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To cite this article: Yongjian Huang, Shucen Huo & Yikun Dong (19 Aug 2025): Exploring the role of AI in smart grids: a 20-year bibliometric-based overview, International Journal of General Systems, DOI: [10.1080/03081079.2025.2547187](https://doi.org/10.1080/03081079.2025.2547187)

To link to this article: <https://doi.org/10.1080/03081079.2025.2547187>



Published online: 19 Aug 2025.



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# Exploring the role of AI in smart grids: a 20-year bibliometric-based overview

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## ABSTRACT

This study integrates bibliometric mapping with qualitative content analysis to explore the evolving role of artificial intelligence (AI) in smart grid operations. Unlike prior reviews that focus on specific subdomains, this research offers comprehensive insights into both macro-level trend identification and micro-level thematic patterns. Drawing on 1,272 Web of Science publications (2005–2024), our macro-level analysis highlights publication growth trends, influential authors, and key research institutions shaping the AI-smart grid research domain. At the micro level, we employ keyword co-occurrence clustering to identify eight thematic clusters. Moreover, to move beyond descriptive mapping, we introduce a Research Potential Evaluation model to evaluate emerging research opportunities within clusters including load management, load forecasting, power grid optimization, and smart grid operation and maintenance. The findings contribute valuable insights into the current state and future trajectory of AI-smart grid integration, providing a framework to guide innovation and further research in this rapidly evolving field.

## ARTICLE HISTORY

Received 5 April 2025

Accepted 8 August 2025

## KEYWORDS

Artificial intelligence; bibliometric; clustering methods; smart grids

## 1. Introduction

The accelerating global demand for electricity, coupled with the growing integration of renewable energy sources, has introduced unprecedented challenges to traditional power distribution systems. Modern power networks are now expected to cope with highly volatile energy flows, real-time demand fluctuations, and the increasing complexity introduced by decentralized generation systems such as rooftop solar panels and microgrids (Liu et al. 2025). These complexities expose the limitations of legacy infrastructure in ensuring reliable, efficient, and flexible power delivery. To address these challenges, smart grids have emerged as a transformative solution. By incorporating advanced communication, sensing, and control technologies (Lv et al. 2024), smart grids facilitate real-time monitoring, decentralized decision-making, and intelligent energy management across residential, commercial, and industrial sectors. In this context, efficient power management and intelligent load balancing are not only technical necessities but also key enablers for achieving sustainability and grid resilience (Panda and Das 2021). Within this transformation, Artificial Intelligence (AI) has become a key enabler for smart grid intelligence.

By leveraging AI technologies, such as machine learning, deep reinforcement learning, and data-driven optimization, modern power systems can achieve real-time forecasting, adaptive load control, fault detection, and self-healing capabilities. As research on AI applications in smart grids has proliferated, a growing number of review studies have attempted to synthesize key developments, technical pathways, and emerging directions across the field.

Table 1 illustrates the evolution of analytical approaches in key literature reviews in the field of smart grids & AI. Early studies relied on systematic content analysis, and primarily focused on analyzing AI's integration into sustainable energy systems, such as optimizing energy management for low-carbon smart grids and improving load forecasting methods (Ali and Choi 2020; Fallah et al. 2018; Ramchurn et al. 2012; Raza and Khosravi 2015; Zhang, Han, and Deng 2018). Recently, the focus of research has shifted towards investigating the use of advanced AI applications, including deep learning (DL) (Kotsiopoulos et al. 2021; Massaoudi et al. 2021; Mishra et al. 2020), AI (Omitaomu and Niu 2021), and blockchain integration (Hua et al. 2022; Kumar et al. 2020).

Although a few recent studies have begun to adopt bibliometric methods, for example, in the fields of emergency manufacturing (Xie et al. 2020; Xie et al. 2023; Xie et al. 2025; Xie, Huang, and Chen 2025) and quality function deployment (QFD) (Jiang et al. 2024; Zhou et al. 2024). However, their application within the smart grid context remains limited. Even Massaoudi et al. (Massaoudi et al. 2021), one of the few bibliometric studies in this area, concentrated exclusively on DL applications, aiming to promote its adoption in practice. A comprehensive, system-wide bibliometric analysis that captures both the historical development and emerging directions of AI in smart grids is still lacking.

To fill this gap, our research introduces a dual-method framework that integrates bibliometric mapping with content analysis, systematically analyzing 1,272 publications from 2005 to 2024 (as shown in Table 1). Unlike prior reviews that focused narrowly on specific technical subdomains or relied solely on expert-driven interpretation, our approach provides a broader and more objective perspective. Specifically, we employ VOSviewer and CiteSpace tools to visualize the knowledge structure, track keyword co-occurrence, and detect temporal evolution in the field of AI applications in smart grids. This enables us to monitor real-time research dynamics and identify emerging hotspots in a data-driven manner. Furthermore, we use a Research Potential Evaluation (RPE) model to assess both the maturity and recent attention of eight major thematic clusters, thereby offering a forward-looking roadmap that can guide future research directions in this rapidly evolving domain.

The paper is structured as follows: Section 2 describes data collection and the re-search methodology of Bibliometric and Content Analysis. Section 3 provides an overview of publication trends, institutional/national contributions, journal mapping and leading authors. Section 4 explores the key features and potential of the field. Finally, Section 5 presents general trends in the smart grids, and future research directions.

## 2. Data and methodology

### 2.1. The data collection

The study aims to systematically analyze the role of Artificial Intelligence (AI) in optimizing smart grids operations, and we used bibliometric tools such as CiteSpace (Chen 2006),

**Table 1.** Overview of key literature reviews in smart grids & AI.

Title	Publication	Year	Scope	Methodology	Time Span	Scale
Putting the "smarts" into the smart grid: A grand challenge for artificial intelligence	Ramchurn, Sarvapali Det al. (Ramchurn et al. 2012)	2012	smart grids & low-carbon economy	content analysis	1988–2011	40
A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings	Raza, Muhammad Qama and Khosravi, Abbas (Raza and Khosravi 2015)	2015	smart grids & power load forecasting	content analysis	1942–2014	125
Review on the research and practice of deep learning and reinforcement learning in smart grids	Zhang, Dongxia et al. (Zhang, Han, and Deng 2018)	2018	smart grids & DL, RL, DRL	content analysis	1998–2018	70
Computational intelligence approaches for energy load forecasting in smart energy management grids: State of the art, future challenges, and research directions	Fallah, Seyedeh Narjes et al. (Fallah et al. 2018)	2018	smart grids & intelligence load forecasting	content analysis	1986–2018	105
State-of-the-art artificial intelligence techniques for distributed smart grids: A review	Ali, Syed Saqib and Choi, Bong Jun (Ali and Choi 2020)	2020	distributed smart grids	content analysis	1987–2020	146
Distributed energy resources and the application of AI, IoT, and blockchain in smart grids	Kumar, Nallapaneni Manoj et al. (Kumar et al. 2020)	2020	smart grids & DER	content analysis	2000–2020	177
Deep learning in electrical utility industry: A comprehensive review of a decade of research	Mishra, Manohar et al. (Mishra et al. 2020)	2020	smart grids (EUI) & DL	content analysis	2010–2020	197
Machine learning and deep learning in smart manufacturing: The smart grid paradigm	Kotsiopoulos, Thanasis et al. (Kotsiopoulos et al. 2021)	2021	smart grids & ML, DL	content analysis	1977–2020	237
Artificial intelligence techniques in smart grid: A survey	Omitaomu, Olufemi A and Niu, Haoran (Omitaomu and Niu 2021)	2021	smart grids	content analysis	1981–2020	162
Deep learning in smart grid technology: A review of recent advancements and future prospects	Massaoudi, Mohamed et al. (Massaoudi et al. 2021)	2021	smart grids &DL	<b>bibliometric analysis</b>	1980–2020	220
Applications of blockchain and artificial intelligence technologies for enabling prosumers in smart grids: A review	Hua, Weiqi et al. (Hua et al. 2022)	2022	smart grids & low-carbon economy	content analysis	1998–2022	115
Our study		2024	smart grids & AI	<b>bibliometric analysis and content analysis</b>	<b>2005–2024</b>	<b>1272</b>

**Note:** DER: distributed energy resources; DL: deep learning; RL: reinforcement learning; DRL: deep reinforcement learning; EUI: electrical utility industry; ML: machine learning.

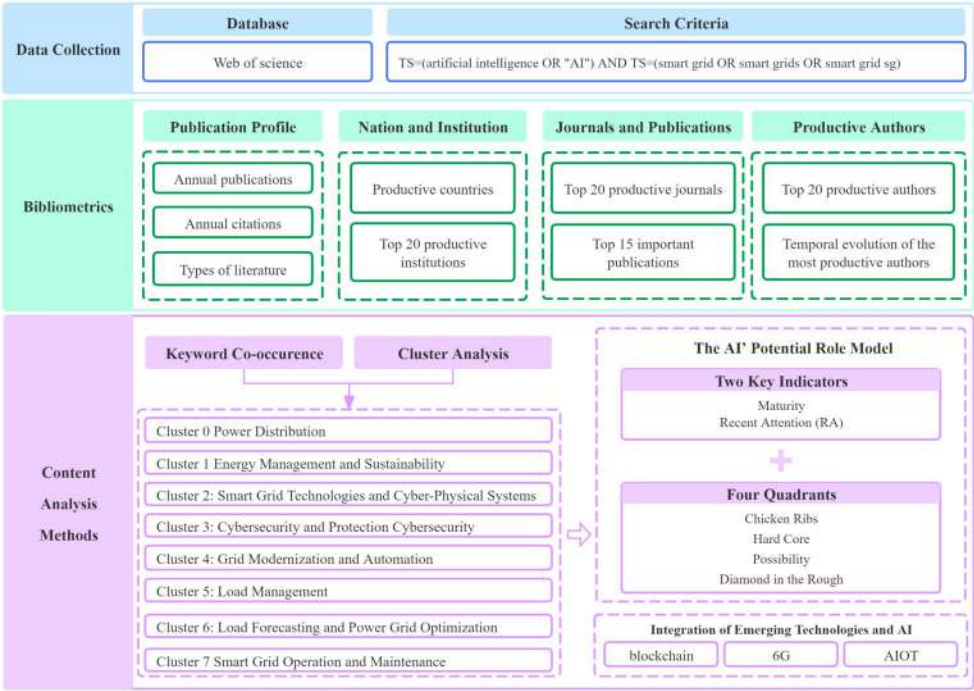
VOSviewer (Van Eck and Waltman 2010), and collected publication data from Web of Science Core Collection. Web of Science is a citation-indexed database, including SCI, SSCI, A & HCI three sub-databases, covering many fields such as natural sciences, engineering technology, social sciences, arts and humanities. Through WOS, users can retrieve current and past information in various disciplines from more than 9,000 core academic journals of global reputation, and the data can go back to 1900, tracing more than 100 years of scientific and technological literature and its impacts, so the data we get from WOS is more comprehensive. The initial search was done in the "Topic" field of WOS, and in Advanced search by the formula  $TS = (\text{artificial intelligence OR "AI"}) \text{ AND } TS = (\text{smart grid OR smart grids OR smart grid sg})$ .

Using smart grids & AI as a search criterion can capture the diverse applications of AI, including improving grid functionality, covering key areas energy efficiency management, load optimization, real-time control and cyber security. This study will focus on the interdisciplinary convergence areas of smart grids & AI, aiming to provide a comprehensive view of the transformative role of AI in the smart grids. This search was updated on 10 September 2024, and included literature published between 2005 and 2024, yielding 1,278 documents. After excluding document types like "data papers" and "retracted publications", a final set of 1,272 publications remained, comprising research articles, conference papers, review papers, editorial materials, and book chapters. As of September 2024, these 1,272 documents had been cited 24,388 times by other works within the WOS database, resulting in an average of 19.17 citations per paper. It is important to note that the field of AI in smart grids continues to evolve rapidly. This review provides a snapshot of major research trends over the past decade, based on the literature available up to the retrieval date.

## 2.2. *Bibliometric and content analysis*

Bibliometrics, originally introduced by Pritchard (Pritchard 1969), analyzes bibliographic data using mathematical and statistical methods, and is now an important tool for the systematic review of research results in various fields (Fahimnia, Sarkis, and Davarzani 2015; Garfield 1979). At the macro level, this study uses bibliometric tools, VOSviewer and CiteSpace, to systematically map the knowledge structure and collaboration networks in the field of smart grids & AI. Specifically, we analyzed the annual distribution of publications to understand the evolution of research output over time, while focusing on top-performing countries and institutions to observe the geographic and institutional contributions to advancing the field. In addition, by identifying and examining journals and active authors, we obtained the main sources of the most influential research and authors with key contributions to the field.

At the micro level, this study combines bibliometric techniques with qualitative content analysis to provide a detailed study of specific contributions and emerging research areas in the field of smart grids & AI (Pedrini and Ferri 2019). Firstly, this study used cluster analysis to identify eight key thematic clusters. To assess the development potential of each theme, we used the Research Potential Evaluation (RPE) framework, which was originally proposed by Zhou et al. (Zhou et al. 2024). The model categories clusters into "Hard Core" and "Diamond in the Rough", with the former representing mature areas with high research impact, and the latter representing emerging areas that have received more recent attention but are less mature. As shown in Figure 1, our analytical framework begins



**Figure 1.** The framework of this paper.

with bibliometric indicators to outline the structural features of the field and follows with content analysis to identify research themes, trends, and knowledge gaps.

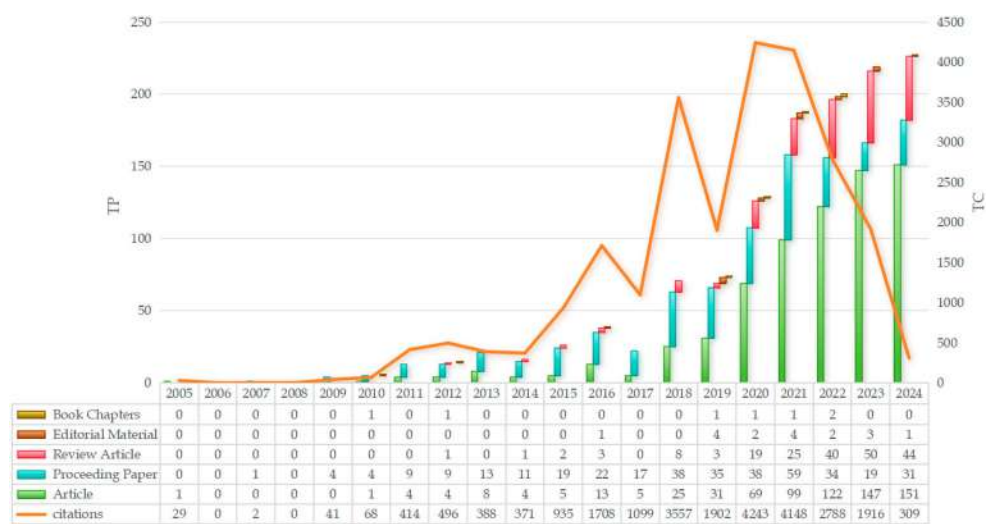
### 3. Overview of publications

#### 3.1. Annual distribution of publications

Following a thorough search and filtering process, five categories of publications were selected for this study: Articles, Proceedings Papers, Review Articles, Editorial Materials, and Book Chapters. Among these, Articles accounted for 53% of the total, Proceedings Papers made up 29%, Review Articles 15%, others 3%. These papers were published in 347 journals and presented at 267 conferences, citing a total of 58,632 references from 37,569 authors across 18,918 institutions. Figure 2 illustrates the annual publication trends in smart grids & AI research from 2005 to 2024, revealing key insights into the field's developmental stages, types of publications, and shifts in research focus over time.

