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An Approach to the Sensitivity Analysis in Variation Simulations considering Form Deviations

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Abstract

In tolerance and variation simulations, sensitivity analyses are used to assess the influences of tolerance specifications and geometrical deviations on the assembly key characteristics and to support product and process developers in deriving more suitable tolerancing decisions and in optimizing manufacturing and assembly processes. However, established methods to the sensitivity analysis in the context of variation simulations disregard important statistical dependencies, which occur when considering form deviations. To overcome these shortcomings, an approach to the density-based sensitivity analysis in variation simulations considering form deviations based on Skin Model Shapes is presented. The method is highlighted and discussed employing a typical tolerance analysis case study.

Keywords: Sensitivity Analysis, Tolerance Analysis, Skin Model Shapes.

1. Introduction

In tolerance and variation simulations, sensitivity analyses are used to assess the influences of tolerance specifications and geometrical deviations on the assembly key characteristics and to support product and process developers in deriving more suitable tolerancing decisions and in optimizing manufacturing and assembly processes. Today, the most commonly used sensitivity and contributor analysis approaches in the context of variation simulations are local sensitivity analysis methods [1], which disregard important statistical dependencies, that may occur when considering fully three-dimensional tolerance zones, tolerances for patterns of features, and form deviations [2]. To overcome these shortcomings, an approach to the density-based sensitivity analysis in variation simulations considering form deviations based on Skin Model Shapes is presented in this contribution and highlighted employing a typical tolerance analysis case study.

The paper is structured as follows. In the following section, related works concerning the sensitivity analysis in the context of tolerance analysis and variation simulations are discussed. Thereafter, the tolerance analysis approach based on Skin Model Shapes is briefly highlighted. After that, the novel density-based sensitivity analysis method for variation simulations is introduced and explained in a tolerance stack case study. Finally, a conclusion and an outlook are given.

Nomenclature

KC	Key Characteristic
SA	Sensitivity Analysis
δ_i	Moment-independent Sensitivity Measure

2. State of the Art and Related Work

Sensitivity analysis, which is sometimes also called contributor analysis in the context of geometrical variations management [1], aims at studying the relationship between the different sources of uncertainty in the model input and uncertainty in the model output [3]. These relationships are commonly quantified by sensitivity indices or measures expressing the relative importance of the model inputs to its output. In the context of geometrical variations management and computer-aided tolerancing, sensitivity analysis is mainly used to estimate the influences of the different tolerances in the tolerancing scheme on the key characteristics in order to improve the tolerance design or to assess the effects of different locating schemes and assembly sequences on the KCs [1,4]. Beside this, it may also "provide insights with respect to the correctness of the analysis (i.e. analysis verification), which input uncertainties dominate the output uncertainties, and how to appropriately invest resources to reduce uncertainty in analysis results" [5].

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In this regard, different sensitivity analysis approaches have been applied in the context of tolerance analysis and variation simulation, such as the arithmetical contributor analysis, the statistical contributor analysis, and the high-low-median sensitivity analysis [1], which are *local* methods, as well as a *global* variance-based sensitivity analysis framework [2] and a sensitivity analysis method based on fuzzy arithmetic [6].

More particular, the arithmetical contributor index $S_{i,a}$ for a tolerance t_i is based on the linearity coefficient ξ_i of the corresponding tolerance, being defined as the partial derivative of the functional relationship with respect to t_i ($\xi_i = \partial f(\boldsymbol{t})/\partial t_i$), the specification limits of t_i, and the arithmetical range of the key characteristic obtained from worst-case evaluations [7,8]. Based on a slightly different definition, the statistical contributor index $S_{i,s}$ also considers the statistical tolerance range of t_i and of the key characteristic, which may be obtained from analytical approaches for the convolution of input distributions or based on the Monte-Carlo simulation [9]. In contrast to that, the high-low-median analysis employs one-at-a-time samplings where each tolerance is varied between a high and a low value while keeping all others at the median [1,3].

