GIO White Paper: AI-enabled Industrial Innovations

September 2024

GLOBAL INDUSTRY ORGANIZATIONS

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This document has been produced by the Global Industry Organizations Roundtable initiative, which has been formed as an environment for discussion and open exchange amongst global industry organizations involved in digital transformation and/or ICT across multiple vertical industries.

This whitepaper is the result of a collaborative effort between multiple industry organizations encompassing AI innovations in manufacturing industries. It is a living study of the latest "work in progress" and is intended for general informational purposes only and does not take into account the reader's specific circumstances, and only reflects a current view of the manufacturing and automotive industry developments.

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Greetings from the “Kitchen of Innovation”

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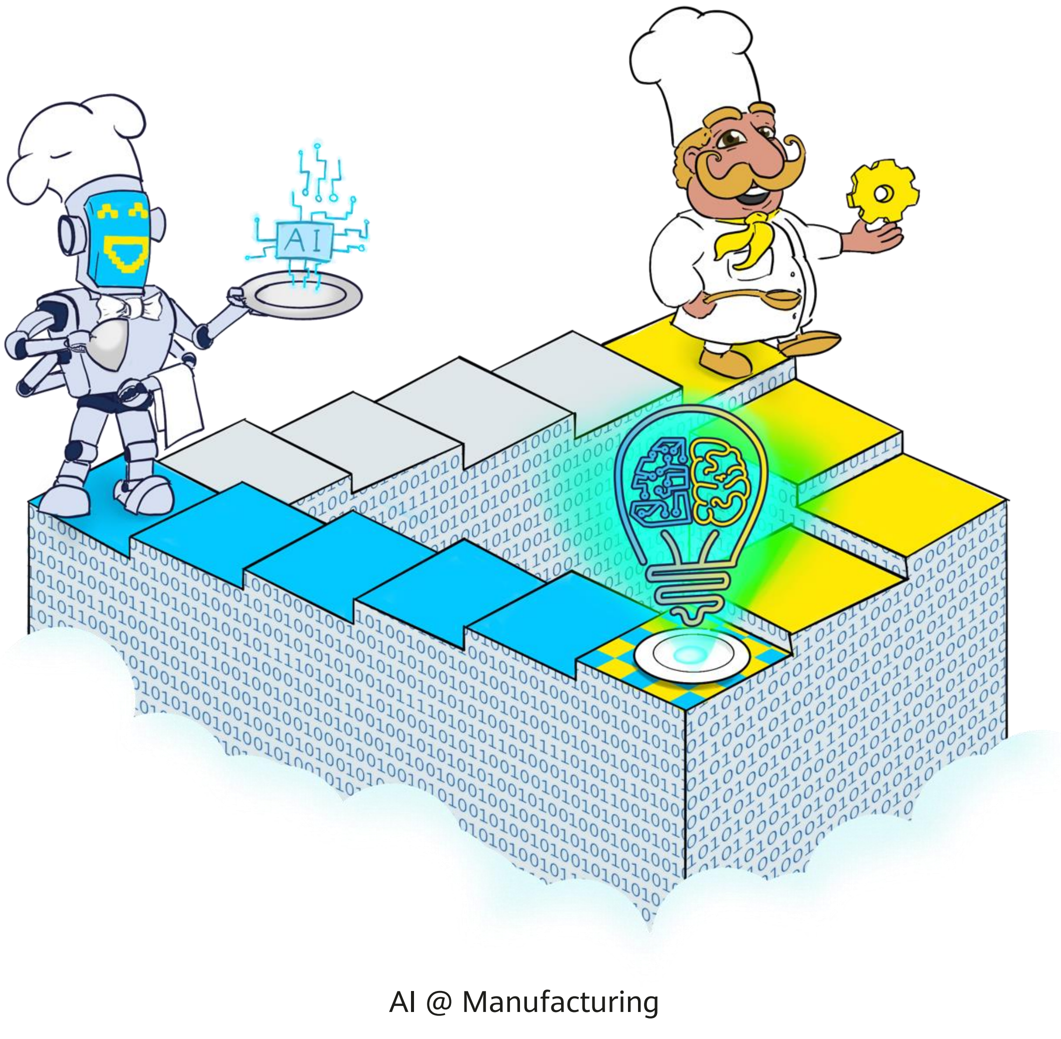
Innovation APPetizers for Manufacturing



AI @ Manufacturing

Unexpected recipes from mixed teams of Human and AI cooks

Editors and Key Authors

Prof. Dr. Jürgen Grotepass, Dr. Christopher Ganz, et al.

Foreword

“Greetings from the kitchen” - Innovation APPetizers for Manufacturing is the title of this use case selection. The cover picture is designed in a way to embrace both human-based and cutting-edge AI-enabled innovation in manufacturing, embodying the fusion of bits and gears.

Both chefs have different capabilities and strengths, symbolized by the different pathways they take. The Penrose staircase is interpreted as “cloud service” for both chefs and indicates that the different ways taken will come together. In the meeting point the innovation bulb gets electrified. Blue and yellow energies flow, making the bulb shine green on the served dish. When human and AI teams start to cooperate in innovation, creating value in data spaces, we may be surprised.

This collection of AI-enabled innovations in manufacturing results from GIO’s round table discussions and the authors’ intercultural experience of developing and deploying industry 4.0 solutions across sectors and geographies while working for global companies and being active in various industry organizations.

Innovation is about approaching things differently and finding new ways of doing things. It is about breaking away from traditional thinking and embracing new ideas, even when they seem unconventional or risky. This approach to innovation requires a willingness to take risks and embrace surprise, as it is often through embracing the unexpected that we can find the most significant breakthroughs and advancements.

Innovation also requires a certain level of adaptability and flexibility, as we must be able to pivot and adjust our approach when things don't go as planned. This can be challenging, as it requires us to let go of our preconceived notions and be open to new ideas and perspectives. But by embracing this mindset, we open ourselves up to new opportunities and potential solutions that we may not have considered otherwise.

This booklet on innovation appetizers is about learning to expect the unexpected and dealing with surprises – without losing acceptance of the solution.

The innovation stories listed in Section "Innovation APPetizers" start with quotes, each one selected from thought leaders in history, philosophy, and science or have been taken from artworks the authors got influenced by. This design to start from a different viewpoint when developing the innovation story is a practice in mind shift, breaking away from traditional ways of problem-solving.

This practice is gaining importance as digitalization enables the transformation of industries, resulting in the convergence of OT, IT, and telecommunication industries. Different ways of problem-solving, different standards, pain points, and KPIs may result in a clash of views in multiple stakeholder collaborations. This calls for a dialog, making the interaction between the three key players – solution provider, integrator, and end-user/operator – success enablers for innovations.

Contents

Introduction

This booklet summarizes innovation recipes where, in some cases, "old fashioned" AI such as machine learning, a neural network (NN), and in some cases, rather new developments such as generative, model-based artificial intelligence have added flavors to the appetizers. Fusing human and AI capabilities will lead to designing new products, processes, or even ways of manufacturing.

The human decision-making process is quite error-prone, as we know from Nobel Memorial Prize in Economic Sciences laureate Daniel Kahneman 2011[1]. His main thesis is a dichotomy between two modes of thought resulting in decision-making: "System 1" is fast, instinctive, emotional, and biased, whereas "System 2" is slower, rational, energy-consuming, and statistics-based. Most of the time, we think to act from "System 2", but in fact, we remain acting from "System 1".

As Innovation deals with the unexpected, restricting ourselves to our "system 1" reminds the authors of a quote from Antoine de Saint-Exupéry's book "Pilote de Guerre" (1942): "Dans ma civilisation, celui qui diffère de moi, loin de me léser, m'enrichit" (In my civilization, he who differs from me, far from harming me, enriches me). He identifies diverse views as something enriching. Sometimes, the most successful innovations are those ideas developed through collaboration, cooperation, and a willingness to listen to and learn from others, nowadays also including AI systems. In this sense, the quote can be seen as a reminder to approach innovation with an open mind, a willingness to learn, and a focus on finding solutions that benefit everyone.

AI-based decisions rely on data and, in most cases, on trained models optimally verified by human experts. With growing complexity, AI may suggest solutions humans have not thought of. In this sense, AI today is an automated support of "System 2". We, therefore, find that mixed teams of AI and human actors would be the best innovators when it comes to finding new solutions. With generative AI in mind, we see that a new innovation culture is evolving.

*1 Kahneman, D. (2011): Thinking, Fast and Slow, Penguin, 496 pp., ISBN 978-0141033570.

As in any intercultural experience, we need cultural learning and communication expertise to deal with the foreign and unexpected to transform our surprise into acceptance. Being surprised is one of the six basic and universal emotions that were found to be constant across all cultures (Paul Ekman). The learnings are on both sides, as the future design of artificial intelligence systems needs to foresee learning loops to cope with human surprise and deliver background information on data and models used when asked for.

This book is meant as an intercultural learning exercise and living work in progress on dealing with innovation and its support by artificial intelligence. It is also intended to be an invitation to all readers and start-up companies interested in innovation to act as co-authors and share their solutions and ideas with the growing AI community. In the long run, this will contribute to developing and deploying AI systems trusted by design to follow the users' intentions.

As AI is in its early days, the time is now to guide its development, to "educate" its capabilities to ensure our intentions are met. The binary code on the Penrose staircase is a "machine-readable" message from the authors, targeted to describe the vision and mission of the team's journey. If you want to know its meaning already now, you can get support from generative AI tools to translate it for you to save time. But as time goes by – digesting the innovation appetizers we present in the following chapters – you will know and also get the extract in the outlook section of this book.

Expect the Unexpected – Cooperating with AI in Innovation

Innovation is the introduction of something new (e.g., products, services, processes) that creates value for customers. It can involve the development of new ideas, the use of new technologies, such as AI, or the implementation of new business models. The key aspect of innovation is that it must create value for customers when being introduced in an industrial solution. Recently many innovative AI solutions and AI use cases are being reported, but the customer value must be evident in the solution on the customers' premise, not in the enabling tool or process (AI).

The common approach in the innovation of industrial processes is describing a problem or use case in the context of today's solutions without AI. These are often tailored in a way to be useful for human operation. The most obvious expectation and approach to introducing AI is very often to replace human labor and interaction with AI.

But the limitations of humans are not those of AI, and the limitations of AI are not those of humans. This approach, therefore, falls short. Instead, a use case should be decoupled or abstracted from human limitations, and a new approach should be considered, building on the strengths of AI. Such AI-based solutions shall incorporate human strengths to create a system that exploits AI and human strengths. But human strengths shall preferably be executed by humans, not mimicked imperfectly by machines.

Because any AI approach requires large data sets, that need to be correct, consistent, labeled, and complete, the following limitations have to be complemented by human intelligence:

- AI systems are not able to detect causality, but they are strong at finding correlations
- AI is building on existing data, unable to project into areas where data is not available (as from models)
- solutions are reflecting all shortcomings of the training data set (bias, etc.)

Human intelligence on the other hand builds on mental models that are trained on less data and can be used to extrapolate.

Cooperating with AI in innovation can bring many benefits, as it allows organizations to process and analyze large amounts of data quickly and accurately. However, it is important to expect the unexpected when working with AI, as it will sometimes produce unexpected results or behave in ways that humans may not anticipate.

One of the key challenges of working with AI is that it is often difficult to fully understand how it reaches its conclusions or makes its decisions. This is especially true when dealing with complex machine-learning algorithms that are trained on large amounts of data. While these algorithms can be very effective at finding patterns and making predictions, they may not always be able to explain their reasoning or provide a clear understanding of how they arrived at a particular outcome. This lack of transparency can lead to unexpected results and make it difficult for organizations to anticipate and mitigate potential risks or challenges. For example, an AI system might make a decision that is not in line with an organization's values or goals, or it might produce a result that is not aligned with human expectations.

To address this challenge, organizations need to have clear goals and expectations for their AI projects, as well as robust processes in place to ensure that the AI systems they are using are aligned with their values and goals. This might include regular reviews and audits of the AI system to ensure that it is behaving as intended, as well as ongoing training and development to ensure that it remains up-to-date and accurate. For suppliers of AI systems, this may include systems updates when integrated into machines, systems, or automation solutions sold to other nations that have other values or restrictions on data usage.

- Not all AI is smart

Despite the current hype and admiration of artificial intelligence, it is to be noted that not all AI solutions are indeed intelligent. There are ample examples, where AI behaved in surprisingly stupid ways. This is largely caused by its dependency on good training data that is used to create the underlying neural networks. Training an AI system is a good example of a garbage in – garbage out situation: improperly selected training data leads to a system that reflects all the shortcomings and weaknesses of the training data set. And if later in use, the system encounters a situation that is outside the area that it was trained on, its behavior is unpredictable. So, neither the size of the network nor the size of the training data gives an indication of the quality of an AI solution. It is mostly the data that it was trained on that does. Since that data is often selected by humans, this is interaction between AI and humans that is often overlooked, and that has to be mastered.

- Not all smart systems are AI

On the other hand, not every technical system that looks smart is based on today's perception of AI (neural networks). Complex industrial installations, such as refineries, power plants, or similar, have been operating for decades without the use of AI. Deterministic control algorithms have evolved to a level that easily gives the impression of intelligence to the outside observer. Take for example model-predictive control: the system's sensor readings are used to identify its current state. That state is then run through the equations of a dynamic model to simulate different commands to the system's actuators. An optimization algorithm is used to find the best actuator command that will bring the system closest to the desired state. That command is given to the physical actuators to run the process. This algorithm is repeated in each control step, in some cases even in sub-second intervals. Since the dynamic model equations are based on the laws of physics, the system can deal with situations that it has not encountered before, i.e., where no prior data is available. A human operator then monitors the behavior of the system and drives the operation by adjusting setpoints only.

In summary, "cooperating with AI" in innovation can bring many benefits, but it is important to expect the unexpected and to be proactive in addressing potential risks and challenges. This includes having clear goals and expectations, ensuring that the AI systems being used are aligned with values and goals on company or even national level, and managing expectations on both, limitations of AI systems and human capabilities.

Innovation APPetizers

This chapter summarizes small as well as breakthrough innovations introduced as industrial use cases, each one challenging by the topic given and surprising by its final solutions. The technology readiness levels vary from demonstrator status resulting from actual deliverables from R&D projects up to industry-mature solutions on the market. The examples taken are part of the authors' professional experience and have been developed while working for global companies in the field of ICT (information and communication technologies) and automation to innovate manufacturing processes.

Different challenges have to be tackled at different stages during a product or manufacturing process and lifecycle. Therefore, the use cases listed in the next chapter are categorized into the following three groups:

- Design and Engineering
- Operations
- Maintenance

Industries are currently progressing in the twin transition process (digital and green) with the carbon footprint of products and processes becoming a new currency. With access to data, AI will be a key enabler in turning empirical process knowledge into predictive solutions. Such solutions will yield savings for customers and related value chains.

In more traditional industries, such as steel and rubber, model creation for predictive and prescriptive AI still is a journey. Experience accumulates collaboratively over time. This is because process data in front-end processes are still missing, calling for sensor integration to generate them, as targeted in brownfield updating.

Use cases in traditional manufacturing industries face some more challenges and bottlenecks as they

- are often customer-built and not comparable to other installations, i.e., data from similar installations are often irrelevant.
- are engineered to perform a specific task, the outcome from normal operations is known a priori and follows the engineered structures and physical principles: mostly this is done based on physical models. Unlike consumer analytics, industrial customers are therefore not interested in understanding the average (normal) operation, but in finding the outliers (unexpected, failures)
- the specific task a plant or machine is designed for is executed repeatedly. Collected data only varies minimally, confirming the a-priori knowledge. Data about the unexpected and the failures are very rare and hardly sufficient to draw statistical conclusions from.
- have different lifecycles during industrial installation in the spectrum: engineering – operation – maintenance. All phases are equally important for the performance of a plant. Furthermore, the lifecycle of a plant is longer than the software that runs it.
- Many industrial processes are dangerous. Errors can lead to damage and fatalities, even to larger-scale environmental damage. Try and error is not an option.

Data and information about industrial processes are scarcer than the data sets the large-scale AI solutions have been trained on. Furthermore, data sets are the property of the industrial enterprise and are often not easily available.

The current R&D initiatives in Europe (GAIA-X, Catena-X, Manufacturing-X) are focusing on solving some of these problems by funding the digital transformation of manufacturing industries. The Data Governance Act, adopted by Parliament on 6 April 2022, aims to boost data sharing in the EU so that companies and start-ups will have access to more data that they can use to develop new products and services. The full potential of artificial intelligence can only be exploited when stakeholders and users have access to big data.

"Data only has value if it is aggregated, refined, and used in the right way," said Angelika Niebler (a German lawmaker from the European Parliament), who steered the legislation through Parliament. "Some businesses might not even know what can be done with data from, for example, their industrial machines. Through more data sharing new business models can emerge, more efficiency can be achieved, or products can be improved."

In this sense, each innovation use case listed below may become a starting point of a journey the reader might like to follow up on, learning what can be done with data. Therefore, we like to call them innovation appetizers to make curious and to introduce new and “hot” recipes from the kitchen of innovations - human and AI teams are serving as starters (design and engineering phase), main course (operations), and dessert (maintenance).

The innovation use cases are preceded by a quote to address the topic involved and are closed with information on the value proposition and key performance indicators for business.

Innovation is about changing viewpoints, asking the right questions, and daring the new. To introduce the spirit of innovation, each use case will be headed by a quote to start from a different perspective when developing the innovation story. This is a practice of mind shifts, breaking away from traditional ways of problem-solving.

Quote	
Nur wer das Fürchten nie erfuhr, schmiedet Nothung neu.	*He who the force of fear ne’er felt Nothung shall he forge.*
Richard Wagner: ‘Siegfried’, 1st Act, Scene 2	

Wagner's opera "Siegfried," relates to asking the right questions with Siegfried being daring enough to ignore habitual ways of sword making being unbiased from long-lasting, traditional guild’s expertise. He succeeds in finding the new solution of forging the sword.

In this sense, it is possible that the idea of overcoming fear and embracing the unknown could be related to the process of innovation, as innovation often requires taking risks and venturing into uncharted territory. To come up with new and creative solutions to problems, one must be willing to challenge their assumptions and think outside the box, even if it means venturing into areas that may be unfamiliar or uncertain. This willingness to embrace change and take on challenges can be an important aspect of successful innovation. This is especially true when dealing with AI as new tools used in Innovation.

In each of the use cases, we will point out what customer value it will provide. In the industrial, B2B environment that we are covering in this book, value is in the end cash generated through the new solution. In an investment decision, the net present value often has to be calculated, where the positive cash flow from the solution has to be considered. We therefore indicate the areas, where the solution will have a positive impact on the customer's cash. For that, we use the radar chart that is shown in Figure 1.