From 2005 to 2010, publication numbers were minimal, showing that AI integration in smart grids research was in its initial stages. Both total publications (TP) and citations (TC) were low, reflecting limited academic attention. After 2011, there was a steady increase in publications, indicating growing interest in AI's potential for grid management. This growth became more pronounced around 2015, due to technological advancements.

Regarding total citations, from 2005 to 2010, the citation count was extremely low, matching the scant published papers then as the field was nascent with limited impact. From 2011 to 2014, as publications grew, citations rose gradually, reflecting the field's



**Figure 2.** Annual numbers of publications in smart grids & AI from 2005 to 2024.

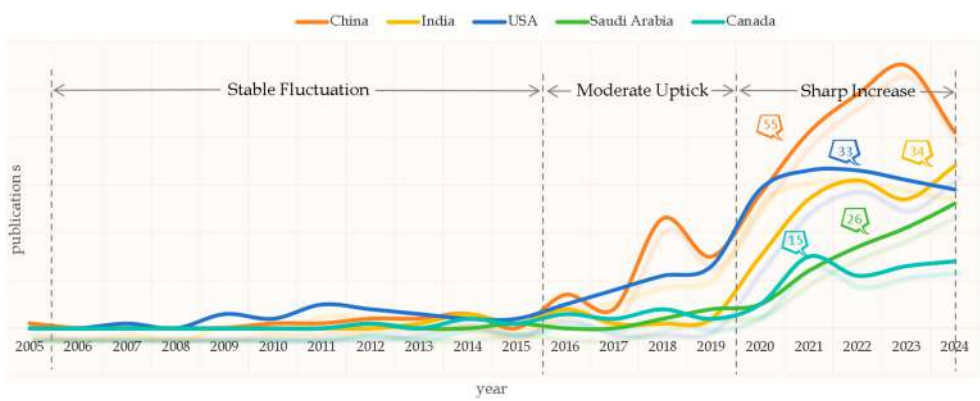
growing attention. Starting in 2015, citation counts soared, peaking remarkably in 2020, signifying the rapid expansion of AI. Given the time lag for new research to garner attention and citations, this dip doesn't imply waning interest. In terms of publication types, articles and conference papers prevailed after 2015, probably due to the swift progress in AI technology. Since 2016, the number of review articles has been rising steadily, suggesting that the field is gradually maturing.

### 3.2. Analysis of nation and institution

Our study covers a sample of 1,865 organizations from 94 countries. Figure 3 highlights the publication trends from 2005 to 2024 in the top five countries in smart grids & AI: China, the US, India, Saudi Arabia, and Canada. Its timeline is divided into three key phases: stable fluctuation from 2005 to 2015; moderate uptick from 2015 to 2019, particularly in China and the US; and sharp increase from 2019 to 2024, which is fueled by the growth of interest in smart grids & AI, during which time China reaches a peak of 55 publications in 2023. China's dominance in the field can be attributed to significant government funding support, which has created a favorable environment for research and development.

We analyze the number of papers published in smart grids & AI in each country and got a geographical distribution map as shown in Figure 4. A color gradient from yellow to red is used, with darker red indicating higher publication output. China has 314 publications, leading in research output, which shows a strong focus on AI-driven smart grid solutions. Key Chinese institutions, such as the Chinese Academy of Sciences and Tsinghua University, are major contributors to this field, reflecting the country's commitment to advancing energy technologies through AI. Following China, the United States ranks second with 214 publications, where institutions like the University of Illinois play a prominent role.

Many countries are now placing great emphasis on investment in AI and energy technologies and are part of their national development strategies. For example, China has enacted policies to prioritize innovation in AI and energy infrastructure. And India, Saudi



**Figure 3.** Top 5 most productive countries in smart grids & AI.



**Figure 4.** Productive countries and top 20 most productive institutions in smart grids & AI.

Arabia and Canada are also significant contributors with 147, 89 and 73 publications, respectively (see Figure 4). We summarize this information in Table 2, which lists the top 10 productive countries and the most active research institutions in the field. Notably, Vellore Institute of Technology and Nirma University in India, King Abdulaziz University in Saudi Arabia, and the Chinese Academy of Sciences are among the most prominent contributors in AI-driven energy research. As more countries join the research of smart grids & AI, cooperation among institutions will become more intensive and globally distributed. However, regions such as Africa, South America and Central Asia have been relatively less engaged in smart grids & AI, which is related to the high cost of developing smart grid technologies and implementing AI solutions, as well as to the fact that these regions prioritize more pressing issues, such as improving access to energy, reducing poverty and promoting

**Table 2.** Summary of productive countries and top 20 institutions in smart grids & AI.

Rand	Organization	TP	TC	TC/TP	Country
1	King Abdulaziz University	17	1134	66.71	Saudi Arabia
2	Vellore Institute of Technology	15	143	9.53	India
3	Aalborg University	14	325	23.21	Denmark
4	King Saud University	14	197	14.07	Saudi Arabia
5	University of Johannesburg	14	79	5.64	South Africa
6	Nirma University	13	307	23.62	India
7	China Electric Power Research Institute	12	1004	83.67	China
8	Aalto University	11	178	16.18	Australia
9	COMSATS University Islamabad	11	408	37.09	Pakistan
10	National Taipei University of Technology	11	145	13.18	China
11	Zhejiang University	11	107	9.73	China
12	Nanyang Technological University	10	198	19.80	Singapore
13	Cardiff University	9	398	44.22	UK
14	Chinese Academy of Sciences	9	220	24.44	China
15	Lebanese American University	9	141	15.67	Lebanon
16	Sejong University	9	235	26.11	South Korea
17	Southeast University	9	110	12.22	China
18	Tianjin University	9	233	25.89	China
19	Tsinghua University	9	1073	119.22	China
20	University of Illinois	9	182	20.22	USA

economic development, thus limiting their attention and resources to advanced technology research.

### 3.3. Analysis of journals and most-cited publications

We analyze the top 20 journals in smart grids & AI, as shown in Table 3, the top 5 journals in terms of publication volume Energies, IEEE Access, Sensors, Sustainability, and Applied Sciences-Basel – are prolific. Energies leads with 108 papers, chased by IEEE Access with 71. Besides, Energies and IEEE Access ranked first and second in total citations (TC) with 2,026 and 1,824, respectively, highlighting their popularity.

Journals like Renewable and Sustainable Energy Reviews, Energy, Applied Energy, IEEE Transactions on Industrial Informatics, and International Journal of Electrical Power & Energy Systems, have high citation impact. Some journals, such as Renewable and Sustainable Energy Reviews with 1,752 citations and an average of 103 citations per paper and Applied Energy with 1,078 citations. These selective journals focus on high-impact topics and attract rigorous submissions, enhancing their impact.

In order to comprehensively analyze the citation trends in smart grids & AI, the top 15 most cited publications are detailed in this paper in Table 4, including each paper's title, journal source, author, article type, year of publication, country, total citations (TC), average number of citations per year (TC/year), number of authors (NA), number of institutions (NI), and number of references (NR). These publications come from ten different countries, reflecting the global interest and collaborative nature in smart grids & AI.

From Table 4, Raza et al.'s review (Raza and Khosravi 2015) on AI-based load demand forecasting for smart grids and buildings is the most cited, with 582 total citations and an average of 64.7 citations per year. Seven of the top 20 "smart grids & AI" journals published top 15 most cited publications, such as Renewable and Sustainable Energy Reviews (four papers) and Applied Energy (two). The papers were published from 2011 to 2021, peaking in 2018. Recent papers like Aslam et al.'s 2021 paper (Aslam et al. 2021) (251 citations, 83.7

**Table 3.** Top 20 journals by publication volume in smart grids & AI.

Rank	Journal	TP	TC	TC/TP	Field	IF	YI	YN
1	Energies	108	2026	18.76	Energy & Fuels (Q3)	3	2013	2024
2	IEEE Access	71	1842	25.94	Computer Science, Information Systems (Q2); Engineering, Electrical & Electronic (Q2); Telecommunications (Q2)	3.4	2017	2024
3	Sensors	27	417	15.44	Chemistry, Analytical (Q2); Engineering, Electrical & Electronic (Q2); Instruments & Instrumentation (Q2)	3.4	2012	2024
4	Sustainability	27	442	16.31	Environmental Sciences (Q2); Environmental Studies (Q2); Green & Sustainable Science & Technology (Q3)	3.3	2018	2024
5	Applied Sciences- Basel	21	200	9.52	Chemistry, Multidisciplinary (Q2); Engineering, Multidisciplinary (Q1); Materials Science, Multidisciplinary (Q3); Physics, Applied (Q2)	2.5	2019	2024
6	Frontiers in Energy Research	19	34	1.79	Energy & Fuels (Q3)	2.6	2021	2024
7	Electronics	17	268	15.76	Computer Science, Information Systems (Q2); Engineering, Electrical & Electronic (Q2); Physics, Applied (Q2)	2.6	2019	2024
8	Energy Reports	17	283	16.65	Energy & Fuels (Q2)	4.7	2021	2024
9	Renewable & Sustainable Energy Reviews	17	1752	103.06	Energy & Fuels (Q1); Green & Sustainable Science & Technology (Q1)	16.3	2014	2024
10	Applied Energy	14	1078	77	Energy & Fuels (Q1); Engineering, Chemical (Q1)	10.1	2018	2024
11	IEEE Transactions on Smart Grid	14	592	42.29	Engineering, Electrical & Electronic (Q1)	8.6	2011	2024
12	IET Generation, Transmission & Distribution	14	182	13	Engineering, Electrical & Electronic (Q3)	2	2018	2024
13	IET Smart Grid	11	177	16.09	Engineering, Electrical & Electronic (Q2)	2.4	2019	2024
14	IEEE Transactions on Industrial Informatics	10	627	62.7	Automation & Control Systems (Q1); Computer Science, Interdisciplinary Applications (Q1); Engineering, Industrial (Q1)	11.7	2016	2024
15	International Journal of Electrical Power & Energy Systems	10	565	56.5	Engineering, Electrical & Electronic (Q1)	5	2019	2023
16	Electrical Engineering	8	13	1.63	Engineering, Electrical & Electronic (Q3)	1.6	2021	2024
17	Energy	8	678	84.75	Energy & Fuels (Q1); Thermodynamics (Q1)	9	2014	2024
18	Energy and AI	8	353	44.13	Computer Science, Artificial Intelligence (Q1); Energy & Fuels (Q1)	9.6	2020	2024
19	IET Renewable Power Generation	8	21	2.63	Energy & Fuels (Q3); Engineering, Electrical & Electronic (Q2); Green & Sustainable Science & Technology (Q3)	2.6	2020	2024
20	Sustainable Energy, Grids and Networks	8	580	72.5	Energy & Fuels (Q2); Engineering, Electrical & Electronic (Q1)	4.8	2016	2024

Note: TP: Total Publications; TC: Total Citations; TC/TP: Citations per Publication; IF: Impact Factor; YI: Year of Inception; YN: Year of Latest

**Table 4.** Top 15 most-cited publications in smart grids & AI.

Rank	Title	Source	Author	Type	Year	Country / region	TC	TC/ year	NA	NI	NR
1	A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings	Renewable and Sustainable Energy Reviews	Raza & Khosravi	Review	2015	Australia	582	64.7	2	2	128
2	Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey	IEEE Transactions on Industrial Informatics	Alshakoon & Yu	Review	2015	Australia	316	35.1	2	2	95
3	Review on the Research and Practice of Deep Learning and Reinforcement Learning in Smart Grids	CSEE Journal of Power and Energy Systems	Zhang et al.	Review	2018	China	301	50.2	3	2	70
4	Distributed Intrusion Detection System in a Multi-Layer Network Architecture of Smart Grids	IEEE Transactions on Smart Grid	Zhang et al.	Article	2011	USA	282	21.7	5	2	54
5	Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review	Renewable and Sustainable Energy Reviews	Antonopoulos et al.	Review	2020	UK	275	68.8	9	4	355
6	Putting the 'smarts' into the smart grid: a grand challenge for artificial intelligence	Communications of the ACM	Ramchurn et al.	Article	2012	UK	273	22.8	4	1	40
7	Incentive-based demand response for smart grid with reinforcement learning and deep neural network	Applied Energy	Lu & Hong	Article	2019	Korea	265	53	2	1	60
8	Load forecasting, dynamic pricing and DSM in smart grid: A review	Renewable and Sustainable Energy Reviews	Khan et al.	Review	2016	Pakistan	263	32.9	5	2	101
9	A Dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach	Applied Energy	Lu et al.	Article	2018	Korea	262	43.7	3	1	59
10	A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids	Renewable and Sustainable Energy Reviews	Aslam et al.	Review	2021	Cyprus	251	83.7	6	4	154
11	Deep reinforcement learning for power system applications: An overview	CSEE J. Power Energy	Zhang et al.	Review	2020	China	248	62	3	3	115
12	System Considering Demand Responses, Smart Technologies, and Intelligent Controllers	IEEE Access	Shareef et al.	Review	2018	United Arab Emirates	238	39.7	4	3	128
13	Bi-directional long-short-term memory method based on attention mechanism and rolling update for short-term load forecasting	International Journal of Electrical Power & Energy Systems	Wang et al.	Article	2019	China	197	39.4	4	1	26
14	A High Precision Artificial Neural Networks Model for Short-Term Energy Load Forecasting	Energies	Kuo & Huang	Article	2018	Taiwan	196	32.7	2	2	37
15	Managing Electric Vehicles in the Smart Grid Using Artificial Intelligence: A Survey	IEEE Transactions on Intelligent Transportation Systems	Rigas et al.	Review	2015	Greece	172	19.1	3	2	90

Note: TC: Total Citations; TC/year: Total Citations per Year; NA: the Number of Authors; NI: the Number of Institutions; NR: the Number of References.

per year), Antonopoulos et al.’s 2020 paper (Antonopoulos et al. 2020) (68.8 per year), and Zhang et al.’s 2020 paper (Zhang, Zhang, and Qiu 2020) (62 citations) show the growing focus on AI in smart grids. These three papers focus on enhancing smart grid resilience,

**Table 5.** Top 20 Productive Authors.

R	Author Name	University	Country/region	TP	TC	H	C/P	≥200	≥100
1	Lin, Yu-Hsiu	National Taipei University of Technology	Taiwan	15	235	17	16	0	0
2	Tanwar, Sudeep	Institute of Technology, Nirma University	India	13	307	52	24	0	0
3	Javaid, Nadeem	University Islamabad	Pakistan	10	335	53	34	1	1
4	Kumari, Aparna	Nirma University	India	8	238	19	30	0	0
5	Srivastava, Gautam	Brandon University	Canada	7	145	53	21	0	0
6	Gadekallu, Thippa Reddy	Jiaxing University of China	China	6	178	55	30	0	0
7	Chebak, Ahmed	Mohammed VI Polytechnic niversity	Morocco	6	74	15	12	0	0
8	Zhang, Dongxia	China Elect Power Res Inst	China	5	664	80	133	2	2
9	Hernandez, Luis	Universidad de Valladolid	Spain	5	405	24	81	0	1
10	Carro, Belen	Universidad de Valladolid	Spain	5	405	25	81	0	1
11	Baladron, Carlos	Universitario de Valladolid	Spain	5	405	19	81	0	1
12	Aguiar, Javier M.	Universidad de Valladolid	Spain	5	405	16	81	0	1
13	Rezgui, Yacine	Univ Oum El Bouaghi	Algeria	5	347	47	69	0	2
14	Sarigiannidis, Panagiotis	University of Western Macedonia	Greece	5	162	29	32	0	1
15	Guerrero, Josep M.	University of Aalborg	Denmark	5	95	132	19	0	0
16	Vale, Zita	Instituto Politecnico do Porto	Portugal	5	58	45	12	0	0
17	Faheem, Muhammad	University of Vaasa	Finland	5	25	24	5	0	0
18	Zjavka, Ladislav	Technical University of Ostrava	Czech	5	11	9	2	0	0
19	Lloret, Jaime	Universitat Politècnica de València	Spain	4	323	52	81	0	1
20	Sanchez-Esguevillas, Antonio	Universidad de Valladolid	Spain	4	310	13	78	0	1

TP: Total Publications; TC: Total Citations; H: H-index; C/P: Citations per Publication; The categories ≥200 and ≥100: the number of that have received citations equal to or above 200 and 100 citations.

efficiency, and prediction via AI and deep learning, emphasizing aspects like cybersecurity, energy forecasting, and system optimization, demonstrating AI's pivotal role in building smart grid infrastructures.