These local sensitivity analysis approaches are typically implemented in commercial computer-aided tolerancing packages and have for example been applied to the uncertainty analysis for a crank-slider and a disk cam mechanism in [10] and for the sensitivity analysis of parallel manipulators in [11]. They share the advantage of being computationally efficient and as they partially rely on linearity coefficients, their formulation is close to partial derivatives, which can be "thought of as a mathematical definition of the sensitivity" [3].

However, the information offered by these local sensitivity approaches is limited, since they are "only informative at the base point where they are computed" [3], which is inadequate for non-linear analysis models [3]. Indeed, since many commercial CAT software packages employ linearised tolerance analysis models, this disadvantage is negligible. Nevertheless, since tolerance analysis problems are in general not linear, global sensitivity analysis approaches have been used to study tolerancing problems e. g. in [2], where *variance*-based sensitivity analysis methods [3,12] have been employed. These variance-based methods ground "on a decomposition of the variance in the model output into components each depending on just one input variable, components each depending on two variables and so forth" [13]. Thus, they "provide a factor-based decomposition of the output variance" [14] and overcome the shortcomings of local sensitivity analysis methods. Different approaches for the estimation of variance-based sensitivity analysis indices have been proposed, such as specific sampling methods (e. g. [15]), the (extended) Fourier amplitude sensitivity test ((E)FAST), random balance design, or the Sobol algorithm, which require the model to be evaluated at specific points in the input space [13]. Moreover, a method for the estimation of these indices from given data has been presented in [13].

However, these variance-based methods "implicitly assume that this moment [the variance] is sufficient to describe output variability" [14], which is not the case for many problems. Hence, current approaches to sensitivity analysis employ moment-independent sensitivity indices [16,17], which overcome the limitations of variance-based methods, are also applicable in the presence of correlations among the input parameters [16], and "unveil statistical dependencies that would not be captured using variance-based statistics" [18]. They ground on the estimation of conditional probability densities and are therefore called *density*-based sensitivity indices, with details being described e. g. in [16]. These approaches introduce the moment-independent sensitivity index δ_i, which "represents the normalized expected shift in the distribution of Y [the model output] provoked by X_i [a particular model input]" [16]. These approaches have yet been applied in a generic approach to the sensitivity analysis in geometrical variations management [19].

Beside these methods, some toolboxes for the sensitivity analysis and uncertainty quantification have been proposed recently, such as the GSAT [20] and the SAFE toolbox [21]. Additionally, a review of recent developments in sensitivity analysis can be found in [22].

Thus, it can be seen, that though important advances in the field of sensitivity analysis have been made in recent years, these advances have not yet been transferred to the applications of tolerance analysis and variation simulation. Hence, the aim of this paper is to provide a novel approach to the sensitivity analysis in variation simulations considering form deviations based on Skin Model Shapes, which overcomes the highlighted limitations.

3. Tolerance Analysis based on Skin Model Shapes

The concept of Skin Model Shapes has been developed as a response to the shortcomings of established computer-aided tolerance analysis approaches [23], which imply drawbacks regarding the consideration of form deviations, regarding the combination of three-dimensional tolerance zones, envelope and independency principle, material modifiers, and datum precedence, and consequently regarding the conformance

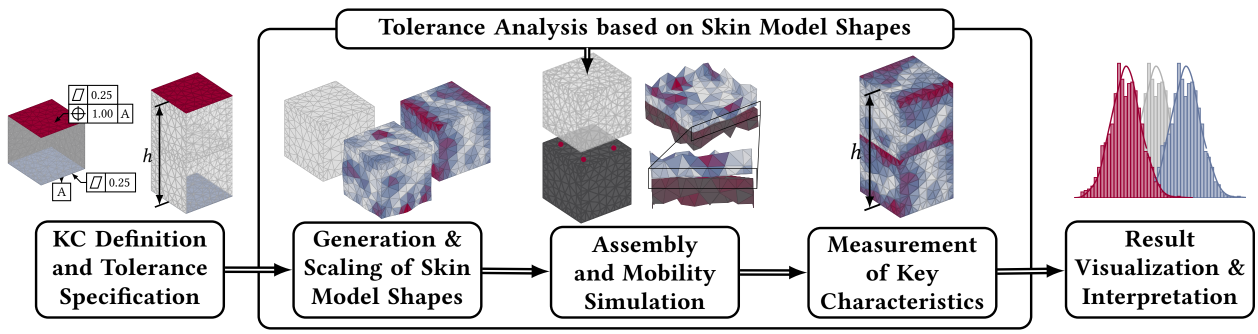

Fig. 1. The Tolerance Analysis Approach based on Skin Model Shapes following [26].

to international standards for the geometrical product specification (see e. g. [24] amongst many). It offers a new paradigm for the modelling of geometrical deviations as well as for the tolerance analysis based on discrete geometry representations, such as point clouds and surface meshes, considering form deviations and in conformance to tolerancing standards [25].

