]. The trolleys' stiffnesses are identified from real tests and a detailed FEA model [13] and modeled with a uniform distribution function. Again the upper and lower limits are assumed with a 10% variation from the nominal value.

All distribution functions are defined to be independent of each other, therefore the stochastic parameters are uncorrelated.

STOCHASTIC SIMULATION

Stochastic Simulation is a generic term for different methods to simulate an uncertain system according to its probability and state functions. The most famous and commonly used algorithm is the Monte Carlo Method. The main advantage of the Monte Carlo Method is its nearly all-purpose applicability to simulate and analyze probabilistic systems. Prerequisite is a numerically and semantically correct deterministic model of the system and the definition of the probability density functions for uncertain parameters.

Figure 6 displays the principle of the Monte Carlo Method. The Stochastic Simulation has a good scalability and can be easily parallelized, because the single random samples can be computed independently from each other.

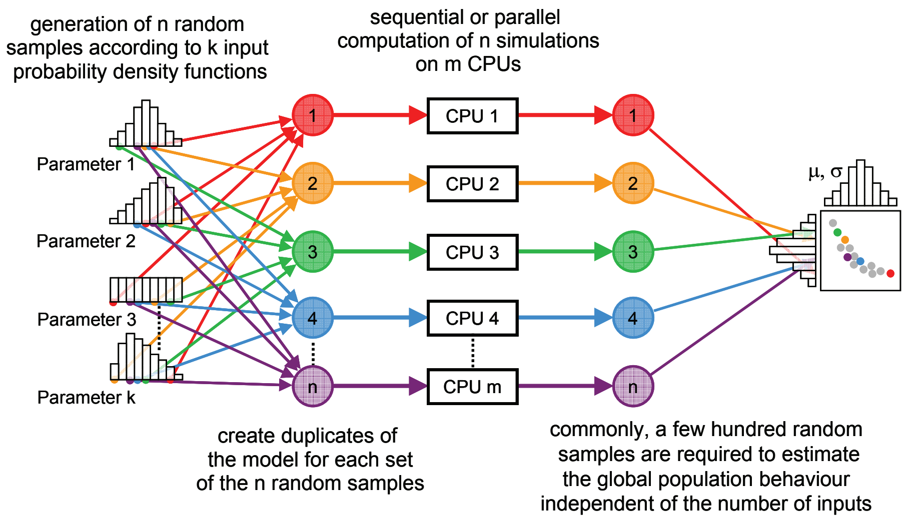

Figure 6: Stochastic Simulation with Monte Carlo Method

Hence with a sufficient number of processors (CPUs) the Stochastic Simulation time can be as short as the time of a deterministic simulation. Stochastic Simulation is a very efficient meta-computing technique because it draws the random samples with respect to the probability density functions of the system. Figure 7 shows a two-dimensional projection of the samples drawn with a commonly used 2-level full factorial Design of Experiments (DoE) technique in comparison with the random samples from the Monte Carlo Method.

It is easy to understand that DoE samples represent only rare states of the system. The number of DoE levels can be increased to get more samples near the mean behavior of the system. However, a 2-level DoE already needs 2^{10}=1024 samples for a system with 10 parameters, like the example of this paper. Increasing the number of levels to 3 will result in 3^{10}=59049 samples; a number unsuitable to solve when using FEA since it leads to enormously high computational cost. For a comprehensive overview of Stochastic Simulation please be referred to [1] and [4].

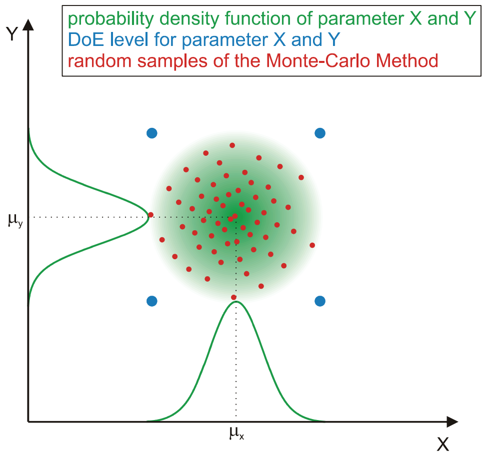

Figure 7: Comparison of sample location from Monte Carlo Method and DoE

The Stochastic Simulation of the example chosen in this paper is executed with 1024 random samples. The samples are drawn with the updated Latin Hypercube Sampling (LHS) instead of a Simple Random Sampling. The LHS ensures a better distribution of the samples in the probability space which prevents sample clustering and agglomeration. LHS also realizes any correlations defined between the uncertain parameters with unparalleled reliability.

