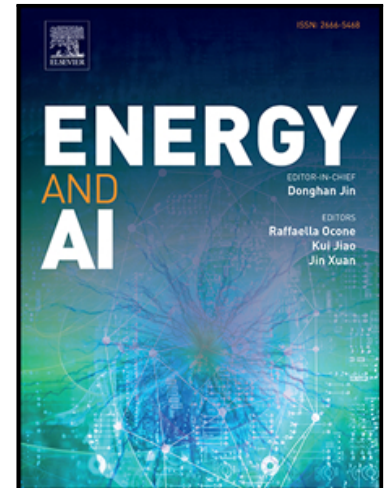# Journal Pre-proof

Reviewing 40 years of artificial intelligence applied to power systems
– a taxonomic perspective

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Reviewing 40 years of artificial intelligence applied to power systems – a taxonomic perspective

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Highlights

- Web search-based analysis of 258'919 publications between 1982 and 2022

- Considering 19 use cases along power system supply chain and 6 AI domains

- Most researched power system supply chain elements are retail, generation and transmission

- AI domains with highest research coverage are "learning" (45%) and "planning" (14%)

- Current AI taxonomy complicates in-depth studies on benefits and risks

Graphical Abstract

Artificial intelligence

Number of yearly publications
500k
400k
300k
200k
100k
0
1980 1985 1990 1995 2000 2005 2010 2015 2020

Power sector
30k
25k
20k
15k
10k
5k
0
1980 1985 1990 1995 2000 2005 2010 2015 2020

Integration & interaction
Perception
Communication
Learning
Planning
Reasoning

AI domain
Integration & interaction   Learning
Perception   Planning
Communication   Reasoning

1982
50.6%
12.7%
10.8%
5.7%
1.27%
19%

2022
57.6%
12.5%
11.6%
8.57%
8.19%
1.48%

Abstract

Artificial intelligence (AI) as a multi-purpose technology is gaining increased attention and is now widely used across all sectors of the economy. The growing complexity of planning and operating power systems makes AI extremely valuable for the power industry. Until now, there has been a lack of clarity regarding the specific points along the power system supply chain where AI applications demonstrate significant value, as well as which AI domains are best suited for such applications. This study employs an AI taxonomy and automated web search to qualitatively and quantitatively unveil the biggest potentials of AI in the power industry. Our analysis, based on a review of 258'919 publications between 1982 and 2022, reveals where AI applications are particularly promising. We consider six AI domains (reasoning, planning, learning, communication, perception, integration & interaction) and 19 use cases from the power supply chain (i.e., generation, transmission networks, distribution networks, isolated grids/ microgrids, market operations and retail). Our findings indicate that, as of now, the focus is predominantly on AI applications in power retail (55%), transmission (14%) and generation (13%). Most analyzed works describe applications built on algorithms of the AI domains "learning" (45%) and "planning" (14%). Results also suggest that the current definition of AI domains is ambiguous, and they highlight missing information on the actual use and successful implementation of AI in power system use cases.

Keywords: *Artificial Intelligence; Power Systems; Electricity; Taxonomy; Policy*

Highlights:

- Web search-based analysis of 258'919 publications between 1982 and 2022
- Considering 19 use cases along power system supply chain and 6 AI domains
- Most researched power system supply chain elements are retail, generation and transmission
- AI domains with highest research coverage are "learning" (45%) and "planning" (14%)
- Current AI taxonomy complicates in-depth studies on benefits and risks

Word count: 8573 words

1. Introduction

Artificial Intelligence (AI) encompasses various technologies (e.g., expert systems, machine learning, deep learning, reinforcement learning, computer vision, natural language processing) that can complement and extend human cognitive capabilities (e.g. compare AI Watch [1]).

It should be noted that there are still many distinct definitions of AI in use today, some of which embrace a technical, system perspective [2] or definitions that place a special emphasis on how AI systems interact with humans [1].

The term AI itself is not new; it was first coined several decades ago. The theory of the "four AI seasons" are typically used to describe how AI has evolved and been used in research and society over the past few decades [2]. These seasons involve an AI Spring, the initial appearance of AI concepts (1940s), AI Summer and Winter, with the further extension of the initial concepts, followed by growing doubts of the applicability of AI to societal challenges and cut in research spending (1960s). AI Fall follows (1980s onwards), with AI applications achieving remarkable progress such as beating chess world champion Gary Kasparov, and the AI present (2015 onwards), with a revival of artificial neural networks and the emerging field of deep learning.

Today, AI is considered a fundamental technology in the digital transformation of societies as well as a source of innovation and growth potential with broad fields of application in the fields of finance, medicine, energy, transport, among others [3].

A recent survey from McKinsey [4] showed that the adoption of AI in businesses is dynamically progressing, with more than 50% of survey respondents already using AI technology in at least one business function. Most common business functions are service operations, product and service development, and marketing and sales. The top three use cases across all businesses are service operations optimization, AI-based enhancement of products, and contact-center automation [4].

A growing interest in AI systems and their applications across economic sectors, including the energy sector, has been sparked by recent scientific advancements. The following breakthroughs are of particular interest:

- **Increased hardware performance** paralleled by **decreasing unit costs**, a key driver behind the progress in AI systems, e.g., graphics processing units allowing for fast model training and iteration ([2], [5]– compare also **Figure 1**).

- **Deep learning**, with a breakthrough in computer vision (detecting objects, understanding actions), and **reinforcement learning**, a method for teaching goal-oriented behavior [6].

- **Recent advances in neuroscience**, that improved our understanding of biological brains, which eventually transferred to new concepts in AI research, such as such as episodic and working memory, attention, continuous learning, imagination, etc. [7].

- **Transfer learning**, where knowledge acquired by a trained model can be re-applied during the training process for a new task, and reduces the data requirements [6].

- **AutoML**, or automated machine learning, i.e. the process of automatically selecting the best model architecture for a specific task (e.g., algorithm selection or hyperparameter tuning). It does not require advanced technical competences in AI [8], and hence might be an appealing option for companies that require efficiency improvements under constrained access to skilled labor.

As a result, more businesses in and beyond the energy sector are operating with the support of AI [9], [10]. Although currently, its utilization is limited, AI is said to have a large potential for decarbonizing power systems [11]. According to the World Economic Forum's latest analysis, AI applications can help unlock 1.3 trillion US dollars (USD) of value by reducing the investment required for power generation through flexibility solutions, 188 billion USD by providing models for extending lifetime and utilization of power system components (such as transformers) and reduce overall power system costs in a range of 6-13% through AI-enabled system control and balancing [11].

Finally, it is widely believed that AI can also contribute positively to a majority of the United Nations' "Sustainable Development Goals" (SDGs). A recent study demonstrated how AI may enable 79% of all targets across all SDGs, mainly through technological improvement. On the downside, AI may also hamper 35% of all targets of the SDGs [12] e.g. through additional energy and material requirements, highlighting the need for policy design, regulatory oversight and transparency of AI use across all sectors.

However, currently available research lacks a comprehensive analysis of the present and future potential uses of AI in power systems, considering different AI subfields, so-called domains. AI domains are theoretical, scientific areas defined as a part of the larger AI taxonomy [1]. AI domains include categories such as reasoning, planning, learning, communication, perception and interaction & integration. They are a valuable tool to study and compare the evolution of different AI algorithm groups over time within an economic sector (e.g., artificial neural networks, metaheuristics, rule-based systems, reinforcement learning).

This study represents the first systematic and taxonomic overview of AI use cases in the power sector, considering the whole power system supply chain and distinguishing between the various AI domains.

