A Modular Federated Learning Architecture for Integration of AI-enhanced Assistance in Industrial Maintenance

A novel architecture for enhancing industrial maintenance management systems in the automotive and semiconductor industry.

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1. Introduction

Artificial Intelligence (AI) plays an increasingly important role for implementation and failure-free operation of Cyber-Physical Production Systems (CPPS). Recent market studies reveal the considerable attention and increasing rate of investment for AI-enhanced maintenance as one of the major use-case of AI in Industry 4.0 (Brügge et al. 2021). AI systems enable the improvement of various Key Performance Indicators (KPI), ultimately leading to a reduction in costs and optimizing plant management in smart factories (Fink et al. 2021; Passath et al. 2021). However, their development, implementation and deployment require a high level of expert knowledge and cost-intensive (computational) resources as well as reliable infrastructure (Fischbach et al. 2020). In addition to expert and prior knowledge, the available data is also an essential criterion for successful implementation of an AI system. At the same time, manufacturing enterprises in diverse sectors have very high expectations from any kind of AI solution comparing to conventional solutions. A study by Arinez et al. (2020) shows that research on AI in industrial context and specifically in manufacturing is mainly limited to laboratory environments. This is due to the high effort required to overcome existing (non-)technical barriers for implementation and integration of AI systems in the manufacturing systems and processes. In the course of digital transformation, it becomes more and more imperative that manufacturing enterprises consider the disruptive nature of AI technologies while understanding the demands on organizational change and competence building to realize the full potential of AI (Schumacher/Sihn 2020).

The study conducted by Henke et al. (2016) concludes that manufacturing enterprise use only 20-30% of their data and therefore leave an enormous, untapped potential. In addition, according to Gandomi and Haider (2015), about 80-95% of all business-relevant data is available in unstructured form, i.e., text. From these

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facts, it can be deduced that it is necessary to go beyond the conventional approach, which states that data in production only comes from machines via mounted physical sensors. The variety of data structures, i.e. multi-structured data sources, offers a new possibility to introduce new kinds of virtual sensors. Those virtual sensors can provide an even better data basis for subsequent decisions by analyzing expert knowledge hidden in texts. A notable example is maintenance, where related preventive and troubleshooting processes mostly provide written machine inspection, failure and maintenance reports created by maintenance technicians. These reports reflect human experiential knowledge about conditions, faults, causes, and solutions recorded in unstructured form. The use of Text Mining (TM) realizes the untapped value of existing unstructured or semi-structured textual data. TM is defined as applying AI algorithms and methods to text to find valuable patterns (Gao et al. 2020; Hotho et al. 2005). Therefore, an AI-enhanced system is needed to extract the full information available in the industrial environment to derive the required KPIs for optimizing manufacturing and maintenance processes.

The goal of this paper is to introduce an architecture for a modular cognitive maintenance system. The main objective is to design a system, which utilizes the unexploited potential from combining structured and unstructured data, by using AI technologies. The proposed AI-enhanced approach should improve various operational KPIs in particular availability and OEE, which will ultimately lead to a reduction in costs in industrial maintenance. The main research question of this paper is therefore, "How should the architecture of a modular cognitive maintenance system be designed to ensure industrial applicability in the context of maintenance?"

The rest of the paper is structured as follows: Section 2 describes the functional capabilities for AI-enhanced Assistance Systems. Section 3 presents a cognitive maintenance system, named ARCHIE. Section 4 explains its application using two use-cases from the automotive and semiconductor industry, respectively. Finally, Section 5 discusses the results in the use case and highlights avenues for future research.

2. Functional capabilities for AI-enhanced Assistance Systems

Functions typically associated with human intelligence include reasoning, learning, and self-improvement. AI as a sub-discipline of computer science aims to develop systems able to perform tasks that typically require human intelligence. AI itself is defined by Russell et al. (2010) as "the designing and building of intelligent agents that receive percepts from the environment and take actions that affect that environment". In Industrial AI, the focus is on developing, integrating, validating, and deploying AI systems in industrial processes, services, and systems (Peres et al. 2020). In this context, five dimensions in industrial AI were identified by Peres et al. (2020), namely i) infrastructure, ii) data, iii) algorithms, iv) decision-making and v) objectives.

