Contributions to an FMEA/FMSA Based Methodology to Improve Data Quality of Cyber Physical Production Systems Through Digitalisation: a Use Case Approach

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***Abstract*—The increasing digitalisation of machinery enhances production facilities by laying the foundations for advanced data analysis. To ensure effectiveness, it is essential that the collected data is of the highest quality for optimal use in various applications. The quality of data is subject to a variety of influences. This includes the design and operation of data acquisition for production systems. The implementation of Failure Mode and Effect Analysis (FMEA) and/or Failure Mode and Symptom Analysis (FMSA) has been proven to be challenging due to the time-consuming and labour-intensive nature of the process. In addition, the results can vary depending on the knowledge and expertise of the team performing the analysis. To address these challenges, a methodology based on the FMEA/FMSA framework is developed using historical and operational data. Consequently, the assessments made during FMEA/FMSA became objective, eliminating reliance on the expertise and background of the team conducting the evaluation. To illustrate the feasibility of our approach, we utilise the case study of an intelligent machine test bed. From Art to Science: Our contribution advocates for a paradigm shift in FMEA/FMSA frameworks, moving from more or less subjectively designed individualistic concepts towards objectively established, harmonised solutions.**

***Keywords*-FMEA; FMSA; Data-driven FMEA; Failure analysis; Sensor data quality; Sensor data error detection.**

I. INTRODUCTION

This section examines the motivation, challenges, aims, research questions and contributions of this study. The objective of our study was to improve the quality of Cyber Physical Production Systems (CCPSs) data through digitalisation by implementing a methodology based on Failure Mode and Effect Analysis (FMEA) and/or Failure Mode and Symptom Analysis (FMSA). CPPSs are comprised of self-governing and collaborative components and subsystems. These elements are interconnected based on contextual factors, spanning all production levels. The integration extends from individual processes and machinery to comprehensive production and logistics networks [1]. The FMEA/FMSA methodology has historically been challenging to implement owing to the labour-intensive and time-consuming nature of the process. Furthermore, outcomes may vary depending on the level of expertise and experience of the team performing the analysis. To address these challenges, a technique that involves examining historical and present-day production information has been developed. This approach was confirmed using an experimental apparatus by selecting suitable sensors and data assessment methods to forecast and recognise malfunctions.

An Internet of Things (IoT) application may have hundreds or thousands of sensors that produce vast amounts of data, but these data are rendered useless if the quality of the sensor data is poor. In this study, the term sensor refers to a physical sensor that measures the changes in physical quantity, e.g., temperature, humidity, and light intensity of the sample or surroundings. Poor data quality may lead to incorrect decision making results. Sensor data quality plays a vital role in IoT applications as they are rendered useless if the data quality is bad [2]. The IoT describes the network of physical objects—“things”—that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet. These devices range from ordinary household objects to sophisticated industrial tools [3].

A. Motivation

The ongoing digitalisation of machinery is enhancing production facilities, laying the groundwork for advanced data analysis. To fully leverage this potential, it is crucial that the data collected are of sufficient quality to be effectively utilised for various purposes. Therefore, the careful selection of appropriate sensors for specific applications is crucial. This study proposes a methodology for the Artificial Intelligence (AI)-compatible digitalisation of CCPSs, aimed at empowering companies to independently modernise their existing equipment or implement digital technologies in new machinery.

B. Challenges

Although FMEA is a useful and established technique, it can present certain challenges in failure analysis. This process can be labour-intensive and time-consuming, particularly when applied to intricate or extensive systems or products. Moreover, outcomes may vary based on the knowledge and background of the team members involved, leading to potential inconsistencies and subjectivity. There is also a risk of incompleteness or inaccuracy if certain failure modes or effects are not recognised or underestimated, or if the underlying assumptions or data are incorrect or outdated. Finally, the effectiveness of FMEA may be diminished if the recommended actions are not properly executed or if the analysis is not regularly updated to reflect current conditions [4] [5].

Additionally, many organisations have developed their own methods for assessing failure risk; therefore the standards may be employed as a starting point with added individualised adaptations. Consequently, while FMEAs remain one of the most used techniques for failure and risk assessment, the manner in which they are conducted remains highly diverse. In contrast, other reliability and quality techniques, such as Reliability Prediction (RP), Reliability Block Diagram (RBD), and Fault Tree Analysis (FTA), have defined structures and remain fairly consistent applications. FMEAs are more fluid in terms of their implementation and structure.

C. Aim

Many organisations face significant challenges due to unforeseen equipment failures, which often result in considerable production delays and unplanned costs. As companies embrace Industry 4.0 and enhance the digital capabilities of their manufacturing sites, there is a concurrent increase in the integration of sensors within machinery. These sensors are designed to collect vital operational metrics and relay them for further examination. The aim is therefore to implement a scientifically grounded, data-driven objective approach for managing the FMEA/FMSA methodologies.

D. Contribution

We propose enhancements to a methodology based on FMEA/FMSA to improve the data quality of CCPSs. To demonstrate the concept's viability, a case study was conducted using a test platform at the Dresden Technical University. The fundamental concept involves enhancing the FMEA/FMSA methodology through a data-driven approach.

