dena German Energy Agency

dena-REPORT

Artificial Intelligence for the Integrated Energy Transition

Assessing the technological status quo and categorising fields of application in the energy industry

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Contents

Executive Summary

The topic of artificial intelligence (AI) is trending across the world. A “system rivalry” can be observed on the international stage, with the USA and China as established AI nations. Europe is trying to counter these two heavyweights with an ethics-based approach to AI that puts people’s rights and needs in the spotlight. Intra-European cooperation projects, such as the planned Franco-German “Centre for Artificial Intelligence”, are intended to help Europe keep up with **global competition in this burgeoning field**. When it comes to using AI in the energy sector, European actors have already made it onto the leaderboard (cf. Chapter 1).

However, public discussion of AI in general and technical discussion of possible applications of AI in the energy system are still marred by **great uncertainty** and sometimes a lack of expertise. AI is often confused or even equated with terms such as machine learning, big data, neural networks or deep learning. This is hardly surprising, given that the term “artificial intelligence” is itself based on a concept that has not been clearly defined: intelligence.

This uncertainty about what AI is impedes the development of this important technology for the integrated energy transition. In light of this, the present report aims to **objectify and classify the ambiguous concept of artificial intelligence** (cf. Chapter 2). At the same time, it will demonstrate to economic, expert and political actors in the energy industry the diverse potential of this technology as well as concrete fields of application.

The unique opportunity offered by AI is that of mastering the complexity of a decentralised and integrated energy transition with ultra-modern technology. And, as it turns out, **AI applications can be found in all value-creation stages of the energy industry** (cf. Chapter 3, Figure 14).

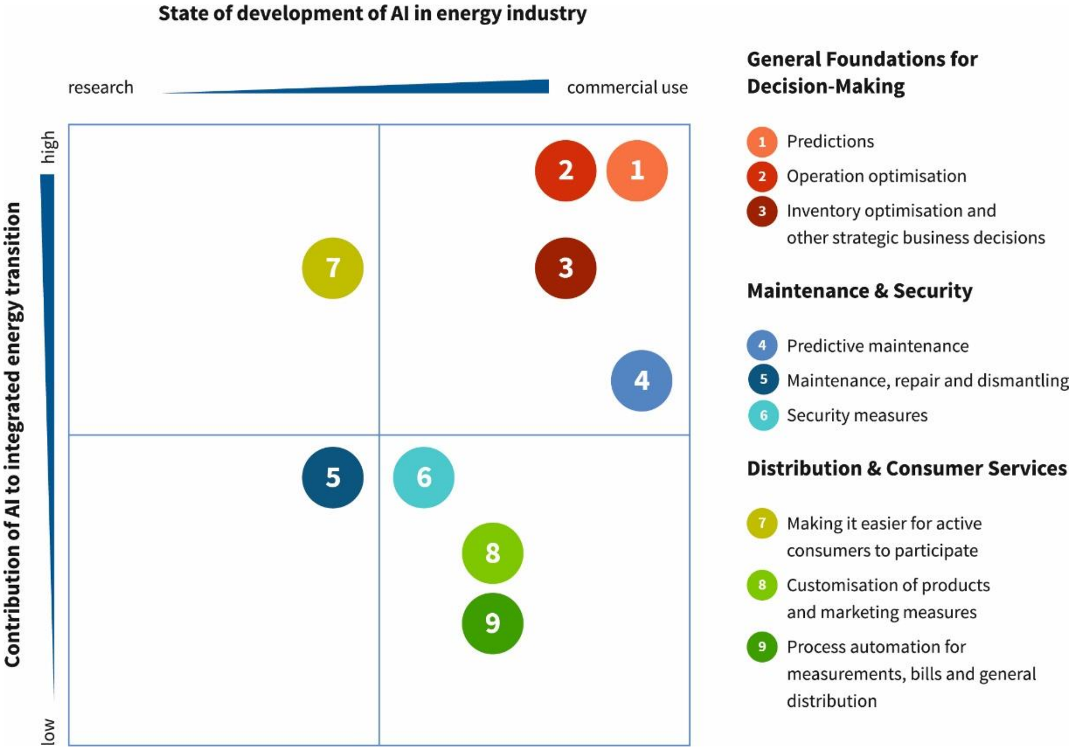

Figure 1 Relative classification of fields of application of AI in the energy industry [Source: own graphic]

In all, **nine fields of application** were identified and assessed with regard to their contribution to the integrated energy transition and their state of development in order to pave the way forward. Figure 1 summarises this classification. The fields of application include general foundations for decision-making such as forecasts and improvements, applications in the maintenance and security cluster as well as new services for modern distribution and making it easier for active consumers to become involved. Numerous examples that illustrate the value of AI to the integrated energy transition have already been implemented successfully. This analysis has shown that **the most promising approaches for the integrated energy transition are already highly advanced**.

However, the report also shows that there is still **much to be done (cf. Chapter 4)** to establish AI in the energy industry. Building up knowledge of AI in the energy sector is a process that requires continuity. This requires the involvement of political actors as well as companies in the energy industry and digital economy. **Proactive knowledge-building within companies**, an **IT expert offensive** and **cooperation between established actors and innovative digital companies** are all vital areas of action.

In addition, governments must recognise that data is increasingly becoming a key resource – also and especially when it comes to applying AI in the energy industry. **Developing a data economy** in consideration of the contribution of data to the integrated energy transition can help to **reconcile the required data availability and data quality with the requirements of data protection and informational self-determination**.

dena will continue to focus very closely on the topic of AI in the years to come. A report containing a more in-depth analysis and assessment of the nine fields of application of AI for the integrated energy transition is expected to be published in the summer of 2020.

1 All signs point to artificial intelligence

1.1 The place of AI in the world of tomorrow is hotly debated

Europe and the world

Today, the topic of artificial intelligence (AI) is part and parcel of discussions in public debate and cross-industrial expert circles. The endless stream of news reports – such as the news of a complex three-dimensional simulation of our universe conducted quickly and accurately by researchers at Princeton University using AI for the purpose of researching the development of our universe – testifies to the dynamics of the development of this technology and its potential.[1] Extensive discussions about the sustainability of AI (ecological, economic, social) show just how controversial this technology is.[2] Unlike blockchain, which can function as a digital infrastructure technology for a variety of use cases[3], the different forms of AI can themselves represent the respective applications.

Expectations are high for AI, and the global race for supremacy over this technology of the future has begun – with the USA and China in joint first place[4]. The EU has also recognised the significance of AI and wants to respond to the challenge with increased cooperation and a European strategy for artificial intelligence.[5] Accordingly, the EU is expected to "increase investment in AI research and development in the public and private sector by at least 20 billion euros by the end of 2020"[6]. Additional resources for developing AI technology in key sectors will be mobilised and companies and start-ups will be supported by means of public-private partnerships and the European Fund for Strategic Investments (EFSI), among others.[7]

For a long time, the discussion surrounding AI has not just been about economic hegemony. Several ethical issues which, at their core, relate to societal coexistence are also tied into this subject. A quote by Chancellor Angela Merkel at the Digital Summit of 4 December 2018 in Nuremberg summarises the system rivalry and European position perfectly:

„

Private companies in the United States of America have a great deal of access to data.
The state in China has a great deal of access to data.
Those are two extreme positions that we do not want (...).

"

Dr Angela Merkel, German Chancellor[8]

According to Roberto Viola, Director-General of the European Directorate General for Communications Networks, in the EU there is a desire for artificial intelligence that takes into account people's rights and needs.[9] In light of this, the "High-Level Expert Group on Artificial Intelligence" appointed by the EU Commission has

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[1] t3n (2019).
[2] Cf. the studies by PwC (2018) and McKinsey (2018) and company initiatives such as Microsoft (2019).
[3] Cf. dena (2019).
[4] manager magazin (2018).
[5] European Commission (2018a).
[6] European Commission (2018b).
[7] Ibid.
[8] Merkel, Angela (2018).
[9] Die Zeit (2019).

developed four fundamental ethical principles: AI should respect human autonomy, have no negative impacts on society, function fairly and remain transparent.[10] According to Roberto Viola, the responsible method of dealing with AI could become the European hallmark in a market currently dominated by China and the USA.[11] In a similar vein to the European General Data Protection Regulation (EU-GDPR), it seems that the EU wants to use its common politico-economic position of power to establish European rules as a global benchmark. Even though this may contradict the relatively weak position of Europe compared with the AI superpowers of the USA and China, philosopher Thomas Metzinger asserts that "Europe has taken over intellectual leadership".[12]

Germany in Europe

Having already become embedded in the European framework, the topic of AI has also made its way into political and societal discussions in Germany. In the current coalition agreement between the CDU, CSU and SPD, there are a number of references to the topic of AI. In this respect, the coalition agreement primarily focuses on a high-tech strategy for cutting-edge research and education in Germany, the exploitation of economic potential and the consideration of the societal and social effects of AI.

In June 2018, the **Commission of Inquiry "Artificial Intelligence – Social Responsibility and Economic Potential"** was created. It consists of members of the German Parliament as well as relevant experts and seeks to investigate the opportunities and potential brought by AI and the challenges associated with it until mid-2020.[13] At the Digital Summit 2018, the German government also published its **"Artificial Intelligence Strategy"** with the aim of "making Germany and Europe a leading AI location and helping to ensure the future competitiveness of Germany".[14]

12 priority areas of action in the "Artificial Intelligence Strategy"

1. Boost research efforts in Germany and Europe in order to be a driver of innovation
2. Innovation competitions and European innovation clusters
3. Transfer into the economy, strengthen SMEs
4. Stimulate start-up dynamics and bring them to fruition
5. World of work and job market: shape structural change
6. Improve education and attract specialists/experts
7. Use AI for sovereign tasks and adapt competencies of the administration
8. Make data available and simplify use
9. Adjust regulatory framework
10. Set standards
11. National and international interconnectedness
12. Lead debate within society and further develop the political scope of action

The areas of action in the AI strategy of the German government (see box) give an idea of the range of topics involved in the discussion about AI: aside from specific use cases (e.g. sovereign tasks) and economic objectives (e.g. stimulating start-up dynamics), issues relating to technical and regulatory requirements (e.g. standards and regulatory framework) as well as societal consequences (e.g. structural change) also play a

[10] European Commission (2019).
[11] Die Zeit (2019)
[12] Deutschlandfunk (2019).
[13] Deutscher Bundestag (2018)
[14] Die Bundesregierung (2018).

role. This highlights the diversity and complexity of the topic. The launch of the "AI Standardisation Roadmap" and the creation of a "Specialist Unit for Artificial Intelligence", for example, are proof that the Federal Ministry for Economic Affairs and Energy (BMWi) is putting particular emphasis on AI. The 7th energy research programme "Innovations for the Energy Transition" and the funding of 50 lighthouse applications for safeguarding the environment, climate and resources serve as additional evidence that the German government is increasingly considering the fields of energy and climate through the prism of AI.

The German government is especially concerned with European collaboration when it comes to AI, and in particular **cooperation with France**. Its express goal is to create a "publicly administered centre for artificial intelligence" [15] together with French partners. Accordingly, in the Aachen Treaty of 22 January 2019 between Germany and France, it is stipulated that "cooperation in the field of research and the digital revolution, including [...] artificial intelligence" shall be enhanced. Both nations would "set up a coordination process and a common funding scheme in order to foster common research and innovation programmes".[16]

1.2 AI has already made its way into the energy industry

It goes without saying that the technological development of AI has not stopped short of the energy industry. In the context of the integrated energy transition, the various technical facilities, infrastructures and markets from the energy, industry, building and transport sectors must be coordinated and integrated into an optimised and intelligent energy system.[17] In light of the huge but often untapped data potential in the sector and the increased and increasing complexity of the energy system due to the rising number of assets and actors, the energy industry provides a fundamentally favourable environment for the use of AI.

Start-ups and SMEs are making inroads into the energy sector with AI applications

Across the world, there are already numerous examples of AI activities in start-ups, companies and research institutes from the energy sector. In a sector analysis, dena has identified a selection of 104 such organisations across the world.[18] Figure 2 provides an overview of the actors identified.

What is clear is that start-ups and SMEs play a prominent role in the use of AI in the energy sector. Well over half of all organisations identified (61 percent) are start-ups or SMEs, followed by research institutes at 23 percent, with the remaining 16 percent being large corporations. Regionally, the spotlight falls on Europe (49 percent) and the USA (33 percent), but some exciting AI activities within the energy sector can also be observed in countries like Israel and India. In spite of its relatively strong position with regard to the development and application of AI, China is not as well represented in the energy industry – which, however, may be due to the relatively low visibility of possible Chinese activities.

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[15] Coalition agreement (2018), p. 24.
[16] Aachen Treaty (2019).
[17] dena (2018).
[18] The data given reflects the current status of ongoing research into current AI activities in the energy industry. The research primarily focuses on English-language online publications. We therefore make no claims as to the completeness or representativeness of the data. For more details and other organisations, please go to www.dena.de/ki.

