dena ANALYSIS

Artificial Intelligence – from Hype to Reality for the Energy Industry

An in-depth analysis of fields of application for AI in the energy industry

Imprint

Publisher:
Deutsche Energie-Agentur GmbH (dena)
Chausseestrasse 128 a
10115 Berlin
Tel.: +49 (0)30 66 777 - 0
Fax: +49 (0)30 66 777 - 699
Email: info@dena.de
Website: www.dena.de

Authors:
Lisa Kratochwill, dena
Philipp Richard, dena (project leader)
Linda Babilon, dena
Felix Rehmann, dena
Sara Mamel, dena
Dr Sebastian Fasbender, dena

Peer reviewers:
Dr Marian Klobasa, Fraunhofer Institute for Systems and Innovation Research ISI
Sabine Pelka, Fraunhofer Institute for Systems and Innovation Research ISI
Dr Patrick Plötz, Fraunhofer Institute for Systems and Innovation Research ISI
Dr Ludwig Einhellig, Deloitte
Johanna Kappl, Deloitte
Kamila Behrens, Deloitte

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Foreword

Digitalisation and artificial intelligence – from necessity to sustainability

Digitalisation is already in full swing in the energy industry. It is being driven by proper and important debates about the sustainability and energy efficiency of digital technologies, which are affecting and changing almost every part of the energy industry. At the same time, it is very important to consider digitalisation projects in general, and AI projects in particular, from two different sides.

On the one hand, nearly all value-creation stages in the industry simply have to be digitalised. How else will millions of decentralised power generators, storage systems and consumers otherwise be able to be orchestrated in future so as to maintain energy supplies even in extremely decentralised structures? How else will it be possible to technically realise a future market design 2.0 of any kind whatsoever that can create, forward and process market signals to the second, and implement semi- or fully-automated control systems from these? How else can an integrated energy system evolve that brings together the transport, gas, heat and electricity sectors, puts the fluctuating products of renewable energies to the best possible use and is closely entangled with our European partners?

The answer is already clear: there can be no transformation of the energy system without digital networking among others by means of smart meters, but also based on innumerable sensors and coupled to high-performance computing centres. What's more, new sectors are also emerging here that promise some attractive scalable markets for digital products and services.

On the other hand, we need a timely debate on sustainable digitalisation and sustainable artificial intelligence. Only by ensuring that the basic standards of the circular economy and sustainability are observed, for both the creation of digital hardware and the development of software, will we be able to establish a firm foundation for the digital energy system of the future.

The sequence of the measures is decisive

Generally speaking – and this shows that we are on the right track – much has been put into proper order by the numerous valuable discussions over the past 10 years. It has become clear that a new market design will depend on the technical opportunities offered by the digital systems in the background. We now know that any information and communication system for the energy industry has to be created just as safely and securely as the energy physics system itself. This should be the focus of our work. In order to create a basis on which the process, product and service landscape can be built in the energy industry, politics and the sector now have to focus their attention on the digital infrastructure. At the same time, kicking off a debate about the sustainability of resource and energy-saving hardware and software is an important step. This will allow the integrated energy transition to take a giant leap forwards – thanks to innovative technological progress, which sets standards for the rest of the world, paired with an approach that regards humans as an integral part of potential new solutions.

dena as a forerunner for the practical implementation of innovative technologies

We at the Deutsche Energie-Agentur are also changing the role we play in part. Having successfully developed the thematic field of digitalisation for ourselves over the past few years, and having dealt with and de-emotionalised digital topics together with the political sphere and the market, the implementation phase of the energy transition is now becoming increasingly important for us too. With the newly founded Future Energy Lab – an implementation lab for digital technologies in the field of application of the energy industry - we will commissioned by the Federal Ministry for Economic Affairs and Energy (BMWi)be attempting to test topics such as blockchain and artificial intelligence in a broad circle of stakeholders. The analytical report you are holding in your hands should make a vital contribution here by explaining the potential artificial intelligence offers for the energy industry using practical examples and recommended courses of action, and by paving the way for a number of projects to implement this technology in future for the purpose of sustainability and an integrated energy transition. Our special thanks are in this context due to the BMWi, that actively supports our efforts and made the creation of this report possible.

We remain committed and hope that you will be inspired by what you read!

Yours

Andreas Kuhlmann
Chief Executive
of the Deutsche Energie-Agentur (dena) —
the German Energy Agency

Philipp Richard
Team Leader Energy Systems and Digitalisation
of the Deutsche Energie-Agentur (dena) —
the German Energy Agency

Executive Summary

The topic of artificial intelligence (AI) remains very popular. In 2019 alone, turnover totalled around 60 billion euros across all sectors in the German economy with services and products that included the direct use of AI (ZEW, 2020). AI is unstoppably evolving from an almost indeterminate next-generation technology into a technical reality. Accordingly, discussions about the topic are becoming increasingly application-related. This is important and appropriate, seeing as how AI has been far too generalised over the past years. On the one hand, it was inordinately hailed as the irreplaceable saviour for many industries, and on the other decried as a far too risky technology that would eliminate the direct influence of humans over a number of important decision-making processes. The predominant opinion nowadays is more expedient, concentrating equally on questions of benefits and risk aspects across all affected sectors and differentiating between safety-relevant as well as economic, political and social perspectives when assessing individual application cases. This is both a crucial and indispensable step, considering that the various kinds of AI cover an enormous spectrum of statistical, self-learning algorithms that are backed up digitally by a huge computing power, and that indubitably could have a big influence on human processes, areas of activity and responsibilities in all fields of life.[1]

AI is also becoming more and more important in the energy industry. The penetration rate in this field is already higher than anticipated and, in all probability, will continue to rise in the coming years. This is also indicated by a recent study published by the Federal Association of the Energy and Water Industry on the topic of AI in the energy industry (BDEW, 2020). However, this development will not progress at the same pace in all areas of the energy system, but also very differently in this industry. For example, some individual fields of application (use cases) will adapt the new technology much faster and more profoundly than others.

AI continues to display its biggest potential wherever it can be used to optimise complex systems and processes, thus allowing extensive cost blocks to be reduced or the revenue side to be scaled. In the meantime, these aspects reflect the classic expectations on digitalisation. At the same time, they still continue to implicate the potential of “hitting the jackpot”, of using AI in the energy industry too so as to achieve disruptive breakthroughs and provoke technological leaps, thus boosting the speed of the successful transformation of the energy system.

The present analysis is based methodically on the fundamental dena work “Artificial Intelligence for the Integrated Energy Transition: Assessing the technological status quo and categorising fields of application in the energy industry” that was published in September 2019. The current report assesses the use cases (nine potentially suitable fields of application for AI within the energy industry) identified therein in terms of technical, economic, social and regulatory issues and classifies these for an overall orientation with respect to their technological development, economic assessment as well as their contribution to the integrated energy transition. Figure 1 shows the respective advantages of the investigated fields of application as the result of the analyses performed and illustrates the need for socio-political and regulatory action.

[1] See also dena, 2019.

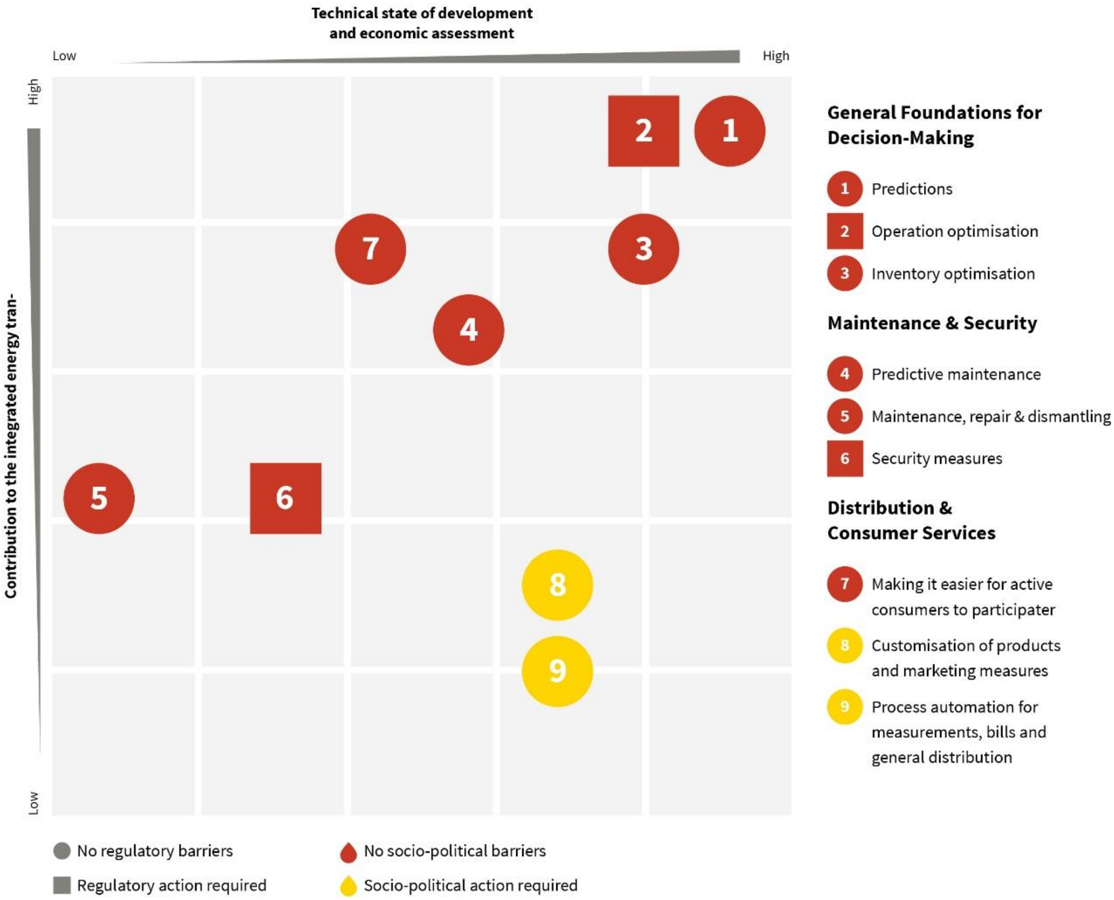


Figure 1: Overall assessment of the fields of application

Cluster "General Foundations for Decision-Making"

There have now been a number of considerations on the use of AI as a general foundation for decision-making. Its use along the entire energy industry value-creation chain can help towards making more exact predictions of the capacity utilisation of the grid as well as for predictive planning of the feed-in and power generated. Another goal is to obtain data for the assessment of investment decision to optimise consumption and the operation of the grids themselves. Concrete fields of application for AI in this cluster include **predictions**, **operation optimisation** as well as **inventory optimisation and other strategic business decisions**. In this case, AI provides the basis for a number of further processes in the energy industry and makes a correspondingly significant contribution to the integrated energy transition. If these processes are interpreted as a kind of basic service for fields of application that build on this, the paramount importance of the reliability of the applications becomes clear because of their huge effect on subsequent processes. The topicality, quantity and quality of the data thus play a key role here. The technical and economic potential in this cluster is in general very high.

The biggest challenge lies in how to deal with the critical infrastructure (e.g. maintaining the balance between supply and demand on the market and grid level, averting and resolving line overloads through grid congestion with the help of congestion management, averting IT attacks on the energy system), in particular in grid operation, where an extensive use of the technology can realistically be expected. On account of the increasingly decentralised energy landscape – small-scale generators, flexible consumers and integrated stores – the amount of data to be processed is increasing commensurate with the requirements on the power grid. In this respect, the availability of up-to-date grid data will be crucial if AI is to achieve its full potential, whereby the necessary data for certain grid levels is largely missing at present.

The situation is different in the value-creation stages of power generation and trading (e.g. price prediction through primary data such as time series on the load and RE generation in different meteorological years, consequences of optimum storage strategies for prediction price time series), where the majority of the necessary data is already available. The use of AI can make a major contribution to the integrated energy transition here and at the same time generate added economic value for companies. As a result, applications have already been established in this cluster in the field of power generation and trading.

Cluster “Maintenance & Security”

The use of AI in this cluster, above all in the value-creation stages of power generation and transport, can help to guarantee a safe operation of an installation and to minimise downtimes of power-generation installations. Thanks to the use of drones and robots in the two fields of application of **Predictive Maintenance** and **Maintenance, repair and dismantling**, the degree of complexity increases, initially leading to high investments. With costs falling in future for maintenance robots, smart assistance systems and drones, AI-assisted maintenance processes are also likely to make an economic contribution (e.g. by avoiding unnecessary outage and downtimes for installations, reducing the risk for maintenance staff and lower maintenance costs). The biggest challenge for **Security measures** are the regulatory requirements with respect to data security. The greater resilience of the energy system that can be achieved by this means that the use of AI in this area is an important precondition for further fields of application (e.g. making it easier for active consumers to participate, smart grid operation with a variety of power generators and flexible consumers).

The question of the kind of data and associated data security requirements also plays a crucial role here. The majority of energy industry uses of AI are based on technical data recorded by sensors and are thus uncritical when it comes to personal rights. However, in cases where AI accesses personal data, maximum transparency and traceability have to be ensured. Only when the benefits of using AI are absolutely clear and the way AI works is transparent for the end user can the use of the corresponding AI application be seen as a sensible contribution towards the integrated energy transition.

Cluster "Distribution & Consumer Services"

AI applications in this cluster are aimed at improving services for consumers and stepping up customer relationships. Consequently, more personal data will be used here compared to other clusters to **make it easier for active consumers to participate**, to **customise products and marketing measures** and to allow **process automation for measurements, bills and general distribution**, so that the focus will be more on social and regulatory questions.

The analysis shows a high likely potential for AI applications, above all with respect to making it easier for active consumers to participate (e.g. energy management to increase the private consumption from photovoltaic (PV) battery systems in households, the identification of small-scale efficiency potentials, the automated settlement of sales of self-generated electricity), which would not be economically viable without AI in most cases. AI will also grant smaller actors access to established processes from the energy industry and thus enable them to interact on the energy market for the first time.

The debate revolves around data

The present report shows that AI is often used across all clusters in processes, that although they could still be realised without this technology (e.g. forecasting RE generation, calculating optimum investment or storage strategies), whose potential for optimisation and thus the additional benefits resulting from more efficient processes as well as the associated reduction in costs, justify the additional effort for implementing AI. The use of AI in the energy industry allows more data to be processed, or for the first time in some complex application cases, and thus more concise and better results to be achieved.

The public technical discussion of AI is dominated by questions about the use and availability of data. Indeed, the availability of data in certain areas up to now has proven to be a limiting factor. Empirical data for training the models is often lacking due to the limited measurement technology that is installed, or the existing data is not of the necessary quality and/or may not be used on account of regulatory restrictions. The poorer the data basis, the lower the chance of AI applications being implemented in the corresponding field of application (FoA). High requirements on AI, such as those that exist for robotics, also increase the demands on the data basis and are therefore a further hurdle to its implementation.

With regard to data privacy and data security, generally regarded as the biggest impediment to the use of AI, this analysis does not reach a clear-cut verdict: For the majority of those application cases investigated, regulatory framework conditions are not a basic impediment to the use of the data. However, high regulatory requirements do exist in individual cases that serve to protect personal data. Nevertheless, these data security requirements do not constitute a disqualifier for the implementation of AI. Rather, work has to be done to ensure a fundamentally transparent and fair handling of data that places companies themselves under an obligation, but also assumes the creation of test instruments to control the proper use of corporate and personal information, at least on a random basis.

Anchoring AI in the energy industry: everyone has to pull together

The analysis clearly shows the continued need for action so as to establish AI correctly and profitably in all areas of the energy industry, and thus exploit the full potential of this technology for the integrated energy transition. The economy (E), politics (P) and research (R) are called upon in equal measure. In order to give the relevant actors some kind of orientation for the measures that have to be taken, it is not just the estimation of the respective contribution to the integrated energy transition that is important but also the complexity of its implementation and the time this is expected to take. Figure 2 illustrates recommended courses of action that are of overriding general interest for the industry, and names the most important actors who are involved (cf. Chapter 4.2.1).

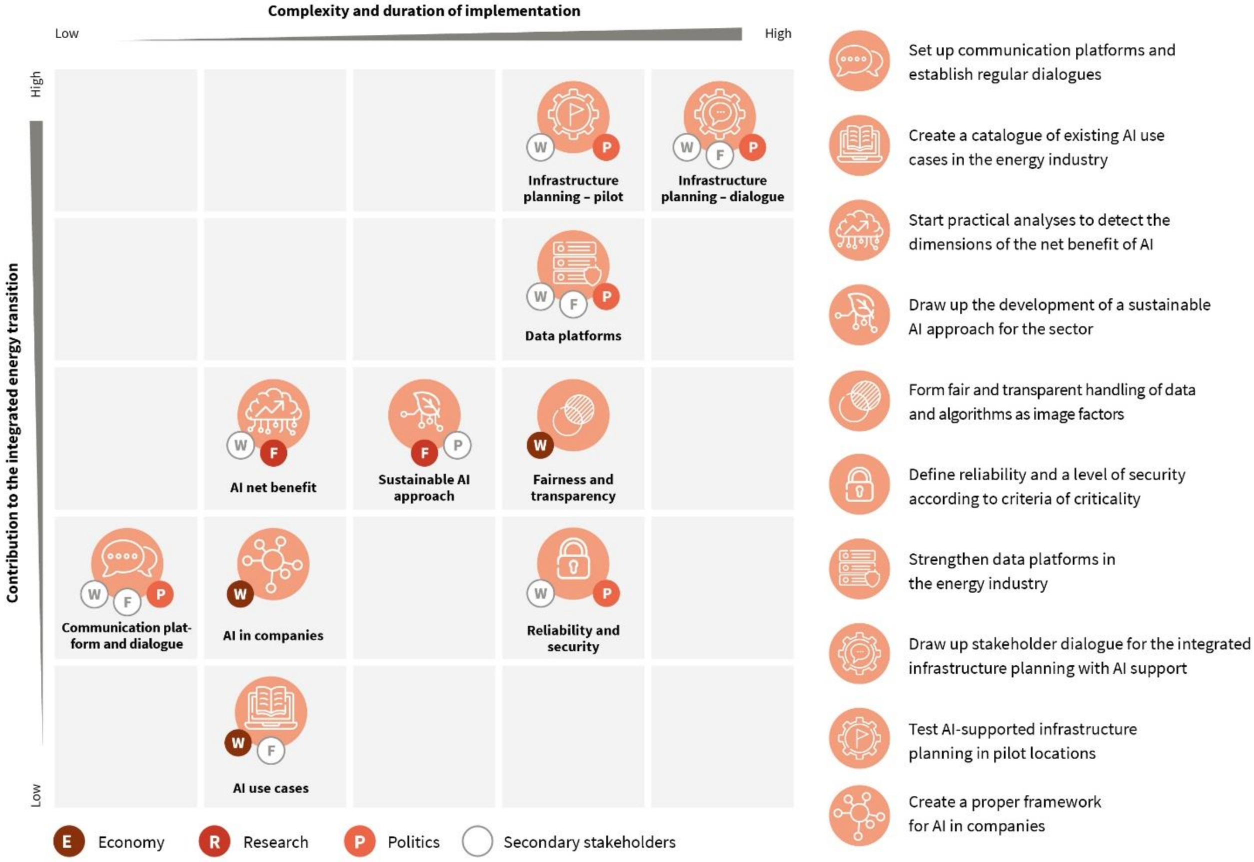


Figure 2: Classification of the global recommended courses of action[2]

[2] This shows those actors directly involved in each case (main actor - in colour, secondary actor - white), even though other actors may be involved indirectly.

- **Set up communication platforms and establish regular dialogues**: The first AI projects in the energy industry show that linking the digitalisation and energy sectors will be particularly crucial for the extensive use of artificial intelligence in the future. Established actors in the energy industry should contribute their experiences and innovative young start-ups new potential solutions, and the exchange between the two consolidated by regular virtual meet ups.
- **Create a catalogue of existing AI use cases in the energy industry**: A collection of existing concrete use cases for AI in the energy industry should inspire actors from the digital and energy sectors to come up with their own applications and encourage an exchange with those actors who already use AI in the corresponding form or for the corresponding purpose.
- **Start practical analyses to detect the dimensions of the net benefit of AI**: Based on selected planned or implemented concrete illustrative processes, it should be possible to estimate or calculate the net benefits of the AI application(s) used in each case. To this end, and with the help of a reference scenario, the potential CO_2 savings as well as further benefit factors should be compared to the increased consumption of resources and energy and transferred to a concept for the timely classification of the net benefit.
- **Draw up a sustainable AI approach for the sector**: Together with stakeholders from the energy and digitalisation sectors, a concept should be drawn up to establish the sustainable use of AI. A group of independent experts should meet up regularly to discuss various aspects related to environmental issues, economics, innovative power, regulation and society.
- **Expand the fair and transparent handling of data and algorithms as image factors**: Appropriate methods have to be established that make the fulfilment of the requirements on transparent and fair AI models more understandable for even non-IT experts. Existing actors from the digitalisation and energy industries should hereby provide active support.
- **Define the reliability and a level of security of AI according to criteria of criticality**: AI applications in the energy industry should be assessed as regards their criticality by a central authority. Certification requirements are to be defined together with the responsible institutions on the basis of this assessment.
- **Strengthen data platforms in the energy industry**: The development of an efficient and competitive data infrastructure should be accelerated to make high quality data available so that AI can be used, and at the same time ensure its safe and transparent use. In addition, the fair and transparent exchange of data must be enabled within the competitive and at the same time regulated framework of the energy industry.
- **Draw up stakeholder dialogue for the integrated infrastructure planning with AI support**: Basic requirements for support for the implementation of complex infrastructure projects by AI are a common understanding of all actors involved and an exchange between representatives from various sectors that involves AI experts. This will require an integrated approach involving all affected parts of the infrastructure (e.g. electricity, building, mobility, construction etc.).
- **Test AI-supported infrastructure planning in pilot locations**: The actual implementation of the measures for an AI-supported planning of the infrastructure should be piloted exemplarily in several municipalities in a first step. The experiences gained with these pilot projects can then serve as a basis for recommendations on establishing a Germany-wide, AI-supported and optimised infrastructure planning.
- **Create a proper framework for AI in companies**: To allow the specific identification of possible optimisation methods, the individual corporate processes will have to be analysed as regards their suitability for automation through the use of AI. The following measures should help energy companies prepare for the future challenges of using AI.

- Strengthen the AI competence of the staff and a culture of trying and testing
- Create an analytical selection procedure for new projects related to AI
- Use AI ambassadors in the company to transfer knowledge
- Collect the AI competences in a catalogue of measures as a basis for strategic decisions and personnel development
- Establish an expert system for independent learning in the company

Generate opportunities from challenges

Figure 3 shows measures that should contribute to the positive development of the identified fields of application in the energy sector in addition to the global recommended courses of action. Those fields of application relevant for the corresponding measure will be marked separately. These are geared particularly to application-based research.

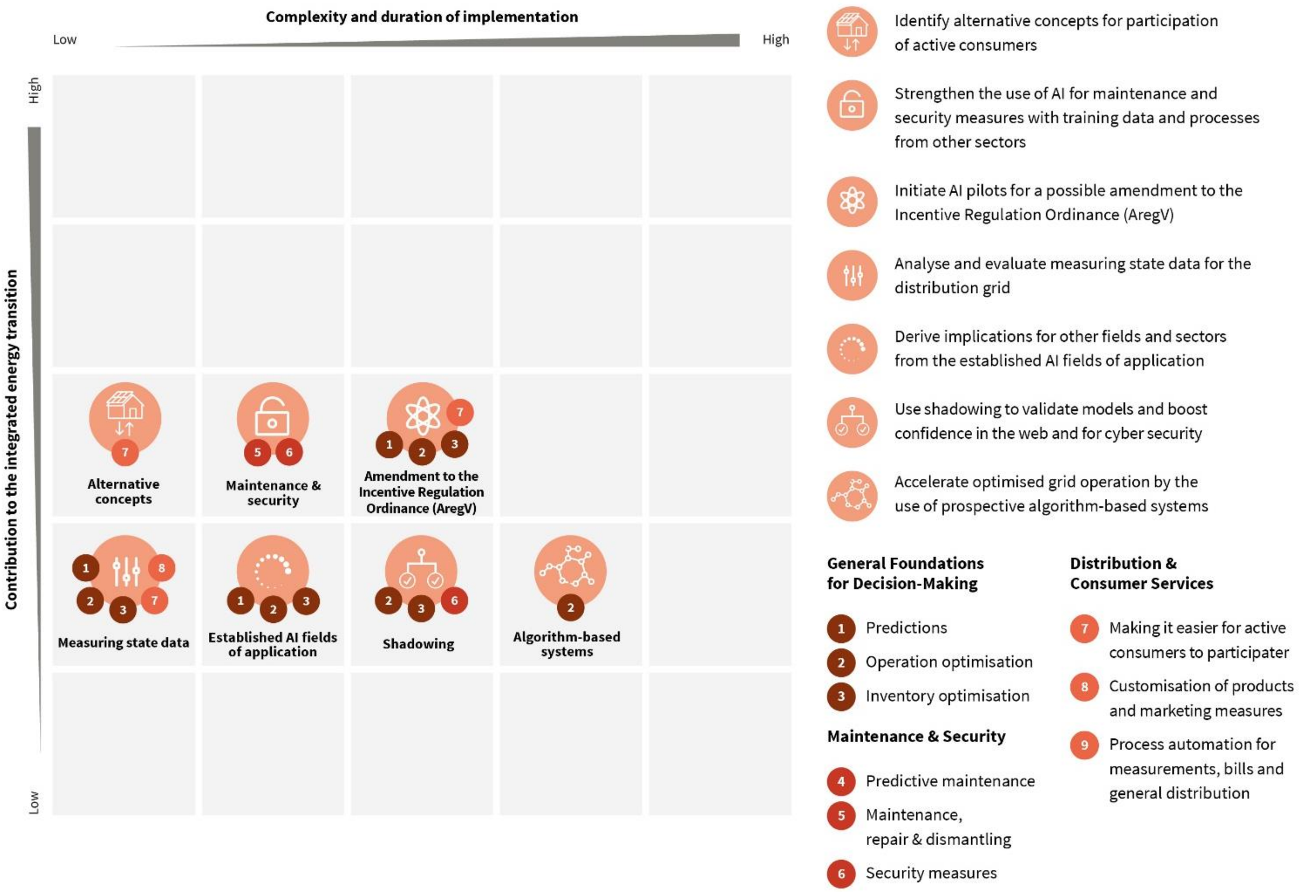


Figure 3: Classification of the recommended courses of action for a specific field of application[3]

[3] The most relevant fields of application in each case are marked, even though other fields of application may also be affected indirectly.

- **Derive implications for other fields and sectors from the established AI fields of application**: Implications for the use of AI in other areas of the energy industry as well as other sectors are to be deduced from the large number of established use cases, that are often already an industry standard, in the course of a series of workshops.
- **Strengthen the use of AI for maintenance and security measures with training methods and processes from other sectors**: Sectors or industries with similar processes should be used to supplement or substitute their own data basis to counteract the existing lack of data in this FoA to identify faulty or critical processes and situations, particularly when training the AI.
- **Identify alternative concepts for participation of active consumers**: A significant contribution to the integrated energy transition is expected from the participation of active consumers, whereby a more active implementation is only expected in the medium term on account of the data basis that has been lacking up to now. This is because the technical infrastructure for data collection is still in its infancy. Research should help identify alternative data collection concepts that satisfy the energy industry requirements on the reliability of data records.
- **Analyse and evaluate measuring state data for the distribution grid**: Whereas the distribution of the measuring systems amongst the consumers and power generators is already regulated by the MsbG, a prior analysis is needed to identify significant nodes when it comes to installing the measurement technology and sensors in the distribution grid. The effort needed to install the measuring technology is offset by savings, for example through a more accurate redispatch from power-generation facilities and flexible consumers. In this respect, it is expedient to offer incentives for grid operators to install measuring technology that records data and determines the grid status.
- **Use shadowing to validate models and thus boost confidence in the web and increase cyber security**: A temporary parallel test operation, so-called shadowing, can validate alternative operating modes for power grids in advance and thus help boost confidence. Shadowing can also be used to prevent cyber attacks on critical infrastructures by identifying critical grid status at an early stage.
- **Accelerate optimised grid operation by the use of prospective algorithm-based systems**: On the grid control side, AI-based monitoring measures and AI-assisted feed-in management face investment-related hurdles. The increased prospective and predictive use of algorithm-based systems during grid operation could help to avoid congestion from the outset.
- **Initiate AI pilots for a possible amendment to the Incentive Regulation Ordinance (AregV)**: Showcase projects are recommended with regard to the investment framework for distribution grids, within which it should be possible to predict whether a widespread use of AI will lower the costs for grid operators, for example, through pilots. Based on the results, the regulatory authorities can then take more accurate case-by-case decisions to cover the costs of grid regulation.

The results of the present analysis and the identification of a course of action unmistakeably indicate the advantage of **starting the pilot phase with concrete projects**. A mutual exchange of knowledge is indispensable to advance the still very young, and in some cases very complex, topic of AI in the field of the very technically demanding and highly regulated energy sector. In this respect, the creation of interdisciplinary teams made up of experts from various domains in the digital and energy industries will be crucial for its success. This will allow both sides to profit from each other’s expertise and cooperative projects can be realised. This is the only way to **exploit the full potential of AI for the energy industry** and thus make a **significant contribution to the integrated energy transition**.

1 The hype about artificial intelligence

Artificial intelligence (AI) has long been a hot topic in the technology sector. Large companies such as Google, Amazon or Baidu have been working for years on taking the lead in the field of AI. For example, the four American technology giants Google, Apple, Facebook and Amazon alone took over nearly 40 AI start-ups between 2010 and 2018, including DeepMind, a British AI start-up whose overall goal is to solve intelligence, which was bought by Google in 2016 for a staggering 400 million US dollars – the company's biggest takeover in Europe to date. The Chinese counterpart to Google, Baidu, operates two research and development labs in Silicon Valley in the USA that focus on AI and data centres. What's more, a large number of countries have published their own national AI strategies over the past few years (dena, 2020).

One thing is clear: **the hype about AI is real**. Even the Federal Minister for Economic Affairs and Energy, Peter Altmaier, had this to say about AI back in November 2018: "There's hype in Berlin! You can't get away from this topic." Though it would appear that the question here is not so much whether AI is just a trend that will soon be forgotten, like so many other technologies. On the contrary, the only question about this technology is the speed at which it will develop and spread. When and how fast AI will spread in the individual markets and which framework conditions and degrees of freedom will it be granted to replace human intelligence in future areas of activity in every industry? These are questions that the energy sector in particular will have to ask itself.

AI is changing the energy sector

Flashback: One headline in the Die Welt newspaper in December 2018 read: "Artificial intelligence is the driver of digital change" (Welt, 2018). This is undoubtedly one of the core competences of digitalisation and is indispensable for the energy industry and its digital transformation. In an essay on his blog "Gates Notes" in 2017, Bill Gates, the co-founder of Microsoft, appealed to all college graduates worldwide: *"If I were starting out today and looking for the same kind of opportunity to make a big impact in the world, I would consider three fields. One is artificial intelligence (…). The second is energy, because making it clean, affordable, and reliable will be essential for fighting poverty and climate change."* (Gates, 2017)[4].

According to Kerstin Andreae, an industry expert and Chief Executive of the Federal Association of the Energy and Water Industry (BDEW), the energy industry is facing far-reaching, if not fundamental changes, with the introduction of AI: *"The use of artificial intelligence will change a number of industries in the foreseeable future to the same extent as computers and the Internet did in their time. So it's not hype but a real change, that of course will not stop at the energy industry".*

[4] Apart from AI and energy, Gates also considers a focus on biosciences important.

A number of signals from the industry indicate that digitalisation in the energy industry is currently receiving a big boost that would appear to answer the question as to when – namely right now: triggered by the global attempts at climate action and greatly accelerated by the corona crisis, more and more business activities are being shifted to the digital cosmos – at an as yet unparalleled speed. This development would appear to be irreversible so that the motto for the energy industry is likely to be: **Digitalisation is here to stay!**

But will it in fact be possible to transfer the findings of international AI research and developments, which are currently taking place at great speed in other industries, to the energy sector? In which use cases could the technology first make its appearance on the market? And are there any general industry- or application-specific restrictions that could delay or even completely challenge its use – for example with a view to a sensitive and responsible handling of user data or the necessity of high-security digital systems to control tomorrow's energy grids?

Data provides the basis for the use of AI in the energy sector

If you ask individual AI experts, most agree that the potential for using AI is extremely high in the energy industry – and indeed: Data dominates the future market fields more than in almost any other sector of industry and digitalisation is in full swing. The possible fields of use along the digital value-creation stages[5] range from data generation (e.g. data traffic through weather and power generation by the RE installations), data distribution and exchange (e.g. data to control grids and for market communication) and data trading (e.g. exchanging prognostic data for smart trading mechanisms), right through to data use (e.g. consumption data to control houses and identify user behaviour).

Consequently, a symbiotic consideration of the two fields of AI and energy appears vital. The technological developments of the past decades in the field of digitalisation and the increasingly global will to decarbonise the energy system, including the new applications based on this (cf. Chapter 2.2) have led to a huge increase in the data that has to be analysed by the actors in the energy industry, which has to be processed with increasing speed and accuracy (vision of the real-time processing of information in the individual segments of the energy sector). It is very likely that future obstacles regarding data processing will also be able to be overcome by the use of artificial intelligence.

AI and energy – boon or bane?

Alongside all of the apparently positive effects this new technology has or could have on the energy industry, some critical voices can also be heard. In November 2019, the Frankfurter Allgemeine Zeitung ran a headline: "Why we shouldn't trust AI". The article described the risks of leaving the control of critical infrastructures, such as energy and water supplies, up to AI, thus opening the door wide for security loopholes and cyber attacks. AI has to learn using existing data and is therefore easy to manipulate using falsified data, according to the article (Anderl, 2019).

[5] It is generally advisable to introduce and establish an analogy to the energy industry's classic value creation model (generation, distribution, trade and use of energy) in the energy sector for the parallel digital system to be created.

On the subject of security and AI, the question inevitably arises as to how to ensure that data is protected. Data may well be worth protecting, on the one hand in view of the security of the energy system (including corporate data, grid data), and on the other due to social requirements (personal data). The conflicts surrounding personal data also concern the Study Commission “Artificial Intelligence – Social Responsibility and Economic, Social and Ecological Potential” that was set up in June 2018 and consists of members of the German Parliament and experts from the AI sector. In a meeting of the Commission in January 2020, the Federal Commissioner for Data Protection and Freedom of Information, Ulrich Kelber, explained that although the Data Protection Act is an “essentially necessary protection mechanism”, it does not necessarily constitute an impediment for research into and the development of AI. Data protection should rather be seen as an opportunity to set oneself apart from the established AI nations USA and China, for example, with “AI made in Europe” (Kelber, 2020).

The problems related to data protection and security loopholes are offset by the enormous potential of AI-based systems to contribute towards the integrated energy transition. Nevertheless, the use and storage of the data needed to train AI algorithms is inevitably linked to the discussion on how much energy and resources AI consumes. Because only an AI application that either guarantees the “green” use of energy (keyword: Green IT) and/or directly or indirectly saves more energy or resources during use than it consumed in its training and operation can make a contribution to the integrated energy transition. It thus comes as no surprise to learn that the reduction of the technology’s electricity consumption is the topic of numerous research and commercial projects, some of which pursue very different approaches. Google, for example, is attempting to set up an initial version of a carbon-intelligent computer platform to reduce the consumption of resources by their data centres whilst maintaining or even improving their performance. Tasks within a data centre should hereby be shifted to times of the day when there is a higher supply of RE. Ana Radovanovic, Research Scientist at Google, explains: *“However, it is also possible to shift flexible computing tasks between different data centres so that more work gets done when and where this is more environmentally friendly."* (dpa, 2020)

1.1 AI has already made it on to the agenda of European politics

At the moment, framework conditions for AI are being discussed in the EU as well as the individual member countries and suggestions and strategies are being worked out on how to safeguard the concrete benefits of AI in individual economic sectors as well as society as a whole. The European Commission (EC) has implemented measures to support the development of AI over the period of the next multiannual EU financial framework (2021–2027), for example to encourage research into the energy and data efficiency of AI. In addition, data exchange as well as the further development of the regulatory framework (supported amongst other things by so-called regulatory sandboxes) is to be encouraged at both a national and European level. A support centre should hereby help to facilitate the development of AI applications for companies and the public sector.

The German way

The ways in which AI can be implemented and regulated better are also being discussed within Germany. One of the primary goals of the German AI strategy is to make "AI made in Germany" a globally recognised seal of approval and, this is a pre-eminent USP, to always focus on the benefits of AI for citizens and to only use the technology for the good of society, the environment and the state.[6] *"Artificial intelligence is clearly a key technology that harbours a great potential for the Germany economy. However, we need reliable norms and standards to further advance "AI made in Germany,"* says Ulrich Nussbaum, State Secretary in the Federal Ministry for Economic Affairs and Energy (cf. Nussbaum, 2019). In the opinion of Prof. Dr Katharina Zweig (2020), Director of the Algorithm Accountability Lab at the TU Kaiserslautern, however, regulation is only needed for a small part of the algorithmic decision-making systems (ADM systems), namely for those with learning components that make decisions about people. According to Oliver Süme, CEO of eco – Verband der Internetwirtschaft e. V., the planned evaluation of the General Data Protection Regulation (GDPR) should be used to set the course for AI applications. The correct legal framework that *"allows some scope and encourages innovations"* is an important fine-tuning instrument to make headway in the global competition for AI and digitalisation. *"One key goal is to significantly increase the amount of high-quality data that can be used in research and development as well as in corporate and civic applications and to hereby protect European values that are anchored in the constitution such as fundamental rights, including the individual rights and the right of self-determination with regard to public information, as well as the principles of law and social justice and that of democracy"* (Süme, 2020).

1.2 Develop strategies to put everything into practice

Generally speaking, all industries will have to invest more in developing the efficient use of energy for digital processes into a marketing and sales argument in future. This will have a positive effect on the company's image and throw more of a poorer light on companies who are not making any sustainable efforts in this direction. What's more, we have to kick off a discussion about the basic purpose of AI-supported computing processes. Past experience has frequently shown that all too often, developments that are driven purely by economics force ecological reasons onto the sidelines. During the advancement of digitalisation in general and AI in particular, these developments could be repeated with disastrous effects unless a regulatory political framework and corporate attitude are established in due time that allow a clear differentiation and evaluation of various applications.

In the light of current discussions about the AI hype, the aim of this present report is to categorise the very promising fields of application for AI in the energy industry according to technical, economic, regulatory and social aspects and carry out an initial evaluation. It follows on from and broadens the dena analysis "AI for the integrated energy transition: assessing the technological status quo and categorising fields of application in the energy industry" that was published in September 2019. In the present analysis, nine fields of application were identified for AI in the energy industry so as to provide a basis to knowledge-building on the topic in politics, the economy and the general public.

[6] www.ki-strategie-deutschland.de/home.html

The dena analysis “Global Trends in Artificial Intelligence and Their Implications for the Energy Industry” that was published in March 2020 looked at the issue from a more general perspective. The main focus of this analysis was on current developments in the field of AI in the USA, China, Israel and Europe as well as their consequences for the German and European energy industry.

Building on this, the present report investigates the opportunities and challenges of the individual fields of application and classifies the resulting recommended courses of action according to their complexity and potential contribution towards the energy transition. This creates a basis for the development of a strategy for this important technology for energy systems of the future that can be used by decision-makers in the energy and digital industries as well as in research and politics. Stakeholders in the energy industry and AI insiders were consulted to obtain the broadest possible overview of the sector. We are very grateful to them, as we are for the scientific support from Deloitte and the Fraunhofer Institute for Systems and Innovation Research.

Our particular thanks go to the following persons: Elie-Lukas Limbacher (BDEW), Lukas Klingholz & Robert Spanheimer (Bitkom), Alassane Ndiaye (DFKI), Klaus Frank & Rainer Hoffmann (EnBW), Christian Schröder (E.ON), Hauke Thaden (EWE), Adrian Beyertt (Fresh Energy), Daniel Trabold (Fraunhofer IAIS), Marc Peters (IBM), Oliver Warweg (Fraunhofer IOSB), Frederik vom Scheidt (KIT), Emma Leibfried, Jesco Renner & Mario Gnädig (Netze BW), Tobias Romberg (Next Kraftwerke), Christoph Mayer & Eric Veith (OFFIS), Fabian Karl & Marilen Ronczka (PPC), Jonas Danzeisen (Venios).

2 The manifold opportunities and challenges for AI in the energy industry

2.1 New challenges for the present-day energy system

Efforts to achieve climate protection goals by focusing in large part on renewable energies have led to a decentralisation of the energy system. This shift has, in turn, handed digitalisation a key role in the overall success of the energy transition. Above all, a modern energy system requires flexibility to cope with the varied requirements of increasingly complex systems. In keeping with the need to harmonise millions of energy producers, storage systems and consumers of every type and size in future, digital hardware and software will become an essential connecting link to facilitate technical coordination in the energy system of tomorrow. AI can help us to derive information from a wealth of data, understand context and connections, exploit efficiency potentials and implement targeted measures – all in largely automated processes.

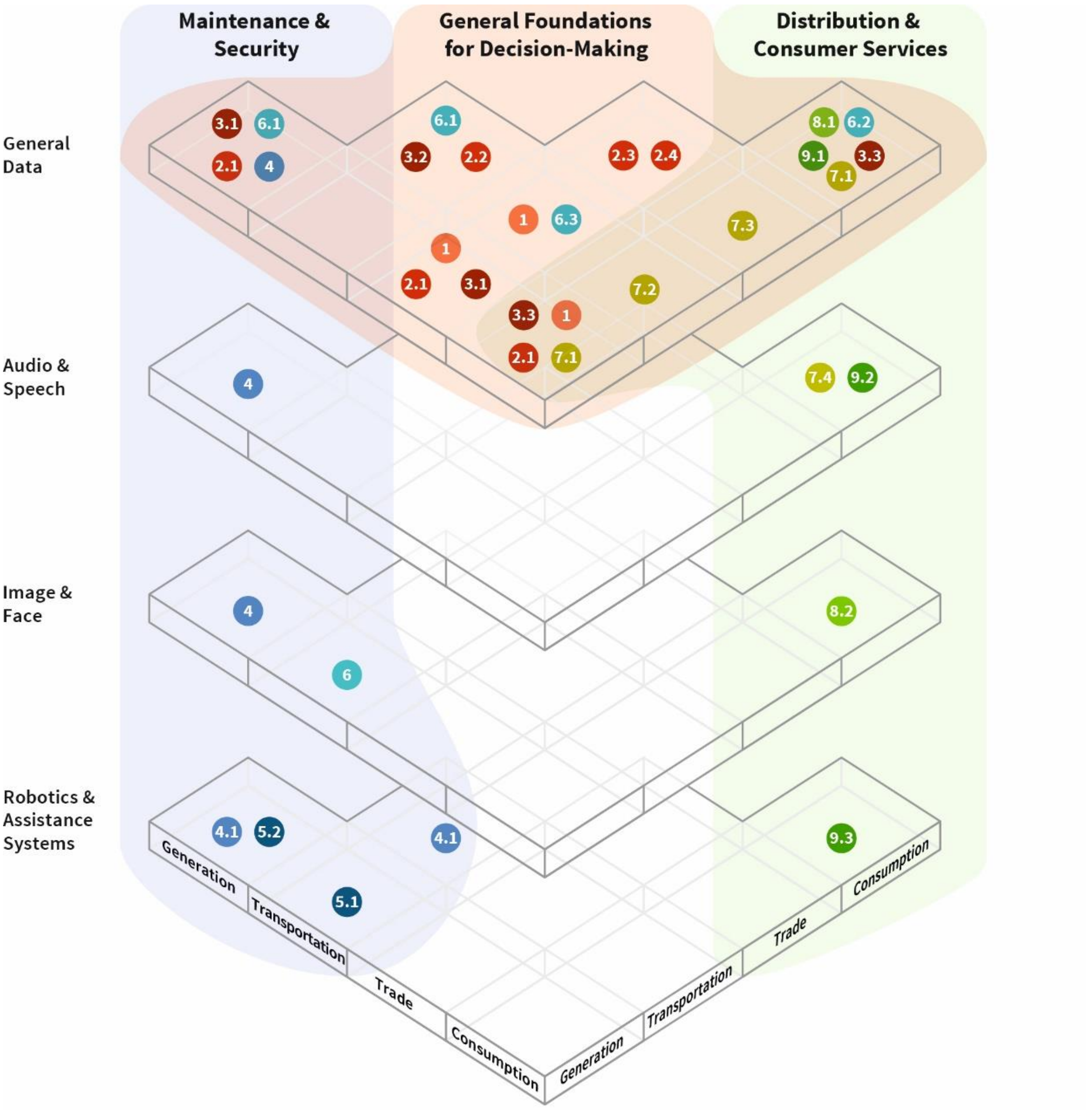
AI as a tool to fight climate change

The development of AI has taken great strides forward in recent years, with AI now coming to be used in more and more areas. The use of AI is expected to make a significant contribution to the integrated energy transition. Building on the findings of the previous report and the identification of relevant fields of application, this report pursues the question of exactly what form this contribution might take and how it can be implemented (dena, 2019). Climate Change AI, a global coalition of prominent engineers and scientists working to enhance the contribution of AI to limiting climate change, describes the situation as follows: *"While no silver bullet, machine learning can be an invaluable tool in fighting climate change via a wide array of applications and techniques"* (Climate Change AI, 2020). Clearly defined use cases are required in order to translate the theory surrounding this valuable tool into practical applications to fight climate change.

2.2 The nine fields of application for AI in the energy industry

The previous report identified nine fields of application (FoAs) for AI in the energy industry (see Figure 4). In the present analysis, these fields of application are classified according to technical, ecological, regulatory and social issues. These FoAs are divided into three clusters, namely **General Foundations for Decision-Making**, **Maintenance and Security**, and **Distribution and Customer Services**.

The type of AI used is broken down into four application groups. Many applications involve the use of technical data on electricity generation and consumption, economic data on prices and costs, geographical data and other data on weather conditions. These AI applications are pooled under the term general data. Two other groups of AI are based on audio and speech recognition on the one hand and image and face recognition on the other. The fourth type of AI comprises complex applications in the field of robotics and assistance systems. Applications in the energy sector entail the use of all types of AI.



