APPLICATION FIELDS OF ARTIFICIAL INTELLIGENCE IN THE ENERGY SECTOR - A SYSTEMATIC OVERVIEW

Sabine Pelka, Nico Calabrese, Marian Klobasa,
Fraunhofer Institute for Systems and Innovation Research ISI,

Abstract

AI is a promising technology to accelerate the energy transition. Participation shall be enabled by customized products and services, the efficiency shall be increased by a higher degree of automation and a greater utilization of the given assets. Several examples applied in research and the industry can be found, but a structured overview of the application fields of AI in the energy sector, possible development paths and its drivers is missing. By the development of a framework to map the applications and an extraction of application examples from the literature, three superordinate clusters are identified with nine application fields for artificial intelligence in the energy sector.

In the cluster "general foundations for decision-making", applications for predictions, operation and asset optimization support the market integration of renewables and allow a higher utilization and better long-term planning of the grid, generation plants and storages.

In the cluster "maintenance and security", applications enable an efficient, smooth and reliable operation of the grid and of generation assets by predictive maintenance, by assistance services for technical measures and by security measures. The cluster "distribution and consumer services" comprise of applications where benefits for the consumers are created by enabling a better participation at the energy transition. This is done with the help of tailored predictions and optimization advices, customized products and process automation of retailing and customer services.

In general, the most used applications in the energy industry are found in the cluster "general foundations for decision- making", as those are straightforward applications based on advanced data analytics (the so-called narrow AI). Applications based on more advanced AI methods (e.g. different forms of input and output data like video, audio or other physical data- the so-called broader AI) can be found in the other two clusters. For a broader application of AI in the energy industry, the most important bottlenecks referring to a missing work force, needed technology improvements and adaptions of the regulatory framework which have to be addressed.

1. Introduction

With forecasting, scheduling and billing, the energy sector is traditionally a data driven industry developing even further because of digitalization. Existing business models are adapted, and new business models are created, in particular, by linking several stages of the energy value-creation chain. Individual examples for AI applications in the energy sector (especially in research) are widely known. In recent times, examples for planning or process improvements due to artificial intelligence[1] (AI) have emerged. Looking into research publications of AI and comparing the sectors for application of AI, energy had the third largest share of AI-related publications from 1996 to 2016 (OECD 2019).

Therefore expectations of the impact of machine learning algorithms and the application of artificial intelligence are high in the energy sector, but a comprehensive and systematic overview of application fields of artificial intelligence in the energy sector is missing. This gap is addressed[2] with this paper by developing a framework for AI applications in the energy sector based on a literature review and interviews with different stakeholders.

---

[1] The most frequently used AI branch is Machine Learning (ML) that 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. In the course of the paper, most AI application refer to ML

[2] The results are part of a report by Klobasa, Pelka and Plötz, which can be downloaded here: https://www.isi.fraunhofer.de/en/competence-center/energietechnologien-energiesysteme/publikationen.html

The main goal is to identify possible impacts of AI applications on the integrated energy transition, the current stage of the development and main drivers and barriers for future development. After explaining the methodology in the second chapter, the AI and energy related categories for the framework are derived from literature and the framework is designed. In the fourth chapter, the application examples are extracted from the literature, assigned into the framework and clustered into application fields to give an overview about the state of AI in the energy sector. The chances, barriers and drivers of the further development of AI are derived from interviews with experts and documented in chapter five. The final chapters are the discussion of the results and conclusion on the main application fields.

2. Methodology

The present application fields are identified by a **literature review** and by conducting interviews with stakeholders. The literature review and the identification of the application fields is done in three steps.

- First, a framework for mapping the present applications is developed. Therefore, categories representing energy and artificial intelligence applications are respectively chosen from the literature. The categories aim to be comprehensive and concise. This is tested incidentally in the second step. If needed, the categories are adapted.
- In the second step, examples from the literature are extracted and filed in the framework. For the examples applied in research, a systematic literature review with peer-review journals is conducted. For the examples applied in the energy industry, also grey literature is screened.
- Third, the applications are clustered into application fields to map the present state and derive trends for AI in the energy sector.

