A FOLLOW-UP ON THE METHODICAL FRAMEWORK FOR THE IDENTIFICATION, ANALYSIS AND CONSIDERATION OF UNCERTAINTY IN THE CONTEXT OF THE INTEGRATION OF SENSORY FUNCTIONS BY MEANS OF SENSING MACHINE ELEMENTS

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ABSTRACT

When integrating sensing machine elements for in-situ measurements in technical systems, special attention must be paid to uncertainty to ensure the reliability of the provided information. Therefore, a methodical framework for the identification, analysis and consideration of uncertainty was already developed in prior research, which still offers room for improvement regarding the included methods and tools. Therefore, in this contribution, the initially proposed methods and tools are adapted and extended to enhance their efficiency and applicability and to reduce their error proneness in order to increase the acceptance of the framework in practice. First, the identification of uncertainty is improved by means of an extended effect graph for an automated identification of disturbance factor induced data and model uncertainty. Second, the significance of the subsequent evaluation of uncertainty is enhanced by replacing the initially proposed local sensitivity analysis with a global sensitivity analysis. Finally, a flowchart is proposed that supports the identification of applicable and promising strategies for the development of measures to consider critical disturbance factor induced uncertainty.

Keywords: Uncertainty, Robust design, Design methods, sensory function, effect graph

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1 INTRODUCTION AND MOTIVATION

As a result of the progressing digitalization due to Industry 4.0 and current trends like predictive maintenance and condition monitoring, a demand regarding information about process and state variables of technical systems arises (cf. Matt and Rauch, 2020). To satisfy this demand, sensory functions must be integrated into technical systems. Based on the distance between the point of origin of the quantity to be measured and the point of measurement, a distinction can be made between ex-situ measurements - lat. "outside the original location" - and in-situ measurements - lat. "in the original location" (cf. Hausmann *et al.*, 2021). The latter results in a reduction of the transmission path of the quantity to be measured and thus in reduced uncertainty due to the minimization of conversions and transformations. A promising approach to realize in-situ measurements is the use of Sensing Machine Elements (SME), which build upon the primary mechanical functions of conventional machine elements and enhance their functionality in terms of sensory functions (cf. Vorwerk-Handing *et al.*, 2020a). An example for a SME is the sensory utilizable rolling bearing by Schirra *et al.* (2018), which enables the measurement of the load applied to the bearing by its electric capacitance. Since conventional machine elements are part of almost every technical system and are typically located in or close to the process zone, their substitution by SME offers great potential regarding the retrofit of sensory functions into technical systems. However, despite the minimization of the transmission path of the quantity to be measured, the transmission path can still be subject to uncertainty, e.g., due to disturbance factors, which jeopardizes the reliability of the information provided by SME (cf. Hausmann *et al.*, 2021).
In order to identify, analyze and consider this uncertainty when integrating sensory functions into technical systems by means of SME, Welzbacher *et al.* (2022) introduced a methodical framework. However, as already pointed out in Welzbacher *et al.* (2022), the framework still offers room for improvement regarding the included methods and tools. Therefore, in this contribution, various adaptions and extensions of the initially proposed methods and tools are presented and described. The goal is to enhance the efficiency and applicability of the methods and tools and reduce their error-proneness to increase the acceptance of the methodical framework in practice.
The remaining contribution is organized as follows: Section 2 presents the state of the art, in particular of the methodical framework by Welzbacher *et al.* (2022), and the fundamentals that form the basis for later improvement of the framework. In Section 3, the methodical framework is improved in terms of various adaptions and extensions of the included methods and tools utilizing the previously presented fundamentals. The contribution ends in Section 4 with a brief conclusion and an outlook.

2 FUNDAMENTALS AND STATE OF THE ART

In this section, the state of the art and the fundamentals for the subsequent improvement of the methodical framework by Welzbacher *et al.* (2022) are described. First, the term "uncertainty" is defined and different classification approaches are presented. In this context, the term "disturbance factor" is defined and linked to uncertainty. Then, the methodical framework by Welzbacher *et al.* (2022) is outlined. In this context, weaknesses of the initially proposed methods and tools regarding efficiency, applicability and error-proneness are highlighted. Furthermore, an effect graph for an automated identification of sensory utilizable physical effects is presented. Finally, strategies for the consideration of disturbance factors and thus achieving robustness in mechanical systems and processes are described.

2.1 Uncertainty and disturbance factors

Uncertainty is defined, according to ISO-Guide 73:2009, as "[…] the state, even partial, of deficiency of information related to, understanding or knowledge of, an event, its consequence, or likelihood." (International Organization for |Standardization, 2009). In general, uncertainty is characterized by various aspects and can thus be distinguished using different approaches, as shown in Figure 1. In the following, only the classification approach based on the uncertainty's manifestation is described, since it forms the basis for the methodical framework by Welzbacher *et al.* (2022). Regarding information about the remaining approaches, the reader is referred to additional literature, e.g., Walker *et al.* (2003).
The classification of uncertainty according to its manifestation refers to the location in the system, its model, respectively, in which uncertainty occurs. As illustrated in Figure 1, a distinction is made between context uncertainty, data uncertainty, model uncertainty and phenomenological uncertainty.