This aims to identify FMEA/FMSA components objectively, reducing dependence on the assessment team's expertise. The efficacy of this method in determining the likelihood of "failure occurrence" has been previously validated through the application of deep learning techniques to historical and operational data in the aviation industry [6]. Our methodology expands the data-driven approach to encompass other elements of FMEA/FMSA, establishing a comprehensive data-driven framework to promote a fundamental transformation in the manufacturing industry's methodology. In contrast to Blancke's [7] stochastic technique, which calculates probabilities even with limited data, our the data-driven approach relies on historical and operational data collected during the utilisation phase.

Our research illustrated that objective methods can be developed to determine the elements of FMEA/FMSA. When examining a specific scenario, it is crucial to choose appropriate sensors that provide the required data. Subsequently, suitable algorithms must be devised to enable failure detection, prognosis, and an unambiguous diagnosis. The case study focused on "pitting" and "inadequate lubrication" as examples of failure scenarios, employing appropriate sensors to formulate strategies for detection, diagnosis, and prognosis.

E. Paper organisation

The structure of this paper is outlined as follows. An overview of relevant existing research pertaining to the described problem is provided in Section II. A detailed description of the strategy is presented in Section III, whereas Section IV demonstrates the feasibility of this strategy through an example. The presentation of the main results and discussions based on these results constitute the content of Section V. Finally, Section VI summarises this contribution and draws perspectives for future work.

In summary, our work proposes a fundamental change in approach, moving away from subjectively crafted individual concepts in the application of the FMEA/FMSA frameworks. Instead, we advocate the adoption of objectively established, harmonised strategies. To illustrate our concept, a case study of a test platform is established, and the validity of our methodology is demonstrated through two distinct failure scenarios. The challenges associated with our approach lie in the appropriate selection of sensors to provide the necessary data and development of suitable data-processing algorithms.

II. Related work

This section primarily examines the current advancements and relevant research regarding data-driven FMEA/FMSA methodologies, including similar approaches such as fuzzy logic, while also introducing the fundamental concept behind these systems.

The methodology of Failure Modes and Effects Analysis (FMEA) was first established within the United States military in the 1940s. It is a methodical approach for the identification of all potential failures within a given design, manufacturing, assembly process, product or service. This technique is widely recognised as a common tool for process analysis.

Filz [6] introduced a data-driven FMEA approach that utilises Deep Learning (DL) models on historical and operational data from industrial investment goods during the use phase. The proposed methodology aims to enhance transparency and provide decision support for the maintenance and planning of these goods. The framework is validated through a case study in the aviation sector, demonstrating a fault prediction accuracy of approximately 95%. By incorporating these findings into a data-driven FMEA framework, the assessment of risk and failure occurrence becomes objective, rather than subjective. Notably, the estimation of failure probabilities does not rely solely on employees' experience and knowledge. Instead, data analytics tools are employed to forecast component-specific failure probabilities, using historical and operational data as a knowledge source. These outcomes are then integrated into an FMEA methodology, enabling dynamic risk evaluation of individual components and higher-level modules [6].

The study [8] establishes a methodology to enhance failure analysis by incorporating data-driven approaches to complement traditional techniques like FMEA. Specifically, Association Rule Mining (ARM) is employed to identify correlations between failure modes and their associated characteristics that tend to occur simultaneously. Subsequently, Social Network Analysis (SNA) is utilised to visualise and examine these relationships. The primary contribution of this research lies in its support for maintenance management, which combines conventional failure analysis with a data-driven strategy. The proposed framework is demonstrated through a real-world case study involving a hydroelectric power plant.

Blancke [7] introduces a comprehensive approach to multi-failure mode prognosis that employs graph theory and stochastic models to address the intricacies of failure mechanisms as a system. Through the utilisation of Prognostic and Health Management (PHM) and Physics-of-Failure (PoF) technologies, the likelihood of failure mode occurrences can be dynamically assessed, even when historical data is limited. These approaches concentrate on equipment degradation processes and aim to model failure mechanisms based on physical principles, utilising existing predictive techniques.

Nevertheless, existing FMSA lacks the capability to evaluate the efficacy of crucial technical specifications necessary for predictive maintenance, such as detection methods (their ability and scope), diagnostic procedures (identifying fault type, position, and intensity), or prognostic capabilities (accuracy and forecasting range). Nordal [9] introduces an innovative Predictive Maintenance (PM) evaluation framework to address these shortcomings. This framework incorporates priority indices that facilitate the comparison of detection, diagnosis, and prognosis techniques' efficiency using qualitative descriptions alongside quantitative values.

Similar to FMECA and FMEA, FMSA suffers from certain limitations, yielding potentially skewed outcomes and inherent uncertainties in its development. These issues stem from its algorithmic structure and reliance on expert-based knowledge inputs. To address these shortcomings, Murad [10] introduces a fuzzy logic application as a supplementary tool for FMSA, aiming to diminish the impact of such uncertainties. The methodology is illustrated through a practical case study involving a Kaplan turbine shaft system. The study compares the monitoring priority number (MPN) derived from FMSA with the fuzzy monitoring priority number (FMPN) obtained through the application of fuzzy logic. This comparison demonstrates how the proposed approach enhances the assessment of detection and monitoring techniques and strategies.

