INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED11
15 - 18 AUGUST 2011, TECHNICAL UNIVERSITY OF DENMARK

EVALUATION OF SOLUTION VARIANTS IN CONCEPTUAL DESIGN BY MEANS OF ADEQUATE SENSITIVITY INDICES

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ABSTRACT
Every engineering product is exposed to a multitude of uncertain influencing factors during the different stages of its life cycle. While much effort is invested to deal with this uncertainty during production and use, it often is not adequately taken into account in product development. Moreover, especially in the early design stages well-know methods of probabilistic uncertainty analysis often cannot be applied adequately. They necessitate an elaborated concept or even a mathematical description of the underlying relationships. In this contribution an approach to assess the influence of different design parameters in a network of physical effects is proposed, based on available methods for sensitivity analysis. The different indices are examined with regard to their applicability during Conceptual Design. Quantitative, but usually highly complex methods are thereby complemented by qualitative ones. In this way, the approach allows to deal with the changing as well as usually low level of information and supports the evaluation of concepts on an abstract level of description.

Keywords: Uncertainty, physical effect, sensitivity, Conceptual Design

1 INTRODUCTION
Each engineering product is exposed to a multitude of uncertain influencing factors during its life cycle. Usually, these factors are connected to production or use processes and lead to deviations from planned product or process properties. The effects, e.g. material variation, geometry deviations or higher loads than those expected, can result in high quality costs or in severe safety-related as well as economic consequences. Accordingly uncertainty can have a strong influence on product reliability. Whereas uncertainty always exists when product properties or process properties are either not determined or deviations of these properties occur [1], the reliability describes the probability that a product does not fail under given functional und environmental conditions during a defined period of time [2]. In practice both, uncertainty and the resulting reliability are of increasing relevance. With regard to the customer expectations of quality and the corresponding quality costs, uncertainty can have a decisive influence on the probability of a market success. Customers in the automotive industry for example, rank product reliability as one of the most important properties on a regular basis. Nevertheless, the number of recalls has increased significantly in the last years due to integration of software and sensors, to high complexity and to an increasing cost pressure [2].
While uncertainty is mainly related to manufacturing or use, it often results from decisions made during product development. Designer misjudgement regarding achievable power, stress, strength, disturbances, etc. may have a significant impact on the occurring uncertainty and thereby on the probability of product failures. Moreover, especially in early design stages the product is merely characterized by customer requirements or abstract product ideas. Decisions based on assumptions can result in a poor concept and an inappropriate solution that causes numerous faults. Because of this particularly strong impact on the later product quality [3, 4, 5, 6], there is a need for approaches that allow an evaluation of uncertainty as early as possible.
At the same time, especially in the early phases of design well-known methods of probabilistic uncertainty or sensitivity analysis cannot be applied adequately [7]. The product is merely characterized by abstract product ideas, so that underlying interdependencies as well as the whole diversity of relevant influencing factors cannot be described mathematically, if at all. An analysis by means of quantitative methods, such as Monte Carlo (MC) simulations or intervals, therefore is often

unfeasible. Even qualitative methods such as the Failure Mode and Effects Analysis (FMEA), the Failure Tree Analysis (FTA) or the Event Tree Analysis (ETA) require extensive product knowledge [7]. Few attempts were made to bridge the gap between qualitative and quantitative approaches. Quantified decision trees permit a reliable decision with regard to economical benefit of information gathering activities [6]. In contrast, the Variation Mode and Effects Analysis (VMEA) derives a rough mathematical model based on qualitative information in an Ishikawa-diagramm. The calculation thereby relies on the method of moment, that is an expansion of a taylor series. [8] However, these approaches only serve as basis for further analysis and do not identify uncertain influences. As a result, the identification of uncertain influences as well as the analysis of their causes or consequences is at least difficult in the early design stages. [3, 4, 7]

In this contribution different methods of sensitivity analysis are examined with respect to their applicability to abstract product models based on physical effects. Based on an uncertainty model, this contribution supports designers in choosing methods and in the evaluation of yet abstract concepts. After a review of physical effects in conceptual design, a developed uncertainty model is presented. Then, based on the following review of sensitivity indices, an approach to identify suitable methods for the evaluation of different influencing factors is presented. Thereby the example of the piezoelectric effect should deepen the understanding. The conclusion shows further research topics and possibilities for an extension of the presented topic.