The procedure for the tolerance analysis based on Skin Model Shapes is shown in Fig. 1 [26] and starts with the generation and scaling of Skin Model Shapes based on specified tolerances and KCs [27]. During this stage, the form deviations of each part feature are scaled to the form tolerance specifications [27]. Moreover, rotational and translational feature deviations are introduced, so that the generated Skin Model Shapes also conform to the specified tolerances of orientation and location [27]. After this, the generated and scaled Skin Model Shapes have to be virtually assembled employing various assembly simulation approaches [28]. Furthermore, mobility simulations can be performed to assess the effects of the geometrical part deviations on the mobility behaviour of the mechanism under consideration [29]. Finally, the relevant key characteristics have to measured from the simulated assemblies and the results are to be visualized and interpreted.

4. A novel Approach to the Sensitivity Analysis in Variation Simulations considering Form Deviations

Due to the inherent complexity of three-dimensional tolerance analysis problems, there is a strong need in geometrical variations management to support product and process developers in assessing the sensitivity of product key characteristics to changes in part specifications and geometrical deviations. Consequently, as can be seen from the state of the art, various approaches to the sensitivity analysis for variation simulations exist. However, it lacks a versatile sensitivity analysis approach, that is capable of handling non-linear relationships between the inputs in variations simulations, such as part tolerances or feature deviations, and its outputs, such as distributions of various key characteristics and feature deviations after the assembly.

Thus, in the following, a density-based SA approach for the use in tolerance analyses and variation simulations based on Skin Model Shapes is highlighted. For the sake of comprehensibility, it is illustrated in a graspable tolerance stack-up problem considering tolerances of form, orientation, and location.

4.1. Introduction of the Case Study

The case study is a tolerance stack of three parts, which are assembled on a geometrically perfect planar ground (see datum A in Fig. 2) by three-point moves. The key characteristics of the assembly group are the parallelism (*par*) and the position (*pos*) deviations of the top feature of part 3 with reference to the ground as datum (see Fig. 2). The three parts share the same tolerancing scheme given in Fig. 3, which is to control the key characteristics of the assembly.

For the case study, statistical tolerance analyses (1,000 runs each) have been performed with and without consideration of form deviations assuming independent 6σ Gaussian probability distributions for the tolerance specifications (see Fig. 4 (left)), which is a typical assumption in early tolerancing activities in industrial practice. The resulting distributions of the key characteristics *par* and *pos* can be seen from Fig. 4 (right), where it can be found, that the consideration of form deviations (bottom) leads to distinctly wider distributions of the KCs due to irregular contact points between the part features. Moreover, given the tolerancing scheme of the three parts, it can be expected, that the main contributors to KC *par* are the parallelism tolerances of parts 1, 2, and 3, while the main contributors to the KC *pos* are the position tolerances of parts 1, 2, and 3.

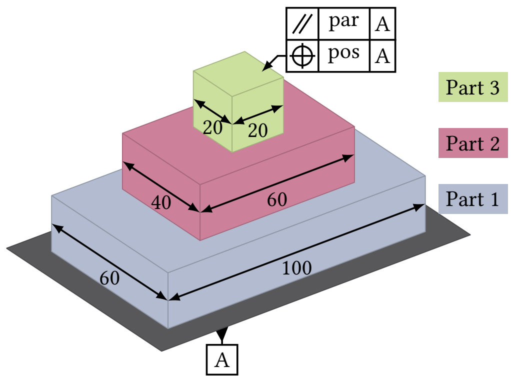

Fig. 2. Assembly Group and Key Characteristics *par* and *pos*.