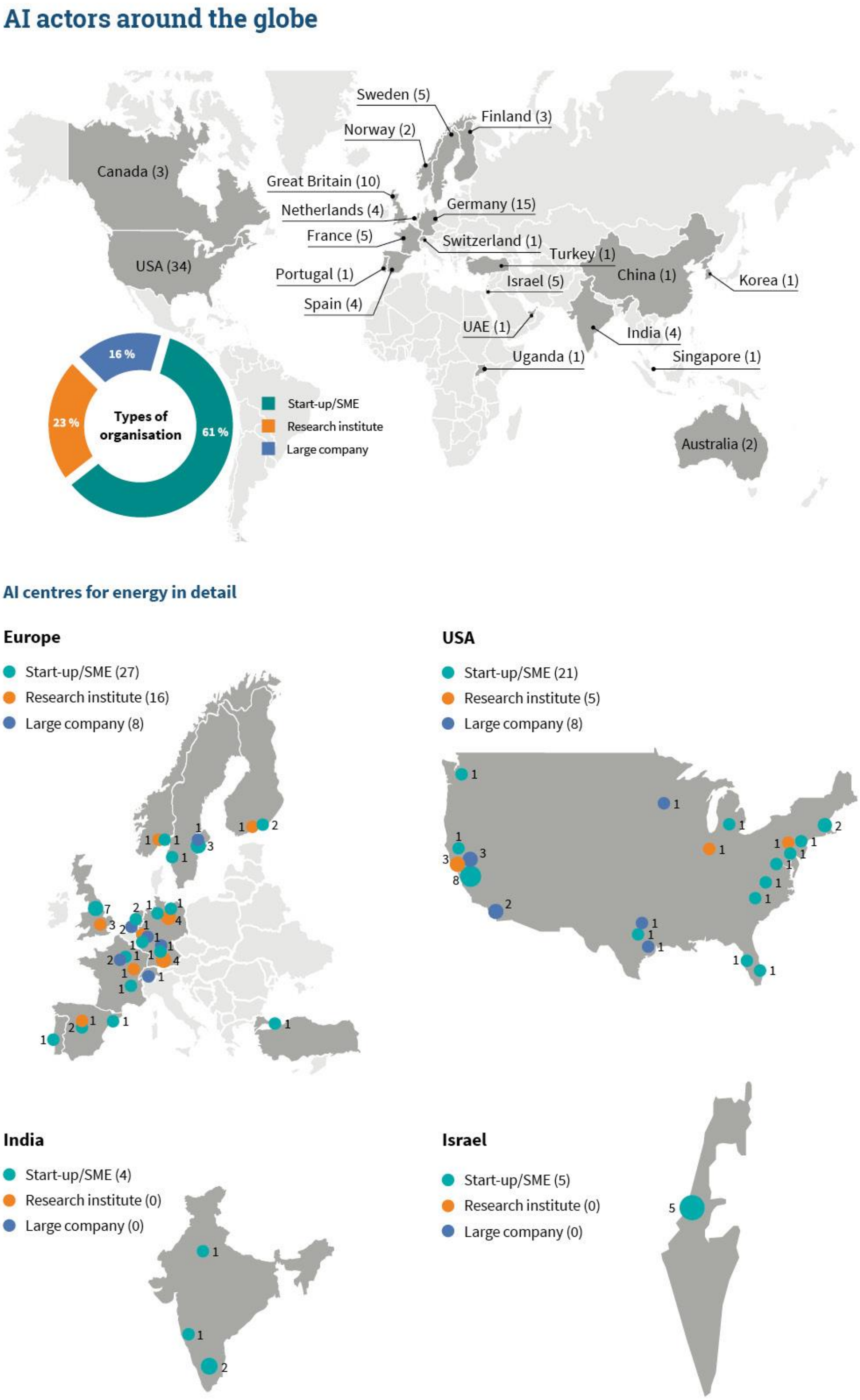

Figure 2 Overview of a selection of global actors in the energy industry [Source: own graphic]

The majority of German companies believe that AI will have a positive impact on the energy transition

A representative survey[19] of a total of 250 managers from the German energy industry conducted on behalf of dena showed that companies in the German energy industry overwhelmingly consider AI to be an opportunity. According to the survey, almost two thirds of the companies believe that the general effects of AI on future life will be positive or somewhat positive. Only 14 percent fear potential drawbacks from AI.

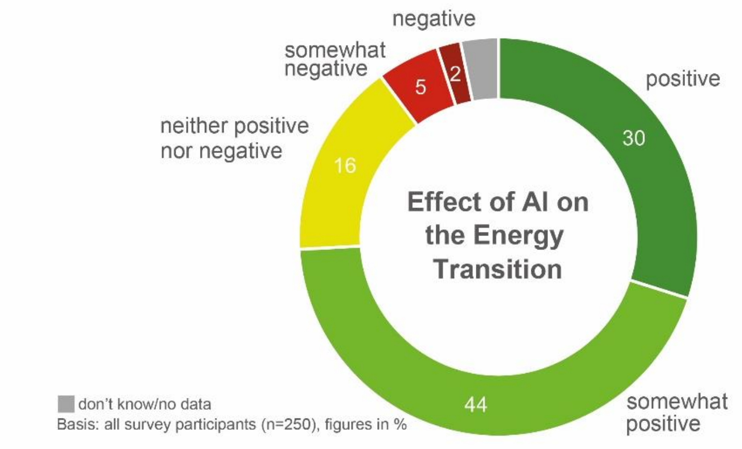

Figure 3 Assessment of the effects of AI on the energy transition in Germany [Source: own graphic]

The potential of AI is especially well regarded when it comes to the implementation of the energy transition (cf. Figure 3). Roughly three quarters of the companies (74 percent) predict overall positive effects. Only 7 percent expect an overall negative impact on the energy transition. The effects of AI on the energy transition are deemed more positive in particular by larger companies (more than 100 employees) and companies that are already actively educating themselves about AI and thus have a greater knowledge of the field.

82 percent of respondents are convinced that AI will play an important role in the future in the integrated energy transition – i.e. the fusion of the energy sectors electricity, heat and transport – and the cross-sector optimisation of the energy system.

Additionally, over three quarters (79 percent) think that an increase in productivity is possible for companies in the energy sector. Almost as many (77 percent) are of the opinion that new business models will arise within the energy sector thanks to AI. Just under half (49 percent) assume that the use of AI will foster economic growth in the energy sector and 41 percent believe that new jobs will be created in the energy industry thanks to AI.

Even today, those surveyed expect AI to bring opportunities in a variety of fields. First and foremost, they consider the use of AI to be very positive for smart cities (87 percent) and in the management of energy consumers (85 percent). Following on from these, the fields of mobility (79 percent), building control (78 per-

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[19] From 24 April to 8 May 2019, Midline Energy surveyed 250 managers of companies from the energy industry in Germany on behalf of dena on the topic of "Artificial Intelligence in the Energy Industry". The majority of companies surveyed are involved in traditional areas of the energy industry, such as the consumption, trade, generation and transportation of energy. Two thirds of the companies employ between 10 and 49 staff, 11 percent have 50 to 99 employees and 22 percent have at least 100 employees.

cent), energy management (76 percent) and energy efficiency (75 percent) as well as energy stores (73 percent), power distribution (72 percent) and smart buildings (70 percent), among others, also achieved high scores.

Moreover, the ratings are even higher for the near future. Those surveyed consider the use of AI to be a realistic option for almost all fields and sectors involved in the energy transition in five years' time, i.e. 2024. With the exception of product distribution, the approval ratings in this case stand at at least 85 percent.

Cautious reserve prevails among decision-makers in the energy industry

In spite of the generally positive attitude towards AI, the survey also showed that only a handful of companies in the German energy industry have already invested in AI (7 percent) or have definite plans to do so (6 percent). Just under one half of the companies surveyed have adopted a wait-and-see approach and just over one third do not think that there is any need to invest in AI (cf. Figure 4).

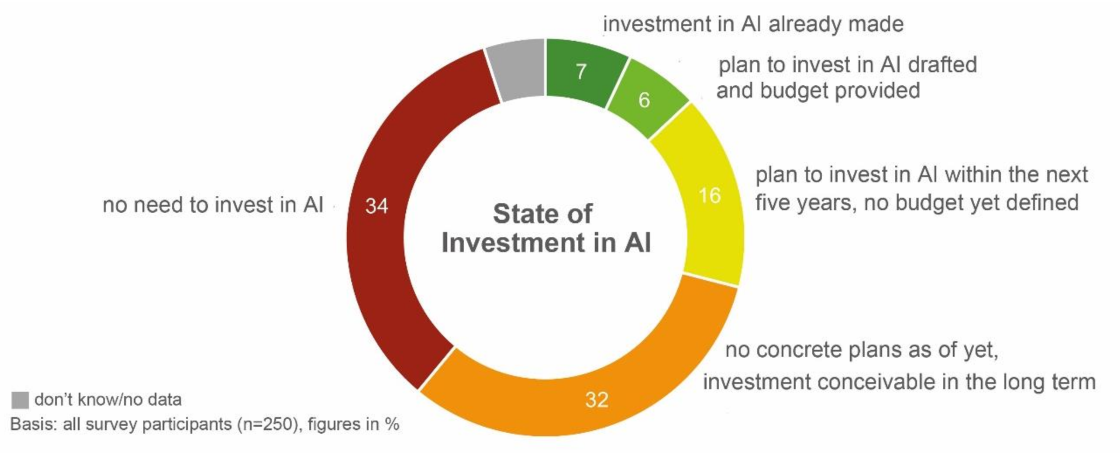


Figure 4 Assessment of the state of investment in AI in the energy sector [Source: own graphic]

The cautiousness of the companies surveyed could also be explained by the fact that knowledge of AI within companies in the energy industry is still relatively limited: only 17 percent of those surveyed feel that they are well or very well informed about the topic of AI. In contrast, 38 percent claimed to be less or not at all well informed about AI. 46 percent consider themselves to be moderately well informed. On the whole, the German energy industry fells on average less well informed than the business economy in Germany. In one survey, just under one third of actors in the German business economy claimed to be well or very well informed about AI.[20]

The present report is aimed at closing this information gap. In the following chapters, AI will therefore be explained in detail and classified in an understandable manner. A systematic analysis and preliminary assessment of fields of application of AI in the integrated energy transition will follow on from this. This report is therefore intended to give decision-makers – from the energy industry and digital economy as well as from the political sphere – guidance on how to lay the foundations for using a technology that will be vital for the energy system of the future.

[20] BMWi (2018).

2 What is AI? – An objective classification of the trending term

2.1 AI: Definitions and distinction from related terms

2.1.1 Definitions of artificial intelligence

Artificial intelligence (AI) is the intelligence of machines. Machines are artificial systems or agents that can receive and process external data and produce results. Computer programs and algorithms are important examples of machines – in the broader sense of the word – that can potentially exhibit intelligence. AI therefore contrasts with the natural intelligence of humans or animals.

The greatest difficulty in defining AI is the ambiguity of the term "intelligence". Even experts have trouble defining this term. A central aspect of intelligence is the ability to make decisions autonomously on the basis of information and to act accordingly to achieve the desired goals.[21] This involves gathering information relevant to achieving the goal, reacting in a flexible manner to the surroundings or to altered information, learning from experience and making decisions despite being uncertain and within a limited time frame.

Intelligence generally comes in various forms: cognitive intelligence (i.e. thinking about and drawing conclusions on the surroundings, objects or abstract concepts and acting accordingly) and emotional intelligence (i.e. the ability to recognise emotions and react appropriately, as well as many other abilities relating to human behaviour). An artificial system that incorporates all aspects of human intelligence would be referred to as "strong AI". In contrast to this, modern systems can only solve very specific problems and can therefore only be considered intelligent in certain areas. This is referred to as "weak AI". The following human abilities are considered to be the most important for acting intelligently: logical reasoning, perception of world and language, general knowledge, learning, understanding human language, planning and looking ahead, moving and manipulating objects, and recognising emotions.[22]

As evidenced by the distinction between strong and weak AI, it is not always easy to decide whether AI is being used in real-life applications. However, based on the aforementioned aspects of intelligent behaviour, it is possible to distinguish between more intelligent and less intelligent behaviour of computer programs or machines, i.e. stronger and weaker AI. Some of the use cases for the energy industry mentioned below use mathematical and statistical methods that have been known for many decades and, in some cases, since the early 19th century. However, thanks to substantial data availability or by becoming embedded in decision-making processes, they have been given a new lease of life and can become part of AI.

Other definitions of AI focus on specific scientific disciplines. AI is then defined more narrowly as a "branch of IT with the aim of enabling machines to perform tasks 'intelligently'".[23, 24] This lends weight to computer programs and IT as disciplines, since a great deal of important progress has been made in this area over recent years. In the broader sense, AI also relates to statistics, robotics, mathematics, linguistics, cognitive sciences and philosophy.

[21] Poole, David et al. (1998), p. 1.
[22] Ibid.
[23] Backes-Gellner, Uschi et al. (2019).
[24] Poole, David et al. (1998).

2.1.2 Closely related terms

The various aspects of intelligence in machines and computer programs have led to new, closely related terms.

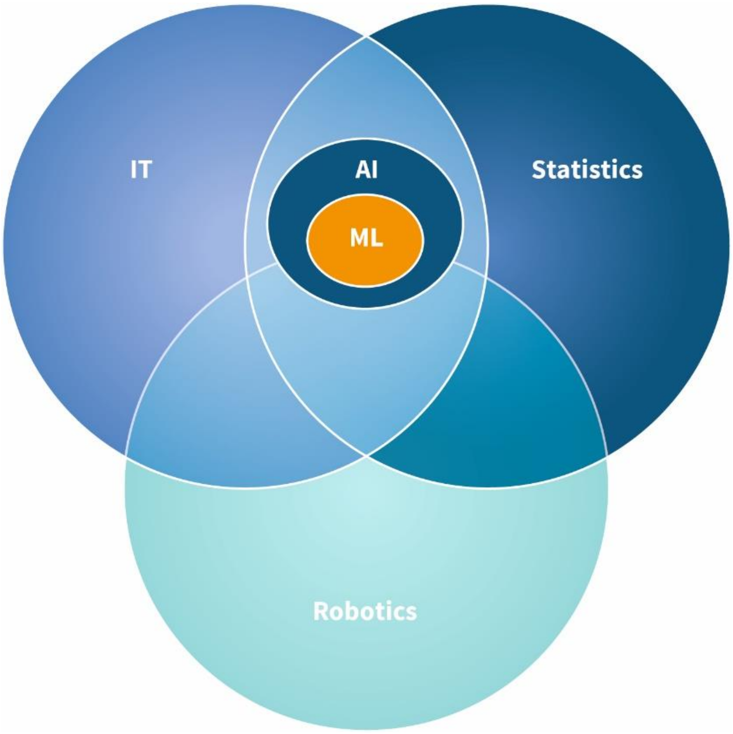


Figure 5 Locating AI and ML between academic disciplines [Source: own graphic]

Machine learning (ML) is a branch of AI and deals with algorithms and statistical models that enable computer systems to learn, i.e. enables them to perform a given task autonomously and without direct instructions, e.g. recognising patterns in several different cases.[25]

Statistical learning is a branch of statistics with an emphasis on modelling and prediction. In a nutshell, statistical learning can provide instruments and tools for modelling and understanding complex sets of data.[26] Statistics in general is ultimately a branch of mathematics used for gathering, organising, analysing and interpreting data.[27]

Deep learning is a set of ML methods that use **artificial neural networks (ANN)** (cf. Chapter 2.3.2). It is called *deep* learning, because these ANNs consist of a large number of layers between the input and output levels. Deep learning is used in particular in the field of speech recognition and translation as well as image processing.

[25] Bishop, Christopher M. (2006).
[26] James, G. et al. (2013).
[27] Romijn, Jan-Willem (2014), p. 1.

What has big data got to do with artificial intelligence?

