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# White Paper

## Data Driven Production – Application Fields, Solutions and Benefits

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## Abstract

In the fourth industrial revolution, the growing digitalization integrates new technologies, such as smart sensors, new communication standards, cyber-physical systems, big data analysis, and the Industrial Internet of Things (IIoT), into the manufacturing industry. In this new age of manufacturing, every component represents a potential data source enabling new methods for data-driven production systems. Prominent application fields in discrete manufacturing are identified by literature research from current developments and enriched with use-cases from projects at the Institute of Production Management, Technology and Machine Tools (PTW). A superior application field resulting from data-driven production is introduced with arising business models. While such applications demanded much effort in the past, artificial intelligence (AI) encountered a turning point which enables systems to learn complex tasks without being explicitly programmed. However, AI has not yet reached the same level of penetration in the manufacturing industry compared to other sectors, such as healthcare and finance. In this paper, the barriers and challenges are outlined and addressed with recommendations for an implementation approach. Another challenging change for future industrial companies is the accomplishment of appropriate IT-infrastructure, especially at the operational level of the production network. Conventional infrastructures such as the strictly hierarchically layered automation pyramid, which does not support skip-level function integration, won't be longer feasible due to the increasing number of network participants in the future IoP. Central questions about IT-infrastructure and networking, such as platforms and services, communication networks, interoperability of distributed systems, security, and wireless technologies are discussed and assessed from the PTW point of view.

Keywords: Digitalization, Business Models, Data Handling, Artificial Intelligence, IT-Infrastructure

## Executive Summary


In future manufacturing, several tasks across all participants in the value chain will certainly be enhanced by data-driven methods. As data can be diverse, various application fields are conceivable. This whitepaper presents four central application fields from the production level where serious to even disruptive changes can be expected: 1) Condition Monitoring & Predictive Maintenance 2) Quality Management 3) Process Monitoring and Optimization 4) Energy Monitoring and Flexibility.

On top of the presented application fields and their use-cases, new business models are arising. Industrial companies have started to expand their innovation strategy from a product-centric to holistic services and business model approach.

- One trending business model with high relevancy for the manufacturing industry are X-as-a-service models such as pay-per-x. This whitepaper presents a pay-per-stress payment model which is based on diverse data from the machine to determine the "Machine Stress Factor".

- A second business model is presented with distributed manufacturing where companies use geographically spread manufacturing units to decrease delivery time. In the future we expact that only raw materials and data will be transported over long distances.

- The high-performance value chain (HPVC) aims to combine the high product individualization of an engineer-to-order concept with the productivity of mass customization.

- From engineering to printing via standardized STL-files, additive manufacturing is prone to make distributed manufacturing with the benefits of mass production possible.

Since data is generated at all production levels, information is gathered from various data sources with different communication protocols.

- There are different ways to acquire data, which differ in integration effort and achievable sampling frequency. These are: Standard protocols (e.g. OPC-UA), open Interface (e.g. APIs), integration solutions (e.g. compile cycles), and external solutions (e.g. external sensor integration).

- Depending on the production level, the ranges of measuring frequencies can be classified.

- We assume that the data integration and preparation effort in the manufacturing industry lie between 80-85% due to the diversity of data sources with different structures and semantics.

- The successful application of data analytics requires the interaction between manufacturing domain experts and data science experts.

- The rising trend to automated machine learning (AutoML) enables non-data science experts to apply machine learning. However, AutoML does not fully replace the data scientist. It does only automate repetitive and time-consuming tasks. According to our experiences, AutoML is outperformed by data scientists, but sufficient results are available faster.

One central application that is enabled by data-driven production is Artificial Intelligence (AI). A typical function of AI is the data-driven approach to maximize the possibility of success for a complex task.

- Our experiences show, that no general recommendation of best fitting methods according to different problems can be given. We propose a case-based approach by using the experiences and expertise of a data engineer to obtain the best results.

- Supervised regression and classification methods have been proven to be very useful for several tasks such as tool condition monitoring. The family of ANN's, SVMs, and

RF are widely used and considered to be one of the best algorithms.

- Clustering are less used at the machining process level compared to supervised methods. However, they can be applied to unlabeled data to recognize unknown patterns that might be used, for example, to detect outliers.

- Reinforcement Learning (RL) has the challenging problem of the long learning phase in real-world applications, such as in manufacturing environments. A possible solution can be provided by training RL algorithms in simulation environments.

- The use of AI brings the following key advantages: A better system understanding, cost-neutral or low-cost monitoring solutions, additional value that can be generated in various scenarios, from quality assurance to predictive maintenance, and efficient control of very complex systems.

The digital twin provides completely new impulses for the modeling and simulation since it combines the virtual representation of unique products or product-service systems with the associated data that is generated throughout the life cycle of the asset and beyond.

- The relevance of digital twins for the manufacturing industry lies in their ability to allow running simulations in different disciplines and different life-cycle phases.

- Especially in the context of AI in production, digital twins are a major enabler, since the virtual data generation can overcome the obstacle of gathering a lot of real data for complex models.

IT and especially internet-technologies such as web-services or remote procedures are entering the manufacturing OT with disruptive changes. Due to the increasing number of network participants in the coming IIoT, today’s IT infrastructures won’t be longer able to meet the requirements.

- Different levels of automatization pyramid with respective protocols and bus-systems will be consolidated to ethernet-based communications.

- Increasing demands are: More participants, regular reconfigurations, software-defined-networking instead of manually configuring switches, etc.

- Hardware, operating systems, data management are handled by others. IIoT-Platforms allow companies to concentrate on functionality

- PLCs and machine control will be outsourced to a control-cloud. This provides the necessary computing power for sophisticated algorithms and also enables the easy deployment of new or improved algorithms to existing equipment.

- Under the rigid architecture of the automation pyramid, not only the integration between IT and OT is difficult, but skip-
level function integration is not supported.

- The vertical sharing of real-time data breaks also the classical timeliness of the different hierarchical planes. A flexible version of the automation pyramid is proposed to achieve flexible cyber-physical systems (CPS) which will be of key importance for future networking in production.

Security is another key requirement in the factory of the future. A special case of information security is ICT-security. All ICT-security systems aim the three security goals confidentiality, integrity, and availability.

- Nowadays, in automation, the zone concept is often used, where different zones with restricted physical and logical access and unencrypted communication inside them are defined.

- Ensuring the protection gaols while maintaining flexible manufacturing IT-infrastructure requires well-defined standards. A widely known standard is the OPC UA.

## Contents

# 1. Data-Driven Production

Digitalization already led to diverse changes in the economy and society. Especially systems, where much data is generated, can profit well from digital technologies. Due to the growth of automation and connectivity in the manufacturing industry, data is available on an unprecedented scale in production systems and its quantity is constantly increasing. The European Commission expects the global data volume to increase by 530% from 2018 to 2025 [1]. At the same time, the computing power, storage capacity, and machine equipment are getting cheaper. Cloud providers enable external cloud-based databases, exchange of data with diverse communication protocols, real-time streaming, etc. The collaboration between every connected device in an industrial environment with platforms and services based on the digital backbone initiates the Industrial Internet of Things (IIoT). One level below, we understand the Internet of Production (IoP) as the transfer of the IIoT to the world of production to solve more specific tasks in manufacturing [2].

## 1.1. Benefits and Use-Cases

Data-driven production describes the data-based optimization of all production processes. Data can include sensor data, identification numbers/codes, control data, product data, image data, etc., which might come from shop floor equipment, operators, the supply chain, or other sources [3].

The resulting benefits with regard to the Overall Equipment Effectiveness (OEE), which can be expressed by the key factors productivity, quality, and availability, are highly promising. Conventionally time-triggered events can be converted into condition-triggered events, that significantly optimize the OEE. Predictive maintenance, for example, increases the availability by forecasting the machine's condition. Productivity can be increased by capturing several influencing factors [4]. The computer records the machine status, such as *On/Off, setting-up* or *machining,* or the *production volume* automatically and analyzes potentials for improvements [5]. Although quality assurance does not concretely contribute to value creation, it takes an essential role within the value chain, especially for economical reasons. Vision-based in-line quality control is already widely used in production to detect tool wear or workpiece failures, such as unevenness, ripple, or grooves [6] but previously unused control data, or other sensor data, might additionally detect hidden failures, such as structural changes in metallic materials. In some cases, the machine data from the control system might be sufficient for prediction but often, additional data is required from sensors and virtual or numerical models. Furthermore, data-driven production can significantly contribute to waste minimizing and cost savings [7]. The data can be compared against any Key Performance Index (KPI) to discover correlations [3]. Using the production downtime as KPI, for example, can reduce maintenance costs. Long-term cost savings can be enabled through energy-minimal production. It includes process design, product design, energy supply, and the operation of production facilities.

The Institute of Production Management, Technology and Machine Tools (PTW) has several application fields in the context of data-driven production. The goal is to use existing data from all layers of industrial production for various applications to improve quality, productivity, and availability. The PTW takes focus on discrete production and collects machine internal data as well as external sensor data for condition monitoring and predictive maintenance, quality management, single process and process chain optimization, and energy monitoring. Figure 1 shows these central application fields in production and depicts different use-cases realized at the PTW. While the mentioned application fields come from the production field, further use-cases from other industrial application fields, such as autonomous transport, cognitive assistance, robotics, and process-mining can be found in [8]. All of these use-cases are often enhanced by model-based approaches where physical correlations are analyzed and new data-based approaches where the applicability of artificial intelligence is evaluated.

