Overview, Trends and Future Applications of Artificial Intelligence in Manufacturing

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Abstract

Artificial Intelligence (AI) has the potential to further improve manufacturing efficiency and enhance competitiveness of manufacturing companies. The application of state-of-the-art computer science technologies always lead to productivity improvement for the operator, as well as enabling new and more productive workflows for planners, designers and managers. Appling new insights and concepts from computer science in the engineering domain was in the past decades dominated by central IT systems such as ERP, MES, PLM or CAD-CAM. Recently more cloud applications offered benefits such as high availability and low maintenance effort. Now a new wave of toolset is mature enough for widespread adoption. This paper gives a short overview over such applications and use cases of AI in manufacturing, groups the use cases into categories and presents some exemplary use cases in detail. The paper closes with recent trends and some potential new developments and future outlook on new methods and tools.

Keywords
Smart Manufacturing, Industry 4.0, Artificial Intelligence, Machine Learning and Data Analytics

1. Introduction
Artificial Intelligence (AI) in general made significant progress in recent years. These new developments such as Deep Learning, improved Loss Functions, Generative adversarial networks (GAN) and Natural language processing (NLP) are mature enough for widespread adoption in the consumer market. Many of these technologies find can be applied in domains outside of computer science. This paper gives an overview over such applications and use cases of AI in manufacturing, groups the use cases into categories and presents some exemplary use cases in detail.
From predicting maintenance needs to optimizing supply chain operations there is a plethora of use cases for AI in the manufacturing domain. AI can be considered as key enabling technology in the Manufacturing sector, as it feeds the value of the production system chain and has the ability to innovate processes, products and services. With successful implementation of the whole digital manufacturing chain benefits can range to 25% (de Boer et al. 2022).
According to market research carried out by *Precedence Research* and *Market Research Future* the global market for Artificial Intelligence in Manufacturing is expected to grow by 2025 at a CAGR of 33.5%., hit 30+ billion USB by 2030 and increase 10 fold by the year 2030 (Dhapte 07/2023; Precedence Research 2023). This market consists of 30% software solutions, 50% hardware products, and 20% services. Theses software includes packages, include IoT-platforms, products as well as industry specific niche applications. For instance, the predictive maintenance and machinery inspection segment is estimated to gain a significant market volume by 2032. The hardware segment consists of edge devices, Tensor Processing Unit (TPU) and other Machine Learning (ML) specific hardware dedicated for shopfloor usage. Especially the computer vision segment is expected to expand fast.
The current adoption rate is high, but as with any emerging technology, there are challenges that must be addressed to ensure a successful implementation. This paper will first discuss the challenges, afterwards in chapter 3 present the Use cases and in the chapter 4 show the manufacturing specific deployment of AI/ML models.

2. Manufacturing specific Challenges of AI Implementation
Challenges hinder the swift adoption or cause implantation project to fail entirely. These challenges can be categorized into data preparation and data quality, complexity of processes, maintenance and repair of AI systems, data privacy

and security, and employee acceptance and training (Wuest et al. 2016). Further breaking down these categories into their individual characteristics:

Data preparation and quality:
AI systems require high-quality data to make reliable predictions and decisions. In production, it can be challenging to collect and prepare suitable data as it often comes from different sources and may be incomplete (Kusiak 2018; Chang et al. 2015) or unstructured and unbalanced (Moyne and Iskandar 2017; Provost 2000; Li et al. 2008; Choi 2010; Wang and Japkowicz 2010) . Activities in this area include modeling with incomplete data, automated pre-processing to supplement missing data, and semantic processing of recorded data.
Complexity of processes: Production processes can be very complex, often involving multiple variables and interactions between different components. This makes it difficult to develop AI systems that consider all relevant factors and dependency structures to make precise and robust predictions and decisions. Modeling production processes requires deep process understanding and domain knowledge (Lu 1990) and prior knowledge of causal relationships (Chand and Davis 2010; Schmidt and Lipson 2009; Castelvecchi 2016; Krause, Perer, and Ng 2016). This challenge can only be addressed by building deep process understanding or transferring knowledge from similar processes. Regular exchange between companies and sharing of best practices are sought in this regard.

