



INDUSTRIE 4.0 DEEP DIVE.

The guide to understanding
the fourth industrial revolution
and the technologies that create it.

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Executive Summary

Industrie 4.0 can be understood as the fourth industrial revolution, heralded in through a convergence of technologies that lean heavily on continuous data gathering and artificial intelligence in a networked environment to present a new form of agile, responsive, and customizable manufacturing.

This e-book, written collaboratively by experts in the fields of robotics, manufacturing, IoT, engineering, aims to provide an overview of the technologies that drive the current changes in the way we work and manufacture. It describes how Industrie 4.0 came to be and dives into all the components that come together to create this new industrial paradigm.

Historical perspective and future possibilities

The beginning of machine-assisted linear production was defined by highly detailed specifications, a single or highly hierarchical system integrator, and the mass production of items. Changes to the product or system required a complete tear-down and rebuild.

This type of system was only economically viable to large manufacturers, in big plants producing huge volumes. In contrast, Industrie 4.0 applies to facilities of all sizes. An Industrie 4.0 manufacturing facility collects data at all stages of its production process allowing it to make regular, intelligently informed decisions about productivity, safety, and efficiency. The exemplar of Industrie 4.0 heralds in a new understanding of manufacturing that is agile, lean, highly customizable, and viable at all scales.

Artificial intelligence and data-driven insights

AI has been of interest to the manufacturing industry since the 1980s and has been applied across the entire production cycle from the planning and design phase, system and maintenance design, to its latest iterations in collaborative robots.

Recent advances in sensors mean that all aspects of the factory can be under real-time continuous monitoring, generating an enormous amount of data. Advanced analytics provide the potential to convert

these large datasets into actionable insights in real-time. Manufacturing facilities have long been deeply embedded with sensors of all kinds, but significant advances in wireless network technologies now facilitate inter-sensor communications which are fundamental to the functioning of industrial IoT. These advances have also reduced the capital costs allowing access for smaller manufacturers.

The availability of relevant data and the systems to analyze it makes automation of some or all of the production process within a manufacturing facility possible. It offers control to operations of all sizes to understand its functions to a granular level without additional management or complex quality control.

Companies wishing to meet the aspirations offered by Industrie 4.0 will embrace a data-driven approach to both their facilities and approach to the market.

Hardware and human interface

A fundamental aspect of Industrie 4.0 is the evolution and continuous improvement of robotic systems. Even as recently as a decade ago, robotics were accessible to only the largest of factories. Today robotics are being implemented into production facilities of all sizes.

The evolution of robotics to more affordable, versatile, and easier to operate machines

has also brought the collaborative robot, or ‘cobot,’ to the factory floor. These small, lightweight, and significantly cheaper robots work collaboratively alongside human workers to increase productivity, create safer work environments, and augment human quality control abilities. Initially, these cobots acted as guides and heavy lifters, assisting humans with repetitive heavy labor, but have since evolved into active machines that can employ their ‘senses’ to work intuitively with humans on complex assembly tasks. Cobot makers and the manufacturing industry will need to collaborate cleverly to ensure the future development of these robots are enhancing work environments and sensitive to global employment demands.

As Industrie 4.0 moves closer to its guiding goals of higher efficiency, flexibility, customization, and productivity with lower costs through automation, the factory workforce will shift from focusing on high-physicality and low cognitive demanding roles to enhanced, more cognitively rewarding positions.

Conclusion

Industrie 4.0 will continue to evolve and expand with both technological advances and broader adoption across industries. Increasing automation and data-driven manufacturing will have positive impacts on economies, productivity, and innovation while ushering in a new era of human-robot relations.

How this e-book came to be collaborative

This e-book investigates the current changes in the way we work and manufacture. It's sponsored by KUKA, developer of industrial robots and solutions for factory automation. As a sponsor for this series on Industrie 4.0, KUKA supports the spreading of knowledge about the technologies that create our factories of the future.

The Industrie 4.0 series is written as a collaborative effort from experts in the field. After we at Wevolver wrote an outline of the articles we made a call-out in the Wevolver community for contributors. With their wide range of background and deep expertise, these contributors crafted this and other chapters in this e-book and we are grateful for their dedication.

Industrial Revolutions

Introducing Smart Manufacturing

The fourth industrial revolution and the technologies that create it explained: The whole is bigger than its parts.

On the origin of Industrie 4.0

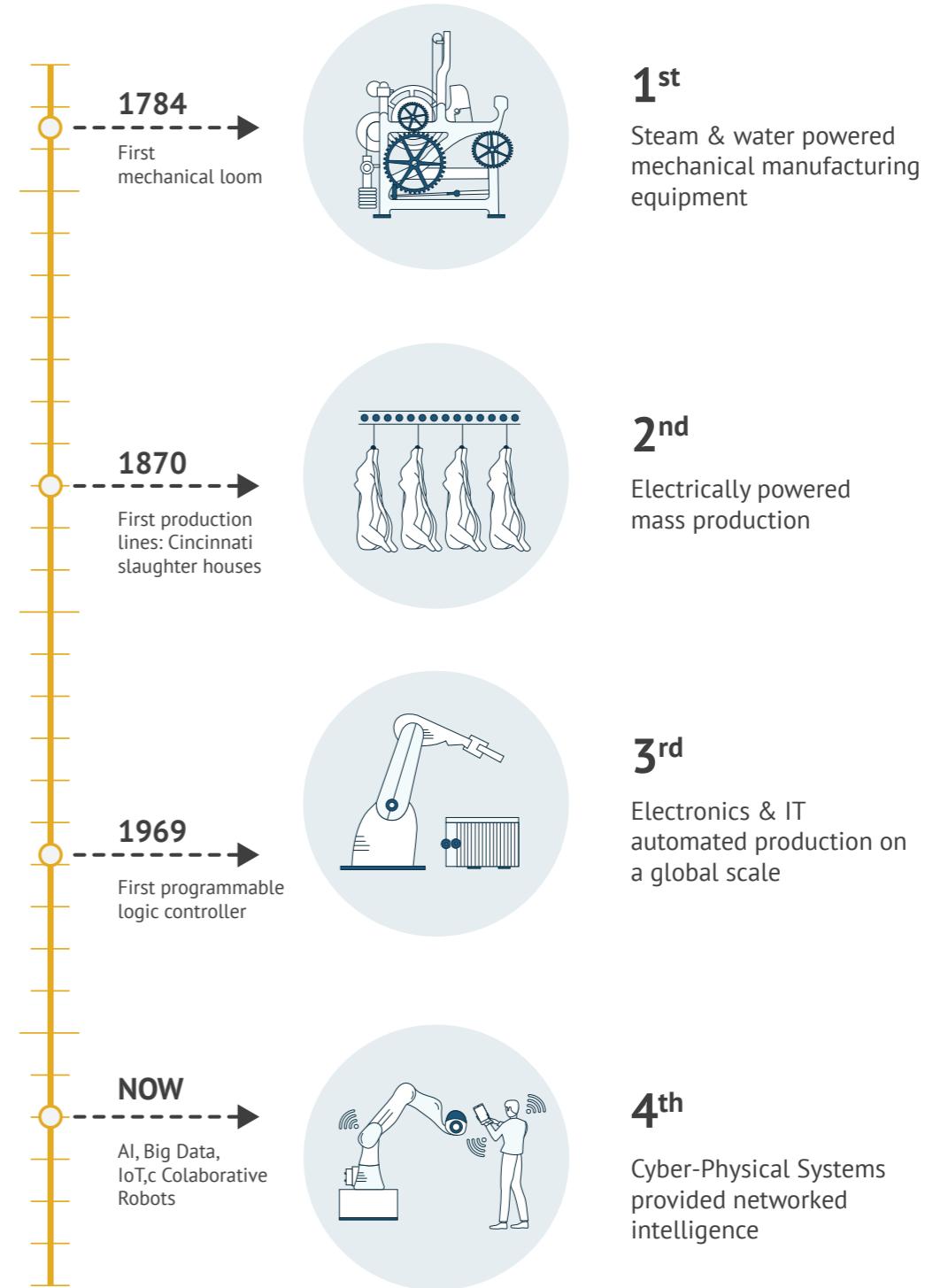
In industrial history, we can separate four revolutions that fundamentally changed the way goods are manufactured. The first started at the end of the 18th century with the introduction of water and steam based mechanical production. In the 20th century, the second phase was defined by mass production and assembly lines using electrical energy, supported by human labor.

After the introduction and later mass implementation of computing power, the third industrial revolution started in the 1970s. Increased control and reliability was enabled through electronics, information technology and automatic production. High reliability was a must, since industrial deployments are often related to critical processes. A malfunctioning could potentially put lives at risk or induce structural damage. To provide such high reliability, industrial deployments during the third industrial

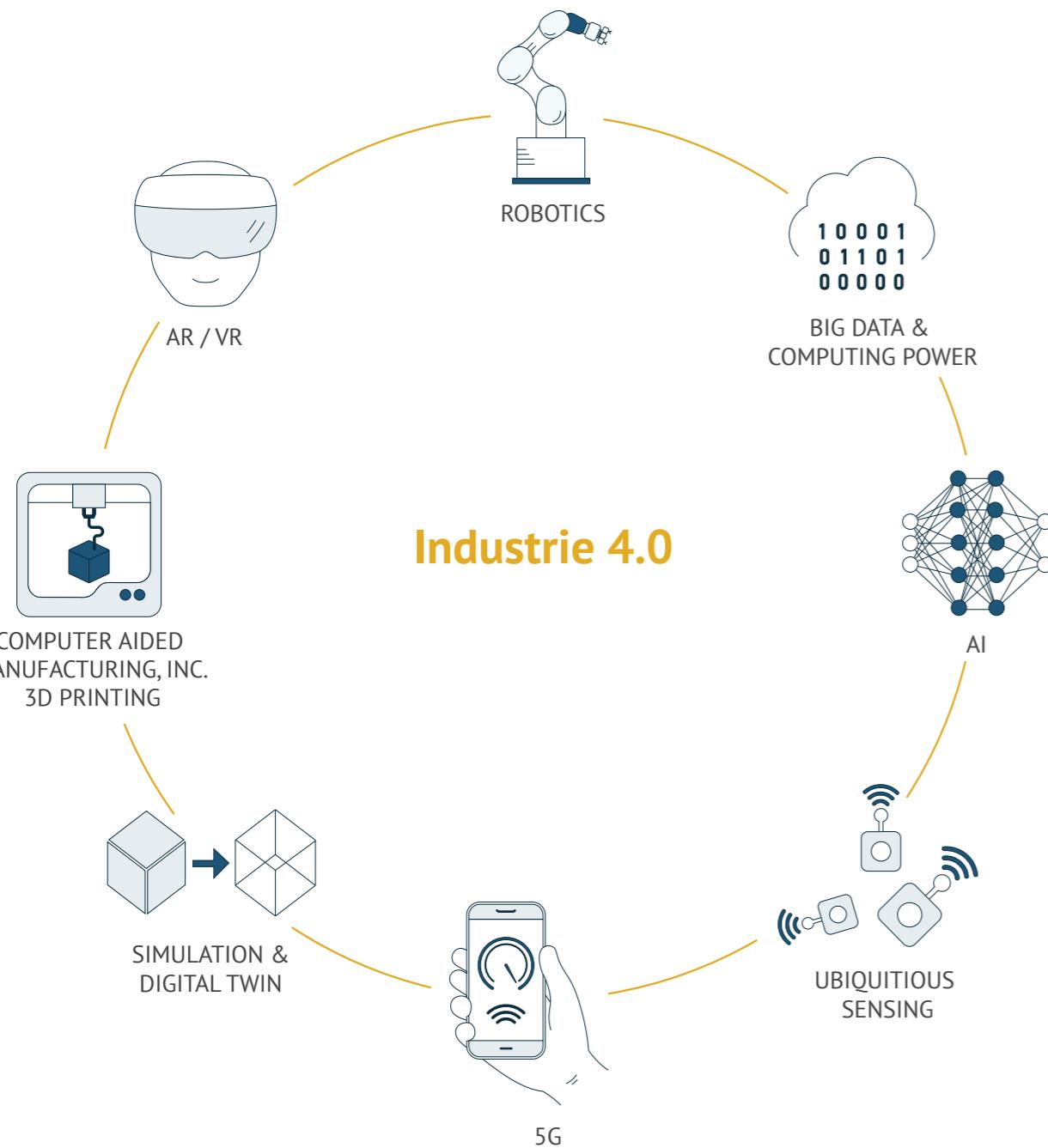
era relied on costly and inflexible network infrastructures. This suited the predominant paradigm of linear production: Write highly detailed specifications, have a system integrator implement them, get the line up and running, do some minor adjustments, produce and finally tear everything down and start over for the next product.

Instead of the primary goal being to produce ever larger volumes at decreasing costs, the new challenge is to produce individualized products - or at least an exploding number of variants - at mass production costs. The new need for such customized, but mass produced items, has driven the need to rethink business models, strategy and organizational structures.^[2]

This new creed; from highly optimized to highly flexible, asks for a more agile way of manufacturing. The business drivers are changing. From mass production to mass customization. From low-cost country sourcing to proximity sourcing. From distanced automation to human-machine interaction.



The technologies that form the basis of Industrie 4.0.



With the rise of digital enabling technologies and novel manufacturing techniques, industry could evolve. To connect the physical world with the virtual world, the fourth industrial revolution established networked intelligence, integrating the internet of things with the manufacturing process.

From a technological perspective, Industrie 4.0 can be summarized as the trend to incorporate computer aided manufacturing with automation, wireless networks, continuous data gathering, and artificial intelligence.^[3] A shift in paradigm. From incremental improvements on existing systems, mechanics, electronics and low-level control, to innovation in algorithms, data, connectivity and usability. Digitally enabling technologies like big data, AI, and 5G are exponentially growing and thus driving Industrie 4.0.

As physical processes are digitized (i.e. represented & controlled in the cyber world), data becomes more and more important. Concepts like 'digital twin' (creating a digital replica of a physical entity, like a robotic system) are used to optimize cyber-physical systems (embedded systems integrating computation, communication and physical processes). They can range in complexity, from a single microcontroller chip to complex, multipart devices and are enabling digital representation and control. Rather than general purpose devices, they are often built for a specific task, with relatively lower computational power and low power wireless communication.

As the systems range in complexity and size, so do the manufacturers. Whereas the latest, most intricate implementations of Industry 4.0 might only be feasibly implemented by large enterprise scale manufacturers, small and medium scale manufacturers might have even more to gain. New capabilities can either be production steps that could only be performed manually before - like tasks requiring sensitive force control - or production steps that could not be done at all, e.g. certain parts produced by means of computer aided drawing and additive manufacturing.^[4] However, they might be as simple as converting paper-based processes to digital, pulling more sensor data from machines, and running basic analytics on cloud stored data. Industrie 4.0 is poised to affect the manufacturing industry across the board.

To show you the influence of these technologies on industry, we will guide you through an imaginary smart factory, Wecycle. This exemplary factory builds custom bicycles from raw material to finished product. On a guided tour we will start by showing how advances in big data analytics, AI and computing enable digitization, then by looking how massively increased connectivity and sensing make communication possible and last by describing the influence of digital manufacturing, digital twins and human robot collaboration.

Big data analytics and artificial intelligence

Through the widespread deployment of sensors and smart devices in current factories, massive amounts of data are gathered. These datasets are referred to as big data. Big data is characterized across four properties: volume, velocity, variety and value. Volume represents the generation and storage of large amounts of data, velocity refers to the renewal rate of data points and their timely analysis. Variety indicates the types of structured and unstructured data gathered from different sources. Last, value refers to the hidden information stored in these datasets. To gain value for the end user, the data needs to be converted using analysis into actionable insights that drive business decisions.

In the industry, big data is gathered through sensors and CPS. It is extracted from industrial processes, then stored, processed and analyzed through machine learning algorithms, and at the end of the cycle translated back to the production process.

This is where we will introduce the first step in our Wecycle smart factory, the arrival of our raw material. Import taxes and border closures related to elections, terrorism, disease and other sources of volatility have crystallized thinking about redundancy and predictive analytics in supply chain design. Predictive factors in trade can all influence the time, cost and availability of shipments

by sea, rail or air. By analyzing information about shortage of materials, predictive big data analytics have calculated high probabilities for delays for Wecycle. Warned by previously lowered production output after a similar event, our factory has been able to gain access to a different material provider so work can continue as planned.

The heavy raw materials, in our case aluminium sheets, are precisely moved by autonomous ground vehicles, moving in confined spaces, towards a set of furnaces and hydraulic presses to be shaped into bike frames. Using recognition patterns, learned from previous datasets, problematic defects in the can be found using machine learning. The tiniest deviations in the metal sheets are compared with previous materials. By using big data analytics, real-time scanning allows for faster anomaly detection, optimizing the process.^[5] Bike frames with visual defects are automatically expelled from the production line and ordered into different sets to be recycled, repurposed or checked again.

The cyber-physical systems at Wecycle are able to acquire real-time data, perform computations and communicate with each other. The systems are responding to intelligence from within the factory and from across the entire supply chain. Now the challenge is to have a network that can handle these new requirements. Increasingly higher loads on the mobile and cloud computing systems that clean, collect and analyze data are prone to overload older computing frameworks and networks.



Bike frames pressed out of aluminium sheets.