Such analysis has several benefits, for example it allows for an analysis of the technical or economic potential of particular AI domain for the power industry. Another benefit is that a fine-grained assessment of the presence of AI domains along the power system supply chain allows for an improved understanding of regulatory effects on the use of AI, as foreseen under the European AI Act [13]. Hence, the presented study intends to address that gap, providing answers to the following research questions:

1) How can we structurally assess the use of AI in power systems today, considering AI applications across the power industry from taxonomic perspective (AI domains)?

2) What does the current body of literature reveal on where across the power system supply chain AI is used today? In other words, where is likely the biggest disruption potential of AI located along the power supply chain?

3) Which AI use cases are most commonly reported in power system research?

To our knowledge, the presented study comes first presenting a taxonomic review analyzing jointly the volume of academic works on AI applications in power systems (how many studies in total, publication years, AI domains, power system use cases) and their evolution over time. This work aims to answer the identified research questions by offering a holistic analysis of the above-mentioned gaps. It covers the last 40 years of AI research in power systems.

The paper is organized as follows: While Section 2 sheds some light on the drivers behind the growing usage of AI in the power sector, Section 3 provides an overview of studies that reported a variety of use cases of AI in power systems. The methodology is presented in Section 4. The study concludes with an in-depth discussion of obtained results (Section 5), new research avenues (Section 6) and a set of conclusions (Section 7).
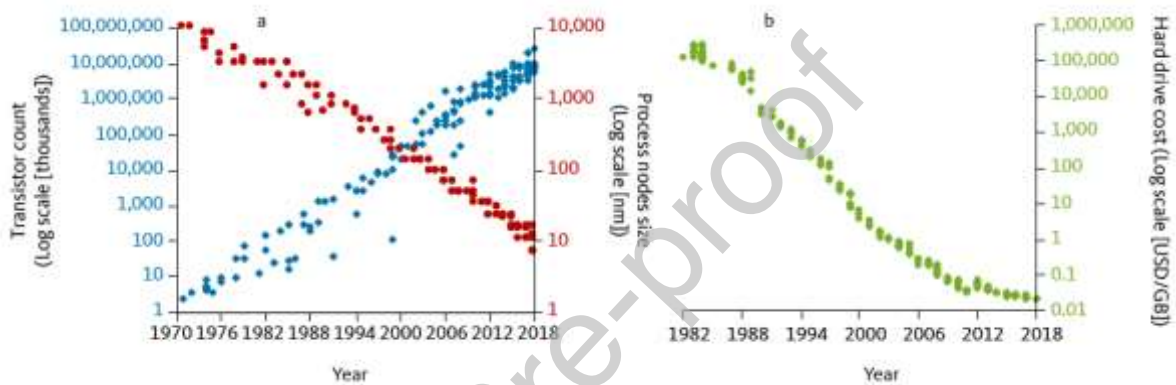
Figure 1: Evolution of computing power, cost and data storage [5]. The figure shows the number of transistors per CPU and technology node generation (a), memory costs per gigabyte (b).

2. Why AI is increasingly used in the power sector

Electricity is expected to cover over 50% of the final energy consumption by 2050 (net zero scenario) [14]. Hence, as current trends show energy systems transforming into digitalized, electricity-dominated systems, the focus of the present studies is on the applications of AI specifically to power systems.

Pulling factors for employing AI in power systems originate from system restructuring and decarbonization, also coined as the 4D "digitalization", "decarbonization", "decentralization", and "deregulation" [15]. It has been found that the vast majority of emerging digital technologies and business models used in the power sector make use of big data and artificial intelligence [16].

Resulting system needs of 4D power systems raise the interest of major stakeholders in power systems to employ AI [17], predominantly electricity network operators (Transmission System Operators – TSOs, Distribution System Operators – DSOs), energy retailers, energy services companies, consumers, traders, energy policy makers or energy communities. The emerging system needs, which could potentially be addressed through AI, can be clustered into three groups:

1. The **increasing complexity of planning and operating electrical grids and electricity markets** due to the higher number of actors and services. The current electric system was not designed to accommodate diversified and distributed power generation sources, particularly renewable generation with variable production patterns (e.g., [18]). Thus, new tools are

needed that can assess and frame uncertainty in power system planning [8]. In addition, climate change [19] and man-made hazards (e.g., cyber-attacks [20]) require new measures to mitigate rising levels of risk in critical infrastructure such as power systems [21].

New operational challenges include the prompt identification and analysis of grid frequency deviations [22] or the automated detection of anomalies in wind power generation [23]. In an energy sector that is growing increasingly unpredictable, uncertain, complex, and ambiguous, AI can help maintain a high confidence level in decision making.

2. The **increasing utilization of sensors** such as smart meters and internet-of-things technology lay the foundation for new business opportunities that extract value from collected data and, eventually, may improve energy efficiency and/or decrease costs for consumers and companies. It has been stated that AI can create new business opportunities by processing and valuing new data streams of the power sector, particularly in smart homes and buildings, automation in industry (industry 4.0), as well as through improved power system asset management and maintenance strategies [24].

3. The current trend observed in many power systems around the world is **a transformation of the functioning of electricity wholesale and retail markets**. New market schemes, e.g. local markets or energy communities with peer-to-peer trading [25] require fast mechanisms for resource allocation and billing. AI can help to achieve the required automation of decision making in such increasingly complex market environments, e.g., for the tasks of unit commitment, balancing load and supply under microgrid schemes or revenue allocation, at community energy system level [26], [27].

The application of AI to the energy sector is, however, not completely new. The first state-of-the-art review was published in 1989 under the name "expert systems" [28]. Several AI systems used in the electricity system were reviewed in 1997 [29]. In fact, basic expert systems and neural networks have been used for more than 30 years in the energy sector. But with increased computational power their capabilities increased, which is why they are nowadays continuously applied to modern power system challenges, such as renewable energy forecasting, microgrid operation or monitoring and large-scale power system operation (such as in [27], [30]–[32]).

3. Related work on most common use cases of AI in power systems

Today, AI applications can be found along the whole electricity supply value chain. AI is used to enhance energy system operation and optimization [22], [33], electricity network planning [34], [35], consumer behavior, tariff analysis [36], [37], electric load or renewable power forecasting [31], [38] and policy making [39].

Recent studies have shown that AI ranks among the most utilized digital technologies in energy systems and particularly in power systems [16]. In the last years, a few studies on AI applications in energy systems have been published (e.g., [10], [40], [41]). However, studies remained selective in use case choice and analyzed AI domains, thus the outcomes cannot be used for a conclusive assessment of which AI domains are most promising for a given use case or where along the power supply chain AI is most likely to be most beneficial.

In the following, we present a relevant yet not non-exhaustive review of different studies that reported AI's potential and use cases of AI for power systems.

An overview of the history of AI in energy systems, its potential and current applications, particularly for power systems, and a technological outlook has been presented in [10]. Authors analyze the usefulness of AI applications for the planning and operation of solar and hydrogen power generation (including siting and production forecasts) and the use of AI in electricity supply and demand management control (including predictive maintenance control, energy trading, load forecasts and the identification of energy theft).

The International Renewable Energy Agency (IRENA) rigorously assessed the potential use cases of AI in the power sector with a special emphasis on the integration of variable renewable energy technologies [17]. Identified use cases include the improved solar and wind power forecasts, maintaining grid stability and reliability, enhanced demand forecasts, the realization of efficient demand side management, optimized energy storage operation and optimized market design and operation.

A very similar set of use cases has been identified by the Electric Power System Research Institute (EPRI) in a study from 2019 [8]. The latter report also highlights a few challenges that AI use poses to the power industry (difficulty to access large datasets, required data labelling efforts, ethics concerns stemming from biased AI model conclusions, as well as data privacy and security concerns).