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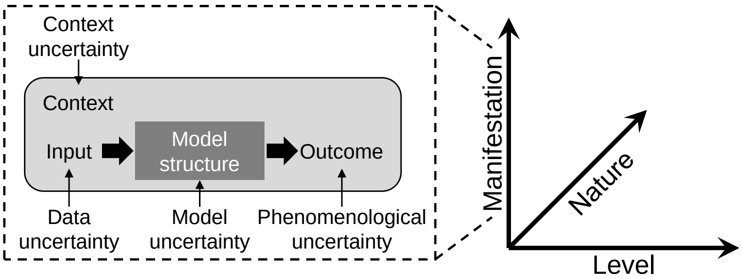

Figure 1: Classification of uncertainty (Welzbacher et al., 2022, based on Kreye et al., 2011 and Walker et al., 2003)

The context of a system describes the circumstances and conditions surrounding the system, i.e., its use context. Consequently, *context uncertainty* describes the potential influence of the system's context on the system, e.g., by disturbance factors. According to Welzbacher *et al.* (2021), disturbance factors are any unwanted and thus unintended inputs of a system that negatively influence its behavior. According to their origin, they can be distinguished into internal - originating within the system boundary, e.g., in form of secondary variables - and external disturbance factors - originating outside the system boundary, in the environment (cf. e.g., Taguchi *et al.*, 2004). *Data uncertainty* is connected to the system's input, which not only includes the actual system input but also design parameters that are included in the system model. Uncertainty located within the system model itself is designated as *model uncertainty*. This manifestation describes consciously as well as unconsciously made modeling inaccuracies, such as simplifications of the relationships between different function variables or regarding the structure of the system. The final manifestation, *phenomenological uncertainty*, occurs when relevant information is unknown at the point of modeling and refers to the unpredictability of the future. According to Kreye *et al.* (2011), it is not possible to describe or model this manifestation completely. (cf. Kreye *et al.*, 2011; Walker *et al.*, 2003; Vorwerk-Handing *et al.*, 2020b)

2.2 Methodical framework for the identification, analysis and consideration of uncertainty

The methodical framework by Welzbacher *et al.* (2022) for the identification, analysis and consideration of uncertainty in the context of the integration of sensory functions by means of SME, shown in Figure 2, is based on prior research by Vorwerk-Handing *et al.* (2020b) and Engelhardt *et al.* (2009).

Figure 2: Structure of the methodical framework by Welzbacher et al. (2022)

In the first step of the framework, occurring uncertainty is identified. Therefore, the use context of the sensory function is first analyzed regarding therein occurring internal and external disturbance factors in order to identify context uncertainty. To ensure a systematic procedure in this analysis, the disturbance factor control list by Welzbacher *et al.* (2021) is utilized. In the control list, standardized disturbance factors are listed according to their respective physical (sub-)domains together with their characterizing flow and effort variables according to multipole-based modeling theory, the product of which is the (sub-)domain specific power. Subsequently, data uncertainty is identified. Therefore, the inputs of the system model are analyzed regarding a temporal variability, e.g., due to wear, associated measuring uncertainty and dependencies on occurring disturbance factors. To identify the latter, which comes about via physical effects, the characterizing flow and effort variables of occurring disturbance factors are considered as inputs and the inputs of the system model as outputs. For a systematic identification of physical effects linking these variables, the multipole-based effect catalog by Vorwerk-Handing (2021) is used. However, since this catalog only exists in an analog form and therefore has to be searched manually, the identification process is laborious and error prone. This is due to the fact that dependencies can be established not only via a single physical effect, but also via several linked physical effects. Moreover, model uncertainty is identified. Therefore, on the one hand, physical effects and principles used in the system model are checked for inadmissible simplifications and assumptions, e.g., by research in literature. On the other hand, not included relationships between function variables of the system model but also between function variables and the characterizing variables of occurring disturbance