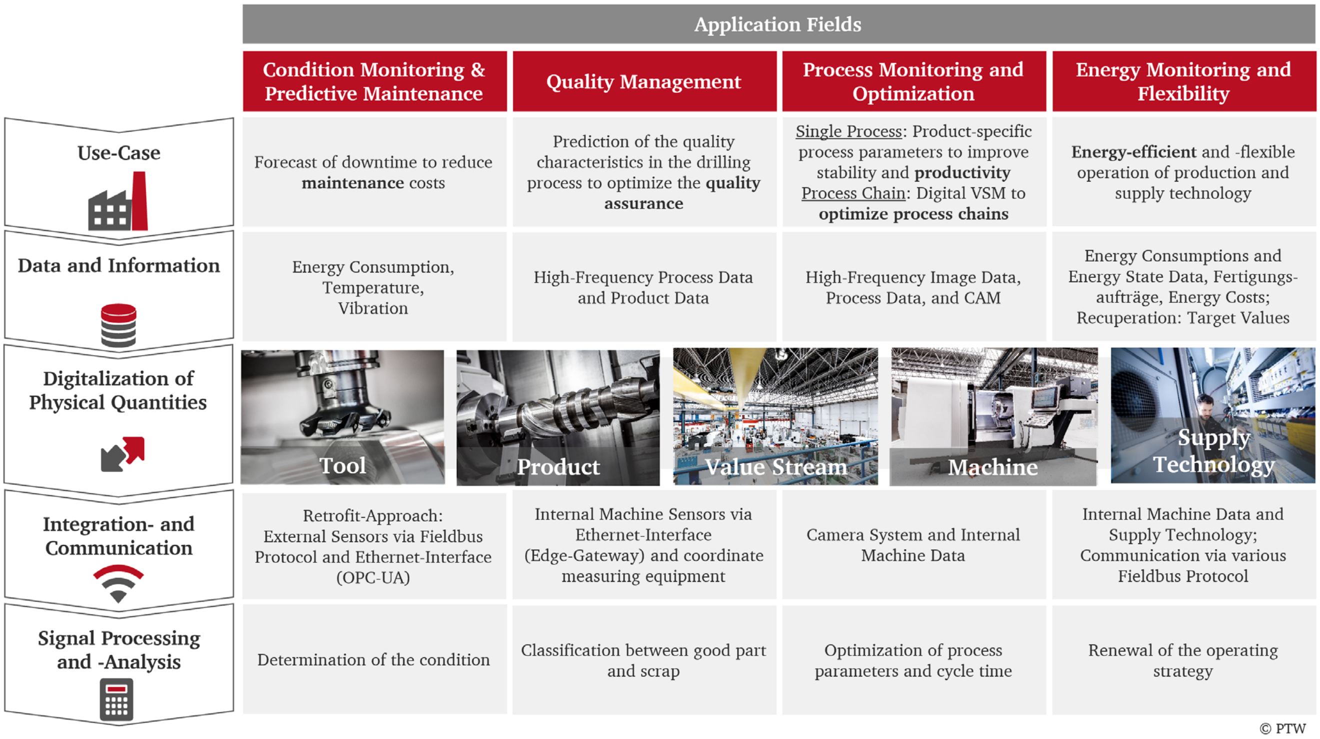


Figure 1: Data-driven production use-cases at the PTW, acc. to [9]

**Condition monitoring and predictive maintenance** are getting increasingly important in several industrial applications but also for consumer products. In the automotive industry, for example, vehicle system monitoring is used to prevent vehicle breakdowns to reduce overall vehicle operating costs and to increase vehicle availability [10,11]. In the discrete manufacturing industry, predictive maintenance can be used to predict impending failures, mitigate machine downtime, and evaluate the remaining useful life (RUL) of machines or machine components [12]. Especially, the prediction of tool wear emerges as a practicable implementation for predictive maintenance. At the PTW it could be shown that that real-time in-process tool wear monitoring can work with internal machine data, external sensor data as well as image data. The used data depends on the use-case. For example, internal machine data is fused with external sensor data from a sensor integrated tool holder to establish RUL regression models to calculate the machine component wear throughout its life cycle [13]. The development of these models will have a significant influence on the future of manufacturing since they will not only improve the OEE and reduce costs but also initialize new arising business models (BM).

Furthermore, the acquisition of high-frequency data enables new perspectives to achieve **quality management**. While quality assurance in machining was previously ensured after machining, for instance by manual inspection, the operator's self-assessment using simple measuring equipment, or with Coordinate Measuring Machines (CMM), the digital future indicates a new trend towards data-based approaches. Machine vision, for example, provides a low-cost method for in-line quality assurance and enables a piece-wise quality check without significant loss of time. However, for in-process quality control, vision-based methods are often not applicable due to disrupting factors. Times-series data overcome this limitation and allow real-time in-process quality assurance and quality control. By the example of a turning process, it could be proven that in-process workpiece failure detection can be enabled by using high frequency (250-500 Hz) machine internal data, which are automatically extracted by an industrial PC [6]. Therefore, typical workpiece failure characteristics that might occur in a preprocess were identified beforehand and categorized into six classes, such as cavities and cracks. Besides quality assurance, which is a passive method to detect anomalies in production, autonomous quality control provides preventive quality assurance by detecting irregularities and real-time intervention by adapting process or control parameters. One example was shown by the Fraunhofer

Institute for Production Technology (IPT). They integrated vibration sensors into the clamping system, which measures process vibrations during machining, to reduce instabilities with an adaptive control system [14].

**Process optimization** in machining is typically ensured by manual tasks and continuous improvement processes. Conventional manufacturing systems exhibit stiff processes while current trends, such as product individualization, require more flexible production systems [15]. For this reason, adaptive process planning and -control will take essential roles in future manufacturing. This can be realized by combining big data with different KPI models, which measure the success of optimization.
The machining process can be optimized regarding productivity, quality, and efficiency. Therefore collected data is compared against optimized KPIs to discover the conditions that meet the requirements [3]. A widely applied use-case is presented by intelligent machining parameter optimization, such as optimizing feed rates to minimize machining time [16], adaptive chatter control for productivity [17], self-optimizing control for product and tool quality assurance [18], and optimal cutting conditions to reduce $CO_2$ emissions and machining costs [19]. The vision of autonomous planning of product-specific process parameters and tool path optimization is coming closer through high-frequency image data, process data, and Computer-Aided Manufacturing (CAM) [15,20]. Furthermore, sensor integrated machine tools allow in-process monitoring and control through real-time data processing.
However, even if every single process is optimal, the overall process chain could be sub-optimal [21]. The scheduling and sequencing of job processing at different machines can be very challenging due to complex and stochastic production scheduling problems. As a consequence, the production planning and control is conventionally done heuristically leading to sub-optimal solutions. Data-driven simulation-based optimization approaches allow real-time decision making according to the current system state. For this purpose, a well-structured data-exchange framework between the shopfloor, MES, and ERP are necessary. Thereby, the MES builds the central data hub which feeds the simulation model with data to obtain optimized dispatching rules [22]. Intelligent algorithms, e.g. the genetic algorithm, are often used for optimization problems in manufacturing, such as for distributed process planning [23], minimizing makespan, cost of production and total rejects [24], operation sequencing [25], and cutting parameter optimization during a CNC end-milling process [26].
Besides production planning and scheduling, data-driven approaches can further optimize already working production lines. A well-known method to analyze how material, data, or information is transferred from A to B is provided by value stream mapping (VSM). However, conventional static VSM is not suited to visualize complex value streams with large product variety and dynamic changes in production. Therefore, data assistance in the form of process mining can be used for the analysis of complex value streams taking variety and dynamics into account [27]. Furthermore, production data can be analyzed and visualized in real-time to monitor deviations in an early state. At the PTW a production line, which manufactures pneumatic cylinders with band saws, turning, and milling machines, is equipped with suiting sensors according to Fleischer et al. [28], which gather start and stop signals of each process to visualize the VSM in real-time. Based on the digital shadow, historical data can be used to evaluate the current value stream regarding any KPI, in this case, the cycle time, to generate recommendations for improvement. [29]

E**nergy and sustainability** constitute another sector where digitalization and data analysis enables new potentials. Especially large companies with complex industrial energy systems are facing the challenge of complying with both targets: Energetic efficiency and environmental sustainability. In this context, the ETA research factory at PTW focuses on the aspects of transparency (prediction, forecasting) and optimization of energy efficiency as well as energy flexibility. In energy systems, needed data is usually available, for example through energy meters [30]. An affordable implementation of energy transparency could be enabled by virtual energy metering points, which use the data to predict the energy and resource demand [31]. The data-driven model, in this case, a feedforward neural network, uses process and additional state data, such as PLC data, NC core data, and data from decentral control units, as model inputs to predict the energy consumption. Advanced signal processing and machine learning techniques enable further methods, such as short-term load forecasting of production machines

[32]. The short-term forecast of electric loads is realized at the ETA factory with a forecasting horizon of 100 seconds. The forecasting is accurate and long enough to enable several advantages, such as optimal energy purchasing, energy costs reduction by peak load management, or energy-adaptive production planning. Regarding the latter point, the PTW researched on data-driven approaches for implementation and proved that energy savings are achievable in the double-digit percentage range [30]. Implementations of energy-adaptive production planning and optimized supply system control are realized with multiple optimization techniques like genetic algorithms or deep reinforcement learning. Since this method requires a high amount of data, it is recommended to pre-train the neural networks by utilizing digital twins in simulation environments [33].

On top of the presented use-cases, there are newly arising business models (BMs) enabled by data-driven production. The *Plattform I4.0* developed a 2030 vision where digital ecosystems take a central role [34] and analyzed digital BMs for the industry 4.0 [35]. One use-case is shown with "Collaborative Condition Monitoring", which conforms at the same time to the intention of the European project GAIA-X [36]. Due to their importance and primary role, the BMs are treated separately in the next section.

### 1.2. Business Models

In the era of digitalization, continuous innovation is the core competency to survive in the market [37,38]. Recent developments in gathering process data, analyzing extensive amounts of data in real-time and connecting machines in production as well as the integration of the entire business model (BM) environment are expected to improve production efficiency [39]. Companies have started to expand their innovation strategy from a product-centered to holistic services and BM approach. [40] BM innovation promises sustainable competitive advantages as they can only be imitated to a limited extent other than new performance features or lower costs. This is due to non-transparency for competitors or complexity, especially when combined with cutting edge technology. The classical transactional approach of selling a product gives way to a customer-centric interactional approach. The product is the vehicle for a long-term customer relationship to aim for personalized value creation based on in-depth customer understanding. In the long run, this approach is more sustainable than process or product innovation alone. [41] However, BM innovation is the most complex form of innovation. In general, "a business model describes the rationale of how an organization creates, delivers, and captures value". [42] The BM is a specific realization of the business strategy and therefore has a significant role in the interface to the value generation of a company. Innovating the business model is about questioning the dominant way of making business and create new original models to meet existing or previously unknown customer needs. [43,44]

In the advent of data-driven production and its foundation technologies new BM have great potential to offer previously unknown or impossible approaches as well as to benefit from new ways of collaboration. From the private sector and information technologies (IT) industry, the customer got used to using platforms such as transparent app stores for the mobile phone, using flexible on-demand and streaming services such as Netflix instead of purchasing, shared economy systems such as Airbnb, or completely new services. The customer got used to high usability, efficient and automated processes, and high flexibility with minimal risk-taking. [45] This experience has a great impact on business to business (B2B) business models:

- "Why not using a flexible subscription model rather than buying manufacturing equipment?"
- "Why not sharing my process data to enable partners to offer me individualized services?"
- "Why not purchasing Apps on my machine when I actually need them?"