General Foundations for Decision-Making

- **1 Prediction**

- **2 Operation optimisation**
- 2.1 Optimised use of assets
- 2.2 Increasing network capacity utilisation
- 2.3 Risk management
- 2.4 Monitoring market power

- **3 Inventory optimisation and other strategic business decisions**
- 3.1 Power plant investment
- 3.2 Network investment
- 3.3 Investment in decentralised generators/stores and new consumers

Maintenance & Security

- **4 Predictive maintenance**
- 4.1 Drones for predictive maintenance

- **5 Maintenance, repair and dismantling**
- 5.1 Repair work using augmented reality
- 5.2 Nuclear decommissioning using robots

- **6 Security measures**
- 6.1 Cyber defence
- 6.2 Fraud detection
- 6.3 Checking balancing groups

Distribution & Consumer Services

- **7 Making it easier for active consumers to participate**
- 7.1 Energy management
- 7.2 Automated smart charging
- 7.3 Virtual power plant aggregation
- 7.4 Smart home with virtual assistant

- **8 Customisation of products and marketing measures**
- 8.1 Customer clustering
- 8.2 Personalised advertising

- **9 Process automation for measurements, bills and general distribution**
- 9.1 Document sorting and automatic responses
- 9.2 Hotline androids
- 9.3 Self-service

Figure 4: The nine fields of application for AI within the energy industry value-creation network

Analysing these fields of application requires an understanding of characteristics specific to the energy industry and AI. Classification analogous to the existing value-creation stages forms the basis for the economic assessment. The actors involved and legal framework conditions are particularly relevant to the regulatory and social dimensions of this analysis. AI-specific characteristics, such as the allocation to respective AI application groups (Audio & Speech; Image & Face; Robotics & Assistance Systems, and General Data) form the basis of the technical assessment. The description of each field of application is supported by a representative example process divided into preliminary AI work (i.e. investment and data collection) and AI worksteps according to Hammond[7] (i.e. *recognising and understanding* information before *deducing*, *inferring* and *acting)*.

The assessment is conducted at the level of abstraction of the respective field of application, which means it can take different forms depending on the value-creation stage. In the **General Foundations for Decision-Making** cluster, where discrepancies in assessment outcomes is to be expected, a distinction is made in relation to the differing nature of the fields of application, such as between grid-related applications and applications related to electricity generation and trading. Regulated grid operation represents a special case, particularly for the regulatory assessment, and must therefore be considered on its own merits. Furthermore, one FoA cannot be considered entirely in isolation from another. For example, predictions and forecasting forms the basis for a number of other applications. Although maintenance, repair and dismantling is a field of application focused on implementing measures with the help of AI, such technologies can also be used to plan measures.[8] While profitability could be the primary motivation for optimising maintenance operations with AI, it might also yield operation optimisations and assist with predictive maintenance.

2.2.1 Predictions

Artificial intelligence can improve predictions and forecasting for electricity generation and trading (see Table 1, Figure 5) and for grid operation (Table 2, Figure 6).

- AI-assisted predictions for generation and trading can forecast the production and demand of fluctuating renewable energies (REs) earlier and more precisely and thereby improve their commercial exploitation.
- AI-assisted forecasts for grid operation make it possible to improve calculations of local grid capacity utilisation and identify critical grid statuses sooner. These predictions relate to both feed-in (especially from decentralised, fluctuating RE sources) and current consumption from the grid, which facilitates a comprehensive assessment of grid capacity utilisation (in particular by applying predictions for similar areas to blind spots within the grid). The grid statuses achieved as a result of the use of AI serve as an input for more complex applications in a subsequent stage where AI systems take actions.

Statistical machine learning (ML) methods and the use of artificial neural networks (ANNs) have been established in this field of application for some time. The need for coordination between generation and consumption means forecasting is a fundamental component of the energy industry across several value-creation stages (generation – trade, transportation – trade, generation – consumption).

[7] The Periodic Table of Artificial Intelligence according to Hammond (2016) is examined in further detail in the previous study.
[8] These aspects are addressed to some extent in the sections on **Predictive Maintenance** and **General Foundations for Decision-Making**.

AI field of application

Predictions – generation and trading

AI characteristics

Type of AI application
General Data – quantitative predictions of future events or situations

Learning method
Regression, ANN, classification, clustering

Data basis
Historic production time series, sensor data, external data (weather, GIS data, etc.)

Implementation of AI in the energy industry

Actors affected
Installation operators, traders, suppliers, energy providers

Relevant value-creation stages
Generation, trading

Relevant processes in the energy industry
Power station operation, tender preparation, electricity procurement and tariff setting in distribution, balancing

Other characteristics

Related legal framework conditions of this FoA
Energy Industry Act (EnWG), Metering Point Operation Act (MsbG), Renewable Energy Sources Act (EEG), Combined Heat and Power Act (KWKG), Core Energy Market Data Register Regulation (MaStRV), GDPR, Federal Data Protection Act (BDSG), PSI Directive

Examples of companies
energy meteo systems GmbH, IS Predict GmbH, Enercast GmbH, 4Cast GmbH, Consolinno Energy GmbH, Data Revenue GmbH

Table 1: Profile of predictions – generation and trading

Predictions (generation and trading) in the example of price forecasts

Installation operator/trader*

Preliminary work

- **Investments****
  Acquisition of secondary data (e.g. weather data)
- **Data collection**
  Collecting & preparing primary data (e.g. historical exchange price and fuel price time series, time series on load & RE production in different years, installed power in the power plant portfolio)

AI steps

- **Training**
  Demonstrating connections between **historical** prices, **historical** generation and other available data
- **Recognising**
  Recognising connections between current prices, **current** generation and other available data
- **Inferring/learning**
  Inferring future prices based on expected generation and other data
- **Acting**
  \+ See FoA operation optimisation: Deducing bidding strategies

* Implementation by service providers also possible
** Standard measures (e.g. investments in computing power and recruiting IT experts) not explicitly listed here

Figure 5: Example process for predictions – generation and trading

AI field of application

Predictions – grids

AI characteristics

Type of AI application

General Data – quantitative predictions of future events or situations

Learning method

Regression, ANN, classification, clustering

Data basis

Movement data from sensors in the grid (intelligent metering system, transformer station, substation), core data from grid operator database, weather data

Implementation of AI in the energy industry

Actors affected

Grid operators

Relevant value-creation stages

Transport (incl. distribution)

Relevant processes in the energy industry

Grid capacity utilisation, balancing

Other characteristics

Related legal framework conditions of this FoA

Energy Industry Act (EnWG), Metering Point Operation Act (MsbG), Renewable Energy Sources Act (EEG), Combined Heat and Power Act (KWKG), Core Energy Market Data Register Regulation (MaStRV), GDPR, Federal Data Protection Act (BDSG), PSI Directive

Examples of companies

PSI Software AG, Gridhound GmbH, Smart Operator - innogy SE

Table 2: Profile of predictions – grids

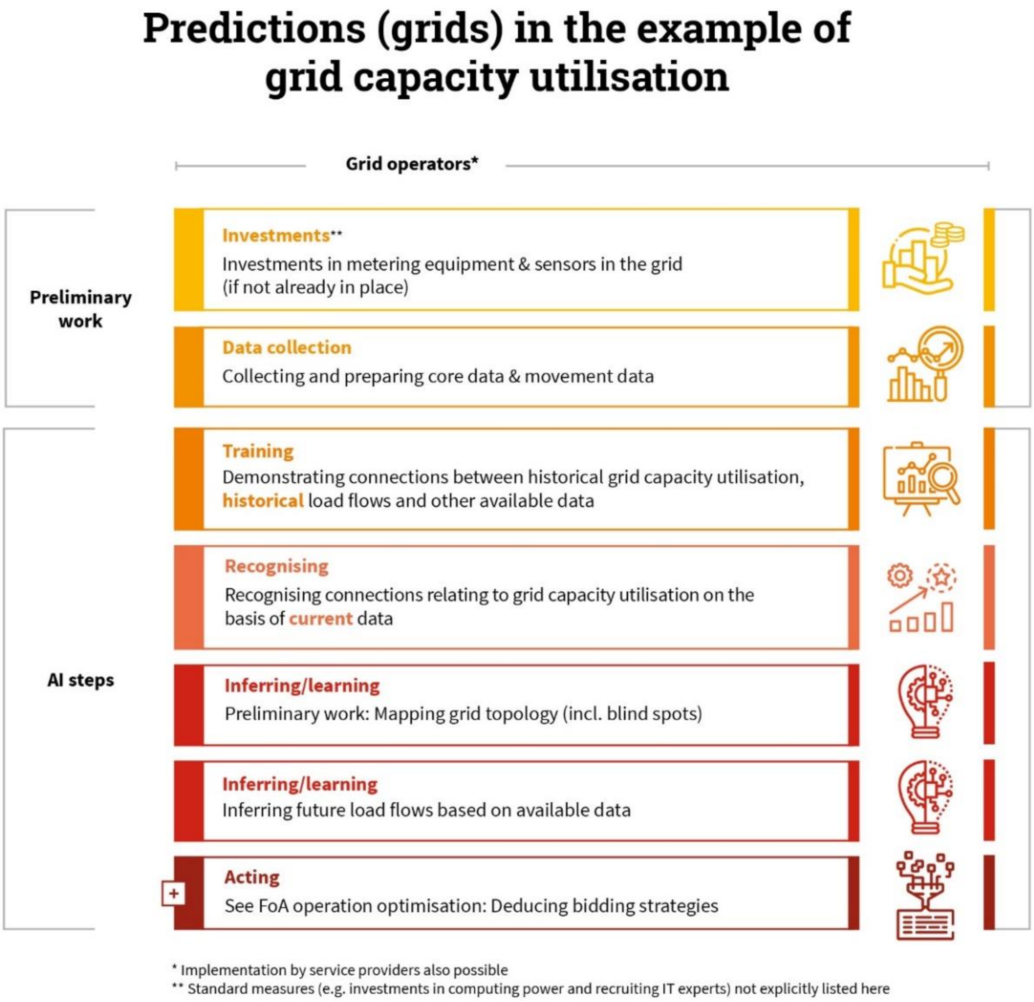


Figure 6: Example process for predictions – grids

2.2.2 Operation optimisation

In relation to operation optimisation, AI is used to optimise and improve operational strategies. The greatest potential in terms of practicability appears to lie in applications to optimise operational planning for electricity-generation facilities (see Table 3, Figure 7) and applications to optimise grid operation (see Table 4, Figure 8).

- **Optimised operational planning for electricity-generation facilities**:
  - Optimisation of supply-dependent generation, such as adjusting wind/photovoltaic power plants according to wind strength/insolation or reacting to spot prices (e.g. shutdown in the case of negative electricity prices).
  - Optimisation of supply-independent power generation, such as operational planning for conventional power stations, with due regard to technical aspects (e.g. ramp-up times, partial-load performance) and external factors (electricity prices).
- **Optimised grid operation**: e.g. monitoring of grid capacity utilisation, grid congestion management through targeted transfer of controllable loads from a time when grid capacity is exhausted to a time with available capacity.

AI field of application

Operation optimisation – generation and trading

AI characteristics

Type of AI application
General Data – optimisation

Learning method
Classification, reinforcement learning, regression, ANN, clustering

Data basis
Installation characteristics, generation data, sensor data, weather data, electricity price time series

Implementation of AI in the energy industry

Actors affected
Installation operators, traders, suppliers, energy providers, consumers

Relevant value-creation stages
Generation, trading, consumption

Relevant processes in the energy industry
Operational planning; controlling generation systems, consumers and storage systems

Other characteristics

Related legal framework conditions of this FoA
Energy Industry Act (EnWG), Metering Point Regulation Act (MsbG), Ordinance on Incentive Regulation (ARegV), Ordinance on Electricity Grid Access Charges (StromNEV)

Examples of companies
open energy Ltf., IS Predict GmbH, SunSniffer GmbH & Co. KG, Solytic GmbH

Table 3: Profile of operation optimisation – generation and trading

Operation optimisation (generation and trading) in the example of large-scale storage systems

Installation operator*

Preliminary work	**Data collection**	Updating technical data on the storage system (incl. wear after cycles) and determining potential opportunities on different markets (incl. market rules)
AI steps	**Training**	Evaluating different bidding strategies according to yield on the basis of **historical** price time series on different markets and fictitious bids
	Recognising	Recognising expected yield of different bidding strategies on the basis of current price forecasts
	Inferring/learning	Inferring an optimal storage strategy for forecast price time series
	Acting	Generating bids

* Implementation by service providers also possible

Figure 7: Example process for operation optimisation – generation and trading

AI field of application

Operation optimisation – grids

AI characteristics

Type of AI application

General Data – optimisation, image and face

Learning method

Classification, reinforcement learning, regression, ANN, clustering

Data basis

Movement data from sensors in the grid (intelligent metering system, transformer station, substation), core data from grid operator database, weather data

Implementation of AI in the energy industry

Actors affected

Grid operators

Relevant value-creation stages

Transport (incl. distribution)

Relevant processes in the energy industry

Grid capacity utilisation, balancing, maintaining voltage, monitoring blind spots, monitoring frequency, identifying disruptions in electricity quality

Other characteristics

Related legal framework conditions of this FoA

Energy Industry Act (EnWG), Metering Point Regulation Act (MsbG), Renewable Energy Sources Act (EEG), Ordinance on Incentive Regulation (ARegV), Ordinance on Electricity Grid Access Charges (StromNEV)

Examples of companies

Venios GmbH, Gridhound GmbH, Fraunhofer Institite of Optronics, System Technologies and Image Exploitation IOSB

Table 4: Profile of operation optimisation – grids

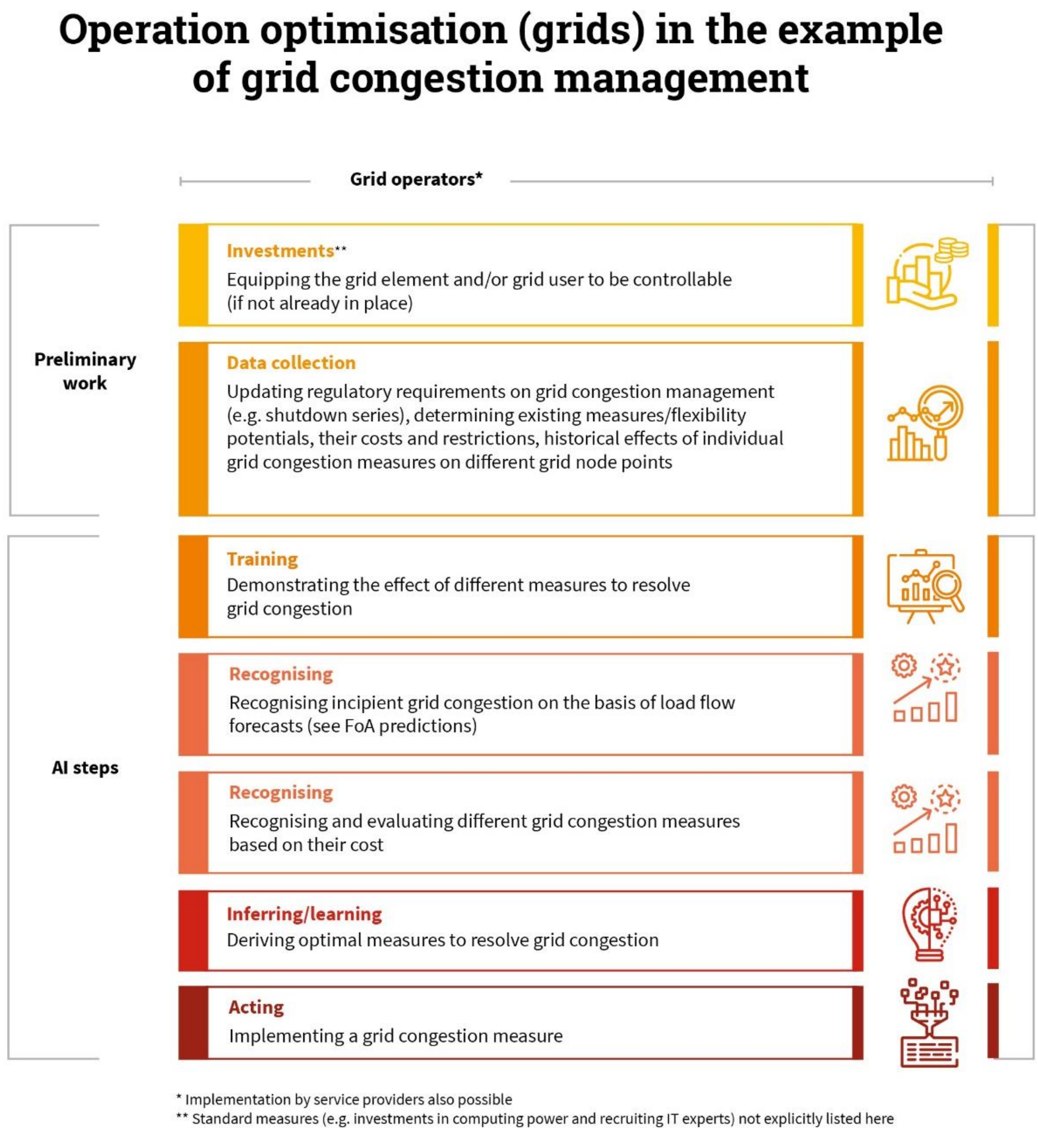


Figure 8: Example process for operation optimisation – grids

2.2.3 Inventory optimisation and other strategic business decisions

Using AI provides support in decisions relating to inventory optimisation, a field of application characterised by long-term, capital-intensive measures. In this context, the added value of AI lies in its ability to take into account a wealth of data and requirements that need to be considered in the optimisation process. Data from geographical information systems (GIS data) is an important basis in this field of application. AI makes it possible to integrate and use GIS data more comprehensively in system planning. Inventory optimisation for electricity generation and trading (see Table 5, Figure 9) relates to installations that are not subject to regulation. By contrast, inventory optimisation in the context of the grid (see Table 6, Figure 10) falls under the scope of incentive regulation and must therefore be regarded as a separate area of application.

- **Planning for power-generation facilities**: Determination and balancing of potential long-term returns (especially electricity prices) and costs (investments, operating and maintenance costs).
- **Planning for grid infrastructure**: Analysis of long-term grid capacity utilisation and determination of potential means of increasing grid capacity (grid expansion, intelligent grid operation management).

In this field of application, the use of AI is focused on optimising planning documentation. AI can learn to take a wealth of data (incl. user preferences, GIS data, etc.) into account in its analyses and incorporate this data into investment decisions. In general, AI does not implement actions autonomously and instead issues recommendations for action.

In the context of grids in this field of application, AI uses so-called digital twins of the part of the grid in question to produce a precise depiction of the real network based on real-time data. This is then used to make virtual investment decisions regarding grid operation resources and thereby determine an optimal strategy for expansion of the grid.

Table 5: Profile of inventory optimisation and other strategic business decisions – generation and trading

Inventory optimisation and other strategic business decisions (generation and trading) in the example of selecting and investing in building-specific heat and electricity supply systems

Installation operators, PSCs*

Preliminary work	**Data collection**	Updating costs and technical data of building-specific heat and electricity supply technologies
AI steps	**Training**	Demonstrating the connection between heating demand and/or generation potential and building-specific data, GIS data, weather data, historical consumption data and socio-demographic data
	Recognising	Recognising the cost-efficiency of heat and electricity generation technologies on the basis of a number of price forecasts and different usage constellations
	Inferring/learning	Deducing optimal investments in building technologies given the prevailing framework conditions

* Implementation by service providers also possible

Figure 9: Example process for inventory optimisation and other strategic business decisions – generation and trading

AI field of application

Inventory optimisation and other strategic business decisions- grids

AI characteristics	Implementation of AI in the energy industry	Other characteristics
Type of AI application General Data – optimisation	**Actors affected** Grid operators	**Related legal framework conditions of this FoA** Energy Industry Act (EnWG), Metering Point Regulation Act (MsbG), Renewable Energy Sources Act (EEG), Ordinance on Incentive Regulation (ARegV), Ordinance on Electricity Grid Access Charges (StromNEV)
Learning method Classification, reinforcement learning, regression, ANN, clustering	**Relevant value-creation stages** Transport (incl. distribution), consumption	**Examples of companies** envelio GmbH, Venios GmbH, Gridhound GmbH, Supper & Supper GmbH
Data basis GIS data, socio-economic data, grid data, load data for installations/buildings	**Relevant processes in the energy industry** Planning and investments	

Table 6: Profile of inventory optimisation and other strategic business decisions – grids

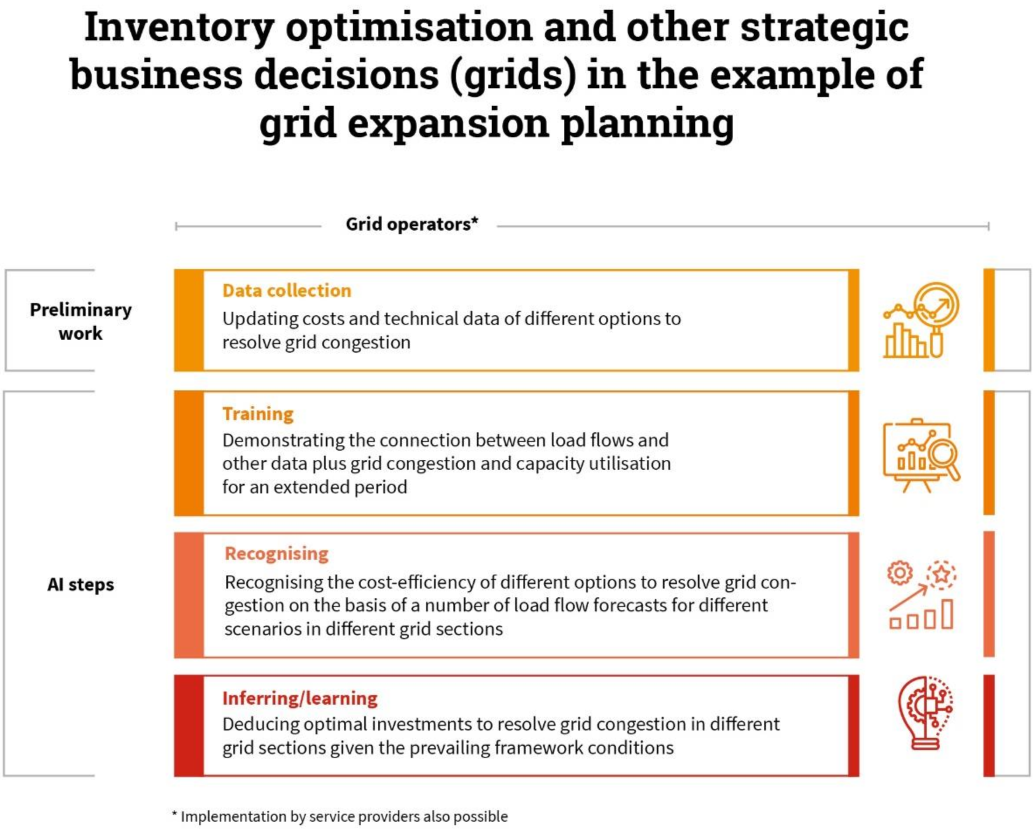


Figure 10: Example process for inventory optimisation and other strategic business decisions – grids

2.2.4 Predictive maintenance

The aim of this FoA is to schedule servicing and maintenance operations in line with needs on the basis of collected sensor data (see Table 7). This FoA also involves the use of complex AI methods, such as drones, which draw on AI-based image recognition to identify faulty elements of grid infrastructure. Predictive maintenance also offers significant potential when it comes to maintaining inaccessible systems and installations, such as offshore wind turbines (see Figure 11).

Technical systems are currently monitored using a wealth of measurement and control data that could form the basis for AI applications. The first step is to train the AI to identify a connection between measurement data and system failures or deterioration. In the second step, the AI uses the insight gained to derive appropriate recommendations for action. AI does not act independently in this field of application.

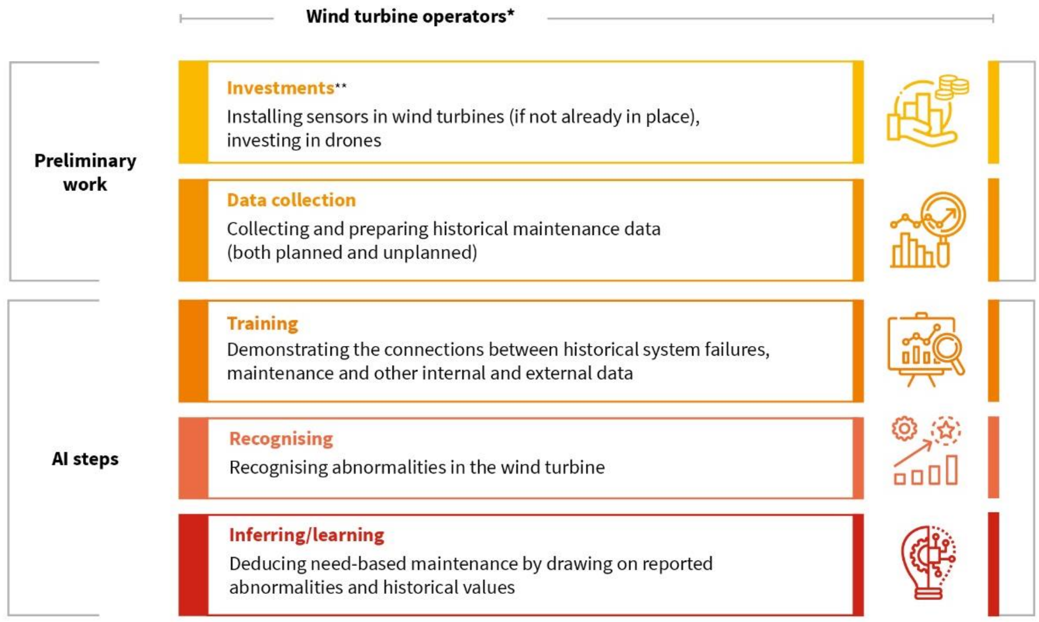
AI field of application

Predictive maintenance

AI characteristics	Implementation of AI in the energy industry	Other characteristics
Type of AI application General Data, Audio & Speech, Image & Face, Robotics & Assistance Systems	**Actors affected** Grid operators, installation operators, maintenance service providers	**Related legal framework conditions of this FoA** GDPR, Satellite Data Security Act (SatDSiG)
Learning method Classification, regression, ANN	**Relevant value-creation stages** Generation, transport (incl. distribution)	**Examples of companies** IS Predict GmbH, NEXT Data Service AG, OnCare.Acoustic - Voitch GmbH & Co. KGaA, HELJO Industries, Hessendrohne - Terra Active Networks GmbH, Schleswig-Holstein Netz AG, PipePredict GmbH
Data basis Production and installation data (incl. image and audio data), load data, weather data, GIS data, maintenance data	**Relevant processes in the energy industry** Predicting maintenance requirements, determining maintenance intervals, procuring spare parts	

Table 7: Profile of predictive maintenance

Predictive maintenance in the example of wind turbines out at sea



* Implementation by service providers also possible
** Standard measures (e.g. investments in computing power and recruiting IT experts) not explicitly listed here

Figure 11: Example process for predictive maintenance

2.2.5 Maintenance, repair and dismantling

Applications in this field serve to support repairs to facilities by diagnosing problems and providing information (virtually) and also to perform maintenance, repair and dismantling tasks using drones and/or robots (physically). AI assistance systems use augmented reality to evaluate on-site status and then interact with the repair technician to provide support. AI-based robots can perform repairs and dismantle technical systems in hostile or inaccessible environments (see Table 8). AI processes in this field of application learn to identify faults and damage to facilities and thus draw conclusions to assist in repairs (see Figure 12).

Different types of AI are used in this FoA, including AI systems based on audio, voice, image, facial and sensor data. AI can use this data to identify a potential need for repairs and issue potential solutions or even perform these repairs directly using a robot.

AI field of application

Maintenance, repair and dismantling

AI characteristics	Implementation of AI in the energy industry	Other characteristics
Type of AI application General Data, Audio & Speech, Image & Face, Robotics & Assistance Systems	**Actors affected** Installation operators, maintenance service providers	**Related legal framework conditions of this FoA** GDPR, Energy Savings Act (EnEG), Energy Savings Regulation (EnEV), Air Traffic Regulation (Luft-VO)
Learning method Classification, ANN	**Relevant value-creation stages** Generation, transport (incl. distribution)	**Examples of companies** ROBDEKON competence center, SMART-Kletterroboter, Siemens AG
Data basis Sensor data, audio and image data from installations	**Relevant processes in the energy industry** Implementing maintenance, repair and dismantling	

Table 8: Profile of maintenance, repair and dismantling

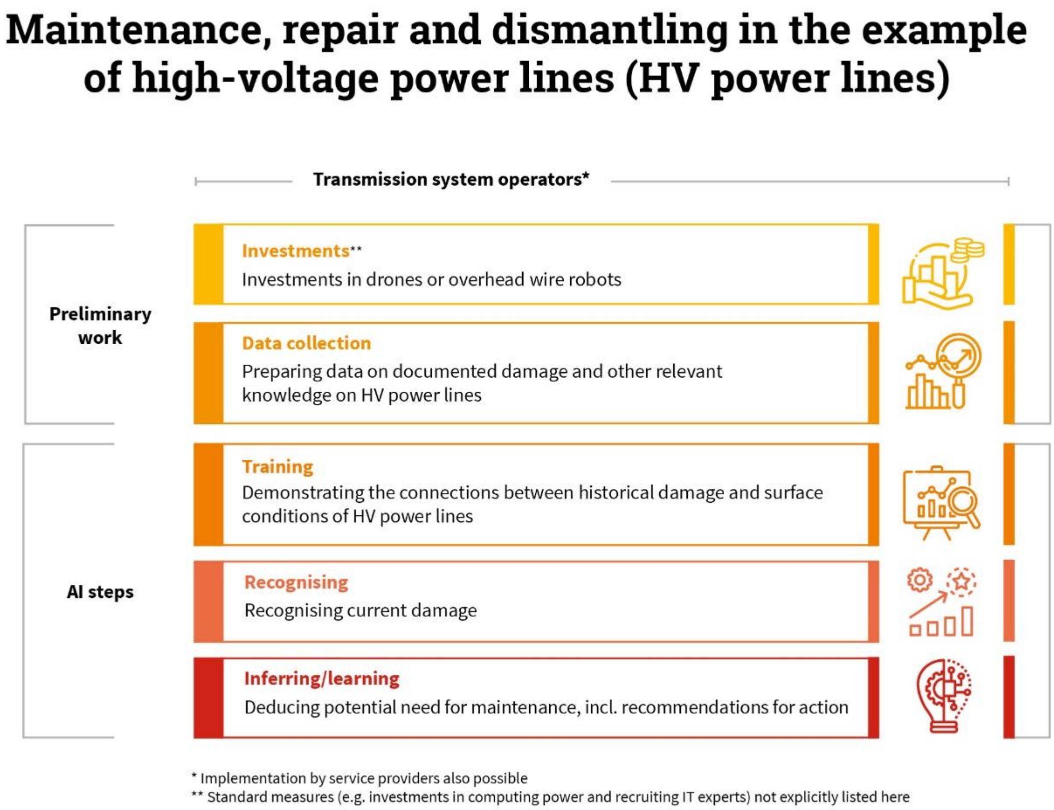


Figure 12: Example process for maintenance, repair and dismantling

2.2.6 Security measures

AI systems implemented in the context of security measures serve to identify and defend against hostile attacks in both the physical world (e.g. by evaluating surveillance cameras) and the virtual world (cybersecurity). The focus in this regard is on critical, system-relevant infrastructures, such as grid infrastructure and infrastructure at large electricity-generation installations (see Table 9).[9] Preliminary work in this area involves collecting and processing past data on assets' regular processes and any irregularities to date (e.g. unauthorised interventions). Upon this basis, the AI can identify current irregularities, notify the units involved and initiate countermeasures (see Figure 13). This FoA involves the use of complex AI methods that can also act independently to prevent damage to energy systems and ensure greater resilience.

[9] This relates in particular to attacks with a political and/or significant financial dimension.

AI field of application

Security measures

AI characteristics	Implementation of AI in the energy industry	Other characteristics
Type of AI application General Data, Audio & Speech, Image & Face	**Actors affected** Installation operators, grid operators	**Related legal framework conditions of this FoA** GDPR, data-security law (e.g. Critical Infrastructure Regulation [Kritis-VO]; requirements such as BNetzA IT security catalogue)
Learning method Classification, ANN	**Relevant value-creation stages** Grid, generation	
Data basis Virtual sphere: internal process data. Physical sphere: e.g. databases of personnel with access authorisation	**Relevant processes in the energy industry** Evaluating unwanted virtual and physical access, implementing suitable defence measures	**Examples of companies** Safeplaces - EnBW Energie Baden-Württemberg AG, zeroBS GmbH

Table 9: Profile of security measures

Security measures in the example of cyberattacks on system-critical power-generation installations

	Installation operators*
Preliminary work	**Data collection** Collecting and preparing historical data on regular asset processes and past irregularities (i.e. unauthorised accesses)
AI steps	**Training** Demonstrating the connections between established past irregularities and asset characteristics
	Recognising Recognising current irregularities
	Inferring/learning Notifying affected units, deducing countermeasures
	Acting Implementing countermeasures

* Implementation by service providers also possible

Figure 13: Example process for security measures

2.2.7 Making it easier for active consumers to participate

AI applications can help prosumers[10] and other active consumers to increase their rate of self-supply and generate additional revenues through interaction with the grid and electricity markets. This FoA involves the same applications as the **General Foundations for Decision-Making** cluster. Key focuses include adjusting the behaviour of consumers by identifying small-scale efficiency potentials and using load-shifting to take advantage of flexibilities. AI can also help to increase prosumers' self-supply rates and optimise investment decisions relating to new domestic appliances, decentralised power-generation installations and battery storage systems. The distinctive feature of this FoA lies in the potential to facilitate operational and inventory optimisation for the consumer while taking user-specific preferences into account by using AI to achieve a high level of automation (see Table 10). In order achieve this, the AI uses data on historic consumption behaviour to issue recommendations tailored to individual users (see Figure 14).

AI field of application

Making it easier for active consumers to participate

AI characteristics	Implementation of AI in the energy industry	Other characteristics
Type of AI application General Data	**Actors affected** Consumers, aggregators, energy service providers	**Related legal framework conditions of this FoA** GDPR, ePR, Renewable Energy Sources Act (EEG)
Learning method Regression, classification, reinforcement learning, ANN	**Relevant value-creation stages** Generation, distribution, transport (incl. distribution)	**Examples of companies** Kieback&Peter GmbH & Co. KG, ENER-IQ GmbH, Recognizer Group GmbH, Fresh Energy GmbH, Shine - GreenCorn Networks AG, Sonnen GmbH, Gridsense - Alpiq Holding AG
Data basis Smart meter data, weather data, electricity price series	**Relevant processes in the energy industry** Load management, balancing, planning, investments	

Table 10: Profile of making it easier for active consumers to participate

[10] Prosumer: A consumer who also produces electricity with their own power-generation systems.

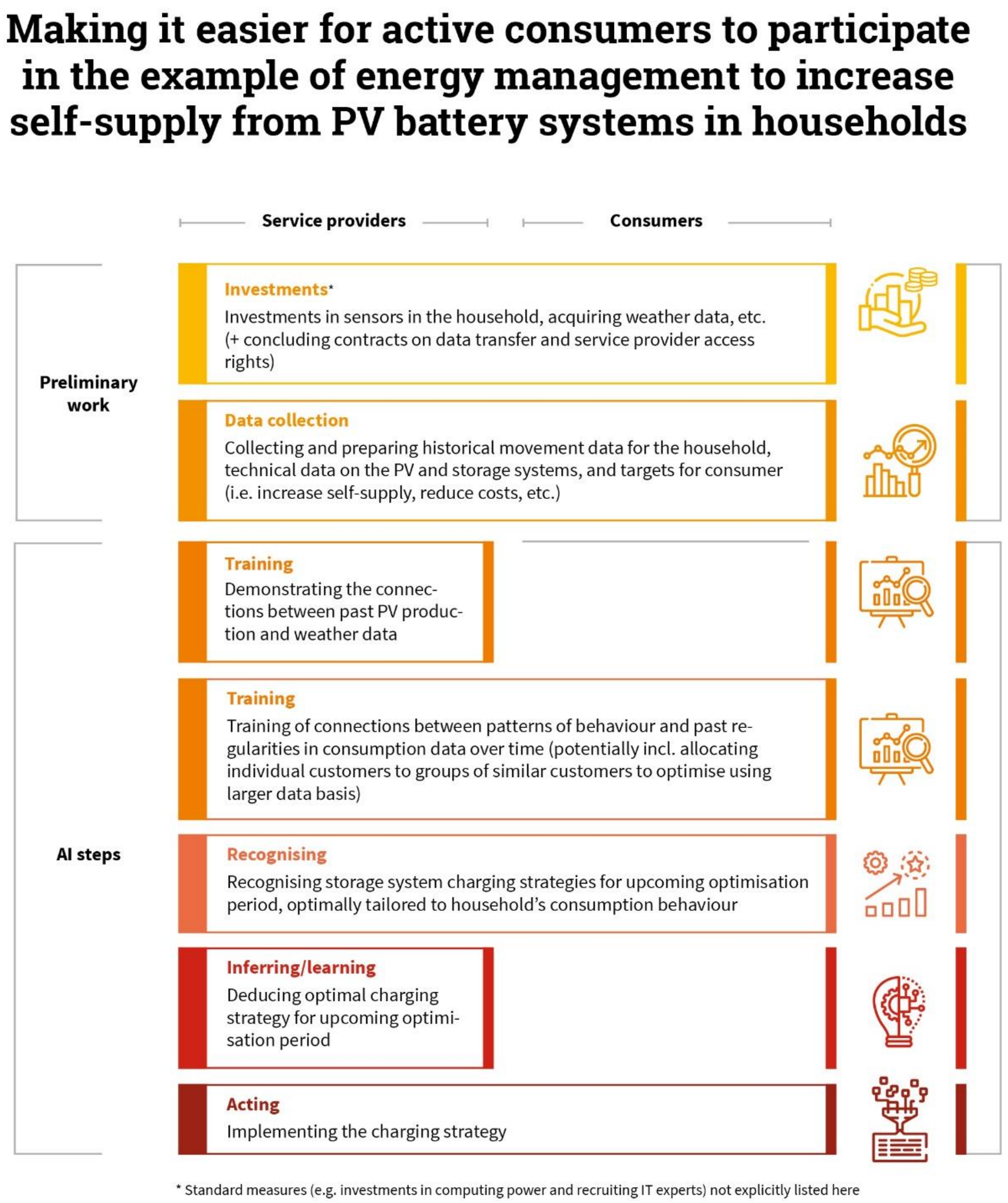


Figure 14: Example process for making it easier for active consumers to participate

2.2.8 Customisation of products and marketing measures

This FoA involves designing marketing measures and products specifically tailored to customers and customer groups with the aim of increasing returns and/or reducing costs. In order to achieve this, AI is integrated to compile customer groups whose preferences can then be identified and subsequently combined with corresponding marketing measures and products. Product optimisation and the monetisation of customer data represent a significant and practical area of application.

It is possible, for example, to effectively analyse customer interactions using intelligent procedures and uncover patterns in customer behaviour. AI can also identify particularly energy-intensive applications and use this insight to deduce a more suitable energy product (e.g. a PV installation) or more efficient applications.

This also makes it possible to generate individual sales forecasts, personalised offers and other measures and to implement customer-specific measures, such as measures to increase energy efficiency in buildings (see Table 11). Customer data previously considered worthless can thus be tapped as a new source of revenue (see Figure 13). Moreover, integrating AI technologies in so-called churn analyses makes it possible to forecast customer cancellations and losses (Klar, 2019). In this field of application, AI is also used to implement specific actions.

AI field of application

Customisation of products and marketing measures

AI characteristics	Implementation of AI in the energy industry	Other characteristics
Type of AI application General Data, Audio & Speech, Image & Face	**Actors affected** Distributors, service providers, consumers	**Related legal framework conditions of this FoA** GDPR
Learning method Clustering, classification	**Relevant value-creation stages** Distribution	**Examples of companies** COSMO CONSULT AG, QlikTech GmbH, ORAYLIS GmbH Business Intelligence
Data basis Customer data, sociographic data (Sinus-Milieus, customer segments, etc.), structural and consumption data, data from customer surveys	**Relevant processes in the energy industry** Developing marketing measures and strategies aimed at specific target groups	

Table 11: Profile of customisation of products and marketing measures

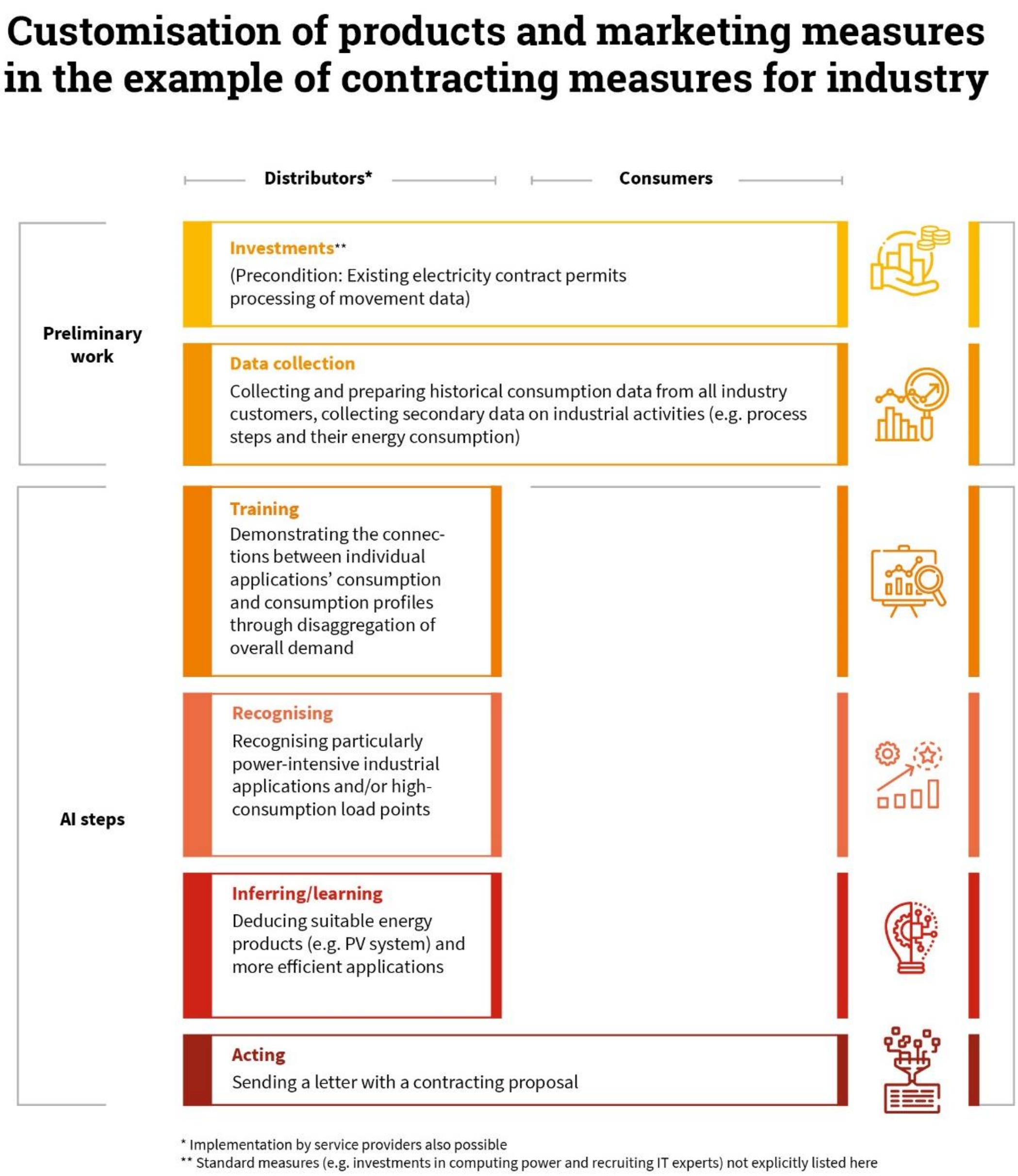


Figure 15: Example process for customisation of products and marketing measures

2.2.9 Process automation for measurements, bills and general distribution

In this FoA, AI enables distributors and metering point operators to cope with the rising volume of transactions involved in distribution (e.g. in the case of new applications such as intelligent EV charging, the use of small-scale flexibility, or optimised operation of household energy storage systems) in automated and more cost-effective processes in the future. Automating processes can deliver efficiency gains (in respect of time and costs) in meter operation and in sales activities (see Table 12).

AI makes it possible, for example, to sort incoming documents automatically, to record and evaluate meter data, and to increase the level of automation in billing processes and customer contract management. Preliminary work required in this FoA includes collecting and processing customer data. During the training phase, the AI uses this data to learn to identify behavioural patterns and cluster customers together (see Figure 16).