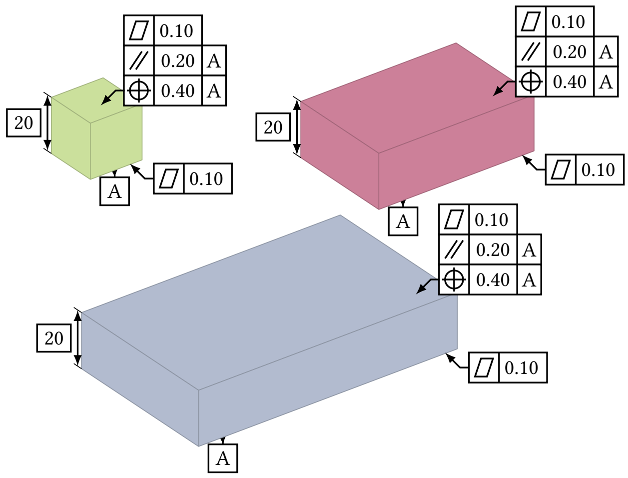

Fig. 3. Part Tolerancing Schemes.

4.2. Overall Sensitivity Analysis Approach

The overall approach to the SA in variation simulations based on Skin Model Shapes is shown in Fig. 5. It employs density-based sensitivity approaches (see [18]), which allow the estimation of global sensitivity measures (i.a. the moment-independent sensitivity index δ) of given input data $\boldsymbol{X}$ to corresponding output vectors $\boldsymbol{Y}$ by an efficient MATLAB code. This straightforward approach allows both assessing the sensitivity of the assembly key characteristics with regard to the tolerance specifications for improved tolerance allocation as well as checking the effects of part feature deviations on the KCs and relevant assembly deviations for eased tolerance specification. It can be used in the presence of form deviations as well as in the case when the form deviations are considered nil.

In the following, this general approach is highlighted for three possible applications in tolerancing with the first aiming at assessing the sensitivity of the KCs w.r.t. the tolerance specifications, the second focusing on determining the sensitivity of

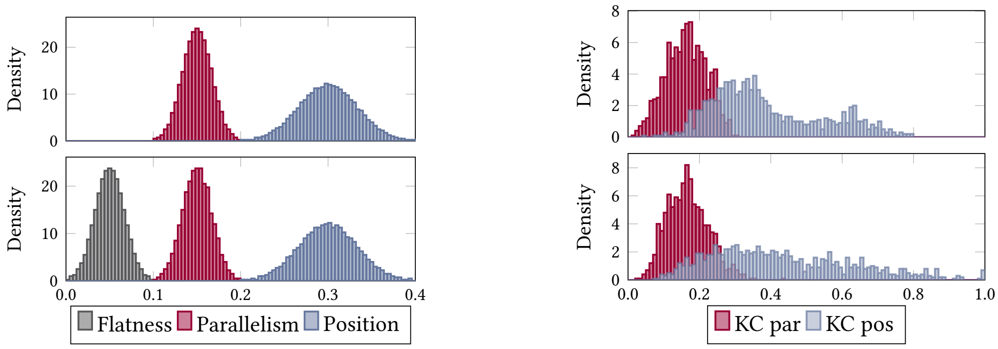

Fig. 4. Inputs and Outputs of the Statistical Tolerance Analyses for the Case Study: (left) Assumed Statistical Distributions for the Tolerance Specifications, (right) Resulting Distributions of the Key Characteristics. Both Figures: (top) without Consideration of Form Deviations, (bottom) with Consideration of Form Deviations.

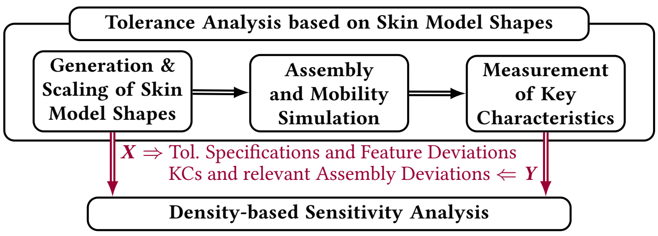

Fig. 5. General Approach to the SA based on Skin Model Shapes.