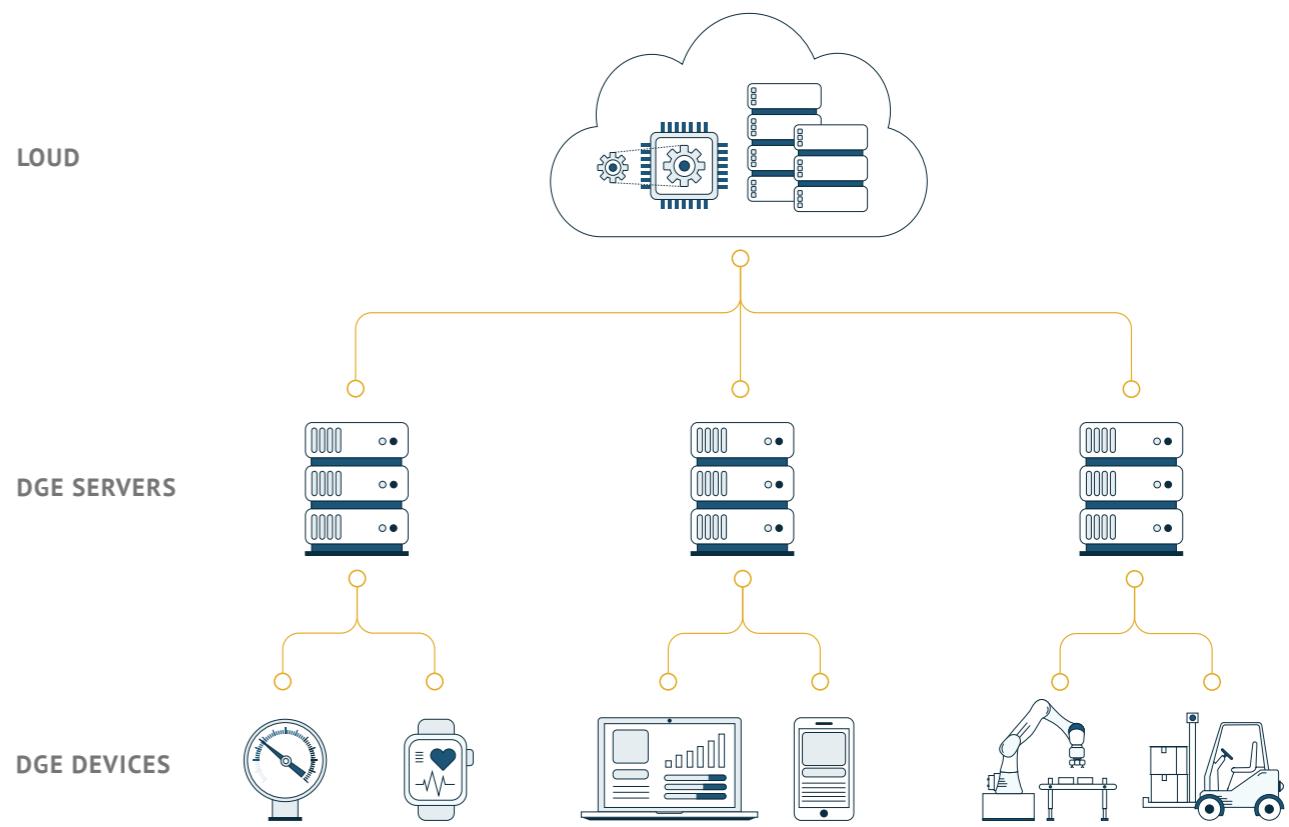
Sensing

The sensor systems at Wecycle generate enormous amounts of data. Wecycle's smart sensor systems are a combination of a sensor, microprocessor and a wireless communication technology. A collection of those is able to convert a wide variety of inputs (e.g. temperature, pressure, humidity, weight, gas displacement, vibrations) into data and transmit it through the network. Sensor systems are essential parts of smart factories, and in our Wecycle example, vibration analysis is used to detect defects that could lead to material failure. Due to their networking capabilities, the sensors can work together, being placed at multiple positions next to a vibrating plate. The mechanical sensors are connected with optical sensors to cross reference vibrational data with a visual inspection. Although in-line devices for quality control (like cameras) have been around for a long time, gains in analysis speed and the resolution of sensor data now make real-time defect control possible. In Industrie 4.0 less humans are needed to stand by the line and examine products. Error checking was always time consuming and never watertight. Now it can be automated and executed with more precision than humans can achieve.

Edge computing

The data gathered at Wecycle by the smart sensors connected to the frame production process needs to be analyzed. It can be sent towards the cloud to be computed, or it can be processed at the 'edge'. An overwhelming amount of data can clog both the gateway and cloud. This is one of the main reasons to use a distributed computing architecture that aims to process data streams at their origin.

Most advanced Industrie 4.0 network architectures are based on 'edge computing', rather than sole cloud computing. A first wave of processing and filtering of the incoming data is performed at the place where it is gathered, relieving computing systems and reducing latency. There is no need to query all data from cloud-based data centers. One can directly and quickly retrieve data from one of the mobile edge nodes. With the use of this technique, the data from all bike frames at Wecycle that have passed inspection is further compressed, while defect analysis is forwarded to the cloud to assist further inspection reports.



Edge computing.

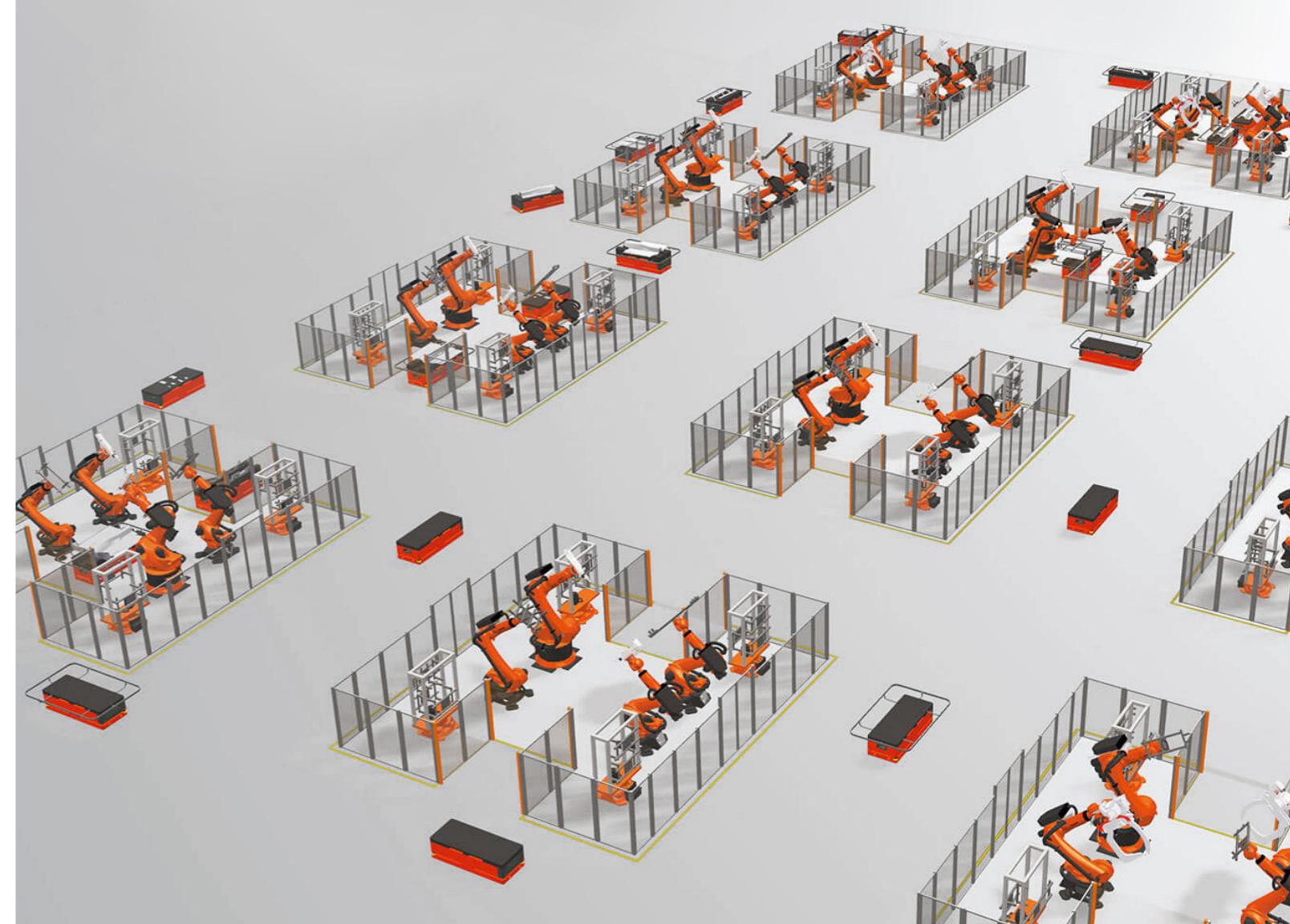
Connectivity

Wireless communication technology is of key importance to connect digital and physical systems. Significant advances have been made in sensor development to allow low-cost, efficient communication protocols. Currently, the most used protocol for wireless communication is the WirelessHART (Highway Addressable Remote Transducer) protocol. Released in 2007, there are more than 30 million devices connected. However, due to the increasing demand of wireless networking, the demand has arisen for an upgrade. The extent to which cyber-physical systems can transfer and communicate data is significantly increased through 5G networks. Newer networks will have much higher capacity than current LTE or wireless networks and transmission speeds are promised to be a 100 times faster and have low latency - of less than a millisecond. More so, it manages to provide this capacity in a sensor saturated environment (e.g., in a plant with 1000s of devices).

In this way, 5G enables remote HD video surveillance in our Wecycle factory, or real-time monitoring and feedback between our sensors and hydraulics. On our floor, real-time measurements of temperature are communicated to the furnaces and hydraulic presses, to adjust as needed. If the humidity changes, the pressure drops or the temperature rises slightly, all production variables are adjusted accordingly. This ensures minimal change

in the technical specifications of the bikes. The local 5G networks in our factory make it possible for intelligent production components to communicate ad-hoc with each other – without having to install fieldbus cables and configure the communication participants. This makes it easier to move and change different components of the manufacturing process. It also increases network reliability, and promises to lower device cost and energy use. 5G allows functions that were previously located at the central control level to be moved to the edge nodes, allowing controller systems to be leaner. Overall speed is increased through pre-processing and security is enhanced through decentralized storage.

Because our components are wireless, and thus flexible to move, a concept like matrix production^[6] can be used. Matrix production allows us to produce multiple interchangeable parts on one single system, thus allowing increased type variety, more frequent changes of models, and quantity fluctuations in production. Now, when a new bike model is introduced, there is no need to alter and optimize the entire manufacturing floor. The design of the modular systems and their placement on the floor can simply be altered. Through its agile design, Wecycle is able to offer personal customization at the cost of mass production.



Matrix production.

Computer aided manufacturing and digital twins

The increased importance of customization and personalization have led to changes in behaviour for consumers and producers alike. The concept of computer aided manufacturing has long been a part of the manufacturing process. Further advances

in modelling, simulation and computer aided design tools, combined with continued development of additive (3D printing) and subtractive (e.g. CNC machining) manufacturing practices have made it possible to build shapes and products that were previously unfeasible, both physically and economically.

Real-time monitoring and feedback is assisted by the digital twin (also called 'digital shadow'). First introduced by researcher Michael Grieves back in 2002^[7],

'digital twin' stands for the use of digital models of physical objects to simulate the behaviour of a real manufacturing process. It couples a physical process with a digital equivalent for optimization in a virtual setting. Real-world data, gathered from the print and manufacturing process, is transmitted into the modelled system to complete simulations, validate the system, and dynamically adjust it where needed.^[8,9]

Customizable parts can now be mass produced on next generation 3D printers.^[10] These are capable of performing real-time quality analysis and real-time adjusting by using sensors and computer vision. When the print is faulty, issues are processed to optimize production. Materials are optimized for batch processing, and through compact and modular design, the production space needed for the printers is minimized. Advances in material science have led to printed parts becoming as strong as injection moulded ones for certain applications.

The handlebars from Wecycle are 3D printed in the highest grade polymers, adjusted to arm length and hand size. Customer length and weight is requested upon ordering, and fed into an algorithm to personalize the saddle shape, fabricated in a multi-part printing process with hard and soft materials. Additional, optional electronics, such as remote controlled lights, digital locks, GPS and automatic locks are added based on customer requests.

Human robot collaboration & enhancing human capabilities.

The robots used in these processes have gained increasingly larger roles. They are becoming more autonomous, more flexible, and more cooperative. To facilitate the next step in human-machine interaction, collaborative robots (cobots) have been adopted in industry.^[11] They have a function to play in the field between manual (assisted) labour and fully automated production.

Collaborative robots allow for new opportunities in which the human worker is in the same workspace, with robotics systems assisting with non-ergonomic, repetitive, uncomfortable or even dangerous operations.^[12] A cobot can check, optimize, and document the results of its own work while being connected to the cloud. Thanks to integrated sensor and communication systems, cobots can directly collaborate with their human "colleagues," safely handle sensitive products, and don't require a protected space. In order to truly work together, they are programmed to ensure that their behaviour can be tuned or altered by operators, and that they're increasingly aware of humans in situations where man and machine are dependent on one another.

Humans are working closely with collaborative robots.



^[13] This in contrast to ‘dumb’ industrial robots which will continue repeating pre-programmed movements regardless of what’s in their path.

At Wecycle, a cobot applies adhesive to the frame for custom stickers, saving factory space since the cobot does not have to be separated from the human workers aiding in final assembly. Another cobot helps a human worker to adjust screws in hard to reach, unergonomic places.

Such collaborative working environments are further supported by augmented reality (AR) and virtual reality (VR) technology. AR/VR gives humans the ability to display their steps, or ask for virtual support, either from an AI or from remotely working human experts.^[14] They can receive immediate visual feedback, reducing the need to remember complex sequences.^[15]

At Wecycle, AR goggles point the workers towards the correct size and position of all the screws used in final assembly. The finished bikes are now moved by a cobot on an autonomous platform, ready to be packaged and sent off.

Towards the industry of the future

The Wecycle factory tour is over. In a nearly completely automated and autonomously learning scenario, a personalized bicycle has been produced. The process has been governed by data and automation. By using analysis, real-time feedback can be used to continuously optimize and change manufacturing. The cyber-physical systems on a factory floor connect and work with sensors, machines, humans and artificial intelligence. Flexibility and efficiency in the factory has improved quality and efficiency.

The examples mentioned in this chapter are some of many, and there are thousands of case studies out there. Investments in Industrie 4.0 continue to be made. Modern times call for processes that are able to run without human interference. In case of a crisis, we rely on industrial production to continue. To feed us, to support our infrastructure or to supply means of transport. Manufacturing is no longer bound to a single discipline. It has become a part of society where computer scientists work together with engineers. A place where artificial intelligence meets production line workers. The full value of Industrie 4.0 is likely to be realized in the next decades and we are surely to see better, more adapted, smarter factories in the years ahead.

Data-Driven Intelligent Production

How big data, advanced analytics, and AI are changing manufacturing.

Analytics in manufacturing: historical perspective

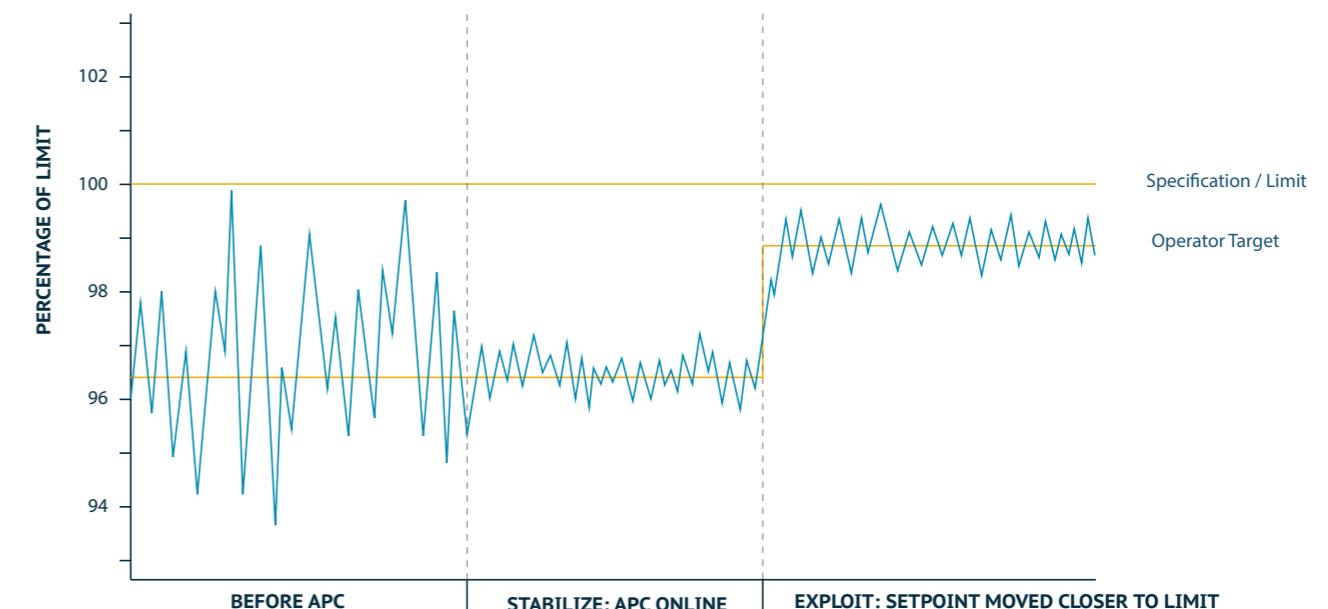
Data analytics encompass a range of approaches with the ultimate goal of extracting knowledge and applying it to anticipate and solve problems. The large volumes of data that can be collected from manufacturing processes in real-time enables advanced algorithms to be applied for decision-making.

