WHITEPAPER

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Digitalization in Industry

– an Austrian Perspective

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The White Paper "Digitalization in Industry - an Austrian Perspective" is an R&D service commissioned by the Austrian Climate and Energy Funds (Klima- und Energiefonds), carried out by the cooperation doctoral school SIC! (Smart Industrial Concept) in the course of the International Energy Agency Technology Cooperation Programme Industrial Energy-related Technologies and Systems (IEA TCP IETS), Annex XVIII: "Digitalization, Artificial Intelligence and Related Technologies for Energy Efficiency and GHG Emissions Reduction in Industry".

Executive Summary (EN)

The digital transformation is already influencing many aspects of daily life. Also, in industry, digitalization has become an essential part of business and research. Digitalization measures offer possibilities to increase the productivity and flexibility of an industrial process and thus, improving its efficiency, saving energy and reducing costs. Moreover, digitalization can contribute to the transition towards renewable supplied and sustainable production. Nevertheless, to benefit from these promising outcomes, there are still some challenges to overcome.

Naturally grown industrial establishments have created a heterogeneous landscape of technologies, which impedes a straightforward implementation of digitalization methods and complicates data handling. Although the term "digitalization" is on everyone's lips, especially energy-intensive industries still lack a profound basis and potential energy savings are often not considered in this context. On the one hand, we identified that interfaces between different digitalization measures and existing industrial technologies are significant issues. On the other hand, the availability and quality of (big) data, which is further dependent on available sensors, affects all analyzed measures and acts as a critical element and enabler for a successful implementation. More than that, there is a need to emphasize the potential of digitalization measures to reduce energy and emissions in the industry. Thus, it is essential to clarify which digitalization measures already exist, how and where they can be applied, what their benefits are and what other technologies or methods they require. This White Paper contributes to the enhancement of digitalization measures, focusing on the reduction of energy in energy-intensive industries, by:

- defining, placing and classifying essential terms,
- giving an overview of past and current digitalization projects in the Austrian industry, and
- identifying and analyzing 15 relevant digitalization techniques and technologies in detail, including a definition, their requirements, gaps and barriers, possible applications, as well as a future outlook and an assessment of their potential.

Figure 0.1 shows an overview of the structure, content and most important outcomes of the White Paper and classifies the chapters by the level of detail and the type of information.

Overall, the White Paper demonstrates that digitalization measures show great potential to support the design, operation and maintenance of industrial applications. However, they can also contribute to a reduction of energy and emissions, especially in energy-intensive industries. Considerable progress has been made in the last years towards a digitalized industry and scientific as well as industrial research is increasingly focusing on this topic. However, the further development of digitalization methods is not the only key to success. First, standardized interfaces between existing establishments and different digitalization methods are required, especially in industrial applications with a heterogeneous landscape of technologies. Secondly, the full potential of digitalization measures can only be exploited with the concurrent advancements of technologies and the establishment of an appropriate infrastructural basis. More than that, to achieve a wide-ranging digital transformation of the industry and an appreciation by stakeholders, users and the society, benefits as well as drawbacks of new advanced methods and technologies need to be clarified.

Figure 0.1.: *Summary of the content and outcomes of the White Paper. (WS ...average interest of workshop-participants in this topic from not interested (red) to very interested (green), P... number of investigated Austrian projects)*

Executive Summary (DE)

Die digitale Transformation beeinflusst bereits viele Aspekte des täglichen Lebens. Auch in der Industrie ist die Digitalisierung zu einem wichtigen Bestandteil von Wirtschaft und Forschung geworden. Mithilfe von Digitalisierungsmaßnahmen können Produktivität und Flexibilität von industriellen Prozessen verbessert werden und im Weiteren Effizienzsteigerungen, Kostenreduktionen und Energieeinsparungen erzielt werden. Außerdem kann die Digitalisierung dazu beitragen, Produktionsprozesse nachhaltiger zu gestalten und vermehrt erneuerbare Energien einzusetzen. Nichtsdestotrotz müssen noch einige Herausforderungen bewältigt werden, um von diesen vielversprechenden Ergebnissen profitieren zu können.

Heterogene Technologielandschaften, die durch natürliches Wachstum vieler Betriebe entstanden sind, verkomplizieren die Datenverarbeitung und generell die Implementierung von Digitalisierungsmaßnahmen. Obwohl die Digitalisierung in aller Munde ist, fehlt es in einigen Bereichen noch an einer fundierten Grundlage und die Digitalisierung wird selten mit der Reduktion von Energie und Emissionen in Verbindung gebracht. Große Herausforderungen stellen insbesondere Schnittstellen zwischen verschiedenen Digitalisierungsmaßnahmen selbst, und mit bestehenden industriellen Technologien dar. Außerdem ist die Verfügbarkeit und Qualität von großen Datenmengen für jede Digitalisierungsmaßnahme von großer Bedeutung. Daher ist es wichtig klarzustellen, welche Digitalisierungsmaßnahmen bereits existieren, wie und wo sie angewandt werden können, und was ihre Voraussetzungen und Vorteile sind. Dieses White Paper soll die Anwendung von Digitalisierungsmaßnahmen in der energieintensiven Industrie unterstützen und beschäftigt sich daher mit den folgenden Punkten:

- Platzierung, Klassifizierung und Definition wichtiger Begriffe,
- Überblick über Digitalisierungsprojekte in der österreichischen Industrie, und
- Identifikation und Analyse 15 relevanter Techniken, Technologien und Anwendungen der Digitalisierung. Die Analyse beinhaltet Definition, Anforderungen, Lücken und Barrieren, mögliche Anwendungen, Zukunftsperspektiven und Potenziale.

Die Struktur, der Inhalt und die wichtigsten Ergebnisse des White Papers sind in Abbildung 0.2 zusammengefasst. Das White Paper unterstreicht, dass Digitalisierungsmaßnahmen die Entwicklung, den Betrieb und die Wartung von industriellen Anlagen maßgeblich verbessern können und Emissionen sowie Energieverbrauch verringern können. An der großen Anzahl österreichischer Projekte kann erkannt werden, dass sich auch die Forschung zunehmend auf dieses Thema fokussiert. Doch die Weiterentwicklung von Digitalisierungsmethoden ist nicht der alleinige Schlüssel zum Erfolg. Standardisierte Schnittstellen zwischen bestehenden industriellen Anlagen und verschiedenen Digitalisierungsmaßnahmen sind erforderlich, insbesondere bei heterogenen Technologielandschaften. Außerdem kann das volle Potenzial der Digitalisierung in der Industrie nur mit einer ebenso technologischen Weiterentwicklung anderer Bereiche und der Schaffung einer angemessenen infrastrukturellen Basis genutzt werden. Schlussendlich spielt auch die Wertschätzung und Akzeptanz aller Beteiligten und der Gesellschaft eine entscheidende Rolle, um eine weitreichende digitale Transformation der Industrie zu erreichen.

Abbildung 0.2.: *Zusammenfassung des Inhalts und der Erkenntnisse des White Papers. (WS... durchschnittliches Interesse der Workshop-Teilnehmer an den Themen von "nicht interessiert"(rot) bis ßehr interessiert"(grün), P... Anzahl der untersuchten österreichischen Projekten)*

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Aim of the White Paper

The White Paper aims to give basic definitions, set the context and identify trends of digitalization, artificial intelligence and related technologies. It focuses on energy-intensive industry sectors and the reduction of energy consumption and greenhouse gas emissions, as well as the increase of efficiency. It identifies relevant digitalization measures and shows their potential impact and priority areas for further research. As a result, research and development opportunities for the strategic development of digitalization measures can be derived. Also, the White Paper highlights Austrian centers of excellence and projects that deal with digitalization in industry.

Structure of the White Paper

The introduction of this White Paper gives an overview of the broad topic "Digitalization in Industry" and defines and describes relevant terms and phrases. Also, it emphasizes the relevance of digitalization to reduce energy and emissions in the industry.

The next chapter provides an overview of the current situation in Austria, based on publicly available statistics. The focus in this chapter lies on digitalization, energy consumption and greenhouse gas emissions in the energy-intensive industry. Furthermore, Austrian centers of excellence in the field of digitalization are presented. They are grouped by Competence Centers, Inter-organizational Expert Committees as well as Academic and Educational activities. To provide an idea of the ongoing activities in Austria, selected, publicly accessible projects are presented. For each project, the potential impact on energy and emission-related aspects are analyzed.

The central part of the White Paper is divided into the two chapters "Digitalization Techniques and Technologies" and "Digitalization Applications". For this purpose, we identified 15 topics that aim to cover the most relevant digitalization measures in the energy-intensive industry. The selected topics can be seen in Table 0.1.

Table 0.1.: *Analyzed digitalization techniques, technologies and applications*

Digitalization Techniques and Technologies	**Digitalization Applications**
Big Data	Collaborative Business Models
Open Platforms	Technology Upscaling
Sensor/Smart Meters	Predictive Maintenance
Digital Twinning	Advanced Control
Data-driven Modeling	Supply Chain
Block Chain	Optimization
Flexible Components	Demand Forecast
	Cybersecurity

The analysis of the topics includes a definition, a general description, their requirements and application fields. Additionally, barriers and needs, as well as the potential and future outlook are presented. Finally, important findings and key messages of the White Paper are summarized in the conclusion.

In the Appendix of this White Paper, the outcomes of a national workshop with the title "Digitalisierung in der Industrie" (Digitalization in Industry) are presented. This workshop was held in November 2019 in the course of the Annex XVIII, to get further insights into this topic from an industrial perspective. The Appendix includes a short description of the workshop in general, the participants, factsheets that served as an introduction/glossary, as well as a summary of the outcomes. As this workshop was conducted in Austria in German language only, also the appended information is presented in German.

Background

This White Paper was compiled as part of the IEA IETS Annex XVIII by the scientific consortium of the cooperative doctoral school SIC! (Smart Industrial Concept). The Annex XVIII is led by Industrial Energy-Related Technologies and Systems (IETS), which is a technology collaboration program by the International Energy Agency (IEA). The Annex XVIII has the title "Digitalization, Artificial Intelligence and Related Technologies for Energy Efficiency and GHG Emission Reduction in Industry". The first task of this Annex has the objective to get a common understanding of the topic and build up an international network of researchers and stakeholders in the area of digitalization in industry. SIC! is an interdisciplinary doctoral school that focuses on holistic approaches for the digitalization of industrial process. It consists of several industrial partners and three scientific partners: TU Wien, Austrian Institute of Technology (AIT) and Montanuniversität Leoben.

1. Introduction

1.1. The Big [Digital] Picture

The digital transformation is touching many aspects and areas in daily life. In industry, digitalization has also become an important part of business and research, which is changing traditional production systems. This ongoing process in the industry is often called the **4th Industrial Revolution**. As energy sources and human workforce were an enabler for the first and second industrial revolution at the end of the 18th and middle of the 19th century, **Information Technology (IT)** in combination with robotics and automation were the driving forces for the third revolution in the 20th century. Today, the networking of **Cyber-Physical Systems (CPS)** is now going to change the industrial environment. In this context, the term **Industry 4.0** was introduced by the German government to support research and development projects in this field. Industry 4.0 refers to the intelligent networking of machines and processes for the industry with the help of **Information and Communication Technology (ICT)** [107].

A CPS is an integration of computation with physical processes, where both cyber and physical parts of the system influence its behavior. The design of such CPS focuses on the intersection between cyber and physical systems, not the union [84]. This leads to the challenge of complexity for CPS, because the physical, the cyber as well as the communication view has to be considered during design. It requires an understanding of the joint dynamics of software, networks, and physical processes. If CPS are used in the manufacturing industry, they are also called **Cyber-Physical Production Systems (CPPS)**. These systems are embedded into a **Smart Factory**, which interlinks people, machines and resources. In this context, "smart" means the ability to learn, adapt and self-organize, to perform intelligent actions. To reach these goals, **Artificial Intelligence (AI)** can be applied.

In general, applications for AI in combination with a technical process can be divided into four different categories [86], which are shown in Figure 1.1. These categories can be distinguished by their interaction between a technical or physical process and an AI software component. In Figure 1.1, the AI component is called **Intelligent Control** and represents some general concept of computation. The intelligent control can utilize AI algorithms and its related technology.

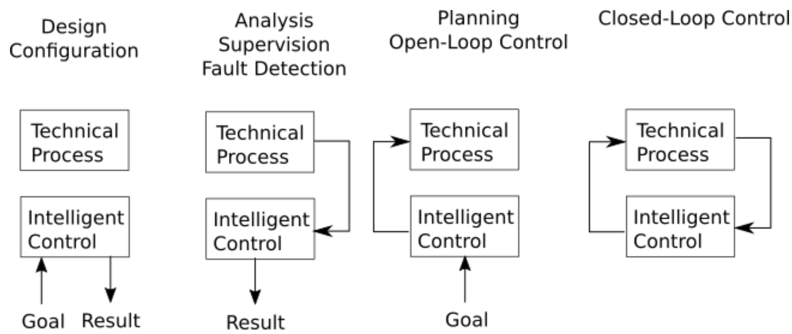

Figure 1.1.: *AI applications in combination with technical processes (Based on [86])*

These four categories can be seen in the context of industrial applications as follows:

Design and Configuration | The task of the intelligent control is to seek a structure for a technical process so that it can fulfill its purpose and meeting certain constraints. The intelligent control supports the engineering process. Typical applications are in the planning of a particular component or a whole system.

Analysis and Supervision | The physical process is under the supervision of intelligent control. The information from the process is used to analyze the behavior of the system. Typical applications in industry are fault detection and root cause analysis.

Planning and Open-loop Control | Interventions into the physical control process take place by the intelligent control to reach some defined goal and based on a specific state. Information is not returned by the process immediately. Typical applications in energy-intensive industries are unit commitment planning or economic dispatching.

Closed-loop Control | It is applied to guarantee a certain behavior of a physical process despite any influence of the environment on the process. Process state information is returned immediately to the intelligent control. Typically, advanced control strategies, like model predictive control, are applied in controllers for energy systems.

In general, AI can be divided into the area of knowledge and rule-based or symbolic AI and data-driven or sub-symbolic AI. Knowledge-based systems have some kind of explicit representation and rules, where knowledge is stored formally. Based on that knowledge, new knowledge can be inferred by an inference engine. This has advantages for interpretable results of such systems. The major problem is the handcrafted knowledge engineering process, which is very time consuming and very hard to perform for real-world problems. For example, intuition and experience of experts are hard to grasp formally. Also, the monotonic behavior of the most knowledge bases, which means that additional rules cannot undo another rule, has its drawbacks in many applications.

The increasing amount of data, caused by a decrease in storage costs and the increase in computational power as well as the improvement of algorithms, facilitates the use of **Data-driven** AI, like **Machine Learning (ML)**. These algorithms do not need to build handcrafted models. They learn out of labeled data and build rules as they build correlations between inputs and outputs. Such algorithms, like **Artificial Neural Networks (ANN)**, show very good performance at tasks, like classification, pattern recognition, and regression problems. As retraining with new labeled data can change the internal model, these algorithms are not monotonic but have the disadvantage that their results are usually not comprehensible. This can lead to various ethical and technical problems. Therefore, research has started to develop explainable AI algorithms. This is a very young field of research and has not established any general concepts, yet.

Most of these data-driven AI algorithms need a large amount of training data to perform well. In industry, these data come from different sources and in different formats, which have to be accessed in various ways and are unfortunately often unstructured. A very important data source for industrial processes is data. So-called **Smart Sensors** are further developments of traditional sensors, which are already able to process these data and communicate it with additional information.

Most industrial plants already have a lot of sensor information for process control. According to IEC 62264 [67], process control can be divided into several levels of an **Automation Pyramid**, which is shown in Figure 1.2. Especially at the level for **Supervisory Control And Data Acquisition (SCADA)**, a large volume of sensor data is produced. In combination with other aspects like velocity and variety of the data, the term **Big Data** is used. Sometimes other aspects are also mentioned, which can lead up to ten V-words (volume, velocity, variety, veracity, validity, etc.). There is no clear definition of big data, but the term can be used whenever standard solutions for data handling and processing are no longer applicable to generate added value [80].

In all levels of the automation pyramid, data is produced, processed or stored. Sensor data is usually stored in particular time-series databases or **Open Platform Communications Unified Architecture (OPC UA)** servers. The **Manufacturing Execution System (MES)** and the **Enterprise Resource Planning (ERP)** system uses relational databases or cloud services based on web technology. These are heterogeneous data sources, where data are stored in different formats and schemas. **Data Fusion** has to be performed to interlink this information to make it available and accessible for various kinds of applications.

Information is communicated between all levels of the automation pyramid by a so-called "vertical communication". Improved computational capability, reduced hardware costs, the availability of broadband Internet and open web standards are key factors that the **Internet of Things (IoT)** has already reached industry, where it is sometimes called **Industrial Internet of Thing (IIoT)**. This trend is pushing web technology into the field level, which leads to a reduction of hierarchy levels in the automation pyramid and convergence between classical **Information Technology (IT)** and **Operational Technology (OT)**, which is applied in the industrial control system environment. This convergence leads to a smoother implementation of this vertical communication. For energy-intensive processes, for example, this facilitates control functions in the field to take energy prices from the market into account or sensors in the field to trigger actions at company level.

The full potential of such a convergence can only be reached, if the involved software systems provide open interfaces to enable the interaction with third-party software. Such open platforms are software systems that provide open interfaces that other software can use and build upon their functionality.

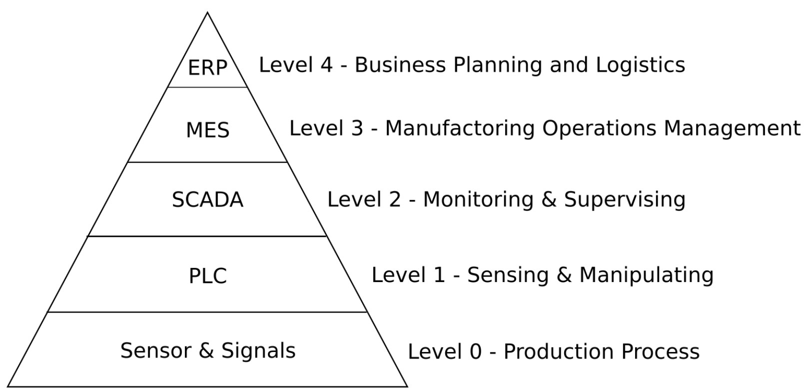

Figure 1.2.: *Automation pyramid*

All of the above-mentioned digitalization techniques and technologies can be applied in the energy-intensive industry, e.g. in **Predictive Maintenance**, **Advanced Control**, **Optimization**, etc. But still, a lot of challenges and obstacles have to be solved to enable the vision of Industry 4.0, like retrofitting existing processes with their heterogeneous infrastructure or the mismatch between the lifespan of manufacturing machines and IT equipment as well as the interoperability problems of various hardware and software systems. To tackle these challenges, an interdisciplinary approach with expertise from the field of informatics, mechanical and control engineering as well as economics has to be applied.

1.2. A Perspective on Digitalization in Industry - RAMI 4.0

In the context of Industry 4.0, a Reference Architecture Model (RAMI 4.0) is defined [1], which is shown in Figure 1.3. It is used to achieve a common understanding of standards, tasks and use cases. Therefore, three different aspects or dimensions are used by RAMI 4.0: It expands the hierarchy levels of IEC 62264, which is already shown in Figure 1.2, by Product and Connected World, defines six layers for an IT representation of an Industry 4.0 component and considers the life cycle of the product or system according to IEC 62890. The Life Cycle & Value Stream is divided into a Type and an Instance phase. The Type phase is part of the engineering phase, which ends when a prototype is available. An Instance is the system or product when it reaches the operational phase in the life cycle.

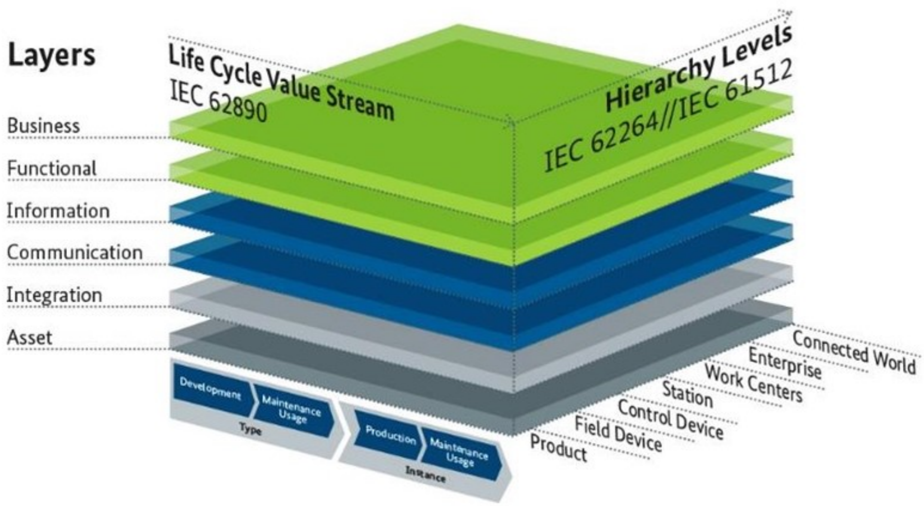

Figure 1.3.: *Reference architecture model for Industry 4.0 (RAMI 4.0) [108]*

The dimension of Hierarchical levels describes only a functional assignment. For Industry 4.0, the product, as well as the collaboration with external entities, plays a key role. Thus, these levels are also considered in RAMI 4.0. The IT representation of a component is divided into six Layers: Business, Functional, Information, Communication, Integration and Asset Layer.

Business Layer | Some aspects of the business layer include the mapping between business models and the resulting processes, the legal and regulatory framework conditions and the linkage between different business models.

Functional Layer | The functional layer provides a platform for horizontal integration of various functions. It also provides a run time and modeling environment for services that support business processes and a run time environment for applications and technical functionality.

Information Layer | The information layer provides a run time environment for (pre)-processing of events, execution of event-related rules, the persistence of data, ensuring data integrity and consistent integration of different data for obtaining a higher data quality. This is achieved via service interfaces and by receiving and transforming events that are processed by the Functional Layer.

Communication Layer | The communication layer is concerned with data communication and data models.

Integration and Asset Layer | The integration layer is the interface between the real and the digital world. It provides information about the underlying assets. Computer-aided control of the technical process, as well as interactions with humans over human-machine-interfaces (HMI) take place on this layer.

With the help of RAMI 4.0, tasks and workflows can be broken down into manageable pieces. The three dimensions help to provide context to new technologies, applications and use cases in industry. Also current and future standards and services can be located in RAMI 4.0 to identify overlapping as well as missing standardization efforts.

1.3. Digitalization in the Context of Energy Systems

Recently, the relevance of threats by climate change became more important to a bigger audience. Young people started demonstrating and raising their voices for energy transition and against environmental pollution. Also, we can see increasing numbers of famous defenders of climate protection measures. The related challenge is extensive decarbonization, which also influences our daily life, e.g. by means of production of consumption goods or energy supply for mobility, households, and industry. Crucial factors for a successful realization of decarbonization are the further development of energy infrastructure and new (breakthrough) technologies for energy supply and production processes. Digitalization measures can highly support the optimal integration of technologies and usage of infrastructure. For example, AI and its related technologies can enhance resource efficiency in industrial processes, which is a crucial factor for a successful realization of Industry 4.0. [3]. But, these applications are just one aspect of the digitalization process, as additional resources and other side-effects on the economy and society has to be considered. Simultaneous consideration of the savings by and new demands from digitalization measures in the energy-intensive industry are rare. One attempt is proposed in [63] and can be seen in Table 1.1. Table 1.1 shows a taxonomy of some measures in the context of digitalization and their impact on energy consumption and further on greenhouse gas emissions (GHG), depending on the related energy carriers. This taxonomy relates to the impact of ICT with effects on different levels (scope of impact) and changes in energy consumption. In the first level of this taxonomy, direct effects over the whole life cycle of ICT equipment are defined. In this level, the scope of impact includes the embodied energy that was used during manufacturing, the operational energy consumption, as well as the energy used for disposal at the end of its lifetime. Additionally, in the next levels, the indirect effects, which are likely to be much higher than the direct ones [81], are also listed in Table 1.1. The scope of indirect effects can vary from just the single service or technology, where the efficiency can be increased or it can be substituted with a new service or technology. A new service or technology is not always less energy-intense than the replaced one. An energy reduction can also lead to so-called rebound effects, which introduce additional energy consumption. Direct rebound effects are caused by price-elasticity effects. This means that an increase in efficiency or productivity can cause an increase in energy consumption, due to lower costs for the same consumption. Indirect rebound effects are caused by the cross-price-elasticity of complimentary service.

On the long-term, economy-wide effects of digitalization are macro-economic changes across economic sectors, which can further lead to transformational effects, also changing human preferences.

Table 1.1.: *Taxonomy of ICT energy effects and their net energy use (Based on [63])*

Scope of Impact	**Effect**	**Net Energy Use**
Embodied energy Operational energy Disposal energy	Direct	Increase Increase Increase
Efficiency Substitution Direct rebound	Indirect: Single service	Decrease Increase or decrease increase
Indirect rebound	Indirect: Complementary services	Increase
Economy-wide rebound (Structural change)	Indirect: Economy-wide	Increase or decrease
Systemic transformation	Indirect: Society-wide	Increase or decrease

As shown in Table 1.1, various aspects have to be considered, concerning the effects of digitalization on energy consumption. It has to be demonstrated that additional resources for the deployment of new systems can generate sufficient opportunities, to achieve resource productivity and efficiency gains to make them not only economically feasible but also sustainable. If this is possible, these technologies will be applied in various fields in the energy-intense industry and enable new, so-called "smart services" in combination with new business models [82].

2. Situation in Austria

Digitalization and Energy

Crucial factors for a successful realization of decarbonization are the further development of energy infrastructure and new (breakthrough) technologies for energy supply and production processes. Digitalization measures can highly support the optimal integration of technologies and usage of infrastructure.

To be able to reach future climate goals and support the optimal integration of technologies and usage of infrastructure by digitalization, measures have to be taken not only on an international, but also on a national level. Therefore, in this section a specific focus is laid on Austria. To understand the challenges in the national production sector, especially the energy-intensive industrial production, a summary of the current situation is given. Consequently, the following energy and greenhouse gas emission relevant aspects are presented and discussed:

- Currently used energy carriers and the shares of final energy consumption by the sectors with challenges arising from the state-of-the-art and a future outlook.
- Overview of current centers of excellence in the field of digitalization to show areas of interest and specific focuses reaching from competence over specific educational programs to companies.

Furthermore, to show the effort in this field, a choice of digitalization projects and applications in the Austrian industrial sector is shown. Also, realized educational programs, as well as centers of excellence are presented.

2.1. Energy Consumption and GHG Emissions

Energy Carriers and Energy Consumption in the Austrian Industry

In the following an overview of the current situation regarding energy consumption in the Austrian production sector is given, based on data provided by Statistik Austria [125, 126]. In total 93.7 TWh final energy were consumed by the industrial sector in 2017. In Fig. 2.1, the utilized final energy carriers are shown. As electricity generation is still characterized by a high share of fossil primary energy carriers, the bigger share is still covered by fossil energy carriers. In Fig. 2.2, the share of final energy, in total 93.7 TWh, for specific production sectors is shown. Important consumers are the sectors pulp and paper, non-metallic minerals and glass, engineering as well as food and tobacco production. Also chemicals and petrochemicals, as well as iron and steel are big energy consumers. Nevertheless, for those two, the total energy consumption is even higher as Fig. 2.2 reveals, which is explained in detail below.

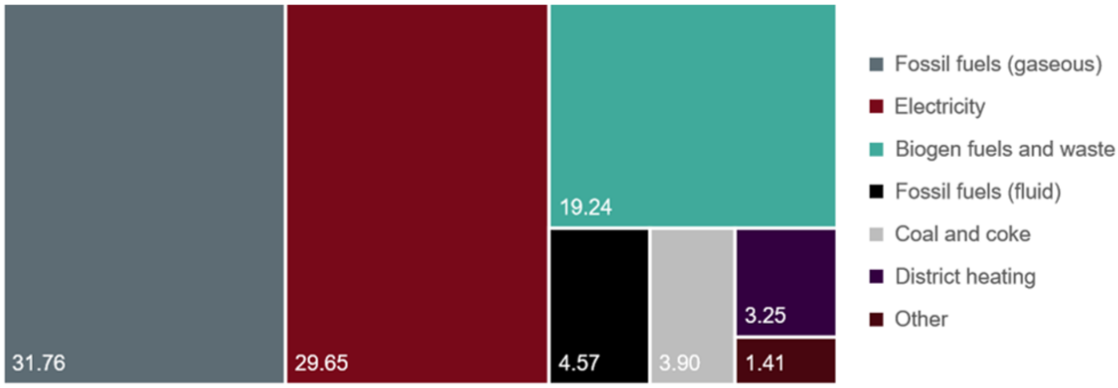

Figure 2.1.: *Energy carriers for final energy consumption in Austrian industrial sector 2017, values in TWh (Data from [125])*

Nevertheless, these figures do not show the entire picture as they do not take the following aspects into account:

- Corresponding primary energy for electricity generation from fuels with respective efficiencies. For detailed information regarding the relation between (not only industrial) conversion input (103.1 TWh) and output (67.4 TWh), see [125].
- Energy input to and efficiency of conversion in specific facilities e.g. the coke facility and blast furnace in the iron and steel production process. This is defined as "consumption of the energy sector" (21.7 TWh) and conversion input (24.5 TWh, partly regarded in Fig. 2.1 and 2.2 as final energy after conversion) in [125], compared to approximately 10 TWh of final energy in the iron and steel sector.
- Energy of crude oil and natural gas liquids used as conversion input (105.1 TWh) or rather material input for refineries as well as consumption of the energy sector in mineral oil processing and for the exploitation of oil and gas (5.95 TWh) [125] or as feedstock in chemical industry, compared to approximately 12 TWh of final energy in the sector chemicals and petrochemicals.

However, these shares are of particular importance when talking about decarbonization. From the list above, one can see that several fossil energy carriers are neglected in the final energy consumption statistics. This is still presented here, as it comes together with detailed data regarding the energy carriers, the shares for sectors and also the usage of the energy (e.g. space heating, steam generation, furnaces, etc.).