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factors are systematically searched for. Therefore, the effect catalog by Vorwerk-Handing (2021) is used again, which makes also this process laborious and error prone. (cf. Welzbacher *et al.*, 2022)
In the second step of the framework, the identified data and model uncertainty is evaluated to determine its criticality for the reliability of the information provided by the sensory function. Therefore, the data and model uncertainty is evaluated using a modified Failure Mode and Effects Analysis (FMEA). In this method, uncertainty is evaluated using three different criteria: severity, deviation and impact. *Severity* addresses the level of uncertainty connected to a function variable or input of the system model. In contrast, *deviation* refers to the maximum relative deviation of the value of a function variable or an input resulting from the considered uncertainty. *Impact* describes the sensitivity of the model in terms of a deviation of its output caused by an uncertainty affected function variable or input. For the evaluation of the impact, a local sensitivity analysis is conducted to determine the uncertainty caused variation of the model output due to a variation of an uncertainty affected input by 0.5% from its originally assumed value. However, the results obtained from this sensitivity analysis have only limited significance, since, on the one hand, not the entire definition range of an uncertainty affected input is considered but just the limits of the definition range. This is especially critical when the system model contains non-linear, non-monotonic relationships. On the other hand, in some cases, the variation of an uncertainty affected function variable or input by 0.5% assumed by default, may be too high or too little, leading to an over- or undervaluation of its impact. (cf. Welzbacher *et al.*, 2022)
Based on the results of the evaluation of the considered data and model uncertainty, a decision is made in the third step, whether an uncertainty is critical for the reliability of the information provided by the sensory function or not. Therefore, rigid threshold values are defined. (cf. Welzbacher *et al.*, 2022)
Finally, measures for the elimination or reduction of critical uncertainty are developed. However, for this final step, no support in form of a method or tool is yet given. (cf. Welzbacher *et al.*, 2022)

2.3 Effect graph

Against the background of an automated identification of sensory utilizable physical effects that can be used to fulfil an application-specific measurement goal, Kraus *et al.* (2022) developed an effect graph based on the multipole-based effect catalog by Vorwerk-Handing (2021). The graph consists of two parts: the graphical user interface and the effect database, cf. Figure 3. A brief description of the effect graph is given in the following; for a detailed description, the reader is referred to Kraus *et al.* (2022).

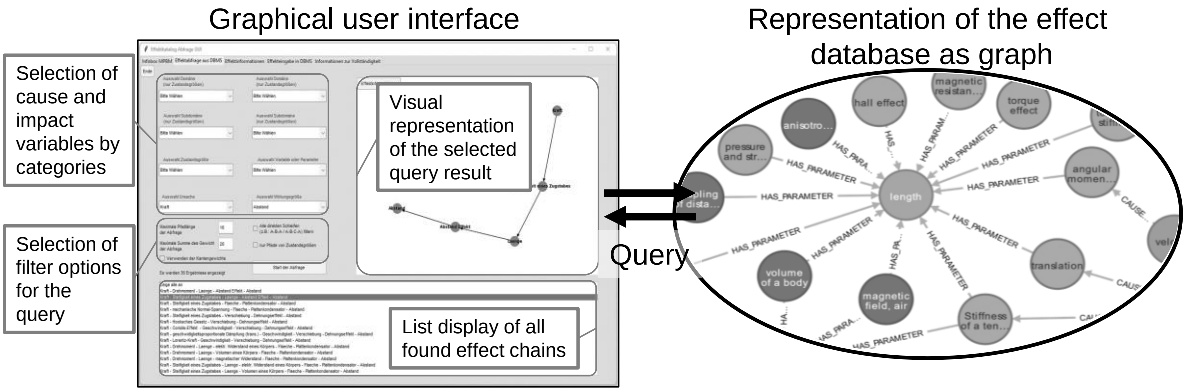

Figure 3: Structure of the effect graph by Kraus et al. (2022)

The effect database contains physical effects, their respective laws as well as their influencing variables and parameters. These are modeled in a graph data structure using nodes and edges. The graph consists of three layers: state variables, design parameters and effects and their multipole-based modeling substructure. For each layer, different types of nodes are used, indicated by the different shades of grey in Figure 3. The nodes are linked via two types of edges, one linking state parameters and the other linking additional relevant parameters to their respective physical effects. The user interface enables the user to send queries to the effect database. Therefore, the user must select the start and end point in terms of state variables. In addition, the user has different options to filter query results, e.g., regarding the maximum length of the effect chain. To obtain sensory utilizable effects and effect chains, nodes linked by edges are visited. The query results are then listed in the lower part of the user interface and can visually be displayed on the right side. In addition, the interface offers the opportunity to retrieve further information about physical effects, e.g., regarding therein made simplifications. (cf. Kraus *et al.*, 2022)

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2.4 Robust design strategies

According to Taguchi *et al.* (2004), a technical system or process is robust "[…] when it has limited or reduced functional variation, even in the presence of noise". To achieve robustness of a mechanical system or process, Mathias *et al.* (2010) introduced three Robust Design strategies, cf. Figure 4. It must be noted that these strategies are no arbitrary independent alternatives but build on each other. Mathias *et al.* (2010) prioritize their strategies - as shown in Figure 4 - from right to left.

