KI-Net: AI-Based Optimization in Industrial Manufacturing—A Project Overview

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Abstract. Artificial intelligence (AI) is a crucial technology of industrial digitalization. Especially in the production industry, a great potential is present in optimizing existing processes, e.g., concerning resource consumption, emission reduction, process and product quality improvements, predictive maintenance, and so on. Some of this potential is addressed by methods of industrial analytics beyond specific production technology. Furthermore, particular technological aspects in production systems address another part of this potential, e.g., mechatronics, robotics and motion control, automation systems, and so on. The problem is that the field of AI includes many research areas and methods, and many companies are losing the overview of the necessary and appropriate methods for solving the company problems. The reasons for this are, on the one hand, a lack of expertise in AI and, on the other hand, high complexity and risks of use for the companies (especially for SMEs). As a result, many potentials cannot yet be exploited. The KI-NET project aims to fill this gap, whereby a project overview is presented in this contribution.

Keywords: Artificial intelligence · Digital twin · Robotics · Systems engineering · Knowledge graphs · Manufacturing

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1 Introduction

AI technologies bring significant advantages in analyzing complex data and supporting people in solving complex problems or relieving them of time-consuming and error-prone tasks. The strength of AI technologies lies in their ability to discover complex relationships, generalize, and independently extract information and policies from data without relying on explicit domain-specific knowledge.

Therefore, they are indispensable for evaluating data from a constantly growing number of sensors installed as part of the Internet of Things (IoT) and Industry 4.0, thus generating added value. At the same time, AI technologies can solve problems with a manageable number of algorithms and procedures, which cannot be solved with regular (i.e., requirements-driven) programming procedures.

Information and Communication Technologies (ICT) allow for more efficient and flexible industrial process design, leading to new products and expanding business areas and markets. AI is a critical technology for industrial digitalization with enormous potential for improving existing production processes, particularly in manufacturing and production. For example, AI can entirely automate the quality assurance of manufactured products, intelligently predict machine maintenance to save costly downtimes, and analyze complex data to optimize production processes and products.

However, digitalization is challenging for small and medium-sized enterprises (SMEs). It is widely assumed that the average level of digitalization among many SMEs in the manufacturing and production field can be notably improved. One significant problem is that AI frequently needs numerous other essential technologies (e.g., Big Data, Robotics, Digital Twins, and the Internet of Things). Often, finding the right expertise is far from a trivial task.

In the framework of the KI-NET project, a cross-border competence network has been formed as part of a project to explore, research, develop, and provide essential building blocks for AI-based optimization in industrial production. The goal was to help SMEs access targeted AI applications in production and maintenance processes. This paper is intended to give an overview of AI's applicability in manufacturing and production. The final goal is to help companies, especially SMEs, leverage the Industry 4.0 concept to bring breakthroughs in this context.

Therefore, the main contributions of this work can be summarized as follows:

- We introduce the KI-NET project that aimed to bring best practices in AI to the SMEs in the manufacturing and production sector.
- We show the results we obtained during the project's execution around prototypical solutions for systems engineering processes, digital twins and robotics, knowledge representation, and knowledge graphs.

The rest of this paper is structured as follows: Sect. 2 presents the state-of-the-art in digitalization of SMEs in the field of manufacturing and production. Section 3 presents the project objectives. Section 4 reports the main results derived from the KI-NET project. Furthermore finally, we end with conclusions and lessons that can be learned from this research project.

2 Related Works

Industry 4.0 is a term that expresses the fourth industrial revolution. This revolution brings an essential new aspect of the adaptive, dynamic, flexible individual manufacturing and production processes and its intelligent control based on an appropriate combination of data-driven and knowledge-driven technologies. This way, it is possible to use a transparent availability of a large amount of data, right down to the individual sensor on the machines. With the transition to Industry 4.0, a whole range of topics arises that are new aspects in this application area, such as AI, or that have been given a new status, such as security.

Furthermore, AI is a collective term for various subfields that pursue emulating human-like abilities (image recognition, language interaction, strategy development, situation assessments, etc.) in an algorithmic or information-processing manner. In other words, it aims to at least imitate the cognitive abilities of a human being to a certain extent. Many methods and techniques have great applicability in this context. For example, industrial maintenance [5], root cause analysis [8], optimization [4], time-series analysis [7], and so on.

It is important to note that the networking of heterogeneous objects, such as machines, sensors, actuators, and simulated components, has given rise to collective terms such as (Industrial) Internet of Things in the context of Industry 4.0. Other methods require a physical intervention of computing processes in industrial systems and thus form cyber-physical systems (CPS). Edge devices make it possible to connect individual hardware components and entire factories across geographical borders and outsource data, computing power, and user software to the cloud. The need for this global networking has led to the development of communication standards such as OPC Unified Architecture (OPC UA) and Time-Sensitive Networking (TSN), which enable secure, real-time, platform-independent, and manufacturer-independent data exchange. These basic technologies are being developed or further developed in the context of Industry 4.0 and are a prerequisite for using AI in the industrial environment.