"Big data" refers to volumes of data that are too big, too complex or that change too quickly to be evaluated using conventional data processing methods. In the broader sense, "big data" or "big data analytics" also refers to the methods for evaluating such data volumes.

In terms of methodology, there is overlap between big data and AI in the fields of pattern recognition and ML, for example. One key link is that many AI methods require large volumes of data in order to learn and/or be trained. This has only recently become possible for some relevant applications with the advent of large volumes of data and their fast availability. Large volumes of data – and therefore also big data to a certain extent – are a prerequisite of AI for many applications.

2.2 AI is nothing new

Literature and philosophy on human-like machines such as the golem, Mary Shelley's Frankenstein, Isaac Asimov's Laws of Robotics and certain Greek myths provide early visions of AI. The scientific discussion of AI in the strictest sense began in the mid-1950s (Turing test 1950, Dartmouth Conference 1956). Focusing on developments within IT and statistics, several big leaps have been made since the Second World War in particular:

- 1940s: Development of the principle of ANNs
- 1950s: Mathematical bases for ML and first use of the term "artificial intelligence"
- 1960–1980: Missing data and overly complex methods for existing computers. Stagnation of development and little success.
- Since 1990s: Achievements in AI in many applications thanks to improved algorithms, more data and greater computing power.
- 1996: AI wins at chess against the reigning world champion
- 2000s: Large increase in data volumes and computing power
- 2011: AI wins quiz show
- 2017: AI is the best Go player in the world[28]

Much of what we now call AI relates to certain methods in statistics that have been known for a long time and used for decades (cf. also Chapter 2.3.2). However, what really got things off the ground was the availability of significantly larger volumes of data. This has made it possible to increasingly apply the mathematical methods to everyday problems.

There is therefore a wide range of applications for AI and complex data analyses today. It is important to note that throughout the historical development of AI, significant breakthroughs (best chess player, solving logical problems) were often criticised as being mere "computing" as opposed to "actual intelligence" or "true thinking" (so-called AI effect).[29] We are therefore quick to consider many important AI applications that already exist

[28] The board game "Go" has its origins in ancient China in the second millennium BCE, making it more than 4000 years old. Go is played with black and white counters on a board with 19x19 lines. Go is just as simple as it is complex, which is what makes it so fascinating. It has only a few, easy-to-learn rules, but offers an almost unlimited number of potential moves thanks to this.

[29] McCorduck, Pamela (2004), p. 204.

today as being "normal" computer operations. Nevertheless, many of these operations were inconceivable not so long ago and should be considered aspects of intelligent behaviour. The following examples serve to illustrate this:

- Machines already play complex **board games** such as chess and Go better than any human. One famous breakthrough in chess was when Deep Blue beat then chess world champion Garry Kasparov in 1997 – making it the first computer to do so. A noteworthy breakthrough in more recent times came at the end of 2017 with the development of the program *AlphaZero*, a computer program which learns how to play complex board games by itself. In contrast to earlier programs, this program merely requires the playing rules as input instead of millions of games played by humans. After just eight hours of practice, this new program was already better than the program that beat the best human Go player in 2016.[30]
- **Spam filters** have been part of email programs for many years. These filters weed out unwanted messages such as adverts or those with criminal intent. To do this, the programs are trained using example emails that have already been classified by humans as "spam" or "not spam". The algorithm learns how to identify spam on the basis of these examples, and/or calculates the probability that a given email is spam based on the words it contains.
- There has also been significant progress in the field of **machine speech recognition** in recent years. Personal computer assistants such as Siri and Alexa – to which you can speak directly – have become a part of everyday life for many people. Some such programs can not only execute commands, but also engage in simple conservations. Further progress is expected in this area over the coming years.
- **Machine translation** of texts from one language into another has reached a level of quality and speed that makes it useful in a variety of everyday situations. For example, Google Chrome automatically translates websites at the request of the user, and the web translator DeepL translates short texts free of charge. The translations are often good enough to be usable, even if they are not as good as human translations. Overall, translation is a complex task, as many skills are required in order to understand a text completely: linguistic knowledge, an understanding of the world, the ability to reason, and the emotional intelligence to gauge the character of the text.
- In **finance**, automatic algorithmic trading is an example of complex tasks that have been taken over by machines. The standardised reports on balances and other key figures that need to be prepared on a regular basis in the financial and banking sector can now be drafted automatically by computer programs.

AI is already on par with humans in some niche applications and, in some cases, even superior. However, when it comes to more complex applications such as automated driving, AI is still in its infancy. It will probably take several years or decades before AI produces truly great results in these domains.

The development of AI over the coming years will be dominated by a **rapidly expanding volume of data**, **increasing computing power** and **growing expertise in many organisations**. This will give rise to more applications and improvements of AI systems:

- In addition to high-profile achievements in other games such as poker (for which information is lacking in contrast to chess or Go), personal assistants (like Siri) and speech recognition can be expected to continuously improve and soon become part of everyday life. AI will likely be able to take simple phone calls on

[30] Silver, David et al. (2018).

our behalf and of course accept phone calls as well. Because hotlines and customer service departments are used by many companies, these applications will likely catch on and be supplemented by chatbots.

- In the field of mobility, a great deal of work is being put into automated driving. Studies predict market introduction of fully automated driving in top-of-the-range cars from 2025 onwards.[31]
- Thanks to the increasing volumes of data, predictions of time series and customer behaviour will become more accurate and lead to wider dissemination of the respective applications. Many corporations are in the midst of setting up their own big data and data analytics departments, which should start bearing fruit in the coming years.

These are just some prominent examples of how advanced AI applications will likely increase productivity within companies and provide assistance to humans in several simple routine activities in the near future, freeing up more time for creative, demanding or enjoyable activities.

2.3 The diversity of AI: Introduction to tasks and methods of artificial intelligence

2.3.1 What AI can do: From recognising to inferring and acting

Human action encompasses a wealth of different tasks and abilities. AI systems can already perform some such tasks and in future will be able to perform more. Since intelligence comprises the three aspects of (1) receiving and recognising information, (2) processing, inferring and learning, and (3) acting appropriately, “recognising”, “inferring” and “acting” can – for the purpose of simplification – be discerned as elements of AI systems.

These abilities can be applied individually or in combination to various types of data or inputs. There are a huge number of options for the input data: often it is general audio data, speech, images or videos, text, purely numerical data or motion data. Many specific tasks, such as speech or object recognition, can be devised for AI by combining different types of data according to their usability. Some of these tasks are shown in the so-called **Periodic Table of AI** in Figure 6 and Table 1.

[31] Krail, Michael et al. (2019), p. 34.

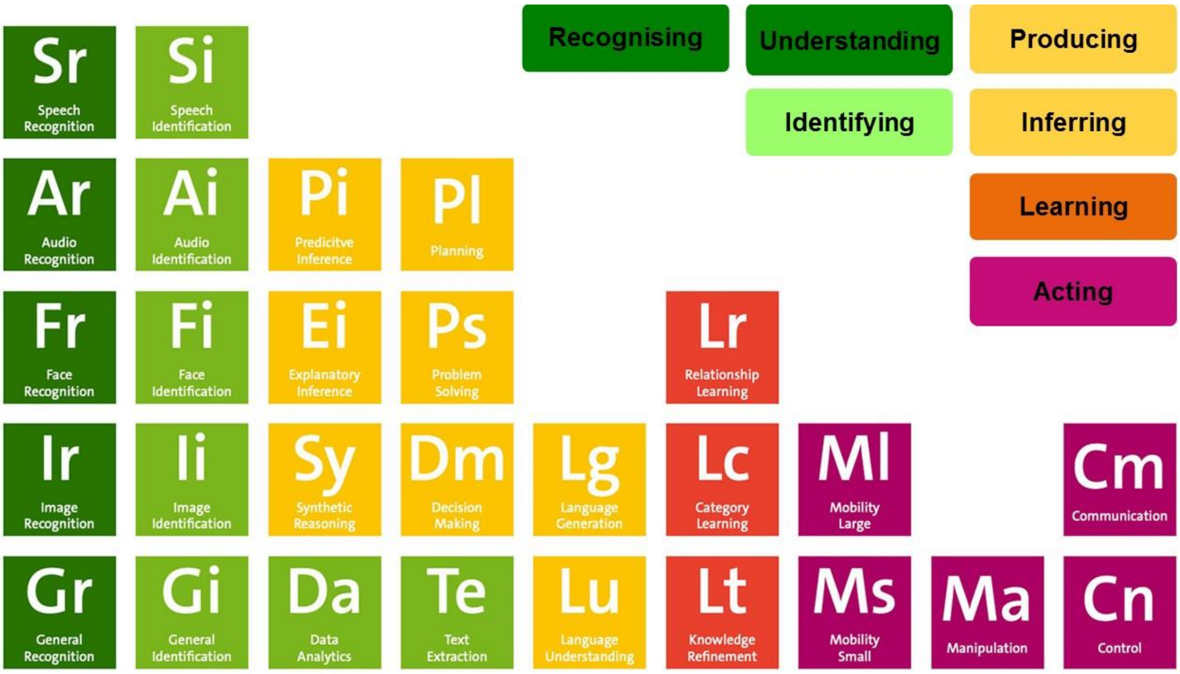


Figure 6 Periodic Table of Artificial Intelligence [Source: Hammond, Kris (2016)]

Highly complex applications are composed of several components of the periodic table or several parts of AI. For example, an autonomous vehicle must be able to recognise moving objects like a pedestrian as such. It must then predict the next movements of the person and compare these with its own trajectory and thus estimate the risk of an accident. If there is a risk of an accident, it must alter its own movement accordingly, e.g. by braking, and at the same time continuously monitor further changes in its surroundings. A high degree of AI can be achieved from a similar combination of several complex subtasks involving recognition, information processing, inferring amid uncertainty and corresponding actions.

Table 1 Explanation of the applications from the Periodic Table of AI [Source: own graphic based on Bitkom (2018a), p. 17f]

Group	Element	Abbr.	Brief description
Recognising	Speech Recognition	[Sr]	Recognising spoken language and/or general emotional states in an audio signal.
Recognition	Audio Recognition	[Ar]	Recognising certain types of noise (alarms, device distress, car engine) in an audio signal.
Recognising	Face Recognition	[Fr]	Recognising faces and emotional states in images and video signals.
Recognising	Image Recognition	[Ir]	Recognising specific types of object in images or video signals.
Recognising	General Recognition	[Gr]	Analysing sensor data in order to recognise different types of object and/or situations from the signal alone.
Recognising	Speech Identification	[Si]	Recognising an individual voice in an audio signal.
Recognising	Audio Identification	[Ai]	Recognising audio signatures (e.g. a specific engine or a specific door hinge) from audio signals.
Recognising	Face Identification	[Fi]	Recognising specific people in images or video signals.
Recognising	Image Identification	[Ii]	Recognising a specific object in an image or video.
Recognising	General Identification	[Gi]	Building on the functionality of General Recognition [Gr], analysing sensor data in order to identify objects and/or situations from the signal alone.
Recognising	Data Analytics	[Da]	Analysing data in order to recognise certain facts and/or events represented by said data.

Recognising	Text Extraction	[Te]	Analysing texts in order to extract information about entities, time, location and facts contained exclusively within the text.
Inferring	Predictive Inference	[Pi]	Predicting events or states in the future based on an understanding of a current state or the functioning of the world.
Inferring	Explanatory Inference	[Ei]	Explaining events or states in the real world based on the understanding of earlier states.
Inferring	Synthetic Reasoning	[Sy]	Using evidence in order to support conclusions about the real state of the world, a prediction or an explanation.
Inferring	Planning	[Pl]	Creating a plan of action based on objectives, an understanding of the state of the world and the knowledge of actions and their consequences.
Inferring	Problem Solving	[Ps]	Devising a solution to a problem that may or may not be linked to the use of actions (see Planning [Pl]).
Inferring	Decision Making	[Dm]	Selecting a particular plan or solution based on available facts, alternative solutions and a series of objectives.
Inferring	Language Generation	[Lg]	Generating natural spoken texts and/or explanations based on a certain understanding of the world.
Inferring	Language Understanding	[Lu]	Creating a semantic representation of the meaning of a text that shows the context and a certain understanding of the functioning of the world.
Inferring	Relationship Learning	[Lr]	Identifying relationships between features in order to predict a set of hidden features when others are visible.
Inferring	Category Learning	[Lc]	Identifying new categories of semantic values based on groups of features.
Inferring	Knowledge Refinement	[Lt]	Rewriting existing knowledge or rules in response to them being used to support actions or conclusions.
Acting	Mobility Large	[Ml]	Controlling autonomous vehicles that interact with other vehicles.
Acting	Mobility Small	[Ms]	Controlling robots that move through internal spaces, work, and interact with humans.
Acting	Manipulation	[Ma]	Handling of objects with which humans work on a regular basis.
Acting	Communication	[Cm]	Mechanisms that assist with various forms of communication between human and machine.
Acting	Control	[Cn]	Intelligently controlling other machines if no manipulation or handling is required in the physical world (e.g. automated trade).

The Periodic Table of AI shows the wide variety of ways in which AI can be used. For the purposes of the further discussion, it would be useful to group the many different AI applications into **application groups** in order to be able to classify the methods of AI and their potential in the energy industry more easily later on.

- The application group **Audio & Speech** includes
  - recognising, understanding, or generating speech and audio data,
  - recognising people based on their voice.
- The application group **Image & Face** includes
  - recognising objects, symbols and writing in images,
  - recognising people and understanding facial expressions.
- The application group **Robotics & Assistance Systems** includes
  - targeted movements and dealing with obstacles,
  - physical interaction with people or objects,
  - written, oral or physical interaction with people (e.g. chatbots and social intelligence skills belong in this category).
- The application group **General Data** includes other applications, such as
  - recognising patterns,

- mathematical data processing,
- quantitative prediction of future events or states.

These groups are not always clearly distinguishable, as more complex applications are often based on a combination of more simple applications. Nevertheless, the four aforementioned application groups constitute a useful typology of applications without it being necessary to go into the technical details of AI. This typology is explored further in Chapter 3.

A semi-quantitative assessment of the current stage of development of a particular application group with regard to technological maturity, market penetration, complexity and development potential has shown that the degree of maturity is already very high for *General Data* and *Image, Video & Face*. At the same time, there is still potential for development. The assessment in the following table is based on the Fraunhofer study on ML[32] and the opinion of the consulting scientists of this report.

