ARTIFICIAL INTELLIGENCE FOR THE INTEGRATED ENERGY TRANSITION

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ASSESSING THE TECHNOLOGICAL STATUS QUO AND CATEGORISING FIELDS OF APPLICATION IN THE ENERGY INDUSTRY

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SUMMARY

The application possibilities for artificial intelligence in the field of energy industry offer a wide range of potential and great opportunities for better solving the challenges in this area.

In the energy sector, decentralisation, digitalisation and greater involvement of actors (democratisation) result in increasingly complex systems that have to meet a wide range of requirements. This is where AI-based solutions come in to manage and optimise these complex systems and further advance automation. The study identifies the most promising application areas for AI on the basis of a broad screening of application examples and examines their contribution to a more sustainable energy economy. The identified examples can be assigned to a total of nine fields of application, which can be summarised under three superordinate clusters:

AI APPLICATIONS FOR THE IMPROVEMENT OF DECISION BASES

These include AI applications that optimise the use of generation assets and the operation of related infrastructures. Planning of investments in facilities, networks and other infrastructure can also be improved by AI methods. Predictions of generation and demand as well as of network states will become more applicable in a better, simpler and faster manner as well as on a more local scale on the basis of learning AI systems.

AI APPLICATIONS FOR MAINTENANCE AND SAFETY SUPPORT

AI systems support the maintenance of energy systems in the energy sector. A large field is predictive maintenance, which enables condition-based maintenance strategies and thus reduces costs and increases the reliability of the energy system. In addition, the defence against cyberattacks and fraud attempts with AI methods is a promising field of application.

AI APPLICATION FOR DISTRIBUTION AND CONSUMER SERVICE

The third cluster comprised new AI-based consumer services that enable the easier participation of active consumers (e.g. through energy management, smart charging and virtual power plants).

AI systems can make the greatest contribution to a more sustainable energy industry by evaluating data. There already are a large number of AI applications in commercial use in this area, which can already perform very specific and delimited tasks today. Such applications, also referred to as “weak AI”, are already being used or offer greater potential in future by improving the decision-making basis for the operation of grids, generation plants, etc. An AI application in the sense of “strong AI” has so far only taken place to a very limited extent in the use of robots and assistance systems that are used for “asset maintenance” and “distribution and consumer services”. Examples of this are drones, which can automatically detect faulty system parts for the maintenance of networks. The development and application of more complex AI systems (use of artificial neural networks (ANN) and the subsequent application of robotics and assistance systems based on them) still require research for a more comprehensive application. In order for AI systems to develop and be applied, the availability of data in accordance with the consumer’s right to self-determination, the handling of ANN as black box models in the sense of the GDPR and as a confidence-building measure, as well as the standardisation of the processes and data formats concerned are decisive. The energy industry has traditionally been a data-intensive industry based on established data processing procedures. Their further development towards the use of AI is therefore the next logical step for the implementation of a sustainable energy industry.

It is already evident today that, in addition to technical developments, a large number of other questions and aspects need to be clarified and taken into account in order to use AI to a larger extent in the energy industry to increase sustainability. Future research questions among others include which technical possibilities exist, which data are used and how can they be collected in a transparent and comprehensible way? It must also be clarified which basic principles and ethical principles should be followed in order to guarantee informational self-determination.

1 INTRODUCTION AND OBJECTIVES

The term "artificial intelligence" (AI) is mentioned eight times in the coalition agreement between CDU, CSU and SPD. This implies the importance attached to this issue. The twelve priority fields of action derived at the "Digital Summit" 2018 in Nuremberg give an idea of the breadth of the discussion. This ranges from concrete application cases (e.g. AI for government tasks) to technical and regulatory requirements (e.g. availability and usability of data) and social issues to targeted goals (e.g. awakening start-up dynamics). This in turn shows the multi-layered nature and complexity of the subject.

Apart from the original AI sciences such as computer science and engineering, the field of energy had the third largest share of AI-related publications from 1996 to 2016[1]. The energy industry has traditionally been a data-intensive sector, developing further as a result of digitalisation. Existing business models are adapted, and new business models are created, in particular, by linking several stages of the energy value-creation chain[2]. This results in a multitude of fields of application for AI in the resulting value-creation network. For example, the maintenance of power plants in the generation sector can be carried out in a more targeted manner, the forecasts for renewable energies can be improved for energy trading, the grid utilisation can be increased, and tailor-made products can be offered to customers.

Individual examples such as these are widely known. However, a structured representation of the fields of application is at times only available to a limited extent. This void is addressed by an analysis report[3], which was developed in the context of the project "EnerKI–Einsatz künstlicher Intelligenz zur Optimierung des Energiesystems" (EnerKi – Use of artificial intelligence for the optimisation of the energy system) of the German Energy Agency (Deutschen Energie-Agentur GmbH; dena). The present study lays the foundations for this. In the first part of the study a technological classification with a definition of terms, tasks and methods of AI and the state of development is given. In the second part, central fields of application of AI in the energy industry are shown and their significance for the integrated energy transition is classified. Finally, central framework conditions for the establishment of AI in the German energy industry are identified. This provides an overview of the potential of AI in the energy industry and its framework conditions.

1 2019_OECD_Measureing the digital transformation (2) n. d.
2 Richard / Vogel 2017
3 Download the analysis at https://www.dena.de/fileadmin/dena/Publikationen/PDFs/2019/dena-ANALYSE_Kuenstliche_Intelligenz_fuer_die_integrierte_Energiewende.pdf

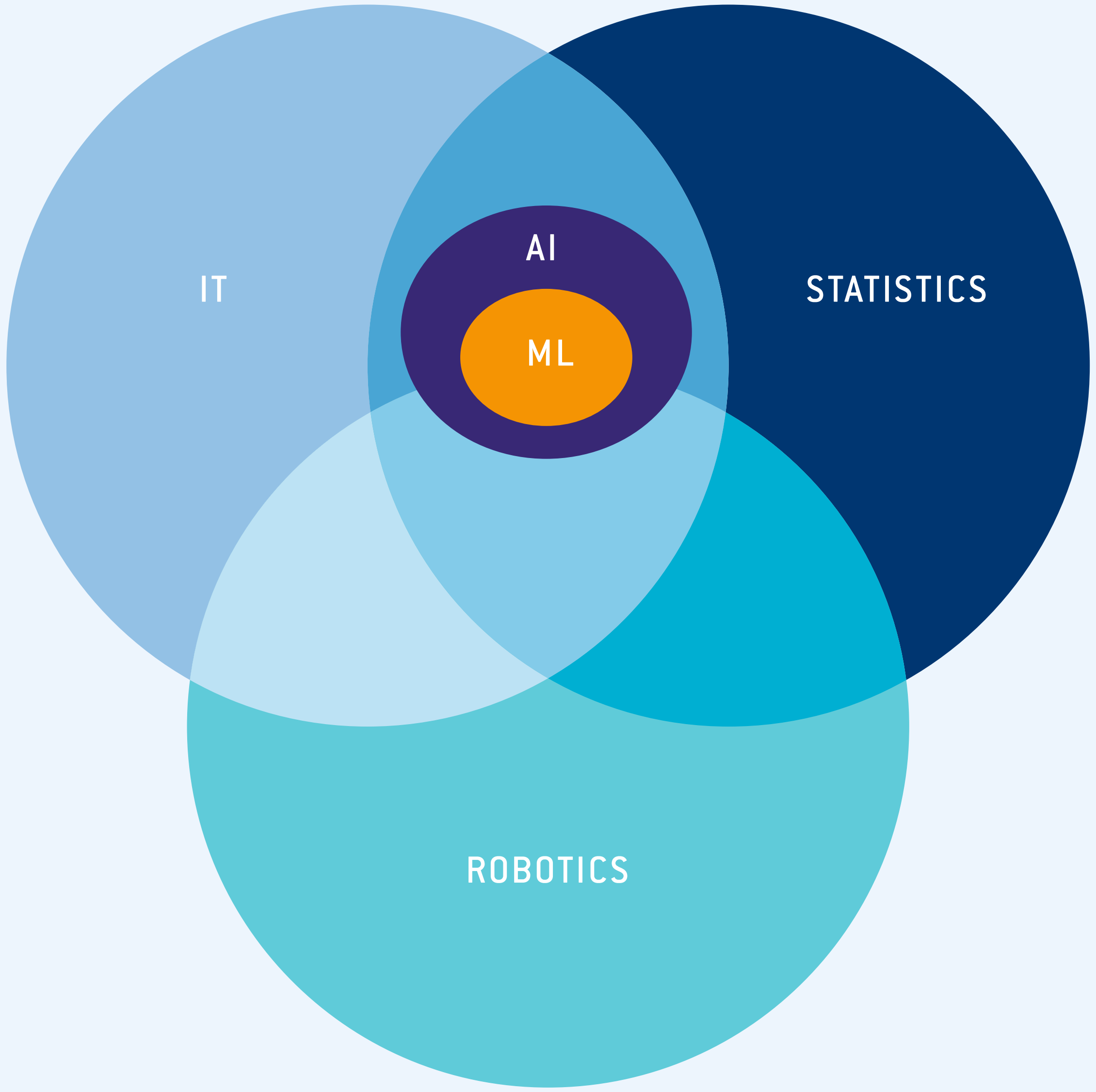


FIGURE 1 Locating AI and ML between academic disciplines, own representation

2 GENERAL TECHNOLOGICAL CLASSIFICATION

2.1 WHAT IS ARTIFICIAL INTELLIGENCE?

2.1.1 DEFINITIONS OF ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is the intelligence of machines. Machines are artificial systems or agents that can record and process external data and output results. Computer programs and algorithms are therefore important examples of machines, in the broader sense, that may show signs of intelligence. AI therefore is contrasted with the natural intelligence of humans or animals.

The greatest difficulty in defining AI is the dazzling concept of intelligence. Defining it is also difficult in the various (scientific) disciplines. A central aspect of intelligence is the ability to make one's own decisions based on information and to act to achieve one's own goals[4]. This includes collecting information relevant for the achievement of objectives, reacting flexibly to the environment or changed information, learning from experience and making decisions under uncertainty and in limited time.

Intelligence generally comprises different forms: Cognitive intelligence, i.e. the ability to think and reason about the environment or objects or abstractions and acting accordingly, and emotional intelligence, i.e. the ability to recognise and respond adequately to emotions, as well as many other abilities of human action. If there was a system that encompassed all aspects of human intelligence, one would speak of "strong AI". As opposed to this, today's systems can solve very specific problems and can therefore be regarded as intelligent only in certain areas. This is referred to as "weak AI". The most important human and animal abilities that are part of intelligent action are logical reasoning, perception of the world and language, general knowledge, learning, understanding human language, planning and looking ahead, moving and manipulating objects, and recognising emotions[5].

4 Poole/Mackworth/Goebel 1998, p. 1
5 Ibid.

As the distinction between strong and weak AI suggests, in specific applications it is not always easy to decide whether an AI is involved. However, according to the above aspects of intelligent behaviour, it is appropriate to speak of more or less intelligent behaviour of computer programs or machines, i.e. stronger or weaker AI. Some of the application examples below in the energy industry use mathematical and statistical methods that have been known for many decades or in some cases since the early 19th century but are gaining momentum due to extensive data availability or by being embedded in decision-making processes and can become part of AI.

Divergent definitions of AI focus on specific scientific disciplines. AI is then defined[6 7] somewhat more narrowly as "a branch of computer science with the aim of enabling machines to perform tasks 'intelligently'". Computer programs and computer science are highlighted as disciplines here, as many important advances have been made in recent years. In a broader sense, however, AI also concerns statistics, robotics, mathematics, linguistics, cognitive sciences and philosophy.

2.1.2 CLOSELY RELATED TERMS

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

Machine Learning (ML) is a branch of AI and deals with algorithms and statistical models that enable computer systems to learn, i.e. that they can perform a given task independently and without direct instructions, e.g. recognising patterns in many examples[8].

Statistical learning as compared to ML is a branch of statistics with a focus on modelling and prediction. In short, statistical learning can provide instruments and tools for modelling and understanding complex datasets[9]. Finally, statistics in general

6 Backes-Gellner and others 2019
7 Poole/Mackworth/Goebel 1998
8 Bishop 2006
9 James, G., Witten, D., Hastie, T. & Tibshirani, R. n. d.

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.

is a branch of mathematics used to collect, organise, analyse and interpret data[10].

Deep learning is a group of methods of machine learning that use artificial neural networks (cf. Chapter 2.3.4). *Deep learning* is the term used because these artificial neural networks (ANN) have a large number of layers between the entrance and exit levels. Deep learning is specifically used in particular in the field of speech recognition and translation as well as image processing.

2.1.3 WHICH APPLICATIONS ALREADY EXIST TODAY?

Today there already is a very wide range of applications for AI and complex data analysis. It should be noted that in the historical development after important breakthroughs (best chess player, solution of logical problems) it was often criticised that this is not "actual intelligence" or "real thinking", but only "arithmetic" (so-called AI effect)[11]. Many important AI applications that already exist today are therefore quickly assessed by us as being "normal" accomplishments of computers. Nevertheless, just a few years ago many of these achievements would have been far beyond the technology of the day and have to be recognised as parts of intelligent behaviour.

Machines already play complex games like chess or the board game Go better than any human being. The breakthrough in chess with Deep Blue, the first computer to beat the then world chess champion Garry Kasparov in 1997 is well known. A notable recent breakthrough came at the end of 2017 with the development of the "AlphaZero" program. This is a computer program that independently learns complex board games. It just needs to know the rules and winning conditions and then learns to become an excellent player by playing millions of games against itself. Unlike previous programs, the program no longer requires millions of human matches to be made available as input. After only eight hours of practice, this new program was stronger than the program that had beaten the best human Go player in 2016[12].

