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Uncertainty Analysis of a Calculation Model for Electric Bearing Impedance

P. Welzbacher ✉, S. Puchtler, A. Geipl and E. Kirchner

Technical University of Darmstadt, Germany

✉ peter.welzbacher@tu-darmstadt.de

Abstract

The integration of Sensing Machine Elements (SME) is a promising approach to obtain reliable data about relevant process and state variables of technical systems. However, the quality and reliability of the provided data strongly depends on the corresponding calculation model of the SME and the therein included uncertainty. Consequently, in this contribution, the calculation model of a sensory utilized rolling bearing, as exemplary SME, is systematically analyzed using existing methods and tools to identify uncertainty that critically affects the quality and reliability of the data provided.

Keywords: uncertainty, systematic approach, design methodology, sensing machine elements, sensory utilised rolling bearing

1. Introduction and Motivation

As a result of the progressing digitalization in the context of Industry 4.0 and the implementation of cyber-physical systems, a substantial need regarding information about technical systems and processes arises, e.g. in order to increase their efficiency or sustainability (cf. Matt and Rauch, 2020). However, the acquisition of this information in terms of data about characteristic state and process variables is often challenging and can typically be realized in multiple ways (cf. Martin *et al.*, 2018).
In this context, Sensing Machine Elements (SME) represent a promising approach to obtain information about relevant state or process variables within technical systems. SME build upon the primary mechanical functions of conventional machine elements and enhance them with sensory functions (cf. Vorwerk-Handing *et al.*, 2020a). Moreover, since machine elements, such as rolling bearings, are an essential part of almost every technical system, SME offer a great potential regarding the retrofit of sensory functions into technical systems that were not developed against today's background. Shifting the point of measurement to a position in - or at least close to - the process zone using SME reduces uncertainty arising within the transmission path of the quantity to be measured - so-called measurand - from its point of origin to the point of measurement (cf. Hausmann *et al.*, 2021). However, the quality and thus the reliability of the data provided by SME, such as the sensory utilized rolling bearing by Schirra *et al.* (2018), heavily depend on their corresponding calculation model. In this context, the calculation model is the inverted measuring function, according to JCGM 200:2012, that quantitatively describes the relation between the input of the SME - the measurand - and the corresponding output - the emitted (electric) signal - based on the laws of the utilized effects and principles (cf. Bureau international des poids et mesures, 2012). Since these models are oftentimes quite complex and include multiple inputs - intended as well as unintended in case of disturbance factors -, special attention must be paid to their evaluation in terms of uncertainty.
Consequently, to ensure the quality and reliability of data provided by SME, it is reasonable to analyze their underlying calculation model with regard to the associated uncertainty. For this purpose, there

are already some frameworks that are theoretically applicable, such as the Uncertainty Mode and Effects Analysis (UMEA) by Engelhardt *et al.* (2009) or the thereon based approach by Vorwerk-Handing *et al.* (2020b). However, oftentimes it remains unclear how the different methods and tools included therein can be applied effectively to the calculation model of a SME depending on the prevailing level of information and knowledge about the individual uncertainty factors. Especially when the level of information and knowledge about different factors causing uncertainty is not uniform, a mere qualitative or quantitative analysis is oftentimes not expedient.
The aim of this contribution is therefore to investigate if an existing framework and the therein included methods and tools can be utilized or adapted to systematically analyze uncertainty in the calculation models of SME. As an exemplary SME, the sensory utilized rolling bearing by Schirra *et al.* (2018) is considered, which is the subject of current research at the authors' institute. The results of the analysis enable a reduction of the overall uncertainty within the calculation model of the sensory utilized rolling bearing and thus an increase in the quality and reliability of the data provided.

2. Fundamentals

This section describes the fundamentals for the subsequent uncertainty analysis of the sensory utilized rolling bearing's calculation model. First, the term "uncertainty" is defined in order to achieve a uniform understanding. Subsequently, different approaches for its classification are outlined that are utilized in the further course of this contribution. Finally, the fundamentals of the sensory utilized rolling bearing and its calculation model are introduced and described.