2 UNCERTAINTY AND ROBUSTNESS IN CHAINS OF PHYSICAL EFFECTS

Within Conceptual Design, a basic solution principle for a given design problem is elaborated. The aim is to generate a set of possible solutions and to choose the most promising one. In a deductive approach the basic solution principle thereby can be gradually elaborated with the help of product models on different levels of abstraction. [9]

Frequently proposed, abstract product models in this stage of product development are physical effects or physical working principles [9, 10, 11]. They represent physical laws, i.e. the relation between two or more physical parameters. In this way different, physically possible solutions for the design problem can be found based on a function structure which summarizes the product functions to perform. Moreover, as there are usually different applicable effects, different product variants can be described without a prefixed product idea or definition of geometric and material properties. [9] Lists or catalogues of physical effects [8] can thereby help to widen the solution space, Figure 1. Other approaches to support this generation of solution variants were proposed in literature [12, 13].

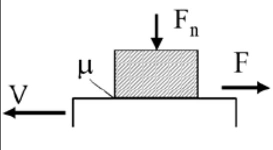
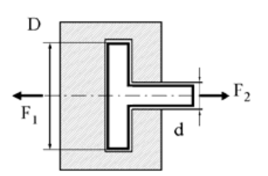
Effect	Graphical description	Mathematical description	Example
Coulomb friction $F_1 = f(F_2)$ 01.01-8		$F = \mu F_n$ μ Reibwert	**Brake, friction closure**
Cohesion Solid bodies $F_1 = f(F_2)$ 01.01-1		$F_1 = F_2$ für $D > d$	**Form closure**

Figure 1 Physical Effects

In practice, the search for physical effects and the following concretization of geometric and material parameters in working principles cannot be divided precisely. Possible solutions are achieved by the variation of effects as well as the variation of properties and designers usually search for effects that include the necessary properties. For the choice of the most promising solution principle an evaluation

on each level of concretization is necessary. In this way, only solutions that match the customer requirements are further elaborated and used for the generation of new variants in the next concretization step. The effort for elaboration and evaluation is reduced. [9]
However, uncertainty and reliability frequently play a minor role in early design stages [2]. Chains of physical effects or working principles thereby offer a possibility to improve the evaluation. Derived from a function structure, they indicate different input factors necessary to perform the product function and by a first mathematical description of their relation to the desired output, quantitative methods of uncertainty and sensitivity analysis could be applied. In this way, potential uncertainty drivers could be identified. In Figure 2 a simplified chain of physical effects for a piezoelectric valve is shown. According to the inverse piezoelectrical effect a voltage generates an electric charge of the piezoelectric material, e.g. a crystal or ceramic, and leads to a mechanical strain in this way. The clamped actuator then reaches a maximal force which depends on the elongation and its material stiffness. In this chain a variation of each input factor could affect the resulting force, used to open the valve. The higher the influence of one input parameter in a chain of physical effects is with regard to the desired output, the higher is the need for an adjustment. Nevertheless, it has to be mentioned that a mathematical evaluation is often difficult. Most methods necessitate more information and can only be used after a further concretization of the product through sketches, models or experiments [6, 9]. For a decision adequate methods are necessary.