These ideas are discussed in science and industry as well. However, a consistent and comprehensive overview is not known. Some attempts are made based on use-cases [46] or in more scientific approaches [47]. The following overview of potential future business model archetypes is based on the mentioned literature, the work of [17,48,49], and the experience of PTW. The Business-to-Business(B2B) platform (or IoT-platform) [50], everything-as-a-service model [45], data as an independent economic factor, and the new form of collaboration and customer integration due to data are presented. The key BM dimensions follow the definition after [42]:

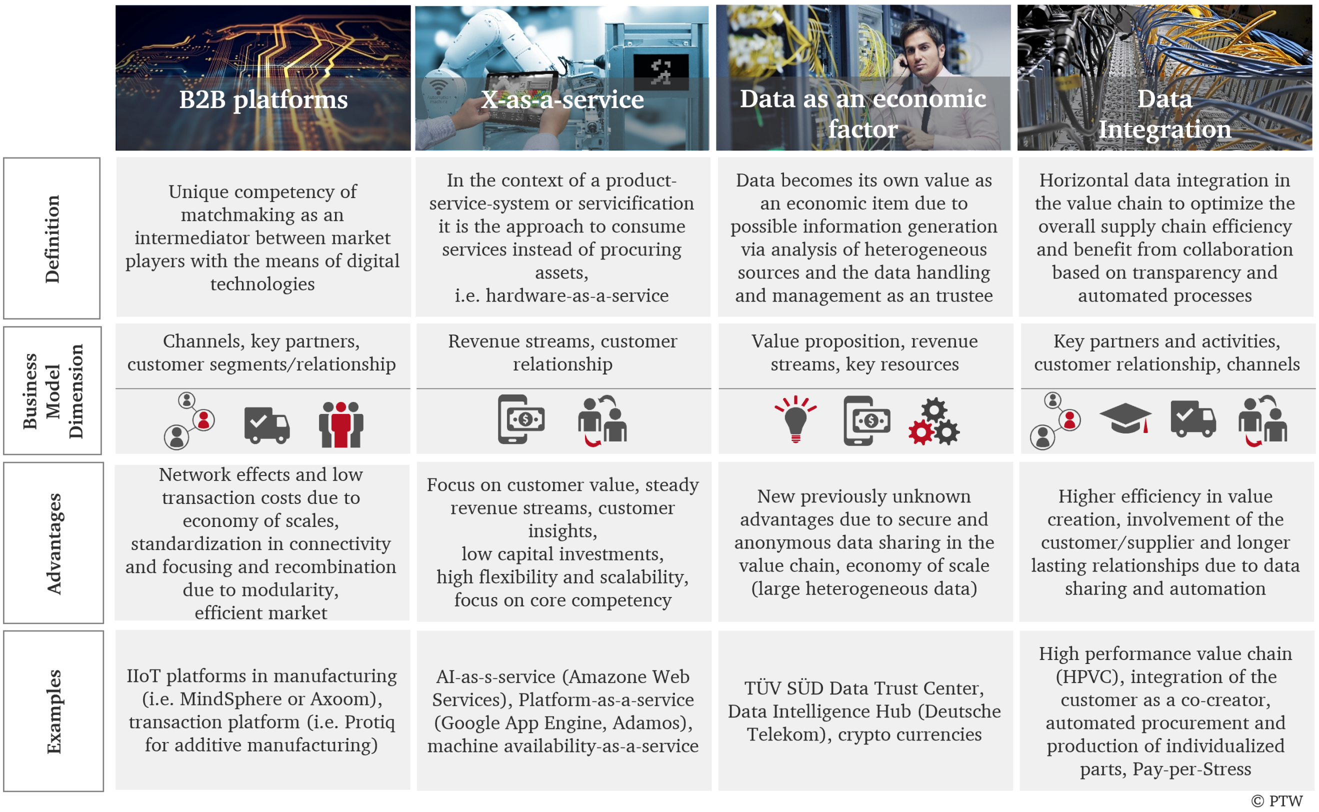


Figure 2: Business Models in Manufacturing

Besides this overview, the existing models can be digitally enhanced by optimizing processes through available data, automation, and analytics. Following, two business model types are discussed in depth.

**Pay-per-X models** is a trending BM in manufacturing. The acquisition costs of machine tools and other production equipment can be a financial challenge. Variable and flexible payment models can be beneficial, especially in a volatile market with fluctuating orders and thus no stable revenue streams. Leasing with fixed rates per period can be seen as the classic form of a variable payment model by transferring the use of an economic asset limited in time for a fixed amount of money. The advantages of variable payment models for the customer are the conservation of liquidity and reducing initial capital required distributed and predictable costs over time, remaining bank credit line, and up-to-date equipment due to faster replacement. [51] For the supplier, leasing expands the market especially for complementary services, such as predictive maintenance services, and allows for higher revenue in the after-sales market. Since the use of a leased investment, i.e. machine tool, does not always correlate with its actual wear and fair-market value and the need for better liquidity by linking incoming with outgoing cash flows, the pay-per-x models arise. They can better align the incentives of the user and the supplier. With the supplier in this context, we define the leasing company and the manufacturer as a simplification. The “X” in the name is the indicator that relates to economic relevant value and defines the calculation of the leasing fee. [52,53] Due to the trends in digitalization potential indicators expanded. This allows the share of economically relevant information beyond company boundaries. As described in [13] several classes of pay-per-X models can be observed in research and industry (Table 1).

Table 1 Pay-per-X payment models

| | Payment model | Exemplary indicator | Manufacturing implementation |
|---|---|---|---|
| Input oriented | Pay-per-use | Hours of use | Cutting-by the hour for machine tool |
| | Pay-on-availability | Machine availability | Smart performance and productivity |
| | Pay-per-stress / -machine wear | Machine stress | First attempts for machine tools [13] |
| Output oriented | Operator model | Miles of use | Rolls-Royce [43] |
| | Pay-per-piece | Produced parts | Pay-per-print models |
| | Pay-per-sold-products and –savings | Sales volume | Cost per part model with guaranteed savings for tools in machining [54] |

Depending on the objectives of the customer and the supplier and their incentives, the models can be differentiated whether the indicator is related to the input (i.e. machine usage) or the output of the process (i.e. the number of machined products). Several forms of risks can be shared, i.e. reduced income due to volatile machine utilization. [13] The indicator is chosen to create transparency in the BM and thus create new value for both, supplier and customer. In several industry branches, companies are integrating pay-per-x models based on IoT-platforms. The reason for this can be heterogeneous. Zuora's Subscription Economy Index indicates that companies that offer subscription-based business models tend to be more successful in the long run [55]. A significantly higher revenue growth rate with subscription-based BM in manufacturing companies can be observed. [55]

In most cases, the pay-per-X model is accompanied by complementary service offers and can be seen as a vehicle for better customer insights, long-lasting relationships combined with constant revenue streams, and sales support. Furthermore, the integration of new technologies into the market can be accelerated. **Pay-per-stress** is a special form that is based on the same data sources as modern maintenance models but has to be extended by efficient data analytics. It focuses on the actual wear of an asset due to the usage of the machine and enables deep customer insights. [13] In the case of assets that degrade significantly on basis of how the asset is used, the pay-per-stress model can lead to more transparency. The supplier generally does not have information about the asset condition, though the asset is his legal property and the damage on the asset is not always visible for the customer as well. However, he aims to maximize asset utilization and efficiency, neglecting a potential decrease of the machine value due to asset stress, whereas the lessor wants to preserve the residual asset value. Continuous high asset stress and especially asset overload can lead to gradual, not immediately apparent damages and thus leads to reduced asset availability. With a pay-per-stress model, both lessor and lessee can benefit from transparent asset condition and a better cause-effect relation understanding. [13]

The second BM**, distributed manufacturing,** is a decentralized form of manufacturing where companies use geographically spread manufacturing units and is advantageous in a dispersed globally, volatile market where delivery time is important. The most relevant trends for this approach are sustainability, logistic costs, mass customization, the democratization of design and open innovation, market, and customer proximity. A shift from mass production to individualized products can be observed [56]. These flexible systems are integrated with suppliers and other key partners through the value chain. [57] Some experts expect that in the future only raw materials and data will be transported over long distances. To achieve the level of efficiency of a centralized system, the whole production network has to be taken into account and inter-organizational coordination is the key competency. [58] The coordination and collaboration in the context of the BM made possible by the specific use of data-based manufacturing, as described in the following in two use-cases of the PTW.

The high-performance value chain (HPVC) aims to combine the high product individualization of an engineer-to-order concept with the productivity of mass customization. This is done by integrating the customer via web-based technologies which enable him to define an individualized product in the solution space of the manufacturer. This solution space depends on the capabilities of the manufacturer and therefore can be highly automated. This leads to a short delivery time with low costs. [59] Though customer-integrated value creation is already been introduced in 2001 [60], the availability of manufacturing data allows new possibilities and more efficient approaches. This includes automated configuration systems, design-automation, knowledge-based engineering, workflow-management systems, and robotic process automation. The integration of all these systems in combination with data sources throughout the company makes this approach innovative. Besides the internal use, i.e. to optimized product ramp-up or accelerated development of operating resources or the individualization steps, [61] results of ongoing research presents the following three applications in business models [59]:

Table 2 Application of HPVC in business models

| | Individual components as stand-alone-products | Provision of individualized operating supplies | Individualized components of modular products |
|---|---|---|---|
| Approach | Customer as the creator (co-creation process) | Speed-as-a-service: speed is important and costs are secondary | Individualization in a modular product is enabled |
| Field of application | Spare-parts in after-sales market optimization | Enabler for availability-as-a-service models | One unit in a manufacturing network individualizes the standard product |

The characteristics of Additive Manufacturing (AM) make the technology perfectly adequate for distributed manufacturing and make new forms of collaboration and thus business models possible. [62] Besides its potential for highly flexible manufacturing of individualized products due to the lack of required tools and equipment, the key factor in the context of IoP is the highly digital process chain. From engineering to printing via standardized STL-files, the digital twin, in combination with modern process monitoring and data analytics via AI is prone to make distributed manufacturing with the benefits of mass production possible. [63] The integration of AM with IoP and new forms of production control systems, i.e. decentralized production control systems, can unfold additional competitive advantages [64]. AM in combination with IoP has a positive effect on time-to-customer and time-to-market, a reduction of safety stocks, and spare parts. [65]
Even production at the customer site can be realized and leads to highly integrated value chains and completely new forms of customer relationships. The business to customer market dominated by 3D-printers with synthetic materials (i.e. FDM printer) shows the way for the future of metal AM in the B2B markets, exemplary the open-innovation mindset and sharing of data via standardized platforms. In interaction with the current rise of B2B-platforms, the "Protiq Plattform" is a representative example of innovation in business models, which links suppliers and customers as a marketplace for industrial 3D-printing [66]. However, current major obstacles are cybersecurity due to the change of sensitive information across company borders. In the B2B market, several potential business models are possible, which aim to improve value for the customer or even make new values possible. Exemplary models are [65]:

Table 3 Exemplary business models of AM in the context of distributed manufacturing

| General focus | New value proposition | Supply chain efficiency |
|---|---|---|
| Improving existing models | Enabler for design optimization and customization [67] | Cost-efficient production especially for small batches [64] |
| Creating new models | New repair services (high-speed repair of costly parts) [68] | new supply chain concepts, i.e. quick response manufacturing and spare parts on-demand [69] |

## 2. Handling of Big Data

The amount of data accumulated in a company is constantly increasing. This data is generated at all production levels of the enterprise. Depending on the use-case, a wide variety of information is required from these levels. This information comes from various data sources with different communication protocols, which must first be consolidated in order to evaluate them. Furthermore, this information occurs at different time intervals. Especially in use-cases on the machine level, high-frequency data can quickly lead to large amounts of data. Figure 3 illustrates typical process steps for a big data handling process and superimposes Automated Machine Learning (AutoML) as key for scalability and acceptance for industrial application on top of the signal processing chain. This whitepaper focuses on the very first steps of the data handling pipeline and the challenging issues of proper semantics, and automated procedures.