Table 2 Comparison of AI methods on a semi-quantitative scale (low, medium, high, very high) [Source: own graphic]

Application group	Example tasks	Technological maturity	Market penetration	Complexity	Development potential
Audio & Speech	▪ Speech recognition ▪ Information extraction ▪ Translation	Medium	High	High	Very high
Image, Video & Face	▪ Image recognition ▪ Autonomous driving ▪ Security measures	High	Medium	High	Very high
Robotics & Assistance Systems	▪ Autonomous driving ▪ Handling objects	Medium	Low	High	High
General Data	▪ Forming data groups ▪ Object classification ▪ Predicting values	Very high	High	Medium	High

2.3.2 How AI works: Methods of artificial intelligence and machine learning

Now that we have looked at the general description of AI and its fields of application, we shall now delve deeper into selected methods of AI in general and ML in particular. In so doing, we will largely disregard mathematical details. The various methods already in use today can be broadly divided into three groups based on their learning style:

- **Supervised learning** means that the results of a learning task already exist and the computer can directly compare its result with the correct result. This rather laborious approach is only possible if there is a large amount of data with the correct result. Often, these are sets of data that have already been classified by humans.
- **Unsupervised learning** means that the correct result is unknown and the computer must detect patterns itself. In this case, the raw data is sufficient for the computer to recognise patterns in it.
- **Reinforcement learning** works using feedback from interactions with the surroundings. It is often applied in robotics, as this often involves direct feedback from the surroundings.

[32] Fraunhofer (2018).

Examples and additional subgroups are organised according to learning task and learning method in Table 3. Additionally, Figure 7 shows the methods most commonly used by data scientists and ML experts (multiple answers are possible). It should be noted that mathematical methods such as ANNs can also be used in a variety of fields, for example in supervised as well as reinforcement learning.

Table 3 Classification of AI/ML methods [Source: own graphic]

Learning style	Learning task	Learning method	Model	Example
Supervised	Regression	Linear regression	Regression line	Prediction of prices
		Classification and regression tree method	Decision tree, random forests	Prediction of data
	Classification	Logistic regression	Dividing line	Prediction of an outage
		Iterative Dichotomiser (ID3)	Decision tree	Categorisation of data
		Support vector machine (SVM)	Hyperplane	Forming client groups
		Bayesian inference	Bayesian models	Grouping data
Unsupervised	Clustering	k-means	Cluster midpoints	Identification of client groups
	Dimensionality reduction	Principal component analysis (PCA)	Combined features	Simplification of complex decisions
Reinforcement	Sequential decision-making	Q-learning	Strategies	Learning how to play complex games
Miscellaneous	Miscellaneous	Backpropagation	Artificial neural networks (ANN)	Prediction of an outage

Logistic regression, decision trees, random forests and ANNs are among the most commonly used methods. These and other important methods will be explained briefly in the following based on individual application examples. It is sometimes difficult to distinguish between statistics, statistical learning, AI and ML, and sometimes this distinction depends on the application in question. These methods were selected based on their prevalence in many applications, but completeness cannot be guaranteed.

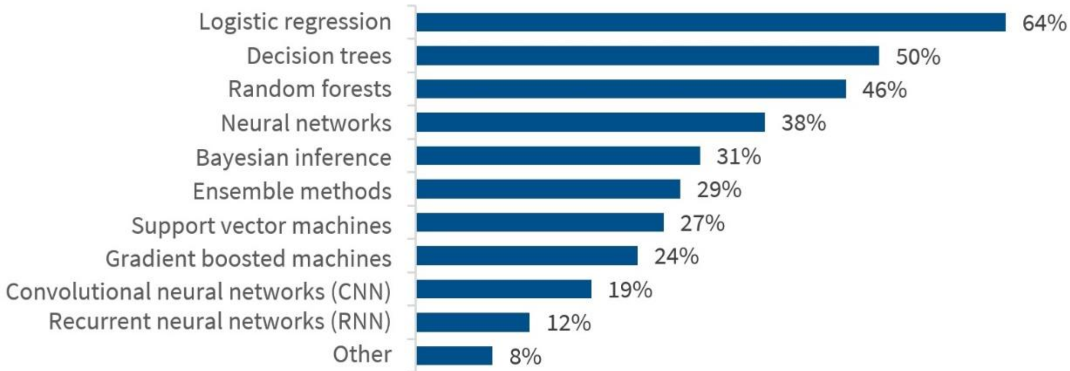


Figure 7 The methods most commonly used by data scientists and ML experts [Source: Fraunhofer (2018), p. 18]

Supervised methods

As described above, supervised methods are characterised by the fact that the result is already known for a certain number of cases. These cases can be used to train a model or computer program such that it predicts the result of new cases as accurately as possible. For the purposes of training, the known result must be compared with the model prediction so that the model can learn from its mistakes. In general, these errors are measured quantitatively as an absolute or percentage deviation.

Linear regression

One of the most common methods in quantitative models is regression. More specifically, regression refers to a whole family of methods in which a relationship between one or more dependent variables and one or more independent variables, the influencing factors, is established. The dependent and independent variables may be a number (e.g. a price, the age of the customers or the required power in kW), but they may also be a category, such as the type of household (single-person or multiple-person household) or something else.

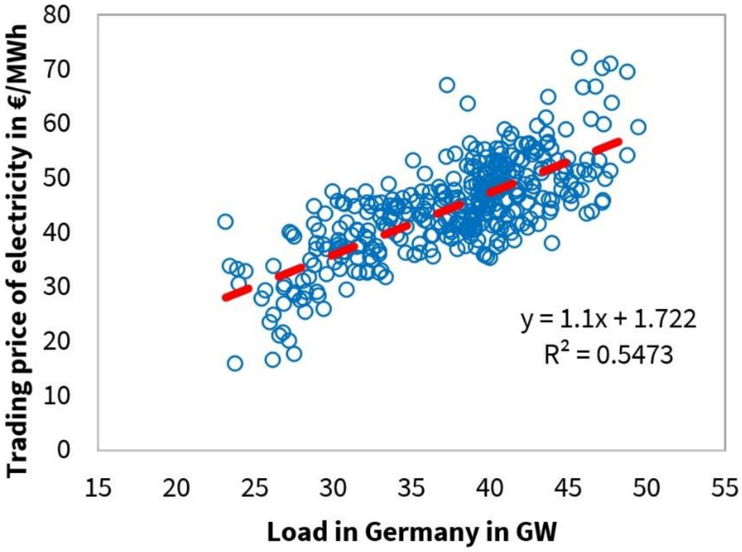


Figure 8 Simple linear regression between the trading price of electricity and the load in Germany (the hours of the year 2010 are shown as blue circles and a simple regression line can also be seen) [Source: own graphic]

The simplest case of regression is linear regression with a dependent and an independent variable. As an example, Figure 8 shows the trading prices of electricity in €/MWh as a function of the hourly load in Germany for all hours of the year 2010 (shown as blue circles). A distinct correlation can be observed: during hours of low load the prices are rather low, and during hours of high load the prices are, on average, rather high.

A regression model of this kind can cope with a very large number of variables and is overall very flexible, since mathematical transformations of the input data are also possible. At the same time, these models are calculated very quickly and are very easy to interpret. For decades, regression models have been a standard tool in statistics, and there is a great deal of empirical knowledge on the subject as well as lots of suitable software and comprehensive literature. However, in statistics, the aim of regression is mainly to find and interpret correlations between variables. In many AI applications, however, high prediction accuracy is often more important than interpretability, and therefore regression models are modified slightly in practice.

The high flexibility and speed of regression models make them a key tool for AI and ML.

Decision tree and random forests

In many applications, it is often helpful to apply simple decision-making rules when predicting a value or attribute. A decision tree does exactly that: it provides a string of simple decision questions that gives the most probable result at the end of each branch. A beneficial characteristic of trees of this kind is that they are easy to understand. Decision trees are particularly easy to interpret, in contrast to deep ANNs, for example.[33] Figure 9 shows a simple example of a decision tree.

A single decision tree is easy to interpret, but the predictions it produces are not as accurate as those given by other methods. Therefore, it is common practice to create a very large number of decision trees (each with subsets of the data) and to use the weighted sum of the predictions of the individual decision trees for the result. The term "random forests" is used to refer to a large number of trees based on random samples.

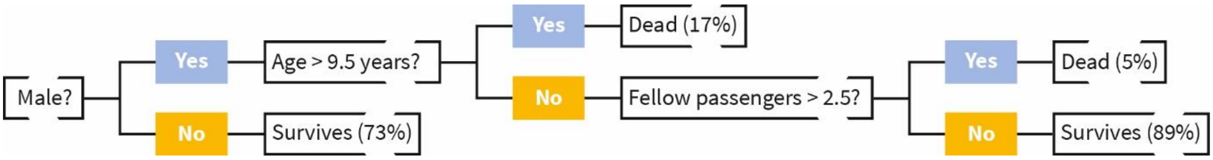


Figure 9 Decision tree for surviving the sinking of the Titanic (the questions are answered for the individual passengers; the percentages in brackets indicate the probability of survival for the passengers of a particular group) [Source: own graphic based on Portilla, Jose Marcial (2015)]

Classification and logistic regression

Classification involves assigning individual observations to a specific group based on existing examples. There may be two or more groups. This task is very important in many applications, for example in order to make automatic decisions about scrap during manufacture or to assign customers to particular known groups.

The most commonly used classification method is logistic regression. Logistic regression is a variant of the aforementioned linear regression model. Here, the dependent variable is not a continuous number, but rather an index of the group affiliation. Most often, two groups are used, i.e. a yes/no decision (e.g. "Scrap yes/no?" or "Client open to advertising yes/no?"). For observations that belong in the group, the dependent variable adopts the value 1. For all other observations, it adopts the value 0. This method can be universally applied to several groups. Logistic regression is one of the most commonly employed classification methods, as it is very fast, can learn using little data and can deal with complex relationships using said limited data. Strictly speaking, logistic regression is not a learning method, since the fundamental mathematical model is trained using data at the start and then stays the same (or has to be constantly retrained). Furthermore, the logistic regression model is not as simple or understandable as the decision tree model, for example.

Unsupervised methods

If there are no already-solved problems available for the training and AI has to uncover patterns itself, unsupervised methods are used.

Clustering

The aim of clustering is to identify groups of similar observations in data. The identified groups are referred to as "clusters". There is a whole host of algorithms available for this. One of the most common algorithms is the

[33] Fraunhofer (2018).

k-means method, in which the number of groups to be found must be prespecified. Based on this, the algorithm determines the best midpoints for the specified number of groups and assigns each observation to the most relevant group.

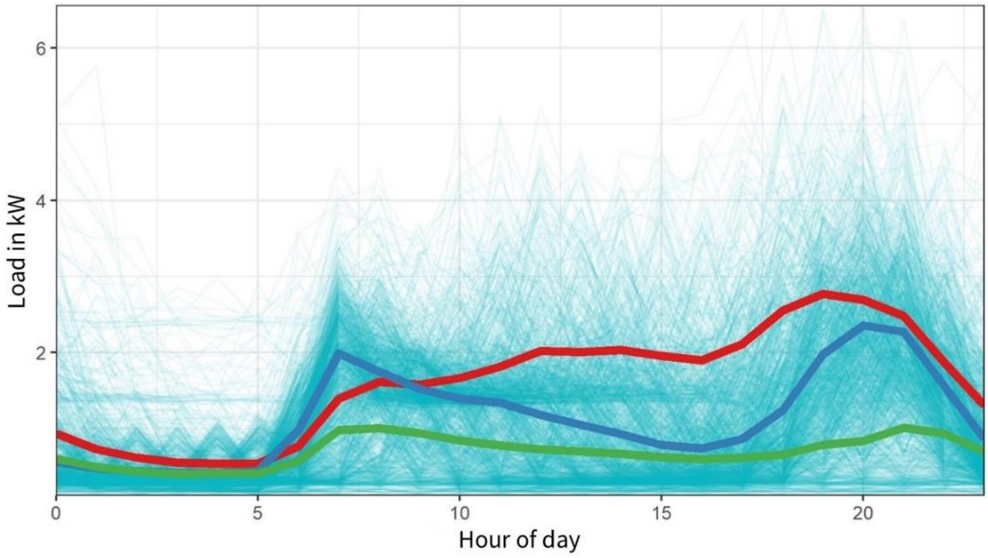


Figure 10 Load curves versus hours in the day, averaged from 1456 days in a household south of Paris [Source: own graphic based on Viola, Luciano Guivant (2018)]

Figure 10 shows an example of clustering using the k-means algorithm. The data consists of the average hourly load in kW of a household over 1,456 days. Each day is considered an observation; the variable is the load throughout the 24 hours of the day. All 1,456 diurnal cycles are represented as very fine translucent lines in the figure. The many days are then divided into three groups by means of the method, wherein the load profiles of the three group midpoints are shown as thick lines in the same figure:

- The dark-green group has a very low load profile that is almost constant throughout the day. These may be days on which the residents are not at home and may have travelled away.
- The red group shows a high load throughout the entire day with a slight peak in the evening. These could be weekend days or holidays on which the residents are at home and are cooking or washing a lot.
- Finally, the blue group seems to represent work days – with a peak in the morning and evening and a lower load in the afternoon.

Dimensionality reduction

In some applications, a very large number of attributes or factors may influence the result. Often, these factors are also closely related to one another and correlate closely with one another. In these situations, it is often helpful to check whether individual variables or a combination of several variables are significant to the result. Dimensionality reduction methods help to pick out the most significant combinations of factors from the multitude of influencing factors. These linear combinations of factors are referred to in mathematics as principal components; the method for identifying them is called principal component analysis.

Other methods

Artificial neural networks (ANN)

An early idea in AI research was to develop intelligence by replicating aspects of the human brain. In the brain, a vast number of so-called neurons are interconnected in multiple layers. The fundamental concept of ANNs is to replicate these structures artificially using a computer program.

Despite the fact that this idea came early on, significant progress has only been made in the last ten years, with some interesting results, above all in image and video data and speech and text data. Today, ANNs can sometimes recognise faces and objects with fewer errors than human estimations. Complex tasks such as translating texts, answering questions and emails, condensing news into reports, composing music and texts, and producing images are therefore all possible today.[34]

Using deep ANNs has proven particularly successful, i.e. ANNs with a relatively large number of layers of “nodes” implemented in software. These “nodes” are referred to as artificial neurons (see Figure 11). During the learning process, the weights – i.e. numerical values at the connections between nodes – are altered until satisfactory results are obtained. In their inner layers, the networks autonomously produce compact representations from the raw data, making many pre-processing programs redundant and the actual task easier to learn. Deep ANNs produce expressive models that can also be trained efficiently in parallel computer systems. This often only bears fruit with substantial volumes of data. Since it is not readily apparent to the user what the weightings in an ANN mean and how exactly the tasks come into being, these models are referred to as “subsymbolic” models, in contrast to symbolic models such as decision trees (see Figure 9 above) or the knowledge bases of earlier expert systems.

