Managing the uncertainty in data-acquisition by in situ measurements: a review and evaluation of sensing machine element-approaches in the context of digital twins

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Abstract: The acquisition of data is important for the digitalisation of production and product development as well as for digital twins. In the scope of this contribution, the integration of sensors close to a process for measuring the quantity of interest at its point of origin is presented. Therefore, a classification of measurement locations in *in situ* and *ex situ* measurements based on the complexity of the required transfer path of the quantity of interest and the prevailing uncertainty is proposed. A promising way for sensor integration are sensing machine elements (SMEs), which are suitable for capturing data for digital twins due to their simple applicability, measurement at the point of interest as well as reduced structural changes. In a short overview, possible uncertainties for different measurement locations are presented and potentials as well as challenges for the in situ measurement in the context of digital twins are derived.

Keywords: uncertainty; digitalisation; metrology; sensor integration; in situ measurement; digital twin; sensing machine element; SME.

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Biographical notes: Maximilian Hausmann studied Business Administration and Engineering at the RWTH Aachen, Germany, specialising in Mechanical Engineering with a focus on design technology and operations research and management. Since 2020, he works as a Research Assistant at the Institute for Product Development and Machine Elements (PMD) at the Technical University of Darmstadt, Germany. He is working on a DFG-funded project with the title 'Product development with sensor-integrating machine elements – mastering the uncertainty of in situ acquired data in the mechatronic system'. The aim is to model the structure-integrated signal and energy transfer through a mechanical system from a sensor integrated into a machine element to the data processing unit at the end of a structure-integrated transfer path.

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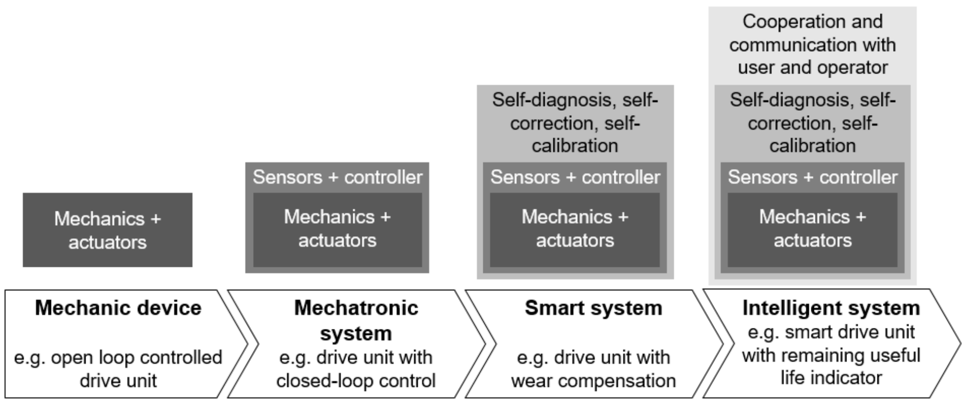
1 Introduction

The ongoing megatrend of a comprehensive digitalisation in production as well as product development has the aim of a full integration of information, communication and industrial technologies (Zhou et al., 2015; Hirsch-Kreinsen et al., 2019). This also includes the approach of digital twins, which can represent products and processes in the digital world with the help of suitable models. The development and application of digital twins require a vast amount of product and process data (Schleich et al., 2017). This further requires, that processes and products must be enabled for digital interaction. This need is enabled by the progressing development from mechanic devices via mechatronic systems and smart systems to intelligent systems as seen in Figure 1 (Binder and Post, 2012; Vorwerk-Handing et al., 2020). In order to be able to access the wide variety of data required for a large-scale digitalisation, technical systems must be equipped with suitable sensors. Thereby, the integration of sensors into a system and the identification and consideration of uncertainty in the context of data collection represent one of the main challenges in development of digital products and processes and in the context of digital twins (Vorwerk-Handing et al., 2020; Schleich et al., 2017).

This contribution gives an overview of sensing machine elements (SMEs), which offer opportunities for the acquisition of quantities of interest directly at their point of origin. Due to their design as machine elements, the applicability is as basic as possible and the required installation space is in general the same as that of conventional machine elements. A particular focus is on the uncertainty of those sensor applications. Therefore, the work first summarises the current state of research in the field of measuring uncertainty identification, evaluation and consideration. For this purpose, after a definition of the term uncertainty, the uncertainty mode and effect analysis (UMEA), as a method for the identification and the evaluation, and robust design approaches, as an approach for the consideration of uncertainty, are presented. Based on this uncertainty consideration, a classification of possible measurement locations into so-called in situ and ex situ measurement positions as well as associated subclasses is proposed. This classification supports the approach of SMEs, which are currently subject to research. SMEs allow the measurement location to be brought as close to the process as possible and thus manage the complexity and the existing uncertainty of the measurement task. In Section 3, the uncertainty of the three different SME approaches and of a conventional off-process sensor concept is briefly described. This allows a derivation of potentials and challenges for in situ measurements in the context of digital twins in the last section of this contribution.

