INTERNATIONAL DESIGN CONFERENCE - DESIGN 2012
Dubrovnik - Croatia, May 21 - 24, 2012.

USE OF METHODS OF SENSITIVITY ANALYSIS FOR SIMULATION PLANNING

J. Reitmeier and K. Paetzold

Keywords: uncertainty, data quality, sensitivity analysis; simulation planning

1. Introduction

Today, it is an important competitive factor for enterprises to create high-quality products based on innovative ideas within a short time. To reduce the time for development, the strategy is increasingly pursued to ensure the product functionality respectively the product properties by virtual validation throughout the development process. For this purpose, a large number of various methods and tools is available. Experiences from several projects with companies show, that the methods and tools are well-known and widely used indeed, but, a coordination between development teams concerning available data for simulations does not take place. This consequently leads to not useful significant additional expenses by the duplication of work; simulations will be executed later than it would be possible during the development process and, therefore, helpful information for the decision process is not available at the right time. This results in the need for a simulation planning as a parallel process with the objective to optimize the integration of methods and tools of simulation into the development process.
To create a holistic approach for simulation planning four aspects have to be considered:

- The selection of appropriate methods of modelling respectively simulation tools depends on available data and the expected results from a simulation. This requires linking up the methods of modelling to a process model. With this step a framework for simulation planning is given [Paetzold 2010].
- The difficulty for the simulation planning is that especially in the early stages of the product development data and information are uncertain and incomplete. They only get detailed and completed with the development progress and the increasing degree of product maturity connected to it. In order to be able to describe the quality of data simulations are based on, a statement concerning the cause of uncertainties is required; this can be based on a classification of data in turn. Conclusions about the quality of the simulation results can be derived with respect to the uncertainty analysis of used product data which in turn are usable as information for task management [Reitmeier 2011].
- In principle, simulations are used for the analysis. The developer determines characteristics as a task within the synthesis; these must be verified by analysing the resulting properties [Weber 2005]. Based on this differentiation a classification of data is determined which has to be stored in an appropriate data model; data processing as well as the planning of simulations result from this model.
- A previously detailed planning of simulations is neither possible nor wise. As product data only occur in the progress of the development a context specific approach to simulation-based property validation is required. Therefore, additional indicators that support the flow control are required to complete previous considerations.

The focus of this paper is to describe methods with respect to the last aspect.

Data and information arise in the course of the development. This concretization finally leads to the fact that development steps have to be repeated with respect to new insights and changed boundary conditions (iteration loops are unavoidable). Objective respectively orientation of the virtual product development is essentially dependent on the simulation results, which in turn are strongly influenced by the underlying database. It must be considered, however, that the characteristics determined by the developer are more or less important for a specific property validation (based on a specific simulation method). Therefore, an approach is presented to identify criteria on the basis of sensitivity analysis that precise the progress of development, give indications if iterations are necessary and which process steps should be focused on within these iterations. In addition, a way is shown to concretize interfaces within a development project (between product functions as well as development teams) by the link-up of the results of a sensitivity analysis and a data model and consequently the interdisciplinary collaboration is supported.

For this purpose, general considerations on the use of results from the sensitivity analysis is shown firstly, then the procedures and relevant results from each method of the sensitivity analysis are discussed in more detail. The conclusion is the evaluation of the methods of sensitivity analysis with respect to their capability to process control and concretization of data in the context of simulation planning.

2. General considerations for the use of sensitivity analyses

The aim of current research activities is to develop a holistic approach for the continuous validation of product properties throughout the development process by means of simulations. However, data quality must be pre-defined depending on the current process step if simulations are to be efficiently executed. Similarly, the used model quality constitutes a crucial factor, as it depends on the availability of information respectively progress/level of detail of available product models and thus, determined indirectly by data quality. It is aimed to more transparently describe simulation output, based on the importance (sensitivity measures) of design parameters in conjunction with their quality assessment, to make them assessable and reduce respective uncertainties

The detailed FORFLOW process model [Krehmer et al. 2009] provides the basis for a holistic approach for simulation planning; modelling and simulation methods can be accordingly assigned [Paetzold 2010]. The next step is to link up methods of sensitivity analysis as well as these give indications concerning the level of influence of individual characteristics on specific properties. The models used for property validation can also be used for sensitivity analysis. Simulations are steps of analysis, characteristics that are determined with in the synthesis step provide the model parameters and, therefore, constitute the “set- screws” to modify product properties. Depending on the modelling approach and fineness (in turn depending on the process step and the focus of analysis in turn) specific properties are analysed by a simulation. Typically, several properties are analysable with one simulation. The problem is that simulations are afflicted with more or less uncertainty. The model quality respectively the model fineness is dependent on available information and thus, closely linked with the process step. This means that simulation results have always to be evaluated with respect to the currently available data and information quality, and, therefore, are always subject to uncertainty. This, however, determine the progress within virtual development processes (e.g. iteration management), which can be considered to be quite critical without information about the quality of simulation results.