Spam filters have been part of e-mail programs for many years. These filters sort out unwanted messages, such as advertising or criminal messages. The programs are trained with e-mail examples that have already been classified as "spam" or "non-spam" by people. The algorithm learns to recognise spam based on the examples or calculates the probability that it is spam based on the words contained in the e-mail.

There have been equally important advances in machine speech recognition in recent years. Personal computer assistants such as Siri or Alexa, with whom you can talk directly, are now part of everyday life for many people. Some of these programs not only can execute commands, but also have simple conversations. Further progress is expected in the coming years.

Machine translation of texts from one language into another has reached a quality and speed that makes it useful in everyday life for many problems. The Google-own browser Chrome if requested automatically translates web pages for the user, and the site www.deepl.com translates short texts free of charge. The translations have reached such a level that they are often useful, even if they do not reach the quality of human translations. All in all, translations are a complex task, as many skills are needed to fully recognise a text: linguistic knowledge; an understanding of the world; the ability to infer from reasoning; and also, emotional intelligence to be able to assess the character of the text.

In the finance sector, automatic algorithmic trading is an example of complex tasks performed by machines. The standardised reports on balance sheets or similar key figures that have to

10 Romijn 2014, p. 1
11 McCorduck 2004, p. 204

12 Silver n. d.

Periodic Table of AI

The so-called periodic table of AI is one of several attempts to sort and categorise the number of application types of AI. For this purpose, different input data (such as language, audio, faces, images, language, text, data or others) and skills (such as recognition, understanding, identification, inferring, creating, learning or action) are distinguished. The combinations then result in possible AI tasks such as speech recognition or object recognition.

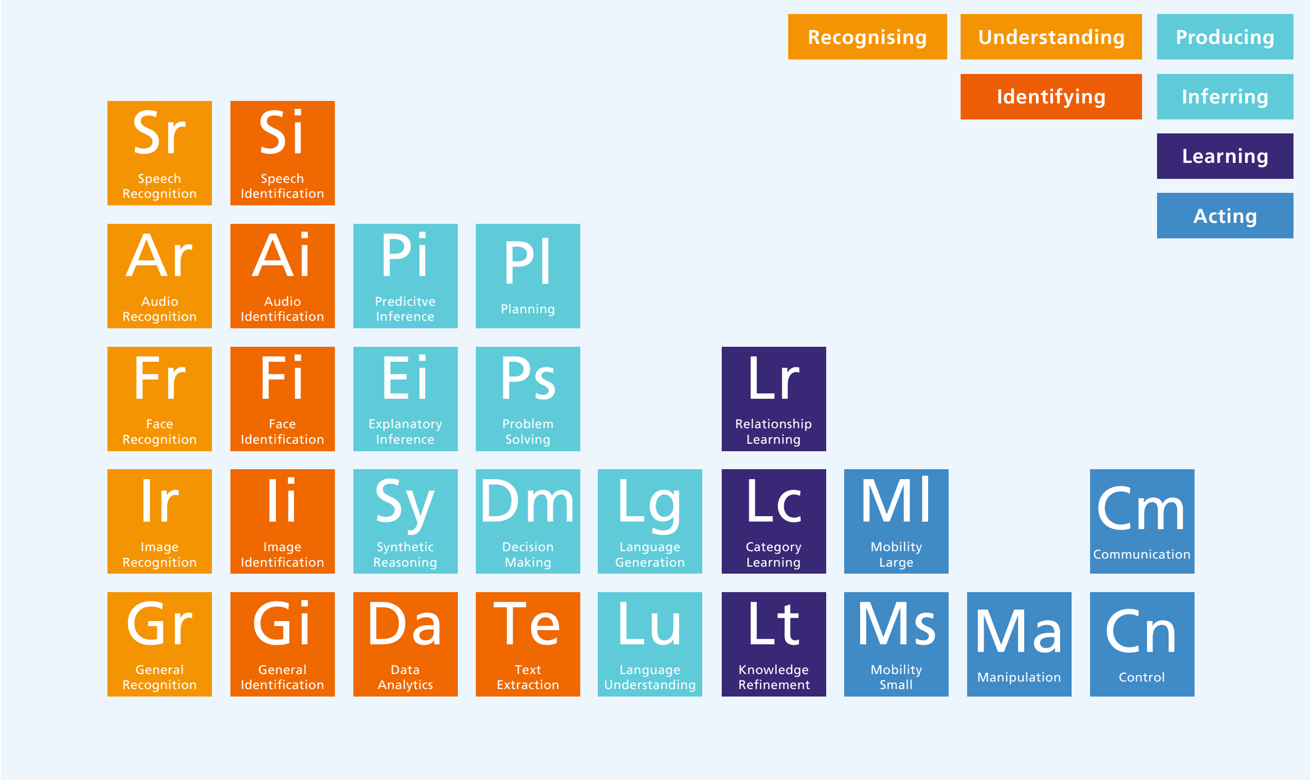


FIGURE 2 Periodic Table of Artificial Intelligence, source: Hammond (2016)

be created frequently in finance and banking can now also be generated automatically by computer programs.

2.2 TASKS FOR ARTIFICIAL INTELLIGENCE

Human action encompasses a wealth of different tasks and abilities. AI systems can already fulfil some of these tasks today and in the future. Since intelligence encompasses the three aspects of (1) the reception/recording and recognition of information, (2) processing, inference and learning, and (3) adequate action, "recognition", "inference" and "action" can be distinguished as elements of AI systems. These capabilities can be applied individually or in combination to different data or inputs. There are many possibilities for the input data: often they are audio data in general, speech, images or videos, faces, text, purely numeric data or motion data. The combination of data and their usability results in many specific tasks for AI. Some of them are shown in the so-called periodic table of the AI in[13] Figure 2 and Table 1.

Very complex applications consist of several components of the periodic table or several parts of AI. For example, an autonomous vehicle must recognise moving objects such as a pedestrian as such. It must then predict the person's further movement and compare it with its own trajectory or assess the risk of an accident. If danger looms, it must also initiate and carry out an adequate change in its own movement, for example by braking, and at the same time always check the further changes in its environment. A higher degree of AI results from a similar composition of many complex subtasks with recognition, processing of information, decisions under uncertainty and corresponding actions.

13 Hammond 2016

TABLE 1 Exemplary illustration of the selection of applications of the periodic table of AI

Group	Element	Abbr.	Brief description
Recognition	speech recognition	[Sr]	The recognition of spoken speech and/or emotional states in general in an audio signal.
Recognition	audio recognition	[Ar]	Detecting certain types of sounds (alarms, equipment stress, car engine) in an audio signal.
Recognition	face recognition	[Fr]	The recognition of faces and emotional states in images or video signals.
Recognition	image recognition	[Ir]	Detecting certain types of objects in pictures or video signals.
Recognition	general recognition	[Gr]	Analysing sensor data to detect object types and/or situations from the signal alone.
Recognition	speech identification	[Si]	The recognition of an individual voice in an audio signal.
Recognition	audio identification	[Ai]	Recognising audio signatures (a specific engine or doorbell) from audio signals.
Recognition	face identification	[Fi]	Recognising specific persons in pictures or video signals.
Recognition	image identification	[Ii]	The recognition of a specific object in an image or video.
Recognition	general identification	[Gi]	Analysing sensor data to identify objects and/or situations from the signal alone.
Recognition	data analytics	[Da]	Analysing data to identify specific facts and/or events that represent that data.
Recognition	text extraction	[Te]	Analysing texts to extract information about entities, time, places and facts contained exclusively in the text.
Inferring	Predictive inference	[Pi]	Predicting events or states in the future based on an understanding of a current state and how the world works.
Inferring	explanatory inference	[Ei]	Explaining events or states in the real world, based on the understanding of previous states.
Inferring	synthetic reasoning	[Sy]	Using evidence to support conclusions about the real state of the world, a prediction, or an explanation.
Inferring	planning	[Pl]	The creation of an action plan based on goals, an understanding of the state of the world and knowledge of actions and their consequences.
Inferring	problem solving	[Ps]	Creating a solution to a problem that can be associated with or without the use of actions (see Planning [Pl]).
Inferring	decision making	[Dm]	Selecting a specific plan or solution based on existing facts, alternative solutions and a set of objectives.
Inferring	language generation	[Lg]	Creating natural language 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]	Recognising relationships between features, to predict a set of hidden features when others are visible.
Inferring	category learning	[Lc]	Recognising new categories of semantic values based on feature collections.
reasoning	knowledge refinement	[Lt]	Revising existing knowledge or rules in response to them being used to support actions or conclusions.
action	mobility large	[Ml]	Controlling autonomous vehicles that interact first and foremost with other vehicles.
action	mobility small	[Ms]	Controlling robots that move through interiors, work and interact with people.
action	manipulation	[Ma]	Manipulating the same objects that people regularly work with.
action	communication	[Cm]	Mechanisms that support the execution of different forms of communication between human and machine.
action	control	[Cn]	Intelligent control of other machines when no manipulation or action is required in the physical world (e.g. automated trading).

Source: Own representation based on Bitkom, 2018, p. 17f

The periodic table of AI shows in an exemplary way how diverse their tasks and possibilities are. For further discussion, however, it makes sense to group the many tasks in order to be able to classify the AI methods and the potentials in the energy industry more easily later. We therefore combine the tasks of the AI into the following five applications:

1. The handling of **speech or audio** includes e.g.
   - recognising, understanding, or creating speech and audio data
   - the recognition of persons by voice.
2. The handling of **images, videos or faces** includes e.g.
   - the recognition of objects, characters or also writing in images
   - the recognition of people and the understanding of facial expressions.
3. **Robotics** includes e.g.
   - targeted movement and dealing with obstacles
   - physical interaction with people or objects.
4. The **human-machine interaction** is for example
   - the written, oral or physical interaction with people. These include chatbots and social intelligence skills.
5. The **data in general** include other applications such as
   - pattern recognition, mathematical data processing, quantitative prediction of future events or states, and other applications.

These groups are not always clearly separable, as more complex applications are often based on a combination of simpler applications. However, the five groups mentioned form a useful typology of applications without having to get into the technical details of the AI. This typology will be further used in Chapter 3.

2.3 METHODS OF ARTIFICIAL INTELLIGENCE RESPECTIVELY MACHINE LEARNING

After the general description of AI and its fields of application, now technologically different forms of AI and ML will be presented in more detail. These can be divided into groups according to the learning style or task. The most important processes and model types are briefly presented below without claiming to be exhaustive. Mathematical details are largely dispensed with.

2.3.1 OVERVIEW

Very many different methods of statistics, AI and ML are already in use today. These can be roughly divided into three groups according to the learning style:

- **Supervised learning** means that the results of a learning task are already available, and the computer can compare its result directly with the correct result. This very complex approach is only possible if a large amount of data already exists with the correct result. Often these are data records that have been classified by humans.
- **Unsupervised learning** means that the correct result is unknown and the computer itself has to discover structures. Here the raw data are sufficient to recognise patterns.
- **Reinforcement learning** works through feedback from interaction with the environment. This is often used in robotics, where there is direct feedback from the surroundings.

Examples and further subgroups according to learning task and learning procedure are summarised in Table 2. In addition, Figure 3 shows the methods most frequently used by Data Scientists and ML experts (multiple answers are possible). Note that a mathematical procedure such as ANN can also be used in different areas, e.g. in both supervised and reinforcement learning.

Among the most frequently used methods are logistic regression, decision trees, random forests and ANN. These and other important procedures with individual application examples are briefly presented in the following. The distinction between statistics, statistical learning, AI or ML is sometimes difficult or application-dependent. The selection of the methods presented is based on their frequency in many applications but does not claim to be complete.

2.3.2 SUPERVISED PROCEDURES

Supervised procedures are characterised by the fact that the result is already known for a certain number of cases. These can be used to train a model or computer program to predict the outcome of new cases as accurately as possible. For training, the known result must be compared with the model prediction so that the model can learn from its mistakes. As a rule, such errors are measured quantitatively as absolute or percentage deviations.

Linear regression
One of the most common methods for quantitative models is regression. More specifically, it is a family of methods in which a relationship is established between one or more dependent variables and one or more independent variables, the influencing factors. The dependent and independent variables can be a number (e.g. a price, the age of the customers or the output demanded in kW), but also a category such as the type of household (single or multi-person household) or others.