Contextual information about the reasons for mapping and identifying current state of applications is done by complementing qualitative content analysis of the literature and by doing interviews with different stakeholder. With semi-structured interviews, the potential of AI in the energy sector, its barriers and drivers are identified. Five experts in the energy domain who either supply or use AI services are interviewed about their prominent use cases, their implementation, up- and downsides of the AI and lessons learnt. The information from the interview transcripts is extracted in three steps.

- First, a coarse deductive category system is derived from the interview questions. The transcripts are analyzed by assigning information from the transcripts to the categories.
- Second, inductive categories are created based on the assigned information in the categories. With this refined category-system the transcripts is analyzed a second time.
- At the end, the assigned information is aggregated and processed.

3. Design of the framework for mapping AI applications in the energy sector

With the help of the literature analysis, main parameters for the analytical framework are defined, which consists of the categories for the energy and the AI context of the applications.

AI-Categories - Two distinguishing rationales for the AI categories are identified.

- First, Fraunhofer 2018; Backes-Gellner et al. 2019; World Economic Forum 2018 differentiate by the form of the input and output, which can be visual, audible, physical or solely based on data. Physical applications, such as robots, combine visual, audible or elements solely based on sensor data (also called broader AI) and are a more complex and advanced application compared to the others.
- Second, it can be differentiated by the value creation step of AI. According to Hammond

2016, AI asses a certain situation, creates meaning by inferring and responds. For an AI application, those steps occur solely or are combined for a more complex composition.

Energy Categories - For the energy dimension, a common approach is to classify the application according to the energy value chain of generation, transmission, trading and retail. Given the interdependencies of value chain steps, this approach falls short to capture the nowadays complexity of the applications. To address this shortcoming, business model languages are screened. Vu et al. 2019 evaluate different business model languages for business models in the energy transition and highlight the eBusiness Model Schematics by Weill and Vitale 2001, e3value by Gordijn and Akkermans 2001, the value network by Schneider et al. 2016, the Smart Grid Architecture Model (SGAM) by Dänkes et al. 2014 and the ABC model by Schäffler 2018. The SGAM is selected for three reasons.
First, the three-dimensional structure combines technical, economic and processual aspect, which are all relevant for AI applications.

- Second, the modular structure of the interoperability aspects at the z-axis fit to the structure of AI applications.
- Like stated in the previous paragraph, AI application can combine different forms of input and output (visual, audible etc.), steps of value creation (assessing, inferring, responding) or occur solely[3].
- Third, Richard and Vogel 2017 modify the SGAM and propose to mirror the energy value chain steps at the x and y axis to create overlapping fields combining two steps of the energy value chain to express the interdependencies of the value chain steps for new business models in the energy transition.

All in all, the framework is based on the SGAM. For the energy dimension, the energy value network by Richard and Vogel 2017 is used are the x and y axis. Deciding between the two kinds of identified AI categories, the input and output format is selected. The AI categories are general data, audio & speech, image & face, robotics & assistance systems. By these, the kind of application is not only well described, but also the state of development is expressed. Ranking from general data as the most straightforward approach to robotics as a form of broader AI, the advancement is stated.

4. From application examples to application fields

As a starting point, literature is reviewed for AI application examples in the energy sector. Perera et al. (2014), Cheng und Yu (2019), Hossain et al. (2019) and Mosavi et al. (2019) give an overview of examples applied in the energy research. Prediction is identified as a key application for every step of the value chain. For the generation and the grid, AI is used to monitor and increase the utilization of the assets, to choose the capacity and location of future investments and for predictive maintenance. AI supports these decisions not only for large scale assets, but also for small scale assets at the household level. For trading, energy management systems, customer service and billing, AI is used for automation of the processes. Additionally, AI is used to analyze customer data for customized products or marketing measures. Looking at the AI methods, classification approaches are frequently used for the optimization of asset utilization and investments and for predictions regression. For analyzing more complex relations, artificial neuronal networks (ANN) are used.