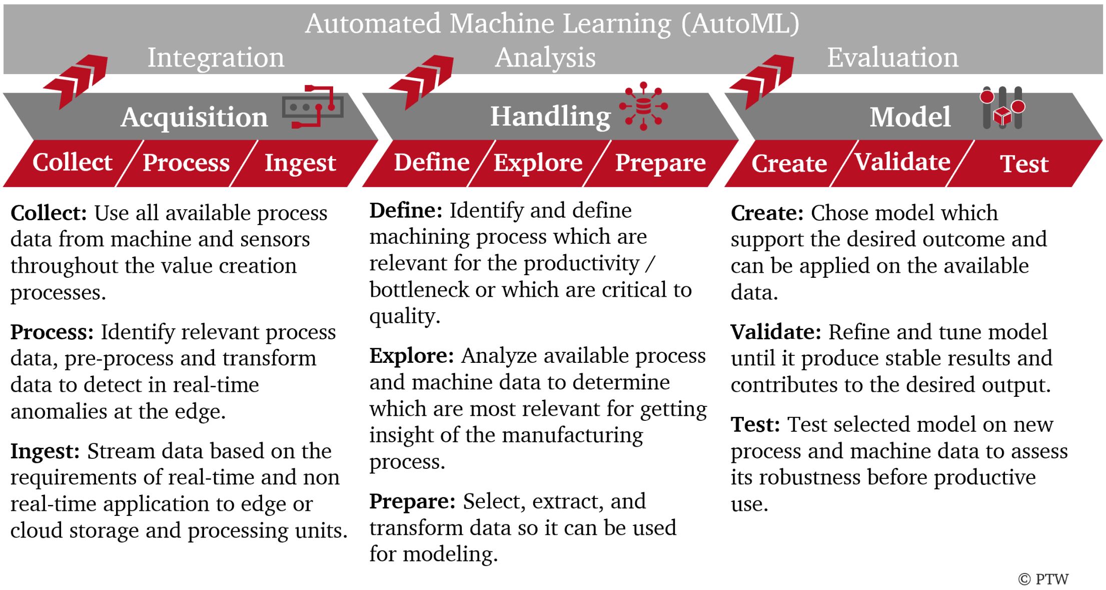


Figure 3: Pipeline for big data handling in manufacturing

**Data collection:** For the collection of data in the production environment, two basic scenarios can be distinguished. On the one hand, a “greenfield” scenario allows to start from scratch, i.e. IoP solutions could be implemented and put into operation without caring for competing legacy systems. The latest technology in the field of "cyber-physical systems" can be used and directly included in the planning of the production building. [70] In the “brownfield” scenario, the presence of legacy systems and legacy software, which perform isolated and discrete functions, creates potential challenges to enable existing production systems to IoP. For the acquisition of data out of brownfield equipment, PTW has tested different possibilities for the IoP qualification of machine tools.

**Data from existing equipment:** For this purpose, the existing data basis should first be analyzed. Modern production systems usually already contain many installed internal sensors. These are necessary to perform the control and regulation functions of the machines and can be transferred to a comprehensive monitoring system via NC and PLC interfaces. [6] Examples for a machine tool are internal drive signals like current, torque, and power of the drive motors, actual and target encoder positions, control deviations, and speeds. There different ways to acquire data, which differ in reachable sampling intervals and generated volumes of data per time interval which are shown in Figure 4. [71]

| | Standard protocols (multi-vendor) ADAPT | Open Interfaces (vendor specific) EXTEND | Integration solutions (vendor specific) INTEGRATE | External Solutions (multi-vendor) INTEGRATE |
|---|---|---|---|---|
| **Reachable sampling intervals** | 100 – 200 ms | 10 – 15 ms | 1 – 4 ms | 0.00001 – 1 ms |
| **Volume of data** | ~ 5 Kbyte / sec | ~ 0.1 Mbyte / sec | ~ 1 – 2 Mbyte / sec | ~ 50 – 100 Mbyte / sec |
| **Possible use cases** | Energy monitoring | Condition monitoring | Quality prediction | Quality prediction, uncertainty detection |
| **Examples** | OPC-UA, MQTT, Modbus,…. | APIs, SDKs | Compile cycles, APIs, SDKs | External sensor integration (proprietary solutions) |

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Figure 4: Comparison of the different possibilities for machine data extraction in the brownfield [71,72].

As shown in Figure 4, typically pre-installed OPC UA servers on the machine controller allow low-intensity access to internal machine data. Based on the performance, which depends on the implementation of the OPC UA Server by the control manufacturer, sampling intervals of 100-200 ms can be achieved with this approach. Possible applications include monitoring the energy consumption of machines or triggering alarms. Recent trends follow the approach of installing clients on the machine side and running the servers as central devices. This leads to simplified maintenance efforts. Depending on the use-cases, for instance, prediction of the workpiece quality, higher data rates in the order of magnitude of the interpolation cycle of the machine control system, are needed. By using APIs offered by the control manufacturer and specially developed gateway hardware and software, sampling intervals in the range 10 - 15 ms can be achieved. Software solutions for such a recording are already commercially offered by various companies. To access the data equidistantly in the frequency of the position control cycle of the machine (1 – 4 ms depending on the machine) integration in the bus system of the machine or special vendor specific software components (e.g. Compile Cycles by Siemens) are needed. One prominent example for high frequency data collection is the Sinumerik Edge developed by Siemens for current 840D controllers. For this solution, a special compile cycle called HF Probe has to be installed on the controller. In conclusion, it always depends on the user and the required use-case or the target to define which sampling frequencies are necessary and what effort has to be invested in the integration of the data acquisition in production environments.

**Additional sensor integration:** There are many different possibilities for tapping the communication interfaces of the production equipment and integrating external sensors as shown in Figure 4. For an illustration of the different communication layers from connection to data transfer, the second dimension of RAMI 4.0 can be considered. On the asset level, numerous manufacturer-specific bus systems are used for communication in machine tools. Examples are SERCOS III, Profibus, Profinet, Ethercat, Modbus TCP. Each of these systems has a proprietary structure and for sensor integration and data connection, expert knowledge must be applied to the respective system. No clear standard can be established in this aspect. In the transition from the connection to data transfer and application, the OSI layer model is used to describe the different possibilities for communication. There, the lower levels contain standards such as Ethernet and Wifi, and in future also Time-Sensitive Networking (TSN) and 5G. These are already established and used for data transmission. Differences in the IoP area can be seen in the upper layers Session, Presentation, and Application. This is where HTTP, MQTT, and OPC UA are established. [73] Currently, the MQTT (Message Queuing Telemetry Transport) protocol is frequently used because of its lean and simple implementation. However, OPC-UA is slowly becoming a cross-vendor and cross-industry standard. In addition to the pure sensor values, OPC UA enriches the data channel with standardized semantics respectively information models and additional security functionality so that production equipment from different manufacturers can communicate with each other. In addition to the two main protocols used for M2M communication, others are emerging such as CoAp, DDS, AMQP, and IO-Link. [71]

**Data processing and ingestion:** The different approaches for the processing and analysis of the generated data can roughly be differentiated into batch and streaming based approaches. The different approaches can be seen in Figure 5. In the local approach (1) the data is stored on Edge PCs. Analyses are restricted to the respectively connected machine. For more extensive analyses across several machines and processes and for the training of AI models, the data have to be transferred to a central system. This central data storage enables holistic data analysis and usually offers enough computing power to train AI models. In streaming analytics (approach (3)), data is processed in real-time as soon as it arrives. The data is cached for a limited period so that the decision rules can also access historical data to a limited extent. Due to the limited data that has to be kept in memory and the data aggregation that usually takes place afterward, the memory requirements of this approach are lower. [71,74]

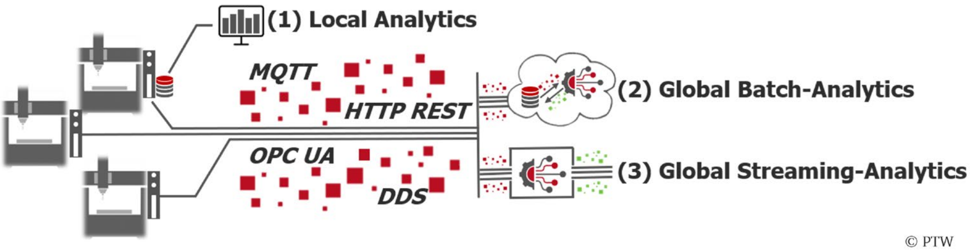




Figure 5: Approaches for the processing of data [71].

In addition to determining the extent to which the data is to be collected and processed, it is necessary to determine a suitable sampling interval for data acquisition, the respective application and the behavior of the system under consideration must be taken into account. Concerning the use-case, it must first be defined which level of detail must be available to meet the information requirement. After the level of detail of the use-case has been defined, the dynamics of the phenomena to be captured play an important role. In terms of behavior, plants and components can be divided into the following three classes. [75]

- **Constant**: The system or component exhibits constant behavior when switched on
- **Cyclic**: The system or component, which is usually switched on and off employing a two-point controller, repeats a characteristic load profile with each active period
- **Variable**: The system or component shows a variable behavior

Plants and components classified as cyclic or constant show a low-dynamic or almost static behavior. Systems with variable behavior, on the other hand, are classified as highly dynamic. Depending on the production level, the ranges of measuring frequencies for the three types are classified in the literature as depicted in Figure 6 [76,77].

| Production level | Behavior | Sampling interval |
|---|---|---|
| **Production site & network** | almost static | 30 sec – 15 min |
| **Production cell to segment** | almost static | 1 min – 30 min |
| | low-dynamic | 30 sec – 5 min |
| | highly dynamic | 1 sec – 1 min |
| **Process to machine** | low-dynamic | 1 sec – 5 min |
| | highly dynamic | 0,25 ms – 1 min |



Figure 6: Typical measuring frequency bands at different production levels at industry, acc. to [76,77].

