WORLD MANUFACTURING FOUNDATION

BACK TO THE FUTURE

EMERGING TOPICS FOR LONG-TERM RESILIENCE IN MANUFACTURING

AI AS AN ENABLER FOR LONG-TERM RESILIENCE IN MANUFACTURING

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The views and opinions expressed by whitepaper contributors are given in their personal capacity and do not necessarily reflect the views of the organisations for which they work or committees of which they are members.

For more information on the project and to read other topic-focused whitepapers that are part of the initiative, please visit https://worldmanufacturing.org/report/back-to-the-future-emerging-topics-for-long-term-resilience-in-manufacturing/

INTRODUCTION

Artificial Intelligence (AI) will increase the level of intelligence in the manufacturing industry by promoting, inter alia, the matching of production and demand, improving quality inspection, increasing product yield, reducing product failure rates, and improving production efficiency.[1] While the last decade of Industry 4.0 was determined by technology-driven innovation, the coming years will focus on data- and intelligence-driven innovation. In this perspective, AI is an enabler for the transition from smart factories towards intelligent factories with self-optimising and self-healing characteristics. While smart factories are capable of applying previously acquired knowledge, intelligent factories will be able to autonomously acquire new knowledge and apply it for self-optimisation purposes.[2]

The 2020 *World Manufacturing Report: Manufacturing in the Age of Artificial Intelligence* has already reported on the potential of AI in manufacturing. AI applications impact the resilience, efficiency, and scalability of manufacturing operations and have become increasingly significant during recent disrupting events like the current COVID-19 pandemic[3] or the blockage of the Suez Canal[4]. Resilience is defined as the ability of a system to withstand potentially high-impact disruptions and is characterised by the ability of a system to proactively mitigate or absorb the impact of disruptions, and quickly recover to normal conditions.[5] According to several scholars, Industry 4.0 and AI play a major role in achieving more resilient factories and circular value chains.[6,7]

The aim of this whitepaper is to develop recommendations for the adoption of AI in factories based on identified challenges, for long-term resilience in cognitive manufacturing.

CONTEXT

To significantly increase the long-term resilience of manufacturing companies, the following eight challenges have been identified and must be overcome.

Complementing employees' skills in manufacturing processes

The implementation of AI tools and Industrial IoT solutions on the manufacturing shop floor are aimed at automating tasks which are currently predominantly carried out by human operators. Data analysis arising from quality control, visual inspection, and maintenance operations are examples of tasks that are increasingly being automated. Machine learning and data availability is now allowing for the possibility of analysing and correlating data, which was previously not possible due to limitations of processing and human cognition. New methods of human-robot interaction through AI-powered assistants are also becoming a reality. As a result, optimisation of processes and manufacturing systems is increasingly possible. This leads to an increased efficiency and effectiveness in manufacturing, making the industry more resilient.

Increasing corporate agility and reducing procurement bottlenecks

Companies adopting agile supply chains and reconfigurable manufacturing systems develop a substantial competitive advantage. However, these production systems are hard to manage because of the small batch sizes, numerous shop floor configurations, significant variability, and inaccurate predictability of parameters (demands, lead times, capacities, etc). In this context, planning and scheduling based on simple rules and human intuition lead to suboptimal decisions, and do not provide the reactivity required to deal with uncertain events. Intelligent planning algorithms may automatically prescribe optimised production plans and schedules. These tools can also provide robust and flexible plans by taking advantage of the massive amount of data generated on the shop floor.

Reducing time to market
Product life cycles are becoming shorter, while the demand for customised products is increasing. This increases both product-side and production-side complexity.[8] In particular, the so-called time-to-market is an essential factor for the market success of a new product in order to be able to withstand the strong competitive pressure. In today's company practice, knowledge in the form of existing CAD design models or established design procedures is often not yet used systematically.[9] Project knowledge is thereby attached to specific employees.[10] The question of how the implicit knowledge of existing solution principles can be formalised in order to use it systematically and pass it on to new generations of engineers and products in an automated way, leads to a new type of feedback interaction between humans and AI.

Strengthening factory resilience and robustness
The ability to produce the same quality and quantity of product when faced with unexpected disruption is a requirement for improved business agility and rapidly changing needs. Resilient manufacturing, with the ability to quickly adapt to disruption, has become increasingly important after challenges experienced during the COVID-19 pandemic. According to a survey conducted by the Capgemini Research Institute, 68% of the surveyed manufacturing enterprises reported that it had taken 3 months to recover from supply chain changes that occurred due to COVID-19.[11] Reducing machine downtime through AI can provide flexible resource management and keep the losses at a minimum, demonstrating the potential of AI to strengthen factory resilience and robustness.