### 3.4. Productive authors analysis

In bibliometrics, the impact of authors can be measured by the number of publications and citations they have made in the field, reflecting their contribution to and recognition of a particular research area. In this section, we analyze the top 20 most productive authors out of 4,704 authors in the field (see Table 5). Table 5 contains the authors' names, affiliation, country or region, total publications (TP), total citations (TC), h-index, citations per publication (C/P), and the number of publications receiving more than 200 and 100 citations, respectively. Where the h-index data is derived from the WOS core ensemble, authors with a high number of citations are prioritized in case of a tie. We find that these 20 prolific authors represent countries as diverse as China, India, Canada, and Spain, highlighting the global nature of smart grids and AI research.

The analysis reveals that topping the list is Lin, Yu-Hsiu from National Taipei University of Technology, with 15 publications and 235 citations. Lin's work frequently leverages advanced AI methodologies to improve the accuracy and responsiveness of load identification and energy disaggregation processes. Josep M. Guerrero from Aalborg University is the author with the highest h-index. Despite having only five publications in this field, his research on hierarchical control of AC/DC microgrids, advanced control architectures

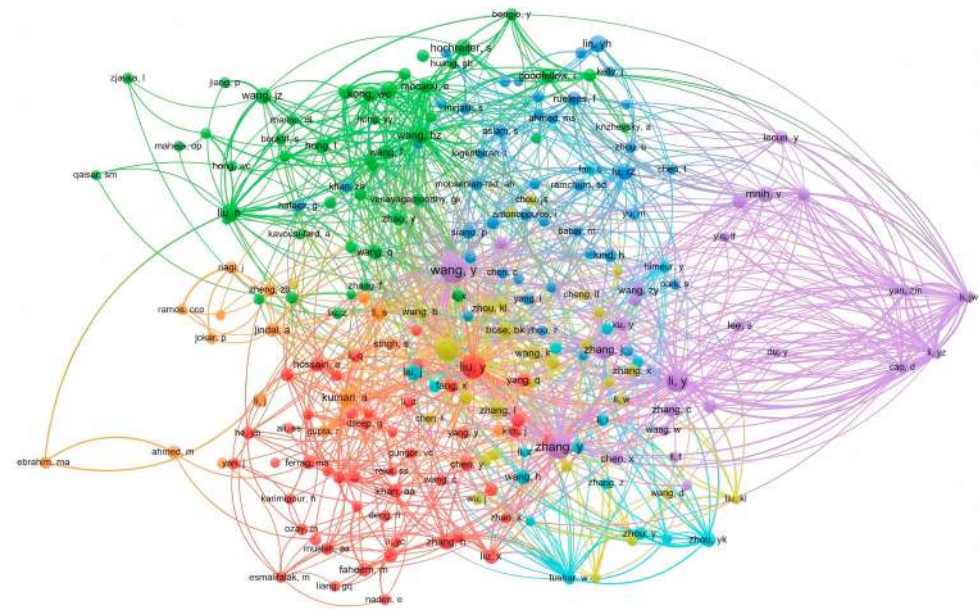
for smart microgrids, and power electronics for wind turbines has had a significant impact, with regular publications in top journals such as IEEE Transactions on Industrial Electronics and IEEE Transactions on Power Electronics Publications. Notably, Zhang, Dongxia from the China Electric Power Research Institute, although having only 5 publications, leads the top 20 authors in both total citations (664) and average citations per paper (133). Zhang's two review articles, "Review on the Research and Practice of Deep Learning and Reinforcement Learning in smart grids" (Zhang, Han, and Deng 2018) and "Deep Reinforcement Learning for Power System Applications: An Overview" (Zhang, Zhang, and Qiu 2020), have been cited over 250 times each, highlighting the critical relationship between smart grids and DRL. Zhang also has the highest number of papers with over 200 citations (2 publications), and Javaid, Nadeem from Pakistan is the other author with a single publication that surpasses 200 citations. In addition, Spain leads with six authors, including Hernandez, Carro, Baladron, Aguiar, Rezgui, Lloret, Sanchez-Esguevillas, who have co-authored five papers, accumulating a total of 405 citations. The team from Spain has produced a substantial work with a similar publications and citations. A significant factor in their productivities is the funding they received from the INNPACTO agreement of the Ministry of Economy and Competitiveness of the Government of Spain. This support has enabled the team to make frequent contributions to the field within a brief period, with many of their papers achieving high citation counts and substantial impact.

Figure 5 presents a co-citation network of highly cited authors. Based on a citation threshold of 20, a total of 224 authors were included, resulting in 13,659 co-citation links and over 44,000 co-occurrence instances. Clustering analysis revealed seven main research communities. Notably, Wang, Y. (145 citations), Zhang, Y. (123), Liu, Y. (115), Ahmad, T. (103), and Li, Y. (103) emerged as the most influential figures, forming the core of tightly connected scholarly sub-networks. Their prominence reflects not only their high individual impact, but also their central role in bridging thematic areas such as load forecasting, optimization, and AI-based energy management – indicating strong intellectual cohesion and a mature collaborative ecosystem within the field.

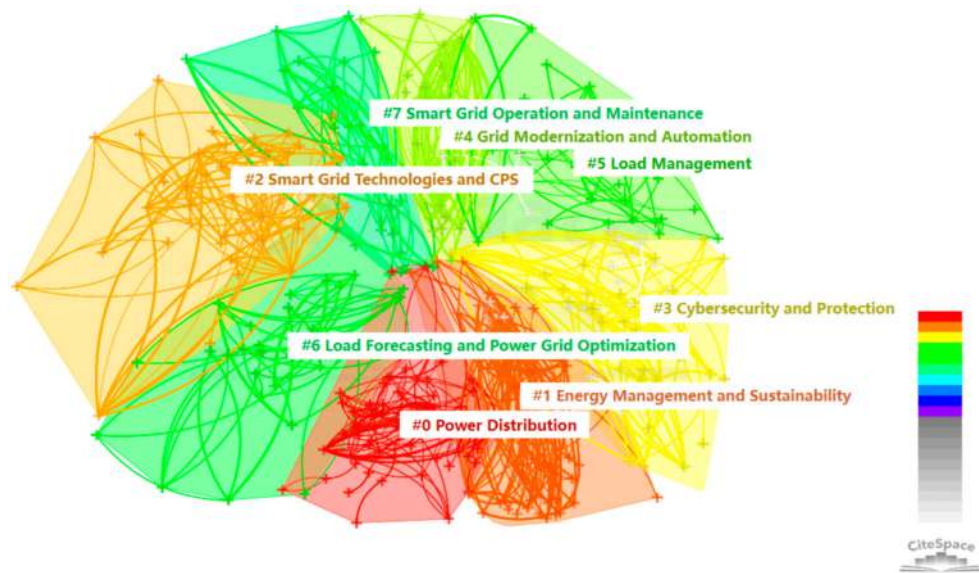
## **4. Research domains and potential analysis**

### **4.1. Analysis of research domains via keyword clustering**

In this section, we conducted a keyword co-occurrence cluster analysis of the literature in smart grids & AI, which reveals research themes and hotspots by clustering similar keywords. These clusters represent different research areas. The size of each cluster reflects the volume of research activities, while the proximity between clusters indicates the relationship between research areas. Using knowledge mapping techniques, we identified and examined eight topic clusters, as shown in Figure 6. These clusters cover different but inter-related research areas: power distribution, energy management and sustainability, smart grid technologies and CPS, cybersecurity and protection, grid modernization and automation, load management, load forecasting and power grid optimization, and smart grid operations and maintenance. In the following analysis, the eight keyword clusters are discussed in the order of their average emergence time, based on keyword co-occurrence and timeline mapping. This chronological structure reflects how research priorities in AI and smart grids have evolved over the past two decades.



**Figure 5.** Co-citation network of highly cited authors in smart grids & AI.



**Figure 6.** The clusters of keyword analysis in smart grids & AI.

**4.1.1. Cluster 4: grid modernization and automation**

Since its emergence as a research focus in 2007, this area has become increasingly important, especially with the integration of electric vehicles (EVs) into the grid. Research has shown that AI facilitates vehicle-to-grid (V2G) optimization by balancing energy flows, reducing peak loads and managing EV charging costs (Dong et al. 2023; Othman et al. 2023; Rigas, Ramchurn, and Bassiliades 2015).

Habibidoost et al. (Habibidoost, Mohammad, and Bathaee 2018) further highlighted the role of electric vehicles as emergency power sources, combining behavioral insights with technological solutions to enhance grid reliability. In distributed energy systems, AI-driven approaches propose new strategies for grid modernization and automation. Recent research directions include dynamic load management, resilience-focused network reconfiguration, and multi-intelligence frameworks enabling real-time resource coordination and trading between microgrids (Arévalo and Jurado 2024; Driesen and Katiraei 2008; Guerrero et al. 2020; Kumar Nunna and Doolla 2013; Tao et al. 2022; Zhang, Gari, and Hmurcik 2014).

#### **4.1.2. Cluster 1: energy management and sustainability**

Since 2010, this research area has focused on optimizing energy management through AI-driven solutions, facilitating demand-side strategies, and advancing sustainability initiatives (Ahmad et al. 2021; Almudayni et al. 2025; Ponnusamy et al. 2021). Shafiullah et al. (Shafiullah et al. 2022) highlighted the challenges of microgrid management and emphasized the need for innovative solutions to address these challenges. Recent studies have elaborated on a variety of AI-based approaches to energy management (Choi and Kim 2025; Guru, Perumal, and Varadarajan 2021). In terms of improving grid security, Ding et al. (Ding et al. 2022) state that the increasing complexity of smart grids (SGs) requires advanced defense mechanisms like blockchain and AI to effectively respond to cybersecurity threats. The vision of Industry 5.0, discussed by Verma and Ullah et al. (Ullah et al. 2020; Verma et al. 2022), points to the fact that the integration of AI, blockchain, and robotics will be future energy management system components. Current research continues to demonstrate the potential of AI applications (e.g. machine learning, demand response techniques and neural networks) to optimize energy consumption and increase flexibility in power distribution (Ahmad et al. 2022; Antonopoulos et al. 2020; Guru, Perumal, and Varadarajan 2021; Rangel-Martinez, Nigam, and Ricardez-Sandoval 2021; Yuce, Rezgüi, and Mourshed 2016). New research points to the promise of emerging technologies like 6G in enhancing energy efficiency in peer-to-peer transactions and smart battery management, although challenges such as device compatibility and energy consumption remain (Yap, Chin, and Klemeš 2022).

#### **4.1.3. Cluster 3: cybersecurity and protection**

Cybersecurity and Protection has become a fundamental concern since 2010 due to the digitization of smart grids, which makes them vulnerable to cyber-attacks. An early study by Y Zhang et al. (Zhang et al. 2011) introduced the smart grid Distributed Intrusion Detection System (SGDIDS), which uses artificial intelligence-based techniques to detect malicious activities and enhance grid security. Follow-up studies by Hernandez et al. (Hernandez et al. 2013) and Merabet et al. (Merabet et al. 2014) emphasized the importance. Later on, electric vehicles (EVs) were integrated into smart grids, and Rigas et al. (Rigas, Ramchurn, and Bassiliades 2015) identified cybersecurity risks posed by EVs and advocated the use of AI-based management systems to address these challenges. More recent studies by Zhang et al. (Zhang, Han, and Deng 2018) and Lu et al. (Lu and Hong 2019) explored the application of Deep Learning (DL) and Reinforcement Learning (RL) in countering emerging cyberthreats that thereby enhance the security and resilience of smart grids.

#### 4.1.4. Cluster 2: smart grid technologies and cyber-physical systems (CPS)

This research area emerged in 2013, a field enhanced by CPS (Cyber-Physical Systems) that uses artificial intelligence to optimize grid management, improve resilience, and enable real-time decision-making. The convergence of computing, communications and physical systems in emerging areas such as the smart grid presents unique security challenges for CPS. Existing solutions are insufficient to cope, and innovative approaches and interdisciplinary efforts are needed to ensure reliability and security in these complex, dynamic environments (Alguliyev, Imamverdiyev, and Sukhostat 2018; Cintuglu et al. 2017; Deller, Lee, and Vincentelli 2012; Li et al. 2014; Liu et al. 2017; Mo et al. 2012; Shi, Krishnan, and Wen 2022; Yu and Xue 2016). Rahman et al. (Rahman et al. 2017) emphasized on AI-driven approaches such as load forecasting and demand response to improve grid stability even under unpredictable conditions. Similarly, Rawat et al. (Rawat et al. 2016) developed a multi-level AI fault detection system to enhance grid security and operational efficiency. By integrating machine learning (ML) with optimization algorithms such as the L-BFGS method, smart grids can effectively balance loads and improve grid reliability, as demonstrated by Zhang et al. (Zhang et al. 2023).

