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A Bibliometric Analysis on the Application of Deep Learning in Wind Energy Forecasting

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ABSTRACT

In recent years, the intersection of deep learning (DL) and wind energy forecasting has seen substantial academic growth, reflecting both the rise of artificial intelligence in engineering and the global transition toward renewable power systems. This study presents a comprehensive bibliometric evaluation of scientific publications related to DL-based wind forecasting, covering the period from 2013 to 2024. Data were extracted from the Web of Science (WoS) Core Collection using the keywords “deep learning” and “wind.” Through quantitative analysis, the research explores publication dynamics, citation behaviors, and the collaborative networks of leading authors, institutions, and countries. Additionally, trends in keyword usage and thematic focus were assessed to identify core research areas and evolving interests in the field. This paper aims to provide researchers and energy forecasters with a structured overview of the academic terrain, highlighting influential contributions and strategic directions for future investigations into hybrid deep learning models for wind energy prediction.

Keywords: Deep learning, wind forecasting, bibliometric analysis, network analysis
JEL-Classification: Q42, C45, Q47, C55

1. Introduction

The increasing urgency of climate change has prompted a global shift toward renewable energy systems, among which wind power plays a central role in sustainable electricity generation. [1] However, the inherently intermittent and nonlinear nature of wind requires sophisticated methods to ensure accurate forecasting [2]. Traditional statistical models like ARIMA, exponential smoothing, and regression-based approaches have been widely used in wind prediction but are limited in capturing complex temporal dynamics and chaotic patterns in wind behavior. [3] This limitation has led researchers to explore advanced machine learning approaches, particularly deep learning (DL) algorithms. [4] DL models, notably Long Short-Term Memory (LSTM) networks, have been recognized for their capability to model sequential data and capture long-term dependencies in time series, making them particularly suitable for wind speed forecasting. [5] Their success is rooted in their ability to adaptively learn patterns from vast and noisy datasets without requiring handcrafted features. [6]

Recent hybrid frameworks have combined LSTM with signal decomposition techniques such as Empirical Mode Decomposition (EMD), Wavelet Transform (WT), and Variational Mode Decomposition (VMD), achieving significant performance improvements in short-term forecasting tasks. [7], [8] These decompositions isolate high- and low-frequency components, enhancing model learning by focusing on distinct temporal behaviors. [9]

In addition, CNN-based models have proven effective in extracting spatial features from meteorological data, which, when integrated with LSTM in hybrid architectures, yield improved spatiotemporal forecasting performance. [10] Some studies have further enhanced these models using attention mechanisms that allow the network to focus on relevant time steps in sequences [11]. Another promising direction involves combining DL with metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) to tune hyperparameters and improve predictive accuracy [12], [13]. These optimization techniques are especially useful for DL models with numerous tunable parameters. The rise of Transformer-based architectures, originally developed for natural language processing, has expanded into time-series applications including wind forecasting due to their self-attention mechanisms and scalability to long sequences. [14] These models, along with Bidirectional LSTM and CNN-LSTM variants, are now part of a growing toolkit in renewable energy analytics. [15] Probabilistic forecasting using Bayesian deep learning methods has also gained momentum, as they provide both point estimates and uncertainty bounds—a critical feature for energy grid planning under uncertainty. [16] These models are increasingly used by power utilities for risk-aware scheduling and maintenance planning. [17]

Transfer learning, which allows knowledge transfer from one wind farm to another, has proven to be valuable, especially when data availability is limited in new geographical locations. [18] Domain adaptation and pretraining strategies help mitigate data scarcity challenges. [19] Federated Learning (FL) offers a privacy-preserving alternative for training DL models across multiple decentralized wind farms without sharing raw data. [20] This is particularly beneficial for utility companies operating in regions with strict data governance regulations. [21] The incorporation of auxiliary meteorological variables such as humidity, temperature, and pressure into DL frameworks has been shown to significantly enhance forecast performance through multivariate modeling strategies. [22], [23] Additionally, including atmospheric and topographic features improves generalizability across terrain types. [24]