Data must be collected, organized and cleaned before analysis, and each step affects the precision of the algorithm used. Data analytics for industrial processes has traditionally relied on conventional statistical modelling approaches. Companies in manufacturing industries successfully integrated engineering, science, and statistical modelling tools to develop large-scale process automation platforms. These systems are often known as 'Advanced-Process-Control' (APC) systems. They enable

companies to optimize the efficiencies of their machines and processes.

For example, an inspection tool in a semiconductor factory might measure inspection points on a silicon wafer, and store the data in associated databases. The APC system, analyzing these output parameters, decides whether the building recipe (the input parameters) needs to be altered to adjust for errors.^[16] This is nothing new, however, as more industrial IoT devices and metrics become embedded within automated processes, different types of structured and unstructured data including sensor data, images, videos, audios, and log files are being collected. In order to process the increasingly larger, heterogeneous datasets that are associated with Big Data, more advanced approaches are required.

Manufacturers can leverage their data to inform decision-making and identify new or un(der)-used opportunities to improve productivity and efficiency.^[17] While they expect that successful implementation of Industrie 4.0 concepts will lead



A fictional example of how an Advanced-Process-Control system is used to optimize a production line's efficiency.

to a reduction in manufacturing costs, about a quarter also believe that the most critical outcome of the fourth industrial revolution for their business is increasing agility in operations. Still, implementation is a challenge^[18]: Data integration and security, process flexibility, and the strict performance requirements for systems contribute to under-utilization of data in manufacturing settings.

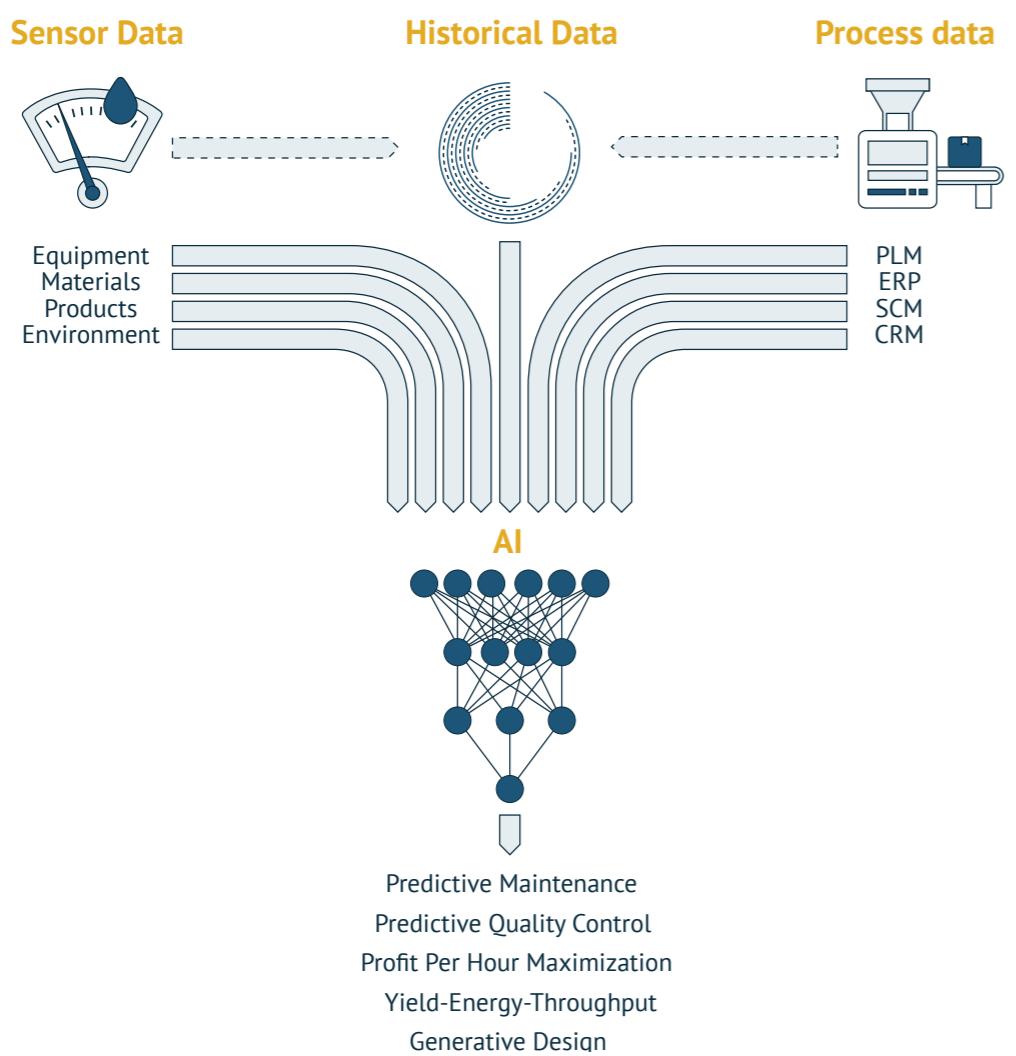
Furthermore, the implementation of process automation through APCs has often been restricted to large-scale processes, primarily due to the large capital expenses associated with equipment purchases and installation, and the return on investment (ROI) is rarely favorable for small-scale processes. In addition, the manufacturing sector has lagged behind other sectors in investing

in IT systems that enable them to capitalize on their data to increase efficiencies in small scale processes.

Fortunately, that is changing. Several technological advances have changed this pattern of lacking IT investment in the manufacturing sector. Advances in computational infrastructure, particularly cloud-based platforms, have enabled efficient storage and management of large data volumes.^[19] Enterprise Resource Planning (ERP) systems, which were traditionally used to manage back office functions, have become web-based, enabling the integration of main business processes with collaborative functions such as Supply Chain Management (SCM), Product Lifecycle Management (PLM) and Customer Relationship Management (CRM).

Low-cost and long-lasting sensors can now be connected through wireless networks, enabling large amounts of data from the factory floor to be collected in a scalable and cost-effective manner. Information from IoT devices in the factory can be combined with wider enterprise datasets to optimize productivity and efficiency in a highly flexible manner in response

to demand. The reduced cost of intelligent sensors, accessible software, and advances in analytical tools has made room for a more bottom up approach to manufacturing automation. Insights and intelligence can now be achieved on much smaller scales, opening up the concepts of Industrie 4.0 to smaller enterprises.



Onwards to Big Data and advanced analytics

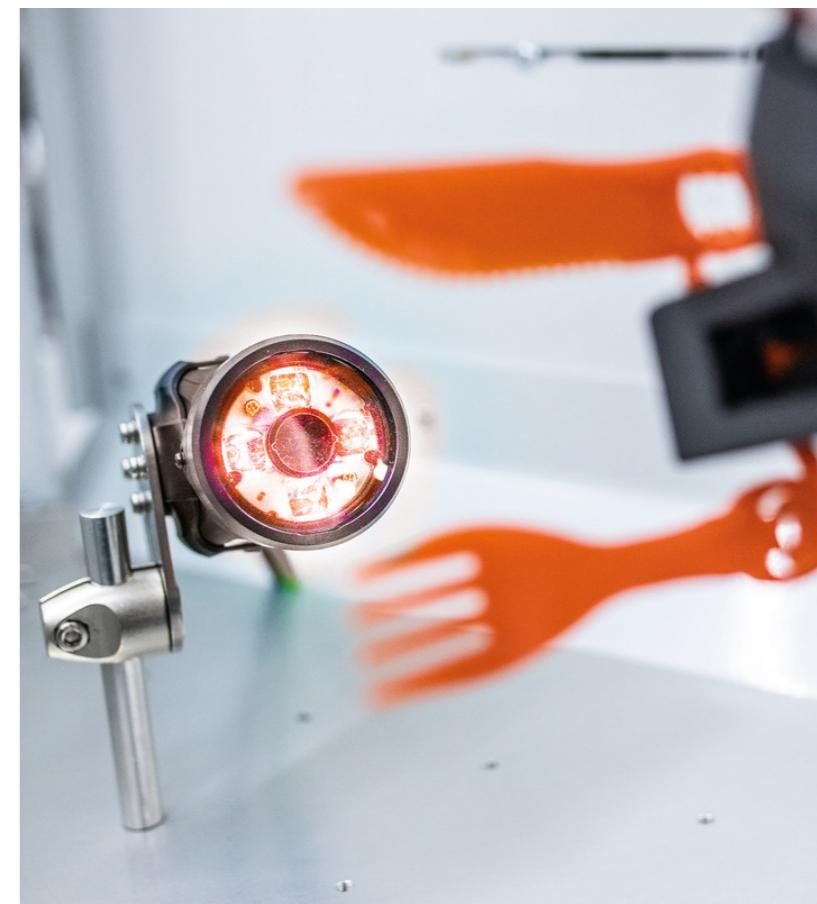
The main difference in data analytics between the third and fourth industrial revolution is the shift to a more proactive approach that anticipates problems before they occur and promotes corrective actions ahead of time. Algorithms can be descriptive (“what has happened”), diagnostic (“why an event has happened”), predictive (“what will happen”), or prescriptive (suggesting a course of action). That shift in paradigm, from reactive to proactive, can be seen in many industry practices.

Of the general population of big data, most sets are unstructured (about 95% [20]), text, images, audio and video are all common examples. In order to prove value, there is a need to organize and structure datasets, to homogenize the data that reside in different systems and sources (e.g., sensors, automation devices, business information systems). Or, to improve the algorithms to better adapt to heterogeneity. These are the challenges for more advanced analytics. Due to high volume, the size of big data sets can create the opportunity to study data from heterogeneous sources. But due to the massive samples, conventional statistical methods can be outdated. Furthermore, computational methods that have worked fine on smaller samples might fall short in efficiency on these new, larger datasets.^[21]

Big Data

This has been made possible by the rise of big data. As defined in our first chapter, big data is characterized across four properties: *volume*, *velocity*, *variety* and *value*. Volume represents the generation and storage of large amounts of data, velocity refers to the renewal rate of data points and their timely analysis. Variety indicates the types of structured and unstructured data gathered from different sources. Last, value refers to the hidden information stored in these datasets. Stored, because data is essentially worthless without data management and analytics.

Automated visual inspection of the production of sustainable cutlery. Image: KUKA



Advanced Analytics

The process of identifying factors that drop efficiency, or cause defects or quality deviations in the manufactured product is called *root cause analysis (RCA)*. Traditionally manufacturers rely on on-site expert knowledge for this. And while experience is valuable, production lines are often so complex that awareness of every component and sub-process and their relationships is humanly impossible.

In Industrie 4.0 **automated root cause analysis** can be implemented to evolve from reactive and preventive to predictive practices. Beyond increasing accuracy and shortening investigation times for problems, automating root cause analysis can inform predictive maintenance and predictive

quality control. We'll first explain these concepts and then show examples of how automation and artificial intelligence can help optimize these processes.

Identifying process causality in fault detection can be difficult when relying solely on process knowledge or experience. **Predictive maintenance** analyzes big data of the historical performance of equipment or production lines to forecast future failures and limit downtime. Here, big data, is the field that treats ways to analyze and extract information from data sets that are too large or complex to be dealt with by traditional data-processing techniques. This type of structural monitoring replaces manual inspections that require human intervention otherwise needed to prevent equipment failure.

Predictive quality control aims to improve production quality and reduce costs through predictive alerts and automated anomaly detection. Advanced analytics may also aid in determining the variables that have the highest impact on quality issues, helping to prioritize issues. Real time operational visibility enables engineers to drill down into any individual machine and its sensors, to determine its impact of overall quality levels. Predictive quality alerts may be formulated based on business rules combined with automated anomaly detection, again to reduce human error and downtime.

Data can be incorporated into automated data analytics pipelines to enable simultaneous analysis and visualization in real time. There are several advantages to building automated data analytics capabilities. Having greater visibility of processes in real time enables engineers to manage systems more effectively by detecting when key performance indicators (KPIs) deviate.^[22] In these cases, corrective action can be implemented faster to resolve issues and improve productivity. Operational reporting, using descriptive and diagnostic analytics is widely used across many manufacturing industries.

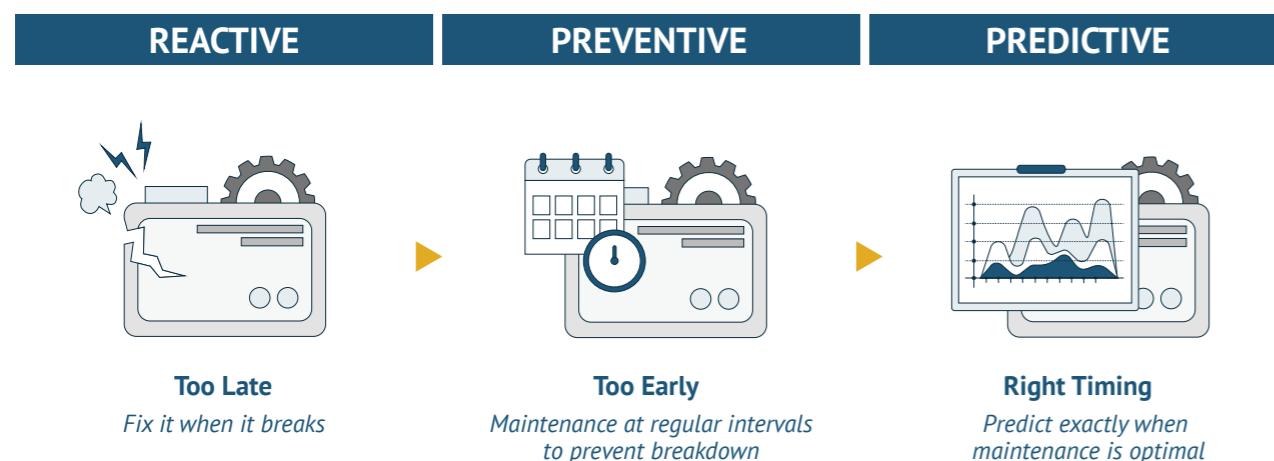
There are many examples of predictive maintenance, root cause analysis and optimization. Exemplary systems used in industry are *Profit-per-Hour (PPH)* maximization tools, *Yield, Energy, and Throughput (YET)* analytics and *zero defect manufacturing*.

1. Profit-per-hour (PPH) maximization tools analyze all the relevant variables that impact the total profitability of a manufacturing company. They can take thousands of parameters within an integrated supply chain and manufacturing environment and provide intelligence on how best to capitalize on the conditions.^[23] Data is combined from multiple sources that track incoming raw materials, inventory, automated processes performed by cyber-physical systems, and factory outputs. Analyzing these variables from across diverse parts of the organization can diagnose specific problems and aid in root cause analysis or find bottlenecks in production lines.

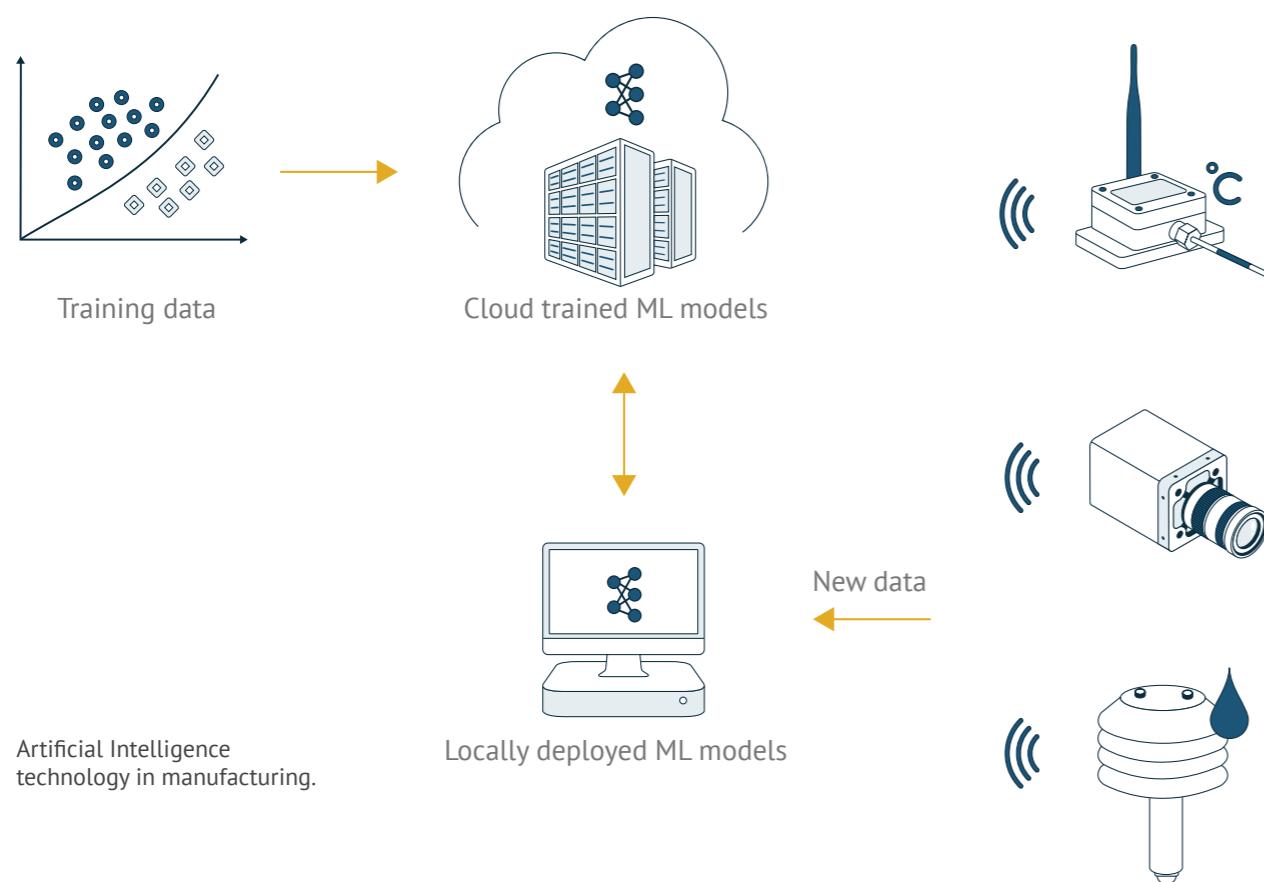
2. By analyzing individual processes and process inter-dependencies, supply chains can be optimized for transportation times, assembly line flow rates, and fluctuations in demand. Such YET analytics ensure the most efficient operation of individual production units during operation, helping to increase their yields and throughput or to reduce the amount of energy they consume. These insights can help to build factory-wide flexibility by forecasting the impact of disruptions or optimizing energy consumption per individual unit.