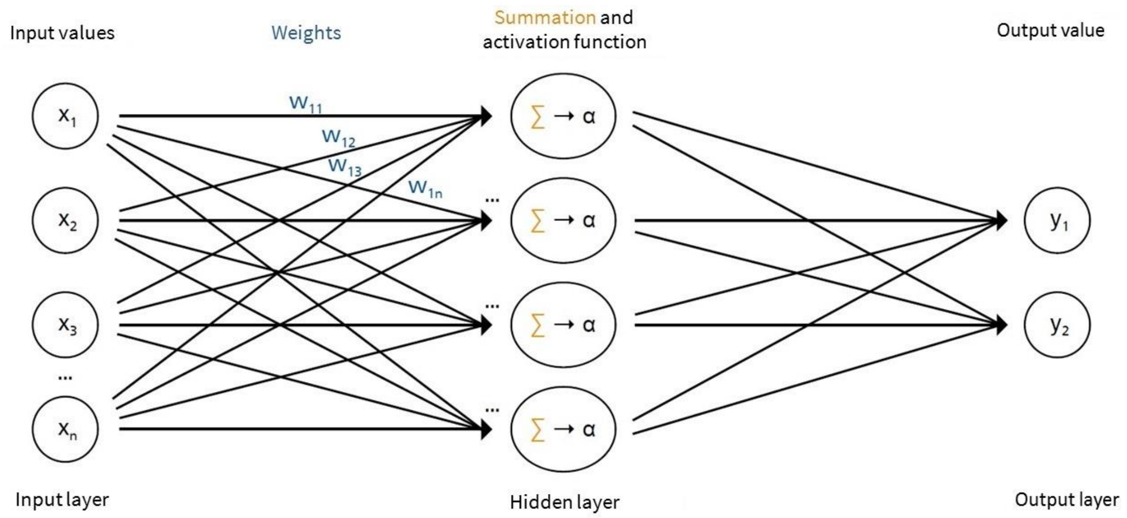


Figure 11 Schematic representation of an ANN [Source: Fraunhofer (2018)]

There are many network architectures that have individually proven effective for different types of data and tasks. Since the networks can on the whole be trained from input to output, the term “end-to-end learning” is also used. Deep ANNs have been very successfully applied in “deep Q-networks” in reinforcement end-to-end learning for games and robots.

[34] Fraunhofer (2018).

One application example for deep ANNs is recognising handwritten numbers such as postcodes or handwritten counter readings. A comprehensive training database called MNIST (Modified National Institute of Standards and Technology database) is available for this application. It comprises 60,000 training images and 10,000 test images consisting of 28x28 pixels in grey scales (Figure 12 shows some example images). The best modern methods for identifying the numbers correctly are deep ANNs. They are able to identify 99.5 percent of the images correctly and are therefore comparable to human capabilities.

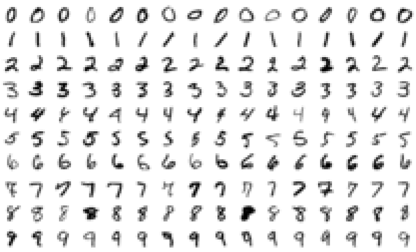


Figure 12 Example figures from the MNIST database of training and test data of handwritten numbers [Source: Dato-on, Dariel (2018)]

Reinforcement learning

Reinforcement learning is the third group of AI methods. Here, the program is not prescribed any explicit strategy, but rather learns by itself through trial and error. In contrast to supervised learning, the algorithm does not require any correct solutions, but rather scans for possible actions and obtains a variety of solutions in various states. The algorithm tries to find a balance between the exploration of new states and previously successful paths. In mathematical terms, these algorithms are sometimes also deep ANNs. Methods of reinforcement learning are for example used as algorithms in strategy games such as chess or Go and are now better than all human players. All they need are the rules of the game and the information about when a game has been won. Based on this, the algorithms learn strategies independently by playing against themselves again and again.

The sheer variety of tasks and methods in AI clearly shows that there is no single AI, but rather a plethora of AI configurations whose development is at very different stages and whose application options sometimes differ greatly from one another. In the following, we will present existing and likely fields of application of AI within the energy industry.

3 The fields of application of AI in the energy industry are manifold

A comprehensive decarbonisation of all sectors through optimisation across sector boundaries is at the heart of the integrated energy transition. The aim is to master the increased complexity of the energy system resulting from the closer interconnectedness – associated with the energy transition – of the increasing number of assets and actors using digital technology. In this regard, AI is expected to make a significant contribution to the integrated energy transition, in that it will be possible to analyse and evaluate the data generated during the digitalisation process efficiently using AI methods.

But how will AI be used in the energy industry specifically? How can AI applications contribute to a successful integrated energy transition? How much progress has been made in the relevant applications? These questions will be addressed systematically in three steps:

(1) Analysis of fields of application of AI in the energy industry (Chapter 3.1)

Current AI applications from research and the energy industry and those likely to surface in the near future shall be extensively screened. Based on the strategic tool *Map of Digital Dynamics*[35] developed by dena, these example applications will be assigned to the various market segments in the digital energy world. These applications shall also be assigned to the AI application groups introduced in Chapter 2.3.1: *General Data, Audio & Speech, Image & Face* and *Robotics & Assistance Systems*. Finally, similar applications will be grouped into fields of application.

(2) Assessment of the contribution of fields of application of AI to the integrated energy transition (Chapter 3.2)

The fields of application of AI shall be assessed in terms of their contribution to the integrated energy transition. This assessment will be carried out on the basis of the following five criteria: Contribution (1) to the integration of renewable energies, (2) to the increase in energy efficiency, (3) to the reliability of supply, (4) to the increase in system efficiency and (5) to the increase in acceptance of and participation in the integrated energy transition.

(3) Classification of the state of development of the fields of application of AI (Chapter 3.2)

Finally, the current state of development of the fields of application of AI in the energy industry will be assessed and classified. AI has already been implemented in certain areas. At the same time, there are many approaches currently being developed and researched.

3.1 AI can be applied in the entire value-creation network of the energy industry

Comprehensive research into current developments and plans within the field of AI applications forms the starting point for identifying the relevant fields of application. Studies and other resources on national

[35] dena (2017a).

activities[36, 37, 38, 39] as well as international findings[40, 41, 42, 43, 44] were considered during the investigation of application examples from research and the energy industry. The research included an extensive screening of current plans being developed in the energy industry and in the field of research. However, the completeness of this research cannot be guaranteed. The aim was to paint a detailed picture of the current AI landscape within the energy sector.

The systematic classification of the application examples of AI in the energy industry is based on a schema that has an energy industry dimension and an AI-specific dimension (see Figure 13).

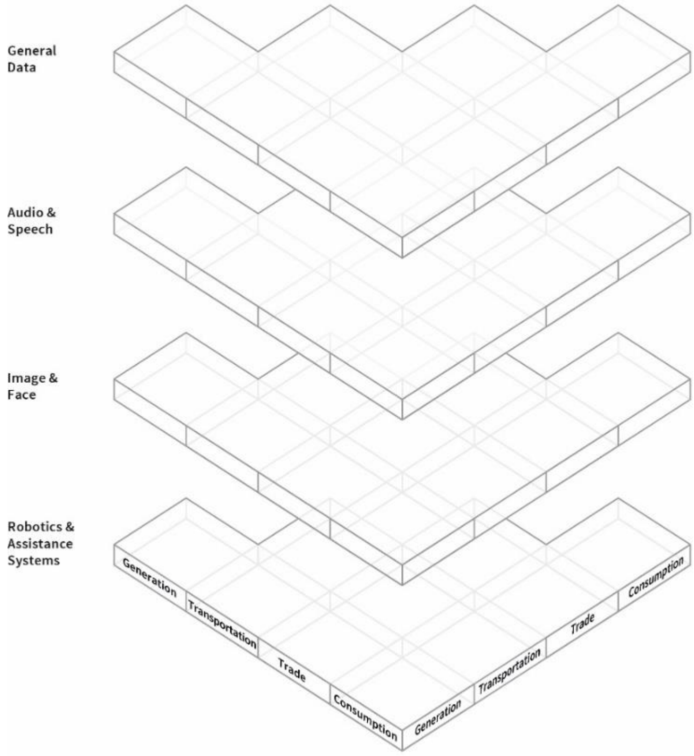
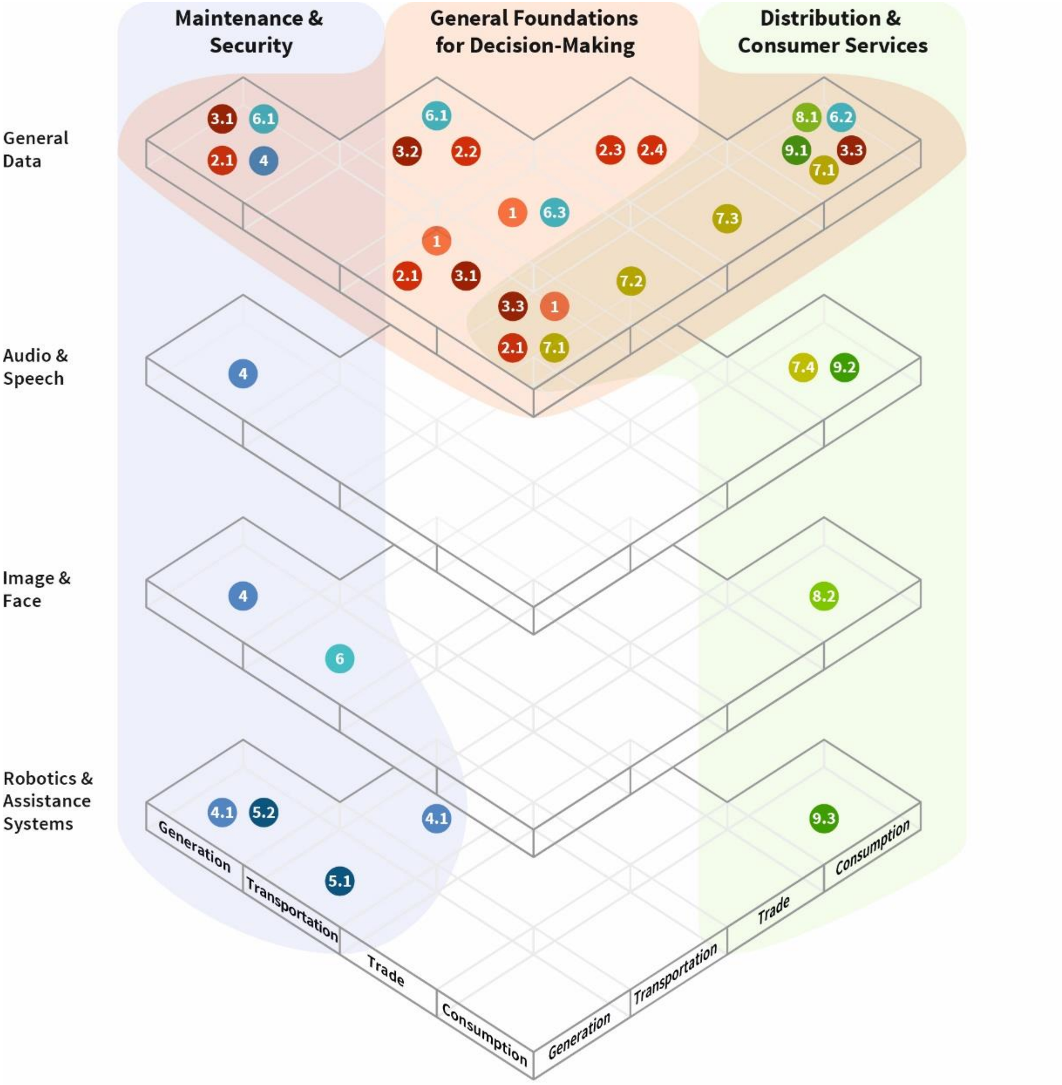


Figure 13 Schema for classifying the AI application examples within the value-creation network of the energy industry [Source: own graphic based on dena (2017a)]

dena's *Map of Digital Dynamics*[45] forms the basis for the energy industry dimension of the matrix. The clear-cut distinction between the stages of the classic value-creation chain in the energy industry – consisting of generation, transportation, trade and consumption – will become increasingly blurred with the digitalisation and decentralisation of the energy industry. New market segments that combine several value-creation stages will emerge and therefore produce a value-creation chain in which AI applications can also be placed and/or classified. The AI-specific dimension relates to the AI application groups set out in Section 2.3.1: *General Data, Audio & Speech, Image & Face* and *Robotics & Assistance Systems*.

[36] PwC (2017).
[37] Ndiaye, Alassane (2019).
[38] Edelmann, Helmut; Fleischle, Frank (2018).
[39] Plattform lernende Systeme (2019).
[40] Backes-Gellner, Uschi et al. (2019).
[41] Microsoft (2018).
[42] OECD (2019a).
[43] OECD (2019b).
[44] World Economic Forum (2018).
[45] dena (2017a).

From application examples to fields of application and superordinate clusters



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 14 AI application examples and their assignment to fields of application and superordinate clusters [Source: own graphic]

Figure 14 gives an overview of the aggregated AI application examples and their schematic assignment within the value-creation network.

As it turns out, AI applications can already be found in practically all market segments of the energy industry value-creation chain today. AI applications are also prevalent in market segments that emerge at the interface between several value-creation stages.

What is particularly striking is that most application examples use AI methods for general data analysis. The proportion of examples that apply AI in the field of Audio & Speech or Image & Face is still rather small. The use of complex AI systems such as robots or assistance systems is also rather rare. There is only a handful of application examples in this area, e.g. maintenance drones or robots for decommissioning nuclear installations.

This reflects the results of a representative survey of 250 management staff of the German energy industry conducted on behalf of dena. According to the survey, general data processing is the biggest field of application of AI in the energy sector at 96 percent. Speech and audio processing is less prevalent at 69 percent and 63 percent, respectively, as is image and video processing at 63 percent.

The high concentration of AI applications in general data processing in particular includes examples that use "weak AI". Although more complex AI methods that are developing in the direction of "strong AI" are starting to be used, they are still far less prevalent. The development and dissemination of AI applications within the energy sector is therefore similar to the situation in other fields of application.