Recent studies have also emphasized the value of explainable AI (XAI) in wind forecasting, where methods like SHAP and LIME help stakeholders understand the internal decision-making process of complex models. [25] This interpretability is essential in critical infrastructure systems where transparency and accountability are required. [26]

Autonomous control of wind turbines using Deep Reinforcement Learning (DRL) has emerged as a parallel trend, optimizing real-time turbine settings to maximize power output and reduce mechanical stress. [27] These models adapt dynamically to changing wind patterns and operational conditions. [28] From a systems perspective, DL is now embedded into hybrid energy systems combining solar, wind, and energy storage, offering enhanced load balancing and energy dispatch optimization. [29] These integrated models are crucial for smart grid development. [30] Despite technical advancements, large-scale adoption of DL in wind forecasting remains limited. To understand the broader landscape, bibliometric analysis serves as a valuable tool for mapping research trends, identifying influential works, and guiding future investigations. [31], [32] This bibliometric review, based on Web of Science data between 2013 and 2024, reveals a rapid increase in publications after 2018, with China, the U.S., and Germany leading contributions in this domain. [33] This trend correlates with the surge in hybrid DL model development and the adoption of ensemble learning strategies. [34] Keyword co-occurrence networks highlight evolving research interests, shifting from general terms like "neural network" to specific architectures such as "Transformer," "CNN-LSTM," and "BiLSTM" in recent years. [35] Citation burst analysis further uncovers pivotal publications that triggered paradigm shifts in the field. [36] Highly cited authors such as Wang, Li, and Zhang have led research in model hybridization, uncertainty quantification, and multi-source data integration. [37] Key publication outlets include journals like Renewable Energy, Applied Energy, and IEEE Transactions on Sustainable Energy. [38] Institutional collaboration networks show tight clusters of academic–industry partnerships, particularly among Chinese universities and European energy companies, indicating a maturing research ecosystem. [39] Funding support from government agencies has also played a pivotal role in accelerating DL-based forecasting research. [40] Visualization tools such as VOSviewer and Bibliometrix have allowed us to identify the evolution of thematic areas within this research, from single-variable forecasting to holistic energy system modeling. [41] This visual mapping helps in understanding the knowledge structure and its development over time. [42]

In addition to thematic evolution, our study sheds light on methodological shifts—from simple feed-forward architectures to hybrid and ensemble models capable of handling multi-resolution, noisy, and heterogeneous data. [43] These developments point toward the increasing complexity and maturity of the field. [44] Moreover, real-time deployment of DL models in SCADA systems has shown operational viability, offering capabilities like fault detection, anomaly prediction, and automated turbine control. [45] Such applications underscore the transition of DL from theoretical exploration to practical implementation. [46]

In summary, this paper aims to offer a comprehensive bibliometric landscape of deep learning applications in wind energy forecasting, identifying key contributors, emerging themes, and research gaps. [47], [48] The integration of intelligent algorithms with real-time energy systems has already reshaped forecasting practices and will likely continue to evolve rapidly. [49] By mapping the intellectual structure and collaboration patterns in this field, we provide strategic insights for researchers, utility companies, and policy-makers seeking to advance sustainable energy initiatives. [50], [51] Ultimately, we hope this review will serve as a foundational resource for guiding future innovations in data-driven wind forecasting. [52], [53] The following sections of this study will present the data source and methodology used for the bibliometric analysis (Section 2), followed by the key findings in terms of publications, citations, prolific authors, and collaborative networks (Section 3). [54] Section 4 discusses the implications of these findings and outlines future research opportunities. [55]