Sensitivity Analyses examine the correlation between input and output parameters in a system [Saltelli et al. 2000], [Saltelli et al. 2008]. The effect of the input parameters on the system response is evaluated by varying the input parameters [Rüppel et al. 2007]. Originally designed to analyse uncertainties of input parameters (interpreted as disturbance variables), nowadays, sensitivity analysis are also used to include estimations concerning the model (e.g. properties or parameters of a model) in evaluations [Schwieger 2005]. Therefore, input parameters as well as the model itself can be checked up on their validity. This implicates that input parameters are, with respect to the current literature in the context of sensitivity analysis, as opposed to systems theory, include individual model variables, model parameters or the entire model as well [Schwieger 2005]. In the context of the simulation planning, this means that the input parameters of a sensitivity analysis represent the characteristics defined by the developer and their influence on properties (output variables of a sensitivity analysis) is shown. Consequently, the results of a sensitivity analysis are variances of the properties as a function of variances of the characteristics. The interaction of "set- screws" and obtained product properties is getting more transparent (see chapter 4). The sensitivity analysis is used to determine parameter sensitivities of a solution [Schwarz 2001]. In this case the term "solution" stands for the three components of a sensitivity analysis: these are the selected input parameters, the model (which is existent as an equation or a system of equations in terms of a sensitivity analysis) and the output parameters (which are, ideally, within the permissible range of values). In principle, the following objectives are focused on by means of sensitivity analysis (Table1):

Table 1. Objectives by means of a sensitivity analysis

Objectives	In General [Saltelli *et al.* 2000] [Schwieger 2005]	Context "Simulation Planning"
model validation	• analysis whether the used model corresponds to reality = validity statement	• general requirements for modelling
identification of important input parameters	• ranking of input variables in terms of their influence on the output parameters (qualitative statement) • calculated influence (quantitative statement)	• characteristics can be ranked with respect to properties → information concerning relevance
elimination of unimportant input parameters	• identify input parameters that have a negligible impact on system response → reduction in complexity [Rüppel *et al.* 2007]	• support for the weighting of parameters respectively classification („contribution") • utilization in terms of meta information for the data preparation
identification of model properties	• model properties (e.g. monotonicity) are identifiable • analysis of dependencies between the input variables that are caused by the model	• interrelation between characteristics and properties • interrelation between characteristics
identification of the critical design space	• the design space represents all possible input configurations • the aim is to display areas within the design space where the system response is not permitted [Rüppel *et al.* 2007]	• provides the framework for the concretization of product data • completes interface description
model optimization	• identification of important and less important input variables and the evaluation of model parameters to improve the model. • reducing the model complexity in order to execute simulations more effectively	• indication concerning required level of detailing and iterations
risk assessment	• limit function at which the model fails to identify responsible input variables • qualitative information regarding the influence of input parameters can provide an appropriate basis	• supports property validation • completes the data description

Figure 1 shows the approach of a sensitivity analysis. The "Δ" is the variation of the input parameters respectively the values margin of the output parameters. Furthermore, sensitivity measures, also known as sensitivity indices, are introduced and provide the numerical basis of valuation. Thus, a comparative assessment of the sensitivity of individual parameters is possible.

3. Description of the general methods of sensitivity analysis

In the following, the most important methods are briefly described, on explicit description (e.g.

underlying mathematics) is not focused. For more detailed information in this area see e.g. [Saltelli et al. 2000] and [Schwarz 2001]. It is aimed to explain the operation of the methods respectively to show the results of a sensitivity analysis in order to be able to assess them in terms of support of simulation planning. Chapter 4.1 shows further reflections on the practical integration into processes.