Maintenance and repair of AI systems:
AI systems need to be maintained and repaired, just like other machines and equipment in production. AI models need to be managed, kept up-to-date, and undergo monitoring to continuously monitor their operation. Automated tools for this purpose are collectively referred to as MLDevOps (Machine Learning DevOps). MLDevOps (Kreuzberger, Kühl, and Hirschl 2023; Albino and Others 2022) is a discipline that focuses on the integration of machine learning into DevOps processes (Halstenberg, Pfitzinger, and Jestädt 2020). It combines the principles of DevOps and ML engineering to automate and optimize the development and deployment process of machine learning models. Solutions from computer science need to be adapted for suitability in production.

Data privacy and security:
Since AI systems collect and analyze large amounts of data, it is important to ensure that the data is secure and the privacy of employees and customers is protected. AI systems can also be vulnerable to hacking and other security threats, so it is important to take appropriate security measures (Rahman, Wuest, and Shafae 2023)

Employee acceptance and training:
The introduction of AI systems can cause uncertainty and resistance among employees, especially if they fear that their jobs may be replaced by the technology. It is important to involve employees early in the introduction process and provide training to ensure that they understand and can accept the technology (Bergs 2020; Hatfield and Winkler 2020).

3. Overview of Applications of Artificial Intelligence in Manufacturing

Early ideas and concepts of applies machine learning to manufacturing tasks go back to 1990s (Monostori et al. 1996). By now, there are already countless successful implementations of Artificial intelligence (AI) in the manufacturing industry by improving efficiency, productivity, and quality across various stages of the production process (Mayr et al. 2019). These use cases can be group by their common objectives (Juergen Lenz, Wuest, and Westkämper 2018). Figure 1 shows exemplary use cases grouped into the domains.

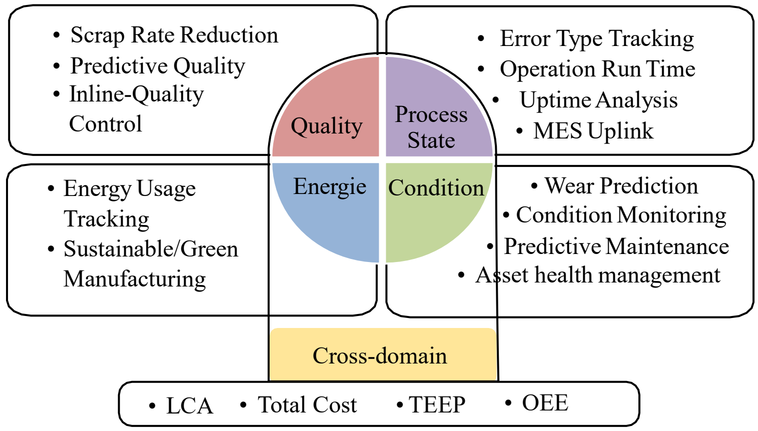

Figure 1. Objective in Manufacturing with Domain Groups (Juergen Lenz, Wuest, and Westkämper 2018)

A second approach of grouping use cases is according to their AI-maturity. Evaluating the maturity in regard to digital transformation readiness is common industry practice. Standard models are for instance Industry 4.0 Maturity Index which is specifically tailored for the manufacturing sector and focuses on the adoption of Industry 4.0 technologies. It typically consists of several levels, ranging from level 0 (no digitalization) to level 4 (fully integrated and automated processes) (Zeller, Hocken, and Stich 2018). Other maturity models derive the digital maturity and the necessary measures to achieve the company's individual target image of digital transformation (De Carolis et al. 2017; Schumacher, Erol, and Sihn 2016; Weber et al. 2017; Mittal et al. 2018). Similarly, the maturity of the AI itself enabled different levels of autonomy. The same idea as a autonomous vehicle operation can be descripted by the level of autonomy (Car and Driver 2017), the AI autonomy can be placed into levels from 1-5. The EU Project consortium *ConnectedFactories* enhanced this approach to include the human centric viewpoint (ConnectedFactories 2022). This group of AI-maturity levels shown in Figure 2.