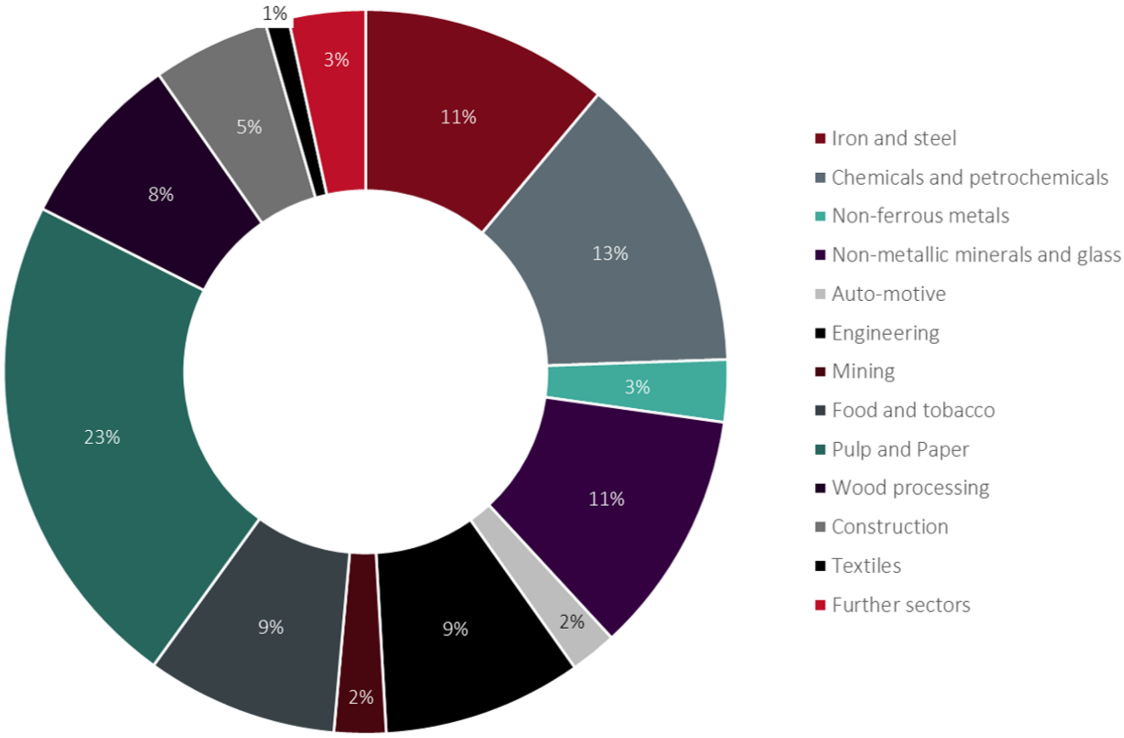

Figure 2.2.: *Shares of industrial energy sectors of final energy consumption in Austria in 2017 (Data from [126])*

GHG Emissions in the Austrian Energy and Industry Sector

National emissions trends are published and reported to the European Union annually [93]. Fig.2.3 shows the development of total emissions without the removals from land use, land-use change and forestry (LULUCF), energy-related emissions and process-related emissions in the last decades.

Furthermore, the share of total energy-related emissions is compared to the total emissions and accounts for approximately 70% of total emissions. The energy-related emissions result mostly from fuel combustion. Approximately 20% of energy-related emissions are caused by fuel combustion in the manufacturing industry, see Fig. 2.4.

Fig. 2.5 shows the share of process-related emissions. A major share of those emissions results from chemical conversions in the metal sector, the mineral sector (e.g. ceramics, glass, cement) and the chemical sector.

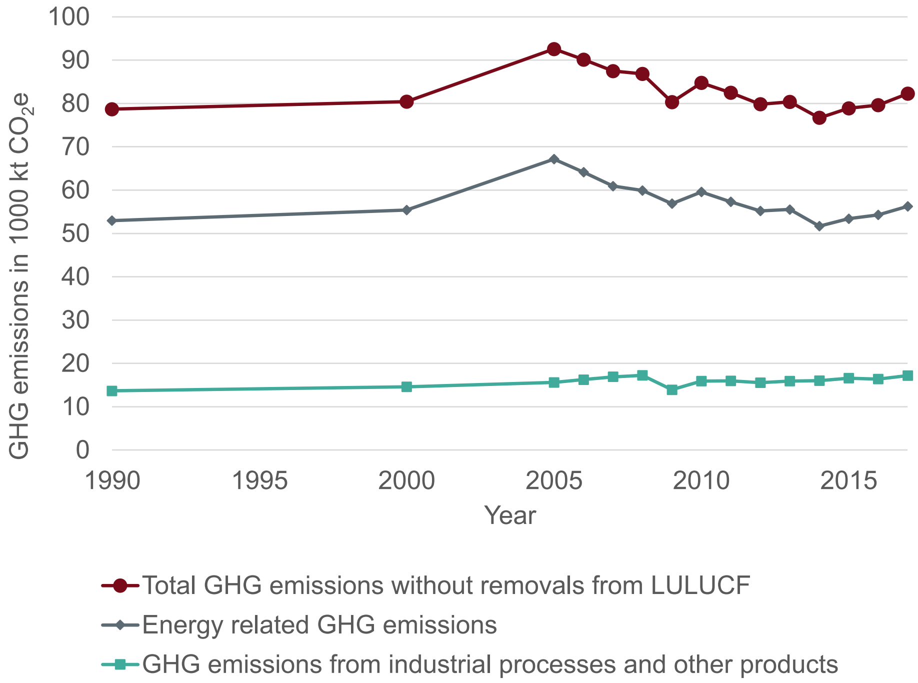

Figure 2.3.: *GHG emissions in Austria without removals from LULUCF from 1995 (basis year) until 2017, (Data from [93])*

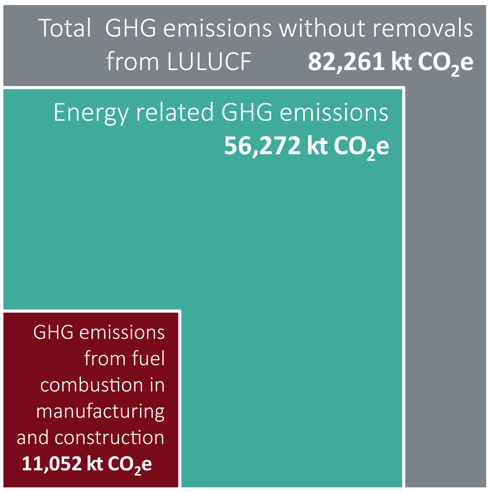

Figure 2.4.: *Relation of energy-related and fuel-combustion-related emissions in industrial sectors in 2017 (Data from [93])*

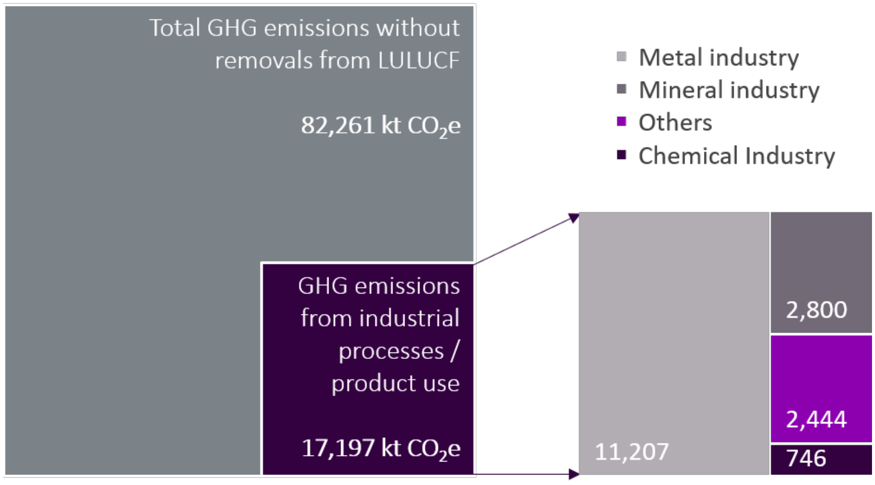

Figure 2.5.: *Relation of emissions from industrial production processes from total emissions without removals from LULUCF in 2017 (Data from [93])*

Future Challenges for Industrial Energy Supply

The industrial production sector and the national energy system are going to change within the next decades, given the fact that national and global measures are necessary to achieve climate goals. Therefore, energy consumption and greenhouse gas emissions need to be reduced as well as the share of renewables increased. Fig. 2.1 reveals that in order to decarbonize industrial energy supply more than 40 TWh of current fossil final energy carriers (fossil fuels and coke) have to be replaced. Considering the energy input for conversion processes and the 'sector energy' in the production of chemicals, iron and steel leads to even higher amounts of fossil energy carriers that must be replaced. Furthermore, to decarbonize the electricity, generation must be shifted from fossil primary energy carriers to renewable sources. A decarbonized Austrian energy supply for industrial production processes might lead to the following:

Increased Final Energy Consumption Despite Efficiency Measures | Now, several fossil energy resources are defined as conversion input and not considered in the final energy consumption. Furthermore, high-caloric by-products from the conversion are used as energy carrier in further process steps. In the case of decarbonization, these by-products need to be replaced. Therefore, new production routes have to be developed and implemented, which leads to the replacement of conversion input by final energy consumption (e.g. steel production).

Higher Shares of (Renewable, Fluctuating) Electricity to Fulfil the Energy Demand | With an increasing share of renewable electricity – mainly with the characteristics of fluctuating generation – also the complexity of ensuring grid stability and simultaneous supply and demand will increase. Typically, the grid infrastructure needs to change in the long-term.

Related burdens and tasks are e.g. temporal mismatch and spatial distance of electricity generation and demand, as well as a required highly efficient and cascadic usage of high caloric energy carriers and raw material. Digitalization and corresponding information and communication technology (ICT) solutions might help to successfully manage the related challenges and realize an interconnected energy system with industrial prosumers.

In the following, some examples for use cases with relevant key technologies and applications supporting a transition to an energy-efficient, low-emission industry are listed. These shall highlight the importance of digitalization techniques for decarbonization attempts along with the above described changes in technology and infrastructure:

Accurate Forecast Systems | Often realized with accurate modeling, digital twins and machine learning algorithms, for renewable generation and the (industrial) demand

Business Models | Promoting the production and consumption (prosumers) of locally generated renewable electricity over borders of factory locations and enterprises realized with easy financial transactions (blockchain), secure and standardized information exchange (cybersecurity and open platforms)

Building of Virtual Power Plants | To support grid stability measures including fast aggregation, analysis and processing of data, flexible energy conversion components, accurate modeling and forecasting, secure and standardized information exchange

Implementation of Smart Sensors, Data Analysis Models and Advanced Controls | Closing the loop to the process, to prevent inefficient operation points of industrial production systems and optimize operation in a multitude of objectives/goals.

2.2. Austrian Centers of Excellence

In Austria, activities in the field of digitalization, energy and industry can be found in various organizational structures. Experts are available from competence centers, over research institutions and inter-organizational committees. Furthermore, several educational programs contribute to ensure qualified humanpower in the future. A choice of relevant Austrian companies performing projects, development and activities in the field of digitalization and information and communication technology (ICT) are presented in the following section.

Competence Centers

In Austria, several K1 centers are working on relevant and future topics and technologies. They are part of the COMET program (Competence Centers for Excellent Technologies) with the aim to build up and focus competencies through excellent cooperative research with a medium- to long-term perspective [40].

Know-Center GmbH | The Know Center GmbH[1] - Research Center for Data-Driven Business and Big Data Analytics - in Graz was founded in 2001 and collaborates today with more than 50 partners from industry and science. Since 2015, a big focus is laid on big data and data-driven business. The development of e.g. the following technologies is addressed: Visually interactive user interfaces for interaction with large amounts of data; security concepts for data platforms and the Internet of Things (IoT); methods for processing large data streams in real-time [43]. A specific focus is laid on industrial applications, in order to e.g. optimize processes or implement process automation and enterprise resource planning (ERP) systems in the business field industrial data analytics. Within this business area, the latest methods of data analysis, including advanced statistical methods, are used to process enormous amounts of rapidly generated industrial data [79].

ABC - Austrian Blockchain Center | Founded in 2019, the Austrian Blockchain Center[2], partnering with Austrian companies from different sectors (energy supplier, insurance, public service, etc.) and research institutions, works on: Cryptographic basics; technology and data security; cryptoeconomic modeling and business applications; blockchains in manufacturing and emerging industries; data science methods for blockchain analysis and prediction; legal and political aspects. Contributing to the Austrian blockchain action plan, they aim to develop among others efficient, secure and data protection compliant payment channel networks in blockchain applications as well as new consensus methods and data protection in blockchains. Furthermore, they strive for software engineering and simulation environments for blockchain applications [41].

CDP - Austrian Center of Digital Production | Founded in 2017, the Austrian Center of Digital Production[3] collaborates with at the TU Wien, University of Vienna and the Economic University of Vienna. Furthermore, industrial partners from the production sector

[1] https://www.know-center.tugraz.at/
[2] https://blockchain-center.at/
[3] https://www.acdp.at/

are working with the CDP. A central challenge for manufacturing companies will be to support an automation, control and documentation chain that is as closed as possible; the center handles the entire process steps from acquisition to delivery: Virtualization of product and production systems to allow complete product specification and reliable process planning. The development of automated product design shall accelerate the construction phase but also the work preparation. Standardized protocols for machine-to-machine communication support the implementation of flexible, reconfigurable automation systems. Furthermore, digital production platforms and networks lead to the dynamic formation of virtual smart factories. [42]

Pro2Future | Pro2Future[4] was started in 2017 and collaborates with scientific partners and (energy-intensive) industry form Upper Austria and Styria. This competence center aims at developing the next generation of industrial ICT, cognitive products and industrial systems. Products and production systems shall be equipped with human-like cognitive abilities such as perception, understanding, interpretation, memorization and learning, reasoning and corresponding cognitive-driven autonomous action. Therefore, three basic areas for ongoing work are defined: (i) Machine perception and awareness, (ii) Cognitive robotics and shop floors, and (iii) Cognitive decision systems. Those areas will provide the technical basis for (iv) Cognitive products and (v) Cognitive production systems.

Inter-organizational Expert Committee

Industrie 4.0 Österreich | The association Industrie 4.0 Österreich[5] was founded in 2015 as an initiative of the Austrian Federal Ministry of Transport, Innovation and Technology (BMVIT), as well as employers and employees associations. Representatives from industry, (academic) research organizations, private and public service sector, software development and implementation as well as interest groups form specific expert groups to develop strategies for the sustainable and successful implementation of digital transformation in the context of Industry 4.0. The aim is to use technologies and innovations through digitalization in the best possible and socially acceptable manner and to implement them responsibly [139]. The expert groups focus on the following topics: pilot factories; norms and standards; research, development and innovation; qualifications and competences; regional strategies; the employee in the digital factory; intelligent logistics; new business models and security and safety [140]. Furthermore, use cases from producing Austrian companies are reported, e.g. usage of digital sensors to realize automatized lot size one production, sensor-based light management, digital logistic support, etc. Industrie 4.0 Österreich also supports arranging the event series Business Safari Industrie. Within two-day-excursions, different Austrian best-practice companies with regard to Industry 4.0 applications, are visited regularly [135].

[4] http://www.pro2future.at/start-en/
[5] https://plattformindustrie40.at/

Digitalisierungsagentur - Digitalization Agency | The Digitalization Agency is intended to serve as a central platform for important digitalization measures to master the challenges of digital transformation. Therefore, specific projects are opened up and implemented with a particular focus on smart and medium enterprises (SMEs), expertise and know-how is provided, digitalization opportunities are communicated and stakeholders and actors are brought together. Furthermore, the agency advises the federal government and politicians and coordinates activities and projects in the areas of digital infrastructure, economy, education and society, research, development and innovation, as well as data protection and data management. Strategic development of the Digitalization Agency is coordinated from experts of Austria's competence centers, research institutes, the federal government, as well as industrial players [45].

Academic and Educational Contributions

In the following educational programs, degree programs, research institutions, specific departments, endowed professorships and doctoral schools are listed contributing to the field of digitalization in industry.

Endowed Professorships

Endowed professorships, often financed by industrial partners, federal organizations or research institutions with common interest show and highlight specific areas of interest.

Industry 4.0: Adaptive and Networked Production Systems | The endowed professorship "Industry 4.0: Adaptive and Networked Production Systems" was established in 2018 by the Alpen-Adria University Klagenfurt (Institute for Applied Computer Science) and the Graz University of Technology (Institute for Software Technology). A research field will be established at the interface of artificial intelligence, operation research and production management. The development of solutions based on modern methods of artificial intelligence for relevant practical operational tasks in production, logistics and management shall be promoted [4].

Human Centered Cyber-Physical Production and Assembly Systems | The BMVIT-endowed professorship "Human Centered Cyber Physical Production and Assembly Systems" at the Institute of Management Sciences at the Faculty of Mechanical Engineering and Industrial Management of the TU Wien is co-funded by the Austrian Research Promotion Agency (FFG) the several industrial companies. Industrial production and value creation has lately been triggered by industrially usable, networked digitization and automation solutions. The sector is changing in terms of organization, work equipment, division of labor between human and machine, work content and skills as well as corresponding qualifications. Additionally, the design of production systems is changing towards agile, IT-supported planning and control supported by new tools. This research group works on the design, use and further development of digitally networked assembly systems in the sense of an integrated socio-technical work system design. The continuous creation of prototypical demonstrators in the pilot factory Industry 4.0 in close coordination with other participating institutes plays a central role [68].

Industrial Energy Systems | TU Wien and the Austrian Institute of Technology established an endowed professorship in 2015 for the research field "Industrial Energy Systems". The following topics are worked on: Technologies to increase energy efficiency; optimized use of thermal components and optimization of operating strategies; development of methods for the increased flexibility of energy supply and production. [12]

Doctoral schools

SIC! – Smart Industrial Concept | The cooperation college SIC![6] focuses primarily on digitalization and decarbonization in the producing industry. Therefore, three scientific partners, the TU Wien, the Austrian Institute of Technology and the Montanuniversität Leoben collaborate with partners from industry, engineering, energy supply and technology providers. The overall goal is to develop methods for the energy-optimized operation of industrial plants and their energy conversion, distribution and storage units. This shall make a significant contribution to support the integration of renewable energy sources in increasingly volatile systems and markets. The model of a complex industrial energy system is scientifically developed and tested. Thus, the basis for targeted implementation in industrial production systems and energy-supply environments shall be provided [141].

Resilient Embedded Systems | Within this doctoral school, starting 2019 at the Faculty of Informatics at TU Wien in collaboration with FH Technikum Wien, novel methods to design, verify and implement safe, secure and dependable computing architectures subject to real-time constraints are developed. The topics cover all aspects of the direct interaction of computer systems and their environment: from the lowest level of circuit and hardware architectures to safety-critical cyber-physical systems like industrial automation, building automation and smart grids, healthcare, spacecraft, and automotive including networking infrastructures. Challenges regarding industrial applications in designing such systems are among others: meeting of real-time and power/thermal constraints; stopping operation in the case of failures is often not feasible, "trial-and-error-style programming" is not an option in many applications; emergent behavior originating from autonomous operation must be understood and controlled; integration and complexity issues created by the upcoming Internet of Things must be managed; etc. [38].

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[6] https://sic.tuwien.ac.at/home/EN/

Pilot Factories

Pilot Factory 4.0 | Several industrial partners and technology providers collaborate with three institutes from the faculty of Mechanical and Industrial Engineering of TU Wien at the Pilot Factory 4.0[7]. The Pilot Factory 4.0 is a demonstration plant for smart production and cyber-physical production systems and also deals with new concepts and solutions for variant serial production (low volume – high mix). Developing, testing and improving new strategies for industry requires a realistic testing environment – real machines, real production chains, a real product. This is offered at the pilot factory where students can work on the production of genuine, usable products. Components from 3D printers are chosen because they are relatively complex objects that can be produced in a variety of variations. The production is therefore sufficiently challenging to be scientifically interesting. Scientific know-how about optimal production techniques can be developed, which then benefits the economy. At the same time, the pilot factory will play a decisive role in the teaching and further education paths. The following areas of application are dealt with: Machining in robotic flexible manufacturing cells; robotic laser processing for joining / cutting and additive / hybrid manufacturing; in-house logistics with a focus on lean methods and autonomous handling systems; lean assembly and worker assistance systems for assembly processes. Furthermore, the following digitalization-relevant topics are addressed: Internet of Things technologies and solutions for flexible automation; solutions for vertical integration along the automation pyramid ("from shop floor to top floor"); solutions for horizontal integration along the value chain (manufacturing, internal logistics, assembly) across the different production stages; life cycle integration from product development through production preparation to production with the continuous mapping of real systems through a so-called digital twin, see Section 3.4.

Smartfactory@tugraz | Located and operated at the Technical University in Graz, the smartfactory@tugraz[8] is funded equally by the BMVIT and industrial partners. This model factory in which state-of-the-art mechanical manufacturing and assembly facilities are combined with advanced information technology products to form a cyber-physical production system aims to create a unique place for research, teaching and knowledge transfer in the field of digitalized manufacturing. Within the environment of producing real products, they also offer a development environment for sustainable new and individual solutions. smartfactory@tugraz is aimed in particular at companies from trade and industry, whereby the needs of SMEs are of great importance.

Educational and Degree Programs

In 2017 an application-case-based survey was performed to determine Industry 4.0 relevant qualification requirements and their effects on the Austrian educational landscape. Also a screening

[7] http://pilotfabrik.tuwien.ac.at/en/
[8] http://www.smartfactory.tugraz.at/

of the Austrian education and training landscape with regard to Industry 4.0 relevant courses was done. Clear differences were found in the temporal dynamics in which individual educational institutions adapt their course offerings to changing framework conditions. The tertiary education sector shows that significantly more universities of applied sciences (Fachhochschulen - FHs) offer Industry 4.0 relevant degree programs than universities. While 71% of the FHs offer courses related to Industry 4.0, 29% of the Austrian universities list corresponding curricula in their courses. For the latter, the term industry 4.0 could not (yet) be found in any study program, whereas for FHs, the term was already used in the curricula. Individual universities of applied sciences offer courses of study that are directly related to the topic of industry 4.0 or directly aimed at it, such as the Bachelor's programs "Smart Engineering of Production - Technologies and Processes" at the FH St. Pölten and "Automation Technology" at the FH Oberösterreich. At the universities, the degree of specification (Industry 4.0) is lower; the focus is on the most comprehensive education possible in the respective fundamentals, such as mechanical engineering, mechatronics, etc. However, this in no way diminishes the importance of the university as an important Industry 4.0 educational institution in Austria, but only illustrates the different field of tasks and activities compared to the FHs. Nevertheless, a trend towards increased attention for Industry 4.0 applications can be detected at universities when taking the increasing number of relevant endowed professorships during the last four years into account. In the secondary education sector, Industrie 4.0 relevant courses are primarily found at the higher technical colleges and the vocational schools (apprenticeship) in industry. Further industry 4.0 relevant continuing education courses are also offered at WIFI (2017 more than 350 relevant courses) and BFI (2017 over 200 relevant courses) [97]. Beginning with October 2019, new degree programs will start at Johannes-Kepler university (JKU) in Linz. With a bachelor's and master's degree in the field of artificial intelligence[9] JKU is among the first European universities offering specific programs with a focus on this crucial topic.

Innovation course – DigiTrans 4.0 | The objective of this course[10] (held from 09/16 to 11/18) was to lead the participating companies into the era of industry 4.0. Therefore, a network across faculties was build up to combine business IT and production IT leading to interlaced information flows along the value-added chain. This step-by-step implementation of Industry 4.0 was achieved through the modular and interdisciplinary structure of the innovation course dealing with product lifecycle management, models and methods for digital transformation, industrial communication and automated manufacturing systems, value added networks, integration engineering and gender and workplace 4.0. Due to the multidisciplinarity of the consortium a knowledge gain in the implementation of future-relevant fields of technology was expected.

[9] https://www.jku.at/en/artificial-intelligence/
[10] https://www.digitrans.at/

2.3. Digitalization Projects in the Austrian Industry

The following section briefly describes projects carried out in the Austrian industrial sector. First, an overview of completed projects with a focus on the production itself is presented. For those projects the authors analyzed the potential impact of the project on energy and emission-related aspects. Further, several digitalization approaches relevant to energy supply are listed. Finally, an overview of similar projects is given, which are realized in the institutes preparing this white paper.

Examples for Industry 4.0 Applications in Austrian Projects

The summaries hereafter are reported as use cases, projects and applications for Industry 4.0 in the report about relevant qualification requirements in the Austrian educational sector with regard to industry 4.0 [97]. The impact on energy and emission-related aspects is derived within this white paper.

Company: ABB AG

Scope: Usage of intelligent systems in pulp and paper production combining the reporting for industrial and purchase processes (overall enterprise levels)

Benefit: Process optimization, efficient production, enabling of forecasts, analyses and reports for the complete production process

Impact: In general, optimized processes and good forecasts allow an increase in energy efficiency and a reduction in energy consumption of the process. Therefore, also the total emissions can be reduced.

Company: AMAG AUSTRIA METALL AG

Scope: Data collection over the whole process chain to increase product quality (mainly production level)

Benefit: Daily measurements can be enhanced and included in quality assessment, side parameters can be evaluated and analyzed, correlations can be found, improved handling of big data (data reduction and aggregation)

Impact: Data acquisition alone does not increase the energy efficiency on the first hand. However, when data is processed and analyzed to increase the product quality, also a reduction in energy consumption can be achieved. Vivid examples for this are e.g. more accurate drying in the food industry. Often products are dried to a higher extent than necessary to avoid mold formation. With suitable sensors and data, product quality (optimal dry content) can be enhanced while energy can be saved.

Company: AVL LIST GmbH

Scope: Integrated and open development platform to combine virtual (prototype) and real (test) world for system simulation over the entire company (cyber-physical system implementation)

Benefit: Support of optimizing the required product (car) features, early-stage interaction of components and operation strategy, in general: improved dealing with complexity

Impact: With a sophisticated simulation / virtual environment for test systems, products can be optimized and energy consumption, both in the design and operation phase, can be reduced. Therefore, efficiency increases and emissions can be lowered.

Company: BRP Powertrain GmbH

Scope: Optimal usage of collected data and together with FFG optimization of the (prospective) digital architecture in enterprises with corresponding development of standardization (overall enterprise levels)

Benefit: Application of Industry 4.0 tools, implementation of programming software, construction tools, planning and scheduling tools, interdisciplinary team building and knowledge enhancement

Impact: Optimized planning and scheduling tools on an overall enterprise-level allow efficient interaction between all departments/ teams / units. Together with implemented standardization this can lead to the faster adaption of lessons learned in e.g. the production and test process. Better and shorter development times also allow a reduction of resource consumption, e.g. regarding energy consumption.

Company: ELMET Elastomere Produktions- und Dienstleistungs-GmbH

Scope: Automation of production monitoring: fully automatic monitoring, analysis, inspection and documentation of parts or products over the whole enterprise system

Benefit: Process optimization, efficient production, minimizing of failures, improved quality, advanced competitiveness

Impact: Optimized, high-quality, efficient processes with minimized failure rates lead to a better, more efficient usage of raw materials and energy resources. Consequently, the efficiency of energy consumption can be increased while the emissions can be reduced.

Company: EPLAN Software and Service GmbH

Scope: Full automation/digitalization of the value chain (from engineering to the production of switch cabinets) of the Friedhelm Loh Group

Benefit: Improved value creation and quality, reduced costs, better adaption to specific client requirements

Impact: A digitized value chain allows the minimization of raw material, energy input and storage room/warehouse capacities with adapted room conditions. Thus, also the energy consumption and emissions are reduced.

Company: EVOLARIS NEXT LEVEL GmbH

Scope: Development/introduction of digital assistance systems for employees in production processes (prospective application will be elsewhere)

Benefit: Definition of requirements of assistance systems for employees, testing of developed systems, evaluation of technology experience, development of further (application) projects

Impact: Tools supporting employees directly responsible for production processes allow a faster recognition of inefficient operation conditions, plant aging or forthcoming failures. By early recognition of such states measures can be taken to maintain an efficient operation and avoid increased (energy) consumption levels.

Company: FILL GmbH

Scope: Installation of a fully automated processing line/plant at a customer for the production of crankcases to allow further customers process information and quality control as it is in in-house production

Benefit: Component of the plant control themselves according to process parameters, product related data is all-time available, therefore, online control and adaptions are possible, data collection of each component

Impact: Fully automated processing lines allow the minimization of raw material, energy input and storage room/warehouse capacities with adapted room conditions. A comprehensive data collection also leads to early recognition of inefficient operation conditions. Thus, also the energy consumption and emissions can be reduced.

Company: Fronius International GmbH

Scope: Creation of awareness for the topic area of Industry 4.0 in the entire company (workshops, presentation of best practice examples, etc. in the company)

Benefit: Creation of awareness, deriving of opportunities and chances for Fronius, first implementations of own ideas

Impact: Within such workshops also the awareness for energy supply-related aspects can be increased.

Company: KEBA AG

Scope: Data mining/analytics in production to find correlations of products, frequency of orders or models, client variance, etc. and improve the forecast of orders and customer behavior (main impact on production and supply chain)

Benefit: Visualization of order behavior of clients, classification of clients, forecasts of the orders and production, individual solutions

Impact: Better forecasts allow minimization of raw material input, energy consumption and warehouse capacities. Thereof, energy consumption and GHG emission levels can be lowered.

Company: KUKA ROBOTER CEE GmbH

Scope: Development, construction and use of a sensitive lightweight robot to enable human-machine-collaboration

Benefit: For the supplier of the new product advances in competition and the position in the market can be achieved. Customers will benefit in the future when individual solutions for their processes can be found

Impact: Individualized solutions lower the overproduction of goods and warehouse capacities. As Industry 4.0 tools such as robots allow "specified mass production" without significant increase in energy consumption, such projects also contribute to efficiency increase. Such projects allow the fulfillment of customer satisfaction increases while the energy consumption level remains constant.

Company: Logi.cals GmbH

Scope: Automation solution (offering a closed integration and test environment for software) which can be applied to overlapping enterprises and locations

Benefit: Interaction of software development of the customer and logi.cals, faster reaction to and correction of errors, faster and better application for the client

Impact: Faster interaction and communication between different locations of an enterprise can lead to faster reaction to inefficiencies and failures, e.g. in development processes. Thus, resource consumption can be lowered.

Company: Logi.cals GmbH

Scope: Integration platform for digitizing and integrating engineering value chains/processes (the developed tool will be offered to potential future customers)

Benefit: Modeling of plants can be done faster and more efficient

Impact: Fast and efficient plant modeling allow the conservation of resources. Energy consumption, both in the set-up, as well as in the operation phase can be optimized. Emissions will be reduced.

Examples for Digitalization Applications in Industrial Energy Supply

Examples in Section 2.3 illustrate that an important focus lies on digitalization and networked production processes of the various applications in companies. Furthermore, e.g. Siemens realized several projects in the field of digitalization of the process industry, which also cover the digitalization of actual energy supply and energy conversion issues [117]. Further projects are continuously reported on the innovation blog of Siemens [70].