In conclusion, the data-driven FMEA approach remains understudied to the best of our knowledge, only Filz [6] addressed the topic by handling the component "occurrence" of FMEA through a use case from the aviation industry. Our approach extends the data-driven strategy to the other components of FMEA/FMSA by setting up a generalised data-driven strategy to facilitate a fundamental shift in the manufacturing sector's approach. Unlike the stochastic approach of Blancke [7], which can determine probabilities from scarce data, the data-driven method relies on historical and operational information gathered during the usage phase. This transformation entails moving away from the traditionally employed subjective, individualised concepts in FMEA/FMSA frameworks towards more objective, standardised solutions. This transition represents a significant evolution in addressing critical analytical methodologies.

III. Strategy

In this section, we explicitly delineate the focus of the underlying investigation and provide a concise overview of the motivations and objectives of this study. Furthermore, we outline a strategy that can be employed to achieve these goals. This is in relation to the detailed use case study presented in Section IV.

The term "failure modes" is used to denote the various potential ways in which a system or component may malfunction. Failures encompass any errors or defects, particularly those affecting customers, and can be either potential or actual. The subsequent analysis of such failures is termed "effects analysis", the aim of which is to ascertain the ramifications of these malfunctions. The severity of consequences, frequency of occurrence, and ease with which failures can be identified are the three factors on which failures are to be ranked. FMEA aims to implement measures to eliminate or mitigate failures, beginning with those with the highest priority. FMEA also serves to record existing knowledge and actions concerning failure risks, aiding continuous improvement efforts. In the context of design, the FMEA is employed to avert potential failures. Subsequently, it is utilised for control purposes, both prior to and during ongoing process operations. Ideally, FMEA commences during the earliest conceptual stages of design and continues throughout the entire lifecycle of the product or service [11].

The initial stage of the FMEA methodology involves identifying all conceivable failure modes within a product or process. Subsequently, the potential origins and consequent effects of these prospective failures must be ascertained. The next step involves evaluating the risk level associated with each failure mode, using predetermined criteria. Finally, methods must be devised to detect, reduce, or avert failures with the aim of aligning the product or process with overarching quality and risk objectives.

The Risk Priority Number (RPN) yields a quantitative outcome, offering a straightforward approach to assessing risk: elevated RPN figures signify increased risk levels. This facilitates the creation of risk management protocols for organisations. For example, a company might establish a policy prohibiting the release of products with RPNs exceeding a specified limit. Consequently, RPN enables uncomplicated risk evaluation and contributes to the formulation of risk-reduction strategies.

The measure RPN is calculated using the following three components:

- Severity (Sev): Indicates the gravity of potential consequences should an issue arise. A higher value denotes increased severity.

- Occurrence (Occ): Reflects the likelihood of an issue arising. To determine the frequency of occurrence, all potential causes of failure and their probabilities must be considered. A higher number indicates an increased risk of occurrence.
- Detection (Det): This signifies how challenging it is to identify an issue. A higher score suggests that an issue is less likely to be spotted by engineers during product development testing or by customers after release. Hence, a higher value implies a lower probability of failure detection.

RPN is computed by multiplying the severity, occurrence, and detection, as defined in Equation 1. Utilising a scale of 1 to 10 for each factor results in RPN values ranging from 1 to 1000 [12].

$$RPN := Sev \cdot Occ \cdot Det. \tag{1}$$

The following is a concise overview of the stages involved in the FMEA procedure [13]:

a) Identify a process for analysis: Select a procedure known to be troublesome in your establishment or one that is commonly problematic across various facilities.
b) Establish a charter and appoint a team facilitator and members: The leadership should provide a project charter to initiate the team. Leadership assigns the facilitator, whilst team members are individuals directly involved in the process under scrutiny.
c) Outline the process: Clearly delineate the process steps to ensure all team members comprehend what is being examined.
d) Determine potential issues at each process stage: This is where those directly involved in the process describe problems that may or do arise.
e) Prioritise problems for resolution: Improvement efforts will concentrate on issues that occur frequently and/or significantly impact user safety, even if infrequent.
f) Formulate and implement modifications to mitigate or prevent problems: The team decides on the most effective process alterations to reduce the risk of harm to residents.
g) Assess the efficacy of process modifications: As with all improvement initiatives, the impact of the implemented changes is evaluated.

Additionally, the FMEA process involves creating a team of professionals with expertise across different domains. The expert team establishes Key Performance Indicators (KPIs) for potential failure modes based on the scope of FMEA. These KPIs can serve as the foundation for subsequent maintenance activities, as the methodology revolves around these failure modes. This framework offers valuable guidance for implementing a data-driven FMEA in any maintenance-related enterprise. The outcomes can be utilised to manage resources, such as workforce or replacement components, and to support decision-making in the implementation of specific maintenance tasks, including servicing, inspections, or repairs [6].

The FMEA's methodological approach involves the determination of three risk factors by chosen team members. As a result, the information in the FMEA is frequently ambiguous or uncertain. Moreover, the FMEA is carried out by "experts", which introduces elements of subjectivity and incompleteness. Furthermore, the FMEA team determines the values for severity, occurrence, and detection based on their expertise and empirical knowledge [14].

The objective of FMSA is to choose monitoring technologies and approaches that optimise the confidence in diagnosing and prognosticating any given failure mode [15]. This methodology is essentially a modified version of FMECA [16] [17] and an expanded form of FMEA, concentrating on the indicators produced by each identified failure mode and the subsequent selection of the most suitable detection and monitoring techniques and strategies.