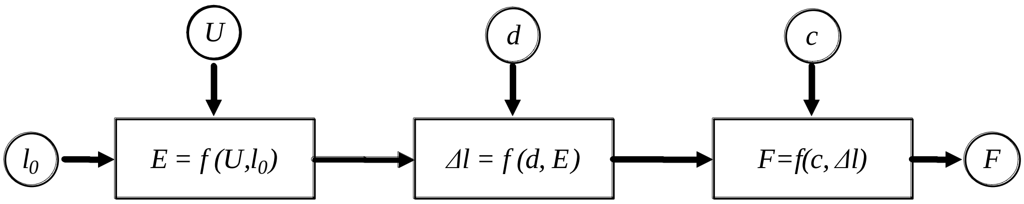


Figure 2. Example of a chain of physical effects

3 UNCERTAINTY MODEL

Methods for an analysis of existing uncertainty usually are applicable according to the knowledge about underlying interdependencies and the probable range of input factors. However, during product development the level of information clearly differs. Described in an abstract way first, the products properties are specified gradually. The usually used distinction between aleatoric and epistemic uncertainty therefore is not sufficient to describe the uncertainty level. For this reason an extended categorization of uncertainty was developed. In this elaborated model, uncertainty is divided into three categories according to the increasing state of knowledge [1], Figure 3.

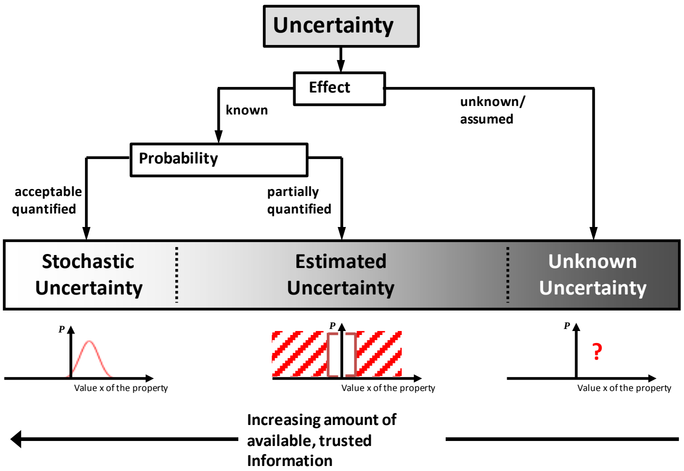


Figure 3. Categories of uncertainty, probability distributions and information [1]

Based on the knowledge about the effect and the probability Unknown Uncertainty, ***Estimated Uncertainty*** and ***Stochastic Uncertainty*** are differentiated. Referring to product development the model indicates that the level of uncertainty can change if it is possible to gather information. While there are several steps between the categories, e.g. between an entirely described probability density function (pdf), a frequency distribution, a single variation parameter and an interval, there are no sharp boundaries. The model is an easy way for a first categorization of uncertainty. The definitions are the following ones [5]:

> ***Unknown Uncertainty*** *describes the situation that both the effects and the resulting deviation of a regarded property of uncertain processes are unknown. Based on this state of knowledge, no decisions can be made on the control of uncertainty. Unknown uncertainty often occurs in the beginning of product development when only little information about a future product is known and the product's properties are not determined yet.*
>
> ***Estimated Uncertainty*** *describes a situation in which the effects of a regarded uncertain property are known. However, the probability distribution of the resulting deviation is only partially known. For example, this is the case when incomplete information about the expected properties of a product is known during the product development or if during manufacturing the product's properties are analyzed randomly only.*
>
> ***Stochastic Uncertainty*** *occurs when the effects and the resulting deviations of a regarded uncertain property are sufficiently (ideally completely) described by a probability distribution. Stochastic uncertainty is present after extensive analysis of properties in terms of quantifiable experiments and measurements.*

4 SENSITIVITY ANALYSIS BASED ON PHYSICAL EFFECTS

To choose appropriate methods for an analysis of chains of physical effects by means of sensitivity analysis, a survey of different methods as well as a classification scheme is necessary. After the presentation of applicable methods, they are therefore divided into categories that are the basis for an adequate application during conceptual design.

4.1 Review of Sensitivity analysis

In a broad range of applications, e.g. engineering systems, capital budgeting, economics, or environmental analyses, the expected output vary due to a potential variation of influencing factors. Based on a change of one single input factor or the simultaneous variation of several factors, the reliability of a product, the future net present value of an investment etc. can change significantly. The term Sensitivity Analysis describes different methods to estimate, to calculate, or to experimentally determine indices describing the impact uncertain influencing factors have on a desired output. The aim is to assess their importance and the relation between measurable variables.