Company: Agrana Stärke GmbH - Applicant, Siemens - Technology Provider

Sector: Food, Agrana is a starch and bioethanol producing company from the food sector

Scope: Fully integrated production (starch and bioethanol production monitored together) route with interacting PCS (Siemens SIMATIC PCS 7), manufacturing execution system (Siemens SIMATIC IT) and an existing ERP systems

Benefits: Increased productivity, 100% exploitation of used resource, autonomous operation of both product routes but interlinked steering and control, optimized human resources for maintenance and training, use of excess heat in the production process, energy savings realized with optimized controllers

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Company: Stiegl Brauerei - Applicant, Siemens - Technology Provider

Sector: Food, Stiegl is an Austrian Brewery

Scope: Holistic automatization and visualization of the brewhouse with Siemens SIMATIC S7 and the software WinCC, recipes can be controlled and adapted by the brewing master

Benefits: Increased flexibility and efficiency, ensured high quality, linking of data from various sources and platforms

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Company: EDS4.0 - Applicant, Siemens - Technology Provider

Sector: Digitized water management and planning

Scope: Water systems, as well as wastewater treatment plants are digitalized to ensure safe and secure system states. Therefore, Siemens life cycle engineering tool COMOS is used.

Benefits: Lower maintenance costs, high supply reliability, avoided mistakes

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Company: Takeda - Applicant, Siemens - Technology Provider

Sector: Pharmaceutics

Scope: Implementation of an energy management system (Simatic B.Data) to fulfill requirements of the energy efficiency law. Energy flows are systematically recorded

Benefits: Identification and quantification of energy-saving potentials, visualization of flows

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Digitalization Approaches in Projects within the Consortium

Within the consortium working on this white paper several (industry-related) projects are carried out in the field of digitalization attempts to reduce energy consumption and greenhouse gas emissions. The projects related to the energy supply of industrial processes are shortly described in the following.

Online Optimization of a Complex Industrial Power Plant | VTU Energy GmbH (now ENEXSA GmbH) developed together with Voestalpine Stahl GmbH an online optimization of a complex industrial power plant in the steelmaking sector using a novel fast and accurate modeling approach. This optimization is very fast but also very accurate. It is able to consider storages, batch processes and highly fluctuating load profiles and does not violate any technical constraints. It is based on Ebsilon Professional, which is a thermodynamic modeling solution. The aim of the optimization solution is the most profitable short-term operation of the power plant under current and forecasted operating conditions fulfilling the heat and steam demand of the steelmaking plant. By providing explicit advice on the setpoints of the individual plant equipment, the system closes the gap between the optimization of the long-term energy trading and the actions of the power plant operators at the very moment. [106]

OxySteel | The project OxySteel within the energy region NEFI contributes to climate goals. It encompasses the increase of energy efficiency by the use of novel technologies and the evaluation of DSM potentials in a steel mill. The first goal is tackled by the development and implementation of a new process design using oxy-fuel combustion and CCU. The second objective is to identify flexibilities for the increased use of renewable energy sources and possible grid services.

EDCSproof | Also carried out within the framework of NEFI the project EDCSproof aims at developing an online, predictive and holistic, reconfigurable control concept for industrial energy supply systems, which supports the integration of renewables by using energy storages, works as a flexible consumer for electric grids (demand side management considering dynamic tariffs), increases efficiency by optimal control of the overall system, and utilizes waste heat by using high-temperature heat pumps ($\leq 150°C$), hence showing a future concept for decarbonizing using the possibilities of digitalization. This also includes a user-friendly human-machine interface for efficient input of production plans, visualization of current and predicted plant states, and possible intervention by operators and managers. The expected project result (as part of the NEFI thematic model region) is a widely applicable, cross-sector energy concept for subsequent implementation at the sites of the project partners, as well as for a vast majority of companies. The energy efficiency and thus the competitiveness of the producing industry will be increased, the share of renewable energy will be supported and the pioneering role of Austria strengthened. In addition, plant engineers, automation experts and technology manufacturers will benefit from additional business cases in the long-term.

HySTePS | In another project from NEFI, HySTePS, the aim is to develop and experimentally test an innovative hybrid storage concept to increase the storage capacity of Ruths steam accumulators in operation by up to 40% by applying additional latent heat storages. The mid-term goal is to reduce the retrofit investment costs required to half of an equivalent Ruths steam accumulator. This results in shorter payback periods (3-5 years), and thus enables economically feasible energy efficiency measures.

DigiBatch | The project DigiBatch develops a workflow and IT components to provide small and medium-sized enterprises in particular with a simple and cost-effective tool for quality and production assurance and for preserving core knowledge about the production process. Targets are to show how physical models from existing simulation environments can be linked with empirical knowledge from the knowledge base and with real-time data from the current process. As digital twins of the core process in a cloud platform, they can be coupled centrally into the current optimization cycle at the enterprise level.

AdaMo | In AdaMo, AIT and AutomationX deal with the burden that industrial bioprocesses require more efficiency in the product life cycle. The goals are an acceleration of the time to market, lower manufacturing costs and better productivity. The biotech industry is therefore calling for new methods to evaluate the large amounts of data already available and to ensure efficient, targeted experimental design and the transfer of knowledge along the product life cycle. AdaMo uses basic mathematical methods for a better understanding of the applicability of model-based methods in bioprocess engineering. Numerical tools will be adapted and implemented in easy-to-use workflows to generate, calibrate, verify and implement models, as well as to increase their fields of application and robustness.

3. Digitalization Techniques and Technologies

3.1. Big Data - Integration and Fusion

The term "big data" was coined under the explosive increase of available digital data sources and storage abilities. The field of big data deals with processing data in the context of this increasing data availability. However, what distinguishes big data from conventional data? Gartner defines big data as:

Definition

> *"Big data is high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making." [50]*

A more general approach was taken by D. Laney [83] by characterizing big data along three dimensions:

- Volume - characterizing the data quantity and number of data sources,
- Variety - referring to the diversity of data types and sources including unstructured data such as audio, video or text, and
- Velocity - referring to the speed with which the data is generated, analyzed and processed.

More aspects were added to this list, forming the so-called "V's of big data". Although there have been considerable discussions from both industry and academia on the definition of big data, a unified definition is still missing. As can be seen from the "V's", one key aspect of big data is the variety of data types and data sources.

Data Integration and Fusion | Data integration and data fusion are dealing with this heterogeneity of data. They refer to the process of merging multiple heterogeneous data and information sources regarding a single subject into a more consistent, accurate and useful representation compared to any individual data source. The aim is to establish a basis for the seamless integration of multiple and diverse data sources and data types. In practice, this means that data available from various sources (e.g., process control, resource planning systems) and from various types (e.g. textual or graphical) is put into a standardized format and combined to a single database or data stream. The use of standardized data schemes, semantic data models, as well as data ownership issues are important aspects involved in data integration and fusion.

Applications

At present, although the importance of big data has been generally recognized, companies and industry (apart from large Internet companies such as Google and Amazon) are still struggling to implement and tap the potential of big data applications. There is, however, a large set of potential use cases for big data applications in all industrial sectors [22, 91]. These use cases range from maximized yield in chemical processes to improved digital marketing activities in the automotive industry. The high number and the variety of potential use cases exemplify the ability of big data applications to transform all business layers, from management to sales or production processes. This is exemplified by the following projects:

HotCity - Gamification as Data Collection Opportunity for City Planning | For the development of districts with high energy efficiency and increased use of locally available and sustainable energy sources, detailed spatial identification of possible energy potentials is necessary. In particular, waste heat from industry (e.g. foundries and food production as well as commerce as data centers and supermarkets) can make an important contribution to heating and hot water production in plus-energy districts. Small waste heat sources are not recorded and do not appear in available databases. Thus, the identification of these sources is associated with various difficulties. In the project HotCity, gamification will be used to collect data for energy-oriented neighborhood planning through crowd-sourcing. The goal is to identify and locate waste heat sources in the cities of Vienna and Graz. The project investigates whether and with what effort relevant data can be obtained using this gamification approach, e.g. by taking photographs of chimneys and re-cooling systems. Using innovative approaches from Artificial Intelligence and big data Analysis as image localization and recognition, a spatially detailed potential assessment might be possible. [64]

GEL OpenDataPlatform | The transition from a fuel-based, unidirectional to a renewable, decentralized energy system requires the widespread adoption of new technological innovations. The main goal of the project GEL OpenDataPlatform [52] is the development and implementation of an open data platform (ODP) for the energy sector to provide easy access and an overview of relevant data and interdependencies of integrated energy systems. Consumption patterns and, based on that, forecast models will be developed, providing a better understanding of load flows and enabling the identification of flexibility options in the energy system. The ODP aims to provide all end users insight into their energy consumption or efficiency data, allowing a comparison with similar households and tailor-made recommendations for energy-relevant measures.

Gaps and Barriers

Cyber-physical systems are found throughout all industrial sectors. This is a main distinguishing factor compared to online businesses, since information and communication technology (ICT) is embedded in the entire system instead of only in the enterprise IT backend. As a result, there are significant barriers to be overcome before the potential benefits of big data-related technologies are realized. A survey [31] of business information experts in the DACH region (Germany, Austria and Switzerland) shows that only 23% already use the possibilities of big data to a certain degree. Although big data is generally seen as promising, the main barriers in the use of big data-related applications are the expected high costs and the missing skilled personnel and experience. The barriers to implementing big data-related applications in the energy-intensive industry range from technical to societal and organizational issues [131, 16]:

Lack of Experienced Workers | Comparatively few people on the job market are experts on big data management and, at the same time, have the necessary domain know-how of the respective industrial sector. Thus, a critical challenge will be ensuring the availability of skilled workers such as data scientists and engineers who have expertise in analytics, statistics, machine learning, data mining, and data management.

Privacy | Data security and privacy concerns regarding big data are a significant barrier to industrial companies.

Digital Data Sources | Availability and access to data is the foundation for big data analytics. Digitization and automation of infrastructure, however, requires upfront investments to enable the use of real-time high-resolution sensor data of industrial processes. This involves large-scale and heterogeneous data acquisition, efficient data storage, massive real-time data processing and data analysis, data curation, advanced data retrieval and visualization, intuitive user interfaces, interoperability and linking of data, information, and content.

Costs | The development of big data analytics tools within an organization requires substantial investment in data recording, storage, analysis, etc.

No Experience with Data-Driven Business | Establishing new business models that are based on big data analytics is hindered by potentially long innovation cycles.

Potential and Future Outlook

Massive amounts of data are collected in industrial production operations today, coming from different domains such as control, management, sales or consumers. The potential to use this data to achieve further improvements in process and business performance is a key driver for big data-related technologies. This trend is fuelled by the supply of data in very large volumes due to ubiquitous computing as well as the connectivity of devices, referred to as the Internet of

Things (IoT). Big data will be the basis for many applications in the energy-intensive industry including forecasting, digital twins, energy efficiency improvements, optimal control or design optimization.

Industrial Internet of Things (IIoT) | Data in the context of IIoT comes in large amounts, is a mixture of structured and unstructured information and often has to be processed in real-time. Data sources exhibit significant differences in quality, coverage, accuracy and timeliness. Thus, managing, extracting and understanding valuable knowledge from multiple data sources in industrial processes is a significant challenge. As a result, many existing solutions become improper to handle big data due to the high computational complexity.

Data as Resource | Big data offers tremendous untapped potential value for many sectors. It is regarded as one of the key economic assets of the future with the potential to transform industrial sectors. Big data applications in the energy-intensive industry range from increasing operational efficiency and product quality to new marketing and sales strategies and precisely targeted products and effective distribution. Due to the presence of cyber-physical systems, the industrial needs and requirements are, however, essentially different from big data technologies employed by online data businesses and, thus, not directly applicable. Nevertheless, the benefits of sharing and linking data across domains and also industrial companies allow organizations to create new value that no single organization could achieve by itself.

3.2. Blockchain

A blockchain is a shared or distributed data structure or database running on a digital network that contains digital transactions, data records and executables, that continuously expand in chronical order. Transactions within the structure are aggregated into "blocks", which are added at the end of the "chain", making it a time-stamped and continuously growing list of records.

Definition

> *"Blockchains are shared and distributed data structures or ledgers that can securely store digital transactions without using a central point of authority." [6]*

First, to create a new block, a transaction has to be initiated. The content may contain a variety of actions, most commonly being the transfer of value between users. Next, the new transaction is distributed around the network to be verified by peers. Peers are millions of distributed computers within the blockchain network. After successful validation, the transaction can be included in a new block. At this point, the transaction is considered confirmed. Finally, the new block will be added to the end of the chain and become a permanent part of the network. Since each block is time-stamped and cryptographically linked to previous blocks, a chain of records is formed. Figure 3.1 shows the difference between a centralized, where there is one single trusted authority, and a distributed transactional system, where every member holds a copy of the transaction. Figure 3.1 also shows a blockchain transaction, where users agree on a transaction that is then included in a block. The blocks' validity is confirmed by distributed nodes of the network and the block is added to the chain before the transaction is confirmed and finalized. [6]

There is no individual place where the data is stored, it is rather a network of millions of computers that own the information collectively. Therefore, there is no central authority over the blockchain. Information is completely transparent and for everyone to see. [6]

Since each blockchain database is managed autonomously using a peer-to-peer network and a distributed time-stamping server, participants can verify and audit transactions independently and relatively inexpensive. The concept of time-stamped and linked unique blocks also removes the possibility of duplicating digital assets and thus solving the problem of double-spending, in which a digital token can be spent more than once. [6]

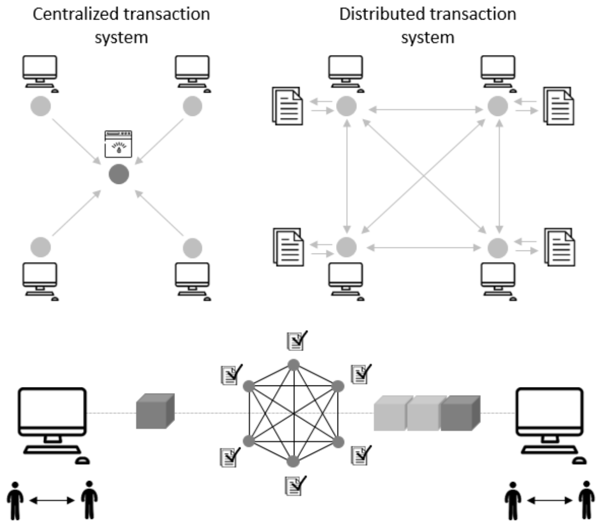

Figure 3.1.: *Visual representation of centralized and distributed transactional platforms (above) and of a blockchain transaction (below)*[1] *(Based on [6])*

Applications

To get an overview of the state of the art of this digitalization technology, relevant Austrian projects and applications are described below:

Cryptocurrencies | Probably the best-known application for blockchain is cryptocurrency. In this context, blockchains are used to create digital assets that are used as a medium of exchange – digital cash. While cryptographic algorithms ensure the integrity of the financial transaction, the peer-network controls the creation of additional units and verifies the transfer of assets. Besides the popular Bitcoin and Ethereum, there are currently more than 2400 different cryptocurrencies [23]. Austrian companies such as Coin Factory Austria or Hydrominer offer crypto mining from 100% renewable energy. This is particularly exceptional considering that blockchains generally consume huge amounts of energy. In addition to cryptocurrencies, the Österreichische Post has introduced the first crypto stamp, the first blockchain stamp worldwide [55].

Open Government Data (OGD) Vienna City | In order to provide transparent government data to the public, the City of Vienna started the OGD project. This blockchain pilot enables independent checks, whether data records of the city existed at a specific time. By opening its data records, the City of Vienna is taking another step towards implementing its open government strategy, being a pioneer in this area. Digital food vouchers are another application that have already been tested successfully. The employees of the City

[1] Icons made by Freepik and Pixel perfect from www.flaticon.com

of Vienna have the opportunity to use meal allowances in the form of food stamps. Food stamps in paper form, however, involve a high level of logistical and organizational effort. Blockchain now helps to automate and optimize the related processes. [102]

Smart City Viertel Zwei (District Two) | Smart City Viertel Zwei is a pilot project within the heart of Vienna that focuses on sustainable urban living. Energy consumed by residents is sourced from a nearby geothermal power plant as well as photovoltaic systems on the roofs of the houses in Viertel Zwei. Using blockchain, the generated excess electricity is democratized and can be fed back into the grid via smart contracts when the demand is higher and more lucrative. [112]

Grid Singularity - D3A Energy Market | The D3A (Decentralized Autonomous Area Agent) is a decentralized energy exchange developed by Grid Singularity to enable a decarbonized, decentralized, democratized and digitized energy system. Basically, the D3A exchange is a set of smart-contracts, which are based on blockchains, necessary to create decentralized energy exchanges with a low barrier of entry. Hence, D3A allows energy devices of arbitrary scale to trade with their peers on a scalable market platform. The D3A exchange engine is available open-source. Energy companies and consumer groups can use the D3A UI to improve operations and make investment decisions, leading to the potential deployment of the D3A exchange engine to run their decentralized and distributed smart grid efficiently. In brief, the D3A showcases and harnesses the potential of trans active grids, renewable energy sources and peer to peer energy trading for all stakeholders in the energy transition. [25]

To give some perspective, enliteAI is a homepage that keeps track of the Austrian blockchain landscape and provides an overview of companies, platforms and institutions leading the development of blockchain development in Austria (Figure 3.2). [18]

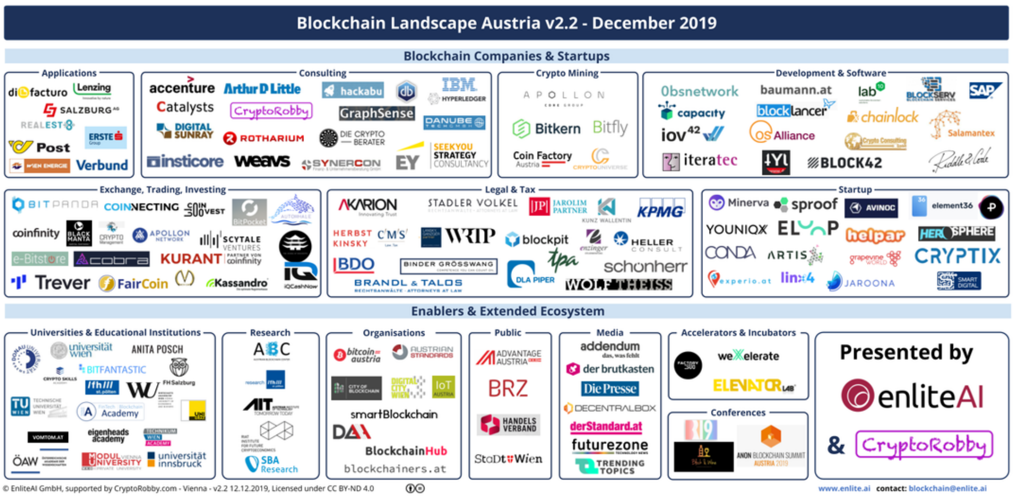

Figure 3.2.: *Blockchain Landscape Austria [18]*

Gaps and Barriers

The following gaps and barriers towards a successful implementation of blockchains in various applications could be identified:

High Energy Demand | One of the main challenges that the blockchain technology faces are high sustainability costs. To run the highly energy-demanding computations on a mining network, enormous amounts of electricity are needed. For example, the energy consumption of the Bitcoin mining network equals that of the entirety of Ireland. [17]

Network Security | Privacy and anonymity being a big feature also means that blockchains are hard to govern and lack vigilance by the authorities. This leads to the formation of darknet marketplaces with various criminal intentions. Therefore, industries might find it challenging to implement blockchain platforms without any significant improvement in the existing technology and network security. [17] (The government of Vienna has taken its first steps in the OGD Vienna City project.)

Subsequent Editing of Information | As approved transactions are almost impossible to modify and will stay on the peer-to-peer network indefinitely, accidentally sent information via blockchain to another user are almost impossible to revert. [17]

Potential and Future Outlook

Blockchains have been gaining in significance in the last years and show potential for various industrial applications. Three applications with high potential for future research are energy management, food and beverage industry and the pharma industry:

Energy Management | The Startup Transactive Grid uses Ethereum blockchain technology to enable the transaction between customers in decentralized energy generation schemes. This allows people to generate, buy, and sell energy to their neighbors effectively. Energy management is one of many industries that has historically been highly centralized. For example, in the US and UK, the transaction of energy is dependent on an established power holding company like Duke Energy or National Grid or dealing with a re-seller that buys from a big electricity company. A distributed ledger could minimize (or even eliminate) the need for intermediaries, which, in this context, refers to rethinking the traditional energy-exchange process. Other companies have used blockchain as a path toward providing access to renewable energy, too. For example, two major Spanish power companies - Acciona Energy and Iberdrola — are using blockchain to certify that energy is clean by tracking its origins. [13]

Food and Beverage | In the past, there have been a lot of disturbing slip-ups in the food and beverage industry, referring to E. Coli, salmonella or accidental horse meat. The blockchain technology could help manufacturers and distributors avoid these accidents by monitoring the food supply chain and tracing contamination issues to their root using a decentralized ledger that records, stores, and tracks data. It also benefits the food processor, which can avoid sending harmful items to distributors, the retailer (which can lead to reducing as well as responding more quickly and effectively to recalls) and the consumer (who can trust that what they buy is safe). In this way, blockchain serves as an accountability platform. For example, a simple implementation for blockchain-based tracking can use a QR-code, which shows a product's full journey to a customer's cart, when it is scanned. [13]

Pharma Industry | The pharma industry is usually a slow-moving industry despite its focus on innovation, better regulation regarding production and smarter medical data security. For instance, research can be published earlier, without scientists worrying about their intellectual property. If a report is published through a blockchain-enabled system, there will be a permanent record of its existence, preventing others from claiming it as their own. Blockchain can also enforce safer drug production. If errors are made, they can be caught and traced to the source. This helps prevent recalls, or at least allows manufacturers to quickly contact retailers to lessen the impact of unsafe drugs on patients' health and businesses' finances. [13]

3.3. Data-driven Modelling

Although the concept of data-driven modeling (DDM) and machine learning (ML) is not quite new, a variety of definitions exist. In order to get a better understanding of DDM and ML, this section will focus on their characteristics and how they are distinguished from each other.

Definition

> ***Data-driven Modeling:*** *"Data-driven modeling (DDM) is based on the analysis of the data characterizing the system under study. A model can then be defined based on connections between the system state variables (input, internal and output variables) with only a limited number of assumptions about the "physical" behavior of the system." [122]*
>
> ***Machine Learning:*** *"ML theory is related to pattern recognition and statistical inference wherein a model is capable of learning to improve its performance of a task, based on its own previous experience" [94]. "Examples of ML models include artificial neural networks (ANNs), support vector machines (SVMs), and relevance vector machines (RVMs)." [7]*

Contrary to a physically-based model that relies on our understanding of physical equations, a data-driven model uses mathematical equations based on analysis of concurrent input and output data, using few or no assumptions about a device's physical behavior. Data-driven models can use ML methods and are capable of autonomously finding relations between system variables without the explicit knowledge of the system's exact physical behavior. Actual (observed) output data is compared with predicted output data and ML algorithms aim to minimize the difference, as shown in Figure 3.3. By understanding the connections of system variables, DDM can be utilized for complex industrial or energy-related applications where conventional physical models are impractical or do not exist at all. [122]

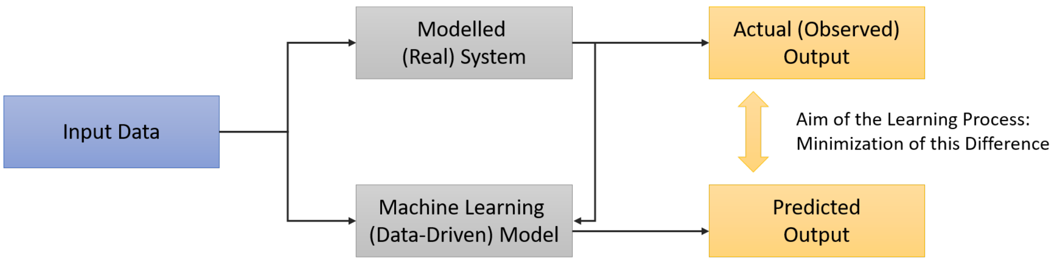

Figure 3.3.: *Learning in data-driven modeling (Based on [122])*

Artificial Intelligence (AI) | The attempt to create a human-like, cognitive intelligence with the ability to learn and to solve problems on its own. It is the greater objective and the driving motivation for the development of DDM and ML.

Machine Learning (ML) | ML can be described as a subset of AI that focuses on training a machine on how to learn. It is related to pattern recognition and statistical inference, wherein a model is capable of learning to improve the performance of a task, based on its own previous experience [7]. This is achieved by either supervised or unsupervised learning.

Supervised Learning | In addition to the raw input data, the desired output is fed to the algorithm. Therefore, the system already knows what the output is supposed to look like and only has to figure out how to get there. The algorithm is being taught with a training data set that guides the machine. A schematic representation of supervised learning is shown in Figure 3.4. Algorithms used for supervised learning include linear regression, support vector machines, decision trees and artificial neural networks. [138]

Unsupervised Learning | For this process, we use the same input data as before but without the desired output. Therefore, the system has no reference data at all. This increases the complexity, as there are no a priori known connections between the variables. Classification algorithms are used to determine the closeness of variables and values and similarities between objects to group and label them. A schematic representation of unsupervised learning is shown in Figure 3.4. Algorithms used for unsupervised learning include artificial neural networks, clustering, and anomaly detection. [138]

Applications

In the following industrial Austrian projects, DDM has been successfully integrated:

Voestalpine Linz and VTU Energy - Time Line Optimization System | The Austrian company Voestalpine produces steel and high-performance metals. The high amounts of energy required for steel production are provided by the Voestalpine Linz power plant, which consists of six gas-fired power blocks where electrical power, process steam, and district heat are converted from process off-gases (from the blast furnace, coking plant and steel mill). Depending on absence or excess of power, electricity is either bought from or sold to the electricity market. In order to optimize the highly complex processes of the various stages of steel production, changing prizes of energy and gas have to be taken into account. Therefore, a thermodynamic model, in combination with DDM, has been integrated into the plant management. Process data created by the thermodynamic model is used by a data-driven model and can be utilized for optimizations in real-time. Plant operators are supported in finding optimal process set points for achieving maximum profit. [106]

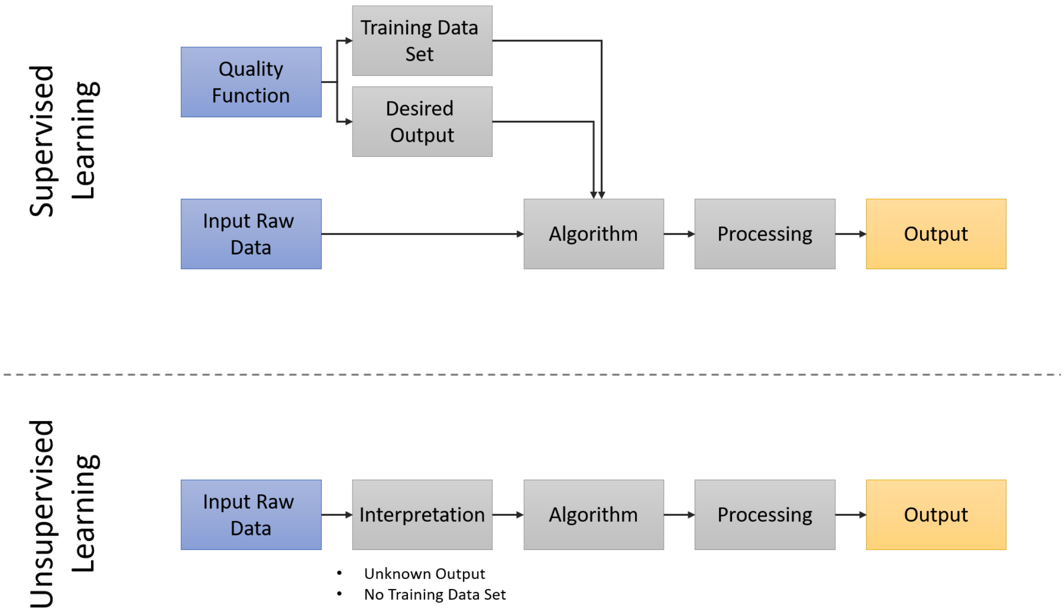

Figure 3.4.: *Schematic representation of supervised/unsupervised learning (Based on [138])*

Oil and Gas Industry | DDM is providing numerous advantages for the oil and gas industry. Companies rely heavily on sensor-based data to monitor the efficiency of production and the future performance of their reservoirs. The huge amount of data that is created from various sources often comes in an incoherent manner. Conventional physically-based models either require high computational effort and still lack reasonable process times, or they are unable to process the data at all. However, without the need to understand the physical behavior of the system, DDM is utilized to find relationships between these data sets. Once the connection of system variables (input and output data) is established and the model sufficiently trained, it can be used to increase the production capacity of reservoirs, simulating fluid flow, or forecasting extreme events. [21]

Gaps and Barriers

One of the main gaps for DDM lies in handling new and unknown input data. Since models are created by using historical training data sets, the capabilities of each individual model are limited by the extent of these training sets. Processing input data within the scope that the model was trained for will likely produce the desired output data. However, complex applications may often present diverging inputs that the model is unable to process correctly due to insufficient training. This, in combination with the underlying fact that DDM does not consider exact physics behind a process, can lead to output data that is simply incorrect and unusable. Therefore, the accuracy of DDM goes hand in hand with the availability of sufficient training data. [90]

Potential and Future Outlook

Using available industrial data, DMM has a high potential for different industrial applications, including energy demand and generation forecasting, complex process models or hybrid models for error prediction:

Energy Demand and Generation Forecasting | The uncertainties of energy demand, combined with the weather-related generation of wind farms and photovoltaic facilities, poses a great challenge for the application of renewable energy sources. Since grid stability relies on the balance between energy production and consumption, the implementation of these renewable energy sources into the grid can be difficult. An efficient integration can be achieved by either accurate demand forecasts or the utilization of extensive energy storages (e.g. pumped hydroelectric energy storage). In the future, renewable energy providers will increasingly use data-driven forecast models to gain better insight into short-term and long-term energy demand and volatile generation and how to adapt energy production and demand accordingly.

Fast Reacting Process Models in Complex Industrial Applications | Conventional physical models can be complex and computationally intensive. Even with high-end hardware solutions, computing times can be too high for process optimization and control models. Sufficiently trained data-driven models that have established the relationships between input and output data are able to decrease computing times drastically. In this way, real-time data can be used to quickly respond to changing process parameters and adjust operating points accordingly, in order to improve process quality and energy efficiency.

Hybrid Models for Error Prediction | Research that has been conducted to examine the use of DDM for hydrological models (e.g. river flow forecasting) suggests combining physically-based models with data-driven models. The goal is to implement DDM as an error prediction mechanism. The physically-based model is seen as the primary model, simulating certain water-related variables. Produced output data is compared to actual recorded data and errors are calculated. A secondary model, the data-driven model, is trained on the recorded errors and can be used to correct errors of the primary model. Therefore, data-driven models may not only be used for discrete applications, but also for error prediction and correction of other physically-based models. [122]

3.4. Digital Twinning

Industry 4.0 in general aims for wide-ranging digitalization to revolutionize manufacturing processes and transform conventional factories into smart factories. One of the technologies that is developed extensively for this latest industrial revolution is digital twinning and thus the focus of this section. [111]

Definition

> *"Digital Twin is a virtual representation that matches the physical attributes of a "real world" factory, production line, product or component in real-time, through the use of sensors, cameras, and other data collection techniques. In other words, Digital Twin is a live model that is used to drive business outcomes, and can be implemented by manufacturing companies for multiple purposes [111]:*
>
> - *Digital Twin of an entire facility*
> - *Digital Twin of a production line process within a facility*
> - *Digital Twin of a specific asset within a production line"*

Digital twinning describes the process of mapping a physical system or asset to a digital platform in order to create an identical virtual mirror image. The complexity of a digital twin depends on the application. It can range from simple machines to production lines or entire factories. In the first step, a virtual model of the physical asset is created. According to the application of the digital twin, the model can be an exact replication with each individual component or a simplified version that only displays process-relevant parts of larger machines within a production line. The next step is to connect virtual and physical counterparts by utilizing the Internet of Things (IoT). The IoT is a concept, in which basically any device - mechanical or digital - is connected in a network with the ability to transfer data without the requirement of human interaction. Within the IoT, physical components that are equipped with sensors provide constant real-time data to the virtual system in order to keep the two synchronized. After the connection between the two spaces has been created, the digital twin can be put to use. Tweaks on products or processes can be simulated on the virtual system and only be implemented physically once proven successful in the digital environment. Real-time data of wear and tear parts provide the base for predictive maintenance, where repairs are done just-in-time and unnecessary maintenance intervals can be reduced without the risk of component failure. [136, 89, 145]

With the excellent scalability of digital twins and the growing IoT comes a wide-ranging field of applications including energy optimization, digital machine building, performance tuning, predictive maintenance and optimizing product life cycles. [96, 116]

Applications

The following chapter will introduce three applications where digital twinning has been successfully implemented. Each of these projects has been developed by Austrian companies and provides a deeper insight into how this technology is used to improve industrial and energy-related applications:

VERBUND - Hydropower 4.0 | The pilot power plant Rabenstein is part of the project Digital Power Plant 4.0. It is testing the conceptual design and integration of digital systems to increase efficiency and reliability. Intelligent sensor concepts, such as acoustic monitoring systems linked to an AI, provide data for anomaly detection and projection models that are used to create a digital twin of the power plant. Using the sensor data, the digital twin can predict the remaining service life of crucial machine parts and initiates maintenance before failures occur. Additionally, the digital twin can be used to simulate different operating modes without disrupting the power plant's daily operation routine. [47, 116]

ANDRITZ – IDEAS Simulation Software | ANDRITZ has created a digital twin application for the pulp and paper industry. It combines the simulation software IDEAS with an execution platform where human interactions can be implemented into continuous processes. This enables simulations of the life cycle of an entire facility, including feasibility studies and online optimizations. Various design scenarios can be simulated to maximize performance and eliminate design flaws early on. Necessary equipment specifications can be identified and bottlenecks during operation avoided. In addition, the digital twin provides a virtual training platform for operators similar to a flight simulator. During actual operation, real-world measurement can be used for real-time online process optimizations. [121]

AEE – Institute for Sustainable Technologies – Building Tracker | A currently ongoing project lead by AEE INTEC focuses on the optimization of energy demand and thermal comfort for the Raiffeisen passive house high-rise building in Vienna. The goal is to create a digital twin of the building to monitor the actual energy demand as well as multiple influences such as weather, ambient temperature, interaction with heat networks, integration and use of renewable energy and user behavior in real-time. Data gathered this way will be used in an innovative building energy management system to create a nearly zero energy building. Once applied successfully, this principle could be implemented in other buildings or even whole urban districts. [44]

Gaps and Barriers

Despite the promising outlook for digital twinning, there still are some challenges that need to be addressed.

IoT | Although the digital twin may never represent its physical counterpart to 100 %, the more data is provided, the better the replication can get. Correspondingly, improvements in the IoT will go hand in hand with improving the basis for every digital twin. Currently, there is a fragmented state of connectivity with many closed platforms and single-use applications that needs to shift to a more comprehensive IoT. [10]

Incomplete System Data | Insufficiently modeled systems and a lack of measured data will lead to a limited representation of the digital twin. Workflows could be displayed incorrectly and faulty parts dissimulated. Energy optimizations based on incomplete data may actually increase overall power demands instead of decreasing them. For sensitive industrial or energy related applications, a deficient digital twin could very well be detrimental to the system.

Limited Flexibility | Despite the promising capabilities of this technology, the digital twin is limited by its physical counterpart. Simple, straightforward processes may lack in flexibility and variable parameters that can be modified in order to achieve system improvements. These applications will have to adapt processes and workflows to provide a broader field of engagement.

End-to-end Visibility | Current digital twin applications face the challenge of reaching both physical and digital spaces at the same time. For this challenge, augmented reality technologies will provide future solutions. For example, with immersive holograms, machine-to-machine-to-people collaboration is possible and both physical and digital spaces are accessible simultaneously. [71, 5]

Management of Real-time and Historical Data | In general, data for digital twins has to be managed in two directions. Data from the physical asset is fed to the virtual part to keep it updated, and in return from the virtual twin to apply action at the real one. All that generated data has to be captured and processed in an efficient way. In addition to the real-time data, historical data sets have to be created that can later be used for offline analysis. These huge amounts of information call for enabling technologies in computation, data processing and data management. [96]

Data Security | To utilize a digital twin, huge amounts of data have to be collected and securely stored. Estimations show that by 2023, 75 % of digital twins will have at least five endpoints where data can be accessed, each of them posing as an area of weakness. As digital twin applications will grow in size, so will the number of endpoints and thus the potential risk of compromise. [32]

In summary, there is a general lack of in-depth research for digital twin, related to energy and industrial applications. Although several pioneer projects have proven feasibility in different areas, further extensive research is vital for digital twinning to become a standardized technology for energy-intensive industrial plants.

Potential and Future Outlook

Digital twinning shows great promise and a vast field of applications, including:

Power Generation and Distribution | Entire windfarms, nuclear facilities and coal plants can be duplicated, analyzed and monitored, using digital twinning. Environmental changes affecting windmills and turbines can be identified and ideal operating points adjusted accordingly. Power grids will be transformed into smart grids where energy service providers can use real-time data to make strategic decisions. This proves especially useful for the integration of renewable energy sources like PV facilities that currently lack efficiency due to the need for complex control engineering.

Energy Management | As ISO 50001 energy management certifications are becoming a state-of-the-art requirement for modern companies, they are subject to regular energy audits. In Austria, these energy audits must be performed for large enterprises regularly in accordance with the law. Digital twins can provide comprehensive data regarding the efficiency of individual machines and processes. This data will be used to increase overall performance and productivity as well as to aid energy audits.

Peak Load Reduction | Unnecessarily high peak loads of production lines or facilities can be avoided by looking at the entirety of more complex processes. Simulations made by the digital twin can identify opportunities to optimize process sequences and thus even out the overall energy demand and reduce energy costs.

Production Flexibility | Using real-time data, future digital twins will enable facilities to adapt to changing environments and market needs dynamically. This will help to optimize production processes, product quality and general flexibility of factories.

To give a final perspective, Gartner ranks digital twinning among the top ten strategic technology trends of 2019 and estimates a vast application of digital twins by 2020. [49]

3.5. Flexible Components

Definition

"In the context of engineering design one can define flexibility as the ability of a system to respond to potential internal or external changes affecting its value delivery, in a timely and cost-effective manner. Thus, flexibility for an engineering system is the ease with which the system can respond to uncertainty in a manner to sustain or increase its value delivery." [143]

The term "flexible component" is applied differently in different industries:

Manufacturing Industries | In terms of manufacturing industries, flexible components are parts of modular production systems, which are capable of performing a variety of tasks within a given scope of applications. Also new technologies like 3D-printing or laser cutting can be seen as flexible new components in this context.

Energy-intensive Industries | In terms of energy-intensive industries, flexible components are parts of the plant that allow to adjust or shift the energy generation and consumption according to external drivers, like fluctuating energy prices or outside temperature changes. For example, these components can be energy converters such as generators, heat pumps or different types of energy storages.

State of the Art

Today there are many different types of flexible production systems that differ in automation level, system flexibility and type of different possible tasks that are executable. The targets of flexible manufacturing are flexibility in time, resources and operations. Compared to conventional mass production with fixed production lines and several similar units, the implementation costs of flexible production systems are rather high. [48]

In conventional production systems, lot sizes as big as possible are preferred to minimize the specific production costs. This is achieved by reducing set up times and other cost factors that are directly related to the change of the currently manufactured product. By "lot size one", the ability to produce one piece of a product according to specifications given by the customer is understood. New production technologies like 3D-printing are nowadays mostly used in the sector of rapid prototyping or small series production. These additive production methods can help to reduce time and resource consumption and help drive the development and realization of "lot size one". [139]

In industries with high power and heat demand, a combined heat and power (CHP) generation, especially when a fuel source like biomass is available on site, is preferred. This is caused by the higher efficiency of CHP generation compared to a simple heat supply like a burner. Most of the time, heat and power are not needed simultaneously at the amount provided by CHP. This causes a necessity for flexible components like energy storages, which can help to bridge the gap between demand and supply. Commonly used thermal energy storages (TES) are sensible TES, where the energy is stored through the temperature change of the storage material and latent TES, where the energy is stored by phase transformation of the storage material like melting and solidifying. Other available systems are steam storages and thermochemical energy storages. Also electric energy storages are gaining in importance, because their high relative costs are constantly sinking.

The transformation of energy is an alternative, which in some cases yields an improvement to solutions that only use storages. Transformations like power to heat (P2H) or power to gas (P2G) are already in use. Power to heat is achieved by the usage of electric boilers or heat pumps. Power to gas uses surplus electrical energy to split water into hydrogen and oxygen through electrolysis. The hydrogen is then directly stored and used as an energy source or mixed with carbon dioxide and then converted to methane.

In the following, some recent projects that aim for the implementation of flexible components into industrial applications are presented:

EDCSproof | The project EDCSproof, which is carried out within the energy region NEFI, aims at developing a novel control concept for industrial energy supply systems. This system supports the integration of renewables by using energy storages and heat pumps among other measures.

HySTePS | Another project within NEFI is HySTePS. It has the aim to develop and test an innovative hybrid storage concept in order to increase the capacity of Ruth's steam accumulators by up to 40%. The concept is visualized in Figure 3.5. This improvement has the target to reduce retrofitting investment cost for Ruth's steam accumulators and thus the reduction of payback periods (down to 3-5 years).

Heat Recovery at Kärntnermilch reg.Gen.m.b.H | At the dairy factory of Kärntermilch, flexible components have been integrated for an optimization of the plant operation and reduction of the operation costs. Among several measures, a new steam boiler and exhaust gas heat exchangers reduced the energy consumption by 2,36 MWh per year. [11]

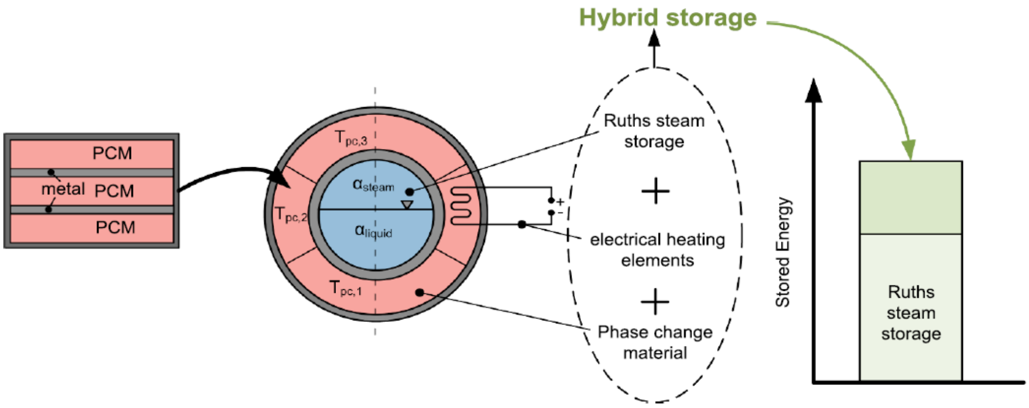

Figure 3.5.: *Hybrid TES concept for storing steam and electrical energy [35]*

Gaps and Barriers

For a successful and efficient integration of any flexible component into existing processes, detailed knowledge of the process is crucial. Requirements for this are:

Big Data | Often process data gets recorded and stored but remains unused because of the sheer complexity and amount of data. Big data analysis tools are needed to extract information like energy usage profiles that are important for the implementation of flexible components.

Data-driven Modeling | If enough and the right data is extracted from a process, it is possible to build a digital model for a specific purpose of it. With the help of this model, it is possible to identify potential improvements through a change of the design or the integration of flexible components.

Open Platforms | Over the life cycle of plants, parts need to be changed because of failure, wear or loss of efficiency. After some years, parts might not be available or state of the art anymore. In many cases, old parts are then replaced with more flexible components. In most cases, these new components have different operating systems, which need to be connected to the existing production system and information system. Standardized information interfaces would enable an easier integration of new components and technologies.

Sensors/Smart Meters | Design optimization and integration of flexible components require information about the component and the entire process. The data from sensors and smart meters, respectively their retrofitting, can be used for data-driven modeling and a description of a system or entire process. Thus, the further development of sensors and smart meters, combined with a standardized communication, can enhance the integration of flexible components in industry.

Potential and Future Outlook

In the energy-intensive industry, replacements of machinery are often very costly and the rather long plant life cycles are barriers for innovations. Nevertheless, to remain competitive and also to be able to meet new environmental requirements, flexibilities are needed. Flexible components help to operate systems as profitable as possible, which is crucial because of rising energy costs and additional costs for CO_2 emissions through emission certificates. The tendency towards fluctuating renewable energy sources like wind and solar power also requires certain flexibilities on the consumer side [109]. Thus, different types of flexible components will be required. The following applications show high potential for the future:

Retrofitting of Existing Plants | The ongoing development into the direction of Industry 4.0 sets high targets for industrial applications. Competitiveness, changing buyer behavior as well as the protection of the environment require an increase in flexibility and an adaptation of business strategies, in order to stay profitable. The increasing share of renewable energy sources in the grid and the fluctuating energy prices require an adjustment of the energy usage profile. Simultaneous design- and operational optimization of plants - with the help of mathematical programming or generic algorithms - can support the analysis of potential applications of flexible components.

New TES Types | TES with adjustable charging and discharging behavior are possible improvements for existing systems. For example, a hybrid storage concept combining a Ruths steam storage, electrical heating elements and a latent TES was analyzed by Dusek [35]. This concept increases the flexibility between the usage of thermal and electrical energy.

Local Integration and Sector Coupling | Optimized integration of thermal networks especially low-temperature district heating networks combined with heat pumps yield potential for flexible future applications, especially when heat and electric networks are optimized simultaneously.

3.6. Open Platforms

In software computing, an open platform is a software system that has provisions for open application programming interfaces (APIs). A platform is, thereby, defined as a group of technologies that are used as a base upon which other applications, processes or technologies are developed. Whether or not a platform is open can be defined in more general terms.

> **Definition**
>
> *A platform provides the basis for the development of other applications, processes and technologies. A Platform is considered "open" if there are no restrictions regarding its development, commercialization or use. Only reasonable restrictions that are non-discriminatory among all platform participants may exist. [36]*

In this way, a third party can integrate with the platform to add, change or build upon its functionality. In contrast, platforms that do not have such provisions are called closed platforms. It is noteworthy that all open-source platforms are open platforms, but not all open platforms are open source. To give a well-known example, Microsoft Windows has an open API, yet its source code is closed and proprietary.

Platforms as Middleware | Any IoT (Internet of Things) device has to connect to other IoT devices and - mostly cloud-based - applications to transfer information. The gap between the device sensors and data networks is filled by these IoT platforms. They function as the middleware between hardware, i.e., sensors and machinery, and application, such as data storage and analytics. Thus, these platforms need to easily integrate and connect with heterogeneous devices using various communication protocols and applications including those from third-parties. Rapidly evolving IoT ecosystems also require developers to have control over the entire system, its source code, integration interfaces, deployment options, data schemes, connectivity and security mechanisms.

Closed Platforms as State of the Art | Proprietary or closed approaches for connectivity, data management, security and collaboration were long considered the norm in many companies and industrial sectors. Domain- and vendor-specific solutions emerged and often became the de facto standard for specific solutions within companies. As a result, many companies and factories comprise a diverse combination of older machines, newer machines and tools, each relying on different protocols and platforms from different vendors. This incompatibility amongst existing and available devices creates additional efforts and hampers the rapid development of Industry 4.0 or Industrial Internet of Things (IIoT). [103]

Open Platforms Enabling IIoT | Open industrial standards and platforms, in contrast, allow for solutions that are interoperable, modular and vendor-independent. They offer the possibility to ease the integration and communication of devices and machinery. They simplify various issues that arise in the implementation of Industry 4.0, e.g., provision of standardized communication protocols, easier interoperability of various devices from different vendors, etc. In this way, open approaches are an efficient, secure and often lower cost solution. Thus, open platforms are a crucial component in every IoT ecosystem.

Applications

The need for open platforms in the context of Industry 4.0 was already recognized by many stakeholders, resulting in different initiatives and projects:

Eclipse Foundation | The Eclipse community is dedicated to the development of open-source software solutions. The community comprises leading organizations from information and operational technology and, among other specialized solutions, provides open source technology in the context of IIoT. [56]

STIP - Secured Trustworthy IoT Platform | This project addresses the development and dissemination of an open framework for IoT solutions in the context of security, communication, privacy management and interoperability. The Secured Trustworthy IoT Platform (STIP) uses a scalable and open framework in order to address market place demands for Industry 4.0, industrial automation or predictive maintenance applications. [127]

GEL OpenDataPlatform | The transition from a fuel-based, unidirectional to a renewable, decentralized energy system requires the widespread adoption of new technological innovations. The main goal of this project [52] is the development and implementation of an Open Data Platform (ODP) for the energy sector to provide an easy access and overview of relevant data and interdependencies of integrated energy systems. Consumption patterns and, based on that, forecast models will be developed providing a better understanding of load flows and enabling the identification of flexibility options in the energy system. The ODP aims to provide all end users insight into their energy consumption or efficiency data, allowing a comparison with similar households and tailor-made recommendations for energy-relevant measures.

Open Industry 4.0 Alliance | A recently founded alliance amongst engineering, automation and software companies with the goal to overcome and avoid closed approaches in the implementation of Industry 4.0 in Europe and beyond. [103]

Gaps and Barriers

Open platforms and standards are expected to play a significant role in the large-scale rollout of the IIoT. The following gaps and barriers towards the implementation of open platforms in industry were identified:

Scalability | Scalability describes the ability of a software - in this case, a platform and its infrastructure - to manage increased demand. Advanced IoT platforms have to ensure scalability in terms of the number of endpoints and data streams connected to the platform. This poses significant requirements on the platform's load balancing capabilities, computing power and storage, or network performance.

Standardization | Although many initiatives and groups are working to develop open standards for the implementation of Industry 4.0, there is still no widely used international standard to implement these technologies. This would, especially for small and medium-sized enterprises, be a key factor regarding the security of investment in the transformation of their information and control infrastructure towards IIoT. Secure standards and norms are also a condition to achieve a high number of network partners and, thus, to unfold the economic potential of Industry 4.0. Open standards and platforms will therefore play an essential role. [114]

Cybersecurity | Up to now, industrial control systems were operated relatively securely due to the physical isolation of such systems, the use of trademarked control protocols, legacy hard-/software or non-routable company networks. The ongoing digitalization and adaptation to IIoT bring about IT capabilities like remote access, monitoring or control. The use of open standards and platforms to enable this transformation, exposes industrial control system to a potentially increased security risk. This is due to open technologies being easily accessible, widely used and well documented. [8]

Potential and Future Outlook

A key part of creating successful Industry 4.0 solutions will be inter-connected heterogeneous devices and applications that can be seamlessly integrated through IoT platforms. Thus, software that relies on open and standardized approaches will provide the key building blocks that will promote interoperability and flexibility. This is recognized by many reputable companies that started to pave the way towards an open and standardized implementation of Industry 4.0 appliances and solutions.

3.7. Sensors/Smart Meters

Definition

> ***Sensor:*** *"A device that responds to a physical stimulus (such as heat, light, sound, pressure, magnetism, or a particular motion) and transmits a resulting impulse (as for measurement or operating a control)." [30]*
>
> ***Smart Meter:*** *A smart meter is an intelligent electricity meter that receives and transmits digital data and is integrated into a communication network. [148]*

Sensors | A sensor is a technical component that can measure certain physical or chemical properties qualitatively or quantitatively as a measurand. This measured variable is recorded and converted into a further processable electrical signal. There are different approaches to classify sensors. On the one hand, they can be divided into active and passive sensors, which either generate an electrical signal based on the measuring principle or require auxiliary energy supplied from outside. On the other hand, they can be divided due to their measuring principle (e.g. mechanical, resistive, piezoelectric, capacitive, optical, acoustic, magnetic sensors) [61]. Smart sensors represent a new classification category. They process data in an intelligent way, provide additional information about their environment or about themselves and can communicate within a sensor system (e.g. to improve measurement accuracy) [150] .

Smart Meters | A smart meter is an electronic device for the digital measurement and control of the consumption and supply of energy, mainly in the form of electricity and heat but also for resources like water and gas. They are connected to a communication network in which they provide and receive information. In the electricity industry, intelligent meters, together with automatic load and resource management, are part of smart grids [148]. In the following, only the use of smart meters as electricity meters is regarded.

Applications

Sensors have always played a significant role in the acquisition of information on physical or chemical states/reactions and are used countless times in the industry. They are utilized for monitoring processes and for control purposes. With the ability to capture and process more and more sensor data, they additionally serve now as a foundation for modeling, optimization, advanced control, predictive maintenance, production planning and automation. The collected sensor data is usually connected to a physical value. In the past and up to this day, only a fraction of the data is preprocessed and used in real-time for control tasks. Most data is stored in a database, where it needs to be manually retrieved for further postprocessing and use. [33]

In the modern industrial environment, sensors and sensor systems are embedded in Cyber-Physical Systems (CPS) in order to be able to use the data effectively, to support the quality control of the products, to guarantee the maintenance and efficient utilization of the production facilities and to practice product lifecycle management. Smart sensors share the collected data and serve as a basis for production decisions and actuator actions. [51]

Sensor Fusion | Smart sensors communicate with each other in real-time to do self-calibrations and check measurements for errors in order to deliver accurate results. Therefore, data of several different sensors are linked to derive more precise measurement data or higher-value data. Sensor fusion is used on the one hand to detect and correct erroneous measurement data from individual sensors, but also to draw conclusions about the state of the system, which are only possible with the aid of several sensors. Sensor fusion is crucial for safety-critical systems to use different redundant sensors in order to avoid wrong decisions based on incorrect measurement results. For cost reasons, a combination of cost-effective but error-prone sensors is often used instead of costly but more reliable sensors. [51]

Soft-sensor | Sometimes measurements of properties and parameters of products and processes are needed for which there is no sensor available and never can be available. The so-called soft-sensor is a combination of several physical sensors and an algorithm for real-time calculation of these new quantities in a process. A soft-sensor can also generate more knowledge from fewer implemented sensors. [87].

Smart Meters | Smart meters are mainly known and used as electricity meters. They measure power consumption and send and receive data over a communications network. This allows the grid operator to measure the customers' electricity consumption online at short intervals rather than manually at certain time points. With more accurate consumption data, the electricity grids also can be better regulated. Customers can better analyze their own data and reduce their costs by saving energy from silent consumers or better aligning their user behavior with electricity prices [148]. In Austria, smart meters are allowed to record data every 15 minutes and transmit it once a day to the electricity provider. The smart meters are allowed to transmit unidirectional data via an interface but are not allowed to perform control tasks [20].

In the following paragraphs, sensor and smart meter applications are described:

imPACts | As part of the COMET K project imPACts, researchers at the TU Wien and the pharmaceutical company Sandoz GmbH from Tyrol were able to develop a new tool for the industry: the all-in-one monitor for biochemical processes. The process is mathematically simulated on the one hand and measured on the other. By combining this information, the most probable process state can be estimated at any moment (soft-sensoring). [152]

Engine Testbed AVL | An application for sensor fusion is to locate measuring devices equipped with transponders in an engine test bench of AVL. A two-dimensional localization of the transponders is achieved by the fusion of direction and distance estimates [54].

usePat GmbH | The Vienna-based usePAT GmbH has developed a novel ultrasonic technology for process analysis. Ultrasonic add-ons, applied in combination with numerous process probes, improve the accuracy of measurements directly in processes. In some cases, measurements in industrial liquids are made possible in the first place. Real-time and inline sensors (e.g. turbidity, oxygen or generally optical sensors) are increasingly being used in various industrial areas such as water & wastewater management, biotech, pharmaceutical, (petro-)chemical as well as food and beverage industry. Films often form on the sensors, which can influence or falsify the measurement results. usePAT counteracts this problem with the Sonicwipe application by preventing or removing these contaminants. As a result, probes no longer have to be removed from the process so that it can run continuously. The ultrasonic trap Soniccatch bundles small particles, such as crystals, suspended particles, but also oil droplets and air bubbles in liquids and presents the resulting agglomerates of the process probe. Even the examination of living cells is possible, thanks to Soniccatch, without disturbing the process flow by the measurement technology. Time-consuming and resource-intensive sampling is no longer necessary. Accurate and reliable data is essential in order to guarantee effective process control according to everything Industry 4.0 stands for. The continuously generated, improved measurement data creates new possibilities for process optimization and cost savings in industrial and R&D applications. [28]

Gaps and Barriers

In the energy-intensive industry, the need was recognized to map the production process in detail in order to achieve progress to operate the plant optimally. Therefore, concepts are needed to gain useful information from the sensor systems and process the huge amount of data [33].

Accurate Data | For the application of sensors in high-level tasks such as predictive maintenance, production planning and advanced control, accurate and preprocessed data is needed [152]. Therefore sensor fusion and soft-sensoring are important to avoid inaccurate or incorrect measurements and allow the sensors to communicate directly with actuators to optimize production output. Other techniques are stochastic methods to identify erroneous data.

Communication | For smart sensors, it is necessary to provide a smart and secure communication architecture in order to achieve trouble-free communication of all sensors based on a uniform protocol, which all sensors transmit and understand. Thus, all process sensors communicate via standardized and secure interface and data formats [87]. This is particularly important in the energy-intensive industry, where many plants are grown historically and sensors and production systems have been integrated over a longer period of time. Therefore, sensors should preprocess the collected data and communicate/store them in a general data protocol [33].

Pre-sorting of Data | Availability of actuator and sensor signals must be guaranteed in all levels of a company, up to and including corporate resource planning [76]. However, the typical IT infrastructure in the industry is not designed for big data evaluations [37]. One solution could be that smart sensor systems only report data to all hierarchy levels of an organization when certain events occur (data filtering). Otherwise, the data will be marked and stored for further processing, but will not affect the classic IT infrastructure of a company.

Data Processing | Smart sensor systems and the collection of data are thereby supported by a new development in computing and communication/information technology, the Internet of Things (IoT). The goal of the IoT is to collect relevant information from the real world automatically, link it with each other and make it available in a network. The huge amount of data captured by sensors needs to be stored and processed efficiently. Cloud computing services can help, but the security issues occurring need to be addressed [57].

Potential and Future Outlook

Sensors and smart meters enable more efficient operation of plants and are the foundation to increase flexibility and integrate fluctuating energy producers (e.g. renewable energies). To implement sensors in a plant, it is important to ensure compatibility and secure communication. Areas for further research and development are:

Development and Integration | The integration of energy-efficient and autonomous sensors in an existing sensor system is a special task for the sensors, communication standards and the IT infrastructure. Successful sensor integration provides the basis for sensor fusion and soft-sensors [152]. Sensor fusion and soft-sensors have a special significance for the energy-intensive industry because they facilitate self-calibrations, error-checking, etc.

Retrofitting and Compatibility | Compatibility and retrofitting capability of sensors into existing sensor systems and plants are necessary because in the energy-intensive industry, plants have often grown historically and have been expanded or modified over the years. Intelligent analysis techniques are needed to determine the potential of sensor applications and the demand for sensors.

Data Security | Security issues, according to connected sensor systems, need to be addressed to apply smart sensor services in the energy-intensive industry.

Flexibility and Efficiency | Smart sensors, together with smart meters, can be used to better coordinate energy production and energy consumption. Therefore activities in the energy-intensive industry can be coordinated with the energy production from external sources to increase efficiency.

Integration of Fluctuating Energy Producers | With the help of smart meters as a key ingredient, it becomes possible to integrate fluctuating energy producers (e.g. solar plants) into the power grid, without compromising grid stability.

4. Digitalization Applications

4.1. Advanced Control

Basic process control, such as classical PID-based control schemes, are designed and built within the process components itself to ensure the basic requirements for operation and automation. Advanced process controls are usually added at a higher layer, often later, to take into account specific performance or economic improvement opportunities and optimization potentials in the process. It links process knowledge with control techniques in an intelligent way and allows to consider coupled, multi-variable system dynamics [146].

Definition

> *"Typically, advanced control methods involve more complex calculations than the conventional PID controller algorithm. Advanced control has the following features [2]*:
>
> - *Process modeling and parameter identification (off-line or on-line)*
> - *Prediction of process behavior using process model*
> - *Evaluation of performance criterion; subject to process constraints*
> - *Optimization of performance criterion*
> - *Matrix calculations (multi-variable control)*
> - *Feedback control"*

The development of advanced control is moving towards model-based control, which are control systems that explicitly implement a process model in the control algorithm [19]. Thus this chapter focuses on model-based control, especially adaptive and model predictive control. Other examples for advanced and model-based control techniques are: fuzzy control, robust control, neural network-based control, optimal control, etc. [2].

Adaptive Control | Parameters of models or controllers may depend on the operating state of the component. Adaptive control, including gain scheduling and auto-tuning can adapt parameters according to the operation state. In Figure 4.1, a gain scheduling scheme is depicted with w as desired outputs, u as computed control inputs and y as measured outputs. Adaptive control requires process data and identification techniques for operating ranges and parameters. Additional, intelligent and stable algorithms for switching between models and control parameters are required.