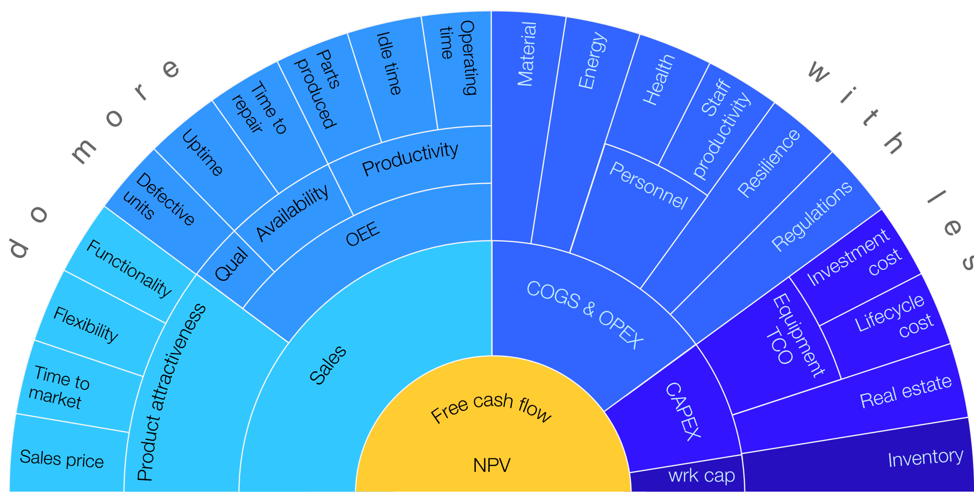


Figure 1: Value radar chart used to indicate areas of customer value

The areas to the left of the chart help to increase products sold, either through selling more or to produce more using the equipment by increasing the operational equipment effectiveness (OEE). On the right side of the chart are cost items that may be reduced: cost of goods sold (COGS), operational expenses (OPEX), or capital expenses (CAPEX). The parts to the lower right are changes in working capital. Solutions that we found impacting manufacturing influenced inventory levels. Solutions that have an impact on accounts receivable or payable are probably more related to business process automation and are not included in the radar for the sake of simplicity.

Please be aware that the cash levers listed on the radar are not complete. There may be aspects impacting top or bottom line that we don't spell out. Those will be added in the commenting text next to the chart, where the values are explained per use case. In our analysis over the years, the radar has proven to be quite comprehensive and complete for most industrial applications.

First Course – Design and Engineering

As the first course, we like to serve some inspiring appetizers from design and engineering processes as most innovations have their starting point here.

The design of products and systems focuses on reaching the customer's requirements and technical specifications whereas engineering combines the fields of science and math to solve the given problem at the customer's site.

Nowadays we see a shift in the engineering definition: From the traditional design and engineering of machines to the "engineering" of socio-technical systems (acatech), where also society and the environment become new stakeholders in the value chain. Politics are requesting a new focus on the circular economy along the product lifecycle, starting at the design stage and ending at recycling and the reuse of material. The latest example is the adherence to European requirements on energy and product carbon emissions to meet the twin transition targets (digitalization and green). Sustainable digital technologies could enable carbon neutrality in the EU by 2050.

"Model-based systems engineering (MBSE) is the formalized application of modeling to support system requirements, design, analysis, verification, and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases. MBSE technical approaches are commonly applied to a wide range of industries with complex systems, such as aerospace, defense, rail, automotive, manufacturing, etc." (extract from Wiki)

Errors happening in the design and engineering stage are very costive to correct in later stages, as the system performance is strictly linked to the system boundary set in the design stage. However, the rise of digital twins allows the simulation of physical properties and environmental parameters in early product stages, without the costive need for prototype building anymore. Thus, errors can be avoided, material and energy consumption reduced, and recycling of prototype hardware avoided.

Furthermore, connectivity to cloud-based services and access to digital twins may lead to more flexible system boundaries. This allows resilience and adaptivity of systems by deploying cloud services when needed. As data and feedback from operations get available, the stages of engineering and operations start to overlap.

Quote	
Une cathédrale est bien autre chose qu'une somme de pierres. Elle est géométrie et architecture. Ce ne sont pas les pierres qui la définissent, c'est elle qui enrichit les pierres de sa propre signification.	*A cathedral is much more than a sum of stones. It is geometry and architecture. It is not the stones that define it, it is it that enriches the stones with its own meaning.*
Antoine de Saint-Exupéry, 'Pilote de Guerre'	

Use Case: Generative AI in product design and engineering

For a manufacturing company, staying competitive is crucial to success. The recent successes in generative AI have led to the idea of using such methods for product design and engineering. By harnessing the power of machine learning and data analytics, companies can create innovative and effective products that meet the needs of their customers.

Customer's challenge

A lot has been written on AI applications in production optimization and maintenance. Also, among this selection of use cases, several papers focus on improving a plant's operation.

However, errors in the design and build of a plant can hardly be corrected at runtime or, if so, at a very high cost. Once the plant is set up, it may operate for years in the "as built" configuration without changes (process plants). Discrete manufacturing plants may be re-configured when new product lines are being produced.

Over the lifecycle of a plant, we can, therefore, identify three cycles:

- Plant design, construction, and operation
- Product design and production
- Product manufacturing and maintenance

All include the operation of the production. Optimizing the operation by adjusting equipment setpoints can be based on a large amount of continuously collected operational data. However, for the product re-design cycle, collected data fromearlier products may not be relevant, and it is done much less frequently to provide sufficient data. The plant design cycle is mostly not even a cycle – a plant is built and then operated until it is dismantled after a few decades. Data is, therefore, hardly available to optimize a plant design based on measured data.

Both plant engineering and product design must rely on the availability of simulation capabilities that provide the relevant data to optimize. Once this is achieved, the plant is built, or the factory is adapted to produce the new product family.

● AI-based challenges and opportunities

Generative AI algorithms have recently received much attention by releasing solutions like ChatGPT and Dall-E, to name some of the most discussed approaches. Generative algorithms not only map an input data set to an output data set, but they also typically have more complex structures. One class of algorithms is the generative adversarial networks (GAN). In such a setting, two networks bet against each other. One, the generator, is trained to create outputs from input data sets, e.g., images from a description. The other, the discriminator, receives original input as well as artificially generated one from the generator and is trained to judge whether the input is generated or is original. When the discriminator detects artificial input, this information is fed back to the generator to learn to create a more realistic output and trick the discriminator into rating the generator output as genuine. In that system, the generator becomes better over time.

Such a system can be compared to a master and a critic: the master provides a piece of work, and the critic rates it as good or bad. The master then learns which works are rated good and, over time, only receive good reviews.

This concept can be applied to product design. The system is receiving the specifications of a part. The generator can create designs for parts that should fulfill the specs. The discriminator rates these against the specifications, and the generator creates new designs that become better and finally meet the specs. To make such systems more effective, they not only rely on AI models. Generative design tools are capable of modeling and simulating the physical properties of the parts and, therefore, assess the performance of the design by simulating its behavior and comparing it to the design specification.

A human designer selects the final design from a set of generated ones with similar performance or adjusts the parameters throughout the process to improve designs based on human experience.

The resulting generated designs often have a more organic look: the design allocates material along force fields and stress vectors, which results in structures as often seen in nature, especially in the growth patterns of plants. These patterns that have evolved throughout the earth’s history are among the most effective structures. Such structures are not efficiently produced by traditional subtractive machinery. To create them, additive manufacturing is often the production method of choice.

Generated designs can be more efficient in terms of material used and weight. They can result in entirely new design concepts humans didn't perceive before.

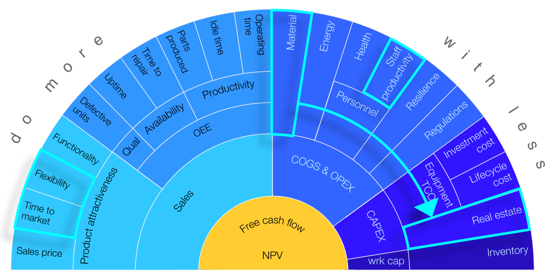
A special case is software. Software is designed as text (programming languages), and for texts, the recent language-based models (e.g., ChatGPT) are well suited. There are lots of references where ChatGPT has been asked not to write an essay or paper but computer software. It does so reasonably well. In software, we can already observe that the engineering task may focus more on conceptual questions in the future, while the details of writing correct and secure code may move to an AI agent. This is possible even if it is software as specialized as PLC applications: Siemens presented PLC code generation using ChatGPT at the Hannover Fair 2023.

Generated value

Generated design is typically more efficient in material use, resulting in a lighter (lower weight 'real estate') product.

Automatically creating variants for review increases staff productivity.

A more automated design increases the product configuration's flexibility and shortens the market time.



Conclusion

The rapid advancements in generative algorithms, particularly in language, imaging, and video, promise a huge potential also in engineering. As they show their advantages in software engineering, similar solutions that don't comprehend computer languages but the language of physics can provide great support in designing products or components faster. Furthermore, they would more precisely fulfill the specifications that the human designer gives. Many of the PLM vendors offer such packages today, and we will probably see more advancements in this field in the near future.

To really benefit from the new approach and the resulting optimal designs, manufacturing needs to adjust in many applications to include additive manufacturing capabilities to be able to create the resulting shapes. Together, generative design and additive manufacturing create new opportunities and offer much more powerful tools to design engineers.

Quote	
Zukunft ist kein Schicksalsschlag, sondern die Folge der Entscheidungen, die wir heute treffen.	*The future is not a stroke of fate, but the result of the decisions we make today*
Franz Alt	

Use Case: Product Carbon Footprint tracing in Product and Process Design

Decisions we can already make today affecting the future of products and processes will usually start at their design stage. The target is to make them as sustainable as possible "by design", looking at the whole lifecycle. Encompassing also their recycling and second use of material, the design stage addresses circular economy needs from the "cradle to the grave" of products and processes.

Customer's challenge

The sustainable products initiative (SPI) is part of Europe's "Green Deal" coming up with new regulatory requirements to declare the Product Carbon Footprint (PCF). The PCF may be covered by the digital product passport.

Industries in all sectors will probably be required to provide certain product information in the form of a Digital Product Passport (DPP4.0) [2].

DPPs could be a big step forward for more sustainable products and consumption, boosting energy and resource efficiency by enabling new business models based on, e.g., digital data sharing. DPPs could also substantially contribute to improved energy and material supply security for a resilient economy", argues Prof. Dr.-Ing. Dieter Wegener, VP and Head of External Cooperation at Siemens Technology & Chairman of ZVEI Industrie 4.0. Management Circle [3].

In this sense, the digital product passport contributing to sustainability has become a new currency, giving a competitive advantage against those suppliers who don't comply.

The first demonstrator of a highly integrated product was demonstrated at the Hannover Fair in 2023 by ZVEI [4]. As a use case, a control cabinet has been chosen, consisting of multiple modules, each one being described by its digital twin (asset administration shell) [5].

*2 https://www.zvei.org/en/subjects/zvei-show-case-pcfcontrolcabinet

*3 https://www.youtube.com/watch?v=OPCSgWFx3NM

*4 German Association of Electrical Engineers and Digitalization: https://www.zvei.org/en/

*5 https://schaltschrankbau-magazin.de/workflow-prozesse-dienstleistungen/mehrwert-veranschaulichen/

As one sub-model within each asset administration shell includes the product carbon footprint (PCF) data for its manufacturing, the integrated carbon footprint of the whole cabinet can be calculated easily by summing up all individual PCFs during the assembly of each module. Transparency is given as the QR code of each module, and the resulting one from the integrated product can easily be accessed to monitor the data, as displayed below.

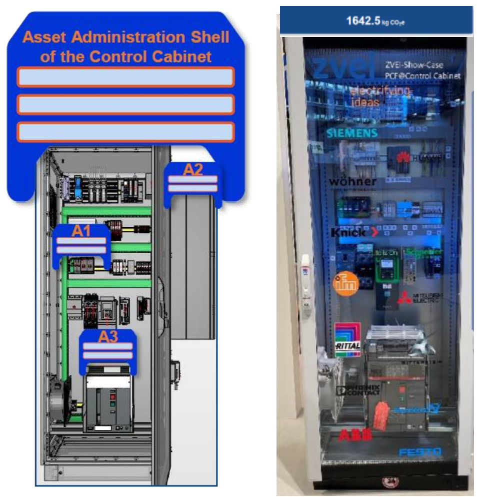


Figure 2: ZVEI Show-Case "PCF@Control Cabinet" demonstrating the first Digital Product Passport (DPP4.0)

Figure 2 shows the DPP demonstrator, which indicates the overall PCF value as all the PCF scores of all components being integrated get traced and summarized. The DPP4.0 concept, as proposed by the ZVEI, is based on two essential pillars that were developed within the framework of the Industrie 4.0 initiative:

- the digital nameplate (DNP4.0) via IEC 61406 (Identification Link) and
- the Asset Administration Shell (AAS) according to IEC 63278 (under development)

As can be seen in Figure 3, the engineering process consists of many interfaces between the companies and the IT systems involved. In addition to the fact that the engineering data must be transferred, the data of the individual components must also be transferred from the suppliers to the system integrators. In this simple example, there are already 15 companies involved, from which data on 56 different products and components, which finally lead to a system of 93 parts in total, are required to fulfill the value add.

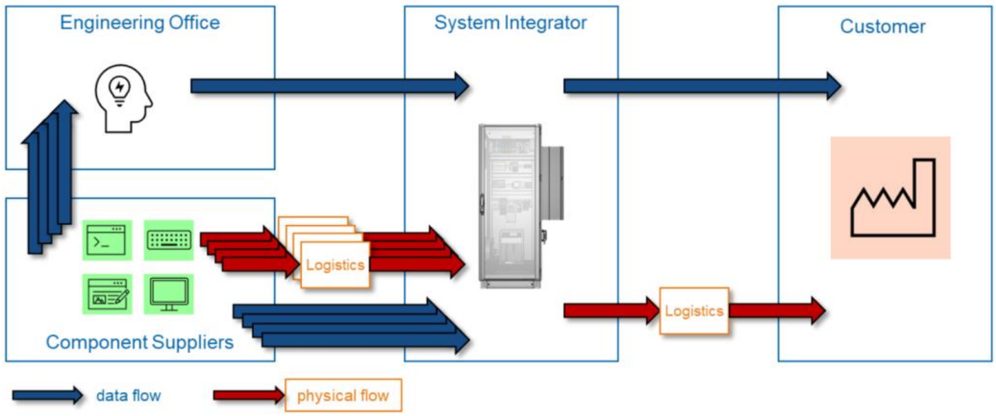


Figure 3: Data sharing in the value chain between the engineering office, system integrator, and customer

- ## AI-based Challenge

To contribute to the sustainability of production and products, one already has to design products, taking their complete lifecycle into account. This includes monitoring the entire supply chain as well as the recycling and re-use of components and materials.

AI tools will be needed to analyze and select the digital twins of components offered by various suppliers in digital markets. During the engineering stage, components will be chosen, optimizing multiple parameters, e.g., matching the technical specifications, the environmental requirements on energy and PCF consumption, customer requirements on delivery time and costs, and supply chain resilience.

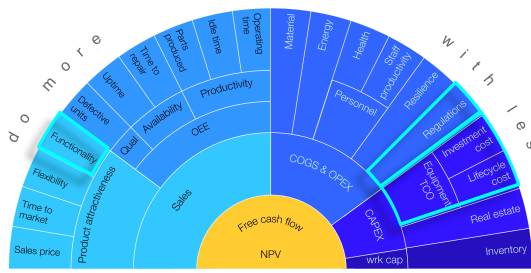
This current gap identifies a need for further R&D to develop future generative pre-trained AI models to access and analyze the digital twins of assets and production capabilities offered in digital marketplaces.

Generated value

Regulatory compliance: Competitive Advantage due to CO2 tracking of products and reduction of tons of paper documentation for products.

Product attractiveness: DPPs will help stakeholders and consumers make more informed decisions about the products they purchase and use, the product's embodied environmental impact, or recycled materials content [6].

Lifecycle cost: DPP provides the necessary information to re-use/recycle a product.



Conclusion and Outlook

The demonstrators at the Hannover Fairs 2022/2023 impressively show how product information can be made available with the help of the Asset Administration Shell (AAS) in conjunction with the Digital Nameplate (DNP4.0) and can be used automatically in relevant processes.

This was exemplified by calculating the product carbon footprint (PCF) of the control cabinet across the supply chain. Through this applicable technical solution for providing product information, the solution also represents a concept for a Digital Product Passport (DPP4.0).

AAS aims to ease system integration and lower engineering efforts. This will be supported by additional meta-information of AAS as sub-models. This may lay the foundation to integrate with other networks even deeper, like GAIA-X and Catena-X [7].

*6 https://betterfuturefactory.com/nl/insights/digital-product-passport/

*7 https://www.zvei.org/fileadmin/user_upload/Presse_und_Medien/Publikationen/2022/Mai/Show-Case_PCF%40ControlCabin/22-05-25_Whitepaper_ZVEI-Show-Case-PCF-Control-Cabinet-HMI2022.pdf

Quote	
故其战胜不复 而应形于无穷	*Do not repeat the tactics which have gained you one victory, but let your methods be regulated by the infinite variety of circumstances.*
Sun Tzu: “The Art of War” – Chapter 6: “weak points and strong”	

Use Case: 5G enabled Value Creation

In the past, we have built perfect machines – and still do. But as opposed to mass production scenarios and specifications tailored to customer requirements by fixed design, we now face new challenges to make systems adaptive, resilient, and sustainable.

Customer’s challenge

Wired solutions of machines and fixed design have gained us “past victories” for mass production, but now we may think of adding wireless connectivity allowing data-based value generation and not differentiating anymore between hardware, software, and services being connected. Machines and modules may be connected within and beyond factory limits to allow new production paradigms, such as shared production scenarios.

5G allows brownfield updating of machines making the system boundary more flexible, as data-based cloud services allow to integrate more functions as originally foreseen.

With “cable-like” (deterministic) wireless network solutions (5G+: 5G and beyond) getting available on the market, legacy machines can be updated with 5G, adding further modules and sensors on demand and deploying smart cloud services, e.g., for quality and process control. This is meant by the term “brownfield updating” of existing machines, e.g., allowing production machines needed for welding, milling, drilling, and CNC manufacturing to be connected to the cloud for data-based online process automation. As a result, better qualities are yielded at reduced CO2 footprints as no further hardware will be needed on the shop floor, and digital twins of assets allow complex simulations and service provision in the digital space.

● AI-based challenge

AI-based challenges may be discussed in a spectrum of different innovation use cases related to 5G-based Smart Manufacturing as presented during Hannover Fairs and webinars of the 5G-ACIA (Alliance of Connected Industries and Automation).

Use Case 1 – Safety and Module Certification (Infrastructure as a Service: IaaS):

Safety-relevant machine verification is offered as a cloud service. Safety risks are accessed via the digital twins of the assets that are operational on the shop floor, and virtual certificates are given. AI services for environment screening and object detection are used to monitor if additional safety risks occur that have not been planned. Further R&D is undertaken to also include the risk of AI services itself to develop trusted services.