#### 4.1.5. Cluster 0: power distribution

Since 2013, power distribution has become a key focus of smart grid development, driven by the integration of Distributed Generation (DG) and Multi-Intelligent Systems (MAS) as described by Heydt et al. (Heydt 2010). Ruiz Romero et al. (Ruiz-Romero et al. 2014) explored the complexities of DG integration, highlighting the need for advanced control mechanisms, robust protection systems and synchronized communication protocols needs. From a sustainability perspective, Kakran and Chanana (Kakran and Chanana 2018) discuss the environmental benefits of demand side management and demand response, while also pointing out the technical challenges of global smart grid deployment.

MAS offers a decentralized approach that enables real-time decision-making, fault management, frequency control, and resource allocation. Earlier studies, including those by Al-Agtash et al. (Al-Agtash 2013) and Colson et al. (Colson and Nehrir 2013), introduced agent-based architectures to support bi-directional power flow and autonomous microgrid operations. In order to enhance grid performance, later studies by Kilkki et al. (Kilkki et al. 2014) and Qin et al. (Qin et al. 2017) improved MAS applications by focusing on frequency control and multi-agent coordination. By facilitating real-time decision-making and grid flexibility, MAS has been shown in numerous studies to improve resilience, stop cascading failures, and stabilize smart grids (Babalola, Belkacemi, and Zarrabian 2018; Ben Meskina et al. 2017; Ben Meskina et al. 2018; Castillo-Cagigal et al. 2016). In order to enhance the overall performance of the system, Castillo Cagigal et al. (Castillo-Cagigal et al. 2016) created the MuFCO algorithm, which demonstrates how MAS can coordinate grid activities under periodic situations. Similarly, other researchers investigated grid restoration and MAS-driven fault management, emphasizing how well it reduces grid outages (Ahmad et al. 2021; Zhang et al. 2023).

Addressing issues with power distribution also requires artificial intelligence. AI applications including predictive maintenance, fraud detection, and energy management can improve service dependability and grid security, according to research by Barja-Martinez et al. (Barja-Martinez et al. 2021). In order to automate attack responses and safeguard privacy, Khan et al. (Khan et al. 2023) suggested combining blockchain technology with

**Table 6.** Summary of approaches integrated in smart grids & AI.

Approach	Categorization	Functions in Smart Grids	References
Multi-Agent System (MAS)	Distributed Management	Manages distributed grid operations and coordinates multi-agent tasks for flexibility.	(Al-Agtash <a href="#">2013</a> ; Babalola, Belkacemi, and Zarrabian <a href="#">2018</a> ; Basso et al. <a href="#">2016</a> ; Ben Meskina et al. <a href="#">2017</a> ; Ben Meskina et al. <a href="#">2018</a> ; Castillo-Cagigal et al. <a href="#">2016</a> ; Chang, Xu, and Sun <a href="#">2022</a> ; Colson and Nehrir <a href="#">2013</a> ; Khan et al. <a href="#">2020</a> ; Kilkki et al. <a href="#">2014</a> ; Merabet et al. <a href="#">2014</a> ; Nunna and Doolla <a href="#">2012</a> ; Perkonigg, Brujic, and Ristic <a href="#">2015</a> ; Pournaras et al. <a href="#">2019</a> ; Qin et al. <a href="#">2017</a> ; Shafiullah et al. <a href="#">2022</a> )
AI in Energy Management (EV Integration)	Energy Coordination	Optimizes vehicle-to-grid (V2G) integration to reduce peak loads and manage charging costs.	(Dong et al. <a href="#">2023</a> ; Othman et al. <a href="#">2023</a> ; Rigas, Ramchurn, and Bassiliades <a href="#">2015</a> )
ML Security Protection	Cybersecurity	Mitigates cybersecurity risks, enhancing data management and system security.	(Ahmad et al. <a href="#">2022</a> ; Ahmad, Wazirali, and Abu-Ain <a href="#">2022</a> ; De Santis and Rizzi <a href="#">2024</a> ; Rahman et al. <a href="#">2017</a> ; Rawat et al. <a href="#">2016</a> ; Syed et al. <a href="#">2021</a> ; Ullah et al. <a href="#">2020</a> ; Zhang et al. <a href="#">2023</a> )
ML Fault Detection and Diagnosis	Fault Analysis	Predicts faults to maintain grid stability and prevent outages.	(Misra et al. <a href="#">2013</a> ; Rawat et al. <a href="#">2016</a> ; Russell and Benner <a href="#">2010</a> )
AI Load Forecasting	Predictive Modeling	Predicts electricity demand for grid stability and energy optimization.	(Ahmad et al. <a href="#">2021</a> ; Antonopoulos et al. <a href="#">2020</a> ; Omitaomu and Niu <a href="#">2021</a> ; Ozcanli, Yaprakdal, and Baysal <a href="#">2020</a> ; Zhang, Zhang, and Qiu <a href="#">2020</a> )
AI Security and Fault Detection	Security Detection	Detects faults and counters cyber threats, enhancing resilience.	(Abdel-Basset, Moustafa, and Hawash <a href="#">2023</a> ; Ahmad, Wazirali, and Abu-Ain <a href="#">2022</a> ; Bakkar et al. <a href="#">2023</a> ; Rahman, Yan, and Fapi <a href="#">2024</a> ; Rawat et al. <a href="#">2016</a> ; Shi et al. <a href="#">2020</a> ; Syed et al. <a href="#">2021</a> ; Ullah et al. <a href="#">2020</a> )
AI Grid Optimization	Resource Optimization	Manages grid complexity, improving efficiency through reactive power optimization.	(Alfaverh, Denai, and Sun <a href="#">2020</a> ; Nutakki and Mandava <a href="#">2023</a> ; Wasim Khan et al. <a href="#">2021</a> ; Zhang et al. <a href="#">2014</a> )
ML Load and Demand Forecasting	Data Prediction	Accurately predicts short- and long-term energy consumption patterns for grid optimization.	(Ahmad et al. <a href="#">2018</a> ; Al Mamun et al. <a href="#">2020</a> ; Allal et al. <a href="#">2024</a> ; Almalqa and Edwards <a href="#">2017</a> ; Aslam et al. <a href="#">2021</a> ; Choi <a href="#">2019</a> ; Eren and Küçükdemiral <a href="#">2024</a> ; Fallah et al. <a href="#">2018</a> ; Hernandez et al. <a href="#">2013</a> ; Khan et al. <a href="#">2020</a> ; Lu, Hong, and Zhang <a href="#">2018</a> ; Qu, Qian, and Pei <a href="#">2021</a> ; Reddy et al. <a href="#">2023</a> ; Ul Islam, Rasheed, and Ahmed <a href="#">2022</a> ; Wang et al. <a href="#">2019</a> ; Yan et al. <a href="#">2018</a> )

artificial intelligence. The potential of AI in power electronics optimization was highlighted by Zhao et al. (Zhao, Blaabjerg, and Wang [2021](#)). To clarify and ease cross-comparison of methodologies in the smart grid field, we organized prominent methods like MAS into Table 6, which presents eight key methods, their classifications, main functions in the smart grid framework, and representative references.

#### 4.1.6. Cluster 5: load management

Load management has been around since 2015, reaching its publication half-life in 2019, and the continued growth of the field is driven by advances in artificial intelligence and machine learning that optimize energy distribution and balance grid demand. Research

has emphasized AI as an important component in modern load management systems and recent studies have developed machine learning based load forecasting models for smart grids (Al Mamun et al. 2020; Almalaq and Edwards 2017; Aslam et al. 2021; Fallah et al. 2018; Mocanu et al. 2016). As suggested by Almalaq et al. (Almalaq and Edwards 2017) and Fallah et al. (Fallah et al. 2018), the application of AI improves the operational efficiency of smart grids by predicting energy loads and automatically responding to consumption patterns, thus reducing waste and balancing supply and demand. In addition, AI optimizes the operation of microgrids integrated with renewable energy sources. For example, Wang et al. (Wang et al. 2019) introduced a Bi-LSTM-based short-term load forecasting model that improves accuracy, especially in grid automation. Ozcanli et al. (Ozcanli, Yaprakdal, and Baysal 2020) highlighted the ability of AI in maximizing non-linear data that is used for load forecasting, renewable energy prediction and fault detection, driving the more resilient and flexible grid development.

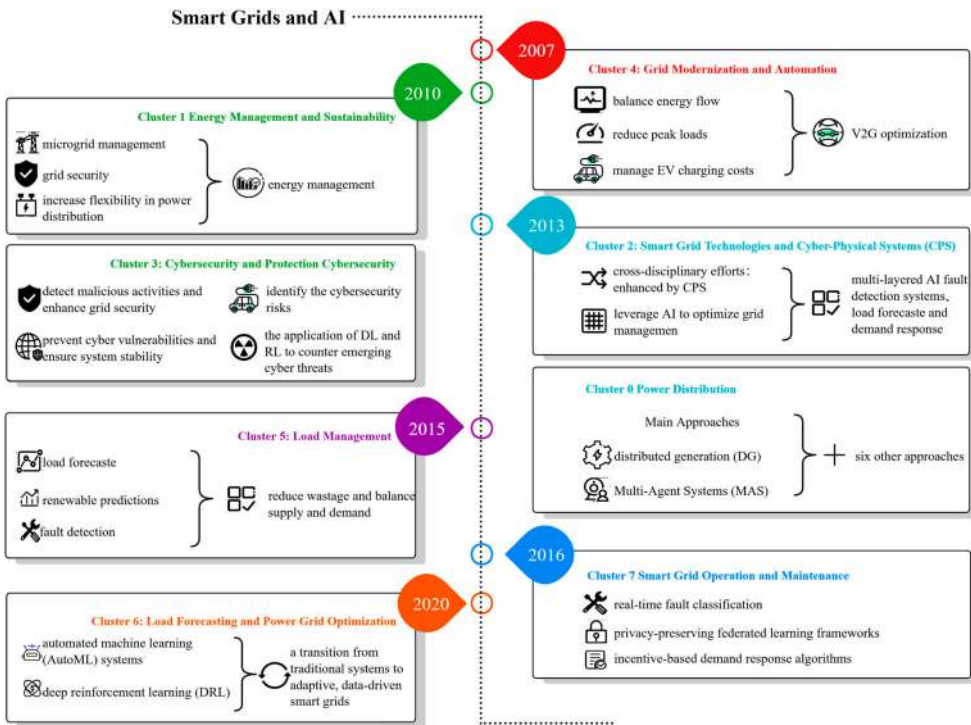
#### **4.1.7. Cluster 7: smart grid operation and maintenance**

Smart grid operations and maintenance has emerged since 2016, focusing on fault prediction, detection and diagnosis to help operators proactively manage potential faults and ensure grid stability. Artificial Intelligence and Machine Learning (ML) are core tools in this field that manage the complex data and operational demands of predictive maintenance and grid optimization (Ahmad et al. 2021; Qu, Qian, and Pei 2021). Russell and Benner (Russell and Benner 2010) proposed an intelligent Distribution Fault Prediction (DFA) algorithm that effectively prevents power outages by diagnosing faults before they escalate, emphasizing the role of AI in preventive fault management. Similarly, Misra et al. (Misra et al. 2013) proposed Learning Automata Power Management (LAPM) system to dynamically allocate power, prevent unauthorized usage and enhance grid stability through real-time optimization.

For fault detection and diagnosis, AI-based models like reinforcement learning (RL) and decision trees offer significant advantages over traditional approaches, as shown by Shi et al. (Shi et al. 2020) and Bakkar et al. (Bakkar et al. 2023), who demonstrated their systems' effectiveness in enhancing grid resilience against equipment failures and cybersecurity threats. Recent studies further reinforce grid resilience through advanced methods such as real-time fault classification, privacy-preserving federated learning frameworks, and incentive-based demand response algorithms, which enhance the smart grid's efficiency and robustness under complex operational conditions (Abdel-Basset, Moustafa, and Hawash 2023; De Santis and Rizzi 2024; Lu and Hong 2019).

#### **4.1.8. Cluster 6: load forecasting and power grid optimization**

Since 2020, Load Forecasting and Power Grid Optimization focuses on grid stability and energy optimization through AI-driven models that predict electricity demand and improve resource allocation. In power grid optimization, AI methods have proven adept at navigating the complexities of smart grids (Khan et al. 2020; Nutakki and Mandava 2023; Zhang et al. 2014). For example, Almalaq et al. (Almalaq and Edwards 2017) and Wang et al. (Wang et al. 2019) investigated the application of automated machine learning (AutoML) systems in optimizing model selection and short-term load forecasting. In addition, AI innovations such as deep reinforcement learning (DRL) and the integration of the Artificial Intelligence of Things (AIoT) have revolutionized decision-making within smart



**Figure 7.** The timeline overview of clusters in smart grids & AI.

grids. Zhang et al. (Zhang, Zhang, and Qiu 2020) illustrated how DRL merges deep learning and reinforcement learning for robust optimization in complex energy scenarios, while Zhang et al. (Zhang and Tao 2021) emphasized AIoT's ability to manage heterogeneous data in real time, fostering intelligent decision-making across distributed energy systems. This increasing reliance on AI is further supported by Ozcanli et al. (Ozcanli, Yaprakdal, and Baysal 2020) and Antonopoulos et al. (Antonopoulos et al. 2020), who demonstrated that deep learning and machine learning models enhance load forecasting, fault detection, and demand response, ultimately improving system flexibility and reliability. These AI-driven approaches mark a significant transition from traditional systems to adaptive, data-driven smart grids, as highlighted by Werbos (Werbos 2011) and Hernandez et al. (Hernandez et al. 2013).

Figure 7 provides an overview of the primary clusters and developments in the integration of smart grids and Artificial Intelligence over time. Each cluster represents a specific focus area, from Cluster 4: Grid Modernization and Automation to Cluster 6: Load Forecasting and Power Grid Optimization, illustrating the chronological evolution and technological advancements in the field.

#### 4.2. Research potential model

In this section, we use a modified Research Potential Evaluation (RPE) model based on the framework developed by Zhou et al. (Zhou et al. 2024) to assess AI's potential in smart grids. Maturity and Recent Attention (RA) are two important markers that are combined

in the RPE model. Using citations, publications, and output recency, RA determines the level of recent interest in a subject of study. Maturity assesses the field's development by looking at the ratio of highly cited papers to total publications. These indicators show different trends, capturing interest intensity and longevity in AI smart grid applications. High RA clusters suggest new or revived focus areas where AI innovations are advancing fast. High Maturity clusters often mean stable research findings and closer-to-implementation applications. When adapted for smart grids, the RPE model offers a holistic view of AI's potential, integrating recent trends and practical maturity. This helps stakeholders gauge AI's current impact and its readiness for real-world use.

To evaluate research potential, we utilized the following formula for RA:

$$\text{Recent Attention} = \frac{\text{TC}}{\text{TP} \times D} \times \frac{1}{R} \quad (1)$$

where TC is total citations, TP is total publications, TC/TP is the average number of citations per publication. D represents the time span over which the publications in a particular research field have occurred. R represents the "half-life of publication", or the time span over which the most recent 50% of publications have been made.