2.1. Uncertainty - Definition and Classification Approaches

According to ISO Guide 73:2009, uncertainty is "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 causes a deviation of objectives from the expected - in a positive and/or negative way - and thus leads to a risk, which is critical if it results in a failure and ultimately a hazard (cf. International Organization for Standardization, 2009; Deutsches Institut für Normung e. V., 2015).
Uncertainty is characterized by various aspects and can therefore be distinguished using different approaches. Already existing classification approaches focus on the nature of uncertainty, its degree or its point of appearance in the systems model - so-called manifestation. It must be noted that these classification approaches are not mutually exclusive, but compatible and also complementary, cf. Figure 1 (cf. e.g. Walker *et al.*, 2003; Engelhardt *et al.*, 2010).

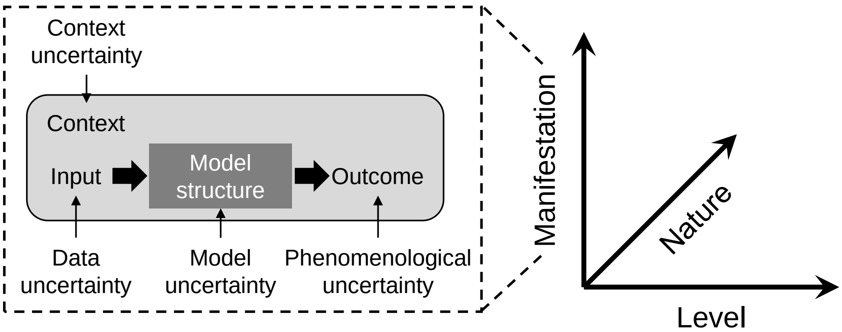

Figure 1. Classification of uncertainty (cf. Walker *et al.*, 2003; Kreye *et al.*, 2011)

The *nature of uncertainty* refers to its reducibility by an increase of information. In this context, uncertainty is distinguished into epistemic uncertainty and aleatory uncertainty. Epistemic uncertainty is caused by a lack of information and thus can be reduced by gaining more information, e.g. by experiments or more precise measurement methods. In contrast, aleatory uncertainty is caused by an inherent variability, e.g. due to the stochastic nature of an empirical quantity. Hence, aleatory uncertainty cannot be reduced by an increase of information, whereas epistemic uncertainty can be reduced. (cf. Oberkampf *et al.*, 2002; Walker *et al.*, 2003; Grebici *et al.*, 2008)

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In contrast, the *level of uncertainty* refers to the amount of information available and/or reliable regarding an uncertainty. In this context, the spectrum ranges from "total ignorance" or "nescience" - no information available - up to "determinism" - complete information available. In reality, determinism is oftentimes an unachievable ideal. (cf. Walker *et al.*, 2003; Weck *et al.*, 2007)
The *manifestation of uncertainty* refers to the location in a system model in which uncertainty occurs, cf. Figure 1. A distinction is made between context uncertainty, data uncertainty, model uncertainty and phenomenological uncertainty. In general, the context of a system describes the circumstances and conditions surrounding the system. This includes, e.g., the use context of the system but also the political, market and cultural context. *Context uncertainty* describes the potential influence of the system's context on the system itself, e.g., in terms of disturbance factors. In contrast, *data uncertainty* is uncertainty that is connected to the input of the system, its model, respectively. This not only includes the actual input of the system or its model in the form of data, but also, e.g., design parameters that are utilized within the system's model. *Model uncertainty*, however, is located in the system's model and describes inaccuracies - made consciously or unconsciously - in the modelling process, e.g. simplifications, that may result in a deviation between the behavior of the model and the real system. Finally, *phenomenological uncertainty* is present if some relevant information is unknown at the point of formulation, modelling, respectively. It can be described as unpredictability of the future due to unknown events or influences. Per definition, it is not possible to describe or model this manifestation completely, since there may always be an influence occurring from an unexpected event. However, it is possible to reduce this manifestation by applying a systematic approach, e.g., in the modelling process. (cf. Kreye *et al.*, 2011; Walker *et al.*, 2003; Weck *et al.*, 2007; Welzbacher *et al.*, 2021)

2.2. Sensory Utilized Rolling Bearing

Measuring process forces in rotating machines is usually attended by various difficulties. The integration of sensors in the flux of force may require a redesign of the technical system as well as additional installation space. Other sensor concepts are easier to integrate but rely on a longer transmission path of the measurand and therefore comprise higher uncertainty as discussed earlier. A novel approach in this context is the utilization of a ball bearing as a load sensor (cf. Schirra *et al.*, 2018). This requires no major change of the system's design and allows a measurement directly in the flux of force.

