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NON-PROBABILISTIC UNCERTAINTY ANALYSIS IN EARLY DESIGN STAGES

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1. Introduction

Decisions in the course of product design are often characterized by a lack of knowledge about future product properties, acting disturbances within the product life cycle, existing interdependencies etc. For the development of robust products these effects must be considered as early as possible. At the same time, well known and common methods of probabilistic uncertainty analysis often cannot be applied adequately in early design stages. They require a mathematical description of the underlying cause and effect relationships as well as a full stochastic description of possible variations. Consequently, adequate strategies for the analysis of uncertainty in product design are necessary.
In this contribution, an approach for the analysis of uncertainty in life cycle processes and opportunities for the application of non-probabilistic analysis methods based on simpflified models are shown. The paper is structured into six sections. Based on a short review on uncertainty in product design in section two, a consistent approach to describe and visualize uncertainty in process chains of the product life cycle is presented. It is the basis for an evaluation of uncertain influences already during early design stages and thus for the evaluation of concepts in terms of robustness. Thereby, section three also includes existing challenges for the application of quantitative analysis methods. In section four a fuzzy analysis is presented. Afterwards, the example of a multilevel process chain for the manufacturing of precision holes illustrates the applicability, the achievable accuracy and respective benefits of a simulation compared to a fuzzy analysis approach. The conclusion shows further research topics and possibilities to derive adequate strategies for the analysis of uncertainty in different stages of the design process by means of non-probabilistic analysis methods.

2. Uncertainty in product design

The aim of product design is the development of products that fulfill the customer expectations in terms of performance, reliability, appearance, etc. From the usually large space of possible solutions, the designer has to find adequate concepts and has to choose an appropriate final design. Within a structured approach, the product is gradually specified based on subsequent design decisions until the complete shape of components, the overall layout, materials etc. are defined.
Product design is characterized by a high degree of uncertainty due to the complex nature of development processes, the increasing requirements, the lack of knowledge about varying influences within the products life cycle, etc. For example, if actual properties of products, processes, or the underlying cause and effect relationships are unknown, design decisions are based on assumptions. The same applies, if there is no time for an extensive analysis of possible scenarios and of the value ranges of influences. Frequently, the consequences are poor concepts and inappropriate solutions that require iteration cycles within the development process or in the worst case cause numerous faults during use [Dentsoras 2008]. In case of a load-carrying mechanical system, designers misjudgments regarding achievable power, stress, strength and disturbances may have a significant impact on the use

process and could cause severe failures of components or the whole product. There are numerous types of uncertainty occurring in different stages of the design process. They have gained growing interest in literature [Kreye et al. 2011]. Available approaches describe possible causes of uncertainty within development [Aughenbaugh and Paredis 2006], [Vandepitte and Moens 2011], propose a holistic classification of uncertainty in development [Kreye et al. 2011], focus on uncertainty that affect the efficiency and the duration of development processes [Chalupnik et al. 2009], or offer a direct support for the choice of analysis methods based on a structured description of the possible value ranges [Engelhardt et al. 2010].

An important aspect of uncertainty in product design is the available level of information for adequate design decisions. Usually, uncertainty of data and uncertainty of the applied model are distinguished. It is obvious that every model is a simplification of real world relationships, particularly product and process models used for concept evaluation [Dentsoras 2008]. An example are physical effects or working principles which usually neglect existing disturbances. In contrast, there are different reasons for uncertain data. On the one hand, uncertainty directly results from sequential design decisions because the future product is still unknown. Especially in early design stages, neither the full range of possible solutions and the corresponding product properties, nor their possible variations due to uncertainty in production processes can be described explicitly. On the other hand, even if external influences, e.g. use conditions for the product or machines, are relatively well known, their variation often cannot be specified exactly due to the finite sample of data, unawareness of extreme events, etc. [Aughenbaugh and Paredis 2006], [Vandepitte and Moens 2011]. Uncertainty of the design process itself is primarily connected to a changing context, like market conditions or the political situation, and to the complexity inherent in the process [Kreye et al. 2011], [Chalupnik et al. 2009]. The complex execution of development processes, e.g. coordination of resources probably within an international network of different locations, could result in a delayed and costly development process.

This contribution focuses on the uncertainty of used models and available data, i.e. the effect in terms of applicability and accuracy of quantitative analysis methods for an evaluation of uncertainty and product robustness in early design stages. A lack of knowledge about technical influences within the product life cycle, the existing cause and effect relationships, as well as the resulting effects may lead to severe deviations of the expected product behavior during use and need to be taken into account.