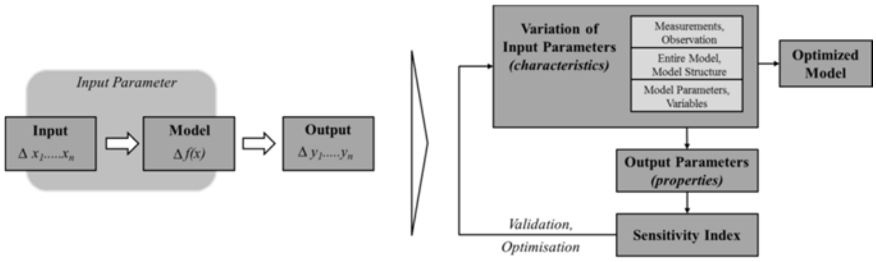


Figure 1. Basic concept of a sensitivity analysis based on [Schwieger 2005]

3.1 Factor screening

The factor screening determines the qualitative influence of input parameters and model on the output parameters. That way, parameters with a high influence on one or several output parameters can be separated from those parameters that have less influence. The approach for the calculation of the sensitivity measure is based on the design of experiments.

The one-at-a-time (OAT) design as the simplest type of screening method is exemplarily mentioned. Only one factor of the input parameters is varied and the system response is measured. For each factor, additionally two extrema are determined which can be interpreted as the limitation of the factor space (in terms of a range of values). Sensitive factors that affect the model are identified by the differences of the magnitudes of the output parameters and the extrema of the input parameters [Saltelli et al. 2000].

Although, as already stated, screening methods provide only qualitative information; they are often applied in the context of global sensitivity analysis to reduce the computational effort. Parameters can be deleted from the equations by means of factor screenings. It has to be mentioned that parameters can be combined into groups of parameters as well. For example, if an input parameter exerts no influence on the observed output, but affects other input parameters, then these input parameters can be summarized. Thus, a parameter of the model equation is deleted, but the effective correlation between the parameters is retained.

Therefore, screenings are often useful to get a basic prioritization of the parameters. If the developer knows that only a few parameters must be considered, the application of these techniques is not necessary. This is useful when the developer has no information which characteristics are the decisive „set- screws“, to achieve required properties. In addition, the evaluation of the data quality at hand can be facilitated: only the most essential parameters are evaluated in terms of quality and integrated into the decision-making process for the planning of simulations. Therefore, this can be performed more efficiently.

3.2 Local sensitivity analysis

The sensitivity of several input parameters concerning a specific value of the output can be analysed by means of local methods (e.g. critical minimum or maximum, optimum). Consequently, a local sensitivity index is calculated with respect to one specific output. As the influence of small changes in input parameters is focused on, derivations of differential equations respectively differential coefficients and difference quotients are the resulting sensitivity indices. Thus, local methods are also known as differential analyses.

In the context of property validation local methods of sensitivity analysis can provide an indication of combinations of characteristics that lead to critical (and therefore, unwanted) product properties. Consequently, the developer receives indications of the usable ranges of values of characteristics to optimize his solution.

Different methods are available within local methods. The sensitivity measurements are generally determined by the partial derivatives of output parameters to input parameters. The results are

sensitivity coefficients that are combined to form a sensitivity matrix. For the evaluation of one input parameter a column vector occurs, a row vector when evaluating one output parameter. By means of the normalized standard deviations of the input and output parameters, the weighting of the input parameters is realized. This means that a column vector shows the relation between a characteristic and a multitude of properties and a row vector shows the relationship between several characteristics and one property. This approach also corresponds to the methodology of the variance-based sensitivity analysis, which is considered in the context of global methods (see chapter 3.3).
The main advantage of the local methods is the low computational effort. This allows for applying local methods for calculating the sensitivity measurements when analysing complex models, whereas the choice of starting values is important for the quality of the results. In addition, it is possible to consider the correlations between the input parameters with local methods, which is not, respectively, just faultily possible with the screening methods.

3.3 Global sensitivity analysis

By means of local methods only one or a few input and output parameters in precisely defined areas are analysed, global methods can analyse the entire design space. Thus, these methods are valid for the entire model range, which in turn leads to a model independence of global methods. Furthermore, it is possible to vary more than one input parameter and analyse their influence on the output parameters [Saltelli et al. 2008].