Data-based analytic approaches rely on a large amount of data and variables or features. However, a large amount of features results in the so-called curse of dimensionality [78]. In general, each additional feature considered in an analysis increases the dimensionality of the input space, while each additional row (instance) simply increases the amount of data in the input space. With a fixed amount of data (number of instances), the generalization from training to test data becomes exponentially more complex as the dimensionality of the input space (features) increases. This leads to two conclusions: First, the larger the data set with regard to the number of instances, the better the generalization is expected to be. Second, only those features that provide added value should be considered in the analysis. For this reason, in machine learning, there is the area of feature selection where this added value is examined, and a final data set is selected for the respective use-case. Furthermore, the amount of data should only be as high as necessary for the results, since a lot of data leads to very high computing capacities.

**Data handling issues** Data Analytics algorithms require a lot of data, which are collected by sensors and provided in the management platform for analysis. While the availability of data at all hierarchy level is increasing, a considerable effort is required to transfer this data into a database for data analytics applications with suitable semantics and proper context information. A wide variety of data exchange protocols currently exist in industrial environments, which require different information to configure a data point. Currently, this information must be manually parameterized in the management systems. Moreover, the uniform connection of these protocols to a management system is often associated with considerable manual effort. This represents an enormous obstacle for data analytics procedures since corresponding personnel capacities must be created without an immediate return on investment. In practice, the data sets are often incomplete and contain incorrect metadata, which is problematic for the final phase of data modelling. The data structure of the controllers represents a further obstacle in data acquisition. These typically provide a large amount of information (e.g. list manuals of control systems). However, these are usually very disorganized with few self-explanatory variable names. The identification of the variables to be integrated into a monitoring system is very time-consuming, as machine- and process-specific know-how is required. In addition to the control and sensor data of one data source, data analytics applications usually require metadata as well as relationships with product specific transactional data. Many of the present management and enterprise systems are not designed for the use of AI procedures and large amounts of data. For this reason, edge devices are currently being used increasingly for the execution of evaluation algorithms [71]. Then a reduced amount of data is sent via the network to the enterprise level. Here, the high-frequency data connection of the machine controls to the edge device and the fast execution of algorithms on the edge device is particularly challenging. Finally, another obstacle in data analytics applications is that many commercially available management systems do not support higher sampling rates than one second. Therefore, they cannot be used for data analytics applications that require higher frequency data.

**Automation:** As already described above, data acquisition and processing (data structure and acquisition in a central management system) requires very high manual effort. Rich Caruana, a senior researcher at Microsoft, stated that 75% of the efforts in the developing of data-driven models are taken up by data preparation [79]. While he argues from the perspective of the IT sector, we even assume that the data integration and preparation effort in the manufacturing industry lies between 80-85% due to the diversity of data sources with different structures and semantics and complex tasks such as synchronization. However, there are currently few possibilities for automation, which makes this issue a future research topic. The field of data analytics can already be automated without any problems. However, this should be treated with caution. The model development that has led to the best result for one model does not necessarily have to be effective for other systems and data as well. Nevertheless, especially in the area of data preprocessing, a standard process can be defined that can be automated and made available as a service for further reuse. Furthermore, in the field of data analytics research, the area of automated machine learning (AutoML) has been developed, which provides methods and processes to automate the data analytics process. Most AutoML approaches so far have focused on the automatic selection of learning algorithms and the optimization of hyperparameters [80,81]. First attempts of applying AutoML techniques in manufacturing are shown in Krauß et al. [82] and Kißkalt et al [83]. However, these approaches are not yet fully developed, because important steps such as data preparation, have to be done manually. This field also represents a current research area at PTW. Model execution, however, can be fully automated using Data Streaming Analytics.

**Multiple skills** are required to implement Data Analytics applications in a company. First of all, as for all analytical tasks, a high level of domain specific know-how is required. Additionally, data acquisition requires in-depth knowledge of industry communication standards and data integration. Finally, to develop data-driven analytical models, data science or AI expertise is required. On the one hand, programming skills are required for the implementation of the algorithms. On the other hand, a variety of methods for the different areas of data analytics (data preprocessing, model creation, model optimization) are available. The selection of the methods to be applied, which have to be made depending on the use-case, thus turn out to be a complex task.
In summary, the successful application of data analytics requires the interaction between manufacturing domain experts and data science experts to perform the following tasks:

- Data Preprocessing
- Selection and creation of suitable features
- Selection of suitable algorithms for model generation
- Optimization of the hyperparameters of the algorithms

## 3. Artificial Intelligence in Production

One central application that is enabled by data-driven production is Artificial Intelligence (AI). Data analysis with AI is one of the forefront topics of the German government [84]. Several announcements, such as “ProLern” [85], drive AI research and application in the German industry. In the context of this research report, we understand AI as the science and engineering of designing intelligent machines [86]. One method to achieve AI is machine learning which describes a computer program that uses a learning process to recognize patterns in the data to make predictions [87]. A typical function of AI is the data-driven approach to maximize the possibility of success for a complex task.

### 3.1. Application Fields and Methods

In the industry, the purpose of using AI can be technical-, business- or competence-based. From a technical point of view, a typical task is to reduce production downtimes through predictive maintenance. A task from a business perspective is to create business value such as an accelerated time to market [88]. Competence-based AI tasks relieve employees, e.g. through assistance systems. The main AI tasks from a technical point of view in manufacturing are to improve efficiency/productivity, reduce operational cost, and to improve product quality [89].

Machine learning techniques provide suitable instruments to apply data analytics for complex applications. They can be divided into supervised, unsupervised, and reinforcement learning. Supervised learning methods learn from training data that comprise input data as well as their corresponding output data, also called labels, while unsupervised learning methods discover classes within the input data, or determine the distribution, or reduce the dimensionality without using any output data in the learning phase [90]. The technique of reinforcement learning strives to find an expedient strategy for a predefined task by trial-and-error to maximize a reward [91].

The methods used to fulfill the task are diverse. The best satisfying method strongly depends on the data (data type, data size, data completeness, data correctness, etc.) and the use-case. In the literature, some guides can be found, such as from Scikit learn [92], which provide a general overview for choosing the right method. However, our experiences show, that no general recommendation of best fitting methods according to different problems can be given. Since each use-case provides varying datasets and pursues different goals, we propose a case-based approach by using the experiences and expertise of a data engineer to obtain the best results. An effective procedure for choosing the right estimator is the intuitional approach to evaluate different methods for a given task. Since common high-level programming languages, such as Python, provide a broad range of open-source machine learning toolboxes, many methods are easy to implement and can thus simply compared with each other. The decision should result from the triad of personal experience of the data engineer, the appearance of the data, and the literature review about similar use-cases. However, future trends such as AutoML and transfer learning show good prospects for automation and transferability with the objective to make AI more applicable.

Table 4 shows an illustrative overview of central AI application fields at the shopfloor level and the main AI tasks. The matrix depicts commonly used algorithms with use-cases from the three machining processes milling, turning, and drilling. The tasks are evaluated for their applicability for each use-case and marked with green for high, yellow for neutral, and red for low applicability. Coinciding with our experiences, commonly different algorithms are evaluated, compared with each other and the most suiting algorithm is selected. However, usual algorithms, such as ANN, SVM, CART, and RF, turn out to be widely used for several AI tasks in manufacturing. A comprehensive review of further AI use-cases categorized into the different machining processes can be found in Kim et al. [93] and Jemielniak et al. [94].

**Supervised regression and classification** are preferably used if labels can be assigned to the data. Especially in the manufacturing industry regression and classification methods have been proven to be very useful for several tasks such as tool condition monitoring. The family of ANN's and the SVR are widely used regression algorithms promising high accuracies [93]. For classification tasks, the SVM and the RF are widely considered to be one of the best algorithms [87,95–97].

**Clustering** methods discover classes based on similarity and are typically used to classify unlabeled data. At the machining process level, they are less used compared to supervised methods. However, they can be applied to unlabeled data to recognize unknown patterns that might be used, for example, to detect outliers. In some terms, clustering methods are closely related to outlier detection, since both methods use comparable mathematical approaches, such as distribution, densities, and distances. Prominent algorithms are provided for example by the distribution-based Expectation-Maximization (EM), distance-based k-means, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. [94,98,99]

**Reinforcement Learning** (RL) is learning how to match situations to actions in order to maximize a scalar reward signal. This is done by trial and error interactions with a dynamic environment to identify which actions bring the highest immediate and subsequent rewards [100]. A major challenge of the RL algorithms is to balance between the exploitation of already known, promising actions and the exploration of the solution space to achieve further improvements. Another challenging problem is the long duration of the learning phase in real-world applications, such as in manufacturing environments. A possible solution can be provided by training RL algorithms in simulation environments and applying them to a real-world problem. This approach is already used, for example in robotics [101], energy-systems control [33], and production planning [102].

Table 4: Overview of central AI application fields in machining and commonly used algorithms.

| Application Field | | | Use Case | | Regression | Classification | Clustering | Reinforcement Learning |
|---|---|---|---|---|---|---|---|---|
| Quality Management | Product | Process Monitoring | Workpiece surface roughness prediction | | MLR. [103]<br>DNN, CNN. [104]<br>MLP. [105,106]<br>CART. [107]<br>SVR, MLP. [108]<br>SVR. [109,110] | kNN, CART, RF, SVM. [111]<br>kNN, CART, SVM. [112]<br>CNN. [113] | | |
| | | | Product/Process quality check | | CART, MLP, SVM, RF. [114] | CART. [115]<br>CNN. [6]<br>SVM. [116]<br>AutoML. [82] | HAC. [116] | |
| | | | Uncertainty/fault detection | | MLP, SVR, BN. [117] | LDA. [118]<br>ANFIS. [119]<br>RF. [120] | k-means, fuzzy C means. [121] | |
| | Machine / Components | Condition Monitoring | Tool breakage monitoring | | SVR. [122] | SVM. [123]<br>MLP. [124] | k-means. [125] | |
| | | | Tool wear monitoring | | CNN, kNN, SVR. [126]<br>RF. [127,128]<br>ANN, SVR. [129]<br>SVR. [130]<br>AutoML. [83] | CNN. [131–133]<br>NBC, SVM, ANN, RF. [134]<br>SVM. [135]<br>ANN. [136]<br>RF. [137] | | |
| | | | RUL prognostic | Machine tool | MLP. [138] | SVM. [139] | | |
| | | | | Spindle bearings | RNN, CNN. [140]<br>MLP. [141]<br>GP. [142,143] | | | |
| | | | | Cutting tool | ARIMA, GB, RF, RNN. [144]<br>SVR. [145]<br>BN. [146]<br>ARIMA. [147]<br>Neuro-Fuzzy. [148,149] | | | |
| | | | | Machine spindle-tool holder | RVM. [150] | | | |
| | | | | Machine tool ball screws | GPR. [151] | | | |
| Process Optimization | Machine | Autonomous Machining | Intelligent System Control | | BL. [152]<br>MLP. [153,154]<br>Neuro-Fuzzy [155]<br>MLR, MLP. [156] | | | GA. [20]<br>GA. [157] |
| | | | Machining Parameter Optimization | | MLP. [158,159]<br>MLP, RF. [160] | | | GA. [161] |
| | | | Tool Management | | | | FCM. [162] | |
| | | Energy Monitoring | Energy consumption prediction | | GPR. [163,164]<br>MLP. [165] | | | |
| | | | Energy consumption forecasting | | MLP. [32] | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Process Optimization | Process Chain | Production Planning | Productivity boosting | GPR. [166]<br>BN. [167]<br>RNN. [168]<br>ANN. [169] | | k-Means [170]<br>SOM [171]<br>k-means, DBSCAN, EM. [99] | RL [172,173]<br>RL [174,175]<br>DQN. [102] |
| | | | Reduction of energy consumption | GBRT. [176] | kNN [177] | | GA. [178]<br>DRL. [33] |
| | | Production Control | Online rescheduling | RF. [179]<br>CART. [180] | SVM. [181]<br>kNN, DT. [182] | | RL [172,173]<br>RL [183]<br>RL. [184] |

