ARE WE THERE YET?

STEPS TO TAKE FOR ***ADOPTION OF AI*** *IN MANUFACTURING INDUSTRY*

Manufacturing industries have come a long way by transitioning from purely analog-style production to digitally connected systems. They acquired many in-depth insights in their respective processes. However, the journey of digitization in the manufacturing sector is far from over. Industry 4.0 and 5.0 frameworks present us with the underlying intermediate steps where AI is one of them. However, realizing them may be more challenging for some than others. Note that AI is not an end goal by itself, yet it can serve as an essential support, both as an integral tool for enabling this change and as a technology for specific applications. Examples include predictive maintenance, quality assurance and process enhancements. At our research group Ambient Intelligence, we strive to enhance the uptake of AI by applying insights from fundamental research to real-life use cases in industry. So, what we observe is that we are not yet there: additional steps are required for successful adoption of AI in manufacturing. In this article, we reflect on our observations and provide handholds for more effective utilization and embedding of AI in manufacturing industries.

AI has been around for over 70 years, with a steep rise in interest since 2010, especially with deep learning entering the field. More recently, since foundation models became available to the larger public through services like ChatGPT and DeepSeek, the interest in AI has increased exponentially. One striking thing about AI in general is the perception of what it is or could do. This influences one's expectations about such technology leading to unprecedented hype and fear of 'missing the boat'.[1] Mainly, because of not being able to keep up with technological growth and competition, due to lack of knowledge or personnel. Through our projects, we try to dampen such sentiments when we discuss matters with manufacturing companies. Yes, much is possible with AI, but what is more important is figuring out what could be enhanced in contemporary manufacturing processes – AI is a tool, not an end goal. However, there are many facets to manufacturing processes that can benefit from AI, such as optimizing planning, modelling processes and aiding digital twins for improved design and efficiency, predicting product quality and maintenance needs, and automating repetitive tasks.[2]

In our research projects, we have worked together with companies at various stages of digitization in their manufacturing processes. From lean assembly straits at Scania Production[3] and necessity for digital infrastructure at SMEs[4] to high-tech and high-volume productions at ASML and Canon Production Printing[5]. There are challenges all along the way. One main challenge of AI is data: the availability of data, its quality, and how it is governed. Looking at quality assurance for products as an example, we see a dilemma in the manufacturing industry. In high-volume production, products cannot be thoroughly tested from a cost perspective; conversely, each defective product or process results in extra costs as well as damage to the manufacturer's reputation. Predictive modelling can help assure the quality of products and thus reduce bottlenecks introduced by manual quality control. In essence, data related to manufacturing (used materials, system states) together with the manufacturing process (usage characteristics) can be utilized to develop passports on the quality of individual products.

However, for SMEs, this cannot be easily realized due to various limitations such as the availability of labelled data. Even if the company has all the process data available from raw material to the finished product and sale of the product, one cannot train a complete, predictive model since it is rarely known what the eventual product quality is. Furthermore, a central question is whether the data themselves are of sufficient quality to base a model on. For example, given only a few measurements on failed products, are these measurements trustworthy, and what is the quality of the model based on them? These challenges necessitate investigation into methods and techniques for predictive modelling of manufacturing processes. Moreover, this example exposes that AI adoption is not a single-step process. Creating models through AI based on data requires data of sufficient quality: these need to be gathered and stored, which in turn require processes related to connectivity, for example, through IoT-based solutions.

Methods for data acquisition and IoT have matured over time, and these frameworks are standardized. However, deploying them in a manufacturing environment is beyond trivial.
In our experience, the hindrance can be as simple as access to the existing network infrastructure. Certain B2B service agreements require a higher level of security before a new device is introduced into the network. Advances in federated learning allow data to remain on-premise of companies, without the data being shared externally. This provides a promise of data protection, yet even access to models trained on federated data can be re-engineered to pinpoint certain data attributes to one data source, thus a vulnerability and security threat. Such constraints on data sharing are another concern that hinders wider adoption.

For adopting AI in manufacturing, we provide four guidelines based on project experiences and scientific literature.

1.First and foremost: start with a goal. This can already be challenging, especially because it needs to be sufficiently specific to allow for actual usage and implementation of AI. This is a process of discovering and refining a problem statement.

2. Second, and supporting the first guideline: adopt a methodology. At our group Ambient Intelligence, we use CRISP-DM as a standard for our data- and AI-related projects. A recent extension on this is called CRISP-DMME: the CRoss-Industry Standard Process for Data Mining Methodology for Engineers. It provides an overview of specific phases related to handling data and AI, with additional emphasis on engineering processes.

3. Third: determine how AI could be embedded in your organization, especially focusing on how it influences the role of people in the processes. Adopting AI successfully requires personnel to familiarize with it and have sufficient AI literacy to be aware of its possibilities, shortcomings, and how they and the company can best benefit from it.

4. And finally, the fourth: join forces. Connect to existing and shape new initiatives through projects or learning communities, to experiment and learn from other companies and knowledge institutes.

For AI in manufacturing, it pays off to take a step back and gain an overview of the entirety of the manufacturing process. Defining the challenges and possible shortcomings of the existing situation can reveal where action needs to be taken. With best practices and practical examples aplenty, the need to pause before taking steps in this journey is almost minimal. Set a goal, use a method, and start experimenting with AI. ■

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