Presentation of a causal model of failure patterns for the development of knowledge-based AI models

S. Kupjetz [(1)], W. Zenn [(2)], S. Röding [(3)]

Introduction and fundamentals

Machine tools are used in industry and trade to process components that are used in various sectors. There are various types of machines such as milling, turning or laser cutting machines. Automation and networking in production has increased, whereby increasing overall equipment effectiveness (OEE), reducing waste and optimising quality are crucial for a profitable production process. This requires regular maintenance of the machinery.

There are various maintenance strategies such as Reactive Maintenance (RM), which is carried out after a failure, and Preventive Maintenance (PM), which is carried out at fixed time intervals based on the machine's service life. Traditional methods are reaching their limits due to the increasing complexity of production systems, and more advanced methods such as Predictive Maintenance (PdM) and Prognostics and Health Management (PHM) are needed. PdM considers the actual condition of the equipment and is based on load, while PHM focuses on understanding failure modes, precursors, degradation mechanisms and predicting remaining useful life. Although these methods initially require more effort and technological maturity, they enable early intervention before failures and extend equipment life, resulting in reduced maintenance compared to RM and PM.

The PHM strategy comprises several phases: preliminary analysis, monitoring, diagnostics, health assessment and prognostics. Preliminary analysis, in which relevant components are identified, is followed by monitoring of normal operating behaviour and anomaly detection. Diagnostics is concerned with tracing anomalies back to their causes. After the diagnosis and identification of system faults, the health of the machines is assessed, followed by prognostics to predict the remaining service life. There are different models for prognostics, with knowledge-based or hybrid approaches using expert knowledge to implement customised models that, due to their structure, can potentially be trained with less data than purely data-driven approaches.

A probabilistic approach has been developed for the quantitative mapping of cause-and-effect relationships in the event of failures, which extends the FMEA methodology using Bayesian networks (probFMEA)[1,2]. Bayesian networks provide an algebraic basis for visualising and evaluating complex systems holistically. They are a type of probabilistic graphical model and consist of directed acyclic graphs in which random variables are represented by nodes and dependencies between them are represented by edges. Conditional probability tables (CPTs) can be used to express the dependencies of individual variables as a function of others. Bayesian networks update the probabilities of nodes based on new observations using Bayes' theorem. They are used in areas such as artificial intelligence and diagnostics in healthcare.

The whitepaper describes the creation, challenges, and advantages of a probabilistic FMEA using the example of a laser cutting machine. A hybrid approach is chosen that combines expert knowledge and

---

[1]Fraunhofer-Institut für Betriebsfestigkeit und Systemzuverlässigkeit LBF, Darmstadt

[2] TRUMPF Werkzeugmaschinen SE + Co. KG, Ditzingen

[3] WITTENSTEIN SE, Igersheim

data from various sources, structures them in an FMEA and transfers them into a Bayesian network that serves as the basis for PHM.

Identification of representative systems and components for analysis

In the ProKInect project, a 2D laser cutting machine consisting of various subsystems, assemblies and components from different manufacturers was selected as the object of investigation (see Figure 1). This machine can cut metal sheets by moving the laser cutting head in three spatial directions. The required torques are transmitted to the racks by electric motors via a pinion mounted on the gearbox.