The results of a Stochastic Simulation can be viewed with any standard FEA postprocessor sample by sample. Yet the real power of Stochastic Simulation can be achieved with statistics. It is useful to check the stability of the system at first. This is done by calculating first and second order statistic moments which can be performed within Altair HyperStudy. Since the result data has nominal scale the arithmetic mean $\overline{x}$ and standard deviation $\tilde{s}$ can be derived. To get a comparable dimensionless number the Coefficient of Variation (CoV)

$$c_v = \frac{\tilde{s}}{\overline{x}} \qquad \text{(Eq. 1)}$$

is calculated for the result parameters of the Stochastic Simulation. The following result parameters mainly refer to the force impulse applied to the front wall of the overhead stowage bin. Table 1 displays the observed result parameters with their associated CoV.

Table 1: CoV of the result parameters

parameter	CoV [%]
maximum force	15,6
time at maximum force	11,6
duration of 1st force impulse	40,3
total force impulse duration	26,7
shape of force impulse	34,2
number of maxima	25,1
kinetic energy of 1st trolley	33,6
kinetic energy of 2nd trolley	33,5

All CoVs of the result parameters are lower than the CoV of the parameter "gap between trolleys" (CoV=57,8%) which is the highest of all input parameter CoVs. Hence under consideration of the chosen result parameters the system is confirmed to be stable. For more elaborate methods to measure the stability and robustness of a system by evaluating the entropy or the sigma levels please be referred to [7].

The second step in analyzing the Stochastic Simulation results is to get an overview of the dependencies between uncertain parameters and the system result. Therefore the extracted simulation results are imported into MATLAB and the statistic relation measures are determined. In this case the nonlinear rank correlation by Spearman

$$r_{SP} = \frac{\sum_{i=1}^{n}\left(rg(x_i)-\overline{rg}_X\right)\cdot\left(rg(y_i)-\overline{rg}_Y\right)}{\sqrt{\sum_{i=1}^{n}\left(rg(x_i)-\overline{rg}_X\right)^2\cdot\sum_{i=1}^{n}\left(rg(y_i)-\overline{rg}_Y\right)^2}} \qquad \text{(Eq. 2)}$$

is used. The correlation coefficient r_{SP} measures the monotonic dependency between the samples of two parameters. A correlation close to 1 signifies a probable positive dependency, a correlation close to -1 signifies a probable negative dependency between the investigated parameters. The symmetric correlation matrix is obtained by calculating the correlation coefficients of all parameter combinations. Figure 8 displays a color visualization of the correlation matrix enabling an intuitive understanding of the system parameter relations.

Trivia are quickly checked first. The dependencies between peak deceleration, duration of the deceleration impulse, and the initial velocity are easily identified. Likewise the influence of the initial velocity and the mass of each trolley regarding the kinetic energy of the respective trolley can be verified.