As already mentioned, sensitivity analysis is widely used in practice. Based on experiments, estimations or existing models the influence of potential changes in input variables on complex systems is analyzed in advance. The aim is to understand complex systems, to identify priorities for further analysis, or to give a support for managerial decision. [14, 15] Another focal point of sensitivity analysis is the development of economic or environmental models. Questions thereby are related to the calibration of models, factor prioritization to deepen the analysis, factor fixing to reduce model complexity or the evaluation of interactions between the different input factors. [14]

The easiest way of a sensitivity analysis is screening [14, 15, 16]. Based on available data, either from a simulation or from experiments, the relation between two variables can be evaluated with the help of scatterplots. In such a graphical representation of data the difference between the influence of two variables x_1 and x_2 on the output Y can be seen, Figure 4. However, scatterplots only indicate the influence of one input factor. Also the relation between two input variables is not taken into account. Nevertheless they give a first, visual impression of the underlying relations and are usually the starting point for an analysis. [14, 15]

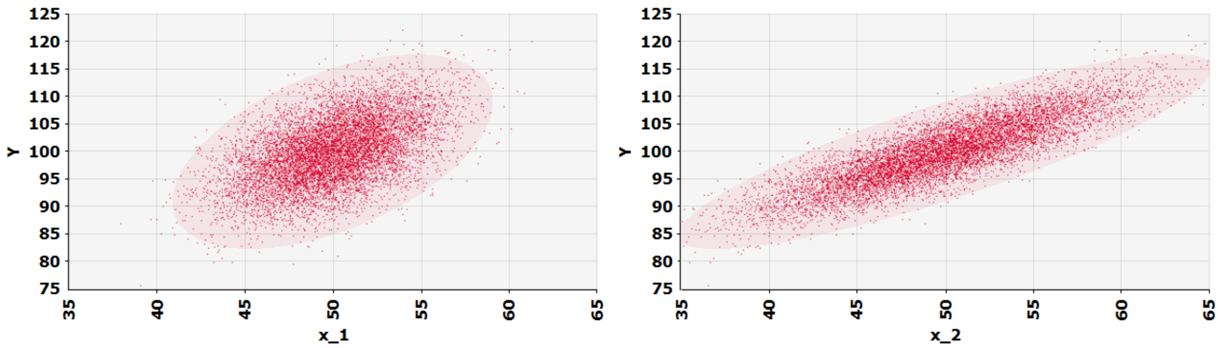


Figure 4. Scatterplots as basis for screening of influences

A possibility to describe the observed relation in one specific measure are correlation coefficients [15, 16]. Correlation coefficients are based either on the nominal value or on the rank and describe the relationship between two variables. With a value between -1 and 1 they indicate if the output variable tends to increase or decrease with a change of input. While correlation coefficients are based on the same information displayed in scatterplots, they also are subject to the same restrictions. The relation of more than two variables is not captured and only a linear relationship can be determined [17]. Directly connected to the information provided by correlation coefficients are sensitivity analysis based on regression techniques. Regression analysis is based on the evaluation of a, in first instance, linear relationship between variables.

$$\hat{y} = b_o + \sum_{i=1}^{X} b_i x_i \tag{1}$$

The regression coefficients $\boldsymbol{b_j}$ indicate the change of output $\boldsymbol{y}$ and therefore can be interpreted as the sensitivity index for $\boldsymbol{x_j}$. The calculation is usually based on the minimization of the sum of least squares [15, 16]. Whereas linear regression also only applies to linear relationships between input variables without any correlation, these aspects can, in contrast to correlation coefficient, be introduced in the analysis. The major challenge is the necessary, a-priori identification of a suitable form [16]. Another extension are sensitivity indices based on normalized regression coefficients that take into account the variation of input and output factors [17].
Especially in the field of capital budgeting or project management Sensitivity analysis is often understood as a procedure to calculate the effect of one single change in the input keeping all others factors fixed. With the description of this varying input parameter by an interval, the possible maximum and minimum value of output as well as the minimum value that justifies an investment can be calculated. The latter is normally referred to as Break-Even Analysis [15, 18]. An extension of this approach is the calculation of different scenarios with simultaneous changes of variables. Even if the possibilities of modern sensitivity indices are nowadays also used to evaluate the business performance or the probability of a project success [17], the calculation of scenarios is common practice.
The most used sensitivity indices for the analysis of an existing mathematical model are based on derivatives [14, 16]. Under the assumption that the underlying relation between the variables in Figure 4 can be expressed mathematically, it is obvious that the derivative of the output $\boldsymbol{Y}$ to the input factors $\boldsymbol{x_1}$ or $\boldsymbol{x_2}$ can be interpreted as the sensitivity to these variables.