---

[3] The one-dimensional AI is called narrow AI, the multi-dimensional broad AI

By assigning the mentioned examples applied in research and adding examples applied in the energy industry in the framework, nine application fields for artificial intelligence in the energy sector and three superordinate clusters are identified in the framework (see figure 1). The clusters and their applications fields are explained in the following.

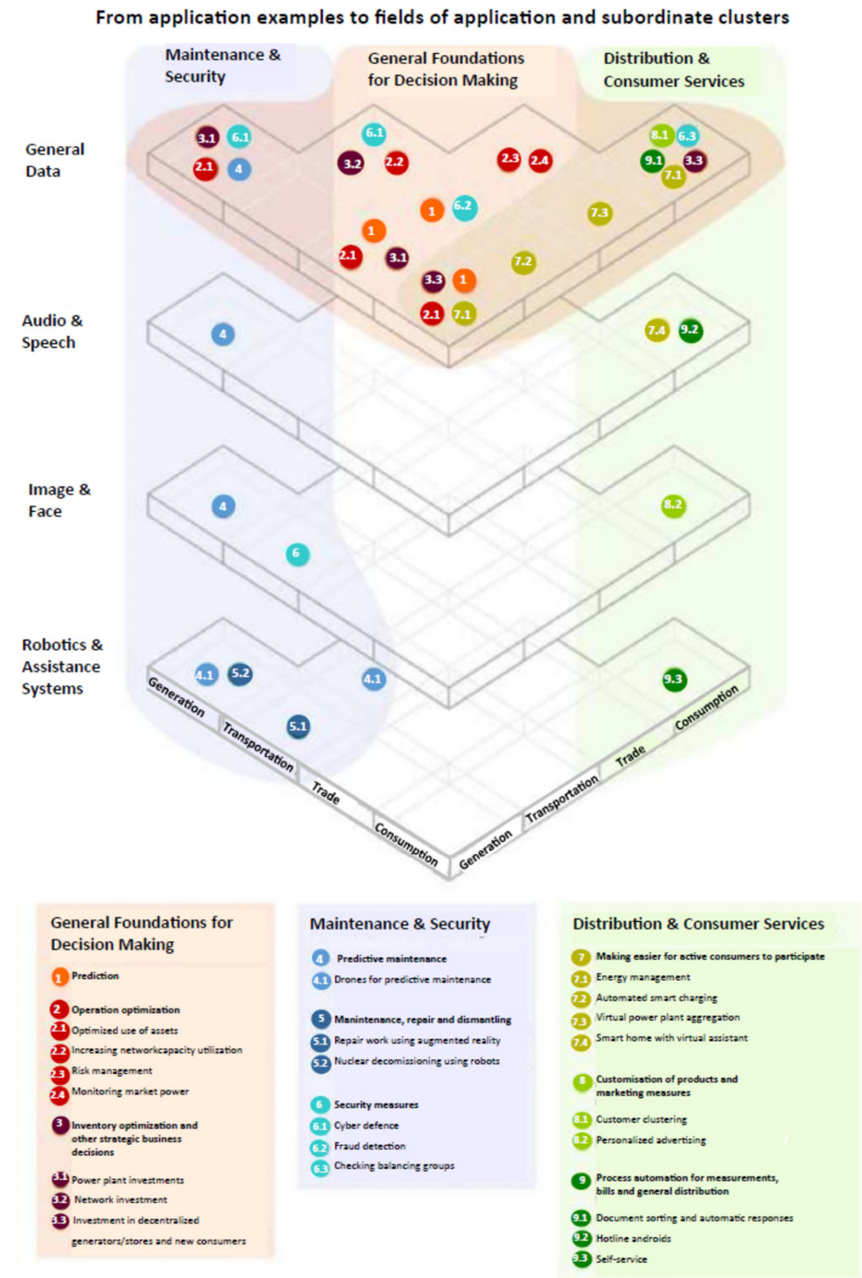

Figure 1: **The AI framework and its application fields for the energy industry**