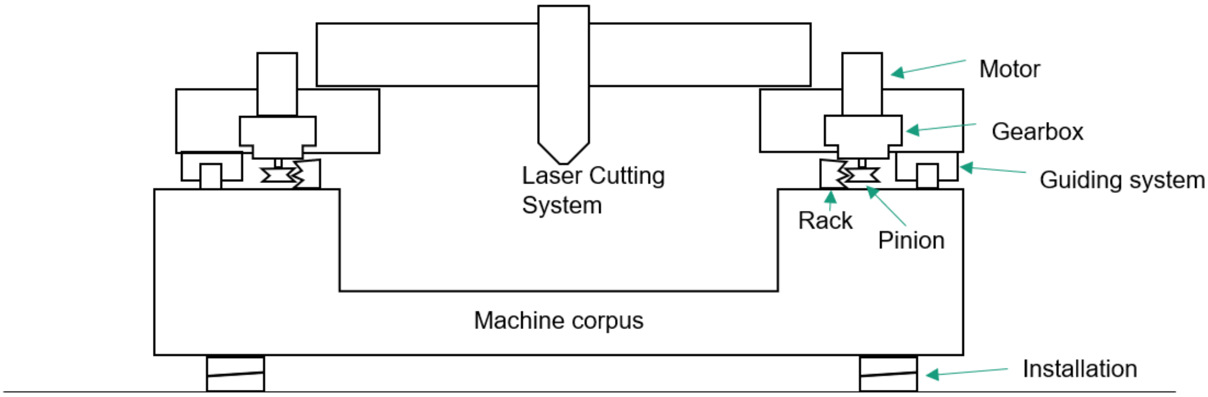

Figure 1: Drawing of the 2D laser cutting machine

For the reliability analysis, the focus was on failure modes that can lead to system failure or costly and lengthy service calls, have an impact across multiple components and manufacturers, and can ideally be detected with sensors. These failures are often not detectable by simple analytical methods or individual sensors but require in-depth system knowledge as a basis for AI methods and the collaboration of multiple data and information sources. The FMEA methodology is used to systematically analyse the system for failures and their causes and effects. The machine is first broken down into its individual components (see Figure 2). Together with experts from different areas, possible failures are listed for each section and each component. For example, the main events could be a machine standstill or contour errors caused by problems such as increased vibrations in the drive axle or a warped machine body.

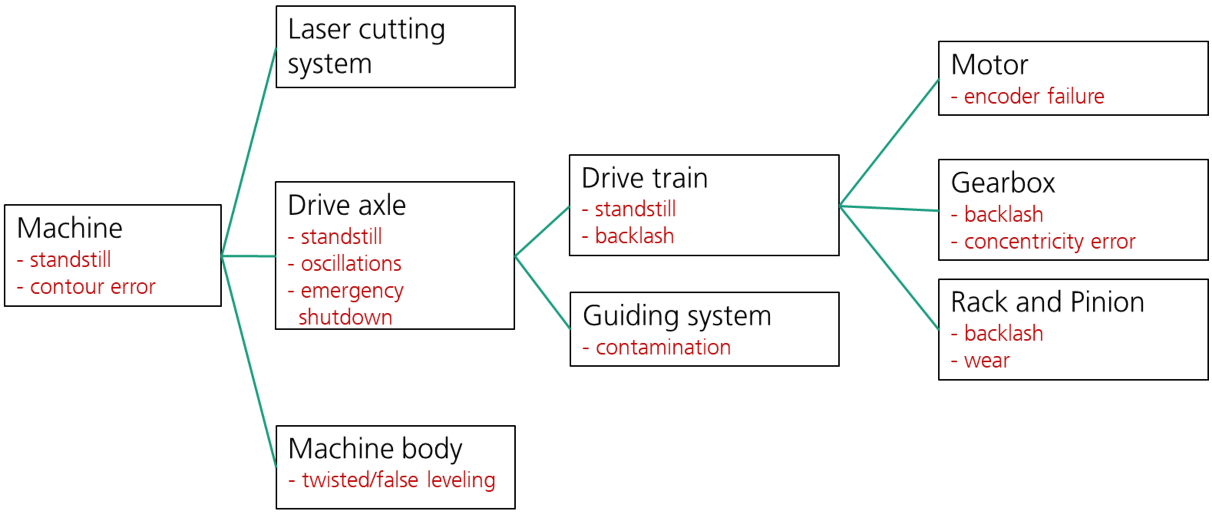

Figure 2: System structure of the 2D laser cutting machine with relevant failure modes

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

The causes and consequences of failure modes were identified in collaborative meetings and a failure network similar to an FMEA was created. Databases from the service department provided the basis for selecting relevant failure patterns. The documentation of service calls was used to determine the number of customer calls and the associated service work and to identify critical machine areas or components. In addition to data-driven approaches, root cause analyses and interviews with service personnel were also conducted to gain a subjective view of relevant failure patterns and identify challenging or time-consuming problems. Development department experts also dealt with failure diagnosis and analysed causes of failure to adjust product quality.

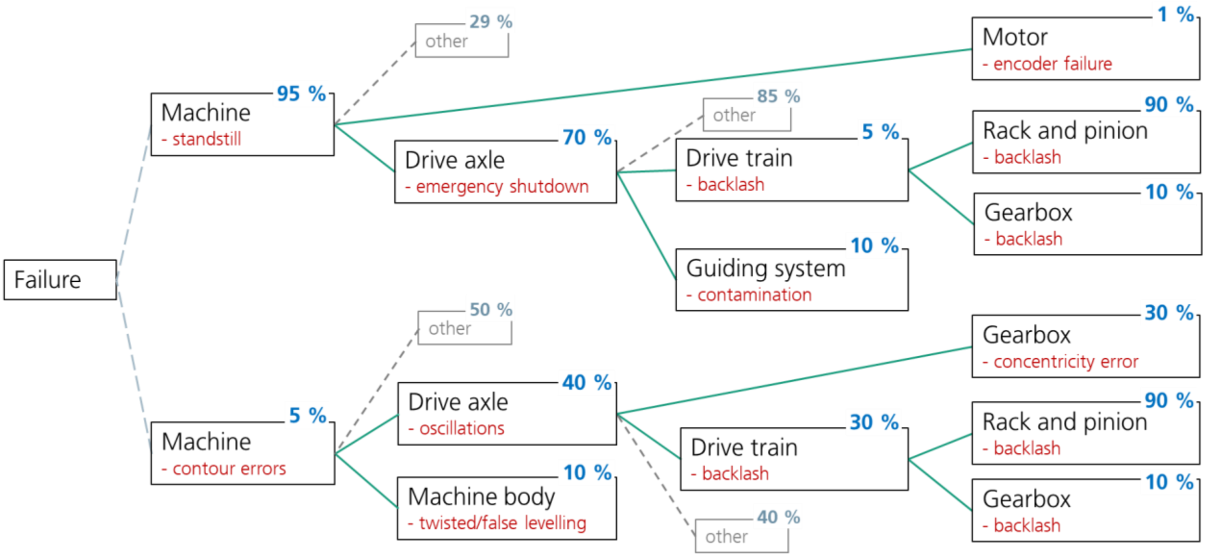

Figure 3: Probabilistic failure network of the 2D laser cutting machine

Based on this information, a probabilistic FMEA was derived that describes the possible effects of component failures and their propagation in the system. The failure network structure of the machine was created with relative probabilities and a quantitative assessment of the failures and their causes (see Figure 3). E.g., if the state machine standstill is present, the probability that it comes from the drive axle (emergency shutdown) is 70 %, from motor (encoder failure) 1 % and from other causes 29 %. The sum of these causes is 100 %. Starting from the higher-level failure modes, the probabilities were derived through the system levels to internal and external causes, using data such as returns to the service area or service call documentation. Three main problems arose when determining the relevant failure probabilities. Firstly, there is a suspicion of a high number of unreported cases of defective components, as a simple replacement is often quicker and more economical than a complaint. Secondly, components that fail outside the warranty period are often replaced without recording the cause of failure, which leads to insufficient data on failure and effect modes. Thirdly, the service logs are often not detailed enough or incomplete, which also leads to uncertainties in the estimation of failure probabilities and the mean time between failures (MTBF). The procedure for determining the MTBF is shown in Figure 4. In the case of the relatively new machine analysed, there was also a lack of sufficient failure data to derive a failure probability. One solution was to utilise data from similar machines. To support the uncertain database, the expert knowledge of engineers from various departments was crucial to determine a failure probability or at least its order of magnitude.