The second key metric, Maturity, is calculated using the ratio of highly cited papers to total publications:

$$\text{Maturity} = \frac{\text{Number of highly cited papers}}{\text{Total number of papers}} \quad (2)$$

Building on the eight thematic clusters identified in the previous section, we compute values for RA and Maturity using Zhou's methodology (Zhou et al. 2024) to derive the RPE of smart grids. These computations, as summarized in Table 7, allow for a detailed assessment of each cluster's research dynamics and potential.

Key indications of research emphasis, RA, and maturity are shown in Table 7 for each of the eight clusters in the area of smart grids & AI. This shows a range of developmental stages and research dynamics. Clusters with lower RA values, such as Cybersecurity and Protection (Cluster 3), Energy Management and Sustainability (Cluster 1), and Power Distribution (Cluster 0), indicate a consistent yet well-established focus. Smart grid Technologies and CPS (Cluster 2) and Grid Modernization and Automation (Cluster 4) stand out as foundational fields, with above-average maturity and an emphasis on practical AI integration.

In contrast, more emergent clusters, including Load Management (Cluster 5), Load Forecasting and Power Grid Optimization (Cluster 6), and smart grid Operation and Maintenance (Cluster 7), exhibit high RA values but lower maturity. This high RA signals active exploration, pointing toward their potential for substantial future development.

#### 4.3. Research potential evaluation

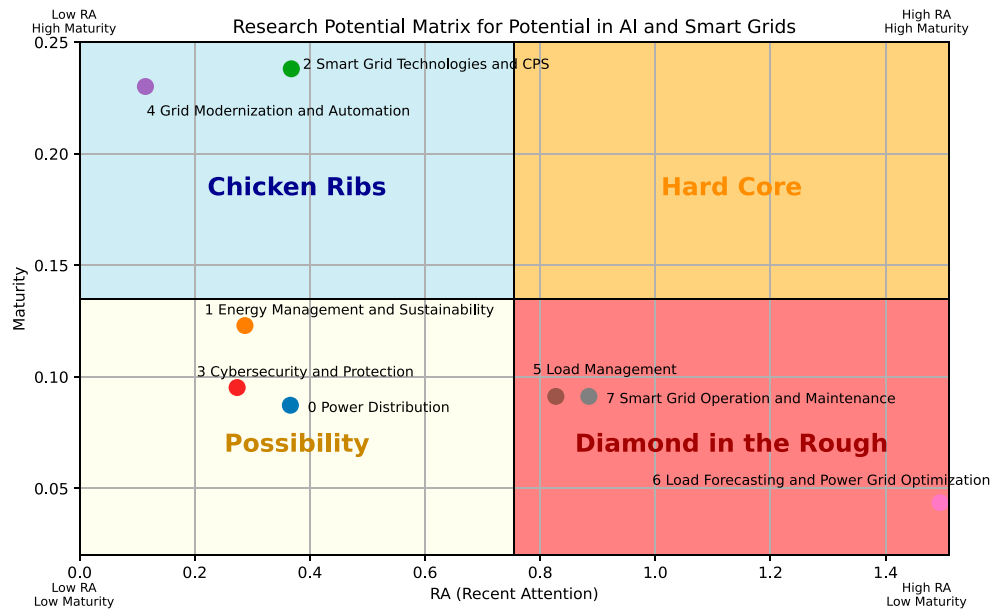
We can classify the eight clusters based on where they fall on the RA and Maturity axes of the Research Potential Matrix for smart grids & AI (see Figure 8). By highlighting which fields are more established and which are still developing, this classification provides information on where future research endeavors may have the most influence.

**Diamond in the Rough (High RA, Low Maturity):** This quadrant represents emerging research fields that have gained significant attention recently but have not yet matured.

**Table 7.** Some indicators of the eight clusters.

Cluster	TC/TP	Start year	End year	Mean year	D	R	NH	RA	Maturity
Cluster 0 Power Distribution	19.15	2013	2024	2019	10.83	4.83	22	0.3661	0.0873
Cluster 1 Energy Management and Sustainability	35.07	2010	2024	2015	13.83	8.83	31	0.2872	0.1230
Cluster 2 Smart Grid Technologies and CPS	23.22	2013	2024	2018	10.83	5.83	60	0.3678	0.2381
Cluster 3 Cybersecurity and Protection	29.63	2010	2024	2016	13.83	7.83	24	0.2736	0.0952
Cluster 4 Grid Modernization and Automation	22.77	2007	2024	2012	16.83	11.83	58	0.1144	0.2302
Cluster 5 Load Management	35.28	2015	2024	2019	8.83	4.83	23	0.8272	0.0913
Cluster 6 Load Forecasting and Power Grid Optimization	16.20	2020	2024	2021	3.83	2.83	11	1.4946	0.0437
Cluster 7 Smart Grid Operation and Maintenance	40.38	2016	2024	2018	7.83	5.83	23	0.8846	0.0913

Note: TC: total citations; TP: total publications; TC/TP: average citations per publication; D: time span of publications; R: half-life of publications; NH: number of highly cited papers; RA: recent attention; Maturity: ratio of highly cited papers to total publications.



**Figure 8.** RPE model of AI in smart grids & AI.

Clusters such as Load Management (Cluster 5), Load Forecasting and Power Grid Optimization (Cluster 6) and Smart Grid Operation and Maintenance (Cluster 7) fall into this category. These areas have high potential for future growth, as their high RA indicates that they are receiving increased attention, but their lower maturity levels indicate that there is still much room for exploration and development. As maturity levels increase, these

clusters are expected to move to the "hard core" quadrant, cementing their position as core, high-impact areas of smart grids and AI research.

Since 2020 and continuing through 2024, load forecasting and grid optimization have been major areas of study. The intricacy of the smart grids has been effectively managed in this context by sophisticated AI techniques including deep learning (Antonopoulos et al. 2020; Ozcanli, Yaprakdal, and Baysal 2020; Zhang, Zhang, and Qiu 2020) and Artificial Intelligence Internet of Things (AIoT) (Khan et al. 2020; Mazhar et al. 2023; Nutakki and Mandava 2023; Zhang et al. 2014; Zhang and Tao 2021). The importance of AI in predictive maintenance and real-time problem detection has also been brought to light by the emphasis on smart grid operations and maintenance. By creating algorithms that can analyze vast volumes of grid operational data, identify anomalies, and provide real-time insights into the grid's health, a number of recent studies have improved this subject (Abdel-Basset, Moustafa, and Hawash 2023; De Santis and Rizzi 2024; Lu and Hong 2019; Misra et al. 2013; Russell and Benner 2010). According to this expanding body of research, AI is changing grid maintenance from a reactive to a proactive mode, eventually making defect detection and load control possible.

**Hard Core (High RA, High Maturity):** The absence of clustering in this quadrant might be caused by several factors. Mature areas could have reached saturation, leading to fewer breakthroughs and a decline in RA. In the Smart Grid domain, traditional aspects like core system design and traditional energy management technologies may have hit research saturation. Such maturity might result in fewer groundbreaking advances, causing stagnation in RA as incremental improvements replace transformative ones. Clusters with high maturity but low attention may reflect stable and highly evolved yet less dynamic applied technologies or methods, thus attracting less academic attention. In contrast, "Load Forecasting and Power Grid Optimization" (Cluster 6) with lower maturity has drawn much attention recently. This interest may arise from its potential to enhance real-time grid performance and handle complex energy demands, making it a focus for innovative AI-driven approaches. Researchers may prioritize it due to its direct application in predictive modeling and optimization within the smart grid domain, where AI and machine learning can bring new efficiencies and improved system resilience.

This quadrant includes clusters such as Energy Management and Sustainability (Cluster 1), Cybersecurity and Protection (Cluster 3), and Power Distribution (Cluster 0). Although these fields are not as active or mature as others, they still hold potential for growth. If attention increases, these fields may shift towards the Diamond in the Rough quadrant, indicating potential future research frontiers. However, these areas have lacked attention in recent years, possibly because the research has reached a stage of incremental progress rather than groundbreaking developments, diverting focus from these more traditional areas. Moreover, the emergence of new technologies like deep learning and artificial intelligence has shifted the focus towards applications in real-time optimization and predictive analytics, which are being more intensively studied within newer research clusters.

**Chicken Ribs (Low RA, High Maturity):** This group includes clusters with high maturity but lower RA, such as Smart Grid Technologies and CPS (Cluster 2) and Grid Modernization and Automation (Cluster 4). This implies that even while tremendous progress has been accomplished, unless these sectors are reenergized by new ideas or innovative approaches, they may no longer provide much promise for ground-breaking innovation.

As foundational fields for smart grids, they have likely reached a point where further incremental progress is less impactful, with diminishing returns on investment. Earlier studies, for example, extensively investigated the role of AI in supporting electric vehicles (EVs) (Dong et al. 2023; Othman et al. 2023; Rigas, Ramchurn, and Bassiliades 2015) and in optimizing distributed energy systems (Arévalo and Jurado 2024; Driesen and Katiraei 2008; Guerrero et al. 2020; Kumar Nunna and Doolla 2013; Tao et al. 2022; Zhang, Gari, and Hmurcik 2014) to modernize and automate grid infrastructure. Now that these technologies are well-integrated, the focus of both academic research and practical applications on these fields has naturally declined. Given their current level of development, shifting research efforts to emerging, high-potential fields may be more strategic than continuing to invest in these mature clusters.

Clusters with lower RA values, such as Cybersecurity and Protection (Cluster 3), Energy Management and Sustainability (Cluster 1), and Power Distribution (Cluster 0), indicate a consistent yet well-established focus. Smart Grid Technologies and CPS (Cluster 2) and Grid Modernization and Automation (Cluster 4) stand out as foundational fields, with above-average maturity and an emphasis on practical AI integration. In contrast, the clusters with high recent attention but low maturity, including Load Management (Cluster 5), Load Forecasting and Power Grid Optimization (Cluster 6), and Smart Grid Operation and Maintenance (Cluster 7), reflect the forefront of AI-enabled smart grid transformation and represent emerging directions with considerable future development potential.

For Cluster 5, future work is expected to focus on real-time, context-aware load control using reinforcement learning and user behavior modeling, with an emphasis on multi-agent coordination for decentralized demand-side response. For example, during extreme weather events such as heatwaves or cold spells, electricity demand surges unpredictably across residential zones. A critical research question could be: How can multi-agent systems dynamically coordinate user-side appliances (e.g. air conditioners, electric vehicles) to flatten peak loads without compromising comfort? Research may explore adaptive pricing mechanisms, decentralized decision models, and simulations using real-world smart meter datasets. Cluster 6 is likely to evolve toward hybrid AI models that integrate diverse data sources (e.g. weather, user patterns, sensors) to improve forecasting accuracy and support co-optimized scheduling frameworks. Real-time feedback from AIoT will play a key role in enabling autonomous energy systems. Cluster 7 may advance through predictive maintenance, self-healing infrastructures, and federated learning for decentralized diagnostics. Interpretable AI and digital twin integration will be central to enhancing operational resilience and trust.

#### **4.4. Integration of emerging technologies and AI in smart grids**

The integration of artificial intelligence (AI) with emerging technologies – such as sixth-generation (6G) wireless communication, blockchain, and the Artificial Intelligence of Things (AIoT) – is becoming a key trend in smart grid innovation. These technologies enhance AI's effectiveness by improving communication latency, data transparency, and decentralized decision-making. Bibliometric analysis shows that out of 1,272 papers included in this study, 112 (8.8%) discuss blockchain, 30 mention 6G, and 9 refer to AIoT or edge intelligence – indicating rising research interest in the past five years.

Several recent studies show that combining 6G with distributed AI significantly improves performance in load forecasting and system responsiveness. For example, Yap et al. (Yap, Chin, and Klemenš 2022) demonstrated that 6G-enabled smart grid platforms could reduce communication delays by up to 90%, and Husnood et al. (Husnood et al. 2023) reported improved prediction accuracy in federated learning environments. Meanwhile, many studies highlight blockchain's role in decentralized energy trading, demand response, and fraud prevention. For example, Aljarrah et al. (Aljarrah 2024) integrated AI-based forecasting into blockchain smart contracts, leading to more efficient energy bidding, while Hua et al. (Hua et al. 2022) showed that blockchain-AI frameworks improved trust and reduced conflicts in microgrid energy markets. In the case of AIoT, scholars focus on how such applications enhance fault detection, reduce downtime, and optimize distributed energy control. For example, Ukoba et al. (Ukoba et al. 2024) reported energy savings through embedded AI in solar systems, and Awaisi et al. (Awaisi, Ye, and Sampalli 2024) found that AIoT-based monitoring significantly reduced maintenance delays in substations.

But edge devices still face constraints in running large AI models efficiently (Gooi, Wang, and Tang 2023), and blockchain-based systems often suffer from scalability and consensus delays (Kaur et al. 2021). On the 6G side, many current prototypes lack standardized energy communication protocols (Chowdhury et al. 2020), while cross-platform integration continues to pose interoperability and cybersecurity concerns (Segun-Falade et al. 2024). These issues underscore that while the potential is enormous, technical and infrastructural maturity still lags behind. Much of the work ahead lies in advancing algorithms and in solving practical bottlenecks that currently limit the widespread adoption of these innovations in power systems.

## 5. Conclusions and discussions

### 5.1. Conclusions

By employing a dual approach that integrates bibliometric analysis with qualitative content review, this study offers an in-depth examination of AI's role in smart grid research, analyzing 1,272 articles from the Web of Science database spanning 2005 to September 2024.

Firstly, this study takes a macro approach to analyzing the literature, using CiteSpace and VOSviewer to examine trends in research output, including the rapid increase in publications, influential journals, collaborations between key institutions and countries, and prolific authors. Our results point to a maturing area since there has been a consistent increase in smart grid articles including AI, especially after 2015. This analysis also highlights the contribution of prolific journals like *Energies* and *IEEE Access*, which facilitate the rapid dissemination of research results. In addition, we assessed prolific institutions and authors, noting the large number of collaborations led by major contributors from countries like China, India and Spain.

Second, using keyword clustering analysis, we give a thorough overview of each cluster by means of in-depth content analysis, explaining the underlying circumstances, approaches, and developing areas of interest. For example, we talk about how machine learning algorithms are increasingly being used in resilience measures, real-time demand

response, and predictive modeling, and how these developments enhance operational reliability and energy efficiency.

In addition, we assess the research potential and maturity of each identified cluster based on the Research Potential Evaluation (RPE) proposed by Zhou et al. (Zhou et al. 2024). The RPE model shows that Load Management (Cluster 5), Load Forecasting and Power Grid Optimization (Cluster 6) and Smart Grid Operation and Maintenance (Cluster 7) were positioned in the "Diamond in the Rough" quadrant, where high RA and low maturity indicate emerging fields with considerable room for development.

## **5.2. Discussions of general trends in the future**

Based on the thematic clustering in Section 4.1 and the cluster-specific discussion of research gaps in Section 4.3, this section synthesizes higher-level insights and proposes several practical directions for future research on AI applications in smart grids. These directions aim to offer more targeted and actionable guidance. Researchers can refer to the following cluster-driven trends to identify opportunities in algorithm design, system-level deployment, and interdisciplinary integration.