3. Lastly, zero defect manufacturing is a trend towards eliminating defects from manufacturing processes and may take several approaches including detection, repair, prediction, and prevention.^[24]

The Evolution of Maintenance Strategies



A practical example of applying AI solutions to predict and prevent process inefficiencies comes from a semiconductor producer that had problems with broken wafers: by analyzing live and historical data from the wafer production line they were able to pinpoint the issue to the baking temperature. Then, correlations between statistical deviations in temperature and statistical deviations in the speed of the cooling conveyor belt were identified, enabling the company to solve the problem.^[25] The power of such an AI solution lies in the ability to leverage unstructured data, like humans can.



Artificial Intelligence technology in manufacturing

Artificial Intelligence (AI) has been a topic of interest in the manufacturing sector since the 1980s. Early work in AI applied first-order logic (a statement may be true or false depending on the values of its variables, also called 'predicate logic') to the operational management of computerized production processes.^[19] This approach

permits a descriptive and non-procedural representation of knowledge related to the operation of a production line. The user only had to specify what to do and not how to do it. Many of the early examples of AI were characterized by structured contents (data that adheres to a relational model that can be analyzed) and centralized control structures.

To mimic human-like behavior in an automatized process, AI must be able to adapt to, and extract intelligence from the widest sources of data possible.^[26] Whether it be text-based, visual, auditory or anything else that might hold information suitable for processing. Manufacturing environments are dynamic and decision problems are often unstructured. As the systems continuously change, logic operations for manipulating processes must be continuously reviewed. Fortunately, current AI tools have reached the inherent capability to respond to dynamic conditions within manufacturing settings.

Modern implementations of AI in manufacturing leverage a variety of techniques including **Machine Learning (ML)**, and its subsets: *Deep Learning (DL)* and *Reinforcement Learning (RL)*. These different subsets of AI all involve the construction of algorithms that learn from and make predictions on data. They may be distinguished based on their respective approaches to solving problems. ML algorithms can be classified according to the broad approaches employed in algorithm development: *unsupervised learning*, *supervised learning* and *semi-supervised*

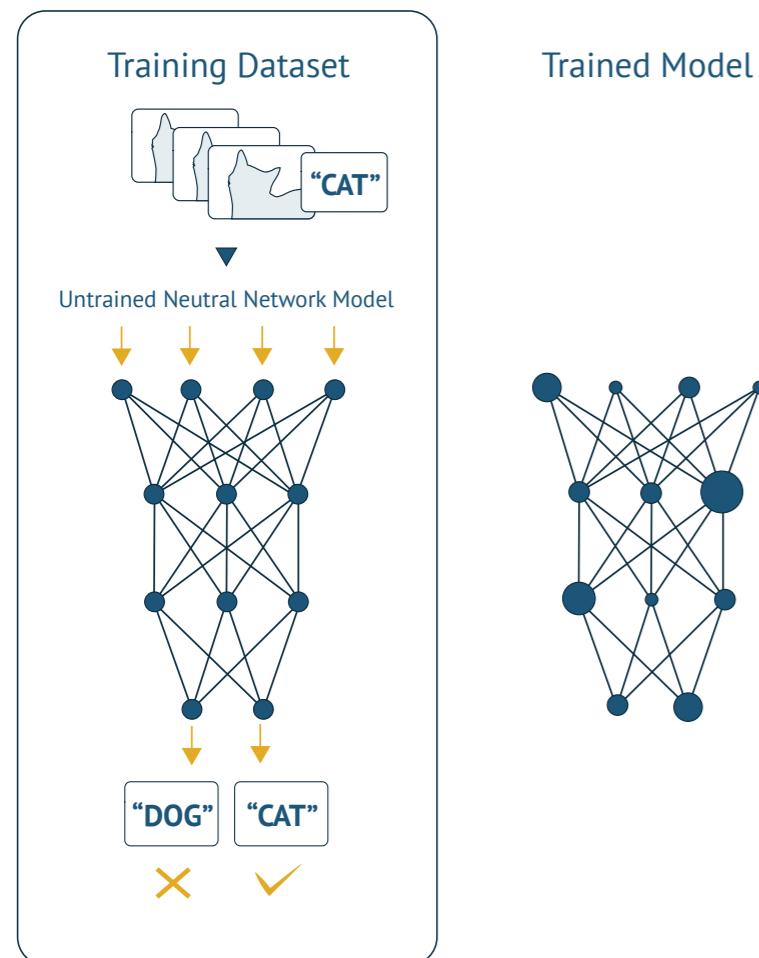
learning. The first, unsupervised learning, looks for previously undetected patterns in a data set with no pre-existing labels and with a minimum of human supervision, the second maps an input to an output based on example input-output pairs, while the last combines a small amount of labeled data with a large amount of unlabeled data during training.

Application of these models has been made possible by the availability of large datasets and the required computation infrastructure for training and deployment. Unsupervised and supervised ML approaches are widely implemented in process industries, accounting for between 90%-95% of existing applications.^[27] ML can be used as a predictive modeling tool for both process and quality control. Different ML algorithms are suitable for different processes: For example, dynamic relationships between process data are particularly useful for process optimization. Hierarchical multilevel models may be used to describe the relationships between different key performance indicators (KPIs). Lastly, distributed ML can be leveraged to analyze metrics across diverse machines and processes with different data types and sampling frequencies.

Deep Learning

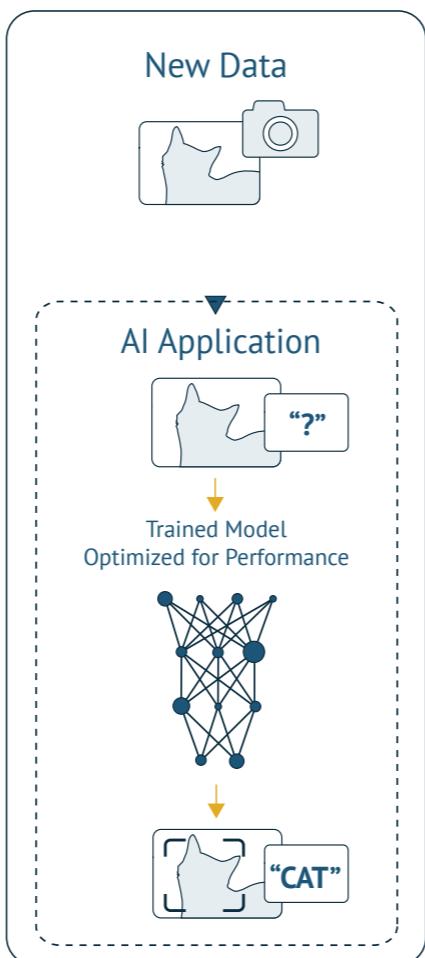
TRAINING

Learning a new capability from existing data



INFERENCE

Applying this capability to new data



Both ML and DL derive their models from training datasets and apply that learning to new data. DL is a subset of machine learning, but contrary to basic machine learning, deep learning networks often rely on multiple layers of artificial neural networks (ANN), each contributing to different interpretations of a dataset. While basic machine learning models often need guidance from an engineer, a deep learning model can determine on its own whether a prediction is accurate or not.

DL has been effectively used in domains with complex data such as image classification. In contrast, RL approaches learn dynamically by adjusting actions based on continuous feedback mechanisms to optimize a desired output.^[28] AI methods can be employed in isolation to specific processes or in combination by applying multiple methods sequentially or simultaneously.

Deep learning classification models have been used to improve data collection and organization, leading to the identification of possible defective products over multiple assembly lines.

A different AI subset, active learning, uses Natural Language Processing (NLP) to enable knowledge transfer directly from humans to collaborative robots (cobots).^[29] Human-robot collaboration has recently gained traction in many manufacturing settings where they offer advantages in flexibility and can lower production costs. Unlike traditional manufacturing robots which are designed to work autonomously, cobots

are intended to interact with humans^[30]. For these interactions to succeed, the robot must recognize human intentions. A recent study implemented a recurrent convolutional neural network (RCNN)-based system that provides early recognition of specific human activities.^[31] It has been employed to enable cobots to perform quality inspection cases without the assistance of a human. In a later chapter in this series we will dive more deeply in cobots and human-robot collaboration.



AI enables autonomous mobile robots and cobots to become part of the factory floor.

AI is influencing all aspects of Product Lifecycle Management (PLM), including the design phase. Increasingly Generative Design tools are used. These algorithms automatically generate optimized design options in 3D CAM modeling programs for achieving a set of design goals. Multiple iterations of a product can be designed and compared using different metrics and constraints. This enables engineers to quickly generate a range of design options to filter and select the ones that best meet their goals and constraints.

Another example of applying AI in the manufacturing industry is the automation of visual inspections.^[32] We'll return to a semiconductor production line once more: During the manufacturing process damages such as scratches or cracks can make the product unusable for further processing or end up in the final product. By combining a deep learning algorithm with computer vision techniques, defects can be detected in milliseconds, by quickly selecting a faulty area, and then using DL to assist in interpretation using heat maps.^[33]

Implementing artificial intelligence in manufacturing

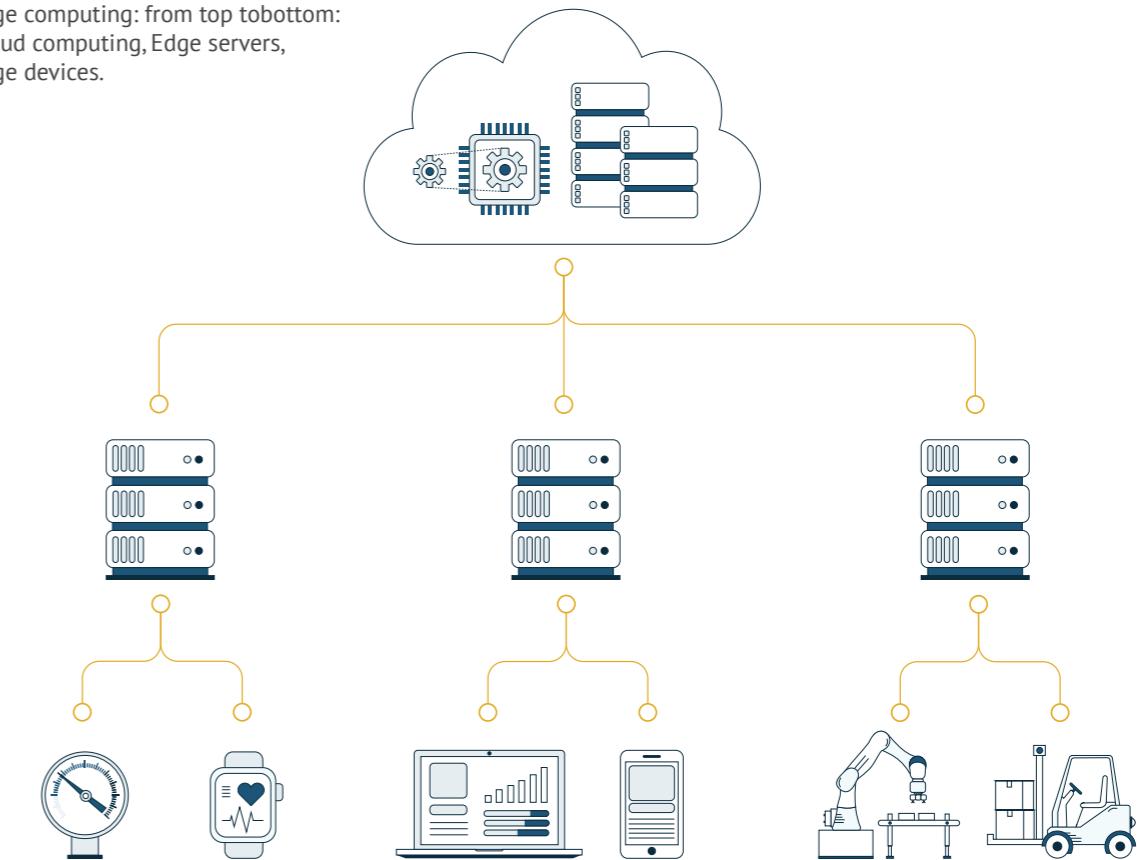
Data quality

High quality, curated datasets are essential for training ML models for specific scenarios, especially for neural networks. However, the availability and scope of datasets with appropriate quality standards is often limited. Data must also be cleaned, and its quality evaluated prior to applying the ML algorithms for model development. Missing data, outliers, and any differences between sample variables must be identified and addressed appropriately.^[34] Because the use of AI systems depend on the precision of their models, this data preprocessing is an important and time-consuming step, requiring significant computational and storage capabilities.

Cloud and Edge Computing

In Industrie 4.0 applications, algorithms must be very adaptable in order to guarantee performance in real world settings. Both the training and scaling of ML models is challenging because large models can involve millions of parameters and large datasets. It requires the scalable storage, distributed processing, and powerful computing capabilities that cloud infrastructures provide.

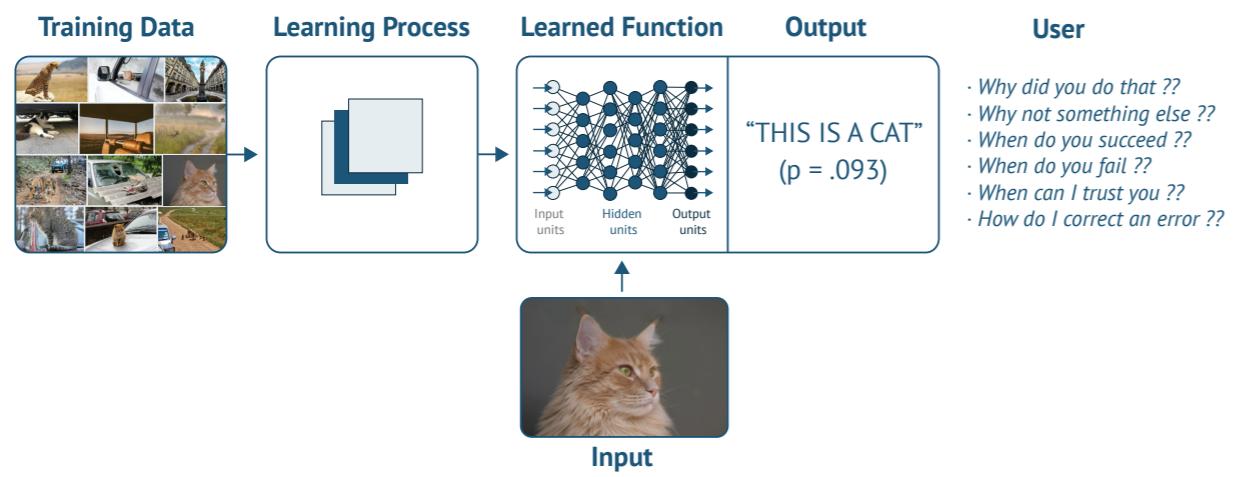
Edge computing: from top to bottom:
Cloud computing, Edge servers,
Edge devices.



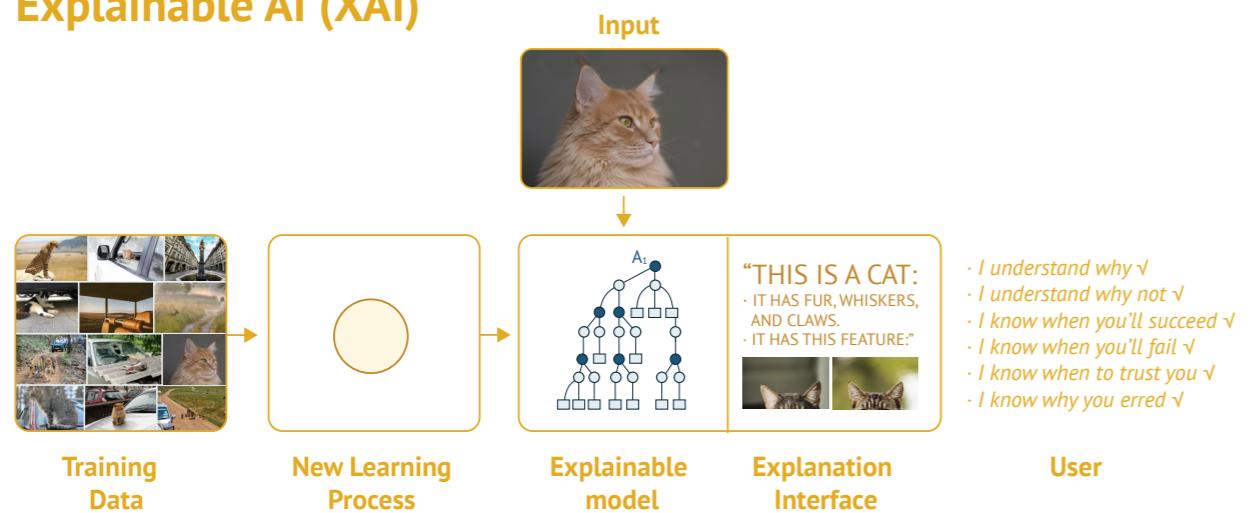
Clearly, the amount of data and computations required to make manufacturing more intelligent comes at a price. Firstly, there are the literal costs of bandwidth usage, data storage, and computing. Secondly, the large amount of data can overwhelm a company's networks and IT systems. A third problem is long and unpredictable latency, resulting from sending data to a cloud datacenter and performing computations there before sending information and commands back to the factory floor. This is especially problematic for time-sensitive use-cases.