General foundations for decision-making - the first cluster is called "general foundations for decision-making". It contains the application field prediction, operation optimization and inventory optimization. Predictions can be used for different cases in the energy sector. Especially, predictions of fluctuating renewables with a high regional or temporal resolution identify single peaks more precisely like shown in Sharma et al. 2011 and Crespo-Vazquez et al. 2018. Predictions can be used for short-term (operation) or long-term (inventory) optimization. For instance, Fraunhofer IOSB uses AI for fault detection in the grid and enabling a higher grid utilization (Fraunhofer 2019). Furthermore, in China, 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 network expansion measures can be planned with a forecast error of less than 1 percent (Dai, Niu, Han 2018).

Maintenance and security - the second cluster is called "maintenance and security". It comprise the maintenance planning based on measured data instead of regular terms, the so called predictive maintenance. GE states that the average annual cost for unplanned operating breakdowns of approximately $49 million for offshore oil and gas platform can be halved by predictive maintenance (CXP Group 2018). The other two application fields are the operational assistance for maintaining, repairing or dismantling assets and security measures[4].

Distribution and consumer services - in the last cluster "distribution and consumer services", benefits for the consumers are created from three angles. First, they are enabled to contribute to the energy system by improved energy services. With the high automation degree of AI, prediction and optimization services cannot only be used for large scale assets, but also for small scale generators and household consumers, which would not be economically feasible otherwise. Examples are MacDougall et al. 2016; Lopez et al. 2019; Valogianni 2016; Jurado et al. 2015. Furthermore, the processes for billing and customer services become faster and leaner by automation and the products and marketing measures become more customized.
All in all, two states of AI can be identified for the three clusters. Whereas the cluster "general foundations for decision making" is concentrated at the general data layer and broadly distributed in the energy dimension, the other two clusters have a high concentration on one side of the energy value network and combine different AI application groups. The first cluster which use only one AI application group (also called "narrow AI") is more established in the industry than the others. In contrast to that, the other two show more sophisticated applications that make use of several AI application groups. It is expected that further applications using multiple dimensions of the framework will be established in the future. Which application fields are expected by the experts of the interview and which barriers they face to evolve the described potential is shown in the following paragraphs. The chances, barriers and drivers are differentiated by work force, technology and regulatory framework.

5. Chances, barriers and drivers of AI in the energy sector

Chances, barriers and drivers of AI in the energy sector are extracted from the literature in the first step and then contrasted with the results of the interviews. Khashei und Bijari 2011 and MacDougall et al. 2016 summarize the up- and downsides of AI in contrast to conventional statistical methods, such as time series regressions with ARIMA (Auto Regressive Integrated Moving Average) in three points.

[4] for a more detailed description, please check the report by Klobasa, Pelka and Plötz, which can be downloaded here: https://www.isi.fraunhofer.de/en/competence-center/energietechnologien-energiesysteme/publikationen.html

First, AI can identify non-linear developments, but especially for ANN, the results are not traceable from the model run. Second, the model is based on data. Therefore, it is independent from the limited or specific knowledge and bias of the editor. Third, it is robust towards single missing data in a time series. At the same time, a multitude of data is needed for creating the model. Additionally, Döbel et al. 2018 highlight the high computational power and training time that is needed for creating and running the model. In the case of Makridakis et al. (2018), a double computational power is needed for ANN compared to ARIMA. At the same time, once a model is developed, the model runs can be highly automated. Whereas the mentioned points by the literature mainly concerned technology aspects, the interviewed experts also mentioned barriers and drivers concerning the work force and the regulatory framework. The results of the interviews are presented in the following divided by work force, technology and regulatory framework.