A recent, more detailed study [9] clusters nine broad application domains of AI in power systems into three fields, namely 1) maintenance and security, 2) general foundations of decision making and 3) distribution and customer services. The applications are further characterized by AI capabilities (audio and speech, image and face recognition, robotics and assistance systems and general data). The nine applications are then ranked according to their contribution to the energy transition as well as their maturity (closeness to commercial markets). The analysis by the authors reveals that the most developed and beneficial AI use cases for the energy transition are those that are specifically related to general foundations of decision-making (predictions, operations optimization, inventory optimization, predictive maintenance and strategic business decisions) [9].

The World Economic Forum (WEF) [11], locates the most promising applications in the areas of load and renewable energy forecasting, energy demand management, materials discovery and innovation, as well as grid operation and optimization. The WEF study argues, in line with previous findings above, that AI applications have particularly attractive use cases in power grid operation and optimization, as the decarbonizing power systems require vast amounts of asset reinforcement and replacement.

The study of [41] proposed a three-dimensional indicator that allows for the assessment of the benefit of AI applications in the energy sector (not only power systems), considering a variety of use cases. The developed indicator considers economic saving potential, regulatory risk and technological maturity (via TRLs). Authors compare AI applications in 15 use cases, finding that applications are most mature for forecasting, maintenance and fault detection. However, the authors do not differentiate between different AI domains exploited in each use cases. In addition, the choice of use cases did not follow a systematic approach and thus remained arbitrary.

More recently, a couple of academic studies addressed the use of AI (including machine learning) in energy/power systems. For example, the studies [42] and [43], survey AI applications for power systems, but on rather arbitrarily chosen use cases (e.g., energy management, energy saving, smart

grids, fault diagnosis, electricity consumption and generation forecasting). Similarly, the study of [44] provides a comprehensive overview of AI and machine learning applications to energy systems. While the authors provide interesting insights on research trends and connections between subfields in energy, their analysis on AI applications aims to cover the whole energy system and therefore lacks details on power system use cases.

On the other hand, the recent study of [45] sheds light into the power system applications of machine learning, but with a focus on distribution systems only. The work of [40] provides a review of AI applications for power systems, but with special emphasis on deep learning and thus neglecting older approaches of AI such as algorithms of the domains "Reasoning" or "Planning". While the study of [46] reviews the current challenges and opportunities of explainable artificial intelligence for energy and power systems, whereas the recent study of [47] details a few selected AI applications specifically beneficial for renewable energy integration.

However, all above-cited, recent studies do neither differentiate between AI domains, nor use a comprehensive, rigorous system of power system use cases.

4. Methodology: Characterizing use cases of AI applications in the power sector

In this section, AI applications in power systems are characterized. Characterization considers the power system supply chain elements, AI power system use cases (lending from [9], [11], [16]) and AI domains [1]. We define an AI application as a specific combination of a power system supply chain element, a use cases and an AI domain (**Figure 2**).
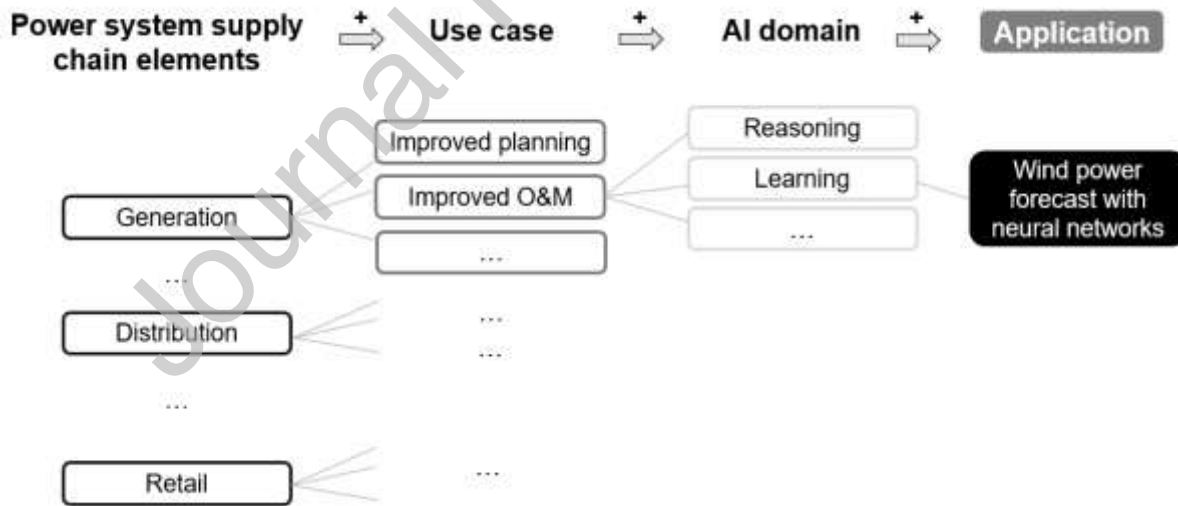
Figure 2: From power system supply chain element use cases to AI applications.

This study is building on the previous mentioned works in Section 3, as well as on the studies of [9], [40]–[42].

In the following points, we provide further detail on the dimensions considered in our assessment of AI applications in the power sector.

- **Power sector use cases.** We approach the analysis of AI applications along use cases in a manner similar to how we handle the analysis of digital technologies as a whole, as in [9], [11],

[16]. In these works, the authors delineate use cases along the power system supply chain elements: generation, transmission networks, distribution networks, market operations and retail (the demand side). Here, an additional category is added with isolated grids/microgrids, as they are an emerging paradigm with particular characteristics that are normally part of distribution systems, but may operate as autonomous systems under isolated conditions, i.e., disconnected from the bulk power system [48].

For each supply chain element, typical use cases of AI target the enhancement of either planning or operation and maintenance (O&M) practices (e.g., compare [9], [11], [24]). In addition, as will be shown in the analysis, some use cases show how AI can be used to automate grids. In Retail, additional use cases exist that provide utilities deeper insights into user behavior and preferences. For market operations, the main use cases consist of enhanced price forecasting, increased flexibility through operation of local energy markets or energy communities as well as automated peer-to-peer trading and aggregation.

- **AI domains.** These domains are part of the broader AI taxonomy and standardization efforts developed by the Joint Research Centre (JRC) of the European Commission [1]. As mentioned earlier, AI domain include "Reasoning", "Planning", Learning", "Communication", "Perception" and "Integration & Interaction", which is very similar – if not identical – to frameworks used in many other works, e.g., [49], or [9]. The latter work lists for example AI domains called "Recognizing", "Understanding", "Producing", "Inferring", "Identifying", "Learning", "Acting/interacting", where a strong overlap can be seen ("Learning" and "Interacting" the same, "Recognizing" and "Identifying" similar to "Perception" or "Producing" similar to "Planning").

Table I: AI domains and subdomains *[1]*.

AI domain	AI subdomain
Reasoning	Knowledge representation Automated reasoning Common sense reasoning
Planning	Planning and Scheduling Searching Optimization
Learning	Machine learning
Communication	Natural language processing
Perception	Computer vision Audio processing
Integration and Interaction	Multi-agent systems Robotics and Automation Connected and Automated vehicles

- **Research maturity**. Assessing technological maturity is usually performed using NASA's Technological Readiness Level (TRL) framework [50]. The respective framework introduces 9 different *TRLs*, from TRL 1 representing basic technology research, where only fundamental concepts are introduced on a purely theoretical level, up to TRL 9, where a technology is already in use and fully integrated into the operational practices of an organization. The *TRLs* of a product or service cover different development phases such as basic technology research, proof-of-concept, technology development and demonstration as well as

system/subsystem development and eventually system test, launch and operations. The *TRL scale* is a widely used framework, that has been applied to assess and compare the maturity of processes in the health sector [51] and recycling [52], among others. A recently published study provided insight into the overall maturity and forecasted future maturity of AI domains using the *TRL* framework as well as readiness-vs-generality charts [49]. However, assessments of technological maturity using TRL are limited to expert opinions and thus remain qualitative, and, to a certain degree, subjective [53].