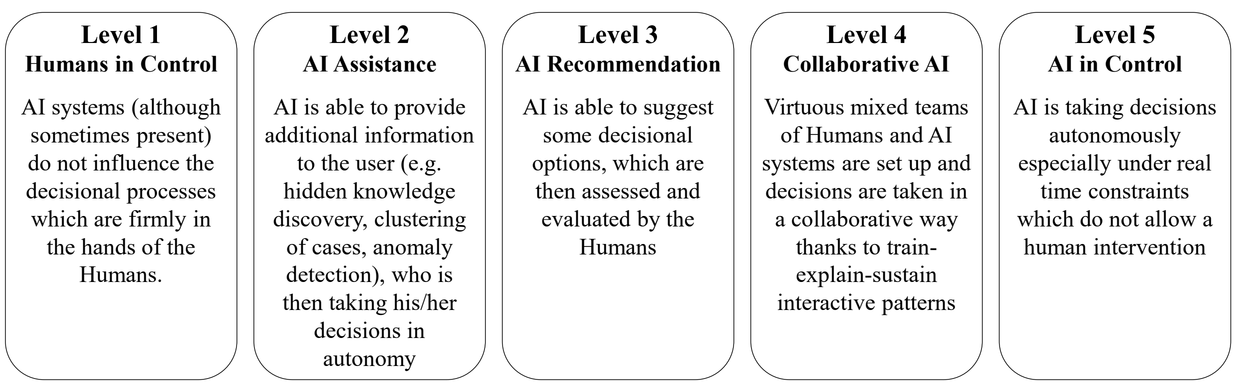

Figure 2. AI maturity levels from the human-AI interaction viewpoint (ConnectedFactories 2022)

At level 1 humans in in control. No AI autonomous system is making decisions. Workers, Engineers and Managers are in full control of any business process. At level 2 the AI is assisting. Here operators are supported by advanced AI apps on top of industrial IoT analytics, and engineers are supported in generative design and assessment of option. At level 3 the AI gives recommendations. Operators can consider AI enabled decisional knowledge from plant digital twins, and engineers get recommendations about best options. At level 4, AI is used collaboratively. Operators interact with AI and machines. Engineers create mixed teams with AI systems. At level 5 the AI is in control. Smart systems act in a closed loop control. AI can be embedded in processes, workstation or system level. AI driven virtual decisional rooms are part of daily operation.
In terms of industry adoption level 1-3 are already numerously implemented. Level 4-5 use cases are in the concept research stage with low technology readiness level.