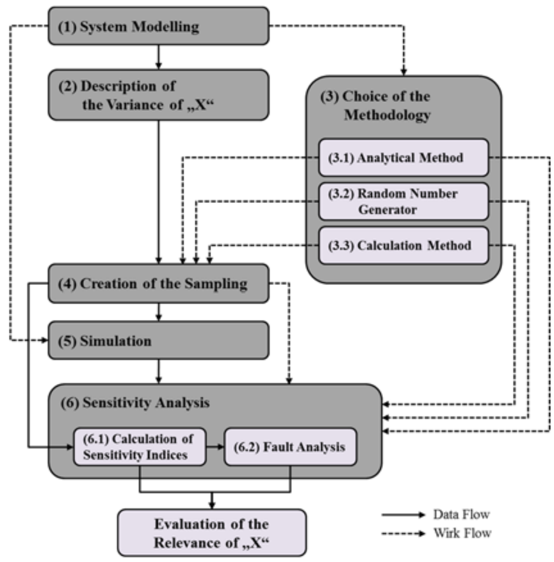


Figure 2. Procedure of a global sensitivity analysis according to [Han 2011]

The basic approach of a global sensitivity analysis is shown in Figure 2 [Han 2011]: The system description (1) is carried out by means of mathematical description of the context and wording of the equation system. The description of the variance of the input parameters (2) is realized by density functions, with which the averaged expected value (middle position) of the input parameters and the range of the entire distribution can be expressed (variance). The possible distributions are normal or uniform distributions. The quality of the calculated results crucially depends on the quality of the chosen model, i.e. conversely, that a sensitivity analysis only provides meaningful results, if a minimum of data quality for the modelling is already available. The choice of the methodology (3) depends on the model properties and in this context three aspects have to be considered: firstly, the choice of the investigation method, secondly, the choice of the method by which the samples are generated, and thirdly, the determination of the calculation method. Samples (4) are generated by a random number generator, at which the method for the generation of the sample is directed to the required calculation method of the sensitivity indices. The totality of all samples results in the sample matrix. This is passed to the simulator (5). The higher the number of simulation runs, the higher the quality of the detected correlations. There is a quadratic relationship between the sample size and a linear increase in the accuracy of the results [Schwieger 2005]. The type of sensitivity indices (6) depends on the chosen calculation method (e.g. elementary effects, main effects, total effects, etc.). To verify the significance of the detected results, an error analysis is applied. Exemplarily, a so-called resampling can be used in this context. In the following, important methods of global sensitivity analysis are briefly explained (detailed description see e.g. [Saltelli et al. 2000] or [Schwarz 2001]).

The **regression analysis** is used when an output parameter "y" and one or several input parameters can be linked together. The strength of the correlation can be quantified. This allows to identify input parameters, that have no influence, respectively, several input parameters that include redundant information with respect to "y". Overall, the use of regression analysis is useful, when only one output parameter is of interest while several input parameters are varied. In addition, an error term takes non-systematic and, therefore, random disturbances into account. The cause of the disturbances is based on the model. A model always represents the reality just partly. Not every behavior of the output can be described only by the influence of input parameters. In reality, there are additional disturbances, such as an energy loss through friction. This results in an error between the true output and the output generated by the model. The standardized regression coefficients are introduced and describe the sensitivity based on regression analysis. These give information about the linearity of the model at the same time [Saltelli et al. 2000]

Results of **variance-based methods** are sensitive measures that can be used regardless of any restrictions. This means that the entire range of values of the parameters can be considered to simultaneously analyse several input and output parameters and additionally work regardless of the model properties. Within the sensitivity measures of variance-based methods it is differed between main effects (so-called 1st order sensitivity indices, the influence of a parameter to the variance of the output parameter) and total effects (so-called aggregate effects that characterize correlations of the input parameters). The objectives of the variance-based methods are the quantitative identification of important input parameters and a risk assessment. It is possible to gain knowledge about important and unimportant parameters to optimize the model. When assessing the risk it is focused on keeping the output value within a target variance in the focus of attention. This requires that the influences of each input parameter to the variance of the output parameters are eliminated [Saltelli et al. 2000].