A solution comes in the form of **edge computing**, and the concept of "*AI at the Edge*." In such a computing environment edge devices (e.g. smart sensors or other industrial IoT devices) carry out a substantial amount of computation, storage, and communication locally. The edge nodes either preprocess data before transmitting it to the cloud, or execute the whole AI application locally from input to output, enabling efficient real-time intelligence at the point of need.^[35]

Today's AI



Explainable AI (XAI)



Prototyping and Explainable AI

Current plug-and-play AI solutions are often developed to address only specific problems. Therefore, in most instances, companies must employ experimental and agile approaches to implementing AI tools more widely. Rapid prototyping and small-scale deployment are useful in determining the optimal analytical approach prior to rolling out operational AI systems.^[36] This also reflects the role of smaller enterprises, and their possibilities in Industrie 4.0.

Furthermore, to realize the potential of advanced analytics, manufacturers must focus on developing capabilities and skills across the organization. To assist the development of AI-based models, it is imperative to build trust and transparency. One of those attempts is Explainable AI (XAI), referring to methods and techniques that apply AI such that its results can be understood by human experts. This is in contrast to the "black box" element of model design.^[37,38] In machine learning, even model designers cannot explain why the AI arrived at a specific decision. XAI aims to make algorithms self-explanatory.

Combining data, analytics and AI to transform manufacturing.

Many companies have become interested in implementing advanced analytics, including AI-based approaches in manufacturing settings. Fast adopters can create a competitive technological advantage by using new tools to improve their production systems and resource allocation.^[39]

Big data, advanced analytics, and artificial intelligence tools have the potential to transform the manufacturing sector. Advanced analytics can aid manufacturers in solving complex problems as well as revealing hidden bottlenecks or unprofitable processes. The exponential increase in the volume of data available for analysis has prompted the adoption of more sophisticated models, leveraging advances in AI and computational infrastructure. These technologies provide the link between machine automation, information automation and knowledge automation. Ultimately, **the conversion of data to insights** will drive manufacturing productivity, efficiency and sustainability in the near future.

Networks And Sensors

How ubiquitous sensors and next generation wireless connectivity are enabling Industrial IoT

Networks in current industrial IoT applications

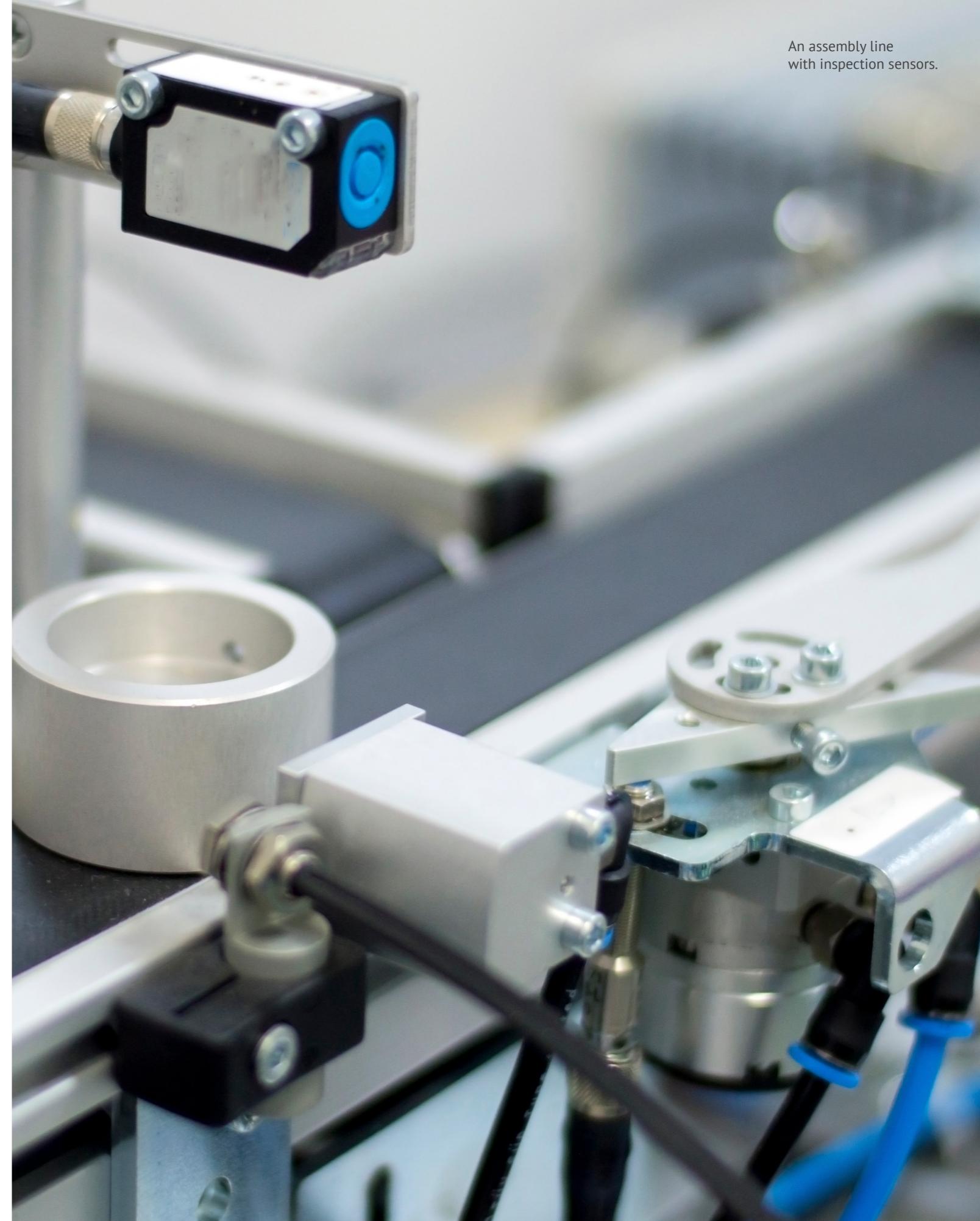
Over the last four decades, advances in microelectronics have led to the development of numerous low-cost, multi-purpose sensors. These are capable of detecting changes in environmental variables, including temperature, humidity, pressure, and the presence of chemical compounds. Sensors are deployed in sensor nodes to obtain information about their environment and transmit the data to a computer for processing and interpretation.

Sensor technology

A sensor node usually includes a transceiver with an antenna for data transfer, a microcontroller for controlling the sensors, and an energy source. Sensor nodes are resource-constrained, with limited

computing power, memory capacity, and battery life.^[40] Sensors vary in terms of resources, ranging from simple devices that collect and transmit low data volumes to complex designs.

A sensor network is composed of a collection of sensor nodes. Traditionally, in industrial settings, networks of sensors are connected by wired infrastructure.^[41] Processes are monitored and controlled using established digital technologies.^[42] These systems are reliable but time-consuming and expensive to install and maintain. For large-scale manufacturing, the capital costs of installation can be economical when connecting a significant number of devices. However, for smaller manufacturers, the upfront cost of installation is usually prohibitive. These systems also lack flexibility and scalability, as it is challenging to modify hardwired infrastructure retrospectively. To enable Industrie 4.0, reliable, flexible, and scalable deployment, networking, and monitoring of a large number of sensors is necessary.



An assembly line with inspection sensors.

Towards wireless networking technologies

Wireless Sensor Network (WSN) technology is the key to connecting entities in manufacturing settings. WSNs consist of spatially dispersed sensors for monitoring physical parameters and disseminating collected data to a central location. In WSN platforms, sensors connect to computing infrastructure via wireless communications technology. WSNs built for industrial

environments share essential characteristics, including low operating costs, energy-efficiency, self-organization, and self-configuration.^[43] They should be able to be rapidly deployed in a manner that allows for scalability, flexibility, and simple upgrading. Each of these characteristics place design constraints on sensors and networks such as dependability, IP connectivity, security, low power consumption, standards compliance, and cost.^[44]

Modern sensor nodes contain more computational power compared to earlier generations. These devices can process data at the edge of the network, closer to where it is generated and used. This reduces the bandwidth and latency associated with data transfer between devices, enabling real-time data analytics. Sensor nodes may also connect with a local network through a gateway that acts as a bridge to the rest of the system. Gateway devices typically have more resources than sensor nodes, enabling data to be stored and processed closer to the edge of the network.

network in which every device serves as both a signal source and repeater. This system design enables automatic redirection of data in the event of a disruption in the network.

ISA100.11a is a wireless standard developed specifically for the automotive industry.

WIA-PA (Wireless Networks for Industrial Automation and Process Automation) was developed by the Chinese Industrial Wireless Alliance as a secure alternative to wired communication protocols and is popular in the industry in China. These standards are designed for low power device connectivity and have been successfully deployed in process automation in the oil and gas, chemical, pulp and paper, and glass and mineral processing industries.^[50, 51]

Wireless technology standards and protocols

In recent years, significant progress has been made in device design and standards such as IEEE 802.15.4 and IEEE 802.15.1.^[45] IEEE 802.15.4 is the base technology for standards such as ZigBeePRO,^[46] WirelessHART^[47] ISA100.11a,^[48] and WIA-PA.^[49]

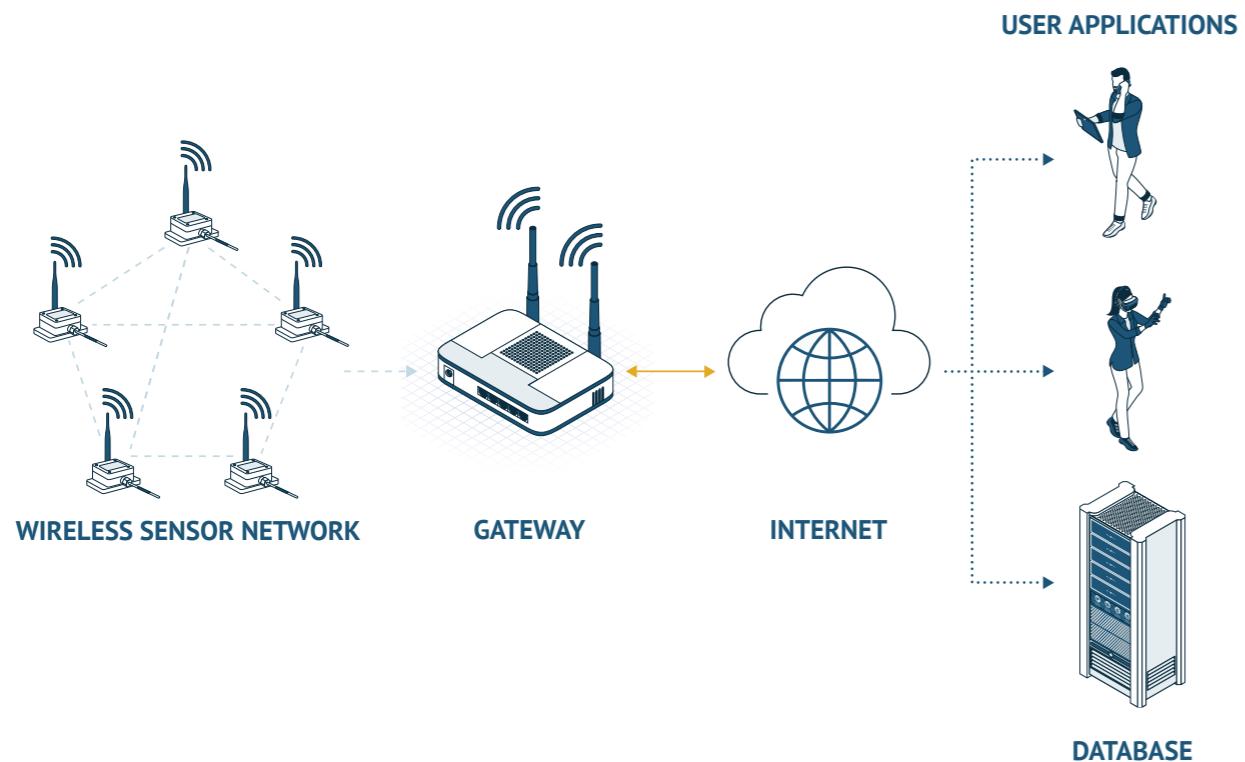
ZigBee is a wireless transfer protocol used in personal area networks requiring low power, low data rate, and proximity. It is typically used in applications that require long battery life, secure networking, and limited data transmission.

WirelessHART is a protocol that extends traditional HART communications through wireless connectivity. It is highly encrypted to protect data, with a more extended range than Zigbee. Sensor nodes form a flat mesh

Current issues and vulnerabilities

The hardware and firmware components of sensor nodes and the network can cause a variety of defects in WSNs.^[52] WSNs are inherently complex systems due to heterogeneity in sensor devices, network infrastructure, and applications. These complexities can lead to system faults and need to be addressed through well-designed system architectures that account for firmware and hardware constructions, as well as operating system (OS) kernels.^[53]

WSN systems can also be vulnerable to disparities in network connectivity



and function. Security attacks have been documented on ZigBeePRO, WirelessHART, WIA-PA, and ISA100.11a standards.^[53] Security concerns are an essential issue for any business, and new research is focusing on designing network architectures and devices to combat security breaches. Blockchain technology also offers potential for improving security in remote monitoring applications by applying cryptographic algorithms to ensure the confidentiality of data on WSNs.

Interference from devices complying with other standards operating in the 2.4GHz range, such as IEEE 802.11, have also been observed. These problems lead to transmission errors and inefficiencies from energy depletion, increasing operational costs. Post-deployment tools continuously monitor WSNs by detecting network, firmware, or hardware issues.^[54]

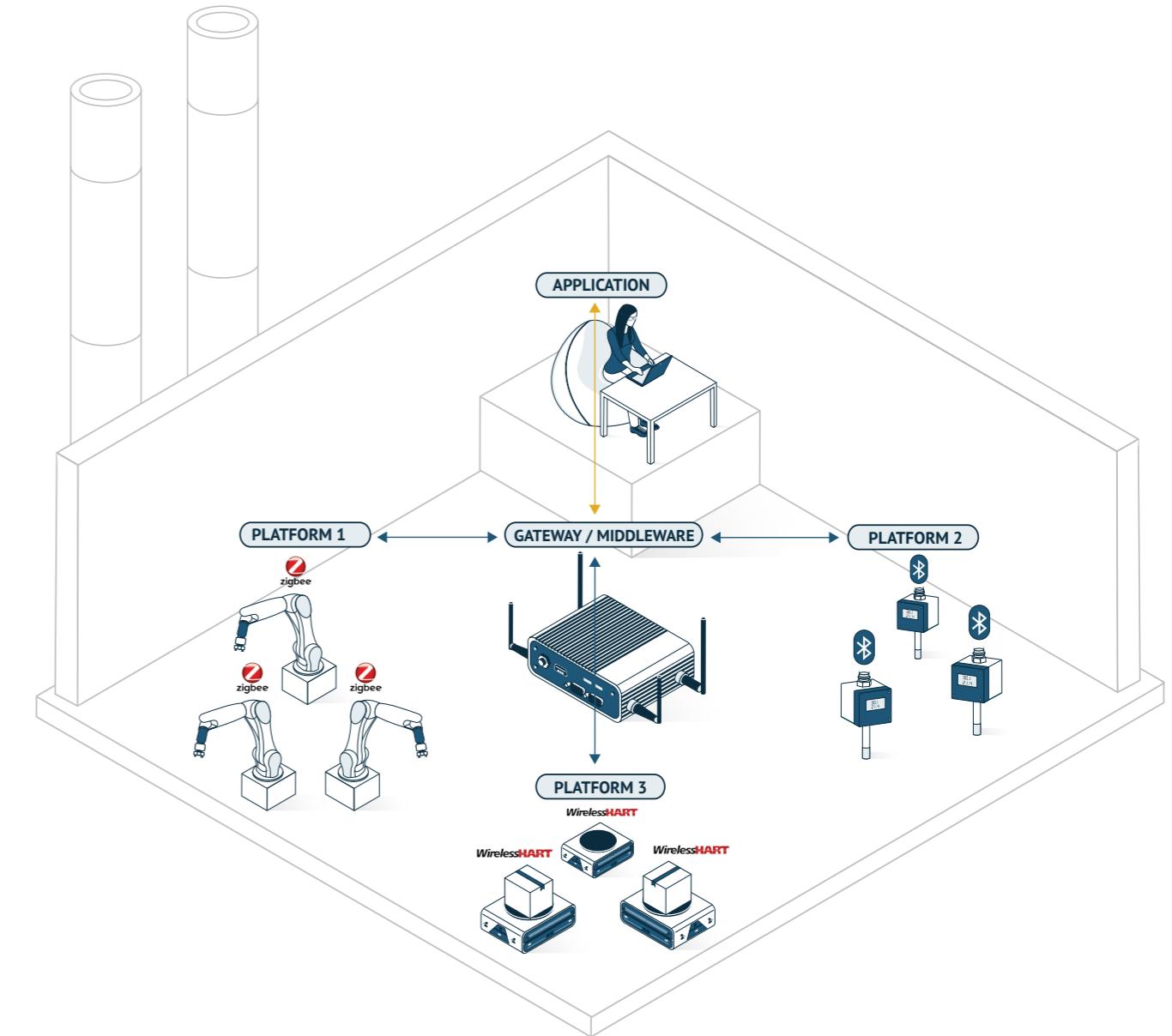
Interoperability between standards and devices

These systems enable manufacturers to analyze sensor data to inform decision making in real-time. However, many of these tools have been designed for specific applications and require dedicated hardware, consume power, and are complex to configure and use. Also, they might not allow for centralized management of sensor networks using various industrial standards. A classic problem that affects all IoT implementations is the lack of interoperability between standards and devices.