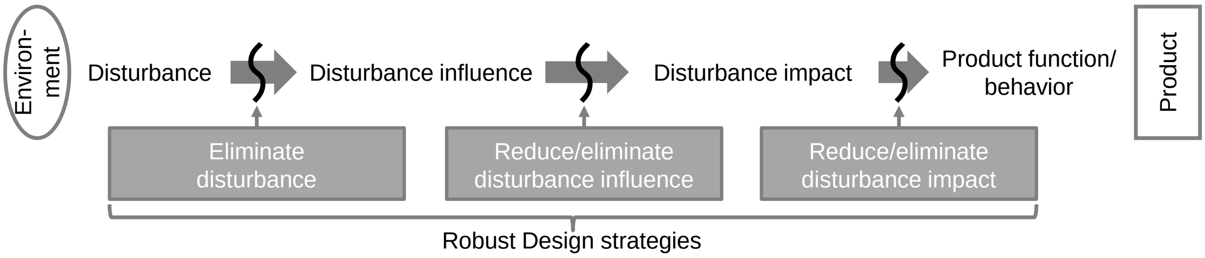

Figure 4: Robust design strategies by Mathias et al. (2010)

- "*Eliminate disturbance*": In this strategy, it is assumed that the appearance of the disturbance in the environment can be eliminated or reduced to such an extent, that it does not cause a relevant influence and impact in the system anymore. Therefore, the environment of the system and thus its use context have to be restricted accordingly. However, since this strategy results in a limitation of the application range of the system, it is oftentimes not suitable. (cf. Mathias et al., 2010)
- "*Reduce/eliminate disturbance influence*": In this strategy, it is assumed that the disturbance occurs, but its influence on the system can be eliminated or reduced. Therefore, measures are required that are typically based on additional components that "interrupt" the influence of the disturbance, e.g., an insulation. (cf. Mathias et al., 2010)
- "*Reduce/eliminate disturbance impact*": In this strategy, it is assumed that the disturbance occurs and has an influence on the system. In order to reduce or eliminate the impact of a disturbance, the system must be planned and designed in a way that the disturbance influence does not have a harmful impact on the system function or behavior. This strategy usually does not require additional components, but corresponding measures must already be taken into account in early design phases to be effectively applicable. (cf. Mathias *et al.*, 2010)

3 IMPROVEMENTS OF THE METHODICAL FRAMEWORK

In this section, the methodical framework by Welzbacher *et al.* (2022) for the identification, analysis and consideration of uncertainty in the context of the integration of sensory functions by means of SME is improved by adapting and extending the included methods and tools. The adaptions and extensions aim to enhance the efficiency and applicability of the methods and tools and reduce their error-proneness. The adaptions and extensions are presented in the order of application of the addressed methods and tools in the framework and aim to increase the acceptance of the framework in practice.

3.1 Identification of uncertainty

As described in Section 2.2, the identification of disturbance factor induced data and model uncertainty in the methodical framework by Welzbacher *et al.* (2022) relies on the analog effect catalog by Vorwerk-Handing (2021), which makes it laborious and prone to error. To overcome this limitation, the effect graph by Kraus *et al.* (2022) is adapted and functionally extended to be applicable for a systematic identification of this type of uncertainty. By allowing for an automated identification, the efficiency of the identification process can be enhanced while simultaneously reducing its error-proneness.
In order for the effect graph to be applicable for this purpose, the disturbance factor control list by Welzbacher *et al.* (2021) is first generalized and then integrated into the effect graph's user interface, as shown in Figure 5. The generalization of the disturbance factor control list is reasonable in this context, since disturbance factors from the same physical (sub-)domain are characterized by the same flow and effort variable and thus result in the same type of energy flow into the system. Hence, disturbance factors from the same (sub-)domain are summarized in the user interface of the effect graph under the respective caused type of energy flow. By doing so, the user does not have to select each occurring disturbance factor from the same physical (sub-)domain, but only the thereby caused type of energy flow.

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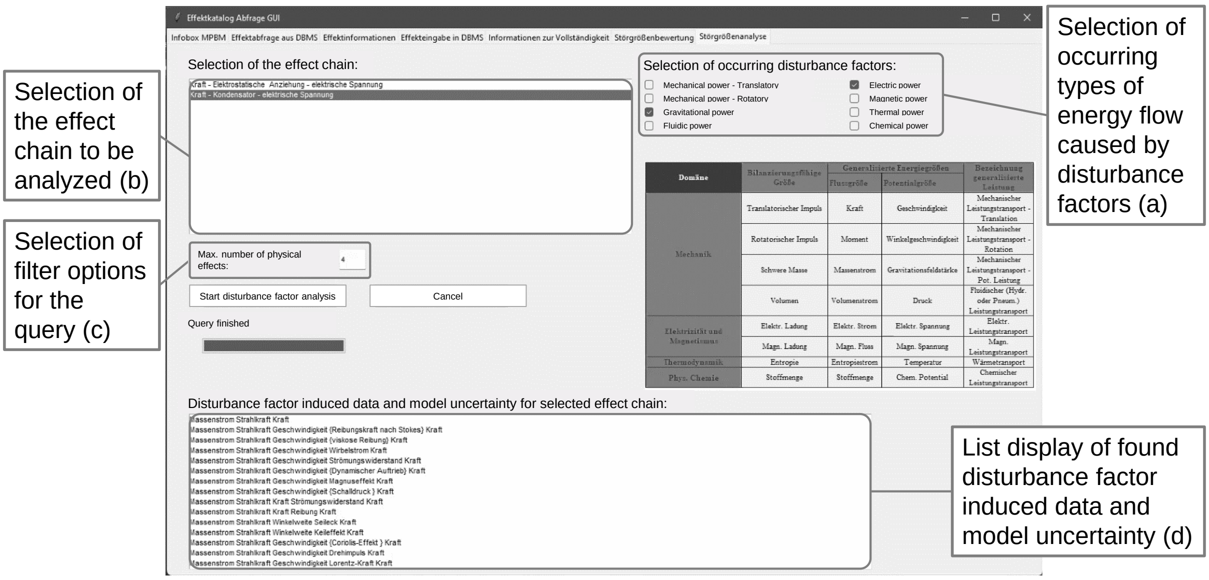