First, while our dataset covers publications up to September 2024, our analysis shows that the integration of AI into smart grid infrastructure is evolving rapidly. Future research should focus on adapting large foundation models, such as Transformers and large language models (LLMs), to grid-specific tasks including fault detection, energy dispatch, and event prediction. It is also important to explore how these models can be embedded into digital twin frameworks for real-time simulation and decision support under uncertain conditions (Antonesi et al. 2025). Furthermore, generative models such as GANs could be used to create synthetic fault scenarios, enrich scarce training data, and test model robustness against cyber-physical disturbances (Efatinasab et al. 2025).

Second, Load Management (Cluster 5 of Section 4.1) holds great potential in this area. Looking ahead, exploration should focus on reinforcement learning-based control strategies that respond dynamically to shifting demand, renewable generation variability, and price fluctuations. Belief-based multi-agent reinforcement learning has been applied to coordinate EV charging in residential communities, demonstrating its potential in decentralized control settings (Joshi, Tipaldi, and Glielmo 2025). Building on this, researchers could investigate how to use multi-agent reinforcement learning to enable coordination among residential devices, EVs, and battery storage systems without centralized control. Another promising direction is to integrate demand response mechanisms with user behavior prediction models to optimize control actions at both household and system levels. Notably, these approaches should also consider safety constraints and fairness to ensure practical deployment in heterogeneous energy environments.

Third, in the area of Load Forecasting and Power Grid Optimization (Cluster 6 of Section 4.1), improving short-term forecasting accuracy remains critical for operational planning. Recent studies have already demonstrated the effectiveness of advanced hybrid models for electricity load forecasting, such as the combination of Transformer architectures with multi-objective optimization algorithms to achieve both deterministic and interval forecasting performance (Du et al. 2025). At the same time, research on integrated energy systems has begun to address source-load forecasting uncertainty in multi-objective co-optimization frameworks, reflecting a growing emphasis on jointly

improving prediction and dispatch strategies under real-world variability (Su et al. 2025). Future work could further explore hybrid AI architectures that incorporate heterogeneous input features (e.g. weather, economic indicators, sensor data) and use AutoML techniques to support scalable deployment across different regions. These forecasting-optimization pipelines should also be evaluated under realistic operational constraints such as ramp rates, reserve capacity, and battery degradation, to ensure robustness in practical applications.

Fourth, Smart Grid Operation and Maintenance (Cluster 7 of Section 4.1) is another emerging application area for AI. Recent studies have demonstrated the feasibility of achieving privacy-preserving fault detection through collaborative anomaly detection frameworks, which enable distributed learning across multiple entities without exposing sensitive data (Zeng et al. 2025). Accordingly, future research could explore predictive maintenance strategies that integrate local diagnostic data from substations or transformers with globally trained models collaboratively developed across different utility providers. Such approaches can improve fault prediction accuracy while maintaining strict data privacy. Moreover, combining these techniques with digital twin systems and explainable AI could assist system operators in making transparent and real-time decisions during outages or equipment failures.

In addition to technical advancements, the long-term effectiveness and responsible deployment of AI in smart grids also depend on resolving several foundational, cross-cutting issues. First, future research should address the urgent need for high-quality, standardized, and interoperable datasets, which are essential for improving model accuracy, enabling replicability, and supporting large-scale deployment. Second, as AI models increasingly rely on fine-grained, user-level consumption data, attention must be paid to privacy protection and data ownership. Establishing transparent, consent-based governance frameworks and evolving regulatory mechanisms will be key to building trust in AI-enabled grid operations.

Beyond technical and regulatory aspects, researchers should adopt a more interdisciplinary perspective that integrates insights from economics, social sciences, and environmental studies (Huang et al. 2024). Economically, AI offers opportunities to reduce operational costs, improve asset utilization, and enhance market responsiveness through predictive analytics. Socially, important questions remain regarding user acceptance, fairness, and explainability of algorithmic decisions in energy management. Environmentally, AI-driven optimization can accelerate the integration of renewable energy sources and promote cleaner, more resilient grid infrastructures. Addressing these interconnected dimensions will be critical to ensuring that AI-enhanced smart grid systems are not only efficient but also sustainable, inclusive, and ethically aligned.

## **Disclosure statement**

No potential conflict of interest was reported by the author(s).

## **Data availability statement**

Data supporting reported results can be found in the article. Additional datasets generated or analyzed during the study are available from the corresponding author on reasonable request.

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## References

- Abdel-Basset, M., N. Moustafa, and H. Hawash. 2023. "Privacy-preserved Generative Network for Trustworthy Anomaly Detection in Smart Grids: A Federated Semisupervised Approach." *IEEE Transactions on Industrial Informatics* 19 (1): 995–1005. <https://doi.org/10.1109/TII.2022.3165869>.
- Ahmad, T., H. X. Chen, R. G. Huang, Guo Yabin, Jiangyu Wang, Jan Shair, Hafiz Muhammad Azeem Akram, Syed Agha Hassnain Mohsan, and Muhammad Kazim. 2018. "Supervised based Machine Learning Models for Short, Medium and Long-term Energy Prediction in Distinct Building Environment." *Energy* 158:17–32. <https://doi.org/10.1016/j.energy.2018.05.169>.
- Ahmad, T., R. Madonski, D. D. Zhang, Chao Huang, and Asad Mujeeb. 2022. "Data-driven Probabilistic Machine Learning in Sustainable Smart Energy/Smart Energy Systems: Key Developments, Challenges, and Future Research Opportunities in the Context of Smart Grid Paradigm." *Renewable and Sustainable Energy Reviews* 160:112128. <https://doi.org/10.1016/j.rser.2022.112128>.
- Ahmad, R., R. Wazirali, and T. Abu-Ain. 2022. "Machine Learning for Wireless Sensor Networks Security: An Overview of Challenges and Issues." *Sensors* 22 (13): 4730. <https://doi.org/10.3390/s22134730>.
- Ahmad, T., D. D. Zhang, C. Huang, Hongcai Zhang, Ningyi Dai, Yonghua Song, and Huanxin Chen. 2021. "Artificial Intelligence in Sustainable Energy Industry: Status Quo, Challenges and Opportunities." *Journal of Cleaner Production* 289:125834. <https://doi.org/10.1016/j.jclepro.2021.125834>.
- Al-Agtash, S. 2013. "Electricity Agents in Smart Grid Markets." *Computers in Industry* 64 (3): 235–241. <https://doi.org/10.1016/j.compind.2012.10.009>.
- Alfaverh, F., M. Denaï, and Y. C. Sun. 2020. "Demand Response Strategy Based on Reinforcement Learning and Fuzzy Reasoning for Home Energy Management." *Ieee Access* 8:39310–39321. <https://doi.org/10.1109/ACCESS.2020.2974286>.
- Alguliyev, R., Y. Imamverdiyev, and L. Sukhostat. 2018. "Cyber-physical Systems and Their Security Issues." *Computers in Industry* 100:212–223. <https://doi.org/10.1016/j.compind.2018.04.017>.
- Ali, S. S., and B. J. Choi. 2020. "State-of-the-art Artificial Intelligence Techniques for Distributed Smart Grids: A Review." *Electronics* 9 (6): 1030.
- Aljarrah, E. 2024. "AI-based Model for Prediction of Power Consumption in Smart Grid-smart way towards Smart City Using Blockchain Technology." *Intelligent Systems with Applications* 24:200440. <https://doi.org/10.1016/j.iswa.2024.200440>.
- Allal, Z., H. N. Noura, O. Salman, and K. Chahine. 2024. "Leveraging the Power of Machine Learning and Data Balancing Techniques to Evaluate Stability in Smart Grids." *Engineering Applications of Artificial Intelligence* 133:108304. <https://doi.org/10.1016/j.engappai.2024.108304>.
- Almalaq, A., and G. Edwards. 2017. A review of deep learning methods applied on load forecasting. 2017 16th IEEE International Conference on Machine Learning and Applications (Icmla), 511–516.
- Al Mamun, A., M. Sohel, N. Mohammad, Md. Samiul Haque Sunny, Debopriya Roy Dipta, and Eklas Hossain. 2020. "A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models." *Ieee Access* 8:134911–134939. <https://doi.org/10.1109/ACCESS.2020.3010702>.
- Almudayni, Z., B. Soh, H. Samra, and A. Li. 2025. "Energy Inefficiency in IoT Networks: Causes, Impact, and a Strategic Framework for Sustainable Optimisation." *Electronics* 14 (1): 159. <https://doi.org/10.3390/electronics14010159>.

- Antonesi, G., T. Cioara, I. Anghel, Vasilis Michalakopoulos, Elissaios Sarmas, and Liana Todorean. 2025. From Transformers to Large Language Models: A Systematic Review of AI Applications in the Energy Sector Towards Agentic Digital Twins. arXiv preprint arXiv:250606359.
- Antonopoulos, I., V. Robu, B. Couraud, Desen Kirli, Sonam Norbu, Aristides Kiprakis, David Flynn, Sergio Elizondo-Gonzalez, and Steve Wattam. 2020. "Artificial Intelligence and Machine Learning Approaches to Energy Demand-side Response: A Systematic Review." *Renewable and Sustainable Energy Reviews* 130:109899. <https://doi.org/10.1016/j.rser.2020.109899>.
- Arévalo, P., and F. Jurado. 2024. "Impact of Artificial Intelligence on the Planning and Operation of Distributed Energy Systems in Smart Grids." *Energies* 17 (17): 4501. <https://doi.org/10.3390/en17174501>.
- Aslam, S., H. Herodotou, S. M. Mohsin, N. Javaid, N. Ashraf, and S. Aslam. 2021. "A Survey on Deep Learning Methods for Power Load and Renewable Energy Forecasting in Smart Microgrids." *Renewable and Sustainable Energy Reviews* 144. <https://doi.org/10.1016/j.rser.2021.110992>.
- Awaisi, K. S., Q. Ye, and S. Sampalli. 2024. "A Survey of Industrial AIoT: Opportunities, Challenges, and Directions." *IEEE Access* 12: 51. <https://doi.org/10.1109/ACCESS.2024.3426279>.
- Babalola, A. A., R. Belkacemi, and S. Zarrabian. 2018. "Real-time Cascading Failures Prevention for Multiple Contingencies in Smart Grids through a Multi-agent System." *IEEE Transactions on Smart Grid* 9 (1): 373–385. <https://doi.org/10.1109/TSG.2016.2553146>.
- Bakkar, M., S. Bogarra, F. Córcoles, Javier Iglesias, and Wael Al Hanaineh. 2023. "Multi-layer Smart Fault Protection for Secure Smart Grids." *IEEE Transactions on Smart Grid* 14 (4): 3125–3135. <https://doi.org/10.1109/TSG.2022.3229848>.
- Barja-Martinez, S., M. Aragües-Peñalba, I. Munné-Collado, Pau Lloret-Gallego, Eduard Bullich-Massagué, and Roberto Villafafila-Robles. 2021. "Artificial Intelligence Techniques for Enabling Big Data Services in Distribution Networks: A Review." *Renewable and Sustainable Energy Reviews* 150:111459. <https://doi.org/10.1016/j.rser.2021.111459>.
- Basso, G., M. Cossentino, V. Hilaire, Fabrice Lauri, Sebastian Rodriguez, and Valeria Seidita. 2016. "Engineering Multi-agent Systems Using Feedback Loops and Holarchies." *Engineering Applications of Artificial Intelligence* 55:14–25. <https://doi.org/10.1016/j.engappai.2016.05.009>.
- Ben Meskina, S., N. Doggaz, M. Khalgui, and Zhiwu Li. 2017. "Multiagent Framework for Smart Grids Recovery." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 47 (7): 1284–1300. <https://doi.org/10.1109/TSMC.2016.2573824>.
- Ben Meskina, S., N. Doggaz, M. Khalgui, and Zhiwu Li. 2018. "Reconfiguration-based Methodology for Improving Recovery Performance of Faults in Smart Grids." *Information Sciences* 454:73–95. <https://doi.org/10.1016/j.ins.2018.04.010>.
- Castillo-Cagigal, M., E. Matallanas, F. Monasterio-Huelin, Estefania Caamano Martin, and Alvaro Gutierrez. 2016. "Multifrequency-coupled Oscillators for Distributed Multiagent Coordination." *IEEE Transactions on Industrial Informatics* 12 (3): 941–951. <https://doi.org/10.1109/TII.2016.2537759>.
- Chang, X. Y., Y. L. Xu, and H. B. Sun. 2022. "A Distributed Online Learning Approach for Energy Management with Communication Noises." *IEEE Transactions on Sustainable Energy* 13 (1): 551–566. <https://doi.org/10.1109/TSTE.2021.3119657>.
- Chen, C. M. 2006. "CiteSpace II: Detecting and Visualizing Emerging Trends and Transient Patterns in Scientific Literature." *Journal of the American Society for Information Science and Technology* 57 (3): 359–377. <https://doi.org/10.1002/asi.20317>.
- Choi JS. 2019. "A Hierarchical Distributed Energy Management Agent Framework for Smart Homes, Grids, and Cities." *IEEE Communications Magazine* 57 (7): 113–119. <https://doi.org/10.1109/MCOM.2019.1900073>.
- Choi, N., and H. Kim. 2025. "Technological Convergence of Blockchain and Artificial Intelligence: A Review and Challenges." *Electronics* 14 (1): 84. <https://doi.org/10.3390/electronics14010084>.
- Chowdhury, M. Z., M. Shahjalal, S. Ahmed, and Yeong Min Jang. 2020. "6G Wireless Communication Systems: Applications, Requirements, Technologies, Challenges, and Research Directions." *IEEE Open Journal of the Communications Society* 1:957–975. <https://doi.org/10.1109/OJCOMS.2020.3010270>.