### 3.2. Enablers, Benefits, Challenges, and Implementation Approach

According to the experience of the PTW Institute, the **rapid progress in the practical application of artificial intelligence** can primarily be contributed to the following developments (see also [88]):

- The amount of data recorded in production is many times higher today than it was a few years ago [185]. Although a large number of data points recorded in the ETA research factory cannot yet be seen as an industry standard, we see strong developments in this direction.
- There are many toolkits and libraries for the development of AI applications, also used at PTW, many of which are open source. Examples are Tensorflow or OpenAI baselines ([186], [187]).
- The performance of AI algorithms has improved significantly in recent years. Hernandez et al. [188], for instance, identify a performance increase by a factor of 44 from 2012 to 2019 for image recognition problems using neural networks, which means a doubling of performance every 16 months.
- Computing power and storage capacity have risen sharply and are more cost-effective than ever before. They can be obtained through in-house hardware or from cloud providers such as Amazon, Google, and Microsoft [189].

The last two points mentioned above, i.e. the combination of increased computing power and increased algorithmic efficiency, result in a strong increase in effective compute, as shown in Figure 7.

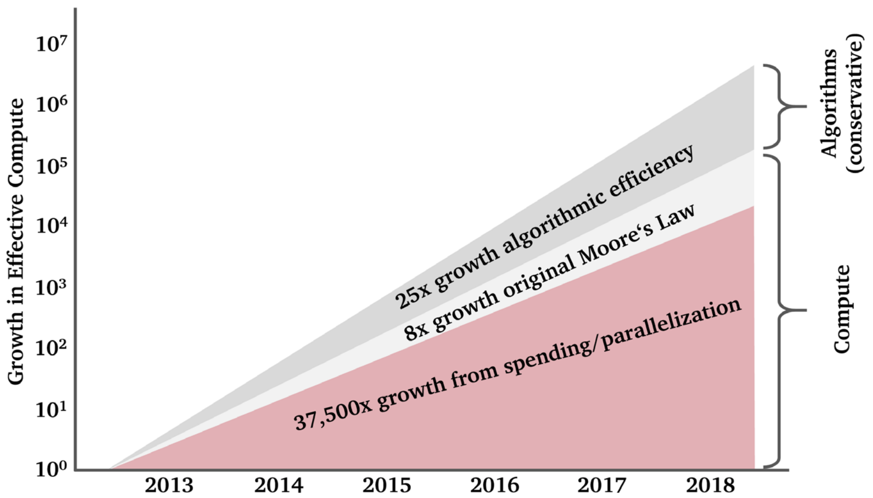


Figure 7: The notion of effective computing allows the combination of the AI and Compute trend [188].

Both the current state of the technology as well as current trends therefore offer extensive possibilities for the application of artificial intelligence methods. However, since they are not readily applicable to all problems, the potentials, and advantages, as well as the risks and hurdles of using AI methods, should be considered carefully. The different use-cases for AI methods applied at the PTW have already been explained above. In summary, the following **main advantages** for AI for the use in production can be identified:

- Despite the black box problem of deep neural networks, a **better system understanding** can often be provided by learning algorithms. This enables, for example, the forecasting of energy consumption and thus effective demand-side management. By learning their dynamics, systems and machines can also be controlled more effectively and measured data can be interpreted better (e.g. [190], [32]).
- AI methods offer **cost-neutral** or **low-cost monitoring solutions** that can be implemented by using existing machine data or low-cost sensors. Additionally, they allow for easier interpretation of sensor data that classically is quite challenging to interpret in an automated manner (e.g. from cameras). Thus, additional value can be generated in various scenarios, from **quality assurance** to **predictive maintenance** and **scrap and standstill prevention** (e.g. [191], [6]).
- The use of advanced AI methods allows for the **efficient control of very complex systems** with many nonlinearities, which is rarely possible with conventional control systems. For example, **industrial supply systems can be controlled** in a more cost and energy-efficient manner or the energy consumption of production can be **reduced by AI-optimized production planning**. It is also possible to **optimize individual processes** such as SLM. (See [33], [178], [192])

Therefore, we conclude that AI is suitable **for very complex tasks** and **offers the potential for significant cost savings while simultaneously increasing product quality**. The required data is available in increasing quantities and both the computing power and the performance of the applied algorithms are sufficient to generate technological and economic benefits today and increasingly so in the future. However, in order to be able to use AI methods effectively, knowledge of the currently existing **disadvantages and risks** is essential, which we list according to their relevance below:

1. **Insufficient AI user knowledge**
2. **Low transparency**
3. **Insufficient and low-quality data**
4. **High Training and adaptation effort**

In summary and while keeping in mind the above-mentioned problems, we still see great potential for the use of AI technology in production. This view is supported by a study done at Mittelstand-Digital where over 80 % of the experts surveyed stated that the use of AI is particularly suitable for production [193]. Considering the hurdles mentioned above though, we see the following steps as particularly important for the **successful application of AI methods**:

1. **Build up AI user knowledge**: In order to correctly assess the potential of AI, it is necessary to build up knowledge or to obtain it from external sources to clarify the potentials and limits of the methods and to avoid wrong decisions or excessive expectations (often, AI is not the only or even the best solution to a problem and simpler measures might be sufficient). Of particular relevance are application-oriented case studies, which can be used for assessment. For individual projects, the introduction of a guideline can also be useful. When introducing AI methods, the threshold should be kept as low as possible and the measures should be linked to existing systems or processes instead of creating a parallel system, if possible. All this is fundamental to developing trust in the technology and thus reducing the hurdles of application.
2. **Create Transparency and reliability:** the disadvantages explained in the point “low transparency” are significant obstacles on the way to application. The black box problem can be tackled by integrating fall-back mechanisms, which overwrite the "decisions" of AI-algorithms with those of less intelligent but semantically understandable heuristics. This can effectively prevent critical decisions from preventing the potentially profitable application of AI methods (see [33]). AI applications should also be designed in such a way that allows the user to assess the result (e.g. the indication of probability values for image recognition or the output of control

signals). There is also a growing number of freely available tools that address the transparency problem and should be applied where possible (e.g.: OpenAI Microscope for image recognition).

3. **Provide the necessary data in proper quantity and quality:** Good data is essential for the functionality of AI applications. The success strongly depends on the availability of pools of context-based, logical, and qualitatively high-grade data [194]. Coming back to point 1, we emphasize to the great benefit of case studies that resemble the desired application. This helps correctly choose sensors and the right amount of data and thus enables investments to be directed more effectively. Once the necessary sensors/data points are selected, it must be ensured that a suitable system for the transmission of data from origin to evaluation point is made. The right system differs significantly depending on the application case (e.g. the required frequency of data acquisition). If the data is not sufficiently large, has poor quality, or suffers from unbalanced samples, then we would also like to emphasize on synthetic data generation originate from (simulation-)models [153,195,195] or to (pre-)train the model in a virtual environment (e.g. reinforcement learning with digital twins) [33,102].
4. **Create the necessary computing system for the application:** The optimal computing system can vary greatly depending on the application. In the spectrum from cloud services to edge devices, also hybrid forms exist and often offer good compromises. AI use-cases with artificial neural networks have a high computational demand in the training phase, whereas in most cases the use of a fully trained network is much less computationally intensive. If the training takes place only once or a few times and the focus is on the application of fully trained nets, a division into training in the cloud and application on an edge device can be useful. If the training load is permanently high, also the purchase of proprietary hardware can pay off. We see that high-performance compute power is available for the vast majority of use-cases (either as off the shelf hardware or cloud services). In our opinion, the selection of the right system should be the focus.

## 4. Digital Twin

### 4.1. Definition

In 2003, John Vickers, an engineer at NASA was one of the first to coin the term *Digital Twin*, which can be described as "a virtual, digital equivalent to a physical product" [196].
Currently, there are numerous definitions of the term [197]. An extensive overview of definitions found in literature is provided in [198]. In general, we find the definition proposed by Rasheed et al. (see [199]) to be most suitable and in good agreement with other sources[1] relevant in the PTW context:

*"A digital twin is defined as a virtual representation of a physical asset enabled through data and simulators for real-time prediction, monitoring, control, and optimization of the asset for improved decision making throughout the life cycle of the asset and beyond."* [199]

The definition from the international academy for production engineering (CIRP) the was published in 2019:
*A digital twin is a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system(a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases."* [197]

The structure of digital twins is displayed in Figure 8. In summary and according to Stark and Damerau, a digital twin consists of [198]:

1. A **unique instance** of the **universal digital master** model, tailored to its specific purpose
2. An individual **digital shadow** of a product, i.e., **data** measured and acquired **during the operation and use** of the physical asset

[1] We refer to [197,200] and the definition provided in *CIRP Encyclopedia of Production Engineering* [201].

3. A meaningful **linkage** of the **unique instance** and a digital shadow using, e.g., **algorithms, simulation models, correlations**, etc.

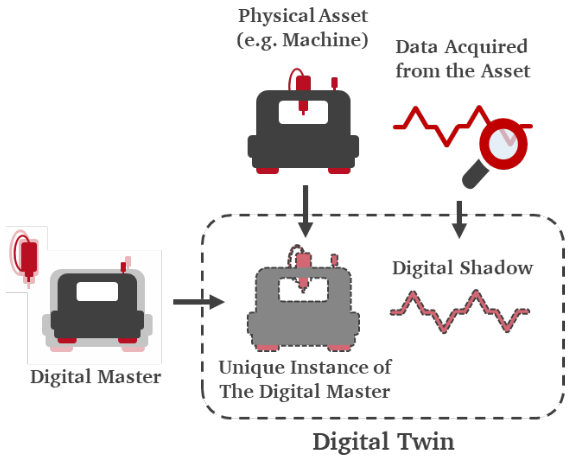


Figure 8: Generalized Structure of Digital Twins.