Model Predictive Control | In model predictive control (MPC), a dynamic model is used to predict the potential output over a prediction horizon. Thus, it can calculate the optimized

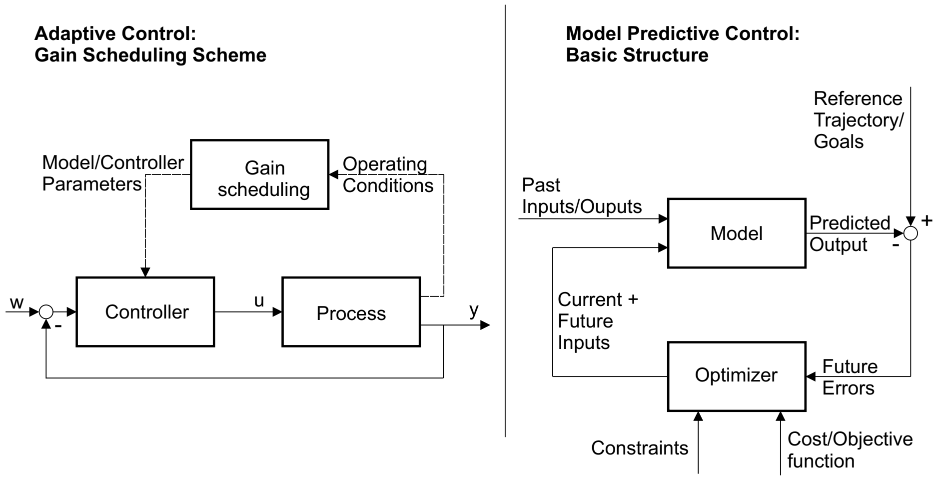

Figure 4.1.: *Basic Structure of adaptive control (left) and model predictive control (right)*

control inputs over the control horizon in order to achieve a particular optimal result, see Figure 4.1. Thereby, an objective function is minimized to get the desired behavior of the controller for the whole control horizon. Then, only the first computed control input is applied to the system. The states of the system to be controlled are updated after one timestep and the computation of the new optimal control inputs, as well as the prediction of the system behavior, is executed again (called the "receding horizon" principle). An observer for unmeasured states or disturbances can also be introduced. Model predictive control is beneficial for highly coupled process variables and can explicitly consider soft and hard constraints, as well as load/disturbance predictions. With sufficiently accurate models of the system dynamics from balance equations or data, accurate sensor measurements in real-time, desired trajectories (goals) over the prediction horizon and the constraints on input and process variables, superior system performance can be achieved in a safe way, see Figure 4.2. [73]

Decentralized Control | The entire system is controlled by a decentralized control concept consisting of several independent controllers. This results in better scalability of the control task and simplifies subsequent changes or adjustments in the controlled plant. The challenge of decentralized control is stability and performance.

Requirements

The most important requirements for the use of advanced control methods in industrial applications are described below:

Modeling Techniques | Most of the advanced control techniques rely on models, hence model building is a very important part. Models can be divided into three categories. A white-box

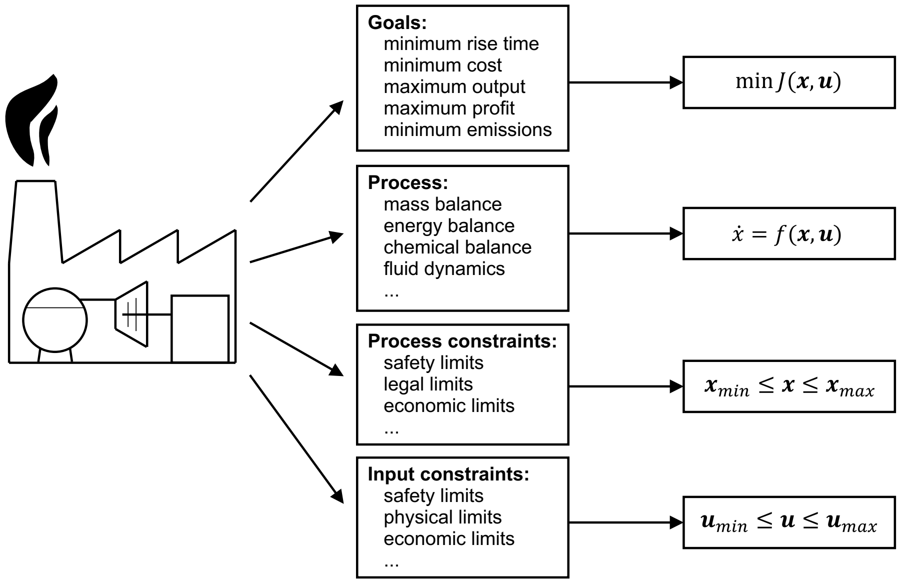

Figure 4.2.: *Requirements for applying model predictive control*

model uses a well-known physical relationship in mathematical form to describe a certain behavior. Black-box models, also known as (purely) data-driven models, are only built upon data without exploiting any physical knowledge. In grey-box modeling, physical knowledge and obtained data are combined, which often achieves good results in practice.

Sensors | Every model needs data (for modeling and validation purposes) and information of relevant parameters. Therefore, one requirement is the availability of reliable data in a sufficient quantity. Modeling and subsequent advanced control thus benefits from the advances in sensor technology and from the constantly improving algorithms for data processing. Real-time data provided by sensor systems help to take control actions before undesirable situations occur.

Computation Power | Advanced control demands for high computation power. In order to be able to use a "Model-predictive Controller" (MPC), high computing power is needed, since an optimization problem has to be solved in each time step. The dynamics in a process determine the size of the required time step and thus specify the required computing power. The required computing power also depends on the prediction and control horizon, as well as on the implemented constraints.

Reliable Predictions | Reliable predictions of disturbances (e.g. weather forecasts, electricity price, demand for products) are necessary.

Applications

Advanced model-based control can be applied and is found in nearly every industrial sector. Usually, they combine different process components with basic controllers at a higher level and try to achieve a global operation optimum while following constraints. In this way, several variables to be controlled and correlated can be set simultaneously by several influencing variables. They are often used in the process industry, where the relevant system dynamics are slow enough and the control quality of classical PID control is not sufficient. However, advanced controllers need a significant modeling and parameter tuning effort. Therefore, the application of these modern control methods is often a question of benefits versus efforts. The use of MPC can be increased, if the modeling and controller adaptations are streamlined and further automated.

Strip Processing Line of Voestalpine Stahl GmbH | In the steel industry, continuous annealing furnaces are used for the heat treatment of strip products. In order to ensure the continuous operation of such annealing furnaces, the steel strips are conveyed through the furnace as an endless belt. Heat treatment consumes large amounts of energy, is costly and has a direct impact on product quality. In order to meet the high demands on the quality of the end product, each strip must be heated to a defined target temperature in the annealing furnace. Since an annealing furnace is a complex thermodynamic multi-variable system with multiple dependencies, controlling the strip temperature is a demanding task. A nonlinear model-predictive controller determines optimal trajectories for fuel supply and belt speed so that the belt temperature follows its target signal. In addition, the controller maximizes product throughput and minimizes energy consumption. The basis of this control concept is a mathematical model for the strip temperature. [99]

Potential and Future Outlook

In a complex system without advanced control, operators of industrial process plants will always move within a safe range and preserve resources in order not to reach and violate limits. This way of operating a plant is rarely financially optimal. Advanced controllers can optimize or use trajectories from an offline optimizer and compute control inputs under consideration of constraints [77]. This will lead to improved automated operations of industrial plants and generate additional profits. However, model building and implementation of such advanced control systems are time-consuming. Therefore, self-adjusting and data-driven modeling techniques, as well as self-tuning and "hot-plugin" advanced controller types are potential research fields.

SIC! | In Austria, an initiative in research for offline optimization techniques and advanced control strategies of energy-intensive industrial plants under the usage of knowledge-based ontologies is SIC! (Smart Industrial Concept) [119].

EDCSproof | This project aims to develop a future concept for the decarbonization of industrial energy supply systems through the opportunities of digitization. The focus is laid on online, predictive and holistic, reconfigurable control to increase efficiency through optimal control of the overall system. The concept is optimized in the laboratory [149].

4.2. Collaborative Business Models

The idea behind collaborative business models (CBM) is to forge alliances between companies to gain mutual benefits. According to their approach on value generation, models can be categorized into: sharing, specialization, and allocation models (Table 4.1).

Definition

> *Collaborative business models are business models that forge alliances between several companies to increase the economic efficiency of each member, sharing know-how and resources. [88]*

Sharing Models | Sharing models operate on the same level within a value chain and can be seen as horizontal. By combining similar competences and know-how, partners can form networks to reach markets on a greater scale. The split of capture value is typically pre-agreed upon and equal, or respective to what is contributed.

Specialization Models | Specialization models describe alliances between completely different but complementary businesses and can be seen as diagonal. Value revenue is less predictable and these models often have to be reorganized within their life cycle. According to risk and commitment, each partner carries its own costs and revenue.

Allocation Models | Allocation models are used for ventures where partners usually do not have the same, but overlapping capabilities and can be seen as vertical. The driving force behind them is mutual risk management. Responsibilities are designated according to each partners' field of expertise in an effort to minimize the overall risks. Individual performance is then typically tied to incentives or targets. [88]

In summary, CBMs aim to create platforms where participants can share technologies, expertise, and know-how to benefit from each other. Once trust between partners has been established, a collective mindset can be developed where the overall value generation of the alliance is associated with individual success. [88]

Requirements

Trust between collaborators, appropriate communication channels and structured information storage have been identified as some requirements for CBMs. In the age of digitalization, vast amounts of data are being collected for basically any field of business. The problem however is, that this data is often held by many individual parties in a distributed fashion. A lack of willingness to share data in collaborations is often based on the fear of losing one's competitive

Table 4.1.: *CBS model categorization (Based on [88])*

	Sharing	Specialization	Allocation
Value creation			
Economies	Scale	Skill	Risk
Capabilities	Similar	Complementary	Overlapping
Relationship of the partners	Horizontal	Diagonal	Vertical
Value creation potential	Predictable	Unpredictable	Increased predictability
Value capture			
Mechanism	Pre-agreed split	Each partner carries own revenue/cost	Incentives tied to performance
Value delivery			
Interdependence	Reciprocal	Pooled	Sequential
Level of integration	High	Low	Focused

edge. Therefore, trust between partners needs to be built in order to pool data and technologies. Systems need to be developed, which ensure equality of contributions to the collaboration by each entity.

Digital Twin | Collaborative development projects require access to current states of design for all participants. Requirement changes of products or processes are easier implemented in early stages of every development. The Internet of Things opens new dimensions of easily accessed real-time data that can then be used to keep a digital twin updated. Connecting two or more digital twins of individual partner companies allows them to create a digital twin network. This network can be used as an open, collaborative platform where each partner can share information, technologies and progress of ongoing co-developments. [101]

Blockchain | Collaborations need an extensive amount of data exchange between the participants. Without a comprehensive structure for data transfer and storage, data redundancies and a lack of full knowledge can arise. This problem could be solved with blockchain technology. Blockchains are transparent to all participants, tamper-proof, and chronologically structured. With these characteristics, blockchain networks become a viable option for trustworthy data infrastructure solutions. Additionally, smart contracts can be implemented to increase workflow autonomy without the need for human interaction. [29]

Applications

The following section will review three different use cases where CBMs have been applied successfully. Each of these applications uses one of the models introduced in the section above and will explain how they are used to generate value.

Star Alliance - Sharing Model | The Star Alliance has 27 member airlines and is a great example for combining similar capabilities. By combining flight routes and flight times of different members, passengers are presented with an overall greater choice of flights and more convenient travel times. Long-distance flights with one or more transfers can be split between airlines to ensure travel availability. This way, members can sell tickets to each other and create overall value. Additionally, lounge costs (among other things) at every airport can be reduced by simply sharing only one lounge. [124]

Senseo - Specialization Model | A collaboration between Philips, which produces the coffee machine called Senseo and the coffee brand Douwe Egberts, which supplies the Senseo demonstrates the benefits of specialization models. These two companies operate in completely different areas of business and their expertise overlap is zero - a perfect example for complementary capabilities. With the shared interest of a large consumer base, profits are linked between both partners and they are invested in each other's success. [88]

ProRail - Allocation Model | ProRail is a Dutch government organization tasked with railroad construction and maintenance. Using CBMs, risks for each project can be split between ProRail and the respective contractor. Each partner is allocated to risks that they are able to influence best. For example, delayed official building permits are carried by ProRail as they are a government entity, and risks of malfunctioning equipment are carried by the contractor. Since each partner is interested in staying within budget, they are incited to reduce their own risks without having to worry about the other partners' risks. [88]

Virtual Power Plants & Flexibility Pooling | CBMs are used to facilitate the implementation of renewable energy sources on large scales. The key phrase is "Virtual Power Plant" (VPP). VPPs create networks of decentralized power generation facilities, storage systems and flexible power consumers and operate as a central control unit. They offer the service of energy management and distribution in smart ways. Individual small wind farms and PV facilities cannot provide enough reliability to ensure grid stability. In addition, the minimum bid size on markets may prevent them from selling energy at all. These challenges led to the development of CBMs that are used for flexibility pooling techniques such as VPP. By aggregating several small units, their energy production can be forecasted and optimized to achieve better production balance. Individual energy outputs can be combined to reach the required bid size. Flexible power consumers are incentivized to operate outside of peak load times, where energy prices are lower. This, in turn, will relieve the load on the grid, and energy profiles are flattened. [142]

Potential and Future Outlook

CBMs hold great promise to increase corporate profits and drive the development of innovations. By sharing information, technologies and know-how between collaborators, they can complement each other and increase their capabilities. Risks of new developments can be split and are easier to manage. Furthermore, alliances between smaller companies may enable them to compete with bigger competitors.

4.3. Cybersecurity

Cybersecurity is the practice of defending computers, networks and data from malicious attacks. The Oxford dictionary defines cybersecurity as:

Definition

> *"The state of being protected against the criminal or unauthorized use of electronic data, or the measures taken to achieve this." [110]*

It is rapidly gaining importance as companies are adapting to the IoT paradigm, i.e., the application of interconnected and interrelated electronic devices. The abuse of information and communications technology (ICT) has become a major concern for companies, individuals as well as governments. In its "Global Risk Report 2019", the World Economic Forum listed cyber threats as one of the most critical risks threatening the world economy [133]. In 2016, companies revealed breaches of more than four billion data records, more than the combined total for the previous two years [66]. Also, the financial costs of cyberattacks are rising. The cost of cybercrime to businesses over the next five years is expected to be 8 trillion US $ [132]. Cybersecurity issues represent highly relevant challenges in the context of Industry 4.0, where operation and information technology are tightly interconnected.

Requirements

The convergence of information technology and operational technology makes industrial companies more vulnerable to potential cyber-attacks. Standard cybersecurity approaches are often human-centered, e.g. identity and access management or cryptography technologies, or they are based on static rules, e.g for automated intrusion detection. Emerging technologies, however, are pushing the abilities of cybersecurity solutions. To provide and uphold a reliable level of cybersecurity, the following digitalization techniques and technologies are becoming more relevant:

Blockchain | The strength of blockchain in the context of cybersecurity comes from providing an infrastructure that is trusted by all transaction participants and decentralized by design. In comparison, traditional databases are kept in a single place, making it easier to attack. All transactions added to a blockchain are digitally signed, including a timestamp, making it easier to trace the authorized owner of the data and the time period. Blockchain technology can also help eliminate human errors, e.g., companies can authenticate users while avoiding a user-created password [65].

Machine Learning | Machine learning-related technologies, i.e. the process of training machines to learn from experience, can be used in cybersecurity. These methods are capable of learning from past cyberattacks, enabling organizations to respond to threats at greater speeds and avoid the use of static rule-based approaches. Artificial intelligence can be used to detect unusual patterns in encrypted web traffic automatically and Internet of Things (IoT) environments to, e.g. enable fast and reliable intrusion detection. Thus, they can help organizations to reduce the lack of resources and skills.

Applications

Industrial control systems are widely used throughout all industrial sectors. These industrial control system components are distributed and interdependent physically, geographically or logically. Hence, one critical component could depend on the accurate functioning of another critical component. Potential cyber-attacks pose a big threat to the Industrial Internet of Things (IIoT) and complicate or delay the implementation of Industry 4.0, especially due to the increased interconnection and dependence of information and operation technology as a key part in industrial processes. Thus, systematic implementation of cybersecurity measures is needed to guarantee the security of industrial control systems, including but not limited to supervisory control and data acquisition (SCADA), distributed control systems and process control systems.

IoT4CPS | The digitalization and increasing connectivity of (critical) cyber-physical objects enables the development of new applications but also leads to new safety and security related requirements in the design, testing, production and operation of these systems. The objective of this project is to integrate security levels across all dimensions in order to ensure trusted interaction across devices, machines and networks; maintain integrity, authenticity and confidentiality of information; and sufficiently protect production data and intellectual property. IoT4CPS [72] will develop guidelines, methods and tools to enable safe and secure IoT-based applications for automated driving and smart production.

INDICAETING | Threat intelligence, consisting of indicators of compromise and tactics, techniques and procedures, is of uppermost importance for identifying cyber threats using signature-based detection techniques. However, large IT infrastructures are often insufficiently protected because such approaches rely on predefined attack dictionaries that have to be maintained manually, which requires time- and resource-consuming activities as well as expert knowledge about the attack itself and the system at hand. For this reason, the main goal of this project is the definition of a methodology for an automatic or semi-automatic extraction of actionable threat intelligence from raw and unstructured log data allowing timely reaction to imminent threats. The proposed approach is thereby able to gather security-relevant information about previously unknown attacks using self-learning anomaly detection techniques that process log streams from arbitrary sources in real-time [69].

synERGY | Cyber-physical systems (CPS), e.g. those used in value-added networks to realize distributed manufacturing, are vulnerable to various kinds of cyber-attacks. As a consequence, reactive security techniques must be applied to CPS, which rely upon the ability to detect attacks in a timely and accurate manner. Today's security solutions usually address only single layers, which are often not able to take account of the full picture, especially in the case of complex and stealthy multi-stage attacks. This leads to an operator having a limited view regarding the root cause of an attack, which can reduce the overall availability of a CPS. Therefore, the objective of synERGY [129] is to develop new methods, tools and processes for cross-layer anomaly detection, to enable the early discovery of both cyber- and physical-attacks, which will have an impact on the security of CPS. To achieve this, synERGY will develop novel machine learning approaches to understand a system's normal behavior and detect consequences of security issues as deviations from the norm.

DECEPT | While there exist numerous behavior-based anomaly detection approaches for enterprise-IT security, they are not easily applicable to other domains, e.g. embedded systems and IoT. They are usually highly optimized for specific purposes, are tightly bound to domain-specific technologies and rely on a specific syntax of investigated data or events. DECEPT [26] will provide a generally applicable cross-domain anomaly detection approach that monitors unstructured textual event data (i.e. log data of any form, encoding, size or frequency) and implement un-supervised self-learning-based on artificial intelligence solutions.

SIGI | Developing integrated security concepts and architectures and secure migration strategies from legacy systems to novel, automated solutions is crucial. Industry 4.0 systems can only be implemented on a wide scale if suitable security standards are established. Moreover, security issues are connected to matters of usability, acceptance and economic efficiency. First and foremost, both management and staff must develop awareness for security issues. The goal of this study is to raise the awareness for the crucial role of security in Industry 4.0. To this end, the current security posture of Austrian manufacturing companies is assessed. Automation and interconnectedness bring about novel security requirements, which are systematically collected and evaluated. Finally, opportunities and barriers for Austrian industries are identified. A set of best-practice actions will be derived that can support Austria's industry and security sector in increasing their level of information security. [118]

Potential and Future Outlook

Connected, distributed and interdependent devices used in industrial control systems will increase the susceptibility to cyber-attacks. A high level of cybersecurity is a key requirement in the implementation of Industry 4.0 and demands sophisticated solutions. Thus, cybersecurity is expected to evolve drastically and to create robust self-healing and self-defending networks by leveraging, e.g. machine learning/artificial intelligence and blockchain-based opportunities. On the other side, these technologies can also be used to automate cyber-attacks and improve their abilities. With an increased need for cybersecurity, the field will emerge from a niche profession, including the evolution of new professions and domain expertise. More than three million cybersecurity job openings are expected by 2021, however, accompanied by a severe workforce shortage [24]. Corporations will need to make cybersecurity an integrated building block in their adaptation to Industry 4.0 and the IIoT.

4.4. Demand Forecasting

Definition

> *"Demand Forecasting refers to the process of predicting the future demand for the firm's product. In other words, demand forecasting is comprised of a series of steps that involves the anticipation of demand for a product in future under both controllable and non-controllable factors." [27]*

Demand forecasting describes the effort to predict the future need of products or services. It is used by manufacturers, energy producers and service providers, to accurately estimate needs and adapt a system's operation accordingly. By predicting the future demand of a product, companies can use this information to plan and schedule their production and avoid conditions of over- or underproduction. Acquisition of resources and manpower can be made more accurately and the overall efficiency is improved (e.g. fewer materials or energy needed). Energy producers rely on forecasts to ensure grid stability, where balancing production and consumption is vital. Especially renewable energy sources such as wind farms and photovoltaic facilities are volatile, as they are highly dependent on weather, climate and seasonal conditions. As a result, forecasting of energy demand is equally important as forecasting of energy generation. Therefore, demand forecasting is also understood as generation forecasting within this paper. Demand forecasting is an important technique that predicts the future demand of a product or service and helps companies to make strategic decisions to meet market expectations in the most efficient way possible. Additionally, energy production and consumption can be balanced with accurate forecasting. [53, 27]

Requirements

The challenge for demand forecasting lies in acquiring sufficient data for the predictions and models that can subsequently process this data accurately. The following data sources and data analysis methods are required:

IoT and Big Data | By connecting sensors and smart meters over the Internet of Things (IoT), networks can be created that are capable of collecting comprehensive amounts of data. Big data technology can then be utilized to structure and manage all of this information efficiently with reasonable computational effort.

Digital Twin | Digital twin-driven smart manufacturing describes one approach on how digital twins can be utilized to aid demand forecasting. By connecting digital twins of entire organizations within a supply chain, a global production network can be created. With real-time data of local production systems provided by each individual factory, the network can adapt to dynamic changes in demand and requirements. Quantity adjustments due to fast-moving markets can be addressed quickly to avoid bottlenecks or the production of excess goods. Regarding quality, smart factories will be more responsive to required design changes and demands from the customer side. This will enable companies to shift towards mass personalization with the capability of efficient "lot size one" production. [85]

Blockchain | By design, blockchain networks are transparent to all participants. Each transaction has to be verified by peers and is visible to the public. After a successful exchange of assets, these transactions are stored chronologically and are immutable. With access to all this data, manufacturers and service providers are enabled to analyze consumer behavior and estimate future customer demand. Therefore, implementing a blockchain network can transform supply chains into demand chains, where accurate forecasting is enabled. [113, 123]

Data-driven Modelling (DDM) - Machine Learning (ML) | Research in energy demand forecasting has reviewed several DDM techniques such as artificial neural networks (ANNs), support vector machines (SVM) and fuzzy logic to be utilized for future predictions in energy demand. If sufficient training data sets are available, these models are capable of generating accurate forecast models. However, problems can emerge from unexpected irregularities and contingencies. Feeding data to a model that deviates too far from the scope that it was trained for will cause nonsensical results. In addition, depending on the field of application, advantages vary for each model. ANN-based DDM has been identified to lead in performance, but also require higher computation times due to the sophisticated structure. SVM based DDM ,on the other, hand is able to maintain accurate results even in the case of insufficient data points. In conclusion, DDM is viable for modern demand forecasting. However, the challenge remains, to first identify which model fits what application best and second to train the model sufficiently. [53]

Applications

The following examples show important demand forecasting applications in industry:

Energy Demand Management | As mentioned before, electrical grid stability is a major challenge due to the lack of fast-reacting and cost-efficient technologies that would allow storing electricity in large amounts. The supply and demand balancing act always requires grid system operators. On the one hand, energy producers face highly variable demand, since electricity consumption is affected by a range of factors. Cold weather will increase the need for residential heating and major events will affect consumer behavior. For example, according to [60]: “In Britain, National Grid prepared for a 1.2 GW surge in demand as the country stayed up to watch the results of the Brexit referendum come in overnight on June 23–24, 2016.” On the other hand, output from renewable energy networks is volatile in itself. One research that has been conducted to review energy demand management systems shows that 18 different forecasting models are currently used by different nations. [128, 60]

Online Optimization | Real-time online optimization enables operation at optimal process points (e.g. Voestalpine Linz and VTU Energy - Time Line Optimization System, introduced in Section 3.3). In order to perform online optimizations, information on short-term demands (e.g. steam) as well as potential renewable capacities (e.g. Photovoltaics (PV)) has to be available. Incomplete data or faulty models, however, can lead to incorrect forecasts. This would cause process parameters to strive towards unrealistic settings, which may not be physically possible or impairing the overall outcome. [106]

Supply Chain Management | Accurate forecasting models are important for basically every supply chain. Demand forecasting facilitates raw material acquisition and production planning. Resource inventory is kept at a level that ensures no shortages without overstocking and products are manufactured in a timely manner. This is especially important for the food industry to avoid spoilage of fast perishable goods. Predictive maintenance data is used to ensure the availability of spare parts to eliminate risks of production downtime. Additionally, strategic decisions regarding new product launches and discontinuation of old products can be made according to market needs. [104]

Potential and Future Outlook

Demand forecasting is already widely used in numerous industries. Within this section, the identified benefits are summarized and a brief insight into required future research is given.

Increasing Energy Efficiency | With accurate forecasts, (near) real-time optimizations can calculate optimal process points and storage capacities throughout entire process cycles. In addition, synergies between individual process sections can be identified and the overall energy efficiency maximized.

Enable the Utilization of Renewable Energy Sources | Industrial applications need reliable and steady energy supply. Shortages in renewable energy generation have to be predictable in order to balance them with conventional alternatives. Therefore, reliable forecasting is a key requirement for the implementation of large scale renewable energy sources.

Environmental Impact and Reducing Costs | Demand and generation forecasts are required to enable the transitions away from fossil fuels to gain self-sustainability. With more alternatives to carbon-based energy generation, CO_2 emissions will be reduced and the environment protected. In addition, at the same time, resources and energy costs can be reduced.

Future Research | The key requirement is sufficient relevant data. Methods for comprehensive data acquisition are needed and have to be implemented for effective demand forecasting. In addition, there are plenty of different forecasting methods and only modern data-driven ones can operate autonomously without human input. Future research is required to further develop these methods to guarantee self-reliance and accuracy. Different applications require different models and the challenge remains to design models that can produce accurate output with given data and reasonable computational effort.

4.5. Optimization

Definition

Optimization is generally understood to be the search for the best possible solution in the sense of a certain goal in a decision-making area, whereby frame conditions can be taken into account. [46]

Optimization can be seen as the search for the best possible solution with a certain goal and possible boundary conditions. It is noteworthy, though, that optimization is used colloquially with the meaning "improvement". However, depending on where it is being used, the term "optimization" is understood differently:

Mathematical Optimization | Mathematical optimization, which is also referred to as mathematical programming, is the selection of the best element from a set of available alternatives [46].

Process Optimization | Process optimization is a methodology used in engineering to select the optimal process design within a range of possible alternatives by creating a mathematical formulation of the given problem. Thus, mathematical optimization can be applied to this methodology.

The following types of optimization are usually distinguished:

Design Optimization | Design optimization deals with the optimal construction of systems. New plants are planned or existing plants are retrofitted for given operating conditions.

Operational Optimization | Operational optimization deals with the optimal operating mode of plants. For given boundary conditions, the optimal way of operation is determined. This includes the decisions of turning machines off or on, how much is produced at which time and at what percentage of capacity the machines are working on.

Controller Optimization | Basic process controllers fulfill the task of keeping the process in given parameters to ensure operation. Advanced process control is used to link process knowledge to control techniques and deploy tools like model-based control for the improvement of performance.

Requirements

The global optimization of processes requires detailed information whose acquisition makes a multitude of demands in different fields:

Demand Forecasting | As exact as possible knowledge of frame conditions such as electricity price developments, electric energy demand, heat demand or order lists are one of the foundations for an appropriate optimization.

Big Data | Big amounts of data are often collected, but not or only partially used. Proper preparation and usage of data like energy demand, temperatures or pressures helps to gain information necessary for the optimization of processes.

Sensors/Smart Meters | The ongoing collection of real-time data allows a continuous improvement of the used models, which improves the quality of optimization results.

Open platforms | Unified communication protocols would allow for an easier integration of different programs, for example, when special optimization programs are needed.

Applications

Optimization is applied in all industrial sectors. The need to minimize effort while maximizing the profit to stay competitive is omnipresent. Electric power supply networks, where an optimized operation is crucial because supply and demand always have to match to keep the network stable, have to deal with increasing volatilities from renewable energy sources.

Often a lot of data acquisition is already implemented in factories, but most of the time only a fraction of it is used. Through proper processing of the collected data, added value can be generated. The implementation of data analysis tools has the barrier of high initial costs but the option of significant savings over time. A better understanding of the need for optimization with the target of resource conservation and cost savings over a longer period of time despite high initial investment costs has to be integrated into corporate policies. In the following some applications of optimization are shown:

Energy Optimization of Wastewater Treatment Plants in Austria | Self-sufficient municipal wastewater treatment plants that produce more energy than they consume are able to reach up to 180 % energy generation compared to the energy needs. This is possible by using CHP generation by means of biogas from anaerobic sludge digestion and additional measures like wastewater heat recovery and the usage of heat pumps. [100]

Optimization of the Energy Usage at Josef Manner & Comp. AG | Optimization of CHP-heat recovery from cooling water and exhaust gas for process heating and optimization of the absorption refrigeration system led to savings of up to 2,36 MWh per year in the factory of the famous Viennese confectionery manufacturer. [74]

Potential and Future Outlook

Optimization of systems is one of the main steps which has to be taken towards Industry 4.0. In future systems, optimization has to be a continuous process to reach an ongoing improvement. Optimizers need to be refined to fit the needs of individual tasks. Combined with digital twins, major improvements are possible. Fluctuating energy prices and energy trading in short time intervals demand that the operation plan is being re-optimized in shorter and shorter time intervals. [92] Various core areas of the field have to be improved or expanded to reach these goals:

Modeling | Elaborate, detailed models often have the disadvantage that the computing effort causes a long processing time. Often these models need to be simplified for a real-time usage. Data-driven models offer the advantage of low computational effort with the disadvantage of the poor transparency of the model. One special feature of data-driven models is that it is possible to design the model to learn from real-time data and thus improve over time. It allows to make changes of the characteristics through events such as wear or fouling into account and still deliver accurate predictions even after longer times of operation. [62]

Big Data | Comprehensive data acquisition is needed for future smart factories where all components are cyber-physical-components, which are monitored by more sensors than comparable components today. Additionally, there is going to be a lot more information that the products itself will carry throughout the process with them. The right handling and processing of this data are one of the big challenges that have to be mastered. [9]

Open Platforms | Development of the industry goes hand in hand with the development of communication. A reduction of the communication barriers between different systems leads to a more efficient data distribution within the system, which is needed for real-time optimization.

4.6. Predictive Maintenance

Definition

> *Predictive maintenance is a philosophy or attitude that, simply stated, uses the actual operating condition of plant equipment and systems to optimize total plant operation. [95]*

Predictive maintenance is a forward-thinking approach to proactively maintain machinery and equipment to keep downtime to a minimum. The process uses measurement data of sensors, accurate models of parts and estimation techniques. [15]

Today, modern industrial plants already record a multitude of data about load, utilization, physical states, environmental conditions, etc. Corresponding sensors can often be retrofitted to older plants at a low cost. By recording and evaluating these data over longer periods of time, detailed forecasts can be made about the failure behavior of critical components. In particular, creeping changes in behavior are investigated, such as a gradual rise in temperature or increasing vibrations and noise. Thus, maintenance can be scheduled before the corresponding malfunction occurs, spare parts can be ordered in advance, production downtimes can be avoided or at least reduced, maintenance procedures can be prioritized. [15]

Requirements

The following requirements were identified for the application of predictive maintenance in industry.