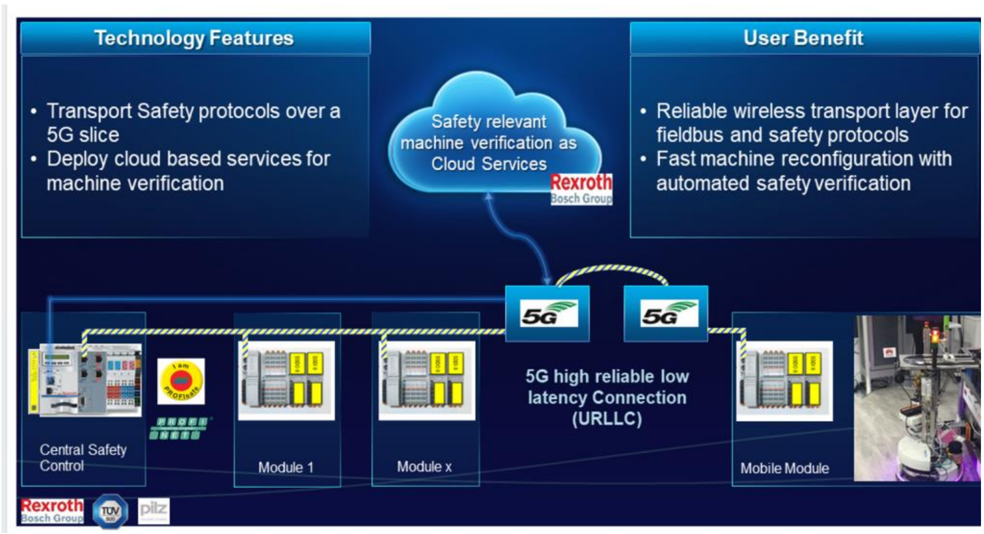


Figure 4: Fast Machine Reconfiguration with automated safety verification (Eco Connect Rom, 2019)

The latest safety certification scenarios for adaptive, wireless connected machines are based on digital twins of the assets being in operation on the shop floor, as demonstrated in Figure 4. The risk being related to the asset on the shopfloor e.g., robot is described by its digital twin for a given environment scenario. AI is used to monitor the environment if the context is still as planned – and even to look into the future for some seconds. This predictive risk management leads to new dynamic certification processes. Central safety control loops are no longer limited to wired connected assets. If an emergency stop is initiated also wireless connected machines would stop.

Use Case 2 – Value adding through AI services during product transport: Value adding for AGVs in Logistics as depicted in Figure 5: Using transportation time for Quality Control on Demand. With brownfield updating of the AGV a Camera with 5G connectivity is integrated.

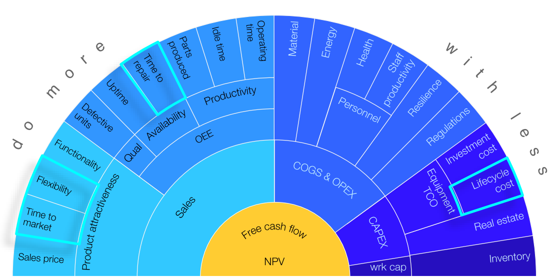
Image data is sent to the edge during the transport of the product for quality assessment. In the best case, the AGV is transporting the good to the next production step or to the customer. If defects are identified during transport the AGV will deliver the product to the maintenance area requesting a human operator for support.

The AI service for quality control includes the training of the AI model and updating the database with further data coming from multiple other machines sharing the same use case. This is called "federated learning" allowing best performance for all locations, as defects will be detected at all locations – once they have been identified at a single machine or location.

Figure 5: Brownfield update of an AGV with the testbed for 5G-enabled Quality Inspection (HMI2022)

Generated value

Flexibility: 5G provides the necessary flexibility in production to better target customer needs.



Time to market: Factory floor reconfiguration is faster if machines connect wirelessly.

Lifecycle costs: The infrastructure investment can be re-used for various factory configurations over its lifetime.

5G technology is therefore expected to increase worldwide production industry gross domestic product (GDP) by up to $740 billion by 2030 [8].

Conclusion and outlook

Novel industrial scenarios of networked production and AI services can be enabled by 5G+ wireless connectivity. A variety of testbeds for 5G-enabled robots and manufacturing have been created, and related evaluation results are published (5G-ACIA, Hannover Fairs 2021-2023).

Further Information and References

https://5g-acia.org/testbeds/testbed-5g-based-smart-manufacturing-and-industrial-ai-services/

https://5g-acia.org/insight/endorsed-testbeds/.

[*8] Adib, D. (2019): 5G's Impact on Manufacturing - $740BN of Benefits in 2030. STL Partners, London

Quote
If the only tool you have is a hammer, it is tempting to treat everything as if it were a nail.
Abraham Maslow 1966

The law of the instrument, the law of the golden hammer, is a cognitive bias that involves an over-reliance on a familiar tool [9].

● Use Case: Cloud Manufacturing on the Example of Wiring Machines

Electrical engines are built using traditional wiring machines. However, the machines' designs restrict the wiring of new engine product lines, which are out of scope by geometry or design.

● Customer's challenge

The electrical motors market industry is projected to grow from USD 135.61 billion in 2023 to USD 214.06 billion by 2031, exhibiting an annual growth rate (CAGR) of 5.32% during the forecast period (2023-2031) [10].

High product costs and complex wiring technology call for new adaptive manufacturing solutions capable of manufacturing a variety of different product lines spanning from electrical motors for consumers, to machinery and automotive. The growing market potential of electrical engines calls for agile production capabilities and building blocks, such as a family of conventional robots.

● AI-based challenge and future opportunities

The winding process has been rethought beyond the functioning of traditional wiring machines – as a welding process. Instead of wiring the copper wire, robots insert fork-like needles into customized stator holes. In the second production step connectivity is reached by welding the needle elements forming the connected wire of the engine, as demonstrated in Figure 6.

This process innovation is human-made but may also be a good example of how AI in the future can analyze digital twins and identify different production capabilities that could be used to manufacture products. General AI models having access to digital twins (asset administration shells) of products and process capabilities may come up with new solutions for any existing manufacturing processes.

*9 https://en.wikipedia.org/wiki/Law_of_the_instrument

*10 https://www.wbk.kit.edu/wbkintern/Forschung/Projekte/AgiloDrive/index.php

The process engineer will have to decide which solution to approve or reject.

In Figure 6 below, agile Production Capabilities are introduced based on robust robot building blocks. They showcase the different manufacturing processes of electrical engines. The design has changed, the engine stator is 3D printed and needles are inserted and connected by robots.

Engineered design (traditional)

- Wiring of motors on traditional winding machines
- Design constraints of the products (engines) are related to the winding process

Innovated design (using different capabilities)

- The wiring process is redefined. Inserting needles and connecting them by welding
- Matching the requirements of products and production skills using agile building blocks

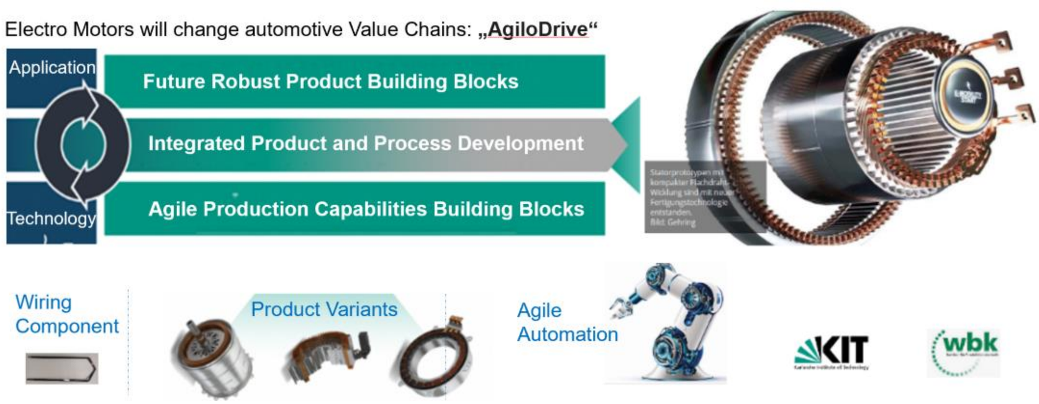
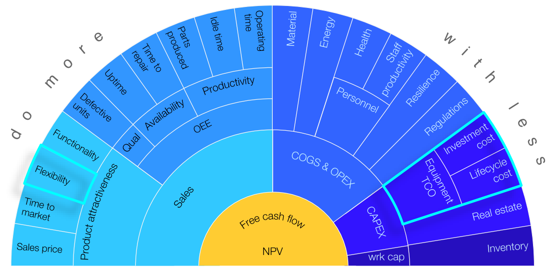


Figure 6: The KIT project AgiloDrive showcases Agile Production Capabilities Building Blocks

Generated value

Equipment TCO: Flexible, robotics-based wiring methods make dedicated wiring machines obsolete. Robots can be reconfigured to cover other product variants, whereas the flexibility of the wiring machine is limited to a defined range of products.

Flexibility: no new machines are required to produce a customer-specific motor.



Conclusion

Cloud Robotics Innovations lead to intelligent robots with higher computing efficiency and lower power consumption. Manufacturing costs can be reduced due to less hardware needed. Product and process carbon footprints are lowered in the product lifecycle.

Quote
Seeing is believing, but feeling is the truth.
Thomas Fuller (17th century writer)

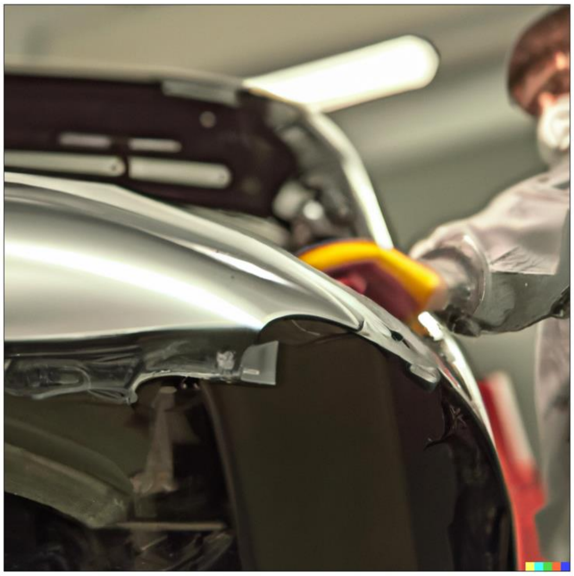


Figure 7: Dall-e generated: “Personnel stroking car in production for defect detection”

Use Case: Optical Inspection

Design an optical system capable of detecting invisible properties! This is surely an engineering challenge.

This Innovation appetizer covers two domains: design and operation, but the innovation was done in the design domain proving its value during operations.

Customer’s challenge

Body in white (BIW) is the stage in automobile manufacturing in which a car body's frame has been joined together, that is, before painting and before the motor, chassis sub-assemblies have been integrated into the structure [11].

Car bodies in white are oily and thus don’t reflect any light. Therefore, surface defects are not visible to human eyes and have to be felt by trained manual quality “inspection” personnel while the body in white is being transported to the paint shop. Stroking the whole car to feel and repair surface defects like bumps and dents to comply with quality management requirements, as shown by Figure 7.

*11 https://en.wikipedia.org/wiki/Body_in_white

Any defect slip would cause extra costs because they get visible after the coating process and have to be repaired and repainted again at very high costs and loss of time. Because of unreliable manual inspection results depending on the individual and subjective capabilities of the inspection staff, the task was to innovate the process: To design a process integrated vision system for objective detection of surface defects on the body in white while it is transported to the paint shop.

The beginnings result from the public-funded Bavarian R&D project “ABIS-Automated Body Inspection System”. Because 3D data acquisition of a whole car was not feasible due to multiple constraints, e.g., timing and inline process integration, the project took advantage of a patent, allowing data capture in one shot. The basic idea behind this was to use projector-camera pairs, with the projector projecting a grey-level sinewave pattern to a surface area at an inclined angle, with the camera being perpendicular to the surface region of interest. Any surface defect results in a local phase shift being detected in the picture, allowing the calculation of its exact 3D dimension.

As the picture dimension would cover only an area of 20cm x 20cm, the system design resulted in a portal integrating multiple camera and projector pairs. While the body in white was transported to the paint shop on a conveyor passing the robot portal, each projector and camera pair was guided to the correct position utilizing the car’s CAD file and actual position during motion. This way, the whole car could be inspected seamlessly as depicted in Figure 8.

Figure 8: Evolution of the Automatic Body Inspection System “ABIS” from manual to robot-based

AI-based challenge

Machine learning algorithms – on the basis of support vector machines – had been trained to detect and classify surface anomalies at accepted detection and “false positive” rates. It took the network of 12 PCs two seconds to identify and localize defects in 25,000 data sets per car. Detected defect positions were communicated to an inkjet robot to mark them for repair.

Another challenge solved was to guarantee a long-term process capability avoiding local optima or data training following process shifts happening temporarily. Therefore, also historical data had been trained to be displayed as a “traffic light” indication together with the actual defect being indicated in the spectrum of “green” as accepted defects and “red” as not accepted defects, as shown in Figure 9.

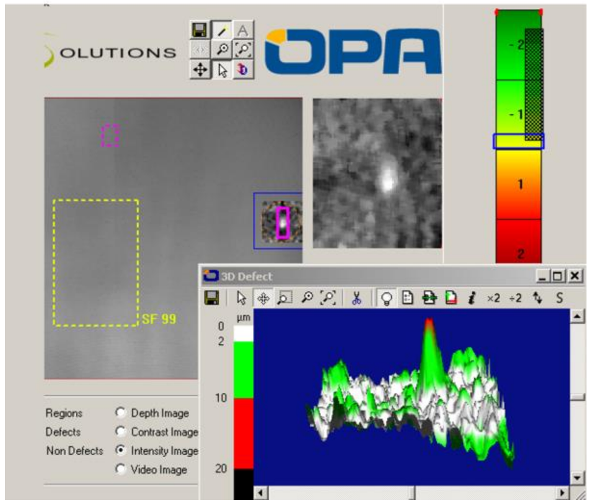
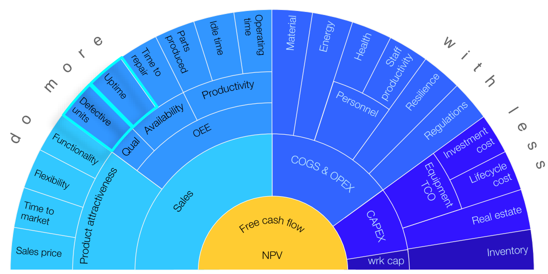


Figure 9: User Interface developed in preceding BMBF funded R&D project "OPAQ" [12]

Generated value

Reduction of downtime of production lines in automotive, reduction of process costs and hidden quality costs due to process improvement from average process maturity of 4 sigma to 6 sigma.



Cost reduction by 10% of sales per sigma maturity increase as downtime costs millions of $ per hour.

Gains in process efficiency by inline solution (30%), quality increase (from 5 sigma to 6 sigma).

Conclusion

With a growing database and short feedback loops to previous processes, the root cause of defects can be identified and eliminated. Even the tools in the press shop and press conditions could be optimized as any remaining foreign material in the tools would generate serial defects that needed to be repaired in the BIW process.

With this innovation and system evolution production process control and quality assurance tasks can be combined in one system. The data transparency of reliable and objective measurement data enables plant operators to monitor both the production processes and the quality of the manufactured body components [13].

*12 https://quality-engineering.industrie.de/allgemein/unsichtbare-fehler-sichtbar-machen/

*13 ZEISS and GOM, https://www.zeiss.com/metrology/innovation-magazine/zeiss-car-body-solutions.html

Quote	
Voici mon secret. Il est très simple : on ne voit bien qu'avec le cœur. L'essentiel est invisible pour les yeux.	*And now here is my secret, a very simple secret; it is only with the heart that one can see rightly, what is essential is invisible to the eye.*
Antoine de Saint-Exupéry, 'Le petit prince', Chapter XXI	

The next generation of mobile wireless networks (5.5G) will feature interesting sensing capabilities.

- ## Use Case: 5.5G- Fusion of Physical and Cyber World

With the development of future networks（5.5G）, expected to arrive by 2030, a new world of connectivity and data space access "for everyone and everything" may be reached as the physical and cyber world is fusing – opening new windows for innovations of automation in manufacturing.

- ## Customer's challenge

Value creation in data spaces is based on data traceability in manufacturing industries' supply chains and has been enabled by the conversion of both worlds, industrial internet (IIT) and operational technologies (OT). But nowadays also the telecommunication industry is enrichening manufacturing industries, offering new kinds of wireless design and operation modes, e.g., brownfield updating of machines and processes.

The customer's challenge is that the telecommunication industries' standardization processes (3G, 4G, 5G+) are progressing at far higher speeds than the manufacturing industries with many legacy systems in place creating the need to maintain interoperability, sometimes even for decades.

A new spectrum in the terahertz range, certainly faster speeds potentially measured in the terabyte per second range, a latency below one millisecond, hyper positioning down to the centimeter level, and certainly more devices connected per square kilometer has the potential to innovate automation in manufacturing use cases.

5.5G and 6G will be a continuum fusing the physical with the cyber world, as depicted in Figure 10 below.

Each 5.5G network element will natively integrate communication, computing, and sensing capabilities, facilitating the evolution from centralized intelligence in the cloud to ubiquitous intelligence on deep edges. The AI part is inherent to the network as being part of the infrastructure allowing large-scale applications in the future. A distributed machine learning architecture built on deep-edge intelligence will be vital to meeting the large-scale intelligence requirements of future society and manufacturing.

Figure 10: 5.5G and 6G will become a platform for AI and sensing

Networked Sensing: 5.5G will feature networked sensing capability. Driven by the continuous increase in frequency bands, bandwidths, and antennas, communications systems will integrate wireless sensing capabilities to explore the physical world through radio wave transmission, echo, reflection, and scattering. They will also provide high-resolution sensing, localization, imaging, and environment reconstruction capabilities to improve communication performance and support a broader range of network service scenarios. It covers a range of use cases, such as localization for device-based or even device-free targets, imaging, environment reconstruction and monitoring, and gesture and activity recognition [14].

Extreme Connectivity: Future networks will provide universal high-performance wireless connections and ultimate experience with speeds comparable to optical fibers. Tbit/s peak rate, 10–100 Gbit/s experienced rate, sub-millisecond level latency, a tenfold increase in the density of 5G connections, centimeter-level localization, millimeter-level imaging, and E2E system reliability based on controllable error distribution will not only enable human-centric immersive services in the future but also accelerate full-scale digital transformation and productivity upgrade of vertical industries[14], outlined in Figure 11.

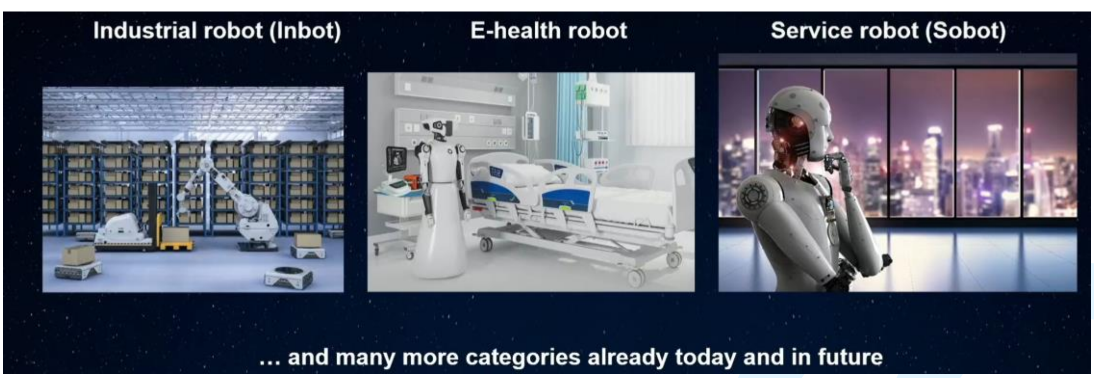


Figure 11: Hannover Fair 2023: 6G may Change how Robots be Designed in the Future, Huawei [15]

*14 https://www-file.huawei.com/-/media/corp2020/pdf/tech-insights/1/6g-white-paper-en.pdf?la=en

*15 https://www.hannovermesse.de/event/6g-enabled-future-robotics/vor/104321

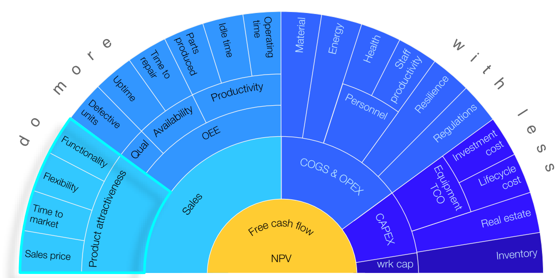
● AI-based challenge

AI will be both a service and a native feature in the 5.5G communication system, and 5.5G will be an E2E (end-to-end) system that supports AI-based services and applications. Specifically, air interface and network designs will leverage E2E AI and ML (machine learning) to implement customized optimization and automated operation, administration, and management (OA&M).