Reducing complexity in data-based decision-making
Currently, the success of AI-enhanced decision-making approaches largely depends on such data properties as: the availability, quality, consistency, validity, up-to-dateness, completeness and comprehensiveness of industrial data spaces. In future, the integration of AI technologies in manufacturing will result in additional complexities due to model properties. The major emerging challenges are:

1. multi-dimensional, non-linearity modes in decision models that are influenced by multi-structured, multi-channel data sources
2. unanticipated variability of decision factors and preferences over time
3. undiscovered interdependencies and uninterpretable semantics among predefined decision preferences and external influential factors
4. a lack of industry-related methodologies for the incorporation and explication of human-specific, experiential knowledge to feed KPIs, and
5. a lack of trustworthy AI due to sophisticated, but for humans inexplicable, models and algorithms.

Intelligent risk assessment and mitigation
Today's manufacturing enterprises employ productivity-related KPIs to shape the foundations of strategic and operational decisions. The specific, non-integrative analytical models used for feeding these KPIs do not allow for a comprehensive, anticipative identification of risks, nor do they allow for a definition of actionable measures to ensure stability and profitability in production, which would ensure resistance towards market volatility during unexpected societal and economic crises. Data-driven risk assessment and mitigation approaches should be introduced which i) predict the economic impact of productivity KPIs on business resilience, and ii) prescribe plausible measures for quick adaptation to disruptions, while maintaining continuous operations and safeguarding human resources, assets and brand quality.

Reducing cybersecurity risks
With the increasing local and global connectivity of factories, the danger of cyberattacks poses major risks, such as operational downtime of production lines or the theft/loss of strategic corporate information. AI can be used for intrusion detection by passively monitoring the entire network and identifying anomalies or threats. Similarly, the AI-based Deep Packet Inspection method examines data packets passing through firewalls, searching for potential non-com-

pliant traffic, viruses or spam to determine whether a data packet may pass or not. It is neither sensible nor economically advantageous to send all the data obtained at edge-computing level to a higher-level platform for analysis purposes. AI is therefore increasingly required at the edge to select and filter the relevant data, transmitting fewer corporate data over the Internet and at the same time, saving bandwidth and reducing latency times. The correctness of the data is a fundamental prerequisite for correct AI decisions. For this reason, both the machines at the edge and the transmitted data must be effectively protected against all types of cyberattack. IoT security gateways, VPN and secure digital platforms involving federated learning or differential privacy[12] are needed to meet this challenge.

Addressing ethics when using AI in manufacturing
As the manufacturing industry is pushing the boundaries of efficiency and productivity, the use of AI is becoming more pervasive, and investment in this technology is bringing new value alongside new challenges. As AI is becoming more mainstream, negligent applications of this technology could lead to problematic outcomes, including the reluctance to accept or use it. Principles and values of trustworthy AI, that guide the ethical development and deployment of AI within the specific context of its application to manufacturing, should be developed - not only to the end product or services, but rather to cover the entire value chain from design and engineering, planning, supply chain management, factory automation, IoT and the workforce.

OPPORTUNITIES AND RECOMMENDATIONS

To overcome the identified challenges and to fully exploit the opportunities of AI as an enabler for long-term resilience in manufacturing, we have formulated the following key recommendations for AI in the areas of product design, planning and scheduling, manufacturing, factory maintenance, big data and cybersecurity, while also addressing ethical aspects.

AI in product design
AI design assistants are able to identify patterns in the human design process and contribute towards the prediction of necessary design steps, while ensuring that the duplication of previous design developments is avoided by identifying similar components in a database to the one under construction.[13]

AI assistant systems for product design rely on a large number of CAD design data-sets being accumulated, and used as training data. Using state-of-the-art machine learning algorithms, design assistants are able to detect patterns in the human design process and can predict the next construction step.13 These kinds of AI assistants see humans as the ultimate decision maker. Augmented intelligence is created when the adaptive system is able to continuously improve the model output based on the inclusion of a human's acceptance or rejection of a forecast.[14]

The aspect of AI assistant systems functionally assisting humans by compensating for human disadvantages, such as being unable to deal with unmanageable amounts of historical design data, should be emphasised at this point. AI systems aim to resolve the discrepancy between continuously developing design requirements and the individual employee's skill level.[15] Furthermore, such AI assistance systems used in design should be based on understandable AI concepts to maximise user confidence, as most machine-learning methods are described as black-box models.[16]

AI design assistants significantly influence the knowledge-intensive work of design engineers. Here, both quantitative and qualitative advantages arise. Machine- learning models are able to detect design patterns from the data of existing product designs and thus contribute to efficient knowledge management. This will reduce the number of design duplicates and ultimately the time for product development. Furthermore, design assistants enable humans to focus on the creative part of the product development process. Humans and AI systems can work together in function-enhancing interaction.