$$S_i = \frac{\partial Y}{\partial x_i} \tag{2}$$

Unfortunately the derivative only captures the sensitivity to a certain influencing factor when the model is linear. Based on a calculation at one base point, models of unknown linearity only can be adequately evaluated in a stepwise manner [14, 15]. Another decisive limitation is the neglect of uncertainty, inherent in the input variables. As seen in Figure 4 the input variation can have a significant influence on the variation of ***Y*,** even if the derivative indicates the same importance of both variables. Therefore often a sigma-normalized derivative is proposed [14].

$$S_{x_i}^{\sigma} = \frac{\sigma_{x_i} \partial Y}{\sigma_Y \partial x_i} \tag{3}$$

In comparison to the mentioned methods, variance decomposition based indices represents the portion of the output uncertainty caused by one input parameter. Corresponding methods are based on a High-Dimensional-Model-Representation (HDMR) that decomposes the underlying model. Under the assumption of independent input factors the variance of ***Y*** can be decomposed into the contribution of each input variable. The sensitivity is then defined as the fraction of the overall variance contributed by one input factor. While global indices explain the overall influence of uncertainty in the model input to the uncertain output, they are computationally expensive. [14, 16, 18]

$$V(Y) = \sum_{i=1}^{nX} V_i + \sum_{i=1}^{nX} \sum_{k=i+1}^{nX} V_{ik} + \ldots + V_{12\ldots nX} \tag{4}$$

Figure 5 summarizes the presented approaches of sensitivity analysis. The methods thereby are distinguished according to the information necessary for their application, regarding both the description of input variables as well as the underlying model. Sampling-based, mathematical and estimation-based methods rely in any case on an existing model. In contrast, experimental based methods also can be applied when only a data set for the output-variable is available. Whereas the different experiment-based methods rely on the same data-set, the necessary information-for the application of sampling-based, mathematical or estimation-based methods differs significantly. The initial assessment of sensitivity could be based on subjective, expert knowledge or a comparable product. With an existing model that describes the underlying relationships mathematically, experts could then make a first rough guess about the influence of model parameters. Afterwards the underlying information gradually increases until the whole range of the possible input values is taken into account by means of frequency distributions or pdfs.

Sampling	Mathematical		Estimation	Experiment	
Variance-decomposition	**Derivative-based**	**Nominal-range-based**	**Expert knowledge**	**Statistical methods**	**Graphical methods**
▪ Sobol's index ▪ Neural Networks	▪ Derivatives ▪ Sigma-normalized derivatives	▪ Interval analysis ▪ Break even analysis	Estimation based: ▪ on expert ▪ on existing products ▪ on existing model	▪ Korrelation ▪ Regression ▪ ANOVA ▪ FAST	▪ Screening
▪ established model ▪ probabilistic description of input	▪ established model ▪ (Variation of input)	▪ established model ▪ (Interval description of input)	(established model)	Output data from simulations or experiments	Output data from simulations or experiments

Figure 5. Classification of Sensitivity methods

4.2 Classification of methods

As shown above, there is a wide variety of methods for a sensitivity analysis. The presented methods strongly differ in terms of necessary information, analyzing effort, computing time etc. depending on the used model accuracy and the available uncertainty description of input factors. *Saltelli et al.* [14] distinguish law-driven and data-driven models to show the aim of the effectuated analysis. Whereas law-driven models are based on accepted laws and are normally attributed to a complex system to predict its probable behavior, data-driven models try to describe reality based on empirically collected data. In the latter case the aim is to identify relevant parameters and thereby fields for a more detailed analysis. Furthermore, sensitivity indices are frequently classified in local and global analyzing techniques. Whereas local indices only take into account the influence of an input change at one fixed point, e.g. derivative-based approaches, global methods take into account the whole range of possible values. They are usually based on simulations and require a detailed, stochastic description of uncertain input factors and much more computational effort than local ones [14]. Other classification approaches distinguish mathematical, statistical, and graphical methods [15] or sampling-based and derivative-based methods [16].