While we would expect high publication rates translating into increased industry applications, the latter point remains rather speculative as there is currently no open accessible register that would allow one to analyze the real-world applications of AI, in the power sector and beyond. Therefore, in this work, rather than relying on subjective assessments, we characterize the use of AI applications in the power sector through their **Research Maturity (RM)**. We define research maturity as the degree of advancement of AI employment in a certain power system supply chain. We estimate the research maturity by determining the relative share of work dedicated to a given use case by comparing published research listed in a major scientific platform using Boolean queries in the Scopus index[1]. Scopus is the largest abstract and citation database of research literature covering more than 5,000 publishers. In this work, the search field was limited to title, abstract and keywords, to avoid counting publications which only mention the searched queries and are not directly related to the subject area. Document types were not limited, allowing for articles, conference papers, book chapters, etc.

The query keywords used for the research maturity assessment include the identified power system use cases and AI domains extracted from [1] in **Table I**. The complete list of queries is listed in Annex 2.

Finally, we quantitatively compare the relative abundance of research across all identified power system supply chain elements, use cases and AI domains. We introduce the notion of Relative Research Intensity (*RRI*), that relates the identified volume of research conducted on a specific power system supply chain element, use case and AI domain to the total amount of identified research.

We thus define the *RRI* of an AI application in the power sector (*i*), within a power system supply chain element (*j*) (Eq.1).

The *RRI* is then estimated as the relative quantity of inventoried research (books and book chapter, indexed scientific journal and conference papers), i.e. the research volume (*RV*), of one AI application (*i*) in relation to the average research volume per AI application (*ARV*) over all identified applications for a given power system supply chain element (*j*).

$$RRI_{ij} = \frac{RV_{ij}}{ARV_j} \tag{1}$$

The *ARV* is defined as the arithmetic mean of all identified research for a given power system supply chain element ($ARV_j = \sum_i RV_{ij} / \sum j$). For the assessment of research maturity (*RM*), we rely on the determined values of *RRI*, clustered into three categories. The determined categories are "low maturity" (corresponding to RRI < 0.66), "medium maturity" (RRI ≥ 0.66 & RRI ≤ 1.0) and "high maturity" (RRI > 1.0). Hence:

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[1] SCOPUS Search API; the data was downloaded from Scopus API between April 15 and April 17, 2023 via http://api.elsevier.com and http://www.scopus.com.

$$RM_j \in \{Low, Medium, High\} \qquad (2)$$

The *RM* are calculated for each AI application with results being reported in **Table II**.

## 5. Results and discussion

Two sets of queries were created with the goal of answering the research questions defined in section 1, and following the methodology described in section 4. The first set of queries focused on extracting general information on the state of AI research in the power sector. The second set of queries narrowed the search by specifying the applicable power system supply chain elements, AI domains and specific use cases. The exact queries used as inputs to the Scopus API search are shared as supplementary material. The quantification of amounts of research dedicated to each AI application eventually allowed to draw some conclusions on the technological maturity of each AI application and the identification of most utilized AI domains across the power supply chain (generation, transmission, distribution and so forth).

5.1. Evolution of the use of AI in power systems

As a first step in the analysis of the body of AI research in the power sector, the evolution of yearly publications in AI were extracted for the past 40 years, from 1982 to 2022.

Figure 3 shows the trend of yearly publications for AI in general (**Figure 3 (a)**) and AI in the power sector (**Figure 3 (b)**), where results are classified per AI domain. Results show that AI has seen an exponential increase in the number of yearly publications, with an average 10% yearly growth rate. In 2022 alone, over 500'000 publications are recorded. The power sector understandably represents a small part of the global AI research, about 25'000 publications in 2022, but follows a similar growth. In terms of AI domain trends, 'Learning' is seen as the most dominant category, representing 57.6% of published works in the power sector in 2022 (**Figure 3 (c)**). Through this overview of the existing body of research, three major observations can be made:

- The use of AI in research is undergoing exponential growth, and its applications in the power sector follow similar trends, highlighting the increasing interest, and likely, the disruption potential of AI technologies in the field.
- Following the AI Watch definition of AI domains, the key AI domains for the power sector are currently the domains 'Learning', 'Planning' and 'Perception'.
- While there is a long history of the use of optimization techniques in the energy sector (including mixed-linear integer programming, dynamic programming, etc.), the current AI taxonomy is very constrained to rather metaheuristic algorithms. For example, in [1], search keywords include "Bayesian optimisation", "evolutionary algorithm", "genetic algorithm" and "gradient descent" (which is arguably also relevant for the AI domain "Learning" too, but not mentioned there) and does not list popular metaheuristic algorithms. Latter include "Ant Colony Optimization", "Particle Swarm Optimization" or "Artificial Bee Colony" algorithms [54]. Their exclusion and the lack of preciseness for this domain has arguably the effect that the AI domain "Planning" is relatively underrepresented in the identified body of literature (only 12.5 % in 2022).
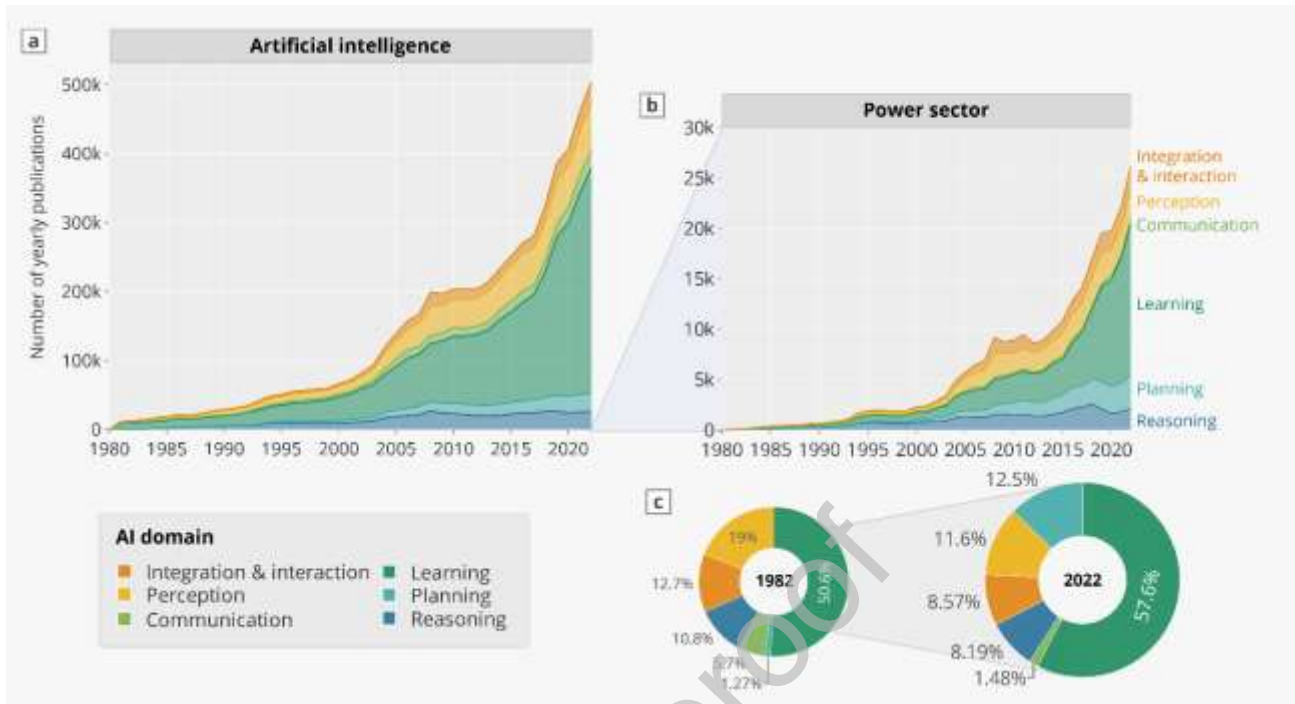
Figure 3: **(a)** Evolution of the number of yearly research publications in AI over the past 40 years, categorized per AI domain. **(b)** Evolution of the number of research publications in AI applied to the power sector. **(c)** AI domains distribution of yearly publications in AI applied to the power sector, comparing 1982 and 2022.