3. Analysis of uncertainty in process chains

To support the design of robust products and to increase the probability of a market success, the effect of uncertain, technical disturbances must be considered as early as possible. Two different aspects need to be distinguished. Uncertain influences within the product life cycle either lead to a product that does not meet the expectations after production or result in unfavorable process output because of the product performance during use. In any case, uncertainty results from processes and could lead to unexpected process results in terms of product properties or product behavior. [Eifler et al. 2011]. Consequently, a consistent approach for the evaluation and the identification of relevant influencing factors in process chains is essential for the analysis of uncertainty in product design.

First, a simple process model for the structured visualization of life cycle processes and the existing, technical disturbances as well as an uncertainty model for the description of possible variations are presented. Second, the main challenges for a probabilistic analysis during early stages of the design process are summerized.

3.1 Consistent description of uncertainty in process chains

For a consistent description of relevant influences as well as their interdependencies in and between processes a process model specifically adapted to an analysis of uncertainty was elaborated, see Figure 1. Based on a structured description of states and processes, the elaborated model offers a consistent approach for the identification and visualization of relevant influencing factors within a chain of technical processes. Between two states, properties of material, components, or the whole product are changed by use of different appliances, e.g. forming, machining, assembly devices or the product during use processes. Thereby, the initial variation of properties as well as external noise factors, such as temperature, dirt, humidity and manual operations, can affect the resulting variation after the process. Possible external influences are grouped into four categories, disturbances, information, resources, and user. Essential for the analysis of influences in processes is the system boundary that delimits the object of analysis and thereby defines the considered cause and effect relationships [Eifler et al. 2011].

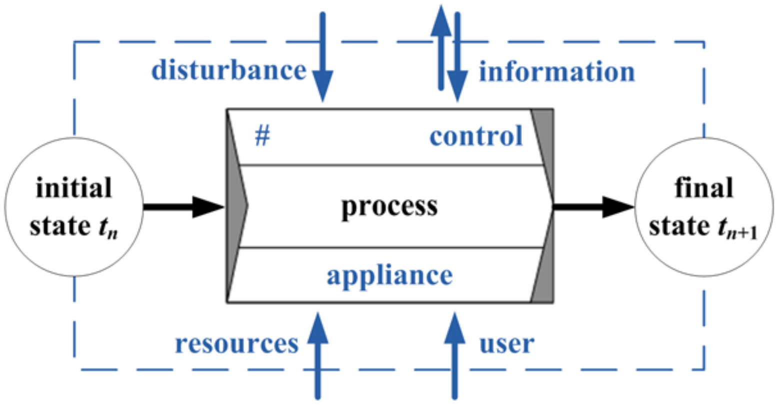

Figure 1. Modelling uncertain influences in process chains [Eifler et al. 2011]

The structured modeling of uncertain processes is complemented by a description of product properties, process properties, or external influences based on an uncertainty model, see Figure 2. According to the available information about the resulting effect as well as the range of possible value, uncertainty is described by three categories, “Unknown uncertainty”, “Estimated Uncertainty”, and “Stochastic Uncertainty”. The level of uncertainty changes with the available amount of trusted information. An essential aspect of the uncertainty model are smooth transitions, i.e. a gradually increasing accuracy of description. An example is a one-sided enclosure of possible values between “Unknown Uncertainty” and “Estimated Uncertainty” [Engelhardt et al. 2010].

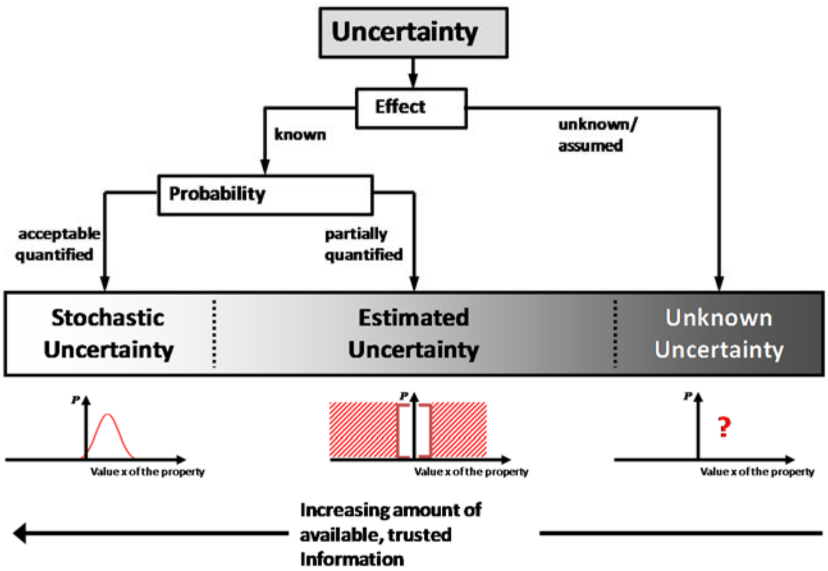

Figure 2. Categories of uncertainty [Engelhardt et al. 2010]