In order to employ AI technologies in industrial context effectively, it should be ensured that the used data, the structure of the data and the data quality, as well as the correct interpretation of the discovered knowledge, is guaranteed. Especially in manufacturing, data is usually combined from different sources (e.g. machines, processes), which in turn are recorded in various data formats (e.g. structured and unstructured) (Ansari 2020). This problem of multiple data formats is aggravated by the fact that the recorded data is often very noisy (e.g. incomplete, inconsistent, or even faulty). This requires focusing on preparing and selecting the data, which consumes considerable time and resources in real world use cases and industrial projects. Therefore, only with appropriate pre-processing steps can the developed AI algorithm achieve optimal results with the selected data (Ansari et al. 2021).

In the era of Industry 4.0, the importance of lot-size one increases, which places high demands on workers' cognitive abilities in production and maintenance (Ansari et al. 2018). In particular, flexibility, adaptability and problem-solving abilities are required (Zdravković et al. 2021). The realization of comparable cognitive skills in an AI-based agent system holds immense potential for developing industrial assistance systems. Those systems provide intelligent functions that can, inter alia, facilitate solving common problems of make-to-order production such as high manufacturing costs, long lead times and varying quality levels (Zaeh et al. 2009). These problems can be overcome while at the same time assisting workers in their work processes by using cognitive systems (Li et al. 2019).

In manufacturing and maintenance systems, cognitive capabilities refer to the ability for machines and processes to be equipped with cognitive skills and cognitive controls that enable them to assess their scope of action and act autonomously (Park et al. 2009). A cognitive control system consists of three general functions (Park et al. 2009), namely i) capturing information from the environment, ii) draw conclusions from the information acquired based on existing knowledge, and iii) act to implement a reasoned change in the environment. These three functionalities allow technical systems to "know what they are doing" (Zäh et al. 2007). Production and maintenance planning in such a system should be autonomous and proactive (Hu et al. 2019; Iarovyi et al. 2015). Planning should be able to schedule multiple production and maintenance activities simultaneously, online, reactively, and opportunistically. Therefore, a corresponding feedback loop of current state information to the respective controls should be realized (Zhao/Xu 2010). Based on Zhao and Xu (2010), the following five extended functionalities should be fulfilled by a human-centered cognitive assistance system in production and maintenance planning:

i) Data acquisition with physical and virtual sensors.

ii) Automatic decision making

iii) Self-adaptation to sudden and unforeseen changes.

iv) Complete understanding of the production and maintenance process

v) Human-centered information support

These functional capabilities are implemented jointly by software, hardware, artificial (e.g. machine), human, and organizational agents. Those agents are then mapped into a cooperative multi-agent system (Jones et al. 2018).

Considering the state of the art in applying cognitive and AI-enhanced systems in maintenance, it can be summarized that despite the availability of data from various information channels, they are still hardly used in combination. Therefore, subsequent use of the extracted information to build a learning system that utilizes different machine data and human experiential knowledge to optimize maintenance processes is also missing. The existing body of knowledge analysis clearly reveal that a corresponding application is lacking in both research and industrial context. Some of these concepts have been implemented. However, the holistic implementation with the human being in the loop is still missing in the current research and industrial landscape.

3. ARCHIE: Architecture for a Cognitive Maintenance System

The objective of human-centered cognitive systems is to automate manufacturing processes further and assist workers in their cognitive tasks (Fischbach et al. 2020). This can be achieved by using the untapped potential of combining unstructured and structured data in order to extract hidden knowledge. The designed Architecture for a Cognitive Maintenance System (ARCHIE) aims at realizing the aforementioned AI-enhanced approach for a human-centered assistance system. ARCHIE incorporates physical and virtual sensors that capture machine states, parameters, human knowledge, and skills to optimize relevant KPIs. This includes a reduction in documentation time, Mean Time Between Failures (MTBF) and Mean Failure Detection Time (MFDT), as well as an increase in uptime, leading ultimately to an improved Overall Equipment Efficiency (OEE). The design principle of ARCHIE is based on the consideration of data from multiple channels. Data is collected by physical sensors (e.g. machine data, image data) and virtual sensors (e.g. audio, text). This data collection can provide a comprehensive picture of the environment and thus provide the cognitive maintenance system with an optimal set of necessary information. This data includes the objective machine and process information provided by connected systems and the subjective assessments of machine operators and maintenance staff, based on their respective skill levels.