TABLE 2 Classification of ML and AI methods

learning style	learning task	learning methods	model	example
monitored	regression	linear regression	regression line	prediction of prices
		classification and regression tree methods	**decision tree, random forests**	prediction of data
	classification	**logistic regression**	dividing line	failure prediction
		iterative dichotomiser (ID3)	**decision tree**	categorization of data
		Support Vector Machine (SVM)	hyperplane	form customer groups
		Bayesian inference	Bayesian models	group data
unmonitored	clustering	k-means	cluster centres	identification of customer groups
	dimension reduction	principal component analysis (PCA)	composite characteristics	simplification of complex decisions
encouraging	sequential decision making	Q-Learning	strategies	learning complex games
various	various	backward propagation	**ANN**	failure prediction

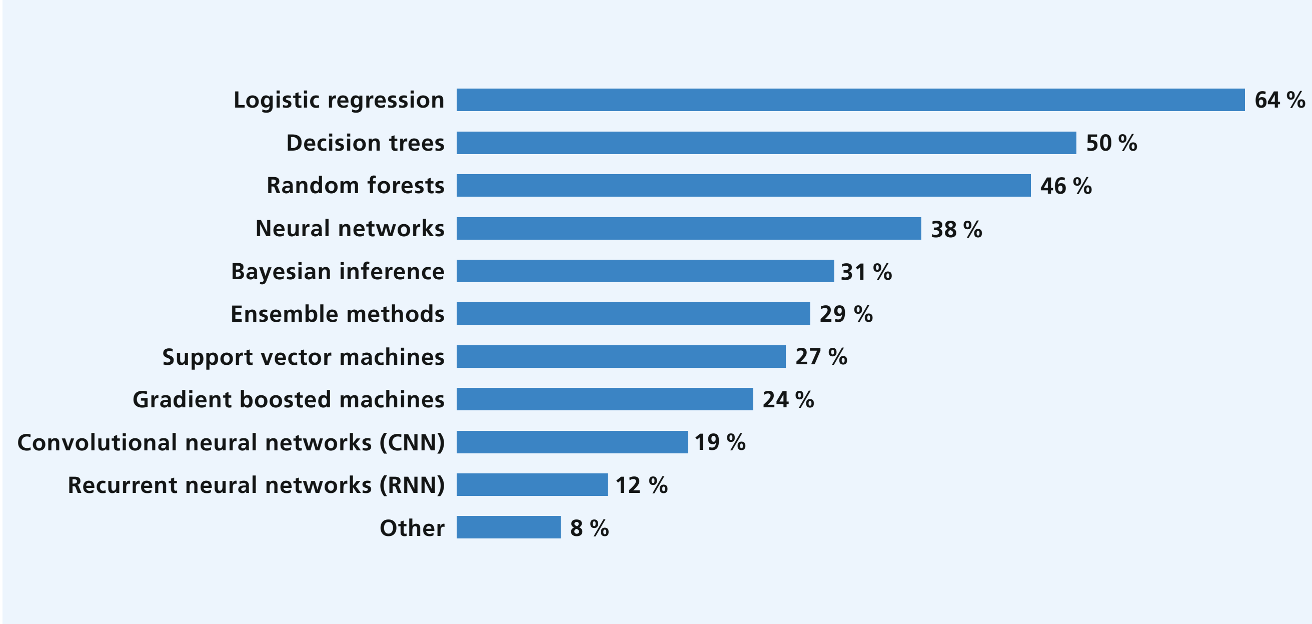


FIGURE 3 The methods most commonly used by data scientists and ML experts, source Fraunhofer (2018, p. 18)

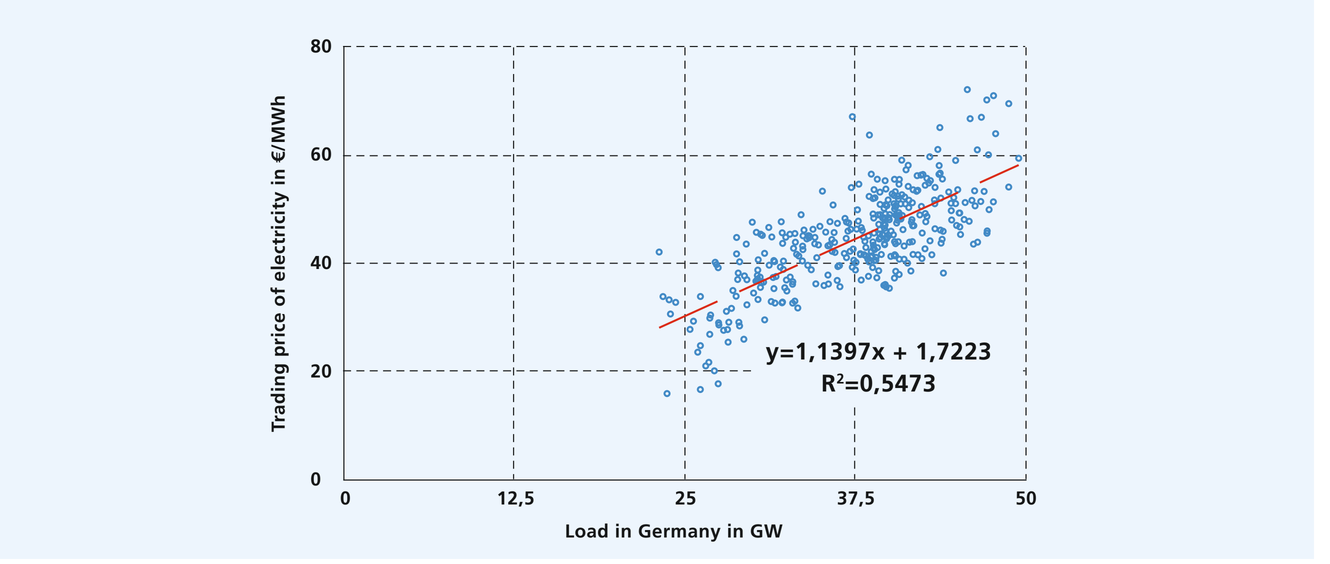


FIGURE 4 Simple linear regression between the trading electricity price and the load in Germany (shown are the hours of 2010 as blue circles and a simple regression line), own representation

The simplest case of regression is linear regression with one dependent and one independent variable. Figure 4shows as an example the trading prices of electricity in €/MWh as a function of the hourly load in Germany for all hours of 2010 as blue circles. You can see a clear link: In hours with low load the prices are rather low and in hours with high load the prices are rather high on average.

Such a regression model can handle many variables and is generally very flexible, since mathematical transformations of the input data are also possible. At the same time, these models calculate very quickly and are easily interpreted. Regression models have been a standard statistical tool for decades, and there is a great deal of experience, suitable software and extensive literature available. In statistics, however, the main goal of regression is to find and interpret relationships between variables. In many AI applications, however, high predictive accuracy is often more important than interpretability, so that regression models were slightly adapted in practice.

Due to their high flexibility and speed, regression models form a central tool of AI and ML.

Decision tree and random forests

In many applications, it is useful to use simple decision rules to predict a value or attribute. A decision tree delivers exactly that: a chain of simple decision questions that returns the most probable result at the end of each branch. A useful feature of such trees is their easy comprehensibility. Decision trees can be interpreted particularly well, unlike deep neural networks, for example[14]. Figure 5 shows a simple example of a decision tree.

A single decision tree is easy to interpret but does not allow as accurate predictions as other methods. Therefore, often very many decision trees are created (each with subsets of the data) and the weighted sum of the forecasts of the individual decision trees is used for the result. "random forests" is the name given to the many trees on the basis of random samples.

Classification and logistic regression

Classification covers the task of assigning individual observations to a group on the basis of existing examples. There may be two or more groups. This task is very important in many applications, e.g. in order to automatically decide on deficient products in manufacturing or to assign customers to certain known groups.

The most commonly used method of classification is logistic regression. This is a variant of the linear regression model described above. In logistic regression, the dependent variable is not a continuous number, but an index of group membership. The most common case is the one with two groups, i.e. a yes/no decision (such as "deficient product yes/no?" or "customer open towards advertising yes/no?"). The dependent variable takes the value one for observations belonging to the group and the value zero for the others. This procedure can easily be generalised to several groups. Logistic regression is one of the most frequently used methods for classification, because it is very fast, can learn even with little data and can also handle complex relationships or cases in the data. Strictly speaking, however, it is not a learning method, since the underlying mathematical model is trained once on the basis of data and is then fixed or has to continuously be re-trained. In addition, the model of a logistic regression is not as easy and comprehensible to represent as, for example, decision trees.

14 Fraunhofer 2018

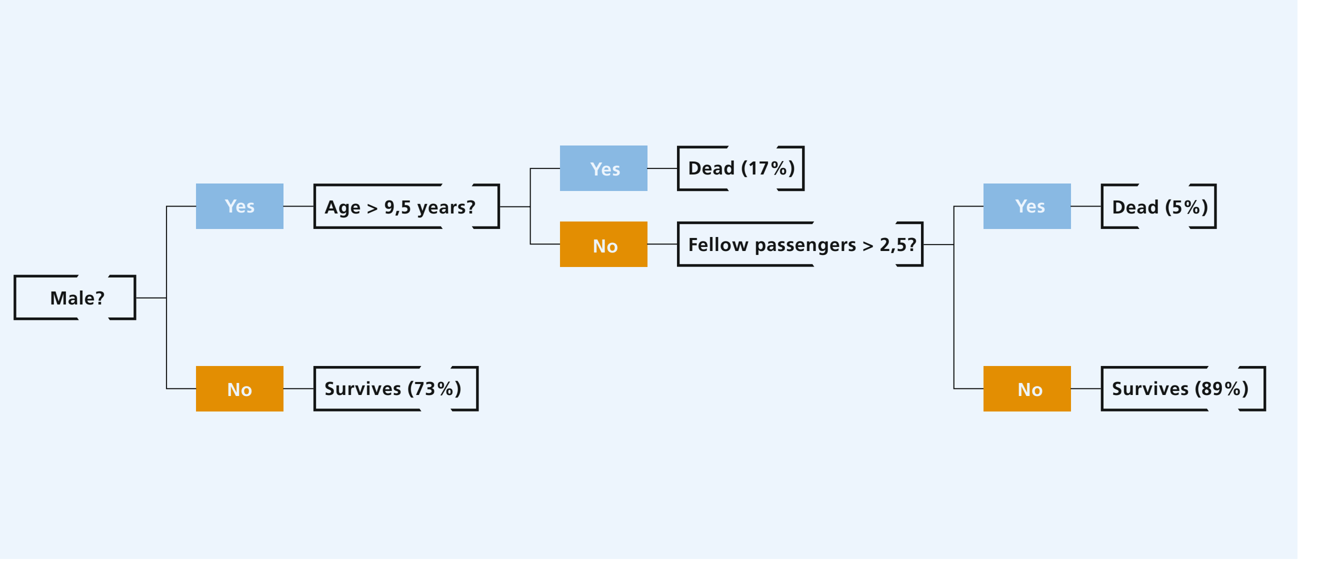


FIGURE 5 Decision tree for the survival of the Titanic sinking (the questions are answered for the individual passengers, the percentages in brackets indicate the survival probability for the passengers of this group) own representation based on Portilla (2015)

2.3.3 UNSUPERVISED PROCEDURES

If there are no tasks already solved for training and the AI has to uncover structures itself, this is referred to as unsupervised procedures.

Clustering

The aim of clustering is to discover groups of similar observations in data. The identified groups are called clusters. There are a number of algorithms for this. One of the most common algorithms is the k-means method. The number of groups to be found must be specified, and the algorithm then iteratively determines the best centres for the specified number of groups and determines the best group for each observation.

Figure 6 shows an example of clustering using the k-means algorithm. The data include the mean hourly load in kW of a household over 1,456 days. Each day is considered an observation, the variable is the load in the 24 hours of the day. All 1,456 diurnal cycles are shown as a very thin transparent line in the figure. The many days are now divided into three groups using the method, the load curves of the three group centres are shown as thick lines in the same figure.

The three groups can be described as follows. The dark green group has a very low load profile, which is almost constant throughout the day. Possibly these are vacation days, in which the inhabitants are not at home, but travelling. The red group, on the other hand, shows a high load throughout the day with a slight peak in the evening. These could be weekends or holidays when the residents are at home and, for example, cook or wash a lot. Finally, the blue group seems to cover workdays–with one morning peak and one evening peak and little load in the afternoon.

Dimension reduction

In some applications, a large number of attributes or factors can influence the result. These factors are often closely related and correlated. In such situations it is often helpful to check whether single variables or a combination of several variables are particularly important for the result. Dimension reduction methods help to select the most important combinations of factors from the multitude of influencing factors. These linear combinations of factors are mathematically called principal components, and the method of identifying them is called principal component analysis.

2.3.4 FURTHER METHODS OF ARTIFICIAL INTELLIGENCE

Artificial neural networks (ANN)

An early idea of AI research was to develop intelligence by emulating aspects of the human brain. In the brain many so-called neurons are interconnected on several levels. It is the basic idea of ANN to artificially reproduce these structures with a computer program.

Despite the early idea of ANN, only in the last ten years or so has it been possible to achieve very great progress with interesting accomplishments, especially concerning image and video, voice and text data. Today, ANN can sometimes recognise faces and objects with fewer errors than humans. Complex tasks such as translating texts, answering questions and e-mails, condensing news into reports, composing music and texts or producing images are all possible today[15].

Particularly successful were deep ANNs, i.e. those composed of relatively many layers of "nodes" realised in the software, which are referred to as artificial neurons (see Figure 7). When learning, the weights, which are numerical values at the connections between the nodes, are changed until the outputs are good enough. In their inner layers, the networks independently extract compact representations from the raw data, which makes many pre-processing programs superfluous and makes the actual task easier to learn. Deep ANNs form expressive models that can also be efficiently trained in parallel computer systems. This often only works well with very large amounts of data. Since it is not easy for people to understand what the weightings in an ANN mean and how exactly the outputs are created, we here refer to them as "sub-symbolic" models, in contrast to symbolic models such as the decision trees (see Figure 5) or the knowledge bases of earlier expert systems.

There are a number of network architectures which have proven to be effective for different data types and tasks. Since the networks as a whole can be trained from the raw data to the output phase, this is also referred to as end-to-end learning. A very successful application of deep ANN are the "deep Q-networks" in encouraging end-to-end learning for games and robots.

An example of an application for deep ANN is the recognition of handwritten numbers, as is necessary, for example, for the recognition of postal codes or handwritten meter readings. A comprehensive training dataset called MNIST (Modified National Institute of Standards and Technology database) is available for this purpose. This includes 60,000 training images and 10,000 test images of 28x28 pixels in grey scales (Figure 8 shows some sample images). The best methods today to recognise the correct numbers are deep ANN. These are able to recognise over 99.5 percent of the images correctly and are therefore comparable to human abilities.