- Cintuglu, M. H., O. A. Mohammed, K. Akkaya, and A. Selcuk Uluagac. 2017. "A Survey on Smart Grid Cyber-physical System Testbeds." *IEEE Communications Surveys & Tutorials* 19 (1): 446–464. <https://doi.org/10.1109/COMST.2016.2627399>.
- Colson, C. M., and M. H. Nehrir. 2013. "Comprehensive Real-time Microgrid Power Management and Control with Distributed Agents." *IEEE Transactions on Smart Grid* 4 (1): 617–627. <https://doi.org/10.1109/TSG.2012.2236368>.
- Derler, P., E. A. Lee, and A. S. Vincentelli. 2012. "Modeling Cyber-physical Systems." *Proceedings of the IEEE* 100 (1): 13–28. <https://doi.org/10.1109/JPROC.2011.2160929>.
- De Santis, E., and A. Rizzi. 2024. "Modeling Failures in Smart Grids by a Bilinear Logistic Regression Approach." *Neural Networks* 174:106245. <https://doi.org/10.1016/j.neunet.2024.106245>.
- Ding, J. G., A. Qammar, Z. M. Zhang, A. Karim, and H. Ning. 2022. "Cyber Threats to Smart Grids: Review, Taxonomy, Potential Solutions, and Future Directions." *Energies* 15 (18): 1699. <https://doi.org/10.3390/en15186799>.
- Dong, J. W., A. Yassine, A. Armitage, and M. Shamim Hossain. 2023. "Multi-agent Reinforcement Learning for Intelligent V2G Integration in Future Transportation Systems." *IEEE Transactions on Intelligent Transportation Systems* 24 (12): 15974–15983. <https://doi.org/10.1109/TITS.2023.3284756>.
- Driesen, J., and F. Katiraei. 2008. "Design for Distributed Energy Resources." *IEEE Power and Energy Magazine* 6 (3): 30–39. <https://doi.org/10.1109/MPE.2008.918703>.
- Du, P., Y. Ye, H. Wu, and Jianzhou Wang. 2025. "Study on Deterministic and Interval Forecasting of Electricity Load Based on Multi-objective Whale Optimization Algorithm and Transformer Model." *Expert Systems with Applications* 268:126361. <https://doi.org/10.1016/j.eswa.2024.126361>.
- Efatinasab, E., A. Brighente, D. Donadel, M. Conti, and M. Rampazzo. 2025. Towards Robust Stability Prediction in Smart Grids: GAN-based Approach under Data Constraints and Adversarial Challenges. arXiv preprint arXiv:250116490.
- Eren, Y., and I. Küçükdemiral. 2024. "A Comprehensive Review on Deep Learning Approaches for Short-Term Load Forecasting." *Renewable and Sustainable Energy Reviews* 189(Jan. Pt.B): 1.1–1.22. <https://doi.org/10.1016/j.rser.2023.114031>.
- Fahimnia, B., J. Sarkis, and H. Davarzani. 2015. "Green Supply Chain Management: A Review and Bibliometric Analysis." *International Journal of Production Economics* 162:101–114. <https://doi.org/10.1016/j.ijpe.2015.01.003>.
- Fallah, S. N., R. C. Deo, M. Shojafar, Mauro Conti, and Shahaboddin Shamshirband. 2018. "Computational Intelligence Approaches for Energy Load Forecasting in Smart Energy Management Grids: State of the art, Future Challenges, and Research Directions." *Energies* 11 (3): 596. <https://doi.org/10.3390/en11030596>.
- Garfield, E. 1979. "Is Citation Analysis a Legitimate Evaluation Tool?" *Scientometrics* 1 (4): 359–375. <https://doi.org/10.1007/BF02019306>.
- Gooi, H. B., T. Wang, and Y. Tang. 2023. "Edge Intelligence for Smart Grid: A Survey on Application Potentials." *Csee Journal of Power Energy* 9 (5): 1623–1640. <https://doi.org/10.17775/CSEEJPES.2022.02210>.
- Guerrero, J., D. Gebbran, S. Mhanna, A. C. Chapman, and G. Verbič. 2020. "Towards a Transactive Energy System for Integration of Distributed Energy Resources: Home Energy Management, Distributed Optimal Power Flow, and Peer-to-peer Energy Trading." *Renewable and Sustainable Energy Reviews* 132. <https://doi.org/10.1016/j.rser.2020.110000>.
- Guru, D., S. Perumal, and V. Varadarajan. 2021. "Approaches towards Blockchain Innovation: A Survey and Future Directions." *Electronics* 10 (10): 1219. <https://doi.org/10.3390/electronics10101219>.
- Habibidoost, M., S. Mohammad, and T. Bathaee. 2018. "A Self-supporting Approach to EV Agent Participation in Smart Grid." *International Journal of Electrical Power & Energy Systems* 99:394–403. <https://doi.org/10.1016/j.ijepes.2018.01.003>.
- Hernandez, L., C. Baladrón, J. M. Aguiar, Belén Carro, Antonio Sanchez-Esguevillas, and Jaime Lloret. 2013. "Short-term Load Forecasting for Microgrids Based on Artificial Neural Networks." *Energies* 6 (3): 1385–1408. <https://doi.org/10.3390/en6031385>.

- Heydt, G. T. 2010. "The Next Generation of Power Distribution Systems." *IEEE Transactions on Smart Grid* 1 (3): 225–235. <https://doi.org/10.1109/TSG.2010.2080328>.
- Hua, W., Y. Chen, M. Qadrdan, Jing Jiang, Hongjian Sun, and Jianzhong Wu. 2022. "Applications of Blockchain and Artificial Intelligence Technologies for Enabling Prosumers in Smart Grids: A Review." *Renewable and Sustainable Energy Reviews* 161:112308. <https://doi.org/10.1016/j.rser.2022.112308>.
- Huang, Y., M. R. Qader, J. Zhou, and X. Zhang. 2024. Prediction and Path Planning Framework of X City's Carbon Emissions Based on the Long Short-Term Memory Network Model." *Polish Journal of Environmental Studies*. <https://doi.org/10.15244/pjoes/199609>.
- Husnoo, M. A., A. Anwar, N. Hosseinzadeh, Shama Naz Islam, Abdun Naser Mahmood, and Robin Doss. 2023. "A Secure Federated Learning Framework for Residential Short-Term Load Forecasting." *IEEE Transactions on Smart Grid* 15 (2): 2044–2055. <https://doi.org/10.1109/TSG.2023.3292382>.
- Jiang, Y. J., J. Zhou, Z. Li, and Yankai Zhu. 2024. "Total Quality Management & Business Excellence: A 33-Year Overview Using Bibliometric and Content Analysis." *Total Quality Management & Business Excellence* 35 (5-6): 631–669. <https://doi.org/10.1080/14783363.2024.2328252>.
- Joshi, A., M. Tipaldi, and L. Glielmo. 2025. "A Belief-Based Multi-agent Reinforcement Learning Approach for Electric Vehicle Coordination in a Residential Community." *Sustainable Energy Grids and Networks* 43. <https://doi.org/10.1016/j.segan.2025.101790>.
- Kakran, S., and S. Chanana. 2018. "Smart Operations of Smart Grids Integrated with Distributed Generation: A Review." *Renewable and Sustainable Energy Reviews* 81:524–535. <https://doi.org/10.1016/j.rser.2017.07.045>.
- Kaur, M., M. Z. Khan, S. Gupta, Abdulfattah Noorwali, Chinmay Chakraborty, and Subhendu Kumar Pani. 2021. "MBCP: Performance Analysis of Large Scale Mainstream Blockchain Consensus Protocols." *IEEE Access* 9:80931–80944. <https://doi.org/10.1109/ACCESS.2021.3085187>.
- Khan, P. W., Y. C. Byun, S. J. Lee, D. H. Kang, J. Y. Kang, and H. S. Park. 2020. "Machine Learning-Based Approach to Predict Energy Consumption of Renewable and Nonrenewable Power Sources." *Energies* 13 (18): 1–16. <https://doi.org/10.3390/en13184870>.
- Khan, A. A., A. A. Laghari, M. Rashid, H. Li, A. R. Javed, and T. R. Gadekallu. 2023. "Artificial Intelligence and Blockchain Technology for Secure Smart Grid and Power Distribution Automation: A State-of-the-art Review." *Sustainable Energy Technologies and Assessments* 57: 103282. <https://doi.org/10.1016/j.seta.2023.103282>.
- Kilki, O., A. Kangasrääsio, R. Nikkilä, A. Alahäivälä, and I. Seilonen. 2014. "Agent-based Modeling and Simulation of a Smart Grid: A Case Study of Communication Effects on Frequency Control." *Engineering Applications of Artificial Intelligence* 33:91–98. <https://doi.org/10.1016/j.engappai.2014.04.007>.
- Kotsiopoulos, T., P. Sarigiannidis, D. Ioannidis, and Dimitrios Tzovaras. 2021. "Machine Learning and Deep Learning in Smart Manufacturing: The Smart Grid Paradigm." *Computer Science Review* 40:100341. <https://doi.org/10.1016/j.cosrev.2020.100341>.
- Kumar, N. M., A. A. Chand, M. Malvoni, K. A. Prasad, K. A. Mamun, F. R. Islam, and S. S. Chopra. 2020. "Distributed Energy Resources and the Application of AI, Iot, and Blockchain in Smart Grids." *Energies* 13 (21): 5739. <https://doi.org/10.3390/en13215739>.
- Kumar Nunna, H. S. V. S., and Suryanarayana Doolla. 2013. "Multiagent-based Distributed-Energy-Resource Management for Intelligent Microgrids." *IEEE Transactions on Industrial Electronics* 60 (4): 1678–1687. <https://doi.org/10.1109/TIE.2012.2193857>.
- Li, H. S., A. Dimitrovski, J. B. Song, Zhu Han, and Lijun Qian. 2014. "Communication Infrastructure Design in Cyber Physical Systems with Applications in Smart Grids: A Hybrid System Framework." *IEEE Communications Surveys & Tutorials* 16 (3): 1689–1708. <https://doi.org/10.1109/SURV.2014.052914.00130>.
- Liu, Y., Y. Peng, B. L. Wang, Sirui Yao, and Zihe Liu. 2017. "Review on Cyber-physical Systems." *IEEE/CAA Journal of Automatica Sinica* 4 (1): 27–40. <https://doi.org/10.1109/JAS.2017.7510349>.
- Liu, J., X. Xu, L. Wang, X. Liu, Y. Song, and X. Song. 2025. "Adaptive Weight Adjustment Technology for Reinforcement Learning Reward Indicators Based on the new-type Power System." *International Journal of General Systems* 2025: 1–23. <https://doi.org/10.1080/03081079.2025.2455733>.

- Lu, R. Z., and S. H. Hong. 2019. "Incentive-based Demand Response for Smart Grid with Reinforcement Learning and Deep Neural Network." *Applied Energy* 236:937–949. <https://doi.org/10.1016/j.apenergy.2018.12.061>.
- Lu, R. Z., S. H. Hong, and X. F. Zhang. 2018. "A Dynamic Pricing Demand Response Algorithm for Smart Grid: Reinforcement Learning Approach." *Applied Energy* 220:220–230. <https://doi.org/10.1016/j.apenergy.2018.03.072>.
- Ly, S., Y. Qin, W. Gan, Z. Xu, and L. Shi. 2024. "A Systematic Literature Review of Vehicle-to-Everything in Communication, Computation and Service Scenarios." *International Journal of General Systems* 53(7-8): 1042–1072. <https://doi.org/10.1080/03081079.2024.2345876>.
- Massaoudi, M., H. Abu-Rub, S. S. Refaat, Ines Chihi, and Fakhreddine S. Oueslati. 2021. "Deep Learning in Smart Grid Technology: A Review of Recent Advancements and Future Prospects." *Ieee Access* 9:54558–54578. <https://doi.org/10.1109/ACCESS.2021.3071269>.
- Mazhar, T., H. M. Irfan, I. Haq, I. Ullah, M. Ashraf, T. A. Shloul, Y.Y. Ghadi, Imran, and D. H.Elkamchouchi. 2023. "Analysis of Challenges and Solutions of IoT in Smart Grids Using AI and Machine Learning Techniques: A Review." *Electronics-Switz* 12 (1): 242. <https://doi.org/10.3390/electronics12010242>.
- Merabet, G. H., M. Essaaidi, H. Talei, M. R. Abid, N. Khalil, M. Madkour, and D. Benhaddou. 2014. "Applications of Multi-agent Systems in Smart Grids: A Survey." *International Conference on Multimedia Computing and Systems (ICMCS)*, 1088–1094.
- Mishra, M., J. Nayak, B. Naik, and Ajith Abraham. 2020. "Deep Learning in Electrical Utility Industry: A Comprehensive Review of a Decade of Research." *Engineering Applications of Artificial Intelligence* 96:104000. <https://doi.org/10.1016/j.engappai.2020.104000>.
- Misra, S., P. V. Krishna, V. Saritha, and M. S. Obaidat. 2013. "Learning Automata as a Utility for Power Management in Smart Grids." *IEEE Communications Magazine* 51 (1): 98–104. <https://doi.org/10.1109/MCOM.2013.6400445>.
- Mo, Y. L., T. H. J. Kim, K. Brancik, D. Dickinson, Heejo Lee, A. Perrig, and B. Sinopoli. 2012. "Cyber-physical Security of a Smart Grid Infrastructure." *Proceedings of the IEEE* 100 (1): 195–209. <https://doi.org/10.1109/JPROC.2011.2161428>.
- Mocanu, E., P. H. Nguyen, M. Gibescu, and W. L. Kling. 2016. "Deep Learning for Estimating Building Energy Consumption." *Sustainable Energy* 6 (05): 91–99. <https://doi.org/10.12677/SE.2016.65010>.
- Nunna, H. S. V. S. K., and S. Doolla. 2012. "Demand Response in Smart Distribution System with Multiple Microgrids." *IEEE Transactions on Smart Grid* 3 (4): 1641–1649. <https://doi.org/10.1109/TSG.2012.2208658>.
- Nutakki, M., and S. Mandava. 2023. "Review on Optimization Techniques and Role of Artificial Intelligence in Home Energy Management Systems." *Engineering Applications of Artificial Intelligence* 119:105721. <https://doi.org/10.1016/j.engappai.2022.105721>.
- Omitaomu, O. A., and H. R. Niu. 2021. "Artificial Intelligence Techniques in Smart Grid: A Survey." *Smart Cities* 4 (2): 548–568. <https://doi.org/10.3390/smartcities4020029>.
- Othman, A., G. Kaddoum, J. V. C. Evangelista, Minh Au, and Basile L. Agba. 2023. "Digital Twinning in Smart Grid Networks: Interplay, Resource Allocation and Use Cases." *IEEE Communications Magazine* 61 (11): 120–126. <https://doi.org/10.1109/MCOM.001.2200823>.
- Ozcanli, A. K., F. Yaprakdal, and M. Baysal. 2020. "Deep Learning Methods and Applications for Electrical Power Systems: A Comprehensive Review." *International Journal of Energy Research* 44 (9): 7136–7157. <https://doi.org/10.1002/er.5331>.
- Panda, D. K., and S. Das. 2021. "Smart Grid Architecture Model for Control, Optimization and Data Analytics of Future Power Networks with More Renewable Energy." *Journal of Cleaner Production* 301:126877. <https://doi.org/10.1016/j.jclepro.2021.126877>.
- Pedrin, M., and L. M. Ferri. 2019. "Stakeholder Management: A Systematic Literature Review." *Corporate Governance: The International Journal of Business in Society* 19 (1): 44–59. <https://doi.org/10.1108/CG-08-2017-0172>.
- Perkonig, F., D. Brujic, and M. Ristic. 2015. "Platform for Multiagent Application Development Incorporating Accurate Communications Modeling." *IEEE Transactions on Industrial Informatics* 11 (3): 728–736. <https://doi.org/10.1109/TII.2015.2428633>.