The digital twin aspires to the most exact representation of a real physical, technical, socio-technical robustness system for a parallel active simulation [7]. The purpose of the Digital Shadow is to create error-free and traceable data sets in order to create a valid basis for the subsequent analyses. Based on the digital shadow, the digital twin delivers the desired identical image of reality by adding process models and simulations [202]. The digital shadow sets up the basis of advanced analytics in the context of Industry 4.0. This enables us to answer **descriptive, diagnostic, and prescriptive tasks** in the production environment [203].

### 4.2. Challenges and Implementation

In implementing the concept of the digital twin, various challenges are faced. As summarized in [204] these are:

Data:

- data acquisition, gathering, and processing of large data sets
- data fusion
- data standardization
- uncertainty quantification
- the trustworthiness of data and data security

Model:

- models interoperability (e.g. FMU)
- high-fidelity computational models for simulation and virtual testing at multiple scales
- modeling of physical part variations
- synchronization between the physical and the digital world to establish closed loops

As these challenges are overcome the interlinkage between the physical asset and its digital twin can be accomplished in various ways and for various purposes, for which Stark and Damerau propose the *Digital Twin 8-dimension Model* (see [198]).

From our perspective and in agreement with Negri et al. [205], the relevance of digital twins for the manufacturing industry lies in their ability to allow running simulations in different disciplines and different life-cycle phases, to support a **prognostic assessment at the design stage** and also a **continuous update of the virtual representation** of the asset by a real-time synchronization with sensed data. This allows the representation to reflect the current status of the system and to perform

**real-time optimizations**, **decision making**, and **predictive maintenance** according to the sensed conditions. [205]
Typically, once a sufficiently accurate digital twin is obtained, we find multiple use-cases that generate added value by utilizing the available data. Especially in the context of AI in production, digital twins are a major enabler, since the virtual data generation can overcome the obstacle of gathering a lot of real data for complex models. Additionally, virtual sensors can comparatively easily be set up and thus expand the available data of the physical asset to be analyzed or optimized.

# 5. Future IT-Infrastructure in Manufacturing

## 5.1. Requirements for scalability and success

Most of the requirements for the future manufacturing IT are not new in a general sense but differ widely from the requirements that prevail today in the operational technology (OT) environment. Today's requirements are mainly influenced by automation technologies, whereas future requirements come from internet technologies as well as the control and automation domain. Due to the increasing number of network participants in the coming IoP, statically defined networking will be no longer feasible. Therefore to keep up with the growing number of stations, future IT will need to adopt software-defined-networking-techniques (SDN) [206]. The risk of a network outage is increased by the fact, that future manufacturing will need to be reconfigured often. Using SDN greatly diminishes the risk of a misconfiguration threatening to cause a network outage. [207]

New technologies, that manufacturing IT might encounter, are for example the operation of a data center, with everything that this includes (e. g. virtualization technologies, especially OS-level, load-balancing, redundant data storage …). These are not new technologies in general, but they have not been used in the manufacturing environment before. However, depending on the data security needs of a company, all the necessary know-how can easily be outsourced to one of the major cloud-computing-providers. The different levels of the automation pyramid (as described in chapter 6.1), that are today using a multitude of different, vendor-specific communication protocols and -systems, will probably be unified to an Ethernet-based communication system. To suffice the different real-time-requirements of the involved systems, the future production network should support the extensions to ethernet currently under development named Time-Sensitive Networking (TSN), which allows for a mix of real-time and non-real-time traffic to appear on the same network. [208,209]

Unlike safety, the security of production equipment has long been overlooked. It took a few prominent breaches and following manipulations of industrial equipment in general, and specifically industrial control systems, for this topic to surface. The most prominent of these security breaches would be the Stuxnet worm which targeted plants of the Iranian nuclear program in 2010 [210]. Other attacks targeted critical infrastructures like the Ukrainian electrical power grid, which has been subject to two attacks in 2015 and 2016 [211]. However, attacks are not restricted to nationwide targets, as the example of a German steelmill shows, which has been damaged through a cyber-attack in 2014 [212]. With the transition from disconnected control systems to a connected IoP the original notion, that even the networked control systems (ICS, SCADA …) are air-gapped from insecure networks like the internet, doesn't hold anymore [213]. The main security requirement for the production IT of the future (as well as todays) is, therefore, to establish functioning patch management for the production equipment, similar to the patch management for normal IT equipment. This should not be a big problem, where the equipment is based on the Microsoft Windows platform. The real challenge lies in patching vulnerabilities in the industrial control systems, that haven't been designed with updates in mind. [214]

## 5.2. Platforms and Services

Gawer and Cusumano define three essential characteristics of an industry platform, the first being that it provides a core technology as part of a technology system that can be reused in several products. These products – or applications, in the context of cloud computing platforms – originate from different companies. Secondly, the platform itself provides little or no value to the customer, the user value comes from the applications based on the platform. A third characteristic is the generation of a network effect with a growing number of users, leading to quasi-standards. [215,216]

The current market of platforms that focus on production plants or production equipment is growing. The two main types of platforms that appear are firstly cloud computing platforms and secondly localized platforms usually called edge-computing platforms. For the cloud platform part, currently the major cloud provider Amazon has a 47,8 % share of the market with its amazon web services (AWS). The following are Microsoft (15,5 %), Alibaba (7,7 %) and Google Cloud (4 %) [217]. To these general clouds, some companies developed specialized manufacturing clouds targeting OEM. Two examples of these would be the ADAMOS joint venture, based on Cumulocity by Software AG, or the Grob net4industry. Both comprise specialized apps with the general IoT-functionality of the underlying cloud-system. Additionally, component manufacturer Siemens has developed their own cloud platform that they populated with apps for their sensors, actuators, or control systems, but opened up to apps and data source by third parties.
All these different cloud platforms are heading for the same problem, the automation industry finds itself in today. This problem is a multitude of incompatible field buses, all of which a component vendor needs to support to compete on the market. For the cloud platform business, only a few of the growing number of platforms will succeed and stay on the market. And those remaining will have to entertain the possibility of opening up and engaging something called the "cloud federation" as proposed by DIN SPEC 92 222. This means standardized interfaces, allowing the cloud platforms to exchange data so that a customer has only to interact with the platform of his choice. [218,219]
This applies even more to the edge platform market. As of today, nearly every component manufacturer, that offers some sort of edge computing or aggregation technology, does so with their own edge platform. Major industry players like Siemens are trying to motivate other component manufacturers to join their platform Sinumerik Edge, which promises easy deployment of applications through Siemens Mindsphere, if the component manufacturer is willing to pay the fees associated with using the platform. The competition of edge platforms is shown again with Siemens, which offers a competing Industrial Edge to their Sinumerik Edge, both targeting manufacturing environments.

All these platforms differ in the underlying business model, as described in chapter 1.2. Another differentiator is the openness of the platform, meaning the availability of design and implementation details to developers. Mainly two forms are apparent today: The first relies on established standards, which are openly documented. This allows for a wide variety of compatible products to be developed. The platform-provider focuses on the availability of computing power and some basic applications, which often include asset management, user- and role management, and the like.

The functionalities for the internet of production are developed as services (SOA: Service Oriented Architecture) and need to be deployed to the respective systems by developers. Independent of the cloud-provider or edge-platform this is usually achieved by a virtualization technique called containerization. Containers are a lightweight alternative to virtual machines and the number one tool for working with containers is Docker [220,221].
The PTW uses docker- and LX-containers to bring analytics-apps to edge-devices installed in machine tools. The containers can be managed without physical access via a public cloud and are able to be deployed in the same fashion without reconfiguration on different machines. The big advantage is the development of services agnostic of the underlying hardware.
Encapsulating only a single service in a container – that communicates with other containerized services – leads to a microservice architecture, which has benefits in the easy replacement or upgradability of functionalities and allows for a simple reuse of existing services in new developments [222].
One drawback with containers is their larger attack area since they are not completely isolated virtual machines, which needs to be considered while developing containerized services. Due to the fact that docker is a generic IT-tool, container security is already focused in research. [221,223]

## 5.3. Control of machines and production infrastructure at future IoP systems

Today's control systems are situated in hierarchical production systems and serve mainly two purposes. The first and most significant task is to ensure that machinery and production equipment follow the planned process. In the case of machine tools, this means a predefined NC-program, for programmable logic controllers the processing of input values conforming to the programmed logic.
Additionally, control systems provide access to information and data of the underlying field level for higher-level functionalities such as visualization on the human-machine-interfaces. Communication between control and field level is usually carried out via fieldbuses (e.g. to ensure deterministic timing), whereas the communication towards higher levels (HMI, SCADA …) is often implemented using industrial Ethernet. This means that control systems act as communication gateways or entry points to the field level. [224]
In the context of "Industrie 4.0", especially big-data-analytics, the data of field level devices is deemed valuable for analytics. By this, the function as a communication gateway providing access to data is going to be of growing interest. Additionally, control systems contain an implied information model of the field devices, which enables them to provide not only the data from the devices but also enrich this data to information. These information interfaces will be able to be configured at runtime, opposed to the static programming of the interfaces of today's control systems [225].

The functionality of the typical PLCs and machine controls will be reduced to simple I/O-management and motion control cycles. The programmed logic for PLCs or the advanced functionalities of the machine controls (interpretation, trajectory generation, coordinate transformations, interpolation of trajectories) will be outsourced to a control-cloud. This provides the necessary computing power for sophisticated algorithms and also enables the easy deployment of new or improved algorithms to existing equipment. [225]
This edge cloud needs to be situated somewhere near the production (hence the naming as an edge cloud), due to high demands regarding real-time-communication towards the machinery [226]. This edge cloud offers functionalities of a real cloud-computing-solution, e.g. easy deployment and updating of all the control systems. For non-real-time-functionalities, like reprogramming or simulations of a new production program, the edge cloud can be accompanied by a private or public cloud not situated in the production environment. This offers the benefits of not having to own and maintain the hardware, needed only occasionally. Whether this would be a private or a public cloud is dependent on the needs and abilities of the respective production companies.

The overall control systems (including the cloud-based control software or "apps") will be more flexible than today's systems which need to be reprogrammed for each change in the production system configuration. They will be aggregated of many modular systems with just one or a few tasks each.
This is comparable to microservices or service-oriented architecture in software-development [227]. An architecture using modular components allows for a more cost-efficient reconfiguration of the production systems, which will be necessary due to trends like mass-personalization of products and hence a drop in the typically produced batch sizes. [207,225]
Future production systems might even get rid of manual reconfiguration efforts completely by adopting self-organizing and self-optimizing functions. This new architecture of control systems offers many benefits over today's rigid automatization architectures. The centralized availability of information about the production process and the involved machinery allows for analytics and improvements as described in the first chapters of this paper. One example is the reduction of the peak power demand of a production machine by timely adjustments to single subsystems of the complete machine tool, which should be easily transferable to complete production plants, offering huge savings in energy expenses [228,229].