For an appropriate analysis of physical effects by means of sensitivity analysis, the existing classifications need to be extended. Especially because the knowledge about the product as well as the knowledge about the range of influencing factors changes significantly during the development process, both must be considered. The developed classification scheme is based on the presented uncertainty model and supports the choice of an appropriate method, Figure 6.

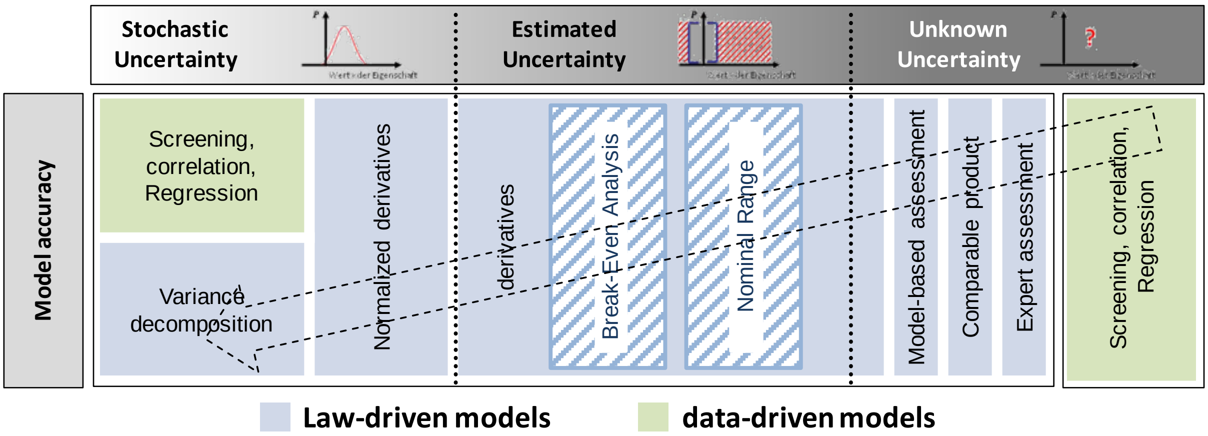


Figure 6. Classification of sensitivity indices to support the assessment of sensitivity during Conceptual Design

In the classification two different aspects for the application of sensitivity indices are distinguished. Vertically, the model accuracy is shown. The more accurate models are, the more favorable the application of complex sensitivity indices is. Horizontally, the uncertainty model indicates the trusted information describing the uncertainty of input factors that also define the applicable methods. The distinction, shown by colours, matches the difference between law- and data-driven models. The only prerequisite for statistical and graphical methods is the availability of the data-set that must not necessarily be the result of experiments. Based on a mathematical model, the probabilistic description of all influencing factors and an effectuated simulation, the corresponding methods also can be applied. A rough procedure for an assessment of sensitivity in conceptual design is indicated by the dashed arrow. Even though the analysis of physical effects is clearly law-driven, usually the uncertainty of input factors is only partially described in the beginning. Moreover, disturbances are not taken into account in chains of physical effects. In the course of the analysis the available information as well as the used model gets more accurate. However, in many cases an application of sophisticated methods is neither necessary nor favorable, because of the effort associated with the analysis. The designer has to decide if a more detailed description of input factors is reasonable. Frequently, the use of graphical representation and the interview of experts could be useful for a first estimation and to reduce the necessary effort for a more detailed description. In comparison a detailed probabilistic