The collected holistic data landscape enables the targeted deployment of maintenance measures, at the right moment, on the right machines, with the most suitable maintenance technicians. This directly improves KPI's such as availability and performance. Indirectly, the human-centered support of maintenance activities can improve the quality of these activities and therefore influence the KPI quality. Those improvements result in a general increase in the OEE.

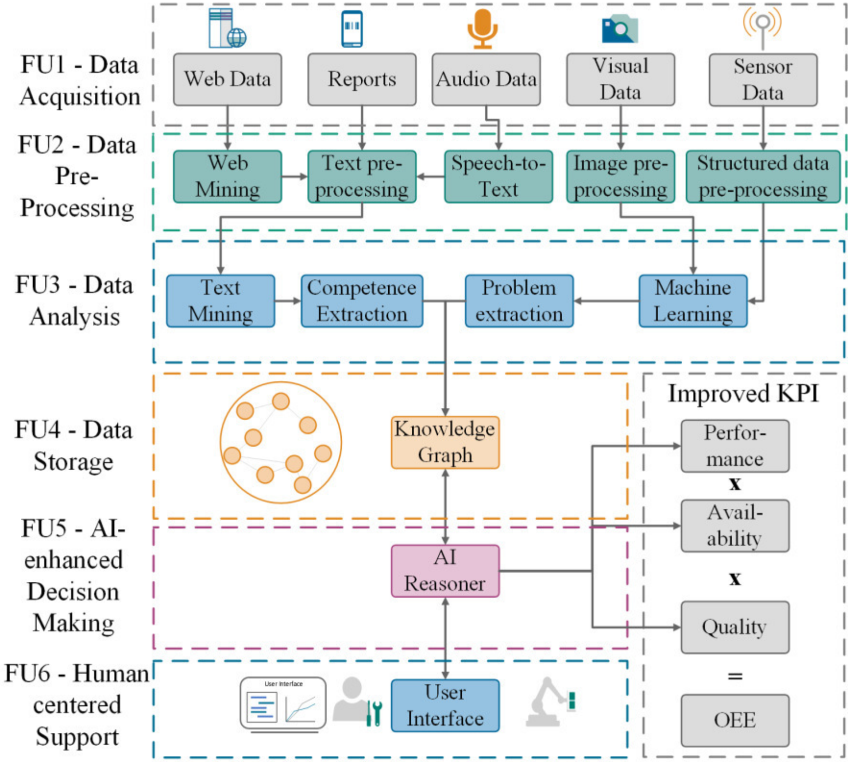

Figure 1: Design principle and functionality of an Architecture for a Cognitive Maintenance System (ARCHIE)

As depicted in Figure 1, ARCHIE is composed of 6 major functional units (FUx).

FU1 - Data Acquisition: The architecture of ARCHIE provides flexible interfaces to meet the idea of multi-channel data acquisition. Data sources can be captured as a.) structured data from sensors, and b.) unstructured data (e.g., text, image, or audio data which is converted to text).

FU2 - Data Pre-processing: Depending on the data source, the pre-processing modules in ARCHIE prepare the content for the subsequent analysis module. In the case of structured data such as sensor data, these are normalized for the downstream Machine Learning (ML) models or one-hot encoded in the case of categorical data. Audio data, such as speech recordings, are transformed into textual data using speech-to-text algorithms. Textual data can also be extracted from corporate knowledge resources via web scraping. The textual data is tokenized, stop words are removed, followed by lemmatization and part-of-speech tagging to identify semantic relations in the sentence structure and to prepare the text for downstream analysis. In particular, use-cases, it is also necessary to create use-case-specific dictionaries in order to deal with technical vocabulary or enterprise-specific words.