AI field of application

Process automation for measurements, bills and general distribution

AI characteristics	Implementation of AI in the energy industry	Other characteristics
Type of AI application General Data	**Actors affected** Distributors, metering point operators, grid operators, consumers	**Related legal framework conditions of this FoA** Energy Industry Act (EnWG), GDPR, administrative decisions of the BNetzA
Learning method Classification	**Relevant value-creation stages** Distribution, transport	**Examples of companies** Traffiqx - b4value.net GmbH, digitale Werke GmbH, Watson - IBM Deutschland GmbH, eprimo GmbH
Data basis Smart meter data, customer data, historical customer communications	**Relevant processes in the energy industry** Billing, balancing, customer service	

Table 12: Profile for process automation for measurements, bills and general distribution

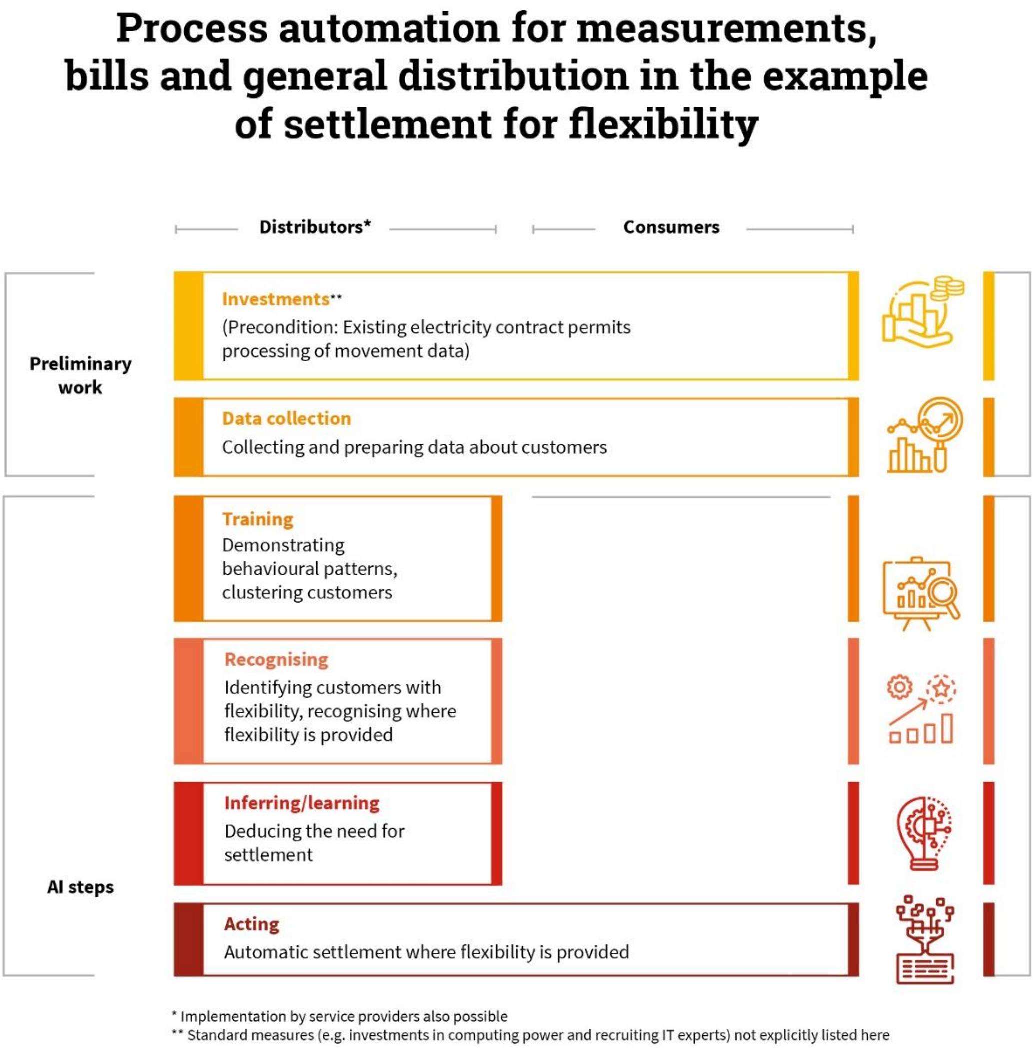


Figure 16: Example process for process automation for measurements, bills and general distribution

The most widespread type of AI in the fields of application examined here is systems related to general data analysis. In contrast, there are few examples of AI systems that involve audio & speech recognition or image & face recognition. Complex AI systems such as robots and assistance systems have only been deployed in specific use cases to date (e.g. drones to perform servicing, robots to dismantle nuclear facilities). AI applications for the purpose of general data processing are based on “weak AI”, a form of AI that only derives solutions within the limits of a clearly defined area of application. More complex AI methods moving towards “strong AI” are coming to be used in individual cases but are not yet widespread. Such methods are used in cases where AI acts independently, i.e. where AI is given autonomy.

3 Evaluating applications for AI in the energy industry

The following assessment is divided into sections focusing on technical, economic, regulatory and social dimensions. In each dimension, this report firstly identifies key criteria that are then condensed into indicators, thereby provide a basis upon the assessment can be conducted. The assessment comprises a qualitative, written element as well as a semi-quantitative element in which an ordinal scale is used to depict the degree to which central questions can be answered in the affirmative and criteria are deemed to be fulfilled. This scale ranges from (1) “does not apply at all” to (5) “applies to a large degree”. Individual fields of application are allocated to indicators based on relevant literature, existing application examples in accordance with Chapter 2.2, and by means discussing the assessments with experts in the digital and energy sectors. The aim is to facilitate comparisons between fields of application. Individual chapters outline the indicators used in this assessment in further detail, examining them for each individual field of application and their wider application across multiple fields. The assessment also examines critical indicators (also known as knock-out criteria) that suggest it will be impossible or difficult to implement an application example in practice and therefore result in a low rating for the field of application in question.

3.1 Technical assessment

Technical requirements such as sufficient data availability, the availability of the requisite computing power and algorithms, and the ability to use AI methods safely in the field of application in question must be met in order to ensure the usability of AI applications in the energy sector. However, even if these technical conditions are met, this does not guarantee that the application of corresponding approaches will also represent a contribution to the integrated energy transition.

Dealing with each FoA in turn, the following assessment therefore examines whether the technical conditions for the successful use of AI in the energy sector have been met and, furthermore, whether the use of AI can make a contribution to the integrated energy transition. This assessment is divided into two categories and refers to numerous indicators. The first group of indicators allows us to **grade the state of technical development** in a field of application and classify the potential technical and data-related challenges involved in implementation. The second group makes it possible to grade the potential reduction in CO_2 in the FoA and, therefore, the **contribution to the integrated energy transition**. The indicators in these two categories and the grading of individual fields of application in respect of the aforementioned questions are addressed in further detail later in this report.

We have identified a total of four indicators that influence the state of technical development of AI methods and the practicability of their implementation in the energy industry. These four indicators are:

- **Technical maturity**
- **Diffusion of AI**
- **Availability and quality of data**
- **Security of the energy system**

Each field of application is graded on the basis on several central questions: Is the state of technical development and/or the technical maturity of AI advanced in this FoA? Is the operational application of AI dependent on further technological development – i.e. is the required computing power available today or is further development required? What is the status of AI diffusion in this FoA and how is this expected to change in future? If AI is already in widespread use in a given application, it can be assumed that the technical conditions required for the use of AI have been met to a sufficient degree. However, applying AI in a more meaningful way is also dependent on sufficient data availability and quality. Ultimately, AI can only be applied when enough training data exists. A further aspect of relevance to the technical implementation of AI projects in the energy industry is ensuring that the application of AI does not present a threat to the security of the energy system (i.e. data security, especially in relation to customer data; cybersecurity, especially in relation to critical infrastructure). The latter is considered a technical criterion as security represents an additional requirement to be fulfilled.

The following criteria are used to assess the contribution of an FoA to the integrated energy transition:

- **Diffusion and integration of RE**
- **Improvement of system operation**
- **CO_2 reduction**

On the one hand, the assessment considers what the impact of the application of AI might be for the integrated energy transition in respect of the integration of RE and how fluctuating RE sources can be incorporated in system services. It also examines whether the application of AI might lead to operational improvements in parts of the energy system, with potential benefits of this including the freedom to shut down conventional power stations without compromising supply security and the ability to operate systems at lower costs. Finally, the assessment analyses whether the impact of AI on CO_2 reduction in the energy system might be facilitated through improved integration of RE, or whether the application of AI might also entail negative effects, e.g. higher energy consumption.

Owing to the complex nature of the topic, many dimensions of this assessment also overlap with other elements, such as in examining the technical robustness of processes that have an impact on European data flows. In this regard, the European Commission considers an open and assertive approach to data flows as the cornerstone of social requirements of the EU Data Strategy (EC, 2020).

3.1.1 General technical assessment of all fields of application

Technical maturity

Scientific literature and a series of commercial applications already provide examples of the use of AI in almost all the fields of application examined in this report. These examples, which relate to several fields of application, serve as evidence that AI systems have already achieved a sufficient level of technical maturity. In certain areas, however, there remains a need for further development, such as in relation to forecasting RE feed-in with high spatial resolution, analysing high volumes of video data in real time, and applying big-data solutions (> 100 GB of data per day) in practice. The growing use of hybrid computing models – which often use sophisticated calculations to combine several approaches – shows that computing power is not a limiting criterion for the vast majority of the fields of application assessed here.[11] These hybrid models often combine AI models with existing expert knowledge. Yet, it is important to note that training and comparing different models can be a very time-intensive process, which can pose a problem in time-critical contexts. Although a significant improvement in computing power would make it possible to use more complex models or make updates more frequently, it would not alter the fundamental possibilities regarding the application of existing solutions.

In principle, the fields of application examined herein appear to have been developed to a sufficient degree to enable their widespread application in the energy industry. One exception to this description is robotics, with potential applications including automatic dismantling of installations and systems. Autonomous robots that could be used in such contexts are still in an early stage of development, meaning that their commercial use is undoubtedly still several years away. There also remains a need for further technical development of hybrid systems that integrate expert knowledge in AI models and could be applied in the energy industry in future (Fraunhofer, 2018).

[11] The proportion of hybrid models in scientific literature relating to AI in the energy industry has more than doubled since 2000 (cf. vom Scheidt et al., 2020, Fig. 6).

Diffusion of AI

The various fields of application generally differ in terms of the degree to which they are specialised for use in the energy industry. In some certain fields of application, AI techniques require significant adaptation to specific aspects and characteristics of the energy industry, for example in relation to grid optimisation or the area of maintenance, repair and dismantling. By contrast, existing AI methods are already broadly applicable in other areas, such as process automation and forecasting of feed-in, loads and prices – that is to say, AI methods can now be applied in the energy industry without the need for considerable adjustments. Several further applications, particularly those relating to transmission and distribution grids, are strongly focused on the hardware used in the energy industry (i.e. specific technical systems) and require specific data of their own that cannot be transferred from other areas of the energy industry.

If they can display technical maturity in relation to a specific use case, if sufficient data of suitable quality is available to train the required AI models, and if it can be demonstrated that they offer attainable added value in commercial terms, AI methods diffuse quickly in individual fields of application. In many cases, these conditions have already been met for applications related to predictions, operation optimisation and inventory optimisation, which means that rapid diffusion of AI methods can be expected in these areas. This assumption is also confirmed by the significant number of related commercial offerings already in existence. However, this does not apply to applications that require the installation of additional hardware such as smart meters or measurement devices to measure grid states. Consequently, due to the low availability of relevant data, power grids represent an exception in respect of the diffusion of AI, which is otherwise expected to proceed apace.

Availability and quality of data

Viewed as a whole, applications involving data that is generally available or that can be collected without significant effort are already well developed in technical terms and are often commercially available in the energy industry even today. Weather data, for example, is available in high temporal and spatial resolution for extended periods. By the same token, price time series and data on feed-in from RE systems is available in high quality and for extended periods and can be used to train AI models (vom Scheidt et al., 2020). This data is primarily used for predictions and forecasting and for operational and inventory optimisation in relation to generation and trading.

When it comes to grids, the data situation is more complex, with data on the state of individual grid components still not available in the same temporal and spatial resolution as data on other topics, such as the weather. The availability of such data will improve as the corresponding measurement technologies become more widely available, which will also facilitate the use of similarly complex AI processes as described above on a wider scale in relation to power grids. Actors in the energy industry need to collect data and gain experience in order to customise their sales approach and automate the processing of customer interactions. Third-party providers are not in a position to provide data relevant to such processes in the same quality as for weather data or price time series.

Security of the energy system

As a general rule, AI applications for the integrated energy transition do not represent a risk or threat to the security of the energy system, either today or in the near future. One justification for this assessment is the somewhat decentralised nature of the energy transition: the manipulation of individual systems and installations is unlikely to lead to major failures in the overall system.

Furthermore, in many cases AI primarily serves to improve existing processes and procedures and is not generally given ultimate responsibility for operating systems or installations in the energy industry. It is instead restricted to certain processes where it can provide support. Nevertheless, it is conceivable that AI procedures could be developed and trained to attack the energy system. The focus of the present report, however, is on AI applications designed to make an active contribution to the integrated energy transition.

In the long term, using AI to optimise large areas of the energy system or even the system as a whole – including the areas of generation, distribution and consumption – harbours greater economic potential than optimising individual systems. By the same token, however, using AI on this scale would also allow an external attack to cause greater damage. Appropriate security measures must therefore be put in place in future to protect against attacks of this type.

Diffusion and integration of RE

The use of AI can certainly contribute to the energy transition by positively influencing the integration of RE and helping to avoid grid congestion. AI applications that promote improved forecasting, operation optimisation and inventory optimisation in particular offer the potential to achieve higher returns using the same assets. Such applications make this possible by optimising how energy facilities operate, such as improving the alignment of wind turbines to increase their output or using intelligent control methods to reduce the energy consumption of heating systems. In both aspects, operational optimisations entail an additional reduction in CO_2 emissions due to the reduction in the use of conventional energy sources.

Improvement of system operation

Supply security is primarily improved by the ability to better predict fluctuations in power generation and consumption as well as system failures. The use of AI therefore appears reasonable, in particular in the areas of predictions and optimisation of generation, distribution and consumption.

CO_2 reduction

For many applications, it is not possible to quantify the direct reduction in CO_2 emissions achieved through the use of AI given the difficulty outlining a reference scenario with which to calculate savings, particularly in relation to design and plausibility. This is due to the high complexity and temporal variability of the energy system. It would be possible to make a comparison if the use of AI resulted in more efficient operation. One example is using intelligent control algorithms in building control processes, where the amount of heat saved makes it possible to calculate the resulting reduction in CO_2 emissions. Just as complex as determining the direct reduction in CO_2 emissions is calculating the indirect reduction in CO_2 emissions by switching from fossil fuels due to AI-optimised RE generation.

3.1.2 Technical features of the fields of application

In order to explore overarching aspects of the technical assessment in further detail, this section examines features specific to individual FoAs.

Predictions

AI is already in widespread commercial use in the field of predictions and forecasting, above all in relation to RE generation but also in some areas of trading. This is also confirmed by scientific publications on the topic. According to vom Scheidt et al., around 60 per cent of scientific publications on the topic of AI predictions and forecasting in the energy industry concern the prediction of PV power generation, while around one-third relate to the generation of wind power (vom Scheidt et al., 2020). High-quality data is available in sufficient volumes in these areas, and improved predictions made possible through the use of AI can be applied directly and yield benefits in corporate contexts. Over time, a series of providers have begun to offer systems with predictive capabilities to companies as a service (keyword: software-as-a-service)[12]. AI can also be used to predict the status of transmission and distribution grids, though such applications have not yet become commercially established due to the lack of data in high temporal and spatial resolution. As a result, the use of AI in this field is currently limited to research projects.

Practical example: enercast – using neural networks for precise power forecasting

enercast offers self-learning products to precisely forecast the power output of wind and solar power systems and thereby integrate RE in power grids and energy markets. Unlike a modelled system that needs to be updated manually, enercast's neural networks develop in tandem with the external conditions. RE installations are usually situated in natural surroundings without the predictability of a laboratory. In such settings, neural networks can prove particularly profitable. The forecasting process starts by inputting data about the installation into the system, such as its nominal output and location. Similar installations can also serve as reference points. Historical data on installation output can be used as a reference to calibrate future forecasts and make the results more precise. The neural networks are trained using historic relationships between weather data and output data. The longer the period for which the neural networks are given data, the more precise and detailed the depiction of reality they create.[13]

In light of the improved integration of RE and optimised forecasting of RE feed-in and expected loads it facilitates, the use of AI in this context clearly represents a contribution to the integrated energy transition. When applied in the context of power grids, AI can reduce grid overloads. In the context of power generation and trading, the use of AI is already reducing the need for control energy. It is important to distinguish between simpler processes, such as regression models, and more complex processes, such as ML and ANNs. The former have been applied in practice for longer and require relatively little training data. The latter have grown in importance in recent years due to rising data availability. Hybrid models are also taking on a more prominent role overall (vom Scheidt et al., 2020). The complexity of the algorithms varies from one application to the next.

Due to the high number of commercial AI applications that are already in use and the resulting optimised feed-in of RE, the technical viability of this FoA is considered high.

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[12] cf. www.pwc.de/de/energiewirtschaft/evaluation-automatisierter-energiehande-intraday-markt.pdf [German only]. The scope and quality of the service depends on a number of factors; however, such services always require historical data and interfaces to the most up-to-date data available.
[13] Further information: www.enercast.de

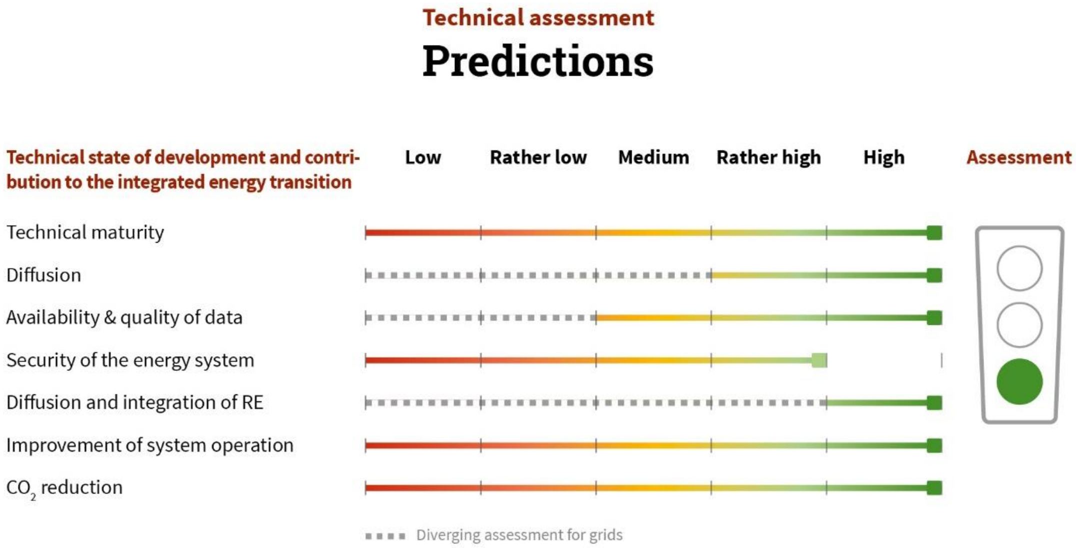

Figure 17: Technical assessment of predictions

Operation optimisation

As a general rule, the process of optimising a large-scale power-generation facility proves more complex than optimising a building or individual devices. Commercial use of AI in this context will therefore likely be a long time coming. Above all, the low diffusion of real-time measurement devices required to provide corresponding data presents a barrier to the large-scale optimisation of power grids. Smart meters will provide more data on power consumption in future, which will facilitate operation optimisations on a larger scale and for large parts of the energy system. Such developments offer greater optimisation potential than smaller-scale measures. Real-time grid operation and intelligent grid control are therefore key focuses of current research in this area (vom Scheidt et al., 2020).

Practical example: Gridhound – creating digital twins for distribution grids to efficiently monitor grid status

The grid simulation provided by Gridhound makes it possible to efficiently monitor grid status. In order to shed light on blind spots within a distribution grid, Gridhound conducts a sensitivity analysis to ensure metering points are optimally positioned and uses the measurement data provided to simulate capacity utilisation across the distribution grid. Adopting a purposeful, systematic approach to metering point placement reduces the need for such technology from an average of 33 per cent to just 5 per cent of nodes. Based on the real-time transparency over the grid this makes it possible, when observed for extended periods, to issue recommendations for efficient use of available grid capacity and grid expansion based on measurement values and in line with demand. This approach has been tested with distribution grid providers including Bayernwerk Netz, which has a higher concentration of photovoltaic systems than the German average. Thanks to the ANNs, it took just 8.5 microseconds to determine the status of the grid, with an average error rate of just 0.7 per cent.[14]

[14] Further information: www.gridhound.de/

In respect of the security of this FoA, it would be possible for an attacker targeting power grids to simulate a false grid situation to the grid operators by feeding manipulated data into the system, which could result in the grid overloading as a result of incorrect grid control. Yet, although this scenario is conceivable, given the methods to identify false data that already exist (see the example of “False data injection” in the FoA security measures), the risk of this actually occurring appears rather low. If attacks of this type were limited to individual areas of the grid, e.g. one section of the distribution grid, their impact and the resulting damage would also be limited as only a small section of the grid would be affected.
Better operational planning and higher yields from RE installations reduce the need for conventional power generation and, by reducing CO_2 emissions, make a direct and appreciable contribution to the integrated energy transition. AI methods such as ANNs used for quantitative forecasting of future events support overall management of the power grid by assisting with system control, maintenance coordination and resource optimisation. Forecast data on the state of the grid also serves as an input for a wide range of other AI applications (dena, 2019). As energy generation increasingly shifts to a decentralised structure, the complexity of the power grid and forecasting data are becoming ever more important (keyword: smart grids).

Although the technical maturity of AI applications is lower in the context of grids than for power generation and trading, this situation can be expected to improve in future due to an increase in data availability. Optimising how infrastructure is operated thus represents a significant contribution to the integrated energy transition and the technical assessment overall is highly positive.

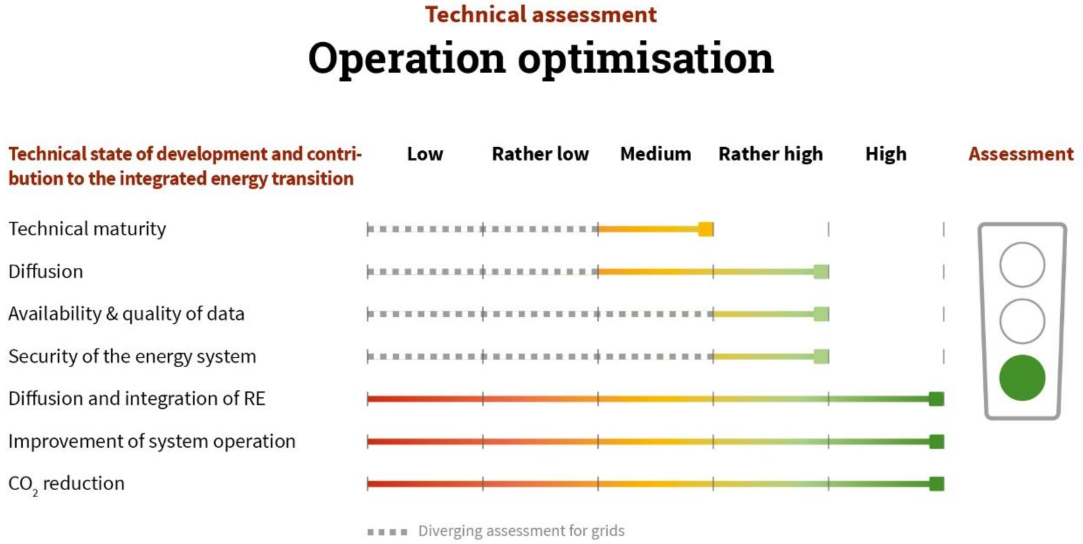

Figure 18: Technical assessment of operation optimisation

Inventory optimisation and other strategic business decisions

The high degree of technical maturity in this area is evidenced by a series of AI applications that are already commercially available, such as technologies to support the construction of RE generation installations and charging infrastructure for electric cars. A range of geo-referenced data (e.g. weather, traffic, etc.) for location planning is already available, can usually be processed quickly and thereby facilitates numerous applications of AI. In some cases, however, there is a lack of data with high spatial and temporal resolution. Obtaining such data could lead to further applications of AI in the field of inventory optimisation.

Grid infrastructure planning is also supported by AI applications. By taking existing data into account, AI helps to estimate the long-term utilisation of grid capacity and thus provides guidance for decisions on whether an increase in grid capacity is necessary (use of intelligent components, e.g. in grid expansion). This allows grids to be expanded in line with demand and facilitates optimal utilisation of grid resources.

The application of AI does not present any direct benefits for planning conventional power stations or for conventional system operation. However, AI technologies deliver indirect benefits by generating more realistic figures regarding the utilisation of such installations during the planning phase. For instance, AI applications make it possible to predict peaks in power generation and demand more accurately and reserve capacity accordingly. At the same time, service life is a decisive factor in location planning for many conventional power generation and distribution installations.

Nevertheless, AI can assist in the planning of long-term, capital-intensive measures by providing a basis for decision-making. The advantage of AI lies in its ability to take high volumes of data into account, including user preferences, GIS data and historical prices. Digital twins can therefore provide support in contexts such as building construction and commissioning and issue automated instructions when components need to be replaced (Gross et al., 2020). Typical learning methods in this area include classification, reinforcement learning, regression, ANN and clustering.

Given that active investment planning can resolve grid congestion, this FoA contributes to the integration of RE. In light of the fact that AI is already applied today in the management of energy assets, the technical viability of AI applications in this FoA is regarded as high.

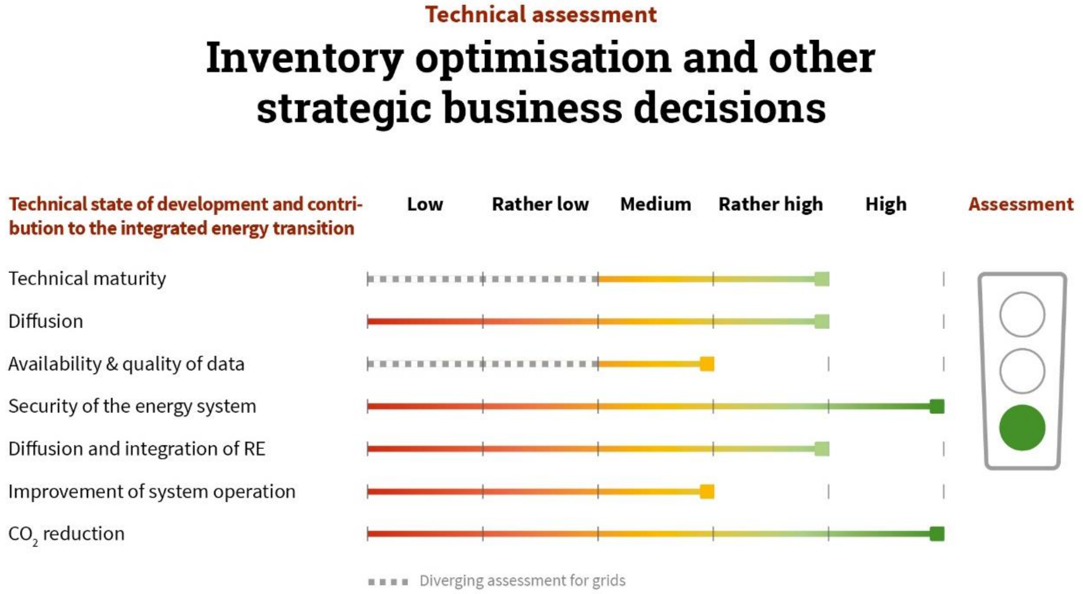

Figure 19: Technical assessment for inventory optimisation and other strategic business decisions

Predictive maintenance

Predictive maintenance and the related FoA of maintenance, repair and dismantling both aim to reduce the effort involved in maintenance and repair tasks and thereby lighten the workload on personnel. Although maintenance, repair and dismantling relates to the implementation of measures and aims to assist employees by providing specialist knowledge and empirical values, predictive maintenance is a field of application focused on planning measures; this FoA is therefore predictive by nature and entails forecasting. Nevertheless, there are applications and objectives that relate to both fields of application, such as minimising the risk to personnel. Without AI, it would not be possible to perform the comprehensive data evaluation that underpins predictive maintenance.

The availability of data and the technical maturity of AI for predictive maintenance in the context of power-generation installations are already very high, an assessment supported by a series of commercial applications in use today (e.g. using drones to inspect wind turbines, conducting noise tests for hydroelectric power plants). According to figures from IDC Energy Insights, 13 per cent of European energy providers currently use AI for predictive maintenance across Europe, while a further 12 per cent plan to use AI in this field (IDC, 2019). It can be assumed that the use of AI in predictive maintenance will become established as standard industry practice in the relatively near future.

To date, there have only been a handful of commercial examples of AI being applied in predictive maintenance in power grids (for exceptions, refer to the practical example in 3.2.2), as grid data and grid state information cannot be determined solely through direct measures in or on installations themselves. The use of predictive maintenance is not limited to large-scale or inaccessible assets. In addition to complex methods (e.g. using drones), comparatively simple methods are also in use, such as the installation of (additional) sensors. Integrating historical data in calculations enables AI methods to establish the relationships between symptoms of deterioration and system failures, which makes it possible to identify abnormalities. Classification, regression and ANNs are typical methods used in this field. Applications of this type are usually implemented in practice with the Internet of Things (IoT) technology LoRaWan.[15]

Hybrid expert systems combine specialist knowledge from human experts with insights gleaned from data processing and ML. Though such systems need to be developed further, they represent another interesting method of applying AI. Using AI in this manner offers significant potential, particularly in the context of grids, where it could make it possible to bypass the issue of limited data availability to some extent. However, models of this type still require further technical development (Fraunhofer, 2018).

Predictive maintenance does not result in direct CO_2 savings, but can reduce costs and thus render system operation more economical for the operator. This can lead to increased use of RE.

In view of the number of applications already in practice today, applications in this field can be regarded as making a significant contribution to the security of the energy system. However, as such applications do not directly reduce CO_2 emissions, their contribution to the integrated energy transition is regarded as medium. The overall technical assessment reaches a similar conclusion.

[15] See: https://www.stadt-und-werk.de/meldung_26015_Den+Spagat+hinbekommen.html/druck/meldung_29002_Trafostation+im+Internet+der+Dinge.html [German only]

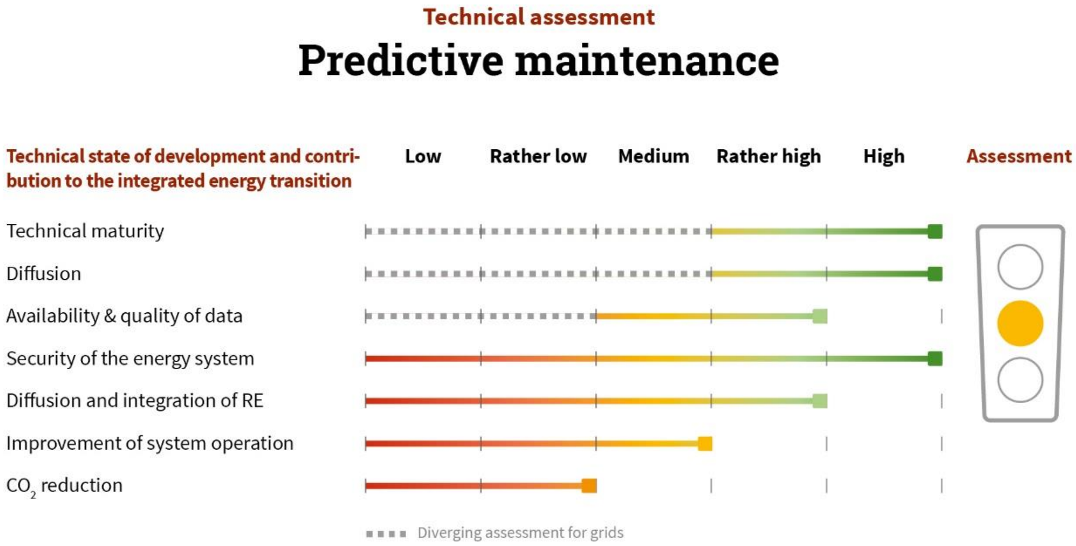

Figure 20: Technical assessment of predictive maintenance

Maintenance, repair and dismantling

Numerous applications already exist in the field of maintenance, repair and dismantling; the use of robots to dismantle hazardous or inaccessible facilities is a central use case. However, the autonomous robots required for such applications remain in an early developmental stage. This is primarily due to the high complexity and variability of the tasks to be executed, which makes development, training and researching the robots an expensive and time-consuming process. Consequently, only a few commercial offerings currently exist and applications in this field are predominantly in an exploratory research phase. One example of an application currently under development is SMART climbing robots (SMART = Scanning, Monitoring, Analysing, Repair and Transportation), which act as a service cabin for wind turbines and can be used in any weather conditions.[16]

Another application is improved planning of complex and protracted dismantling processes in the energy industry. In principle, AI could provide assistance in this area, but currently lacks the training data required to carve out a specific application. Data availability can be improved in future through more extensive and standardised documentation when problems occur. While the use of AI in this field is not associated with a direct CO_2 reduction, the use of AI could cut costs in the field of maintenance, repair and dismantling. As soon as such an application becomes commercially available, this could improve the cost-effectiveness of system operation.

All in all, this FoA contributes to the security of the energy system, but lacks the reliable data sources it requires to do so on a meaningful scale. As with predictive maintenance, it is not possible to quantify CO_2 reductions for this FoA. The overall technical assessment of this FoA therefore returns a low rating.

[16] See: https://www.fh-aachen.de/fachbereiche/maschinenbau-und-mechatronik/forschung-projekte/forschungsprojekte/smart-kletterroboter/ [German only]

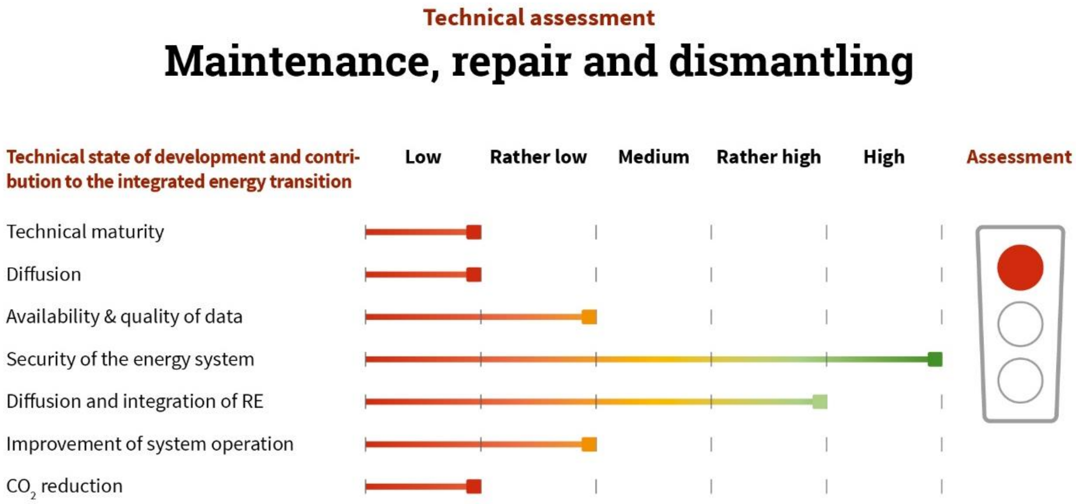

Figure 21: Technical assessment for maintenance, repair and dismantling

Security measures

Cyberattacks targeting critical infrastructure can compromise supply security (Berman et al., 2019). In the field of IT security, AI can use sensors to help detect external denial-of-service attacks and false data injection.[17] Digital twins make it possible to identify critical grid statuses at an early stage. The ability to detect systematic discrepancies in balancing groups also allows us to uncover exploitative and abusive market behaviour by individual actors. Analysing irregularities and data from regular processes is a basic requirement for this application. The low level of training data related to cyberattacks represents a barrier to the development of such models, in part also because of the lack of associated activities. The lack of transparency into the comparatively complex algorithms and the guidance for decision-making they produce can also be problematic for users (Bakovic et al., 2020).

In the physical world, AI image recognition can be used to automatically detect dangerous situations (EnBW, 2018). According to IDC Energy Insights, 5 per cent of energy providers across Europe currently use AI in their security measures, while a further 15 per cent plan to use AI in this field (IDC, 2019). In addition to the lack of available data, AI is yet to reach a high level of technical maturity in the context of security measures. Artificially creating and simulating relevant scenarios is one potential means of obtaining the required training data.[18]

It is not possible to discern an appreciable contribution to the integrated energy transition in this FoA: it does not directly reduce CO_2 emissions, support the integration of RE, or improve system operation to a meaningful extent. AI has the potential to improve the security of smart grids, but the availability and quality of data remains insufficient to achieve this potential. As a result, the overall result of the technical assessment is a low rating.

[17] A denial-of-service (DoS) attack involves flooding a website with superfluous requests, thus overloading the server and rendering the website unavailable. False data injection is a form of attack in which sensors are fed false data in the form of signals (He et al., 2018).
[18] A project at Argonne National Laboratory has adopted this approach and is training AI using previously resolved (simulated) scenarios to reduce the computing time when applied in real life; for more details, see: www.anl.gov/article/artificial-intelligence-can-make-the-us-electric-grid-smarter.

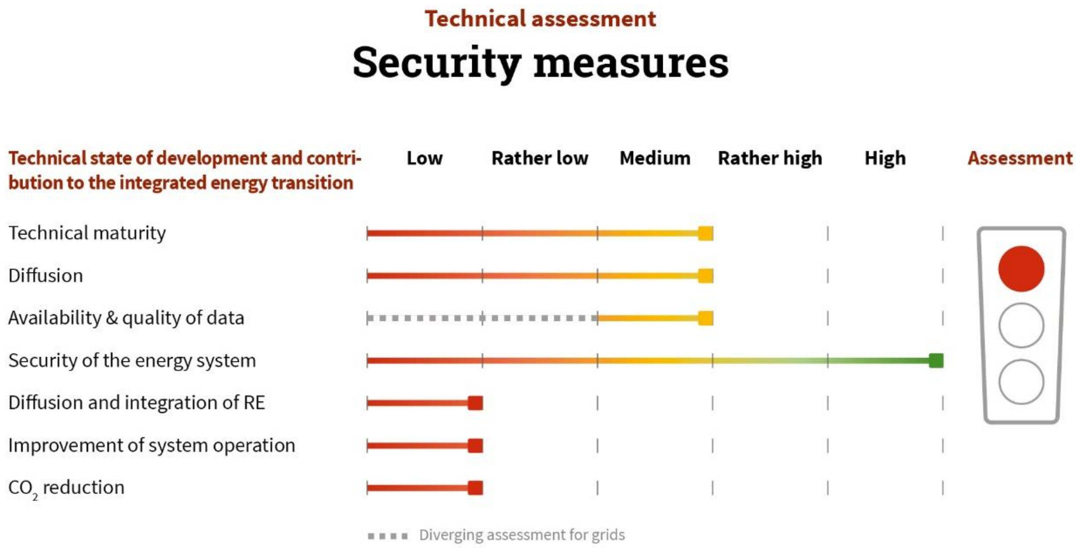

Figure 22: Technical assessment of security measures

Making it easier for active consumers to participate

AI has already been commercially deployed to help make it easier for active consumers to participate in the energy market and is well developed in technical respects. The AI learning methods used (regression, classification, reinforcement learning and ANNs) mean that the computational power in this FoA is not high. However, the slow-paced diffusion of controllable devices in private households has curbed the ability of this FoA to achieve its full potential. It is possible that this attainment gap will be bridged in future as intelligent metering systems (iMSys) become more widely available. One exception to this lack of diffusion is the integration of PV systems in private households, which is already highly advanced. The dissemination of controllable devices in commercial, trade and service settings could stand to progress somewhat faster.

Using AI to control individual consumers and loads can result in localised disruption in the energy system. In the context of individual buildings and households, however, the impact of such disruption is localised and therefore does not represent a security flaw for the overall energy system.

By optimising the relationship between generation and consumption, this FoA can make a contribution to the energy transition, such as through efficient heating control systems (i.e. highlighting inefficiencies in heating behaviour, e.g. heating one room while a neighbouring room is being cooled) or adjusting consumption according to weather data and expected PV power generation. This in turn makes it possible to avoid fossil fuels and reduce CO_2 emissions.

Due to the slow-paced diffusion of controllable devices in private households and the rather high overall potential for CO_2 reductions, the technical assessment delivers a medium rating for this field of application.

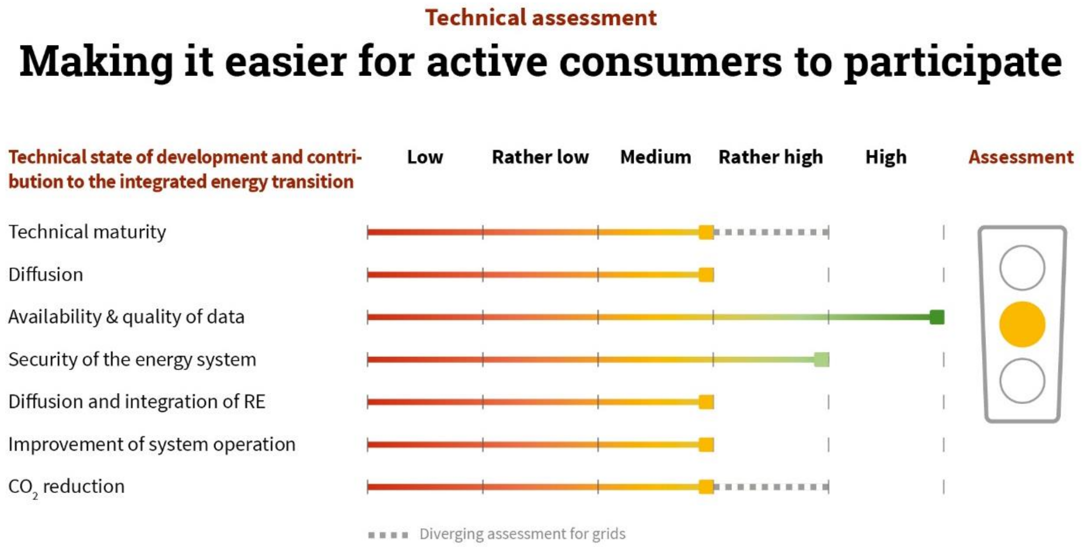

Figure 23: Technical assessment of making it easier for active consumers to participate

Customisation of products and marketing measures

Customising products is already common practice in some parts of the industry. However, it will be some years before the practice takes hold in a majority of companies because developing a suitable process and resolving data protection issues are topics that each company must solve for themselves. These companies firstly need to collate data from various sources in order to offer products and services with the highest possible level of customisation. Gathering a variety of customer data, such as their address and consumption figures, also entails potential regulatory challenges (see Chapter 3.3). According to figures from IDC Energy Insights, 5 per cent of European energy providers currently use AI for sales recommendations, while a further 18 per cent plan to use AI in this area (IDC, 2019). More widespread use and commercialisation of AI technologies should therefore be expected in this FoA in the near future.

The impact of this FoA on the integrated energy transition is rather low. However, targeted marketing activities could make RE products more appealing and thereby help RE to disseminate more rapidly. All the same, this will not have a direct, measurable impact on CO_2 emissions. Applications in this field therefore represent supporting measures at most.

Product customisation is already common practice in some companies, but given that such applications only make a limited contribution to the integrated energy transition, the technical assessment returns a medium rating for this FoA.

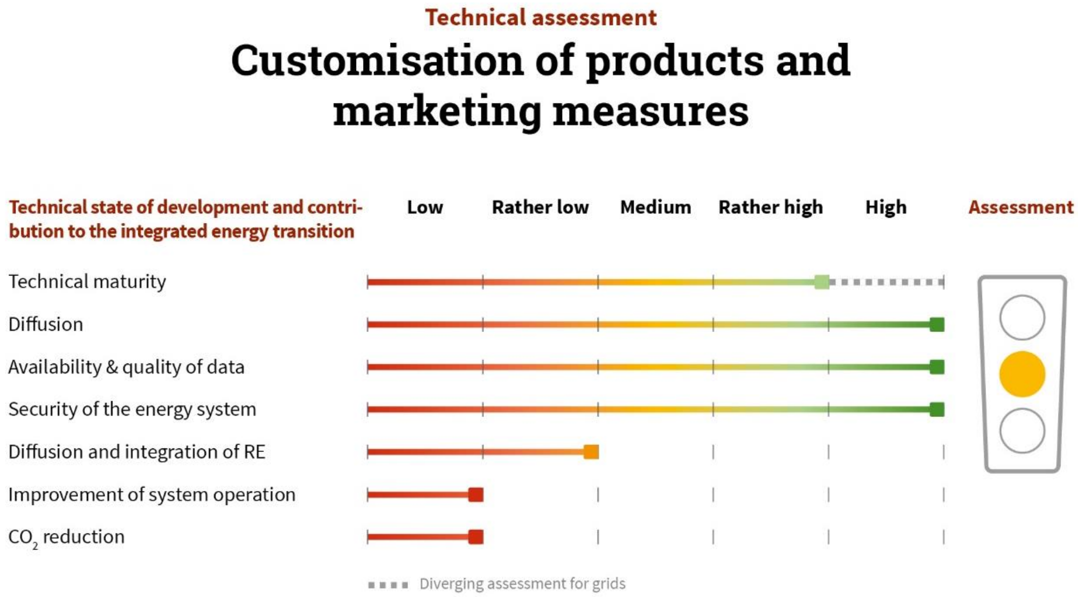

Figure 24: Technical assessment for customisation of products and marketing measures

Process automation for measurements, bills and general distribution

Automating processes can deliver efficiency gains (in terms of costs and/or time) in relation to both meter operation and sales activities. Standard processes involving customer contact – especially automatic billing programs and other similar services where data is available in sufficient volumes and sufficient quality – are already in commercial use. Across Europe, 10 per cent of energy suppliers already use automated customer service systems, while a further 13 per cent plan to use technologies for this purpose (IDC, 2019). It is important to prevent external parties from accessing customer data disclosed and processed in this context in order to comply with data protection requirements.

AI can be used to facilitate automated recording and analysis of customer communications, in particular telephone communication, which in turn makes it possible to identify and classify customers' needs and requirements.[19] This can improve the analysis of available customer data and thus help to better understand their problems and needs. Upstream and downstream processes, products and marketing measures can also be improved and further customised as a result.

The automation of meter readings, billing and sales activities does not have a discernible impact on the integrated energy transition, especially because the optimisation potential is identical for both RE and fossil fuels.

Given that there is no identifiable impact on the integration of RE, but in consideration of the fact that such methods are already in widespread use today, the technical assessment returns a medium rating for this FoA.

[19] Natural language processing (NLP) methods are used for this purpose; see for example: https://medium.com/syncedreview/natural-language-processing-in-call-centres-b572da4da5dc.

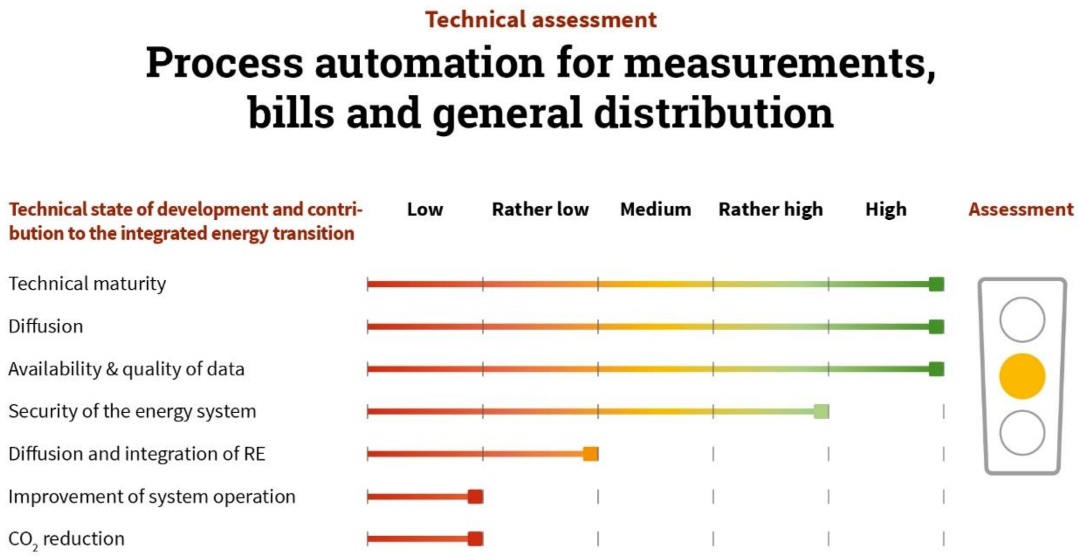

Figure 25: Technical assessment for process automation for measurements, bills and general distribution

Summary of the technical assessment

All in all, few technical hurdles stand in the way of the use of AI in the energy industry. Admittedly, the fact that the data required to achieve the significant potential of AI is still not available is an issue prevalent across several fields of application (in particular for the grids). Technical maturity, on the other hand, rarely appears to present a problem.