This bibliometric roadmap enables informed decision-making in academia and industry, ensuring that DL-driven wind forecasting remains aligned with technological, regulatory, and environmental goals. [56], [57] With the renewable energy sector expanding globally, understanding the trajectory of forecasting innovation has never been more important. [58] Hence, this study not only captures the current state of the art but also aims to inspire further exploration into high-impact, reliable, and interpretable deep learning models for next-generation wind energy systems. [59], [60] As data availability, computing power, and algorithmic complexity continue to grow, so too will the potential of DL in shaping the future of energy prediction. [61]

2. Bibliometric Analysis

2.1. Data Source And Methodology

The Web of Science (WoS) is a widely used academic database that indexes high-impact journals across various scientific disciplines and provides detailed metadata, including citation counts, author profiles, and article bibliographies. It is frequently utilized in bibliometric research due to its comprehensive coverage and structured citation indexing. The WoS Core Collection encompasses several indices, such as the Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI), Emerging Sources Citation Index (ESCI), and the Conference Proceedings Citation Index, among others. These indices collectively provide access to scholarly content dating back to 1900.

In this study, a systematic bibliometric analysis was conducted to explore the evolution and trends in the application of deep learning techniques in wind energy forecasting. The search query used in the Web of Science database was "Deep learning" AND "Wind", and a total of 3,067 publications were initially retrieved. However, to ensure consistency and focus, the analysis was limited to articles only, resulting in a refined dataset of 2,518 articles published between 2013 and 2024. The first relevant article in this field was published in 2013. All publication data were extracted from the WoS database on August 3, 2025, and no additional filters or manual exclusions were applied.

The exported dataset included various bibliographic attributes such as title, abstract, keywords, author names, affiliations, publication year, and country of origin. Quantitative metrics including total publications (TP), total citations (TC), average citations per publication (TC/TP), and the H-index were calculated to assess the scientific impact of the research outputs. Bibliometric mapping and visualizations were conducted using R Studio (Bibliometrix package) and VOSviewer. These tools enabled the construction of co-authorship networks, keyword co-occurrence maps, and country-level collaboration diagrams.

The bibliometric mapping revealed that People's Republic of China was the most active contributor in this domain, leading in both publication volume and citation impact. The analysis also included temporal trend evaluations, identifying peak years of publication activity, and thematic evolution of keywords. The comprehensive visual and numerical outputs presented in this study offer valuable insights into the trajectory of deep learning research applied to wind energy forecasting.

2.2.Academic Publications and Citations

Using the Web of Science database, a total of 3,067 publications were retrieved under the query "Deep learning" and "Wind". Among these, the majority of the records belonged to the article category, comprising 2,518 entries. Although other document types such as proceeding papers, review articles, or early access publications are commonly seen in similar fields, the dataset exported in this study contained only a limited number of non-article records.

Specifically, only three entries were classified under the book chapter category (incollection). These two types—articles and book chapters—together constituted the entirety of the

bibliographic records included in the BibTeX export, making up nearly 100% of the dataset. Document types like corrections, retractions, letters, or editorial materials were either absent in this dataset or were not indexed as distinct categories in the exported format.
The significant dominance of article-type publications in this field indicates a strong inclination toward peer-reviewed scientific outputs, while the near absence of other types suggests a relatively narrow distribution of publication formats. This concentration around journal articles also reflects the academic rigor and technical depth typically associated with research in deep learning applications for wind energy forecasting.

Figure 1. Research Design

Figure 2. Document Types of The Publications

As shown in Figure 3, most articles on deep learning in wind energy forecasting were published under Energy Fuels (834 articles) and Engineering Electrical Electronic (728 articles). These were followed by Computer Science Artificial Intelligence (316), Green Sustainable Science Technology (276), and Environmental Sciences (274). The diversity of categories highlights the interdisciplinary nature of the field.

In addition, areas such as Information Systems, Thermodynamics, and Remote Sensing had notable contributions, each ranging from 150 to 250 publications. These results indicate strong ties between deep learning applications and both engineering and computational disciplines. According to Figure 4, Engineering (24.6%), Energy Fuels (14.4%), and Computer Science (11.4%) dominate the field, collectively exceeding half of all publications. Other disciplines, including Environmental Sciences, Thermodynamics, and Physics, contribute smaller shares, typically under 10%.