Reinforcement learning
Encouraging or also reinforcing learning is a third group of AI procedures. The program is not given an explicit strategy, but rather it learns solely through success and failure. Unlike supervised learning, the algorithm does not need correct solutions, but searches the area of possible actions and obtains different solutions in different states. The algorithm tries to find a balance between the exploration of new states and previously successful paths. Mathematically the algorithms are partly also deep ANN. Procedures of reinforcing learning are used, for example, as algorithms in strategy games such as chess or Go and are now better than all human players. They only need the rules of the game and the information when a game is won, then the algorithms learn strategies independently by playing against themselves again and again.

Expert systems and symbolic knowledge
In addition to the strongly data-driven learning processes, there are also less data-intensive approaches towards AI. Expert systems are an important group. These are programs that have knowledge prepared by people and can draw their own conclusions. The knowledge is limited to special fields and is often in the form of if-then rules. This knowledge must be brought into a form suitable for computers by humans. Such expert systems can automatically draw conclusions. From the input "Socrates is a human being" and the deposited rule "If something is a human being, then it is mortal" the system can then draw the conclusion "Socrates is mortal". Despite this simple example, such systems are useful when many cases and complex rules have to be observed. Applications are to be found above all in the area of medical diagnoses. The creation of knowledge by humans is particularly complex in expert systems.

2.3.5 CONCLUSION ON THE METHODS OF ARTIFICIAL INTELLIGENCE

An evaluation of the current stage of development of the respective AI processes according to technological maturity, market diffusion, complexity and development potential shows that the degree of maturity is already very high, especially for image and face recognition and for data in general. At the same time, there is further potential for development. The classification in the table below is based on the Fraunhofer study on ML[16] and the authors' assessment.

2.4 DEVELOPMENT OF ARTIFICIAL INTELLIGENCE TO DATE

After presentation of the central procedures of AI, the development of AI to date is described. Literature and philosophy on human-like machines such as the golem, Mary Shelly's Frankenstein, Isaac Asimov's Laws of Robotics and Greek legends already reveal early visions of an AI. The scientific examination

15 Ibid.

16 Ibid.

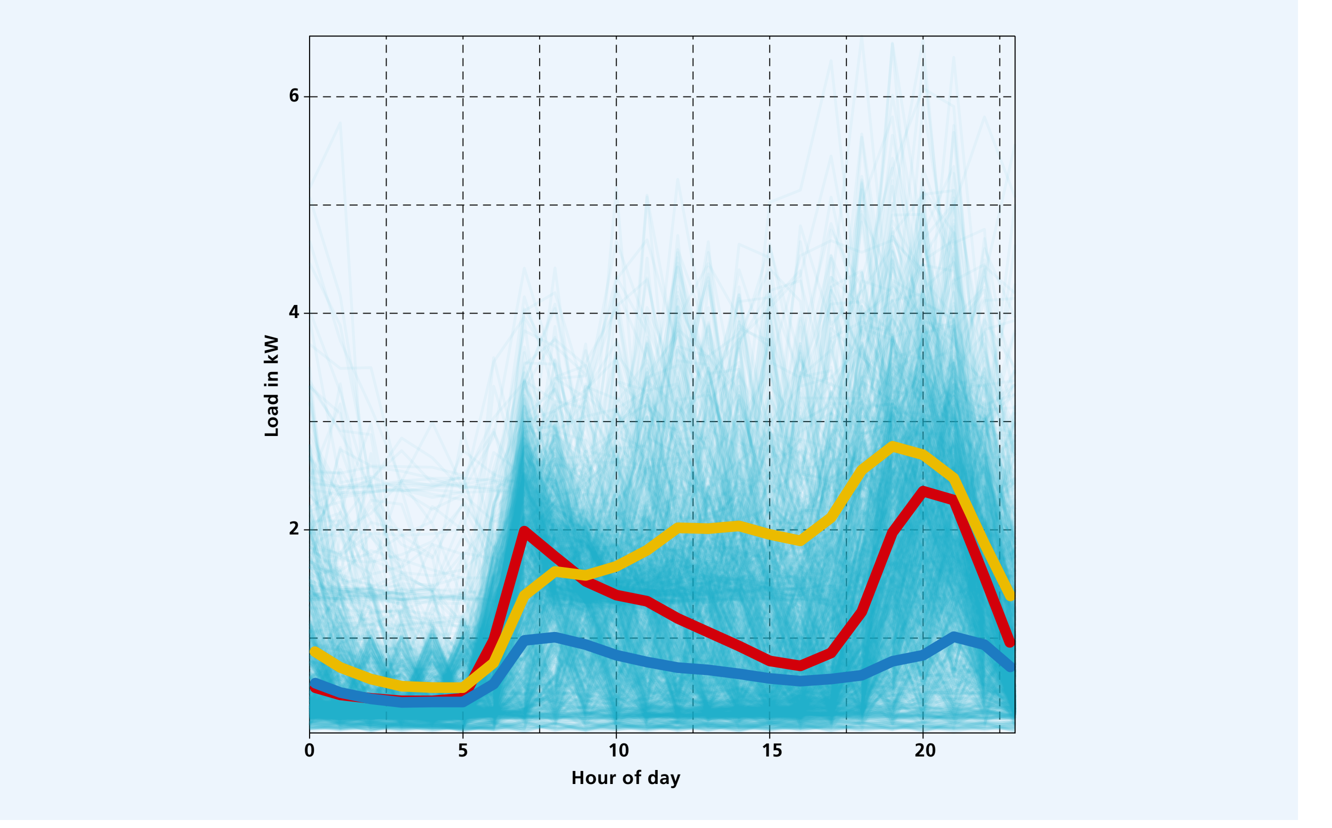


FIGURE 6 Load curves over the hours of the day, averaged from 1,456 days of a household south of Paris, own representation based on Viola (2018)

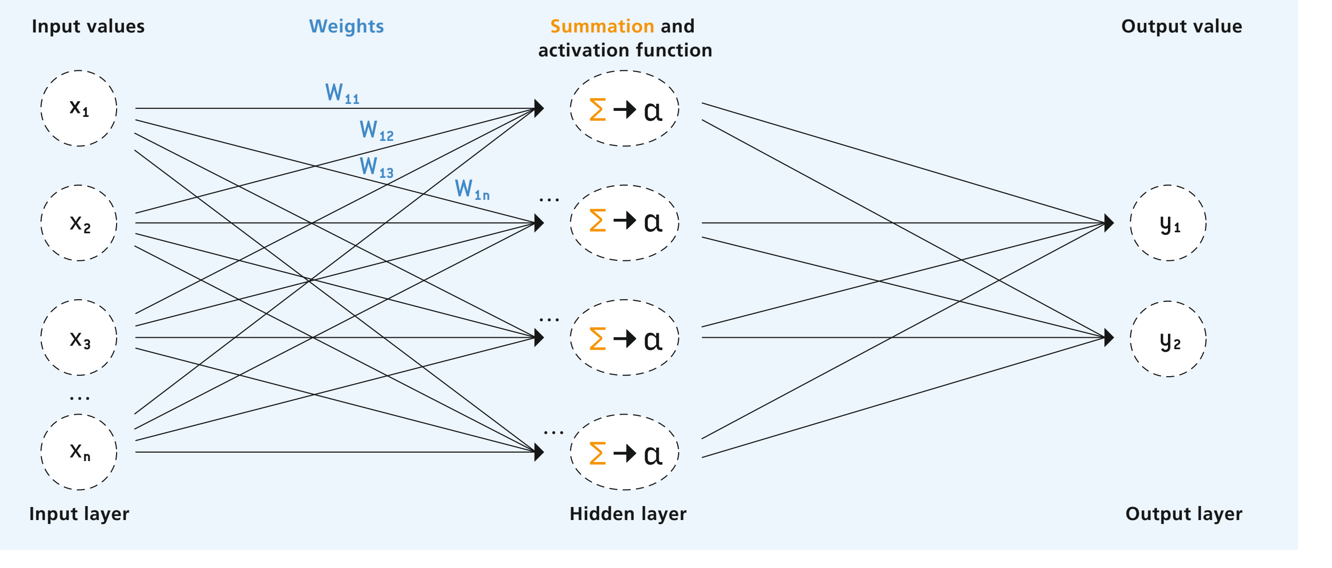


FIGURE 7 Schematic representation of an ANN, here in the form of a feed-forward network, Source: Fraunhofer (2018)

FIGURE 8 Example digits from the MNIST dataset of training and test data of handwritten digits, Source: Kaggle.com (2018)

Table 3 AI methods on a semi-quantitative scale (low, medium, high, very high)

Application area	Exemplary tasks	Method	Degree of maturity	Market diffusion	Com-plexity	Potential
Speech and audio	Speech recognition, information extraction, translation	Deep learning, neural networks, text mining	Medium	High	High	Very high
Image and face	Medical image recog-nition, autonomous driving	Deep learning, neural networks	High	Medium	High	Very high
Robotics & assistance systems	Autonomous driving, handling of objects	Encouraging learning, Q-learning	Medium	Low	High	High
General data	Forming groups of data, classifying objects, pre-dicting values	clustering, decision trees, regression, deep ANN	Very high	High	Medium	High

of AI in the narrower sense began in the mid-fifties of the 20th century (Turing Test 1950, Dartmouth Conference 1956).

With regard to developments in computer science and statistics, strong progress has been made, especially since the Second World War:

- 1940s: ANN principle developed
- 1950s: mathematical fundamentals for ML and the first use of the term "artificial intelligence"
- 1960–1980: lack of data and methods too complex for the existing computers; stagnation in development and few successes
- From the 1990s onwards: AI successes in more appli-cations due to better algorithms, more data and more computing power
- 1996: AI wins at chess against the world champion
- 2000s: large increase in data volumes and computing power
- 2011: AI wins a quiz show
- 2017: AI is best Go player worldwide

Much of what is now called AI are, in principle, partly long-familiar statistical methods that have been used in the field of statistics for decades. A decisive change in the current situation, however, is the availability of significantly larger amounts of data. This leads to the ability to increasingly apply mathematical procedures to everyday problems.

2.5 FUTURE DEVELOPMENT

The current state in the field of AI can be summarised as follows: In individual niche applications, AI is already on a par with humans today or in some cases even superior. In complex applications such as translating or driving, however, AI is still at an early stage, and really good performances are likely to take several years or even decades. Nevertheless, today and in the near future, AI can provide support for people in many simple routine activities and thus generate more productivity in companies and free up more time for creative, demanding or nice activities.

In the following, an overview is given of the expected future development of AI in the medium term (until 2025) and its influencing factors, which are based on the availability of data and computing capacity.

The future development of AI in the coming years will be dominated by strongly growing data volumes and increasing computing power. These enable further applications and improvements of AI systems. In addition to the high-profile successes in other games such as poker (where, in contrast to chess or Go, only incomplete information is available), personal assistants (such as Siri) and speech recognition will continue to improve and soon become part of everyday life. AI will be able to handle simple calls for us and of course will also be able to take calls. Since hotlines and customer service are relevant to many businesses, these applications will quickly gain acceptance and be complemented by chatbots. In the area of vehicles, great efforts are currently being undertaken in the area of automated driving. Studies assume a market launch of fully automated level 4 driving in the luxury class from 2025 onwards[17].

The increasing amount of data, and also the increasing expertise in many organisations regarding the analysis of data by data scientists but also with the help of AI methods, will improve predictions of time series or customer behaviour and lead to a further dissemination of these procedures. Many companies are currently setting up their own big data and data analytics departments, and the first fruits of these developments should be visible in the coming years. Even if the improvements will often only be a few percentage points compared to the status quo, this can still provide an interesting advantage and further development from the point of view of the companies. or customers or users.

In addition to advances in technology and application, the relevance of legal and ethical issues will continue to increase: who may use which data, how can informational self-determination be implemented, which measures are carried out voluntarily or on instruction? In the area of autonomous vehicles there are already corresponding ethical discussions, and questions of data protection are also often discussed regarding social networks. However, reports on automatic face recognition in autocratic systems are becoming more frequent in German media. A discussion of the legal framework and restrictions in Germany (protection of privacy versus, for example, combating terrorism) is to be expected in the coming years.