AI has the ability to contribute to the integration of RE and reduce CO_2 emissions, particularly in the fields of **predictions**, **operation optimisation** and **inventory optimisation**. In other fields of application, AI predominantly boosts efficiency regardless of the type of power generation involved (i.e. conventional or renewable). **Security measures**, **making it easier for active consumers to participate**, **customisation of products and marketing measures** and **process automation** are fields of application in which AI can make relatively little contribution to the energy transition.

Applications in the fields of **predictions**, **customisation of products and marketing measures** and **process automation** demonstrate a high level of technical maturity. In technical terms, the least promising fields of application are **maintenance, repair and dismantling** and **security measures**. In these areas, AI is either a long way from becoming commercially viable or its contribution to the integration of renewable energies and reducing CO_2 is very low.

3.2 Economic assessment

Different actors have different motivations for turning to AI. Some wish to increase the utilisation of their assets, while others hope to achieve higher prices, increase their sales or minimise unnecessary asset downtimes. At the same time, the desired use of AI methods always entails significant cost and effort. For example, AI technologies require initial investments in computing power and on-site sensors. The cost-benefit ratio determines the economic viability of individual fields of application. Nevertheless, a field of application may be considered worth pursuing on the basis of its outstanding contribution to the integrated energy transition despite being economically inefficient initially. As a fundamental rule, any consideration of the cost-benefit conundrum must include a long-term view of the economic impact. Although costs are usually incurred immediately upon introduction of an application (e.g. investments in computing power, drones, etc.), the expected benefit may only manifest itself over the long term (greater customer loyalty due to more personalised approach, avoiding system downtimes, etc.).

In addition to the individual microeconomic impacts (e.g. increase in profits due to precise AI-assisted forecasting) for individual stakeholders in the energy industry (power generation, trading, grid operators (GOs), consumers, etc.), the use of AI also has a macroeconomic impact with implications for all of society. For instance, security measures in both physical and virtual worlds increase overall supply security and thereby contribute to a high quality of life and the appeal of Germany as a business location. Efficient and secure grid operation facilitated by AI also benefits consumers, who enjoy high supply quality in return for low grid fees. The use of AI-based tools and resources also enables consumers to optimise their own power supply and actively participate in processes in the energy industry (known as the “democratisation of the energy industry”). This in turn can create a better understanding of the demands of the energy industry and lead to greater consensus around the topic of climate protection.

Figure 26 classifies the various FoAs in temporal and economic terms. AI applications relating to grids and security measures improve supply security and are therefore included in the macroeconomic dimension. Predictions, operation and inventory optimisations relating to power generation and trading, predictive maintenance, process automation and customisation in sales activities increase cost efficiency in companies and therefore belong to the microeconomic level. Opportunities for consumers to participate in the energy system increases the appeal of the energy transition and can simultaneously boost its overall social acceptance. Consequently, this field of application is positioned between the two economic dimensions. In the temporal dimension, fields of application are classified based on their stage of technical and economic development (see Chapters 3.1.2 and 3.2.2).

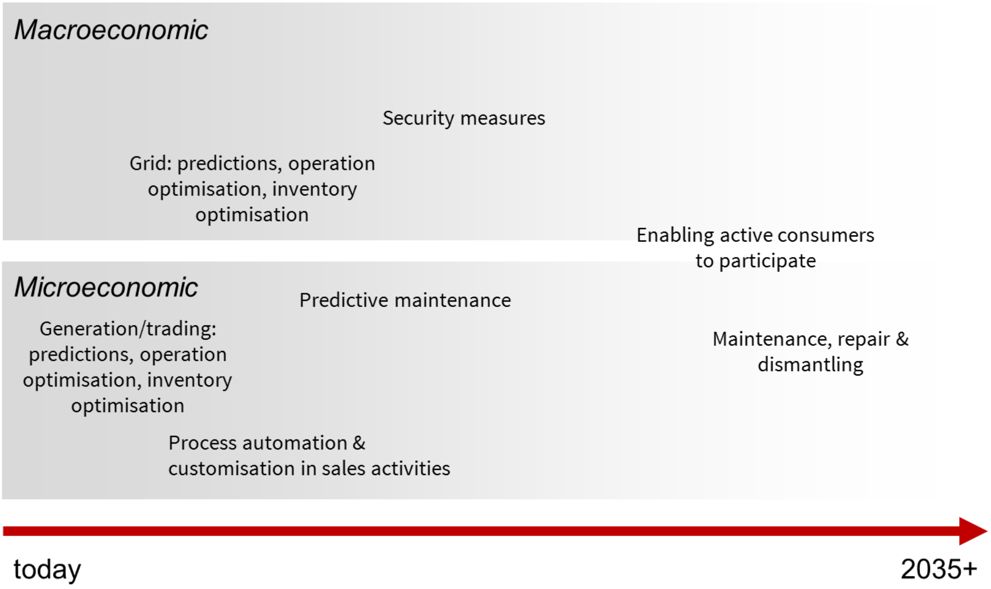

Figure 26: Temporal and economic classification of fields of application

The indicators used in the economic assessment are classed as relating to either costs or benefits. The costs of a field of application arise either from undertaking investments or developing processes, structures and skills. This allows us to identify the following indicators:

- **Investments in computing power or on-site installations**
- **Acquisition of AI competencies**
- **Making data available**
- **Adapting processes**

Unlike aspects relating to the benefits of using AI, most aspects relating to costs are universally applicable to all fields of application. The assessment of costs is therefore predominantly conducted in the following, general section of the assessment, with application-specific aspects analysed in further detail in Section 3.2.2.

The economic benefits of a field of application for AI are determined by the associated increase in efficiency and profits. Within these two categories, it is possible to define the following indicators:

Increase in efficiency

- **Achieving higher asset utilisation or more targeted use of assets**
- **Avoiding unnecessary expenses or more targeted investment in assets**
- **Avoiding unnecessary financial losses**
- **Relieving burden on users**

Increase in profits

- **Achieving higher prices**
- **Generating additional sales potential or unlocking new resources**

These aspects could take on either an indirect or a strategic role for the user. In this way, using AI can render a company more attractive (e.g. through greater digitalisation due to modernisation of corporate structure) and thereby afford the company a decisive advantage, such as in grid operators' licence-award processes. Another example is the increased ability to tap new markets as a first mover by offering charge management in the form of a virtual power station – even if the critical mass of electric vehicles will not be reached for several years. In addition, better access to customers often presents cross-selling opportunities for other products.

Not every aspect specified is relevant for every field of application; for this reason, the fields of application in question are specified for each individual benefit indicator addressed in Section 3.2.1.

3.2.1 General economic assessment of all fields of application

Investments in computing power or on-site installations

It is possible to make a distinction between two types of investment. For one, users invest in hardware and software to operate AI models. Ensuring that sufficient computing power is available is a decisive factor in this context; users can either establish their own computing centres or look to cloud computing. Although computing power is sufficient for the applications energy companies are using at present, the future use of data with high geographic and temporal resolution, image files and sound files means that computing power requirements will rise in time (Calabrese, 2019).

This is associated with increased power consumption, the extent of which depends heavily on the design of the model used, the computing time, the processor used and the processor's power. Following the headlines proclaiming that the AI developed by Alpha Go consumed 50,000 times more energy than human intelligence during the game against the Go world champion (Briman, 2016), Google DeepMind used new processors and an amended ANN structure to significantly reduce its energy consumption (Hassabis et al., 2017). The International Energy Agency expects similar developments in relation to the power demands of computing centres. The current consumption level of approximately 200 TWh worldwide is set to remain constant in the years to come, based on the assumption that rising demand for electricity will be balanced out by efficiency gains (IEA, 2019).

In addition, on-site installations are required for data collection and control purposes. Particular investment in this field is required in the distribution grid and on consumers' premises.[20] Distribution system operators are (DSOs) increasingly fitting central grid nodes (e.g. local power transformer stations) with remote-readable sensors (EY, 2018). The existence of effective, standardised on-site infrastructure is a decisive factor in whether the potential highlighted here spreads at the consumer level. It is hoped that intelligent metering systems (iMSys) will serve as the basis upon which products (e.g. load flexibilisation with dynamic tariffs) can be made available to customers. The delayed roll-out of such systems and the fact their functionality remains limited has inhibited their diffusion to date. Supplementary components for iMSys interfaces and alternative data collection and control techniques are currently being developed to compensate for these weaknesses (ibid.).

[20] For individual exceptions, see Chapter 3.2.2, Practical example – predictive maintenance.

Acquisition of AI competencies

Companies have a choice of three methods by which to meet the need for AI competencies; their choice is usually determined by the company's tasks, circumstances and requirements. In order to develop AI models, companies can either recruit IT specialists, train employees with sufficient existing knowledge, or outsource the development to third-party service providers. This decision depends on how frequently these new AI capabilities will be called upon as well as security requirements, the size of the company, and the availability of specialist staff. In order to use the output of the AI model, employees require sufficient training to give them the insight and understanding needed to classify and scrutinise the output (Brown, 2007).

Making data available

The quality of any AI model is heavily dependent on the availability and quality of the required data (Capgemini, 2017). In this regard, it is important to distinguish between three relevant types of data. Firstly, data that is already available and ready for use; secondly, data that is available but must be prepared for use,[21] and finally data that has yet to be collected or procured (Redman, 2018). It is also possible that relevant information exists that was not originally documented in an automated evaluation (e.g. notes on repair and maintenance measures). In such cases, it is advisable to extract useful data from the existing information and, in doing so, define standards for future documentation.

The reasons behind the lack of the required data can vary. For one, a lack of infrastructure can mean that data simply cannot be collected (see *Investments in computing power or on-site installations)*. Alternatively, the low number of malfunctions can pose a problem for training models to perform analyses to support security measures and predictive maintenance (see *Avoiding unnecessary financial losses)*. Research projects are currently underway to examine the possibility of using artificially generated data on malfunctions (Sarkar, 2018). If sufficient structural data is available to precisely depict assets, process flows can be simulated, which makes it possible to generate malfunction data by virtual means. At the same time, it can be sensible to collect and store data on current conditions for use at a later point in time.

The topic of customer data is dominated by legal uncertainty surrounding the distinction between personal and other data (see Chapter 3.3). A precise definition of customer data and standards on sufficient data anonymisation would prove helpful in this context. It is also possible to compensate for the lack of data by means of legal obligations to provide data, data donations and the creation of data platforms/data trading. For instance, the SINTEG showcase project C/sells aims to develop standardised interfaces and automated processes between individual distribution and transmission system operators in order to facilitate an exchange of coordination sequence data relating to grid congestion (Ebe, 2018). In terms of applications for end customers (e.g. to optimise self-supply rates), compiling data from similar customer groups can help to improve the quality of services.

[21] The issue of data that is available but cannot be used for regulatory reasons is addressed in Chapter 3.3.

Adapting processes

When a company decides to introduce AI, it can create the need to adapt numerous processes. Examples of such adaptations include greater standardisation of data retention and documentation processes (see *Making data available)*. Comprehensible information must be provided to ensure transparency into a model (see Chapter 0) and users must be given a sufficient technical understanding (see *Acquisition of AI competencies)* in order to interpret and use AI output. AI measures can be temporarily implemented in parallel to conventional measures to enable users to better estimate the reliability of AI. Known as shadowing, this makes it possible to compare AI-assisted and conventional methods, increases confidence in the new approach and, at the same time, highlights areas in need of further development. It is also important to define responsibilities and clarify issues surrounding liability (in particular in relation to outsourcing).

Of course, the aforementioned measures can represent significant financial outlay for a company. However, by supporting the digital transformation, these measures simultaneously simplify decision-making processes in a company. Flat decision-making structures enable the AI and authorised users to make decisions. This simultaneously promotes collaboration within (and potentially even beyond) the company (Abdelkafi, 2019).

Achieving higher asset utilisation or more targeted use of assets

Relevant fields of application: Predictions; operation optimisation; making it easier for active consumers to participate

By making operating processes more efficient, AI can help to increase the utilisation of power grids, generation installations and storage systems. Forecasts of further utilisation lay the foundation for this. Building on these forecasts, adjustment measures can be derived and implemented to increase utilisation. For active consumers, this represents an opportunity to optimise their assets.

Avoiding unnecessary expenses or more targeted investment in assets

Relevant fields of application: Predictions; inventory optimisation and other strategic business decisions; predictive maintenance; making it easier for active consumers to participate; customisation of products and marketing measures

In addition to making operation more efficient, AI also facilitates better planning of investments associated with operational matters. AI can help to plan sales and marketing measures and asset maintenance activities more systematically, which can help to avoid unnecessary expenses.

Avoiding unnecessary financial losses

Relevant fields of application: Predictive maintenance, security measures

If assets in the energy industry fail, this can result in a loss of income and supply interruptions, and therefore also a negative economic impact. System-critical assets in particular could have a negative economic impact if they were to fail. Failures can be triggered by internal or external disturbances. One challenge in both of the specified fields of application is the lack of data on cases where problems have occurred. Quite simply, this is in part because problems have not occurred frequently enough to provide a data basis, but also because problems were not documented in the past (see *Data availability)*.

Relieving burden on users

Relevant fields of application: Operation optimisation; maintenance, repair and dismantling; making it easier for active consumers to participate; customisation of products and marketing measures; process automation for measurements, bills and general distribution

Information generated by AI can support users in a number of ways. For one, it can reduce the effort involved in performing standard activities, thereby allowing staff to devote more attention to complex tasks. In terms of automating measurement, billing and distribution processes, AI makes it possible to automate message management and response processes (using chatbots or hotline androids) as well as substitute value and load profile formation. In addition, AI-based assistance systems can provide the necessary information when there is a lack of specialist knowledge or expected (i.e. estimated) values. This applies in particular to operational optimisation in the context of grids, but also to maintenance, repairs and dismantling in the context of power generation. Based on collected data, AI can issue recommendations to diagnose problems and also execute measures to resolve them. In future, wearables (technology products worn by users, such as Google Glass) and robots could assist in maintenance & repair activities. By migrating to automated measures that replace human expert knowledge, companies reduce the risk of human misjudgements, staff absence and staff turnover. AI-based resources can also make it easier for new recruits to settle in a company[22] and thereby also support the work of more experienced employees (keyword: demographic change).[23]

Achieving higher prices

Relevant fields of application: Predictions; operation optimisation; making it easier for active consumers to participate

AI can help to provide a better understanding of achievable prices and derive corresponding recommendations for action. This applies not only to marketers of electricity and flexibility in the electricity market and system services but also to distributors in terms of marketing their products and active consumers looking to optimise their electricity consumption.

Generating additional sales potential or unlocking new resources

Relevant fields of application: Making it easier for active consumers to participate, customisation of products and marketing measures

By deriving relevant information from consumption data, AI can help to generate a better understanding of behavioural patterns and consumer needs, thereby allowing companies to implement tailored measures in response. For many companies, drawing up individual profiles and recommendations would not be financially viable without the use of self-learning systems. The contribution AI can make also depends on the size of the company. On the one hand, large companies are in a better position to introduce large-scale automation and have higher data concentration at their disposal, in part because distribution grid operation can be consolidated more than smaller units. On the other hand, the fact that AI is increasingly easy to access (keywords: open source, outsourcing) means that smaller actors can also use AI technologies. The degree to which a company is open to new technologies is a decisive factor in this regard (Weiler, 2018).

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[22] This requires suitable training concepts for AI (see *Acquisition of AI competencies)*.
[23] An inspection of large energy suppliers' annual reports in recent years shows that, on average, around one-quarter of these companies' employees are over the age of 55. Experts have asserted that power grids and power stations are particularly heavily affected by demographic change.

3.2.2 Economic features of the fields of application

This section analyses the nine fields of application in detail once again in relation to economic issues and based on individual indicators identified as relevant. In this assessment, relevant indicators of the benefits of AI are identified and described specifically for each FoA. Soft factors (e.g. supporting newly recruited employees, making a company more attractive through a higher level of digitalisation) are also qualitatively assessed.

Predictions

The widespread application of AI in the field of predictions and forecasting (see Chapter 2.2.1) underscores how attractive this field of application is from an economic perspective. Indeed, AI predictions and forecasting represent an essential, fundamental element of applications to optimise operations and inventory.

Investments in power-generation capacity and grid capacity are capital-intensive and take a certain amount of time to realise. Reliable long-term forecasts that are generated with the help of AI and take a wide range of parameters into account substantiate investment decisions and minimise the risk of bad investments.

Accurate predictions of the electricity yield of supply-dependent RE allows power to be marketed more precisely, while load flow forecasts can systematically increase grid utilisation and electricity price forecasts improve operational planning for controllable power-generation systems.

Electricity price forecasts can also be used to achieve higher prices. Forecasting prices, analysing these forecasts and maximising profits by dealing in different marketplaces are among the fundamental tasks of an energy trader. If these bidding strategies take on a rather extreme form (i.e. if providers in a monopolistic position exert market dominance or exploit price differences between two markets, known as arbitrage), system costs can increase disproportionately. The elevated control energy market prices in June 2019 are suspected to have been the result of such trading activities (Tix, 2019). The regulator and the market platform operator have considered putting specific regulations in place to counter the rise of such extreme bidding strategies. The use of AI and the capacity to process far more data makes it easier for marketers to explore their options but also makes it easier for the regulator and market platform operator to verify the use of such bidding strategies. The introduction of market-based grid congestion management has created new scope for arbitrage trading. The SINTEG project enera provides an example of how a monitoring system can identify and restrict arbitrage trading (Höckner et al., 2019; Geers, 2019).

In terms of the costs involved in this field of application in the context of grids, there is greater need for investment in sensors (in particular in the context of the roll-out of iMSys) and the processing of existing information. In terms of power-generation, internal company data is available in sufficient volume and quality to conduct for power-generation forecasts.

In all, in respect of the ratio of cost and benefit, the economic assessment of this FoA returns a high rating overall, but a medium rating in the specific context of power grids.

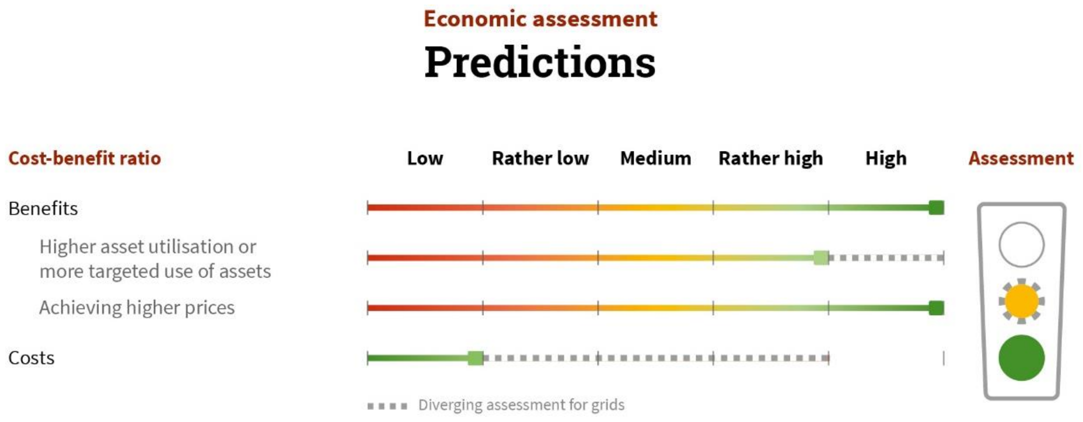

Figure 27: Economic assessment of predictions

Operation optimisation

In this field of application, AI can consider higher temporal and spatial resolution in the data processed in the marketing of supply-dependent RE, which in turn improves the quality of forecasts. In the case of RE generated under feed-in compensation, the transmission system operator markets the generated electricity using a differential balancing group. Discrepancies within a balancing group are passed on to the consumer. In the case of directly marketed RE, the marketer bears the cost for any discrepancies in their role as the balancing group controller.

Unlike supply-dependent RE systems, operational planning can be optimised for controllable power-generation systems and storage systems. Such optimisations facilitate more accurate price forecasting and consideration of different markets, which in turn makes it possible (for example) to minimise the time required to start up and shut down power stations. In relation to storage technologies, precise forecasting of supply-critical periods with high prices enables storage system operators to maximise their capacity by charging and discharging power accordingly, which in turn increases supply security for consumers.

While more accurate forecasts facilitate optimised tender preparation in power generation and trading, in terms of supply-dependent power generation and load on the grid, such forecasts make it possible to determine the utilisation of limited grid capacity more precisely and introduce appropriate measures in the event of grid congestion. AI can help to identify overloaded sections of the grid, especially in relation to the transmission grid. Although existing sensors and grid topology mean that it is already possible to issue precise forecasts for the transmission grid, when it comes to the case of the distribution grid, the lack of sensors combined with the complex, intermeshed grid structure mean that some blind spots still remain. The increasing volume of supply-dependent power-generation in the distribution grid, self-supply concepts and electrified transport and heating applications with high energy demands together create increasingly irregular load flows with peaks in power generation and load. A more precise understanding of grid capacity utilisation is urgently required if present supply quality is to be maintained. To this end, the grid could be reproduced with digital twins – taking into account grid users and grid topology – which would make it possible to simulate grid utilisation. Using data on similar sections of the grid could compensate for sections where little data is available. Suitable replacement data could be allocated to blind spots in automated processes using AI.

As part of the Redispatch 2.0 project (see Chapter 3.3), grid users connected to the distribution grid are increasingly integrated in grid congestion management. When it comes to the effect that connecting and disconnecting grid users has on grid capacity, empirical figures and structural data have their limitations. Digital grid twins can also simulate the effect of different measures to combat grid congestion and thereby determine how such measures can be combined most effectively. The data basis used in such assessments is more comprehensive, which helps to ensure more suitable measures are put in place. This in turn makes it possible to avoid unnecessary, more extensive disconnections and ensures that grid operators can react swiftly (Köppl et al., 2019; E-Bridge, 2017).

Connecting and disconnecting users in a targeted manner also helps to limit instances where grid capacity is exceeded locally. With the number of grid customers with self-supply concepts or electrified heating and transport applications on the rise, consumption and feed-in patterns have become irregular. This can cause unforeseen grid overloads. More extensive data processing activities made possible by AI technologies can provide a precise understanding of consumption behaviour and the effect of adjustment measures (see Chapter 3.3). Corresponding adjustments implemented in coordination with grid customers can reduce the risk of power outages and thereby serve as a stop-gap until such time as the required grid expansion measures are complete or, in specific cases, even avoid the need for expansion entirely (Fritz et al., 2019).

As previously noted in the section of the detailed economic assessment on predictions, AI can help industry actors to achieve higher prices. AI can evaluate different operational strategies to fully exploit price peaks and troughs, taking various scenarios and a wide range of data into account, especially in the case of storage technologies and load flexibility.

Although sufficient data and infrastructure is already available for predictions in the context of power generation and trading, data availability is in need of improvement in the area of grids. Due to the need for investment this entails, this FoA is considered to involve high costs. In respect of the growing demands placed on distribution grid operation, however, AI is also making a particularly important and future-focused contribution to efficient grid operation (e.g. through Redispatch 2.0).

Overall, taking into account the costs and benefits involved, the economic assessment of this FoA returns a medium rating in relation to grids and high rating overall.

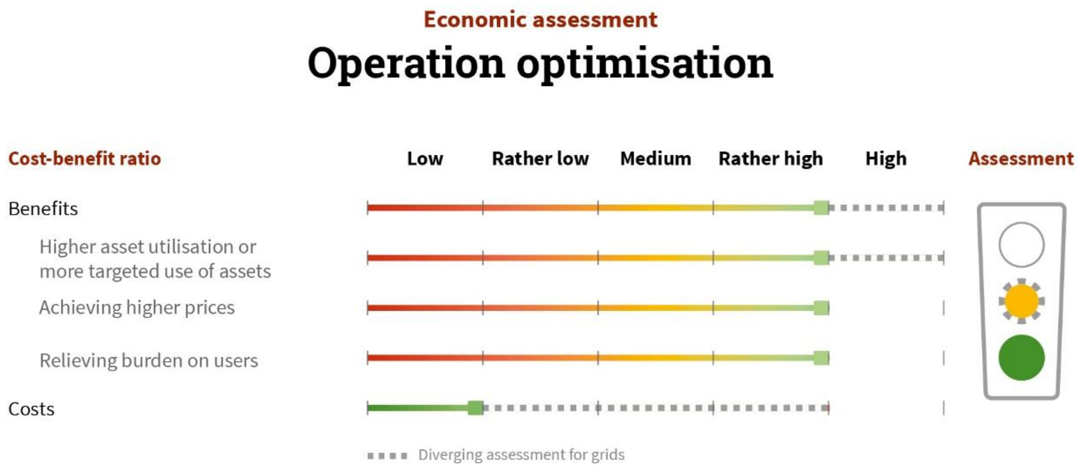

Figure 28: Economic assessment of operation optimisation

Inventory optimisation and other strategic business decisions

In the context of long-term planning, powerful models that take a wide range of data into account are a decisive factor in promptly identifying need for investment and avoiding bad investments.

Practical example: Geospin – using algorithms to find the best locations for charging points

People move in specific patterns and with specific destinations in mind, particularly in cities. The same applies to their use of charging infrastructure. The decision to use a given charging point is influenced by various factors, not least their geographical location. In light of this, it is important to identify the best possible location for a charging point. By drawing on historical usage data from 6,000 charging points and 800 external geographical factors, the company Thüga has collaborated with Geospin GmbH to develop an AI algorithm that recognises geographical usage patterns and then uses these patterns to reliably calculate the expected utilisation of a charging point for any location in Germany. This is even possible for regions where no empirical values exist.[24]

In the field of power generation, numerous parameters need to be predicted and considered in order to guarantee a sufficient power supply at all times over the long term. When it comes to issues of maintaining generation capacity, this affects both the regulator and transmission system operators; however, it also concerns investors, whose investments must cover forecast price peaks on the market in peak load capacities. The choice of technology and the scope of storage capacity depend on a number of factors. With the help of AI, forecasts of relevant parameters (e.g. price, load flexibility) and the process of weighing up different investment strategies can be based on larger volumes of data, thereby making it possible to identify previously unidentifiable patterns and avoid bad investments.

Analogue to the area of power generation, using AI in the context of grids makes it possible to analyse the need for investments, taking different scenarios and alternative measures into consideration in doing so. A digital grid twin capable of simulating grid utilisation and highlighting grid overloads can therefore help to promote grid expansion in line with needs. However, there is a still a need to adapt the basis for planning currently permitted by regulatory requirements (see Chapter 3.3.2).

One emerging area of infrastructure planning is the expansion of charging infrastructure. Additional grid capacity and charging points must be made available where EV owners charge their vehicles. Whether they do so at home, at their place of work, at public or semi-public charging points (e.g. in supermarket car parks) is a question that various types of movement data (logged driving profiles, mobile network data, etc.) can be used to predict. AI can connect a large volume of different datasets and derive corresponding patterns (Geospin, 2018). This makes it possible to install charging points in optimal locations and reduce investment costs.

Similar to previously examined fields of application, sufficient data and infrastructure is already available in the context of power generation and trading, whereby data availability is in need of improvement in the area of grids.

Analogue to the other fields of application in the General Foundations for Decision-Making cluster, the economic assessment for this field of application returns a medium rating in the context of grids and a high rating overall.

[24] Further information: www.geospin.de

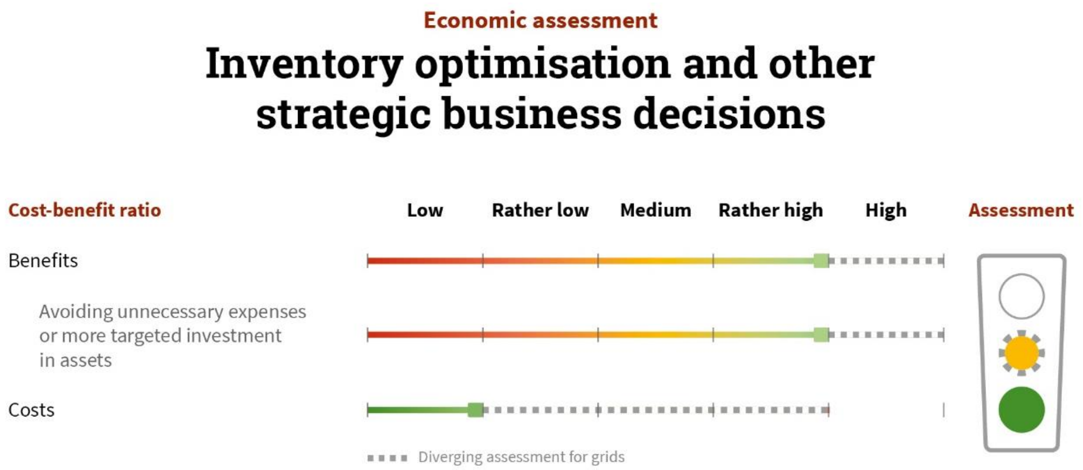

Figure 29: Economic assessment for inventory optimisation and other strategic business decisions

Predictive maintenance

Performing predictive maintenance in line with needs can cut maintenance costs and reduce the risk of financial losses. This issue is particularly pertinent to large-scale assets (e.g. the grid as a whole) and inaccessible assets (e.g. wind turbines out at sea). Without AI, comprehensive data analysis for the purpose of predictive maintenance would not be possible.

Practical example: Schleswig-Holstein Netz AG – using AI today to pinpoint where a power cut might occur tomorrow

Schleswig-Holstein Netz AG is the first grid operator in Germany to implement predictive maintenance in its medium-voltage network. It enables disruptions in the network to be forecast with three times the accuracy of other methods used to date. As a fundamental rule, a forecast is only as good as the data upon which it is based. Consequently, the database for the forecasting model incorporates information from numerous different sources – including both internal data collected by Schleswig-Holstein Netz AG and information procured from outside the company. The predictive maintenance project is part of the Schleswig-Holstein Netz AG digitalisation strategy and is implemented with the support of E.ON Digital SE.[25]

Performing maintenance at regular, set intervals and unnecessarily replacing functional resources can incur avoidable costs in relation to both power grids and power generation. Electing instead to perform maintenance based on operating data and in response to anomalies indicated by this data can reduce unnecessary spending and avoid operational failures. In the case of supply-dependent RE, another potential application of AI is scheduling maintenance to be performed at a time when yields are low.

In many cases, internal disturbances that lead to financial losses concern a lack of maintenance or an unidentified need for maintenance (e.g. due to unexpectedly high wear) on operating resources. Predictive maintenance can avoid both issues. Data-driven inspections can sometimes replace human inspections, especially in the case of inaccessible assets (e.g. wind turbines out at sea). In this case, image and sound recordings made by drones and robots can be evaluated in addition to collected sensor data.

[25] Further information: www.sh-netz.com/de/schleswig-holstein-netz/innovation/predictive-maintenance-.html [German only]

Although sensors are installed in most power-generation settings, there is a need for further investment in the power grid. In the case of more complex measures, the potential use of robots and drones means that even greater investment is required. At present, the cost and weight of robots (such as those used to inspect transmission grids) can vary significantly (Shruthi, 2019). By comparison, modern predictive maintenance applications – which are predominantly based on data processing and do not require additional assistance from robots – can be implemented with comparatively lower costs and make a significant contribution to ensuring that assets operate uninterrupted.

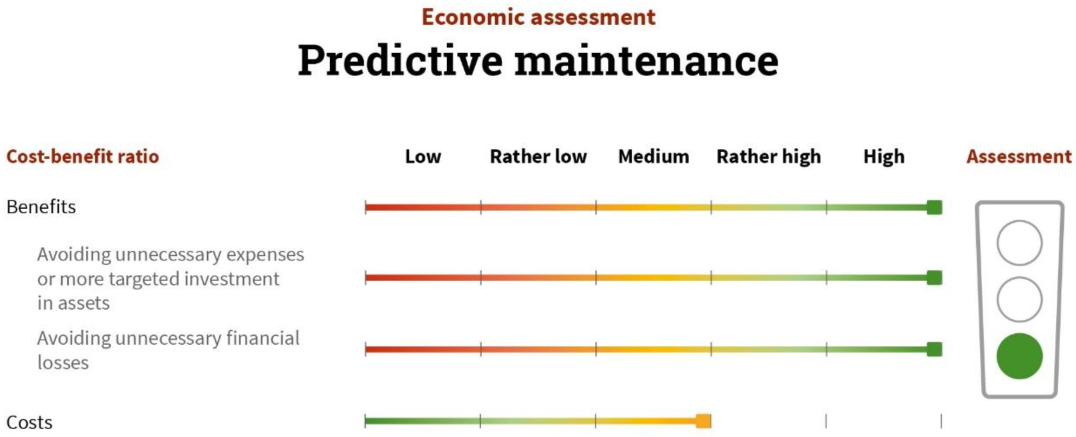

Figure 30: Economic assessment of predictive maintenance

Maintenance, repair and dismantling

Using robotics, drones or assistance systems to perform maintenance and repairs on assets and for their dismantling reduces the burden on employees. In this context, AI undertakes inspections or performs other tasks in locations that are hostile to life or, in the case of repair measures, helps personnel to diagnose the problem and identify potential solutions. This minimises the risk of work-related accidents and offers employees assistance in situations where they lack specialist knowledge and/or empirical values to work from.

Practical example: Siemens AG – automated inspection of overhead power lines using drones

Detecting faults in high-voltage power lines early on is a decisive factor in ensuring supply security. For the most part, conventional visual inspections involve arduous manual work and produce results lacking the requisite precision. Siemens is therefore working together with its partners to devise an entirely novel and innovative inspection method for overhead power lines. Powerful drones conduct inspection flights – even moving out of view of their operator – and carry a significant payload while doing so. The drones carry with them an array of sensors and cameras, all connected in an integrated system. This makes it possible to record 3D laser data, ultra-high-resolution colour images and infrared images in a single step, all stored with precise geographic references. The extensive multi-sensor data generated during the flight is then processed and analysed by smart data software developed by Siemens. This AI-based software is designed to automatically detect and evaluate any faults or problems along overhead power lines.[26]

[26] Further information on this and other research projects involving drones: https://www.bmwi.de/Redaktion/DE/Publikationen/Technologie/drohnen-unbemanntes-fliegen.pdf?__blob=publicationFile&v=14 [German only]

As noted in the technical assessment, robots and drones are generally still in an early stage of development and are therefore not widely available or, if available, are capital-intensive to acquire. Despite its promising potential to reduce the burden on employees and avoid situations with a risk to life, a more positive assessment of this field of application would first require cost reductions alongside further technological developments.

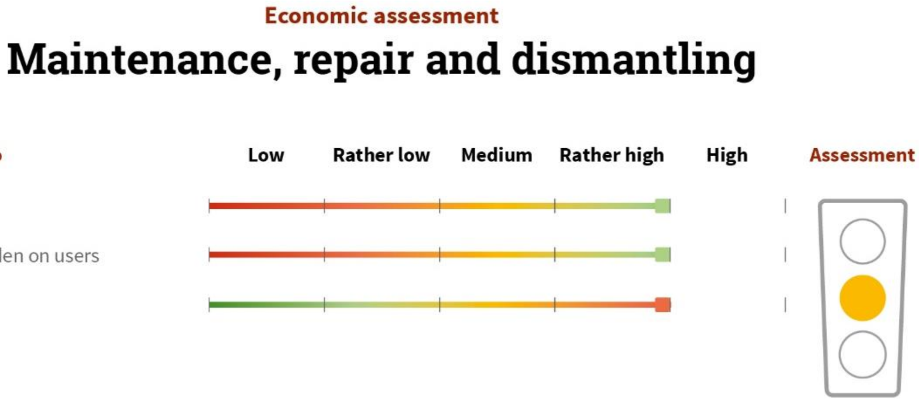

Figure 31: Economic assessment for maintenance, repair and dismantling

Security measures

External disturbances that lead to financial losses include cyberattacks on system-critical power-generation and grid installations, which are becoming increasingly vulnerable as digitalisation progresses. At the same time, energy supplies are a particularly critical infrastructure for daily life. According to figures from the Federal Office for Information Security (BSI), the number of cyberattacks on critical infrastructures more than quadrupled in 2018 compared to the previous year. Roughly 12% of these attacks were targeted at power grids. Despite this increase, Germany did not suffer more extensive power cuts; however, examples from other countries serve as evidence of the potential scale of disruption. In December 2015, for example, malware rendered 30 substations and transformer stations and the emergency system inoperative in Ukraine. The resulting disruption left almost 230,000 people without power (Tobien, 2020). However, beyond their ability to compromise supply security, attacks of this type can also have economic consequences. According to the US Congressional Research Service, cyberattacks on power stations and power grids could result in economic damage in the order of hundreds of billions of US dollars (Berman et al., 2019). AI can help to identify anomalies in installation access logs and track their origins. In addition, AI-based camera surveillance can help to protect physical assets.

As noted in Chapter 0, a lack of training data has hampered the implementation of such technologies to date and increased the costs involved. However, due to its high importance to supply security and in light of the associated economic implications, this field of application is assessed as being highly significant.

Figure 32: Economic assessment of security measures

Making it easier for active consumers to participate

A number of measures from the General Foundations for Decision-Making cluster can also be made available to active consumers due to the high degree of automation made possible by AI. The new participation concept for active consumers requires them to perform similar tasks to marketers of larger-scale power-generation installations. For instance, active consumers themselves have to market the proportion of renewable energies not covered by feed-in compensation. In general, self-supply is the most economically appealing option for active consumers to use the electricity they produce. Just like large-scale power generators, active consumers need to forecast the amount of electricity generated and balance this against consumption. Some forecasting methods are more cost-efficient for active consumers than large-scale power generators, including automated forecasts, remote-control circuits controlled by a service provider to increase self-supply, and recommendations for active consumption adjustments issued by an AI-based energy management system. These methods increase self-supply and relieve the burdens for such tasks from active consumers. Services designed to increase self-supply can be implemented for individual households but also for entire neighbourhoods or companies. AI can also generate recommendations for investments in storage systems and/or the marketing of residual (i.e. unused) electricity.

This makes it possible for not only professional traders but also active consumers to take advantage of price peaks and troughs. Related activities include charging an electric car when prices are low, taking decisions on when to charge and discharge a power-storage system based on price peaks and troughs in a variable tariff, and using a virtual power station to market residual electricity when prices are high. In this context, an AI-operated energy management system that either automatically adjusts controllable consumer devices or issues recommendations on how to adjust consumption can support active consumers, as can an aggregator equipped with corresponding algorithms.

AI can also help to integrate small-scale, decentralised resources. Without the automated analysis made possible by AI, forecasting and deliberately activating and deactivating these power generators, storage systems and flexibly loads would not be financially viable. Furthermore, by implementing extensive optimisations, AI also helps to take into account requirements from the perspective of consumers and the overall system and to reconcile these competing needs.

The lack of a standardised, effective infrastructure for domestic applications hinders more widespread participation by active consumers. The next stage of development, namely the roll-out of iMSys and the ability to control domestic appliances, has the potential to bridge this gap. However, the delayed start of the roll-out of iMSys has complicated the economic implementation of these AI applications. Nevertheless, in the context of the increased diffusion of smart-home applications and increased installation of iMSys, the assessment of this FoA can improve in future.

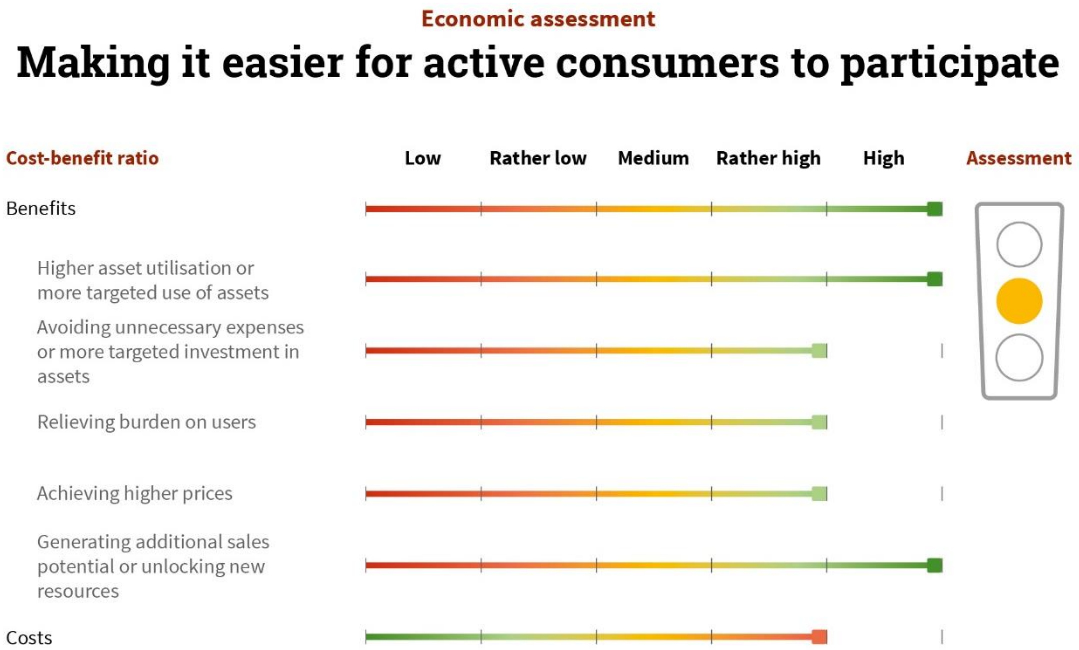

Figure 33: Economic assessment of making it easier for active consumers to participate

Customisation of products and marketing measures

A more accurate understanding of an individual customer makes it possible to offer them products tailored to their preferences, their financial situation and the circumstances where they live. Measures implemented in this vein help the customer to save energy in a targeted manner or to increase their private energy consumption at certain times. In addition, sales operations yield increased profits by avoiding indiscriminate scattergun marketing.[27]

[27] Scattergun marketing: Highly scattered marketing measures without a targeted focus on specific customers.

Practical example: Fresh Energy – using smart meter data to generate added value for individuals

Fresh Energy's white-label app generates added value based on the data from its users' smart meters. Services open to customers include a clear breakdown of the energy consumed by their domestic appliances along with recommendations to replace inefficient appliances. Users therefore benefit from individual advice tailored to their circumstances, while the energy provider gains a better understanding of their customers' needs. In addition, power consumption data can also help to identify anomalies in the consumption patterns of people in need of care – if, for example, no consumption is recorded at a time when power would normally be consumed, a notification can be sent to the individual's relatives or carers.[28]

Avoiding unnecessary capital outlay also has implication for marketing strategies. With the help of AI, companies can cluster their customers based on their preferences, their consumption profile and their willingness to pay, which makes it possible to offer them appropriate products. This allows companies to avoid sending customers unsuitable marketing messages, make more targeted use of their marketing budget, reduce the burden on sales personnel and increase customer confidence in sales measures.

Given that the ability and willingness to pay varies from one customer to the next, how sales departments design and structure their products plays a decisive role. If a company's sales department has insight into these parameters, it can seize opportunities to help customers with greater purchasing power and larger investments to increase their energy efficiency or self-supply. At the same time, more cost-efficient methods or alternative financing options (e.g. contracting) can be used to help connect with and retain customers with less funds at their disposal. Using AI to cluster customer groups based on their preferences and their willingness to pay can assist in this process.

Clustering distribution customers makes it possible to determine the measures best suited to maximising customer value. New data processing methods lay the foundations for connecting hard (e.g. monetary) and soft (e.g. social) factors in a purchase decision with socio-economic data. These methods provide the user with a more accurate picture of which measures are suitable for which customer as well as how each customer should be approached. This makes it possible, for example, to implement energy efficiency measures in ageing building stock,[29] install RE systems in high-yield locations, or invest in energy-storage systems where self-supply concepts have high volumes of residual electricity.

As described in the subsequent section on regulatory aspects, the availability of the data required in this context is an issue in need of review in respect of access rights and their application. In cases where the permission of the data owner is obtained in advance, this field of application can be implemented with little financial outlay and is assessed as having a positive economic impact.

[28] Further information: www.getfresh.energy/

[29] As part of the SINTEG showcase project enera, EWE has developed a calculation tool for light contracting solutions for customers with measured load profiles. Further information: www.ewe.de/unternehmen/licht/berechnungstool [in German].

Figure 34: Economic assessment for customisation of products and marketing measures

Process automation for measurements, bills and general distribution

Implementing AI-assisted automation can remove the burden of monotonous, time-intensive standard tasks from employees, thereby freeing them up to concentrate on more complex tasks instead. This applies in particular to standard processes involving contact with customers. Reminder notice management, billing, logging meter readings and recording a change of address are all processes that can be automated. In the case of learning systems, the implemented measures become more suitable (i.e. more effective) as the volume of interactions increases.

Provided that the processes in question can be digitalised to a sufficient extent, this FoA can be implemented with little financial outlay. Although the costs involved in this FoA are rated as medium, they can vary significantly between individual companies.

The economic assessment returns a high rating overall for this FoA.

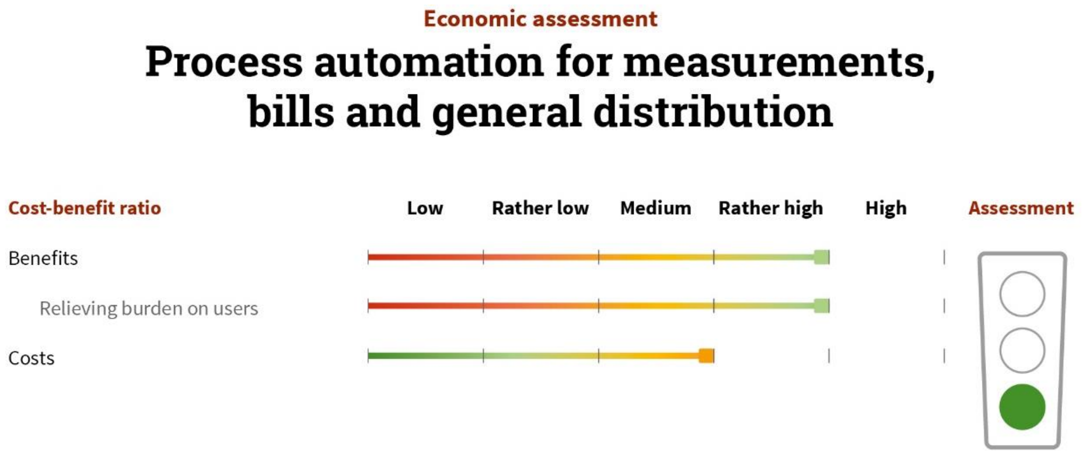

Figure 35: Economic assessment for process automation for measurements, bills and general distribution

Summary of the economic assessment

This assessment has returned a positive rating in respect of the economic appeal of most of the FoAs under examination, provided that no major investments in the form of robotics or drones are required (see **maintenance, repair and dismantling**) or data availability is lacking. The **General Foundations for Decision-Making** cluster is considered particularly attractive in economic terms owing to its existing commercial applications in the energy industry. The application of AI in this cluster makes it possible to market RE in a more targeted manner, make optimal use of power-generation and grid capacities, and plan investments more effectively.