- Ponnusamy, V. K., P. Kasinathan, R. M. Elavarasan, Vinoth Ramanathan, Ranjith Kumar Anandan, Umashankar Subramaniam, Aritra Ghosh, and Eklas Hossain. 2021. "A Comprehensive Review on Sustainable Aspects of big Data Analytics for the Smart Grid." *Sustainability* 13 (23): 13322. <https://doi.org/10.3390/su132313322>.
- Pournaras, E., S. Jung, S. Yadhunathan, Huiting Zhang, and Xingliang Fang. 2019. "Socio-technical Smart Grid Optimization via Decentralized Charge Control of Electric Vehicles." *Applied Soft Computing* 82:105573. <https://doi.org/10.1016/j.asoc.2019.105573>.
- Pritchard, A. 1969. *Statistical Bibliography; An Interim Bibliography*.
- Qin, J. H., Q. C. Ma, Y. Shi, and Long Wang. 2017. "Recent Advances in Consensus of Multi-agent Systems: A Brief Survey." *IEEE Transactions on Industrial Electronics* 64 (6): 4972–4983. <https://doi.org/10.1109/TIE.2016.2636810>.
- Qu, J. Q., Z. Qian, and Y. Pei. 2021. "Day-ahead Hourly Photovoltaic Power Forecasting Using Attention-Based CNN-LSTM Neural Network Embedded with Multiple Relevant and Target Variables Prediction Pattern." *Energy* 232: 120996. <https://doi.org/10.1016/j.energy.2021.120996>.
- Rahman, M. S., M. A. Mahmud, A. M. T. Oo, and Hemanshu Roy Pota. 2017. "Multi-agent Approach for Enhancing Security of Protection Schemes in Cyber-physical Energy Systems." *IEEE Transactions on Industrial Informatics* 13 (2): 436–447. <https://doi.org/10.1109/TII.2016.2612645>.
- Rahman, M., J. Yan, and E. T. Fapi. 2024. "Adversarial Artificial Intelligence in Blind False Data Injection in Smart Grid AC State Estimation." *IEEE Transactions on Industrial Informatics* 20 (6): 8873–8883. <https://doi.org/10.1109/TII.2024.3374374>.
- Ramchurn, S. D., P. Vytelingum, A. Rogers, and Nicholas R. Jennings. 2012. "Putting the 'Smarts' into the Smart Grid: A Grand Challenge for Artificial Intelligence." *Communications of the ACM* 55 (4): 86–97. <https://doi.org/10.1145/2133806.2133825>.
- Rangel-Martinez, D., K. D. P. Nigam, and L. A. Ricardez-Sandoval. 2021. "Machine Learning on Sustainable Energy: A Review and Outlook on Renewable Energy Systems, Catalysis, Smart Grid and Energy Storage." *Chemical Engineering Research and Design* 174:414–441. <https://doi.org/10.1016/j.cherd.2021.08.013>.
- Rawat, S., A. Patel, J. Celestino, and André Luiz Moura dos Santos. 2016. "A Dominance Based Rough set Classification System for Fault Diagnosis in Electrical Smart Grid Environments." *Artificial Intelligence Review* 46 (3): 389–411. <https://doi.org/10.1007/s10462-016-9468-8>.
- Raza, M. Q., and A. Khosravi. 2015. "A Review on Artificial Intelligence Based Load Demand Forecasting Techniques for Smart Grid and Buildings." *Renewable and Sustainable Energy Reviews* 50:1352–1372. <https://doi.org/10.1016/j.rser.2015.04.065>.
- Reddy, G. V., L. J. Aitha, C. Poojitha, A. N. Shreya, D. K. Reddy, and G. S. Meghana. 2023. "Electricity Consumption Prediction using Machine Learning." *Proceedings of the E3S Web of Conferences*, F. EDP Sciences.
- Rigas, E. S., S. D. Ramchurn, and N. Bassiliades. 2015. "Managing Electric Vehicles in the Smart Grid Using Artificial Intelligence: A Survey." *IEEE Transactions on Intelligent Transportation Systems* 16 (4): 1619–1635. <https://doi.org/10.1109/TITS.2014.2376873>.
- Ruiz-Romero, S., A. Colmenar-Santos, F. Mur-Pérez, and África López-Rey. 2014. "Integration of Distributed Generation in the Power Distribution Network: The Need for Smart Grid Control Systems, Communication and Equipment for a Smart City - Use Cases." *Renewable and Sustainable Energy Reviews* 38:223–234. <https://doi.org/10.1016/j.rser.2014.05.082>.
- Russell, B. D., and C. L. Benner. 2010. "Intelligent Systems for Improved Reliability and Failure Diagnosis in Distribution Systems." *IEEE Transactions on Smart Grid* 1 (1): 48–56. <https://doi.org/10.1109/TSG.2010.2044898>.
- Segun-Falade, O. D., O. S. Osundare, W. E. Kedi, P. A. Okeleke, T. I. Ijomah, and O. Y. Abdul-Azeez. 2024. "Developing Cross-platform Software Applications to Enhance Compatibility across Devices and Systems." *Computer Science & IT Research Journal* 5 (8): 2040–2061. <https://doi.org/10.51594/csitrj.v5i8.1491>.
- Shafiullah, M., A. M. Refat, M. E. Haque, D. M. H. Chowdhury, M. S. Hossain, A. G. Alharbi, Md Shafiul Alam, Amjad Ali, and Shorab Hossain. 2022. "Review of Recent Developments in Microgrid Energy Management Strategies." *Sustainability* 14 (22): 14794. <https://doi.org/10.3390/su142214794>.

- Shi, L., S. Krishnan, and S. Wen. 2022. Study Cybersecurity of Cyber Physical System in the Virtual Environment: A Survey and New Direction. 2022 *Australian Computer Science Week (Acsw 2022)*, 46–55. <https://doi.org/10.1145/3511616.3513098>.
- Shi, Z. T., W. Yao, Z. P. Li, Lingkang Zeng, Yifan Zhao, Runfeng Zhang, Yong Tang, and Jinyu Wen. 2020. “Artificial Intelligence Techniques for Stability Analysis and Control in Smart Grids: Methodologies, Applications, Challenges and Future Directions.” *Applied Energy* 278: 115733. <https://doi.org/10.1016/j.apenergy.2020.115733>.
- Su, Z., G. Zheng, G. Wang, Yu Mu, Jiangtao Fu, and Peipei Li. 2025. “Multi-objective Optimal Planning Study of Integrated Regional Energy System Considering Source-Load Forecasting Uncertainty.” *Energy* 319:134861. <https://doi.org/10.1016/j.energy.2025.134861>.
- Syed, D., A. Zainab, A. Ghraieb, Shady S. Refaat, Haitham Abu-Rub, and Othmane Bouhali. 2021. “Smart Grid big Data Analytics: Survey of Technologies, Techniques, and Applications.” *Ieee Access* 9:59564–59585. <https://doi.org/10.1109/ACCESS.2020.3041178>.
- Tao, Y. C. A., J. Qiu, S. Y. Lai, Xian Zhang, Yunqi Wang, and Guibin Wang. 2022. “A Human-Machine Reinforcement Learning Method for Cooperative Energy Management.” *IEEE Transactions on Industrial Informatics* 18 (5): 2974–2985. <https://doi.org/10.1109/TII.2021.3105115>.
- Ukoba, K., K. O. Olatunji, E. Adeoye, Tien-Chien Jen, and Daniel M. Madyira. 2024. “Optimizing Renewable Energy Systems through Artificial Intelligence: Review and Future Prospects.” *Energy & Environment* 35 (7): 3833–3879. <https://doi.org/10.1177/0958305X241256293>.
- Ul Islam, B., M. Rasheed, and S. F. Ahmed. 2022. “Review of Short-Term Load Forecasting for Smart Grids Using Deep Neural Networks and Metaheuristic Methods.” *Mathematical Problems in Engineering* 2022: 4049685. <https://doi.org/10.1155/2022/4049685>.
- Ullah, Z., F. Al-Turjman, L. Mostarda, and Roberto Gagliardi. 2020. “Applications of Artificial Intelligence and Machine Learning in Smart Cities.” *Computer Communications* 154:313–323. <https://doi.org/10.1016/j.comcom.2020.02.069>.
- Van Eck, N. J., and L. Waltman. 2010. “Software Survey: VOSviewer, a Computer Program for Bibliometric Mapping.” *Scientometrics* 84 (2): 523–538. <https://doi.org/10.1007/s11192-009-0146-3>.
- Verma, A., P. Bhattacharya, N. Madhani, Chandan Trivedi, Bharat Bhushan, Sudeep Tanwar, Gulshan Sharma, Pitshou N. Bokoro, and Ravi Sharma. 2022. “Blockchain for Industry 5.0: Vision, Opportunities, key Enablers, and Future Directions.” *Ieee Access* 10:69160–69199. <https://doi.org/10.1109/ACCESS.2022.3186892>.
- Wang, C., T. Bäck, H. H. Hoos, Mitra Baratchi, Steffen Limmer, and Markus Olhofer. 2019. “Automated Machine Learning for Short-Term Electric Load Forecasting.” 2019 IEEE Symposium Series on Computational Intelligence (Ieee Sci 2019): 314–321.
- Wang, S. X., X. Wang, S. M. Wang, and D. Wang. 2019. “Bi-directional Long Short-term Memory Method Based on Attention Mechanism and Rolling Update for Short-Term Load Forecasting.” *International Journal of Electrical Power & Energy Systems* 109:470–479. <https://doi.org/10.1016/j.ijepes.2019.02.022>.
- Wasim Khan, Hassan, M. Usman, G. Hafeez, Fahad R. Albogamy, Imran Khan, Zeeshan Shafiq, Mohammad Usman Ali Khan, and Hend I. Alkhamash. 2021. “Intelligent Optimization Framework for Efficient Demand-Side Management in Renewable Energy Integrated Smart Grid.” *Ieee Access* 9:124235–52. <https://doi.org/10.1109/ACCESS.2021.3109136>.
- Werbos, P. J. 2011. “Computational Intelligence for the Smart Grid-History, Challenges and Opportunities.” *IEEE Computational Intelligence Magazine* 6 (3): 14–21. <https://doi.org/10.1109/MCI.2011.941587>.
- Xie, T., G.-Y. Dai, W.-F. Chen, Chen-Peng Yang, Yong-Jian Huang, and Yao-Yao Wei. 2025. “Pandemic Triggered Emergency Supply Chain Management Innovations: A Scientometric Analysis Based on Bibliometrics and Dynamic Topic Models.” *Disaster Medicine and Public Health Preparedness* 19:e88. <https://doi.org/10.1017/dmp.2025.88>.
- Xie, T., Y.-J. Huang, and W.-F. Chen. 2025. “Multi-dimensional Assignment Model and Its Algorithm for Multi-features Decision-making Problems.” *Expert Systems with Applications* 270:126369. <https://doi.org/10.1016/j.eswa.2024.126369>.

- Xie, T., Y. Y. Wei, W. F. Chen, and Hai-nan Huang. 2020. "Parallel Evolution and Response Decision Method for Public Sentiment Based on System Dynamics." *European Journal of Operational Research* 287 (3): 1131–1148. <https://doi.org/10.1016/j.ejor.2020.05.025>.
- Xie, T., J. Wu, W. F. Chen, Y. Y. Wei, and K. Chen. 2023. "Pandemic and Emergency Manufacturing Innovation: A Scientometric Analysis Using Citespace." *Disaster Medicine and Public Health Preparedness* 17:e502. <https://doi.org/10.1155/2022/4049685>.
- Yan, K., X. D. Wang, Y. Du, N. Jin, H. Huang, and H. Zhou. 2018. "Multi-step Short-Term Power Consumption Forecasting with a Hybrid Deep Learning Strategy." *Energies* 11 (11): 3089. <https://doi.org/10.3390/en11113089>.
- Yap, K. Y., H. H. Chin, and J. J. Klemeš. 2022. "Future Outlook on 6G Technology for Renewable Energy Sources (RES)." *Renewable and Sustainable Energy Reviews* 167:112722. <https://doi.org/10.1016/j.rser.2022.112722>.
- Yu, X. H., and Y. S. Xue. 2016. "Smart Grids: A Cyber-Physical Systems Perspective." *Proceedings of the IEEE* 104 (5): 1058–1070. <https://doi.org/10.1109/JPROC.2015.2503119>.
- Yuce, B., Y. Rezgui, and M. Mourshed. 2016. "ANN-GA Smart Appliance Scheduling for Optimised Energy Management in the Domestic Sector." *Energy and Buildings* 111:311–325. <https://doi.org/10.1016/j.enbuild.2015.11.017>.
- Zeng, F., M. Wang, Y. Pan, S. Lv, H. Miao, H. Han, and X. Yuan. 2025. "Distributed Data Privacy Protection via Collaborative Anomaly Detection." *Electronics* 14 (2): 295. <https://doi.org/10.3390/electronics14020295>.
- Zhang, L. F., N. Gari, and L. V. Hmurcik. 2014. "Energy Management in a Microgrid with Distributed Energy Resources." *Energy Conversion and Management* 78:297–305. <https://doi.org/10.1016/j.enconman.2013.10.065>.
- Zhang, D. X., X. Q. Han, and C. Y. Deng. 2018. "Review on the Research and Practice of Deep Learning and Reinforcement Learning in Smart Grids." *CSEE Journal of Power and Energy Systems* 4 (3): 362–370. <https://doi.org/10.17775/CSEEJPES.2018.00520>.
- Zhang, W., W. X. Liu, X. Wang, and Frank Ferrese. 2014. "Distributed Multiple Agent System Based Online Optimal Reactive Power Control for Smart Grids." *IEEE Transactions on Smart Grid* 5 (5): 2421–2431. <https://doi.org/10.1109/TSG.2014.2327478>.
- Zhang, J., and D. C. Tao. 2021. "Empowering Things with Intelligence: A Survey of the Progress, Challenges, and Opportunities in Artificial Intelligence of Things." *IEEE Internet of Things Journal* 8 (10): 7789–7817. <https://doi.org/10.1109/JIOT.2020.3039359>.
- Zhang, Y. C., L. F. Wang, W. Q. Sun, Robert C. Green II, and Mansoor Alam. 2011. "Distributed Intrusion Detection System in a Multi-layer Network Architecture of Smart Grids." *IEEE Transactions on Smart Grid* 2 (4): 796–808. <https://doi.org/10.1109/TSG.2011.2159818>.
- Zhang, L. Y., G. Yang, C. Song, and Q. Wu. 2023. "Accountable Multi-authority Attribute-Based Data Access Control in Smart Grids." *Journal of King Saud University-Computer and Information Sciences* 35 (7): 101597. <https://doi.org/10.1016/j.jksuci.2023.101597>.
- Zhang, Z. D., D. X. Zhang, and R. C. Qiu. 2020. "Deep Reinforcement Learning for Power System Applications: An Overview." *CSEE Journal of Power and Energy Systems* 6 (1): 213–225.
- Zhao, S., F. Blaabjerg, and H. Wang. 2021. "An Overview of Artificial Intelligence Applications for Power Electronics." *IEEE Transactions on Power Electronics* 36 (4): 4633–4658. <https://doi.org/10.1109/TPEL.2020.3024914>.
- Zhou, J., Y. X. Shen, A. A. Pantelous, and Yanbao Liu. 2024. "Quality Function Deployment: A Bibliometric-Based Overview." *IEEE Transactions on Engineering Management* 71:1180–1201. <https://doi.org/10.1109/TEM.2022.3146534>.