IoT suppliers may have proprietary hardware, software, and communications protocols. It becomes challenging to collect, integrate, and contextualize data in these settings. A recent report by McKinsey & Company estimates that “Of the total potential economic value the IoT enables, interoperability is required for 40 percent on average and nearly 60 percent in some settings.”^[44] Novel approaches that use an “IoT in a Box” concept aim to integrate a connected gateway with a variety of sensors and an application. These systems are designed to be used with multiple suppliers, reducing issues of poor compatibility between entities produced by different manufacturers.

Integrating legacy equipment into IIoT environments also represents a challenge for manufacturers. Older generations of equipment and sensor nodes devices may not be compatible with modern WSNs platforms in software or hardware. The correct drivers and configuration files specific for the equipment may not be available, and it requires considerable on-site time to build custom equipment drivers. In these contexts, equipment libraries that interact with legacy equipment and push data to a centralized platform can help to integrate legacy systems.

IOT PLATFORM INTEROPERABILITY



Towards a new network standard

From a network of wires connecting sensors to a multiplicity of wireless sensor networks. As we mentioned earlier, Industrie 4.0 needs reliability, flexibility and scalability. Although the aforementioned standards and protocols have all been improvements upon earlier networks, there has not yet been a one-size-fits-all solution. Whether due to interoperability issues or security issues, industry is collectively waiting for the mass implementation of 5G networks.

5G: A new standard in wireless connectivity

5G (Fifth Generation) is the most recent standard in wireless technology for digital cellular networks. The 5G frequency spectrum is divided into three classes based on bandwidth. Millimeter waves in the high-band frequencies from 24 GHz to 72 GHz are capable of the fastest speeds reaching up to 1–2 Gbit/s down. However, the signal reach is short, requiring more cells to achieve coverage and has difficulty in traversing solid structures. Mid-band frequencies, between 2.4 GHz to 4.2 GHz, can reach speeds in a 100 MHz wide band from 100–400 Mbit/s down. Finally, low band classes use a similar frequency range as 4G wireless technology.



A cell tower with 5G antennas.

5G networks operate at higher frequencies compared with 4G networks and support a higher device density. The latency of 4G networks averages 50ms and could reduce to 1ms with 5G. As computing transitions from hardware embedded within devices into the cloud, the potential for increased performance, flexibility, and cost-efficiency can be realized. The 5G architecture also allows edge processing resources hosted on a local network. This reduces latency, enabling data to be analyzed and acted on closer to the point of interest.

In addition to security and speed, wireless solutions should provide reliable coverage, predictable latency, high device density, and enable complete visibility and monitoring of equipment and data. A modern manufacturing setting could contain a high density of CPSs and associated sensors. The sheer volume of sensors and data generated requires substantial bandwidth to transmit. Low latency is necessary to facilitate rapid data transfer and analysis in real-time.

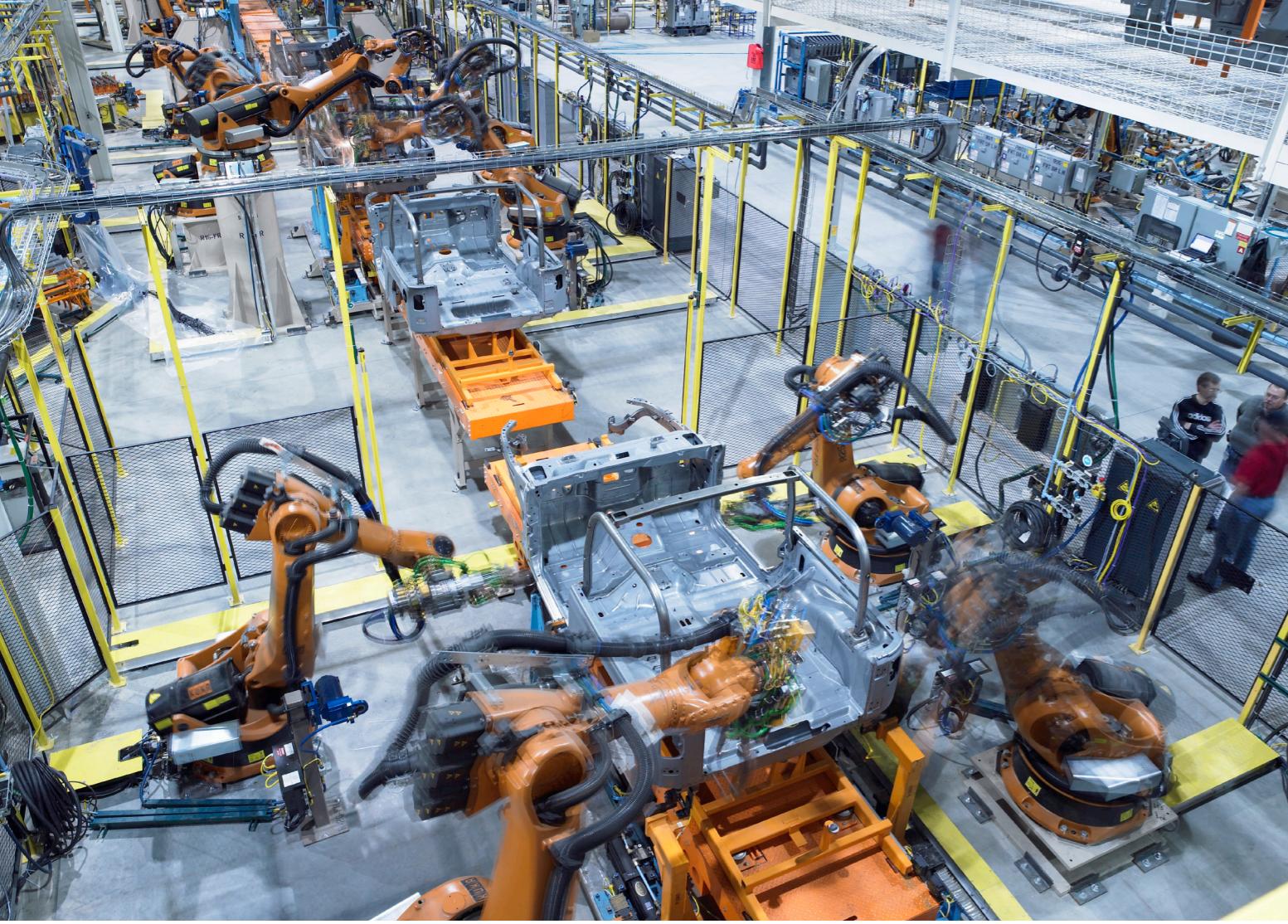
Moreover, low latency enables autonomous applications that require fast response times. Ensuring that network coverage and bandwidth are adequate to reduce latency and interference issues is challenging, but if implemented correctly, 5G eliminates the need for enterprises to implement expensive cable infrastructure. Due to flexible reconfiguration and the predicted widespread adaptation, 5G is also expected to solve interoperability issues. This offers further benefits in security for data and

device integrity and presents an open platform for developing applications and services. Furthermore, because costs are lowering, smaller manufacturers can access these technologies easier than ever before, enabling the democratization of industrial manufacturing.

Case studies

Jeep Gladiator & Wrangler Manufacturing Plant, Toledo, Ohio, USA.

In April of 2019, Jeep and KUKA started the production of the new Gladiator bodyshell in their Toledo plant, using 279 robots and over 60,000 other devices with back-end monitoring systems and a new data management system. The overarching aim is to manufacture high volumes of a wide range of Jeep body shell models and varieties on the same production line.



The KUKA Toledo Production Operations manufacturing plant.

Since KUKA and Jeep first partnered on the Toledo Plant in 2006, the platform has continued to evolve dynamically and has become one of the most efficient body-in-white (the stage in automobile manufacturing in which a car body's components have been joined together) production lines in the US automotive industry, aiming to produce 110.000 bodyshells a year.

To enable networking, and to mirror an “IoT in a Box” concept, KUKA integrated gateways, sensors, and applications. It was one of the first implementations to reduce interoperability issues between devices produced by different vendors.^[55] Now, the manufacturing platform has moved beyond networking production processes and has developed into a fully digitalized lifecycle management platform that controls and monitors the entire value chain in real-time, identifying weaknesses and optimizing capacity utilization.

5G Factory, Oulu, Finland

Another example, and one of the first ‘5G-ready’ factories is the Nokia factory in Oulu.^[56] The plant produces 4G and 5G base stations, and uses Nokia’s private (4.9G/LTE) wireless networks to enable connectivity between their assets, to run analytics on edge computing systems and to maintain a digital twin of their operating systems. 4.9G is also called Pre-5G and is a name for 3GPP release 13 and 14; an incremental upgrade to 4G LTE. It supports data rates of over 3 Gbit/s.

By using autonomous mobile robots from Omron LD, the flow of material to produce the base stations is now automated. By using the network’s low latency, high speed, and ability to connect multiple devices, the mobile robots are able to transport components to their needed location based on communication with production line equipment. The improvements due to the 5G related upgrades led to more than 30 percent productivity gains, 50 percent savings in time of product delivery to market, and a reported annual cost saving of millions of euros.

Evolving Industrial Robots

The developments that took industrial robotics from automation to collaboration.

Industrial robotics for a wider audience

Robotics is entering a much wider field of application. Only ten to fifteen years ago, robotics were almost exclusively used in very large factories. But change is happening: Every day, the amount of people applying robotics in manufacturing is increasing.

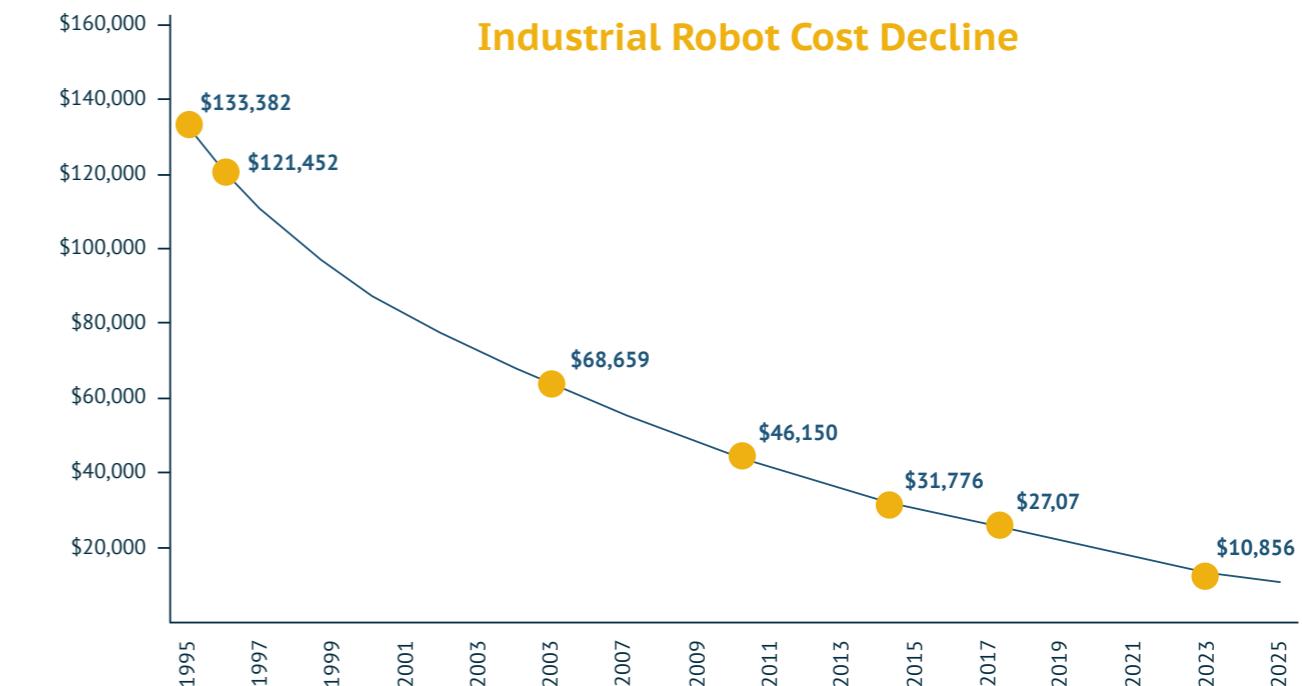
In 2018, global robot installations increased by 6% to 422,271 units, worth USD 16.5 billion (without software and peripherals). The operational stock of robots was computed at 2,439,543 units (+15%).^[59] There are vastly more engineers specialised in robotics than 20, 30 years ago. The increasing workforce creates a larger demand for different robots, for different applications, and circularly, even more people building these robots. By following Wright's Law,^[60] which states that for every cumulative doubling of units produced, costs will consistently decline in percentage terms, it is evident that the cost of industrial robots will keep decreasing in the coming years.

Classically, the advantages of industrial robots

have been better quality and consistency, maximizing productivity and throughput, greater safety, and lower labor costs. On the other side, disadvantages are their high initial investment, the scarcity of robotic expertise, and maintenance costs.

As robotics and automation moves in new directions, so will demand. New, cheaper, and simpler robots will perform tasks now only suitable for larger industrial setups. New areas of robotics will bring humans and robots closer together, and in many new scenarios, robots and people will collaborate rather than compete. In order to successfully build a highly automated manufacturing operation, your robots have to be more individualized, better tailored, and more flexible than ever before.

To show you how robotics technology is advancing to comply with demands, we'll first delve into the past.



The early history of robotics

The classic image of robotics in the manufacturing industry is that of the robotic arm. The patent for the mechanical arm design for Unimate, the very first industrial robot, was filed by George Devol in 1954. Joseph Engelberger, one of the founding fathers of robotics, had the chance to meet Devol, and decided to invest in his invention. In 1959, a prototype robot was used on an assembly line at a General Motors die-casting plant. It was used to transport and weld die-castings onto car

bodies. The patent^[61] states: "The present invention relates to the automatic operation of machinery, particularly to automatically operable materials handling apparatus, and to automatic control apparatus suitable for such machinery."

The evolution of industrial robotics was driven by human needs: The Unimate was built to alleviate human operators from dangerous and harmful tasks. Engelberger started Unimation in 1961, and soon Unimate had become the first mass produced industrial robot, paving the way for automation in the manufacturing industry, and soon beyond.



1961. Joseph Engelberger, engineers George Munson and Maurice Dunne, with Unimate number 001.

Technological advances stacked up quickly to assist robotic development. Whereas Unimate was controlled by storing systematic steps in a drum roll (magnetic memory), the 6-jointed *Rancho arm* became one of the first arms to be controlled by a computer when the project moved to Stanford in 1963. Growing from this prototype, the university created the *Stanford arm* in 1969. It used a programmable logic controller (PLC), a type of computer adapted for the control of manufacturing processes.^[62] Its purpose is to monitor an input, and make decisions based on a custom program to control the state of an output device. An example here would be an input from some sort of sensor or encoder sending an

electrical signal to a motor, moving by means of an AC drive to a certain point at a programmed speed.

PLCs at the time were designed for specific automotive applications, and it was hard to understand for some engineers that a small box could suddenly replace 50 cabinets full of relays and wiring. The leap in functionality involved a plethora of new techniques. Familiar techniques that were used, according to the display text in Stanfords Artificial Intelligence Laboratory, are: "Computer based modeling, planning, object recognition, vision, tactile and force sensing, collision avoidance, control and manipulation."

Industrial robotics took off quickly in the 1970s. In Europe, in 1973, KUKA Robotics introduced the FAMULUS, the first commercially available robot to have six electro-mechanically driven axes. A year later, a five axis micro-processor controlled robot was launched by ASEA (which later became ABB). Globally, more and more companies entered the field in the late '70s, especially in the US and Japan.

In 1982, FANUC entered into a joint venture with General Motors, to produce and market robots in the United States, at which time it had already secured half of the world CNC market. At the height of the robotic boom in 1984, Unimation, the company originally founded by Engelberg, was acquired by Westinghouse Electric Corporation for 107 million dollars.

Research trends driven by the needs of industry

The development of robotics in manufacturing was originally driven by the needs of the automotive industry. The predominant areas of research were kinematic calibration, motion planning and control law.

Kinematic calibration research was, and still is, aimed at improving the accuracy of

a robot across its work volume.^[63] Based on a mathematical model, the process of calibrating is performed in four steps: After the model is made (1), sensors look for the discrepancies between math and reality (2), parameters that differ from their nominal values are identified (3) and the model is updated (4). This is often an iterative method, and fine-tuning kinematic calibration remains an open research question.