5.2. Evolution of AI use cases in power systems

Having seen the general increased AI research trends in the power sector, the second step in this work consisted in studying the evolution of AI use cases in the field. To do so, the queries applied to the Scopus research database were narrowed down to specific use cases (e.g., Improved planning) for all power system supply chain elements (e.g., Generation) and AI domains (e.g., Planning).

Figure 4 shows the distribution of yearly publications for all the considered use cases between 1982 and 2022, categorized per AI domain **(a)** and power system supply chain element **(b)**. In terms of AI domain distribution, results follow a similar pattern to the more general approach of **Figure 3**, where we see dominance from the 'Learning' category, likely due to the numerous applications of machine learning tools such as unsupervised learning, deep learning or ensemble models in the power sector. Compared to **Figure 3**, we see a higher rate of 'Planning' applications, which likely reflects the increasing use of AI tools in the planning, sizing and siting of electricity networks.

Looking at the distribution of AI applications throughout the power system supply chain elements, the highest number of yearly publications is seen in the 'Retail' sector with 54.5% in 2022, followed by 'Transmission networks' and 'Generation'. The 'Retail' field deals particularly with different analysis types of demand patterns. The dominant position of this power system supply chain element comes without surprise, as the power sector has been traditionally customer. As mentioned by *[55]*, electricity demand is therefore a fundamental input to system planning, and particularly, electricity transmission and distribution network planning.

In order to highlight the difference in total amounts of yearly publication over time, **Figure 5** shows the evolution from 1982 to 2022 with the supply chain element categorization. A first observation is that the number of yearly publications identified at this step is approximately half of the numbers observed in **Figure 3**, which is attributed to the increased specificity of the queries when accounting for specific use cases. In other words, this suggests that the used framework of power system use cases and AI domains captures only about 50% of all works identified as research at the intersection of AI and power systems.

However, the general trend still follows similar growth. The distribution of research per power system supply chain element is relatively stable over the period, with a notable increase in the share of work on 'Isolated grid/ microgrids'. This trend is expected to continue alongside a rising uptake of DER, with a growing interest in the field and rapidly increasing capabilities of AI to address optimization and control challenges for designing microgrids.
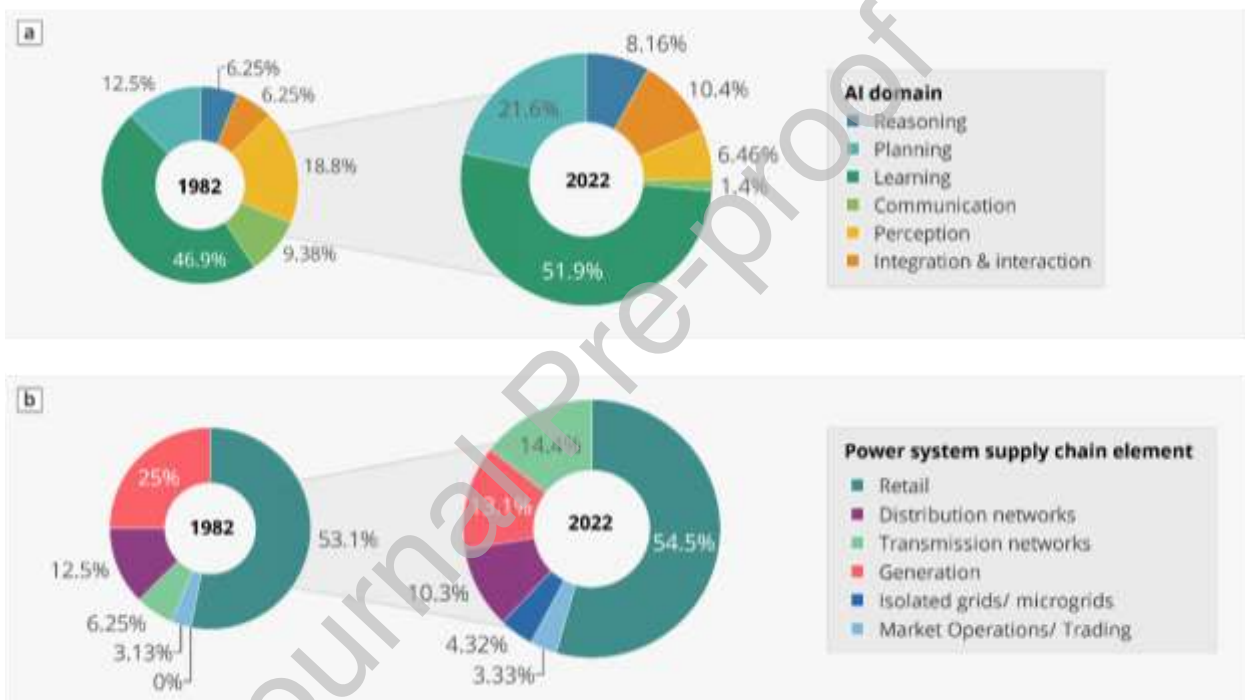
Figure 4: (a) AI domains distribution of yearly publications in AI applied to the power sector, comparing 1982 and 2022. Different queries and filters were applied compared to **Figure 3 (c)**, related to the defined AI use cases. **(b)** Power system supply chain elements distribution of yearly publications in AI applied to the power sector, comparing 1982 and 2022.
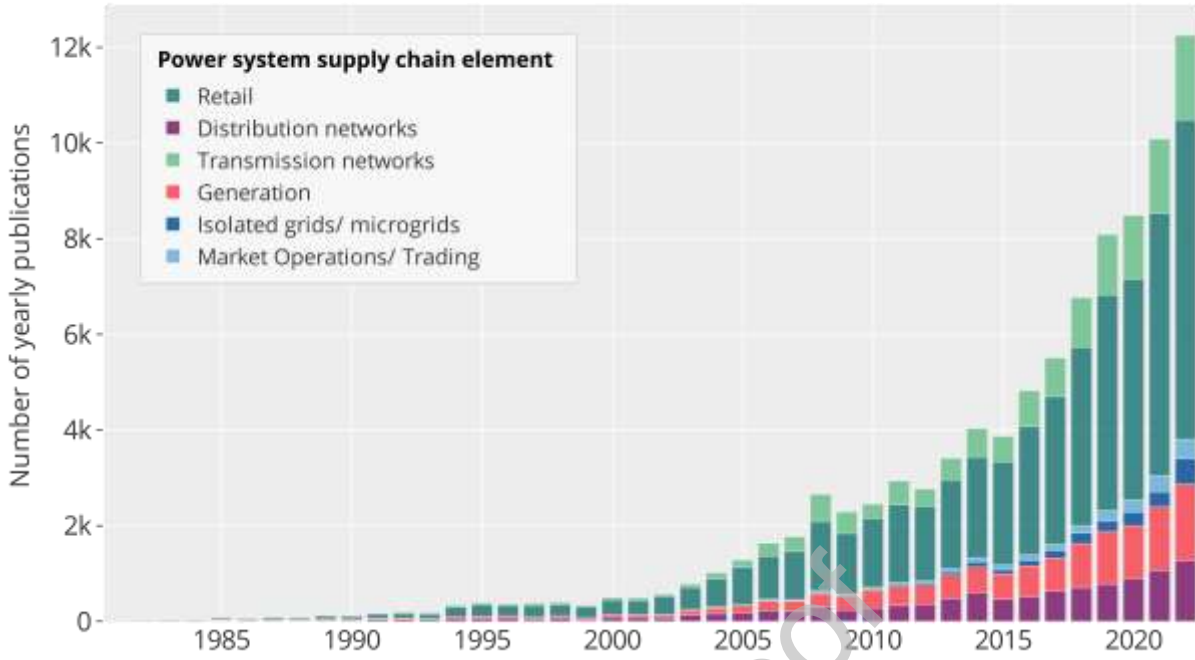
Figure 5: Evolution of the number of yearly research publications in AI over the past 40 years, categorized per power system supply chain element.