Figure 5: Extended graphical user interface of the effect graph by Kraus et al. (2022)

To identify disturbance factor induced data and model uncertainty, the user must first select the types of energy flows caused by occurring disturbance factors (a) and the effect chain that describes the sensory function to be analyzed (b) in the user interface of the effect graph. The user then has the option to apply a filter (c) regarding the maximum permissible length of effect chains to be found that link the disturbance factor characterizing variables and the function variables as well as inputs of the sensory function. When starting a query, the effect graph considers the characterizing variables of the selected types of energy flow as start points and the function variables and inputs included in the system model as end points. By doing so, dependencies between these variables by physical effects, effect chains, respectively, and thus disturbance factor induced data and model uncertainty can be identified in an automated manner. The query results are displayed as a list in the lower part of the user interface (d).
However, the user still has to check the results regarding their actual occurrence. This is reasonable since many physical effects have certain prerequisites for their occurrence. This can be illustrated using the physical effect "Lorentz force" as an example: an electric charge Q that travels with the velocity $\vec{v}$ experiences the Lorentz force $\vec{F_L}$ if it moves perpendicular through a magnetic field with the strength $\vec{B}$. However, if there is no magnetic field or the electric charge moves solely in the direction of the magnetic field, this effect does not occur. Hence, if a single physical effect included in the effect chain of a query result does not occur, this result - but also other results including the same effect - can be discarded.

3.2 Evaluation of uncertainty

To increase the significance of the results in the evaluation of an uncertainty's impact, the local sensitivity analysis proposed by Welzbacher *et al.* (2022) is substituted by a global sensitivity analysis. This allows for a consideration of the entire definition range of an uncertainty affected input or function variable instead of just its local deviation. In addition, the variation of an uncertainty affected function variable or input by 0.5% assumed by default is replaced by the maximum relative deviation determined in the context of the evaluation of uncertainty's deviation. (cf. Homma and Saltelli, 1996)
Since there are various methods for global sensitivity analysis, a list of fixed and desired requirements is defined to identify the most suitable for the intended purpose. Fixed requirements are, e.g., a minimized influence of subjective assumptions on the results and that the method must be model-independent to be applicable to non-linear, non-monotonic models (cf. Saltelli, 2002). Desired requirements are, e.g., that the method requires only low computational cost.
Based on these requirements, methods for global sensitivity analysis are analyzed. Global sensitivity analyses can be divided into moment-independent, non-parametric and variance-based analyses. Moment-independent analyses require high computational cost and often rely on probability densities, the determination of which typically requires subjective assumptions. In contrast, non-parametric analyses are independent of the probability distribution of the used data, however, they are not model-independent. Since variance-based sensitivity analyses meet all defined requirements, they are chosen. Regarding the techniques for these analyses, the Sobol indices, the total-order sensitivity indices