The examples identified can be grouped together into a total of nine fields of application and three superordinate clusters (in Figure 14, the fields of application are each designated a different colour and the clusters are indicated by areas of differently coloured shading):

- **Cluster "General Foundations for Decision-Making":** AI assists various actors, for example with making investment decisions, predicting the capacity utilisation of the grid, the consumption and the feed-in of the power generated more accurately, and optimising operation and/or consumption. AI applications in this cluster are distributed along the entire energy industry value-creation chain and primarily use AI methods for general data analysis. This cluster comprises the following fields of application:
  - **Field of application 1:** **Predictions**
  - **Field of application 2:** **Operation optimisation**
  - **Field of application 3:** **Inventory optimisation and other strategic business decisions**
- **Cluster "Maintenance & Security":** In this cluster, AI can help to minimise downtime of power-generation plants and of the grid and ensure secure operation of plants. AI application examples from this cluster can be found in the value-creation stages of generation and transportation in particular. This cluster comprises the following fields of application:
  - **Field of application 4:** **Predictive maintenance**
  - **Field of application 5:** **Maintenance, repair and dismantling**
  - **Field of application 6:** **Security measures**
- **Cluster "Distribution & Consumer Services":** AI applications in this cluster aim to improve customer relationships and can therefore be found in the value-creation stage of consumption in particular. This cluster comprises the following fields of application:

– <u>**Field of application 7:**</u> **Making it easier for active consumers to participate**
– <u>**Field of application 8:**</u> **Customisation of products and marketing measures**
– <u>**Field of application 9:**</u> **Process automation for measurements, bills and general distribution**

3.2 The nine fields of application – and what to expect from them

The fields of application of AI identified for the energy industry will be explained briefly in the following Chapters 3.2.1 to 3.2.9. A concrete practical example should help to improve understanding of the relevant field of application. It should be noted that the subsequent assessment of the nine fields of application is a qualitative initial assessment for paving the way forward. A more detailed analysis and assessment of the individual fields of application with regard to technical, economic and regulatory matters will follow in a later report.

The classification of the contribution of the individual fields of application of AI to the integrated energy transition is based on five criteria:

- **Integration of renewable energies**: Efficient incorporation of renewable energies into the existing market structures with the aim of determining their feed-in as accurately as possible, preventing curtailment and making it possible to participate in all power markets. Aside from participation in the electricity trade, this also relates to incorporating ancillary services such as operating reserves.
- **Reliability of supply**: Maintaining the balance between supply and demand on the market and grid level. Preventing critical grid states and contributing to existing ancillary services
- **System efficiency**: Implementing the integrated energy transition using as little resources as possible. In so doing, the fields of application of AI are assessed with regard to whether they can reduce the overall costs of the energy system in an existing supply task and/or whether predetermined climate protection measures can be implemented at minimal cost.
- **Energy efficiency**: Reducing the primary energy consumption and contributing to the reduction of the specific energy use and thus to the increase in energy efficiency. This is therefore generally linked to improving system efficiency.
- **Acceptance and participation**: Extent of information provision, consultation, involvement, co-determination and decision-making ability of various actors with the aim of reaching an agreement and cooperating in order to successfully implement the integrated energy transition.

At the same time, **the state of development of the individual fields of application of AI is qualitatively classified**. This includes the identified examples of AI applications that have already been implemented in practice or that are being tangibly developed. It is also considered whether similar developments are taking place in sectors other than the energy industry and whether they can be applied to the energy sector. Furthermore, current research work is also integrated into the assessment.

3.2.1 Field of application 1: Using AI to improve predictions

Many AI application examples relate to improving predictions. Here, statistical ML methods and ANNs are already well established. The need for simultaneity between generation and consumption makes predictions a fundamental component of the energy industry across several value-creation stages (generation – trade, transportation – trade, generation – consumption). With the growing presence of fluctuating renewable energies and the need to increase the capacity utilisation of (distribution) networks and identify critical states at an early stage, this requirement will become more acute in future. The advent of new applications such as e-mobility increases the need for suitable predictions, in order to also determine the load requirement depending on different price signals.[46] Historic data and, if applicable, other parameters from real-time data are used to create the predictions in order to derive future development. This derivation can be significantly improved by using AI in the form of statistical methods or ML.

Example: SINTEG project DESIGNETZ with the German Research Centre for Artificial Intelligence (DFKI)

Within the scope of the SINTEG project DESIGNETZ, scientists from the DFKI are developing three prediction methods based on ML and combining them in order to predict PV power generation. For more information, please go to: https://www.dfki.de/web/forschung/projekte-publikationen/projekte/projekt/de-

Contribution of this field of application of AI to the integrated energy transition

Valid predictions are a key component of the integrated energy transition. Improving predictions using AI therefore makes a significant contribution to its success. By using ML in predictions, a larger volume of data can be processed, as a result of which patterns and predictions can also be derived in consideration of heterogeneous variables and anomalies can be identified better. This makes possible a smaller-scale temporal and spatial resolution and customised predictions.

For example, with more accurate predictions of fluctuating renewable energies, more targeted marketing can be achieved, compensatory measures in the event of imbalances between supply and demand can be introduced and penalties due to payment imbalances can be avoided. Improving predictions using AI can therefore facilitate the integration of renewable energies in particular.

In addition, the use of AI methods for creating predictions can, for example, form a basis for improved grid operation even at lower grid levels. The knowledge of the status of the grid is of great importance to an improved cross-sector capacity utilisation of grid infrastructures. AI-based predictions of the grid status, which can predict the demand side across sectors in addition to the power generation and can integrate and analyse real-time data, therefore contribute to reliability of supply and system efficiency.

Implementing the energy transition in this manner by ensuring a reliable energy supply at minimal cost also contributes indirectly to a greater acceptance of the integrated energy transition.

State of development of this field of application of AI

Various statistical methods and ANNs are already being used in predictions and for optimising commercial generation predictions. Significant improvements have already been made in the prediction of the feed-in of spatially distributed generation portfolios and for individual control areas.

The current state of development of AI-based predictions in the field of research will be explained by way of example with reference to current work. In his paper, Li generates time series forecasts for wind power production using a four-layer ANN.[47] In contrast to conventional forecasts, average values of 10 minutes are produced. In this way, intermittent generation peaks can be predicted more accurately. Sharma et al. address the problem that a forecast of weather patterns must be developed on the basis of location-specific historical values

[46] Cf. dena (2017b).
[47] Li, S. (2003).

that reach far back into the past in order to show anomalies.[48] By using various regression methods, solar power generation can be predicted with 27 percent greater accuracy than in existing prediction models that merely consider historical values from one day.

3.2.2 Field of application 2: Using AI to optimise operation

Building on predictions or other data (e.g. network status data or power plant data), strategies for the operation of assets in the energy industry can be derived. AI application options range from optimised use of conventional and renewable power plants, including a possible gas and/or heat supply (virtual power plants and dispatch optimisation), to optimised grid operation and a higher grid capacity utilisation. When devising operation strategies, external factors (e.g. electricity price trends) and other data available in real time can be used and evaluated using AI methods in order to derive an optimum strategy (e.g. for maximising profits).

Another bigger field of application of AI is detecting the status of the grid, by means of which grid loads can be derived from real-time data and critical grid statuses can be predicted and therefore prevented. Other AI applications that build on from this can improve risk management in the grid or increase the transparency of market trading centres, for example by automatically monitoring and/or analysing commercial transactions. This can then be used to reduce market power, for example.

Example: Security Assessment & System Optimisation (SASO) by PSI

With its Security Assessment and System Optimisation (SASO), PSI gives network operators a system that allows for a focused assessment of the grid status and provides suggestions for resolving detected critical states. Algorithmic methods and computational intelligence (CI) methods such as fuzzy logic or ANNs are used for the decision support. New, hierarchically structured concepts that give a quick overview of the grid status are provided for the visualisation. For more information, please go to:
https://www.psienergy.de/de/loesungen/saso-dso-20/

Contribution of this field of application of AI to the integrated energy transition

Over the last 10 years, there has been a decline in disruptions to supply in grid operation and less of a need for control energy.[49, 50] Despite increasing amounts of fluctuating renewable energies in the system, thanks to better forecasts of power generation and better coordination between the various grid operators[51], it has been possible to ensure reliability of supply. At the same time, in recent years, the cost of grid operation has increased substantially on account of redispatch and feed-in management measures. Optimising operation using AI could be particularly relevant here, in that feed-in management measures could be drastically reduced by adapting the power generation to the actual grid load. AI applications would therefore contribute to the integration of renewable energies.

When optimising operation of an asset, external factors (e.g. electricity price trends), asset-specific characteristics (e.g. travel times to a power plant), but also the expected demand, must be taken into consideration. With an ever-increasing share of renewable energies and with the spread of new applications (e.g. e-mobility),

[48] Sharma, Navin et al. (2011).
[49] Bundesnetzagentur; Bundeskartellamt (2018).
[50] Slight increase from 12.08 minutes to 15.14 minutes in 2017 due to extreme weather events. By comparison, in 2006 it was 21.53 minutes.
[51] In addition to changes in market design.

it is becoming increasingly difficult to determine the external factors. New energy industry assets such as stores and flexible sector coupling technologies could compensate in part for the increasingly fluctuating nature of power generation. New store-specific requirements such as determining the charging and discharging times in consideration of charging restrictions and storage losses must be factored in when optimising operation. In this case, AI methods could contribute significantly to increasing system efficiency on the one hand and reliability of supply on the other by taking into account the plethora of constraints.

State of development of this field of application of AI

Tools for optimising operation are very well established as a commercial application and are already being used in existing virtual power plants. Work has also started on using AI methods and these can be expected to become increasingly used into the future. For example, GE Energy has stated that they want to increase yields from wind power by up to 20 percent by optimising the operation of wind turbines (e.g. aligning them with the wind direction).[52]

One way to optimise operation in consideration of several external and asset-specific parameters is to use ML. Fraunhofer IOSB, for example, is using ML to detect faults. As a first step, the 4.3 million data records automatically gathered per day are compressed to 20 percent of the total data volume and evaluated. As a second step, the ANN is trained based on typical malfunctions. In this way, the ANN can detect anomalies within milliseconds and propose countermeasures.[53] Without ML, it would not be possible to evaluate the data almost in real time.

The proven precision of ML predictions forms the basis for many operational optimisations. For example, Crespo-Vazquez et al. optimise the use of a wind power-store combination in consideration of the storage availability and size as well as the electricity price trends using various stochastic optimisation methods and achieve a yield that is up to 6 percent higher using ANNs.[54]

3.2.3 Field of application 3: Using AI for inventory optimisation and other strategic business decisions

In addition to short-term operation optimisation, AI can also assist with inventory optimisation and other strategic business decisions. As in the case of operation optimisation, external and internal data are compared with one another and foundations for decision-making are generated. These can then be used, for example, to plan new investments and decommissioning of assets or to further develop business areas.

Example: SINTEG project WindNODE with enersis

With its project WindNODE and in cooperation with enersis, SINTEG is developing a platform for automated renovation roadmaps for a city district containing old buildings. By linking user-specific data to generally available data, automated CO2 balance sheets and proposals for action can be developed using AI methods. For more information, please go to: http://www.enersis.ch/smartheat-windnode/

[52] GE Energy (2017).
[53] Fraunhofer IOSB (2019).
[54] Crespo-Vazquez, Jose L. et al. (2018).

Contribution of this field of application of AI to the integrated energy transition

Investment in (or dismantling of) power-generation plants, grid infrastructure for electricity, heat and gas as well as other infrastructural facilities such as charging columns is an important element of the integrated energy transition. If shortages in the system becoming increasingly prevalent, market actors can decide whether to re-invest and by how much in consideration of price predictions and factors within the company (e.g. liquidity, compatibility with existing generation portfolio). The increasing number of power plants and the closer interconnectedness of all power consumption sectors make it more difficult to develop optimum investment strategies on account of the greater complexity of the system. Here, AI methods make it possible to consider a large number of influencing factors and reach better decisions more quickly by means of self-learning systems without it being necessary to analytically model all aspects. As a result, delays in implementing measures and the risk of bad investments can be reduced.

These advantages not only apply to new investments, but also to retrofitting measures for existing assets. ML approaches can potentially be used to more precisely determine whether conditions are appropriate for a particular retrofitting measure (i.e. whether the investment will pay off during the planned service life).

Such decision-making processes for inventory optimisation can be found in all energy infrastructures. Using approaches such as digital twins, virtual future scenarios can be modelled based on real status data and used as a basis for infrastructural development. This particular field of application of AI therefore makes its most significant contribution when it comes to increasing system efficiency, in that it can weigh up the use of innovative grid resources (e.g. series voltage regulators) and the implementation of grid expansion measures.

State of development of this field of application of AI

ML is already being used in power-generation and power-plant planning. There are also commercial software products that use AI methods for planning distribution network infrastructures or urban planning.

Within the field of research, work is being carried out on other AI methods for inventory optimisation of assets. In China, a support vector machine approach is being developed for determining grid expansion measures, for example, in order to predict measures from 2018 to 2022. Verification with historical data has shown that measures can be predicted with a margin of error of under 1 percent.[55] Other work is being carried out to ascertain the ideal locations for wind turbines in consideration of grid congestion and actor behaviour.[56]

3.2.4 Field of application 4: Using AI for predictive maintenance

An important field of application of AI is that of intelligent planning of maintenance work on power plants or the grid infrastructure. Maintenance and repair work often takes place at regular intervals or under exceptional circumstances. If the repair/maintenance cycle is too long, this could lead to intermittent system failures, and if the cycle is too short, this could incur unnecessary costs. Gathering and intelligently evaluating production and plant data in real time makes it possible to guarantee quality and availability and to draw up suitable maintenance plans. In order to identify the appropriate times at which to carry out maintenance work and in order to better prepare technicians for maintenance activities, AI can also be used to analyse audio or image data of the assets. Directly gathering data and analysing the state of repair of a facility can also be improved using AI, e.g. using smart sensors or robotic applications such as drones.

[55] Dai, Shuyu et al. (2018).
[56] Le Cadre, Hélène et al. (2015).