5.3. Evaluation of research maturity of AI applications in the power system

After examining the general trends of AI use cases in AI domains and power system supply chain elements, the technological maturity of each use case is evaluated based on the methodology described in section 4. In summary, the RM is approximated by the relative research volume for a given use case within its respective power system supply chain element.

Before computing the TM, the AI use cases associated with each power system supply chain elements are identified. **Figure 6** shows a matrix of use cases (columns) vs. supply chain element (rows), where the relative distribution of total publications (up to 2022) per AI domain is represented. Use cases that are not relevant to a given supply chain element are marked with N/A. This allows for an overview of the AI research topics most relevant to each use case in the power sector. The dominance of the AI domain 'Learning' is confirmed in most applications, with two notable exceptions:

- For the use case 'Improved planning', the main AI domain is unsurprisingly 'Planning', where most use cases are linked to the enhanced planification of production, grid transmission and distribution.
- For the supply chain element 'Market Operations/ Trading', the AI domain 'Integration and interaction' sees an increased importance, especially for the use case 'prosumer and energy markets'. This is likely linked to the increasing use of agent-based models or intelligent algorithms for energy trading in this new and evolving field.

Figure 6: Relative distribution of total publications in AI domains applied to the power sector as of 2022. Each bar plot represents one AI use case (columns) applied in a given power system supply chain element (rows). For use cases where no application is expected or found, a N/A (not applicable) mark is used.

Knowing the research volumes for each use case, the research maturity is then computed and reported in **Table II**, which compares the RM along identified power system use cases and corresponding supply chain element. It further lists the most prominent AI domain and a few examples of AI applications along the power system supply chain.

Results show that TM across use cases is highest for applications that aim to improve the use case Operations and Maintenance (O&M). This holds equally true for distribution-, transmission- and microgrids as well as for generation. The fact that O&M applications are more mature is not surprising, given that in such use cases, AI applications can bring a direct, measurable value to power system operations. The reduction of maintenance or fuel costs, or extended asset lifetime can directly be measured and tested under laboratory conditions and be financially beneficial in the industry.

In addition, algorithms in the AI domain "Planning" are, unsurprisingly, popular in the power system planning, may it be for siting and sizing of transmission networks, of distribution networks or of power generation units. However, the use of AI in planning exercises is much less frequent than for O&M, which may be related to the nature of the task and AI algorithms currently used. For example, in transmission system planning, decisions on network reinforcement and expansion plans are taken considering a long-term horizon. Here, the benefits (e.g., in terms of higher accuracy) of AI is not as visible as in short-term planning, as the modeler would require more data such as consistent time series over several years, best decades. In addition, network expansion is today mostly scenario-based (e.g., compare recent European network expansion studies from ENTSO-E – TYNDP [56]).

Table II: Evaluation of the technological maturity of AI applications in the power sector (as of 2022).

Power system supply chain element	Use Cases	Most prominent AI domain	Relative Research Intensity (RRI)	Research maturity (RM)	Examples of AI applications
Generation	Improved planning	Planning	0.57	Low	• Siting and sizing of RES generators
	Improved O&M	Learning	1.43	High	• Anomaly detection in wind turbines • Optimize maintenance of RES generators
Transmission networks	Improved planning	Planning	0.85	Medium	• Sizing and siting of transmission assets • Analyze scarcity
	Improved O&M	Learning	2.52	High	• Dynamic line rating • Transmission fault protection
	TSO-DSO coordination	Planning	0.07	Low	• Schedule flexibility-based services
	Grid automation	Learning	0.57	Low	• Automating transmission systems
Distribution networks	Improved planning	Planning	0.82	Medium	• Distribution line routing • HV/MV substation placement
	Improved O&M	Learning	1.71	High	• Automated fault location • Stability analysis
	Grid automation	Learning	0.47	Low	• Automating distribution systems
Isolated grids/ microgrids	Improved planning	Planning	0.51	Low	• Siting and sizing of distributed energy resources. • Generation forecasting. • Energy storage and demand response forecasting.
	Improved O&M	Learning	2.31	High	• Active and reactive power sharing. • Energy management and power quality control. • Protection and fault restoration.
	Grid automation	Learning	0.18	Low	• Automatic isolation/re-connection.
Market operations/ trading	Price forecasting	Learning	1.03	High	• Electricity price forecasting • Residual market curve forecasting
	Aggregation and flexibility	Learning	1.57	High	• Optimized aggregation and bidding of flexible demand
	Energy communities / prosumers/ local energy markets	Integration & interaction	0.43	Low	• Energy management and resource scheduling in energy communities
	Automated trading	Learning	0.97	Medium	• Automating peer-to-peer trading
Retail	Improved planning	Learning	0.20	Low	• Electric load forecasting • DER diffusion and net-load forecasting
	Improved O&M	Learning	0.52	Low	• Optimize electricity demand behind the meter • Choosing optimal electricity tariff per consumer group
	Customer/ demand /load analysis	Learning	2.28	High	• Clustering electricity consumers • Characterize DER adopters

This means power system planners currently model system-level behavior under different scenarios with fixed parameters (e.g., load growth rates, status of electrification, added renewable capacities). Otherwise, algorithms of the domain "Planning" are often optimization algorithms and search algorithms (such as metaheuristics), where "optimal" power system characteristics are rather determined through the algorithm, and are, rather variables than parameters, subject to optimization.

AI applications on use cases related to customer/ demand /load analysis ('Retail') are also very frequent in direct comparisons with other use cases along the power system supply chain. This seems straightforward, as the characterization of electricity demand (including load patterns) are fundamental inputs to any power system analysis or electricity network plan [55].

5.4. Exemplary power system applications using artificial intelligence

In the following sections, we present a few examples for each power system supply chain element to exemplify the use and perspective of AI along the power system supply chain. While the analysis can only stay incomplete and the studies have been hand-picked, they intend to provide a tangible overview over the wide applications of AI with exemplary character only.

AI applications for generation

There is a wide applicability of AI applications on power system generation. AI applications have been developed to optimize maintenance of renewable generation [57], [58], or to detect anomalies [23], e.g., due to potential damage, in their functioning. Recently, many of those applications have exploited advances in deep learning, thus using algorithms of the AI domain "Learning".

Many applications in the supply chain element Generation make use of forecasting, which is used for unit commitment, generation scheduling and economic dispatch problems forecasting in sizing problems, reserve estimation and power system reliability [59]. In fact, forecasting outputs of renewable energy generators, e.g., wind power plants, was among the first, widely used application of AI in the power sector. Wind power forecasting, even as commercial product, with models from the AI domain "Learning" date back more than 15 years [60].