Sensors | The challenge is to obtain accurate, sensitive measurement data. Sensor fusion and soft-sensoring supports the acquisition of credible data and the measurement of "non-measurable" criteria.

Algorithms | Using this sensor data and appropriate algorithms in combination with load-dependent reliability analyses, detailed predictions can be made about the states and failure behavior of critical components. Depending on the components, the ideal service strategy can be derived and configured. [76]

Expertise | The observation of a single machine by its operator is usually not sufficient, the expertise of the machine manufacturer and a corresponding basis for comparison of many machines (including with different operators) are required. Many machine manufacturers offer services that consolidate operational data from individual production sites and use it to make reliable predictions about failure behavior. [15]

Secure Data Handling | Operating data is usually top secret and is very reluctantly passed on to third parties by industrial plants. One solution could be to involve a trustworthy intermediate instance, in order to have an anonymous processing method that only passes on fully anonymized and unrecognizably scaled data [15].

Applications

Predictive maintenance is considered to play an important role in Austria. 90% of the surveyed managers and specialists state that their company already deals with predictive maintenance, 31% attest their company a high degree of progress [147]. Predictive maintenance cannot be assigned to a specific industrial sector and is represented in each. It is mainly used where the failure of a machine part / whole machine means a standstill in production and where replacement is not immediately available. Therefore it plays an important role in production bottlenecks and safety-critical applications.

Another application aspect of predictive maintenance is to use real-time data to enable adaptation of process planning to the current utilization of the line. In the event of local and temporary bottlenecks, the speeds of upstream and downstream production resources can be reduced without reducing output. This leads to a lower utilization and thus, a less heavy load on the components and production machines are preserved. [76]

Smart Maintenance | In the Smart Maintenance project, resource-intelligent, predictive maintenance is developed through condition monitoring, data analysis and fault forecasting on the manufacturing systems of the industrial partners (BMW Motoren GmbH and BRP Powertrain GmbH & Co KG) and embedded in the definition of the maintenance strategy. The other project partners are Messfeld GmbH, Software Competence Center Hagenberg and Montanuniversität Leoben [120]. In a first step, the plants of the industrial partners are evaluated according to cost and risk aspects. This serves to identify critical plants and to forecast faults by means of data analysis. The result is a plant index for each plant, which enables a ranking according to criticality. A machine diagnosis can be carried out by measuring relevant data (e.g. lubricant analysis or temperature measurements). Thus it is possible to identify the condition of the plant as well as damages and their cause. In this project, different maintenance strategies are developed as well [78].

Hydropower 4.0 | In the Hydropower 4.0 - Digital Hydropower Plant innovation program, Verbund AG is investigating interactive troubleshooting and digitized predictive diagnosis of hydropower plants and components. With novel analysis methods and the use of self-learning computer systems, new insights into the current condition of the plant will be gained. Using computer simulations, downtimes and repair times are optimized from the condition records and forecasts - coupled with the "history" of a plant. The aim is to identify the current condition of the important power plant components very precisely in a kind of glass power plant in order to avoid possible failures due to unplanned damage. In the ideal case, the employee receives concrete suggestions for the required spare parts and tools in advance. [115]

Potential and Future Outlook

Most companies see a big opportunity to increase efficiency or create and implement new services with predictive maintenance. Research and development areas are:

Model and Simulation | Data-driven modeling and digital twinning must be further developed, automated and adapted. They are the basis for trustworthy predictions. Model reduction techniques need to be investigated and implemented to get predictions in real-time.

Sensors | New smart sensor systems are required. Sensors with pattern recognition may help to apply prediction maintenance. They must be able to process and provide data in an automated real-time capable way.

Big Data | Big data techniques are required to filter, connect and process the large amount of measured data to enable predictive maintenance. Ontologies may help to connect data in an automated and intelligent way.

Data Security System | Systems that anonymize the data for further company extern processing and make the data handling secure. Accurate rescaling techniques to anonymize data but maintain their validity may be applied.

Services | New services and business models need to be developed. Predictive maintenance need companies who collect data from different operators to get a broad knowledge base. On the foundation of this knowledge base, optimal decision support for predictive maintenance can be offered.

4.7. Supply Chain

Definition

As supply chain, a system of organizations, people, activities, information and resources, which is involved in moving a product or service from supplier to customer is understood. [144]

Depending on the industry, the description of the supply chain has to be more or less detailed to allow the system to be kept in optimal operating condition. For future applications, the communication effort between the individual links in the supply chain will increase drastically to be able to meet the requirements of Industry 4.0. In difference to the supply chain, the value chain consists of activities that create or add value to the product and is mainly targeted at improving the competitiveness.

As shown in Figure 4.3, the supply chain in most companies is structured not linear but more like a tree with branches and roots, which represent the network of customers and suppliers. Dependent on the closeness of the relationships at the different parts of the supply chain, the branches and roots need different levels of management. Aim of supply chain management (SCM) is to provide the right product or service at the right time in the right quality and at the right amount in the right position.

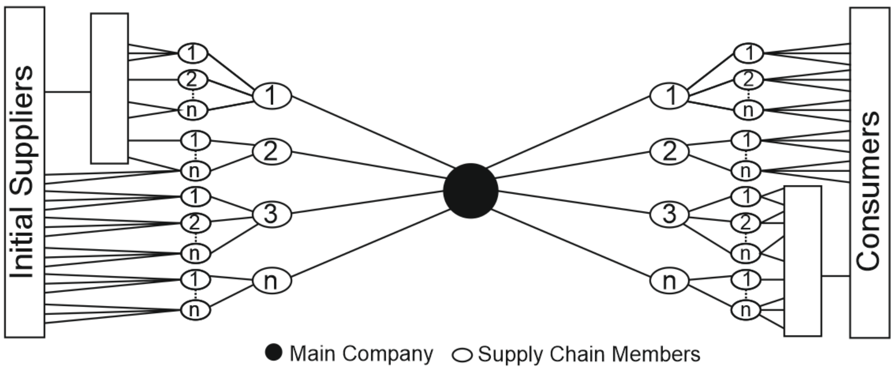

Figure 4.3.: *Supply chain network structure (Based on [34])*

Requirements

A functional SCM is based on detailed knowledge of the whole value chain. This knowledge requires a set of skills:

Big Data & Demand Forecasting | The accumulation and usage of data is needed for the analysis of the process. A lack of essential process data leads to poor predictability. The forecast of the demand for every product or service within the value chain is essential for an efficient supply chain. [134]

Digital Twin | If enough and the right data is extracted from the process, it is possible to build a digital twin of the process. This twin can be used for a better simulation of the collaboration between the members of the supply chain. [134]

Open Platforms | Nowadays, systems from different manufacturers often have problems to communicate with each other properly. With a unified communication protocol, an automated data transfer of the necessary information within the supply chain network would be easier and the making of decisions would be accelerated. [134]

Cybersecurity | A mature SCM in Industry 4.0 needs a high degree of efficient communication between all members of the supply chain. Trustworthy real-time data has to be available and useable. A big challenge is to keep the communication between the different systems save because of the sensitivity of the transferred data. If private data from customers gets stolen or misused, they lose their trust and might not provide their data anymore, which is crucial for competitiveness. [9]

A well-developed SCM can enhance a company's performance when the whole supply chain is able to respond to dynamic market needs. The sharing of information along the supply chain allows for faster adaptions and thus, for an advantage against competitors in the same sector. One of the biggest barriers for collaboration between the members of the supply chain is trust. In these terms, "trust" can be characterized in reliability, predictability and fairness. For reliability, this means that the important data from the partners has to be available on time and in the right quality. Poor data, no data or the right data too late often result in financial loss. Security during data exchange is also very important for the emergence of collaborations [105]. This means for a proper data transfer within and between companies, a secured and standardized communication protocol is needed. SCM plays a big role in a lot of aspects like warehousing, order processing and maintenance and has to be taken into account over the entire life cycle of a plant or enterprise.

Applications

In the following projects and companies, supply chain has successfully implemented:

KEBA AG | Data mining and data analytics in production were applied to find correlations of products, frequency of orders or models, client variance, etc. to improve the forecast of customer behavior. This improvement is used for a better response to the analyzed factors by the supply chain. [130]

Case Study Atomic | A case study has been carried out at the ski manufacturer Atomic. The aim was to determine the necessary adaptions to reach the target of "lot size one", which is necessary to stay competitive. It has been found that an adaption of the supply chain is one of the necessary measures to make customer specified products possible. [11]

Potential and Future Outlook

Further development of SCM demand further developments in some of the core areas that are significant for Industry 4.0:

Sensors/Smart Meters | Especially in energy-intensive industries, the plant life cycles are rather long. To integrate older facilities into futures supply chains, they often need to be upgraded because not enough information about the process is recorded and processed. The costs of these upgrades often discourage stakeholders, but they often lead to additional efficiency improvements within the plants.

Big Data & Demand Forecasting | Essential for an adaptive and responsive supply chain is an efficient and reliable forecast. The amount of data that is available for decision making gets bigger and bigger and comes from many different sources. On the one hand, there is a lot of information from the companies, like production data from the equipment, order data from the customer management or stock information that has to be dealt with which will grow with the ongoing digitalization. On the other hand, the amount of data that comes back from the consumer side like maintenance or service information grows with increasing digitalization degree. Forecasts of the behavior of the consumers dependent on factors like weather forecasts or personal lifestyles are going to refine demand prediction. To use this flood of information, big data analytics solutions need to be enhanced. [9]

Energy Value Chains | The optimal use of energy sources gets more and more important for future business cases. The energy value chain deals with the optimized use of energy resources, for example biomass. Biomass can be thermochemically converted to bio-oil or syngas, directly burned to generate heat or biochemical converted to bio-gas. Depending on the process and the needed type of energy, one of these uses is preferred [151].

4.8. Technology Upscaling

Definition

Technology Upscaling describes the process of enhancing the scale, size, and utilization in which technologies are applied. Technology Upscaling can be divided into four approaches: Growth, Replication, Accumulation and Transformation. [98]

The term "technology upscaling" can be used to describe the enhancement of scale, size and utilization of a technology. This can mean the transition of new niche innovations to mainstream appliances, or enhancing the scale and size of small pilot projects after proof of work has been established successfully. In [98], four approaches on technology upscaling have been presented: growth, replication, accumulation and transformation (Figure 4.4).

Growth | Growth is associated with projects, which start with small groups of participants that increase in number within the life cycle.

Replication | Replication describes duplicating successful projects for similar applications in different locations.

Accumulation | Accumulation is the process of linking individual projects to transfer lessons learned between each other. Contributions from different projects are combined to get an overall better understanding and general know-how is created.

Transformation | Transformation takes a wider approach and refers to a multi-level perspective. This is important, as innovations usually start in small niche sectors and need to be accepted by social networks and government regimes before they can be implemented in a widespread manner. [98]

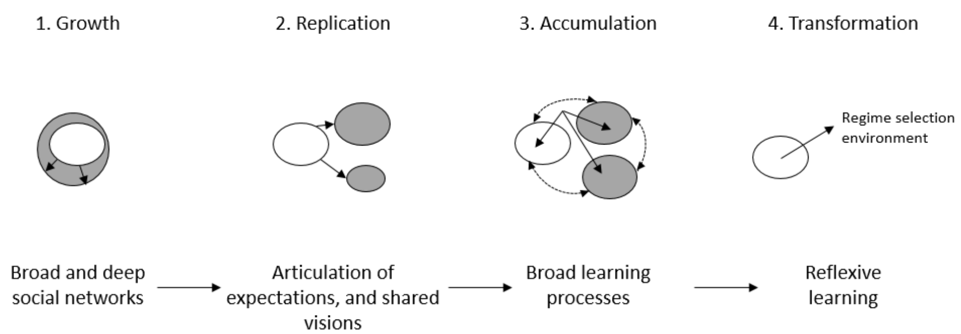

Figure 4.4.: *Methods of technology upscaling (Based on [98])*

Although the definitions here are specifically focused on projects in upscaling energy grids, technology upscaling includes other areas such as products and manufacturing processes. Irrespectively of the application, technology upscaling aims to standardize new technologies and increase the extent to which they operate.

Requirements

The following requirements for technology upscaling could be identified:

Realistic Modeling and Simulations | Although computer-aided simulations can be very accurate, they remain approximations. In order to sufficiently predict how scaling will affect the real-life properties of a system, product, or process, realistic simulations and modeling techniques are vital. This requirement calls for a combination of the IoT and data-driven modeling. With extensive use of smart devices that are connected via the Internet of Things (IoT), an abundance of real-time data can be created. Data-driven modeling (DDM) can then be utilized to process data and minimize deviations between simulated and actual outcomes. In addition, digital twins can be used as the base for executing simulations, as they already represent their physical counterparts in the digital world. [39]

Life Cycle Analysis (LCA) | Since upscaling often comes with comprehensive costs, thorough life cycle cost analysis is required to help support decisions about investments. Therefore, LCAs need to be implemented early on before actual upscaling pilot projects are initiated. [39]

Characterization and Testing | A lack of characterization and testing techniques may result in unexpected real-life performance of products or processes. Each field of application is required to develop individual testing methods to keep track of the scaling process, so that results remain in the desired scope. [39]

Project Timelines | Upscaling technologies and products is a time-intensive assignment. Fast-moving markets can lead to changing requirements that need to be addressed in a timely manner. Therefore, industrial upscaling needs to be pro-active and development lead times kept at a minimum. [39]

Applications

Technology Upscaling is required for basically any innovation to transfer from experimental use to pilot projects and finally to fully commercialized wide-spread applications. To give some insight into their applications, this section will review three use cases of technology upscaling.

Wind Turbine Upscaling | Wind energy gains increasing focus as a renewable energy source. In order to improve the energy output of wind farms, wind turbines and blades are scaled up to operate at higher altitudes with higher wind speeds. Another advantage that viewer large windmills have over many smaller ones is that overall operation and maintenance costs can be reduced. However, higher wind speeds lead to higher wind loads. Design of the drive train and overall structural robustness needs to be addressed within the up-scaling process. [58]

Energy Grid Upscaling | Research has been conducted that reviews four use cases of technology upscaling for energy grid innovations in the Netherlands. Small pilot networks have been created that utilize smart meters and smart home appliances (such as smart washing machines and dryers) in combination with sustainable energy sources in an effort to reach energy autonomy. Technology upscaling was then used to either increase the size of individual networks or replicate them in different locations. Experiences have been exchanged between projects to accumulate overall better know-how in how to create energy self-reliant communities. [98]

Algae and Energy Austria | Besides waterpower, biomass is an essential energy source in Austria. In addition to the conventional biomasses from agriculture and forestry, research has been conducted that identifies microalgae as a potential source for future biomass production. The problem however is, that microalgae have not yet been cultivated on a commercial scale. Challenges like water and nutrition demand, impact on the environment, and water recycling after harvest hold great uncertainty and need extensive research. Systems that are feasible and cost-efficient are still missing. Therefore, technology upscaling research focuses on how to bring algae cultivation from lab-scale to industrial-scale. [59]

Underground Sun Conversion | The development of a large scale storage facility for electricity is the driving goal behind this project, and the functional principle is power to gas (P2G). Excess electricity from wind or solar power is used to create hydrogen from water. The hydrogen can then be transformed to methane by injecting it with carbon dioxide and pumping it into existing natural gas reservoirs. These reservoirs are at depths of over 1.000 meters and contain microorganisms that facilitate the transformation into biogas. Non-storable electricity is therefore transformed into a storable substance. This project is also concerned with the technical ability for upscaling. Process concepts for industrial plant sizes have to be developed to subsequently accommodate the required surface infrastructure. Plant capacities have to match the location's specific conditions. Technology upscaling in this project is used for process development and design of the facility layout. [14] The project partners are: RAG Austria AG, Montanuniversitaet Leoben, Energieinstitut at JKU Linz, acib (Austrian Center of Industrial Biotechnology), University of Natural Resources and Life Sciences Vienna, Axiom GmbH.

CO_2-reduced Steel Production | One approach to reduce CO_2 emissions in the steel production industry, is to replace energy systems that are based on carbon with hydrogen-based ones. Upscaling is used to develop processes that allow direct steel production with hydrogen as a reductive at an industrial scale. Hydrogen can be created from renewable energy sources and therefore the overall production impact on the environment is reduced significantly. [75]

Upscaling of Green Hydrogen for Mobility and Industry - UpHy I | Greenhouse gas emissions (GHG) and depleting fossil fuel reserves are the driving forces behind the development of electric vehicles. While battery-powered vehicles struggle with range and heavy-duty applications, fuel cell technologies powered by hydrogen are a viable option. UpHy I focuses on expanding the hydrogen refueling station network to create a base for future carbon-free infrastructure. Within its scope, official calibration systems for gas quality and hydrogen mass dispersion are developed. Furthermore, the hydrogen production processes are being scaled up to meet infrastructure needs. [137] The project partners are: OMV Refining & Marketing GmbH, HyCentA Research GmbH, VF Service GmbH, Energieinstitut at JKU Linz, and WIVA P&G.

Potential and Future Outlook

Within the energy sector, technology upscaling of renewable energy resources and smart grids will help to shift away from fossil fuels. It has been shown that self-sustaining communities can be established and with appropriate techniques grown in size. Renewable energy autonomy will help to protect the environment and improve the overall quality of life. In the industrial sector, innovations rely on upscaling to reach mainstream production. With sufficient planning, niche products and processes can be scaled to standard inventory.

It can be stated that technology upscaling holds many possibilities, but applications vary significantly for each area. The current lack of experience and know-how often leads to uncertainty regarding scaling benefits and companies are reluctant to risk investments. Therefore, extensive future research is required to establish trusted models and gain sufficient expertise.

5. Conclusion

The White Paper emphasizes that digitalization measures can highly support the design, operation and maintenance of industrial applications. Besides, they can contribute to the transition towards renewable supplied and sustainable production processes. Although considerable progress has been made in the last years, the realization of digitalization methods in the Austrian energy-intensive industry is still not as advanced as in other sectors. Thus, the White Paper identifies and analyzes 15 important digitalization techniques, technologies and applications that are relevant for the energy-intensive industry. Whereas some digitalization measures are already state of the art in certain industrial sectors, others still require considerable research before they can be applied economically. The investigation of Austrian centers of excellence and industrial projects shows that scientific and industrial research is increasingly focusing on digitalization. Several Austrian projects, programs, research centers and degree programs have emerged in the past years and even more are expected in the near future.

Nevertheless, the path towards an advanced digitalized industry is still a difficult and long one, especially for energy-intensive processes. Rigorous research is required to further develop digitalization methods and improve their economics for industrial, energy-related applications. However, the full potential of these methods can only be exploited with the concurrent establishment of a profound knowledge base, advanced technologies, an appropriate infrastructure, as well as the development of standardized interfaces between existing establishments and new digitalization methods and technologies. The benefits and potential, as well as disadvantages and drawbacks of digitalization measures - e.g. high investment costs or considerable energy consumption - need to be clarified to improve the appreciation and acceptance by stakeholders, users and society. Thus, the evolution of a wide-ranging digital transformation in the energy-intensive industry requires collaborative research and activity by the industry itself, research institutions and stakeholders, and benefits from a positive mindset of the society.

Bibliography

[1] Peter Adolphs et al. *Reference Architecture Model Industrie 4.0 (RAMI4.0)*. Tech. rep. July. VDI/VDE-Gesellschaft, 2015.

[2] Pasi Airikka. "Advanced control methods for industrial process control". In: *Computing & Control Engineering Journal* 15 (July 2004), pp. 18–23. DOI: 10.1049/cce:20040303.

[3] Klaus Bauer et al. *Securing the future of German manufacturing industry. Recommendations for implementing the strategic initiative INDUSTRIE 4.0. Final report of the Industrie 4.0 Working Group.* Tech. rep. Federal Ministry of Education and Research, 2013.

[4] Alpen-Adria-University Klagenfurt, ed. *Universität Klagenfurt besetzt Stiftungsprofessur Industrie 4.0 – Universität Klagenfurt*. Klagenfurt, 2018. URL: https://www.aau.at/blog/universitaet-klagenfurt-besetzt-stiftungsprofessur-industrie-4-0/.

[5] Enrique Andaluz. *The Process Digital Twin: A step toward operational excellence*. URL: https://cloudblogs.microsoft.com/industry-blog/manufacturing/2017/10/23/the-process-digital-twin-a-step-toward-operational-excellence/ (visited on 09/11/2019).

[6] Merlinda Andoni et al. "Blockchain technology in the energy sector: A systematic review of challenges and opportunities". In: *Renewable and Sustainable Energy Reviews* 100 (2019). PII: S1364032118307184, pp. 143–174. ISSN: 13640321. DOI: 10.1016/j.rser.2018.10.014.

[7] Andres M. Ticlavilca, Alfonso Torres. *Data Driven Models and Machine Learning (ML) Approach in Water Resources Systems*.

[8] Uchenna P. Daniel Ani et al. "Review of cybersecurity issues in industrial critical infrastructure: manufacturing in perspective". In: *Journal of Cyber Security Technology* 1.1 (2017), pp. 32–74.

[9] Lorenzo Ardito et al. "Towards Industry 4.0 Mapping digital technologies for supply chain management-marketing integration". In: *Business Process Management Journal* 25.2 (2019), pp. 323–346. ISSN: 1463-7154. DOI: 10.1108/BPMJ-04-2017-0088.

[10] Armin Nowshad. *Deloitte erwartet IoT-Siegeszug durch Digital Twins*. Ed. by Deloitte. URL: https://www2.deloitte.com/at/de/seiten/press-release/digital-twins.html (visited on 09/11/2019).

[11] *Atomic: production automatization with digital sensors*. URL: https://%20plattform%22-industrie40.at/atomic-produktionsoptimierung-mit-digitaler-sensorik/?lang=en.

[12] Austrian Institute of Technology GmbH, ed. *Decarbonisation and Digitalisation in Industry: Industrial Energy Systems*. 2019. URL: https://www.ait.ac.at/en/research-topics/sustainable-thermal-energy-systems/decarbonisation-and-digitalisation-in-industry/industrial-energy-systems/.

[13] *Banking Is Only The Beginning: 55 Big Industries Blockchain Could Transform*. URL: https://www.cbinsights.com/research/industries-disrupted-blockchain/ (visited on 09/11/2019).

[14] Stephan Bauer. *Unterirdische Umwandlung und Speicherung von Wind- und Sonnenenergie*. URL: https://www.underground-sun-conversion.at/das-projekt/projektbeschreibung.html (visited on 09/11/2019).

[15] Thomas Bauernhansl et al. *Industrie 4.0 in Produktion, Automatisierung und Logistik : Anwendung, Technologien und Migration*. Wiesbaden: Springer Vieweg, 2014. URL: https://link.springer.com/book/10.1007%5C%2F978-3-658-04682-8 (visited on 07/12/2019).

[16] "Big Data in the Energy and Transport Sectors". In: *New Horizons for a Data-Driven Economy*. Springer, 2016.

[17] Baidyanath Biswas et al. "Analysis of barriers to implement blockchain in industry and service sectors". In: *Computers & Industrial Engineering* 136 (2019). PII: S0360835219303961, pp. 225–241. ISSN: 03608352. DOI: 10.1016/j.cie.2019.07.005.

[18] *Blockchain Landscape Austria*. EnliteAI & Cryptorobby - Vienna. URL: https://www.enlite.ai/works/blockchain-landscape-austria (visited on 09/11/2019).

[19] Coleman Brosilow et al. *Techniques of model-based Control*. Prentice Hall PTR, 2002.

[20] BUNDESGESETZBLATT FÜR DIE REPUBLIK ÖSTERREICH. *Intelligente Messgeräte-AnforderungsVO 2011 – IMA-VO 2011*. 2011.

[21] Chris Carpenter. *Data-Driven Methods Present Potential for Success*. URL: https://www.spe.org/en/print-article/?art=4781 (visited on 09/11/2019).

[22] *Chancen mit Big Data: Use Cases*. Tech. rep. VDI, June 2016. URL: https://blog.vdi.de/2016/06/neuer-vdi-statusbericht-chancen-mit-big-data/.

[23] *CoinMarketCap*. URL: https://coinmarketcap.com/all/views/all/ (visited on 09/11/2019).

[24] *Cybersecurity Jobs Report 2018-2021*. Tech. rep. Cybersecurity Ventures, 2017.

[25] *D3A*. URL: https://energyweb.org/portfolio/d3a/ (visited on 09/11/2019).

[26] *DECEPT - DEtection and Handling of CybEr-Physical ATtacks*. https://projekte.ffg.at/projekt/3321095 (accessed on 14-10-2019). 2019.

[27] *Demand Forecasting*. URL: https://businessjargons.com/demand-forecasting.html (visited on 09/11/2019).

[28] Samantha Derksen. *usePat - accurate measuring solutions*. 2019. URL: https://www.usepat.com/.

[29] Claudio Di Ciccio et al. *Blockchain Support for Collaborative Business Processes*. PII: 1178. 2019. DOI: 10.1007/s00287-019-01178-x.

[30] Merriam Webster Dictionary. *Dictionary*. URL: https://www.merriam-webster.com/dictionary/sensor.

[31] "Die Digitalisierung als Herausforderung für Unternehmen: Status Quo, Chancen und Herausforderungen im Umfeld BI and Big Data". In: *Big Data*. Springer, June 2016.

[32] *Digital Twin Technology Benefits and Challenges*. URL: https://www.identitymanagementinstitute.org/digital-twin-technology-benefits-and-challenges/ (visited on 09/11/2019).

[33] Jonas Dorißen et al. *Den Wert der Daten korrelieren*. 2018. URL: https://www.it-production.com/industrie-4-0-iot/wertschoepfung-big-data/.

[34] Douglas M. Lambert, Martha C. Cooper. "Issues in Supply Chain Management". In: Vol 29, (2000), pp. 65–83. DOI: 10.1016/S0019-8501(99)00113-3.

[35] Sabrina Dusek et al. "Design analysis of a hybrid storage concept combining Ruths steam storage and latent thermal energy storage". In: *Applied Energy* 251 (2019), p. 113364. ISSN: 03062619. DOI: 10.1016/j.apenergy.2019.113364.

[36] Thomas R. Eisenmann et al. *Opening Platforms: How, When and Why?* Tech. rep. Aug. 2008.

[37] Sebastian von Enzberg et al. *Big Data in der Produktion: große Daten = großes Potential?* 2018. URL: https://www.industry-of-things.de/big-data-in-der-produktion-grosse-daten-grosses-potential-a-776716/.

[38] Faculty of Informatics, ed. *Informatics, TU Vienna: Doctoral College Resilient Embedded Systems*. 2019. URL: http://www.informatik.tuwien.ac.at/teaching/phdschool/ResilientEmbeddedSystems.

[39] Sophia FANTECHI et al. *Towards a Roadmap for Engineering & Upscaling: Key Discussion Topics*.

[40] FFG. *COMET Compentence Centers for Excellent Technologies - COMET Centres (K1)*. 2019. URL: https://www.ffg.at/comet-compentence-centers-excellent-technologies-k1-centers.

[41] FFG. "COMET-Zentrum (K1): Austrian Blockchain Center". In: (2019). URL: https://www.ffg.at/sites/default/files/allgemeine_downloads/strukturprogramme/comet_centre_k1c5_factsheet_abc_en_1fp.pdf.

[42] FFG. "COMET-Zentrum (K1): Austrian Center for Digital Production". In: (2019). URL: https://www.ffg.at/sites/default/files/allgemeine_downloads/strukturprogramme/comet_k1_call4_factsheet_cdp_en_update_2018-05.pdf.

[43] FFG. “COMET-Zentrum (K1): Know-Center”. In: (2019). URL: `https://www.ffg.at/sites/default/files/allgemeine_downloads/strukturprogramme/know-center_comet_centre_k1_call3_factsheet_en_2fp.pdf`.

[44] FFG. *Digitaler Zwilling / Building Tracker - Kopplung der Gebäudesimulation mit physischen Gebäuden in Echtzeit.*

[45] FFG. *Digitalisierungsagentur*. 2019. URL: `https://www.ffg.at/dia`.

[46] C. Floudas et al., eds. *Encyclopedia of Optimization*. Boston: Springer, 2008.

[47] Christian FREILER et al., eds. *Digitalisierung in der Wasserkraft*. ISBN: 978-3-85125-586-7.

[48] I. P. Gania et al. “FLEXIBLE MANUFACTURING SYSTEMS: INDUSTRY 4.0 SOLUTION”. In: *DEStech Transactions on Engineering and Technology Research* icpr (2018). DOI: `10.12783/dtetr/icpr2017/17583`.

[49] Jennifer GARFINKEL. *Gartner Identifies the Top 10 Strategic Technology Trends for 2019*. Ed. by Gartner. URL: `https://www.gartner.com/en/newsroom/press-releases/2018-10-15-gartner-identifies-the-top-10-strategic-technology-trends-for-2019` (visited on 09/11/2019).

[50] Gartner, Inc. `https://www.gartner.com/en/information-technology/glossary/big-data` (accessed on 14-10-2019).

[51] Eva Geisberger et al. *Integrierte Forschungsagenda Cyber-Physical Systems*. acatech Studie. acacatech – Deutsche Akademie der Technikwissenschaften e.V., 2012.

[52] *GEL OpenDataPlatform*. `https://www.greenenergylab.at` (accessed on 14-10-2019). 2019.

[53] Iman Ghalehkhondabi et al. “An overview of energy demand forecasting methods published in 2005–2015”. In: *Energy Systems* 8.2 (2017). PII: 203, pp. 411–447. ISSN: 1868-3967. DOI: `10.1007/s12667-016-0203-y`.

[54] Lukas Goertschacher et al. “SIMO UHF RFID reader using sensor fusion for tag localization in a selected environment”. In: *e & i Elektrotechnik und Informationstechnik* 133.3 (June 2016), pp. 183–190.

[55] Ingeborg GRATZER. *CRYPTO STAMP: ÖSTERREICHISCHE POST PRÄSENTIERT DIE ERSTE BLOCKCHAIN-BRIEFMARKE DER WELT*. Ed. by Österreichische Post AG. URL: `https://www.post.at/footer_ueber_uns_presse.php/presse/details/id/1422785` (visited on 09/11/2019).

[56] Eclipse IoT Working Group. *Open Source Software for Industry 4.0*. Tech. rep. Oct. 2017. URL: `https://iot.eclipse.org/resources/white-papers/Eclipse%20IoT%20White%20Paper%20-%20Open%20Source%20Software%20for%20Industry%204.0.pdf`.

[57] Jayavardhana Gubbi et al. “Internet of Things (IoT): A vision, architectural elements, and future directions”. In: *Future Generation Computer Systems* 29.7 (2013). Including Special sections: Cyber-enabled Distributed Computing for Ubiquitous Cloud and Network Services and Cloud Computing and Scientific Applications — Big Data, Scalable Analytics, and Beyond, pp. 1645–1660. ISSN: 0167-739X. DOI: https://doi.org/10.1016/j.future.2013.01.010. URL: http://www.sciencedirect.com/science/article/pii/S0167739X13000241.