Generative design algorithms based on AI techniques have constrained optimisation capabilities within a CAD design environment such that they bring significant improvements and speed to the product design life cycle. This approach can be made more general, by applying it to any type of model (not exclusively CAD), i.e. any digital twin based on a non-geometric representation of reality. Generative design algorithms allow designers to work much more quickly than would otherwise be possible. Generative design produces a large amount of design configurations, which traditionally require long development times and a high level of personnel resources. Consequently, these design configurations require less testing, as they are already in accordance with safety and general usability standards. Moreover, AI can be of use for sorting and selecting the most promising/worthwhile design configurations for further development. The use of generative design in the product design process can significantly reduce the costs associated with the traditional design process, while also enabling a faster launch of products to market.

AI in Planning and Scheduling

Production planning and scheduling aims to allocate the capacity of equipment and personnel by balancing operational efficiency and cost. The use of AI in planning and scheduling includes predictive analytics, prescriptive analytics, and real-time rescheduling.

Predictive analysis in production planning concentrates on the pattern extraction from data-sets to forecast planning and scheduling parameters. Various parameters can be estimated using statistical models and forecasting methods, e.g., demand, lead time, process duration, capacity, yield, machine downtime, etc. Based on the predicted outcomes, managers can easily steer their planning process to enhance flexibility, responsiveness, robustness and productivity in manufacturing. Novel AI-predictive approaches empower the industry to use past observations to build a resilient manufacturing system. Such approaches reduce uncertainty and risk.

While predictive analytics aims to forecast what will happen, *prescriptive analytics* considers various future scenarios and prescribes the optimal production schedule/production plan to the production manager. Suggestions are made based on mathematical representations and simulation of the manufacturing systems. To provide robust and flexible plans, these prescriptive analytics models may account for the uncertainty in the system by using scenario samples or uncertainty sets. Some decisions are selected to be robust and applicable to all scenarios, whereas 'wait-and-see' recourse actions are made for each scenario individually to allow flexibility when reacting to probabilistic events. Recourse actions may include express deliveries of components from local suppliers, subcontracting, temporary labour, or the reallocation of reserved components to end-items that can no longer be manufactured.

AI can also help to implement the production schedule on the shop floor. Schedule conformance remains elusive in most manufacturing environments, and the shift to more responsive supply chain operating models increases the likelihood of adherence issues. Challenges surrounding scheduling and execution can be overcome by improving upon current, traditional methods of data synchronisation. Tools to dynamically adapt to changes leverage an explicit *real-time rescheduling* and feedback connection with shop floor processes. They can highlight areas of risk, increase efficiency, and ultimately repair the schedule. AI-enabled prediction of disturbances from process monitoring can be used to amend the schedule domain model. These may include altering equipment process rates, varying operator availability or constraints, and triggering a continuous optimisation process running at scale in near real-time that creates a range of alternate schedules. These potential countermeasures can then either be suggested to decision-makers or automatically applied to adjust the schedule for a range of objective outcomes.

While planning and scheduling applications of trustworthy AI do not impact fundamental human autonomy or organisational democracy, ensuring understandable AI can foster the adoption of these techniques in planning and scheduling. By providing human-readable decision criteria and outcomes, users and management can increase trust levels to transition to automated decision-making. Particular attention should be paid to technical robustness, data governance, privacy, and accountability.