Overall, the findings reflect a strong focus on applied sciences, while also pointing to growing interdisciplinary interest in the topic.

Figure 3. Top 10 WOS Categories of The Publications

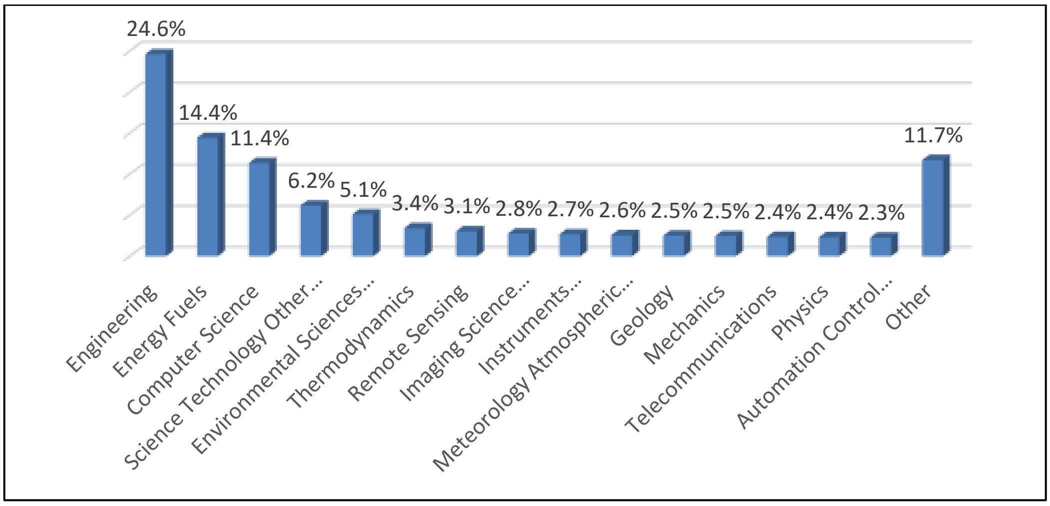

Figure 4. Research Areas of The Publications

Figure 5 presents the annual growth of publications on deep learning in wind energy forecasting. The first article appeared in 2013, and the number of studies remained minimal

until 2018, with fewer than 20 publications annually. A clear upward trend began in 2019, reaching 152 articles, and continued with 244 in 2020. This momentum grew stronger in the following years, with 418 publications in 2021 and 604 in 2022.
In 2023, the number rose to 678, and in 2024, it reached its highest level with 866 publications. The consistent growth reflects increasing academic attention to the integration of deep learning in renewable energy forecasting, especially over the last five years.