In addition to these mathematical methods, **graphical methods** exist as well. Commonly, scatter plots (scatter diagrams) are mainly used to identify and characterize dependencies between two parameter features. Scatter plots can also be grouped into matrices so that a comparative view on the form of dependencies is possible. Furthermore, several scatter plots can be overlaid and combined into one scatter plot. Sensitivity statements regarding to certain configurations of the input parameters are possible by this covering. Thus, graphical methods have the same advantage as the screening methods (see chapter 3.1): Identification of appropriate characteristics as “set- screws” and the more efficient evaluation of data quality at hand in the context of simulation planning.

4. Evaluation of sensitivity analyses in the context of simulation planning

Sensitivity analyses have two main effects. On the one hand they raise the confidence in the model and its predictions are increased by providing a better understanding of how the model output depends on changing input [Saltelli et al. 2000]. On the other hand this evaluation increases the sensitizing within the product development: data providers as well as data consumers become more aware of the relevance of data to be provided, respectively, the utilization of a certain data quality [Reitmeier 2011]. Therefore, an analysis of the parameter sensitivity can help to raise data quality as all individuals that are involved in product development are being motivated to deal proactively with generated data.

Product development shows two fundamental kinds of process steps that are executed alternately: synthesis and analysis. Both steps can be supported by sensitivity analysis. First, it is analysed how design parameters interact and form (un)desired product properties. This increases the transparency (in terms of interaction, weighting, model quality and dependence, etc.) for the product developer and gives him targeted information concerning appropriate and significant “set- screws” (design parameters) for following steps of synthesis as well as iterations to optimize his solution. Secondly, simulation results can be better appreciated, as the impacts of uncertainties concerning input

parameters are part of the resulting evaluation and, therefore, uncertainty influences can be included into the on-going optimization of the solution.
The classification of data mentioned before has to be linked to an appropriate data model to support data processing as well as simulation planning. This is to include the results of a sensitivity analysis (impact of characteristics on properties) and the quality of current development data (uncertainty analysis of characteristic and reference properties). This can be done by matrices (Figure 3). Thus, it is possible to include specific aspects as well as the overall context (networked interaction of all the characteristics and properties) in the evaluation of the quality of simulation results.

		DQ_{RP1}	DQ_{RP2}	DQ_{RP3}		DQ_{RPj}
		Property 1	**Property 2**	**Property 3**	...	**Property j**
DQ_{C1}	**Characteristic 1**	I_{11}	I_{12}	I_{13}	...	I_{1j}
DQ_{C2}	**Characteristic 2**	I_{21}	I_{22}	I_{23}	...	I_{2j}
...	...	...	...	...	...	...
DQ_{Ci}	**Characteristic i**	I_{i1}	I_{i2}	I_{i3}	...	I_{ij}

DQ_{Ci}: data quality of characteristics
DQ_{RPj}: data quality of reference properties
I_{ij}: impact

Figure 3. Data processing by matrices

Just qualitative statements (such as „high“ or „low“) concerning the influence „I_{ij}“ and data qualities „DQ_{Ci}“ and „DQ_{RPj}“ to increase transparency can be as useful as corresponding specific values (e.g. a percentage when complete data security and the greatest possible impact are expressed with 100%) to calculate a concrete quality value of simulation results (see chapter 4.2). If there is no information on data quality and influences, it is recommended to fill the corresponding cell with the value “0”, instead of leaving an empty one, in order to point up the lack of information.

4.1 Reduction of uncertainty in decision-making processes

Thus, the use of sensitivity analysis in the field of virtual product development and product validation holds great potential. The integration of a sensitivity analysis always leads to a better understanding of the internal impacts of the product as relevant and non-relevant parameters can be identified with respect to a specific property validation. Ultimately, appropriate “set- screws” can be identified that help the developer to easier improve his solution.
In the context of the described theory of sensitivity analysis an action alternative is a fixed set of input and model parameters. By varying these parameters, output parameters are changed and new decision alternatives are created. Then, the decision must be made under the influence of multiple (conflicting) goals (e.g. maximization of the stiffness of a component and simultaneous minimization or reduction of the component material) and an uncertain future (e.g. validity of the chosen boundary conditions).
This is especially important when the further process flow (e.g. iterations) has to be determined. The decision space comprises the set of all decisions and is thus identical to the design space of the sensitivity analysis. The product developer creates a decision model and evaluates data by using the instrument sensitivity analysis, which leads to an increasing data quality. For example, it is indicated by the sensitivity analysis at what values of certain parameters the ranking of alternatives is changing and, therefore, other alternatives should be preferred. The quality of simulation results and, therefore, the obviousness of a simulation are highly depending on the fulfilment of data requirements concerning design input data. An iteration management based on the results of simulations postulates a decision-making process. Therefore, the sensitivity analysis is an appropriate tool for improving a decision-making situation and can help to determine more efficient iterations and consequently to reduce development time and risk.
If simulations are to be employed reasonably, a pre-defined data quality with respect to both completeness and certainty is needed [Paetzold 2010]. This is closely connected to the progress of the process. Considerations concerning simulation planning require a detailed process model to efficiently integrate simulation methods into the development process. This also applies to the integration of sensitivity analyses to efficiently support a simulation planning. The detailed FORFLOW process model, that is described in detail in [Krehmer et al. 2009], provides an appropriate basis: Flexibility is one major benefit of this process model; process flows are not fixed entirely, but can be adapted to some degree. This provides the opportunity to manage property validation with respect to the data