The DIN 13379-1 standards [15] [18] advises conducting the FMSA utilising existing FMEA/FMECA [16] [17] process findings, enabling prior fault identification and evaluation. This approach enhances the subsequent assessment's speed and accuracy. The FMSA's primary components involve enumerating symptoms for each abnormal condition type, along with appropriate monitoring methods and estimated frequencies. Subsequently, categorisation occurs using four metrics which, akin to the FMEA's RPN, establish the Monitoring Priority Number (MPN). Similar to FMEA, scores ranging from 1 to 5 are allocated for predefined categories. The standard provides detailed specifications and descriptions of the assessment scales.

The evaluation process commences with the Detection assessment (Det), which characterises the overall recognisability of a fault condition. Subsequently, the failure severity (Sev) is evaluated based on its associated risk, with the rating scale uniquely capped at four. Finally, the anticipated accuracy of Prognosis (Pgn) and Diagnosis (Dgn) is appraised. The ultimate classification for each malfunction type is derived from these four distinct assessments and defined in Equation 2.

$$MPN := Det \cdot Sev \cdot Pgn \cdot Dgn. \tag{2}$$

A high value for MPN is indicative of the efficacy of a procedure for the detection, diagnosis and prognosis of a defect type. Conversely, a low value for MPN does not imply that a malfunction need not be monitored; rather, it suggests that the chosen monitoring method and frequency may yield a low confidence level. As new insights are gained or system modifications occur, reassessment should be undertaken.

The principle that a lower value for MPN corresponds to reduced confidence in detection, diagnosis and prognosis using the chosen technique and monitoring frequency was maintained. However, the original severity scale (1 to 4), unlike the scales for other factors (all 1 to 5), was retained, adhering to the recommendation in ISO standard 13379-1 [18]. Consequently, the expected accuracy for Diagnosis (Dgn) is assessed on a scale from 1 to 5, where 1 indicates the least favourable outcome and 5 denotes the most favourable. This rating system seeks to identify failure modes characterised by detectable but non-reproducible symptoms, as well as those that are unknown or indistinguishable from symptoms of other failure modes.

Given that various companies' use cases rely on distinct datasets, there is no universal set of algorithm parameters that optimally suits all scenarios. Consequently, this framework introduces a generalised approach applicable to diverse use cases, aimed at enhancing the model's precision. A primary objective of the data-driven FMEA framework is to forecast failure probabilities. This task utilises processed operational data from the monitored components and sections of the technical equipment. As the parameters and data types can vary significantly, the selection of the data analytics model is heavily influenced by these characteristics.

The incorporation of operational data from the examined systems enhances automation, reducing subjectivity and reliance on experience. This enables even novice staff to identify and evaluate failure modes, as well as efficiently plan required maintenance tasks with greater precision. Furthermore, utilising operational data improves the comparability of FMEA/FMSA outcomes and enhances the precision of strategies and measures implemented.

To summarise, the data-driven methodology initially employs the conventional FMEA/FMSA technique, which involves identifying all potential failure modes within a product or process and calculating priority numbers. As historical and operational data accumulate, this method is further enhanced. Consequently, the priority figures are adjusted, providing a more accurate and impartial representation of the analytical procedure. The proposed data-driven methodology advocates a paradigm shift in the manufacturing sector, transitioning from subjectively designed individualistic concepts traditionally employed in addressing FMEA/FMSA frameworks towards objectively established, harmonised solutions.

IV. USE CASE

This section illustrates the practicality of the proposed solution concept as described in Section III. To demonstrate this, the concept has been implemented in the "Intelligent Machine Bed" case study from the chair "Machine Tools Development and Adaptive Controls" at Technische Universität Dresden in Germany (see Figure 2 for a picture of the machine bed and Figure 3 for the representation of the IT concept behind it). Additionally, see [19] for a survey regarding digitisation workflow for data mining in production technology applied to a feed axis of a CNC milling machine. The increasing digitisation of Cyber Physical Production Systems (CCPSs) aims to establish a foundation for AI, encompassing data mining and predictive data analytics. The initial objective of the case study was to analyse the system, determine the necessary data sources, measurement points, and sensors to be chosen, assessed, and incorporated into the machine's IT infrastructure based on a specific analysis question and its associated requirements.

The selection of data sources, measurement points, and sensors must be guided by specific analysis questions and their associated requirements. The study included the following steps:

- System analysis focusing on characterisation of all relevant influencing and disruptive factors, along with their impact patterns,
- Identification of appropriate measurement parameters and specifications (e.g., measurement scope, sampling frequency, etc.),
- Formulating of an experimental protocol incorporating variations in influential and disruptive factors,
- Investigating and choosing various sensor categories and types,
- Development and implementation of a framework for data collection, storage, and visualisation for the chosen data sources (including interfaces, protocols, database systems, and IT infrastructure),
- Assessment of the strategy's efficacy for certain data sources and measurement locations and evaluation of its appropriateness for detecting and analysing the intended patterns and their quality.

Figure 1. Pitting damage to a ball rolling element at LWM.