FU3 - Data Analysis: The chosen data analysis unit depends on the data source and data type, which results in the use of different algorithms. In the case of structured data, ML methods are used to perform analysis such as downtime prediction (Ansari et al. 2021) and detection of critical machine failures (Passath et al. 2021) or anomalies, depending on the requirements. For unstructured data, TM models are used to extract e.g. maintenance activities, competencies, or keywords for later semantic annotation of the text. Image data can also be analyzed with ML models to provide further information on potential defects or quality issues.

FU4 - Data Storage: The data storage in ARCHIE takes place within a so-called Knowledge Graph (KG). The KG allows entities from the real world and their relationships to each other to be mapped in a graph structure (Paulheim 2016). Examples for those real-world entities include maintenance technicians, machine operators, fault messages, sensor values of machines, internal maintenance documents, and maintenance reports. However, abstract entities like competence, knowledge, and job description have connections to physical objects and can also be modeled in such a structure (Ansari et al. 2020). In ARCHIE, these entities represent so-called classes with different parameters such as author, sensor value, activity, competence level, which are related to each other. The graph structure of the KG enables a subsequent determination of hidden relations and optimal recommendations for action derived from them. Those recommendations range from selecting the most suitable person for solving a given machine malfunction, recommending maintenance measures for a given problem, or evaluating required competencies for specific machine types.

FU5 - AI-enhanced Decision Making: The AI-enhanced decision-making uses the KG provided in ARCHIE and utilizes it to suggest the most suitable action with the help of statistical and similarity-based learning algorithms. Similarity-based learning algorithms are used, among other approaches, to present potential causes of machine failure or maintenance measures for a given failure. Statistical learning algorithms can be used to extract and evaluate tasks performed or competencies required from maintenance reports. The aggregation of these results from the similarity-based and statistical learning algorithms can then be used to select the most suitable person for an existing machine malfunction and support this person according to his competence level in solving the problem. These algorithms can be implemented with Federated Learning (FL). The use of FL prevents the exchange of sensitive data with the central server and allows the assistance system to be used at consumer devices even without a network connection (Bonawitz et al. 2019).

FU6 - Human-centered Support: The results of the AI-enhanced decision-making are used to provide individualized recommendations and documentation support for machine operators and maintenance technicians. This assistance is additionally supported by a human-centered design that puts the user's needs in the respective maintenance workflow in the middle of the design focus. ARCHIE is based on supporting people in their work through intuitive user design so that no additional time is required due to the usage of ARCHIE by providing the right information at the right time in a suitable way for the task at hand. The operative use also requires a high level of acceptance among the users of ARCHIE. This support is achieved by developing the user interface in very close cooperation with the users and decision-makers in the respective use-cases. However, ARCHIE also provides generic building blocks such as finding similar entries, word suggestions, maintenance task suggestions, assessment of required competencies, and predictions of KPIs. Through this combination of customization to user and use-case, as well as generic, proven building blocks, ARCHIE can demonstrate its added value in maintenance through reduced documentation time, MFDT, faster problem solving and increased documentation quality.

The FUs can be used individually for each use-case. In combination, however, they exploit the full possibilities of ARCHIE. ARCHIE can also be implemented as part of a comprehensive maintenance model such as PRIMA (Ansari et al. 2019). Therefore, the design principle shown in Figure 1 represents a modular structure that allows a partial validation of ARCHIE.

Additionally, ARCHIE addresses the five identified and extended challenges in implementing an AI system in an industrial environment (Lee et al. 2018; Fischbach et al. 2020).

1) **Generalizability:** The developed architecture does not focus on one industry but rather represents a generic architecture that can be adapted to the respective industry, enterprise, and application through minor adjustments. Therefore, the AI algorithms are initially trained on data from scientific studies and European specifications, and only enterprise-specific adjustments are required for fine-tuning. The use of FL allows ARCHIE to be deployed in areas with high data sensitivity requirements or insufficient network coverage.