2.2.1. Fundamentals

A ball bearing, as shown in Figure 2a), consists of two rings separated by rolling elements. These allow a rotational degree of freedom in the relative movement of the rings. The cage ensures uniform spacing between the rolling elements. Rolling elements bear the load and thus a Hertzian contact ellipse develops, cf. Figure 2b). In the fluid friction regime, a lubrication film develops which separates the rolling element from the race by the central film thickness h_{C}. Since commonly used lubricants are of high specific resistance, only minor direct current (DC) passage will occur. That is, only as long as the breakdown voltage is not surpassed and therefore no electric discharge emerges. The lubrication film is thin compared to the Hertzian area and therefore allows an approximation of the resulting contact capacitance, which becomes the characteristic quantity for alternating currents in the kHz regime and beyond:

$$C_{\mathrm{Hertz}} = \varepsilon \cdot \frac{A_{\mathrm{Hertz}}}{h_{\mathrm{C}}}. \tag{1}$$

A rise in load results in an increasing Hertzian area and a decreasing film thickness, consequently, an increasing capacitance. Beside the Hertzian area, the remaining area within the groove, as well as unloaded contacts, contribute partial capacitances (cf. Schirra *et al.*, 2021). Thus, no contact is negligible in the capacitor network derived from Prashad (1988) to calculate the total capacitance, cf. Figure 2a). Like the single contact, the total capacitance of a bearing is dependent on the load the bearing carries and hence a valid principle for sensory utilization. Since the correlation of load and capacitance is nonlinear, models that describe this correlation have to be developed, which is a non-trivial challenge due to the multitude of parameters, domains and dependencies.

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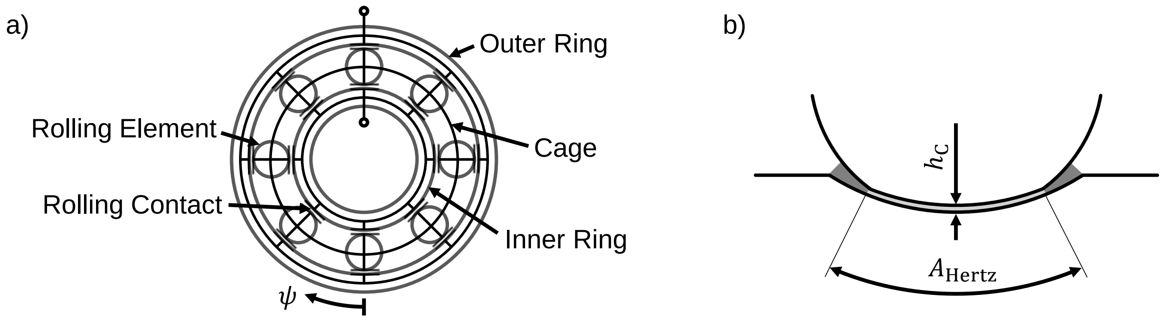

Figure 2. Schematic of a deep groove ball bearing and its corresponding network of contact capacitances (a) and loaded ball-raceway contact with deformed Hertzian area A_{Hertz} and central lubrication film thickness h_{C} (b) (cf. Schirra *et al.*, 2018)

2.2.2. Calculation Model of the Sensory Utilized Rolling Bearing

In the subsequent section, four exemplary inputs of the calculation model of the sensory utilized rolling bearing are introduced that are utilized in the further course of this contribution to illustrate the application of the uncertainty analysis. In the following, the quantities' phenomenological influences on the resulting total bearing capacitance are discussed to give a comprehensible picture of the subsequent considerations.

Number of Rolling Elements (Z)

The number of rolling elements depends on the bearing type and size. In, e.g., deep-groove ball bearings the number of rolling elements is limited due to the assembling process whereas in cylindrical roller bearings it depends on the cage type. In extreme, full complement bearings carry the highest possible number of rolling elements.

In general, more rolling elements imply more contacts, cf. Figure 2a), and with that more capacitances in parallel resulting in a capacitance increase. On the other hand, the load distribution is changed so that each individual rolling element carries less load. This in return causes a thicker lubrication film, a smaller Hertzian area and hence a smaller contact capacitance. Therefore, the influence of the number of rolling elements on the total capacitance is non-trivial.