The FMEA standards typically include widely adopted scales for Severity, Occurrence, and Detection. Whilst the terminology of the following example is tailored to automotive applications, it can be readily adapted for use in other industries [12]. To illustrate this example, please find No. 4 entry below:

- the severity rating scale is "Appearance or Audible Noise, vehicle operable, item does not conform and noticed by most customers (> 75%)",
- the occurrence rating scale is "Isolated failures associated with similar design or in design simulation and testing"

TABLE I. DIAGRAM PRESENTING AN OVERVIEW OF THE SOLUTION CONCEPT WITH HIGHEST PRIORITISED FAILURE CASES ACCORDING TO FMEA.

		Possible failure effects							
System	**Failure type**	**Local effect**	**Final effect**	**Severity**	**Possible cause of failure**	**Failure mechanism**	**Occurrence**	**Detection**	**RPN**
Guide rail	Pitting	Poorer running behaviour, Loss of accuracy, Abrasion	Significant reduction in service life, failure	8	Excessive continuous load	Material fatigue	4	4	128
Guide rail	Installation error	Higher displacement forces depending on the slide position	Reduction in service life	4	Design errors, Assembly errors	Additional tensioning, Friction	5	8	160
Guide carriage	Inadequate lubrication	Higher displacement forces, Increased friction	Wear of the rolling elements	7	Maintenance errors, Damages	Insufficient maintenance intervals	5	5	175
Guide carriage	Pitting	Poorer running behaviour, Loss of accuracy	Significant reduction in service life, Failure	8	Excessive continuous load	Material fatigue	5	4	160

TABLE II. DIAGRAM PRESENTING AN OVERVIEW OF THE SOLUTION CONCEPT. FAILURES WITH THE HIGHEST FMSA MPN.

		Possible failure effects					
System	**Failure type**	**Failure symptoms**	**Failure effect**	**Failure description**	**Detection**	**Diagnosis**	**MPN**
Guide rail	Pitting	Vibration	Vibration excitation, Higher amplitude	Certain damage rollover frequency when travelling over the damage	5	4	20
Guide rail	Pitting	Optical changes	Change in image information	Material breakouts are visually recognisable as part of image recognition due to changes in the raceway	5	4	20
Guide rail	Installation error	Motor current	Higher motor current depending on the carriage position	An installation error results in additional tension, which causes a higher displacement force	3	4	12
Guide carriage	Inadequate lubrication	Motor current	Continuously increased motor current	Insufficient lubrication leads to an increase in the coefficient of friction μ_R over the entire rail	3	4	12
Guide carriage	Inadequate lubrication	Vibration	Vibration excitation	Excitations due to the contact of roughness peaks of the rolling partners, due to the lack of lubricant	3	4	12
Guide carriage	Inadequate lubrication	Ohmic resistance	Reduction in ohmic resistance	There is a change in the resistance between the carriage and the profile rail	3	5	15
Guide carriage	Pitting	Vibration	Damage rollover frequency, Higher amplitude	Certain damage rollover frequency when travelling over the damage during rail and carriage contact	4	4	16

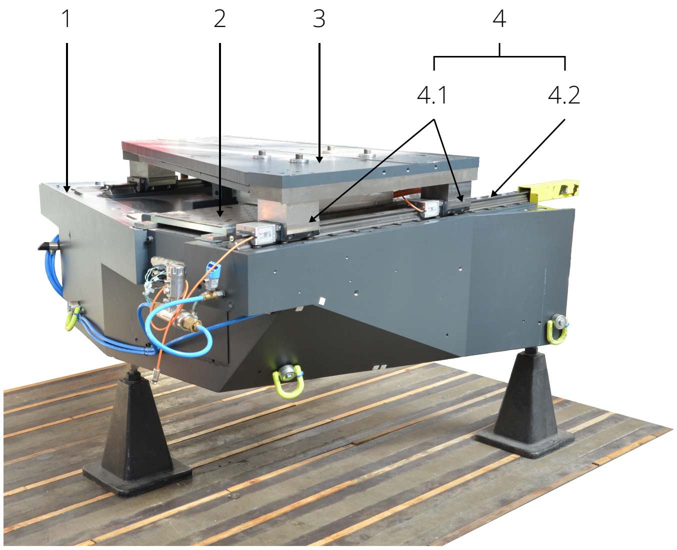

Figure 2. “Intelligent Machine Bed” test stand.

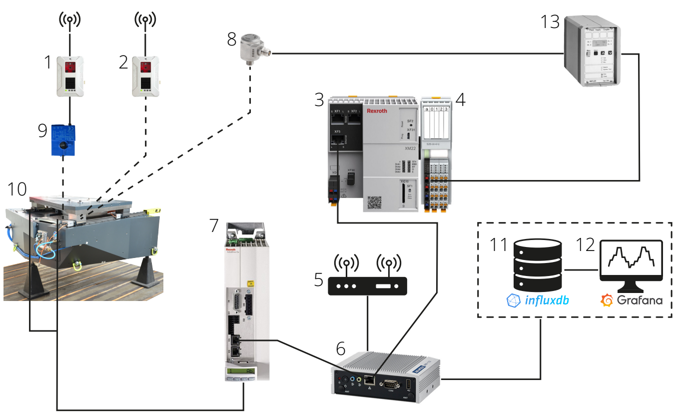

Figure 3. IT concept of the “Intelligent Machine Bed” test stand.