AI in Manufacturing

Quality control is required to detect specific anomaly events and drifting processes, resulting in higher yields, reduced costs, and thus, increased efficiency. Technological innovation is leading the way towards 100% inspections being fully online. This is enabled by advances in process data acquisition capabilities, vision systems, and new machine-learning algorithms. One of the biggest challenges in this field is switching from defect detection to anomaly detection. Quality inspection systems must be able to detect defects never seen before. These events may be less represented in training data-sets collected from the field. New approaches are therefore required that are capable of generalising and applying machine-learning models learned from similar equipment or utilising conditions which can complement existing data with synthetised data or similar data sources. Furthermore, these approaches need to be linked to a root cause analysis, which correlates anomalies to production process changes, to identify which process variable is the one negatively affecting the output quality. Generating labelled data is essential in this regard. Efficient data collection needs to be integrated with human experience, and natural language processing capabilities (e.g. reports or even operator experience), as well as knowledge discovery by information extraction from unstructured data (e.g. existing documentation, blueprints, pictures or written information). Sophisticated, but lightweight, deep- learning methods need to be developed for robust learning which allow closed-loop digital twin control and monitoring systems to correct the problem in real time. There is also a need for the democratisation of AI tools which are independent of particular platforms, as well as the development of data standards, which will allow for industry to form a shared understanding.

Digital Twin technology supports product or machine designers by providing valuable insights into how the product or machine will look and perform in the real world. The development of the IPC-2551 standard establishes the IPC Digital Twin, which comprises the Digital Twin Product, Digital Twin Manufacturing, and Digital Twin Lifecycle frameworks.[17] This standard enables any manufacturer, design organisation or solution provider to initiate application interoperability to create smart value chains, as well as the mechanism to assess their current IPC Digital Twin readiness level. The power and flexibility of the Digital Twin extends further than just a monitoring solution towards real-time, closed-loop control during production. This is enabled by tools such as the Live Twin technology and Virtual Sensors, which complement real, physical sensors for optimal process control. For many years, we have been using data to model processes, machines and manufacturing plants. Now, the latest AI methods allow us to combine machine learning with analytical models. This works very well in applications in which an initial problem is divided into an AI task and a simulation task that, together, deliver one result. The reliability matches that of a simulation, but with improved speed. The Digital Twin should also be a gateway for the consumer to gain information on the materials used within a product design, and on product sustainability. This will open up a whole body of evidence and trust that helps consumer confidence, but which cannot be navigated without the support of machine learning and AI.

Advances in the field of *collaborative robotics* are enabling new and augmented manufacturing workspaces. Workers are operating in the same environment as robots, without restrictions or safeguards.

This requires developments from a safety and security standpoint, as well as in the development of human-robot interaction systems. New manufacturing paradigms, which harness the increased flexibility of pairing humans and robots in a coworking environment, need to be developed. This will allow for industry to take advantage of having the flexibility and cognitive ability of human workers, as well as the repeatability and strength of robotic manipulators.

New techniques for *AI-based worker assistance* are required. These include computer vision and AI-based systems which can, for example, accurately and repeatedly assess and predict a human's movement/behaviour within the cell for increasing safety and efficiency in collaborating workspaces. New methods of human-machine interaction and the development of AI-assistance systems, manufacturing chatbots or digital coaches, are also required in order to retrieve and pass on information between the human, machines and advanced IT systems. These include mixed reality and voice-operated systems, which utilise natural language processing in order to pass on commands, instructions and other useful information.

AI in factory maintenance

Factory maintenance is an integral part of production planning, which contributes to increased productivity, reduced product life cycle costs, and maximised customer satisfaction. For several decades, well-founded industrial maintenance and reliability management strategies have confronted persistent dilemmas such as a decreased ability to react, increasing maintenance costs, the reduced availability of machines, low- to mid-level staff qualification, and a lack of insight into the impact of maintenance on profitability. In the era of Industry 4.0, AI-driven and computational technologies aim to digitalise and intelligentise maintenance processes and systems, and thus introduce new business cases. This aim can be achieved through *predictive and Knowledge-Based Maintenance (KBM)* strategies, models, and solutions.[19] KBM is about employing AI methodologies, methods, algorithms, and tools/technologies for analysis, modelling, and prediction, to reduce the likelihood or frequency of failures, thus increasing availability in production systems and gaining benefits from multi-channel, multi-structured data sources.[18] According to a recent report from Intel focusing on creating lasting value in the age of AI and IoT[20], 80% of the manufacturing companies surveyed were planning to invest in smart technologies and solutions to keep up with their competition in the following two to three years. The top three most popular investments for the participating companies were in AI (51% of respondents planned to invest), predictive/big data analytics (44% planned to invest), and smart machinery (35% planned to invest). This acceptance of companies to embrace AI and sensorised equipment will allow for the implementation of KBM, where the data monitoring of machine/process conditions can be automatically analysed to pick up any rules or patterns that indicate a possible fault, through data-mining systems being applied to accelerometric and sensor measurements, e.g., acoustic, temperature and pressure readings, and further extend the scope towards prescriptive analytics. These analyses can be used for wear forecasting, remaining useful life prediction, process recommendations, etc.[21] In industrial contexts, however, the implementation of KBM is faced with several challenges, surrounding, inter alia; 1) the proper use of multiple data sources, 2) the suboptimal use of multi-structured data, 3) the multi-modality of data, i.e. the missing semantic correlation of information, 4) multiple and overlapping reliability-centered and maintenance strategies and approaches, 5) the multi-dimensionality of maintenance organisation/actors/teams, processes and IT-systems, and 6) the economic and technical plausibility of KBM's business cases.[18] In the future, the scope of today's factory maintenance should be extended towards the industrial implementation of KBM and taking advantage of novel, scalable AI-driven approaches. Two major areas of untapped potential for trustworthy AI as an enabler in factory maintenance are:

1. *virtual assistance* (e.g. voice-guided defect isolation[22], real-time recommender systems[23], automated profitability assessment[24]), and
2. *multichannel sensorisation and intelligentisation* of maintenance processes (e.g. use of Augmented Reality[25], text mining[26], automated scheduling[27]), maintenance ontologies , digital twins[29]).

AI, big data and cybersecurity

To unveil the potential of AI, the manufacturing industry has to consolidate a more comprehensive *data culture* in terms of industrial cybersecurity, data reuse and data sharing.

The manufacturing industry has to move beyond data integration at a factory level, and to be able to deal with multi-tenant scenarios with data generated and managed across the value chain (see DFA[30] Zero-X initiative). The development of new manufacturing services, products or processes relies on access to common data which calls for new technologies to ensure a *multi-level digital continuity* that goes beyond the factory shop floor and operates at the level of connected factories and digital value chains.

B2B connected factories' common data processes will not be based on direct access to the raw data entities themselves. Instead, future data value chains will more likely be developed based on sovereign access to well-curated *high-quality data endpoints*. Industrial agreements will be instrumental in providing trust in the quality of the data presented in such data end-points and its reusability.

Data protection with encryption will be necessary within end-points relating to data processing and storage, as well as during transmission, to avoid manipulation or leakage. The increased connectivity of value chains exposes each additional end-point relating to digital infrastructure data and (micro)service, to potential attack vectors. This creates risks at both the factory and network level that should not be underestimated. Business continuity and automation processes can be potentially disrupted. Companies must, therefore, include the concept of cybersecurity and threat intelligence as an inherent component in any AI digitisation project. A *secure digital platform* helps to meet these cybersecurity-related goals and will help to avoid unplanned downtime and the enormous costs connected to a data breach. The inherent dynamism of AI solutions calls for active, rather than reactive, digital infrastructure protection solutions.

Computing capabilities and connectivity of the hardware available must also be considered when implementing AI for smart manufacturing. Due to the 'Big data' nature of the sensorised equipment being used in manufacturing, it is important to find a balance between using *Cloud Computing* resources, which are highly scalable and have the capabilities for complex analytics to be executed on remote powerful supervisory platforms, and using *Edge Computing*, which is a more localised use of computing/storage resources at the location where data is produced. Edge computing allows for the implementation of efficient algorithms that are not computationally expensive. Conversely, limitations of Cloud computing include the network bandwidth, data transmission speed, security, privacy, reliability, and robustness due to the transmission of raw sensor data from the machine to the cloud. There are opportunities for smart factories to adopt a combination of both approaches, in sense of mixed Edge-Cloud computing and Fog computing, which consist of both cloud and edge resources that reduce latency and network congestion.

Ethics in AI

The unintended consequences of AI technology are that it presents new challenges for the future of work and *raises legal and ethical discussions*. Some concerns are directly related to the way algorithms, and the data used to train them, may introduce biases or perpetuate and institutionalise existing social stereotypes and procedural biases, which may also generate misinformation. Concerns also relate to ethical decision- making by machines on the operation of systems/processes having potentially harmful or negative consequences on humans. Others include data privacy or use of personal information, and Europe has led the way in addressing these challenges.

In April 2019, the European Commission published a report[31] establishing a *European AI strategy* for positioning humans at the centre of all AI development efforts. It provides seven key requirements that AI applications should adhere to in order to achieve the "trustworthy AI" status. These seven requirements are human agency and oversight; technical robustness and safety; privacy and data governance; transparency; diversity, non-discrimination; societal and environmental well-being; and accountability. While many of these requirements are broadly applicable across a variety of different organisations, the specific context in relation to how they should be applied to the manufacturing sector has to be developed. The principles and values that guide the ethical development and deployment of AI in manufacturing should not be limited to the end product or services, it should cover the entire digital value chain from design and engineering, planning, supply chain management, factory automation, and workforce to IoT. These principles and values should not be about meeting some rigid checklist, rather it should be based on a framework to ensure the deployment of AI is fair and equal, accountable, safe, reliable, secure and addresses all privacy aspects.

The EU already has a proposal for regulatory framework to establish standards for ethics in AI[32] and applicable privacy laws such as the General Data Protection Regulation (GDPR)[33] that can be adapted to the manufacturing industry. While this has a broad reach within the EU, there is a *lack of global standards* that govern the development and use of AI, other than those developed by individual organisations. For manufacturing, there is a desire for a consistent regulatory framework on how data is shared and used, both internally and across the world, given the increasingly interconnected global supply chain. Given the linkages that exist between manufacturers to support interconnected functions, operations, and transactions for bringing a product from prototype to its final form, AI development in terms of data sharing and algorithmic development can span multiple organisations, and perhaps even multiple continents across the globe. In the absence of any international guidelines, engagement with stakeholders is necessary to come to a consensus on what principles and values should govern the development and use of AI in manufacturing. Given their pioneering work in this domain, the European Commission could provide valuable insights into these discussions and engage with international stakeholders to develop AI ethics guidelines for manufacturers globally.

CONCLUSION

The core message of this whitepaper is that **AI offers enormous potential for robust and resilient manufacturing** in many respects. A total of **19 key recommendations in 6 application fields** were identified that enhance long-term resilience in manufacturing.

Fields of Application	Key Recommendations (KR)	
Product Design	KR-1	Virtual Design Assistant
	KR-2	Generative Design
Planning and Scheduling	KR-3	Predictive Analytics
	KR-4	Prescriptive Analytics
	KR-5	Real-time Rescheduling
Manufacturing	KR-6	Quality Control
	KR-7	Digital Twin
	KR-8	Collaborative Robotics
	KR-9	AI-based Worker Assistance
Maintenance	KR-10	Knowledge-based Maintenance
	KR-11	Virtual Assistance
	KR-12	Multichannel Sensorisation and Intelligentisation
Data and Cybersecurity	KR-13	Data Culture
	KR-14	Multi-level Digital Continuity
	KR-15	High-quality Data Endpoints
	KR-16	Secure Digital Platforms
	KR-17	Balance of Cloud and Edge Computing
Ethics	KR-18	Discussion of Legal and Ethical Questions
	KR-19	Global Strategy and Standards for AI in Manufacturing

ANNEX

SUCCESS STORY 1 - Siemens

Blackout prevention out of the cloud

Pole-mounted transformers are a common sight in many countries. In India, for example, well over ten million of these transformers are in use. Every year, 15 to 20 percent of the transformers fail, causing blackouts and leading to huge repair costs and lost production.

Oil loss leads to fire risk

The loss of transformer oil is one of the most common causes of the high failure rate. This oil is used to cool the coils inside the transformers and keep them insulated from each other. In poorly maintained devices, where the housings are badly rusted or cracked, the oil can leak out. If the oil falls below a critical level, there is the risk of overheating or of voltage flashover. In these cases, it is not uncommon for the transformers to burst into flames.

Source: Siemens

The **digital twins make it possible to achieve a realistic oil-level simulation** in the cloud using fast computers, so now grid operators can be warned in advance if one of their transformers reaches a critical state. That is a twin that represents the essential principles of a pole-mounted transformer but is not customised down to the level of a specific transformer. It only becomes an **individual twin** when we feed in the measured temperature values from the actual transformer. To obtain these temperature values, the transformers simply need to be retrofitted with four sensors and a router that sends the measured values to the cloud. These values can be used first to determine the shape, size, and rated power of the retrofitted transformer compared with an intact transformer, and then to create an individual twin for it.