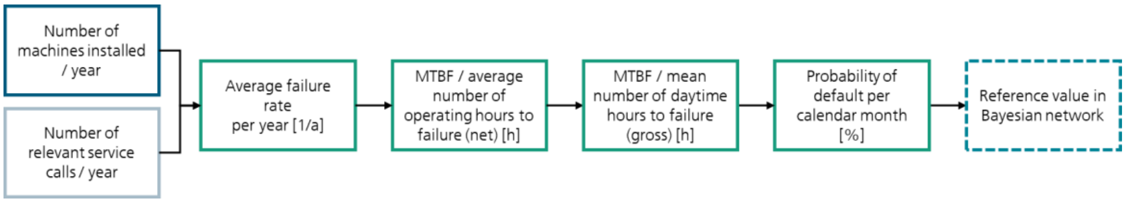

Figure 4: Estimation of the mean time between failures (MTBF) and the probabilities in the Bayesian Network

Conception of approaches for fault detection and prognosis on the basis of accompanying symptoms

The resulting network of causes, failure modes and their effects, including the probabilities of occurrence of individual failure states and conditional probabilities between these states, was converted into a Bayesian network (see Figure 5), which was created using the GeNIe Modeler software and its SMILE engine[4]. Bayesian networks make it possible to quickly and clearly manipulate the probabilities of certain states occurring. Failure causes that were not considered in detail (other causes) were highlighted in blue in the network.

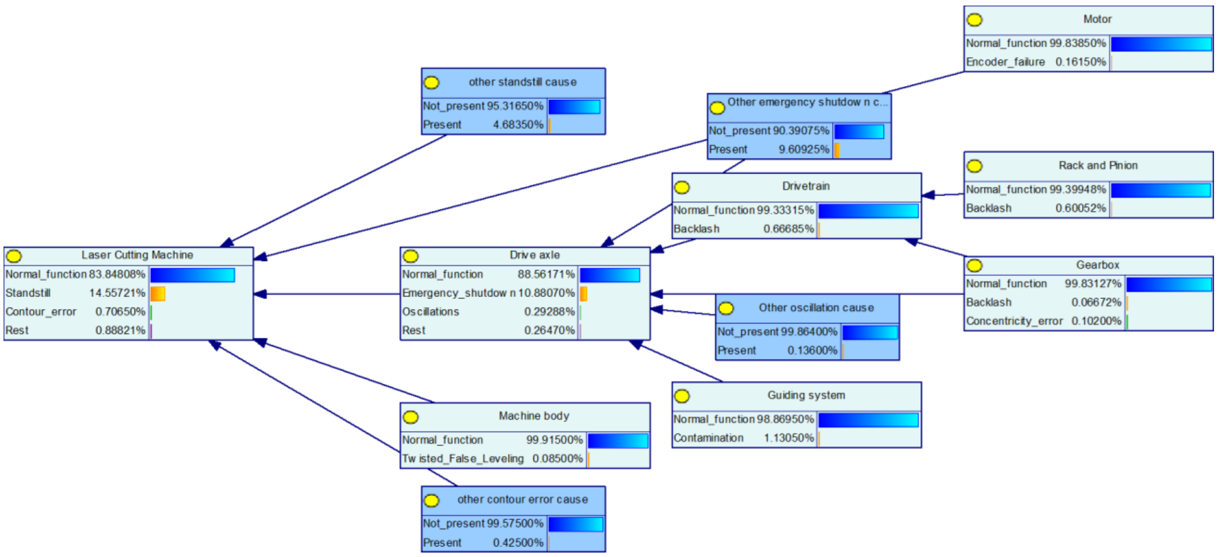

Figure 5: Probabilistic Bayesian failure network

A major challenge in converting an FMEA network into a Bayesian network was the identification of clear causes for failure conditions at higher hierarchical levels. To overcome this challenge, various causes were summarised in order to achieve a compromise between complexity and simplicity. As a result, the cause-and-effect relationships remain documented while usability and comprehensibility are improved. Simplifications had to be made to transform the failure network into a Bayesian network,

[4] GeNIe Modeler from Bayesfusion LLC, https://www.bayesfusion.com/genie/

removing direct connections and adapting the network to a directed acyclic graph to avoid circular connections (see Figure 6).