and

- the detection rating scale is “Product validation (reliability testing, development or validation tests) prior to design freeze using test to failure (e.g., until leaks, yields, cracks).”

a) Severity:
   8: Downtime more than 4 hours. Scrap more than one part. No safety issues.
   7: Downtime 2 to 4 hours. Scrap one part lost. No safety issues.
   4: Downtime less than 30 minutes. No scrap, very minor rework. Operator fix required. No safety issues.

b) Occurrence:
   5: One failure per month.
   4: One failure every 3 months.

c) Detection:
   8: Remote chance that the design controls will detect a potential cause and subsequent failure mode, or equipment control will provide an indicator of an imminent failure.
   5: Moderate chance the design controls will detect a potential cause and subsequent failure mode, or equipment control will will prevent an imminent failure (stop machine) and isolate cause.
   4: Moderate high chance the Design controls will detect a potential cause and subsequent failure mode and may require equipment controls.

For further details and explanations please see [20].

Consequently, it is crucial to identify appropriate sensors, and thus, the corresponding failure detection algorithm for each specific failure scenario. Within this use case, a methodology for the data mining-compatible digitisation of CCPSs is developed, enabling companies to independently upgrade existing machinery or digitise new equipment. By examining the resulting effect pattern descriptions, this study establishes measurement technology requirements and determines suitable sensors and their optimal placement, and thus, the corresponding failure detection algorithm for each specific failure scenario. Following the integration of sensor technology into the machine’s IT infrastructure, an experimental validation was conducted for individual data sources and measurement locations. The results demonstrate that, using this method, an appropriate sensor and corresponding failure detection algorithm can be identified for each examined failure condition.

The fundamental configuration of the “Intelligent Machine Bed”, (see Figure 2) comprises a machine bed (1) and table (3), along with a synchronous linear motor (2) serving as the propulsion system. Two roller profile rail guides (4) regulate the translatory motion, each consisting of two guide rails (4.2) with a pair of guide carriages (4.1). The rails are positioned horizontally on the machine bed.

To provide a more comprehensive understanding, Figure 3 illustrates a schematic overview of the IT concept, incorporating the required sensors. The "intelligent machine bed" (10) houses a control cabinet containing an analogue input module, which is linked to the analogue acceleration sensor (8) via the signal conditioner (13). The input module converts the incoming analogue signals into digital format before transmitting them to the controller. Following this process, the data packets are transmitted to the Node- RED server on the edge computer (6) using Ethernet and User Datagram Protocol (UDP). Node-RED is a visual programming tool that incorporates JavaScript functionality. It enables the connection of various input, output and processing nodes through flows, facilitating the management and supervision of IoT applications.

One of the universal programmable sensor device and prototyping Bosch XDK platforms (1) is linked to the current clamp (9). The second Bosch XDK platform (2), designed for vibration detection, is firmly attached to the measurement location, ensuring the integrated acceleration sensor is positioned precisely where the vibration is to be measured. Both sensor platforms transmit their internally digitised data via WiFi and UDP, utilising distinct ports, to a WiFi router (5). From there, the information is relayed through an Ethernet connection to the edge computer's server. The data from the trainer's drive controller (7) is directly accessed via Ethernet and stored on the Node-RED server. Subsequently, Node-RED transmits all incoming data packets to a database (11) where they are stored. InfluxDB, a database management system specifically designed for time series data, is employed. Various input, output, and processing nodes are linked together to create flows, enabling the control and monitoring of IoT use cases. Finally, the measurement data from the database is transferred to Grafana (12), which enables the graphical visualization of the data.

To establish a dependable foundation for future failure prediction, that is, to have a reliable database for predicting failure scenarios, additional research on anticipated effect patterns is essential to determine sensor technology specifications. The following section provides a more detailed examination of the expected error patterns for the chosen combinations of measured variables and symptoms utilising both quantitative and qualitative characteristics. This analysis is based on Table II, with the objective of achieving an initial categorisation to aid in selecting the appropriate measurement technology.

To enhance comprehension, the cause-effect relationships of failure cases are illustrated using the cause-and-effect principle, as depicted in Table II. This principle, which traces the cause identified in the FMEA to the selected measured variable from the FMSA, allows for bidirectional inference between the cause and measurable variables (cf. [21, p. 77]). As an extension of the cause-and-effect principle, information about the dependencies of the measurand is provided in the form of the influencing variables. These are intended to serve as a guide for subsequent tests, offering potentially adjustable parameters for future experiments on the "Intelligent Machine Bed".

The principle that a lower MPN corresponds to reduced confidence in detection, diagnosis and prognosis using the chosen technique and monitoring frequency is maintained. However, the original severity scale (1 to 4), unlike the scales for other factors (all 1 to 5), was retained, adhering to the recommendation in ISO standard 13379-1 [18].

For example, the anticipated accuracy for Diagnosis (Dgn) was evaluated on a scale of 1 to 5, with 1 representing the least favourable outcome and 5 the most favourable outcome. This rating system aims to identify failure modes with symptoms that are detectable, but not reproducible, unknown, or indistinguishable from the symptoms of other failure modes. The criteria for the diagnosis rating are outlined as follows:

(1) There is a remote likelihood that this failure mode diagnosis will be accurate;
(2) There is a low likelihood that this failure mode diagnosis will be accurate;
(3) There is a moderate likelihood that this failure mode diagnosis will be accurate;
(4) There is a high likelihood that this failure mode diagnosis will be accurate; and
(5) It is virtually certain that this failure mode diagnosis will be accurate [10] [18].