In addition, each 5.5G network element will natively integrate communication, computing, and sensing capabilities, facilitating the evolution from centralized intelligence in the cloud to ubiquitous intelligence on deep edges. An efficient and distributed collaborative learning architecture will be vital for reducing the computational load involved in large-scale AI training. Furthermore, leveraging distributed and federated learning will help optimize computing resources, local learning, and global learning and help meet the new data local governance requirements. In this sense, future core network functions will be pushed toward a deep-edge network, while cloud-based software operations will shift toward massive ML[16].

● Generated value

New products and marketplaces may evolve around AI services. A decentralized platform economy in manufacturing as 5.5G has the potential to merge value chains, existing businesses, or even industries. The sensing capabilities may open new possibilities for new solutions. The early stage of the development still leaves further values open.



● Conclusion and outlook

The evolution from 5G to 6G network will integrate various capabilities such as communication, sensing, computing, and intelligence, making it necessary to redefine the network architecture. The new network architecture should support native trustworthiness and can be flexibly adapted for tasks such as collaborative sensing and distributed learning to proliferate AI applications on a large scale. Data, as well as the knowledge and intelligence derived from it, is the driving force behind 5.5G and 6G network architecture redesign. New data governance architectures support data compliance and monetization, as well as advanced privacy protection and quantum attack defense[17].

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*16 https://www-file.huawei.com/-/media/corp2020/pdf/tech-insights/1/6g-white-paper-en.pdf?la=en

*17 D. K. Pin Tan et al. Integrated Sensing and Communication in 6G: Motivations, Use Cases, Requirements, Challenges and Future Directions, D. Tan, Jia He, +4 authors W. Tong, Published 23 February 2021, Computer Science, 2021 1st IEEE International Online Symposium on Joint Communications & Sensing (JC&S)

Main Course – Operations

As the main course, we like to serve selected appetizers from operations, as innovations have to prove their value here. The digitalization of industries is advancing fast, and standards are becoming available (e.g., OPC-UA and digital twins of assets and services). The data traceability from the shopfloor – OT (operational technology domain) to the IT (industrial network domain) becomes an enabler for new business cases and operational paradigms, with the design and engineering phases starting to merge with operations. Adaptivity, interoperability, and autonomy will become the new key headings for sustainable and resilient manufacturing (Manufacturing 2030, PI4.0).

Although stated in the previous section that the system boundary defined during the design stage limits the operations characteristics, there are new options coming up because both stages start to merge. Sensors may be integrated into legacy systems and machines to generate process data that may be linked by wireless networks (e.g., 5G+, Wi-Fi) to internal hardware (edge devices) or external data centers (public or private clouds). This way, cloud services may be deployed locally to provide capabilities originally not foreseen. This process is called “brownfield updating” and is a necessary step toward the digitalization of manufacturing industries.

In the operation stage, the desired system output will be monitored based on statistical measurements of process performance indicators (process capabilities). These KPIs are used when a process is under statistical control, such as when being established for a while. When quality benchmarks are exceeded, the plant or machine operator will take action to recover the system from the process shift happening. Recent requirements in industrial operations are to meet process maturity of 6 sigma or above, which means a maximum number of 3.4 defects observed in a million produced parts.

Quote
I Get by with a Little Help from My Friends
The Beatles, „with a little help from my friends"

Use Case: Shared Production – "Manufacturing as a Service"

The shared production scenario as depicted in Figure 12 is part of the GAIA-X use cases being public-funded on a national level to enable cooperation based on sharing production resources:

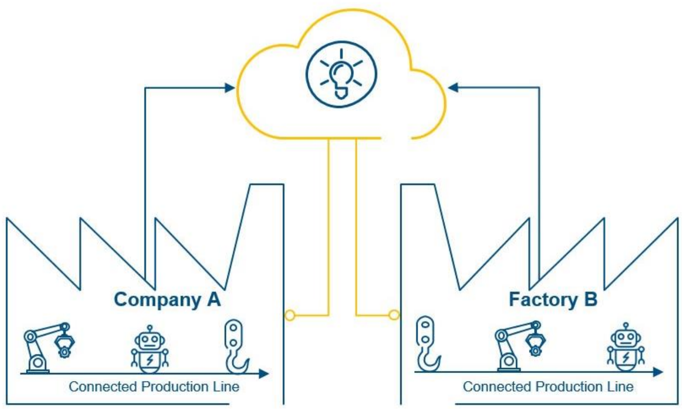


Figure 12: Shared Production: Cross-Factory and Cross-Company Production as a Showcase; SmartFactory-KL Vision 2025 – "Production Level 4"[18]

Customer's Challenge

This production paradigm offers solutions to utilize production capabilities offered in digital marketplaces whenever needed – not being available on the own shopfloor or to offer unused production capabilities to new customers.

The open and modular approach of production enables companies to work more closely and transparently with each other across company boundaries to customize production.

The control of the production and the value-added networks is data-driven, whereby the ownership rights to the data remain guaranteed.

*18 https://www.bmwk.de/Redaktion/EN/Artikel/Digital-World/GAIA-X-Use-Cases/shared-production.html

As in normal value chains, the collection and processing of data can open up potentials for new business models. The difference here is that the potentials could be further increased by the formation of ad hoc value-added networks, and new business models could be developed (jointly) in each case.

This Use Case has been validated as proof of concept at Hannover Fairs 2022 and 2023. Different production lines across Europe have been networked to customize a product as configured by the customer.

Figure 13: The Production Level 4 demonstrator offering a data space to connect production services within and across company limits. Source: SmartFactory-KL / A. Sell

The Production Level 4 demonstrator in Figure 13 is featuring three innovations:

- a module exchange with automated release, across factory limits
- self-learning AI methods based on deep neural networks
- a Gaia-X system architecture to allow connection of different production capabilities

Production Level 4 stands for "shared production" on a scalable trusted architecture[19]. This use case is part of the BMBF-funded R&D project SmartMA-X under the umbrella of GAIA-X[20] as depicted below in Figure 14:

*19 https://www.elektroniknet.de/automation/smartfactory-kl-erarbeitet-shared- production.182372.2.html

*20 3https://www.data-infrastructure.eu/GAIAX/Navigation/EN/Home/home.html

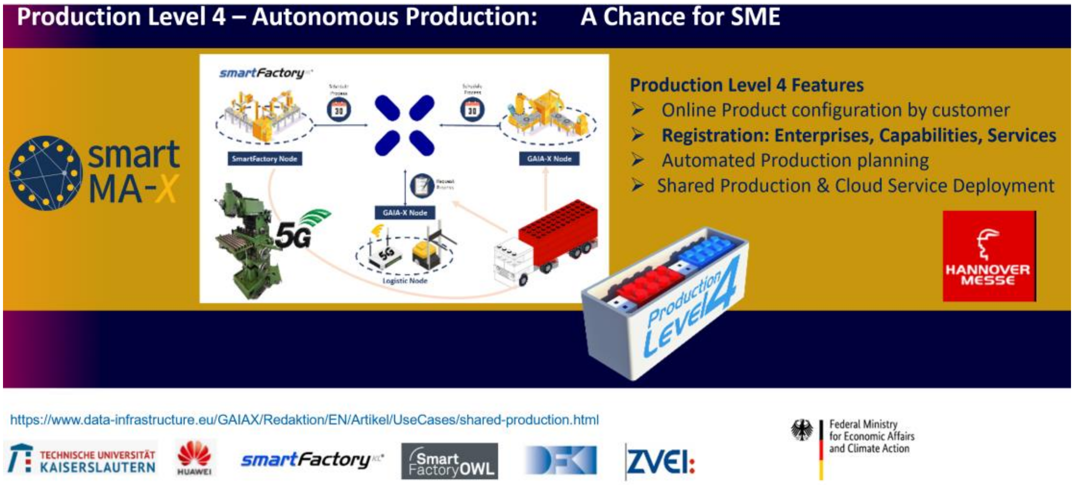


Figure 14: Shared Production features a skill-based, Europe-wide connected smart factory with product carbon footprint traceability or production capabilities used

● AI-based Challenge

The future role of AI will be mainly linked to the engineering stage to find and match appropriate digital twins (AAS: asset administration shells) of production services being offered in digital marketplaces. In the matching process, the AI tool will help the designer to choose among different production capabilities being compliant with customer requirements at best energy and product carbon footprint (PCF) values.

Engineering rethought as Connecting Skills via AAS is depicted in Figure 15. Value generation in GAIA-X compliant Data Spaces based on digital twins of services.

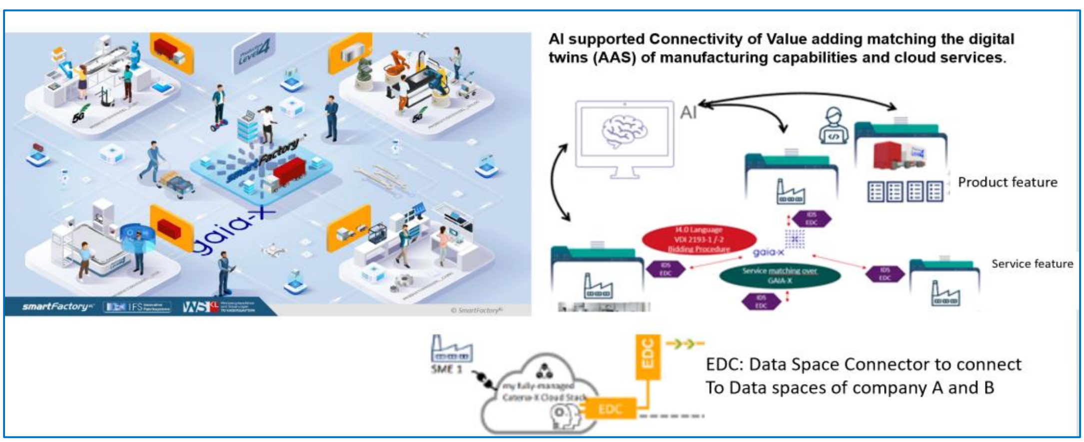


Figure 15: Using EDS Eclipse Data Space Connector for GAIA-X compliant value generation in the ecosystem

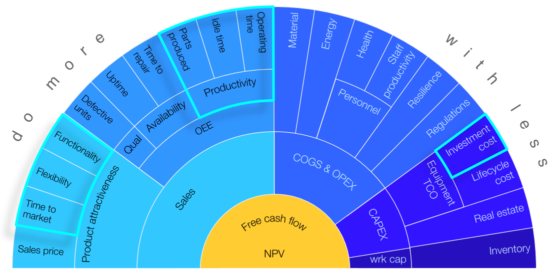
However, AI services are not limited to the engineering stage. They furthermore will support the customer in creating manufacturing ecosystems, connecting partners for shared production needs, and offering an automated auction for contracting.

● Generated value

Product attractiveness: new business models allow offering and requesting production capabilities in new evolving markets.

Investment cost: Using manufacturing services when needed, reduces the investment in new production capabilities on-premise.

Productivity: avoids the risk the production would run idle when contracts follow decreasing customer demands.



● Conclusion

In today's market, full of feature-saturated products and super competitive prices, manufacturers are exploring new service-based business models that will allow them to expand margins and build stronger relationships with customers. Many are discovering that adding services to their portfolios allows them to differentiate their offerings and gain a competitive advantage.

As manufacturing enterprises can address critical challenges by designing flexible factories, sharing assets, and decoupling factory ownership and use, resilience is boosted with the "Production as a Service" paradigm.

The above use case also shows that artificial intelligence, humans, and machines are the dream team of the future and that high-tech production does not drive people out of the factory. The special system architecture of shared production enables resilience and sustainability, organized in the developing industrial data spaces, such as Catena-X[21] as an automotive network and Manufacturing-X[22] as a network spanning across industry segments.

*21 https://catena-x.net/en/#:~:text=Catena%2DX%20is%20the%20first,The%20claim%20is%20data%20sovereignty
*22 https://www.plattform-i40.de/IP/Redaktion/EN/Downloads/Publikation/Manufacturing-X_long.html

Quote	
Wie sich schon die Pfeifen bräunen! *Dieses Stäbchen tauch' ich ein,* *Sehn wir's überglast erscheinen* *Wird's zum Gusse zeitig seyn.*	*See the pipes already browning!* *This small bar I dip therein;* *If it shows a glazed coating,* *Then the casting may begin.*
Friedrich Schiller, Die Glocke	

Use Case: Quality monitoring throughout the production process

In many production processes, quality control is done at the end or significant intermediate points of sub-assemblies. If a quality problem is caused by a machine parameter that is off-specification or an input material flaw, the parts still in the production line before the quality test are also probably faulty. The earliest possible detection of a quality issue helps to improve yield. In the quote, the metal is checked before the casting.

Customer's Challenge

Overall equipment effectiveness (OEE) is a measure of how much can be produced with given equipment. It comprises three aspects: Productivity, availability, and quality. Productivity and availability increase the number of products produced by increasing uptime and production speed. Improving quality is reducing the amount of production that can't be used. Therefore, the material and energy wasted by low-quality can be reduced. This not only has an impact on OEE but also saves energy and material. Therefore, quality is an essential factor in production.

Many production processes today include quality assurance as the last step of production. The finished good is checked against specifications by systematic quality tests or samples from a batch of products. Such samples may be analyzed in-line as part of the production, or they may be analyzed offline in a quality assurance lab.

Bad quality may come from individual production errors, or they may result from a systematic error in the production line. In the latter case, the whole batch must be analyzed and possibly discarded. The production error then must be found and fixed.

If this is done at the end of the production process, a lot of effort has gone into producing a useless batch of product.

Tracking issues earlier in the process would help spare time, material, and energy to finish a faulty product. Production can be halted earlier, and the issue is fixed without producing a whole batch of defective products. Furthermore, broadening test coverage from single samples to assessing every product produced avoids the shipment of faulty products and costly replacement or repair in the field.

● AI-based solution – opportunities

When humans inspect the quality of products, they often inspect them visually. They detect improper coating, cracks, and other issues. As an AI application, image recognition is a well-established and successful application. AI can not only distinguish cats and dogs but also be trained to detect the difference between a valid and a faulty product. Camera use in smartphones has led to ample availability of small, low-priced, and high-quality image-capture devices. While human inspection needs the inspected product to be accessible by the human eye, cameras can be placed in confined spaces, e.g., within a machine, to monitor production quality at any stage of the process.

Not only can a camera detect a fault in a product, but it can also monitor the production as it is executed and detect when something was improperly performed that cannot be detected visually.

A more in-depth analysis in a lab taking samples is difficult to fully integrate into the production since it often needs time and costly equipment. Having sufficient lab test data that can be correlated to sensor readings along the process may lead to a solution where an AI model may be trained to correlate lab measurements to the sensor readings and thus approximately predict the outcome of a lab test from the process sensors. Lab testing can then focus on material labeled questionable by the AI system.

In addition to detecting bad quality early in the process, AI can also help improve quality. Training AI using high-quality product measurements and the corresponding process settings and specifications may result in an optimal set-up of the process, learning from what parameters led to excellent results (“golden batch”).

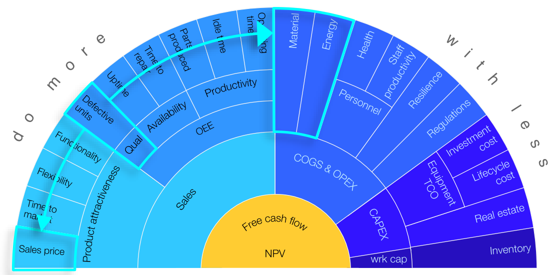
In the production process, the quality of the input material may significantly impact the product's quality. Input quality assessment can be done in the same way as described above. However, if the production quality information from upstream processes can be made available, e.g., in a digital product passport, such information can be shared transparently. Integrating the upstream data with the production data leads to a more complete picture of the quality.

Quality in transport remains to be monitored, whether delivered components have been appropriately treated throughout the supply chain. This requires broader asset tracking along the value chain and can be regarded as a separate use case.

Generated value

The primary value is generated by producing fewer defective units, increasing the OEE.

Since fewer parts are discarded, the energy and material used to produce these can be saved as a secondary effect. Furthermore, the probability of quality issues after delivery is reduced. Therefore, a high-quality product may achieve higher sales prices.



Conclusion

While predictive maintenance is one of the most prominent use cases (described in a separate section), it is worth noting that monitoring the produced product is a highly valuable use case in itself. The two use cases go hand in hand since deteriorating production equipment (detected by predictive maintenance) will most probably lead to faulty products, and detecting defective products may lead to detecting a fault in a machine.

Since the AI model must be trained based on the product's properties, collecting data from bad-quality production is particularly important. The AI model (“good quality”) may also be derived from design data from the engineering tools (as described in the engineering use case).

If quality can be improved by applying AI throughout the process, this results in a higher OEE and reduces waste material and energy.

Quote
The tree of souls ... directly interact with the world through the seeds of the tree
Movie Avatar 1

The Tree of Souls, besides being a connection to Eywa, also works as a way for her to directly interact with the world through the seeds of the tree. The tree can connect directly to the human nervous system by physical contact with its extended root fibers despite humans lacking a neural queue. The roots of the Tree of Souls can initiate a neural link with the Na'vi, like with the Tree of Voices, which allows all of the Na'vi to unite.

● Use Case: Federated Learning for Quality Inspection in networked production

This Use Case of “quality inspection in manufacturing ecosystems” is related to the shared production GAIA-X project “smartMA-X” with SmartFactory-KL as coordinator and has been demonstrated at Hannover Fair 2022. The maturity level is “proof of concept” and is further matured in automotive industry [6].

Multiple production lines have been connected in a “manufacturing as a service (MAAS)” solution to manufacture customized demo trucks, as depicted in Figure 16 and Figure 17. Although the trucks vary in design, shape, material, and process, they share the same need for visual quality inspection. Opposed to the common inspection procedure of processing product and process data on a centralized device on-premise, this solution features edge-based analytics where AI models are deployed locally for each site participating in the shared production scenario.

● Customer’s Challenge

Federated learning (FL) is a machine learning framework that allows multiple devices to collaboratively learn a model without sharing their private data. This offers ample opportunities in critical domains such as healthcare, finance, etc., where sharing private user information with other organizations or devices is risky.

However, FL faces several challenges: communication efficiency, data heterogeneity, system robustness, and privacy preservation. One of the key challenges is client selection, which refers to choosing a subset of clients to participate in each round of FL training. Client selection can affect FL's convergence speed, accuracy, fairness, and scalability.