With the advances of deep learning, an increasing amount of AI applications using artificial neural networks (AI domain "Learning") for renewable generation forecasts have been proposed within the academic literature [61].

With regard to the planning of power generation, AI applications have been widely used in siting tasks, for example using genetic algorithms (AI domain "Planning") or Analytical Hierarchy Processes (AHP – AI domain "Reasoning") to site wind power plants [34], [62] or to locate power-to-gas plants [63].

AI applications for distribution networks

Distribution system planning has benefitted at large from the introduction of AI into network planning, e.g., line routing [64], service area to transformer allocation [65] or distribution network expansion including substation placement [66]. Many developed methodologies rely on algorithms of the AI domain "Learning" and "Planning", using various types of optimization algorithms.

When it comes to operation, AI may assist with automated fault location in distribution systems [67], stability analysis [68] and automated control [69] under smart grid paradigms.

Until today, distribution grid automation with AI that goes beyond conventional automatic control mechanisms remains primarily conceptual, with recent research being focused on the relation between autonomy and automation, emphasizing the role of technology and humans in grid automation [70], business architecture and interoperability between information, and communication technology (ICT) layers in smart grids [71].

AI applications for transmission networks:

Given the long lead times of project implementation, as well as very high capital expenditures for transmission networks, a great amount of research has been dedicated to transmission system expansion planning [72]. The methodological challenges of transmission system expansion planning, together with current practices (and utilized algorithms to solve it) have been consolidated in the aforementioned study. Popular approaches to size and site transmission assets use heuristic [35] and metaheuristic optimization techniques [73] and thus correspond to the AI domain "Planning". Studies using algorithms of the AI domain "Reasoning" are less frequent, with the work of [74] being one example applying rule mining to characterize scarcity events in resource adequacy studies.

On the operational side, studies have been conducted applying AI to transmission system fault protection [75] or dynamic line rating, e.g. [33] or [76] with algorithms predominantly locating in the AI domain "Learning". The study of [77], serves as an early example of applying reinforcement learning (Q learning) to transmission system operation. The latter study presented a methodology for storage forming, large-scale distributed electric vehicle fleets for frequency control.

The increasing uptake of distributed energy resources, mostly present in distribution networks, requires a tight coordination between TSOs and DSOs to exploit flexibility-based services on a system-level in a cost-efficient manner [78]. Different works have been proposed, e.g., using information gap theory and optimization to simultaneously clear flexibility offers on electricity retail and wholesale markets [79], or non-linear programming to optimize the procurement of ancillary services [80]. Popular algorithms proposed for these approaches originate from the AI domain "Planning". The work of [81] summarizes the most prominent modeling approaches for TSO-DSO interfaces.

So far, there are relatively few papers that explicitly address automating transmission systems with AI, besides already mentioned works from [70] and [71], which provide a rather macroscopic perspective on power system automation.

AI applications for isolated grids/microgrids

AI-based controllers are in general well suited for use within microgrid environments since they have shown capabilities to deal with the complexity and uncertainty that are intrinsically related to smart grids (including microgrids). As in other fields, the ability of AI methods to analyze vast amounts of data from various sources has resulted in a great amount of work dedicated to load forecasting, such as in the work presented in [82] and [83]. The work of [83] is of particular interest as it considers uncertainties in load demand based on adaptive online learning. Another important feature of AI that is exploited within microgrid modeling is the ability to compensate for non-complete or inexact models; there are many works focused on primary, secondary and tertiary data-driven model-free control methods.

AI methods have been used for primary and secondary control, especially for voltage and frequency control as in [84], [85] and [86]. Tertiary control such as energy scheduling has also been tackled with AI, specifically in [87] and [88] where reinforcement learning is used.

Reinforcement learning has also been applied to microgrid energy management in [89] and [90]. While there is still much work to do be done to demonstrate the application of AI methods in deployed microgrids, they are playing an important role in unlocking their full potential for achieving sustainable energy systems.

AI applications for market operations/ trading:

A popular application for AI in market operations and trading is price forecasting, e.g., electricity wholesale market prices. In particular, AI technologies utilizing probabilistic time series forecasting have grown rapidly, as they are highly relevant for many applications in energy trading risk management and electricity price forecasting [31]. The work of [91] provides an overview of a variety of prior studies on electricity price forecasting, with a focus on time series forecasting (regression models) and artificial neural networks (both of the AI domain "Learning"). Lately, market and trading forecasts have moved beyond standard price products, further addressing balancing markets [92] and residual market curves for optimized bidding strategies [93].

Likewise, AI has been proven useful for the optimized aggregation and bidding of flexible demand, for example using reinforcement learning [94] or long-short term memory artificial neural networks coupled with control theory [95]. An extensive review of the applications of AI to flexible demand response has been presented in [96].

Recently, several studies have been conducted to optimize the energy management and resource scheduling for energy communities or local energy markets. For example, the studies of [97] and [98] used a reinforcement learning approach to manage energy flows in an energy community with a battery and a PV system while considering feed-in and retail prices.

On the other hand, a reinforcement learning approach considering also different, interconnected consumer grids (residential, commercial, industrial) in a multi-agent setting has been proposed in [99]. Mostly, algorithms of this AI application locate with the AI domain "Learning".

With the rise of AI in electricity market operations, and particularly in trading, regulators became aware of potential market abuse and distortions through so-called automated or algorithmic trading [100]. Thus, it is not surprising that artificial intelligence has been used in return, to detect anomalies in electricity markets. For example, [101] present a regression and screening analysis approach for detecting anomalies in balancing markets. A review of the different algorithms, often of the AI domain "Learning", has been presented in [102].

AI applications on retail

Predicting electricity demand and peak loads are crucial inputs to power system planning, and thus among the more prominent and also most traditional use cases for AI applications (e.g., [55]). Most utilized algorithms applied to this use case belong to the AI domain "Learning", such as multi-linear regression or artificial neural network models [38].

While most load forecasting models apply algorithms (e.g., regression models or artificial neural networks) of the AI domain "Learning" on time series data, [31], a growing amount of work has also been developed to "localized" or "regionalized" load forecasts, so called spatial load forecasts [103]. The latter may also use such "Learning" algorithms, but also employ cellular automata, fuzzy logic (e.g., [30]), that is algorithms of the AI domain "Reasoning", or multi-agent systems (AI domain "Integration and interaction") [104].

In addition, research has been directed to study the effects of distributed energy resources on electricity demand patterns in space and time, using regression models [105], several machine learning approaches and Information Theory [36] or artificial neural networks coupled with agent-based models [106] (i.e., AI domains "Reasoning", "Learning" and "Integration and Interaction").

On the operational side, approaches from the AI domain "Learning" are predominantly applied to optimize demand patterns and achieve global system benefits or local, consumer-centered cost reduction. Presented works include the use of reinforcement learning for cooperative energy management [107], optimizing electricity demand in buildings, e.g. for air conditioning [108], heating [109] or exploiting consumers' price elasticity behind the meter under dynamic tariffs [110].

Most recently, many works also leveraged the rising availability of energy system data and population data (census data) to develop AI-based frameworks to analyze consumer behavior and electricity demand patterns [111]. The work of [112] uses agent-based modeling to assess the added electricity demand through electrified passenger transport under a multi energy system perspective.

AI has also been used to cluster consumers electricity consumption profiles [37], [113], household appliance energy consumption patterns [114], or determine the social-demographic factors associated with DER adoption (e.g., [115] for the case of PV in Dutch households, [116] for EV, PV and HVAC in Portugal or [105] for EV, PV and heat pumps in a DSO service area in the Netherlands).