Coefficient of Thermal Expansion of the Bearing Rings (α_T)

The phenomenon of thermal expansion of steel is well studied and comparably easy and precise to measure. In rolling bearing applications, thermal influences are usually of major relevance, e.g., caused by friction heat or nearby process heat. If the bearing rings have a different thermal expansion coefficient than the rolling elements, the bearing clearance becomes dependent on the temperature. Additionally, the fitting of the inner ring and the shaft, or the outer ring and the housing, respectively, is temperature dependent for different materials and thus influences the bearing's clearance. In return, the clearance has an influence on the internal load distribution and the number of load carrying rolling elements. The effect as stated above applies and the effect on the bearing capacitance is not distinct.

Temperature Difference Between Inner and Outer Ring (ΔT)

Bearings produce heat due to power dissipation by friction. In applications where a bearing is supporting a shaft within a housing, the heat transfer to the housing is promoted by the bigger surface of the outer ring and the typically lower temperature of the housing. Thus, in stationary conditions, the temperature at the outer ring is lower than on the inner ring. This causes the clearance to decrease due to the higher thermal expansion of the inner ring. As stated above, this causes a change in load distribution and consequently in the bearing's capacitance.

Temperature-Viscosity Coefficient ($\alpha_{\eta,T}$)

Elastohydrodynamic lubrication theory is used to characterize the behavior of point and line contacts in rolling element bearings. Corresponding equations for the lubrication film thickness are commonly

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expressed isothermally. Murch and Wilson (1975) derived a correction factor that takes viscous heating in the inlet zone into account. This heating reduces the lubricant's viscosity and causes a reduction in film thickness. The effect increases with the surface speed of the contact partners. A reduced lubrication film causes a rise in contact capacity, cf. Equation (1).

3. Uncertainty Analysis of the Calculation Model

The methodical approach described in the following for the analysis of uncertainty in the calculation model of the sensory utilized rolling bearing is based on the fundamental approach described by Vorwerk-Handing *et al.* (2020b) and ultimately the Uncertainty Mode and Effects Analysis (UMEA) by Engelhardt *et al.* (2009). The basic structure of the approach is illustrated in Figure 3.

Figure 3. Structure of the uncertainty analysis (cf. Vorwerk-Handing *et al.*, 2020b, based on Engelhardt *et al.*, 2009)

In order to be able to assess which uncertainty needs to be addressed regarding a reduction or elimination to ensure the quality and reliability of the data provided, the uncertainty occurring within its calculation model must be identified in the first step. In this context, the classification approach for uncertainty according to its manifestation, cf. Section 2.1, is utilized to ensure the systematics of the identification process. Subsequently, each identified uncertainty is analyzed in the context of an evaluation to determine its respective criticality. Based on this information, a decision can finally be made whether an uncertainty needs to be reduced or eliminated in order to ensure the quality and reliability of the data provided by the SME or not.

3.1. Identification of Uncertainty

In order to identify uncertainty in the calculation model of the sensory utilized rolling bearing, its context must be analyzed in the first place since, e.g., acting disturbance factors may influence quantities or parameters included in its model and cause model and/or data uncertainty. It must be noted that the analysis of the system's context is limited to the (technical) circumstances and surrounding of the bearing that directly affect the system's functionality, i.e. disturbance factors. Since the political, market and cultural context do not impact the system's (technical) functionality but only its success as a product, they are neglected in this analysis. After the identification of context uncertainty in terms of acting disturbance factors, the uncertainty connected to the inputs of the bearing's calculation model and the model itself can be analyzed effectively. By applying a systematic approach in the whole identification process, phenomenological uncertainty is generally reduced (cf. Vorwerk-Handing *et al.*, 2020b). Due to that circumstance, this manifestation of uncertainty is not considered separately here.

Context Uncertainty

For the identification of context uncertainty, the control list for disturbance factors proposed by Welzbacher *et al.* (2021) is used to ensure that no relevant disturbance factors are neglected unconsciously. The control list is structured based on the physical (sub-) domains of the respective disturbance factors, whereby each disturbance factor is characterized - and thus quantifiable - by its domain-specific pair of generalized energy variables according to multipole based model theory (cf. Welzbacher *et al.*, 2021). By quantifying each occurring disturbance factor via its generalized energy variables, the level of uncertainty associated to each disturbance factor becomes obvious. For further information about the utilized disturbance factor control list please refer to Welzbacher *et al.* (2021). An extract of the filled-in control list for the sensory utilized rolling bearing is shown in Table 1.