Example: Predictive IS

The self-learning AI software solution *Predictive Intelligence* by Predictive IS uncovers anomalies in a machine's behaviour, provides transparency on which factors are contributing to a machine's inefficiency, and predicts machine failures. For more information, please go to: http://www.ispredict.com/index

Contribution of this field of application of AI to the integrated energy transition

Smooth operation of power plants and energy infrastructures (in particular the electricity, heat or gas network) and thus intelligent planning of maintenance work are crucial for the integration of renewable energies and ensuring reliability of supply. Maintenance work can be planned and carried out more efficiently by means of AI applications. Providers of predictive maintenance for wind turbines for example promise predictions of operating element failures 60 days in advance and savings in the region of €12,500 per turbine due to unnecessary maintenance work having been avoided.[57] AI applications therefore not only create operational added value, but can also play a role in the integration of renewable energies. At the same time, thanks to early detection and rectification of faults, they also avert the negative consequences for the energy system associated with technical malfunction and therefore help ensure reliability of supply.

State of development of this field of application of AI

Various providers are currently developing predictive maintenance products that optimise maintenance work planning on the basis of characteristic plant and production data. A greater interconnectedness of production facilities within companies but also across value-creation stages is a concept that is currently being elaborated (Industry 4.0 or Internet of Things).

According to Merizalde et al., most predictive maintenance applications build on ML.[58] They consider the use of hybrid models that combine ANNs' learning capability and ability to map non-linearity with the flexibility of fuzzy logic to have particularly great potential. [59] However, there is still some research that needs to be done into this.

3.2.5 Field of application 5: Using AI for maintenance, repair and dismantling

The maintenance, repair and dismantling of energy industry assets requires prior knowledge, equipment and manual skills. AI assistance systems can assist the repairer by providing useful information, e.g. by evaluating the condition of the facility on-site by means of augmented reality, or by physically interacting with the repairer. AI-based robots can carry out maintenance, repair and dismantling work in locations that are hostile to life or difficult to access.

This field of application combines a wide range of AI elements: the condition of the facility can be determined on the basis of audio, speech, image, face or sensor data. Based on this data, causes are deduced and possible solutions are proposed or directly implemented by a robot.

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[57] Boldare (2019).
[58] Merizalde, Yuri et al. (2019).
[59] Fuzzy logic is an approach for dealing with imprecise or vague data based on the fuzzy sets theory expounded by Lotfi A. Zadeh and Dieter Klaua. Elements therefore only gradually become part of a set (and not with the required certainty).

Example: ROBDEKON

Within the scope of the ROBDEKON project, scientists from the Karlsruhe Institute for Technology (KIT), the Fraunhofer Institute for Optronics, Systems Engineering and Image Analysis (IOSB), the FZI Research Centre for Information Technology and the DFKI are developing a robot for use in inhospitable environments. Using a combination of the cognitive abilities of algorithms and the physical capabilities of robotics, nuclear installations, for example, can be decommissioned without endangering human life. For more information, please go to: https://www.iosb.fraunhofer.de/servlet/is/Entry.85406.Display/

Contribution of this field of application of AI to the integrated energy transition

Time delays and errors during the maintenance and repair of energy industry assets can be reduced and risks can be averted using assistance systems and robotics. These systems often build on classification models that categorise the problem and select the most suitable solution from a pool of previously applied solutions.

In locations that are hard to reach, for example offshore wind turbines, robot systems can help to reduce maintenance costs, which are greater than for wind turbines on land. This field of application also harbours great potential for the maintenance and repair of rotor blades and power grids, since access is also more difficult in these cases. The contribution of this particular field of application is therefore that of increasing system efficiency and reliability of supply in particular.

State of development of this field of application of AI

There are already isolated examples of assistance systems such as augmented reality glasses in this field of application. GE has reported an improvement in production of 34 percent with the use of these assistance systems in the maintenance of offshore wind turbines.[60]

However, there is still a considerable amount of research to be done into the evolution of assistance systems into fully autonomous robotic systems. The centre of excellence “Robdekon” is conducting research into the development of robot systems for hostile environments (see above). These robot systems may for example be used to decommission nuclear power plants.

3.2.6 Field of application 6: Using AI for security measures

Within the context of digital applications, not only do risks relating to information and data security increase, new opportunities for monitoring and limiting these risks also emerge. Conspicuous patterns in digital processes in the fields of energy generation, transportation, trade and consumption can be identified and addressed. Cyberattacks on power plants or grids can be spotted more quickly and accurately and appropriate countermeasures can be taken using this particular field of application of AI. In companies, emails containing Trojan horses can be filtered better and tampering of balance sheets and accounts can be reduced.

However, image, face, speech and audio evaluations can also be used to identify and avert hazards (e.g. burglars) outside of the digital sphere. Aside from identifying illegal activities, these evaluations can be used to implement occupational safety measures, for example by sending out a verbal signal when cameras detect that workers have entered the hazard area of a power plant without wearing a helmet.

[60] GE Energy (2017).

Example: zeroBS

zeroBS provides advice and services relating to information and data security. They seek out security loopholes in software and propose options for preventing them from being exploited. Their latest development involves executing these so-called exploit campaigns in an automated manner using ML. For more information, please go to: https://zero.bs/

Contribution of this field of application of AI to the integrated energy transition

According to 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 percent of these attacks were targeted at power grids.[61] As a result of this, the creation of a new agency for cybersecurity is currently being discussed in Germany. Similar plans have already been implemented in the USA, which cited not only reliability of supply but also economic losses as justification for it. According to the US Congressional Research Service, cyberattacks on power stations and power grids could incur economic losses of hundreds of billions of US dollars.[62]

Against the background of increasing decentralisation and integration of the energy system and the growing number of transactions, verification and validation processes will likely become even more important for the security of the energy supply. These can be automated and carried out more quickly and cost-effectively using AI methods.

Therefore, this field of activity makes a significant contribution to reliability of supply and system efficiency.

State of development of this field of application of AI

The first AI applications are already being tested and, in some cases, used, e.g. in the evaluation of cyberattacks or for checking the balancing groups of all grid users of transmission network operators in order to detect misconduct and abuse of market power by individual grid users. Ml is already being used to rapidly check large volumes of data in order to identify various anomalies in the operation of grids and power plants or in client grid usage data.

In the field of research, ANNs – with their high degree of independent learning and autonomous identification of new anomalies – are a very promising approach for security measures. Berman et al. point to the need for sufficient training data in order to further improve ANNs for use in security measures and cyber defence.[63]

3.2.7 Field of application 7: Using AI to make it easier for active consumers to participate

The decentralisation and digitalisation of the energy industry open the door to the active participation of consumers. In fact, more and more consumers have their own power-generation units and stores. AI-assisted decision-making tools for possible consumption adjustments and the use and/or sale of self-generated electricity may be created on the basis of household consumption or generation data, for example, or implemented directly. This makes it easier for the consumer to alter their consumption behaviour or to operate their own power-generation units and sell the electricity.

[61] Bundesamt für Sicherheit in der Informationstechnik (2017).
[62] Campbell, Richard J. (2018).
[63] Berman, Daniel et al. (2019).

In a similar vein to operation and inventory optimisation in large-scale applications (fields of application 2 and 3), AI can also be used to provide decision-making tools for consumers to alter their behaviour (e.g. identifying the potential for small-scale efficiency gains or shifting load in order to increase the consumer's rate of consumption of their own electricity) as well as to optimise decisions to invest in new household appliances, decentralised power-generation facilities or batteries. For this, AI draws on the historical consumption behaviour data in order to give the consumer tailored recommendations.

Example: Shine energy manager

The Shine energy manager helps households to harmonise the power generation of their PV installation with their use of controllable and non-controllable consumer devices. With the help of ML, individual consumption behaviour can be detected using its individual applications and options for altering this behaviour can be displayed. For more information, please go to: https://www.shine.eco/2017/10/10/wie-kuenstliche-intelligenz-das-energiemanagement-revolutioniert/

Contribution of this field of application of AI to the integrated energy transition

The contribution of this field of application of AI to the integrated energy transition can take on a variety of forms, in particular in light of the many small-scale capabilities unlocked by increased decentralisation. AI applications that result in the replacement of inefficient household appliances or the identification of inefficient consumption behaviour reduce energy consumption and increase energy efficiency. AI-assisted operational optimisations of PV installations and stores with a specific peak load cap increase reliability of supply. Automated load shifting in times of high supply facilitate the integration of renewable energies. AI should make it possible to consider individual circumstances and preferences, which in turn could help increase acceptance of the integrated energy transition.

New business models in the digital energy world provide new fields of application for AI in households, such as the use of smart assistants in smart home applications. Energy management systems and smart charging of electric vehicles are other fields of application that are being used in different value-creation stages within the energy industry. Thanks to AI applications, access to the energy system and active participation in the energy industry will become easier for small-scale consumers and households in the future. Customised consumption reports and decision-making tools for investments and operation as well as AI-controlled circuits could all help the consumer with this. Crucially, without automated and adaptive processing of consumer data, it would not be possible to offer these services at a reasonable price or to provide the required level of precision.

State of development of this field of application of AI

Digital assistance systems such as Amazon's Alexa or Google Echo are already widely used in households, but they have so far made few inroads into the energy industry. With the planned roll-out of smart meters in 2019 and the data available thanks to this, new application options will open up for AI. Some operators are already offering AI-assisted identification of specific household appliances based on high-resolution power consumption data. However, AI-based control and management of applications in households is only happening on a commercial scale in certain pilot applications (e.g. the incorporation of household battery storage devices into a balancing power pool).

There are a variety of activities relating to this field of application of AI in the field of research. For example, MacDougall addresses the use of ML for dealing with the relative insignificance of new grid users within the context of sector coupling. She reduces the number of prediction errors relating to the service life of a virtual power plant consisting of household heating applications by using ANNs. The number of prediction errors can be reduced by one third compared with linear regression.[64] Valogianni optimises the private use of rooftop PV installations and electric vehicles using supervised learning and random forests. In this way, consumption of privately generated electricity can be increased to 93 percent during the warmer half of the year.[65] Lopez et al. optimise the way in which electric vehicle charging is managed based on the price of electricity using a variety of ANN methods.[66] Optimisation using deep learning shows the smallest deviation with respect to the global optimum at 0.95 of the average value.

When producing short-term load predictions using random forests, ANNs and fuzzy inductive reasoning, Jurado et al. were able to reduce the amount of prediction errors by 88 percent to 15 percent and limit the algorithm training period to 10 seconds for each hourly dataset.[67] These fast and precise approaches are perspectively suitable for on-site predictions within the smart measuring system. The sometimes strong deviations between the standard load profile and actual household consumption, including consumption of domestically generated electricity or controllable consumer devices, are demonstrated by an analysis of data from Trianel smart measuring systems.[68] The end client is moving forward, but the processes and products in the energy industry are still stuck in a rut. Thanks to a higher degree of automation, more precise adaptation and small-scale analyses, ML can help the energy industry to keep in step.

3.2.8 Field of application 8: Using AI to customise products and marketing measures

The field of application “customisation of products and marketing measures” involves the possibility of developing and selling products specially tailored to the consumer. The corresponding measures may for example be based on structural or consumption data. Using AI, consumer segments can be formed, the relationships between consumers can be revealed, reasons for their behaviour can be identified and tailor-made solutions can be devised. In this way, consumers can be billed based on more individual profiles as opposed to the standard load profile, for example.

Customisation is not only relevant to the product offered, but also to the way in which the product is marketed. For example, by means of customisation, products for increasing energy efficiency in a manner precisely tailored to individual households can be created and promoted. By using real-time data such as the images from a mobile phone camera, AI-based systems can personalise the advertisement shown by drawing on clusterings (e.g. according to demographic markers such as age or gender).

[64] MacDougall, Pamela et al. (2016).
[65] Valogianni, Konstantina (2016).
[66] Lopez, Karol Lina et al. (2019).
[67] Jurado, Sergio et al. (2015).
[68] Seibring, Martin (2016).

Example: Business intelligence software using ML

ML is increasingly being used in business intelligence software, which helps sales departments to segment consumers and generate individually tailored offerings. Additionally, critical groups can be signalled to the sales department, for example customers that are likely to churn or that have poor liquidity. Qlik and Cosmo Consult are examples of business intelligence software providers. For more information, please go to: https://de.cosmoconsult.com/produkte/data-and-analytics/bi-branchenloesungen/bi-energiemarkt-und-versorgungsmarkt/ and https://www.qlik.com/de-de/solutions/industries/energy-and-utilities

Contribution of this field of application of AI to the integrated energy transition

Products and marketing measures specially tailored to the consumer can bring greater benefits to the consumer and thus potentially result in an increase in acceptance of the energy transition. For example, rooftop PV installations can be advertised specifically to consumers with their own home and a south-facing roof surface. Tailored recommendations for increasing energy efficiency can also be given to suitable target groups, for example after identifying households with inefficient electrical appliances.

Consumer preferences are made particularly visible by social media and e-commerce. A study by Matz investigating the purchasing behaviour of 3.5 million Facebook users found an increase in sales of up to 50 percent with personalised advertising.[69] The higher sales potential is also reflected in the direction taken by German companies. According to a survey conducted by Adobe, although only 42 percent of the German companies surveyed currently use personalised advertising, 93 percent of them want to invest in AI by 2020.[70] Particularly when it comes to identifying new and promising market segments, the probability of generating higher turnover with the help of ML increases 2.5 times.[71] At the same time, depending on the specific process costs can be reduced by 15 to 70 percent using faster, more automated approaches.[72] However, it is unclear whether this also increases system efficiency.

State of development of this field of application of AI

Current methods can only map changes in the segments over time to a limited extent and can only process a limited amount of data. While customer segmentation was previously based mainly on demographic data and previous consumption behaviour, nowadays, better segmentation results can be achieved solely using online user profiles. ML methods such as k-means are used for this. These applications benefit from the maturity of developments in business intelligence applications in the field of e-commerce. Furthermore, they can largely be transposed to the energy industry.

3.2.9 Field of application 9: Using AI to automate measurement, billing and general distribution processes

Increasing competition, in particular, is pushing energy company sales departments to make their processes more efficient. AI can help with this by automating processes. Examples of this include automated and self-

[69] Matz, Sibylle C. et al. (2017).
[70] Ilg, Garrett (2018).
[71] MIT Sloan Management Review (2016).
[72] Wilson, H. James et al. (2016).

learning filing of incoming documents, automatically generated responses based on text modules, hotline androids or customer self-service.

Example: Attentive tasks by TraffiQX

As an extension of the process-based TraffiQX platform, attentive tasks serve to categorise and prepare invoices. Incoming documents are assigned and suggestions for further processing are provided on the basis of earlier allocations. For more information, please go to: https://www.traffiqx.net/

Contribution of this field of application of AI to the integrated energy transition

AI applications can streamline existing processes through automation and open the door to new processes with more added value for the customer that were previously far too costly to implement. Provided that the focus is put on the consumer during implementation of such AI applications, this could obviously also lead to an increase of acceptance of the energy transition.