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and the Fourier amplitude sensitivity test have proven to be inadequate, as there is yet no possibility to consider cumulative effects of uncertainty affected inputs in these methods (cf. Homma and Saltelli, 1996). Hence, the Monte Carlo method was chosen. To avoid an accumulation of randomly chosen numbers, quasi-random numbers are used. (cf. Borgonovo, 2007; Pereira and Broed, 2006)
To demonstrate the higher significance of the results from the Monte Carlo method compared to the ones from the local sensitivity analysis in the context of the evaluation of an uncertainty's impact, the Monte Carlo method is applied to the calculation model for electric bearing impedance from Welzbacher *et al.* (2022). For a detailed description of the calculation model and the therewith associated uncertainty, the reader is referred to Welzbacher *et al.* (2022). For the implementation of the definition range of each uncertainty affected input, the respective maximum and minimum deviation determined in the context of the evaluation of uncertainty's deviation is used. Each input is varied separately within the interval limits. Therefore, the Sobol sequence is applied, in which values are selected in such a way that they are distributed as evenly as possible over the interval (cf. Niederreiter, 1988). Since the interval limits are not necessarily included as quasi-random values when using the Sobol sequence, the minimum and maximum values of each input are included in the sensitivity analysis. Identical to the local sensitivity analysis from Welzbacher *et al.* (2022), the result of the analysis is the relative deviation of the model output - the electrical capacitance and resistance - due to a varied input from its value originally assumed in the model. Since the position of the rolling elements within the load zone has a substantial influence on the determined sensitivities, different rolling element positions are considered within the analysis. However, to simplify matters for this contribution, only the case in which a rolling element is in the middle of the load zone is considered. Figure 6 shows the results of the global sensitivity analysis compared to those of the local sensitivity analysis for two exemplary inputs: the nominal diameter of the shaft d and the ratio of the inner groove radius and the ball diameter f_i.

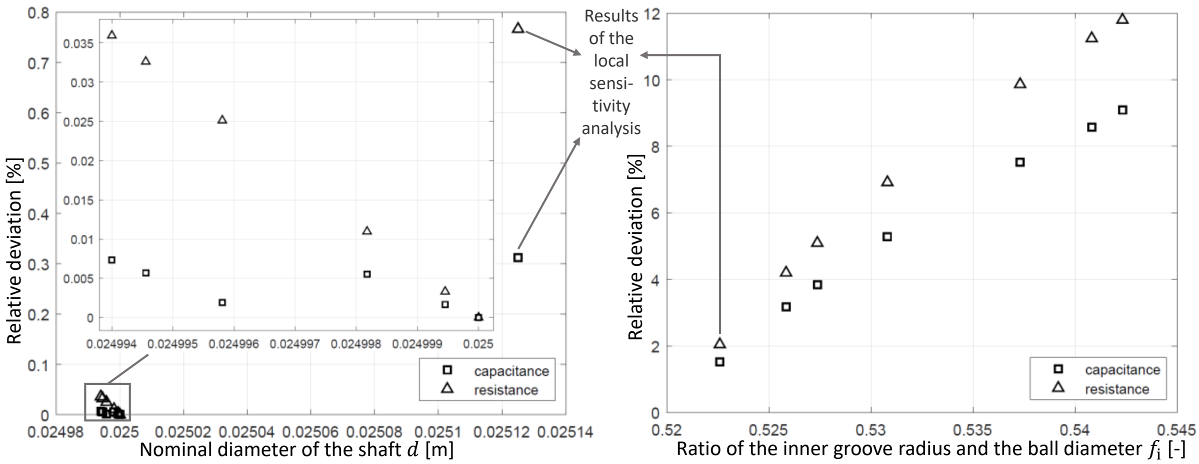

Figure 6: Results of local and global sensitivity analysis for the nominal diameter of the shaft d and the ratio of the inner groove radius and the ball diameter f_i as exemplary inputs

Comparing the results from the two analyses for the nominal diameter of the shaft d, the relative deviations obtained from the local sensitivity analysis indicate a high criticality. However, considering the results of the Monte Carlo method, the deviations of the model output are much smaller than indicated by the local sensitivity analysis. This is due to the smaller disturbance factor induced variation of this input, which is significantly smaller than the 0.5% assumed in the local sensitivity analysis. Hence, the uncertainty is less critical than indicated by the local sensitivity analysis. The opposite can be observed for the ratio of the inner groove radius and the ball diameter f_i. Whilst the results of the local sensitivity analysis imply a low criticality, the results of the global sensitivity analysis indicate the opposite due to a higher uncertainty of this input than anticipated in the local sensitivity analysis.
As demonstrated in the example, the impact of an uncertainty can be evaluated with a higher reliability using the Monte Carlo method than with the local sensitivity analysis. The same applies for the analysis of the cumulative uncertainty of all inputs.

3.3 Development of measures to eliminate or reduce critical uncertainty

As described in Section 2.2, there is no method or tool yet that supports the development of measures to eliminate or reduce critical uncertainty. In this context, especially the elimination or reduction of

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disturbance factor induced data and model uncertainty is challenging. The reasons for that are that, first, it is generally unclear how the Robust Design strategies by Mathias *et al.* (2010) can effectively be transferred to sensory functions to eliminate or reduce critical uncertainty. Second, it is unclear how applicable strategies for a specific application case can be identified. Finally, it is unclear which of the applicable strategies are the most promising and should be prioritized.