Work force - the experts name three barriers that hinder the widespread use of AI. First, prejudice towards AI (e.g. replacing human work force) lead to resistance of the employees. Second, hierarchical structured companies tend to be skeptical towards adapting innovations such as AI, especially when AI takes part of the decision making process and interfere management competencies. Lastly, it is challenging for so far non-AI-users to identify the cases in which the additional effort of AI (e.g. longer training, higher computational power) results in a great added value (e.g. more precise prediction, time saving due to automation). Based on the interviews and the literature analysis, four key prerequisites for using AI can be derived:

- *Complexity*: The causalities of the parameters are not explicit.
- *Regularity*: The decision is made frequently.
- *Data benefit*: Sufficient historical data for the training of the algorithms is available.
- *Data volume*: Sufficient new data is available to be processed in the application.

To tackle the three barriers, a corporate culture must be created that encourages innovation, educate and highlight the potential of AI.

Technology - a pivotal aspect for the adaptation of AI is the availability of data. From the technical perspective, two barriers are identified. First, data is not collected at points of a high informational content. In this sense, data collection does not necessarily be pervasive, but it needs to be done at characteristic points of the given environment. In a project of one interviewed expert, sensors are only installed at 5 to 10 percent of the grid nodes to track the utilization, as the precise utilization of the low voltage grid was not monitored before. Second, the data is available but fragmented in different formats, at different platforms or at a low quality. Unified standards, platforms or interfaces at the company level or national wide help to tackle this bottleneck.
Two aspects of the literature analysis were not prominently mentioned during the interviews. First, as rather simple AI approaches are in use (e.g. regression and classification), the limited traceability of ANN is a minor subject for the experts at the moment. Second, the experts state that for most applications the computational power is not a bottleneck. This could change, if they move from simple regression and classification methods to approaches of broader AI. Whereas additional computational power is well accessible via cloud services, the retrofit of special hardware (e.g. for image processing) is effort and cost intense and need to be planned.

Regulatory framework - no collected data or fragmented data is also an issue in the regulatory context. Open data approaches would help to have sufficient data available for training of the algorithms, but it must be carefully examined to what extent this is allowed by

German data protection guidelines. For instance, standards for anonymizing private data or unified transparent data classes as a guideline for data business cases can be established to accelerate the process. In case of limited available data in the distribution grid, more investment security for additional sensors should be guaranteed. The usage of smart meter data can also contribute to a more transparent low voltage grid.

6. Discussion

The interviews confirm the application fields of AI that have already been discovered by the literature analysis. This is
also the case for most of the drivers and barriers. So far, the focus of implementation in the industry has been set on simpler AI methods. Therefore, the industry does not face some of the major problems found for applications in an early development stage discussed in the research literature (e.g. limited traceability and computational power). Further research is needed to limit the impact of these bottlenecks, before the approaches can be applied in the energy industry. At the same time, the industry can collect experiences with AI applications to better understand and address these problems to enable a smooth transition.
The framework is a first snapshot of the current situation and should be extended with new applications and updated in the future to integrate the further development of AI methods. It is recommended to repeat the screening and clustering of application and integrate it in the framework after some years. At the same time, the interviews can be updated with new and a greater number of experts.

7. Conclusions

Overall by using AI in the energy sector, the three clusters "general foundation for decision-making", "maintenance and
security" and "distribution and consumer services" show potential for a higher degree of automation and more detailed analysis at the same time. This enables a higher level of utilization of the given assets and raising new potentials along the entire value chain. The state of the art research and applications in the energy sector focus either on narrow AI applications or on one step in the energy value chain respectively energy value network. In the future, application can be based on more dimensions of the framework, if the highlighted bottlenecks referring to the work force, the technology and the regulatory framework are addressed.
Several future research questions occur that have to be addressed like “How can AI contribute to more sustainability and environmental protection?”. To answer this question the related business models, relevant actors and the underlying data economy have to be better understood. Also expectations of the society as a whole and ethical guiding principles should be considered and developed further in the future to allow the usage of a broad range of data.