In any case, AI applications in this field of application above all offer economic opportunities for the corresponding companies in the energy industry. At the same time, they also make it possible for the various actors to manage the ever-increasing number of sales transactions (for example due to new applications such as smart charging of electric vehicles, the use of small-scale flexibility or the optimised storage operation of household power stores) in an automated and more cost-effective manner by using AI. Process automation leverages potential for efficiency gains and enhances precision. It is therefore safe to assume that system efficiency can be improved to a certain extent as a result.

State of development of this field of application of AI

According to an article in the Chatbots Magazine, 85 percent of customer support will be automated by means of AI by 2020 and will therefore take place without a company representative.[73] IBM promises to reduce service costs by 30 percent and respond more quickly and precisely to customer needs with its AI-based computer system Watson.[74]

3.3 Conclusion: Many AI applications are already contributing or will soon contribute to the integrated energy transition

Figure 15 provides an overview of the classification of the nine fields of application of AI in the energy industry according to their contribution to the integrated energy transition and their state of development, as set out in Section 3.2.

AI applications in the **“General Foundations for Decision-Making” cluster** are generally considered to have the highest potential. Because these particular applications are providing an unprecedented level of support with the decision-making process in the operation and development of an increasingly complex energy system, they can be expected to add significant value to the integrated energy transition. The expected significant energy transition contribution in this area goes hand in hand with an already advanced state of development.

[73] Chatbots Magazine (2018).
[74] IBM (2017).

However, there is of course considerable scope for further research in this area as well. At the same time, numerous commercially available examples are already showing that they can provide real added value for the user as well.

The picture is somewhat less clear-cut in the case of AI applications in the **“Maintenance & Security” cluster**. Overall, these applications are more specific and their contribution to the integrated energy transition can be considered somewhat less profound than in the case of applications in the “General Foundations for Decision-Making” cluster. Nevertheless, predictive maintenance, i.e. intelligent planning of maintenance and repair measures, already has a broad commercial presence. However, the use of AI-based robots and assistance systems for carrying out maintenance work is not quite so advanced.

The **“Distribution & Consumer Services” cluster** shows the biggest variance. AI is ascribed an important role in making it easier for active consumers to participate and in the exploitation of small-scale, highly decentralised capabilities for the integrated energy transition. Particularly in light of the low levels of monetary leverage and, in some cases, lacking hardware infrastructure such as smart meters, the state of development in this area is not yet very advanced. The same is true for AI applications in distribution, which are ascribed a relatively minor role in the integrated energy transition, even though certain applications have already made their way onto the market.

Overall, it is clear that a large number of AI applications are not only able to contribute to the energy transition in theory, but can already be implemented in practice today or in the near future. Indeed, the most promising approaches for the energy transition are already very high on the evolutionary ladder.

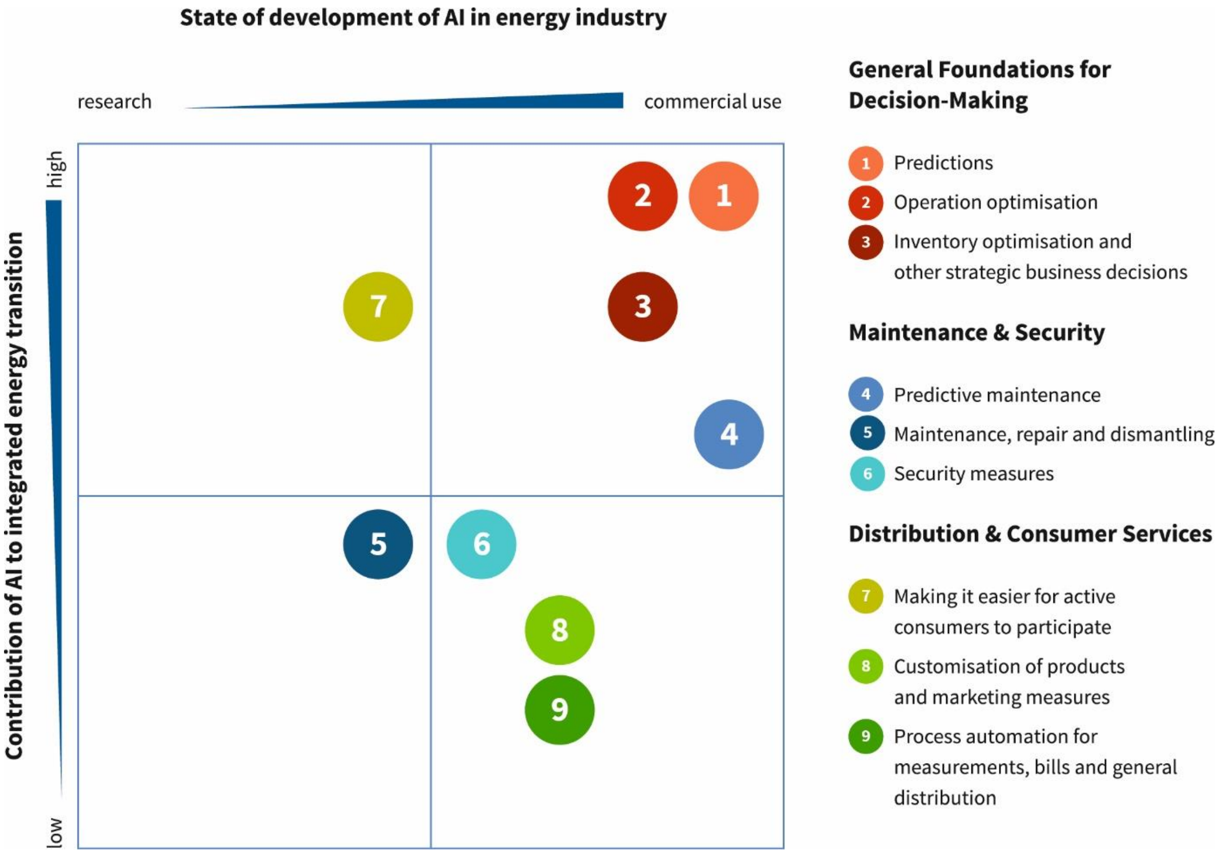

Figure 15 Relative classification of fields of application of AI in the energy industry [Source: own graphic]

4 What remains to be done? – Targeted knowledge-building and establishment of data as key resource

This analysis has shown that AI makes it possible to master the complexity of a decentralised and integrated energy transition with ultra-modern technology. The myriad of fields of application that can be conceived today testifies to their tremendous potential. Nevertheless, their full potential for the energy transition is yet to be unlocked.

4.1 Build up knowledge of AI in companies in the energy industry

The aforementioned dena survey (cf. Chapter 1.2) has clearly demonstrated that the main hurdle for the dissemination of AI applications in the energy sector is the lack of knowledge about AI in energy companies. This view is shared by a staggering 87 percent of management staff surveyed. The proportion of those who feel well informed about AI matters in larger companies with more than 100 employees is at 25 percent a little greater than the industry average of 17 percent, and in companies that are actively planning to use AI technologies, this value stands at 38 percent. Flying in the face of these figures is the fact that companies in the energy industry in Germany have considerable need for information about AI. Therefore, it is of urgent importance that these companies significantly improve their level of knowledge about AI technology, possible fields of application and new business models in order for AI to permeate the energy sector. Governments and businesses both have a role to play in this.

Companies must be proactive

The dena survey also showed that only one third (36 percent) of those surveyed are currently educating themselves about AI (in smaller companies this value is even lower at 27 percent). Even in companies that plan to use AI, only 61 percent of managers surveyed are gathering information about the technology. Meanwhile, 79 percent of those surveyed perceive there to be little to no internal competition pressure with regard to the use of AI. Therefore, companies in the energy industry should more proactively discuss the risks and opportunities associated with AI so that they do not miss out on the development of this technology and fall behind their competitors.

The risk culture in companies should be reassessed in connection with data-driven business models. Many options for making money have yet to be defined, are hard to predict and require companies to follow a trial-and-error approach. Success is therefore hard to plan. But this does not justify inaction. Instead, top management in companies should foster project teams' pioneering spirit and encourage daring digital initiatives. Furthermore, it is probable that, in the future, a balanced risk management of a company's entire portfolio will gain in importance.

Launch an IT expert offensive

Often enough, efforts to boost in-house knowledge are thwarted by the fact that companies struggle to find qualified personnel. Fundamentally, Germany currently does not have enough experts to tap into the potential offered by digitalisation. According to the industry association Bitkom, the lack of IT experts reached new heights at the end of 2018 with 82,000 vacancies for IT specialists.[75] According to a recent survey by Deloitte, 62 percent of German companies complain of a lack of AI skills.[76]

There is therefore a shortage of IT experts when it comes to the development of AI applications for the energy sector. In the short and medium term, politicians and businesses should therefore work together to launch a training offensive for developers with a focus on applications in the energy industry. In order to fill the gap in the short term, options for attracting foreign talent should be explored exhaustively and, if necessary, expanded.

Fundamentally, a very diverse range of job profiles are needed. In addition to mere developers, AI also demands qualified personnel who can comprehensively check, assess and certify algorithms for their suitability. These roles require an understanding of many different disciplines (e.g. data scientists, developers, lawyers, auditors). In the future, interdisciplinary teams may be used for this instead of individual people.

Build partnerships with start-ups

Partnering with young, digitally-minded companies is especially promising for larger companies for the development of innovative AI applications. By virtue of their agility, flexible structures and unbiased ways of thinking, start-ups are able to develop disruptive solutions for the energy transition. As investors, established companies can bring in important success factors such as regulatory expertise, financial support, a network and a client base.

Information and exchange within the scope of the EnerKI project

One approach is the dena project “EnerKI – Einsatz Künstlicher Intelligenz zur Optimierung des Energiesystems” (EnerKI – Using Artificial Intelligence to Optimise the Energy System) funded by the Federal Ministry for Economic Affairs and Energy (BMWi), within the scope of which this analysis was created. The present analysis of fields of application, their potential and associated challenges is just the starting point for a deeper, case-specific analysis. Therefore, within the scope of the EnerKI project and building on the present analysis, dena will carry out

- a detailed assessment of the need for technological development,
- a comprehensive analysis of the economic and business benefits in consideration of the aspect of sustainability, and
- a critical societal and – if necessary – regulatory assessment.

The sector knowledge of the various energy industry actors as well as the positions from civil society will be used in the discussions of expert workshops on the subject. The more comprehensive report is expected to be published in the summer of 2020.

4.2 Bring data into focus as a key resource

AI is only as good as the data used to train it. The aspects of data availability and data quality therefore play a particularly important role. Of the energy industry managers asked in the dena survey, 49 percent view data availability and 41 percent view data quality as a major obstacle before AI can be used in the integrated

[75] Bitkom (2018b).
[76] Deloitte (2019).

energy transition. The associated aspects of data protection (80 percent) and data security (72 percent) are perceived as even more critical. A balanced approach is therefore needed.

Smart meters, smart home systems and the market master data register are important sources of data for the energy industry

Firstly, an exhaustive database from all sectors (electricity, gas, heat, transport) is required for successful application of AI in the energy industry. Accordingly, it should be possible to use data from both the regulated sector (e.g. smart meters, market master data register) and the non-regulated sector (e.g. smart home measuring devices). In light of the increasing importance of data for the dynamic development of the energy transition and the concomitant principle of data economy, politicians and businesses should check – in a more solution-oriented manner – how a high level of data protection and data security can be ensured without merely limiting the number of data exchange relationships.

Secondly, the values-driven push by the EU for an AI that respects people's rights and needs (cf. Chapter 1.1) must be the cornerstone of all AI applications – as the majority of the data comes from these very people. This push is reflected, for example, in the right to informational self-determination, which is a recognised fundamental right in accordance with the case law of the Federal Constitutional Court based on Articles 1 and 2 of the German constitution. This right allows every citizen to determine whether and to what extent their personal data may be disclosed and used. The European General Data Protection Regulation (EU-GDPR) and the Federal Data Protection Act (BDSG) follow this guiding principle.

Data must be assigned a value – based on its contribution to the energy transition

In order to ensure the greatest possible data availability for AI applications on the one hand and at the same time allow for greater self-determination, the value of data must be ascertained.[77] In the past, the principle of "services in exchange for data" failed dismally in many apps and other services. Data usage options are not generally apparent to the people behind the data and trade with data is fragmented and only accessible to a handful of people. Politicians should therefore seek to clarify issues relating to the specific configuration and implementation of a suitable market for trading data in exchange for money.

The following categorisation of data in particular should be considered when developing a data economy within the energy industry:

- Data for reliable operation of the digital, decentralised and integrated energy system
- Data for an economically efficient integrated energy transition
- Data for added business value for companies in the energy and digital industries.

This hierarchy provides direction and can help to structure digital databases such that they can be evaluated.

Defined standards and interfaces promise better data quality

In order to be able to use data for AI, it not only has to be available but also of sufficient quality. The introduction of standards for data formats is one possibility for ensuring efficient data management and analysis. However, the various forms of data collection and processing and the already fragmented market must also be taken into account. As an alternative to uniform data formats, standardised interfaces and processes may also be a solution for harmonising different types of data. Data may be exchanged, for example, on data platforms

[77] Palmetshofer, Walter et al. (2016).

on which data from different systems is gathered centrally and available for use by third parties. On the basis of this data, innovative AI applications for the energy sector could emerge. However, the concrete business model for a data platform of this kind has not yet been defined. Furthermore, the advantages and disadvantages of freely accessible platforms versus data hubs – which hand out data in exchange for payment – must be weighed up and discussed in detail. The three data categories mentioned within the context of the data economy are also relevant to this.

AI-based decisions should be transparent in order to build trust

The transparency of AI-based decisions is a central point of discussion in society today. According to Article 22, Paragraph 1 of the EU-GDPR, data originators have the right “not to be subject to a decision based solely on automated processing”. It is above all crucial that automated decisions are transparent – a challenge for ANNs in particular, since it is very hard to know how they derive their results. Politicians should therefore develop corresponding guidelines for dealing with so-called blackbox models.

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Abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
BDSG	Bundesdatenschutzgesetz (Federal Data Protection Act)
EU-GDPR	European General Data Protection Regulation
ML	Machine learning
PV	Photovoltaics

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dena

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