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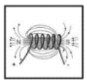
Table 1. Extract of the filled-in control list (taken from Welzbacher *et al.*, 2021)

		Disturbance factor	Picto-gram	Occurrence	Generalized energy variables	Quantification
Mechanics	Acoustics	Structure-borne sound		☒	Force (F) Velocity (v)	-
		…	…	…	…	…
	⋮	…	…	…	…	…
Electricity and magnetism	Electro-magnetism	Electromagnetic field (static)		☒	Magnetic flux (Φ_m) Magnetomotive force (V_m)	-
		Electromagnetic radiation		☒	Magnetic flux (Φ_m) Magnetomotive force (V_m)	-
	⋮	…	…	…	…	…
Thermo-dynamics	Heat-transfer	Heat conduction		☒	Entropy flow ($\dot{S}$) Temperature (T)	$\Delta T = 60°C$
	⋮	…	…	…	…	…
⋮	⋮	…	…	…	…	…

Data Uncertainty

In order to identify data uncertainty, each input of the calculation model is analyzed separately regarding a temporal variability, e.g. due to wear, its dependence on acting disturbance factors but also if it is subject to measuring uncertainty. Based on this information it is possible to determine the current level of uncertainty of each input according to Walker *et al.* (2003). Therefore, research in literature, e.g. in the extended catalogue of physical effects by Mathias (2016) or the physical effect catalogue proposed by Vorwerk-Handing (2021), was conducted regarding the individual inputs and their respective dependencies. In addition, the values assigned to the individual inputs of the calculation model of the sensory utilized rolling bearing were audited. The results for the exemplary considered inputs of the sensory utilized rolling bearing's calculation model from Section 2.2.2 are shown in Table 2.

Table 2. Extract of the identified data uncertainty

		Temporal variability	Dependence on acting disturbance factors	Measuring uncertainty	Level of uncertainty
Bearing	Number of rolling elements (Z)	☐	☐	☐	**Determinism**
	Coefficient of thermal expansion of the bearing rings (α_T)	☐	☐	☒	**Statistical uncertainty**
	Temperature difference between the inner and outer ring of the bearing (ΔT)	☒	☒	☒	**Nescience**
	…	…	…	…	**…**
Lubricant	Temperature-viscosity coefficient ($\alpha_{\eta,T}$)	☐	☐	☒	**Statistical uncertainty**
	…	…	…	…	**…**

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Model Uncertainty

On the one hand, model uncertainty is identified by checking the physical effects and principles utilized in the calculation model for therein made inadmissible simplifications and assumptions. Therefore, research in literature regarding the used physical relations was conducted. On the other hand, the physical effect catalogue proposed by Vorwerk-Handing (2021), which is based on multipole based model theory, was utilized to systematically identify effects between the pre-identified disturbance factors and quantities or inputs of the model that are not yet considered. In this context, the domain-specific flow and effort variables of each occurring disturbance factor are considered as inputs of physical effects that have quantities and inputs of the calculation model as outputs. For further information and a detailed description of the identification process, please refer to Vorwerk-Handing (2021). In the framework of the identification process, no inadmissible simplifications or assumptions in the calculation model of the sensory utilized rolling bearing as well as relevant physical effects that were not yet included were identified.

3.2. Evaluation of Identified Uncertainty

Since context uncertainty and disturbance factors in general do not directly affect the calculation model of the sensory utilized rolling bearing but cause data and model uncertainty, only data and model uncertainty are evaluated in the following (cf. Vorwerk-Handing *et al.*, 2020b). The objective of the evaluation is to determine the criticality of each identified uncertainty in terms of its effect on the quality and reliability of the data provided by the SME. For the evaluation of identified uncertainty, the concept of the modified Failure Mode and Effects Analysis (FMEA) proposed by Vorwerk-Handing *et al.* (2020b) is taken up and adapted in order to be applicable for the evaluation of uncertainty in a calculation model. Vorwerk-Handing *et al.* (2020b) focused on uncertainty occurring within the conceptual integration of sensory functions into technical systems and used the following criteria for their evaluation:

- *Severity*: Level of uncertainty connected to each quantity or input of the system's model.
- *Significance*: Relative contribution of an individual uncertainty to the overall uncertainty, so-called uncertainty budget.
- *Controllability*: Assessment of the ability to control a specific uncertainty by means of robust design measures while taking the effort for their realization into account.