In comparison to concepts such as aleatoric uncertainty (variability) and epistemic uncertainty (imprecision) [Aughenbaugh and Paredis 2006], [Chalupnik et al. 2009], [Vandepitte and Moens 2011], the description mainly refers to uncertainty due to a lack of knowledge. In product design as well as for the description of existing processes, uncertainty is in some extent reducible by a systematic collection of data in an effort to allow a more accurate description of the possible range of values. This particularly holds true in early design stages. Possible variations within the product life-cycle, technical influencing factors and the underlying cause and effect relationships can either not be described accurately or are still completely unknown. Additionally, the indication of the duration of a process under consideration, i.e. the time between initial state t_n and final state t_{n+1} in Figure 1, is essential. A relatively long time span of the process usually leads to a less precise description of the resulting variation of product properties. Thus, a precise evaluation of usually time-dependent influencing factors and their interdependencies becomes more difficult [Eifler et al. 2011].

3.2 Model-based challenges for the application of quantitative analysis methods

A main challenge for the application of quantitative analysis methods is the uncertainty introduced by the available mathematical descriptions. Every model is a simplified representation of the real world interdependencies under consideration. Its inaccuracy results from a general difficulty to model comprehensively all relevant cause and effect relationships as well as from a simplification due to economic reasons in terms of model building, computing time, etc. Therefore, usually not all influencing factors are considered, the physical behavior of components is based on assumptions, different models may fit the observations, etc. The transformation of qualitatively modeled interdependencies into a mathematical description further increases the occurring uncertainty [Kreye et al. 2011].

Especially during concept evaluation, the available, usually highly simplified models do not necessarily fit the object of analysis. Due to a lack of knowledge about future product and processes, existing cause-effect relationships are only captured qualitatively, essential influencing factors are not included, etc. [Dentoras 2008]. For example, the geometry of active surfaces, the systems layout as well as possible internal or external disturbances are not yet considered [Vanderpite and Moens 2011], [Kreye et al. 2011]. Thus, diverse assumptions about correlations or relationships between influences can be found in different approaches [Vanderpite and Moens 2011]. Whereas abstract product or process models by nature do not consider all influences, detailed models are often also uncertain. Especially in complex systems, the number of relevant influences and interdependencies is so large that it is at least difficult to include all of them into a sufficiently efficient model. In combination with unlikely assumptions to facilitate the computation, this leads to an inevitable increase of uncertainty even in the later stages of product design [Vandepite and Moens 2011].

3.3 Parameter-based challenges

In addition to the mentioned uncertain model representation, the second challenge for a quantitative analysis of uncertain influences during concept evaluation is the available description of input parameters, i.e. the existing variation of product properties, disturbances, information etc. Whereas the possible range of future product properties, depending on future design decisions, cannot be described by a single probability density function, the probability of internal and external influences within existing processes is at least hard to assess [Vanderpite, Moens 2011]. Summarized, three aspects need to be distinguished. First and most important, the available data is incomplete due to sequential design decisions, gaps in the data set, finite samples, etc. Second, measurement inaccuracy leads to an inaccurarcy of the collected data. The concluding third aspect is a wide variation of data that cannot be described adequately [Kreye et al. 2011].

4. Fuzzy analysis

Computations in engineering are often done with real numbers or intervals, e.g. to determine safety factors of machine elements. Intervals are used to calculate a possible variation of a quantity by a closed bounded set of real numbers. However, often a more general form than intervals is necessary to describe the imprecision of real data. In this respect, the concept of fuzzy numbers offers an extension to an analysis based on real numbers. A fuzzy number refers to a connected set of possible values. Each value of a fuzzy number gets a weight between 0 and 1 which is called membership function in contrast to intervals where each value inside the interval gets weight 1 [Wiebel et al. 2011], [Wu and Rao 2006]. Figure 3 shows an example of a trapezoidal fuzzy number, see Figure 3a). Intervals in Figure 3b) and crisp numbers in Figure 3c) are special cases of fuzzy numbers. Thus, fuzzy numbers could be used to represent both, objective physical values and a degree of subjective confidence that particular values actually occur.