Some of the customer challenges related to client selection are:

- How do we select clients that have high-quality and representative data for FL training?
- How can the trade-off between communication cost and model performance be balanced when selecting clients?
- How do we ensure the privacy and security of clients' data and model parameters when selecting clients?
- How do we deal with clients' dynamic and heterogeneous nature (such as availability, reliability, resource constraints, etc.) when selecting clients?
- How to design incentive mechanisms to encourage clients to participate in FL training when selecting clients?

● AI-based Challenge

Collaborative learning is achieved with all sites sharing their AI model parameters with the cloud model which interpolates them generating an optimized parameter set and being deployed again on all sites locally as a service. This way faults may be detected on all sites, although some might have occurred on one site only before. The significant and decisive advantage is that all sensitive product and process data stay on-premise, with only AI model weights being shared with the cloud model for collaborative learning.

While the data act is motivating data sharing in industrial data spaces no solution has been developed on how to protect partners acting in data ecosystems to generate value – giving answers to industry concerns. This leads to a situation of an innovation obstacle with unequal knowledge in companies to build on such important digital data, holding back digitalization and value creation.

The IP protecting value generation approach would support industry partners to share data to take benefit from federated services without disclosing sensitive data. As the shared production scenario bases on the production level 4 paradigm, the service is highly scalable. Also, partners are invited to join offering skills on their legacy machines as brownfield solutions are demonstrated to integrate sensors using 5G connectivity to access edge and cloud-based analytics.

The Quality inspection service demonstrated covers the range of detecting surface defects (like bumps or dents) and defects violating the product specifications as described in the product’s asset administration shell (AAS), e.g., as CAD file.

The solution aims to promote data sovereignty, data security, and data interoperability, allowing organizations to collaborate while maintaining control over their data. In this case, a potential user of the service (buyer's view) can download and use the service with its own dataset in its own production line without any significant efforts. To offer the quality inspection service (supplier's view) in Gaia-X the Industry 4.0 compliant way is to describe the quality inspection service (its features, characteristics, properties, and capabilities) with the help of AAS. Depending on the inspection task, additional sensors may get engaged or data from different sources be fused.

Utilizing Gaia-X connectors, partners can connect to the related data space and offer (supplier) or use (buyer) AAS-based description of the software service. That means the service can be found in the Gaia-X service catalog and the service provider can offer the software service via marketplace as shown in Figure 16.

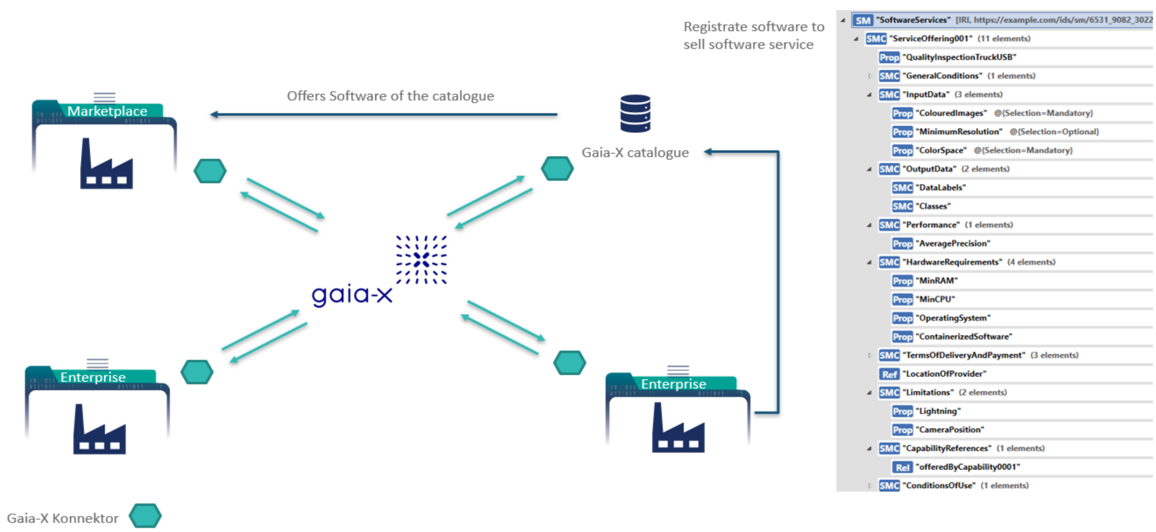


Figure 16: Industry 4.0 data space for software services Industry 4.0 data space for software services

The customer can connect to the related data space, can browse available software services on the marketplace, select one, that matches his requirements, download it (e.g., as a Docker container) and use it in own production line. All this operation is performed with the help of service generalized description available via AAS. Because the "quality inspection" is registered on the marketplace as service as well, the customer can download this service or, if the service is already running on the customer side, just update the model weights from the global federated model.

Because the quality inspection service is based on the federated learning (FL) algorithm, the customer has also an opportunity to contribute to the service by improving the model quality via an additional round of training on his local dataset.

In this use case federated learning (FL) could provide significant benefits for quality control in various domains, such as industrial manufacturing applications. FL's ability to utilize data from multiple sources, while ensuring the data's privacy and confidentiality, mirrors the collaborative dynamics seen in swarm intelligence. FL can enable data-driven machine learning models to leverage the data from multiple sources without compromising the privacy and confidentiality of the data owners. FL can also improve the quality and diversity of the data by incorporating the local knowledge and preferences of different clients.

The integration of FL with object detection yielded significant accuracy and precision enhancements in contrast to isolated client models. Our findings affirm that the global federated model, while avoiding local data sharing, remains resilient even under varying conditions like different lighting, camera angles, and object combinations as depicted in Figure 17.

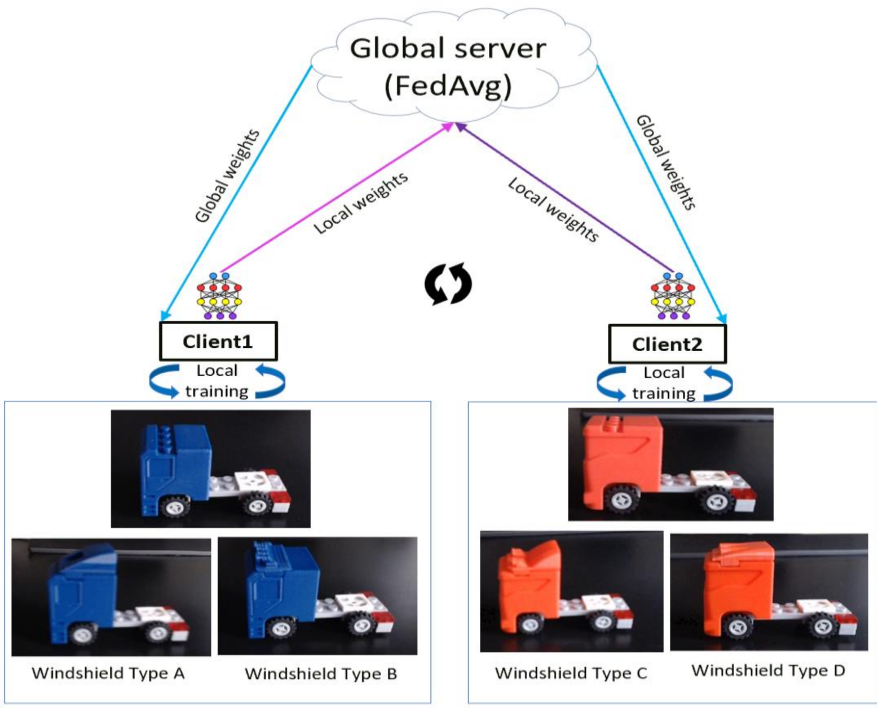


Figure 17: Data Sharing of local AI model parameters for "swarm learning" and update of local models

Emphasizing its scalability, FL's potential extends across diverse sectors. Beyond the illustrated use cases, its benefits are evident in domains where data sharing is constrained by privacy considerations, such as in healthcare or in traffic management for connected vehicles. The cooperative nature of FL, where multiple clients converge to refine a singular global model, optimally positioning FL as a revolutionary tool for enhancing robustness and adaptability in data-driven value creation [5], [7].

The quality inspection task is abstracted from the object and related to the region of interest (ROI) within the object. This way defects can be identified also at production site of client1 (which is manufacturing different truck variants) without any training, although defects had occurred and been trained at production site of client 2 (which is manufacturing different truck designs or components). The inspection task remains the same.

As the inspection task is independent from product design and material properties the global model benefits from all inputs of participating local production units, offering optimized AI model parameters to each partner in return.

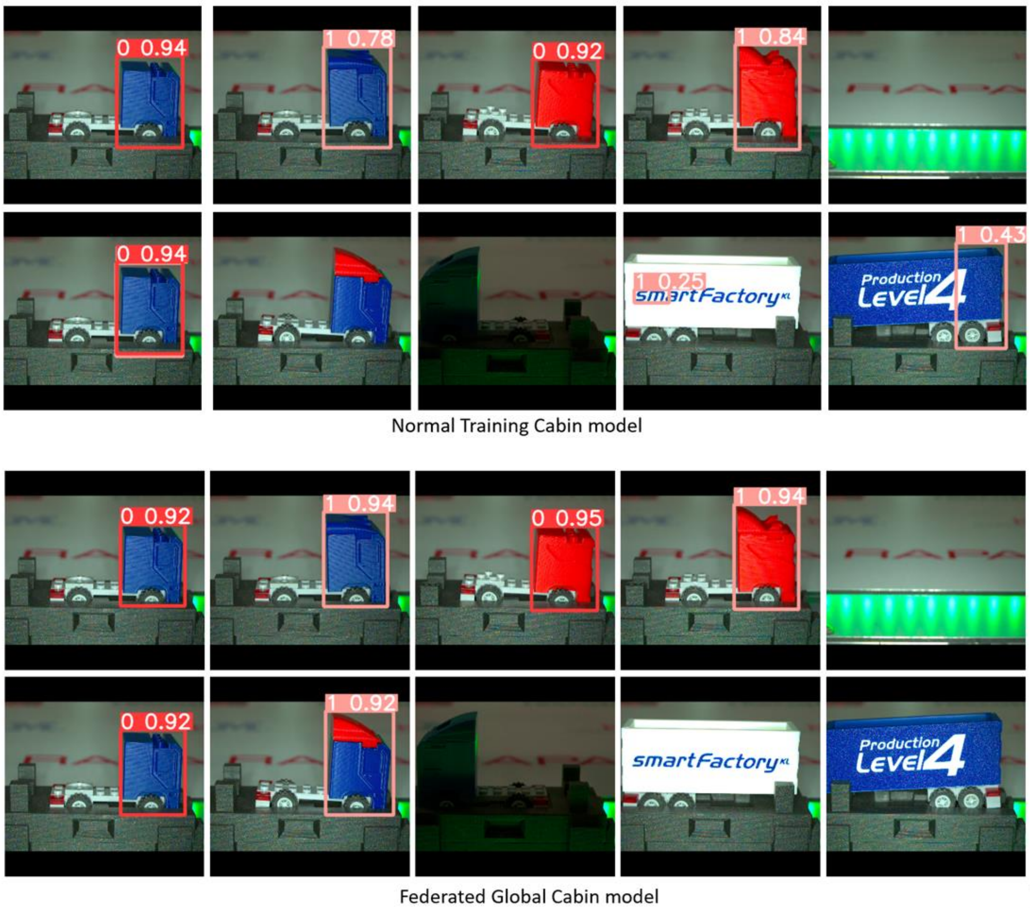


Figure 18: Quality Inspection of trucks of different makes: Comparison of local vs global learning Quality Inspection of trucks of different makes: Comparison of local vs global learning [7]

Figure 18 presents a scene incorporating four truck cabins, bifurcated equally to represent each client's type, and showcasing both classifications: “cabin_with_windshield” and “cabin_without”. The depicted values indicate that the global model outperformed the local models in terms of precision. It consistently achieved higher scores, suggesting that the global model excels in predicting precise bounding boxes, even when confronted with unseen combination types.

Comparatively, the global federated model displayed superior performance revealing its robustness, also by avoiding any false positives on unrelated objects.

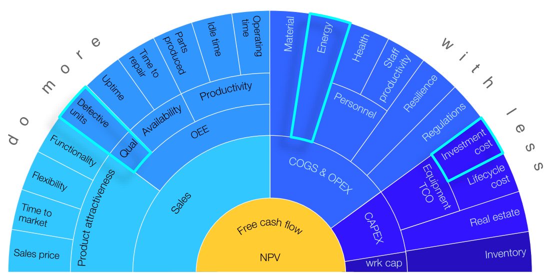
Generated value

In today’s market, full of feature-saturated products and super competitive prices, manufacturers are exploring new service-based business models that will allow them to expand margins and build stronger relationships with customers. Many are discovering that adding services to their portfolios allows them to differentiate their offerings and gain a competitive advantage.

The generated value includes

- Benefit from an ecosystem approach   reduced invest in local HW
- Potential for platform business model   Quality Inspection Service
- Requirement for trusted data sharing within an ecosystem   IP Protecting data sharing

In this use case “quality inspection as a service”, federated learning provides value generation in supply chains at reduced investment costs and higher quality of manufactured products, by service deployment on demand.



Additional Value is the reduced product carbon footprint at higher quality of products.

Conclusion

The IP protection service and enabled optimizing services for quality and process enhancement may lead to further innovation cycles for SME industry partners and could become future business cases by themselves. The main players involved in this case study are all partners participating in a “manufacturing as a service (MaaS)” scenario. Maas opens up various opportunities for buyers and suppliers acting in market places or data spaces:

In buyers' view, MaaS opens the world for flexible production:

- Unleash limitation to own equipment and resources
- Unleash limitation to one location and fixed partners

In suppliers' view, MaaS generates new markets opportunities

- Offering free capacities in an open market place or data space
- Closes gaps with available resources

Quality Inspection up to now had been limited to each partners' factory boundaries in order to protect company related trade secrets. But with the paradigm shift of MaaS evolving, data sharing enables the new solution of "quality inspection as a service", that features IP protection for each partner at a better quality. Product and processes data stay on promise – at all times.

Federated learning (FL) can provide significant benefits for quality control in various domains, such as industrial applications, predictive maintenance, and healthcare. FL can enable data-driven machine learning models to leverage the data from multiple sources without compromising the privacy and confidentiality of the data owners. FL can also improve the quality and diversity of the data by incorporating the local knowledge and preferences of different clients.

Further Information and References

[1] Lifestream Hannovermesse 2022: https://lnkd.in/eRTg-_p3, start: 1:52:46

[2] Livestream - Pitchday "Datenraum Industrie 4.0": https://www.plattform-i40.de/IP/Redaktion/DE/Veranstaltungen/2022/09-Pitchday_Stream.html

[3] Data spaces for everybody: https://www.plattform-i40.de/IP/Redaktion/DE/Downloads/Publikation/aas-dataspace4everybody.pdf?__blob=publicationFile&v=6

[4] SmartMA-X project: https://www.smartfactory.de/en/smartma-x/

[5] Federated Learning SmartFactory-KL Federated AI Use Case presented in Silicon Valley - SmartFactory-KL, https://arxiv.org/pdf/2208.04664

[6] https://www.twin4trucks.de/

[7] https://uweseebacher.org/products/collective-intelligence-the-rise-of-swarm-systems-and-their-impact-on-society?srsltid=AfmBOor_T7j42obnencVZdcc25c7t0b-KYPPvM_alBHUZkRjLftBEUGV

Quote
The future is already here – it's just not evenly distributed
William Gibson

Digitalization of industries is progressing at different speeds. On the shopfloor level the variety and diversity of vendor-specific assets, different data formats, and ICT interfaces hinder enterprises to progress advancing to new, data-based business models - taking the gateway to a digital economy.

William Gibson's quote fits here as the first industrial initiatives lead the way, e.g., Catena-X: The first open and collaborative data ecosystem.

Use Case: Open and Collaborative Value Creation in Manufacturing Data Spaces

Catena-X is a rapidly scalable ecosystem in which all participants in the automotive value chain participate equally, as shown in Figure 19. The goal: to provide an environment for the creation, operation, and collaborative use of end-to-end data chains along the entire automotive value chain.

The founding members in 2021 have been ARENA2036, BASF SE, BMW AG, Deutsche Telekom AG, the German Aerospace Center e. V., German Edge Cloud GmbH & Co, Henkel AG & Co. KGaA, ISTOS GmbH, Mercedes-Benz AG, Robert Bosch GmbH, SAP SE, Schaeffler AG, Siemens AG, SupplyOn AG, ZF Friedrichshafen AG, Volkswagen AG, and the Fraunhofer-Gesellschaft e.V.

Customer's Challenge

The manufacturing industry is undergoing a profound transformation process as it faces multiple challenges from different sources. Some of these challenges are:

- Supply Chain Resilience (ensure material flow across multiple value chain steps)
- Sustainability (trace real PCF data to de-carbonize the value chain)
- Systematic Coverage (interoperability standards and SME readiness)
- Cost of innovation (innovation boosted by shared services built upon open source)

These challenges require the manufacturing industry to undergo a digital and sustainable transformation that will enable it to remain competitive and resilient in a changing world. No market player, neither an OEM nor supplier nor outfitter can solve today's problems on its own[23]. Catena-X aims at competitiveness and sustainability targets at reduced costs of ownership in manufacturing.

● Added value

The collaborative data ecosystem takes the entire life cycle of products and production capabilities into account addressing the upcoming circular economy needs. All steps, from material supply to the manufacturing of products and recycling are included. Further features of the data ecosystem are:

- Model-based product design and new forms of collaboration between the companies involved.
- Digital behavior twins permit the seamless integration of each product and all its sub-components along the entire value chain.
- Marketplace: it enables the monetization of data and models, which motivates partners to offer digital behavior twins on the network.
- The provision of models and a runtime environment allows – above all – small and medium-sized enterprises to access solutions and evaluation procedures.[24]

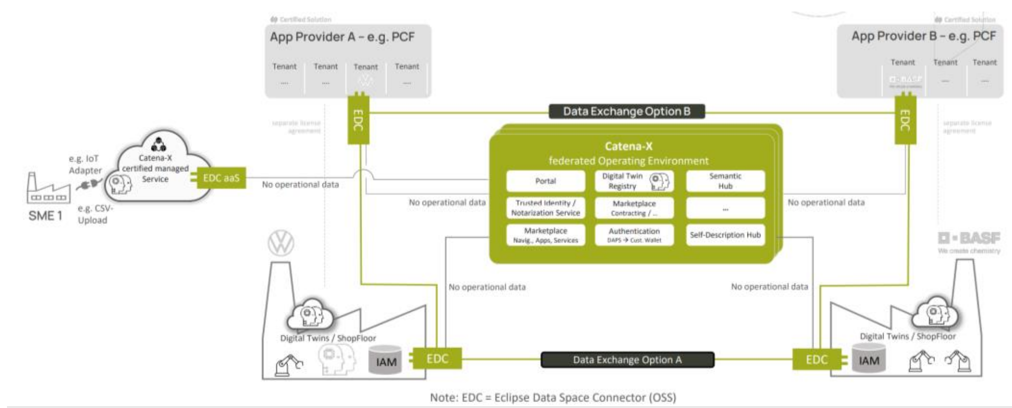


Figure 19: Catena-X Architecture opens up marketplaces for cooperative value creation in data spaces

● AI-based Challenge

AI support is currently being developed in a broad range, covering cloud services for product design and engineering stages, automated operations planning for optimized supply and demand management logistics to forecast supply chain risks, and to comply with the new regulatory frameworks and supply chain laws.