[58] J. HELSEN et al. *Some trends and challenges in wind turbine upscaling*.

[59] HINGSAMER M. *ALGAE&ENERGY:AUSTRIA*.

[60] Penny HITCHIN. *Energy Demand Forecasting in a Rapidly Changing Landscape*. URL: https://www.ge.com/power/transform/article.transform.articles.2017.dec.energy-demand-forecasting-in-a# (visited on 09/11/2019).

[61] Jörg Hoffmann. *Taschenbuch der Messtechnik*. 2015.

[62] René Hofmann et al. “Comparison of a physical and a data-driven model of a Packed Bed Regenerator for industrial applications”. In: *Journal of Energy Storage* 23 (2019), pp. 558–578. DOI: 10.1016/j.est.2019.04.015.

[63] Nathaniel C Horner et al. “Known unknowns: indirect energy effects of information and communication technology”. In: *Environmental Research Letters* 11.10 (Oct. 2016), p. 103001. DOI: 10.1088/1748-9326/11/10/103001. URL: https://doi.org/10.1088%2F1748-9326%2F11%2F10%2F103001.

[64] *HotCity - Gamification als Möglichkeit für die Generierung von Daten zur energieorientierten Quartiersplanung*. https://cities.ait.ac.at/projects/hotcity/ (accessed on 14-10-2019). 2019.

[65] “How Blockchain Will Change Cybersecurity Practices”. In: *Cybersecurity Best Practices*. Springer, 2018.

[66] IBM. *IBM X-Force Threat Intelligence Index 2017*. https://securityintelligence.com/media/ibm-x-force-threat-intelligence-index-2017/ (accessed on 14-10-2019).

[67] *IEC 62264 - Enterprise-control system integration*. Geneva, 2013.

[68] *IMW : Home*. URL: https://www.imw.tuwien.ac.at/cps/home/.

[69] *INDICAETING - INtrusion DetectIon by Correlating Automatically Extracted Threat INtelliGence*. https://projekte.ffg.at/projekt/3079436 (accessed on 14-10-2019). 2019.

[70] *Industrie-Blog und Neuigkeiten - hitech*. URL: https://www.hitech.at/industrie.

[71] *Integrate Industry 4.0 principles with Process Digital Twin*. URL: https://cloudblogs.microsoft.com/industry-blog/manufacturing/2018/08/20/the-cloud-enables-next-generation-digital-twin/ (visited on 09/11/2019).

[72] *IoT4CPS - Trustworthy IoT for Cyber-Physical-Systems*. https://iot4cps.at/ (accessed on 14-10-2019). 2019.

[73] Stefan Jakubek et al. *Adaptive and Predictive Control*. 2018.

[74] *Josef Manner & Comp. AG Optimization of CHP-heat recovery (cooling water, exhaust gas) for process heating, optimzed absorption refrigeration system and heating*. URL: https://edtmayer.at/de/referenzen/nahrungsmittel-energie-energieeffizienz/manner-wien-energieeffizienz.

[75] K1-MET GmbH. *CO2-reduced Steel Production*. URL: https://www.uar.at/en/associated-companies/further-research-institutes/k1-met/co2-reduced-steel-production (visited on 09/11/2019).

[76] Henning Kagermann et al. *Umsetzungsempfehlung für das Zukunftsprojekt Industrie 4.0*. Abschlussbericht des Arbeitskreises Industrie 4.0. acacatech – Deutsche Akademie der Technikwissenschaften e.V., 2013.

[77] Jörg Kempf. *Advanced Process Control: So fahren Sie Prozesseinheiten energieoptimiert*. 2010. URL: https://www.process.vogel.de/advanced-process-control-so-fahren-sie-prozesseinheiten-energieoptimiert-a-248574/.

[78] Alfred Kinz et al. *Smart Maintenance*. WINGbusiness 1/2016, Jan. 2016. URL: https://diglib.tugraz.at/download.php?id=57204fef568bb&location=browse.

[79] Know-Center. *Industrial data analytics*. URL: https://www.know-center.tugraz.at/angebot/geschaeftsfelder/industrial-data-analytics/.

[80] Martin Köhler et al. *Austria - Österreichische Potenziale und Best Practice für Big Data*. Tech. rep. Bundesministerium für Verkehr, Innovation und Technologie, 2014.

[81] Jonathan G. Koomey et al. “Smart Everything: Will Intelligent Systems Reduce Resource Use?” In: *Annual Review of Environment and Resources* 38.1 (2013), pp. 311–343. DOI: 10.1146/annurev-environ-021512-110549.

[82] Gunther Koschnick. *Industrie 4.0: Smart services*. Tech. rep. July. Frankfurt am Main, Germany: German Electrical and Electronic Manufacturers’ Association, 2016, pp. 13–14.

[83] Douglas Laney. *3D Data Management: Controlling Data Volume, Velocity, and Variety*. Tech. rep. META Group, Feb. 2001. URL: http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf.

[84] Edward Ashford Lee et al. *Introduction to Embedded Systems: A Cyber-Physical Systems Approach*. 2nd. The MIT Press, 2016. ISBN: 0262533812, 9780262533812.

[85] Yuqian Lu et al. “Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues”. In: *Robotics and Computer-Integrated Manufacturing* 61 (2020). PII: S0736584519302480, p. 101837. ISSN: 07365845. DOI: 10.1016/j.rcim.2019.101837.

[86] Jan Lunze. *Künstliche Intelligenz für Ingenieure, Methoden zur Lösung ingenieurtechnischer Problmeme mit Hilfe von Regeln, Logischen Formeln und Bayesnetzen*. Ed. by 3. Auflage. De Gruyter Oldenbourg, 2016.

[87] Michael Maiwald. "Die Technologie-Roadmap Prozess-Sensoren 4.0 – Chancen für neue Automatisierungskonzepte und neue Geschäftsmodelle". In: *ATP Plus - Das Magazin der Automatisierungstechnik* 1 (Nov. 2016), pp. 12–21.

[88] Ard-Pieter de Man et al. "Collaborative business models: Aligning and operationalizing alliances". In: *Business Horizons* 62.4 (2019). PII: S000768131930031X, pp. 473–482. ISSN: 00076813. DOI: 10.1016/j.bushor.2019.02.004.

[89] Bernard Marr. *What Is Digital Twin Technology - And Why Is It So Important?* URL: https://www.forbes.com/sites/bernardmarr/2017/03/06/what-is-digital-twin-technology-and-why-is-it-so-important/#3295ac712e2a (visited on 09/11/2019).

[90] J. T. McCoy et al. "Machine learning applications in minerals processing: A review". In: *Minerals Engineering* 132 (2019). PII: S0892687518305430, pp. 95–109. ISSN: 08926875. DOI: 10.1016/j.mineng.2018.12.004.

[91] Mario Meir-Huber et al. *Big Data in Austria - Österreichische Potenziale und Best Practice für Big Data*. Tech. rep. Apr. 2014. URL: https://www.ffg.at/sites/default/files/allgemeine_downloads/thematische%20programme/IKT/big_data_in_austria.pdf.

[92] Lennart Merkert et al. "Scheduling and energy – Industrial challenges and opportunitiesLennart". In: *Computers & Chemical Engineering* 72 (2015), pp. 183–198. ISSN: 00981354. DOI: 10.1016/j.compchemeng.2014.05.024.

[93] Michael Anderl et al. *Austria's Annual Greenhouse Gas Inventory 1990-2017: Submission under Regulation (EU) No 525/2013*. Ed. by Umweltbundesamt. 2019.

[94] Eric Mjolsness et al. "Machine Learning for Science: State of the Art and Future Prospects". In: *Science (New York, N.Y.)* 293 (Oct. 2001), pp. 2051–5. DOI: 10.1126/science.293.5537.2051.

[95] R. Keith Mobley. *An introduction to predictive maintenance*. 2nd ed. United States of America: Elsevier, 2002.

[96] Gianfranco E. Modoni et al. "Synchronizing physical and digital factory: benefits and technical challenges". In: *Procedia CIRP* 79 (2019). PII: S2212827119302422, pp. 472–477. ISSN: 22128271. DOI: 10.1016/j.procir.2019.02.125.

[97] Thomas Moser et al. *Anwendungsfallbasierte Erhebung Industrie 4.0 relevanter Qualifikationsanforderungen und deren Auswirkungen auf die österreichische Bildungslandschaft*. Ed. by Bundesministerum für Verkehr, Innovation und Technologie. Wien. URL: https://www.ffg.at/sites/default/files/allgemeine_downloads/thematische%20programme/Produktion/aeiqu_endversion_20171027.pdf.

[98] Rolf Naber et al. "Scaling up sustainable energy innovations". In: *Energy Policy* 110 (2017). PII: S0301421517304871, pp. 342–354. ISSN: 03014215. DOI: 10.1016/j.enpol.2017.07.056.

[99] M. Niederer et al. “Nonlinear model predictive control of the strip temperature in an annealing furnace”. In: *Journal of Process Control* 48 (2016), pp. 1–13. ISSN: 0959-1524. DOI: https://doi.org/10.1016/j.jprocont.2016.09.012. URL: http://www.sciencedirect.com/science/article/pii/S0959152416301354.

[100] Otto Nowak et al. “Ways to optimize the energy balance of municipal wastewater systems: Lessons learned from Austrian applications”. In: *Journal of Cleaner Production* 88 (2015), pp. 125–131. ISSN: 09596526. DOI: 10.1016/j.jclepro.2014.08.068.

[101] Thomas OHNEMUS. *The Digital Twin Effect: Four Ways It Can Revitalize Your Business*. URL: https://www.digitalistmag.com/digital-supply-networks/2018/06/21/digital-twin-effect-4-ways-it-can-revitalize-your-business-06176757 (visited on 09/11/2019).

[102] *Open Government in Vienna*. City of Vienna. URL: https://digitales.wien.gv.at/site/en/open-government-in-vienna/ (visited on 09/11/2019).

[103] Open Industry 4.0 Alliance. https://www.openindustry4.com/ (accessed on 14-10-2019).

[104] Hellen OTI-YEBOAH. *Why is Demand Forecasting important for effective Supply Chain Management?* URL: https://blog.arkieva.com/demand-forecasting-for-supply-chain-management/ (visited on 09/11/2019).

[105] Farhad Panahifar et al. “Supply chain collaboration and firm’s performance”. In: *Journal of Enterprise Information Management* 31.3 (2018), pp. 358–379. ISSN: 1741-0398. DOI: 10.1108/JEIM-08-2017-0114.

[106] Josef Petek et al. *On-line Optimization of a Complex Industrial Power Plant Using a Novel Fast and Accurate Modeling Approach*. Proceedings of Electrify Europe Conference, Vienna 19-21 June 2018. available from josef.petek@enexsa.com.

[107] Plattform Industrie4.0. *https://www.plattform-i40.de*. Federal Ministry for Economic Affairs and Energy Division for Social Media, Public Relations, 2019. URL: https://www.plattform-i40.de/PI40/Navigation/EN/Industrie40/WhatIsIndustrie40/what-is-industrie40.html.

[108] Plattform Industrie4.0. *https://www.plattform-i40.de*. Federal Ministry for Economic Affairs and Energy Division for Social Media, Public Relations, 2019. URL: https://www.plattform-i40.de/PI40/Redaktion/DE/Infografiken/referenzarchitekturmodell-4-0.html.

[109] Alfred Posch et al. “Strategic energy management in energy-intensive enterprises: A quantitative analysis of relevant factors in the Austrian paper and pulp industry”. In: *Journal of Cleaner Production* 90 (2015), pp. 291–299. ISSN: 09596526. DOI: 10.1016/j.jclepro.2014.11.044.

[110] Oxford University Press. *Oxford English Dictonary*. https://www.lexico.com/ (accessed on 14-10-2019).

[111] Ian Richter. *How Digital Twins are Completely Transforming Manufacturing*. URL: https://blog.seebo.com/digital-twin-technology-cornerstone/ (visited on 09/11/2019).

[112] Marlene Ronstedt. *Urban Development in Vienna Trials Blockchain Energy Sharing*. URL: https://reset.org/node/29341 (visited on 09/11/2019).

[113] S. SAKSHI et al. *Block chaining for transaction with demand forecasting-application in large scale retail chains*.

[114] Christian Schröder. *The Challenges of Industry 4.0 for Small and Medium-sized Enterprises*. Friedrich-Ebert-Stiftung, July 2016.

[115] Florian Seidl. *Hydropower 4.0: VERBUND als Vorreiter der Digitalisierung in der Wasserkraft*. Apr. 2018. URL: https://www.verbund.com/de-at/ueber-verbund/news-presse/presse/2018/04/11/digitalisierung.

[116] Florian Seidl. *VERBUND präsentiert das „Digitale Wasserkraftwerk 4.0“*. URL: https://www.verbund.com/de-at/ueber-verbund/news-presse/presse/2019/04/26/digitales-kraftwerk (visited on 09/11/2019).

[117] Siemens. *Digitalisierung Prozessindustrie - Siemens*. URL: https://www.siemens.at/digitalisierung-prozessindustrie/index.php.

[118] *SIGI - Sicherheit für die digitale Transformation der Produktion*. https://projekte.ffg.at/projekt/3194367 (accessed on 14-10-2019). 2019.

[119] *Smart Indurstrial Concept*. 2019. URL: https://sic.tuwien.ac.at/.

[120] *Smart Maintenance*. Oct. 2019. URL: http://www.lean-smart-maintenance.net/de/5198/.

[121] Sohail Nazari. *IDEAS Digital Twins in Process Industries*.

[122] Dimitri P. Solomatine et al. “Data-driven modelling: some past experiences and new approaches”. In: *Journal of Hydroinformatics* 10.1 (2008), pp. 3–22. ISSN: 1464-7141. DOI: 10.2166/hydro.2008.015.

[123] Pratik Soni. *Blockchain: The Future of Inventory Management Available Now*. URL: https://www.manufacturing.net/article/2018/09/blockchain-future-inventory-management-available-now (visited on 09/11/2019).

[124] *STAR ALLIANCE*. URL: https://www.staralliance.com/en/ (visited on 09/11/2019).

[125] Statistik Austria. *Energiebilanzen: Gesamtenergiebilanz Österreich 1970 bis 2017 (Detailinformation)*. 2019. URL: http://www.statistik.at/web_de/statistiken/energie_umwelt_innovation_mobilitaet/energie_und_umwelt/energie/energiebilanzen/index.html.

[126] Statistik Austria. *Nutzenergieanalyse: Endenergieverbrauch 1993 bis 2017 nach Energieträger und Nutzenergiekategorien für Österreich (Detailinformation)*. 2019. URL: http://www.statistik.at/web_de/statistiken/energie_umwelt_innovation_mobilitaet/energie_und_umwelt/energie/nutzenergieanalyse/index.html.

[127] STIP Project. `http://stip.tech/` (accessed on 14-10-2019).

[128] L. Suganthi et al. "Energy models for demand forecasting—A review". In: *Renewable and Sustainable Energy Reviews* 16.2 (2012). PII: S1364032111004242, pp. 1223–1240. ISSN: 13640321. DOI: `10.1016/j.rser.2011.08.014`.

[129] *synERGY - security for cyber-physical value networks exploiting smart grid systems*. `https://synergy.ait.ac.at` (accessed on 14-10-2019). 2019.

[130] T. Moser, P. Wochner, K. Szondy, F. Fidler, H. Schneider, R. Dorfmayr, S. Schlund, V. Flores. "Anwendungsfallbasierte Erhebung Industrie 4.0 relevanter Qualifikationsanforderungen und deren Auswirkungen auf die österreichische Bildungslandschaft, Wien, 2017." In: ().

[131] "The Big Data Value Opportunity". In: *New Horizons for a Data-Driven Economy*. Springer, 2016.

[132] *The Future of Cybercrime and Security: Enterprise Threats and Mitigation 2017-2022*. Tech. rep. Juniper Research, 2017.

[133] *The Global Risks Report 2019*. Tech. rep. World Economic Forum, 2019. URL: `https://www.weforum.org/reports/the-global-risks-report-2019`.

[134] Ming-Lang Tseng et al. "Circular economy meets industry 4.0: Can big data drive industrial symbiosis?" In: *Resources, Conservation and Recycling* 131 (2018), pp. 146–147. ISSN: 09213449. DOI: `10.1016/j.resconrec.2017.12.028`.

[135] ÜBERALL scene development GmbH, ed. *Industry Business Safari: in Kooperation mit Industrie 4.0 Österreich*. 2019. URL: `https://businesssafari.at/#industry`.

[136] Thomas H.-J. Uhlemann et al. "The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0". In: *Procedia CIRP* 61 (2017). PII: S2212827116313129, pp. 335–340. ISSN: 22128271. DOI: `10.1016/j.procir.2016.11.152`.

[137] *Upscaling of green hydrogen for mobility and industry – UpHy I*. URL: `https://projekte.ffg.at/projekt/3093345` (visited on 09/11/2019).

[138] Ronald van Loon. *Machine learning explained: Understanding supervised, unsupervised, and reinforcement learning*. URL: `https://bigdata-madesimple.com/machine-learning-explained-understanding-supervised-unsupervised-and-reinforcement-learning/` (visited on 09/11/2019).

[139] Verein Industrie 4.0 Österreich, ed. *Ergebnispapier "Forschung, Entwicklung & Innovation in der Industrie 4.0"*. Wien, 2018.

[140] Verein Industrie 4.0 Österreich, ed. *Welche Themen sind für Industrie 4.0 wichtig?* Wien, 2019. URL: `https://plattformindustrie40.at/themen/`.

[141] Vienna University of Technology, ed. *Smart Industrial Concept! Holistic Approach with Digitalization of Industrial Processes and Applications for 2050 and beyond*. 2019. URL: `https://sic.tuwien.ac.at/home/`.

[142] *Virtual Power Plant*. Next Kraftwerke. URL: `https://www.next-kraftwerke.com/vpp/virtual-power-plant` (visited on 09/11/2019).

[143] *Wikipedia Flexibility (engineering)*. 3.10.2019. URL: https://en.wikipedia.org/wiki/Flexibility_(engineering).

[144] *Wikipedia Supply chain*. 5.08.2019. URL: https://en.wikipedia.org/wiki/Supply_chain.

[145] Martyn Williams. *How Digital Twins are changing the energy industry*. URL: https://www.powerengineeringint.com/articles/2018/07/how-digital-twins-are-changing-the-energy-industry.html (visited on 09/11/2019).

[146] Mark Willis et al. *ADVANCED PROCESS CONTROL*. Dept. of Chemical and Process Engineering, University of Newcastle upon Tyne, Apr. 1994. URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.462.7646&rep=rep1&type=pdf#page=2 (visited on 07/12/2019).

[147] Alexander Wimmer. *Predictive Maintenance – österreichische Unternehmen sehen sich gut gerüstet*. 2019. URL: https://www.it-press.at/presseaussendung/IKT_20190116_IKT0001/predictive-maintenance-oesterreichische-unternehmen-sehen-%20sich-gut-geruestet.

[148] Barbara Wimmer. *Zehn Fragen und Antworten zur Smart-Meter-Einführung in Österreich*. Nov. 2018. URL: https://futurezone.at/netzpolitik/zehn-fragen-und-antworten-zur-smart-meter-einfuehrung-in-oesterreich/400333440.

[149] Bernd Windholz. *EDCSPROOF ZUKUNFTSKONZEPT ZUR DEKARBONISIERUNG VON INDUSTRIEPROZESSEN*. 16 2019. URL: https://www.ait.ac.at/themen/sustainable-thermal-energy-systems/projects/edcsproof/.

[150] Jörg F. Wollert. *Ein Plädoyer für smarte Sensoren*. 2019. URL: https://www.vdi-wissensforum.de/news/ein-plaedoyer-fuer-smarte-sensoren/.

[151] Hao Yu et al. "A Value Chain Analysis for Bioenergy Production from Biomass and Biodegradable Waste: A Case Study in Northern Norway". In: *Energy systems and environment*. Ed. by P. T S vetkoc. London: IntechOpen, 2018. ISBN: 978-1-78923-710-8. DOI: 10.5772/intechopen.72346.

[152] Herwig Zeiner et al. *Ergebnispapier Forchung, Entwicklung und Innovation in der Industrie 4.0*. Forschungspapier. Verein Industrie 4.0 Österreich, 2017.

Appendix

A. Report of the Workshop: "Digitalisierung in der Industrie"

In this Appendix, the outcomes of a national workshop with the title "Digitalisierung in der Industrie" (Digitalization in Industry) are presented. This workshop was held in November 2019 in the course of the Annex XVIII, to get further insights into this topic from an industrial perspective. As this workshop was conducted in Austria in German language only, the following information is presented in German.

A.1. Setting und Programm

Die digitale Transformation beeinflusst viele Aspekte des täglichen Lebens. Auch in der Industrie ist die Digitalisierung zu einem wichtigen Faktor geworden, wodurch sich traditionelle Produktionssysteme verändern. Der Umgang mit und die Analyse von großen Datensätzen wird ein Wegbereiter für flexiblere Prozesse, Produktivitätswachstum und Innovation sein sowie die Wettbewerbsfähigkeit maßstäblich mitbestimmen. Doch nicht nur der Produktionsprozess selbst auch die Energieversorgung der Prozesse wird sich durch Digitalisierungsansätze maßgeblich verändern. Heterogen gewachsenen Strukturen und oftmals spezifische und komplexe Prozesses führen bei der Umsetzung von Digitalisierung, künstlicher Intelligenz und verwandten Technologien besonders in der Industrie zu großen Herausforderung.

Im Rahmen des Workshops „Digitalisierung in der Industrie“ wurden am 14.11.2019 in Wien Erkenntnisse aus laufenden Aktivitäten des Annex XVIII „Digitalisierung, Künstliche Intelligenz und verwandte Technologien zur Steigerung der Energieeffizienz und Reduzierung von Treibhausgasemissionen in der Industrie“ der Internationalen Energieagentur (IEA) im Rahmen des Technology Collaboration Programme (TCP) Industrial Energy Technologies and Systems (IETS) präsentiert sowie anhand eines breiten Publikums aus der heimischen Industrie Anwendungen der Digitalisierung sowie die Chancen und Hindernisse der Umsetzung konkreter Technologien diskutiert. Der Workshop wurde im Haus der Industrie (Industriellenvereinigung) durchgeführt und von Instituten und Fakultäten der TU Wien, dem Austrian Institute of Technology GmbH sowie dem Lehrstuhl für Energieverbundtechnik der Montanuniversität Leoben aufbereitet. Am Programm standen einige Impulsvorträgen, ein interaktiver Interessensaustausch sowie eine abschließende Podiumsdiskussion.

A.1.1. Impulsvorträge

Verena HALMSCHLAGER, Rene HOFMANN, Sophie KNÖTTNER, Elvira LUTTER

Annex XVIII - Internationale und nationale Arbeit | Als Einstieg in das Thema wurden in zwei Vorträgen die Hintergründe zur Veranstaltung des Workshops präsentiert. Ein Schwerpunkt lag dabei auf der Darstellung der allgemeinen Zusammenhänge zwischen Internationaler Energieagentur (IEA), den Technology Collaboration Programms (TCPs) im Allgemeinen und dem TCP Industrial Energy Technologies and Systems (IETS) im

Speziellen. In weiterer Folge wurden Inhalte aus dem ausgearbeiteten White Paper und die dahinterliegende Motivation aufbereitet. Abschließend wurde ein Ausblick auf die zukünftige Arbeit im Rahmen des IEA IETS Annex XVIII gegeben.

Ergänzt wurde das Programm durch zwei inhaltiche Impulsvorträge:

Wolfgang KASTNER

Information Technology und Operation Technology - Konvergenz und Integration in das Industrial IoT | Wolfgang Kastner ist Leiter der Gruppe Automatisierungssysteme an der Technischen Universität Wien. Seine Forschungsschwerpunkte liegen in der Entwicklung von Steuerungsnetzen und verteilten Automatisierungssystemen mit besonderem Schwerpunkt auf Industrie-, Haus- und Gebäudeautomationssystemen sowie Smart Grids, einschließlich Sicherheits- und Schutzfragen. Er ist aktiv an der Entwicklung von Ansätzen und Techniken für sichere und zuverlässige cyberphysikalische Produktionssysteme, intelligente Gebäude und intelligente Netze sowie deren Integration in das Internet der Dinge beteiligt.

Wolfgang KIENREICH

Datengetriebene künstliche Intelligenz: Universalwerkzeug für die digitalisierte Industrie der nahen Zukunft | Wolfgang Kienreich studierte Computerwissenschaften in Graz und Kommunikationswissenschaften in Wien. Er gründete ein auf Visualisierungstechnologien spezialisiertes Startup und arbeitete für Hyperwave Research. Seit 2003 ist er am Know-Center in Graz tätig und leitete unter anderem den Forschungsbereich Wissenserschließung und Visualisierung. In den letzten Jahren hat Wolfgang Kienreich über 60 wissenschaftliche Publikationen zu diesen Themen verfasst. Seit 2014 verantwortet er als Direktor die Geschäftsstrategien am Know-Center.

A.1.2. Podiumsdiskussion

Den abschließenden Programmpunkt stellte eine Podiumsdiskussion mit Vertretern aus Forschung, Industrie und einem Consulting Unternehmen dar. Geleitet wurde die Diskussion von Elvira Lutter vom Klima- und Energiefonds. Die Teilnehmenden wurden mit Fragen konfrontiert zu ihrer persönlichen Einschätzung des Fortschritts bzw. den großen Herausforderungen beim Thema Digitalisierung in der Industrie zur Steigerung der Energieeffizienz und Reduktion der Treibhausgasemissionen.

Franz BAUHOFER-WINTER | Lenzing AG - Digitalisierung und die Wechselwirkung mit Energieeffizienz und Treibhausgasemissionen aus der Perspektive des Industrieunternehmens

Friedrich BLEICHER | TU Wien – Pilotfabrik Industrie 4.0 - Digitalisierung aus der Produktionsperspektive, einem Bereich in dem die Digitalisierung schon weiter voran geschritten ist als bei der Energieversorgung von industriellen Prozessen

René HOFMANN | AIT/TU Wien - Digitalisierung und die Wechselwirkung mit Energieeffizienz und Treibhausgasemissionen aus der Sicht eines Experten für Energieversorgung für industrielle Prozesse

Markus HUMMEL | Oxford Energy - Digitalisierung aus der Sicht eines Consultingunternehmens mit unterschiedlicher Kundeschaft und Projekten zur Energieeffizienz und Nachhaltigkeit

Wolfgang KIENREICH | Know Center GmbH - Digitalisierung und die Wechselwirkung mit Energieeffizienz und Treibhausgasemissionen aus der Sicht des Experten für die IT-Aspekte der Digitalisierung

A.2. Teilnehmende

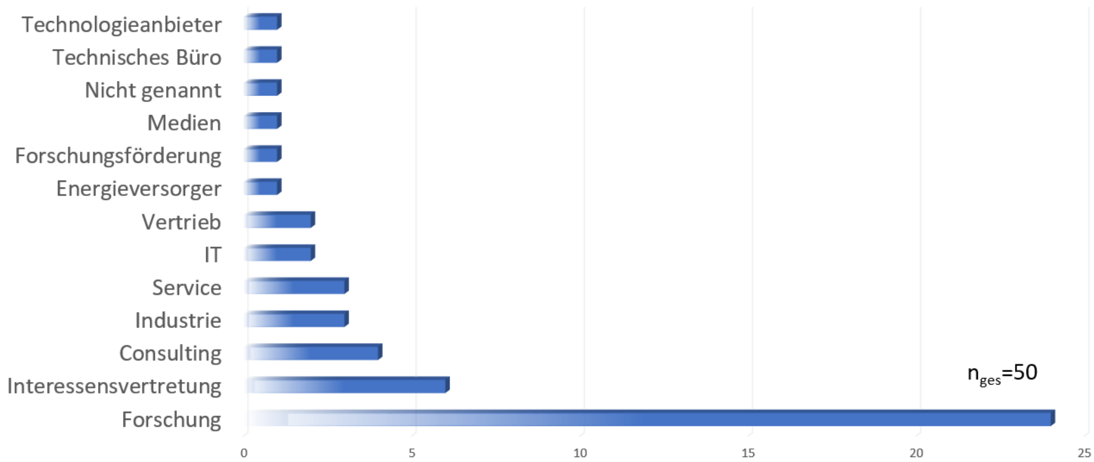

Abbildung A.1.: *Teilnehmende des Workshop nach Beschäftigungssektor*

Die Auswertung der Beschäftigungsfelder der Teilnehmenden, insgesamt 50 Personen, ist graphisch in Abb. A.1 dargestellt. Der hohe Anteil der Teilnehmenden aus der Forschung und Interessensvertretung lässt sich unter anderem durch die Tatsache erklären, dass die Veranstaltung des Workshops von Vertretern dieser Beschäftigungsgruppen organisiert wurde. Des Weiteren lässt sich festhalten, dass insbesonders die Verbindung der Themengebiete Digitalisierung, Effizienzsteigerung und Treibhausgasemissionsreduktion bisher selten behandelt wurde. Das lässt die Vermutung zu, dass zukünftig höheres Interesse denkbar ist.

A.3. Interessensbekundungen

Bei diesem Programmpunkt wurden die Teilnehmenden aufgefordert ihr Interesse an den hier ausgearbeiteten Digitalisierungstechnologien und -anwendungen zu bewerten. Das Bewertungsschema sah wie folgt aus:

- Dieses Thema ist im Unternehmen, in dem ich arbeite bisher nicht in Betracht gezogen worden und ich kann mir aktuell auch keine Umsetzung vorstellen.
- Bisher haben wir uns im Unternehmen , in dem ich arbeite, nicht mit diesem Thema beschäftigt, aber planen es in Zukunft, bzw. es erscheint mir vielversprechend für unser tägliches Geschäft.
- Für das Unternehmen in dem ich arbeite sehr relevant und wir beschäftigen uns schon mit diesem Thema

Die Ergebnisse der Interessensbekundung sind graphisch in Fig. A.2-A.4 dargestellt. Zur Interpretation der Ergebnisse lässt sich noch festhalten, dass ein großer Teil der Teilnehmenden aus den Bereichen Forschung und Interessensvertretung nicht an der Umfrage teilgenommen hat.