Next is the topic of motion planning. Motion planning is the calculation of sub-goals to control the completion of a robot's spatial goal. The algorithms governing motion control for robotics have been in development since the first robot was built, but literature generally splits between two types of algorithms: implicit and explicit. Implicit algorithms specify the behaviour of the robot. In order to solve motion planning problems, the state of the robot and the state of the environment (e.g., obstacles or moving targets) are mapped to a set of inputs to control the robot. Explicit methods on the contrary provide a path or trajectory for the robot from some initial configuration to a target configuration.^[64]

Last, the motion needs to be controlled by control laws. The motion of a robot, called a trajectory, in its essence consists of a series of desired positions, velocities and accelerations. 'Standard' techniques, like proportional derivative control, originated in the late 18th century, but were further developed. Here a control output based on the difference between a set point

and a measured process variable is used to continuously apply corrections. Other more experimental control techniques were developed as well, like applied nonlinear control,^[65] a method in which nonlinear forces could be taken into control (e.g., Coriolis or centripetal forces varying with the square of the speed of the robots motion). Another more recent control method is adaptive control,^[66] in which adapting control laws could regulate changing variables, to account for situations where, for example, the weight of a carried object might decrease.

As robots evolved, the ability to self-adapt to product and environment became more and more important. An example of adaptation is the automation of logistics in postal services. In order to adapt to the size and shape of packages, robots had to be more intelligent so they could change their trajectories based on incoming sensor data.^[67]

Birth of the Cobot: A trifecta of techno- logical development

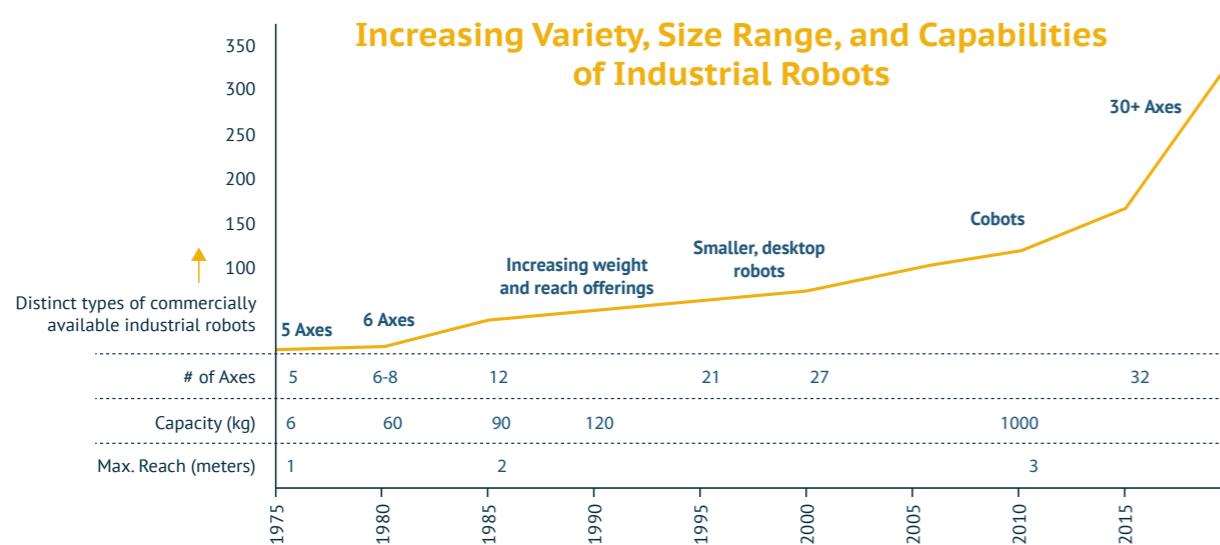
The increasing variety and capabilities of robots drive the growth of the industrial robotics market. Multiple technological developments support more widespread implementation: The adoption of wireless sensing networks (which you can read more about in chapter 3) provides solutions for previous extensive and expensive wiring throughout factories. As sensor and machine are further digitized, data streams start growing. Different AI techniques applied to industrial manufacturing provided robots the ability to operate in more dynamic environments, filled with more uncertain tasks. Intelligence and flexibility

are provided through machine learning algorithms, using the larger availability of data, allowing robots to learn from previous selected examples and historical behaviour.

A separate revolution is taking place to allow remote control of robots. By introducing a remote human operator in the control loop through teleoperation, capabilities are extended. The success of such a system is dependent on communication. Direct control is not possible when signal delays are too high, demanding a robot to take charge when commands are absent. Wireless, remote, and smarter robots are needed and thus developed.

At the same time the first collaborative robot (cobot) is born. The patent^[68] from 1997 filed by James Colgate and Michael Peshkin (Northwestern University) states that a cobot is “*an apparatus and method for direct physical interaction between a person and a general purpose manipulator controlled by a computer.*” This technology arises from a research grant from General Motors that was set up to make robots safe enough to team up with people, to develop ‘operator-assisted’ devices. Traditional industrial robots know little to nothing about their environment, so they can hurt people close to them.

The increase in axes, capacity, and reach, paired with the expanding variety of available types grew the application domains of robotic arms.
Image adapted from McKinsey



Exploiting the strengths of humans and robots

With the arrival of the new millennium, cobots start gaining traction. A typical manufacturing plant, for example an automotive assembly facility, has been transformed by the developments in robotics. The traditional body shop has become a sheet metal pressing, joint-welding automaton. Further on, the outside vehicle structure is painted by robots. However, in contrast to this, the general assembly area has not changed much. The engine, seats, tires and more are all still handled by workers. These varied, complex tasks that require a high degree of dexterity, are where cobots can make an impact.

Automation so far had mostly eliminated dangerous or repetitive tasks, and in the process it also decreased the need for human workers. The rise of the cobot addresses these sectors differently. Or, as Henry Ford II famously said: “Machines alone do not give us mass production. Mass production is achieved by both machines and men.”

Ergonomics define the development of the first passive cobots

The first cobots did not have their own power source, instead a worker provides the force needed to, for example, move a payload. When noticing that the payload is moving in a wrong direction, the cobot guides the object back to its desired trajectory.^[69,70]

Situations where a cobot's guidance and force amplification simplify a complex task and increase the workers' effectiveness are initially the best use cases for this new form of automation. Hence, ergonomics drive the technological development of collaborative robots, and research trends right before the turn of the millennium focus on:^[72]

- **Inertia management** - motions are designed to minimize the apparent inertia felt by the operator;

- **Power assistance** - frictional and acceleration/deceleration forces are partly compensated;

- **Force amplification** - inertial, gravitational and frictional forces are compensated in a similar manner to power steering systems

Interfaces are developed to be easy to use, and safety is improved by minimizing the energy input to the cobotic systems. Modularity and tooling are developed in tandem to enable more flexible and diverse use of these still relatively more expensive devices. General Motors installs a floor-based cobot to help unload doors; this passive tool helps to control the motion of (de)installing doors, limiting the inertia felt by the operator.

Image courtesy
of General Motors^[13]



Beyond the passive cobot

The beginning of the new millennium sees a boost in robotic startups. Universal Robots is founded in Denmark in 2005 to develop a light and flexible cobot. Not long after, global robotics manufacturers enter the growing market of collaborative robots and developments accelerate. The state-of-the-art cobot of today is much more than just a weight-compensator.^[72]

Beyond increasing ergonomics, modern cobots strive for increased human-robot collaboration in industrial settings. They aim to merge robotic capabilities, such as high levels of accuracy, speed and repeatability, with the flexibility and cognitive skills of human workers. Modern cobots can check, optimize, and document the results of their own work while being connected to the cloud. Thanks to integrated sensor and communication systems, cobots safely handle sensitive products, and don't require a protected space. Safety and intuitive control are the guiding principles in the design of cobots, which are programmed to ensure that their behaviour can be tuned or altered as easily as possible by operators. They are also increasingly aware of humans in situations where man and machine are dependent on one another.^[73]

A modern cobot can detect contact immediately to limit its force output.

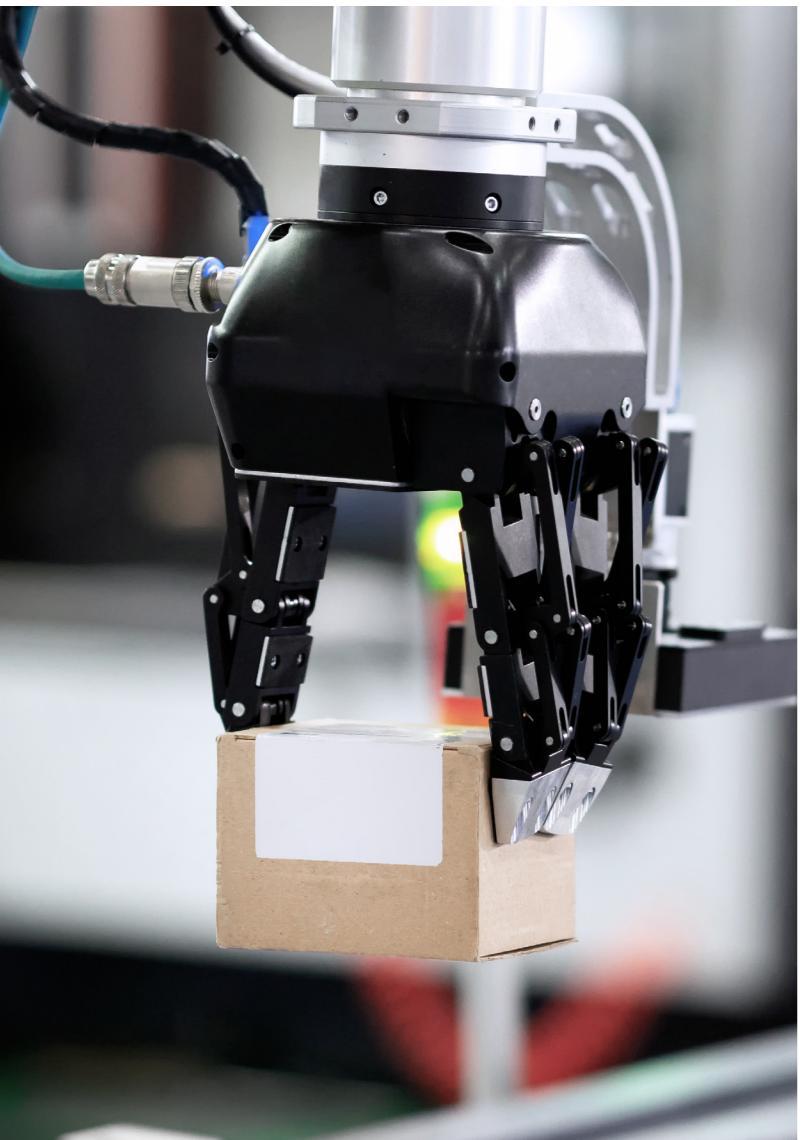
It does this by having joint torque sensors in all axes. Intuitive control is enabled by the ability to program it through simulation, hand-guiding (showing a trajectory by hand) or touch commands on a regular interface.

End-of-arm tooling

We will conclude this chapter by examining the literal end of robotic arms. End-of-arm tooling, such as grippers, play an instrumental role in the value that a robot can bring to the user. In line with the decreasing costs of robotic arms, end-of-arm tooling options are also decreasing in price, and expanding in usability and variety. Developments include new soft robotic grippers, innovative material depositing tools, inspection tools, and assembly tools.

An example are grippers, which nowadays have to perform under demanding circumstances, and even more important, showcase a wide variability. The variability of the objects a robot needs to handle has led to production of commercially available grippers in innumerable shapes or sizes. Furthermore, because a lower capital threshold exists, there is a significant amount of small and medium-sized enterprises working on them and further pushing the boundaries of possibilities.^[74] Traditional mechanical grippers are becoming more versatile, modular and lightweight. More exotic are magnetic, suction, soft and vortex-(maintaining an air gap) grippers.

Through innovation in contact type, manufacturers can avoid harm to sensitive, oddly shaped or volatile products. As we've seen throughout the evolutionary history of industrial robotics, technological developments change the market, and vise versa; market developments push



A gripper by automation company Robotiq, with force, position, and speed control for each finger and 4 different grip modes

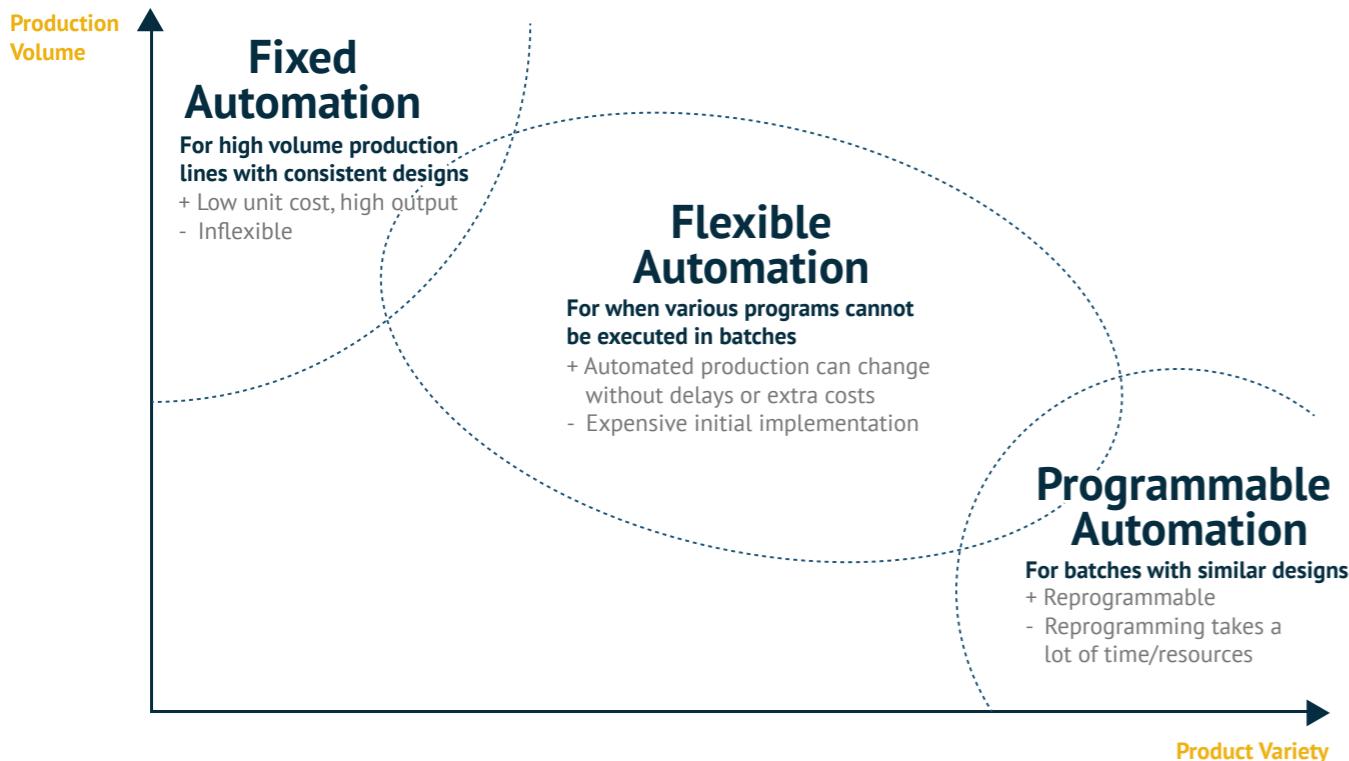
the technology further. The decline in costs of industrial robots is likely to continue, as will the increase in their capabilities. A specific role is designated to collaborative robots and innovations in end-of-arm tooling. Wider technological developments in Industrie 4.0 that are described in other chapters of this e-books, such as AI and wireless networking (5G), will also impact the capabilities of the robots as well as how they will be implemented in our future factories.

Robotic arms have significantly evolved, from the first Unimate to the smartest cobot, from crude welding tools to intelligent soft robotic grippers, and there is likely much more to come.

Flexible Manufacturing

Tools that enhance human capabilities and flexible manufacturing systems are necessary to deliver on the core promises of the 4th industrial revolution.

3 Types of Automation



Flexible manufacturing systems

Industrie 4.0 is largely about a shift from conventional mass production models to mass customization, combining the flexibility and personalization of custom products with the low unit costs expected from mass production. Today, product customization is key to drive sales and increase customer satisfaction. Not all customers want the same products or use them the same way. In the coming years we will increasingly see personalized and more customized products, based on production models like Made-to-Order (MTO), Configure-to-Order (CTO) and Engineering-to-Order (ETO).

Furthermore, thanks to the explosion of e-commerce, manufacturers increasingly will be able to produce exactly what is ordered, moving towards the vision of lean manufacturing and stock-less inventories. This will require flexible and hyper-efficient production lines that can be reconfigured fast to produce different products. Reconfiguration, customization, and adaptation allow systems to react quickly to production changes.^[75]

The most widely accepted definition of a flexible manufacturing system (FMS) is that it is an integrated, computer-controlled complex of numerically controlled machine tools, automated material and tool handling

and automated measuring and testing equipment that can process any product to a predetermined schedule with a minimum of manual intervention and short change over time.^[76] It integrates smart sensors, adaptive decision making models, advanced materials, smart design and machinery.

Flexible manufacturing frameworks enable companies to produce a greater variety of products whilst reducing delivery lead times and inventory requirements.

Smart design processes, for instance, use techniques like computer assisted design and manufacturing to interact with product and prototypes in virtual and physical reality. The entire life cycle of the product can be monitored, simulated, and tracked. We'll show you examples of this later on, when we talk about digital twins and simulation, but first we will look how machining has adapted to become more flexible.

Computer aided design & Computer aided manufacturing

Computer aided design (CAD) and manufacturing (CAM) have long played integral parts of the manufacturing process. CAD uses 2D or 3D software programs to create, analyze, or designs. CAM techniques use the output of those programs to automate a production process. CAM used to rely on subtractive



methods like laser cutting or CNC milling, but the paradigm changed significantly with the rise of additive manufacturing (3D printing) technologies. Continuous improvements in both CAD and CAM enable software and automation to be further immersed within the product life cycle. Major developments have been made to improve the flexibility, speed, volume, and capabilities of these systems.