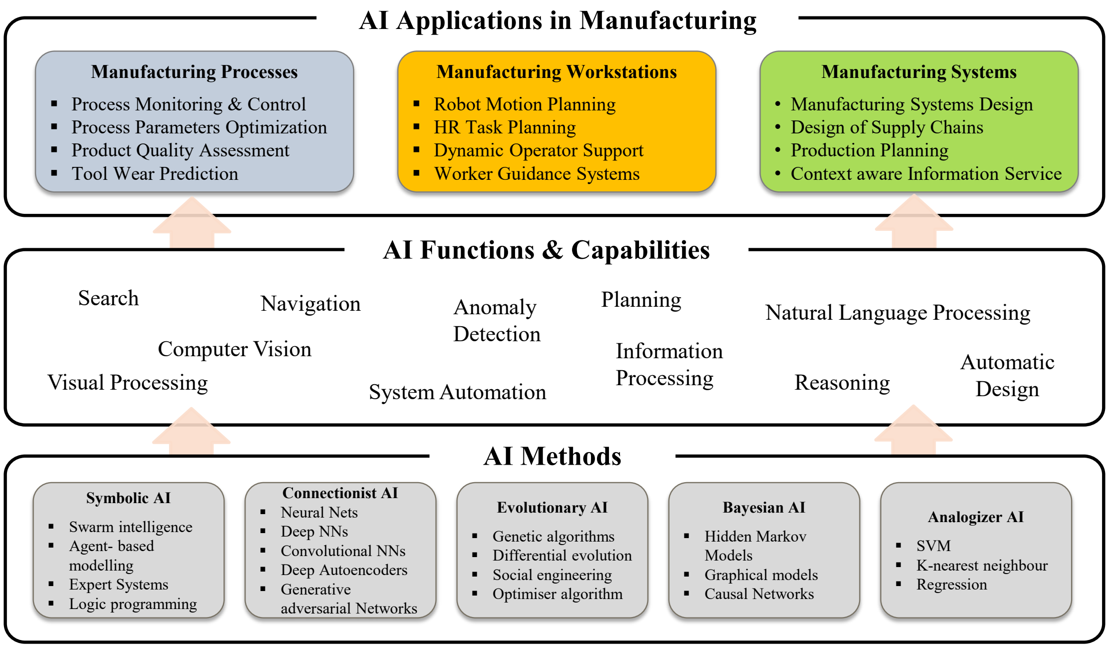

Figure 3. AI Methods - Functions & Capabilities - Applications in Manufacturing (the Artificial Intelligence in Manufacturing Network – AIM-NET 2023)

What is an AI application in manufacturing? Figure 3 shows pathway to build an AI application in manufacturing. A suitable AI method is used to enable functions and capabilities. These functions and capabilities and then applied to solve an objective in the manufacturing context. Examples for AI methods as shown in Figure 3 are Neural Networks, Support Vector Machines (SVM). With these methods capabilities are enabled. Examples of these capabilities are anomaly detection or computer vision. These capabilities are then used to solve a quantifiable objective on the shopfloor. Either on a process, workstation, or system level. Examples for these applications are predictive Maintenance, where AI can analyze sensor data and historical maintenance records to predict when equipment or machinery is likely to fail. By implementing *predictive maintenance* strategies, manufacturers can reduce downtime, optimize maintenance schedules, and prevent costly breakdowns. Another example is *quality control*, where AI enables automated visual inspection systems to detect defects, anomalies, and deviations in products or components. Machine learning algorithms can be trained on large datasets to classify and sort items based on quality standards, ensuring consistent product quality. A third examples is *product design and optimization*. Here, AI algorithms can analyze vast amounts of data and generate insights to optimize product designs. This includes simulations, virtual prototyping, and iterative design improvements, leading to better-performing products and reduced development cycles.

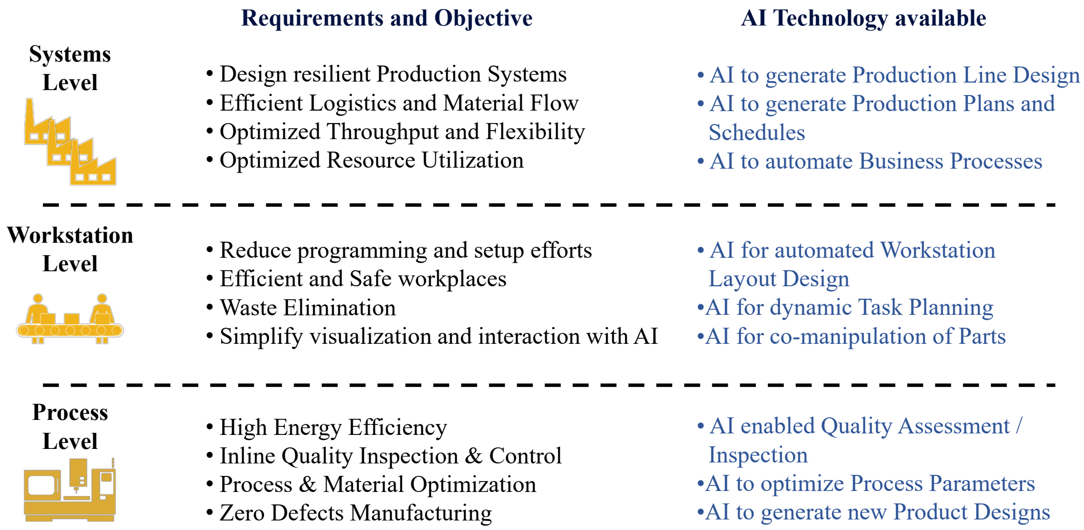

Figure 4. Factory Levels with Requirements and AI Solutions (Chryssolouris, Alexopoulos, and Arkouli 2023)