Diverging from the standard, only two key figures were considered in this study as potential performance indicators. This deviation is due to two factors: firstly, the Severity (Sev) from the FMEA should not be reassessed, and secondly, the Prognosis (Pgn) does not contribute additional value to the assessment. Instead, the focus is on evaluating the probability of detection (Det) and the Diagnostic capability/symptom visibility (Dgn). These two factors combine to form the MPN. In detail, MPN will be calculated as given in Eq. 3.

$$MPN = Det * Dgn. \tag{3}$$

The assessment of monitorability using the MPN is conducted qualitatively through estimation, similar to FMEA's risk priority number. A high MPN indicates a relevant measurand with good monitoring ability. Table II displays the potential measured variables with the highest MPN values for the "intelligent machine bed". Despite high MPN values, certain measured variables may not be feasible owing to structural limitations of the test bed. In such cases, alternative measured variables with the next highest MPN were selected for further analysis. When MPN values are equal, both measured variables are considered in subsequent evaluations.

Implementing the optical detection of pitting errors for the profile rail would have necessitated the redesigning of the existing IT concept, which is beyond the scope of this study, see Figure 1 for a picture of a pitting damage to a ball rolling element. Moreover, optical measurement technology is impractical for detecting defective changes in real-world applications because the cooling lubricant used during the machining processes can obscure damage or interfere with optical measurements. Furthermore, the detection of inadequate lubrication through alterations in ohmic resistance is not a viable option due to the fact that the machine bed is not engineered to withstand electrotechnical influences, such as fault currents from the linear motor. Consequently, the vibration measurement was selected as the primary measured variable for both pitting cases. For instances of inadequate lubrication and installation faults, the alterations in motor current were designated as the measured variables.

To enhance comprehension, the cause-effect relationships of failure cases are illustrated using the cause-and-effect principle, as depicted in Table II. This principle, which traces the cause identified in the FMEA to the selected measured variable from the FMSA, allows for bidirectional inference between the cause and measurable variables, see [21, p. 77]. As an extension of the cause-and-effect principle, information about the dependencies of the measurand is provided in the form of the influencing variables. These are intended to serve as a guide for subsequent tests, offering potential adjustable parameters for future experiments on the "Intelligent Machine Bed".

Vibration excitation occurs when the roller profile guideway lacks adequate lubrication. This occurs due to metallic contact between roughness bumps on the rolling surfaces, which are typically separated by a lubricating film (refer to chapter 2.2.1). These contacts generate vibrations at approximately 104 Hz. Additionally, insufficient lubrication diminishes the damping effect, see [22, p. 44, 55, 102]. The resulting vibrations were manifested as high-frequency broadband components in the acceleration signals detected by the vibration sensors. The amplitude of these vibrations correlates with travelling speeds, intensifying as speed increases, see [22, p. 102, 120].

Insufficient lubrication also alters the coefficient of friction μ_R, which leads to increased friction. This results in a greater friction force, which, similar to the parallelism deviation, causes higher displacement forces, see [22, Eq. 4.2]. Consequently, an increase in the motor current, see [22, Eq. 4.4]. However, Klein's research indicates that meaningful measurements of motor current changes can only be obtained at travelling speeds of 40 m/min or higher, see [22, p. 123]. Unlike assembly errors, inadequate lubrication causes a consistent percentage increase in the motor current along the entire guide rail length, rather than a position-dependent increase. Figure 4.7 of [22] illustrates the cause-effect principle for insufficient lubrication on both measured variables. As per Equation 4.2 of [22], the influencing factors include traversing speed, the load creating the normal force, and the friction coefficient itself. Similar to other error states, a combination of additional errors can also act as an influencing variable.

Control unit drive signals were utilised for diagnostics in drive-based data acquisition. The commonly recorded variables include control signals for the drive, such as currents, positions, accelerations and speeds, along with the corresponding setpoint signals of the control system, see [21, p. 33]. For the failures examined by Walther, see [21, p. 85], the motor current signal varies with the drive-torque, resulting in an increase in its mean value as the drive-torque increases. Consequently, this method is appropriate for diagnosing failures that influence friction, thereby increasing the drive torque, see [21, p. 57].

In conclusion, to demonstrate the practicality of our methodology, we employed a case study involving the "Intelligent Machine Bed" from the "Machine Tools Development and Adaptive Controls" chair, at TU Dresden in Germany. This use case centred on "pitting" and "inadequate lubrication" as practical examples of failure scenarios, utilising appropriate sensors to develop compliant strategies for detection, severity, prognosis, and diagnosis.

V. Outline of the Results

In the following, the results are outlined, the advantages and disadvantages of the proposed solution are discussed and some of the areas in which it is applicable are given.

This study involved developing a method for data-mining-compatible digitalisation of CCPSs for an analytical use case. A system analysis was conducted on the 'intelligent machine bed' trainer by employing adapted versions of FMEA, FMSA, and effect pattern analysis. Structural analysis of the FMEA revealed that the guide carriage and rail had the highest error potential for the trainer, leading to their selection for further examination. Subsequently, pitting and insufficient lubrication were identified as high-priority faults for the carriage, whereas pitting and installation errors were prioritised for the guide rail. Based on these faults, the potential measurable variables were listed and evaluated using the corresponding FMSA. The analysis results indicated that vibration was a suitable measurement variable for detecting pitting and inadequate lubrication. Additionally, the motor current proved to be an appropriate measure for both installation faults and insufficient lubrication.