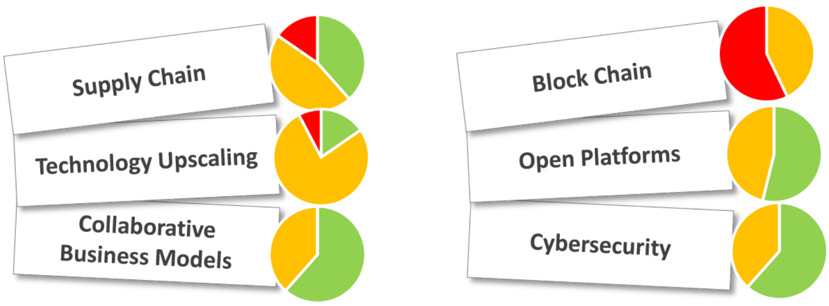

Abbildung A.2.: *Ergebnisse Interessensbekundung*

Abbildung A.3.: *Ergebnisse Interessensbekundung*

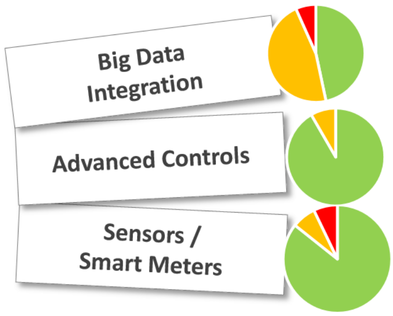

Abbildung A.4.: *Ergebnisse Interessensbekundung*

A.4. Tischdiskussionen

Im folgenden werden die wichtigsten Meldungen bei der intensiven Diskussion der einzelnen Themen in Kleingruppen zusammengefasst.

Block Chain | Block Chains werden als Chance gesehen dezentrale Abrechnung speziell im Sektor der Energieversorgung einfacher zu machen. Andererseits besteht eine gewisse Skepsis, weil die Wissensbasis zu diesem Thema oft nicht ausreichend ist. Außerdem werden der hohe Rechenaufwand der zur Generierung von Block Chains benötigt wird und die schlechte Regulierbarkeit kritisch gesehen.

Offene Platformen (Open Platforms) | Offene Plattformen kommen in weiten Gebieten zur Datensammlung und Datenanalyse zum Einsatz. Weil es keine allgemein gültige Definition von offenen Plattformen gibt ist die Systemsicherheit nicht klar. Ist mit offen eine neutrale Schnittstelle oder Offenheit im Sinne der Standardisierung gemeint? Es wurde unter anderem angesprochen, dass Lösungen oft zu allgemein sind, um für ein spezifisches Problem einen Mehrwert generieren zu können. Ensprechende rechtliche Grundlagen und Vorschriften können in der Zukunft ein Treiber für diese Technologie sein.

Cybersecurity | Ein funktionierendes Cybersicherheitskonzept oder -system wird als Grundvoraussetzung für die weitere Digitalisierung angesehen. Es kann als Ermöglicher oder Treiber angesehen werden. Cyberangriffe sind ernste Probleme in fast jedem Unternehmen und es gibt derzeit keine ausreichenden universellen Verteidigungsstrategien. Cybersicherheit als eigenständiger Service wird immer beliebter. Große Herausforderungen sind, dass die Entwicklung von Industrielösungen eher langsam ist und dass Cybersicherheitssysteme sehr teuer sind.

Lieferkette (Supply Chain) | Eine gut geführte und dokumentierte Lieferkette hilft bei der Suche nach dem globalen Optimum für das gesamte System. Sie verbindet die verschiedenen Aspekte und Aufgaben innerhalb des Produktionsprozesses. Datenbasierte Modelle werden häufig zur Lieferketten-Optimierung herangezogen. Gerade in der chemischen Industrie gibt es ein großes Potenzial bei der Optimierung der Lieferkette und deren Standardisierung.

Kollaborative Geschäftsmodelle (Collaborative Business Models) | Für Kollaborative Geschäftsmodelle sind der Datenaustausch, der Zeithorizont der Anwendung oder der Komponenten und die Sammlung von Daten von großem Interesse. Aus den gesammelten Daten können Geschäftsfälle abgeleitet und die Kernkompetenzen erweitert werden. Die Zusammenarbeit mit Start-ups kann helfen, einen Mehrwert z.B. durch Know-how-Austausch zu generieren.

Technology Upscaling | Der Technologie-Upscaling ist mit den Herausforderungen von Bürokratie, Infrastruktur und hohem Ressourcenbedarf verbunden. Kleine und mittlere Unternehmen haben dafür meist zu wenige Ressourcen und benötigen Risikokapital von größeren Unternehmen mit dem Nachteil des Verlustes an Entscheidungsmacht. Dennoch bietet Technology Upscaling Potenziale in verschiedenen Bereichen und kann durch Digitalisierung vorangetrieben werden.

Fortschrittliche Regelung (Advanced Control) | Fortschrittliche Regelung wird von den Beteiligten im Workshop kontrovers diskutiert. Einige denken, dass bevor erweiterte Regelungen implementiert werden können, bereits eine funktionierende und optimierte Regelung vorhanden sein muss, was oft nicht der Fall ist. In den Gesprächen wurde auch ein Zusammenhang zwischen Energieintensität des Prozesses und Interesse an fortschrittlicher Regelung angesprochen.

Big Data | Die Integration und Analyse großer Datenmengen wird als aussichtsreich angesehen, besonders für die Energiemärkte. Die Qualität und Quantität der Daten ist wichtig für den generierten Mehrwert. Für kleine und mittlere Unternehmen sind das Fehlen ausreichender Datenmengen oder fehlendes Know-how große Hindernisse.

Sensors/Smart Meters | Der zunehmende Druck durch behördliche Vorschriften macht eine geeignetes Monitoring der Prozesse mit Hilfe von Sensoren notwendig. Optimierungen jeglicher Art erfordern zudem ausreichende und zuverlässige Daten, um die Modellierung und weitere Verbesserung von Prozessen zu ermöglichen. Ein entscheidender Erfolgsfaktor ist der Wissenstransfer zwischen Technikern und Management, um deutlich zu machen, warum Investitionen in Sensorsysteme wichtig sind.

Digitaler Zwilling (Digital Twin) | Der Digitale Zwilling wird als ein sehr wichtiger Teilaspekt der Digitalisierung angesehen und von vielen erforscht. Sie helfen bei der Erprobung und Planung neuer Strategien oder Prozesse, indem sie Einblicke in das zukünftige Verhalten von Systemen geben. Das Trainieren und Modellieren von digitalen Zwillingen ist stark von den verwendeten Daten abhängig. Ohne die richtige Menge und Qualität an Daten sind die Ergebnisse möglicherweise nicht zufriedenstellend.

Datengetriebene Modellierung (Data-driven Modelling) | Datengetriebene Modellierung wird von vielen verwendet und erforscht, da sie viel Potenzial bietet. Eine große Herausforderung ist, die richtigen Daten in der richtigen Menge und mit der richtigen Qualität zur richtigen Zeit zu erhalten. Wenn genügend Daten verfügbar sind, können datengetriebene Modelle zu schnellen Ergebnissen führen. Auch Veränderungen im Prozess können gelernt oder aufgezeigt werden.

Prädiktive Instandhaltung (Predictive Maintenance) | Veränderungen in den Instandhaltungsstrategien von Unternehmen werden durch das Potenzial zur Kostensenkung getrieben. Gerade für KMU sind enorme Einsparungen zu erreichen. In einigen sicherheitsrelevanten Fällen muss eine behördlich geregelte Instandhaltung durchgeführt werden, die den Einsatz von prädiktiven Instandhaltungsmaßnahmen verhindert. Für die Implementierung werden gutes Prozesswissen und ausreichende historische Daten benötigt.

Flexible Komponenten (Flexible Components) | Der Einsatz flexibler Komponenten kann die Kosteneffizienz erhöhen und den CO_2-Ausstoß reduzieren. Der aktuelle Energiepreis ist zu niedrig, um als Treiber für die CO_2-Reduktion zu fungieren. Oft sind die Amortisationszeiten flexibler Komponenten zu lang oder die Investitionen passen nicht zu den kurzfristigen Zielen des Managements. Gesetzlich verbindliche Effizienzstandards und das Bewusstsein für Umweltauswirkungen könnten helfen ein Umdenken zu fördern.

Optimierung (Optimization) | Optimierung wird in fast jeder Branche eingesetzt, um wettbewerbsfähig zu bleiben. Barrieren dafür sind oft fehlende Prozessdaten, hohe Implementierungskosten und die interne Koordination innerhalb der Unternehmen. Auch qualifizierte Spezialisten oder die Schulung von bestehendem Personal sind erforderlich.

Verbrauchsprognose (Demand Forecasting) | Die Bedarfsprognose wird als wichtiger Input für die Optimierung genutzt. Insbesondere für den Energiemarkt und die Integration erneuerbarer Energien ist eine angemessene Bedarfsprognose erforderlich. Die Akzeptanz für die Datenerfassung wie bei Smart Metern muss gefördert werden, um die Erfassung ausreichender Daten zu ermöglichen.

A.5. Factsheets

Die Factsheets auf den folgenden Seiten wurden im Zuge des Workshops erstellt. Sie geben einen Überblick über alle behandelten Themen im White Paper und bei der Tischdiskussion und dienten als Vorinformation die Teilnehmenden des Workshops.

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Lieferkette (Supply Chain)

DEFINITION

"Als Lieferkette wird ein System von Organisationen, Personen, Aktivitäten, Informationen und Ressourcen verstanden, das an der Überführung eines Produkts oder einer Dienstleistung vom Lieferanten zum Kunden beteiligt ist."[1]

[1] *Nagurney, Anna (2006). Supply Chain Network Economics: Dynamics of Prices, Flows, and Profits. Cheltenham, UK: Edward Elgar. ISBN 978-1-84542-916-4.*

Anforderungen

Eine gut ausgebildete Lieferkette kann durch schnelles reagieren auf den dynamischen Markt die Leistungsfähigkeit einer Firma fördern. Fortschreitende Digitalisierung führt zu einer verstärkten Kommunikation zwischen den einzelnen Teilnehmer der Lieferkette. Cybersecurity wird immer wichtiger um eine sichere Übertragung der Firmen– und Prozessdaten zu ermöglichen

Anwendungen

- Die Ermöglichung einer Produktion der Losgröße Eins erforderte sehr flexible Lieferketten mit einem hohen Maß an Kommunikation
- Ein Zustand der Industrie 4.0 erfordert ausgeprägte, weit verzweigte und gut koordinierte Lieferketten um ein vollständig autonomes Arbeiten des Systems zu ermöglichen

Technologie-Upscaling (Technology Upscaling)

Anforderungen

Um ausreichend genau vorhersagen zu können wie sich eine Skalierung auf die realen Eigenschaften eines Systems, Produkts oder Prozesses auswirkt, sind realistische Simulationen und Modellierungstechniken von entscheidender Bedeutung. Weiters sollten Lebenszyklusanalysen frühzeitig implementiert werden, um mögliche Gefahren vor einer Investition zu erkennen und Auswirkungen von schnelllebigen Märkten auf die Anforderungen eines Produkts rechtzeitig einfließen lassen zu können. [1]

Anwendungen

- Windkraftwerke: Um die Stromerzeugung zu maximieren, werden die Maßstäbe der Windräder laufend vergrößert. Die Kombination von höheren Windgeschwindigkeiten und längeren Rotorblättern resultiert in höheren Belastungen für das gesamte Windrad. Mit Technologie-Upscaling können diese Belastungen besser simuliert und das Windraddesign optimiert werden. [2]
- CO_2-reduzierte Stahlproduktion: Ein Ansatz zur Reduzierung der CO_2-Emissionen besteht darin, von kohlen- auf wasserstoffbasierte Energieträger umzusteigen. Upscaling wird hier für die Prozessentwicklung verwendet. [3]

DEFINITION

Technologie-Upscaling beschreibt die Vergrößerung des Maßstabes, in welchem eine Technologie eingesetzt wird.

[1] R. Naber et al. 2017
[2] J. Helsen et al.
[3] K1-MET GnbH, last upd. 04.11.2019

Kollaborative Geschäftsmodelle (Collaborative Business Models)

DEFINITION

Kollaborative Geschäftsmodelle sind Geschäftsmodelle, die versuchen, durch Allianzen mehrerer Unternehmen, deren Ressourcen und Know-how zu bündeln, um die Wirtschaftlichkeit jedes einzelnen Mitglieds zu steigern.

[1] A. Man et al. 2019
[2] Next Kraftwerke GmbH, last upd. 04.11.2019
[3] Michaelsampson, last upd. 04.11.2019

Anforderungen

Der Wille für die Zusammenarbeit sowie das Vertrauen zwischen den beteiligten Unternehmen sind Voraussetzungen. Erst dann können Technologien, Know-how und Ressourcen geteilt werden, um gegenseitigen Nutzen voneinander zu ziehen. Es benötigt ein kollektives Verständnis, damit einzelne Unternehmen von Erfolgen der Partnerunternehmen profitieren. [1]

Anwendungen

- Flexibility Pooling: Ein Virtuelles Kraftwerk fungiert als zentrale Steuereinheit in Netzwerken aus dezentralen Stromerzeugern, Speichersystemen und flexiblen Verbrauchern. Intelligentes Energiemanagement ermöglicht dann die Einspeisung vieler individueller Energiequellen ohne die Netzstabilität zu gefährden. Flexible Verbraucher haben die Möglichkeit günstigen Strom außerhalb der Stoßzeiten zu beziehen und reduzieren somit Spitzenlasten. [2]
- Fluglinien: Die Star Alliance hat 27 Mitgliedsfluggesellschaften. Durch die Kombination von Flugrouten und Flugzeiten verschiedener Mitglieder, wird den Passagieren eine insgesamt größere Auswahl an Flügen und günstigere Reisezeiten geboten. [3]

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Flexible Komponenten (Flexible Components)

DEFINITION

"Im Rahmen der technischen Auslegung kann man Flexibilität als die Fähigkeit eines Systems definieren, rechtzeitig und kostengünstig auf potenzielle interne oder externe Veränderungen zu reagieren, die seine Wertschöpfung beeinflussen."[1]

[1] *Wikipedia Flexibility (engineering)*. 3.10.2019. url: https://en.wikipedia.org/wiki/Flexibility_(engineering).

Anforderungen

Um flexible Komponenten erfolgreich in einen bestehenden Prozess integrieren zu können ist eine genaue Kenntnis des Prozesses und der gegebenen Rahmenbedingungen nötig. Im Bereich der energieintensiven Industrie werden Teile der Anlage, die in der Lage sind den Energiebedarf bzw. die Energieerzeugung an äußere Randbedingungen wie schwankende Energiepreise anzupassen, als flexible Komponenten verstanden. Beispiele dafür sind Generatoren, Wärmepumpen und Energiespeicher.

Anwendungen

- Verbesserte Integration erneuerbarer Energien
- Steigerung Wirtschaftlichkeit, Modernisierung von bestehenden Prozessen/Anlagen
- Auslegung von zukünftigen Industrie 4.0 Prozessen mit erhöhtem Flexibilitätsbedarf

Optimierung (Optimization)

Anforderungen

Mathematische Optimierung ist die Auswahl des besten Elements aus einer Menge von möglichen Alternativen [1]. Bei Prozessoptimierung wird ein optimaler Prozesses aus einer Menge an möglichen Alternativen durch die mathematische Formulierung des gegebenen Problems ausgewählt. Prozesswissen sowie gute Vorhersagen sind Voraussetzung für die Optimierung für ein vorgegebenes Ziel (Wirtschaftlichkeit, Umweltschutz…).

Anwendungen

Optimierung wird in allen industriellen Sektoren angewendet. Den Aufwand zu reduzieren bei gleichzeitiger Profitmaximierung um wettbewerbsfähig zu bleiben ist allgegenwärtig.

- Optimierung des Energiebedarfs (Einsatz von Wärmepumpen, Wärmerückgewinnung)
- Optimierung von Energieversorgungsnetzwerken mit Berücksichtigung Erneuerbarer

DEFINITION

Unter Optimierung versteht man im Allgemeinen die Suche nach der bestmöglichen Lösung im Sinne eines bestimmten Zieles in einem Entscheidungsgebiet, wobei in der Regel Randbedingungen berücksichtigt werden müssen.

[1] C. Floudas et al., eds. *Encyclopedia of Optimization*. Boston: Springer, 2008.

Verbrauchsprognose (Demand Forecast)

DEFINITION

Verbrauchsprognosen ermöglichen die Abschätzung der wahrscheinlichen zukünftigen Nachfrage eines Produktes oder einer Dienstleistung. Sie basiert auf der Analyse früherer Nachfragen unter gegenwärtigen Bedingungen.

[1] I. Ghalehkhondabi et al. 2017
[2] L. Suganthi et al. 2012
[3] Arkieva, last upd. 04.11.2019

Beschreibung

Neben dem Erstellen von zeitlich aufgelösten Verbrauchsprognosen wird hierunter auch das Erstellen von Erzeugungsprofilen verstanden. Während ersteres Auskunft über den zukünftigen Bedarf an Produkten oder Dienstleistungen möglichst genau vorhersagen soll, beziehen sich Erzeugungsprognosen bspw. auf die Energieerzeugung einer Photovoltaik-Anlage. Die Herausforderung präziser Prognosen besteht darin, einerseits ausreichende Datenmengen als Basis der Vorhersagen zu generieren sowie andererseits Modelle zu erstellen, welche diese Daten anschließend verarbeiten können. Digitale Zwillinge und IoTs bieten Möglichkeiten zur Datenbereitstellung, während DDM Techniken die Grundlage der Datenverarbeitung darstellen. [1]

Anwendungen

- Lastmanagement: Präzise Bedarfsprognosen erleichtern die Steuerung der erforderlichen Stromerzeugung um Netzstabilität gewährleisten zu können. Zusätzlich erlauben akkurate Erzeugungsprognosen eine großflächigere Einbindung erneuerbarer Energiequellen, welche bspw. wetterbedingt höheren Schwankungen unterliegen. [2]
- Supply-Chain-Management: Ressourcenbeschaffung sowie Produktionsplanung können über Bedarfsprognosen besser den tatsächlichen Marktbedürfnissen angepasst werden. Überstockung von Lagerbeständen kann vermieden werden ohne Produktionsengpässe zu riskieren. [3]

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Digitaler Zwilling (Digital Twin)

DEFINITION

Ein Digitaler Zwilling ist ein virtuelles Spiegelbild eines reellen Objekts oder Prozesses.

[1] G. Modoni et al. 2019
[2] C. Freiler et al. 2018

Beschreibung

Digitale Zwillinge versuchen ein reales Objekt oder einen Prozess auf einer digitalen Plattform abzubilden und dadurch ein virtuelles Spiegelbild davon zu erschaffen. Die Komplexität eines Digitalen Zwillings ist lediglich von seiner Anwendung abhängig und kann von einfachen Maschinen über Produktionslinien bis hin zu ganzen Fabriken reichen. Dementsprechend variieren auch die virtuellen Modelle und umfassen sowohl exakte Nachbildungen aller einzelnen Komponenten als auch vereinfachte Versionen die nur prozessrelevante Komponenten beinhalten. Die Verbindung zwischen reeller und virtueller Welt wird durch eine Vielzahl von Sensoren und Aktoren, welche über das Internet-of-Things-Konzept (IoT) miteinander verbunden sind, hergestellt. Dadurch entsteht ein konstanter Echtzeitdatenfluss der beide Zwillinge stets aktualisiert. [1]

Anwendungen

- Energieoptimierungen: Durch Simulationen an virtuellen Prozessen, können optimale Prozessparameter bestimmt werden. Dies geschieht parallel zum normalen Betrieb, ohne dabei Stillstände zu verursachen.
- Prädikative Instandhaltung: Sensoren auf Verschleißteile können Wartungsarbeiten initiieren bevor es zu einem tatsächlichen Schadensfall kommt. Stillstände durch Ausfälle sowie unnötige Wartungsintervalle werden auf diese Weise reduziert. [2]

Datengetriebene Modelle (Data driven modeling)

Beschreibung

Herkömmliche Berechnungsmodelle beruhen in der Regel auf unserem Verständnis von physikalischen Formeln und Gesetzen. Im Gegensatz dazu versuchen Datengetriebene Modelle (DDM) einen rein mathematischen Zusammenhang zwischen Ein- und Ausgabeparametern eines Prozesses zu finden, ohne dabei auf physikalische Gesetze Rücksicht zu nehmen. DDMs verwenden dazu Methoden des Maschinellen Lernens (ML) wie bspw. Artificial Neural Networks oder Support Vector Machines. Diese ML-Methoden sind imstande Beziehungen zwischen Systemvariablen autonom zu finden, ohne dabei das physikalische Verhalten der Prozesse zu kennen. Der „Lernprozess“ eines DDM erfolgt über vorgegebene Trainingsdatensätze mit bekannten Ein- und Ausgabeparametern. Das Systemverständnis wird an die Differenz der gewünschten zu den errechneten Ausgabewerten angepasst. Die Datenmenge und -qualität der Trainingsdatensätze spielen eine wichtige Rolle in der Erstellung zuverlässiger Modelle. [3]

Anwendungen

Komplexe industrielle Prozesse haben häufig eine Unmenge an variablen Eingangsparametern, welche über physikalische Modelle nur mit erheblicher Rechenleistung oder gar nicht gelöst werden können. Ausreichend trainierte DDMs hingegen sind imstande vergleichbar schnell und mit geringem Rechenaufwand gewünschte Outputs zu liefern.

DEFINITION

Datengetriebene Modelle versuchen über die Analyse von Ein- und Ausgabewerten eines Systems deren Zusammenhang zu verstehen. Physikalische Gesetze spielen hierbei keine Rolle.

[3] D. Solomatine et al. 2008

Prädiktive Instandhaltung (Predictive Maintenance)

DEFINITION

Die prädiktive Instandhaltung ist die proaktive Wartung von Maschinen und Anlagen unter Verwendung des tatsächlichen Betriebszustandes, um Ausfallzeiten auf ein Minimum zu reduzieren und den Gesamtanla-

[1] Thomas Bauernhansl et al. Industrie 4.0 in Produktion, Automatisierung und Logistik, 2014.

Anforderungen

- Sensorik: Akkurate und auf den Betriebszustand sensible Messdaten werden benötigt.
- Expertise: Das Fachwissen des Maschinenherstellers und eine entsprechende Vergleichsbasis von vielen Maschinendaten ist erforderlich.
- Analyseverfahren: Mit lastabhängigen Zuverlässigkeitsanalysen lassen sich detaillierte Vorhersagen über den Zustand und das Ausfallverhalten machen.

Anwendungen

Durch die Aufzeichnung und Auswertung von Messdaten von Anlagenteilen über längere Zeiträume können detaillierte Vorhersagen über das Ausfallverhalten kritischer Komponenten gemacht werden. Insbesondere werden schleichende Verhaltensänderungen untersucht, wie z.B. ein allmählicher Temperaturanstieg oder zunehmende Vibrationen und Geräusche. [1]

- Die Wartung kann vor Auftreten der entsprechenden Störung geplant und priorisiert werden.
- Ersatzteile können im Voraus bestellt werden.
- Produktionsausfälle können vermieden oder zumindest reduziert werden.

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Big Data Integration

DEFINITION

„Big Data bezeichnet Datenmengen deren Menge, Geschwindigkeit und Vielfalt innovative Formen der Informationsverarbeitung erfordern.“ [1]

[1] Gartner, Inc., www.gartner.com

Anforderungen

Riesige Datenmengen werden im Betrieb industrieller Produktionsanlagen gesammelt. Die Datenquellen sind dabei vielfältig, von spezifischen Prozessparametern bis hin zu Verkaufs- und Konsumentendaten. Die Verschränkung und Integration dieser Daten von unterschiedlichen Unternehmensbereichen stellt ein bisher meist ungenütztes Potential dar und gewinnt im Kontext von Industrie 4.0 an Bedeutung.

Anwendungen

Big Data stellt die Grundlage für verschiedenste Arten von Anwendungen. Diese reichen von Prozessoptimierung mittels Machine Learning Algorithmen bis zur Erstellung von Digital Twins.

Fortschrittliche Regelung (Advanced Control)

Anforderungen

- Modelle: Sie sind die Grundlage und können entweder aus datengetriebener Modellierung oder physikalischen Gesetzen erhalten werden.
- Sensoren: Messdaten werden zur Modellierung und Echtzeit-Daten zur Regelung benötigt.
- Rechenleistung: Ein Optimierungsproblem muss in jedem Zeitschritt gelöst werden.

Anwendungen

Die Basis Regelung (meist PID Regler) wird innerhalb der Prozesskomponenten selbst konzipiert und realisiert, um die grundlegenden Anforderungen für Betrieb und Automatisierung zu gewährleisten. Fortschrittliche Regelung verwendet oftmals Modelle um verschiedene Prozesskomponenten mit Basisreglern auf höherem Niveau zu kombinieren und versucht, ein globales Betriebsoptimum unter Einhaltung von Bedingungen zu erreichen. [1]

- Mehrere, korrelierte Variablen können durch mehrere Einflussgrößen gleichzeitig geregelt werden.
- Wird oft in der Prozessindustrie eingesetzt um eine hohe Regelgüte unter Einhaltung von Bedingungen zu erreichen.

DEFINITION

Fortschrittliche Regelung ist meist modellbasiert und wird in der Regel auf einer höheren Ebene als die Basis Regelung (meist PID-Regler) hinzugefügt, um Optimierungspotenziale im Prozess zu berücksichtigen. Sie verbindet Regelungstechnik mit Prozesswissen auf eine intelligente Weise. [1]

[1] Mark Willis et al. ADVANCED PROCESS CONTROL, 1994.

Sensoren / Intelligente Zähler (Sensors / Smart Meters)

DEFINITION

Ein Sensor ist eine technische Komponente, die bestimmte physikalische oder chemische Eigenschaften qualitativ oder quantitativ als Messgröße erfassen kann. [1]

[1] Jörg Hoffmann. Taschenbuch der Messtechnik. 2015

[2] Eva Geisberger et al. Integrierte Forschungsagenda Cyber-Physical Systems. acatech Studie, 2012

Anforderungen

- Akkurate Messungen: Sensoren werden benötigt um den Produktionsprozess detailliert abzubilden und sind die Grundlage um Anlagen optimal betreiben zu können.
- Sensoranwendung: Der Nutzen der Anwendung bestimmt den geeigneten Sensortyp.
- Kommunikation: Eine reibungslose und sichere Kommunikation aller Sensoren auf Basis eines einheitlichen Protokolls wird benötigt.

Anwendungen

Ein Smart Meter dient zur digitalen Messung und Steuerung des Energieverbrauchs, hauptsächlich in Form von Strom. Er kann Daten senden und empfangen, um dem Stromnetzbetreibern und Verbrauchern Online-Informationen zur Analyse bereitzustellen. Smart Sensors liefern zusätzliche Informationen über ihre Umgebung oder über sich selbst und können innerhalb eines Sensorsystems kommunizieren. [2]

- Sensorfusion: Kommunikation zwischen Sensoren um Selbstkalibrierungen durchzuführen und Messungen auf Fehler zu überprüfen.
- Softsensor: Manchmal sind Messungen von Eigenschaften erforderlich, für die es keinen Sensor gibt. Der Softsensor ist eine Kombination aus mehreren physikalischen Sensoren und einem Algorithmus zur Echtzeitberechnung dieser "neuen" Größen in einem Prozess.

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Block Chain

DEFINITION

Eine Block Chain ist eine gemeinsam genutzte, dezentrale Datenstruktur, in einem Netzwerk, in dem eine Liste digitaler Transaktionen in Form von Datensätzen kontinuierlich und in chronologischer Reihenfolge erweitert wird.

[1] M. Andoni et al. 2019

[2] Gridsingularity, last upd. 04.11.2019

[3] Coinmarketcap, last upd. 04.11.2019

Beschreibung

Eine Block Chain ist eine dezentral gemeinsam genutzte, virtuelle Datenstruktur. Für jede neue Transaktion (z.B. Zahlung durch eine Kryptowährung oder Abwicklung eines Smart-Contracts) innerhalb des Block Chain Netzwerkes wird ein neuer Datensatz („Block“) erstellt. Bevor diese neue Transaktion an die bestehende Liste („Chain“) angehängt wird, muss diese im dezentralen Peer-to-Peer Netzwerk durch eine Vielzahl anderer Computer überprüft werden. Nach einer erfolgreichen Bestätigung der Transaktion wird diese ein unveränderlicher Teil der Datenstruktur und somit ein neuer Block in der Block Chain. [1]

Anwendungen

- Energiemärkte: Schaffen einer dezentralen Börse, in der mithilfe von Smart-Contracts frei gehandelt werden kann. Dies ermöglicht die Bildung von autarken Netzwerken aus individuellen, kleinen Energieerzeugern und flexiblen Verbrauchern. Energieerzeugung aus erneuerbaren Quellen, die umweltbedingt größeren Schwankungen unterliegen, werden der Handel in solchen Block Chain Netzwerken ermöglicht bzw. erleichtert. [2]
- Kryptowährungen: Digitale Zahlungsmittel basierend auf der Block Chain-Technologie. Neben den bekannten Währungen wie Bitcoin und Ethereum, gibt es aktuell mehr als 2400 verschiedene Kryptowährungen. [3]

Offene Plattformen (Open Platforms)

Anforderungen

Plattformen im Bereich Industry 4.0 agieren als wichtiger Mittler zwischen der Hardware (Sensoren, etc.) und den Applikationen (Datenanalyse, etc.). Als solches müssen sie in der Lage sein sich mit einer Vielzahl an heterogenen Geräten zu verbinden und es ermöglichen verschiedenartige Anwendungen zu integrieren. Die Verwendung von offenen Plattformen wird dabei als ausgesprochen wichtig angesehen, um die Interoperabilität und Modularität der Plattform für Anwendungen und Geräte von unterschiedlichen Herstellern zu gewährleisten.

Anwendungen

- Schnittstelle zwischen Applikation, Datenbank und Gerät
- Open Platforms bieten offene Schnittstellen und Anbindungsmöglichkeiten

DEFINITION

“Eine Plattform stellt die Basis auf der andere Anwendungen, Prozesse und Technologien entwickelt werden können. Eine Plattform wird dann als offen bezeichnet, wenn keine Einschränkungen hinsichtlich Weiterentwicklung oder Verwendung bestehen.“ [1]

[1] Thomas R. Eisenmann et al., *Opening Platforms: How, When and Why?, 2008*

Cybersecurity

DEFINITION

“Cybersecurity bezeichnet den Zustand des Schutzes gegen die kriminelle oder unbefugte Verwendung von elektronischen Daten oder die Maßnahmen, die ergriffen wurden, um diesen Schutz zu erreichen.“ [1]

[1] Oxford University Press, *Oxford English Dictonary*

Anforderungen

Industry 4.0 erfordert die Implementierung von geeigneten und automatisierten Cybersecurity Maßnahmen. Die zunehmende Verknüpfung und Abhängigkeit zwischen Information Technology und Operational Technology macht Industriebetriebe verletzbarer gegenüber potentiellen Cyberangriffen. Dies erfordert neben den üblichen Sicherheitsvorkehrungen wie Zugriffskontrollen usw. auch neue Lösungen um hohe Cybersecurity-Standards zu gewährleisten.

Anwendungen

Cybersecurity ist Grundvoraussetzung für den sicheren Betrieb von Industrie 4.0 Anwendungen und den Schutz von Daten. Als solches betrifft Cybersecurity alle Unternehmensbereiche, von einzelnen Geräten bis hin zur Schulung von Mitarbeitern.

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