Resource-rich organizations can afford to invest in tailor-made solutions to address some of their challenges. However, there is a clear gap in addressing this issue from a SMEs perspective. By the nature of their business, organizations cannot invest large sums in building solutions that meet their needs.

3 Project Objectives

The KI-Net aimed to bundle the main scientific and technological competencies of AI-based production and maintenance through the partners. The KI-Net project developed a cross-border competence network that explored, researched, and developed fundamental methods for AI-based optimizations in industrial manufacturing. This was intended to facilitate access for companies, especially SMEs, to the targeted use of AI in production and maintenance processes. The project aimed to identify which AI methods were the most suitable for industrial manufacturing tasks. The AI methods included, in particular:

– Systems engineering processes
– Digital twins and robotics
– Data analysis, optimization, and learning techniques
– Knowledge representation and knowledge graphs

The project partners pooled the necessary know-how to be the primary contact for industry, SMEs, and other institutions on this topic. Thus, the public can obtain information and knowledge from a single competence network and access the project partners' abilities.

4 Results

AI is a technology that will permanently change the field of production and maintenance. The presented use cases show the broad spectrum of possibilities for AI-based solutions. In order to develop and deploy AI methods, several requirements must be met. Development processes have to be adapted and extended to support data-driven development. At the same time, existing production facilities must be expanded to enable the development of solutions and integrate AI components into existing production facilities.

The cross-border approach has paved the way for a new research and innovation partnership in the program area (Interreg Austria-Bavaria)and the cooperation between science and industry in the field of AI-based production and maintenance, in line with regional strategies as well as the objective of the coordinated plan for artificial intelligence of the European Commission.

Individual use cases were explored, developed, and prepared in a suitable form for the public. These best-practice examples have been summarized as an application guideline for AI methods in industrial manufacturing and presented to the public at several knowledge transfer events. Furthermore, the results were made available online[1], and the developed knowledge was also integrated into the qualification modules of the project partners.

4.1 Systems Engineering Processes

A process for requirements analysis for AI algorithms has been developed to meet the typical qualitative properties such as precise formulation, quantifiability, allocability, traceability, and freedom from consistency. Furthermore, suitable quality assurance measures have been identified to demonstrate the reliability of AI algorithms specifically for the quality requirements of industrial manufacturing. The identified quality assurance measures have been investigated for their applicability in industrial manufacturing and combined to include quality requirements through a stepwise sample generation approach [2].

The rationale behind this approach is that AI algorithms are frequently used not only as pure software functions but are integrated into systems, such as image recognition methods. Therefore, the domain of systems engineering deals

[1] https://ki-net.eu/.

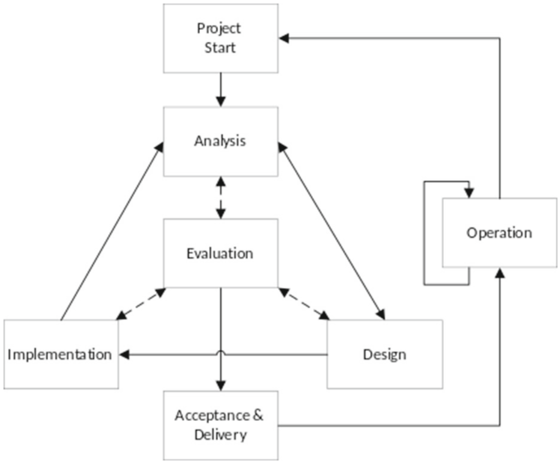

Fig. 1. Workflow example for user support that needs to implement AI in a software system

with integrating subsystems into an overall system. Here, many development mechanisms are based on requirements too. Therefore, suitable tools for system integration into industrial manufacturing processes have been evaluated. A holistic development process for AI-based processes in industrial manufacturing emerges from these activities, which have been made available to companies. Figure 1 shows an overview of this holistic development process.

4.2 Digital Twins and Robotics

This activity aimed to research and develop a software prototype for using digital twins and robotics in industrial manufacturing. Many methods of optimization and AI cannot work in a real operational environment (robot, machine, line, factory). The reason is that iterative search procedures repeatedly perform test runs, or a sufficient diversity of learning data cannot be achieved on a few real machines. In this activity, digital twins - i.e., digital surrogates - are to be developed for facilities, on the one hand, represent the real counterpart as good as possible and, on the other hand, are not subject to various limitations of the real counterparts, such as multiplicity and diversity, costs, space, energy, or simply physical real-time.