2) **Scalability:** ARCHIE aims to be easily scalable from a single component or one-machine use-case to the entire machine group or factory.

3) **Customizability:** To provide ideal support, ARCHIE can be individualized using employee competencies. These enable the provision of information in line with the level of training and qualification or the specific job role.

4) **Reliability:** In modern industrial manufacturing environments, the reliability of AI systems is of paramount importance, as failures can result in high costs. ARCHIE, therefore deliberately relies on a robust algorithmic basis that can handle outliers, erroneous and missing data.

5) **User acceptance:** No AI solution, no matter how sophisticated, will succeed in the industrial environment if the users do not accept it. ARCHIE focuses on human-centered design with an emphasis on intuitive use and gender-neutral design.

4. Proof of Concept Application of ARCHIE in Industrial Use-Cases

4.1. Automotive Industry

In the use-case of maintenance in the automotive industry, an AI-enhanced methodology for a digital shift book has been developed. The goal of the Proof of Concept (PoC) application was to increase the OEE by providing accurate downtime prediction and assistance in documentation (Ansari et al. 2021). In the use-case the FU1-3 and FU6 have been implemented and validated. The automotive manufacturer's data spans three years and includes Rough Problem Level, Fine Problem Level, Defective part, Problem and, Downtime.

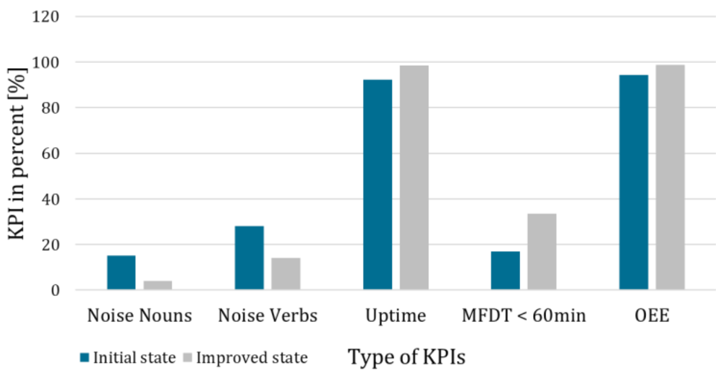

Figure 2: Improvements through the AI-enhanced methodology by Ansari et al. (2021)

The data acquisition unit was implemented using structured and unstructured data from maintenance reports (Ansari et al. 2021). In the pre-processing unit, as described in detail in Ansari et al. (2021), structured data was normalized, and outliers were removed. In the case of the unstructured data, among other things, stop words were removed and lemmatization was performed to extract nouns and verbs. In the data analysis unit, the unstructured text data was vectorized, and the structured data was used as target values for training a ML model. Based on the error description of the machine operator, the developed model allows predicting the expected downtime of the machine. The human-centered support unit was developed as a web application as an assistance system for the maintenance technician during the diagnosis of the causes of the machine failure and the subsequent problem-solving. As shown in Figure 2, the AI-enhanced digital shift book improved the MFDT below 60 min by 97.3%, and ultimately the OEE by 5.3% percent.

4.2. Semiconductor Industry

In the use-case of maintenance in the semiconductor industry, an assistance system has been developed, which uses the data of a digital shift book as a data basis for predicting the necessary competencies for a given maintenance task (Kohl et al. 2021). In the use-case the FU1-2 and FU4-6 have been implemented and validated. The data acquisition unit uses unstructured text data from maintenance reports, including the machine, the machine group, the error description, the cause of the error and the maintenance task carried out. For the pre-processing unit, as described in Kohl et al. (2021), a use-case-specific dictionary was created in addition to stop word removal and lemmatization. The dictionary contains synonyms as well as enterprise-specific expressions. This enabled the TM algorithm to extract the tasks listed in the respective maintenance reports. The approach reduced unique nouns to a tenth and verbs to a fourth of the starting value.