quality at hand. The FORFLOW process model enables to integrate dynamic product models, which are connected to the process step. This is important as on the one hand data have different levels of concretization within specific development phases and on the other hand different objectives are focused on in terms of property validation. An adequate linking of methods of sensitivity analysis and the process model ensures to include all current development parameters, including their links to product characteristics, within the evaluation of the prevailing data quality.

4.2 Evaluation of data and information quality

As shown before, the input parameters can be assessed and weighted by the application of a sensitivity analysis. Thus, the developer can focus on the relevant parameters in the development and improves the quality of the developed solution. The risk decreases that the developed product does not fulfil the requirements. Similarly, simulation results can be better appreciated, as the impacts of uncertainties concerning input parameters are part of the resulting evaluation and, therefore, uncertainty influences can be included into the on-going optimization of the solution.

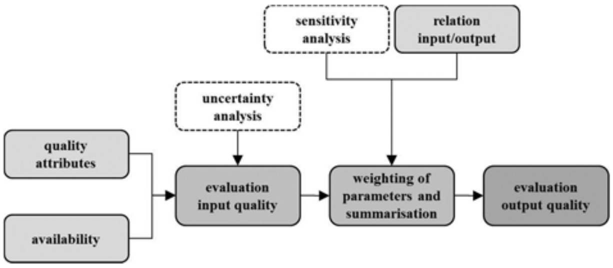


Figure 4. Evaluation of simulation output by a sensitivity analysis based on [Reitmeier 2011]

In addition, it should be noted that the basis for a satisfactory outcome of the sensitivity analysis is the quality of the input parameters. A sensitivity analysis can only be applied if the distributions of input parameters and their variance (in terms of uncertainty) are determined. Based on a good description of the uncertainty of input parameters their domain and consequently the extent of the simulation can be reduced. Here the expertise of simulation specialists has to be included as well to assess the quality of input parameters, which includes a subjective uncertainty analysis. Establishing quality criteria see [Reitmeier 2011]. The uncertainties are objectively examined by an uncertainty analysis, and thus the sensitivity analysis can be improved. The weighting of the input parameters is done by the sensitivity measurements of a sensitivity analysis (Figure 4). This offers the possibility to assess simulation results in a better way, since their occurrence is more transparent and the effects of uncertainty are also reflected by the result. In total, this approach supports to consider uncertainty factors when determining further development steps. If a specific problem is analysed by several sensitivity analysis methods, the sensitivity measurements can only be compared among each other by trend.
The core problem here will be the integration of the sensitivity analysis in the process of virtual product development. The methods can be used for product optimization as well as process optimization. Therefore, both applications offer the chance to reduce development time, to increase the quality and consequently to reduce costs in total.

4.3 Example of use

The exemplary use of sensitivity analyses is shown by the behavioural simulation of the break application of a car with ABS system (Figure 5). The aim is to analyse the impact of changes in selected parameters (m, r and A) on the security relevant breaking distance in a qualitative way. The results are shown in Figure 6 (x-coordinate: time, y-coordinate: breaking distances, corresponding table of values): for reasons of clarity, the explicit representation is restricted to limit values and mean value of the chosen value ranges.
It can be seen that the mass of the car has a significant influence on the breaking distance (difference of 1,75m in the analysed range), the area of the front of the car and the tyre radius have a very small influence. This means that the simulation of the breaking distance has to be executed whenever significant changes in the mass of the car occur: here it is practical to link-up considerations