The modular and standardized architecture of control systems also allows for easy technological upgrades. This applies to hardware changes or extensions as well as software updates. Especially the latter is a benefit of the cloud-structure of most of the applied software, which is already today a big advantage over locally installed software. A further benefit is the development of standardized communication which reduces costs for equipment used to construct machine tools and production equipment in general. This is due to the lack of the necessity to offer one's product with a multitude of interfaces to different fieldbuses [230]. This also increases competition between vendors of automation components, which in turn can offer lower production equipment prices.

# 6. Future Networking in Production

## 6.1. Paradigm Shift: From Rigid to Flexible Production Networks

Over more than 20 years of manufacturing systems and their communication networks have been designed to follow the strictly hierarchically layered 'Automation Pyramid'. The manufacturing functions on the different layers represent functions of a similar type and are usually implemented as logically separated layers, which are connected only to the layer below or above. Specifically, the lower levels (field-, control-, and process management levels) and the higher levels (plant operation and corporate level) are separated into the OT, and IT domains. [231]
In general, modern integration in industrial communication networks, which refers mostly to the various networks forming the foundation of information transfer and data provision, can be differentiated in regards to the automation pyramid in:

- horizontal integration mostly done inside the individual levels of the automation hierarchy and
- vertical integration between the levels of the hierarchy. [232]

For reasons of practicability, academic and industrial activities mainly focused on the design of dedicated automation networks and thus, primarily on *horizontal* integration aspects. Under this rigid architecture, not only the integration between IT and OT is difficult, but skip-level function integration is not supported. However, due to the opportunities from ICT technology integration, vertical integration has become a topic of interest. To exploit this potential every part of a manufacturing enterprise needs to be designed so that communication, integration, and automation can be achieved without constraints. [233] One objective in this context is increasing the flexibility of production environments by improving the reconfigurability and responsiveness of the shopfloor through self-adaptation and self-organization. This flexibility can only be reached by enabling the IT and OT communication systems to interoperate. The vertical sharing of real-time data breaks also the classical timeliness of the different hierarchical planes. [234] To achieve this flexibility cyber-physical systems (CPS) are of key importance. CPS being capable of complex functions across all layers and responding intelligently to changing tasks and conditions and reconfigure themselves. Thus, a flexible version of the automation pyramid is proposed, where the field level features CPS vertically integrating all pyramid layers through articulated functions (in contact with all the pyramid layers) while still a hierarchical structure is preserved (Figure 9). [235] CPS, hence, partly break the traditional automation pyramid and potentially turn the manufacturing environment into a service-oriented architecture (SOA). Thus, CPS enable the rigid communication pyramid to a network of factory communication.

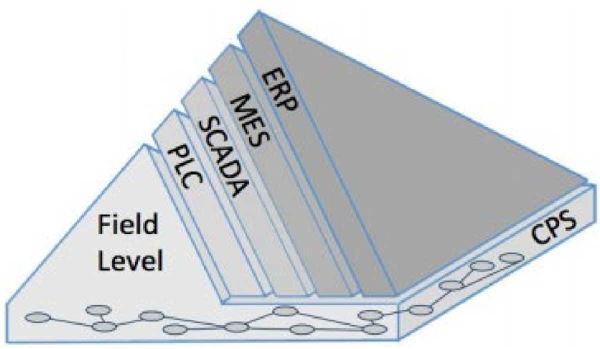


Figure 9: The evolved automation pyramid (flexible network) [235].

## 6.2. Non-Functional Aspects: Heterogeneity, Timing, Security, and Safety

One of the main challenges of the state-of-the-art systems is the **heterogeneity** of the different networks ranging from fieldbus systems in all shades to Ethernet-based or wireless concepts tailored to specific purposes. In this context heterogeneity specifically addresses the following points: [236]

- different media (copper, optical, radio) within a technology,
- different technologies (fieldbuses, industrial Ethernet, industrial Wireless, IT-networks),
- different protocols and services (real-time protocols and best-effort protocols on the same medium), co-existence issues,
- different vendors for networked components, interoperability issues,
- different implementation platforms (including standard IT systems and operating systems, legacy automation components, embedded devices, and IoT components),
- different handling and management concepts and tools.

In future manufacturing, networks will become even more diverse, due to wireless systems experiencing continuous change with additional, mobile devices entering and leaving a single wireless collision domain. Wireless technologies can be beneficial for flexible approaches, if they can adapt to these changing, heterogeneous environments, optimizing the usage of available spectrum for all available devices. On a technical level, this requires the ability to switch communication protocols in real-time, reconfigurability of the radio through software-defined networking interfaces and reconfigurable antennas, and the design of sensor protocols that leverage the capabilities of the wireless network. [236] Furthermore, to enable a truly flexible approach and exploit the respective advantages, a massively distributed computing and storing infrastructure, which dynamically allocates computing and storing resources to flexibly deploy functions in distributed cloud infrastructures, is needed. [237]
A major challenge in the development of distributed systems is that their composition in the development phase is less known compared to the status quo. The industrial components are individually integrated into the system so that its structure is constantly changing. In particular, the functionality is adapted or extended dynamically during the utilization phase. However, while interoperability forms the basis for the realization of distributed systems consisting of networked industrial components, the long-term success depends largely on their modifiability during the utilization phase.

Regarding operation, the main challenge of wireless systems is the **timing** requirement. While the current wired systems were designed to meet the application-specific requirements, it remains challenging to achieve the same deterministic behavior for wireless networks. [236]

**Security** is another key requirement in the factory of the future. Information (IT-) security describes the protection of information to be processed by a system against unauthorized manipulation [238]. A special case of information security is ICT-security (system to be protected is an ICT system) [239]. Hereby all ICT-security systems aim the three security goals confidentiality, integrity, and availability (CIA) [50]:

- Confidentiality dictates that information or data can only be read or modified by authorized users [240]
- Integrity dictates that data cannot be changed unnoticed and all modifications must be fully traceable at all times [241]
- Availability means that authorized users of a system within an agreed timeframe cannot be affected in the exercise of their rights without authorization [242]

As depicted in Figure 10, the integration of ICT-security into the manufacturing industry is associated with diverse challenges, which show some conflicting goals. Nowadays, in automation, the zone concept is often used, where different zones with restricted physical and logical access and unencrypted communication inside them are defined. This concept has emerged because the resource-constrained, connected sensors and components are usually not capable of performing adequate encryption and decryption algorithms. Thus, to enable connected factories, organizational efforts have to be done to ensure consistency. Due to the heterogeneity of platforms and the number of distributed devices, applying adequate security measures and managing security is difficult. [236] Ensuring the protection gaols while maintaining flexible manufacturing IT-infrastructure requires well-defined standards. A widely known standard is the OPC UA which includes security aspects as a central element which, for example, secure the communication between client and server, the authentication of users, the role concept, and audit logs for various events. However, using OPC UA alone does not make an installation secure, since there are still not implemented aspects such as firewalls, OS hardening, anomaly detection, security patch management, etc.

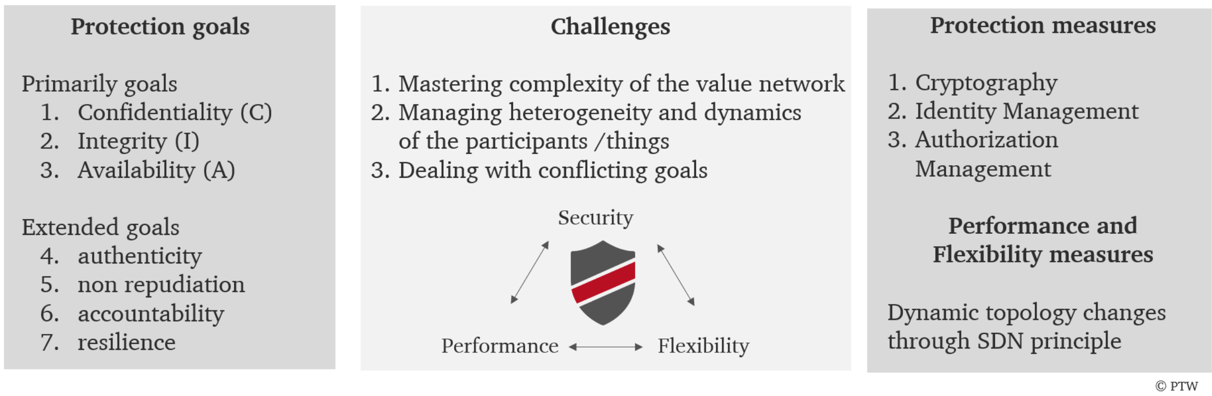


Figure 10: Main aspects of ICT-security in manufacturing.

As data becomes a key asset in modern production, **cybersecurity** is an important enabling factor. It could be shown that the acceptance of AI in manufacturing, as well as business models like AI-as-a-Service, depends on trust in security standards. [243] The loss of data is not only the loss of know-how but directly linked to the business goals. The aim is to establish a cybersecurity system that can deal with the risk of cyber criminality with a tolerable restriction risk. In general, cybersecurity aims to protect systems, networks, and programs from digital attacks, such as accessing, changing, or destroying sensitive information, extorting money from users, or interrupting business processes. Implementing efficient systems is challenging as the number of devices is growing, attacking is becoming more innovative and profitable. Additionally, the security of IoP-systems has some unique challenges [244]:

- A fast system restart is not possible due to the major objective of integrity and availability
- Stricter real-time requirements in production
- Low computing capacities and very long lifecycles of the infrastructure
- Additional areas of protection, e.g. data analysis of production data and loss of know-how

With the rise of AI in manufacturing the complexity of additional threats is rising. However, AI can help to detect and fend off threats more effectively. An example is intrusion detection, where AI can help monitor a network for malicious activity or policy violations due to the capability of pattern recognition. The role of AI is ambivalent in this case. [243]

Cybersecurity by design became an incremental part of modern systems. Nevertheless, in complex IoP-systems all interactions relevant for security cannot be recognized in advance, this is due to rising complexity not only in technology but also in organizational aspects. Security is a problem of complexity. Among others, current research in this area is intrusion detection and prevention, anomaly detection in manufacturing networks, autonomous vulnerability scanner, and cognitive security. [243] Large national-funded projects, e.g. the IUNO project and its successor “IUNO Insec”, are a sign of how important cybersecurity is also seen by the government. [245]

With respect to **safety**, future production networks need to comply with safety integrity levels defined in standards such as IEC 61508. Additionally, the proper and safe functioning of all machines and devices in a wide range of environmental conditions is a specific requirement of the manufacturing industry. Therefore, new communication technologies have to guarantee their functionality in different climatic conditions (dust, humidity, temperature, etc.), mechanical conditions (shock, vibration, etc.), and intrinsic safety conditions (e.g. limiting the power consumption to avoid explosions). [236]

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