Figure 1 Development of mechanical systems towards intelligent systems



Source: Following Vorwerk-Handing et al. (2020), quoted after Binder and Post (2012)

2 State-of-the-art uncertainty of measurement and in situ measurement

The first section of this contribution is intended to provide an overview of the state-of-the-art regarding uncertainty in measurements, the management of this uncertainty, the concept of in situ measurements and the concept of SMEs. For this purpose, the concept of uncertainty in measurements and the methods for managing this uncertainty are introduced first. The further specified classification of possible measurement locations in technical systems is based on the described approaches of uncertainty consideration. The concept of in situ measurements presented in this work is made possible, for example, by SMEs. Therefore, the concept of SMEs is briefly introduced in the last part of this section.

2.1 Uncertainty of measurement

The measurement of a quantity is always associated with uncertainty. Even after the correction of errors through an error analysis, the question about the quality of the measurement result remains. How well does the measurement result represent the quantity of interest being measured? There are many possible sources for uncertainty in measurement. An overview of some possible sources for uncertainty occurring in the measurement of process quantities is shown in the following list (JCGM, 2008):

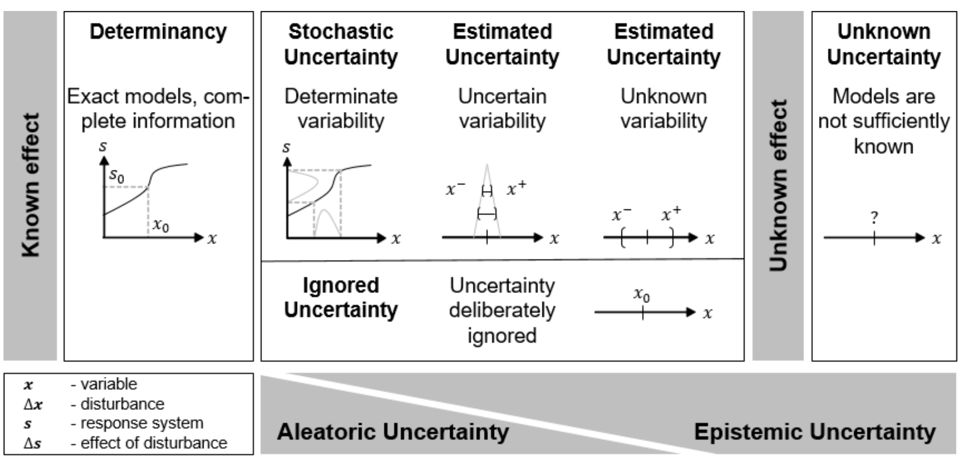
- inaccurate definition of measurand

- incomplete knowledge of the system's internal behaviour
- incomplete knowledge or measurement of the environmental effects
- assumptions during the measurement.

In general, the term uncertainty is defined as the condition of partial or complete lack of information (DIN, 2009; Hanselka and Platz, 2010). In the context of measurement, this implies a lack of information on the real value of a quantity being measured (JCGM, 2008). Uncertainty can be classified in different layers. Kreye et al. (2011) give an overview of five of these layers. Within the scope of the measurement of process data, the layers *nature*, *level* and *manifestation* are particularly of interest and for this reason are briefly presented in the following.

The nature of an uncertainty differentiates between *aleatoric* and *epistemic* uncertainty, as seen at the bottom of Figure 2. Aleatoric uncertainty is caused by the random variation of influencing variables and is also known as variability or stochastic uncertainty. This kind of uncertainty can be reduced but not completely avoided. Even in an almost determined system with complete information, stochastic fluctuations can have an influence and thus be subject to uncertainty. Uncertainty caused by a lack of information is named epistemic uncertainty, also known as model form uncertainty. This kind of uncertainty can be reduced by generating additional information until only the aleatoric uncertainty remains (Oberkampf et al., 2004; Walker et al., 2003).

Figure 2 Classification of uncertainty



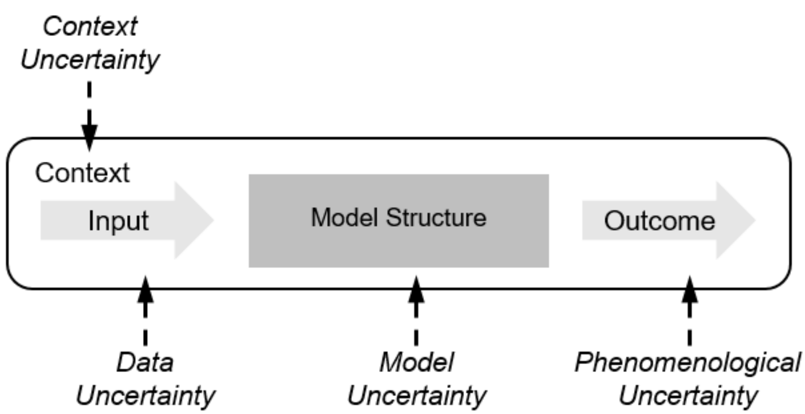
Source: Based on Lotz (2018)

An alternative distinction of uncertainty can be made based on the level of an uncertainty. The level indicates the severity of an uncertainty. *Determinacy* is present in the case of complete information, when a complete description of the system and its behaviour can be given. In the case that both, the model description and the system parameters, are unknown, one speaks about *unknown uncertainty*. If, on the other hand, the uncertainty effect can be described stochastically and thus has a known probability density function, one speaks of *stochastic uncertainty*. In the case, that the uncertainty effect can only be described partially, it is referred as *estimated uncertainty*. The last category is the *ignored uncertainty*, in which the known or estimated uncertainty effects are deliberately ignored.