17 Krail and others 2019, p.34

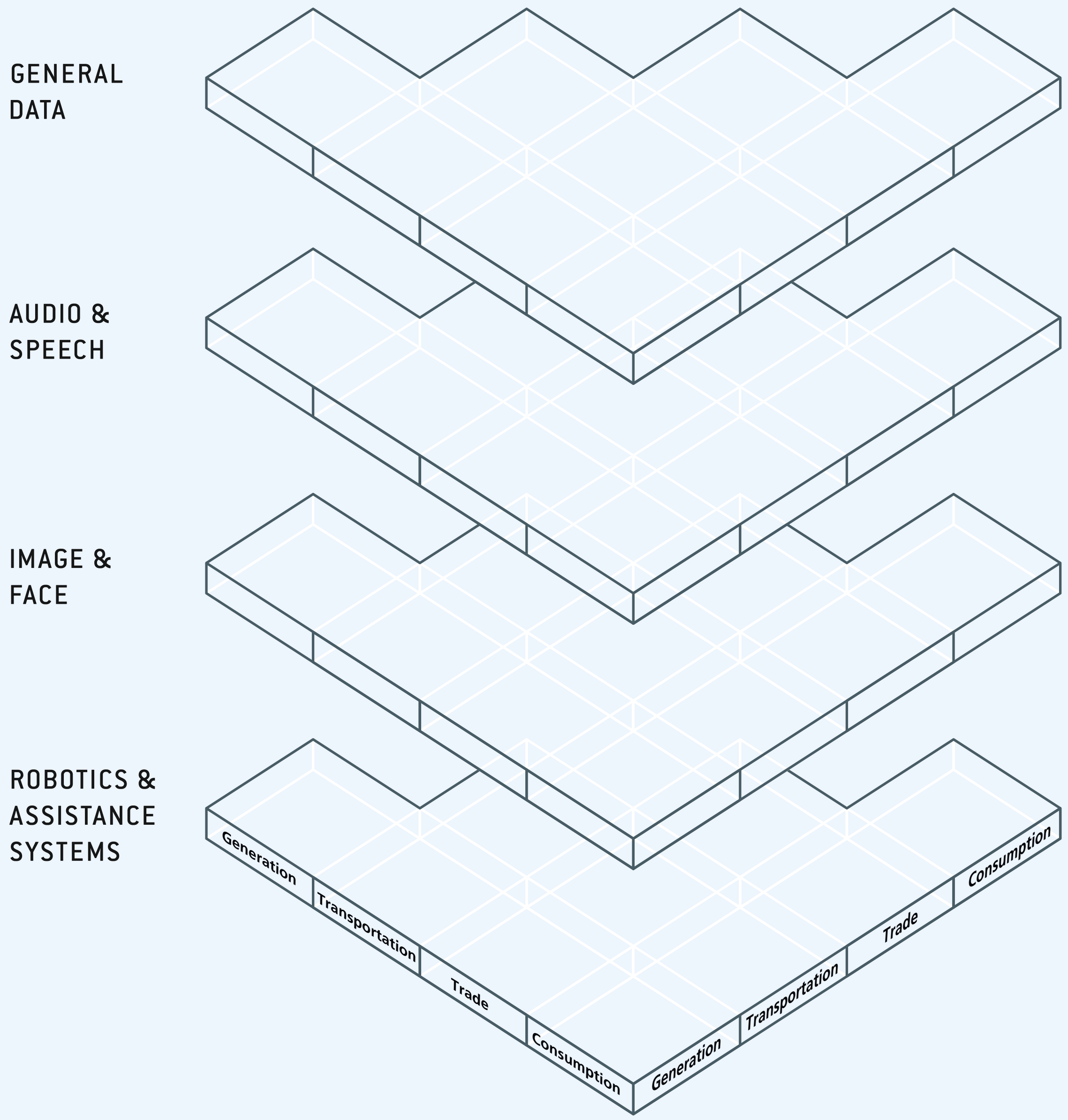


FIGURE 9 Value-creation network KI in the energy industry based on Richard & Vogel, 2017

3 CONTRIBUTION OF AI TO THE INTEGRATED ENERGY TRANSITION

The core of the integrated energy transition is a comprehensive decarbonisation of all application sectors and thus also includes cross-sector optimisation of energy flows. The resulting stronger networking of the increasing number of assets and actors and the resulting increase in complexity in the energy system are to be managed in particular by means of digital technology. At this point, a large contribution of AI to the integrated energy transition is expected, as the amount of data, which has multiplied to an extreme degree with increasing digitalisation, can be efficiently analysed and evaluated via AI methods. But in which areas of the energy industry is the use of AI specifically appropriate? What contributions can AI applications make to a successful integrated energy transition? How far has the development of the respective applications progressed?

These questions will be systematically addressed in two steps below:

1. **Analysis of AI applications in the energy industry**
A broad screening of AI application examples from research and the energy industry both current and foreseeable in the near future takes place. Based on the Map of Digital Dynamics strategy tool developed by dena, these exemplary applications are assigned to the various market fields of the digital energy world. In addition, an assignment is made to the AI application groups General Data, Audio & Speech, Image & Face and Robotics & Assistance Systems introduced in Section 2.2Applications similar to each other are finally combined into fields of application.

2. **Classification of the contributions of the different AI fields of application to the integrated energy transition and the state of development**
The AI fields of application determined in this way are evaluated regarding their respective contributions to the integrated energy transition. This evaluation is based on the following five criteria: contribution to the integration of renewable energies (1), to increasing energy efficiency (2), to security of supply (3), to increasing system efficiency (4) and to increasing acceptance and participation in the integrated energy transition (5).

Finally, the current development status of the individual AI fields of application in the energy industry is evaluated and classified. The use of AI has already been implemented in some areas.

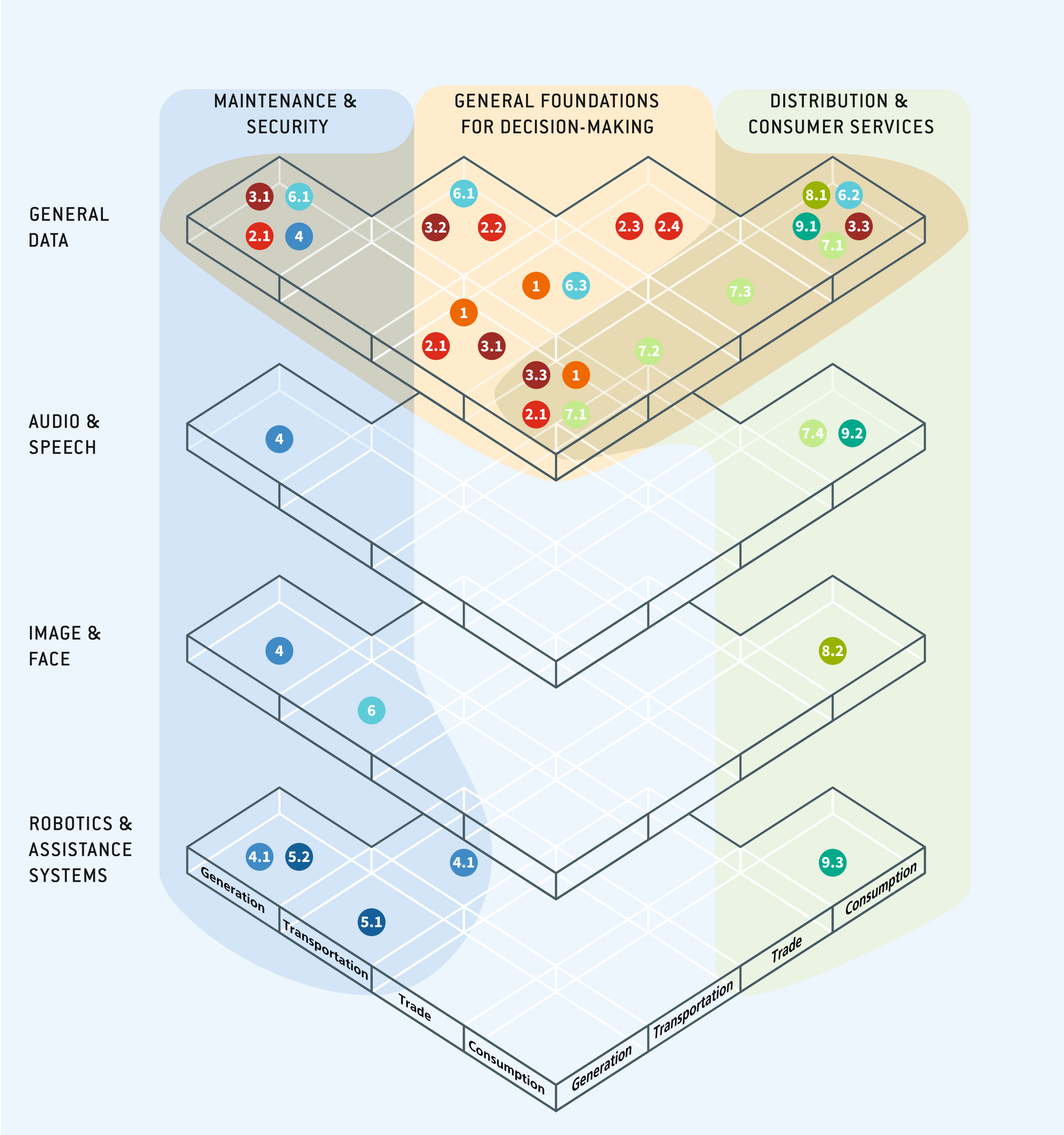
With the help of the steps mentioned, decision-makers from politics and industry will be given an overview of the most important applications of AI in the energy industry and their contribution to the integrated energy transition will be shown.

3.1 THE VALUE-CREATION NETWORK AI IN THE ENERGY INDUSTRY

The starting point for the identification of the fields of application is a comprehensive research of current developments and projects in the field of AI applications. The aim is to get a detailed picture of the current AI landscape in the energy sector. National activities[18 19 20 21] as well as international experiences[22 23 24 25 26] form the basis for the identification of application examples from research and the energy industry. The enquiry includes a broad screening of the current projects being developed in the energy industry and in research.

A systematic classification of the applications of AI in the energy industry is based on a matrix that has an energy industry dimension and an AI-specific dimension (see Figure 9). The energy economic basis of the matrix is the dena Map of Digital Dynamics according to Richard & Vogel[27] dar. The rigid demarcation between the stages of the energy value-creation chain consisting of generation, transport, trade and consumption is increasingly being broken down within the framework of the digitalisation and decentralisation of the energy industry. New business models that combine several stages of the value-

18 PWC 2017
19 Ndiaye 2019
20 Edelmann/Fleischle 2018
21 Platform Learning Systems 2019
22 Backes-Gellner a.o. 2019
23 Microsoft 2018
24 OECD 2019 a
25 OCED 2019 b
26 World Economic Forum 2018
27 Richard/Vogel 2017



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 & 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 10 The nine AI fields of application in the value-creation network

creation chain are formed and often represent relevant fields of application for AI in the energy sector. This dynamic is reflected in the map.

The AI-specific dimension refers to the typical AI applications Audio & Speech, Image & Face, and General Data Processing[28 29 30] presented in Section 2.2 Robotics & human-machine interaction is used as a further AI dimension, as there are several application examples in research and the energy industry AI in this area. Robotics & human-machine interaction are already a combination of different AI elements and thus already represent a more complex form of AI.

3.2 THE NINE AI FIELDS OF APPLICATION

As a result of the evaluation of the national activities and the international examples, a total of nine fields of application and three superordinate clusters can be identified (Figure 10 shows these fields of application in different shades of colour, while the clusters are marked by areas highlighted in colour):

Cluster "General Foundations for Decision-Making": AI supports various actors, for example, in making investment decisions, better predicting grid utilisation, consumption and feed-in of generation, or optimising operation or consumption. AI application examples of this cluster are distributed throughout the entire energy value-creation network and use AI methods primarily for general data analysis. The cluster comprises the following fields of application:

- Field of application 1: Prediction
- Field of application 2: Operation optimisation
- Field of application 3: Inventory optimisation & other strategic business decisions

Cluster "Maintenance & Security": In this cluster, for example, AI makes a contribution to minimising the downtimes of power generation plants and the grid and to ensuring safe plant operation. AI application examples of this cluster can be found in particular in the value-creation stages of generation and transport. The cluster contains 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

28 Fraunhofer 2018
29 Hartmann/Holtel/Weber 2018
30 Platform Learning Systems 2019

Cluster "Distribution & Consumer Services": AI applications in this cluster are aimed at improving customer relationships and are therefore particularly found in the consumption stage of the value-creation chain. The following fields of application are combined in this cluster:

- Field of application 7: Making it easier for active consumers to participate
- Field of application 8: Customisation of products and marketing measures
- Field of application 9: Process automation for measurements, bills and general distribution

3.3 THE CONTRIBUTION OF AI FIELDS OF APPLICATION TO THE INTEGRATED ENERGY TRANSITION AND THEIR STATE OF DEVELOPMENT

The nine identified AI fields of application in the energy industry are briefly presented in the following chapters. Concrete practical examples aim to help improve the understanding of the respective field of application. This is followed by an assessment of the nine fields of application with regard to their contribution to the integrated energy transition and their state of development. The classification of the contribution of the individual AI fields of application to the integrated energy system refers to the following five criteria:

Integration of renewable energies: efficient integration of renewable energies into the existing market structures with the goal of balancing their feed-in as accurately as possible, avoiding curtailed energy and enabling participation in all electricity markets. In addition to participation in electricity trading, this also applies to integration in system services such as balancing energy and redispatch.

Energy efficiency: reduction of primary energy consumption and contribution to the reduction of specific energy consumption and thus to increasing energy efficiency. As a rule, this is also linked to an improvement in system efficiency.

Security of supply: ensuring the balance between supply and demand at the market and network levels. Avoidance of critical network states and contribution to existing system services

System efficiency: implementation of the integrated energy transition using as few resources as possible. It is assessed whether the AI fields of application can reduce the overall costs of the energy system for an existing supply task or respectively whether specified climate protection paths can be achieved at the lowest possible cost.

Acceptance and participation: the scope of information provision, consultation, hearing, co-determination and decision-making competence of various actors with the aim of achieving agreement and participation for the implementation of the integrated energy transition.

In addition, a qualitative classification of the development status of the individual AI fields of application is made in each case. On the one hand, the identified examples of AI applications that are already in practical use or at least in concrete development are included. Similar developments in sectors other than the energy sector, where transferability to the energy sector seems possible, are also taken into account here. In addition, current research activities are also integrated into the evaluation.