To overcome the first reason, the Robust Design strategies by Mathias *et al.* (2010) are taken up, transferred to sensory functions and refined. The refined strategies are explained in the following:

- *Eliminate/reduce disturbance factor*: Depending on the origin of the uncertainty causing disturbance factor - internally or externally, cf. Section 2.1 - two different options for its elimination or reduction exist. Regarding external disturbance factor, it may be possible to eliminate or reduce the disturbance factor by defining and thus restricting the environment [1]. However, this may result in a limitation of the application range of the sensory function (cf. Mathias *et al.*, 2010). In contrast, in case of an internal disturbance factors, it may be possible to eliminate or significantly reduce the disturbance factor itself if the hosting subsystem can be modified [2].
- *Eliminate/reduce disturbance factor influence*: In case of an internal disturbance factor, the emission of the disturbance factor influence may be preventable [3]. This can be done, e.g., by encapsulating the hosting subsystem. However, this option requires the hosting subsystem to be constructively modifiable. Regardless of the origin of a disturbance factor, an additional option exists: the prevention of the immission of the disturbance factor influence, e.g., by shielding the sensory function [4]. Both options typically require additional components.
- *Eliminate/reduce disturbance factor impact*: There are different options to eliminate or reduce the impact of a disturbance factor. Depending on the prevailing level of information regarding the relationship between disturbance factor and caused uncertainty as well as the temporal variability of the disturbance factor, an extension of the model of the sensory function in connection with the integration of additional sensors [5] or a calibration of the sensory function [6] may be possible. In addition, as explained in Section 3.1, many physical effects have prerequisites for their occurrence. Thus, another option is to check if the occurrence of the disturbance factor induced uncertainty can be prevented by modifying the sensory function in such a way that a prerequisite for its occurrence is not fulfilled anymore [7].

Figure 7 illustrates the exemplary application of the refined Robust Design strategies 2, 4 and 5 to a disk pack coupling with an integrated temperature-sensitive sensor bolt for axial shaft offset measurement.

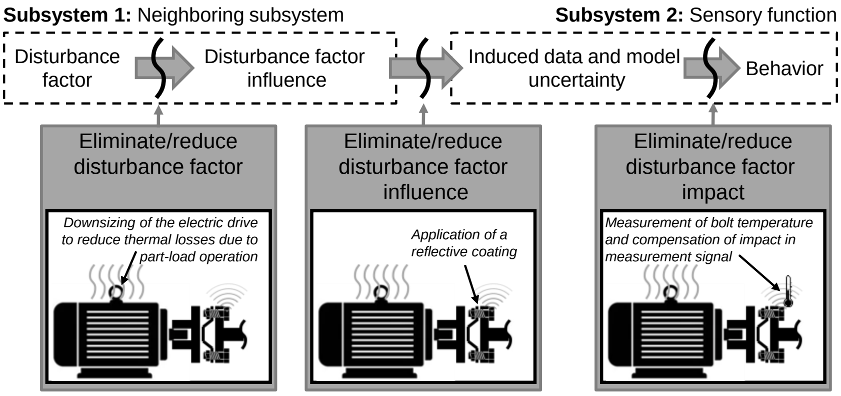

Figure 7: Exemplary application of the refined Robust Design strategies

To address the second reason, a flowchart is proposed, shown in Figure 8, to identify applicable refined Robust Design strategies for the elimination or reduction of critical disturbance factor induced uncertainty in a specific application case. In this flowchart, prerequisites for the applicability and suitability of each refined Robust Design strategy are checked for by means of user questions. To answer the questions, information from preceding steps of the methodical framework is used.

Since there is typically no single cause-effect-relationship between critical uncertainties and causing disturbance factors but multiple uncertainties can be linked to a single disturbance factor and vice versa, the prioritization by Mathias *et al.* (2010) cannot be directly transferred to the refined Robust Design strategies for sensory functions. Instead, to address the third reason, two opposite approaches for prioritization are combined in the flowchart in Figure 8, which are based on a consideration of the number of relationships between disturbance factors and caused critical uncertainties.