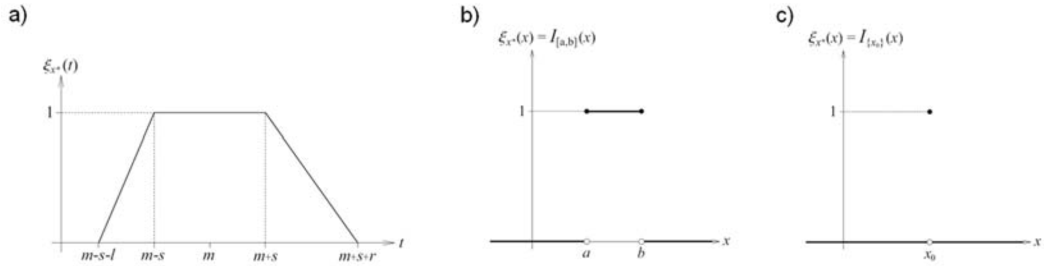

Figure 3. Examples of fuzzy numbers: a) trapezoidal fuzzy number, b) interval, c) real number

Using fuzzy analysis, the resulting variation of a system or a process, i.e. the fuzzy output, can be computed based on an expression of the uncertain input parameters by membership functions. All fuzzy input parameters are discretized using the same sufficient high number of α-levels. With the aid of the deterministic model possible solutions are computed. When the smallest and the largest possible solutions are found the two points of the fuzzy output are known for the actual α-level (see Figure 4).

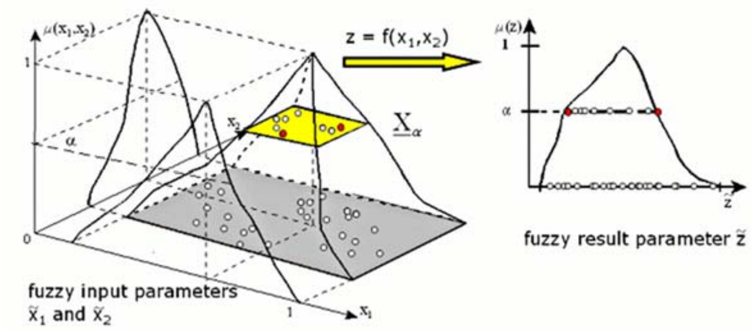

Figure 4. Fuzzy analysis - mapping of fuzzy input parameters on fuzzy output parameters (www.uncertainty-in-engineering.de)

5. Example use case

Depending on the processes of the product life cycle, the variation of product properties as well the product behaviour during use will differ. Therefore, a modification of the chosen product concept or an adaption of the corresponding process chain could be necessary to match the specific customer requirements. Based on the presented approach for the consistent identification and description of uncertainty in process chains, an analysis of relevant influencing factors is necessary. Differences between probabilistic and non-probabilistic methods for the analysis of existing, uncertain influences as well as the respective benefits in early design stages are shown, using the example of the process chain for the production of precision holes. Even for this standard process which is relatively well known, there is a variety of assumptions about the effects of existing influences during the design process. Thus, as early as possible, a way to deal with a wide variety of influences, possible quality measures, substitutional processes, etc. must be found.

First of all, the multilevel process chain and a simplified, mechanical model, used to evaluate the influences of uncertainty on required product properties, are presented. Afterwards, the comparison between a standard Monte Carlo simulation and a fuzzy analysis approach shows limits of a probabilistic analysis as well as possible benefits of non-probabilistic analysis methods.

5.1 Example system

Especially the manufacturing of precision holes has a high importance in production engineering, e.g. the machining of cylinder heads in the automobile production. To reach the required hole quality a combination of a drilling and a reaming process is necessary. With a precedent clamping of the workpiece, a multilevel process chain results. These three subsequent processes, shown in Figure 5, have an important influence on the resulting hole quality, like roundness or radial deviation.

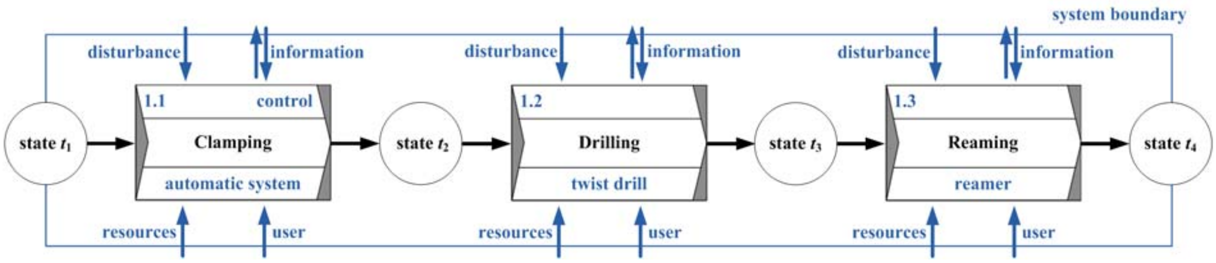

Figure 5. Example of a multilevel process chain for the machining of precision holes