concerning property validation with specific repetitive meetings that focus on the mass of the car and are standard in the context of car development. It should be noted that changes must be viewed in the overall context of the car, thus intensive communication between distributed development teams is required. Here, sensitivity analyses can support as well, as the effect of parameter changes in the context of necessary design changes is shown or even ranges for parameter changes can be possibly determined. Design changes of the front of the car or the bonnet are less relevant in the context of the brake performance; a surface change of 0,8m^2 only causes a change in the braking distance of 0.16m. Consequently, the usefulness of the simulation is only given in severe design changes (rather rare): so it is not stringently necessary to use actual design data when a property validation is triggered by mass changes. The tyre radius that was analysed in the range of standard wheel and tyre combinations can be considered to be even more uncritical.

friction force: $F_R = \mu(\lambda) \cdot F_N$

normal force: $F_N = a \cdot m \cdot g$

speed of tyre: $V_r = \omega_R \cdot r_R$

slip dependant friction factor: $\mu(\lambda) = c_1 \cdot (1 - e^{-c_2 \cdot \lambda}) - c_3 \cdot \lambda$

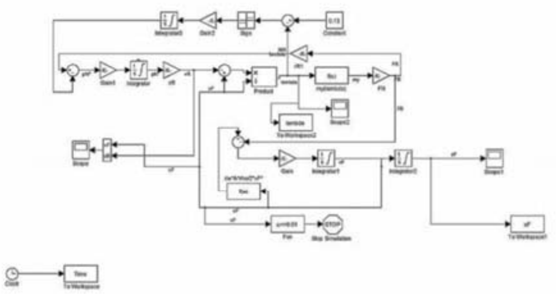
air resistance: $F_L = c_w \cdot A \cdot \frac{\rho}{2} \cdot v_F^2$

slip: $\lambda = \frac{v_F - v_R}{v_F}$

modelling of the tyre: $\ddot{\varphi}_R = \frac{1}{J_R} \cdot (\mu(\lambda) \cdot a \cdot m \cdot g \cdot r_R - M_B)$

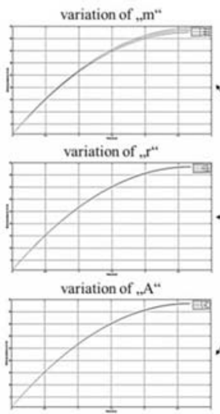
modelling of the car: $\ddot{x}_F = \frac{1}{m}(-c_W \cdot A \cdot \frac{\rho}{2} \cdot v_F^2 - F_R)$

boundary conditions: $v_{F_0} = v_{R_0}$, $w_{R_0} = v_{R_0} / r_{R_0}$, $M_B = 5335 Nm$



v_F	velocity	J_R	moment of inertia of the wheel	ρ	air density	$c_{1/2/3}$	coefficients for calculating friction value
m	mass of the car	A	area of the front of the car	g	acceleration of gravity	ω_R	angular frequency
r_R	wheel radius	c_W	value for air resistance of the car	M_B	brake momentum	a	coefficient for Nick Moment

Figure 5. Simulation model of a brake application based on [Scherf 2003]



m (kg)	$\ddot{x}_F$ (m)	r (m)	A (m^2)	$\ddot{x}_F$max - $\ddot{x}_F$min (m)
1300	42,44	0,320	2,0	
1600	43,32	0,320	2,0	1,75
1900	44,19	0,320	2,0	
1600	43.25	0,315	2,0	
1600	43,32	0,320	2,0	0,14
1600	43,39	0,325	2,0	
1600	43,40	0,320	1,6	
1600	43,32	0,320	2,0	0,16
1600	43,24	0,320	2,4	

Figure 6. Results of the sensitivity analysis

Here, a different focus should be set (e.g. dynamic stability). This example shows that a sensitivity analysis can raise transparency in the context of decision-making processes and give specific advice with respect to an appropriate link-up to the process model or milestones. For the sake of completeness, however, it should be noted that only a single property was focused on in this example. This is common practice in the context of property validation; however, the overall context of product properties has to be considered: for example, the front area of a car (and a related design change) has certainly more influence on the fuel consumption that is object of another analysis.