AI methods play a role in this activity on two levels: On the one hand, they serve for the modeling of the digital twins, and secondly, AI methods can be applied to the resulting digital twins themselves, such as the resulting digital twins themselves, e.g., the optimization of production steps (e.g., path and trajectory planning of robotics [6]) or the (sensor data-driven) prediction of production quality and maintenance indicators [9]. Figure 2 shows an overview of the prototype for Digital Twin that has been worked on.

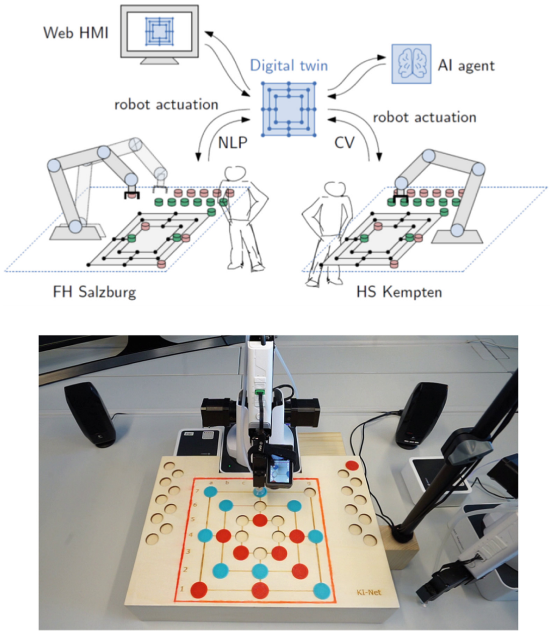

Fig. 2. Overview of the implemented prototype allowing bi-directional communication between Kempten and Salzburg

4.3 Knowledge Representation and Knowledge Graphs

The use of knowledge graphs (KGs) remains unexplored in the industrial domain [3]. However, this does not mean there are no knowledge-intensive approaches to address the problem. There are already strategies that make intensive use of structured information to perform several essential processes [1]. In these approaches, knowledge is usually provided by domain experts who have extensive experience in risk analysis. This approach defines all possible failures and their observable effects on the system. Among several strategies following this approach, the Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA) propose templates to collect this information.

In order to reduce production errors and increase overall quality, these processes must be analyzed in detail and improved. In order to illustrate how production errors can be minimized, a KG is developed. Firstly, a Bayesian Network (BN) maps the processes of a production line and uncovers complex dependencies. Bayesian structure learning automatically learns relationships by gathering data. To keep the workload for SMEs as low as possible, automated learning from data is essential. Figure 3 shows an example of a KG generated from the sensors of an assembly line.

In order to access a comprehensive and accurate analysis of complex systems, BNs are a data-driven technique that is widely used due to their flexible structure in the scope of uncertain knowledge representation and reasoning. Since

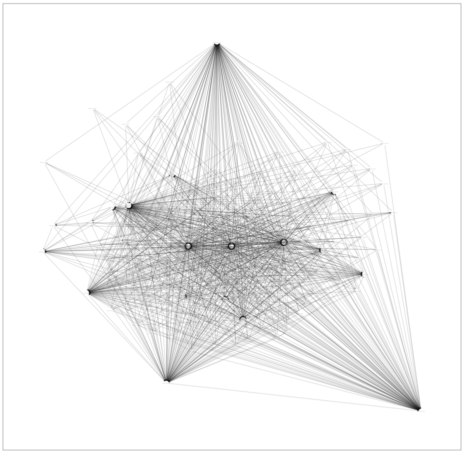

Fig. 3. Example of the kowledge graph generated to facilitate the interpretation of sensors on an assembly lines

structure learning for BNs is not easily interpretable, they cannot be sufficiently informative about dependencies between the variables. Thus, KGs enrich semantic interoperability and exchange information between humans or machines.

5 Conclusions

AI is a crucial technology for Industry 4.0. In fact, several AI-based solutions are already being used productively in production and maintenance. The number of use cases that can be solved with AI will increase continuously due to the rapid further development of AI methods and permanently changing system landscapes. The use cases presented in this paper demonstrate the broad spectrum of possibilities for AI-based solutions. In order to develop and deploy them, several requirements must be met. It is necessary to adapt and extend development processes to support data-driven development. At the same time, existing production facilities must be expanded to enable the development of solutions and integrate AI components into existing production facilities.

Within the INTERREG Austria-Bavaria 2014–2020, the KI-Net project has established a new research and innovation partnership in the program area that has been leveraged. Furthermore, the cooperation between science and industry in AI-based production and maintenance, according to the regional strategies and the objective of the coordinated plan for artificial intelligence of the European Commission, has been intensified. The project results are presented https://ki-net.eu/.

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