3.3.1 AI USE TO IMPROVE FORECASTS

Many AI application examples concern the improvement of forecasts. A combination of statistical methods and ML (especially ANN) has been established for a long time. Requirements for simultaneity between generation and consumption make forecasts an elementary component of the energy industry over several stages of the value-creation chain (generation–trade, transport–trade, generation–consumption). With the emergence of fluctuating renewable energies and the increasing rate of utilisation of distribution networks, this demand will increase in the future. The emergence of new applications such as electromobility also increases the need for suitable forecasts in order to determine the charging requirement also depending on various price incentives. For forecasting purposes, historical data and, if necessary, other parameters from real-time data are used to derive future developments. This derivation can be significantly improved by using AI via statistical methods or ANN.

EXAMPLE: SINTEG Project DESIGNETZ with the German Research Center for Artificial Intelligence (DFKI)

Within the framework of the SINTEG DESIGNETZ project, DFKI scientists are developing three forecasting methods based on ML and its combination for predicting PV generation. **Further information:** https://www.dfki.de/en/web/research/projects-and-publications/projects/project/designetz/

Significance of the AI field of application for the integrated energy transition
Valid forecasts are a fundamental component of the integrated energy transition. Improving forecasts through AI therefore forms an important contribution to its success. ML can be used to process a larger amount of data for predictions, which can then be used to derive patterns and predictions also taking into account heterogeneous variables and to better identify anomalies. This enables a smaller temporal and spatial resolution and thus individualised forecasts. For example, a more accurate prediction of fluctuating renewable energies can lead to more targeted marketing, compensatory measures can be taken in the event of imbalances between supply and demand, and the payment of fines through balance imbalances can be avoided. An improvement of forecasts by AI can thus contribute in particular to the integration of renewable energies.

In addition, the use of AI methods for forecasting can, for example, create the basis for higher network utilisation even at lower network levels and prevent targeted interventions to prevent network bottlenecks. AI-based forecasts of the grid status, which can forecast not only the generation but also the demand side across sectors and integrate and analyse real-time data, thus contribute to the security of supply and system efficiency.

Such a contribution to the implementation of the energy transition, which guarantees a secure energy supply at the lowest possible costs, indirectly leads to a higher acceptance of the integrated energy transition.

Development state of the AI field of application
Various statistical methods are already being used today for forecasting and optimising commercial generation forecasts. In the past, this has already led to significant improvements in the forecasting of the feed-in of spatially distributed generation portfolios and for individual balancing zones. The current state of development of AI-based predictions, as seen from the research side is illustrated using current works. In his publication Li compiles time series forecasts for wind production using a four-layered ANN[31]. Unlike conventional forecasts, average values of 10 minutes are formed. This makes it easier to predict peak generation at certain points. Sharma et al. address the problem that a prediction of weather patterns must be based on far-reaching and site-specific historical values in order to map anomalies[32]. Using various regression methods, they predict solar generation with 27 percent more accuracy than existing forecasting models that take historical values of only one day into account.

3.3.2 AI USE FOR OPERATIONAL OPTIMISATION

Based on forecasts, historical datasets or master data (e.g. grid status data or power plant data), strategies for the operation of assets in the energy industry can be derived. Possibilities of AI applications range from optimised use of conventional and renewable power plants including a possible gas or heat supply (virtual power plants and dispatch optimisation) to optimised network operation and higher degree of network utilisation. When creating operating strategies, external framework conditions (e.g. the development of the electricity price) and other data available in real time can be used and evaluated using AI methods in order to derive an optimal strategy (e.g. for profit maximisation).

Another larger AI field of application is the recording of the network condition, which derives network loads from real-time data and can predict critical network conditions and derive prevention measures. Further AI applications based on this can improve risk management in the network or increase the transparency of market trading places, for example by automated monitoring or analysis of trading transactions. This can then be used, for example, to reduce market power.

EXAMPLE: Security Assessment & System Optimisation (SASO) from PSI

With Security Assessment and System Optimisation (SASO) PSI provides network operators with a system that is supposed to allow a concentrated assessment of the network status and presents proposals for eliminating identified critical states. To provide decision support, algorithmic procedures and Computational Intelligence (CI) procedures such as Fuzzy Logic or ANN are used. New, hierarchically structured concepts are planned for the visualisation, which allow a quick overview of the network status. **Further information:** https://www.psienergy.de/en/solutions/network-control/saso-dso-20/

Significance of the AI field of application for the integrated energy transition
Within the last 10 years, a decline in supply disruptions in grid operation and a lower demand for balancing energy have been observed[33][34]. Despite increasingly fluctuating renewable energies in the system, security of supply has been ensured through better generation forecasting and improved coordination between grid operators[35]. At the same time, the costs for network operation have risen significantly in recent years, particularly due to redispatch and feed-in management measures. Here an operation optimised by AI in which feed-in management measures can be significantly reduced by adapting generation to the actual grid load could be of great significance. AI applications would thus contribute to the integration of renewable energies.

When optimising the operation of an asset, external framework conditions (e.g. electricity price development), internal, asset-specific characteristics (e.g. run-up times of a power plant) and also expected demand must be taken into account. With a further increase in the share of renewable energies and the spread of new applications (e.g. electromobility), it is becoming increasingly difficult to determine the external framework conditions. New energy assets, such as storage facilities or flexible sector coupling technologies, can partly compensate for the increasing fluctuation in generation. With the consideration of storage in the optimisation of operations, new storage-specific requirements are added to the planning of the portfolio among other things. For example, the charging and discharging times are determined taking into account charging restrictions and storage losses. AI methods can make a greater contribution to handling the large number of parameters and variables, thereby increasing system efficiency and ensuring security of supply at the same time.

Development state of the AI field of application
Tools for the optimisation of operations are comprehensively established as commercial applications. The range of applications extends from grid operation to virtual power plants. There are the first starting points of the use of AI methods, and it is expected that these will also be increasingly used. GE Energy wants to increase the wind yield by up to 20 percent by optimising the operation of wind turbines (e.g. adjusting the rotor orientation depending on the direction of the wind)[36].

ML makes it possible to optimise operations by taking into account several external and internal, asset-specific parameters. For example, Fraunhofer IOSB uses ML for fault detection in the network. In the first step, the 4.3 million automatically recorded datasets per day are compressed to 20 percent of the data and evaluated. Based on typical operating faults, the ANN is taught in the second step. This allows the ANN to detect anomalies within milliseconds and propose countermeasures[37]. Without ML an evaluation in almost real time would not be possible.

The shown precision of the forecasts with ML is a basis for many operational optimisations. For example, Vazquez-Crespo et al. optimise the use of a combination of wind energy and storage by taking into account the storage availability and size as well

31 Li 2003
32 Sharma and others 2011
33 Bundesnetzagentur (Federal Network Agency) 2018
34 Slight increase in 2017 from 12.08 minutes to 15.14 minutes due to extreme weather events, compared to 21.53 minutes in 2006
35 In addition to adjustments in market design
36 GE Energy 2017
37 Fraunhofer IOSB 2019

as the electricity price development with the help of various stochastic optimisation approaches and achieve up to 6 percent higher yields with ANN[38].

3.3.3 AI USE FOR INVENTORY OPTIMISATION & OTHER STRATEGIC BUSINESS DECISIONS

In addition to short-term operational optimisation, AI can also contribute to inventory optimisation and other strategic business decisions. External and internal data are compared with each other in analogy to operational optimisation, thereby generating a basis for decision-making. These can be used, for example, to plan new investments and the decommissioning of assets or to further develop business areas.

> **EXAMPLE:** SINTEG project WindNODE with enersis
>
> The SINTEG project WindNODE is developing "enersis", a platform for automated renovation schedules for an urban quarter with old buildings. By linking user-specific data with generally available data, AI methods can be used to create automated CO2 balances or proposed measures. Further information: https://www.enersis.ch/smartheat-windnode/?lang=en

Significance of the AI field of application for the integrated energy transition
The investment in and dismantling of generation facilities, grid infrastructure for electricity, heat and gas as well as other infrastructure such as charging points are relevant aspects for the integrated energy transition. If, for example, scarcity moments increasingly occur in the system, market players decide whether and to what extent new investments should be made, taking into account price forecasts and company-internal framework conditions (e.g. liquidity, complementarity with existing portfolio). The increasing number of generation plants and the stronger networking of all energy consumption sectors make it more difficult to develop optimal investment strategies due to the increased complexity. AI methods open up the possibility to consider a multitude of framework conditions and to achieve better decisions with self-learning systems without having to map all relevant aspects individually. This reduces time delays in measures and the risk of bad investments.

38 Crespo-Vazquez and others 2018

These advantages apply not only to new investments, but also to retrofitting measures for existing assets. Under which conditions a retrofitting measure makes sense (the investment refinances itself within the planned useful life) can be determined more precisely with the help of ML approaches where appropriate. Such decision processes for inventory optimisation can be found in all energy infrastructures. Using approaches such as digital twins, virtual future scenarios can be modelled on the basis of real status data and used as a basis for the further development of the asset.

This AI field of application therefore makes the greatest contribution to increasing system efficiency. Considerations, e.g. between the use of innovative network elements (e.g. series voltage regulators) and the implementation of network expansion measures can be carried out with ML.

Development state of the AI field of application
ML is already used today in the planning of energy generation. Commercial software products that use AI methods also exist for the planning of distribution network infrastructures or urban planning. In China, for example, a support vector machine approach is being developed for determining network expansion measures in order to estimate measures from 2018 to 2022. Validation with historical data has shown that measures can be estimated with a forecast error of less than 1 percent[39]. Other research derives the optimal locations for wind turbines, taking into account grid bottlenecks and actor behaviour[40].

3.3.4 AI USE FOR PREDICTIVE MAINTENANCE

The AI examples in the predictive maintenance field of application cover a wide range, from AI-based evaluation of data to AI-controlled drones for the inspection of the grid infrastructure. This includes the maintenance of production facilities, typical cross-sectional applications such as pumps or a fleet of vehicles. Maintenance and repairs often take place at regular intervals or in the case of extraordinary events. Too long a cycle can lead to temporary failures, too short a cycle generates unnecessary cost. The collection and evaluation of production and plant data in real time enables the ensuring of quality or availability and the drawing up of maintenance in line with the requirements. In addition to AI-based analysis of such data, AI can also be used to analyse audio or image data to determine optimised maintenance times. The direct collection of data and the analysis of the maintenance status can also be improved with the help of AI, e.g. via intelligent sensors or robotic applications (e.g. drones).

39 Dai/Niu/Han 2018
40 Le Cadre/Papavasiliou/Smeers 2015

> **EXAMPLE:** Predictive IS
>
> Predictive IS's self-learning Predictive Intelligence AI software solution detects anomalies in machine behaviour, provides transparency into which factors affect machine inefficiency, and predicts machine failures. Further information: http://www.ispredict.com/index

Significance of the AI field of application for the integrated energy transition
The operation and maintenance of plants accounts for a large proportion of the costs in the energy system. GE Oil & Gas analyses show that offshore oil and gas platform operators have an average annual cost for unplanned operating breakdowns of approximately $49 million, which can be halved with AI-based predictive maintenance approaches[41]. Maintenance work can be carried out more efficiently or, in extreme cases, the loss of revenue due to an operational breakdown can be reduced.

AI-based predictive maintenance approaches can make a contribution to the security of supply in the operation and maintenance of energy infrastructures (electricity, heat or gas networks) if possible failures can be detected early and defective parts can be replaced. Providers of predictive maintenance for wind turbines promise a prediction of operating element failures 60 days in advance and savings of 12,500 euros per turbine due to avoided maintenance work[42]. A part of predictive maintenance is therefore not only the avoidance of unnecessary costs, but also an increase in the utilisation of renewable energies

Development state of the AI field of application
Various suppliers are currently developing products for predictive maintenance that optimise maintenance on the basis of plant and production key data. Additional optimisation potential is offered by stronger networking of production facilities within companies but also across value-creation stages (Industry 4.0 or Internet of Things).

According to Merizalde et al., most predictive maintenance applications are based on ML[43]. They see a particularly great potential in the application of hybrid models, which combine ANN's learning ability and the possibility of mapping non-linearity with the flexibility of fuzzy logic[44]. There is still a need for further research in this area. At the same time, they point out the problem, that the results of ANN are only traceable to a limited extent. Stetco et al. go into this problem of the black box in more detail. The complexity of the methods increases the precision of the results. At the same time, however, it becomes more difficult to comprehend how the results were achieved. Traceability is important both for the further development of the model and for the utilisation of the results. In order to increase transparency in black box models such as ANN, it is important to identify their functionality and attributes. However, the trade-off between precision and traceability remains[45].

41 GE Oil & as/E Digital n. d.
42 Boldare 2019
43 Merizalde and others 2019
44 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 are not assigned to a set or are not assigned with the necessary certainty.

3.3.5 AI USE FOR MAINTENANCE, REPAIR AND DISMANTLING

Maintenance, repair and dismantling of energy assets requires prior knowledge, equipment and manual skills. AI assistance systems can assist the repairperson by providing useful information, evaluating the condition on site or through physical interaction. Robots can also perform maintenance, repairs and dismantling in environments that are hostile to life or are hard to access for humans.

This field of application combines a large number of AI elements of the Bitkom period system. The status can be recorded on the basis of audio, speech, image, facial or sensor data. On the basis of this data, causes are concluded, possible solutions output or implemented directly by a robot.