*23 https://catena-x.net/fileadmin/user_upload/Vereinsdokumente/Catena-X_general_presentation.pdf

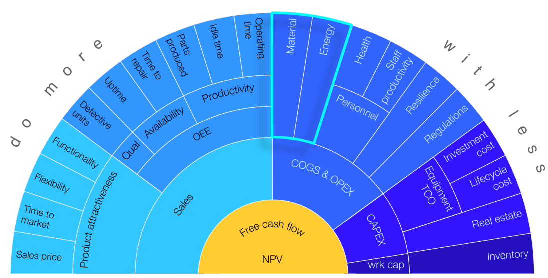
*24 https://catena-x.net/en/benefits/digital-behavior-twins

One key challenge of predictive AI is to get access to process parameters to reduce the total cost of ownership for partners participating in data rooms. When partners register their over – or under –capacity to the market, algorithms automatically orchestrate the requesting or offering of free capabilities when needed. This way production lines will not run idle anymore, producing costs.

Other challenges address new services to comply with supply chain laws and – at the same time – calculate, trace, and comply with product carbon footprint regulations for products and processes.

- **Generated value**

The primary value is generated through reduced total costs of ownership and increased OEE as well as product attractiveness.



Time to market is reduced due to operation in marketplaces. Costs are reduced by sharing reusable services and utilizing standards (EDS). Shift Business from CAPEX to OPEX.

- **Conclusion**

Catena-X has evolved from a nationally-funded R&D project in Germany to an industry alliance. Implementation of the Catena-X concept empowers regional adoption and ensures the flow of data across regions. Additional hubs have been created in France and Sweden and further hubs are planned in South Korea, Sweden, and China.

In times of crisis, geopolitical dependencies, and supply chain risks this open and collaborative data space offers a de-risking and de-coupling approach as participating partners acting in regional and international marketplaces may conduct business with partners in trusted business relationships beyond dependency on rigid supply chain structures.

- **Further readings**

https://catena-x.net/en/#:~:text=Catena%2DX%20is%20the%20first,The%20claim%20is%20data%20sovereignty.

https://www.plattform-i40.de/IP/Redaktion/EN/Downloads/Publikation/Manufacturing-X_long.html

Quote
FIRST WITCH *When shall we three meet again?* *In thunder, lightning, or in rain?* SECOND WITCH *When the hurly-burly's done,* *When the battle's lost and won.* THIRD WITCH *That will be ere the set of sun.*
Shakespeare, "Macbeth", Act 1, Scene 1

The three witches forecast conditions and are evaluating the environment and risk when they shall meet again. The use case "Dynamic Predictive Risk Assessment" is a new certification scheme that has evolved from excluding any risks in defined environments to managing risks that may be forecasted by screening environmental changes.

- ## Use Case: Dynamic Predictive Risk Management

Use of predictive AI and environment screening for risk monitoring and virtual certification.

- ## Customer's Challenge

With IT-OT convergence adaptivity of shopfloor machines goes against traditional certification schemes following the paradigm "never touch a running system".

Certification processes base on fixed system design of robots and machines at environmental conditions that exclude any safety risk. As an example, fences shielding robots from human workforce are mandatory to avoid hazards and accidents – even if the probability of danger may be very low.

Nowadays common workspaces shared by humans and robots demand new certification methodologies allowing adaptive and resilient system designs that can manage the risk by observing the environment the machine is running in. This use case monitors the actual risk level and predicts the risk levels coming up in the next seconds and issues virtual certificates, as shown in Figure 20.

Networked Modular production designs and wireless connectivity of machines require design rules to enable flexible production, encapsulation of safety and security properties and ensure a reliable and safe agent-based or broker-based control and decision process to optimize productivity and safety at runtime … and fulfill upcoming EU regulations.

TÜV SÜD is working on modular safety – a two-step approach utilizing systems of systems of digital twins. The Digital Twin of assets and machines is a key element to achieving trustworthiness – safety, security, and privacy because risk levels and probabilities can be related to different environmental conditions in the use of assets and machines.

A digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity. [25]

Risk assessment involving threat and hazard analysis requires an understanding of the appropriate frequency and fidelity of synchronization as they are essential to ensure the resilience of dynamic use cases.

Only when assessments of changes within the lifecycle have been built into digital-twin capabilities, making trustworthiness part of the digital twin architecture, it is possible to make changes to machines or configurations that are safe and that do not generate an unacceptably high downtime during validation.

● AI-based Challenge

Operational Safety Intelligence uses a holistic understanding of Digital twin-based Systems of Systems (SoS). This needs environment monitoring to detect & understand context changes and resolve conflicts ahead of time.

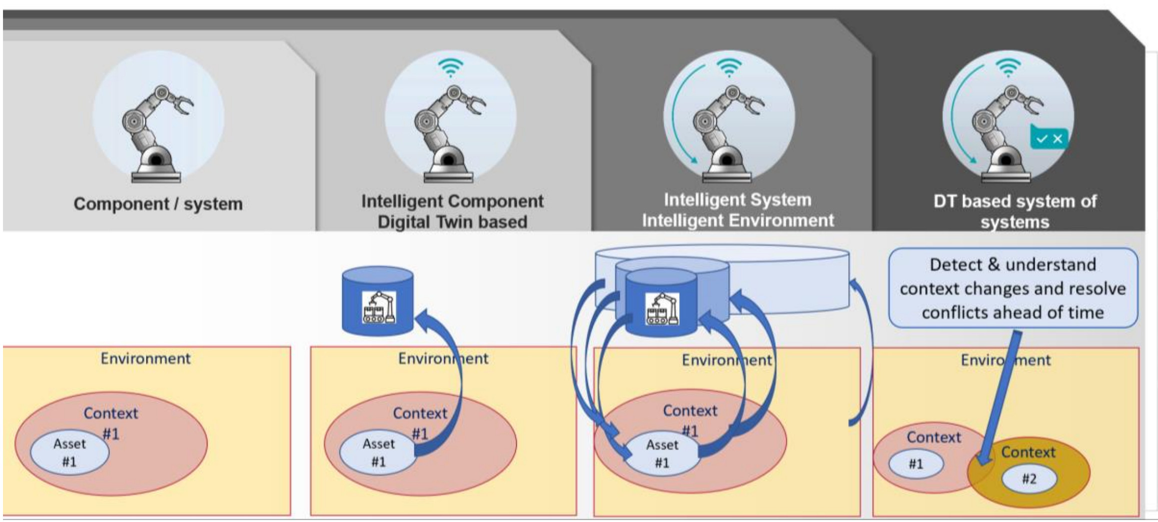


Figure 20: TUEV-SUED Hannover Messe, April 17th 2023 Dynamic & predictive environment screening for risk monitoring and certification

*25 Safety methodology for adaptive safety and dynamic hazard assessments at run time, VDE DKE Tagung in Erfurt, 09.-10. Mai 2023, Dr.-Ing. Detlev Richter, VP Industrial and Energy Products

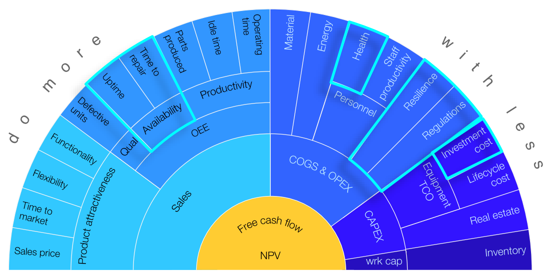
DT's key to winning time for safety-critical decisions – Forward simulations offer a second level – predictive safety.

Risk assessment at runtime is a requirement for IIoT. Operational Safety must be ensured: Time: t0 – Process Safety time and Predictive Safety by DT SoS Time: t0 + Tx being monitored for decision making. Risk Assessment has to become readable for machines – to compare changes between t0 and t1.

AI/ML and probabilistic reasoning are part of the solution for a decentralized safety architecture. Model-based systems engineering is the first step to achieving trustworthiness – DT-based technical lifecycle.

- ## Generated value

Predictive safety analytics helps manufacturer to improve overall workplace safety and regulate business outcomes. Incident rate and lost-time incident rate are reduced.



Investment cost: a predictable safety environment can achieve safety levels with fewer hardware safety measures.

Predictive certification processes allow more flexible machine design, higher output at less lifecycle and investment costs.

- ## Conclusion

Safety professionals are beginning to use data analytics to perform a more objective evaluation of their environment. By harnessing the power of data and predictive analytics, businesses can begin to track safety and reduce risk using leading rather than lagging indicators.

Safety lifecycle management requires DT-based System of Systems. Zero Trust Principle is part of the OT/IT stack to guarantee Data Integrity. The feedback loop of the digital twin is a strong functional safety measure to guarantee integrity.

Quote	
Αυτο *Νόμος* *Αυτονόμος*	*Self / own* *Law* *According to its own laws*
Ancient Greek word meaning	

Customer's challenge

When discussing autonomous systems, most people associate with autonomous cars. There are also discussions on how to make industries more autonomous. The nature of these two applications is quite different and requires distinct approaches.

An autonomous car can operate independently in a changing and, to some extent, unforeseeable environment. It does so by reacting to many external inputs (traffic situations) to follow traffic rules, avoid accidents, and arrive safely at the destination. As a system, it, therefore, has a large number of unstructured inputs (measurements: camera, radar, lidar, etc., and target position) and only two outputs, speed and direction. The internal function of the car (e.g., motor control) is not changed.

An autonomous factory is quite the opposite: The inputs are few and structured (manufacturing orders, material). However, the reaction to that input is much more complex and may comprise changed machine settings and production processes. The internal function of the factory may need to be adapted.

The complexity of the autonomous car lies in its reaction to the complex environment. The complexity in the case of manufacturing lies in its internal alignment to a well-structured and largely foreseeable input.

A highly automated factory with an unchanged product over an extended period can already be regarded as highly autonomous. These plants can operate almost unattended for extended periods, particularly in process industries. In discrete manufacturing, the batches of products are smaller. The product configuration is adapted to customers' specifications in industrial goods as a standard process. But more and more consumer products become more tailored to customer wishes or local market requirements. Changing production to accommodate a new product design becomes a more and more frequent operation. In the shortest loop, a lot size of one (customer-specific product) leads to re-aligning the production process for every product. Therefore, the plant configuration moves from the design cycle to the operations cycle.

An autonomous plant would not only be able to automatically produce a product for which it was built, but it would also be able to adjust automatically and adapt product design.

What we earlier discussed as a part of engineering is now an integral part of production.

Combining the ideas we stated in the engineering chapter with the idea of the self-configuring plant, we arrive at a factory that can be given specifications and produce a product or component that fulfills those autonomously.

In the extreme case where no humans are required on the production floor, the plant design can consider this. Pathways for human observers would not be necessary, safety cages around robots are unnecessary, and even electrical equipment cabinets can be removed (unless they are there to avoid equipment pollution). Removing humans from the design requirements of a plant may produce more efficient factories with a lower footprint.

Repairing such a plant becomes a separate challenge. Whether a fully autonomous plant could repair itself remains to be seen.

● AI-based solution – opportunities

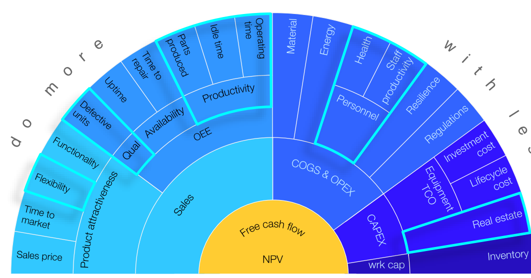
The components of an autonomous plant have already been discussed earlier in this book. A high level of automation is fundamental. Fully automated machines are already state of the art, and the use of robots for assembly and some manufacturing steps is frequently seen in smart factories today. We have already mentioned in-process quality control to ensure the production produces a flawless product. Whether such a plant requires autonomous guided vehicles to move parts and material or whether it can be built around other means of transport is essentially a design decision.

With smaller lot sizes, an essential piece of AI is translating the product design into machine instructions. Such a system needs to be aware of the equipment's capabilities, how to program it, and how to assemble the produced components. The level of intelligence required for this step depends on the breadth of the product portfolio that can be produced. Some product variations only need changes of some machine parameters (e.g., size, color, features added or removed). The adaptation may be significant if a wider variety of products is to be produced. It may even require some of the equipment to become more autonomous itself. For example, today, robots are programmed to do the required moves in a repeated sequence. The autonomous plant may be able to re-program the robots. But the robot may react to a changing environment, adapt to changed components, find screw holes at different positions, or identify the welding trajectory by looking at the part. Making a factory more autonomous means moving design and engineering steps generally executed before something goes into production into operations, reducing complexity in the first place and adding complexity to the latter.

By becoming more autonomous, the factory becomes more flexible and can react to a wider variety of inputs. But even the most flexible factory will only be able to produce something its components can handle. A car factory with welding and metal processing equipment may be capable of producing bicycles. But it will hardly be able to produce sneakers and clothing. Therefore, the “outcome space” of a factory, the possible range of products, is essential in deciding on the desired level of autonomy. Furthermore, the effort to build such a factory may be far too high compared to a solution where some steps remain in human hands.

● Generated value

A high automation level leads to higher productivity and better quality.



Reduced staff requirements result in better health and higher productivity.

Removing human requirements reduces real estate requirements.

Overall, a higher flexibility of the production is achieved.

● Conclusion

A fully autonomous factory may be far in the future and challenging to reach, and removing all human interactions may also not be the most efficient approach. Some applications, though, e.g., subsea operations (as already seen in data centers, power production, or oil & gas extraction) justify the effort. When thinking about conquering Mars, such ideas get traction as well. How to cost-effectively produce at low lot sizes remains a challenge not only for AI. In pre-industrial times, this was how things were produced: hand-crafted piece by piece in a workshop. To go back to such a system without the enormous efficiency gains of industrialization is undoubtedly the challenge of autonomous factories.

Dessert – Maintenance

As third course we want to surprise you with new appetizers from maintenance.

The role of maintenance is to expand the lifetime of machines as long as possible rather than repairing broken equipment.

We see a trend going away from statistical maintenance to deliver services after pre-defined hours of operations have been reached to the delivery of “on the spot” maintenance services – exactly when and where needed. The service action is planned, taking actual machine data and its wear and tear due to vibrations in operations or due to environment conditions into account. Spare parts are ordered in time and service staff being scheduled. Service is no longer untransparent as “a black box”, being paid for the time the maintenance takes, but instead it becomes a business model with dedicated time and resource planning being offered to the customer well in advance, before action is needed.

Maintenance concepts for operators not only require the implementation of classic, standardized maintenance intervals and task lists, but also require the combination of the most diverse sources of knowledge (i.e., customer production plans, sensor measurements on operation and wear, machine history, design) in order to adapt the deployment planning to the individual needs of individual machines. In particular, (future) problems of industrial plants can be identified not only by AI-based analysis of individual machines (“Predictive Maintenance”), but also by also AI-based, cross-customer analyses of machine data (“Peer Group Comparisons”).

Current developments take benefit from data traceability along the value chain of related stakeholders, e.g., utilizing data from the sensor producer, the machine integrator and end user. As these data are proprietary no exchange had been possible before. But new business models evolve to incentify each participant’s contribution, as the overall costs at the customers’ sites may be reduced this way. And the sensor supplier may adapt the sensor design in shorter design cycles matching new customer needs.

Quote
If you can look into the seeds of time, *And say which grain will grow and which will not,* *Speak then to me,*
Shakespeare, 'Macbeth', Act 1, Scene 3

Customer's challenge

When operating an industrial process, interruptions are a nuisance. Any operator's goal is to avoid them. Some interruptions, e.g., to prepare production for a product change, are required for operational reasons. Some interruptions are required for planned maintenance. However, unplanned interruptions may have costly effects.

To avoid these, operators have different maintenance strategies. Preventive maintenance is performing measures that reduce the equipment's failure probability. This can be compared to the regular car service, where oil is changed, and parts with a limited life span are replaced. These tasks can be planned and scheduled to be done when production is halted for operational reasons (reconfiguration, weekends, etc.). Their impact can be planned in the production schedule. Based on the observed condition of the equipment, the maintenance crew may conclude that some repair has to be done. They evaluate the urgency and plan maintenance accordingly. Operation has to be re-scheduled around this intervention.

When equipment fails without being recognized in advance, operation is disrupted. For the duration of the repair, production is interrupted. Even worse, the interrupted production process may result in a product that cannot be used. Some production processes have a lengthy ramp-up time, which adds to the interruption. If equipment is significantly damaged, such outages may be significant and lead to substantial losses.

Therefore, it is in the operator's interest to detect degrading conditions and predict failures as precisely as possible.

AI-based predictive maintenance – challenges

Predicting failure is easy, and it doesn't need AI to do that: any equipment will fail at some point. Even though this is correct, it is not helpful. To create value, the prediction should cover the following aspects:

- What is about to fail? What needs to be done to prevent it from failing?
- When is it likely to fail? How long can we still run the equipment safely?

- ## Condition monitoring

The first question about the nature of the failure is addressed by condition monitoring. The degradation can be seen, heard, or even smelled at a relatively late stage of a developing failure. To detect a failure earlier, AI can help. Data sets from other failures can be used to train the network. Measured data is then passed to the AI system to determine if the equipment shows signs of degradation.

However, AI needs substantial data from various failures for training. And since industrial equipment is built to fail rarely, that data will probably not be available from one site. Therefore, a supplier has to collect data from a large portion of the installed base to collect information from customers through IoT. If customers complain that they don’t want to share data, they must realize that such a solution only creates value if many sites share and that they benefit from other customers having shared data. Therefore, they contribute to the overall quality of the solution they benefit from.

To collect data, the equipment must create data that contains information. In equipment that is moving (e.g., motors, robots, etc.), this is not a problem. Rotating equipment monitoring has been in place for decades, analyzing the frequency spectrum of the collected signals. However, other equipment, such as circuit breakers, do not deliver data indicating whether they still operate correctly until triggered. At that point, the failure is observed, but that is too late. Therefore, as in all AI projects, the key question is: Is the data available that contains information about a developing malfunction?

IoT may be a means to achieve that, but establishing a collection of failure data may require significant investments and time before an AI solution may create value.

- ## Prediction

Condition monitoring may indicate what fails, but it is still a more complex task to tell when it will fail. Simulation may provide an answer to predict how equipment will behave in the future. To predict a failure, aging, wear and tear must be reflected in the mathematical models used for the simulation. Such models are very complex and usually are not included in models used to design a product and simulate how it behaves in operation. Furthermore, even if a failure model was included in a simulation, it isn't easy to map the internal model parameters to the measurements to recreate the observed effects and simulate how they evolve.

Therefore, data-based models such as AI are helpful to explain effects that are observed but not modeled. However, as mentioned in the section on condition monitoring, such data has to be available. For condition monitoring, data from a time instance is sufficient to identify the condition at that particular time. For prediction, data over the time from detection to failure must also be available. In this time interval, the operational conditions, i.e., how the equipment is used, play a role. Such conditions vary between the site where the condition was observed and where a failure is predicted.

Such data sets that show the evolution of a failure are even rarer. Collecting such data suffers from an effect that is referred to as the "censorship problem". Once a failure is detected, most customers will repair the fault before the equipment fails. Therefore, the datasets don't contain the information about when it would have failed without the intervention.