Although sufficient data is generally available within companies for the power-generation and trading stages of value creation, when it comes to power grids (and distribution grids in particular) there is a need to prepare additional data, promote an exchange of data across different grid levels, and install additional sensors. The increasing demands placed on distribution system operators in the context of Redispatch 2.0 also increase the need for a more accurate understanding of load flows in the grid and possible intervention methods to stabilise power grids. The application of AI therefore offers significant potential, both in terms of processing extensive amounts of feed-in and consumption data and also in relation to managing different grid topologies.

Most notably, data availability is a decisive factor in how attractive a field of application is from an economic perspective. In the **Distribution and Customer Services** cluster, clear guidance regarding the use of data and compliance with data management standards could reduce the legal uncertainty surrounding personal data. A lack of empirical data to train models (e.g. in relation to **predictive maintenance** and **security measures**, where there is insufficient data on faults) could be offset by converting existing data from other sources (e.g. hand-written maintenance logs) into the requisite data formats or by using publicly accessible data with similar initial conditions. The roll-out of iMSys and the increase in digital appliances both in homes and in workplaces could fulfil the need for measurement data. Where regulatory and social framework conditions permit, it may be sensible to collect and secure data for other purposes that may arise at a later point in time.

Customisation of products and marketing measures and **process automation** are fields of application that benefit from spill-over effects in other sectors. At the same time, competencies and empirical values from the energy industry relating to predictions, operation optimisation and inventory optimisation of large-scale facilities can be applied to active consumers. The high degree of automation offered by AI means that these services can even be offered on a small scale.

In terms of the costs of using AI, the ongoing costs must be considered in tandem with initial costs of adapting corporate structures to accommodate the models. For instance, companies need to recruit IT experts to create the models or otherwise outsource this task; employees need to be trained on how to use these models and existing processes must be adapted. By the same token, companies become more attractive by migrating to AI methods: the transition modernises their structures and processes, with employees relieved of the burden of time-intensive standard tasks and supported by AI in more complex tasks. These changes also have an effect on the external perception of a company and can attract new customers, business partners and investors.

3.3 Regulatory assessment

The objective of the regulatory assessment is to analyse the practical implementation of AI projects in the energy transition from a regulatory perspective, to identify interfaces to existing regulations, and – with a high degree of abstraction – to evaluate these aspects.

To begin with, the assessment will shed light on the general regulatory framework for the use of AI in the energy industry. Particular challenges primarily arise in relation to access to data and the processing of data. Of course, data is the foundation of the entire digital economy and of AI in particular. The process of securing the required level of data availability gives rise to high IT security requirements in critical energy industry infrastructure. By conducting basic literature research, we have identified and assessed as priorities the following areas of data-related laws and standards:

- **General regulatory principles of the European Union**
- **Data protection law**
- **Data security law**
- **Energy law**
- **Liability law, copyright law and cartel law**

In this chapter, specific analysis of each individual field of application examines which actors and potential addressees of legal norms are relevant and connected in the context of specific applications examples and which legal framework primarily influences their activities and business models. To this end, this assessment will examine the application examples described in Chapter 2.2 with their individual process steps and compare each with the corresponding legal framework.

A final list of the areas of law involved in each application example then examines the following points:

- Which relevant national or European regulations are applicable to the FoA in question?
- To what extent do applicable regulations support or hinder the use of AI?
- Where do regulatory impediments currently exist in Germany and/or at a European level?

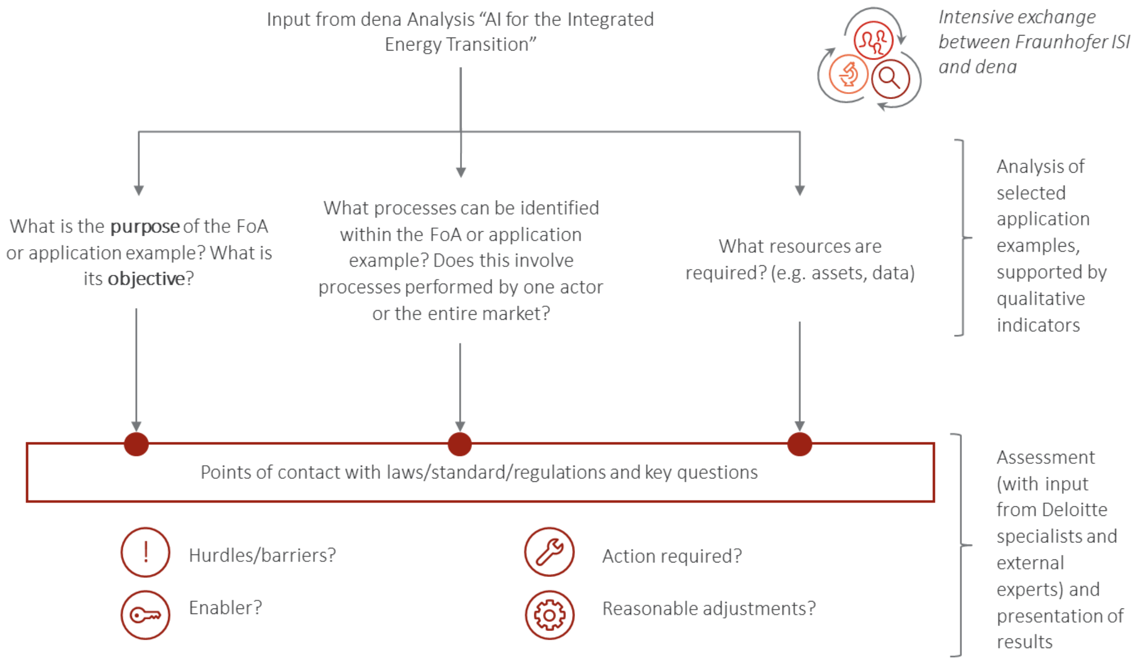

Figure 36: The three pillars of the regulatory analysis

We have developed a distinct assessment method in order to weight and compare the contact points. The objective of this assessment is to examine whether regulatory requirements represent a barrier inhibiting the ability of AI applications to contribute to optimisation of the energy system, and also to shed light on areas in need of amendment or further development. The criteria upon which the assessment of each FoA is based are the complexity (primarily regarding the practicability of regulatory requirements), the level of regulatory maturity, and existing dependencies.

The regulatory system not only includes barriers to progress (e.g. little incentive to invest in field testing of new technologies due to the Ordinance on Incentive Regulation [ARegV]) but also offers factors to support development, such as funding programmes and standardised data interfaces (e.g. iMSys). As a fundamental rule, however, the lower the impact of regulations on a given FoA, the more practicable the FoA will be. The assessment criteria have been developed together with specialists in energy industry and data regulation experts and follow national and international standards for comparable assessments. As this assessment touches on topics from very different areas of regulation, we have also obtained the opinions of experts in different specialist fields.

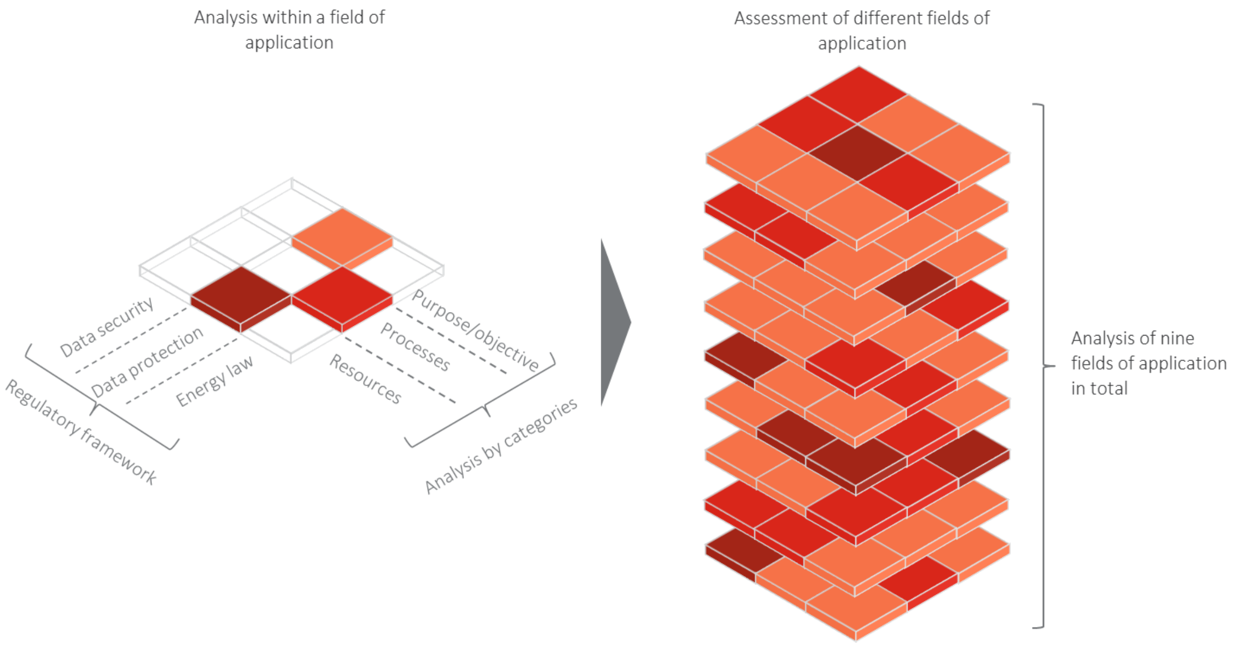

Figure 37: Assessment method for the nine fields of application

In addition to public-law regulations, private-law regulations are also a significant factor in the framework of standards concerning artificial intelligence in the energy industry. Both data collection and data handling typically follow the principle of freedom of contract with due regard to the legal provisions concerning general terms and conditions in Germany. It is also important to consider mandatory regulations of liability law, in particular provisions arising from tort law, as well as mandatory conditions of copyright law and cartel law (Jakl, 2019). The primary focus of this assessment is the access to and processing of data (and personal data in particular). Accordingly, data protection and data security law is also a key focus of this regulatory review.

Some of the terms used herein relate to different areas of regulation and are relevant to more than one application. The following explains important legal terms and laws in further detail.

In relation to AI and data protection, a **filing system** is “any structured set of personal data which are accessible according to specific criteria, whether centralised, decentralised or dispersed on a functional or geographical basis”.[30]

[30] Art. 4 No. 6 of the GDPR.

Literature on the subject is in agreement that **personal data** describes any information “relating to an identified or identifiable natural person”.[31] Examples of personal data include information such as a person’s name or address. Of course, in order to conclude an electricity supply agreement with an end consumer, the supplier will need the customer’s name, address and potentially also their metering point ID (Germany: Messlokation) or point of withdrawal ID (Germany: Marktlokation). In principle, almost all of these pieces of information make it possible to identify a person. AI systems are typically trained using large volumes of training data. However, the principle of data minimisation in relation to personal data pursuant to Art. 5 Para. 1c of the GDPR also applies to AI systems. The processing of personal data must therefore always be limited to what is strictly necessary. In addition, an assessment of the necessity of data processing may conclude that the processing of fully anonymised data is sufficient to achieve a legitimate purpose (Spiecker et al., 2018). Core data in the case of power supply companies (PSCs) such as a customer’s name, address, bank details, customer ID, metering point ID, point of withdrawal ID and dynamic data, e.g. billing data or feed-in data of the ultimate consumer or connection user – provided this is a natural person – represent ordinary personal data.

The **controller** – who is connected to many of the duties and obligations set down in the GDPR – is defined as “the natural or legal person, public authority, agency or other body which alone or jointly with others, determines the purposes and means of the processing of personal data”.[32] Depending on the perspective chosen, it is possible that, under data protection law, the meter operator, grid operator or even the supplier may be responsible for the handling of core data, consumption data and billing data relating to ultimate consumers and connection users who are natural persons. However, within a group of companies in particular, the respective natural or legal person is still responsible within the meaning of data protection law. Although the European Union legislator (European Parliament and European Council) has recognised in principle a legitimate interest in processing data within a group of companies for internal administrative purposes,[33] the provisions of the GDPR do not privilege further data processing within a group of companies (Bartsch et al., 2017). A group of companies therefore still requires fully differentiated authorisation concepts for access to, deletion of and the import and export of personal data in order to comply with the requirements of data protection law set down in the GDPR.

Processors are engaged by the controller to perform data processing and are not controllers within the meaning of data protection legislation. Art. 4 Para. 8 of the GDPR defines a processor as “a natural or legal person, public authority, agency or other body which processes personal data on behalf of the controller”. A processor might be a billing company engaged to execute a contract or a service provider engaged by a PSC in future to operate smart meter gateways (SMGW) according to Section 2 No. 19 of the Metering Point Operating Act (MsbG). Further requirements and obligations of processors, such as the requirement to maintain a record of all processing activities,[34] are set down in Sections 28 et seq. of the GDPR.

[31] Art. 4 No. 1 of the GDPR.
[32] Art. 4 No. 7 of the GDPR.
[33] cf. Recital 48 of the GDPR.
[34] Art. 30 of the GDPR.

Pseudonymisation is described in Art. 4 Para. 5 of the GDPR as "the processing of personal data in such a manner that the personal data can no longer be attributed to a specific data subject without the use of additional information, provided that such additional information is kept separately and is subject to technical and organisational measures to ensure that the personal data are not attributed to an identified or identifiable natural person". Examples of pseudonymisation in the energy industry include processing meter readings under a metering point ID or point of withdrawal ID or using a customer portal under a fictitious username, doing so in such cases without allocating the data to the relevant ultimate consumer. In such cases, the PSC responsible must also ensure by means of suitable technical and organisational measures that the "key" to linking the data to a specific person cannot be readily accessed. The term anonymisation, which was used in Section 3 Para. 6 of the Federal Data Protection Act (BDSG) in the version applicable until 24/05/2018, is not defined in further detail in the GDPR. However, Recital 26 of the GDPR makes clear that the GDPR does not apply to the processing of anonymised data with which it is not or no longer possible to identify the data subject.

The **data protection officer** is appointed by the controller and the processor.[35] The data protection officer instructs and advises the controller and/or the processor and the employees who perform data processing in respect of their duties. In addition, the data protection officer monitors compliance with the GDPR, other data protection regulations of the European Union and its member states, and the strategies implemented by the controller or processor to protect personal data, including the allocation of responsibilities, how employees involved in processing activities are trained and made aware of relevant issues, and all related inspections. Upon request, they also provide advice in relation to the data protection impact assessment pursuant to Art. 35 of the GDPR and are responsible for the cooperation with the supervisory authority. In the course of their duties, the data protection officer takes due account of the risk associated with the processing activities in consideration of the type, scope, circumstances and purposes of the processing.[36]

The data subject – that is, the person whose data is processed – has the **right to rectification** of inaccurate personal data[37] as well as – in certain circumstances – the right to restriction of processing.[38] The data subject can also object to certain forms of data processing.[39] By their very nature, the decisions (taken by the AI) are not visible or transparent to the data subject; they are hidden in a so-called black box. However, the GDPR contains legal norms dedicated to addressing precisely these challenges. For instance, Art. 22 of the GDPR sets down a fundamental right of data subjects not to be subject to a decision based solely on automated processing. This regulation goes hand in hand with information obligations and access rights in Art. 13 to 15 of the GDPR.

[35] Art. 37 of the GDPR.
[36] Art. 39 of the GDPR.
[37] Art. 16 of the GDPR.
[38] Art. 18 of the GDPR.
[39] Art. 21 of the GDPR.

3.3.1 General regulatory assessment of all fields of application

The volume of data produced worldwide is rising rapidly and is expected to rise from 33 zettabytes (ZB) in 2018 to 175 ZB in 2025 (Reinsel et al., 2018). *"In the digital age, data is a key resource with which to achieve social prosperity and participation, a prosperous economy, environmental and climate protection, scientific progress and state actions. The ability to responsibly and autonomously use, link and analyse data is fundamental to technological innovation, knowledge creation and social cohesion."* (BPA, 2019). The German federal government is therefore working out a data strategy "that aims to significantly increase the responsible provision and use of data by persons and institutions in (civil) society, business, science and federal administration in Germany; to prevent the emergency of new data monopolies; to ensure equitable participation and, simultaneously, to systematically counter the misuse of data" (ibid). This data strategy is developed on the basis of the following actionable pillars (ibid):

a) Improving data provision and securing data access

b) Promoting responsible use of data and leveraging innovation potential

c) Improving data competencies and establishing a data culture

d) Making the state a pioneer

As part of efforts to establish a high-performance and competitive data infrastructure that is also secure and trustworthy,[40] the Federal Ministry for Economic Affairs and Energy (BMWi) launched a project under the name GAIA-X tasked with laying the foundations for an open, networked data infrastructure based on European values. The project aims to substantiate the specific technical and economic conceptual work involved in building such an infrastructure, to create a common ecosystem of users and providers from public administration, the health sector, enterprises and scientific instructions, and to establish supporting framework conditions and structures (BMWi, 2019a).

In the estimation of the BMI **Data Ethics Commission**, regulation must not block technological or social innovations or dynamic market development. According to the BMI, rigid and overly explicit laws can restrict scope of action and might increase bureaucratic costs to such an extent that innovative processes in Germany would no longer be able to keep pace with technological developments internationally. On the other hand, the BMI argues, regulatory framework conditions can and must protect essential rights and freedoms and provide legal certainty. This in turn forms the basis upon which all actors, individuals, organisations and institutions can place their trust in a social transformation based on ethical principles. In addition, the BMI believes that, with the ability to regulate on different levels – ranging from primary and secondary legislation to codes, self-administration and voluntary commitments – the legal system offers a tool box with which to create flexible framework conditions capable of adapting to technological progress (BMI, 2019). The collection, use and disclosure of data is therefore associated with a specific need for anticipatory assumption of responsibility.

[40] "We understand data infrastructure as a federated technical infrastructure consisting of components and services that make it possible to access data and to store, exchange and use it according to predefined rules." (BMWi, 2019a).

In order to estimate the consequences of this (including the possibility of violating other people's rights), the following points must be taken into account(ibid):

- Scope of data collection (including accumulation, network and scale effects)
- Technological means of data processing
- Purpose of data processing (giving specific attention to potential changes in the application context and constellation of actors).

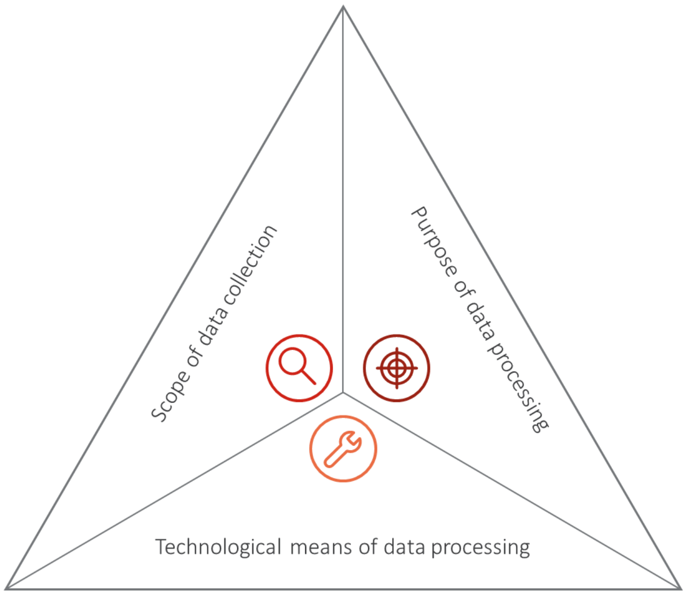

Figure 38: Triangle of data collection and utilisation

Due to the prominent role that AI is expected to play in data processing in future, the European Union aims to invest at least €1 billion per year in AI from the Horizon Europe and Digital Europe programmes during the programming period from 2021 to 2027 (EC, 2018).

Directive on open data and the re-use of public sector information (PSI Directive)

The European Commission considers that action at the European Union level is necessary in order to address the remaining and emerging barriers to a wide re-use of public sector and publicly funded information across the Union, in order to bring the legislative framework up to date with the advances in digital technologies and to further stimulate digital innovation, especially with regard to artificial intelligence.[41] Public sector information represents an extraordinary source of data that can contribute to improving the internal market and to the development of new applications for consumers and legal entities. Intelligent use of data, including data processing using artificial intelligence applications, can have a transformative effect on all sectors of the economy.[42]

[41] Directive (EU) 2019/1024; Recital 3.
[42] Directive (EU) 2019/1024; Recital 9.

The intended purpose of the resulting directive is to promote the use of open data and create incentives for the use of innovative products and services. For this reason, the directive contains minimum requirements for the re-use of research data and practical arrangements to facilitate the use of research data,[43] existing documents in the possession of the public sector bodies of EU member states or public undertakings operating in the water, energy, transport and postal services sectors[44] or operating a public service.[45,46]

In order to facilitate the re-use of data, public sector bodies and public undertakings must make their documents available in any pre-existing format or language and, where possible and appropriate, by electronic means in formats that are open, machine-readable, accessible, findable and re-usable, together with their metadata.[47] As a fundamental rule, the re-use of documents shall be free of charge; however, the recovery of the marginal costs incurred for the reproduction, provision and dissemination of documents as well as for anonymisation of personal data and measures taken to protect commercially confidential information may be allowed. This rule does not apply to public undertakings.[48]

Member states should make practical arrangements facilitating the search for documents available for re-use, such as asset lists of main documents with relevant metadata, accessible where possible and appropriate online and in machine-readable format, and portal sites that are linked to the asset lists.[49] According to Art. 12 Para. 1 of the PSI Directive, the re-use of documents shall be open to all potential actors in the market, even if one or more market actors already exploit added-value products based on those documents. Contracts or other arrangements between the public sector bodies or public undertakings holding the documents and third parties shall not grant exclusive rights.

Energy law and digitalisation

Energy law is also changing in Germany as a result of AI. Current regulatory developments have implications for how established companies trade and make investments. The *Act on the Digitalisation of the Energy Transition*[50] marked the German launch of what is known across Europe as the smart meter roll-out. European regulations in this area date back as far as 2006.[51] The primary objective of the Third Internal Market Package for electricity and gas[52] was to break up the regional monopolies that come to dominate Europe and also to enable cross-border competition in the electricity and gas markets for the first time. In order to achieve this, grid operation was separated from power generation and distribution (in a process known as "unbundling"[53]). In taking this action, the EU hoped to create a functional internal energy market – and, to this end, legal directives also rested upon internal market jurisdiction[54] (Schwintowski, 2018).

[43] According to Art. 10 of the PSI Directive.
[44] Directive 2014/25/EU.
[45] According to Art. 2 of Regulation (EC) No. 1370/2007.
[46] This applies to public companies that fulfil public service obligations according to Art. 16 of Regulation (EC) No. 1008/2008 or, as a shipowner, fulfil public service obligations according to Art. 4 of Council Regulation (EEC) No. 3577/92.
[47] Art. 5 Para. 1 of Directive (EU) 2019/1024.
[48] Art. 6 Paras. 1 & 2 of Directive (EU) 2019/1024.
[49] Art. 9 Para. 1 of Directive (EU) 2019/1024.
[50] Also known as the Metering Point Operation Act (Act of 29/08/2016 (BGBl. I S. 2034) and by its German abbreviation MsbG, this law entered into force on 02/09/2016.
[51] Directive 2006/32/EC of 05/04/2006 on energy end-use efficiency and energy services, now Directive 2012/27/EU of 25/10/2012 on energy efficiency.
[52] Directive 2009/72/EC (electricity) and 2009/73/EC (gas), both of 13/07/2009.
[53] Meter operation has also since become separate from grid operation in Germany. For detailed information, cf. Einhellig et al, 2017.
[54] Today Art. 114 TFEU.

Data communication in intelligent energy grids is precisely regulated in Germany by the Metering Point Operation Act (MsbG).[55] Pursuant to the MsbG, only the actors listed below may process meter data:

- Metering point operators
- Grid operators
- Balancing coordinators
- Balancing group officers
- Direct marketing companies according to the Renewable Energy Sources Act (EEG)
- Energy suppliers
- Any body with the connection user's consent[56]

Personal data processing may also be carried out by a processor (i.e. an external data processing service provider).[57] The MbsG also contains regulations on the issue of when the processing of data from an iMSys is permitted. According to the MbsG, processing is permitted to perform contracts with the respective connection user, as part of pre-contractual measures instigated by the respective connection user, to fulfil legal obligations[58] or to perform a task as the grid operator. According to Section 52 of the MsbG, the aforementioned authorised bodies must facilitate the encrypted electronic communication of personal data, meter data, grid status data and core data in a standard format. Where this concerns meter readings and core data, their format must enable fully automatic processing in the context of processes involving an exchange of data between system participants, including in particular the process of switching suppliers. Personal data must be anonymised or pseudonymised wherever possible given the purpose of processing. Personal data, core data and grid status data from the iMSys must only be communicated between participants in the Smart Metering Public Key Infrastructure of the Federal Office for Data Security (BSI). At the end of 2019, three SMGWs were certified by the BSI (BSI, 2020), which led to the so-called "market declaration" and the start of the SMGW roll-out at the beginning of 2020.[59]

Incentive regulation and digitalisation

Regulating revenues gives energy grid operators an incentive to increase their productivity and reduce costs to increase their potential profits (difference between regulated revenues and actual costs) or to reduce potential losses. In the estimation of the Federal Network Agency (BNetzA), this incentive creates a positive dynamic. The reduced costs each year form the basis for the next revenue regulation, which in turn represents an incentive to further increase efficiency. The grid operator's pursuit of profit therefore leads to cost reductions through a regulator (cost-plus regulation) without the need for detailed specifications of required cost-reduction measures.

[55] Section 49 of the MsbG.
[56] This consent must satisfy the conditions of Article 7 of Directive (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (GDPR) (OJEU L 119/1 of 04/05/2016; L 314/72 of 22/11/2016; L 127/2 of 23/05/2018) as amended.
[57] Section 49 Para. 2 of the MsbG.
[58] Obligations to which the authorised bodies are subject pursuant to the MsbG, the Energy Industry Act (EnWG), the Renewable Energy Sources Act (EEG), the Combined Heat and Power Act (KWKG) and the legal regulations and specifications of regulatory authorities based on these laws; according to Section 50 Para. 1 No. 3 of the MsbG.
[59] Sections 29 et seq. of the MsbG.

Existing information asymmetries between the regulator and grid operator lose at least some of their impact in doing so. The pressure to reduce costs simultaneously creates an incentive to innovate, with innovations generating further cost reductions. These might take the form of product or process innovations (BNetzA, 2015b).[60]

The use of AI should certainly be viewed alongside other IT and software innovations in the context of investment regimes and the approach to costs. If the application of AI leads to efficiency gains or cost savings greater than the costs of using AI, the corresponding regulation does not represent a hindrance.

Artificial intelligence and data protection in data processing – an area of conflict

General data protection law in Germany is significantly shaped by the General Data Protection Regulation (GDPR) at the European level, by the Federal Data Protection Act (BDSG) at the national level, and by state data privacy legislation at the state level. The objective of the GDPR is to protect the fundamental rights and freedoms of natural persons and in particular their right to the protection of personal data (cf. Art. 1 Para. 2 of the GDPR). The GDPR sets down the principles listed below in relation to data processing; further details of national data protection law are a matter for individual member states:

- Lawfulness
- Fairness
- Transparency
- Purpose limitation
- Data minimisation
- Accuracy
- Storage limitation
- Integrity and confidentiality

In geographical terms, according to Art. 3 Para. 1, the GDPR applies to the processing of personal data in the context of the activities of an establishment of a controller or a processor in the European Union, regardless of whether the processing takes place in the European Union or not.

The ePrivacy Regulation (ePR) is set to supplement the GDPR in future. The ePR primarily concerns electronic communication and will address data processing in particular. It will replace the ePrivacy Directive, which German lawmakers had already implemented in large part in the Telemedia Act (TMG) and Telecommunication Act (TKG), and is expected to come into force in the course of 2020. The directive is designed not to restrict the potential for innovation, particularly in relation to AI and blockchain technologies, i.e. compatible processing for machine-to-machine (M2M) communication should remain possible (Bitkom, 2017).

[60] cf. BNetzA (2015b), Evaluation report in accordance with Section 33 of the Incentive Regulation Ordinance (AregV), p. 44.

Virtually any act related in any way to personal data can be regarded as processing this data. Indeed, consideration of this factor was the stated aim behind the development of the GDPR. Art. 2 Para. 1 of the GDPR therefore objectively applies to fully or partially automated processing of personal data as well as non-automated processing of personal data stored or intended to be stored in a filing system. This raises the question of whether personal data can actually be processed in big-data analyses at all and, if so, to what extent. Although Art. 2 Para. 2 of the GDPR contains several exceptional circumstances, *Bartsch* (2018) does not regard these circumstances as usually applicable in the case of PSCs. Violations of the principles of personal data processing can incur a fine of up to €20 million or – including in the case of a company in the energy industry – up to 4% of the offending company's annual global turnover in the previous business year, as well as the potential for further measures from the supervisory authority.

In general, the following points are regarded as processing:[61]

- Processing: collecting, storing, editing, using, transferring, linking or deleting personal data
- Collecting: acquiring and/or gathering data, e.g. through a contact form
- Storing and/or editing data: e.g. saving an email
- Transferring: e.g. forwarding an email
- Using: e.g. submitting a query
- Linking with other data and deleting data: e.g. destroying a data storage device

The scope of the GDPR therefore routinely extends to the processing of personal data by PSCs in Germany.

Artificial intelligence and data security

Data security must be guaranteed in data processing operations. According to Art. 32 Para. 1 of the GDPR, taking into account the state of the art, the costs of implementation and the nature, scope, context and purposes of processing as well as the risk of varying likelihood and severity for the rights and freedoms of natural persons, the controller and the processor shall implement appropriate technical and organisational measures to ensure a level of security appropriate to the risk, including inter alia as appropriate:

- the pseudonymisation and encryption of personal data;
- the ability to ensure the ongoing confidentiality, integrity, availability and resilience of processing systems and services;
- the ability to restore the availability and access to personal data in a timely manner in the event of a physical or technical incident;
- a process for regularly testing, assessing and evaluating the effectiveness of technical and organisational measures for ensuring the security of the processing.

In assessing the appropriate level of security account shall be taken in particular of the risks that are presented by processing, in particular from accidental or unlawful destruction, loss, alteration, unauthorised disclosure of, or access to personal data transmitted, stored or otherwise processed.[62]

[61] Art. 4 Para. 2 of the GDPR.
[62] Art. 32 Para. 2 of the GDPR.

Article 25 GDPR stipulates that data protection must be implemented by design and by default and therefore sets down requirements for product development and implementation in the future. The controller must therefore implement appropriate technical and organisational measures for ensuring the effective implementation of processing principles both at the time that the means of processing are determined and at the time of the processing itself. The GDPR names public tenders as an example of a context in which the principles of data protection by design and by default must be considered. These requirements therefore have a direct impact on IT product development and processes. This should guarantee compliance with the processing principles by ensuring they are proactively (and therefore highly effectively) implemented at an early stage in the design of technical systems.

In addition to implementing appropriate measures,[63] as the addressee of Art. 25 of the GDPR, the controller should ensure by means of the default settings in data processing systems that only necessary personal data is processed.[64] This applies to the amount of personal data collected, the extent of its processing, the period of its storage and its accessibility. This ensures that the principles of data minimisation and purpose limitation are increasingly integrated on a technical level in recognition of the fact that users rarely change default settings. Approved certification mechanisms within the meaning of Art. 42 of the GDPR should make it easier to demonstrate in future that appropriate measures have been put in place.[65]

Given the provisions of Art. 25 of the GDPR, it is essential that PSCs establish a dialogue with the producers of the data processing systems they use. PSCs must also conduct a continuous evaluation of processing operations within the company and develop guidelines and concepts on handling personal data, e.g. in relation to data deletion, blocking, pseudonymisation and access authorisations. Law specific to the energy industry already takes this into account in relation to the use of SMGWs through a strict protection profile and technical guidelines under the supervision of the BSI pursuant to Section 2 No. 19 of the Metering Point Operation Act (MsbG). Naturally, AI must also satisfy these requirements.

Liability law, copyright law and cartel law

In addition to regulations regarding data protection and data security, it is also important to consider mandatory provisions of liability law, in particular provisions arising from tort law, as well as mandatory requirements of copyright law and cartel law. When it comes to the use of AI, two questions immediately appear prescient.

[63] Art. 25 Para. 1 of the GDPR.
[64] Art. 25 Para. 2 Sentence 1 of the GDPR.
[65] Art. 25 Para. 3 of the GDPR.

- Firstly, does AI have a legal personality?
- And secondly, who is liable for damages caused by AI?

In the knowledge that the establishment of legal personalities requires a legal act regarding accountability, there are compelling arguments for the introduction of another legal entity, perhaps in the form of an "ePerson". Such an entity could certainly be introduced but would inevitably raise further issues. Legal experts, however, do not see the need to create an ePerson at the present time. All current problems can be resolved within the existing legal framework. To date, AI systems have not achieved a degree of autonomy that would render it impossible to make a connection to human actions. Instead, gaps in responsibilities regarding AI can be closed by cautiously developing existing regulations. This process should give particular consideration to issues surrounding the allocation of responsibilities and liabilities in the event of technical failure and the distribution of defective technical systems. Such instances would primarily relate to contract law (conclusion of contracts by automated and partially automated systems and the resulting issues of contractual liability), tort law (extra-contractual liability according to Section 823 German Civil Code [BGB], product liability law, Road Traffic Act [StVG], etc.), product law and product safety law (BMWi, 2019b). According to Section 3 of the Product Liability Act (ProdHaftG), a product is defective when it does not provide the safety that one is entitled to expect. A defect in this context is defined as a deviation from the state of scientific and technical knowledge at the time the product was put into circulation. Relevant regulations are set down in legal standards and in DIN, CEN and ISO standards. Furthermore, technical requirements of products that entail a particular level of risk may be set down in special laws.[66] In terms of AI systems, the question of defectiveness not only pertains to the algorithms used but also to the data required to train the system. This assessment is complicated by the currently prevailing lack of technical norms or recognised regulations that can be used as a basis to derive minimum requirements for AI design and learning data pools.

Under what conditions can a fully automatic, intelligent machine receive a declaration of intent? The relevance of the answer to this question is not limited to M2M communication (e.g. in the context of Industry 4.0). Based on the "theory of receipt" (German: Empfangstheorie) currently prevailing in legal thought, there can be little dispute in this regard, no matter how advanced the system is. This is because, according to the theory of receipt, a declaration of intent is received as soon as it reaches the recipient's sphere of influence in such a way that, under the assumption of normal circumstances, the recipient could be expected to know of it. The declaration of intent is thus deemed to be in the recipient's sphere of influence when it reaches a mechanism typically created in order to receive declarations of intent. Exactly how this should be assessed for electronic agents was a disputed topic as early as the early 2000s. However, even then – as in the context of AI today – one assessment was decisive: the recipient determines the structure of their receiving area. This receiving area is therefore attributed to the recipient. The recipient must therefore ensure that their reception area functions properly regardless of its technical make-up. In this sense, mailboxes can also serve as adequate "receiving agents". The recipient only needs to ensure they acknowledge the mailbox content and empty the mailbox at appropriate intervals. In this sense, it makes no difference whatsoever whether an AI manages the mailbox or, in some circumstances, even optimises the mailbox in technical respects. In this regard, the law ensures that the risks – which, given the degree of technical progress (to date, and likely also in future), cannot be excluded from any serious discussion on the matter (cf. Pieper et al., 2019) – are allocated according to the interests involved.

[66] e.g. the Technical Regulations for iMSys in conjunction with the Metering Point Operation Act (MsbG).

The radical changes inherent in the rise of robotics and AI will also become increasingly important for commercial legal protection and copyright law in future (Hetmank et al., 2018). Increasingly efficient algorithms will be capable of creating not only text but also images and films; as producers, algorithms will stand alongside originators and increasingly come to replace them in future. The tried-and-tested institutions and infrastructures of copyright law will therefore have to be adapted to new technological circumstances (Wandtke et al., 2019). In cases where AI is used, all the facts and circumstances of the individual case are used to determine whether an artist or originator has purposefully used the software or algorithm to produce an individual, intellectual creation of their own or whether a programmer programmed the software or algorithm and the programmer and/or the artist is aware of the more or less accidental results of the use of the software and/or the algorithm (Ory et al., 2019/ Lauber-Rönsberg, 2019/ Borges, 2018). A report on civil-law regulations on robotics issued by the European Parliament's Committee on Legal Affairs originally called on the European Commission to elaborate criteria to define "own intellectual creation" for copyrightable works produced by computers or robots, but this request was not included in the final version (Hetmank et al., 2018).

In other areas of cartel law, such as anti-competitive agreements, certain restrictions of sales channels on platforms are only partly prohibited (i.e. only when regulations mandate anti-discriminatory practices on a platform) and new ways of facilitating such anti-competitive agreements have come to light over time. Simultaneously, the prohibition of abusive practices in data-based business models in the digital world has been tightened in the newly revised liability for fines under cartel law and in cartel damages law through the ninth amendment to the Act Against Restraints of Competition (GWB). The new criteria for market dominance as set down in Section 18 Paras. 2a & 3a of the GWB are important for access to AI systems. Section 18 Para. 2a of the GWB now stipulates that a competitive market can be assumed to exist even where a service is provided free of charge – which therefore dictates that abuse of a dominant market position is also possible in the *"economics of free"* due to the corresponding network effects. Section 18 Para. 3a of the GWB then adapts the term market dominance to data-based business models (Jakl, 2019).

3.3.2 Regulatory features of the fields of application

Predictions

Historical product time series and weather data are among the data required to forecast prices in the context of power generation and trading. This primarily involves processing primary data such as historical exchange price and fuel price time series. Installing and using intelligent metering systems is the foundation of the process of forecasting grid status data. As soon as an iMSys operated by a metering point operator (MPO) measures data, any subsequent transfer of data falls within the scope of the Metering Point Operation Act (MsbG).

In the process to be examined here, it is necessary to collect motion data using an SMGW in order to forecast grid status data. The MPO can only collect grid status data on behalf of the grid operator (GO) and only in justified cases.[67]

[67] Section 56 Para. 1 of the MsbG.

These cases include installations (*Anlagen*) according to the Renewable Energy Sources Act (EEG) and the Combined Heat and Power Act (KWKG), interruptible consumer devices (*unterbrechbaren Verbrauchseinrichtungen*) in the low-voltage grid according to Section 14a of the Energy Industry Act (EnWG), and metering points with annual consumption in excess of 20,000 kWh. The GO must also document the collection of grid status data[68] and, in the case of personal grid status data (i.e. grid status data relating to persons), must delete it immediately after successful data transfer.[69]

In addition to motion data, the iMSys also collects core data. According to Sections 46 and 74 of the Metering Point Operation Act (MsbG), or if administrative decisions from the Federal Network Agency (BNetzA) are required pursuant to Section 75 of the MsbG, the MPO may collect core data the first time an installation is connected to an iMSys and upon any significant changes to core data to the required extent and at the required time.[70] In accordance with Section 111e Para. 1 Sentence 1 of the Energy Industry Act (EnWG), the Federal Network Agency operates the Core Energy Market Data Register (MaStR) as an *“electronic directory with data on the energy industry”*. Implementation of this official procedure is regulated by the Ordinance on the Core Energy Market Data Register (MaStRV).[71] The Federal Network Agency implements technical and organisational measures for the register according to Articles 24, 25 and 32 of the GDPR.

The following data is also published in the Core Energy Market Data Register (MaStR):

- Data on units and installations (with the exception of location information, confidential data and data on units considered critical infrastructure)
- Data on market actors (with the exception of natural persons)[72]

However, the Federal Network Agency (BNetzA) grants grid operators access to data that is not made public, including personal data, provided this concerns data on units connected to their network and that this data is necessary for the grid operator to fulfil their legal duties.[73] The BNetzA also grants public authorities access to data.[74] Public authorities may transfer data, including personal data,

- for archiving purposes that are in the public interest,
- for scientific or historical purposes, and
- for statistical purposes.

The BNetzA can grant market actors and authorities access to the data stored in the Core Energy Market Data Register (MaStR) via electronic interfaces.[75]

Data collection using an iMSys or another medium other than the cases specified in Sections 55 to 58 of the MsbG is only permitted provided that no personal data is collected (without prejudice to Art. 6 Para. 1 of the GDPR). In addition, the fundamental regulations on data processing set down in Articles 24 to 32 of the GDPR must be observed.

[68] Section 56 Para. 3 of the MsbG.
[69] Section 64 Para. 2 of the MsbG.
[70] Section 57 of the MsbG.
[71] MaStRV in conjunction with Sections 111e & 111f of the EnWG and Section 6 Para. 2 of the EEG.
[72] Section 15 of the MaStRV.
[73] Section 17 of the MaStRV.
[74] The Federal Network Agency (BNetzA) grants access to data not made public under Section 15 Para. 1 of the MaStRV to the following public bodies: the Federal Ministry for Economic Affairs and Energy (BMWi), the Federal Cartel Office (BKA), the Federal Environment Agency (UBA), the Federal Office for Economic Affairs and Export Control (BAFA), the Federal Office for Agriculture and Food (BLE), the Statistical Office (DESTATIS), federal and state financial authorities and state regulatory authorities (Section 16 Para. 3 of the MaStRV).
[75] Section 30 Para. 2 of the MaStRV.

These regulations set down the existence of a controller who, taking account of the nature, scope, context and purposes of processing, implements appropriate technical measures in relation to the artificial intelligence and organisational measures (e.g. pseudonymisation) to ensure that data processing complies with the GDPR. In particular, such measures must ensure, by means of appropriate default settings, that personal data is not made accessible to an indeterminate number of people without the controller's intervention.[76] Training a model in this FoA involves the model learning to *recognise*, for example, connections between past prices and other existing data (from power generation and trading) or connections between past load flows and other existing data (from the grid). On this basis, the AI can then *infer* future prices or future load flows. The requirements described above are relevant to how data processing operations are handled in this process.

Overview and assessment

Core data and motion data are collected and processed for forecasting purposes. General national regulations on data collection (e.g. Art. 5 to 7 of the GDPR) and data processing (e.g. Art. 24 to 26, 30 of the GDPR, Section 37 of the BDSG) and European Union law (e.g. Art. 5 of the PSI Directive) apply in this context. The requirements of data protection law are manifold. However, no one requirement is a knock-out criterion or would not be practicable in the use of artificial intelligence; these requirements are therefore assessed to have a medium influence overall. Motion data for the purpose of predictions and forecasting is collected with the help of an iMSys. The requirements of the Metering Point Operation Act (MsbG) (in conjunction with the Energy Industry Act [EnWG]) must be observed in this respect (e.g. Section 52 of the MsbG). The MsbG also contains application-specific regulations regarding the collection, processing and use of data (in conjunction with an SMGW). These are less complex and easier to implement; their overall influence is therefore assessed as low. The regulations of the Ordinance on the Core Energy Market Data Register (MaStRV) (e.g. Sections 16, 17 of the MaStRV) apply to the use of core data from the Core Energy Market Data Register (MaStR). For the most part, the data in the register is publicly accessible to ensure greater availability of data pertaining to the energy industry. Given that the MaStRV therefore facilitates and even welcomes the collection and processing of core data, its regulatory influence is considered to be low.

In that there exists a wide range of regulations that the use of algorithm-based systems would be obligated to observe and apply – particularly in relation to energy law, data protection law and data security law – the regulatory system certainly has an influence on this FoA. However, this influence does not represent an impediment limiting its implementation. For this reason, the regulatory system is considered to have a low overall influence on this FoA. From a regulatory perspective, applications in this field are therefore deemed to be highly practicable.

[76] Art. 24 Para. 2 of the GDPR.

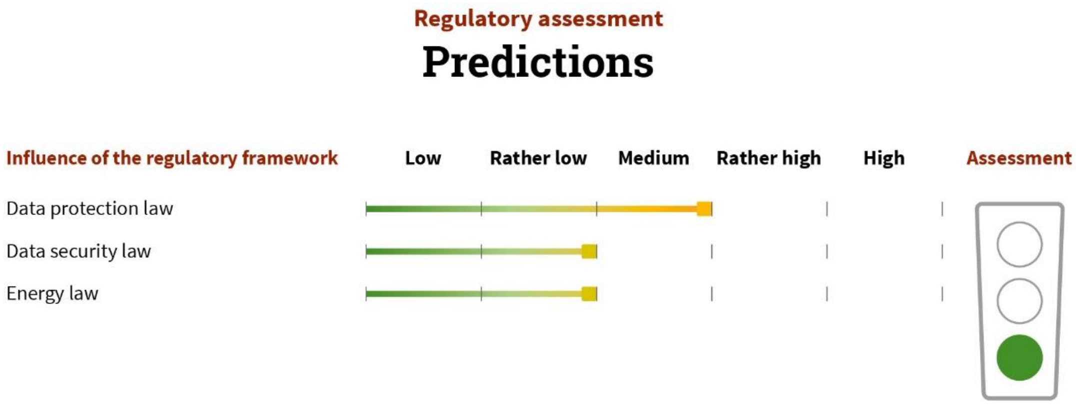

Figure 39: Regulatory assessment of predictions

Operation optimisation

In the case of optimised operational planning of power-generation installations, artificial intelligence could *recognise* different bidding strategies based on current price forecasts and thereby *infer* an optimal storage strategy. When combined with so-called load-profile meter reading,[77] this provides a basis for dynamic and variable tariffs. An iMSys enables a connection user to tie their electricity consumption to price signals. It enables the user to draw more energy when the price is low and reduce their consumption when the price is high (Lüdemann et al., 2016).

In the event of disruptions in the power grid, the GOs are responsible for resolving them and maintaining the supply of electrical energy. Such disruptions might occur, for instance, when the grid frequency or other stability limits are not maintained or when grid congestion occurs for other reasons. The GO has various measures at their disposal to ensure grid stability. The Energy Industry Act (EnWG) distinguishes between four categories of measures: grid-relation measures; market-related measures; the use of reserve power stations, and adaptation measures (Deloitte, 2019).