The mentioned categories are shown in Figure 2 (Engelhardt et al., 2010; Andrews et al., 2004; Stirling, 2003; Walker et al., 2003).

Furthermore, the distinction of uncertainty based on its manifestation in a technical system is presented and illustrated in Figure 3. The manifestation describes the point within a process where the uncertainty occurs. The *context uncertainty* describes the uncertainty regarding the context of a system that can influence the system, for example the surrounding temperature as a disturbance variable. The *data uncertainty*, on the other hand, describes the uncertainty regarding the data entering the system, such as the measurand. The underlying model is subject to the *model uncertainty* that results from the model structure or model parameters. Finally, the outgoing quantities are also subject to an uncertainty, the *phenomenological uncertainty*. This is an uncertainty regarding the quality of the output quantity or the performance of the system under consideration (Kreye et al., 2011).

Figure 3 Manifestation of uncertainty



Source: Following Kreye et al. (2011)

Not only the quantity of interest captured by the sensor is subject to the effect of uncertainty, the sensor element itself, its energy supply and signal transfer are affected as well (Vorwerk-Handing et al., 2020; Stücheli and Meboldt, 2013; Martin et al., 2018a). For this reason, it is important to manage the existing uncertainty and to reduce it as much as possible to obtain high quality results. When designing technical systems that incorporate measuring capabilities, methodical approaches such as the UMEA are suitable for the identification and evaluation of uncertainties. Subsequently, suitable approaches to consider and reduce uncertainty can be applied, such as robust design approaches.

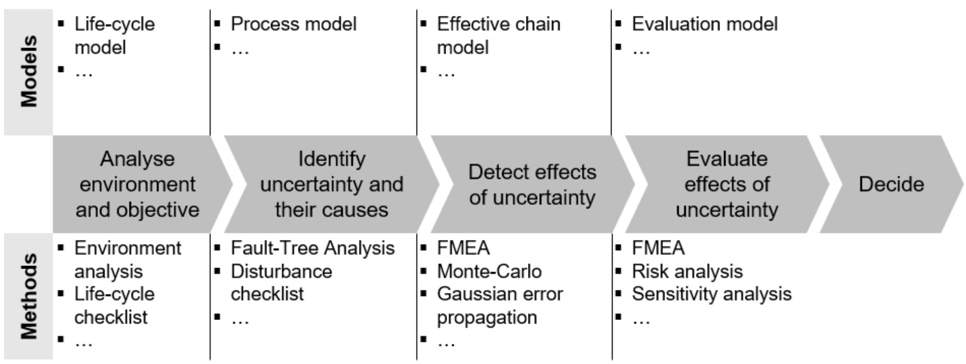
2.2 Managing uncertainty

According to Section 2.1, uncertainty occurs in all measurements. In order to obtain high quality measurement results, this uncertainty must be identified and evaluated. If the effect of an uncertainty is relevant enough, suitable approaches for uncertainty consideration can be selected. One method for the systematic identification and evaluation of uncertainty is the UMEA. The result of the UMEA is a decision regarding the consideration of an uncertainty. Do measures have to be taken or not? In case of required measures, so-called robust design approaches are applied. An overview of robust design approaches is provided after a brief description of the UMEA.

2.2.1 Identification and evaluation of uncertainty with the UMEA

The UMEA is a suitable approach to systematically identify and evaluate the uncertainty in a technical system and the possible influencing variables. The UMEA proposes five steps, from the analysis of the environment and objective to the decision on how to deal with the identified and evaluated uncertainty, and offers suitable models and methods for each step. A brief description of these five steps based on Engelhardt et al. (2009, 2011) is shown in Figure 4.

Figure 4 Procedure of the UMEA



Source: Based on Engelhardt et al. (2009)

In the first step of the UMEA, the system under consideration is separated from its environment. The variables and objects influencing the system are identified. Furthermore, objectives, which are requested from different interest groups, are described. In the next step of the UMEA, the uncertainties occurring in the system are identified. Subsequently, the related causes can be described for each uncertainty. If possible, the causes should be described quantitatively to enable calculations in the following steps. In the third step, the effects of the identified uncertainties on the overall system are calculated and described. Relations between the individual uncertainties are considered as well. In the fourth step, a basis for the subsequent decision-making is derived from the identified uncertainties and the described effects of those uncertainties on the overall system. In the final step of the UMEA, a decision on possible measures to reduce uncertainties is taken. Based on the previously evaluated uncertainties and the defined objectives from Step 1, uncertainties can be reduced with suitable methods, such as robust design approaches, or, if the effect of an uncertainty is not relevant enough, the uncertainty can be ignored (Engelhardt et al., 2009, 2011).

2.2.2 Consideration of uncertainty with robust design approaches

After the decision in the last step of the UMEA, which uncertainties should be considered, suitable measures for managing these uncertainties can be selected in the next step. The approaches of robust design are suitable for the management of uncertainty

(Freund, 2018). These include the eliminating of uncertainty, the suppressing of uncertainty and the reduction of effects of uncertainty. The mentioned approaches are briefly described in the following.

2.2.2.1 Eliminating uncertainty

The first strategy is to eliminate the arising uncertainty. For this purpose, it is necessary to be able to modify the source of an uncertainty. However, this method is only applicable for uncertainties which occur within the system boundaries. For uncertainties, which arise outside the system boundaries, it is only possible to define threshold values for the system use in which the uncertainties may be reduced. Outside these boundaries, however, uncertainty reappears and the system may behave undesirably. An example is the specification of a temperature range of a product's surrounding in the user manual. Within this range, the uncertainty due to an unwanted or unknown temperature influence can be eliminated, outside this range the product is not intended to be used (Mathias et al., 2010).

2.2.2.2 Suppressing uncertainty

A second method is to suppress the influence of uncertainty. For this purpose, measures are applied to prevent the uncertainty from entering the system boundary. Insulating layers against temperature influences can serve as an example here. However, such measures are often implemented in conjunction with additional required components in the product (Mathias et al., 2010).

2.2.2.3 Reducing the effect of uncertainty

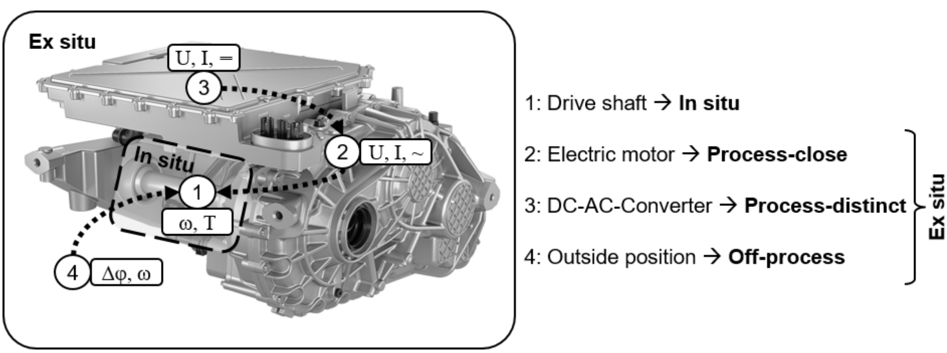
The third strategy to manage uncertainty is to reduce the effect of uncertainty that occurs. For this purpose, the product has to be designed in such a way that the uncertainty effect cannot be harmful to the system. An example of this is a strain-compliant design that can compensate for the influence of variable temperatures. In most cases, no additional components are required for these measures, but the existing elements must be designed for the specific application (Mathias et al., 2010).

The more an uncertainty effect is known, the more likely the uncertainty influence or the uncertainty effect can be suppressed. In case of an unknown uncertainty, the uncertainty influence should be completely eliminated. However, if the uncertainty can be estimated, the uncertainty influences can be suppressed in order to avoid unwanted system behaviour. For the last cases, a complete determination or a stochastic uncertainty, the uncertainty effect can be reduced, since the uncertainty effect is at least stochastically known.

2.3 Concept of in situ measurement

As already described in Section 2.2, one great challenge of metrology is to master the uncertainty that arises during measurement. According to the method of robust design, three measures for the management of uncertainty can be applied to a technical system. These include the elimination of uncertainty, the supressing of uncertainty and the reduction of the effect of uncertainty. One possibility based on these measures is the relocation of the measurement location of the quantity of interest to a location, where the measurement is subject to less uncertainty (Vogel et al., 2018). In addition to this, *in situ* and *ex situ* measurements can be distinguished. With an *in situ* (Latin for 'in the original location') measurement, the quantity of interest is measured directly at its place of origin, whereas with an *ex situ* (Latin for 'outside the original location') measurement, the location of the measurement and the place of origin of the quantity of interest are different. The degree of divergence of these two locations is referred to in the following as distance, whereby the distance is not limited to a classical distance between two points, but also describes the distinction of both locations in relevant properties. The greater the distance between two locations, the more complex the relation between the two quantities becomes and the more disturbance variables can have an influence. The uncertainty increases. Based on the in situ and ex situ measurement categories, this contribution proposes a more detailed classification of the ex situ term into process-close, process-distinct and off-process measurements. This classification is described in the following and shown in Figure 5 and can be used to describe different measurement locations and their suitability for a measurement based on the prevailing uncertainty.

Figure 5 Electric drive unit with different measurement locations



Source: Following Vorwerk-Handing et al. (2020), picture on courtesy of Valeo Siemens eAutomotive Germany GmbH

To illustrate the classification of measurement locations, the torque measurement in an electric drive train for longitudinal dynamics control is used as an example here. Figure 5 shows the electric drive unit with four different realisable measurement locations. The first measurement location is the in situ measurement at position 1. At the drive axle, the drive torque *T* can be measured directly at its point of origin using a suitable torque sensor. The dipole of the drive torque *T* and the rotational speed *ω* constitutes the basis for the drive power calculation and subsequent vehicle dynamics control.

The ex situ measurement locations differ from the point of origin of the quantity of interest. Intermediate measurable quantities can be used to indirectly determine the quantity of interest. The complexity of the model of the transfer path from the measurable quantity to the actual quantity of interest increases with increasing distance. Referring to the elementary functions, these changes can be caused by, for example, the channelling, the transforming, the connecting or the changing of quantities (Roth, 2000). The closest to the in situ measurement is the *process-close* measurement. The distance of the measurable quantity at this location to the initial quantity of interest is marginal. A simple model of the transfer path can describe the transformation relation between those quantities. This is the case, when the alternating current power entering the electric motor is measured at position 2. The dipole of voltage U and alternating current I is converted to the dipole of drive torque T and rotational speed ω by a relatively basic model. In this case, an energy conversation from an alternating current supply to rotational energy exists. A further measurement is the *process-distinct* measurement at position 3, where the complexity of the transfer model of the relation between the measurable quantity and the quantity of interest is significantly greater than in a *process-close* measurement. The corresponding example is the conversation of the dipole of voltage U and direct current I of the battery to the dipole of drive torque T and rotational speed ω. The underlying model has gained in complexity due to a further energy conversation from direct to alternating current. A direct correlation between the measurable quantity and the quantity of interest is no longer obvious and must be analysed in detail. This requires in practical cases the determination of model parameters or reference tables for the correlation between the direct current supply and the delivered torque at a given shaft speed.

The last possible measuring location is an *off-process* measurement. In this location, a sensor is installed next to and not in the process and acts as an unaffected observer from the outside of the process. This allows conclusions to be drawn about the dipole of the change of the torsion angle $\Delta\varphi$ and rotational speed ω of the shaft at position 4. This measurement can be realised, for example, with a magnetoresistive sensor using a differential measuring method. Based on this dipole, the drive torque T can be derived from the torsion of the drive shaft.

As indicated in the descriptions above, the shift of the measurement location of the quantity of interest towards an in situ measurement location is usually accompanied by a simplification of the underlying model of the transfer path. Furthermore, there are, for example, fewer energy conversions, which can have an influence on the complexity of the model, but also on the measurement accuracy due to disturbance variables. Therefore, the integration of sensor technology directly into the technical system, if possible at an in situ position, has the potential to reduce uncertainty and thus increases the reliability of the measurement.

However, in situ measurements are also accompanied by new uncertainties. The integration of sensors directly at the point of origin of the quantity of interest partly requires new sensor principles, whose model descriptions can also be complex. In this context, reference is made to the sensor bearing presented in Section 3.4, where the complex measurement principle is subject to research. Furthermore, disturbance variables and their influence on the measurement within a process and on the energy and signal paths in the system are difficult to detect. In order to reduce these uncertainties, comprehensive research is currently carried out on sensor integration, for example, on the integration of sensor technology directly into existing machine elements. These approaches are presented in the next section.

2.4 Sensing technology and SMEs

As described in the sections before, the aim in metrology is to collect qualitative measurement data with the lowest possible uncertainty. The corresponding measurement locations can be in situ or ex situ. Depending on the selected quantity of interest and measurement location, a large number of sensor principles and sensor concepts can be selected. A sensor converts a quantity of interest into an (electrical) sensor signal. This relationship is also called sensor function. The underlying sensor principles are based on suitable physical principles. In sensor technology, there is a wide range of sensor principles that can be used for a large number of quantities of interest. The measurement of force or torque, for example, can be based on piezoelectric or piezoresistive methods for a direct measurement. For an indirect measurement, where a displacement or strain in the system is detected first, spring elements or strain gauges can be used (Czichos, 2018).

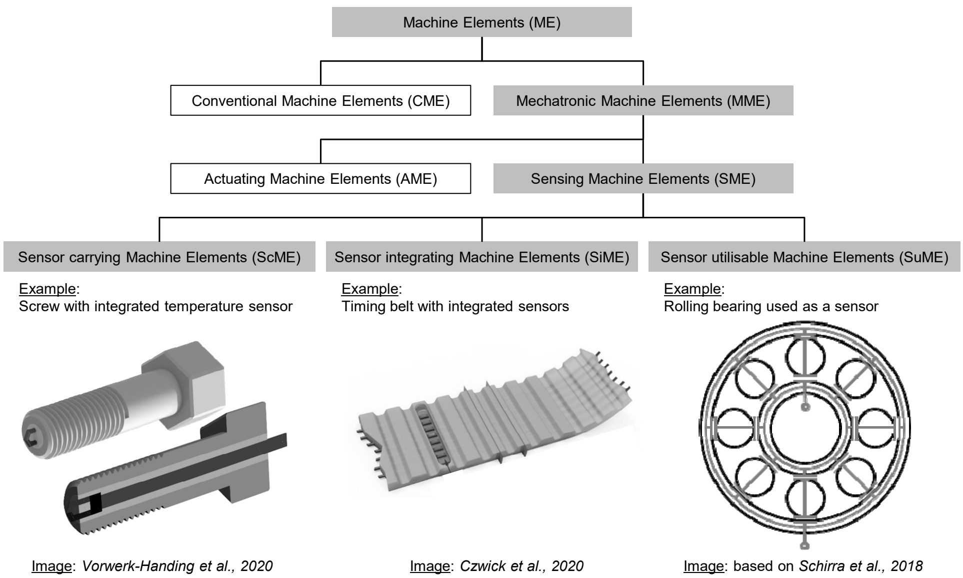
In conventional sensor applications, suitable sensors at positions that are easily to access record the quantity of interest. For this purpose, however, sensors are integrated directly into the technical system, which can take up installation space and lead to design changes in the system (Kirchner et al., 2018). Another method is the indirect acquisition of a quantity of interest by evaluating a suitable intermediate quantity. However, these approaches have a usually high distance to the process. Complex models are required to be able to derive the intended quantity of interest from the measurable quantity. Furthermore, disturbance variables can affect the system. These aspects lead to an uncertainty in the measurement, which has to be controlled. The torque measurement shown in Figure 5 serves as an example. The measurement can be carried out directly using a measuring flange or indirectly by an evaluation of the correlation of the input power at different locations with the drive torque. The direct measurement of the torque is performed at position 1 using a measuring flange inserted into the shaft. This method measures the quantity of interest in situ at the point of origin, but requires additional installation space and can influence the dynamic behaviour of the system and thus the quality of the measurement. Positions 2 and 3, on the other hand, describe the determination of the torque by measuring the input power of the actuator, whereby this relation is described in suitable models. With this procedure, less installation space is required in the system. But, as described in the previous section, the complexity of the transfer path of the quantity of interest and thus the model-uncertainty increases.

In order to reduce the effects of uncertainty on the sensor signal, the needed changes in the installation space and the influences on the mechanical function, recent activities to develop so called SMEs have been initiated. SMEs are machine elements, which are extended by a sensor function. The general aim of the application of these SMEs is to measure as close to the point of origin of a quantity of interest as possible to obtain measurement results directly from the process with less uncertainty. Furthermore, SMEs can be integrated into mechanical systems without major design changes, as they are identical to conventional machine elements in terms of size and mechanical interfaces (Vorwerk-Handing et al., 2020).

Vorwerk-Handing et al. (2020) propose a further differentiation within the group of SMEs. Three types of SMEs can be distinguished. These include the sensor carrying machine elements (ScMEs), where the sensor element is carried by the machine element. Furthermore, the quantity of interest is independent of the mechanical function of the machine element. The temperature measuring screw at the bottom left in Figure 6 serves as an example here (cf., Vorwerk-Handing et al., 2020). In contrast, sensor integrating machine elements (SiMEs) measure quantities of interest that is directly dependent on the mechanical function of the machine element. An example, as included in the central bottom in Figure 6, is the condition monitoring of a timing belt with integrated sensors (cf., Großkurth and Martin, 2019). The third category is the sensor utilisable machine elements (SuMEs). A SuME does not contain a sensor in the classical sense. Instead, the conventional machine element provides the sensor function through its electrical properties. The sensor bearing at the bottom right in Figure 6 is an example for a SuME.

By measuring the bearing impedance, conclusions can be drawn about the bearing condition (cf., Schirra et al., 2018).

Figure 6 Classification of machine elements and differentiation of SMEs



Source: Following Vorwerk-Handing et al. (2020)

3 Examples of uncertainty in measurement in SME and off-process applications

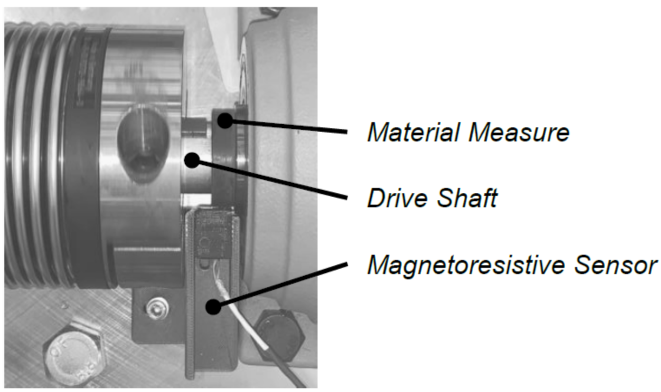
The following section gives examples of ex situ and in situ measurement. In particular, off-process sensors and the tree types of SMEs are considered. The main focus is on the measurement, present uncertainty and possibilities to manage it. The examples are intended to provide an insight and do not claim to be complete.

3.1 Uncertainty arising from off-process sensor applications

A widespread form of sensor applications is the off-process sensors. These are separate sensors which are additionally added into a technical system to detect a desired quantity of interest. Thereby, no sensor integration in the sense of SMEs takes place. Instead, the sensors are located outside of the process and observe the technical system from there. Due to the distance of the measurement location from the process and the associated high complexity of the underlying models, a vast number of disturbance variables can affect the quality of the measurement. Furthermore, a constructive integration of the sensors into the superordinate system is needed. This usually requires additional installation space. The advantage is a standardised use of sensors, including the calibration. In this case, the uncertainty in the sensors is generally well known. But that is only a part of the uncertainty of the complete measuring chain. The disturbance variables acting on the quantity of interest and on the measuring system as well as the uncertainty of the transfer model of the quantity of interest must be taken into account (Martin et al., 2018a).

An example for this type of integration is the condition monitoring of spur gears (cf., Randall, 2011). By magnetically examining a material measure with a fixed number of equal pitches applied to the shaft by a magnetoresistive sensor in relation to the measured angular speed, tooth damage, such as pitting, can be detected. Tooth damage manifests itself in a change in the measured angular speed between the individual pitches as the time required for the individual tooth meshes deviates from the ideal (cf., Martin et al., 2018b). This measurement configuration is shown in Figure 7. In the following, possible uncertainties arising in such an application are discussed.

Figure 7 Off-process magnetoresistive sensor for detecting tooth damage of a spur gear by measuring the angular speed of the output shaft outside the transmission



The integration described above usually requires design adoptions to the technical system and thus leads to an influenced system behaviour. In the example, the sensor has to be placed near the shaft and the material measure on the shaft. Furthermore, the measured angular speed as quantity of interest is influenced by the dynamic behaviour of the technical system. These influences lead to a difficult to describe epistemic uncertainty. A further uncertainty results from the complexity of the underlying model of the technical system due to the distance from the process. The flexibility of the shaft and other machine elements involved, such as bearings, can have an influence on the quantity of interest.

3.2 Uncertainty arising from ScME applications

The first type of SMEs, shown in Figure 6, is the so called ScMEs. In this type, the machine element carries an integrated sensor which, however, records a quantity of interest independent of the initial mechanical function of the conventional machine element. The screw with an integrated temperature sensor as shown in Figure 6 serves as an example here. The temperature sensor, however, works independently of the assembly and load condition of the screw. Besides the technical functionality of a screw, the ScME now also fulfils the additional function of temperature measurement with an integrated sensor element. Instead of measuring the temperature with an additional temperature sensor, it is now possible to measure the temperature directly at the screw tip. However, even with this approach, a number of uncertainties must be taken into account.

Despite the reduced measuring distance to the process, there may still be a distance to the actual location where the quantity of interest, the temperature, occurs. Uncertainty due to the distance to the place of origin of the quantity of interest can still not be excluded, however, ideally they are significantly reduced. Furthermore, in such a system, additional disturbance variables can act from outside or inside the system. For example, the temperature of the housing in which the screw is applied can have a thermal influence on the measured value and thus falsify the desired quantity of interest. Other uncertainties may also result from the energy and signal transfer paths. These are realised with a cable integrated into the screw. This transfer path can be affected by environmental disturbances, which distort the signal and lead to uncertainty.

3.3 Uncertainty arising from SiME applications

Another type of SMEs listed in Figure 6 is the SiMEs, where the sensor is integrated into the machine element and measures a quantity of interest, which is directly dependent on the mechanical functionality of the conventional machine element. The timing belt shown in Figure 6 is used as an example here. A timing belt transmits mechanical energy with a given transmission ratio. The timing belt acts like a string and therewith the pretension force can be measured indirectly through the string equation via the measured eigenfrequencies (Nagel, 2008).

To measure the eigenfrequency an accelerometer is integrated into a tooth of the timing belt (Großkurth and Martin, 2019). For a correct measurement of the acceleration, a correct positioning of the accelerometer is needed. A relative movement between the accelerometer and the timing belt could influence the measured quantity, so uncertainty according to the integration arises and has to be validated. Even though the acceleration can be measured directly, the eigenfrequency is overlapped by the tooth meshing frequency. The interaction between theses frequencies has to be taken into account as well as the distinction between the two. An exact knowledge of the machine element and the interaction during the process is needed to obtain a model, which allows a measurement of the eigenfrequencies. This example shows one of the main advantages of SMEs. Through an intelligent application, the quantities of interest can be measured in a practical way without constructive changes to the mechanical system. However, the uncertainty shifts from the mechanical system to the sensor system. It is necessary to describe the underlying models and the acting disturbance variables accurately.

3.4 Uncertainty arising from SuME applications

The third type of the classification presented in Figure 6 is the SuMEs. In these SMEs, the sensor function is fulfilled without an additional sensor element. The quantity of interest is obtained directly from the electrical characteristics of the conventional machine element. As an example, a rolling bearing as shown in Figure 6 is mentioned. From an electrotechnical point of view, a rolling bearing can be described as a capacitor (Prashad, 2006). Recent research is attempting, among other things, to analyse the load condition of a rolling bearing by appropriate impedance measurements (Schirra et al., 2018). Earlier research was targeting the representation of the rolling bearing in an electrical system model in order to understand the damaging effects of inverter induced currents on rolling bearings (cf., Prashad, 2006).