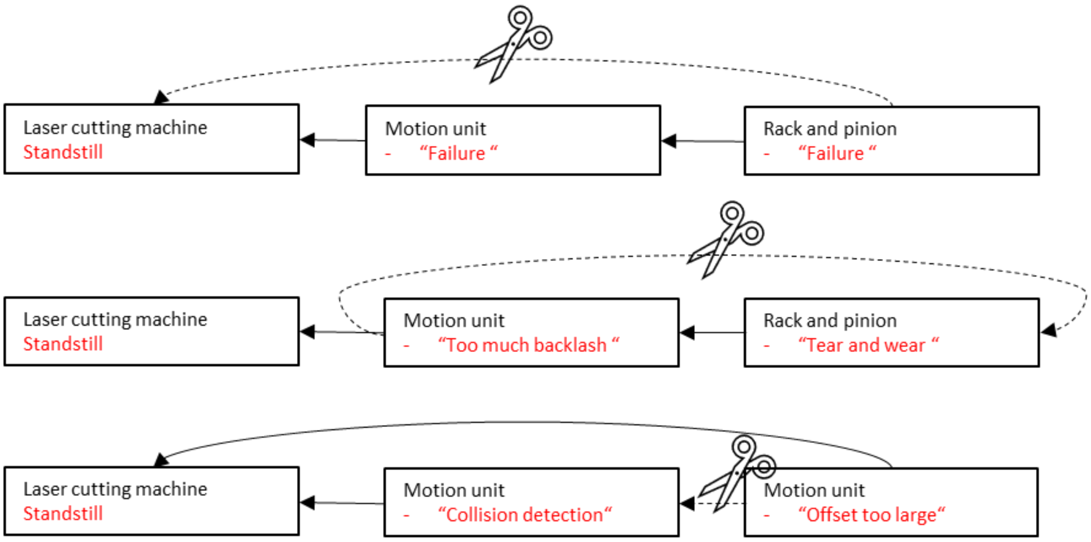

Figure 6: Simplification of cause and effect chains

Based on observed evidence, states of the nodes in a Bayesian network can be changed. For example, setting the failure mode "machine standstill" as "true" can indicate the causes for this state, depending on the conditional probabilities stored in the network (see Figure 7). The "contour error" state can be based on real observations or hypothetical considerations to improve understanding of the failure mechanisms. By excluding certain causes, the actual causes of errors can be narrowed down further and further.

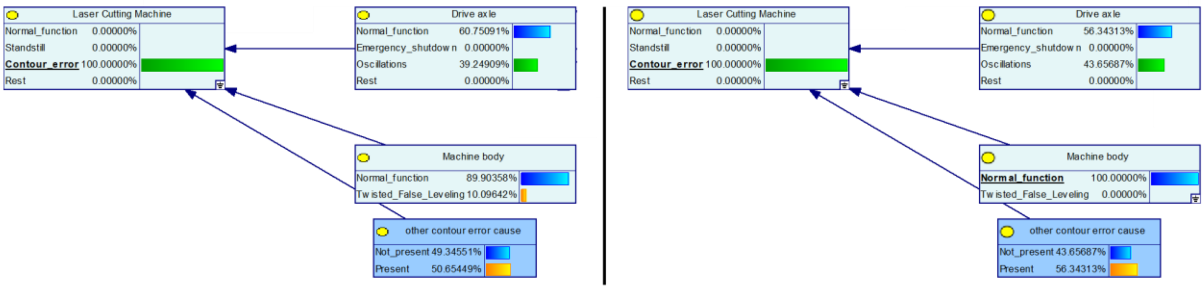

Figure 7: Differential diagnosis with Bayesian Networks – Laser cutting machine with contour error without any additional evidence (left) and negative evidence for titled machine body (right)

The network makes it possible to identify particularly critical paths that could lead to machine downtime or quality losses in production, for example. With the knowledge of failure modes, effects and probabilities, characteristics can be recognised that allow failure states to be monitored on the cause side.