According to Section 14 Para. 1 No. 1 of the Renewable Energy Sources Act (EEG), grid operators can use feed-in management and curtail installations if grid congestion occurs. This authorisation to regulate consumption relates to both directly and indirectly connected installations. In this sense, the scope of application of Section 14 Para. 1 No. 1 of the EEG also extends to upstream grids. Grid operators must therefore equip directly or indirectly connected installations or combined heat and power (CHP) installations in such a way that they avoid grid congestion in a given area of the grid, including the upstream grid. This determination by German lawmakers serves to curtail a potential grid overload. A grid overload can arise, for example, due to high winds or in times of high solar energy feed-in and create a situation in which the distribution grids to which the affected installations are connected need to feed excess electricity into the upstream grid.[78] If this results in grid congestion that cannot be resolved by curtailment of conventional power stations, the grid operator sends a request to the operators of downstream grids to reduce the volume of electricity transferred upstream.

[77] According to Section 2 Para. 1 No. 27 of the MsbG, load-profile meter reading involves taking a series of meter readings every fifteen minutes. Unlike annual meter readings for the purpose of billing standard-load customers, this allows customers to be billed for different rates at different times.
[78] Transferring electricity to an upstream grid is known in German as *hochspeisen*.

Section 14 of the EEG only contains regulations on grid congestion; other small-scale or short-term causes of congestion, such as maintenance and repair work, do not fall within the scope of Section 14 of the EEG and therefore also do not trigger (monetary) hardship compensation pursuant to Section 15 of the EEG (Lülsdorf, 2019). As part of optimising grid operation, AI should *recognise* such grid congestion and *infer* optimal approaches to counter this congestion.

In addition, according to Section 14a of the Energy Industry Act (EnWG), suppliers and ultimate consumers in the low-voltage range will be charged lower grid charges if, in return, they agree that controllable consumer devices with a separate metering point can be controlled for the purpose of efficient grid operation.
Most recently, since the rapid construction of renewable energy installations (REIs) in Germany and the subsequent rise in the proportion of energy feed-in from volatile sources, there has been intense discussion in specialist circles surrounding the term "flexibility". The underlying aim of this discussion is to make the maximum possible volume of electricity generated by REIs available, thereby integrating RE in the existing market as effectively as possible. As REIs are heavily weather-dependent and therefore volatile, there is a need for flexible feed-in capacities to cope with the volatile volumes of electricity they generate. For several years, the term "grid-supportive" (German: *netzdienlich*) has also played a role in this discussion. It is used to describe an application of flexibility with a positive impact on the grid – an application that supports the grid. Grid-supportive services make it possible to control grid loads and energy feed-in more precisely and thereby increase transparency in the grid. The role of the MPO in relation to data management is based on the following definition: *"Grid-supportive services are services that a metering point operator can provide for the grid operator by using an intelligent metering system (iMSys); these services go beyond the scope of standard and additional services of a metering point operator according to Section 33 MsbG and can have a grid-supportive effect"* (Deloitte, 2019).

The benefits of a more strongly market-based structure for congestion management (including the introduction of regional markets for flexibility services) is currently under discussion. The next stage is to outline the opportunities and risks and then examine the legal framework according to the new Internal Market for Electricity Regulation, the Internal Market for Electricity Directive and German law. Special emphasis is placed on the question of the extent to which the risk of strategic bidding by market participants justifies an exception from the principle of market-based congestion management (Weyer et al., 2019).

In any case, on the grid control side, the required investments present a barrier to AI-based monitoring measures and AI-assisted feed-in management. Since 2015, however, the Federal Network Agency (BNetzA) has declined to introduce directly congestion-oriented variable grid charges (and therefore, in effect, AI-assisted congestion management) because congestion-oriented pricing for overloaded sections of the grid *"is hardly practicable in intermeshed electricity grids"* (cf. BNetzA, 2015a).

The increased prospective and predictive use of algorithm-based systems to support grid operation could present a route out of this regulatory dilemma by helping to ensure that congestion does not arise in the first place. Optimised operational planning for power-generation installations and optimised grid operation involves processing (sometimes sensitive) sensor data, weather data and electricity price time series. The regulatory requirements of data collection and data processing described in the general assessment of this FoA apply in this context. The GDPR is applicable and must be observed wherever such activities involve personal data.

Overview and assessment

In principle, an AI algorithm could automatically react to price changes. To do so, however, price signals would first have to be approved or variable grid charges made possible through comprehensive use of iMSys.

The use of iMSys could render this technically feasible in future in the context of grid management, potentially also in conjunction with load-profile meter reading. This would allow PV installations to use AI to adjust themselves based on prevailing wind and solar radiation and thereby facilitate the forecasting of price time series, which would also support congestion planning by grid operators. Nevertheless, the Federal Network Agency (BNetzA) has declined to introduce congestion-oriented variable grid charges, which is why storage systems also cannot be planned in a grid-supportive or infrastructure-supportive manner and cannot exploit their infrastructure-optimising potential. For this reason, the practicability of the two examples named here is assessed as (a) medium for operational planning and (b) low for direct congestion management in the grid.

As REIs continue to be built at great pace, flexibility in the grid will become increasingly significant; this consideration is driving the discussion around increasingly market-based congestion management. A differentiated approach is made possible in practice by the use of iMSys, which allows installations to be controlled via a CLS/control box. In this respect, the Metering Point Operation Act (MsbG) is more of an enabler than a negative impact on this FoA. In the low-voltage grid, Section 14a of the Energy Industry Act (EnWG) opened up pricing opportunities on the consumption side even before the reform. If changes are not made to facilitate congestion-oriented grid charges in future, the use of AI could still leverage potential in relation to congestion prevention. From a regulatory perspective, however, the implementation potential of AI for operation optimisation as an overall field of application (i.e. for market-related and grid-supportive uses) is rated as medium.

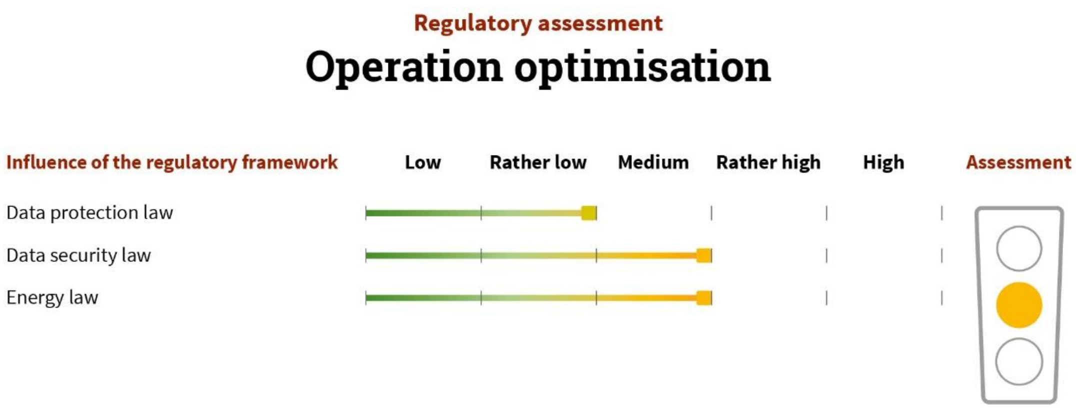

Figure 40: Regulatory assessment of operation optimisation

Inventory optimisation and other strategic business decisions

In this FoA, the first step is to input the costs (prices) of storage technologies and options to counter grid congestion into an AI along with corresponding technical data. Training an AI model in this context is similar to the training involved in the fields of predictions and operation optimisation, but takes place over a longer period of time.

Planning can be defined as *“setting forward-looking objectives and conceptually anticipating the behaviours required to realise them”* (cf. Wolff et al., 2010). However, in addition to reservations over state planning *(“arrogation of knowledge”*, Hayek, 2014), it is difficult to subsume all planning processes under a single, coherent notion. This applies all the more when planning often extends over several stages. Indeed, in infrastructure law, requirements planning only represents the first stage of planning, followed by realisation planning (Schmitt, 2015). As a concept, planning in the context of grid expansion is always sponsor-neutral. Efforts to encourage public participation are primarily hampered by the attribution of planning to private actors. This is made clear, for example, by the case of federal planning, which is officially the responsibility of the Federal Network Agency (BNetzA) but, due to the application requirement, is often misunderstood as private planning undertaken by transmission system operators. However, this is not the case given the high level of public participation required (Franzius, 2015b). A common, fundamental characteristic of all planning is the connection to the public interest (Franzius, 2018).

In use case a) an AI is applied to *recognise* the profitability of different technologies based on price forecasts in different markets, areas of application and bidding strategies, and thereby *infer* optimal investments under the specific framework conditions.
The aspects examined here include the linking of planning and regulation. This begins with the question of the extent to which the regulatory discretion often required by European Union law can follow the model of planning discretion, though this threatens to smooth over the differences between regulatory approaches (Kersten, 2010).[79] It continues with an insight into the anticipatory nature of planning, which presents the question of whether an intelligent regulatory regime represents an alternative to planning or whether, conversely, it would actually require planning specifications.[80] The law on the energy transition ultimately has hybrid manifestations, as emphasised by the grid development planning according to Sections 12a et seq. of the Energy Industry Act (EnWG) (Franke, 2013). Confirmation from the Federal Network Agency is not only a regulatory decision but also simultaneously represents the first step in requirements planning, which is only finally concluded with the Federal Requirement Plan Act (BBPlG) and justification of the plan by the democratically legitimate legislature (Wißmann, 2014).[81]

Planning can only be discussed to a limited extent in the context of wind farms. The asymmetry between detailed grid expansion planning and the “free” decisions of wind turbine operators regarding investments has long been considered problematic for the success of the energy transition (Hermes, 2014/Krawinkel, 2012). Of course, there are spatial planning specifications for such installations, in particular priority and suitability planning according to Section 35 Para. 3 Sentence 3 of the Federal Building Code (Baugesetzbuch (Federal Building Code)).[82] However, such specifications only relate to the location of the installation, without taking into account the grid expansion costs.

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[79] See also Durner, 2011: p. 429 et seqq.; differentiated in Eifert, 2010: p. 460 et seqq., p. 482 et seqq.
[80] For the link in the example of requirements planning for contract physicians according to Sections 99 et seqq. SGB V, cf. Franzius, 2012: p. 56 et seqq.
[81] For criticism of this, cf. Köck, 2016: p. 588 et seqq.
[82] Recast by publication on 03/11/2017 / 3634.

Although investments by transmission system operators are framed by planning law, there is a lack of suitable requirements from planning law for the upstream level of power generation. The management of wind energy under regulatory law also suffers from this issue. However, the change in EEG-funding from price control to a tendering model requires the use of planning instruments. If the tendering model under regulatory law is applied extensively as a competitive measure to determine funding amounts, this will effectively necessitate requirements planning for installations covered by the EEG, which demands more action from the state than has been the case to date (Franzius, 2015a).[83]

Franzius argues that the issue of whether reducing funding could be a method to better coordinate the two levels deserves fundamental consideration. This is because the fundamental problem persists: although, in the case of grid planning, it is all but impossible to designate grid planning as private planning, which would only have to be verified by official confirmation, due to the "system responsibility" of transmission system operators, the situation regarding power generation is quite different. After all, limiting funding cannot hide the fact that that the operators of power-generation installations use common goods (in the form of air or land) free of charge to generate energy and can produce electricity in locations where it incurs high grid expansion costs that are borne not by the operator but by public funds. This could be corrected by means of an amendment to the regulatory regime under the Renewable Energy Sources Act (EEG); however, this raises the question of scale which – as the argument goes – should be abstracted not only from regulatory law but also from upstream planning (Franzius, 2018).

The ALICE project funded by the Federal Ministry of Education and Research (BMBF) researches how wind and gas turbines can learn from their own operating data. The goal of the project is to enable installations such as off-shore wind farms or gas-fired power stations to adapt independently and optimally to changing environmental and load conditions in future. Installations' operating data, information on oscillations, vibrations, wind speeds, temperatures and the rotors' alignment angle could be used to achieve this. Sensors on wind turbines in wind farms record all of these information types several times per minute (BMBF, 2019). The project is therefore concerned with operational and short-term planning using AI.

In use case b), grid infrastructure planning, an AI is tasked with examining the load flow forecast to *recognise* different possible scenarios and their efficacy in countering grid congestion in different sections of the grid and *infer* an optimal investment strategy to counter grid congestion. According to Section 12 of the Renewable Energy Sources Act (EEG), upon request from parties interested in feeding in electricity, grid operators must immediately optimise, reinforce and expand their grids in accordance with the state of the art to facilitate collection, transmission and distribution of electricity from RE or mine gas. In the event of capacity shortages, the GO is also obligated to expand their grid in line with needs to ensure the long-term ability of the grid to satisfy demand for the transmission of electricity. This obligation to expand grids based on current demand is subject to the condition of economic reasonableness.[84]

The growth of RE and the rise of electromobility are placing increasing strain on the power grid. Distribution grids must therefore be reinforced in certain areas and equipped to meet new requirements. Frankfurt-based start-up Venios has developed an AI-based software solution to plan, optimise and control electric distribution grids. Geospin GmbH has also developed an intelligent forecasting model based on self-learning algorithms, which can calculate the expected utilisation of a charging point for any location in Germany.

[83] For further details, see Fehling, 2014: p. 319. On the instrument of requirements planning, see Köck et al., 2017. On the proposal of a "Master Plan for the Energy Transition", see Schmidtchen 2014: p. 126 et seqq.
[84] Section 11 Para. 1 & Section 12 Para. 3 of the EnWG.

This makes it possible to select the optimal location and maximise utilisation of the charging infrastructure for electric vehicles. The forecasting model draws on historical charging data for approximately 6,000 charging points in German cities and rural areas as well as more than 800 additional sources of geographical data (Geospin, 2020). At present, the transmission system operator (TSO) issues a schedule to the distribution system operator (DSO) – a grid node-oriented overall energy volume that the DSO must feed into or draw from the transmission grid. This makes it possible, in particular, to manage the challenges of energy fed from the distribution grid level back to transmission grid level in times when power generation is high or grid load is low (i.e. off-peak hours). The DSO is responsible for implementing this schedule. However, DSOs currently claim that their supporting role as set down in Section 14 of the Energy Industry Act (EnWG) no longer corresponds to their actual responsibility. The regulatory system should therefore standardise an equitable distribution of roles while enhancing the independence of DSOs in the context of system management. In such circumstances, the decentralisation of the energy transition would lead to broadly autonomous distribution grids. The tasks that would accompany this shift would also include independent congestion management, independent supply restoration, voltage maintenance and a physical balancing between loads and feed-in in the distribution grid. These tasks can only be performed by the DSO because only they have knowledge of the grid topology, switching states and current load flows and load forecasts in the distribution grid (E-Bridge, 2016). Algorithm-based systems can help them perform these tasks; in the distribution grid, positive control power on the generation side can be ensured almost exclusively using RE and CHP installations. The lead times for tenders in the control power markets represent a regulatory impediment (including to the use of AI) due to the inherent meteorological uncertainties (Agora Energiewende, 2014). The Federal Network Agency (BNetzA) therefore cut these lead times in a first stage in 2017 and, in doing so, expressly reserved the right to reduce them further (BNetzA, 2017a, 2017b).

In order to prevent RE installations from being disconnected or shut down, the notion of expanding DSOs' opportunities to access market-based flexibility on regional flexibility markets appears worthy of consideration. This preventative measure would – in contrast to control energy – not involve compromising current electricity supplies within the meaning of Section 13 Para. 4 of the Energy Industry Act (EnWG). Market-based electricity acquisition would also take place in the context of bilateral agreements that, in many cases, could present a more economical means of accessing flexibility than tendered control energy.

In Section 14a of the EnWG enacted in 2011, German legislators have standardised a highly promising approach to intelligent grid control in distribution grids. In the estimation of legislators, grid control is necessary because the low-voltage network "can be pushed to its limits by a high number of electric vehicles charging simultaneously" (cf. Deutscher Bundestag, 2011). The intention behind this regulation is to improve the overall efficiency of the energy system. The energy provider EnBW is currently trialling its "flexible heat flows" model to counteract simultaneity effects. The project is understood as a means to modernise Section 14a of the EnWG (Agora Energiewende, 2017). In this context, it is important to note that Section 14a of the EnWG does not clearly define the market roles of DSOs and other stakeholders (and suppliers in particular). Substantiating these standards will require corresponding legal enactment. Ultimately, in technical respects, control and distribution function are performed most reliably by DSOs (Danner et al., 2015).

The decentralisation of the energy transition requires active grid management by DSOs; RE installations and controllable loads have an important part to play in this. By contrast, grid control by TSOs carries the risk of creating a conflict of objectives in the decentralisation of the energy transition. As long as different grid operators compete for the same flexibility, uncoordinated call-offs by TSOs can still cause congestion at the distribution grid level. It therefore appears preferable for TSOs to address only their needs in their dealings with DSOs; specific operational decisions would then be left to DSOs, thus allowing DSOs to regulate the distribution grid like a “power station” (Steinkamp, 2017). From a regulatory perspective, the EU Commission’s Winter Package has alluded to the significant potential to reduce grid costs through greater use of local flexibility resources (EC, 2016). In the context of the Smart Energy Showcase – Digital Agenda for the Energy Transition funding programme, a DSO may – contrary to Section 13 Para. 6 in conjunction with Section 14 Para. 1 Sentence 1 of the Energy Industry Act (EnWG) – forgo establishing a joint internet platform for all DSOs in the acquisition of switchable loads.[85] Sections 39j and 88d of the Renewable Energy Sources Act (EEG) empower the federal government to issue innovation tenders for particularly grid-supportive and system-supportive installations. The intention of this is promote grid-supportive optimisation of flexibility services.[86] The justification for the law states flexibilisation of both the generation side and consumption side as grid-supportive optimisations (Schäfer-Stradowsky et al., 2018).

Overview and assessment

The decentralisation of the energy transition requires active grid management by DSOs; RE installations and controllable loads have an important part to play in this. This results from the grid operator’s obligation to expand their grid in line with current needs according to Section 11 of the Energy Industry Act (EnWG) in order to secure the capacity of the grid for the long term and to satisfy demand for electricity transmission. A flexible grid could help to reduce grid expansion costs. The federal government promotes grid-supportive flexibility optimisation through innovation tenders according to Sections 39j and 88d of the Renewable Energy Sources Act (EEG). In Section 14a of the EnWG adopted in 2011, German legislators laid a promising foundation for intelligent grid control in the area of distribution grids, which still has to be expanded further. This control is required, among other reasons, because the low-voltage grid could be stretched to its limits on a local level if a large number of electric vehicles were charged at the same time. The intention behind this regulation is to improve the overall efficiency of the energy system. In principle, nothing in this field of application presents an argument against the use of AI, which has already begun.

If, in the use of AI, consumption data (such as electricity consumption data) is stored in an algorithm-based system, the AI used inter alia for data processing must satisfy the requirements of Sections 21 and 22 of the Metering Point Operation Act (MsbG). Regulatory requirements from the Energy Industry Act (EnWG), the Renewable Energy Sources Act (EEG) and other legislation tend to act in support of intelligent planning of grid congestion management rather than as barriers. This field of application is therefore assessed as highly practicable from a regulatory perspective.

[85] Section 5 of the SINTEG Regulation.
[86] Section 88d No. 3c of the Renewable Energy Sources Act (EEG); Lülsdorf (2019)

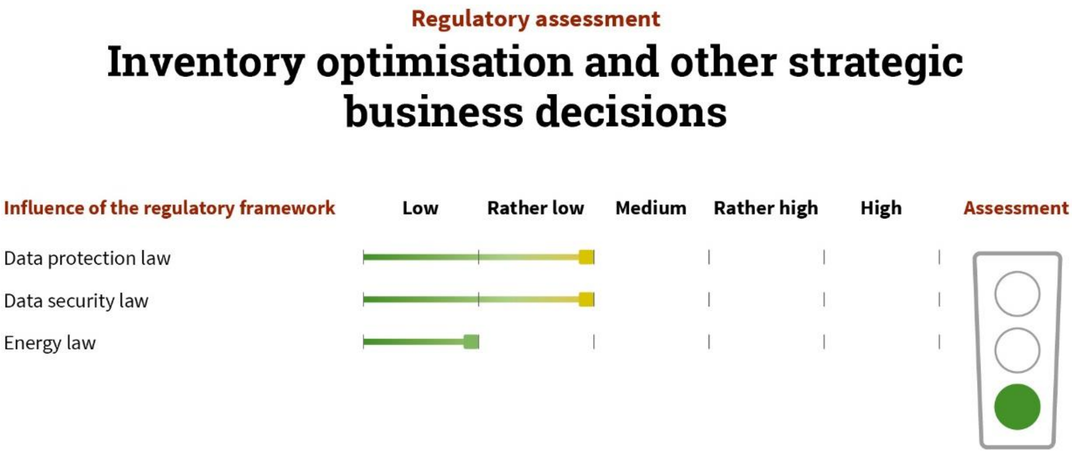

Figure 41: Regulatory assessment for inventory optimisation and other strategic business decisions

Predictive maintenance

The objective of this FoA is to facilitate suitable and needs-based maintenance and repair measures based on collected production data, installation data, load data, weather data, geographical data and maintenance data. Firstly, sensors need to be installed in certain assets (in grids and in power generation) and investments are required in robots and drones. Further preliminary work involves collecting and processing data on maintenance performed to date, both planned and unplanned, and to acquire satellite data and other relevant secondary data. The AI can use historical data as a basis upon which to *recognise* abnormalities and *infer* suitable maintenance to resolve them.

The various technologies used in this context are subject to different regulatory framework conditions. Satellite data offers wide-ranging opportunities to create useful technical applications – from route planning to weather forecasts, and from environmental monitoring to disaster control. Jurisdiction in this area is divided across several levels between the European Union, the federal government and the federal states. The allocation of jurisdiction determines who should be the recipient of a request to release satellite data (Martini et al., 2014). The non-governmental operation of satellites and other earth-remote sensing systems by German companies or from within Germany is subject to approval pursuant to the Satellite Data Security Act (SatDSiG).[87]

Remote access makes it possible, for instance, for machine manufacturers to access data that was generated through operation of the system/device and is held by the system's operator. This could be machine data, production data or data on environmental impacts on the system and control of the system that is read out from a server operated by the manufacturer and, for example, transferred into a private cloud operated by the manufacturer. Once transferred, the data can be analysed, in particular using algorithm-based systems. The manufacturer can then make the latest data (e.g. production data) available very promptly to members of the operator's management via an app. The data collected by the operator and analysis of this data can be made accessible to the operator through industrial IoT platforms offered by various software providers. This can provide the operator with information on the degree of wear, which can be used for purposes including predictive maintenance.

[87] Act to Safeguard the Security Interests of the Federal Republic of Germany from Endangerment by the Distribution of High-Grade Earth-Remote Sensing Data (SatDSiG), BGBl. 2007 I, p. 2590.

Sensors and the analysis of the collected data also provide the operator with information on potential optimisations to system control, e.g. on potential environmental influences such as dust, heat, moisture, vibrations or problems in the ground below the installation. This makes it possible to identify acute wear at an early stage as well as disruptions not evident to the operator. The technology also enables the manufacturer to monitor and regulate certain control settings, including when systems are in the operator's possession.

If it is not ensured from the outset that it will not be possible to trace the analysis provided by the manufacturer traced back to individual persons even in part in compliance with data protection law, clarification is required to determine whether this issue can be avoided.[88] If it is not possible to avoid it entirely, a data protection impact assessment must be conducted according to Art. 35 of the GDPR. It is possible, for example, that the manufacturer may not to be able to attribute data to individual persons or groups, but that the analyses of this data allow the operator's management to conduct prompt performance monitoring of the employees operating the device (Mantz et al., 2017). Analyses performed in the context of remote services represent processing within the meaning of Art. 28 of the GDPR and, given its detailed nature, should be contractually regulated. Analyses offered as remote services are, like benchmarking, based on AI-assisted analysis tools and potentially also on the application of deep learning methods to the data and the algorithms developed as a result. Software and AI algorithms always carry the risk of faults that are unknown upon conclusion of a contract (Lachenmann, 2017). The consequences of such faults could result in an operator incurring significant consequential damages, such as by incorrectly estimating potential production volumes when accepting orders or scheduling infeasible delivery times. The same applies if a manufacturer were to provide incorrect fault reports to the operator or inaccurate wear reports. Consequential damages of this type represent an elevated liability risk for the manufacturer and, at the same time, a substantial problem for the operator. This problem is further intensified in the event that a manufacturer makes technical adjustments to the operation of a system in the possession of the operator (Habel, 2018).

Another regulatory challenge lies in the question of whether and under what circumstances a predictive maintenance service is sufficiently protected against cyberattacks, as advancing digitalisation also opens up new potential angles of attack. The question of security therefore takes centre stage – not least in relation to critical infrastructure[89] and the NIS Directive.[90] In this context, it is important to tighten the requirements of internal IT infrastructure and cyberphysical systems to prevent abuse and manipulation of data and components. State-of-the-art security systems must be implemented and regularly updated in order to counter attacks before they actually happen. In the event of an attack, the question of whether technical systems were indeed state-of-the-art or the attack represents a "zero-day event" must be assessed in each individual case; extensive expert evidence may be required to determine this in subsequent legal proceedings.

Moreover, it is possible to conceive of instances in which the providers of predictive maintenance services would also have to implement technical and organisational measures within the meaning of Art. 32 of the GDPR. The data collected in the course of predictive maintenance could lead to a situation in which a specific person could be identified, thereby making this personal data within the meaning of the GDPR.

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[88] See also Art. 32 Para. 1 of the GDPR.

[89] Critical Infrastructure Regulation (Kritis-VO) in conjunction with the security catalogues of the Federal Network Agency (BNetzA): IT-Sicherheitskatalog für Betreiber von Strom- und Gasnetzen (August 2015) as well as the IT security catalogue for the operators of energy installations that were classified as "critical infrastructure" by the Critical Infrastructure Regulation and are connected to an energy supply grid (December 2018).

[90] cf. Section 8 a of the Act on the Federal Office for Information Security (BSIG); Directive 2016/1148/EU of the European Parliament and of the Council of 6 July 2016 concerning measures for a high common level of security of network and information systems across the Union.

For example, data from a metering point in an area where certain maintenance employees work could be used to draw conclusions as to the quality and quantity of their work (also known as *behavioural tracking;* Faber et al., 2018), which in turn raises issues pertaining to labour law.[91]

Overview and assessment

The analysis of data generated by sensors provides the operator with information on potential ways to optimise system control. In using sensors, however, it is essential to ensure the analysis of this information does not contain any personal data.[92] In cases in which this cannot be ensured, a data protection impact assessment must be conducted pursuant to Art. 35 of the GDPR. The analysis in question may also be carried out by a processor[93] (i.e. an external data processing service provider). As algorithm-based systems carry a risk of errors, it is essential that regulations are put in place in respect of liability law. Technical and organisation measures must be put in place to protect predictive maintenance services against cyberattacks and thereby ensure the highest possible degree of data security. In this context, it is also vital to ensure that internal IT infrastructure and cyberphysical systems meet certain requirements, which involves implementing security systems and updating them regularly. There are, therefore, certain contractual regulations and data-security regulations in this field of application that require particular consideration from the outset. For this reason, the influence of the GDPR is rated as medium. Nevertheless, from a regulatory perspective, this field of application is considered to be highly practicable given that the GDPR does not contain any insurmountable barriers or knock-out criteria.

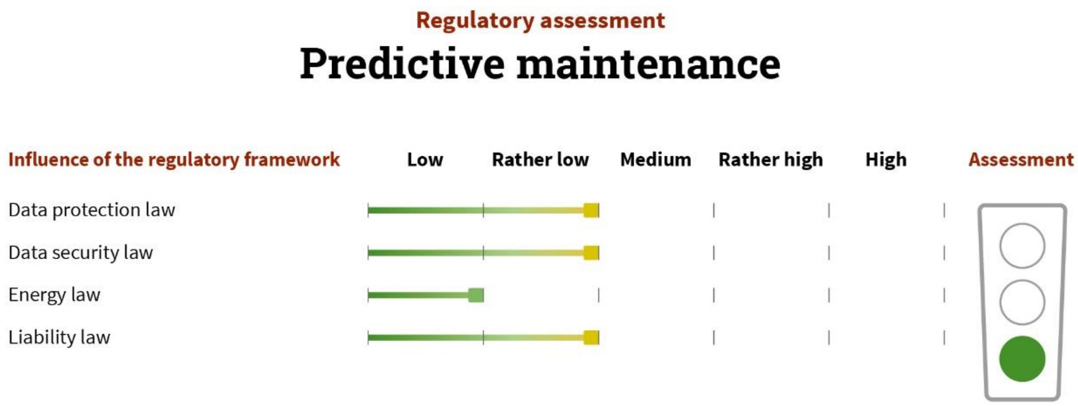

Figure 42: Regulatory assessment of predictive maintenance

[91] cf. Section 87 Para. 1 No. 6 of the Works Constitution Act (BetrVG), which states that the introduction and use of technical devices designed to monitor the behaviour or performance of employees in Germany is subject to the right of co-determination of the respective works council.
[92] Art. 32 of the GDPR.
[93] Art. 28 of the GDPR.

Maintenance, repair and dismantling

This field of application serves to support repairs to facilities by diagnosing problems and providing information (virtually) and also helps uses drones and robots to physically perform work. The Ordinance Regulating the Operation of Unmanned Aerial Vehicles must be considered in relation to the use of drones in this FoA. It states that the operation of such vehicles requires approval when the vehicle exceeds certain weights,[94] is operated less than 1.5 km from residential areas or airfields, or is operated at night.[95] No approval is required when such vehicles are operated by public bodies or under their supervision. If such vehicles are not operated by or under the supervision of public bodies, their operation is also prohibited above or within a horizontal distance of 100 m of the outer perimeters of energy generation and distribution installations unless the operator of the installation has expressly consented to the vehicle's operation.[96] The local aviation authority is responsible for issuing approvals.[97] Upon request, operators of drones with a take-off weight of more than 2 kg must also demonstrate their knowledge of the operation and navigation of flying vehicles, appropriate fundamental principles of aviation law and the local airspace control regulations.[98]

Sensor data, audio data and image data form the data basis for the use of AI in maintenance, repair and dismantling operations. The preliminary work required in this regard involves transferring handbooks, documented problems and their solutions along with other relevant knowledge on assets into a standardised data basis. Nowadays, every system generates large quantities of sensor values and measurement data. However, gaining insight into these values and deriving recommendations for action is only made possible through intelligent analysis of this data. In this context, an AI can *recognise* current problems and *infer* a suitable solution adapted to the current circumstances based on an existing solution. The GDPR is only relevant to this FoA when personal data is used when storing information on maintenance, repair and dismantling activities. In this case, the regulations outlined in Chapter 0 on data collection and processing apply accordingly. As in the field of predictive maintenance, special consideration must also be given to the issues of IT security and the security of cyberphysical systems (in accordance with IT baseline protection[99]). According to *Djeffal* (2019), particular challenges in respect of IT security lie in the fact that AI is currently an emerging technology and its implications for IT security will therefore only become evident over the course of its development.[100] This relates to the technical level in particular, where IT baseline protection should at least convey a broad overview. From the perspective of organisational security and IT baseline protection, taking interactions – and above all those between humans and machines – into consideration is of decisive importance. These interactions are relevant, for example, in relation to speech and image recognition, as such processes enable the machine to interact directly with humans through automated responses. It is also likely that the process of malware definition in particular will increasingly draw on AI-assisted applications in future. This exponentiates the possibilities of AI-assisted IT systems as well as the resulting security requirements.

[94] Where the take-off weight exceeds 5 kg or if the propellant weighs more than 20 g (Section 21a Para. 1 Nos. 1, 2 of the Ordinance Regulating the Operation of Unmanned Aerial Vehicles; published in the Federal Law Gazette (BGBl), 2017, Part I No. 17, in Bonn on 6 April 2017).
[95] Section 21a of the Air Traffic Regulation (Luft-VO).
[96] Section 21b Para. 1 No. 3 of the Luft-VO.
[97] Section 21c of the Luft-VO.
[98] Section 21a Para. 4 of the Luft-VO.
[99] The federal government describes IT baseline protection (German: IT-Grundschutz) as an IT approach developed by the Federal Office for Information Security (BSI) to identify and implement security measures in companies' internal IT systems (BSI, 2017)
[100] For related research questions and a research agenda in this regard, see for example (Amodei et al., 2016)

This is because these requirements would no longer relate solely to system security but also to how technology is handled. These and other issues represent significant challenges for IT baseline protection – but simultaneously entail the opportunity to research and develop AI technologies, even in an early, emergent stage in their development, based on the values of IT security and for the good of society. In doing so, IT baseline protection can succeed not only in keeping pace with technological developments but also in shaping them by setting standards (Djeffal, 2019).

Fundamental requirements of maintenance and repair processes are set down in Section 3 Para. 2 of the Energy Savings Act (EnEG)[101] in conjunction with Section 11 Para. 3 of the Energy Savings Regulation (EnEV).[102] These requirements state that components with a significant influence on the efficiency of systems must be regularly maintained and repaired by the operator. This maintenance and repair requires specific skills; that is to say, the person performing maintenance or repair tasks must possess the requisite specialist knowledge and competencies (including in relation to how an AI functions).

Overview and assessment

The use of AI to assist in system repairs by diagnosing problems or providing information is subject to the same requirements as the field of predictive maintenance. Particular attention must also be paid to IT security and data security regulations (above all Art. 32 of the GDPR). Data protection law therefore has a medium influence on this FoA. The Energy Savings Act (above all Section 3 Para. 2 EnEG) and the Energy Savings Regulation (above all Section 11 Para. 3 EnEV) set out principles for maintenance and repair. If drones are used in the context of maintenance and repairs, the Air Traffic Regulation (Luft-VO) must also be observed. The Luft-VO stipulates that operating a drone is prohibited above or within a horizontal distance of 100 m of the outer perimeters of energy generation and distribution installations, unless the drone is operated by or under the supervision of a public body or the consent of the installation’s operator has been obtained. However, the EnEG and EnEV are considered to have a minor influence on this field of application because they only contain principles for maintenance and repair and not specific, mandatory requirements. This field of application is therefore assessed as highly practicable from a regulatory perspective.

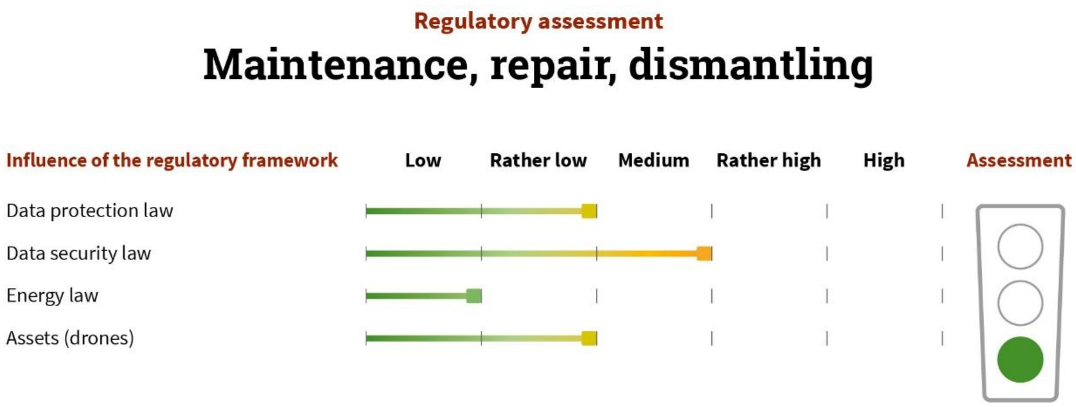

Figure 43: Regulatory assessment for maintenance, repair and dismantling

[101] Energy Savings Act (EnEG) in the version of the publication of 01/09/2005 (BGBl. I p. 2684), last amended by Article 1 of the Act of 04/07/2013 (BGBl. I p. 2197).
[102] Energy Savings Regulation of 24/07/2007 (BGBl. I p. 1519), last amended by Art. 3 of the Regulation of 24/10/2015 (BGBl. I p. 1789).

Security measures

This field of application involves identifying and defending against hostile attacks in both the physical world (e.g. by evaluating surveillance cameras) and the virtual world (cybersecurity). The focus in this regard is on critical, system-relevant infrastructure, i.e. grid infrastructure and infrastructure at large power-generation installations.

Cybersecurity refers to all activities necessary to protect network and information systems, the users of such systems, and other persons affected by cyber threats,[103] while cyber threat means any potential circumstance, event or action that could damage, disrupt or otherwise adversely impact network and information systems, the users of such systems and other persons.[104]

Practical example: EnBW SafePlaces – using video data to automatically identify hazardous situations

EnBW SafePlaces uses artificial intelligence to identify hazardous situations, thereby minimising damage either as it happens or before it even occurs. The system is applicable in public spaces, on building sites and even inside properties. This method of interpreting heterogeneous sensor data (visual or acoustic) goes far beyond simple video surveillance and makes it possible to identify noteworthy situations with a high degree of accuracy. Anonymisation ensures that data protection is ensured and personal rights are protected.[105]

In the legislative process that produced the GDPR, there were discussions as to whether taking cybersecurity measures should be established in law as a legitimate interest of the controller.[106] Some argued that it was necessary to classify IT security as a legitimate interest that justifies processing of some data and applies horizontally across the Regulation (EP, 2013).[107] In its *Breyer* judgement, the ECJ determines the controllers may have a legitimate interest in *“ensuring the continued functioning”* of their services *“beyond each specific use”*.[108] Ultimately, the European legislator opted to include a general formulation in the GDPR rather than a catalogue of specific processing situations and therefore incorporated cybersecurity by referring to the purpose of ensuring network and information security in Recital 49 (Ueberfeldt, 2018). This recital makes specific mention of the *“availability, authenticity, integrity and confidentiality”* of stored and transmitted data. This can be understood as a reference to technical and organisational measures, as similar terminology is used in this context in Art. 32 of the GDPR. Consequently, Art. 32 of the GDPR should be read together with Recital 49. In this context, technical and organisational measures should be geared towards “the state of the art”.[109] This makes it necessary to consider the dynamic integration of cyber risks (BSI, 2017) and makes clear that data-security measures, including cybersecurity products, must be adapted to technical developments (Jandt, 2018).

[103] Art. 2 No. 1 of the Regulation on ENISA and on Information and Communications Technology Cybersecurity Certification.
[104] Art. 2 No. 8 of the Regulation on ENISA and on Information and Communications Technology Cybersecurity Certification
[105] Futher information: https://www.enbw.com/infrastruktur/sicherheitsinfrastruktur/geschaeftskunden/produkte/safeplaces [German only]
[106] See e.g. the justification for Amendment 886, proposed by Alexander Navaro, Nadja Hirsch in 2012/0011 (COD), Amendments (3) 886 – 1188.
[107] Justification for Amendment 892, proposed by Monika Hohlmeier in 2012/0011 (COD), Amendments (3) 886 – 1188.
[108] ECJ, Judgement of 19/10/2016 – C-582/14 (Breyer/Germany), NJW 2016, 3579 (3582).
[109] Art. 32 Para. 1 of the GDPR.

Using the phrase “state of the art” shifted the legal benchmark for permissible and offered products to the top of the list of priorities in technical development, as general recognition and practical application alone are not decisive in determining the state of the art.[110] Referring to the state of the art – in contrast to the “generally recognised rules of technology” – avoids the need for a technical procedure to gain recognition and reduces the time between new technical developments being achieved and implemented (Seibel, 2013). The state of the art specified here therefore requires continuous improvement, development and even redevelopment of technical measures to ensure an appropriate level of protection; the more the cyber risks grow, the greater the level of protection required (Ueberfeldt, 2018).

Overview and assessment

The security of information technology is regarded as a legitimate interest to collect and process data, including personal data in particular. Data may therefore also be processed in the case of camera surveillance in the physical world, provided that the principles of data collection and processing specified in Chapter 0 are observed. Cybersecurity products (including products based on AI) in the virtual world must be adapted and developed in such a way that they satisfy the requirements for the security of processing set down in Art. 32 of the GDPR. Consequently, although certain regulations exist in relation to data protection and especially data security, these represent minor hurdles. These regulations certainly do not represent knock-out criteria for the use of artificial intelligence for security measures in the physical or virtual world. The GDPR is therefore assessed as having a medium influence, meaning that – although a certain degree of effort is required – implementation is by no means impossible from a regulatory perspective.

Figure 44: Regulatory assessment of security measures

[110] cf. Federal Constitutional Court (BVerfG), decree of 08/08/1978 – 2 BvL 8/77, NJW 1979, 359 (362); in relation to the European definition of “the state of the art”, see omnibus law on the implementation of the amended EIA Directive, the IPPC Directive and further EC directives on environmental protection of 27/07/2001 (BGBl I, 1950); BT-Drs. 14/4599, p. 82, 125, 147.

Making it easier for active consumers to participate

The use of AI can support prosumers and other active consumers to increase their self-supply or to generate additional revenues through interaction with the grid and the energy market. The applications of this FoA are similar to those in the fields of predictions, operation optimisation and inventory optimisation. According to Section 3 No. 19 of the Renewable Energy Sources Act (EEG), self-supply is the consumption of electricity which a natural or legal person consumes themselves in the immediate vicinity of the electricity-generating installation if the electricity is not fed through a grid system and this person operates the electricity-generating installation themselves. A high degree of automation with the help of AI underpins the fundamental use cases in this field of application. Before this can be achieved, however, investments must be made in domestic sensors and data transfer agreements must be concluded (incl. access rights for the service provider). The principles of data processing (e.g. Art. 5 of the GDPR) and – in cases where processed data is transferred to a third country or an international organisation – the transfer of personal data (Art. 44 of the DSGVO) apply in this context.

Art. 6 Para. 1 Sentence 1 of the GDPR gives an example of lawful processing of personal data in the context of algorithm-based systems (performance of a contract; European Data Protection Board, 2019). It states that processing is permitted if it is necessary in order to perform a contract to which the data subject is party or in order to take steps at the request of the data subject prior to entering into a contract. A contract within the meaning of the GDPR should be understood to include all contractual obligations (Plath, 2018). However, the data subject must be party to the contract – a contract concluded between the controller and a third party is therefore not sufficient justification for data processing. However, it is not absolutely necessary for the controller to be party to the contract (Albers et al., 2018/Plath, 2018). The stipulation that data processing must be necessary to perform a contract does not mean that processing needs to be essential in the sense of absolutely imperative necessity (Buchner et al., 2018/Schulz, 2018). Instead, it is sufficient if, in due consideration of the interests of all parties involved, there exists no realistic and equally suitable alternative method to achieve the purpose of the contract without or with less data processing.[111] Determining whether data processing is necessary for the purpose of performing a contract according to the aforementioned criteria requires the application of objective criteria (European Data Protection Board, 2019/Buchner et al., 2018). This involves examining whether a direct connection exists between data processing and the specific purpose of the contract (Albrecht et al., 2016). The purpose of the contract must be determined from the objective standpoint of the onlooker (Albrecht et al., 2016).[112] It is therefore necessary to identify the essence (i.e. the specific characteristic) of the service offered (European Data Protection Board, 2019/Buchner et al., 2018). In any event, processing can be deemed necessary if it would not be possible to perform the contract without processing the data in question. If, however, data processing is only expedient or useful, in many cases it will not be deemed necessary in order to perform the contract (ibid.). Therefore, the goal of simply offering a better service, lower prices or faster processing, achieving higher customer satisfaction or providing tailored offerings on the basis of personalised information does not automatically constitute a necessary purpose within the meaning of Art. 6 Para. 1 Sentence. 1 of the GDPR (Buchner et al., 2018/Heberlein, 2018). Instead, such objectives can usually be justified using the legal principle of "legitimate interests" according to Art. 6 Para. 1 Sentence 1 of the GDPR or through consent according to Art. 6 Para. 1 Sentence 1 of the GDPR (Klar, 2019).

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[111] For more information, see European Data Protection Board, 2019: p. 7; cf. also Buchner et al., 2018.
[112] For more information, see Schulz, 2017.

Sensors also enable the collection and processing of motion data for a specific household. Weather data must also be acquired (cf. sections on predictions, operation optimisation) and technical data must be determined for the PV system and storage system. Subsequently, algorithm-based systems can *recognise* connections (e.g. between past PV power generation and the acquired weather data) and regularities in motion data over time and thereby *infer* behavioural patterns. This might involve allocating individual customers to groups of similar customers. Specific "customer data protection" is not part of the GDPR, nor does it feature in previous legislation such as the EU Data Privacy Directive[113] or the Federal Data Protection Act (BDSG). The BDSG treats all persons equally – with the exception of employees, who are subject to special regulations (Section 32 of the BDSG [old version] / Section 26 of the BDSG). Special statutory exemptions that require a contractual relationship in the same way as Art. 6 Para. 1 Sentence 1 of the GDPR apply to customers, suppliers and other contractual partners in equal measure. In business, (potential) customers are certainly the most interesting group of persons; end customers, usually private persons, represent a group that requires special treatment due to their quantity and their critical importance in data protection law. Customer data protection primarily consists of protecting data related to existing or former customers. By extension, it also applies to the data of potential customers. Worthiness of protection relates to the collection of data, e.g. by selecting customer groups; creating pseudonymised user profiles of website and app users with a view to advertising, marketing and sales activities according to Section 15 Para. 3 of the Telemedia Act (TMG) and Art. 8 Paras. 1, 9 and 10 of the impending ePR, such as tracking and retargeting; implementing and evaluating advertising campaigns aimed at individuals; engaging in address trading, and extensively using collected data, including enriching it with additional data ("big data"; Koreng et al., 2018). Using the data generated in this way, the AI can calculate (*recognise*) different charging options for storage systems based on the target value in the upcoming optimisation period and *infer* an optimal charging strategy.

Overview and assessment

The processing of personal motion data in households in the context of algorithm-based systems can be legitimated by the principle of contract performance according to. Art. 6 Para. 1 of the GDPR. This stipulates that processing is lawful so long as it is necessary and the data subject is party to the contract. Processing is deemed lawful if, in due consideration of the interests of all parties involved, there exists no suitable alternative method to achieve the purpose of the contract without or with less data processing. If, on the other hand, data processing is only expedient or useful, it may not be deemed necessary in order to perform the contract. If the data collected by sensors can be transferred using the service technician's contractually defined access rights, the AI can *recognise* similar motion data and behavioural patterns in households, thereby making it possible, for example, to allocate customers to different customer groups. The GDPR does not contain any specific protections for customer data. The regulatory system is therefore deemed to have a low influence on making it easier for active consumers to participate in the energy system. From a regulatory perspective, the use cases are therefore deemed to be highly practicable.