The subsequent phase involved an analysis of the effect patterns, wherein all pertinent qualitative and quantitative variables and the dependencies of the respective measured variables were identified. By utilising the determined effect patterns, requirements, such as measurement ranges and sampling rates, can be formulated and approximated. Based on these requirements and associated research, two distinct systems were developed for each measurement. For each measured variable, sensors of varying types, price ranges, and direct/indirect measurement capabilities were selected and evaluated. The subsequent task involves determining the optimal measurement locations within the system for the selected sensors. Finally, an experimental validation was conducted for individual data sources and measurement locations.

Initially, the groundwork was laid for the existing IT framework, encompassing the integration of sensor technology into the IT system, establishment of a database, and provisions for graphical representations of the recorded measurement data. Subsequently, trial runs were conducted to assess the functionality of the IT system, revealing the necessary modifications which were implemented. The next phase involved analysing specific error cases using the 'intelligent machine bed'. As certain sensor requirements could only be estimated beforehand, preliminary tests were conducted for precise specifications. These tests revealed that the current clamp was already operating beyond its intended parameters, underscoring the importance of preliminary testing when requirements are unclear.

Further experiments were conducted to identify suitable measurement locations on the system. Three distinct measuring points on the carriage and adapter block were examined, considering variations in influencing and disturbance variables. The findings indicated that acceleration measurements in the direction of travel were unsuitable because of the additional acceleration occurrences. Finally, the selected data sources were validated using a test plan that varied the identified influencing variables and error states. Upon reviewing the test datasets, it was determined that one of the two sensors selected per measured variable could diagnose the desired effect patterns, making them appropriate for visibility analysis.

With a focus on the organisation of maintenance activities, data-driven FMEA combines the revealed correlation from past maintenance events with the experience of employees and provides support, especially for inexperienced employees during the planning of maintenance and repair. Therefore, using the developed framework the FMEA, risk assessment is no longer subjective because every employee will have the same results. These results were comparable because the relevant factors were determined based on the data basis of the use phase.

In conclusion, the method developed in this thesis achieves its objective and is thus suitable for analysing CCPSs for data mining purposes in the context of digitalisation. Conversely, the approach to data-mining-compatible digitalisation of CCPSs outlined in this study is not easily applicable to other scenarios, nor is it readily adaptable to different industry sectors.

VI. Conclusion and future work

This study further develops and validates a data-driven FMEA/FMSA methodology to digitise machinery, thereby enhancing production facilities and enabling advanced data analysis. Initially, the setup for FMEA/FMSA components relies on the team's best guesses, but over time as data accumulates, components of FMEA/FMSA are improved by using AI technologies on historical or current data. Moreover, to ensure accurate failure prognosis and/or correct failure type diagnosis, suitable sensors should be selected and detection/-forecasting/diagnostic algorithms should be established. This process can be complex, as the engineering effort required during the development and testing phases is substantial and should not be underestimated. The case study's experiment is overly specific and may not be broadly applicable across various industries. Nonetheless, it demonstrates the technical viability of the concept whilst highlighting some challenges that need to be addressed. Consequently, achieving greater precision in determining FMEA/FMSA components necessitates appropriate engineering research outcomes and adequate sensor technology. This investigation examined the feasibility of a completely data-driven FMEA/FMSA, exploring computational methods to calculate all RPN/MPN parameters, rather than depending on expert pre-definitions.

The existing methodology [6] enabled the creation of a data-driven FMEA by calculating failure likelihoods and employing preset severity and detection parameters for FMEA. The resulting risk/monitoring priority figures for individual failure modes provide valuable guidance and enhanced clarity for maintenance scheduling. This is especially advantageous for new or less experienced personnel in estimating expenses and time requirements for forthcoming maintenance or repair tasks. While predicting failure probabilities is essential, the FMEA/FMSA delivers a more thorough evaluation of failure modes, their consequences and the strategy of avoiding them. A key benefit of this approach is its impartiality in risk assessment, as all staff utilising the developed tool will reach consistent outcomes. Moreover, by anticipating failures during the planning stage, it enables the optimisation of production-related processes, including logistics and the procurement of spare parts. The proposed methodology enhances sustainable maintenance strategies. By accurately predicting faults, the system ensures that parts are only replaced when absolutely necessary, thereby maximising their lifespan. This approach leads to conservation of resources through minimised maintenance operations and less frequent component substitutions.

As production processes and supply chains receive greater focus on optimisation, there exists an opportunity to create an automated FMEA/FMSA system that continuously updates the risk/monitoring priority numbers. This innovative tool could forecast failures in specific machine components, thereby enhancing overall system efficiency. Such an approach has the potential to transform manufacturing systems into self-regulating entities for maintenance operations, based on real-time parameters, see also [6].

In summary, based on finding regarding the FMEA/FMSA components, the development of a knowledge database for failure scenarios, sensors, detection and forecasting algorithms is essential for a data-driven FMSA.

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