However, the criteria defined by Vorwerk-Handing *et al.* (2020b) are only conditionally transferable to the evaluation of uncertainty in the calculation model of the sensory utilized rolling bearing. On the one hand, this is due to the higher complexity of the calculation model of the sensory utilized rolling bearing compared to the measuring concepts considered by Vorwerk-Handing *et al.* (2020b). This entails that the calculation of the uncertainty budget in the context of the evaluation of the significance is no longer possible by simple means of error propagation. On the other hand, the assessment of the controllability requires that potentially suitable measures for the reduction or elimination of each uncertainty are forethought, which entails a significant additional expenditure, e.g. in terms of time and costs. Hence, new criteria were defined as substitutes for the latter two evaluation criteria from Vorwerk-Handing *et al.* (2020b), whereby the criterion "Severity" was adopted:

- *Deviation*: Maximum relative deviation of the value of a quantity - in case of model uncertainty - or an input - in case of data uncertainty - resulting from the considered uncertainty.
- *Impact*: Sensitivity of the calculation model in terms of a deviation of the model's output caused by an individual uncertainty.

The deviation of an uncertainty affected quantity or input is determined via the quotient of the sum of all individual contributions resulting in a deviation of the considered quantity or input, e.g. due to several dependencies from acting disturbance factors, and its originally assumed value. In contrast, the impact of an uncertainty is determined by the relative deviation of the calculation model's output whereby a deviation of the considered uncertainty affected quantity or input by 0.5 % from its initial value is assumed. In error analysis, partial derivatives are typically utilized to determine the propagation of an error, an uncertainty, respectively, and thus its respective impact. For example, the

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relative change of the contact capacitance $\Delta C_{\mathrm{Hertz}}/C_{\mathrm{Hertz}}$ due to a relative change in the lubrication film thickness $\Delta h_{C}/h_{C}$ can be determined via the partial derivate of their relation to

$$\Delta C_{\mathrm{Hertz}}/C_{\mathrm{Hertz}} = -\,\Delta h_{\mathrm{C}}/h_{\mathrm{C}} \,. \tag{2}$$

However, partially differentiating with respect to each quantity and input is not only elaborate, but also impossible for models that utilize neural networks or contain iterative or numeric parts, like the one at hand. Especially in these cases, the application of a sensitivity analysis is reasonable in order to be able to determine the propagation of an uncertainty and thus its impact on the output. Using a sensitivity analysis for the above mentioned example yields to the following relation

$$\Delta C_{\mathrm{Hertz}}/C_{\mathrm{Hertz}} = -\frac{1}{h_{\mathrm{C}}/\Delta h_{\mathrm{C}}+1} \,. \tag{3}$$

Comparing Equation 2 and 3, it becomes obvious that both results converge for small relative deviations and thus deliver comparable results. A deviation of the central film thickness of 0.5 % causes the contact capacity to deviate −0.5 % according to Equation 2 whereas the sensitivity analysis returns a relative deviation of −0.498 % according to Equation 3. Hence, a sensitivity analysis is utilized in the context of this evaluation to determine the impact of an uncertainty, as it is applicable independently of the calculation methods used in the considered model.
To ensure the consistency of the evaluation, rigid schemes were developed for each criterion, similar to Vorwerk-Handing *et al.* (2020b). The evaluation scheme for severity is based on the level of uncertainty and adopted from Vorwerk-Handing *et al.* (2020b), whereby a higher valuation indicates the presence of a higher level of uncertainty. In contrast, the evaluation schemes for the deviation and impact of an uncertainty are based on a logarithmic scale in order to achieve a non-linear distribution of the valuations, which range from 1 - low/little deviation or impact - up to 5 - high deviation or impact. The results of the evaluation of the identified data uncertainty from Table 2 are shown in Table 3.