Publication bibliography

Backes-Gellner, Uschi; Böhringer, Christoph; Cantner, Uwe; Harnhoff, Dietmar; Hölzle, Katharina; Schnitzer, Monika (2019): Gutachten zur Forschung, Innovation und technologischer Leistungsfähigkeit Deutschlands. Gutachten 2019 von EFI Expertenkommission Forschung und Innovation.

Beringer, Fabian; Bienert, Jörg; Rothe, Rasmus (2018): Künstliche Intelligenz - Situation und Maßnahmenkatalog. Positionspapier des KI Bundesverand e.V.

Berman, Daniel; Buczak, Anna; Chavis, Jeffrey; Corbett, Cherita (2019): A Survey of Deep Learning Methods for Cyber Security. In *Information* 10 (4), p. 122. DOI: 10.3390/info10040122.

Bogner, Alexander; Littig, Beate; Menz, Wolfgang (2014): Interviews mit Experten. Eine praxisorientierte

Einführung. Wiesbaden: Springer VS (Lehrbuch).
Boldare (2019): https://www.boldare.com/blog/predictive-maintenance-wind-turbine/. Zuletzt eingesehen am 06.06.2019.
Campbell, Richard J. (2018): Electric Grid Cybersecurity.
Chen, Xia; Dong, Zhao Yang; Meng, Ke; Xu, Yan; Wong, Kit Po; Ngan, H. W. (2012): Electricity Price Forecasting With Extreme Learning Machine and Bootstrapping. In: IEEE Trans. Power Syst. 27 (4), S. 2055–2062. DOI: 10.1109/TPWRS.2012.2190627
Cheng, Lefeng; Yu, Tao (2019): A new generation of AI. A review and perspective on machine learning technologies applied to smart energy and electric power systems. In: Int J Energy Res 43 (6), S. 1928–1973. DOI: 10.1002/er.4333. Crespo-Vazquez, Jose L.; Carrillo, C.; Diaz-Dorado, E.; Martinez-Lorenzo, Jose A.; Noor-E-Alam, Md. (2018): A machine learning based stochastic optimization framework for a wind and storage power plant participating in energy pool market. In *Applied Energy* 232, pp. 341–357. DOI: 10.1016/j.apenergy.2018.09.195.
CXP Group (2018): Digital Industrial Revolution with Predictive Maintenance, study commissioned by GE
Dai, Shuyu; Niu, Dongxiao; Han, Yaru (2018): Forecasting of Power Grid Investment in China Based on Support Vector Machine Optimized by Differential Evolution Algorithm and Grey Wolf Optimization Algorithm. In *Applied Sciences* 8 (4), p. 636. DOI: 10.3390/app8040636.
Dänkes, Christian; Neureiter, Christian; Rohjans, Sebastian; Uslar, Matthias; Engel, Dominik (2014): owards a Model- Driven-Architecture Process for Smart Grid Projects. In: Benghozi P., Krob D., Lonjon A., Panetto H. (eds) Digital Enterprise Design & Management. Advances in Intelligent Systems and Computing, vol 261. Springer, Cham.
Dia, Niu, Han (2018). Forecasting of Power Grid Investment in China Based on Support Vector Machine Optimized by Differential Evolution Algorithm and Grey Wolf Optimization Algorithm. In: Applied Sciences 8(4):636