- Prescription

In line with condition-based and predictive maintenance, a further approach is often mentioned as a possible maintenance strategy: prescriptive maintenance. In this approach, it is predicted what will fail when and what can be done to prevent it. To generate customer value beyond failure prediction, prescriptive maintenance must provide better recommendations than "repair it", and how. In addition to that, an advanced prescriptive algorithm would consider operational boundary conditions and propose possible operational measures to meet the operational targets. This may imply operating at a lower speed or lowering other process variables to be still able to produce within specification but to defer the failure into a time interval when repair is more convenient, e.g., planned outage or time of low production.

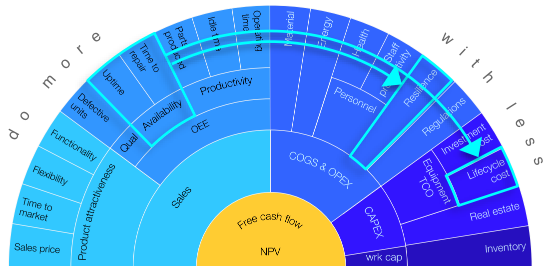
Take, for example, a vessel that is traveling at high seas. The predictive algorithm may indicate a motor failure before the intended port is reached, and the ship would need to re-route to a nearer port. A good prescriptive algorithm would calculate the optimal speed at which the motor would experience less stress so that the failure would only occur after the port is reached, where repair can safely be done.

Prescriptive algorithms not only have to consider the device in question but also incorporate the processes around it and the respective business goals. Operational models need to be available to predict the behavior of the equipment in a degrading condition and its impact on the overall production process. This scope usually goes beyond what is typically covered by AI today and may be very costly to set up. It is, therefore, only applicable to critical, valuable assets.

Generated value

Increasing the uptime and reducing the repair time impact the OEE of the production equipment.

This also results in higher resilience and reduces lifecycle costs since well-maintained equipment lasts longer



Conclusion

Predictive maintenance is a use case often mentioned in the context of IoT and AI in industrial applications. It is to be noted, though, that it is not easy. Mainly, the prediction part is not trivial.

When considering predictive maintenance as an AI application, a supplier must carefully study what data contains the information that indicates a developing failure. And to be useful, that data must be available and adequately labeled.

Therefore, not only IoT data has to be included in the analysis. Service reports containing the failure description, operational data on how the device was used before the failure, and any construction data and models used to design the equipment must also be analyzed. Such can be available in a digital twin of the equipment.

While the fact that equipment will fail at some point is easy, at what point this will happen is very hard.

Quote
The goal of forecasting is not to predict the future but to tell you what you need to know to take meaningful action in the present.
Paul Saffo

Use Case: Prescriptive AI for casting scrap reduction

Each year one of the largest foundries in the Southern Hemisphere produces 129,000 high-quality cast iron automotive components at its plant in Cape Town, South Africa. The plant has an annual melting capacity of 110,000 tons. Figure 22 gives insight into the product and process that needs to be optimized. To compete at a global scale and to realize their vision of becoming the best foundry in the world, the foundry looked to embrace the opportunities that AI solutions could provide.

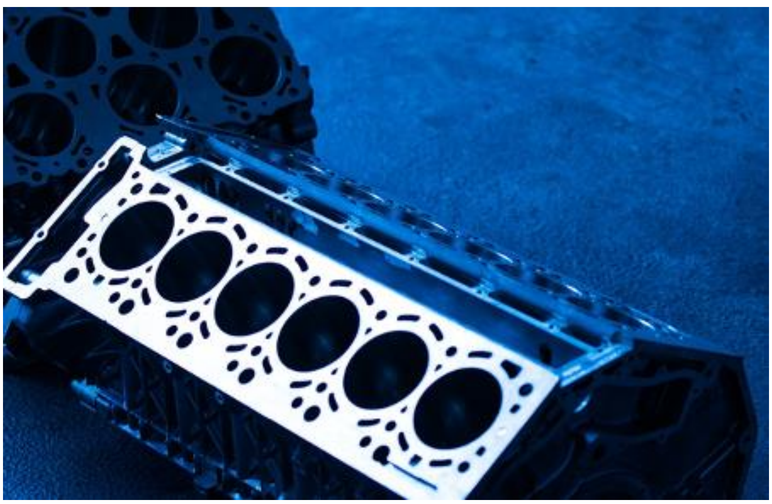


Figure 21: Finished engine blocks produced by the Foundry [26]

Customer's challenge

Historically, this plant experienced a 6% scrap rate and wanted to find a way to optimize its manufacturing process to reduce the cost of scrap.

While the scrap rate was no higher than the industry standard, every defective unit shipped and scrapped in Europe or North America incurred a relatively high shipping and penalty cost.

*26 https://pixabay.com/photos/engine-engine-block-cylinder-1369258/

The main objective was therefore to lower the number of defective engine blocks shipped by reducing the internal and external defect and scrap rates. In turn, this would increase production, and reduce rework. A good engine block is shown in Figure 21. The challenge, historically, is in the level of complexity in the large number of non-linear causal relationships that make up the modern foundry.

All possible traditional engineering methods to optimize the plant thereby resulted in a plateau that was stagnating innovation and plant improvement. Process engineers were faced with an avalanche of data that could translate into millions of possible combinations of plant states. It was no longer possible for them to consume and analyze this data without the help of Artificial Intelligence.

Figure 22: Molten metal transferred to the ladle before casting [27]

● AI-based Challenge

Prescriptive AI solutions are able to analyze vast amounts of process and quality data to identify the best possible operating regions of a particular plant and provide setpoint updates in the form of prescriptions to allow operators to take the plant state from a suboptimal region to a region of best performance. [28]

The AI journey that must be undertaken starts with extracting and transforming data from many different and often disparate sources and subsequently unifying this data for use with prescriptive AI models. At this particular foundry client, historical production data was gathered from PLCs and the plant's central SCADA system. Additional data was taken from Excel and CSV files as well as handwritten forms.

*27 Ladle image: https://unsplash.com/photos/zHK__gTTTds

*28 DataProphet's AI solution: https://dataprophet.com/our-ai/

Ultimately, 15 months of historical data have been transformed into a single view containing 173,000 records and 400 unique process variables.

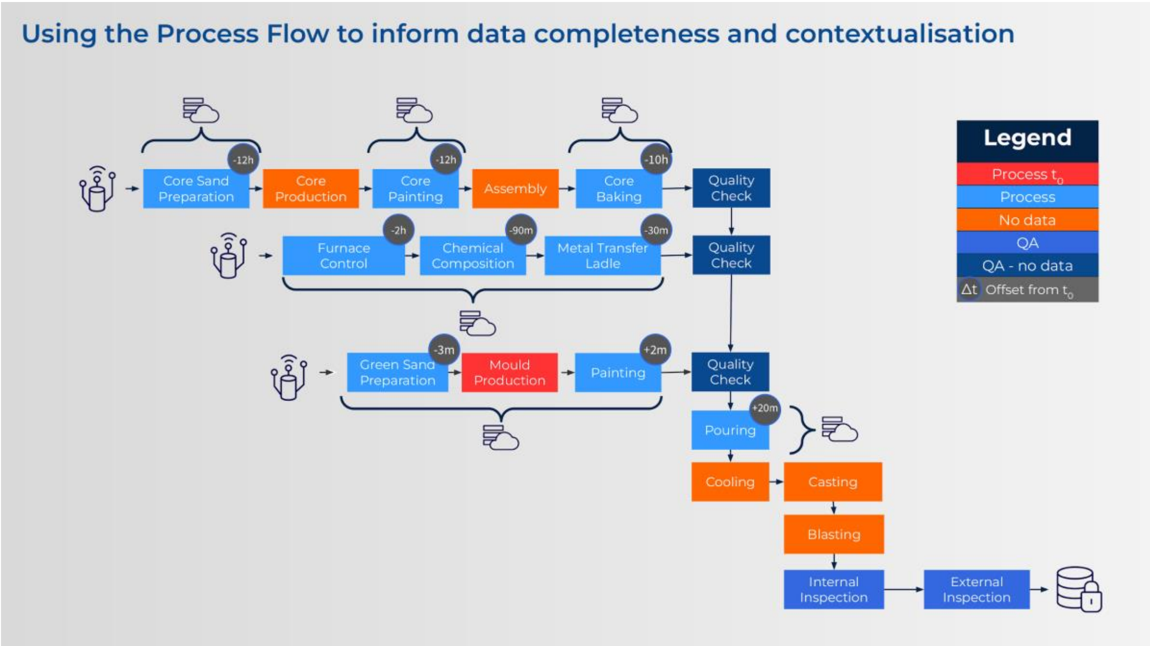


Figure 23: Diagram illustrating the available data along with the material flow of the casting process

Through the application of advanced supervised and unsupervised machine learning methods, as depicted by Figure 23, the optimal operating regime for the client's complex, multi-step, industrial process has been identified. Correlations and interactions between approximately 1,000 parameters from across the plant have been used. Further insight into prescriptive AI functions used and user interaction is demonstrated in Figure 24 and Figure 25.

Since then, the plant is operated within, or very near the identified optimum region, allowing for a minor degree of variability due to non-controllable process parameters. The prescriptions are updated every five minutes based on data that is continuously ingested from the process.

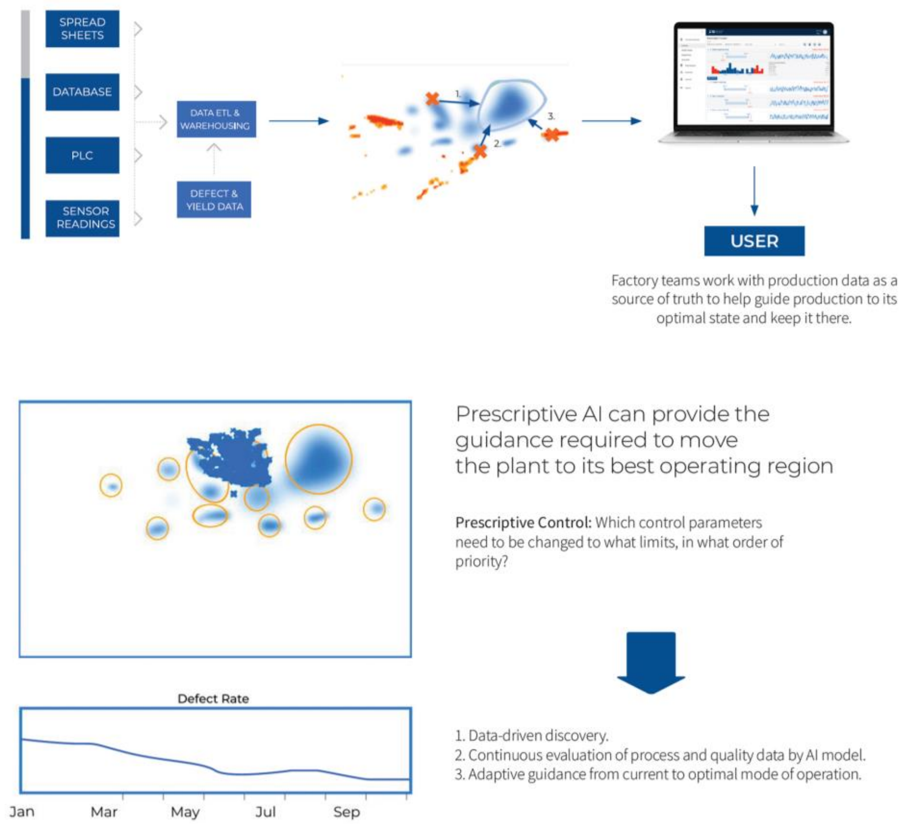


Figure 24: Diagram showing an illustrative view of how the prescriptive AI functions

The solution itself is built with scalability in mind allowing for rapid expansion to additional unit operations within a site or to additional sites altogether. The commonality of data sources will allow for faster expansion. However, the solution is more than capable of integrating with a variety of different sources.

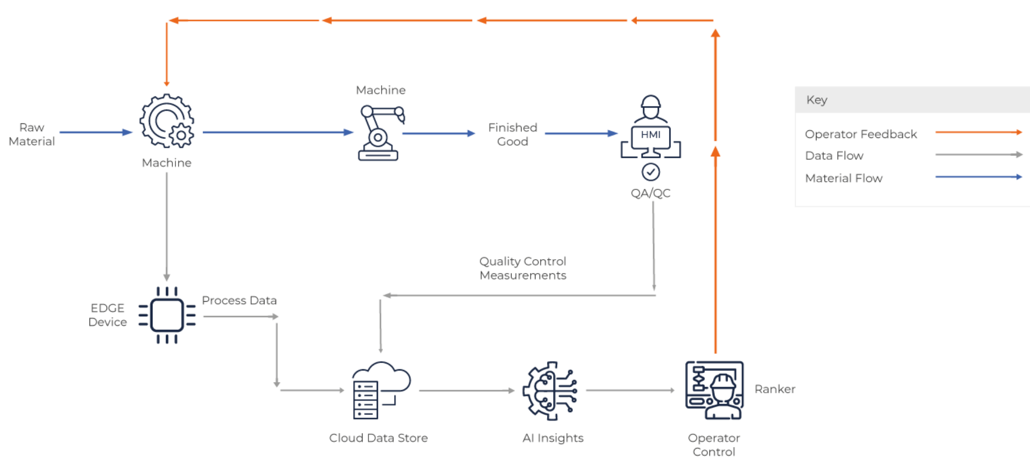
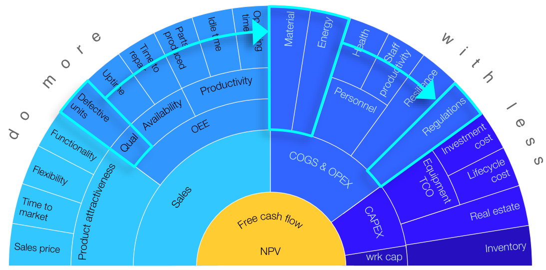


Figure 25: Diagram illustrating the machine/system/user interaction to optimize the process

Generated value

Reduced scrap and defects result in lower material and energy use and increased quality.

This also leads to better compliance with sustainability regulations.



The value can be expressed in more detail as follows[29] :

- Engine block defects have been reduced down to 0.5% for periods of up to three months and achieved an average reduction of 40% over the long term.
- The plant halved its scrap rate in the first month of deployment.
- Within the first three months, an external scrap rate of less than 0.1% on an ongoing basis has been established.
- This results in savings of around $100k per month.
- The increased yield resulted in record production outputs in 2018 and 2019.
- The optimization of process control parameters to achieve zero external defects additionally reduced waste, lowered the plant's production energy usage and prevented the unnecessary transportation of large defective engine blocks.
- Our client saves an estimated 135 kg of carbon dioxide emissions for each defective block not shipped.

Conclusion and Outlook

Predictive AI introduced to traditional industries like foundries in the steel industry can lead to model creation and process understanding and thus have the potential to become sustainability enablers for energy and CO2 footprint savings at higher process maturity and efficiency.

The Foundry CEO remarked: "We might have been able to achieve similar results in the past, but we had absolutely no clue what we did to achieve the good result. With artificial intelligence, we have a really good idea of what we need to do to improve production. Prescriptive AI solutions have resulted in a significant reduction in scrap and rework, making a positive impact on our bottom line." [30]

*29 Engine Block Manufacturing Case Study: https://dataprophet.com/case-study-automotive-foundry/

*30 Foundry CEO Citation: https://metrology.news/data-analytics-provides-real-time-quality-assurance-to-improve-processes/

Quote	
Ὅτι ἡ τριὰς ἐξαίρετόν τι παρὰ πάντας τοὺς ἀριθμοὺς κάλλος εἴληχε καὶ εὐπρέπειαν· πρῶτον μὲν τὰς τῆς μονάδος δυνάμεις ἐνεργοὺς πρωτίστη παρασχοῦσα, περισσότητα, τελειότητα, ἀναλογίαν, ἕνωσιν, πέρας·	*The Triad has a special beauty and fairness beyond all numbers, primarily because it is the very first to make actual the potentiality of the Monad – oddness, perfection, proportionality, unification, limit.*
Iamblichus, Syrian Platonist philosopher, 245 – 325 AC	

In music, a triad is a set of three notes. In this use case, the triad symbolizes three key stakeholders in a supply chain, that shall play well together.

Use Case: Collaborative Condition Monitoring

The Use Case "Collaborative Condition Monitoring" (CCM for short) deals with the collection and use of operating data to optimize the reliability and service life of machines and their components during operation. CCM relates to Manufacturing and targets how cross-company collaboration can generate added value, resulting in reduced costs.

Customer's Challenge

This use case addresses current barriers in the industry and restrictions of existing business models offering a solution based on a new structure of value chains with high scalability.

Up to now, cooperation is primarily bilateral, for example when the factory operator and the machine supplier exchange operating data to plan maintenance services. This cooperation usually engages only two partners and is initiated and enforced via the customer / supplier relationship (including market power).

CCM defines a “tripod” value chain as depicted in Figure 26, consisting of

- Supplier
- Integrator
- Factory Operator

This Value triangle (three-point fractal) is the smallest possible fractal of a multilateral structure[31].

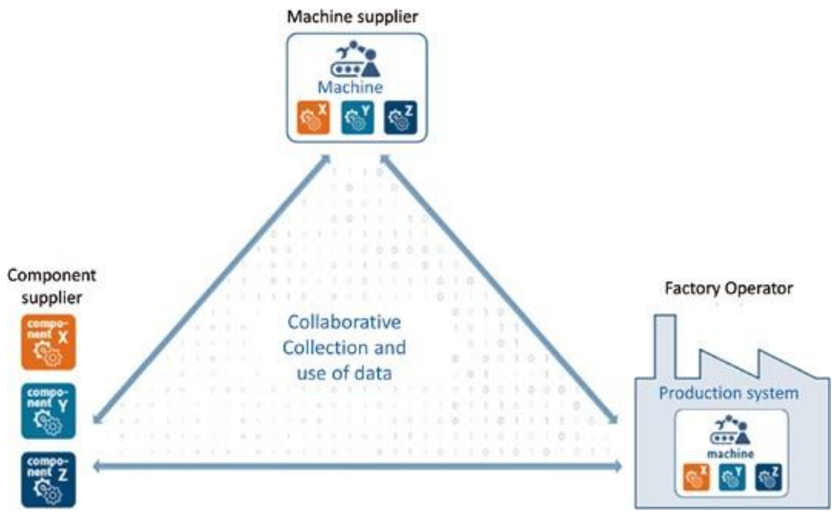


Figure 26: Fractal of smallest ecosystem is building block for larger ecosystems (© Plattform Industrie 4.0)

The fractal can be used to discuss the challenges and requirements of a multilateral collaboration regarding:

- Technical aspects, e.g., Identity, Trust and Data Sovereignty
- Compliance
- Legal aspects
- Mindset, courage for data entrepreneurship
- Usability aspects
- Knowledge gained can be transferred to larger fractal networks

*31 https://www.plattform-i40.de/IP/Redaktion/EN/Downloads/Publikation/Multilateral_Data_Sharing.html

Lack of trust: For actors to share their data, secure data transmission, storage and access rights are required to protect data from competitors or from the theft of know-how (sensitive production data).