A more detailed analysis of the process chain for precision holes identifies the reaming process as the quality determinant key process at the end of the value chain. Thus, the reaming process is the most critical manufacturing step in terms of costs per piece and reject costs. Furthermore, the reaming process also has to deal with an increased number of uncertainties. Like the drilling process, the reaming process is exposed to uncertainties like material influences, e.g. a strength gradient and blowholes, or tool influences, like grinding errors of the cutting edges which lead to runout errors. Additionally, uncertainty results from the pre-drilled hole. For example, a missalignement error between the axes of the pre-drilled hole and the reaming tool is caused by an insufficient positioning accuracy of the machine tool. Also the properties of the pre-drilled hole have an important influence on the resulting quality of the reamed hole. For example, the skewness of the pre-drilled hole, resulting from a radial deviation of the twist drill, leads to a varying depth of cut and thus to fluctuating process forces at the blades during one revolution of the reaming tool. The consequence of unequal process forces is a directed resulting radial force F_{rad} which deviates the reaming tool.
For an early evaluation of uncertainty and its effect on product properties, a simple mechanical model is used. The possible variation of the required hole quality due to a deviation of the reaming tool (Figure 6a)) is explained by a model of a beam (Figure 6b)) and the estimation of the maximum deviation at the blades (Figure 6c)). The measured deviation of the reamed hole for a pre-drilled hole skewness of 200 µm is exemplarily shown in Figure 6d).

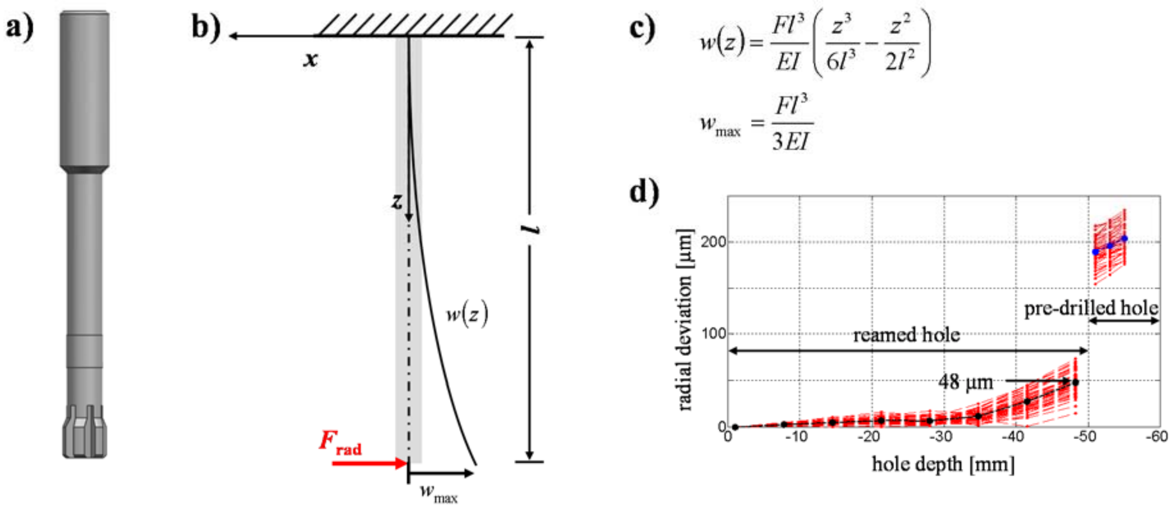

Figure 6. Real tool (a), mechanical model (b), deviation calculation (c) and measured deviation

5.2 Monte Carlo simulation

Sampling based methods of uncertainty analysis are well known and widely used in science as well as in industrial practice [Vanderpite and Moens 2011]. The best-known method is the Monte Carlo simulation. With a random number generator, a large quantity of samples for the input variables is created. A calculation of the model output per sample, results in an approximated density function of the output variable whose accuracy depends on the number of samples.