> **EXAMPLE:** ROBDEKON
>
> In the ROBDEKON project, scientists from Karlsruhe Institute of Technology, the Fraunhofer Institute of Optronics, System Technologies, and Image Exploitation IOSB, the FZI Research Center for Information Technology and the DFKI are developing a robot for environments hostile to humans. With the combination of the cognitive skills of algorithms and the physical skills of robotics, for example, nuclear facilities can be dismantled without endangering humans. Further information: https://www.iosb.fraunhofer.de/servlet/is/Entry.85406.Display/

Significance of the AI field of application for the integrated energy transition
Time delays and errors in the maintenance and repair of energy assets can be reduced and risks avoided through assistance systems and robotics. These are usually based on classification

45 Stetco and others 2019

models that categorise the problem and select the most suitable solution from a pool of previous approaches.

In hard-to-reach environments such as offshore wind farms, robotic systems can help reduce maintenance costs and simplify the repair of rotor blades. Maintenance and repair costs account for the largest share of operating costs and are many times higher than for onshore wind turbines. This field of application is also more important for the maintenance of electricity grids, as access is also more difficult. The contribution of this field of application lies above all in an increase in system efficiency as well as in ensuring and increasing security of supply.

Development state of the AI field of application
Commercial application examples already exist, such as augmented reality glasses from GE as an assistance system. GE reports a 34 percent improvement in production when used for offshore wind turbine maintenance[46].

The next step still in research is the further development of assistance systems into fully autonomous systems. Here the competence centre "Robdekon" researches the development of robot systems for environments hostile to humans. These robot systems can be used, for example, for dismantling nuclear power plants.

3.3.6 AI USE FOR SECURITY MEASURES

Regarding digital applications there is not only an increased threat to information and data security, but also the creation of new ways of monitoring and limiting these risks. Abnormal patterns in digital processes from energy generation, transport, trade or consumption can be identified and addressed. Cyberattacks on power plants or grids can be better identified with the help of this AI field of application and countermeasures can be taken. In companies, emails with Trojans can be filtered more precisely or manipulations in balancing or accounting can be reduced.

But even beyond the digital sphere, evaluations of images, faces, speech and audio can identify dangers (e.g. burglars). In addition to identifying illegal activities, these evaluations can also help to implement occupational health and safety measures. For example, by giving a verbal notice when cameras identify that workers without helmets are entering the power plant.

EXAMPLE: zeroBS

ZeroBS offers consulting and services regarding information and data security. Among other things, they detect security vulnerabilities in software and show ways to limit their exploitation. As their latest case of application, these so-called exploit campaigns are executed automatically with ML. **Further information:** https://zero.bs/

Significance of the AI field of application for the integrated energy transition
According to the Federal Office for Information Security, cyberattacks on critical infrastructures more than quadrupled in 2018 compared to the previous year. Approximately 12 percent of these were aimed at electricity grids[47]. In this context, the establishment of a new agency for cyber security in Germany is being discussed. Similar projects have already been passed in the USA, which cited not only security of supply but also economic damage as justification. According to the scientific service of the US Congress, cyberattacks on power plants and grids can cause economic damage amounting to a few percent of the gross national product[48].

Greater use of small-scale flexibility, optimised charging of electric vehicles and the systematic use of household electricity storage devices increase the number of transactions taking place in the energy system. The verification and validation of these transactions will become increasingly important for the security of the power supply in the future and can be carried out more easily and automatically using AI methods. This field of action thus contributes in particular to system efficiency and security of supply.

Development state of the AI field of application
The first applications of AI for checking the balancing groups of all network users are already being tested by transmission system operators. Abusive behaviour and the exploitation of market power of individual network users are to be identified in this manner. ML is suitable for the rapid testing of large amounts of data to identify various anomalies in the operation of networks and power plants or for network usage data from customers.

In the field of research, ANN with their high degree of independent learning and the independent identification of new anomalies especially represent a promising approach regarding security measures. Berman et al. point to the need for the sufficient availability of training data to further improve ANN for security measures and cyber defence[49].

3.3.7 AI USE TO MAKE IT EASIER FOR ACTIVE CONSUMERS TO PARTICIPATER

The decentralisation and digitalisation of the energy industry opens up the possibility of active consumer participation. Increasingly, they also have their own generation and storage facilities. On the basis of household consumption or generation data, AI-supported decision aids for possible consumption adjustments and the use or sale of self-generated electricity can be generated or directly implemented. This makes it easier for the consumers to adapt their consumption behaviour or to operate their own generation facilities and sell the electricity.

In a similar vein to the operation and inventory optimisation in sections 3.3.2 and 3.3.3, the use of AI can provide decision-making aids for consumers to adapt their consumption behaviour (e.g. identification of efficiency potentials or shifting load to increase their own consumption rate) and also optimise investment decisions for new household appliances, decentralised generation facilities or batteries. For this purpose, the AI uses, for example, data on the consumers' historical consumption behaviour in order to make recommendations tailored to the consumers.

EXAMPLE: Shine energy manager

The Shine energy manager helps households balance the generation of their PV system with their consumption caused by both by controllable and non-controllable consumer devices. With the help of ML, the individual consumption behaviour with its individual applications can be recorded and possible adjustments can be shown. **Further information:** https://www.shine.eco/2017/10/10/wie-kuenstliche-intelligenz-das-energiemanagement-revolutioniert/

Significance of the AI field of application for the integrated energy transition
The contribution of the AI field of application to the integrated energy transition can be manifold. AI application examples, which lead to the replacement of inefficient household appliances, reduce energy consumption and increase energy efficiency. AI-supported operational optimisations of PV systems and storage facilities with a specific peak load cap increase the security of supply. Load shifts to sunny hours improve the integration of renewable energies. The consideration of individual circumstances and preferences should be made possible with AI approaches and can strengthen the acceptance of the integrated energy transition through simple consumer participation.

New business models in the digital energy world offer fields of application for AI use in households, such as the use of intelligent assistants in smart home applications. Energy management systems and the intelligent charging of electric vehicles are further areas of application that are used in various value-creation areas of the energy industry. AI applications will make access to the energy system and active energy management easier also for smaller consumers in the future. Individual consumption evaluations and decision-making aids for investments and operations, as well as automated switching by AI can support the consumer in this. Without automated and adaptive processing of consumer data, these services are not possible at reasonable cost and with the necessary precision. Here, the AI field of application can make a major contribution to integrated energy transition.

Development state of the AI field of application
Digital assistance systems are up to now widely used in households with systems such as Amazon's Alexa or Google Echo, but have so far only been used to a limited extent for applications in the energy industry. With the roll-out of smart meters planned for 2019 and the data made available with them, new application possibilities for the use of AI are unfolding. Individual appliers already offer AI-based detection of individual household appliances on the basis of high-resolution power consumption data. At present, however, control and management of household applications at the commercial level is only sporadic (e.g. the integration of household battery storage into a balancing power pool).

There are a variety of activities relating to this field of application of AI in the field of research. MacDougall discusses the use of ML to manage the small-scale nature of new network users in the context of sector coupling. Using ANN reduces predictive errors over the lifetime of a virtual power plant consisting of domestic heat applications. Compared to linear regression, forecasting errors can thus be reduced by a third[50]. Valogianni optimises the consumption of roof-mounted PV systems and electric vehicles through supervised learning and random forests. For example, she increases its own consumption to 93 percent in the summer half-year[51]. Lopez et al optimise the charge management of electric vehicles depending on the electricity price by using

46 GE Energy 2017

47 Federal Office for Information Security n.d.
48 Campbell 2018

49 Berman and others 2019

50 MacDougall and others 2016
51 Valogianni 2016

different methods with ANN[52]. The optimisation with deep learning shows the smallest deviation from the global optimum of 0.95 of the average value. In addition, they deal with the dilemma between more accurate results through more complex methods such as ANN on the one hand and long computing times on the other hand. In order to ensure the feasibility for new business models, a combination of fast offline optimisation and complex deep learning is recommended.

For short-term load prediction using random forest, ANN and fuzzy inductive reasoning,[53] Jurado et al. were able to reduce prediction errors by 88 percent to 15 percent and limited algorithm training time to 10 seconds per hourly dataset[54]. These fast and precise approaches are in the longer term suitable for a prognosis on site within the intelligent measuring system. The sometimes strong deviations between the standard load profile and the actual consumption of households with own consumption or controllable consumption facilities are illustrated by an analysis of data from Trianel's intelligent measuring systems[55]. The end customer continues to develop, while the energy industry-related processes and products are not yet fully adapted to this. With greater automation, more precise adaptations and small-scale analysis, ML can help keep pace.

3.3.8 AI USE FOR THE INDIVIDUALISATION OF PRODUCTS AND MARKETING MEASURES

The field of application "using AI to make it easier for active consumers to participate " is aimed at consumers who have their own generation facilities or a storage medium. On the other hand, the field of application "individualisation of products and marketing measures" deals with the possibilities of creating and communicating products specially tailored to the consumer. The measures can, for example, be created on the basis of structural or consumption data. With the help of AI, consumer segments can be formed, the relationships between consumers clarified, reasons for their behaviour identified, and custom-fit solutions generated. Individualisation not only affects the product offered, but also the way in which it is marketed. Through individualisation, for example, recommendations and measures for increasing energy efficiency can be created precisely for individual households. The use of real-time data can also be used in this AI field of application, e.g. to make recommendations for the purchase of more efficient devices or to carry out individualised control of heating appliances.

EXAMPLE: Business intelligence software using ML

ML is increasingly used in business intelligence software, which helps sales departments segment consumers and generate individually tailored offers. In addition, critical groups for sales operations can be identified, e.g. customers with a high probability of leaving or lacking liquidity. Providers of business intelligence software are e.g. Qlik and Cosmo Consult. **Further information:** https://www.cosmoconsult.com/products/data-analytics/bi-industry-solutions/bi-for-the-energy-industry/ & https://www.qlik.com/us/solutions/industries/energy-and-utilities

Significance of the AI field of application for the integrated energy transition
Consumer-specific products and marketing measures can lead to greater efficiency in electricity consumption and greater benefits for the consumer. For example, offers for PV rooftop systems can be sent specifically to consumers with a home with a south-facing roof area. Recommendations for energy efficiency measures can also be passed on to suitable target groups (e.g. identification of households with a low energy efficiency in their electrical appliances).

Social media and online commerce in particular make consumer preferences visible. A study by Matz, which examines the buying behaviour of 3.5 million Facebook users, identifies up to 50 percent higher sales with personalised advertising[56]. The higher sales potential is also reflected in the positioning of German companies. According to an Adobe survey, only 42 percent of German companies currently use personalised advertising, but 93 percent want to invest in AI for this by 2020[57]. Especially when identifying new and promising market segments, the probability of generating higher sales with the help of ML increases by a factor of 2.5[58]. At the same time, the faster and more automated approaches can save 15 to 70 percent of existing costs[59].

Knowledge of user preferences improved by ML can be used to provide households with targeted recommendations of measures in the context of the integrated energy transition. The contribution of this field of application therefore lies in particular in increasing energy and system efficiency.

52 Lopez/Gagne/Gardner 2019
53 Cf. application of fuzzy logic to assignment by algorithms
54 Jurado and others 2015
55 Seibring 2016

56 Matz and others 2017
57 Ilg 2018
58 MIT Sloan Management Review 2016
59 Harvard Business Review 2016

Development state of the AI field of application
Established methods can only map changes in segments over time to a limited extent and can only process a small amount of data. Whereas customer segmentation used to be based mainly on demographic data and previous sales behaviour, better segmentation can now be created using user profiles on the Internet alone. ML methods such as k-means are used for this. These applications benefit from the maturity of the developments of business intelligence applications from e-commerce. These can, for the most part, be transferred and used for the energy industry.

3.3.9 AI USE TO AUTOMATE MEASUREMENT, BILLS AND GENERAL DISTRIBUTION PROCESSES

Particularly in view of increasing competition, sales departments of companies in the energy sector are dependent on efficiently structuring their processes. AI can help automating processes. These include, among others automated and learning filing of incoming documents, automatically generated responses based on text modules, hotline androids or self-services for the customer.

EXAMPLE: Attentive Tasks by TraffiQX

As an extension of the process-based platform TraffiQX, Attentive Tasks serves to categorise and prepare invoices. Based on previous assignments, incoming documents are allocated, and proposals are offered for further processing. **Further information:** https://www.traffiqx.net/

Significance of the AI field of application for the integrated energy transition
The AI field of application streamlines existing processes through automation or enables new processes that previously could not have been mapped at reasonable cost. For example, standard processes such as the imputation of missing metering data for billing can be made more precise, or consumers can be invoiced for more individual profiles instead of the standard load profile.

New applications such as the intelligent charging of electric vehicles, the use of small-scale flexibility or the optimised storage operation of household electricity storage systems lead to an increasing number of transactions in the energy system, which in future can be automated and carried out cost-effectively through the use of AI.

The field of application therefore contributes above all to system efficiency and better integration of renewable energies. Process automation leverages potential for efficiency gains and enhances precision and thus also opens up new possibilities for the consumer.

Development state of the AI field of application
According to an article in Chatbots magazin, by 2020 85 percent of customer care will be automated on the basis of AI and will therefore take place without a company representative[60]. IBM promises to be able to save up to 30 percent on service costs with its AI-based computer system Watson and to be able to respond more quickly and accurately to customers' needs[61].