Missing business model: By providing and using data from the various actors in the CCM, added value can be generated, which can have a positive effect on the total cost of ownership, for example in a longer service life of the machine.

An economic advantage can be generated within the digital ecosystem (“digital business model”) by increasing the reliability and service life of components and machines. This requires collaboration between all those involved in the value chain and access to data depending on authorization. Figure 27 demonstrates the cube developed, including interfaces to business, legal and technological requirements.

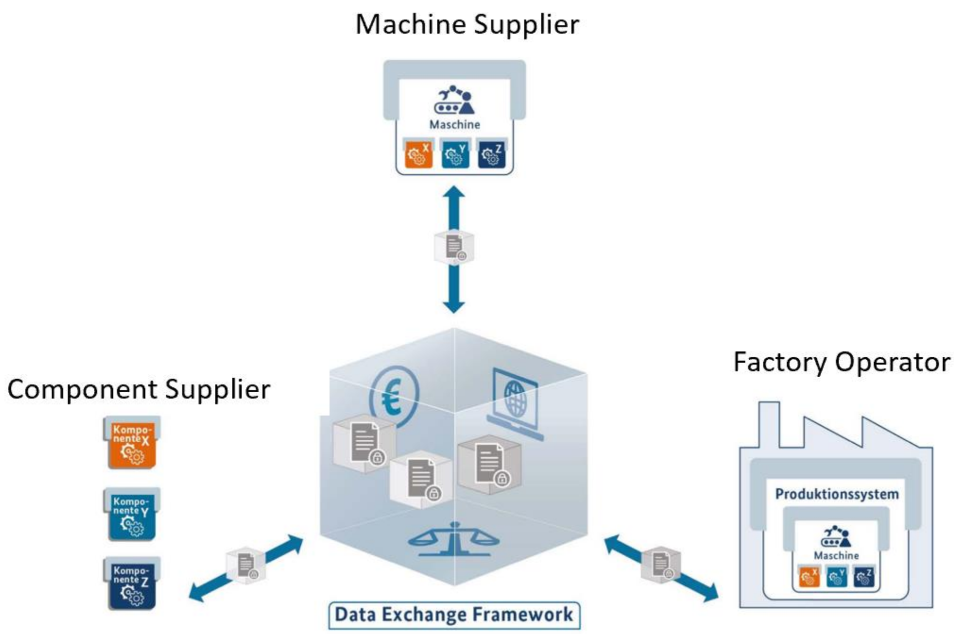


Figure 27: CCM Data Exchange Framework (© Plattform Industrie 4.0)

- ## AI-based Challenge

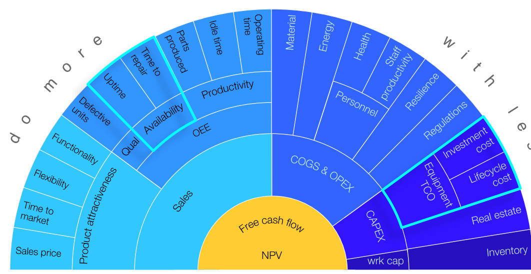
The use of correlation and AI, e.g., machine learning, can result, for example, in the increased service life of machines or components. AI Challenge is to take advantage from the data exchange framework, for example, to get and fuse input from the 3 different types of data from the 3 stakeholders: component supplier, integrator, and factory operator to offer optimized services. Data exchange is supported by using the asset administration shell (AAS) as the standard interface.

- The component supplier provides a component with an AAS that contains data fields for data relevant to service life and reliability.
- The machine supplier delivers his machine with its own AAS which also contains data fields for service life and reliability-related data.
- The AAS of the machine will be upgraded to be able to forward the data of the machine and the components accumulated over the service life of the machine to a neutral platform.
- The factory operator supplements the data with relevant machine usage data (e.g., operating temperatures, maintenance intervals) based on the data fields in the administration shell.

Generated value

An economic advantage is generated within the digital ecosystem by increasing the reliability and service life of components and machines.

TCO is reduced and OEE increased in the digital ecosystem.



Conclusion

Collaborative condition monitoring (CCM) describes an innovative approach that allows various market participants in the network to increase the reliability and service life of production plants and thus create added value for all stakeholders in the value chain.

The CCM approach is a novelty because it is based on multilateral cooperation between companies and competitors and gives rise to new business models. In this context, it is essential that companies competing at an operational level make available the data that is so urgently required for the instantiation of digital business models in the same way as their physical products and recognize this data as non-related to brand and product differentiation[32].

Further Information

Plattform Industrie 4.0 - Event Report: Multilateral Data Sharing in Industry (plattform-i40.de)

*32 https://www.plattform-i40.de/PI40/Redaktion/EN/Downloads/Publikation/collaborative-data- driven-business-models.htmll

Quote
If I had six hours to chop down a tree, I'd spend the first four hours sharpening the axe
Abraham Lincoln

With this quote, Abraham Lincoln pointed out the value of planning and getting the tools prepared to reduce the effort of initiatives to be taken.

Use Case: Service-Meister: An AI-Based Service Ecosystem

The project Service-Meister encompasses a cluster of different cost savings due to delivering services in manufacturing utilizing an AI-based service platform according to Figure 28.

Customer's Challenge

New service tasks and business models lead to an increased need for service staff to maintain or improve mechanical operations, reducing costly downtime of machines. Especially in the environment of Industry 4.0, many machine suppliers and plant manufacturers no longer simply sell their machines but offer them as part of so-called MaaS (Manufacturing-as-a-Service) or subscription models. Up to now, service is being offered and billed based on operating hours – restricting transparency in the service process.

27% of German companies are already using AI in services and customer support – but in 5 years, this is expected to rise to 69%. Networked sensors allow remote access to machine and environmental status data, leading to optimized management of transparent service and maintenance operations.

The ecosystem of Service-Meister Use Cases encompasses:

- Service staff
- AI service platform operator
- Terminal Provider for service operators
- AI solution support centers
- Machine & equipment supplier needing maintenance
- The end user: factory operator

AI-based Challenge

The Service-Meister platform is designed to provide AI systems and components that cover the entire service process – in a 360-degree view. Service technicians must be able to access the information in various working conditions to ensure a good user experience and barrier-free access to the relevant information and solutions.

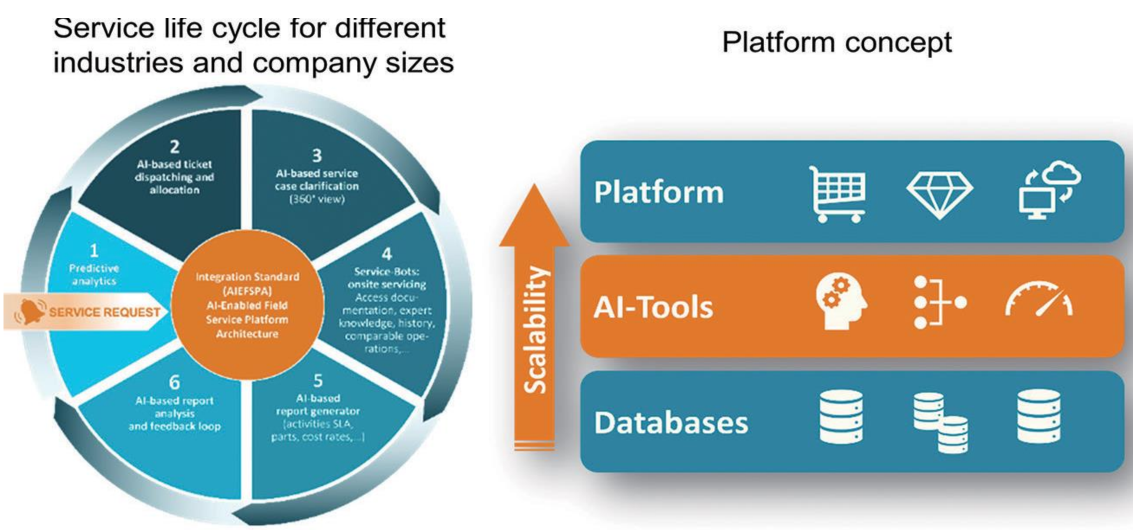


Figure 28: An AI-based service ecosystem for Industry 4.0

Different AI Challenges can be seen related to the different Key Use Cases "speed boats" at participating enterprises:

Krohne: Environment Screening – Keeping an eye on water levels from a distance, determining discharge rates, and identifying problems.

Technology: IoT services like this are increasingly popular as climate change demands smart water management solutions. If more rain falls in winter and there is only occasional heavy precipitation in summer, this can push wastewater pipes to their limits. The consequence of extreme weather conditions: flooding and high water.

Wuerth: Material Supply in Industry – Accelerate service processes Condition Monitoring and Surveillance: detect faults remotely.

Technology: These use cases focus on predictive maintenance

OGE: Service Management – Detect anomalies in gas pipelines, forecast service requirements

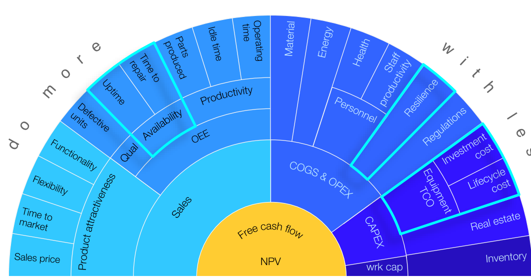
Technology: Open Grid Europe operates its own Competence Center, which is tasked with detecting anomalies in the data streams of all 850 gas leakage sensors.

Trumpf: Efficient planning of service calls, automatic diagnosis of machine data

Technology: Machines are enabled to independently diagnose and analyze problems, and transfer results to a cloud platform where they get evaluated. Maintenance tickets can be automated, and information can be used in a continuous learning and improvement process. This increases system availability and reduces maintenance costs.

Generated value

Reduced investment costs: can be achieved for SMEs by using Reference Architectures and AI-as-a-service platforms made available via the open Service-Meister platform.



This will create low-threshold access to AI technology and a service ecosystem leading to reduced overall costs for service suppliers and at customer sites.

New business models are being developed to monetize targeted services based on reduced downtime of machinery, reduced risks of environmental hazards, and total cost of ownership in the supply chain engaged.

Conclusion

Actually, Germany has been leading AI development and research for 50 years, but so far, no large-scale AI Platform implementations have been developed.

The platform is designed to support the needs of SMEs offering services to their customers. A broad scope of different service demands in the industry is incorporated in the project by “speed boats”, representing different use cases in different industries. This process creates generic services, modules, and blueprints that can be made available to SMEs and ensures the scalability of the solution.

The platform can be operated as a GAIA-X-compliant federation and ensures that digitally sovereign partners can exchange and share their data and create new business models.

Further Information and References

https://www.servicemeister.org/das-konsortium/

Abendroth, J., Riefle, L., & Benz, C. (2021). Opening the Black Box of Digital B2B Co-Creation Platforms: A Taxonomy. In Proceedings of the 16th International Conference on Wirtschaftsinformatik(WI).
https://www.researchgate.net/publication/348326720_Opening_the_Black_Box_of_Digital_B2B_Co-Creation_Platforms_A_Taxonomy

Quote	
Un segno di intelligenza è la consapevolezza della propria ignoranza	*A sign of intelligence is an awareness of one's own ignorance.*
Niccolò Machiavelli	

Figure 29: Dall-E generated picture on generative AI as new spice in “cooking manufacturing innovations”

The use cases presented so far are mostly built on neural networks, which have been trained using use-case-specific labeled data. The challenge in these solutions is not the configuration of the network and its training algorithms but the availability of appropriate data. Even though potential users of AI believe that they have all the required data available, this is very often not the case. Data correctness, completeness, consistency, and accessibility are insufficient to train the system.

Furthermore, training data must be labeled, i.e., the correct answer must be known for a training data set. Particularly in applications such as failure prediction, sufficient data from failures must be at hand. And since devices are built not to fail, such data is rare. Therefore, projects often fail not because of the complexity of AI but because of the lack of data. The latest research on “physical informed neural networks (PINN)” addresses the need to generate data based on mathematical equations or models that match the physical reality behind them.

The latest developments in generative AI, such as large language models (LLM) like ChatGPT, take a broader approach than neural networks. Instead of learning from one use-case-specific data set, they copy how humans learn: by reading books and articles. Due to ample computing resources, they do not limit themselves to a specific use case but read everything accessible online. They learned to extract information and combine it in new ways to generate things they learned as depicted in Figure 29.

Primarily, they generate texts, be it a polite letter, an abstract of a paper, or a poem in any author's style. It is important to note that these models do not "know" what they read or write. They merely calculate which word is likely to follow in a sentence, given the prompt and what has been written before. Unlike information that is retrieved from a website or a database, the output is only likely to be correct. The parts of the output that are wrong are referred to as hallucinations.

In addition to language, other publicly available material, such as images and videos, can also be used to train generative models to create new artifacts. A short text is sufficient to generate a high-quality text, image, or video. While using all these tools is fun and helpful for personal use, there are also some applications in a business environment.

Most of the business processes are documented by text documents. Derived from how LLMs are built and trained, they are well suited for anything that is derived from text that is publicly available. Some of these applications are:

- Chatbots: answering users' questions about something that is too difficult to find or put together from websites or user manuals. For many applications, this is easier than using a search function.

- Text generators: Write a text in a desired style for an audience based on shorter descriptions of the content. Given the amount of time we spend on writing texts in our professional lives, this may make white-collar tasks more efficient.

- Summarizing text: parse a text and answer questions about its content. How much time do we spend reading reports on all sorts of overly wordy things, explaining a situation we already know? This, too, may make many jobs more efficient.

Computer code is a special type of text. There are ample repositories of source code available (e.g., GitHub), which provide a good base for training a programming engine. LLMs have achieved good skills in programming.

A particular challenge in these applications is privacy. If the information you want to use as a base for generation is your company's IP, it cannot have been used to train the systems. Note that the public LLMs process all the text that is put forward to them. Feeding your company's secret design documentation to ChatGPT or any other public system is a no-go.

Furthermore, LLMs need statistics from very large text. If the information critical to your application is only contained in a few folders, it is not sufficient to impact the trained system. We end up with a similar problem that we had with the smaller-scale dedicated neural networks: insufficient access to insufficient data is a frequent obstacle in AI projects.

Another challenge already mentioned is worth considering: hallucinations. If the cost of a wrong response is high, it is not recommended to use LLMs as the only solution. In critical applications, we are used to building redundancy. Also, in human-led processes, another person has to validate a decision, and the reasoning behind it has to be documented. AI systems are no different: if they are used in critical environments, they shall not be the only deciding entity.

If we move from general business applications towards more industrial applications, a few on the radar look quite promising.

Design/engineering: Already before the success of the LLMs, there were applications that used more traditional AI or optimization algorithms to solve design and engineering problems. Generative design allows a designer to enter specifications such as desired physical properties, and the system can create a design, simulate its outcome, and improve it stepwise to arrive at the desired behavior. We have already described this process in our main section on engineering. Such systems now become even more capable. Similarly, the discovery of chemicals, materials, or drugs is more and more driven by generative systems.

Planning/operations optimization: LLMs have also shown some surprising results in this area. Whether it is about planning logistics (internal or external), or resource allocation and scheduling, these complex problems are successfully documented. However, recent research shows that such systems can actually not plan: they assemble planning information from texts that describe earlier plans and put them together in the new context. For many applications, this is sufficient but does not come close to a more traditional system model and mathematical optimizer. There is still a lot of room for improvement here despite early success.

Diagnostics/predictive maintenance: This application is frequently cited of being a candidate for generative design. Note that we have also described the challenges of solving such problems in the maintenance section of our book. With generative AI, the challenges have not gone away. Asking ChatGPT about possible industrial applications of generative AI, it does list the topic as one opportunity. When asked how it would go after it, the description is appropriate: it describes the conventional approach we have also described before. To the question: “You have not used generative AI in your solution.” it openly answers: “Yes, you’re right.” That leaves a lot of room for improvement here too.

The weaknesses described before are currently being addressed by RAG – Retrieval-augmented Generation. Before compiling a response, the system queries a data source that it considers relevant (or that is defined as part of the system). It then feeds this information to its query, like a user inputs supporting documents for analysis. Such solutions tend to contain fewer errors and are more specific to a specific situation that is reflected in the data source. While some of the weaknesses of LLMs can be addressed, we’re back at the point where we need access to sufficient data that is correct, consistent, and complete. This is where we started exploring the foundation models at the beginning of this section.

To conclude, generative AI has shown surprising results in many areas that we haven’t covered here (e.g., entertainment, advertising, etc.). The opening quote from Machiavelli is, being from a time before AI, directed at human ignorance. Following Hahnemann's analysis, quick human decision-making tends not to be fact-based, and AI-enabled decision-making — with missing data — tends to hallucinate. Therefore, both weaknesses need to be overcome in cooperation by using each other's strengths.

When applying AI, we have to be aware of its shortcomings and where it is good at. When designing systems that are supported by generative AI, many system components may not be AI-based, and some may even require human interaction. Therefore, a good understanding of the state-of-the-art and research directed towards addressing their shortcomings is important.

Many organizations, e.g., ZVEI, GIO, or the current initiative of the World Economic Forum, are investigating this. The outcome is progressing quickly, but it is still very much open. If we look back at revolutionary transforming innovation, it has never copied how something was done before: the wheel replaced legs, the combustion engine replaced horses, book-printing replaced manual writing, and a computer does not work like the human brain. Innovation has to move beyond mimicking humans. In doing so, it copies all the human flaws that we want to get rid of with machines.

Outlook

Dear Reader,

If the collection of innovation appetizers has made you curious to taste more of it, you already have made this booklet a success for us. We have chosen this approach as a new version of a bi-directional open innovation approach to initiate a manufacturing-related innovation community that is sharing both the latest use cases from research and innovation as well as giving insight into actual problems in manufacturing industries.

As William Gibson once said, "The future is already here – it's just not evenly distributed"[33], some solutions may already be there in other domains not known to the user in his specific domain. For example, in brownfield, updating legacy machines expert knowledge is already there in telecommunications industries, but experts are needed to install and operate wireless networks. As IT and OT domains start to merge, we see that the customer or user will be supported by services in the near future, making it very easy for him to install and operate private networks by himself.

Furthermore, we strongly believe that the accelerated developments of AI tools e.g., for generative design, together with growing access to data spaces, will fuel innovation processes across different industry domains. But how to take advantage for you, as a user or supplier in your specific domains? One key problem in taking advantage of digitalization opportunities is the lack of IT specialists at manufacturing companies, small or big.

With the industrial metaverse and digital marketplaces evolving, we think that there is a need for action to overcome this bottleneck of innovation needs and IT resources

[*33] The binary code on the staircase in the cover page contains William Gibson's Quote listed above, amended by the reminder: "Now it's time to select which future to support". A call for the united and global effort to contribute to well-being of mankind, health, and sustainability, preserving our lives and our planet.

at companies. Our solution is to link you as an interested partner to AI communities worldwide via different channels, e.g. ZVEI (Germany's Electro and Digital Industry), German Platform Industry 4.0, global industry organizations (GIO) and academic institutes worldwide, we have access to.

To benefit from our initiative, you can

- upload your innovation story – becoming a member of our community.
- upload a problem statement – getting access to AI communities worldwide.
- contact the authors to organize or provide hackathons to find new or alternative solutions.
- upload an AI-based approach looking for an application – getting access to markets.

Welcome to the community!

Contact E-mail (GIO operation team): operation_team@gio.zone