5. Summary

The planned holistic approach for the continuous validation of product properties throughout the

development process by the means of simulations makes development processes more efficient. As shown before sensitivity analyses enable to support simulation planning, as it is pointed out to which extent individual parameters are important to achieve required product properties. Consequently, property validation can be controlled in a more targeted way. In addition, more specific statements about the quality of simulation results are made possible. The meaningful application of sensitivity analysis, however, is bound to a link-up to an appropriate process model and an appropriate way of data processing. The objective of this research is to optimize data and information flows in distributed development processes and to execute more goal oriented iteration loops.
Current focus is the processing of development data based on the distinction between characteristics and properties. Initial studies show a network-like linkage, which can be prepared by matrices. However, a more sophisticated categorization of development data seems to be necessary: we need to clarify in which case data have to be treated as characteristics or properties; here, a dependency on both hierarchy level in the product structure as well as focus of property validation is shown. In addition, such data processing is expected to disclose advanced and more detailed ways to design a sustainable evaluation system and to link sensitivity analyses to the FORFLOW process model. In the final phase the practical validation of the overall approach in an industrial context is intended.

References

Han, S.-O.: Varianzbasierte Sensitivitätsanalyse als Beitrag zur Bewertung der Zuverlässigkeit adaptronischer Struktursysteme. Technische Universität Darmstadt, Fachbereich Maschinenbau, Dissertation, 2011

Krehmer, H.; Eckstein, R.; Lauer, W.; Roelofsen, J.; Stöber, C.; Troll, A.; Weber, N.; Zapf, J.: Coping with multidisciplinary product development - a process model approach. In: Proceedings of the 16th International Conference of Engineering Design (ICED 09), 2009, Stanford University, Stanford, CA, USA.

Paetzold, K..; Reitmeier, J.: Approaches for Process Attendant Property Validation of Products, Proceedings of the 1st International Conference on Modelling and Management of Engineering Processes (MMEP), Cambridge - UK, 19.-20. Juli 2010.

Reitmeier, J.; Paetzold, K.: Evaluation of Data Quality in the Context of continuous Product Validation throughout the Development Process, International Conference on Engineering Design (ICED11), 2011

Rüppel, U.; Bletzinger, K.-U.; Lähr, A.: Vernetzt-kooperative Planungsprozesse im Konstruktiven Ingenieurbau. Grundlagen, Methoden, Anwendungen und Perspektiven zur vernetzten Ingenieurkooperation. Berlin; Heidelberg: Springer-Verlag, 2007

Scherf, H.E.: Modellbildung und Simulation dynamischer Systeme, Oldenbourg Verlag, 2003

Schwarz, S.: Sensitivitätsanalyse und Optimierung bei nichtlinearen Strukturverhalten. Universität Stuttgart, Fakultät für Bauingenieur- und Vermessungswesen, Dissertation, 2001

Schwieger, V.: Nicht-lineare Sensitivitätsanalyse gezeigt an Beispielen zu bewegten Objekten. Habilitationsschrift. München: Verlag der Bayerischen Akademie der Wissenschaften in Kommission beim Verlag C .H .Beck, 2005

Saltelli, A.; Chan, K.; Scott, E. M.: Sensitivity Analysis. Chichester; New York; Weinheim; Brisbane; Singapore; Toronto: John Wiley & Sons Verlag, 2000

Saltelli, A.; Ratto, M.; Andres, T.; Campolongo, F.; Cariboni, J.; Gatelli, D.; Saisana, M.; tarantola, S.: Global Sensitivity Analysis. The Primer. Chichester; New York; Weinheim; Brisbane; Singapore; Toronto: John Wiley & Sons Verlag, 2008

Weber, C.: "CPM/PDD - An extended theoretical approach to modeling products and product development processes", in: Proceedings of the 2nd German-Israeli Symposium on advances in methods and systems for development of product and processes. TU Berlin / Fraunhofer-Institut für Produktionsanlagen und Konstruktionstechnik (IPK), 07.-08. Juli 2005, p.159-179, Stuttgart, Fraunhofer-IRB-Verlag, 2005.

Dipl.-Wirtsch.-Ing. Jochen Reitmeier
Research Assistant
Universität der Bundeswehr München, Institute of Technical Product Developement
Werner-Heisenberg-Weg 39, D-85577 Neubiberg, Germany
Telephone: +49-(0)89-6004-2813
Telefax: +49-(0)89-6004-2815
Email: jochen.reitmeier@unibw.de
URL: http://www.unibw.de/lrt3