Fraunhofer (2018): Maschinelles Lernen. Eine Analyse zu Kompetenzen, Forschung und Anwendung.
Fraunhofer IOSB (2019). Fehler in Stromnetzen mit Künstlicher Intelligenz automatisiert erkennen. [Online] URL: https://www.fraunhofer.de/de/presse/presseinformationen/2019/april/fehler-in-stromnetzen-mit-kuenstlicher- intelligenz-automatisiert-erkennen.html [last visited on 19.07.2019].
Gilliland, Michael (2019): The value added by machine learning approaches in forecast-ing. In: International Journal of Forecasting. DOI: 10.1016/j.ijforecast.2019.04.016.
Gläser, Jochen; Laudel, Grit (2010), Experteninterviews und qualitative Inhaltsanalyse. Als Instrumente rekonstruierender Untersuchungen. 4. Aufl. Wiesbaden: VS Verlag fürbSozialwissenschaften (Lehrbuch).
Hammond, Kris (2016): The Periodic Table of AI. Dezember 2016, http://ai.xprize.org/sites/default/files/xprize_artificial_intelligence_periodic_table.pdf.
Hossain, Eklas; Khan, Imtiaj; Un-Noor, Fuad; Sikander, Sarder Shazali; Sunny, Md Samiul Haque (2019): Application of Big Data and Machine Learning in Smart Grid, and Associated Security Concerns. A Review. In: IEEE Access 7, S. 13960–13988.
Ilg, Garrett (2018): Kontext ist alles - wie das Streben nach Relevanz und Personalisierung einen KI-Goldrausch auslöst. Umfrage von Adobe zur Personalisierung von Produkten.
Jerez, José M.; Molina, Ignacio; García-Laencina, Pedro J.; Alba, Emilio; Ribelles, Nuria; Martín, Miguel; Franco, Leonardo (2010): Missing data imputation using statistical and machine learning methods in a real breast cancer problem. In: Artificial Intelligence in Medicine 50 (2), S. 105–115.
Jurado, Sergio; Nebot, Angela; Mugica, Fransisco; Avellana, Narcis (2015): Hybrid methodologies for electricity load forecasting: Entropy-Based Feature Selection with Machine Learning and Soft Computing Techniques. In *Energy*.
Kaiser, Robert (2014): Qualitative Experteninterviews. Wiesbaden: Springer Fachmedien Wiesbaden.
Khashei, Mehdi; Bijari, Mehdi (2011): A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. In: Applied Soft Computing 11 (2), S. 2664–2675.
Kuckartz, Udo (2016): Qualitative Inhaltsanalyse. Methoden, Praxis, Computerunterstüt-zung. 3., überarbeitete Auflage. Weinheim, Basel: Beltz Juventa (Grundlagentexte Methoden).
Le Cadre, Hélène; Papavasiliou, Anthony; Smeers, Yves (2015): Wind farm portfolio optimization under network capacity constraints. In *European Journal of Operational Research* 247 (2), pp. 560–574.
Li, S. (2003): Wind power prediction using recurrent multilayer perceptron neural networks. In : 2003 IEEE Power Engineering Society General Meeting (IEEE Cat. No.03CH37491). 2003 IEEE Power Engineering Society General Meeting. Toronto, Ont., Canada, 13-17 July 2003: IEEE, pp. 2325–2330.