AI as a computing partner

Once the individual twin is in place, the measured temperature values can be used to simulate the oil level and indirectly determine how full the unit is. That will not work with a traditional simulation, though, because the algorithms in those cases are based solely on physical laws. The amount of time and effort needed for the calculations would be very great. That is why we combined these algorithms with **statistically tractable techniques and methods from the world of AI**. This is the only way to bring the calculation time and effort for the simulation down to the point where the oil level in the transformer can be simulated as often and as regularly as necessary. The ease of retrofitting is not the only benefit offered by this oil-level monitoring method. Compared with other monitoring solutions using sound or weight sensors, for example, it is also **relatively inexpensive**. Where other solutions can cost almost half as much as a new transformer, the solution using four temperature sensors, a router, and cloud-based simulation is available for about one-tenth of the cost of a new unit.
Credits: Hubertus Breuer and Frank Krull

SUCCESS STORY 2 - AISent

AI for quality inspection of bottles

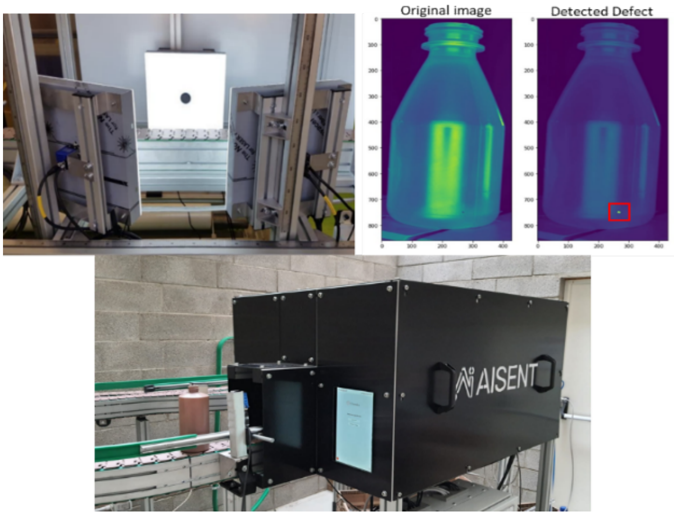
Serioplast is a leading company in the rigid **plastic packaging industry**. Serioplast supplies the FMCG companies (Unilever, P&G, Henkel, L'Oréal etc,) in the home care, personal care, food & beverage and automotive markets. AISent (https://aisent.io/), a deep tech start-up specialised in AI, Machine Learning and Computer Vision supported Serioplast in realising an automated quality inspection.

The requirements on the maximum acceptable defect are very strict and even small spots can cause the bottle to be discarded. Since extrusion blow moulding is a complex process prone to a lot of uncertainties, the shape and type of defects cannot be known in advance. In order to meet the needs, AISent developed a quality inspection machine that does not follow the traditional "defect detection" model but, instead, follows the "**anomaly detection**" paradigm. The anomaly detection approach has several advantages:

1. It allows the creation of a model for the status of health without spelling out every possible defect, one by one. The quality inspection machine may be **able to detect new types of defects** without defining them.
2. It allows a reduction in the cost of data-set gathering. There is no need to acquire images for every type of defect, it is just necessary to acquire healthy bottles. For this specific quality inspection machine, a **synthetic data-set was used**.
3. It allows a measure of the product quality to be obtained. The output is not binary (good/bad) but is a number between 0 (perfect) and 1 (defective). Therefore, the **rejection threshold can be adjusted according to the needs of the customers** (end users, type of product, type of market), spanning from a very strict control to a more flexible approach.
4. The measured quality is used not just for discarding pieces, but it is also used as a **feedback on the process**. A product with low quality can be seen as a symptom of incorrect process variables or low-quality input materials. Using the quality measurements, AISent is building a self-configuring machine to identify the **optimal parameters**, which leads to high-quality output.

The quality inspection solution is installed in Dalmine, Bergamo (IT) and can analyse up to 10,000 bottles per hour. It is composed of 3 cameras and 3 front-lights. The images are elaborated at the edge on an industrial PC and the results are computed in real time, discarding the abnormal pieces. The computer vision algorithm is a proprietary AI, based on Deep Learning.

AI enabled automated anomaly detection for a packaging manufacturer



SUCCESS STORY 3 - TilliT

AI-based IIoT for mature SME manufacturers

TilliT (https://gotillit.com/) offers tangible, high-value applications of AI and IIoT that are available to even the smallest manufacturers which improve resilience, and ultimately enable them to thrive.

Oliveri Sinkware, an Australian manufacturer of kitchen sinks and associated components represents the vast majority of SMEs worldwide. The facility is small on a global scale, with a mixture of modern equipment and machines that are decades old, operated by a skilled long-standing workforce not familiar with digitalised operations. Steel presses, welding and grinding machines lacked advanced logic control, and production processes were managed on paper.