[113] EU Data Privacy Directive: Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data

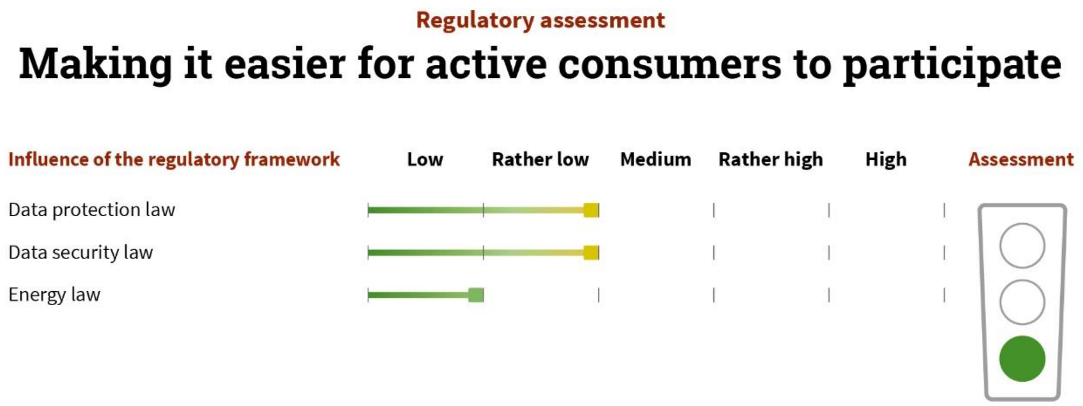

Figure 45: Regulatory assessment of making it easier for active consumers to participate

Customisation of products and marketing measures

The objective of this field of application is to design marketing measures and products specifically tailored to individual customers or customer groups.

In relation to automated decision making, Art. 22 Abs. 1 of the GDPR states:
"The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her."[114]

This does not apply if the decision is made with the express consent of the data subject or is necessary to conclude or perform a contract between the data subject and the controller. Profiling is defined as *"any form of automated processing of personal data consisting of the use of personal data to evaluate certain personal aspects relating to a natural person, in particular to analyse or predict aspects concerning that natural person's performance at work, economic situation, health, personal preferences, interests, reliability, behaviour, location or movements"*.[115] Profiling is subject to the provisions of the GDPR concerning the processing of personal data, such as the legal basis of processing or the principles of data protection. The European Data Protection Board established by the GDPR can issue further guidelines in this regard.[116]

Art. 22 Para. 1 of the GDPR presupposes that a decision is based solely on the automated processing of personal data (including profiling). Against this backdrop, it can be assumed that Art. 22 Para. 1 of the GDPR is actually not applicable in many cases (Dreyer et al., 2018) because the human influence is often still a factor in such processes (Martini, 2018) – even if the human habitually follows the output generated by the AI or is guided to a significant extent by this output in their final decision. Nevertheless, automated tools are increasingly coming to be used in the field of online marketing.[117]

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[114] See also Section 37 of the Federal Data Protection Act (BDSG)
[115] Art. 4 No. 4 of the GDPR.
[116] cf. Recital 72 of the GDPR.
[117] cf. Art. 29 Working Party, Guidelines on Automated Individual Decision-Making and Profiling, WP251rev.01, p. 24, last revised and adopted on 06/02/2018.

According to *Gausling*, a final human evaluation will become increasingly irrelevant in future and evaluation on the basis of Art. 22 Para. 1 of the GDPR will increase further as a result (Gausling, 2019). If a given form of processing, particularly a form using new technologies such as AI, presents a high risk to individuals' rights and freedoms, the controller – with the help of the data protection officer, if one has been appointed – must first conduct an evaluation of the consequences of the planned processing activities for the protection of personal data. This applies in particular to the analysis of personal data using profiling measures.[118]

AI is frequently used in the form of chatbots and digital assistants. In this context, it is important to inform the user of the purpose and scope of the processing of their personal data at the start of the chat or before they use a digital assistant in order to fulfil information obligations according to Art. 13 of the GDPR. Pursuant to Art. 12 Para. 1 of the GDPR, this user information must be provided in a concise, transparent, intelligible and easily accessible form, using clear and plan language. In the case of a chatbot, it is therefore recommended to indicate the processing of personal data in a very simple form in the chat itself, including a link to the data protection provisions containing the requisite information. In the case of digital assistants, this information must also be provided prior to the processing of personal data – and should therefore ideally be displayed prior to installation of the digital assistant and made available via the corresponding app or website (Gausling, 2019).

Overview and assessment

Data protection presents the greatest challenge to product customisation, in particular customisation through profiling (which involves using as much data – and primarily personal data – as possible). According to Art. 22 of the GDPR, data subjects have the right not to be subject to a decision based solely on automated processing. Nevertheless, personal data can be processed (including for profiling purposes) so long as the data subject is informed of the purpose and scope of processing and explicitly consents to this. The controller (with the support of the data protection offer, if applicable) must conduct an evaluation of the consequences and risks of processing. The applicable provisions therefore include several requirements that must be met; however, none represent insurmountable barriers in practice. The customisation of products and marketing measures with the help of artificial intelligence is therefore considered a highly practicable field of application.

Figure 46: Regulatory assessment for customisation of products and marketing measures

[118] Art. 35 Paras. 1 & 2 of the GDPR.

Process automation for measurements, bills and general distribution

Intelligent process automation can improve efficiency in various areas of sales and distribution (customer to supplier; supplier to customer; background supplier processes). This primarily involves repetitive, rule-based processes with high transaction volumes. AI routines in available software tools can use trial-and-error approaches and other methods to *recognise* rules and patterns in existing processes and adapt themselves accordingly.

Data protection law only applies to data collection and processing involving algorithm-based systems when personal data (including pseudonymised data) is the subject of processing. If, on the other hand, the processing only involves anonymised data, data protection law does not apply. In this context, the issue of how consumption data is handled is important. As described in Chapter 0, Art. 4 No. 2 of the GDPR defines the processing of data as an operation or set of operations which is performed on personal data, whether or not by automated means, such as collection, recording, organisation, structuring, storage, adaptation or alteration, retrieval, consultation, use, disclosure by transmission, dissemination or otherwise making available, alignment or combination, restriction, erasure or destruction. Thus, the automated collection and storage of meter readings by power supply companies as part of general distribution processes or to bill for a general energy supply agreement represents data processing. The disclosure of ultimate consumers' personal data by transferring such data to other market partners in the context of business processes in the energy industry, e.g. according to the definition of standard business processes and data formats for implementing electricity supplies to customers,[119] also represents a form of processing (Bartsch, 2018).

In the field of accounting and reporting, robotics provides numerous opportunities to make processes faster and more efficient and, in some cases, to improve their quality with the help of artificial intelligence. Specific examples of such automation currently include (Zülch et al., 2018/Diehm et al., 2018):

- recording incoming and outgoing material assets,
- recording core data,
- reconciling internal balances,
- financial recording of invoices, receivables and their settlement,
- calculating temporary differences between book values on tax balance and consolidated balance sheets,
- generating attachments,
- collecting and collating information in the form of finished reports, and
- accounts-related checks and audits.

[119] BK6–06-009 (GPKE); Order of the BNetzA of 11/07/2006 on the definition of standard business processes and data formats for implementing electricity supplies to customers, BK6–06-009. Current business processes have been replaced by Appendix 1 of Order BK6-18-032 and must be applied in the amended version as of 01/12/2019.

These automated processes are based on the use of software tools, such as Sage One, FreshBooks, QuickBooks Online, Xero and Sage 300 Online. The AI routines in these software tools have been improved through continuous human calibration and sometimes also involve ML (Beyhs et al., 2019).

As of 1 January 2020, the European Single Electronic Format (ESEF) has required all listed companies within the EU to publish their annual financial reports in a standardised digital reporting format. The technical standard specified by the ESEF is Extensible Hyper Text Markup Language (XHTML). The companies in question can embed data in the Inline eXtensible Business Reporting Language (iXBRL) format into XHTML.[120]

The application example of automated responses and hotlines (supplier contacting customer) is subject to similar requirements to the FoA customisation of products and marketing measures. If this entails exclusively automated data processing, the requirements of Art. 22 of the GDPR apply accordingly. In a chat or hotline, the processing of personal data must be indicated in order to fulfil information obligations pursuant to Art. 13 of the GDPR and the obligation to transparency pursuant to Art. 12 of the GDPR.

In this context, the issue of how consumption data is handled is also particularly important. If a given process involves storing electricity consumption data directly in an AI, the requirements of the Metering Point Operation Act (MsbG) apply accordingly. Section 19 of the MsbG exclusively permits the use of technical systems and components that satisfy the requirements of Section 21 and Section 22 of the MbsG for the purpose of the corresponding processes. According to Section 50 of the MsbG, both the DSO and the supplier are authorised to handle data for the purpose of billing.

General distribution processes include, for example, switching electricity supplier. This process could also be facilitated by an algorithm-based system. The legal basis for switching electricity supplier, billing and the supply contract itself are set down in Sections 20a, 40 and 41 of the Energy Industry Act (EnWG). The processes for switching electricity supplier are established in detail by the Federal Network Agency (BNetzA). The GPKE Regulation, in which the German Association of Energy and Water Industries (BDEW) defines current, industry-standard process standards, formally stipulates use of the EDIFACT format. AI could also be applied in a use case such as contract cancellation. In this context, the first thing to consider is that immediate confirmation is needed from the new supplier as to whether they can actually provide an energy supply and from what date. According to the current legal situation, this process must be concluded swiftly and must not exceed three weeks from the registration of grid usage if supply is to start within three weeks. Ultimate consumers must also be able to switch supplier free of charge. The definitions of the business processes in question serve to facilitate the mass-market implementation of the legal requirements of Section 14 of the Electricity Supply Grid Access Act (StromNZV) and Section 38 of the Energy Industry Act (EnWG) and of all processes involved in this context.

Overview and assessment

If personal data (often consumption data, e.g. for billing) is processed by an AI in the context of process automation, the requirements of data collection and processing set down in the GDPR apply accordingly – including for pseudonymised data, but not for anonymised data. Processes where the service provider offers a service to the customer, e.g. chatbots or a hotline, are subject to similar requirements to the customisation of products and marketing measures.

[120] cf. EU Directive 2013/50; ESMA, Final Report on the RTS on the European Single Electronic Format (2017); Henselmann et al. (2018).

In such instances, the processing of personal data must be indicated in order to fulfil information obligations pursuant to Art. 13 of the GDPR and the obligation to transparency pursuant to Art. 12 of the GDPR. The process of switching electricity supplier is subject to the legal basis set down in Sections 20a, 40 and 41 of the Energy Industry Act (EnWG) as well as the supplier switching processes established by the Federal Network Agency (BNetzA). As a fundamental rule, industry-standard process standards (e.g. GPKE Regulation) and process steps defined by the BNetzA should be observed when using artificial intelligence.
It is possible to apply AI in various processes in this FoA. The issue of practicability should be examined in each individual case. If data protection and data security regulations and regulations on process standards can be observed, there is enormous potential to implement AI-based process automation. Therefore, from a regulatory perspective, this FoA is considered to be highly practicable.

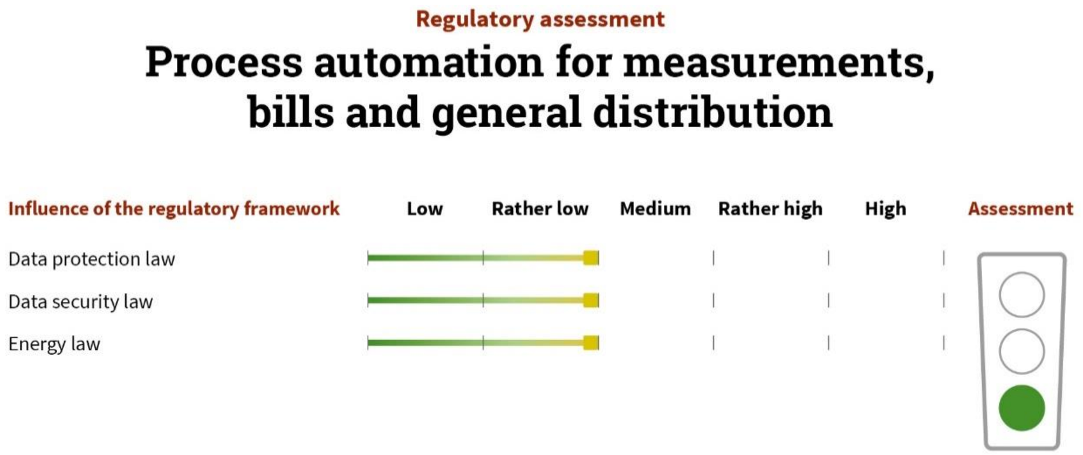

Figure 47: Regulatory assessment for process automation for measurements, bills and general distribution

3.4 Social assessment

Approaches to the social requirements of AI regulation at EU level provide the starting point for the present socio-political assessment. In June 2018, as part of its AI Strategy, the European Commission appointed a high-ranking expert group (Artificial Intelligence High-Level Expert Group, AI HLEG). This Group presented Ethical Guidelines for Trustworthy Artificial Intelligence on 8 April 2019. The AI HLEG acknowledged the potential of AI to be useful in a number of sectors, but also pointed to new legal and ethical challenges implicated in the use of AI. Against this backdrop, the AI HLEG defined the following key requirements that AI systems must fulfil to be considered trustworthy (EC, 2019b):

- Human agency and oversight
- Technical robustness and safety
- Privacy and data governance
- Transparency
- Diversity, non-discrimination and fairness
- Societal and environmental wellbeing
- Accountability

Dettling and Krüger consider further requirements for trustworthy AI to lie in a new and emerging field of regulatory law, namely AI regulation (see Chapter 3.3). In developing this new regulatory law, special consideration should be given to establishing a precise definition of AI, providing a clear understanding of the scope of protection and ensuring a rigorous legal structure (Dettling et al., 2019).

The EU Commission has already defined fundamental pillars for societal requirements in its Data Strategy.[121] Regulations implemented by EU member states should therefore ensure the following points (EC, 2020b):

- The flow of data within the EU must be secured across sectors.
- European regulations and values – in particular the protection of personal data, consumer protection legislation and competition law – must be observed unconditionally.
- Regulations regarding access to and use of data must be fair, practical and clear, and there must be comprehensible and trustworthy mechanisms for data administration. An open yet assertive approach to international data flows based on European values must be adopted.

A statement from the European Economic and Social Committee describes another European initiative related to ensuring an appropriate ethical and legal framework based on the values of the EU and in accordance with the EU Charter of Fundamental Rights. This initiative includes guidelines on existing product liability regulations, a detailed analysis of emerging challenges, and collaboration with interest groups in the European AI Alliance on the development of AI Ethical Guidelines (EC, 2018).

[121] In its White Paper on Artificial Intelligence of 19/02/2020, the EU Commission also referred to regulatory principles (p. 17): “As a matter of principle, the new regulatory framework for AI should be effective to achieve its objectives while not being excessively prescriptive so that it could create a disproportionate burden, especially for small and medium-sized enterprises. To strike this balance, the Commission is of the view that it should follow a risk-based approach.”

The assessment of socio-political requirements is based on the reflections of the AI HLEG on the AI Ethical Guidelines (EC, 2019a) and draws on the basis of the seven requirements for trustworthy AI established therein to examine the societal impacts of AI systems. This report has already examined two requirement areas in the technical and regulatory assessments, namely data quality management (see Chapter 3.3) and technical robustness and safety (see Chapter 0). This leaves five areas compiled into the four assessment indicators below. The indicators for the social assessment are:

- **Social benefit**
- **Transparency and traceability**
- **Self-determination and autonomy**
- **Fairness and non-discrimination**

The first indicator, **social benefit**, concerns the impacts of AI on sustainability, the environment and social interaction as well as other potential social benefits.

The key questions for the second indicator, **transparency and sustainability**, include how transparent the data basis is, the extent to which traceability and accountability are ensured in the use of AI, and how easy it is to explain the basis and results of an AI method. The German Institute for Standardization (DIN) and the German Commission for Electrical, Electronic and Information Technologies (DKE) are currently developing a roadmap to norms and standards for artificial intelligence as part of a collaborative project with the Federal Ministry of Economics and Energy (BMWi). This roadmap should provide an overview of existing norms and standards relating to key aspects of AI and thereby derive recommendations as to what activities are required in future. Improving trust in the technology and associated methods by creating greater transparency is a major focus of the project.

An examination of the third indicator, **self-determination and autonomy**, should reveal the extent to which decisions can still be influenced by humans and whether meaningful human-AI interactions are possible. Potential means of monitoring AI are relevant in this context.

Fairness and non-discrimination is the fourth and final indicator in this social assessment. Key issues for this indicator are the fundamental issue of ensuring data is handled with fairness within the AI, the consideration of biases in data and algorithms, and the extent to which it is possible to investigate and communicate biases.

Further interfaces with the other dimensions of assessment, such as accountability (see Chapter 3.3) or societal and environmental wellbeing (see Chapter 0), are not examined in further detail in the following social assessment.

3.4.1 General socio-political assessment of all fields of application

Social benefit

This report has already examined the social benefit derived from the contribution of AI to the integrated energy transition in the technical assessment. However, there are additional aspects of social benefit that are relevant to this socio-political assessment. These include the impact of AI applications on supply security and the resilience of the energy system (see Chapter 2.2.6). The participation of consumers in the energy market (see Chapter 2.2.7) also generates further benefits without a direct economic impact. Critical AI applications that can cause harm to society or offer no social benefit have not been identified in the fields of application in question here. Consequently, the assessment of the FoAs in relation to this indicator are generally positive.

Transparency and traceability of AI applications

The assessment of transparency within the individual fields of application concerns how transparent and traceable algorithms are for the users of AI technologies. Means of ensuring this vary depending on the user and the area of application, as does the assessment of transparency. System operators, marketers and electricity traders can use AI algorithms to achieve optimisations and are generally very well acquainted with these tools and the data involved. This relates in particular to the fields of application in the **General Foundations for Decision-Making** and **Maintenance and Security** clusters. At the same time, users can directly see the results and impacts of the use of AI and can therefore react immediately to any ambiguities in the results and ensure transparency. They remain responsible for the results of the use of AI, which ensures enduring accountability for the application of AI algorithms. These fields of application are therefore considered to broadly meet the requirements of this indicator. Initial approaches and concepts already exist to ensure the transparency and traceability of more complex AI methods in future by means of AI certification (Heesen, 2020). In this regard, the assessment on the basis of this indicator can be expected to remain positive in future.

Requirements of the explicability and traceability of AI algorithms and the ability to provide feedback primarily concern the developers of software algorithms and use cases in which cloud-based AI algorithms are used and there is no longer a single party responsible (e.g. maintenance systems operated by the manufacturer rather than the installation operator). Therefore, in order to fulfil transparency requirements, AI applications must also be made intelligible and explicable to people without specific IT expertise. Software companies therefore offer tools to make it easier to interpret and understand the output of AI technologies.[122]

Transparency requirements are most important in relation to the **Distribution and Customer Services** cluster, as this involves the use of end customers' personal data. Fields of application that aim to increase interaction with consumers and their participation in energy markets must fulfil transparency requirements so as not to hamper the distribution and implementation of corresponding systems. The GDPR has already set down which data can be used in this context and to what extent (see Chapter 3.3). The social requirements of AI are already taken into account in existing regulations, which is why existing applications are considered to have fulfilled them.

[122] e.g. AI Explainability 360 Open Source Toolkit, online at: http://aix360.mybluemix.net

The collection of end customer-specific data in households is still not widespread, meaning that the use of AI applications – and therefore the requirements for such applications to be transparent – only relate to a comparably small group of users. The re-use of person-specific data that a customer has independently provided on a vendor-neutral platform and that is therefore available to energy-efficiency service providers certainly entails greater requirements in respect of transparency and traceability. However, these requirements are already defined in the existing legal framework.

Self-determination/autonomy

The area of assessment concerning human autonomy and self-determination is highly significant for the **Distribution and Customer Services** cluster in particular. In this context, AI methods can make it easier for consumers to participate in the energy market and enable actors to act with autonomy, e.g. in community-based approaches. Individual preferences and local application optimisations can only be taken into consideration where it is highly cost-effective to do so. In this context, AI methods offer potential methods to use automation to implement autonomous trading processes for small installations and flexible consumers.[123]

In use cases in the **General Foundations for Decision-Making** and **Maintenance and Safety** clusters, AI methods are currently used mainly to support decision-making. This involves issuing recommendations for installation operators, grid operators, electricity traders and installation maintenance teams. Human self-determination and autonomy is therefore preserved. In the medium term, improved AI systems and more experience using AI can be expected to engender a significant increase in the degree of automation and the diffusion of AI technologies, which will in turn increase the pertinence of requirements related to self-determination and autonomy. At that point, it will be important to consider aspects such as facilitating meaningful interaction with AI systems and the ability to influence and examine decisions.

Fairness/non-discrimination

Fairness and non-discrimination are subjects of intense discussion in the context of AI. Over time, generally applicable recommendations and approaches have been defined to meet this social requirement.[124] However, these points do not play a critical role in AI applications commercially available in the energy industry at present. This is because the methods used do not involve AI taking autonomous decisions, with the technology instead restricted to supporting decision-making. It is incumbent upon the parties involved to take fairness and non-discrimination requirements into account. In the medium term, the increase in opportunities for AI to act independently will increase the potential for AI to yield benefits in the energy industry, such as in optimising grid operation. However, fairness and non-discrimination requirements will also increase as a result. Approaches already deployed in other economic spheres (e.g. in credit ratings and medicine) can be applied in this context. Instruments to promote fairness and non-discrimination can be implemented on the basis of data available to train AI systems. Evaluating the output makes it possible to identify and correct biases in the data. To achieve this, fairness requirements need to be defined and considered in the way data is implemented in AI methods.

The use of biased data to train AI systems is not the only cause of discrimination: AI algorithms can also display bias by failing to include certain possibilities in decision trees or implement them as potential solutions.

[123] e.g. shineHub, a digital energy management system for self-supply, which uses self-learning algorithms to optimise its service. For further information, see: www.shine.eco/presse/vollautomatische-eigenstromproduktion-mit-shinehub/ [German only]
[124] e.g. AI Fairness 360 Open Source Toolkit, online at: https://aif360.mybluemix.net

In the use cases in the **General Foundations for Decision-Making** and **Maintenance and Security** clusters, the application of AI primarily relates to technical or economic optimisations based on technical data. These fields of application therefore do not involve person-specific decisions, which means that fairness and non-discrimination are of lesser importance. In the **Distribution and Customer Services** cluster, however, these aspects are more relevant due to the frequent use of person-specific data. Therefore, as the diffusion of AI methods in this cluster increases, it is important to ensure that corresponding requirements are met. The same will apply if AI methods are increasingly used over cloud-based platforms in future, as this will share the responsibility for the use of AI across several stakeholders. Developers and suppliers of AI methods and service providers who support companies in the use of AI methods are already working on tools and management systems to meet these fairness and non-discrimination requirements.[125]

3.4.2 Social features of the fields of application

The following section aims to shed light on social issues apparent in the nine fields of application.

Predictions

Predictions and forecasts represent an important basis for the integration of renewable energies and can be improved significantly with the help of AI. AI is already in widespread commercial use in this field, with various stakeholders actively using the technology. Demands for transparency, fairness and non-discrimination have already been met, as the data used (incl. pricing, power-generation and weather data) is publicly available. Furthermore, evaluating forecasts in retrospect and comparing them with actual events makes it possible to examine their accuracy and provide direct feedback, which can be used to improve future predictions. Human self-determination is not compromised at present as forecasts and predictions are typically only used to support decision-making and are not used in fully automated processes.

Overall, based on the identified indicators, this field of application is considered to meet social requirements to a large extent – that is to say, from a social perspective, there are no critical aspects that hamper implementation of AI or represent knock-out criteria.

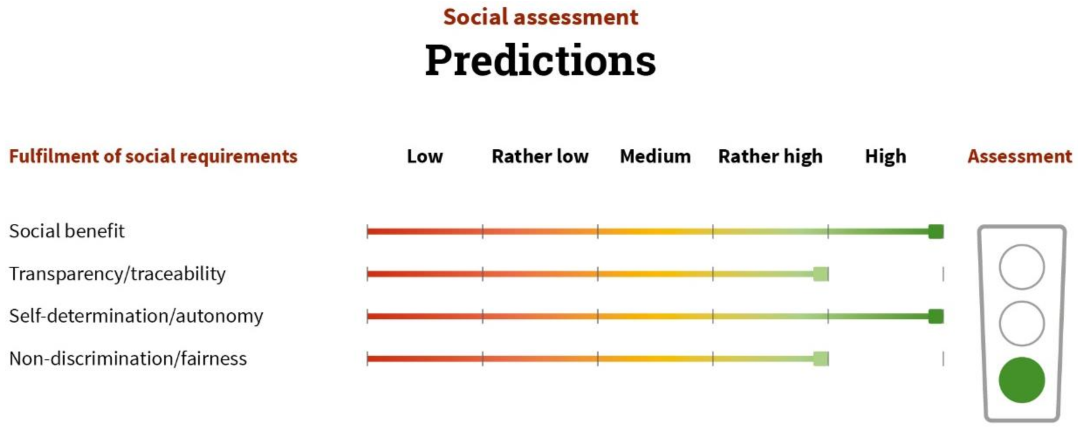

Figure 48: Social assessment of predictions

[125] In addition to the AI Fairness 360 Open Source Toolkit from IBM, corporate consultancies also offer comparable tools, such as CapGemini – Perform AI (https://www.capgemini.com/service/perform-ai/), KPMG – AI in Control (https://home.kpmg/xx/en/home/insights/2018/12/kpmg-artificial-intelligence-in-control.html) and Deloitte's Trustworthy AI™ framework (https://www2.deloitte.com/us/en/pages/deloitte-analytics/solutions/ethics-of-ai-framework.html).

Operation optimisation in generation and the grid

AI is expected to make a significant contribution to the optimisation of power grids by increasing grid utilisation while simultaneously preventing overloads. Another positive impact is the ability to avoid curtailment due to grid congestion when using renewable energies. In addition to the impacts examined as part of the technical assessment, the use of AI in this FoA can also increase supply security and thereby generate an additional benefit. Gathering experience and gaining knowledge of grid states and grid behaviour in the form of meter data presents an additional social benefit, as it can be used to train new employees and help them earn qualifications. Digital twins of grid topology can also be used to gather experience of events and occurrences that only occur rarely in real grid operation. Making it easier to identify critical grid states and system failures can also improve employee safety, e.g. by enhancing employee protections in maintenance and repair operations.

AI can support operational management of the grid by identifying critical grid situations based on a range of grid status data and inferring recommendations of suitable actions for implementation by operational managers. In future, however, we should expect AI applications to implement operation optimisations in automated processes. In addition, potential applications for AI are being developed with the aim of enabling AI to control consumer devices in the low-voltage grid. The criterion of transparency and traceability is more significant in this context as it involves AI technologies making independent decisions. The requirements such applications must meet are the subject of intense discussions at European (EC, 2020a) and national levels. For critical infrastructure, certifying AI applications represents a suitable approach and has been the subject of considerable discussion. Grading the differing security requirements using a criticality pyramid as proposed in a report from the Federal Government's Data Ethics Commission (BMI, 2019) would make it possible to draw distinctions between the applications to be certified. This would make it possible to define appropriate requirements tailored to each FoA; AI applications with less potential to cause damage (e.g. plausibility analyses of smart-meter data) could therefore be subject to far more lenient requirements than applications with greater potential to cause damage (e.g. automated redispatch instructions at power-generation installations). Comprehensive regulations for iMSys already exist in the context of the Metering Point Operation Act (MsbG) (see Chapter 3.3).

Optimising the operation of power-generation installations without taking grid status into account can result in critical situations. AI can be used in this context to achieve more stable grid operation and greater resilience. In cases where more complex AI methods are applied, there is often little transparency into the results.

In this respect, ensuring that AI is transparent in this field represents an important research topic and would enable AI to be used to enhance grid resilience and optimise the behaviour of installations in different electricity markets. Commercially available systems are currently less complex and only serve to support decision-making. In that they do not implement any measures of their own accord, human self-determination and autonomy are not compromised (Nowak, 2020).

Installations in the low-voltage grid are allocated to individual households and therefore to individual people, which is why questions of fairness and non-discrimination need to be taken into account in the use of AI in this area. Although these requirements have already been incorporated into the regulatory framework, it remains to be seen how well they will be implemented in practice in the use of AI methods to optimise operations at the household level.

Overall, an assessment of the individual indicators suggests that the social requirements have been fulfilled to a high degree.

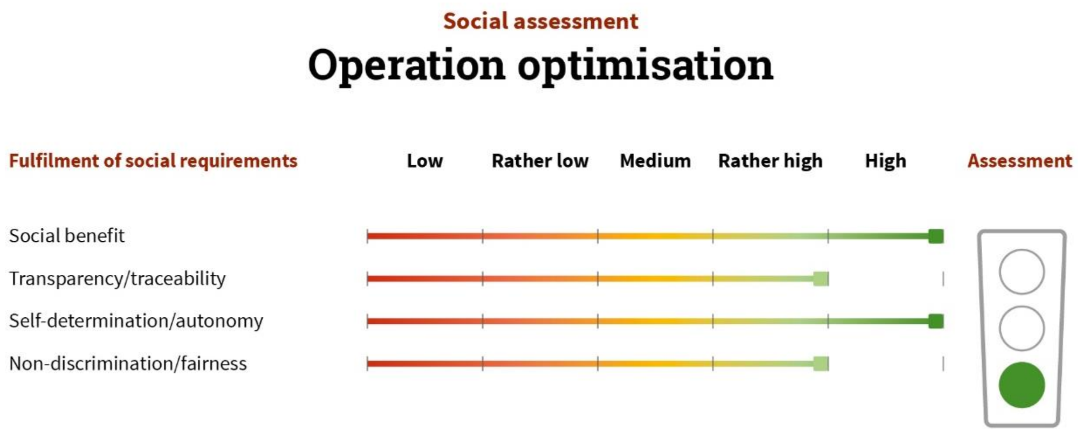

Figure 49: Social assessment of operation optimisation

Inventory optimisation and other strategic business decisions

In addition to aspects of social benefits examined in the technical and economic assessments (incl. better location planning, grid expansion in line with needs), there are further positive effects in this FoA through optimised utilisation of grid capacity and resources. Due to the potential already tapped in relation to power generation through existing data-collection systems (incl. SCADA systems) and analyses using non-AI methods, the additional potential positive impact through the application of AI methods here is considered to be less significant than in relation to the grid. The use of digital twins in combination with operational optimisations makes it possible to test and validate the results of a specific inventory optimisation without applying AI in the real system. Insights derived from the virtual system can then be used as a basis for making amendments in the real system.

In this FoA, AI methods are typically applied by the user (installation operator or grid operator), who uses the AI output to support their decisions. Transparency, fairness and non-discrimination requirements play an important role in creating trust in these applications, ensuring that the recommendations derived from AI methods can be implemented in practice.

However, such requirements are not considered critical in the actual implementation of these applications as they do not generally involve the use of personal data. The decisions in this FoA are also taken by humans, which means than human self-determination is not compromised.

Overall, on the basis of the specified indicators, this FoA is considered to fulfil social requirements to a high degree.

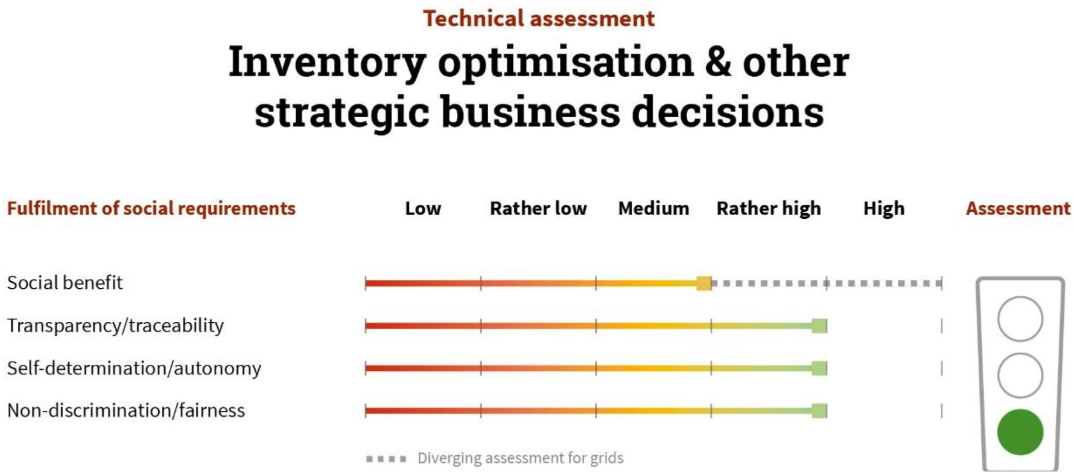

Figure 50: Social assessment for inventory optimisation and other strategic business decisions

Predictive maintenance

Use cases for predictive maintenance relate in particular to the optimised planning of maintenance and repair measures. As a result, this FoA has numerous linkages with the field of maintenance, repair and dismantling, which focuses on how measures are implemented and is examined in the next section. Further social benefits exist in addition to the efficiency gains and economic benefits derived from the use of AI in this FoA. The use of AI methods has positive impacts, for example, for the safety of maintenance personnel if the use of AI can reduce unplanned repairs by minimising failures and disruption in grid operation. In general, the risk of employees suffering accidents is significantly lower during planned maintenance than unplanned repairs.

Transparency and traceability requirements can be deemed to have been met in this FoA if the users of AI own and provide the training data and also review proposed AI measures and output in detail prior to their implementation. However, greater automation of predictive maintenance processes can initially reduce transparency and traceability for users if they are not integrated in the development of AI methods. Specific tools are available for precisely this eventuality; they aim to prevent the use of AI methods becoming a black box and enable the user to understand the output. If status-based maintenance concepts are to be implemented for critical infrastructures on the basis of AI recommendations, AI certification offers a potential means of creating transparency and traceability.

This FoA is also considered to maintain a high degree of human self-determination, as AI is used to support decision-making and does not make decisions independent of humans. The aspects of fairness and non-discrimination are less important in this field of application as it involves the use of technical rather than personal data. Reviewing the input data and the recommendations derived from it makes it possible to identify and correct discrimination.

On the basis of the indicators, social requirements are deemed to be able to be fulfilled to a good extent in this field of application.

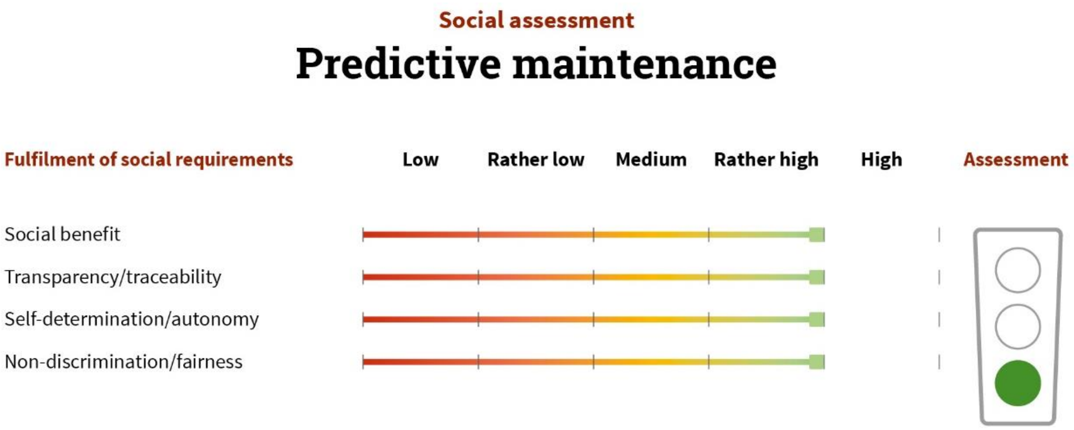

Figure 51: Social assessment of predictive maintenance

Maintenance, repair and dismantling

This FoA provides a social benefit for maintenance personnel and engineers thanks to the safety enhancements made possibly by the use of AI applications to support maintenance operations. Transparency and traceability are ensured in this FoA because the user provides the data, conducts the analyses and draws conclusions when faults are detected. For instance, AI users collect images of faulty components in the distribution grid and use these to train AI systems to detect faults. The user then examines the output and the conclusions reached using AI methods.

Complex AI methods such as expert systems require software developers to implement system transparency in a user-friendly way. One example of this is classification algorithms based on AI, where developers should present the significant input data for classification in a transparent and traceable manner. Where AI applications are used via service providers or cloud-based platforms, these service providers and software developers must meet additional transparency and traceability requirements. Corresponding tools do exist to explain AI output to the users of such technologies. Human self-determination and autonomy are not impaired in this FoA as the responsibility for decisions ultimately still lies with humans. In this context, AI serves only to support human decision-making. It is also easy to ensure fairness in this FoA as the users of AI systems generally provide data themselves and can therefore identify and correct any biases.

The fulfilment of social requirements in the field of maintenance, repair and dismantling is rated as high overall across all indicators.

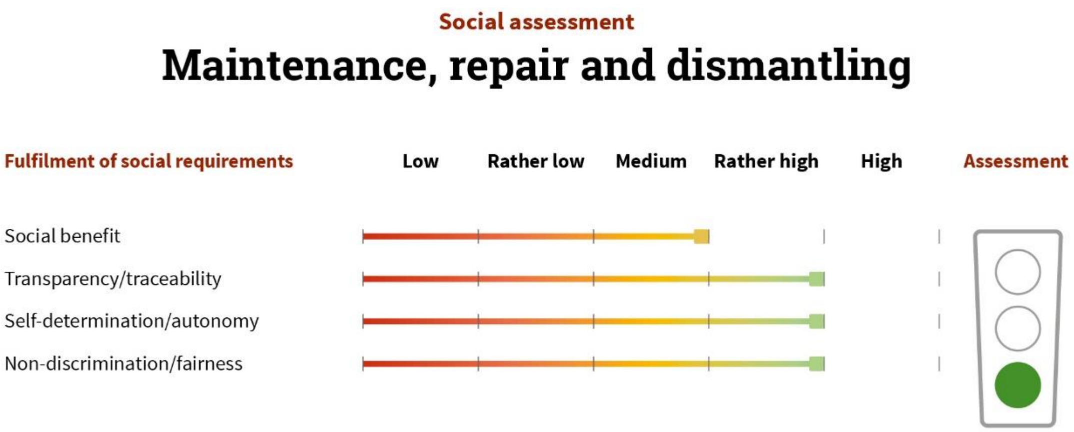

Figure 52: Social assessment for maintenance, repair and dismantling

Security measures

Increasing the resilience of energy systems is a very important aspect of AI and can involve using digital twins to identify critical system statuses in a virtual system and thereby derive measures for implementation in the real system. AI applications can help to uncover improper conduct on the part of market actors faster and with greater precision (e.g. by identifying systematic deviations in balancing groups).

Concurrent with the other fields of application in the **Maintenance and Security** cluster, transparency and traceability can also be ensured in relation to security measures if the users of AI systems can provide training data themselves and examine the output directly. However, in complex systems and models with an array of input data and variables, e.g. grid status models, the need for transparency increases the requirements placed on the AI methods used. Consequently, this issue is a focus of current research projects. AI certification represents one method of meeting these requirements, but such a system still needs to be fleshed out further. In this FoA, users remain responsible for their decisions and use AI systems as a tool to support decision-making. However, if AI increasingly comes to be used in automated processes, stricter requirements will have to be implemented for the task of examining the input data and AI methods for biases and making corrections as required. As it is possible to implement such requirements in this FoA, the fairness indicator is considered to be fulfilled to a high degree.

Following examination of the individual indicators, AI applications in the field of security measures are considered to be able to meet social requirements effectively.

Figure 53: Social assessment of security measures

Making it easier for active consumers to participate

As a field of application, making it easier for active consumers to participate is considered to offer significant social benefits as it uses AI to enable consumers to participate to a greater extent. Customer engagement platforms are among the approaches that aim to increase consumer integration. The implementation of corresponding measures is based on AI methods that learn user preferences and automatically take a number of framework conditions into account. Existing approaches give users the opportunity to communicate their preferences and thereby participate in superordinate electricity markets. Consumers are disclosing more and more personal data in this and other FoAs in the **Distribution and Customer Services** cluster, especially in comparison to the other three clusters. The issue of data disclosure is therefore growing in significance. Local optimisations and a decentralised approach can ensure that this data remains decentralised with AI users. This generally makes it possible to handle data safety and provide transparency and traceability.

Relevant data only needs to be disclosed to superordinate or other coordinating actors in the context of electricity trading and grid operation. The aim of AI applications in this FoA is to afford energy consumers greater self-determination and autonomy. AI helps users to take their own power consumption preferences into account and apply this insight in the context of trading and grid operation, e.g. by communicating available flexibility.

Practical example: OFFIS – using distributed swarm intelligence to optimise RE integration by drawing on decentralised flexibility

The flexibility of battery storage systems makes it possible to compensate for short-term fluctuations in supply-dependent wind and photovoltaic power plants and bring energy supply in line with demand from domestic, commercial and industry consumers. In order to make the best possible use of today's still comparatively expensive storage systems in both economic and technical terms, OFFIS is developing approaches to enable multi-purpose use of battery storage systems in close collaboration with Leibniz University Hannover and be.storaged GmbH. This involves networking individual battery storage systems to form a swarm and offer the resulting flexibilities on different markets. OFFIS uses modern machine learning and distributed artificial intelligence systems to analyse, forecast and optimise potential flexibility decentrally for individual users.[126]

AI processes tend to be automated to a greater extent in this FoA, which makes it important to satisfy the criterion of transparency and traceability. In that concepts for fair and transparent AI currently under development pick up on these requirements, fulfilment of the non-discrimination indicator is also assessed as being rather high.

Overall, an examination of the indicators shows that social requirements are fulfilled to a high degree in this FoA.

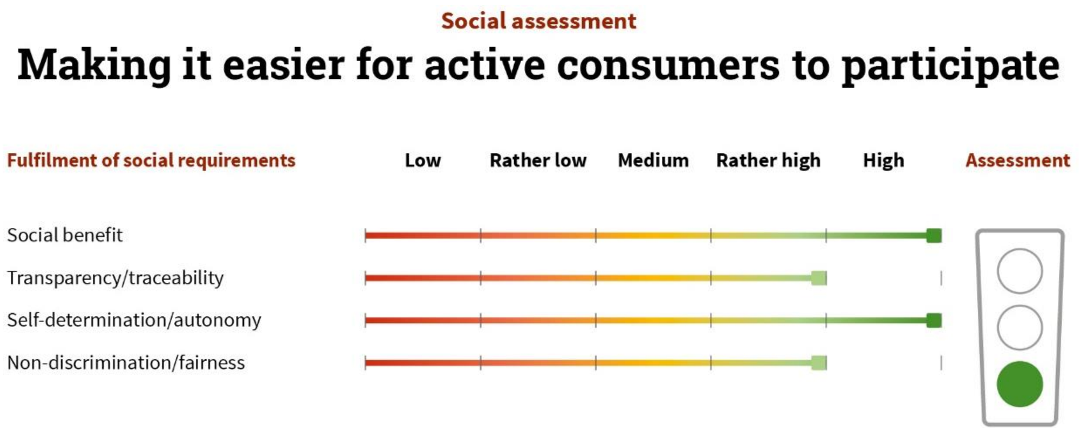

Figure 54: Social assessment of making it easier for active consumers to participate

[126] Further information: https://www.offis.de/en/offis/project/mirage.html

Customisation of products and marketing measures

For companies, the benefits of customising products generally involve increased customer interaction, higher customer satisfaction and, as a result, greater customer loyalty. The most significant benefit for the energy transition lies in the ability to implement energy efficiency measures and increase the appeal of renewable energies. However, these positive impacts and further social benefits directly attributable to the use of AI in this FoA are considered to be rather minor.

AI can certainly contribute to fostering increased social interaction in this FoA and propose specific measures, including in relation to energy efficiency. However, only a handful of use cases with demonstrably significant benefits have been identified in this FoA to date.

Moreover, this FoA draws on personal data more heavily than any of the other fields of application, which makes transparency and traceability requirements particularly important. End customers also need to be given the opportunity to provide feedback on the output of AI methods, as they are not usually the direct user of AI methods and instead only see their output. The GDPR and Federal Data Protection Act (BDSG) already provide an extensive regulatory framework containing information obligations and regulations on automated decision-making (see Chapter 3.3).

Human self-determination and autonomy is significantly affected in this field of application, as product suggestions and marketing measures are increasingly generated by AI in automated processes. This field of application is subject to stricter fairness and non-discrimination requirements than other FoAs, as the developers and users of AI systems are not also the parties affected by AI decisions.

This field is therefore considered to fulfil social requirements to a medium extent, in part because the social benefits are regarded as rather low.

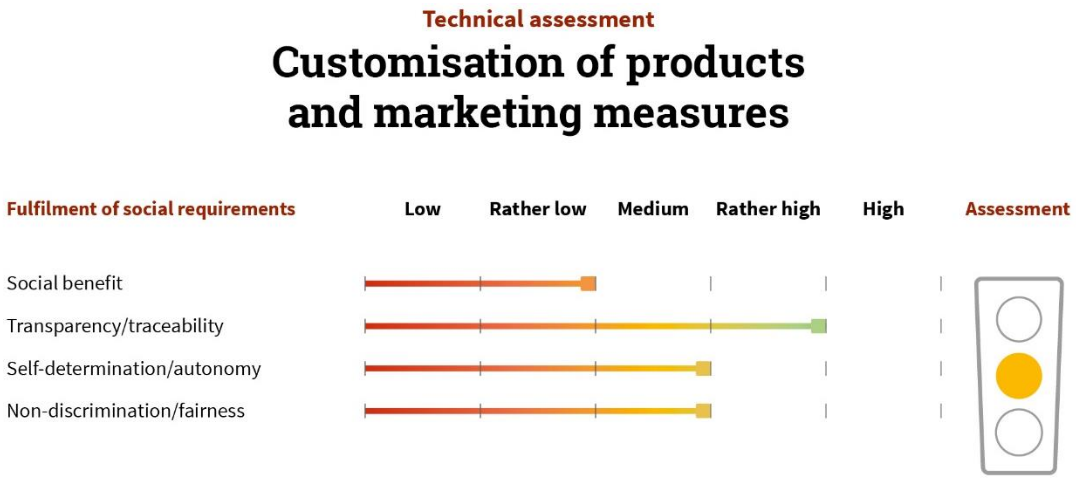

Figure 55: Social assessment for customisation of products and marketing measures

Process automation for measurements, bills and general distribution

General efficiency gains in market and distribution processes in the energy industry (see practical example) represent a social benefit in this FoA. Various applications for AI also exist in relation to grid operation, e.g. schedule communication. However, process standards already exist in this field and can deliver efficiency gains without the use of AI.

If AI facilitated autonomous actions and decentralised optimisation, this would represent a further benefit in this FoA. However, the benefits that using AI offers to society and the energy transition in this FoA are considered less significant than in other fields of application.