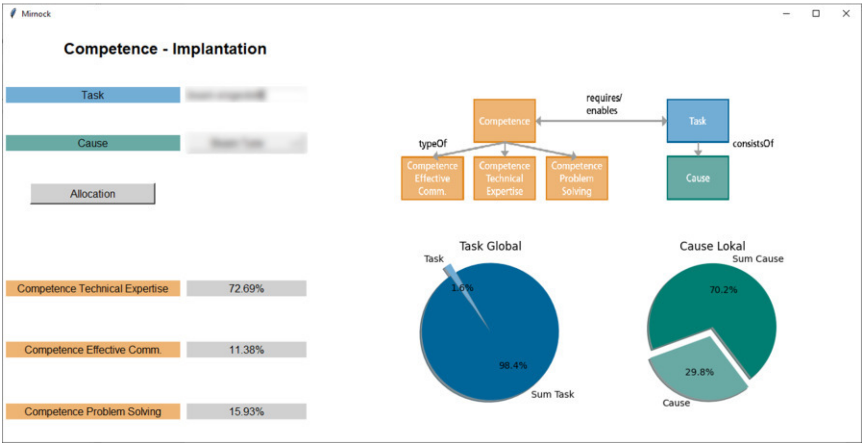

Figure 3: User interface of the assistance system for quantifying the competence distribution based on a task and its assigned cause

Additionally, a competence taxonomy, based on Ansari et al. (2020), for the KG in the data storage unit and a statistical learning algorithm as an AI-enhanced decision-making unit was developed. With those adopted FUs of ARCHIE, the extraction of required competencies for a given maintenance task was achieved. In a further step, the necessary competencies for the respective activity could be broken down to internal competence levels and job descriptions derived from them, with the help of the algorithm and companies' internal job descriptions. For this purpose, as shown in Figure 3, the human-centered support unit, a user interface, was designed. The developed user interface allows for simple querying of the competence distribution based on a task and its assigned cause. This functionality also allows a better and automated allocation of maintenance technicians based on the current task and their corresponding profile. The statistical learning algorithm additionally makes it possible to analyze the evolution of the tasks over time. From these analyses, maintenance managers can derive recommendations for reskilling and upskilling employees and optimizing shift plans according to predicted needs.

5. Discussion and Outlook

This paper presents a transferable and scalable architecture for a cognitive maintenance system of a human-centered assistance system that enables holistic sensing of the environment by using physical and virtual sensors. Therefore, it fills the identified gap in the literature of production and maintenance management and related industrial applications. By focusing on generalizability, extensibility, adaptability, reliability and user acceptance, ARCHIE addresses common challenges in the application of AI systems in the industrial environment. In the presented use-cases, the generalizability, scalability, customizability, reliability and user acceptance were evaluated. The limitations of ARCHIE can be derived from the design of the FUs. As a data-driven approach, the FU1-2 require multiple (digital) data sources. Adopting the FU3-6 for the respective use-case also requires business understanding in particular with regard to the requirements for employing an AI-based system in the industrial IT landscape. It is also worth noting that the deployment phase will confront challenges regarding system integration, especially the interoperability of FU with the corresponding IT systems. The modularly designed six FUs form the basis for an adaptive, cognitive maintenance system that can assist humans during the maintenance process. In particular, the KPIs performance, availability and quality are improved, which leads to an increased OEE. This could be demonstrated by partial implementations of ARCHIE in two industrial use-cases, namely in the automotive and semiconductor industry. The presented architecture and the results of the use-cases show how the implementation of a cognitive maintenance system using AI can improve industrial maintenance by proof of concept evaluation in two use-case.

Important future research areas are the customizability of the cognitive maintenance system for user-specific support, the linking and use of information from information systems in manufacturing and especially maintenance (e.g. Enterprise Resource Planning, Manufacturing Executions System), as well as the automated determination of the criticality of plants and the derivation of RAMS (Reliability, Availability, Maintainability, Safety). Based on the current FUs of ARCHIE and the presented future research directions, further functionalities and new compositions of FUs should be implemented and evaluated in industrial context.

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