Management started with a view that Industry 4.0 is not a specific project, but a strategy and mindset application driven by a need to be digitally connected. They highlighted an approach that tackled high- value areas, starting with the application of AI-driven planning and scheduling and the simultaneous adoption of IIoT cloud-connected equipment and personnel.

Low-cost IIoT Sensors were retrofitted to machines to monitor asset performance and electronically execute production processes. The knowledge base on how machines performed, allowed accurate downtime, setup, changeover and throughput rate information to be built up, identifying areas for improvement. Paper processes were replaced with cloud-enabled digital workflow tools for production tasks, maintenance and quality checks, bringing the operator closer to real-time connectivity with equipment and providing managers with a deeper understanding of factory behaviour.

These performance metrics were fed into a production scheduling system which utilised predictive and prescriptive AI algorithms to resolve the complexity inherent in their processes. Planning personnel could see the status of any process in real time and adjust the schedule as required. Operators spent far less time transcribing tedious notes onto paper and audit records became automatic. Digital orchestration of material, personnel, equipment and processes became possible for the first time in the company's history.

The result was an improvement in throughput rate, reduction in changeover time, lower raw material levels and reallocation of resources to areas of higher-value need within the facility.

Importantly, the ongoing improvements did not require complex industrial automation infrastructure, expensive consulting or the high capital allocation often associated with achieving digital manufacturing operations. This has set the baseline for Oliveri to build on with more advanced technology adoption in other areas of their business.

SUCCESS STORY 4 - Innovalia Metrology

High performance machining autonomy

High precision machining is a key manufacturing process used to produce critical and geometrically complex parts in aeronautics. To meet such demands, each year, the aeronautical sector has to deal with high scrap rates and high numbers of unproductive machining hours and accumulated costs primarily in extensive tests run to ensure process availability, quality and performance.

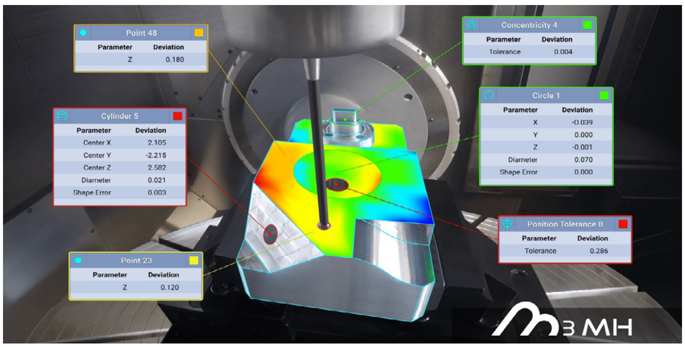
Green & Sustainable Machining

Machining of critical components in aerospace is extremely sensitive, and variances in performance are mainly due to changes in the machine environment (temperature, humidity, etc), material behaviour, equipment/tool ageing and error propagation in multistage processes. Highly skilled human expertise and continuous process optimisation are required for ensuring process repeatability and for tuning and maintaining accuracy in applications at different conditions. **AI can play a critical role in delivering the most awaited autonomy** that will reduce scrap rates, optimise machining performance and energy consumption.

AI to realise machining autonomy

Autonomous machining performance can be leveraged by equally ensuring Machine Tool (MT) accuracy status and equipment availability and optimum set-ups. This demands regular and inline verification of the status of the MT precision and **real-time AI-powered error compensation**, which has a positive influence on high accuracy and cognitive machining process planning and scheduling, helping to reduce expenses on condition-based MT calibration and energy, and material and productivity losses from defective machining processes.

The EU's Qu4lity digital manufacturing flagship project, https://qu4lity-project.eu/, has trialled adaptive manufacturing processes integrating Innovalia M3MH open cognitive 5-axis metrology MT set-up solution with +GF+ smart machining control processes. **Autonomous in terms of machine verification, it improves daily operations by leveraging greener and faster production** (reducing up to 50% of machining time), avoiding process failures, variability in quality output and bolstering continuous improvement simply by gaining better access to and smarter insights from real-time data. The integration of data-driven dimensional metrological intelligence and autonomous compensation modules in machining processes gives operators and MTs the possibility of delivering at any point in time the best possible part based on machine conditions and part geometry. AI-powered MT set-up and measurement, integrated with high precision machining, reverts to increased productivity, reduced operational costs and more sustainable operations with a marginal digital investment cost and low workforce re- and upskilling demands.



Credits: Jesus Alonso and Oscar Lazaro[35]

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