Based on simplified, quantitive models of products or processes in early design stages, a Monte Carlo Simulation allows only a first rough calculation. For example, the presented, simplified model, equation (1), could be used to analyze the resulting tool deviation of the reaming process, and thus to assess the consequences for the required product quality and the relevance of different influencing factors. However, a large number of assumptions are necessary.

$$w_{\max} = \frac{F_{\text{rad}} l^3}{3EI} \tag{1}$$

The existing variation of the radial force ΔF_{rad} or other influences is assumed first, e.g. as a gaussian distribution around the mean $\mu_{\Delta F} = 0$ N with a standard deviation $\sigma_{\Delta F} = 4$ N, Figure 7a). Afterwards, based on the generation of n=10.000 samples and the corresponding calculations of equation (1), an approximated density function for the resulting deviation $\Delta w_{\max}$ is calculated, Figure 7b).

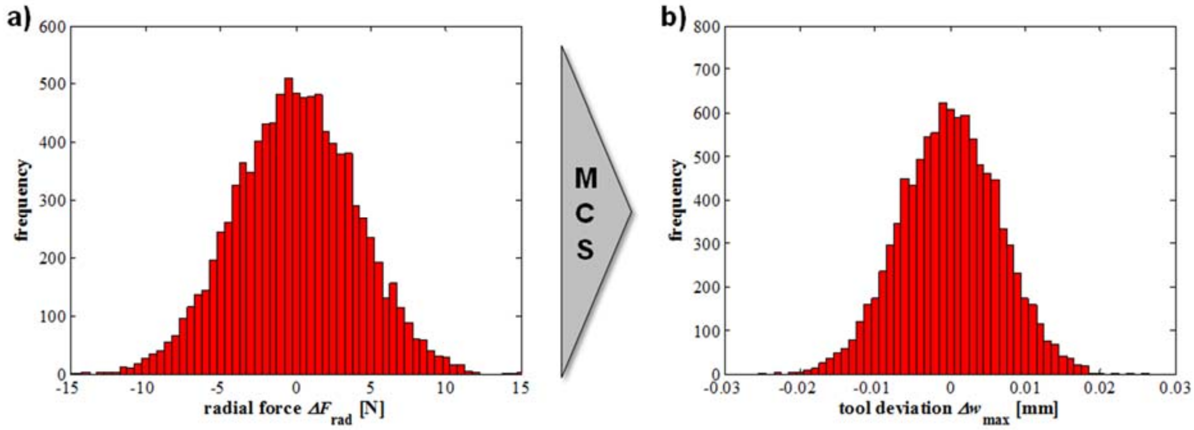

Figure 7. Simulated tool variation $\Delta w_{\max}$

5.3 Non-probabilistic methods

According to the presented approach for an analysis of uncertainty (see section 3.1), the next step is a detailed examination of these relevant influences within the production process, i.e. the identification of reasons that result in varying process parameters and thus product properties. Consequently, influencing factors that result in a radial force F_{rad} leading to a tool deviation *w(z)* need to be identified. As already mentioned, the main uncertainty factors are the skewness of the pre-drilled hole depending on the accuracy of the upstream process as well as misalignment and runout errors, i.e. inaccuracies of tools or machines. They cause a variation of the chip-cross section at each cutting edge and lead to unequal cutting forces at the blades. The consequence is a deviation from an ideal process with a radial force $F_{\text{rad}} = 0$ N. For the example of a reaming tool with six blades, the resulting radial force F_{rad} is calculated by the sum of cutting forces F_{c} and the passiv forces F_{p}, equation (2).

$$F_{\text{rad}} = \sum_{i=1}^{6} F_{\text{p},i} + \sum_{i=1}^{6} F_{\text{c},i} = 0 \tag{2}$$

However, uncertainties or process errors, like a misalignment or the skeweness of a pre-drilled hole, cause a time-dependet variability of the width of cut *b*. As a consequence this leads to a variation of the depth of cut a_{p} and the resulting radial force F_{rad} during the machining process. The examples of the pre-drilled hole skewness, the conditions at the cutting edges, and the machining variables are shown in Figure 8. The variation of the width of cut *b* in Figure 8b) shows the rising difference between the minimum $b_{\min}$ and maximum $b_{\max}$ width of cut over an increasing process time and so a rising depth of drill. Thus, a resulting radial force $F_{\text{rad}} \neq 0$ appears which causes a tool deviation depending on the process time and the corresponding hole depth and tool length *l,* see Figure 6. In contrast, an assumed density function would indicate a possible variation of the entire hole.

Consequently, instead of an assumption about probabilistic distributions, an adequate non-probabilisitc description of influences could offer advantages for a first reliable identification of relevant influences.