3D printing technology specifically continues to expand in its variety and capabilities.^[77] Speed is directly connected to productivity, so development of better printing heads gains much attention, as well as developments in materials. Factors like curing time and other material properties play a big role in the printing process. Furthermore, post-processing can be very time intensive and delicate, making it a big factor to increase production speed in the product cycle.

Hybrid manufacturing

One of the more modern use cases of CAM is hybrid manufacturing. Hybrid manufacturing combines in one machine additive (3D printing) with subtractive techniques to leverage the most valuable capabilities of both methods: The geometrical complexity of additive manufacturing and the high precision of subtractive processes.

The technique is becoming a more common practice especially for metal part machining in aerospace, medical, and tool and die

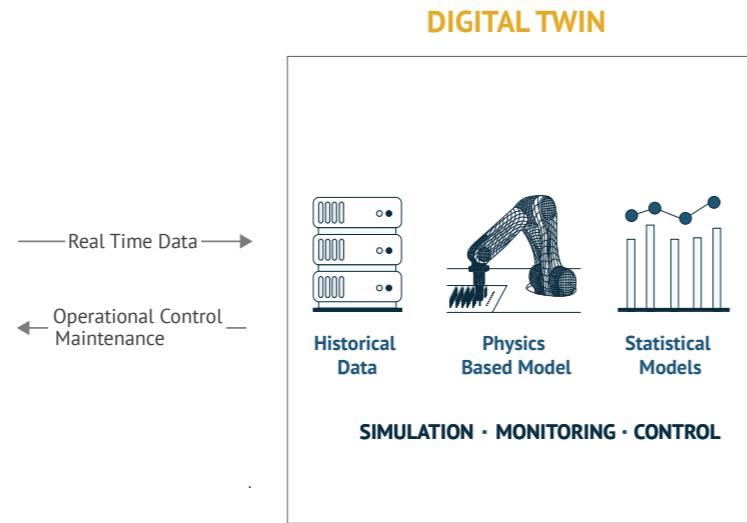
industries. Imagine a five axis robot, which can pick a 3D printing tool from a toolbox to deposit metal. After printing, the robot can change its tooling to a milling bit to start finishing the surface of what has been printed. Changing a single end-tool changes its function, making it a flexible manufacturing system.

Digital twins and simulating the manufacturing process

One of the largest advantages of CAM systems is their ability to be simulated. An efficient assembly line could be mapped out and set up before the first prototype has ever been built physically. Conventional product development is a sequential process; from design to prototype, to assembly line setup, and finally actual manufacturing. A digital twin allows the development stages to be run in parallel, significantly reducing the time-frame from concept to mass production.

Digital twin (or digital shadow) stands for the simulation of a real product or process, that uses the best available physical models, sensors, and data updates to mirror the life of its physical counterpart. A digital twin is used to simulate the behaviour of a real manufacturing process, assisted by real-time

REAL MANUFACTURING SETUP

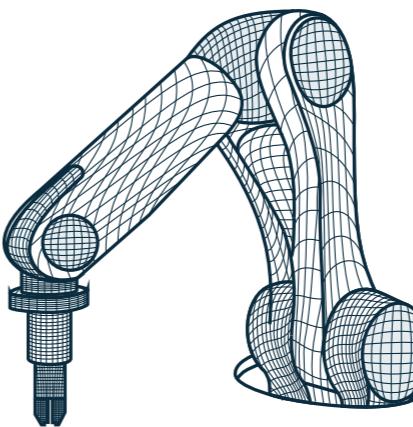


monitoring and feedback. Real-world data is transmitted into the modeled system to complete simulations, validate the system, and dynamically adjust it where needed. This really separates a digital, synchronizing twin with conventional simulated systems that do not provide real-time monitoring and feedback to the field.

Digital twins have high synchronization and fidelity with the physical space, full data interaction and convergence and self-evolution. Full data interaction and convergence is the ability to connect data generated in various physical and virtual spaces with each other, not only from the manufacturing floor, but also the combination of historical and real time data. Self-evolution stands for a digital twins ability to update data in real time, so that the virtual model is continuously improving by comparison between real and virtual. As the assembly process is mapped out

in the digital twin, you can model product functionality and simulate the expected performance at the various assembly stages using the product simulation model. This can be used to develop in-line tests that ensure the product is performing as expected – to weed out early failures, mitigate yield losses and reduce scrap costs. The digital twin provides insights on the operation of the physical process without having to actually execute it.

Using digital twin based simulations, the design process in the manufacturing industry can be iteratively optimized and personalized. Digital twins can be used to quickly test new product functions, behavior, structures and manufacturability. Defects can be found easier, which speeds up verification and testing processes. Furthermore, the whole manufacturing process can be managed easier.



Collaborative solutions to manufacturing

Apart from simulation and digital solutions to manufacturing, humans will often still be the most flexible resource in the production environment. Increasingly humans and robots collaborate to perform even more irregular or complicated tasks.

As we mentioned in our previous article on the evolution of robotics, situations in which human robot interaction is enhanced are made possible by collaborative robots, or cobots. Cobots aim to merge robotic capabilities, such as high levels of accuracy, speed and repeatability, with the flexibility and cognitive skills of human workers by sharing each other's workspaces. An overarching aim of Industrie 4.0 is higher efficiency and productivity through automation, thereby reducing costs. In this context, the role of factory workers and operators will be changing from laborious processes to knowledge intensive one.



Human and cobot working together.

Teaching a robotics system like an intern

So how should workers and robots work best together? One of the difficulties of using robots in industrial processes is often related to the way the human operator is supposed to interact with the robot, since it usually requires specialized knowledge. Conversely, the availability of intuitive ways to interact with robots and program them is one of the key enablers for further adoption of the robotic technologies, also by small companies. Supported by cheaper, more compact, and easier to use robotic systems, small and medium sized companies increasingly are using industrial robots too.

To take full advantage of human skills, it is important that intuitive user interfaces are properly designed, so that human operators can easily program and interact with robots. Specifically, simplified ways to interact with industrial robots in a reduced time, while minimizing user's errors and preserving situational awareness, are needed. A lot of manufacturers are looking for a robotic system that they can teach like an intern: Show once, then perform. By giving corrective feedback and by showing what is important, the required action is defined.

Humans can teach robots on how to perform their actions, especially in cases of uncertainty where robots have not been trained on some processes. A human can instruct a robot to perform quality control on a part that the robot is unable to classify as OK or faulty. In this way, humans can help robots to accelerate their knowledge acquisition process. Such techniques can be part of active learning and Reinforcement Learning approaches, which we talked more about in part two of this series. In the years to come this constructive interplay between humans and robots, will foster accuracy, flexibility and cost-efficiency in production operations.



Designing intuitive interfaces for Human-Machine Interaction

To be effective, humans and robots should be able to work together easily. Hiring experts is expensive and in most practical industrial applications, a lot of effort is devoted to programming tasks. This requires the ability to provide the robot with explicit instructions.

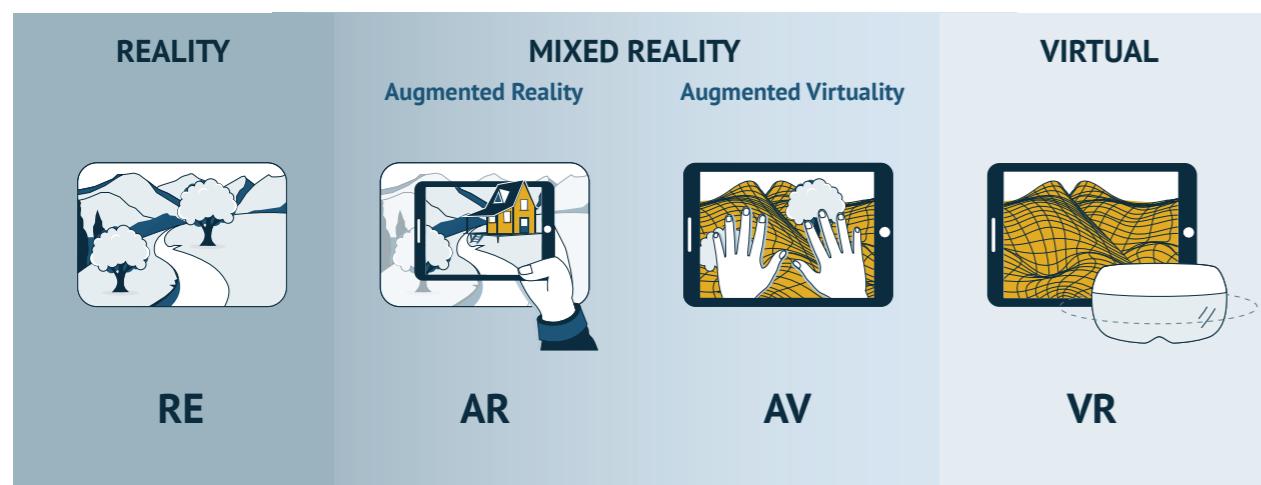
There are many initiatives for standard offline programming, where software tools are used to minimize a robot's downtime. Most tools offer modules for specific processes, such as coating, welding or polishing. Although they are becoming cheaper and more accessible, most technologies are developed independently, and are not yet integrated. Typically, every manufacturer has its own specific software module with their own specific price tag.

In contrast, most newer approaches often promise more intuitive control and command, also allowing less-skilled workers to use robotic assistance. The goal here is to reduce the cognitive requirements put upon the operator, such that the robots can remain accessible to users of all skill levels. The approaches taken to design new user interfaces can mostly be classified in online programming, like traditional lead-through programming, relying on the use of a teach pendant (a control box for programming

the motions of a robot) to move the robot through its required motion cycle, or walk-through programming, allowing the user to physically move the end of the robot through its desired positions. The robot is able to record and reproduce the trajectory afterwards.

Additional sensors and multi-modal interfaces for robotics

Intuitive interfaces can be designed in a human-friendly manner through speech based commands, gesture-based commands, eye tracking, facial expression and haptics; replacing the traditional keyboard to computer relation between human and machine. These developments are sometimes gathered under the term Tactile Internet, describing an environment to control the IoT in real-time using tactile and haptic sensations.



A lot of interest for human-machine interfaces (HMI) has gone towards augmented reality (AR) and virtual reality (VR). These techniques can increase productivity while also enhancing (the feeling of) safety for operators. They are further supported by simulated environments, like the ones created by digital twin technology, and complement humans' innate ability to act and interact with physical objects in a space.

The most promising use cases of AR and VR are thus also related to design, assembly, maintenance, or training. For example during assembly extra information can be displayed in the operator's field of vision using AR. Another example is remote maintenance, an application of AR that is gaining momentum. It supports the technician in maintaining or repairing the machinery from a remote location, thus reducing travel for the engineer of the machine vendor and allowing high level workers to work at multiple locations.^[83]



VR can be used for both programming and robot maintenance.

Models for humans in the production line

The aim of robot-based automation in the production line isn't to simply replace workers but rather make workplaces more productive and to enhance job environments.

A few large industries (i.e. automotive) have replaced many traditional human roles and will continue to automate where possible. Most cases where automation directly replaced human roles led to safer and more efficient environments. Direct "human to robot" replacement reflects only a percentage of global manufacturing, which currently, in general, is still dependent on humans for basic functions.

Some companies' decisions to re-integrate employees back in the production process, after previously automating their work, show other modes of operation besides 'lights-out factories' are possible. There is an opportunity for workers to enjoy job enhancement through working closely with automated processes and industrial robots. In these instances, employees have elevated their career opportunities through relearning that allows them to possess relevant skills for current and near-future industry demand.

When looking at the future, there are three possible models for humans in production lines.^[84] These models don't have sharp boundaries, they form a spectrum and

might co-exist in certain manufacturing environments. The choice for a model depends on the requirements and characteristics each specific case.

- **The process worker concerned with monitoring the mainly automated production process. With limited responsibility this is the end of a development that would eliminate humans from the production line;**
- **The role model. Here, the human is a template for mechanical skills that need to be taught to machines. In this scenario the human is skilled and has a diverse array of tasks, working to better their skills outside of the production process, to be transferred later to robots to gain competitive advantages.**
- **The architect. The factory worker is the bridge between production using cyber physical systems, connecting customers, developers, and production lines.**

That leaves many questions. How do you think humankind and machine will co-exist? What do you think the future of the manufacturing industry is? What roles will humans have? And how will you gain from these developments? In what way are the answers to these questions specific to your industry?

One thing is for sure. The roles humans can take in the factory of the future will require a different set of skills, and most certainly require new or renewed qualifications.

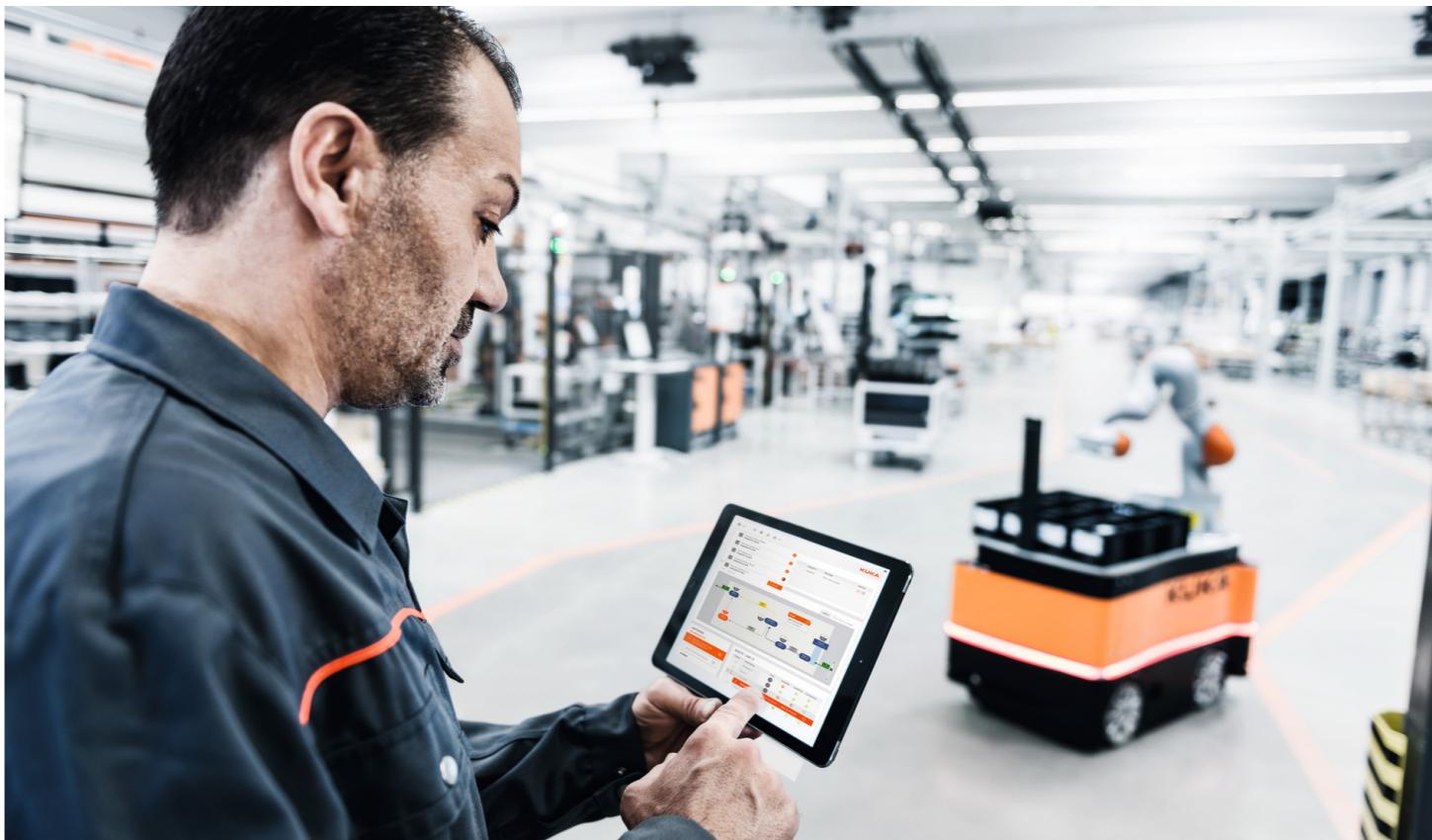
The potential impact of this on our future of work is expected to impact not only manufacturers but also our economies and societies as a whole.



A collaborative robot on the production line.

About KUKA

KUKA is a global supplier of intelligent automation solutions. They offer everything from individual components to fully automated systems. KUKA was founded in 1898 in Ausburg, Germany, and currently has roughly 14,000 employees and sales of around 3.2 billion euro. Their mission is "making life and work easier."



A collaborative robot
on the production line.

KUKA

About Wevolver

Wevolver is a platform & community dedicated to helping people develop better technology. At Wevolver, engineers access knowledge from tech companies and universities.

We believe that humans need innovation to survive and thrive. Developing relevant technologies and creating the best possible solutions require an understanding of the current cutting edge.

Wevolver aims to provide access to all knowledge about technologies that can help individuals and teams develop meaningful products. On our platform, companies and universities publish informative articles, videos, podcasts, and reports, about state of the art technologies. Our own editorial team creates high-quality sponsored content for innovative companies.

The Wevolver platform has won the SXSW Innovation Award, the Accenture Innovation Award, and the Top Most Innovative Web Platforms by Fast Company.

Wevolver is how today's engineers stay cutting edge.



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