Due to the different requirements of use cases in the manufacturing context, the classification into three levels has been suggested multiple times (Chryssolouris, Alexopoulos, and Arkouli 2023), due to similarities of the use cases on each level. Figure 4 shows the three factory levels with requirements and AI solutions for each level.

3.1 AI Use Cases at the Process Level

At the process level typical objectives are a higher energy efficiency, inline quality inspection & control, process & material optimization, and zero defects manufacturing. Modelling of the process can be close to an analytical physical model, work as a block box, or be a combination (hybrid modelling). More accurate models are more costly, and lead to less range of applicability (Byington, Roemer, and Galie 2003). Tool wear assessment and prediction is a common use case at the process level. AI enabled tool wear model can estimate precise remaining useful tool life based on as-is usage and load collective instead of time based usage (J. Lenz and Westkaemper 2017). Another example is crack detection for metal working processes. Very reliable detection was shown by using Convoluted Neural Networks (CNN) (Mittel and Kerber 2019). Over the next 5-10 years, it is expected that AI-based solution at the manufacturing processes level will become increasingly integrated into automated processes. Overall energy use can be reduced and waste eliminated.

3.2 AI Use Cases at the Workstation Level

Typical objectives at the workstation level are reduced programming and setup efforts, efficient and safe workplaces and waste elimination. Typical use cases are predictive maintenance, AI for dynamic operator support, AI-enhanced human-robot interaction (Michalos et al. 2014), and operator assistant/worker guidance (Mark, Rauch, and Matt 2021). One of the exemplary works is a robust gripper for manipulation and joining of work pieces in industrial assembly processes. Researcher developed an AI-based approach for a grip metric based on tactile sensor data capturing the physical interactions between gripper and object. With this approach gripping forces can be measured dynamically and critical situations like slippage can be detected (Wucherer et al. 2023). The maintenance of machining processes is relevance for the process behaviour and the economic impact on the production plans. Predictive maintenance uses modelling to estimate the remaining useful life (RUL) of tools and components. Models have to be adapted to each manufacturing process and context. AI-based approaches can lead to more precise estimates with fewer observations (P. Aivaliotisa, K. Georgouliasa, Z. Arkoulia, S. Makris 2019). Implementing AI at the workstation level can lead to reduction of equipment reconfiguration time, reduction of stressful tasks allocated to human, increase in operator satisfaction and reduction of cognitive stress.

3.3 AI Use Cases at the System Level

At the system level typical objectives are design resilient production systems, efficient logistics and material flow, optimized throughput and flexibility, optimized resource utilization. Implementing AI at the system level has typical use cases such as planning and scheduling the production of IPPS, design of manufacturing systems and work management with AI. One specific optimized resource utilization is system wide monitoring and optimization of energy usage. A study carried out to get data basis for ROI determination of individual energy efficiency measures found a reduction of energy consumption by 28% within the case scenario (Juergen Lenz, Kotschenreuther, and Westkaemper 2017). Implementing AI at the system level can lead significant to reduction of GHG emissions from industry between, increase of workforce that has basic digital skills, and reduction of training duration for human robot interaction. Also, the decision-making time can be reduced up to 60%.

4. Key Takeaways and Outlook

There were many recent breakthroughs in academia in regard to artificial intelligence, such as new algorithm designs and more efficient training. And many successful applications of AI in manufacturing have been demonstrated. The overall industry market for AI in manufacturing is growing fast and a 10-fold market increase is expected until 2030. An AI application consist of an AI-method which enables features and capabilities, in order to fulfill a use case objective. Use cases can be grouped into their level of autonomy and their manufacturing specific objective. Examples show significant improvement on all levels within a factory by applying AI-based applications.

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Biography

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