analysis often is not worth the associated effort. Consequently, three questions are identified that need to be answered for the choice of adequate methods and thereby for an assessment of sensitivity in Conceptual Design. In the first place the ***object of analysis*** and the available needs to be defined. The designer then must account for the existing ***uncertainty level***. However, as especially sampling-based methods require a high computational effort, the last question is related to the necessary ***analysis* and *model accuracy***. The classification scheme supports the designer to assess the benefit as well as the effort of the analysis according to the information and the model available.
The assignment of sensitivity indices to different stages of product development complements earlier research. Methods for an uncertainty analysis were analyzed with regard to their applicability and their benefit during product design, [6]. It was found that especially methods for an analysis based on abstract product models are rare. Approaches only take into account a functional model, [4, 5]. The risk of function failure is thereby evaluated based on database with historical failures in existing products and its influence on the rest of the function structure.

5 ASSESSMENT OF SENSITIVITY IN CONCEPTUAL DESIGN

To illustrate the assessment of sensitivity in Conceptual Design the piezoelectric valve, already presented in Figure 2 is used. Compared to a magnetic valve, the opening force is generated by the material strain of a piezoelectric material instead of by magnetic induction.
In the early phase of Conceptual Design the range of different input factors usually cannot be determined. Under the assumption that even the ratio between the variables is not known, the only way for an assessment of their importance with regard to the resulting uncertainty would be qualitative. Either strongly subjective, referring to the opinion of experts, or applicable only in well-known fields based on a comparable products. With the model of physical effects, the first objective evaluation is possible.

$$F = d \cdot U \cdot c \tag{5}$$

Unfortunately, neither in a rough estimation nor in a derivative the importance of voltage ***U***, the piezoelectric constant ***d*** and the elastic compliance ***c*** for the uncertainty of ***F*** can be observed. Nevertheless, because of the limited number of input factors the calculation can easily be extended to an evaluation of nominal ranges. Based on an interval, i.e. supplementary information about the range of input factors, the effect of a roughly estimated input variation in percent can be determined.
Then, based on the prioritization of the variables, the procedure could be extended gradually to a probabilistic analysis, where appropriate. However, in the easy example the calculation of the HDMR is already based on a threefold partial integration. Especially if the product model is based on a long chain of effects, the necessary effort for the calculation is only reasonable when the aim is a high quality product and the examined factor was already prioritized in the previous steps.
It has to be stated that in the proposed approach gradually new information about the range of input factors is necessary for a deeper analysis. The associated effort usually leads also to new information about other influencing factors. The piezoelectrical modulus for example depends on the temperature. If the relation can be described mathematically, the analysis can easily be extended, according to the necessary model accuracy. Otherwise the underlying relationship has to be analyzed with experiments, which leads to another effort of analysis.

7 CONCLUSION

In this contribution an approach for an evaluation of uncertainty during Conceptual Design is proposed. The focus of the analysis thereby is the abstract representation of products in chains of physical effects. The aim is to find robust solutions for a preliminary identified function structure. Using methods for the estimation or calculation of sensitivity indices, the importance of varying influencing factors for the desired output can be determined. The procedure supports designers in choosing methods and in the evaluation of yet abstract concepts. As an extension to existing methods, exclusively based on function structures, the approach offers another possibility to evaluate solution variants in terms of uncertainty during Conceptual Design.

At the same time, the contribution emphasizes the need for detailed information. Sensitivity indices do not cover influences that are not represented in the underlying model. Based on the increasingly detailed description of the range of input factors, new information about other relationship also should be collected. In the example of a piezoelectric valve it was shown that especially when there are a broad range of disturbances, the information offered by physical effects is not sufficient. Even when key drivers for uncertainty could be identified the later product behavior could vary significantly due to these unwanted influences. Catalogues or lists that not only consider the basic effect, but also take account for possible variations of the input factors as well as disturbances, therefore are a promising way for early phases of Robust Design [19]. If information about impact and range of these factors is available, the methods proposed in this contribution also can be a help for their adequate evaluation. The aim is a robust chain of physical effects or working principles that reduces the probability of product failures during production or use.

ACKNOWLEDGEMENT

The authors would like to thank the German Research Foundation (DFG) for founding this project within the Collaborative Research Center 805.

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