Lopez, Karol Lina; Gagne, Christian; Gardner, Marc-Andre (2019): Demand-Side Management Using Deep Learning for Smart Charging of Electric Vehicles. In *IEEE Trans. Smart Grid* 10 (3), pp. 2683–2691.

MacDougall, Pamela; Kosek, Anna Magdalena; Bindner, Hendrik; Deconinck, Geert (2016): Applying machine learning techniques for forecasting flexibility of virtual power plants. In : 2016 IEEE Electrical Power and Energy Conference (EPEC). 2016 IEEE Electrical Power and Energy Conference (EPEC). Ottawa, ON, Canada, 12.10.2016 - 14.10.2016: IEEE, pp. 1–6.

Makridakis, Spyros; Spiliotis, Evangelos; Assimakopoulos, Vassilios (2018): Statistical and Machine Learning forecasting methods. Concerns and ways forward. In: PloS one 13 (3). DOI: 10.1371/journal.pone.0194889.

Matz, S. C.; Kosinski, M.; Nave, G.; Stillwell, D. J. (2017): Psychological targeting as an effective approach to digital mass persuasion. In *Proceedings of the National Academy of Sciences of the United States of America* 114 (48),

pp. 12714–12719.

Merizalde, Yuri; Hernández-Callejo, Luis; Duque-Perez, Oscar; Alonso-Gómez, Víctor (2019): Maintenance Models Applied to Wind Turbines. A Comprehensive Overview. In *Energies* 12 (2), p. 225. DOI: 10.3390/en12020225. Meyer, Nidal (2014): Praxisleitfaden für unterstützende Maßnahmen von Stromnetzbetreibern. Veröffentlichung von BDEW und VKU.

Mosavi, Amir; Salimi, Mohsen; Faizollahzadeh Ardabili, Sina; Rabczuk, Timon; Shamshirband, Shahaboddin; Varkonyi-Koczy, Annamaria (2019): State of the Art of Machine Learning Models in Energy Systems, a Systematic Review. In: Energies 12 (7), S. 1–42.

OECD Going Digital: Shaping Policies, Improving Lives. OECD Publishing, Paris.

Omar, Salima; Ngadi, Asri; Jebur, Hamid H. (2013): Machine learning techniques for anomaly detection. An overview. In: International Journal of Computer Applications 79 (2).

Palmetshofer, Walter; Semsrott, Arne; Alberts, Anna (2016): Der Wert persönlicher Daten - Ist Datenhandel der bessere Datenschutz? Bericht im Auftrag vom Sachverständigenrat für Verbraucherfragen beim Bundesministerium der Justiz und für Verbraucherschutz.

Perera, Kasun S.; Aung, Zeyar; Woon, Wei Lee (2014): Machine Learning Techniques for Supporting Renewable Energy Generation and Integration. A Survey. In: Wei Lee Woon (Hg.): Data analytics for renewable energy integration. Second ECML PKDD workshop, DARE 2014, Nancy, France, September 19, 2014 ; revised selected papers, Bd. 8817. Cham: Springer (Lecture Notes in Computer Science, 8817), S. 81–96.

Richard, Philipp; Vogel, Lukas (2017): Landkarte Digitale Dynamik. Self-published by the the German Energy Agency (Deutschen Energie-Agentur GmbH ; dena) about the dynamic within the energy transition.

Schwaiger, Roland; Steinwendner, Joachim (2019): Neuronale Netze programmieren mit Python. 1. Auflage (Rheinwerk Computing).

Schweitzer, Heike; Peitz, Martin (2017): Datenmärkte in der digitalisierten Wirtschaft: Funktionsdefizite und Regelungsbedarf? 2017. Discussion Paper des ZEW.

Sharma, Navin; Sharma, Pranshu; Irwin, David; Shenoy, Prashant (2011): Predicting solar generation from weather forecasts using machine learning. In : 2011 IEEE International Conference on Smart Grid Communications (SmartGridComm). 2011 IEEE Second International Conference on Smart Grid Communications (SmartGridComm). Brussels, Belgium, 17.10.2011 - 20.10.2011: IEEE, pp. 528–533.

Stetco, Adrian; Dinmohammadi, Fateme; Zhao, Xingyu; Robu, Valentin; Flynn, David; Barnes, Mike et al. (2019): Machine learning methods for wind turbine condition monitoring. A review. In *Renewable Energy* 133, pp. 620–635. DOI: 10.1016/j.renene.2018.10.047.

Valogianni, Konstantina (2016): Sustainable Electric Vehicle Management using Coordinated Machine Learning.

Vu, Trung; Häbig, Pascal; Fluri, Verena; Schäffler,Harald (2019): C/sells-Arbeitspaket 2.3-Geschäftsmodelle. Forschungsbericht für den Reviewprozess. Hg. v. Institut für Energiewirtschaft und Rationelle Energieanwendung. Stuttgart.

Welsch, Andreas; Eitle, Verena; Buxmann, Peter (2018): Maschinelles Lernen. In: HMD 55 (2), S. 366–382. DOI: 10.1365/s40702-018-0404-z.

World Economic Forum (2018): Harnessing Artificial Intelligence for the Earth. In Collaboration with PwC and Stanford Woods Institute for the Environment.