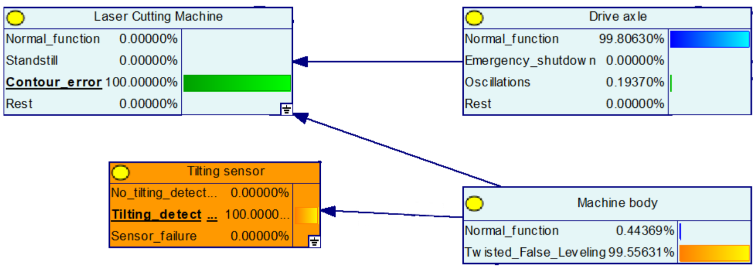

Figure 8: Implementation of sensor input - Laser cutting machine with contour error and detected tilting

These characteristics can be detected by means of sensors, either by existing sensors such as motor and gearbox sensors or by additional sensors. One example of this is the installation of an inclination sensor to rule out certain causes such as vibrations from the drive axle and increase the probability of the actual cause (twisted machine body or incorrect alignment) – see Figure 8.

Summary and outlook

This work shows how a predictive maintenance approach can be designed for networked, complex production machines. This primarily knowledge-based approach is particularly suitable for use cases with little or insufficient failure data, where a purely data-driven approach is not sufficient. The hybrid approach enables a better understanding of the system and therefore a maintenance strategy that initiates early maintenance measures to maintain a high overall equipment effectiveness (OEE). Weak points in the system can be identified using a Bayesian network and highlighted using a critical path. In addition, differentiated diagnostics make it possible to recognise and rule out certain causes of faults.

For the Bayesian network, either features of existing sensors can be used or new sensors can be placed at relevant locations based on the reliability analysis. In the future, the networks could be automatically updated with collected service data and adapted to different application scenarios and machine types. In order to enable even inexperienced users to operate and interpret the networks, work is being done on user-friendliness and operability so that, for example, a service technician on site can intuitively determine the cause of a system failure.

In the further course of the project, hybrid AI models were developed that are based on the network structures obtained from the probabilistic causal models and at the same time offer the trainability and performance of artificial neural networks while meeting the increased requirements for semantic interoperability and explainability of AI.

Information: This whitepaper is based on the publication “Presentation of a causal model of relevant failure patterns for the development of knowledge-based AI models using the example of machine tools” which was presented at the “Tagung Technische Zuverlässigkeit” in Nürtingen in 2023 [3].

Funding: This research and development project is funded by the German Federal Ministry of Education and Research (BMBF) within the “The Future of Value Creation – Research on Production, Services and Work” program (project ProKInect - funding number 02P20A090) and managed by the Project Management Agency Karlsruhe (PTKA). The author is responsible for the content of this publication.

SPONSORED BY THE

Federal Ministry
of Education
and Research

References

[1] Kaiser, B.; Rauschenbach, M. (2015): Probabilistic extension of failure net based FMEA. In: Proceedings of the 25th European Safety and Reliability Conference, ESREL 2015, Zürich, Switzerland, 7-10 September 2015. Boca Raton, London, New York: CRC Press Taylor & Francis Group a Balkema book, pp. 1359–1366.

[2] Rauschenbach, Matthias (2017): Probabilistische Grundlage zur Darstellung integraler Mehrzustands-Fehlermodelle komplexer technischer Systeme. Technische Universität, Darmstadt. Available online at http://tuprints.ulb.tu-darmstadt.de/6920/.

[3] Kupjetz, S.; Zenn, W.; Röding, S. (2023): Presentation of a causal model of relevant failure patterns for the development of knowledge-based AI models using the example of machine tools. In: Technische Zuverlässigkeit 2023: VDI Verlag https://doi.org/10.51202/9783181024096 / https://doi.org/10.24406/publica-1792