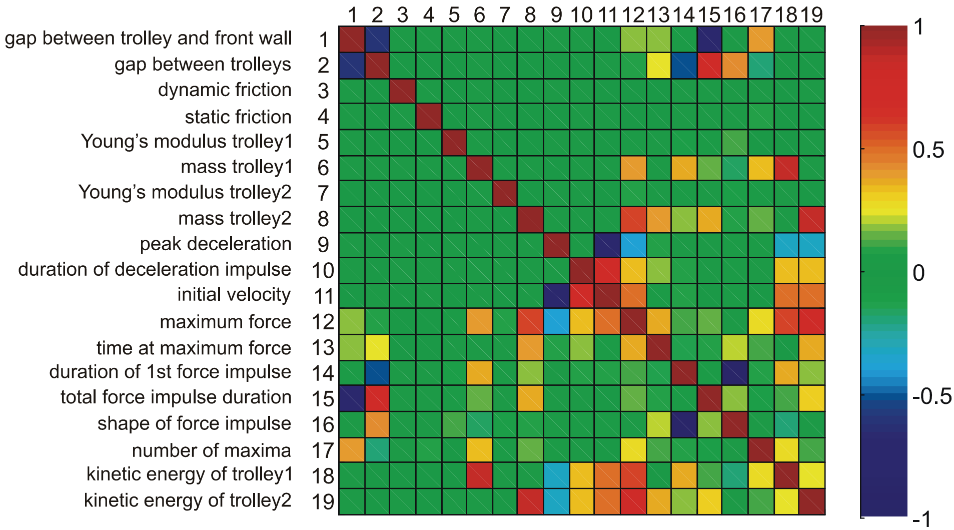

Figure 8: Visualization of the correlation matrix

The specific analysis of the correlation matrix reveals a negative dependency of the total force impulse duration with the gap between trolley and front wall of the overhead stowage bin. This means increasing the gap will decrease the duration of the total force impulse. The gap between both trolleys is positively correlated with the total force impulse duration.

The maximum force shows two positive correlations with the kinetic energies of the trolleys and a slight positive correlation with the initial velocity. These dependencies are comprehensible. More interesting are the correlations between the mass of each trolley and the maximum force, because the mass of trolley2 has a 50% stronger correlation with the maximum than the mass of trolley1.

The stiffness of the trolleys and the friction coefficients show no relevant correlation with the system parameters within the defined intervals. The gap between the trolleys has two correlations with the duration of the force impulse. It is positively correlated with the duration of the total force impulse and negatively correlated with the duration of the 1st force impulse. However, the scatter plot in figure 9 reveals the false conclusion of the negative dependency. Since correlation coefficients only signify probable dependencies and their directions they do not imply a causal connection.

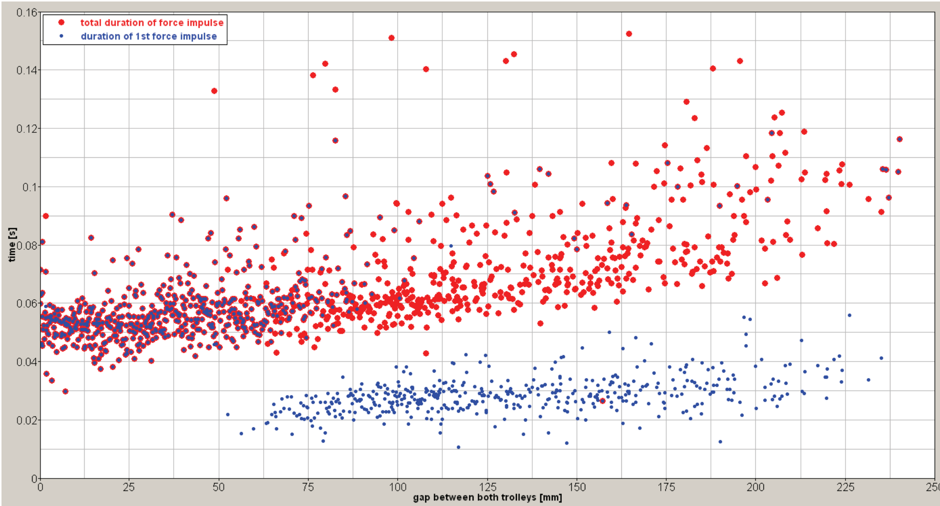

Figure 9: Duration of the 1st and total force impulse according to the gap between the trolleys

Two populations are displayed in the scatter plot. The cloud of the total force impulse duration (red) is continuous and verifies the positive dependency with the gap between the trolleys. The population of the 1st force impulse duration (blue) shows a bifurcation. This indicates the generation of a second force impulse in the system containing gaps of 50mm and more between the trolleys. Scatter plots can be used to analyze the system behavior in detail, because they contain the biggest information content and reveal complex pathologies.

CONCLUSIONS

The studied example leads to the following conclusions. A worst case scenario for the structural loading is characterized by a high maximum force and long impulse duration of the force. This will occur in case of both a small gap between trolley1 and the front wall of the overhead stowage bin and a large gap between the trolleys. In addition the worst case is characterized by a big total mass of carry-on baggage with the heavier parts in the rear of the overhead stowage bin, and a high initial velocity.

This paper demonstrates a suitable way to introduce uncertainty management in CAE which helps to develop more reliable products and to gain deeper insight into system behavior.

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