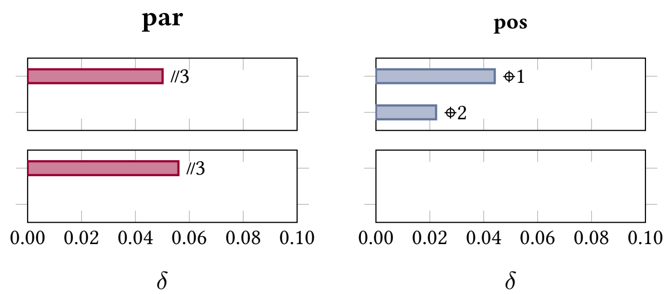

Fig. 6. Results of the Sensitivity Analysis for the Key Characteristics w.r.t. the Tolerance Specifications: (top) without Consideration of Form Deviations, (bottom) with Consideration of Form Deviations.

the KCs w.r.t. part feature deviations, and the third application examining the sensitivity of relevant assembly deviations w.r.t. part feature deviations.

4.3. SA of the KCs w.r.t. the Tolerance Specifications

The first application of the general sensitivity analysis approach is the assessment of the sensitivity of the key characteristics w.r.t. the tolerance specifications of the different parts in the assembly. For this purpose, the density-based sensitivity analysis was performed with the input matrix $\boldsymbol{X}$ comprising the samples from the input distributions of the different tolerance specifications (see Fig. 4 (left)) and the result vector(s) $\boldsymbol{Y}$ being the results of the KCs *par* and *pos* after the tolerance analysis based on Skin Model Shapes (see Fig. 4 (right)). The results of these analyses can be seen from Fig. 6.

It can be found, that the main contributor to the statistical distribution of the KC *par* is the parallelism tolerance of part 3, while the main contributors to the KC *pos* are the position tolerances of part 1 and 2 for the case where the form deviations are not considered. In contrast to that, it can also be seen, that the sensitivity approach is not capable of directly determining the main contributors to the KC *pos* in the case where form deviations are considered (no contributors are identified by the approach). This is because the presence of form deviations obfuscates the contributor situation due to partly overlapping (part-individual) tolerance zones and irregular contact points between the parts.

4.4. SA of the KCs w.r.t. the Feature Deviations

The results of the previous section revealed that the consideration of form deviations hinders the direct sensitivity analysis of the KCs w.r.t. the tolerance specifications. As a response to this, the second application of the sensitivity analysis approach aims at identifying the effects of the feature-individual deviations on the KCs. For this purpose, the feature deviations (being small feature-individual rotations and translations expressed as the SDT [30]), that are introduced during the scaling of the Skin Model Shapes, are collected in the input matrix $\boldsymbol{X}$ to the sensitivity analysis, while the output vector(s) $\boldsymbol{Y}$ captures the results of the KCs *par* and *pos* after the tolerance analysis (with similarity to the first application). These small feature-individual deviations can be considered as "hidden parameters" in the tolerance analysis based on Skin Model Shapes, since they are required to generate Skin Model Shapes, which conform to the given tolerance specifications (the initial model inputs).

The results of the sensitivity analysis for this application are given in Fig. 7, while the legend for the different contributors can be seen from Fig. 8. It can be read as follows: the first symbol, obviously, indicates the tolerance specification, that controls the corresponding feature deviation, followed by the part number with the name of the relevant feature under consideration and its particular deviations in brackets as subscript. For the example given in Fig. 8, the interpretation is as follows: the contributor are the feature rotations (r_y) around the y-axis of feature *top* of part 1, which are controlled by a parallelism tolerance specification. Thus, this systems allows not only to identify the relevant feature deviations but also the corresponding tolerance specifications controlling these deviations.