6. Future research avenues

Our analysis results also highlight several research questions that are relevant to policy makers and business developers working on introducing AI applications in power systems:

- **Currently, a fuzzy AI taxonomy complicates analysis of AI use cases**. In our analysis, we estimate an annual rate of about 25,000 publications per year (as of 2022) at the intersection of power systems and AI. However, using queries from the detailed AI taxonomy and searching for specific use cases across power system supply chain elements, estimates decrease to about 12,500 publications in 2022 or about 50% of the more generic search queries. This shows the high dependency of utilized query sets and the importance of (further-)developing a finely differentiated, consistent AI taxonomy. Likewise, results might also suggest that the used system of power system supply chain elements and use cases could be improved to capture more studies, eventually closing the gap towards the 25,000 identified publications in our coarse query set. Retrieved outcomes may be skewed by the established, partially fuzzy ontology of AI domains. For example, many ambiguities occur as the utilized, common AI taxonomy is non-exclusive and may result in double counting or overlapping. Given an artificial neural network application that analyzes thermal images of substation transformers - would it fall under the AI domain "Perception", that bundles all algorithms for image and audio signal analysis, or "Learning", where artificial neural networks are grouped in? Hence, future work could be directed to sensitivity studies that compare different taxonomies against retrievable outcomes in terms of research volumes across each power system supply chain element.

- **Today, we are missing the full picture of the utilization of AI in the power industry and its future potential**. Considering the absence of detailed information on where and how AI is used in power industry processes, the presented analysis could only rely on web-based

queries of scientific publications to derive an understanding of the maturity of AI applications in the power sector. This comes with some drawbacks. First, it is not given that added volumes of research actually translate into practical solutions applied through utilities. Second, the established framework to assess research maturity is currently rather coarse, consisting of three levels (high, medium, low) and could be further refined. Third, the ease of automated web searches comes at a cost, that is, accuracy. Given the sheer volumes of research analyzed, it is intractable to check the suitability of each identified paper or potential double counting. Although we have performed several cross-checks, the final amount of research on AI applications in the power sector may be actually lower (or higher, if important publication outlets have been unwillingly neglected). Our research further shows that a few areas in power systems are rather under-researched (such as market operations, distribution and transmission grid automation, implementation of local energy markets / energy communities). This raises the question why these areas exhibit at the moment little interest for AI applications, and, under which future conditions AI could be used to enhance the processes in these areas

- **How are risks through AI applications distributed across the power industry?** A future database on AI applications across businesses, as foreseen under the European AI Act, will certainly allow a much more fine-grained analysis of the utilization of AI across different power system supply chain elements. Such a database would allow the improvement of the understanding of potential risks which the applications bear using "black box" algorithms that are difficult to interpret. Such risk analysis is paramount for governments, regulators to assess impacts of economic efficiency potentials and security of supply. It is also important for business developers, as with higher risk higher regulatory requirements will have to be met under emerging AI regulations.

- **Is there a path-dependency in AI research for power systems?** In addition, our results suggest that currently, algorithms of the AI domain "Learning" (including machine learning such as artificial neural networks or regression models and also reinforcement learning) are the dominant tools used of all types of analyzed applications. However, our analysis revealed patterns that show mostly unchanged relative fractions of AI domains in power system applications in the last 40 years. This raises questions on whether this relatively stable relation between AI domains is a result of different, time-invariant technical or economic appeal of a given AI domain for a specific power system use case. Or are these stable fractions of AI domains rather influenced by the earlier popularity of AI applications in a specific power system domain (e.g., applying artificial neural networks to electric load or renewable power generation forecasting).

7. Conclusions

The last 40 years have seen a drastic increase of research conducted on AI applications to the power system. Totaling over 258'919 studies from 1982-2022, the body of literature now adds over 25,000 new publications per year, at growing rates. In this work, we presented a thorough analysis of the history of AI applications in the power system. Our analysis merges a literature-based review of most popular use cases and applications of AI along the power system supply chain with a web-based search on research on AI applications across different AI domains and use cases. We use the recently established taxonomy on AI domains [1].

In general terms, our fine-grained, use-case centered analysis showed that AI algorithms of AI domains "Learning" and "Planning" are the most popular. Today, these AI domains are covering 52% and 22% of research volumes in the field of power systems, respectively.

The research technological maturity of use cases for the power system supply chain elements "Retail" (55%), "Transmission" (14%) and "Generation" (13%) is highest in direct comparison to all other supply chain elements. In case research maturity somewhat reflects industrial utilization levels too, this would suggest that AI applications are attractive in these activities. The use case centered analysis further suggests that currently benefits are being predominantly located/ expected in the field of operation and maintenance.

Eventually, our findings substantiate the ever-increasing amount of funding and research work that has been and is channeled towards research on AI applications in power systems. It remains an open question if and how successful current research on AI applications is translated into practical innovations adopted by the power sector in order to increase its efficiency while driving decarbonization. Certainly, more research will be needed to evaluate the effectiveness of the current, extensive funding while striving towards an optimal balance between required research and necessary practical applications for the set political goals of decarbonized power systems.

Annex 1: Acronyms

AI	Artificial Intelligence	JRC	European Commission's Joint Research Centre
API	Application programming interfaces	O&M	Operation and maintenance
ARV	Average research volume	PV	Photovoltaik
AutoML	Automated machine learning	RM	Research maturity
DER	Distributed energy resources	RRI	Relative Research Intensity
DSOs	Distribution system operator	RV	Research volume
EPRI	Electric power research institute	SDG	Sustainable development goals
EV	Electric vehicle	TSOs	Transmission system operator
HVAC	Heating, ventilation and air conditioning	TRL	Technology readiness level
ICT	Information and communications technologies	USD	US dollar
IRENA	International renewable energy agency	WEF	World Economic Forum

Annex 2: Keyword search using the European AI taxonomy

AI domain	Keywords [1]
Reasoning	case-based reasoning, inductive programming, information theory, knowledge representation, Causal inference, Causal models, common-sense reasoning, expert system, fuzzy logic, graphical models, latent variable models, semantic web, graph theory
Planning	bayesian optimisation, constraint satisfaction, evolutionary algorithm, genetic algorithm, gradient descent, hierarchical task network, metaheuristic optimization, planning graph, stochastic optimization
Learning	active learning, adaptive learning, adversarial machine learning, adversarial network, anomaly detection, artificial neural network, automated machine learning, automatic classification, automatic recognition, bagging, bayesian modelling, boosting, classification, collaborative filtering, content-based filtering, convolutional neural network, data mining, deep learning, deep neural network, ensemble method, feature extraction, generative adversarial network, generative model, multi-task learning, neural network, pattern recognition, probabilistic learning, probabilistic model, recommender system, recurrent neural network, recursive neural network, reinforcement learning, semi-supervised learning, statistical learning, statistical relational learning, supervised learning, support vector machine, transfer learning, unsupervised learning, LSTM
Communication	chatbot, computational linguistics, conversation model, coreference resolution, information extraction, information retrieval, natural language understanding, natural language generation, machine translation, question answering, sentiment analysis, text classification, text mining
Perception	action recognition, face recognition, gesture recognition, image processing, image retrieval, object recognition, recognition technology, sensor network, visual search, computational auditory scene, music information retrieval, sound description, sound event recognition, sound source separation, sound synthesis, speaker identification, speech processing, speech recognition, speech synthesis, natural language processing
Integration and Interaction	agent-based modelling, agreement technologies, computational economics, game theory, intelligent agent, cognitive system, cognitive system, control theory, human-ai interaction, industrial robot, autonomous driving, autonomous vehicle, negotiation algorithm, network intelligence, q-learning, swarm intelligence, robot system, service robot, self driving car, unmanned vehicle

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: