Presentation of a causal model of relevant failure patterns for the development of knowledge-based AI models using the example of machine tools

Vorstellung eines Kausalmodells relevanter Fehlerbilder zur Entwicklung wissensbasierter KI-Modelle am Beispiel von Werkzeugmaschinen

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Abstract

Prognostics and Health Management (PHM) is a key factor for the profitable integration of production machines into digitalised production systems. Condition monitoring, remote diagnosis and the early detection of critical deviations from the process window are required for a stable digitised value creation process, in order to be able to monitor them sufficiently early and in a differentiated automated manner. Strictly data-based approaches fall far short here, as essential information about technical interactions of the causal failure states cannot be taken into account or recorded when setting up condition monitoring and failure diagnosis. However, the implementation of a model-based approach requires detailed knowledge of the physical interactions of the failure mechanisms, which is often difficult to realise for reasons of complexity and expense.

The BMBF research project "ProKInect" is therefore pursuing a hybrid approach that is primarily based on expert knowledge and supported by service and field data. An essential component of this is a concept for creating probabilistic models of the failure causes and effects, from which approaches to fault diagnosis can be derived and their effectiveness evaluated. In the next step, these will be used specifically to set up a new type of condition monitoring employing distributed AI agents (algorithms) which receive defined condition information from components of different manufacturers and can evaluate patterns in the overall context. Using the example of a guided laser cutting system, a probabilistic causal model is created, which is based on expert knowledge of real-world failure modes, the relevant causes and the causal interactions. This is relevant for condition monitoring and enables, among other things, a differential diagnosis among a set of failure causes on the

basis of the recorded symptoms and additional information through evaluation by means of Bayesian networks. With the help of this model, critical paths that are relevant for machine availability can be identified and AI agents can be developed based on this.

1. Introduction

Machine tools are used in industry and craft to process or shape components used in all kinds of industrial sectors. These machines can be used to process various materials, such as metal or wood. There are many types of machine tools such as milling, turning or laser cutting machines. Over time, the degree of automation and networking of production processes has continuously increased. The maximization of the overall equipment efficiency (OEE), the reduction of waste and the optimization of quality are key factors for a profitable production process. To ensure these factors the machinery has to be maintained in certain intervals.

One strategy to maintain the systems is Reactive Maintenance (RM) [1]. It is used after a failure has occurred. Preventive Maintenance (PM) is used when maintenance is based on fixed time intervals depending on the machine's period of use. The maintenance strategy usually depends on many factors like the probability duration and costs of downtime. Due to the increasing complexity of production systems and the correspondingly complex maintenance of the machines, traditional methods (RM, PM) are reaching their limits and more advanced methods like Predictive Maintenance (PdM) and Prognostics and Health Management are needed. PdM accounts for the actual condition of the system and is based on the load. PHM is a fairly new discipline whose focus is on understanding failure modes, the associated precursors, degradation mechanisms and the prediction of Remaining Useful Life (RUL) of components and systems. Although these methods initially require greater effort and a high level of technological readiness, they enable early intervention before failure and extend the life of equipment, both of which result in a reduction of maintenance compared to RM and PM. PdM and PM are effective to a certain degree to reduce machine downtimes but neither one nor the other can take subtle failure causes into account like leakage [1]. A minimal leakage of lubricants can be so minimal that it is hardly detectable but can have serious consequences such as the machine coming to a standstill.

As described in the review paper of Baur et al [2] the PHM maintenance strategy can be divided into consecutive phases (preliminary analysis, monitoring, diagnostics, health assessment and prognostics). Before the essential part of the PHM, the condition assessment and prognosis, can be applied, a preliminary analysis is recommended. It should be determined how much downtime is caused by component failure and how often these failures occur to define the focus and scope of the analysis. In this phase the relevant components which can cause a failure are identified with methods like Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA) and Root Cause Analysis (RCA).

Based on the preliminary analysis it must be determined how the normal asset behaviour can be monitored and how an anomaly can be detected compared to the baseline. Tracing back the evidence of anomalies to the cause of the associated fault is an issue related to diagnostics. In the event of a machine failure, an attempt is made to recognise patterns associated with the faults based on training data. After performing diagnostics and identifying system faults, the health of the machines must be assessed.

Following the assessment of the systems health, prognostics can be carried out to predict the remaining useful life or the probability that the system will operate without a failure. To determine the RUL different models can be used such as a knowledge- or experience-based, model-based, statistics-based, data-driven and combined or hybrid prognostic approaches. The choice of the selected model depends on factors such as complexity and availability of data.

Knowledge-based or hybrid approaches make use of collected expert knowledge, which enables the implementation of tailored models, e.g., based on trainable knowledge graphs of the determined root causes and resulting effects. Accounting for the cause-and-effect chains by means of the underlying AI model structure, the systems can be potentially trained with less data than fully data-driven approaches such as deep neural networks. Furthermore, explainability of the AI model is significantly enhanced by implementing a model structure based on linguistic cause and effect chains as well as probabilistic or possibilistic metrics.

To map the cause-effect relationships of the failures quantitatively, a probabilistic approach was developed that extends the methodology of FMEA using Bayesian Networks (probFMEA). FMEA does not allow a quantitative evaluation and FTA does not allow a coherent holistic representation of complex systems. Therefore, a holistic concept for quantitative FMEA called probFMEA which can be modelled and solved based on Bayesian networks was proposed. Bayesian networks are used for this purpose, which provide the algebraic basis to allow for the quantitative assessment of reliability [3,4,5].

Bayesian networks can visualize knowledge about an uncertain domain and belong to the family of probabilistic graphical models and consist of directed acyclic graphs [6]. Random variables with at least two discrete states are represented by nodes in the graph. Dependencies between the related random variables are symbolized by edges. These conditional dependencies can be estimated using numerical and statistical methods. To express conditional probabilities of a single variable in dependency from others, Bayesian

Networks use Conditional Probability Tables (CPT). Bayesian Networks allow the probabilities of certain nodes in the network to change based on new evidence or observations. When new evidence is obtained, the probabilities of the relevant nodes in the network are updated using Bayes' Theorem to reflect the new information. Bayesian Networks are used, for example, in the field of artificial intelligence and diagnostics in healthcare [7].

This work presents the creation, challenges and benefits of a probabilistic FMEA for a maintenance approach using a laser cutting machine as an example. Therefore, a hybrid approach is chosen, using expert knowledge and data from different sources. The collected information is structured in an FMEA and transferred into a Bayesian Network. It is shown how this network can be used as a basis for PHM.

2. Identification of representative systems and components for analysis

For the ProKInect project, a 2D laser cutting machine was chosen as the machine to be investigated, which consists of various subsystems, assemblies, and components from different manufacturers. The machine can cut sheets of metal by moving its laser cutting head in three different spatial directions. The necessary torques are transmitted from the electric motors to the racks via a pinion, which is mounted on the gearbox. A sketch of such a machine is shown in Figure 1.

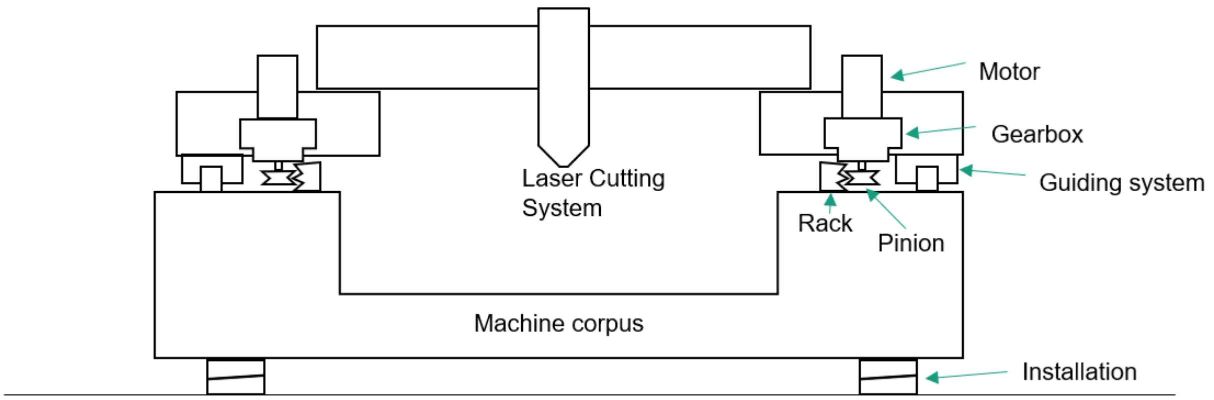

Figure 1: Sketch of laser cutting machine

To determine the scope of the reliability analysis the focus was put on failure modes which may lead to a failure of the system or expensive and lengthy service interventions, have a cross-component and cross-manufacturer effect, and can ideally be detected based on sensor technology. Optimally, the reasons for these failures can be eliminated early enough to prevent an undesired system state with the means of a preventive maintenance approach.

These faults are often not detectable by simple analytical methods or individual sensors but require deep system knowledge as basis for AI methods and cooperation of several data and information sources. To systematically examine the system for faults and their causes and consequences, the methodology of FMEA is applied to the machine. As a first step, it is useful to outline the structure of the system section to be examined. This means that the machine is broken down into its individual components in several detailing steps. Together with experts from different areas, such as development, data analysis and customer service, possible failures for each individual section and component were listed. An example of such a system structure can be found in Figure 2. In this example, the failures modes standstill and contour error are the main events that can occur at the top level. The causes are, for example, increased vibrations in the drive axle or a twisted machine body.

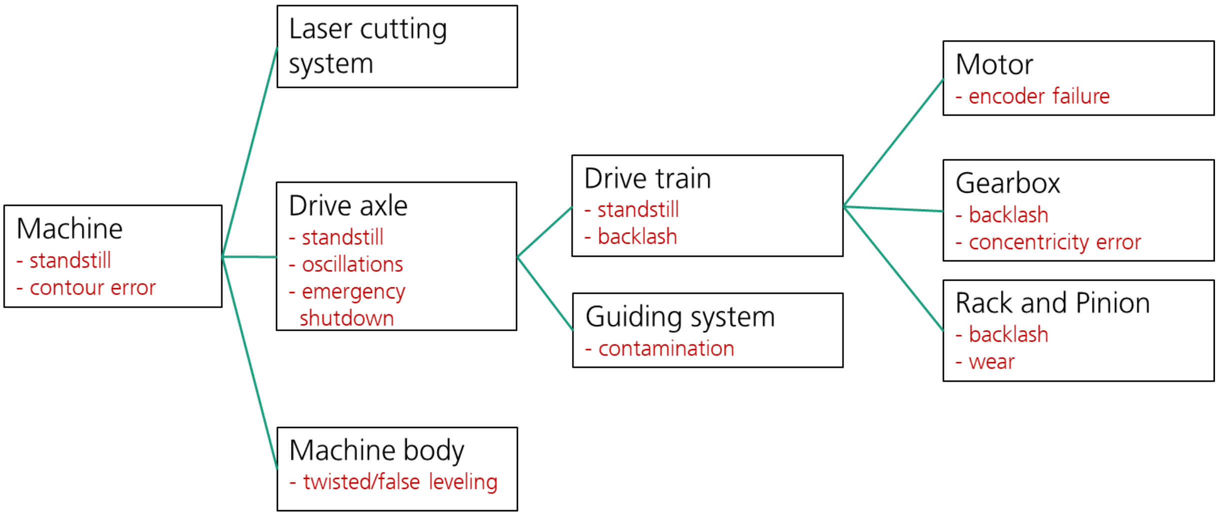

Figure 2: Exemplary system structure of the laser cutting machine with possible failure modes

3. Elaboration of the relevant failure patterns in the form of causal effect models of failure causes and consequences

In collaborative meetings, the causes and the consequences of these failure modes were identified. Based on the collaborative investigations, a failure network similar to an FMEA was created.

The databases from the service department provide a basis for selecting relevant failure patterns. From the documentation of service operations on the machine type to be investigated, the numbers of customer calls and the associated service work can first be determined. Depending on the level of detail of these service call documentations, critical machine areas or components can be identified.

In addition to the data-driven approach, a root cause analysis and interviews with the service department, which provide a subjective view of relevant failure patterns, were carried out. In addition to frequently occurring failures, conversations with service personnel also reveal the

issues that cause a significant amount of effort. These can be problems that are very challenging for the service employee or require a lot of time and perseverance.
Experts from the development department generally also deal with the fault diagnosis of machines. On the one hand, special cases are dealt with here, which require a deep understanding of the system. On the other hand, failure causes are also being investigated on the basis of extensive system understanding from the service data in order to adjust the product quality accordingly.
Based on these three sources of information, a probabilistic FMEA can be derived. It describes the possible effects of occurring component failure modes and possible failure propagation through the system sections of the machine.

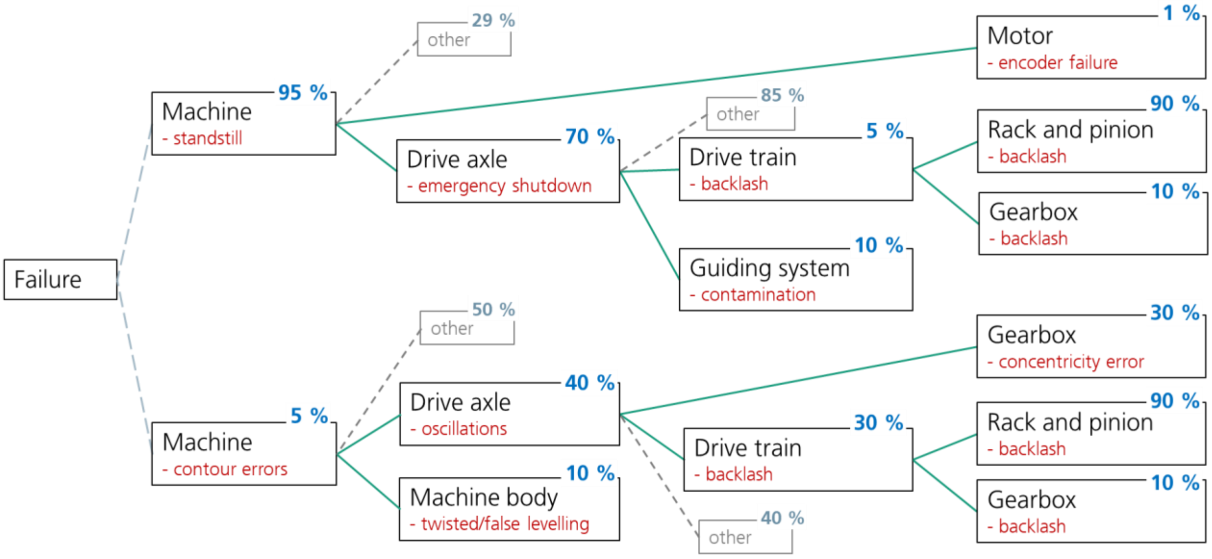

Figure 3: Simplified failure network of the laser cutting machine with failure modes “standstill” and “contour errors”

The failure network of the investigated machine section with the relative probabilities is shown in Figure 3. In the case of a cause that is not the focus of this work, the failure mode is referred to as *other*. In order to create a quantitative failure effect information in the model concerning the probability of occurrence of the individual failures and their causes must be obtained like it is shown in the figure.
Starting with the probabilities of the failure modes at the top system level, the failure probabilities were deduced from the top system level through the different levels to the internal and external causes. Various sources were used for the breakdown, e.g., the corresponding data from returns of components to the service department or from the documentation of service operations on the machine.
Three main challenges occurred during the determination of the relevant failure probabilities. For defect components, it is suspected that there is a large under-reporting of the number of

returns. In the event of a component failure, the corresponding part often is not being returned, as a straightforward replacement is often quicker and more economic than a reclamation. When a component fails out of warranty, a replacement part is often ordered from the component manufacturer without storing any information as to why that component has failed. Therefore, documented cases of failure and effect modes are scarce, leading to uncertainties in the estimation of failure probabilities and Mean-Time Between Failures (MTBF).

A similar challenge was, that the documentation of service operations on the machine are often not detailed enough or incomplete, which also leads to the uncertainties in the probability estimation. Another main challenge was, that the machine under investigation was quite new, and therefore for some failure sequences, there was either insufficient or no failure data to derive a failure probability. One way to counteract this problem was to use data from similar machines that experience similar loads.

To support the uncertain data basis, the use of expert knowledge of engineers from different departments is essential to determine a probability of a failure, or at least the order of magnitude. Figure 4 shows the steps to determine the MTBF and subsequently the failure probabilities.

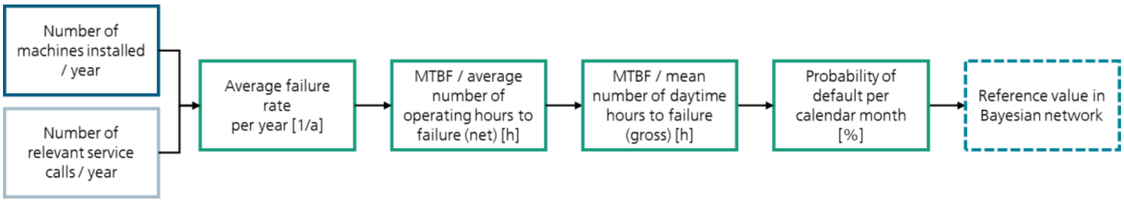

Figure 4: Determination of the MTBF and failure probabilities based on installed machines and related service calls

4. Conception of approaches for failure detection and prognosis based on associated symptoms

The resulting network of root causes, failure modes and effects including probabilities of individual failure states and transition probabilities between those states is subsequently transferred into a Bayesian Network as shown in Figure 5. The Bayesian Network was created with the GeNIe modeler and its underlying SMILE engine[1]. Bayesian Networks make it possible to clearly see the probabilities of occurrence of certain states at a glance with the help of an applications software with a graphical user interface. Causes of errors that were not considered in more detail here (*other causes*) have been highlighted in blue.

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[1] https://www.bayesfusion.com/smile/ - SMILE: Structural Modeling, Inference, and Learning Engine

A major challenge when converting a FMEA network into a Bayesian Network was the identification of a unique root cause for failure states at higher hierarchical levels.

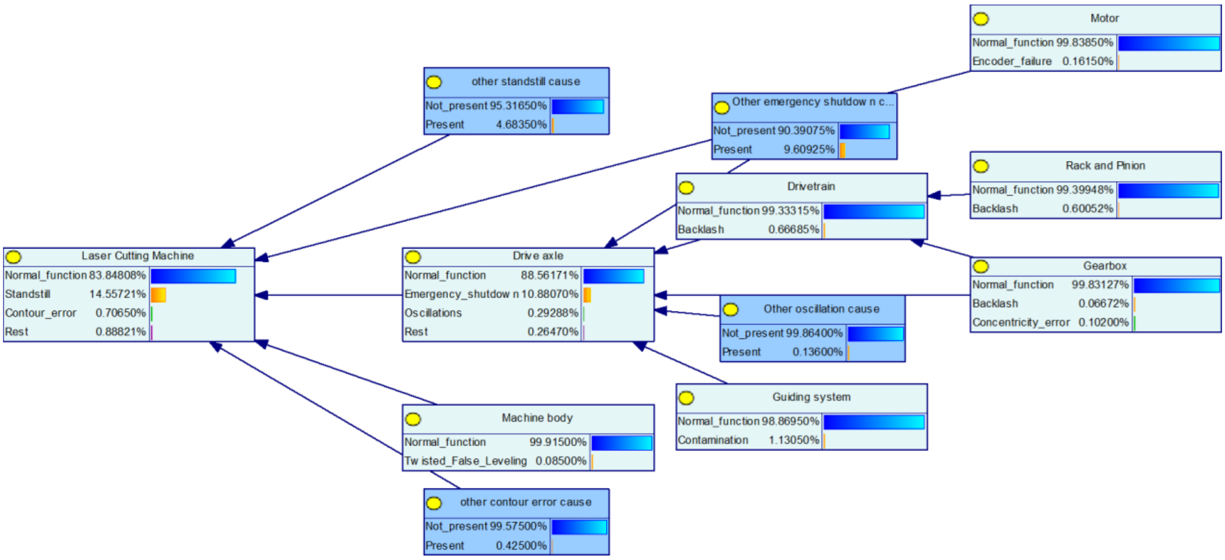

Figure 5: A probabilistic FMEA of the laser cutting machine based on a Bayesian network with Bayesfusion Genie ® (simplified excerpt)

In this case, the resulting tree was pruned by grouping various causes together. For this reason, a trade-off between complexity and simplicity was aimed for, so that the collected cause-effect relationships are still documented while the usability and comprehensibility are improved. In some places simplifications had to be made to transfer the failure network to a Bayesian Network, as can be seen in Figure 6.

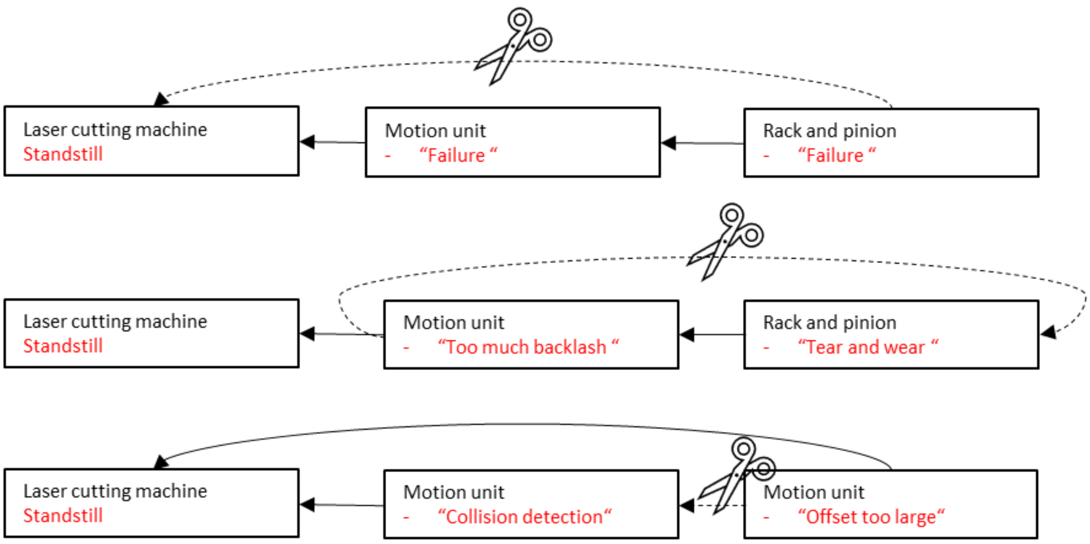

Figure 6: Simplifications for the adaption in a Bayesian network

Some failures have a direct effect on the system level as well as on specific assemblies or components. To simplify the connections and ensure traceability the link between these nodes was removed (see Figure 6 top). As circular connections are to be avoided in Bayesian networks but might be present for specific failure states the network has been adjusted in order to convert the network into a directed acyclic graph (see Figure 6 middle and bottom).

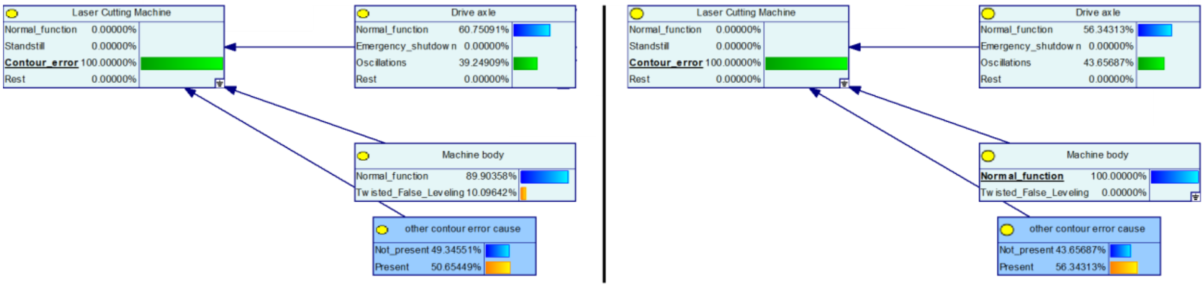

Figure 7: Differential diagnosis of machine failure “contour error” a) without exclusion of a specific cause b) with exclusion of the cause “machine body is twisted / falsely levelled”

Based on observed evidence certain states of the nodes can be changed. In Figure 7 a) the failure mode *machine standstill* has been set as *true* in the network and the causes for this state can be seen depending on the conditional probabilities that were entered in the Bayesian network. The state *contour error* can either be based on an observation of the real machine in use or purely hypothetical to gain a better understanding of the failure mechanisms of the machine. By ruling out certain causes - e.g., *machine body is twisted / falsely levelled* is not the cause of the fault - the actual cause can be narrowed down further and further, as shown in Figure 7 b).

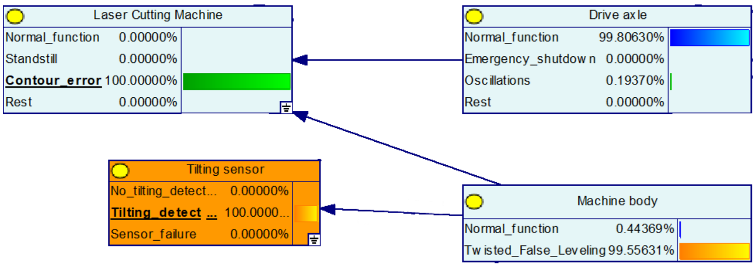

Figure 8: Simplified implementation of a monitoring solution in probFMEA in form of a tilting sensor

With the network, particularly critical paths can be identified or highlighted. Particularly critical are consequences that result in a machine standstill or mean quality losses in production for the machine user, which vary in severity depending on the application context. Using this knowledge about failure modes, effects and probabilities, characteristics can be identified that allow to monitor failure states on the root cause side of the failure network. These characteristics can be accessed using sensor data that is either already provided by machine components, such as motor speed, motor current or gearbox vibration, or can be obtained easily applying additional sensors. On the one hand, this can be done by using existing sensors e.g., from the motor and gearbox across manufacturers. On the other hand, the knowledge can be used to install new sensors in order to detect this condition at an early stage and to carry out appropriate countermeasures in terms of maintenance. As shown in Figure 8, a tilting sensor (marked in orange) can be installed physically to generate new evidence to rule out certain causes like *oscillations* from the *drive axle* and increase confidence in the most likely cause (*twisted machine body* or *false levelling*).

5. Summary and outlook

This work shows how a predictive maintenance approach can be designed that is suitable for connected, complex production machinery. This primarily knowledge-based approach is particularly suitable for use cases where there is little or insufficient data on failures and therefore a data-driven approach falls short. This hybrid approach makes it possible to develop a better understanding of the system and thus also a maintenance strategy that allows maintenance measures to be initiated at an early stage to keep the OEE of the system high. Based on the analysis, weak points of the system can be revealed and highlighted along a critical path by means of the Bayesian network. In addition, differential diagnostics can be carried out to detect and exclude certain causes of failures.

To provide evidence for the Bayesian Network, either features of existing sensors can be used or new sensors can be placed at relevant locations based on the finding of the reliability analysis.

As a future step, the networks could be updated automatically with the collected service data and be adapted to different application scenarios and machine types. In order to enable inexperienced users to operate and interpret the networks, work is ongoing to improve user-friendliness and operability in such a way that it is used, for example, on site by a service technician to determine the cause of a system failure intuitively.

For the ongoing state diagnosis, hybrid AI models will be developed in the further course of this project, which are based on the network structures obtained from the probabilistic causal models and which may have the trainability and performance of artificial neural networks while accounting for the increased demand in semantic interoperability and AI explainability at the same time [8].

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