3.4 CONCLUSIONS ON THE FIELDS OF APPLICATION AND EXAMPLES OF AI IN THE ENERGY INDUSTRY

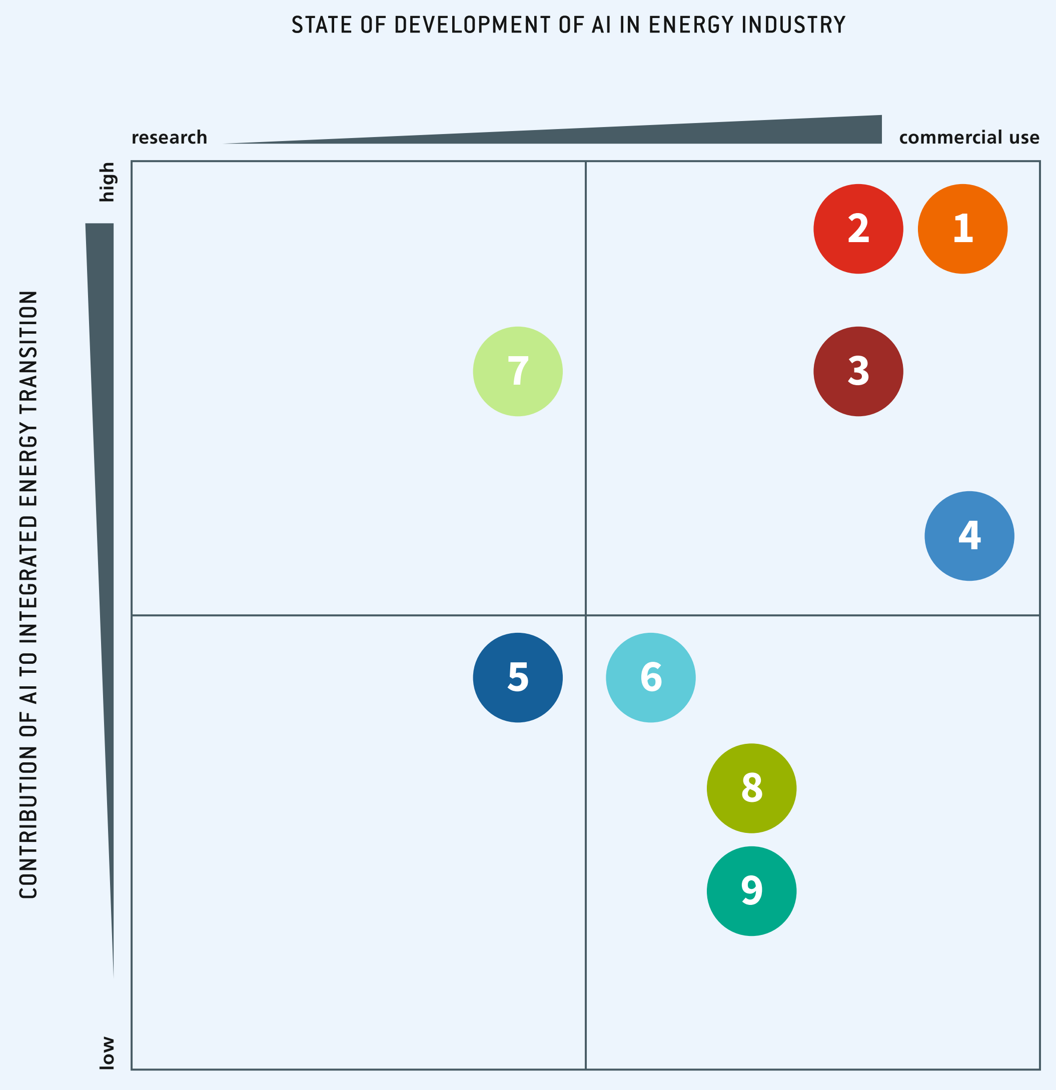
The fields of application are classified in Figure 11 along the dimensions of contribution to the integrated energy transition and AI development status in the energy industry.

The cluster "General Foundations for Decision-Making" shows to what extent AI can make a contribution in the short term to higher capacity utilisation and better long-term planning of energy assets. The high urgency for the integrated energy transition is also expressed in the advanced stage of development. The fact that these fields of application are already in commercial implementation is also related to the fact that the information is already available in the form of data and does not first have to be derived from audio or image files. This allows the AI to concentrate on the evaluation of the data ("weak AI")[62].

In contrast, in the "Maintenance and Security" and "Distribution and Consumer Services" clusters, visual or acoustic information is in parts first collected by AI and then turned into usable data. Especially in the "Maintenance and Security" cluster data are not only collected and conclusions drawn from them, but, in the sense of an approximation of "strong AI", actions are also derived, e.g. for the use of maintenance robots. The handling of this increased complexity is based on ANN. Their use and, in particular the explainability of their results still offer further research potential.

Two trends are emerging in the "Distribution and Consumer Services" cluster. The individualisation of products and marketing

60 Chatbotmagazine 2018
61 IBM 2019
62 Further development potential in the direction of strong AI also exists in the "General Foundations for Decision-Making" cluster



GENERAL FOUNDATIONS FOR DECISION-MAKING

1. Prediction
2. Operation optimisation
3. Inventory optimisation and other strategic business decisions

MAINTENANCE & SECURITY

4. Predictive maintenance
5. Maintenance, repair & dismantling
6. Security measures

DISTRIBUTION & CONSUMER SERVICES

7. Making it easier for active consumers to participate
8. Customisation of products and marketing measures
9. Process automation for measurements, bills and general distribution

FIGURE 11 Classification of AI application fields

measures, as well as process automation, are of subordinate relevance for the integrated energy transition. At the same time, other sectors (in particular e-commerce) are pushing ahead with their development, so that a broader application also in the energy industry is to be expected in the future. On the other hand, the simplified participation of active consumers makes a major contribution to the integrated energy transition. Through automated data processing, AI provides consumers with access to energy industry processes similar to the established players in the "General Foundations for Decision-Making" cluster.

A large number of AI applications can not only make a contribution to the energy transition in theory but can also be used in practice today or in the near future. AI contributes to the organisation of the small-scale nature and the unsteadiness of tomorrow's energy supply and to bring out potentials.

4 THE FRAMEWORK CONDITIONS FOR AI FIELDS OF APPLICATION IN THE ENERGY INDUSTRY

The conditions for AI in Germany and Europe are different from those in the USA or China. An article from the newspaper ZEIT on the ethical guidelines for trustworthy AIs in the EU sums up the situation aptly: "While [so Viola] in China the technology was rather controlled by the state and in the USA it was more driven by companies, in the EU they wanted an AI that takes into account people's rights and needs[63]". According to Roberto Viola, Director-General of the European Directorate-General for Communication Networks, the responsible use of AI could become the European hallmark in the highly competitive market, currently fought over by China and the USA. In this sense, the establishment of AI in Germany and Europe and the potential for AI within this value system and the economic structures are described below. The handling of personal data, the display of legal grey areas, the establishment of standards and processes as well as the establishment in companies are central points.

Handling personal data

According to rulings of the German Federal Constitutional Court, the right to informational self-determination is a recognised fundamental right on the basis of Articles 1 and 2 of the German constitution. As a matter of principle, every citizen may decide for herself or himself about the disclosure and use of her or his personal data. The European Basic Data Protection Regulation (EU-GDPR) and the German Federal Data Protection Act (BDSG) pursue this guiding principle.

At the same time, more and more applications in everyday life are based on a multitude of collected data. For example, the principle of "services for data" has prevailed for a large number of apps and other services. At the same time, the purpose limitation principle and the principle of data economy must always be observed.

In the course of the duty to provide information pursuant to Art. 13 and 14 GDPR, each data subject must be informed about the data processing when the data are collected. According to Art. 20 GDPR, the data subject also has the right to receive the data collected in a structured, common and machine-readable format. However, the possibilities for the use of these data are mostly not obvious to the data subjects, the trade in data is fragmented and only accessible to individuals to a limited extent.

63 Hegemann 2019

Palmetshofer et al. in an expertise for the German Advisory Council for Consumer Affairs examine possibilities to concretise the value of data and to let the originator author participate in it[64]. While doing that they identified three market segments. In the largest market segment, trading data for services, the consumer plays a passive role. At this point, it is important to make data protection risks transparent. Data donations are another segment in which data subjects voluntarily make their data available for added societal value. The trade for payment as the last segment, the authors refer to three uncertainties: First, there are technical barriers to the creation of a market (e.g. access to platforms and billing). Secondly, the question arises as to whether the price obtained justifies the additional effort for the consumer. Thirdly, the competitiveness of this market is ambiguous in comparison to data trading with companies with corresponding network and economies of scale effects. According to the ZEW discussion paper by Schweitzer and Peitz, the trade can be organised via primary or secondary trading and settled via bilateral negotiations or standardised market relations[65]. These open issues need to be followed up in order to pave the way for greater data availability while improving self-determination.

The use of ML depends on the availability of data, which is heterogeneous in the German energy industry. For example, the exchange of master data is standardised via the market master data register (Marktstammdatenregister). The exchange of movement data between network operators has to be organised bilaterally[66]. The collection of consumption data beyond the minimum standard defined in accordance with the metering point operating law (Messstellenbetriebsgesetz) must also be bilaterally agreed with the metering point operator. For the successful use of ML in energy transition, standardised data formats and processes must be introduced, and further data must be collected, and their quality checked.

64 Palmetshofer/Semsrott/Alberts 2016
65 Schweitzer/Peitz 2017
66 Meyer 2014

Elimination of legal uncertainties and standardisation

The EU-GDPR and the BDSG are important legal bases for the handling of data. Nevertheless, legal uncertainties remain. This includes, for example, the demarcation between personal and non-personal data. Article 4 GDPR states that "any information relating to an identified or identifiable natural person […]" is personal data. However, the extent to which data must be anonymised in order to exclude traceability remains a matter for interpretation[67]. In addition to a clear definition, standardised processes for anonymising the data can also help to reduce these barriers to the use of data.

The introduction of standards for data formats is also a prerequisite for efficient data management and analysis. At the same time, the diverse forms of data collection and processing and the market which is already fragmented today must also be taken into account. As an alternative to uniform data formats, standardised processes for the standardisation of different data could also be a approach.

The traceability of decisions based on data evaluations is also a central point of discussion. Under Article 22(1) of the GDPR, data subjects have the right "not to be subject to a decision based solely on automated processing". However, the following paragraphs define some exceptions for automated decisions. Automated decisions become particularly problematic when they are no longer comprehensible. This is particularly the case for ANNs, where it is only possible to deduce the result to a very limited extent. Appropriate manners or guidelines for dealing with black box models are to be developed.

To ensure that legal uncertainties do not become an obstacle to the development of AI in Germany, so-called sandbox environments are discussed[68] in which exceptions are to apply within research projects. However, it is difficult to determine how far-reaching these exceptions should be. Other market participants who cannot benefit from this special status should not be discriminated against. At the same time, there should be no overly comprehensive exemptions.

67 Schweitzer/Peitz 2017
68 Beringer/Bienert/Rothe 2018

The consideration of AI in the strategic positioning of companies and the need for further training

A central aspect for the application of AI in the energy transition is the necessary expertise in companies. Large corporations are already setting up their own internal big data and AI centres and SMEs could purchase expertise for this. Nevertheless, for the meaningful application and implementation in companies, appropriate knowledge of the conditions, possibilities and limits of AI is required. There is a considerable need for further training here. According to a Deloitte survey, 62 percent of German companies complain of a lack of AI skills[69].

The introduction of AI in the energy transition cannot and will not take place overnight. The meaningful and custom-fit application requires a series of steps such as strategy development (understanding business processes, identifying and evaluating potentials, defining goals and plans), data development (checking data availability, investigating data quality, preparing data), data analysis (selecting algorithms and developing models, integrating expert knowledge, taking specific requirements into account) and finally large-scale use (tailored big data and AI architectures, setting up powerful infrastructure, adapting business processes). Lead times for such processes must be taken into account and scheduled.

69 Saballa/Eater 2019

5 CONCLUSIONS

AI is currently one of the most discussed trends within the energy industry. Within the framework of the integrated energy transition, the energy system is becoming increasingly dynamic and smaller scaled. AI can make a significant contribution to dealing with the resulting complexity.

For the assessment of the contribution, a comprehensive screening of application examples is carried out within the framework of this basic report. The identified examples can be assigned to a total of nine fields of application, which can be summarised under three superordinate clusters. These categories are:

- AI Cluster "General Foundations for Decision-Making"
- AI Cluster "Maintenance and Security"
- AI Cluster "Distribution & Consumer Services"

The "General Foundations for Decision-Making" cluster provides the comparatively largest contribution to the integrated energy transition and can already be found in commercial implementations due to its focus on data evaluation in the sense of "weak AI". A comprehensive AI application in the sense of "strong AI" can be found in "Maintenance of Assets" and "Distribution & Consumer Services ". Concerning ANN and in particular, the application of robotics and assistance systems based on it, there is still a need for research for more comprehensive applications.

On the one hand, AI makes it possible for the applications in the energy industry shown to fulfil their function better (e.g. forecasts). On the other hand, some applications are only made possible by AI (e.g. assistance systems). In order for both modes of operation to be able to develop in the future, the availability of data in accordance with the consumer's right to self-determination, the use of ANN as black box models in the sense of the GDPR and as a confidence-building measure, as well as the standardisation of the processes and data formats concerned are decisive. The energy industry has traditionally been a data-intensive industry based on established data processing processes. Their further development towards the use of AI is therefore the next logical step for the implementation of an integrated energy transition.

It is already evident today that, in addition to technical developments, a large number of other questions and aspects need to be clarified and taken into account in order to make greater use of AI.

- Which technical possibilities exist, which data are used and how can these be collected?
- Which basic principles and ethical principles should be observed? How can informational self-determination be guaranteed?
- How can such approaches be technically implemented? Which AI methods (architecture and design of algorithms) make the integration of such basic principles possible?

This enables a comprehensive understanding of the technical possibilities and at the same time an early integration of further societal requirements for the development of AI technologies in the energy industry.

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9 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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