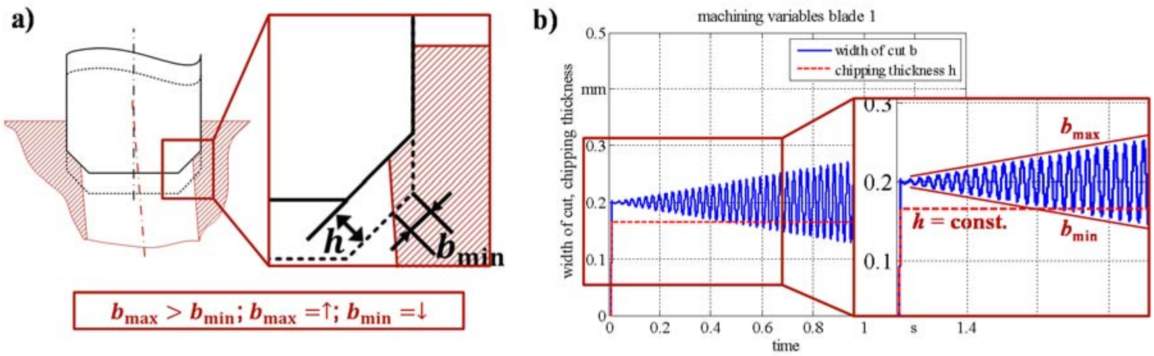

Figure 8. Conditons at the cutting edges a) and simulates width of cut and chipping thickness b)

Another example for an effect that cannot be described accurately by stochastic means is the time-dependent tool wear. Tools are usually changed according to an abort criterion, i.e. the maximum tool wear accepted. A precise description of the nonlinear degeneration of the reamer cutting edges over time is not available. Whereas a description by density functions is at least difficult, the information about abort criteria can directly be transferred into a non-probabilistic description of a possibility function. Thereby, an increasing time span of the analysis leads to a decreasing accuracy of available information.

The example of existing influences within a reaming process of a precision hole shows the necessity of non-probabilistic analysis methods. Consequently, a fuzzy analysis approach is used for the assessment of possible tool deviations instead of a stochastic description. It is based on the simplified mechanical model of the resulting tool deviation, equation (1), which is extended by an elaborated model of acting process forces [Abele et al. 2011]. The cutting force F_c as well as the passive force F_p depend on the depth of cut a_p, the cutting speed v_c, and the feed rate f_z, equation (3). The cutting force model was determined by a multivariate regression function using empirical data.

$$\begin{aligned} F_c(a_p, v_c, f_z) &= a_p^{0{,}909} \cdot v_c^{-0{,}153} \cdot f_z^{0{,}996} \cdot e^{8{,}333} \\ F_p(a_p, v_c, f_z) &= a_p^{0{,}407} \cdot v_c^{-0{,}0724} \cdot f_z^{0{,}541} \cdot e^{6{,}3} \end{aligned} \tag{3}$$

In the fuzzy analysis, uncertainty is described by a possibility function $\pi(\Delta a_p)$ which describes the possibility for a certain value to occur. It either can rely on objective physical values, i.e. data sets, available models, etc., or expresses a degree of subjective confidence based on an expert assessment. Under the assumption that all influences are independent, the individual effects of different influences on the depth of cut are described, see Figure 9a), and an overall possibility function is derived, see Figure 9b). In comparison to the assumed gaussian distribution for a Monte Carlo simulation in Figure 7, specific information about different influencing factors is considered. For example, the possibility function for tool wear indicates an interval due to the available description of the possible range of values by an abort criterion.

The effect of specific events, not regarded within the probability density function, can also be considered. If the skewness of the pre-drilled hole exceeds the chosen depth of cut an air cut appears. This leads to a strong deviation of the reaming tool due to the missing guiding function of the cutting edges in the area of the aircut. Machining test show that the skewness of the pre-drilled hole usually is about 20 to 30 µm. For some cases, also a skewness up to 100 µm or even up to 200 µm is possible. However, higher deviations have a significantly smaller possibility of occurrence than ideal pre-drilled holes. The possible variation is described by the possibility function shown in Figure 9a).