The results of the sensitivity analysis given in Fig. 7 indicate, that the main contributors to the KC *par* are the rotations around the x-axis of feature *top* of parts 1 and 3 as well as the rotations around the y-axis of feature *top* of part 3 when neglecting form deviations, while the only contributor to *par* is the feature rotation around the y-axis of the top feature of part 3 when considering form deviations. All of these deviations are

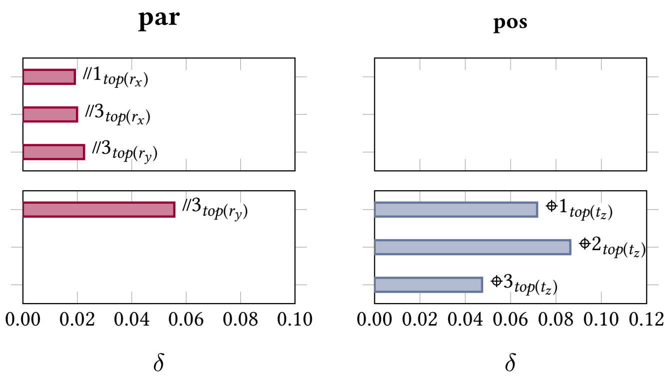

Fig. 7. Results of the Sensitivity Analysis for the Key Characteristics w.r.t. the Feature Deviations: (top) without Consideration of Form Deviations, (bottom) with Consideration of Form Deviations.

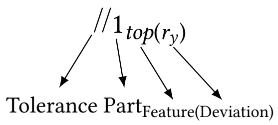

Fig. 8. Legend for the different Contributors.

controlled by the parallelism specifications. In contrast to that, the sensitivity analysis is not capable of identifying a contributor to the KC *pos* when neglecting form deviations, while the translations along the *z*-axis of the top features of parts 1, 2, and 3 are the contributors to the KC *pos* when considering form deviations.

4.5. SA of the Deviations of the Feature of Interest w.r.t. the Feature Deviations prior to Assembly

Based on the results of the previous section, it can be found, that the consideration of the introduced feature deviations in the sensitivity analysis allows for a more detailed assessment of the contributors to the KCs than the mere consideration of the input tolerances in section 4.3. However, it can also be seen, that this application does not lead to fully adequate results, since some contributors, that can be identified by reasoning, are not captured by the sensitivity analysis (both when neglecting and when considering form deviations). Thus, the third application aims not at obtaining the contributors to the KCs but at identifying the contributors to the feature deviations of the top feature of part 3 *after* the assembly based on the feature deviations prior to the assembly. Hence, the input matrix $\boldsymbol{X}$ to the sensitivity analysis comprises the small feature-individual rotations and translations introduced during the scaling of the Skin Model Shapes (similarly to the second approach), while the output vector(s) $\boldsymbol{Y}$ capture the feature deviations (translations along x-, y-, and z- direction as well as rotations around x-, y-, and z-axis) of the top feature of part 3 after the assembly. The results of this application can be seen from Fig. 9, which shows the contributors to the different feature translations (t_x, t_y, t_z) and rotations (r_x, r_y, r_z) of the top feature of part 3 after the assembly when both neglecting (top) and considering (bottom) form deviations. However, for the sake of consistency, only the feature translations along the z-axis (t_z), which refer to the KC *pos*, and the feature rotations around the x- and y-axis (r_x, r_y), which refer to the KC *par*, are discussed in the following.

It can be clearly seen, that the main contributors to t_z are the feature translations along the z-axis of the top feature of parts 1, 2, and 3 with nearly equal contribution both when neglecting and considering form deviations. These feature deviations are controlled by the position tolerances. Moreover, it can be found, that the main contributors to r_x are the feature rotations around the x-axis of the top feature of parts 1, 2, and 3 (increasing contribution), while the main contributors to r_y are the feature rotations around the y-axis of the top feature of parts 2 and 3 (also increasing magnitude). All these feature rotations are controlled by the corresponding parallelism tolerances. More interesting, also the feature rotation around the y-axis of the top feature of part 3 is a contributor to r_x, while the feature rotation of the top feature of part 3 around the x-axis is a contributor to r_y. This can be explained by the fact, that there is a contrary relation between the feature rotations around the x- and y-axis, since both feature rotations are controlled by the same parallelism tolerance (see e.g. [27]). Thus, there is a negative correlation between r_x and the rotation around the y-axis of the top feature of part 3 as well as between r_y and the rotation around the x-axis of part 3's top feature.