Practical example: eprimo – fast customer support thanks to Sophie the chatbot

At eprimo, Sophie is a chatbot familiar with all key service issues. She is capable of responding to general customer enquiries about energy supplies, processing standard requests such as changing contact details, calculating discounts and handling due dates such as meter readings. The automated online adviser is able to settle nine out of ten enquiries that can be allocated to a known issue. In late 2019, eprimo recorded 50,000 to 70,000 chats per month. Chat requests saw a further slight increase during the lockdown brought about by the COVID-19 pandemic, with Sophie taking care of around 3,000 customer contacts per day in April 2020. The one-million-chat milestone was reached at the end of April 2020.[127]

As in the field of customising products and marketing measures, this FoA also uses end customers' personal data, which means that transparency and traceability requirements are particularly relevant. However, these requirements are already effectively addressed by the existing regulatory framework (GDPR, MsbG, EnWG). Self-determination and autonomy are subject to caveats in this field of application because, although the responsibility for decisions remains in human hands, these decisions are increasingly influenced by process automation. The application of AI methods in this FoA is subject to elevated fairness requirements due to the use of personal data. Various actors are involved in the development and use of AI in this FoA. Furthermore, the end customers whose data is used are ultimately not party to the development of AI applications or examinations of their output. There is therefore considered to be little verifiability of biases or measures to correct them.

In summary, on the basis of the specified indicators, the fulfilment of social requirements in this field of applications is rated as medium.

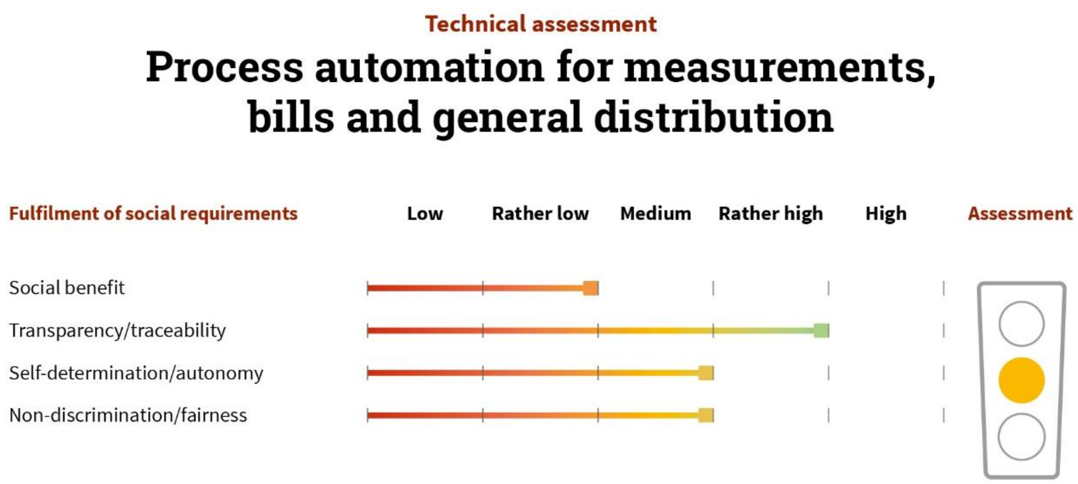

Figure 56: Social assessment for process automation for measurements, bills and general distribution

[127] Further information: www.eprimo.de/hilfe/unser-service/eprimo-ist-fuer-sie-da/wer-ist-sophie-und-wie-hilft-sie-mir-weiter/42c0e2bd62d41a490162d8d8f5a2512a [German only]

Summary of the social assessment

In contrast to the application of AI in other areas (e.g. the healthcare sector or HR management), it is broadly possible to satisfy social requirements of the use of AI in the energy industry. Exceptions do exist, including certain applications that independently make decisions (including regarding people) rather than serving in a supporting role. However, where this is not the case, the requirements of human autonomy and self-determination are not critical. Many AI-assisted processes only use generally available data and technical data on power-generation installations and grid resources – and do not require personal data. Integrating users of AI systems closely in their development, training and validation is vital to ensure that transparency and traceability requirements are met. If the users of AI systems are not integrated in these processes, it is essential that the suppliers of such systems make sure that corresponding criteria are met. This aspect will become particularly important if software manufacturers increasingly supply platform-based AI methods to users with little expertise in such systems who then apply them in the energy industry. The use of personal data also entails stricter transparency requirements. In such instances, the benefits of using AI and the workings of AI systems must be clearly identifiable and transparent. Furthermore, it must be ensured that AI methods used are ethically sound and trustworthy.

4 Evaluation and outlook

4.1 Summary of all fields of application

The in-depth analysis shows that AI can not only make a crucial contribution to the successful transformation of the future of the evermore digital energy system, but is in fact indispensable. Relevant steps were identified for the various actors in the ecosystem to demonstrate the technology's contribution in this context. To begin with, the key statements about the three clusters (general foundations for decision-making, maintenance and security, distribution and consumer services) were summarised before recommended courses of action were suggested on this basis.

Favourable conditions for the use of the AI potential by the energy sector

The evaluation of the nine fields of application in Figure 57 makes it clear that AI has a very broad range of possible uses in the energy sector and that there are numerous opportunities for the sector. At the same time, we have to deal with a complex decision-making arena for an effective and efficient diffusion path in the various energy industry processes; this covers the speed of implementation, the reliability of the application and trust in this as regards data security and data protection, the comparison with regulatory expectations and requirements of the energy system as well as the possible application scope, including its benefit promise and social acceptance. This decision-making process relies heavily on the individual case and cannot be defined and decided globally for all AI application cases. Nonetheless, individual framework conditions must be designed and positioned such that they are equally beneficial to several application cases.

Figure 58 relates the contribution made by AI to the integrated energy transition and the technical developments and economic assessment relative to the nine fields of application. It can be seen that the "General Foundations for Decision-Making" cluster in particular, with the fields of application **Predictions (1)**, **Operation optimisation (2)** and **Inventory optimisation (3)** does or could make a big contribution to the integrated energy transition and, in view of the implementation of projects that are already successful, already has a place on the market, or is under development.

In the same way, the overview shows that the situation is somewhat different in the "Maintenance and Security" cluster with the fields of application **Predictive maintenance (4)**, **Maintenance, repair and dismantling (5)** and **Security measures (6)**. Both the contribution to the integrated energy transition as well as the cost-benefit relationship, the result of technical and economic factors, is rated lower than in the first cluster. There are no major social impediments for the fields of application in both clusters, through **Operation optimisation (2)** and **Security measures (6)** do have to contend with some regulatory challenges.

With a focus on the third cluster “Distribution and Consumer Services”, in which the fields of application **Making it easier for active consumers to participate (7)**, **Customisation of products and marketing measures (8)** and **Process automation for measurements, bills and general distribution (9)** are summarised, it is clear that social factors become more important whereas regulatory barriers are almost irrelevant. The contribution to the integrated energy transition varies throughout these different fields of application. For example, **Making it easier for active consumers to participate (7)** is ascribed a huge potential for the transformation of the energy system, whereas the use of AI for **Process optimisation (9)** and for **Marketing purposes (8)** primarily strengthens the business side of a company.

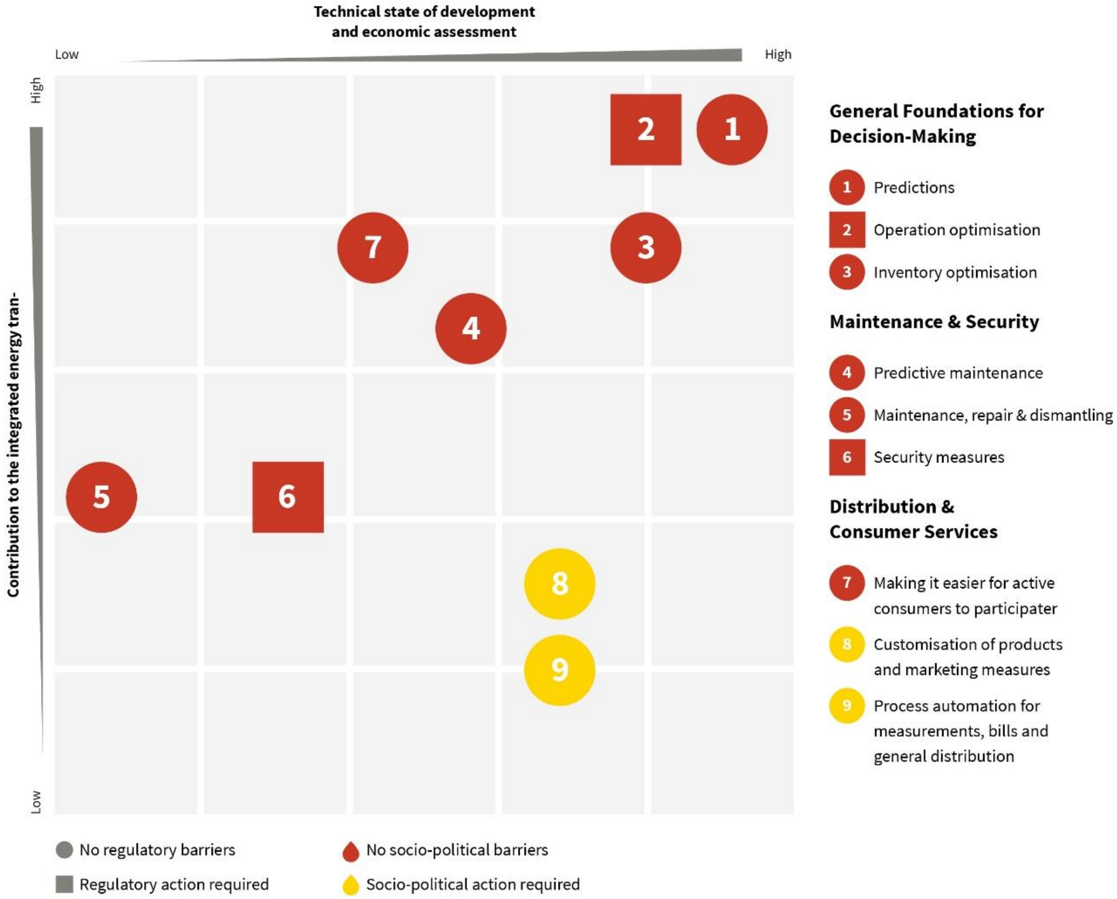

Figure 57: Summarising assessment of the fields of application

Cluster "General Foundations for Decision-Making":

AI in principle provides a very powerful and innovative basis for optimisations within the energy industry inasmuch as its use allows the evaluation of an increased amount of data and it can be used as a basis in planning and implementation decisions. With the expected greater dissemination of sensor data (smart meter roll-out, IoT) and integration of alternative data sources (weather data, structural data etc.), it can be assumed that the data basis for the development of AI-supported processes will continue to grow significantly over the next few years. This is particularly necessary for grid status predictions as well as in the optimisation of operations and inventories for electricity grids, for example. There is often a lack of necessary measurement data from the lower grid levels and flexible consumers, power generators and stores here. Based on this kind of data, **Operation optimisation (2)** can help manage congestion in the grid so as to avoid grid congestion (Redispatch 2.0). This will become particularly relevant when an increasing number of small-scale power generators and a large number of controllable consumers are connected to the grid in future. Corresponding regulations already exist (cf. the Grid Expansion Acceleration Act (NABEG) to accelerate the expansion of national and international extra-high voltage lines). Variable tariffs can also contribute to exploiting the full potential of these small-scale actors and further implementations. The use of AI allows a very large number of individual parameters to be taken into account during pricing.

The integration of a large amount of data (GIS data, price time series for electricity and other energy sources, historical usage data etc.) is used in **Operation optimisation (3)** in the training of AI models, for example for location planning and needs-based grid planning over a longer period of time. Although this often calls for a higher modelling effort and computing power than former methods, this is justified for complex planning tasks (e.g. the targeted expansion of a charging infrastructure) through the much better results. One aspect that is regarded as very technically mature and economically attractive is AI-supported **Prediction (1)**. Thanks to a more accurate marketing of RE products, additional insights into the grid capacity utilisation at the lower voltage levels and a clearer understanding of the demand for electricity and development of loads, AI can make a significant contribution to the integrated energy transition and at the same time serve as a basis for other AI fields of application. In general, regulatory and social requirements are not a great impediment in this cluster. Existing energy industry regulations, in particular the GDPR on data protection and the MsbG, have to be observed. Because AI does not take its own decisions in this case, but is only used as a supporting measure, compliance with fairness criteria and human self-determination by the user has to be checked and cannot be guaranteed by AI itself.

Cluster "Maintenance & Security"

The algorithm-based processes for the use of robots, drones and assistance systems that are used in this technologically demanding and capital-intensive cluster are based largely on internal company data. Consequently, there is no need to collect and check the quality of external data. Most of the applications in the field of automated maintenance and testing (security) are still at the research stage. However, their appeal and consequently their dissemination is likely to increase in the coming years with an expected cost degression. Simple AI regression and classification models are used for the promising applications in **Predictive maintenance (4)** and are currently being developed on the basis of existing sensors.

But since high initial investments are also needed here so that the models can be used (e.g. drones, robots), this could hamper the development and/or dissemination of the applications. The same applies for **Maintenance, repair and dismantling (5)**, where the use of drones and robots is a key application. Since the costs of maintenance robots, smart assistance systems and drones are expected to drop in future, AI-supported maintenance processes (such as detecting faults by means of augmented reality or drones, the use of expert systems, the independent performance of maintenance processes by robots) are likely to make an economic contribution too by lowering costs through needs-based maintenance, increasing the reliability of supplies and reducing the risks for maintenance staff. Both predictive maintenance as well as maintenance, repair and dismantling help to avoid unnecessary outage and downtimes for plants, thus increasing their profitability.

In these two fields of application, the use of robots, drones and assistance systems is the crucial factor for the technical complexity of AI. If used for **Security measures (6)**, on the other hand, the complexity is primarily increased by the necessity of an autonomous AI that should avert possible attacks on and consequential damage to the energy system. The regulatory requirements are particularly high at this juncture in view of the requisite data security because the majority of infrastructures are critical. It is therefore essential that suitable security measures are taken in this AI-supported FoA, which significantly increases the effort for any implementation. The resilience of the energy system can be strengthened by the use of AI as preliminary work for the use of AI in other fields of application (making it easier for active consumers to participate, smart grid operation with a variety of power generators and flexible consumers). In addition, efficient AI methods boost confidence in the system change and thus contribute to the energy transition.

Cluster "Distribution & Consumer Services"

Consumer services that are improved by AI are the focus of this cluster. The involvement of customers necessitates the processing of personal data and the associated higher number of actors who are directly affected make the social requirements more relevant. Compliance with the GDPR and Federal Data Protection Act (BDSG) in particular is a basic requirement for the **Customisation of products and marketing measures (8)**. These kinds of processes and developments (e.g. AI-supported micro-targeting or natural language processing (NLP) systems such as Amazon Alexa) are already very widespread in a number of industries and make a significant contribution to the turnover of the companies involved. The energy sector can build on experiences from other industries here and corresponding measures can increase the appeal and fit of energy products (such as electricity tariffs for specific target groups, PV storage systems or building efficiency software), for example. Conversely, the focus of **Making it easier for active consumers to participate (7)** lies in making established energy industry processes that are controlled by AI (e.g. prediction, combined generation and storage of PV power) economically accessible to smaller actors too. This can facilitate their interaction with the energy market, or even make it possible for the first time. New business segments can thus be opened up and the number of actors in the market increased in the long term by simplifying processes. The use of AI in this field is restricted by the limited number of controllable consumers that currently exist and the as yet inadequate efficient and standardised measurement and control infrastructure. Just as important for a future decentralised energy landscape is the **Process automation for measurements, bills and general distribution (9)**.

The use of the technology in this FoA helps make existing processes more efficient (time, resources) and thus more economical, which in turn paves the way for other AI applications that only become technically and economically feasible through greater automation in this field (for example, the automated assessment of customer contact using NLP). Apart from the direct contribution to the integrated energy transition by the simplified provision of flexibility and the even better integration of RE by smaller actors in sync with the demand for electricity, a further added value can be achieved here through the increased demand for RE by targeted advice or variable tariffs.

4.2 What remains to be done? – The next steps for AI in the energy industry

AI promises to make a particularly big contribution to the energy transition wherever complex systems are already feeling the pressure of digitalisation and/or at the same time, where a large amount of data is available for a more effective settlement of the system and better evaluation of the data. Early action as regards the obstacles in individual fields of application also opens up the possibility of using AI technology in the energy industry in future in the intensity that is needed for a successful energy transition. Established fields of application should be strengthened and the potential offered by currently less widespread applications improved. Transparency and sustainability requirements of the AI process have to be placed at the forefront at all times and attention focused on the relationship between the demand for resources and energy, and the benefits of AI to put a positive slant on the fundamentally appropriate and important discussions about AI-driven process developments. The political sphere has to define proper framework conditions in this respect, but companies are equally called upon, inasmuch as they should regard a more considerate handling of the resources needed to establish and operate digital technologies as a profitable image factor.

What is most important is that the individual actors independently force the use of AI, which can make a contribution to the integrated energy transition. At the same time, they should be networked and joint projects should be carried out. Stakeholder dialogues and joint projects have the advantage of ensuring an exchange of experience between the actors during the establishment of AI without losing sight of the overriding goals. An effective exchange of knowledge about the importance of the data basis and the necessary digital infrastructure (computing power) for various AI projects can also take place in talks. It is essential to establish a basic understanding for the creation and use of AI in all value-creation stages and at all hierarchical levels of the corporate landscape. AI is not a technology that can be integrated in corporate processes primarily by a classic make-or-buy management decision; in the majority of cases it is more of an effective composite work by technology experts in collaboration with the company's own teams of specialists. Only the specialists in each sector are able to judge whether processes that are to be replaced by AI or new processes will satisfy the intended purpose and whether the set goals can be achieved effectively and to a high quality. The permanent training and further development of an AI will shift the focus of work and sphere of responsibility of the specialist teams over the coming years.

4.2.1 Anchoring AI in the energy industry: everyone has to pull together

Different factors are of importance when creating an order that gives actors from the economy, research and politics a guide as to which action has to be taken. In addition to an estimation of which contribution a recommended course of action can make to the successful transformation of the energy system, the complexity of the implementation as well as its duration also play a major role. Furthermore, it has to be ensured that the relevant actors are addressed by the respective measures. This is where not only commercial enterprises but also research and politics come in.

The thematic field of artificial intelligence is currently very dynamic, even though there has not as yet been any broad knowledge formation. Overriding measures thus have to be employed in equal measure to strengthen the technical competence and put the technology to practical tests in the energy sector. In a first step, Figure 58 illustrates recommendations that are of overriding general interest for the sector, whereas Figure 59 presents some suggestions intended to make a positive contribution to the development of concrete fields of application in the energy sector.

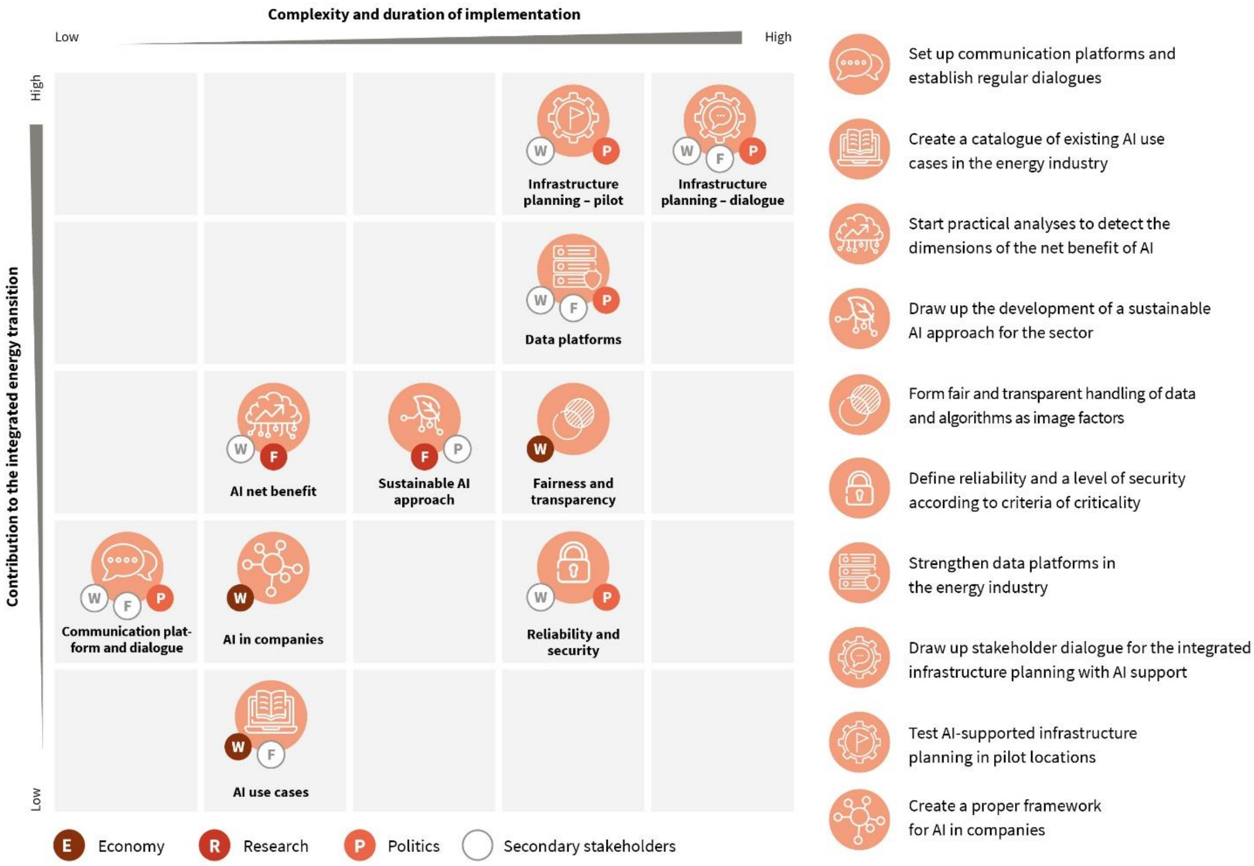

Figure 58: Classification of the global recommended courses of action[128]

[128] This shows those actors directly involved in each case (main actor - in colour, secondary actor - white), even though other actors may be involved indirectly.

- **A: Set up communication platforms and establish regular dialogues**

The first AI projects in the energy industry show that apart from primarily digital-technical knowledge-building, linking the digitalisation and energy sectors will be particularly crucial for the future extensive use of artificial intelligence. A suitable framework has to be created for this purpose, within which interested companies and research institutions can link up easily and effectively and exchange information. The experience of established actors in the energy industry will play just as important a role as new potential solutions from innovative young start-ups as well as experts from the AI scene. This exchange platform will also be strengthened by regular virtual meet-ups in which knowledge will be updated fuss-free by means of guest contributions as well as Q&A sessions, thus ensuring that the status quo on relevant development aspects related to the topic also reach a wider audience. The exchange platform could be realised by dena as a further pillar of the existing Future Energy Labs and also give the sector access to other digital technologies.

- **B: Create a catalogue of existing AI use cases in the energy industry**

Based on the nine identified fields of application in the three developed clusters for AI in the energy industry, concrete use cases that have already been implemented in companies or research institutions will be collected, structured and made visible. This allows actors from the energy and digital sectors to find inspiration for their own potential applications and also swap ideas with actors who already use AI in the corresponding form or for a comparable purpose. The pure collection of application cases should also be coupled to a possibility of exchanging these so as to strengthen the activities (see recommendation A). A first good overview has recently been drawn up by BDEW in collaboration with the company appliedAI. This could become a basis for continuous expansion that could be developed further by all of the actors (BDEW, 2020).

- **C: Start practical analyses to detect the net benefit of AI**

Whereas AI applications on the one hand are often criticised for consuming resources and huge amounts of energy for their creation, training and operation, there are still great expectations on the added value that can be achieved and the benefits for a successful transformation of the energy system and for reaching climate goals. The net benefits of each AI application used should be able to be calculated or estimated by means of selected concrete example processes that have already been implemented in industry or the energy industry, or are being planned. The additional benefit here, for example, is to determine the potential CO_2 savings using a comparative scenario and then compare this to the increased consumption of resources and energy. In addition to these quantitatively ascertainable aspects, qualitative factors also have to be included, such as the better integration of renewable energies thanks to the use of AI, the reduction of the necessary control power or the increase in operational efficiency. The results of these first estimates can be gradually transferred to a concept so as to classify the use of AI in terms of the net energy benefits at an early point in time. In view of the expected extensive and long-term significance of AI for working and computing processes in all industries, the development of a calculation concept should be an ongoing process with its own dynamics and one that can be permanently improved. Work on this should begin directly together with research and the economy.

- **D: Draw up a sustainable AI approach for the sector**

A concept to establish the sustainable use of AI in the industry is to be drawn up during an ongoing series of workshops together with stakeholders from the energy and digital sectors. Pilot projects will be needed in advance so as to take into account findings on possible influencing factors; these will also help reduce the method's complexity (see recommendation C). Based on this, the first step will be to appoint a group of independent experts (appointment or application procedure), which will form a fixed working group and will meet up regularly to introduce various aspects from environmental issues, economics, innovation, regulation and society into the discussions about a transparent and sustainable AI for the energy industry. This working group should be set up immediately to that it can help steer the course of AI applications that are already in use or whose implementation is pending from an early date and effectively support practical projects. The political sphere should also be represented in the group of experts and could act as an initiator.

- **E: Expand the fair and transparent handling of data and algorithms as image factors**

Notions of fairness and requirements on the transparency of AI models have to be taken up equally by developers as well as companies that use AI and taken into account accordingly. Framework conditions and procedures thus have to be developed that can also be understood and applied by non-AI experts. Existing activities in this respect, such as the AI standardisation roadmap under the leadership of DIN or the white paper on AI at a European level, already provide an accepted basis that can be actively grown by actors in the energy and digital industries. It has to be clearly defined just what the individual applications offer in concrete terms and which methods are used so as to ensure the traceability of the application. To this end, it will also be important for companies in future to regard fair and transparent framework conditions for handling data and algorithms as more of a sales argument than a limitation for their stakeholders and thus to promote these more on their own. An analysis of best practice examples, including from other industries, paired with a stakeholder dialogue, could mark the beginning of a common value judgement for the energy industry at a national and European level.

- **F: Define reliability and a level of security according to criteria of criticality**

When AI is used for system-critical applications in the energy industry, the reliability and safety of functions take utmost priority. At the same time, demands for complex certification procedures could make AI too complex and thus unattractive for a broad group of users. Deliberative approaches to categorise the application cases in terms of their regulatory needs, such as the data ethics commission's criticality pyramid,[129] should be welcomed. In any case, AI applications in the energy industry should be assessed in terms of their criticality by a central authority and certification requirements defined together with the responsible institutions on the basis of this assessment. One of these institutions could then act as a central certification office for AI applications in the energy industry. On account of the high system relevance of the energy industry and the simultaneous use of technically complex and fast-changing algorithms, this process is classified as being highly complex. Certification requirements can be waived for less critical applications, but the traceability still has to be guaranteed. A certification procedure can guarantee the long-term confidence in and thus use of these complex systems in the energy industry by all users, something that also contributes to the integrated energy transition, albeit of a more indirect nature.

[129] The criticality pyramid classifies the applications on 5 levels and assigns them appropriate measures: 1) without and with a low damage potential, 2) with a certain damage potential, 3) with a regular/clear damage potential, 4) with a high damage potential, 5) with an unacceptable damage potential. Further information: https://www.bmi.bund.de/SharedDocs/downloads/DE/publikationen/themen/it-digitalpolitik/gutachten-datenethikkommission.pdf?__blob=publicationFile&v=6

- **G: Strengthen data platforms in the energy industry**

The necessary data is generally not always freely available. In some case, external data can be purchased from data providers (e.g. weather data) or from open data platforms and databases that are obliged to publish their content. Up to now, however, large amounts of anonymised and pseudonymised data, for instance from grid infrastructure operators, has not been available for third parties to use in training AI and developing new business models. Other areas of the energy industry have their own reasons (clarification of the responsibility, retention of competitive advantages etc.), some of which are understandable, for their reservations about making data "freely" available. A number of actors have identified new and important markets for data procurement, its processing in a profitable manner, and its trading.

A powerful and competitive data infrastructure is needed to make high quality data available for the use of AI, and at the same time use this safely and transparently. Companies as well as authorities and organisations of all sizes and from all fields are working on this implementation in the European cloud project GAIA-X. This kind of initiative can not only lower infrastructural impediments for AI applications through greater trust in data sovereignty (e.g. the use of interoperability standards, storage of data within one's own jurisdiction) and a faster procurement from authorities or a safer legal framework for the target groups, but can also reduce existing social concerns (e.g. data protection) and impediments (such as complex processes that are hard to understand) on the part of users in the long term. The high potential for optimisation in the energy industry by networking actors, in all value-creation stages, demonstrates the necessity of an interoperable approach and the possibility of aggregating data. Nonetheless, critical issues also have to be discussed in the context of data economy. Apart from the infrastructural requirements, fair and transparent possibilities to exchange data will also be required within the framework of the energy industry that is both competitive and regulated. A project of this kind should be encouraged to realise further potential applications of AI in the energy industry.

- **H: Draw up stakeholder dialogue for the integrated infrastructure planning with AI support**

Planning infrastructures based on an optimised operation of existing systems can be made much more effective with the help of AI-supported methods (for instance AI-supported GIS for better track planning). The requirements not only on the physical grid infrastructure (electricity, heat, gas as well as transport grids) but also on the corresponding digital infrastructure are growing steadily. The clash of the physical and digital infrastructures in particular is making the optimisation of the energy and information grids of tomorrow increasingly complex. At the same time, social factors should not be ignored (e.g. proximity to RE plants). Computer-aided calculations are frequently already necessary when planning infrastructure today. The number of parameters that have to be taken into account, and thus the complexity of the planning, will continue to rise on account of the necessity of a coordinated, planned, integrated energy transition and the concomitant demand for digital infrastructure. Thus, regulations for specific German states have to be given just as much attention as the geographical circumstances or aspects of long-term planning, such as structural support programmes. Planning infrastructures is thus far more than a simple task within the energy industry; in fact, it calls for an integrated approach involving various infrastructural areas (electricity, building, mobility, construction etc.) from all value-creation stages. A common understanding of all actors involved is a basic requirement so that AI can support the realisation of such a complex project. The urgently needed dialogue between representatives from various industries, including AI experts, should thus be based primarily on an exchange at the beginning and be addressed directly as a process.

Politics and research as well industry should be involved so as to identify technically possible, politically sensible, long-term economically and socially viable potential solutions. The goal should be to bring together the complex requirements and processes from all of the affected infrastructural areas and to develop a common solution as a basis for further planning. The focus should hereby lie on overriding national consistencies and basic orientations, without losing sight of the European perspective. However, before the concept for such an AI-supported infrastructure plan is established at a national level, a validation and fine-tuning procedure should be implemented (see recommended courses of action I).

- **I: Test AI-supported infrastructure planning in pilot locations**

In order to implement the potentials of AI-supported infrastructure planning, a way has to be found to move from theoretical considerations to practical planning. One possible first step could be pilot projects for those measures that have been worked out in the stakeholder dialogue, that are implemented jointly in several municipalities. This would lay the foundation for future AI-supported, integrated and cross-sector infrastructure planning. A broad spread of pilot municipalities in terms of size, geographical location and economic interests would ensure that all of the factors for an implementation at a national level are taken into account for a validation and fine adjustment of the method (see recommendation H). AI can help in the implementation of highly complex measures to ensure the success of the integrated energy transition. The experiences gained with the pilot projects thus serve as a basis to draw up recommendations on establishing Germany-wide, AI-supported and optimised infrastructure planning.

- **J: Create a proper framework for AI in companies**

One basic requirement for the successful use of AI in the energy transition is also a willingness on the part of companies to get involved. With the very heterogeneous company landscape in the energy industry, it is very clear that corporate processes first have to be recorded and evaluated individually in terms of their features and possibilities for automation, before identifying specific, possible optimisation methods. Current examples show that AI is often used in processes that promise great benefits on account of their basic potential for digitalisation (keyword: pressure of innovation), but that a general, or even an in-house selection principle is missing when it comes to choosing the fields of application. Whereas a large number of questions remain unanswered as regards the benefits of such innovative technologies compared to the capital that has to be invested, a targeted, systematic approach can nevertheless have a positive effect on the likelihood of a successful implementation of AI.

Questions about the current and future data basis (quantity and/or quality), the complexity of the algorithm to be trained (structure and operation), the personnel (ability and willingness), possible rebound effects (e.g. through additional energy consumption) or process security in view of the, in some cases, complete delegation to non-human process entities (level of trust), are just some examples showing that standardised test methods are of great importance when preparing to launch AI. Companies should therefore get expert advice in the selection phase and gradually build up their own knowledge in the further course of the introduction on which criteria can be used to substantiate decisions. This both ensures the involvement of senior management and creates trust in one’s own course of action. A few important measures will be explained below on how companies can prepare for the use of AI.

- **Make the company technically and organisationally fit for AI**

  Staff skills have to be broadened by management so that AI can be implemented and used in the energy industry, e.g. by training a data-driven view of processes and applications. As well as special AI experts (Data Engineers/Data Scientists), employees at the interface between AI and the energy industry must also be trained and employed in this field. One requirement is a culture of trial and error as well as toleration of new approaches that is supported by the corporate management.

- **Draw up an in-house analytical selection procedure for the use of AI**

  Up to now, companies have often lacked a general or in-house selection principle when choosing a process for the potential use of AI. Initial questions about the current and future data basis (quantity and/or quality), the complexity of the methods to be used, the personnel (ability and willingness) and possible rebound effects must be examined systematically before any decision is taken, even after a relative comparison of various possible methods.

- **Introduce AI ambassadors in the company as mediators**

  The introduction of AI ambassadors may be a suitable method to identify the AI potential in a company, facilitate IT experts and create the necessary framework conditions for the use of AI in the various departments of the company. The creation of this kind of mediator role helps identify AI potential and plan operations in the company, and also builds up confidence in the technology.

- **Draw up a catalogue of measures for training AI competencies**

  The hiring or in-house training of IT experts or the outsourcing of AI-driven processes are tools that can be used by companies to develop or integrate AI competencies. A catalogue of measures, drawn up by industry associations, for instance, should help the company identify their options for training AI competencies. The measures should hereby be classified according to categories such as the field of use for AI, the size of the company, the strategic alignment or the personnel structure. Taking this as a basis, companies can then define their own guidelines for the creation of AI knowledge according to the specific circumstances in the company, and then select individually appropriate measures. This method should show the companies all of their options for acquiring expertise and at the same time ensure a standardised approach thanks to the industry-specific catalogue of measures. Industry associations and politics can contribute to the dissemination of knowledge, the collection of best practice and practical examples, and ultimately to confidence-building in AI with these measures.

- **Make personal knowledge accessible to all by expert systems within the company**

  Independent learning (reinforcement learning) and the expansion of expert systems can release formerly personal knowledge and make it easier for the entire team (particularly new starters) to access and implement. The solutions to problems and recommended courses of action that are then worked out from this knowledge base are determined by if-then formulas, which enable AI to draw its own consequences and at the same time explain how it arrived at its decision to the user. Employees and departments that are to work with the knowledge of the AI systems should be intimately involved in their development so that they can familiarise themselves with the system’s abilities from the outset.

4.2.2 Generate opportunities from challenges

Apart from the generally valid recommendations for the economy, politics and research, the results of the analysis also show a need for action in specific fields of application. This is often of a technical nature (e.g. data is not available, or not in the necessary quality and amount) and is addressed primarily to application-oriented research. Even though there is a huge potential for (necessary) optimisations in the fields of application, particularly where grids are concerned, technical, regulatory, economic and social impediments to their implementation still exist. A classification of the recommendations for the challenges identified in this report as regards the complexity and duration of implementation as well as contribution to the integrated energy transition is shown in Figure 59, analogous to Figure 58.

Figure 59: Classification of the recommended courses of action for a specific field of application[130]

[130] The most relevant fields of application in each case are marked, even though other fields of application may also be affected indirectly.

Strengthen established fields of application, improve potentials for less widespread ones

AI will make a major contribution to improving efficiency in the energy industry in future through its use to improve the quality of predictions and for optimisation in the field of physical and digital energy and data distribution. RE can be integrated in the energy system better through the use of AI, on both the grid and generation side. A more accurate prediction that simultaneously and continuously includes and recalculates a number of parameters such as weather data or price signals from various price components and markets optimises the costs and revenues structure, for example in electricity trading. This means that this is now less of an additional business and more of a necessity that adequately reflects the increasing dynamics on the energy markets caused by the trend towards decentralisation. With this in mind, AI applications in the field of algorithm-supported trading are already firmly established in most energy companies.

The potential to optimise the operation of the electricity grid, which is certain to become a challenge on account of the integration of a large number of small-scale power generators and flexible consumers such as heat pumps and the optimised charging of a large fleet of electric vehicles, is also high. In order to control these much more complex systems in the future, which have to simultaneously satisfy the manifold requirements of a number of different user groups, the use of different kinds of AI will prove helpful. These include ANN for quantitative predictions of future events, sensitivity analyses for the optimum positioning of metering points through simulation, the use of NLP to identify and classify customer requirements as well as the classification of faulty and non-faulty system components. A precondition for all of these AI applications is that useful data is available in sufficient amounts.

- **K: Derive implications for other fields and sectors from the established AI fields of application**

The analysis shows not only the high potential of the fields of application for the cluster "General Foundations for Decision-Making" (**Predictions (1)**, **Operation optimisation (2)** and **Inventory optimisation (3)**), but also the large number of use cases that are already established as well as the relatively low technical, regulatory, social and economic obstacles in this field. Most of them are already industry standards, thus offering the opportunity of deducing the implications for the use of AI in other fields of the energy industry or other sectors. A series of workshops with representatives from the industry should provide the chance to identify analogies, share experiences from use cases in the cluster “General Foundations for Decision-Making” and pave the way for its implementation in other areas. A catalogue of use cases could be of assistance here (see recommendation B). Both the contribution to the energy transition and the complexity increase with the availability and level of detail of the established use cases. Above all, incentives have to be created for companies so that they are prepared to share information about their own processes and products.

- **L: Strengthen the use of AI for maintenance and security measures with training methods and processes from other sectors**

In the fields of application **Maintenance, repair and dismantling (5)** as well as **Security measures (6)**, the lack of data leads to a lower commercial use of AI, even though the automation of processes would mean a great increase in efficiency. However, what is lacking at present is data to identify faulty processes and critical situations.

In order to replace the missing data and methods, particularly for training AI, other sectors with similar processes should be consulted by the relevant companies to supplement or substitute their own methods (see also recommendation M). Companies that have already developed and implemented AI methods are particularly suitable to serve as role models.

■ **M: Identify alternative concepts for participation of active consumers**

A similarly high contribution to the integrated energy transition is expected from **Making it easier for active consumers to participate (7)**, through its active implementation is not expected until the medium term on account of the lack of data. The technical infrastructure for data collection (IoT, SMGW) is currently still "under construction" in some cases whereas the use of corporate and personal data is at the same time subject to restrictive security and protective requirements, and rightly so. Data trading and service platforms (open and closed systems) that provide data in consideration of the rights of self-determination of the data owners, are currently in the planning phase or are being tested in demonstration projects. Smart energy services that use data from companies and end customers promise added value here. On the one hand, their implementation gives reason to expect significant improvements in energy efficiency in both industry and trade as well as the end customer segment, and on the other hand they should encourage the optimisation of the use of decentralised power-generation facilities, storages and flexible energy applications. Research should help identify alternative data collection concepts that satisfy the energy industry requirements on the reliability of data records in a first step. These tasks of identifying existing standards, interfaces and platforms that are initially less complex may have a short-term signal effect for a better understanding of the data basis that is necessary for the digitalisation of the energy system. If the identified alternative concepts can be implemented successfully, this can also make a high or even very high contribution to the integrated energy transition, even though it makes the project much more complex.

AI for grid operation

In the medium term, the amount of data available for training AI applications and automating grid operation will continue to rise through the continued spread of sensors and measurement technology and the smart meter roll-out. Corresponding software products and planning tools that can be operated with a relatively small amount of data are already available for control purposes in distribution and transmission grid operation. This is likely to make it easier to record the grid status at the low and medium-voltage levels, which are penetrated heavily by new power generation, storage and consumption points. Measurement data from only a few critical points in the grid is often sufficient here to determine the status quo. An improvement in the sensor equipment in future will also lead to an optimisation on the algorithms based on this.

■ **N: Analyse and evaluate measuring state data for the distribution grid**

Smart measurement systems play a key role in the provision of data at the lower voltage levels. The compatibility of the measurement systems with added value services and their hardware as well as the extensive range of functions, e.g. for the high frequency provision of meter readings, have to be accelerated as a central requirement. The fast integration of small-scale power-generation facilities as well as flexible electricity consumers and storage within the scope of the Metering Point Operating Act (MsbG).are particularly relevant when it comes to **Making it easier for active consumers to participate (7)**, and they should be equipped with suitable measurement technology at short notice wherever possible.

Whereas the distribution of the measuring systems amongst the consumers and power generators is already regulated by the MsbG, a prior analysis is needed to identify significant nodes when it comes to installing the measurement technology and sensors in the distribution grid. The effort needed to install the measuring technology is offset by savings, for example through a more accurate redispatch from power-generation facilities and flexible consumers. In this respect, it is expedient to offer timely incentives for grid operators to install measuring technology that records data and determines the grid status.

- **O: Use shadowing to validate models and thus boost confidence in the web and increase cyber security**

A temporary parallel trial operation where AI takes over former processes is helpful when it comes to validating models and building up trust in digitally supported systems. Measures to resolve grid congestions or for the better capacity utilisation of power grids can be simulated using a digital twin, for example, without actually implementing these in reality. Thanks to the early identification of critical grid status, this so-called shadowing can also be used to avert cyber attacks on infrastructures that jeopardise the security of supplies.

The lack of any data basis on faulty processes and attacks makes the possibility of a parallel trial operation particularly relevant in this case (see also recommendation K). Pilot projects should therefore be launched as lighthouse projects straight away for a successful comprehensive use of shadowing to ensure system security. This initially calls for a complex analysis of the processes and the system landscape, before the increased system security can indirectly contribute to the integrated energy transition.

- **P: Support optimised grid operation by the use of prospective algorithm-based systems**

The benefits of a more strongly market-based structure for congestion management (including the introduction of regional markets for flexibility services) is currently under discussion. On the grid control side, the required investments present a barrier to AI-based monitoring measures and AI-assisted feed-in management. Variable grid charges could create additional incentives for an optimised grid operation, though the complex regulatory system has so far hampered any solution to the problem. The increased prospective and predictive use of algorithm-based systems to support grid operation may present a route out of this regulatory dilemma by helping to prevent any congestion.

- **Q: Initiate AI pilots for a possible amendment to the Incentive Regulation Ordinance (AregV)**

Showcase projects are recommended with regard to the investment framework for distribution grids, within which it should be possible to predict whether a widespread use of AI will lower the costs for grid operators, for example, through pilots. Based on the results, the regulatory authorities can consequently take more precise case-by-case decisions to cover the costs of grid regulation. The AI instruments proven in the pilot trials provide the DSO with new, field-tested ways to record the decentralised feed-ins and withdrawals in a smarter way and to control these in a grid-supportive way. Although a corresponding amendment to the ordinance is a very complex affair, the optimisation of grid operations is extremely relevant for the decentralised transformation of the energy system. Suitable incentives for the use of AI could therefore accelerate the digitalisation of the energy industry and thus promote the integrated energy transition.

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Abbreviations

FoA	Field of application
AI HLEG	Artificial Intelligence High-Level Expert Group
BMWi	Federal Ministry for Economic Affairs and Energy
BDEW	Bundesverband der Energie- und Wasserwirtschaft (German Association of Energy and Water Industries)
BDSG	Bundesdatenschutzgesetz (Federal Data Protection Act)
BGB	Bürgerliches Gesetzbuch (German Civil Code)
BNetzA	Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen (Federal Network Agency for Electricity, Gas, Telecommunications, Post and Railway)
BSI	Bundesamtes für Sicherheit in der Informationstechnik (Federal Office for Data Security)
CEN	Comité Européen de Normalisation (European Committee for Standardization)
DIN	Deutsches Institut für Normung (German Institute for Standardization)
GDPR	General Data Protection Regulation
DPD	Data Privacy Directive
EDIFACT	Electronic Data Interchange for Administration, Commerce and Transport
RE	Renewable Energies
REI	Renewable energy installation
EEG	Erneuerbare-Energien-Gesetz (Renewable Energy Sources Act)
EC	European Commission
EnEG	Energieeinspargesetz (Energy Savings Act)
EneV	Energieeinsparverordnung (Energy Savings Regulation)
ENISA	European Union Agency for Cybersecurity
EnWG	Energiewirtschaftsgesetz (Energy Industry Act)
EP	European Parliament
ePR	ePrivacy Regulation
ESEF	European Single Electronic Format
ECJ	European Court of Justice
PSC	Power supply company
GIS	Geographic information system

GPKE	Geschäftsprozesse zur Kundenbelieferung mit Elektrizität (standard business processes for supplying electricity to customers)
GWB	Gesetz gegen Wettbewerbsbeschränkungen (Act against Restraints on Competition)
HV	High-voltage
iMSys	Intelligent metering systems
IoT	Internet of Things
ISO	International Organisation for Standardization
iXBRL	inline eXtensible Business Reporting Language
AI	Artificial intelligence
ANN	Artificial neural network
CHP	Combined heat and power
KWKG	Kraft-Wärme-Kopplungs-Gesetz (Combined Heat and Power Act)
Luft-VO	Luftverkehrsordnung (Air Traffic Regulation)
MaStR	Marktstammdatenregister (Core Energy Market Data Register)
MaStRV	Marktstammdatenregisterverordnung (Core Energy Market Data Register Regulation)
ML	Machine learning
MPO	Metering point operator
MsbG	Messstellenbetriebsgesetz (Metering Point Operation Act)
M2M	Machine-to-machine
GO	Grid operator
NLP	Natural Language Processing
ProdHaftG	Produkthaftungsgesetz (Product Liability Act)
PV	Photovoltaics
SatDSiG	Satellitendatensicherheitsgesetz (Satellite Data Security Act)
SMGW	Smart meter gateway
StromNZV	Stromnetzzugangsverordnung (Electricity Supply Grid Access Act)
StVG	Straßenverkehrsgesetz (Road Traffic Act)
TKG	Telekommunikationsgesetz (Telecommunications Act)
TMG	Telemediengesetz (Telemedia Act)
TSO	Transmission system operator
DSO	Distribution system operator
WT	Wind turbines

XHTML	eXtensible Hyper Text Markup Language
ZB	Zettabyte

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