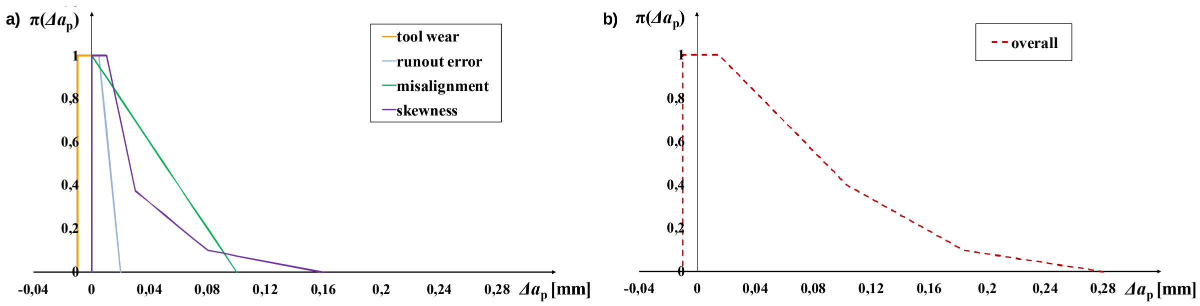

Figure 9. Possibility functions for the variation of the depth of cut Δa_p

The overall function indicates the α-level, i.e. the possibility of occurrence, for a deviation of the depth of cut $\Delta a_p \neq 0$ mm. Based on the overall function, the calculation of the resulting radial force F_{rad} and thus the resulting tool deviation w_{max} is possible based on an α-level discretization of the possibility function $\pi(\Delta a_p)$ and the mathematical description of cause and effect relationships in equations (1), (2)and (3), see Figure 10.

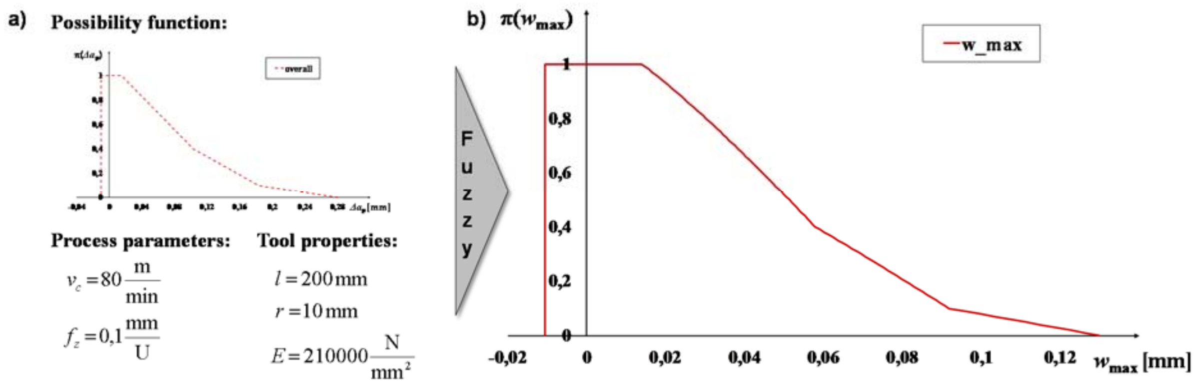

Figure 10. Calculation of the resulting tool deviation w_{max}

6. Conclusion and outlook

The paper presents a consistent approach for the analysis of uncertainty in processes and opportunities for an application of a fuzzy analysis based on simple conceptual models. Thereby, the paper focuses on the identification and the assessment of relevant influencing factors within processes of the product life cycle, e.g. for the evaluation of product concepts or corresponding processes in early stages of product design. Based on a short literature review, these aspects are delimited from other uncertain influences affecting the design process itself. The possibilities for an application of a fuzzy analysis are shown by the example of a multilevel process chain for the manufacturing of precision holes. A consideration of different influencing factors in a reaming process, i.e. misalignement, skewness of a pre-drilled hole, runout errors or tool wear, illustrates the applicability of non-probabilistic analysis methods. Especially, if the existing influences within the process under consideration can hardly be described by stochastic means, due to their complexity, to their multitude, to their time-dependency, etc., an analysis based on possibility function offers considerable benefits. Thereby, the paper further explains the necessity for other applications of fuzzy analysis, for example in the field of tolerance allocation [Wu and Rao 2006].

However, a fuzzy analysis approach does not necessarily meet the requirements of an uncertainty analysis in product design. The example of the reaming process shows that a a common Monte Carlo simulation allows a first rough assessment of relevant influences though it largely depends on made assumptions. Another essential aspect is the usually wide range of influences within use or production processes. Methods that for example allow a first rough assessment of relevant influences even if no mathematical description of interdependencies is available, are necessary.

Therefore, future research will focus on the derivation of adequate strategies for the application of quantitative analysis methods in the course of development. According to different task on subsequent stages of the design process as well as to the available amount of information, adequate methods are necessary. The aim is a considerable decision support for the designer to choose promising concepts, to identify relevant design parameters and to realize an appropriate final design, thus to facilitate the development of robust products and corresponding processes.

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