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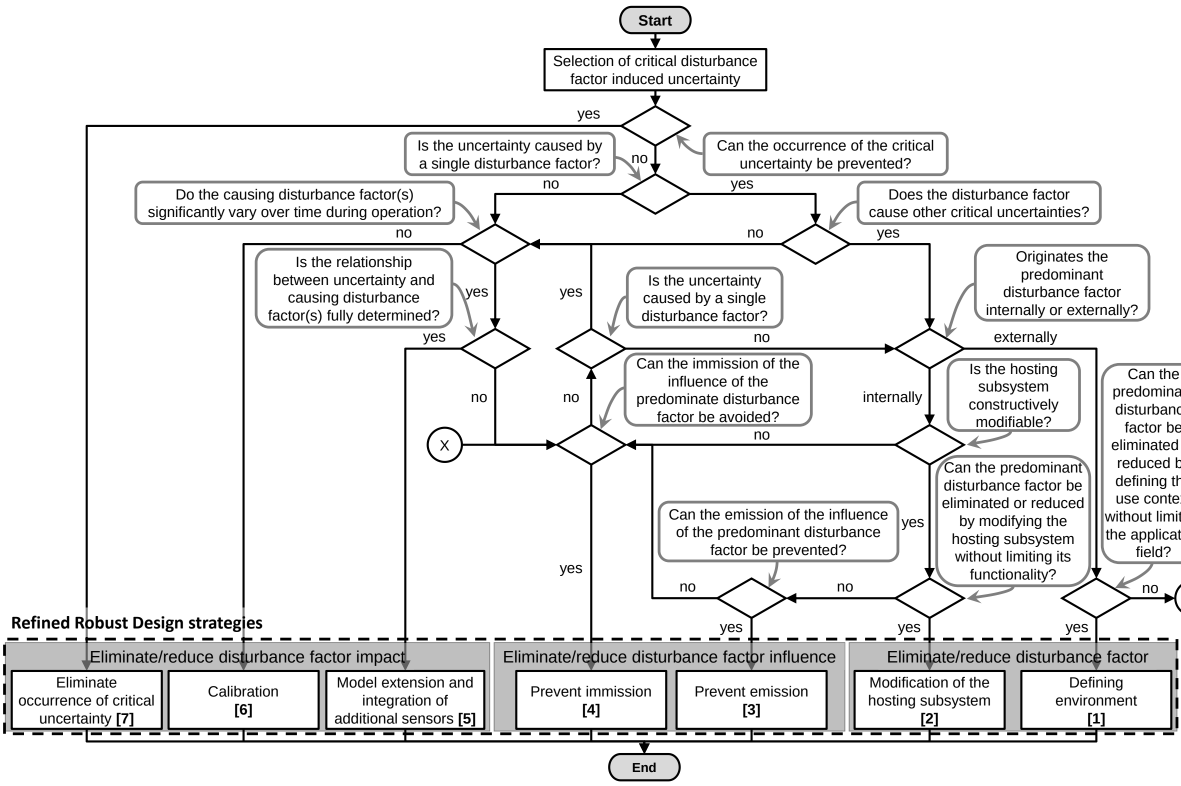

Figure 8: Flowchart for the identification of applicable refined Robust Design strategies

The first approach addresses disturbance factors that cause multiple critical uncertainties. Therefore, it is reasonable to focus on the causing disturbance factor in the first place, since its elimination or reduction has a direct impact on all caused critical uncertainties. Even if it is not possible to achieve an elimination, a reduction may be sufficient to significantly reduce the criticality of the caused uncertainties. The second approach addresses uncertainties that are caused by multiple disturbance factors. In this case, it is reasonable to first focus on the elimination or reduction of the critical uncertainty, since addressing all causing disturbance factors may result in a multitude of measures.

4 CONCLUSION AND OUTLOOK

In this contribution, the methodical framework by Welzbacher *et al.* (2022) for the identification, analysis and consideration of uncertainty in the context of the integration of sensory functions by means of SME was improved by adapting and extending the included methods and tools. The goal was to enhance the efficiency and applicability of the methods and tools and reduce their error-proneness in order to increase the acceptance of the methodical framework in practice.

In the framework by Welzbacher *et al.* (2022), the identification of disturbance factor induced data and model uncertainty relied on the analog effect catalog by Vorwerk-Handing (2021). To overcome the therefrom resulting limitations, the effect graph by Kraus *et al.* (2022) was adapted and functionally extended to be applicable for the intended purpose. Therefore, the user interface of the effect graph was extended by a generalized version of the disturbance factor control list by Welzbacher *et al.* (2021). Based on the user selected types of energy flow, dependencies in form of physical effects between occurring disturbance factors and function variables or inputs of the model can be identified in an automated manner. However, the user still has to revise the query results, since not all found effects may actually occur and result data and model uncertainty. To facilitate this process, a filter is planned that automatically discards query results including a physical effect that was already discarded by the user.

Furthermore, the initially proposed local sensitivity analysis in the context of the evaluation of an uncertainty's impact was replaced by a global sensitivity analysis, Monte Carlo method, respectively. By doing so, it is possible to analyze the entire definition range of an uncertainty affected function variable or input and not only its local deviation. The increased significance of the results of this method compared to the ones of the local sensitivity analysis was demonstrated by exemplary applying both to the calculation model for electric bearing impedance from Welzbacher *et al.* (2022). Further research is

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planned regarding the development of an interface that allows to export the uncertainty including model from the effect graph and import it into MATLAB, where the Monte Carlo method is performed.
Finally, a flowchart was proposed that supports the identification of applicable and promising strategies for the development of measures to eliminate or reduce critical uncertainty for a specific application case. Therefore, the Robust Design strategies by Mathias *et al.* (2010) were transferred to sensory functions, refined in order to be fully applicable and prioritized based on the number of relationships between disturbance factors and caused uncertainty. In the future, the introduction of a KPI is planned that indicates which strategy should be pursued first to minimize the total number of required measures.

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