As the machine element is used as sensor itself, the main uncertainty arises according to the sensory effect. These effects have a high complexity and are subject to a vast amount of disturbance variables. Consequently, these effects are characterised by a high degree of uncertainty. The effects of these influencing factors have to be described to correctly measure the quantity of interest. However, through the use of the machine element as a sensor, even less structural changes to the mechanical system and the machine element, compared to a SiME, have to be made.

4 Potentials and challenges of in situ measurement and its corresponding uncertainty in a digital twin context

Based on the examples Section 3, the following discusses the potentials and challenges of using SMEs, especially in a digital twin context. SMEs use the standard interface of machine elements. Therefore, they can replace a conventional machine element in an existing system and add an additional measurement functionality. An exact understanding of the system and machine elements is necessary for using the SMEs and measures the quantity of interest, as there are various influencing factors, which must be considered in the underlying model. Furthermore, uncertainty due to effects still under research has to be taken into account. To evaluate these uncertainties, the UMEA described in Section 2.2 can be used.

The standardised design of machine elements leads to an easy application of SMEs with reduced epistemic uncertainty. However, the effect of the sensor integration and the structural changes necessary to a SME should be quantified to lower the uncertainty and ensure that the SME fulfils the requirements to the same extent as machine element. The scale factor of machine elements offers SME the potential for a vast application, if the sensor function can be standardised in the same manner as the mechanical function. The in situ measurement has the advantage of less energy conversions. Furthermore, less complex underlying models for the measurement of the quantity of interest can be used. Uncertainty, however, arises through the more complex or less known sensor effects in the machine elements and the disturbance variables acting on the sensor system. Furthermore, uncertainty is arising from the energy and signal paths, as environmental disturbances can distort the signal. Therefore, further research is needed to use SMEs in the same standardised manner as machine elements and take full advantage of the additional sensor function.

The use of embedded sensors, low-power wireless communication and efficient signal processing techniques opens the development of SMEs as well as digital twins (He et al., 2018). The basis for a working digital twin is raw data, which carries information about the physical object. The analysis of these data allows a representation of the physical object as a virtual object (Fuller et al., 2020). The monitoring of physical quantities, such as temperature and humidity, vibrations and noise, rotation speed, liquid leakage, etc., is important for practical industrial scenarios (He et al., 2018). With SMEs, the quantity of interest can be measured directly at its point of origin and with less influence of noise in comparison to a more complex transfer behaviour. For the recent topic of cyber-physical fusion, data acquisition has to be robust and applicable (Tao et al., 2019). The standardised use of machine elements ensures the mechanical functionality of

SMEs and the focus can be set on the sensory extension. This reduces the uncertainty compared to new developed systems. Through the standardised interface, it is possible to use existing mechanical systems for digital twin applications by the use of SMEs to generate the required data. Furthermore, the easy implementation into existing machines and the scale factors of machine elements can boost the development of digital twins as no new design and purchase of a reliable machine is needed (Czwick et al., 2020). Besides all these considerations, the uncertainties described in the previous paragraph must be taken into account, especially to the sensor principle of a SME, the disturbance variables acting on a SME and the quantities affecting the quantity of interest.

5 Conclusions and future works

This contribution reviews the state of the art of uncertainty in measurements as well as its identification, evaluation and consideration and derives from this a classification of measurement locations in mechanical systems. This allows a distinction between in situ and ex situ measurement locations. This distinction can assist in the selection, conceptualisation and design of sensor systems and the management of present uncertainty. The ex situ measuring locations are further subdivided into process-close, process-distinct and off-process measuring locations. Furthermore, the concept of SMEs is presented. This concept enables the integration of sensor functions directly into a machine element and thus as close as possible to the point of origin of the quantity of interest. In this way, a quantity of interest can be measured directly at its point of origin and completely new measurement concepts are made possible. Furthermore, the measurement uncertainty can be managed by reducing the complexity of the transfer path of the quantity of interest, if the uncertainty of the SME itself can be managed, as the uncertainty is transferred from the technical system to the SME. In Section 3, the present uncertainties in an off-process sensor application and in different SME applications are pointed out. On this basis, potentials and challenges for in situ measurements in general and in the context of digital twins in particular are presented.

This contribution addresses the mutual opportunity to enable mechanical systems for the use in Industry 4.0 applications and to feed digital twins with in situ acquired data. SMEs support the data acquisition for the digital twin through their in situ measurement of desired quantities of interest and open the opportunity for an accelerated development of digital twins due to their standardised design. As standard elements, they can be installed into a mechanical system without extensive modifications or influences on the system behaviour. Due to the enabling of in situ measurements, the quantity of interest can be measured directly at its point of origin. Future research is required to increase the amount of mature concepts of SMEs, to describe the structure integrated energy and signal transfer paths to and from SMEs and to utilise the received data for digital twins.

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