Table 3. Results of the evaluation of the data uncertainty from Table 2

		Severity	Deviation	Impact
Bearing	Number of rolling elements (Z)	1	1	**5**
	Coefficient of thermal expansion of the bearing rings (α_T)	3	2	2
	Temperature difference between the inner and outer ring of the bearing (ΔT)	**5**	**5**	**5**
	…	…	…	…
Lubricant	Temperature-viscosity coefficient ($\alpha_{\eta,T}$)	3	**4**	1
	…	…	…	…

3.3. Decision

Based on the results of the preceding evaluation, a reasoned decision can be made whether an uncertainty must be reduced or eliminated due to its criticality for the quality and reliability of the data provided by the sensory utilized rolling bearing or not. Therefore, threshold values are defined for each category - similar to a conventional FMEA - but also the product of the valuations of an uncertainty in the categories deviation and impact, beyond which an uncertainty is considered critical. An uncertainty is considered critical if it exceeds the valuation 3 in one category and/or if the product of its valuations in the categories deviation and impact exceeds the value 5, as indicated in Table 3.
Considering the given valuations in Table 3 for the data uncertainty from Table 2, it becomes obvious that especially the uncertainty connected to the temperature difference between the inner and outer ring of the bearing (ΔT) requires further measures for its reduction or elimination in order to reduce its

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criticality. Potentially suitable measures to reduce its severity and deviation are to directly measure the temperature difference and feed it into the calculation model or to extend the model in order to consider the bearing friction and the resulting heat transfer into the shaft and the housing.

4. Conclusion and Outlook

In this contribution, the fundamental approach by Vorwerk-Handing *et al.* (2020b) was utilized to systematically identify and manage uncertainty in the calculation model of a sensory utilized rolling bearing that critically affects the quality and reliability of the data provided. However, the methods and tools included in the approach - especially the modified FMEA - had to be adapted to be fully and effectively applicable to the calculation model.

In the first step, uncertainty in the calculation model was identified based on its manifestation in the system's model. For the identification of context uncertainty in terms of occurring disturbance factors, as potential cause of data and model uncertainty, the control list by Welzbacher *et al.* (2021) was utilized. In this context, each occurring disturbance factor was quantified according to its respective pair of generalized energy variables. Although the sensory utilized rolling bearing is still in a prototypical stage and operated on a test rig, the quantification of occurring disturbance factors proved to be challenging. E.g., in terms of an occurring heat transfer, it could not be clearly determined whether the heat transfer was by conduction or convection. Consequently, the disturbance factors in the control list by Welzbacher *et al.* (2021) must be reviewed critically and combined reasonably to be applicable in a meaningful way. In order to identify occurring data uncertainty, each input of the calculation model was analyzed regarding a temporal variability, existing dependencies from acting disturbance factors and associated measuring uncertainty. In this context, especially the analysis of inputs with regard to existing dependencies on occurring disturbance factors proved to be challenging, as there is not yet a complete collection of information in this regard. Hence, the development of such a database, encompassing inputs and their dependencies on disturbance factors in general, is reasonable to reduce the effort in literature research and planned in the future.

After the identification of uncertainty, an evaluation is conducted to determine its criticality regarding the quality and reliability of the data provided by the sensory utilized rolling bearing. The identified uncertainty is evaluated regarding its severity, the resulting deviation of the uncertainty affected quantity or input and the corresponding sensitivity of the calculation model. Based on the results of the evaluation, a reasoned decision can be made whether an uncertainty requires further measures to be reduced or eliminated or not. Therefore, threshold values were defined. However, the results of the evaluation and the thereon based decision must be questioned critically. In particular, if several inputs affected by uncertainty are evaluated as non-critical, they can still add up to a relevant contribution to the overall uncertainty. To solve this problem, the usage of dynamic instead of rigid threshold values is conceivable, e.g. based on the relative share of an uncertainty in the overall given valuations. Following up, it is planned to develop a framework for the systematic derivation of suitable measures to eliminate or reduce uncertainty from its respective valuations. In this context, the nature of an uncertainty - cf. Section 2.1 - must also be considered to ensure the effectivity of the measures to be developed.

Finally, the methodical approach described and the included methods and tools for the analysis of uncertainty are fully transferable to future extensions of the calculation model of the sensory utilized rolling bearing, like e.g. other types of rolling elements. This is because the fundamental structure of the calculation model remains identical. However, the extent of transferability of the approach to calculation models of other SME still needs to be further investigated and is planned for the near future.

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