4.6. Discussion of the Results

The previous three sections aimed at applying the general sensitivity analysis approach to different applications in toler-

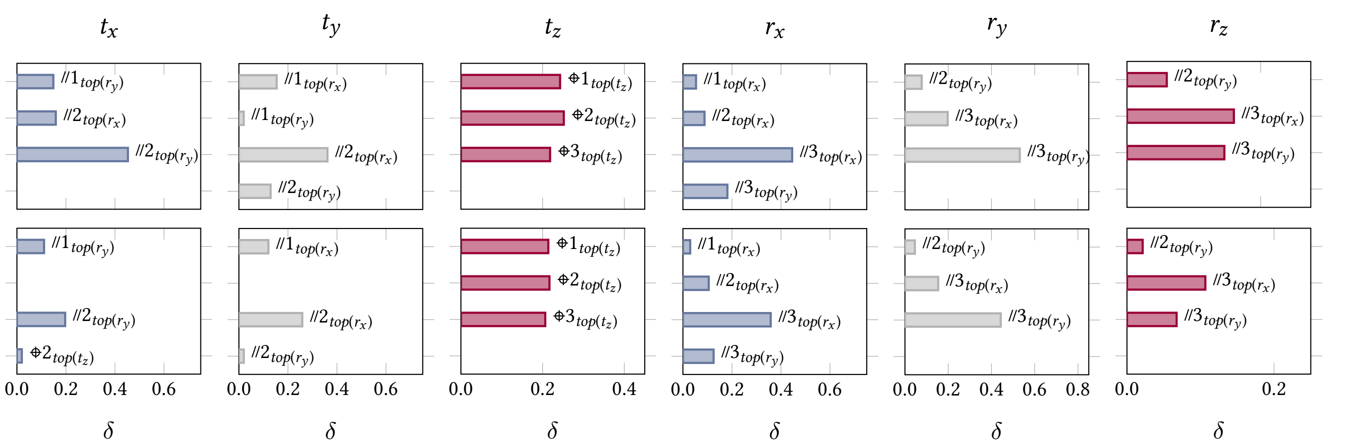

Fig. 9. Results of the Sensitivity Analysis for the Deviations of the Feature of Interest: (top) without Consideration of Form Deviations, (bottom) with Consideration of Form Deviations.

ance analysis and variation simulation based on a comprehensible case study. However, also more complex case studies have been analysed by the authors where similar results have been obtained. In this regard, section 4.3 focused on the SA of the key characteristics w.r.t. the tolerance specifications. However, considering the comparably weak results, it can be found, that the sensitivity analysis for three-dimensional tolerance analysis models merely based on the input and output tolerances is a complex undertaking, even for rather simple case studies and particularly in the presence of form deviations. As a response to this, section 4.4 highlighted the SA of the key characteristics w.r.t. the feature-individual deviations introduced during the scaling of the Skin Model Shapes. Though these results were more plausible, they also fell short of expectations. Consequently, section 4.5 described the SA of the deviations of the feature of interest after the assembly w.r.t. the feature-individual deviations prior to the assembly. The results were quite promising, since all expected contributors were identified and also their corresponding contribution seemed plausible. Thus, the main insight of the presented analyses is, that the sensitivity analysis in three-dimensional variation simulations considering form deviations should be based on the feature-individual deviations prior and after the assembly.

5. Conclusion and Outlook

In computer-aided tolerance analysis and variation simulations, sensitivity analysis methods support product and process designers in assessing the effects of geometrical part deviations, tolerance specifications, and process parameters on product key characteristics. However, most of the existing approaches employ local SA methods, which are not suitable for non-linear problems, while the few approaches to the global sensitivity analysis in variation simulations are merely based on variance-based SA methods, which only focus on the second moment of the output distribution. As a response to these shortcomings, this paper presents a general approach to the density-based sensitivity analysis for variation simulations considering form deviations based on Skin Model Shapes. Based on the obtained results for three different applications, it can be found, that the sensitivity analysis in three-dimensional variation simulations considering form deviations should be based on feature-individual deviations prior and after the assembly.

However, future research issues are the consideration of parametrized form deviations and of different statistical input distributions as well as the application of this SA approach in motion tolerancing to obtain the contributors to variations in the mobility behaviour of systems in motion.

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