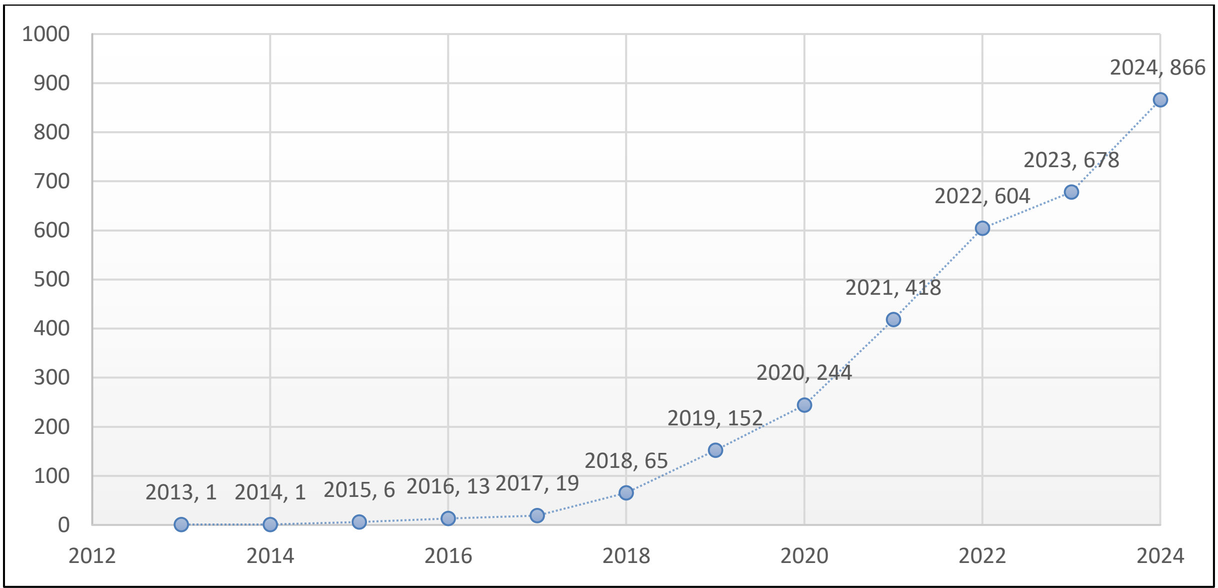

Figure 5. Annual Publications

Figure 6 displays the annual citation totals (TC) and average citations per publication (TC/TP) in the domain of deep learning applied to wind energy forecasting. Citations remained low until 2018, then began increasing significantly after 2019. A major rise occurred in 2020, continuing steadily through 2024, when total citations reached their highest point.
The TC/TP ratio followed a similar trajectory, peaking in 2024 at over 25 citations per article, showing that recent publications gained rapid attention. Earlier years like 2019 and 2020 also had relatively high TC/TP values, indicating that articles from those years became key references in the field.
These results suggest that both the quantity and influence of publications have grown, especially over the past five years.

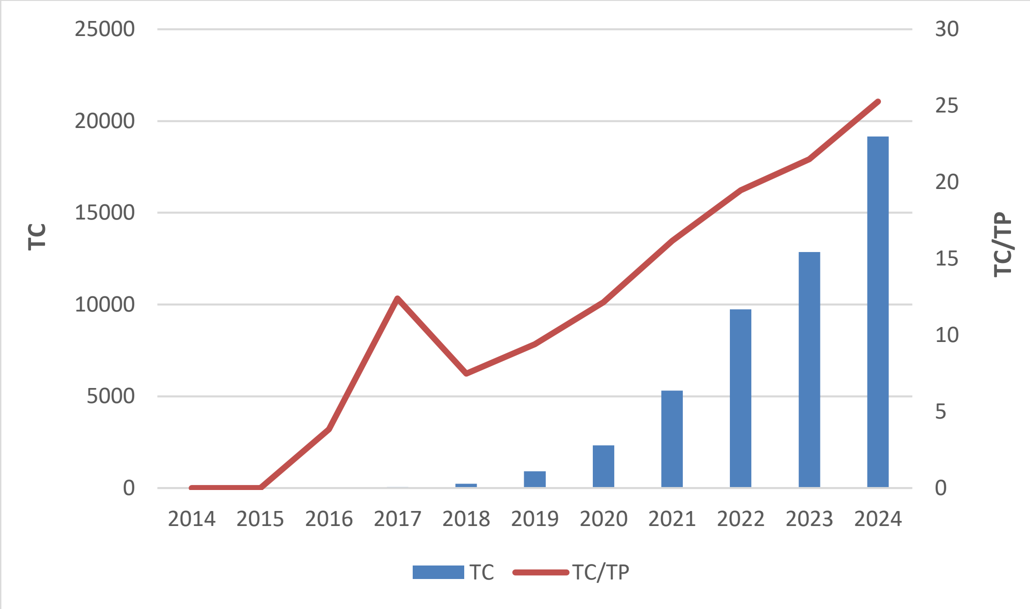

Figure 6. Citation Trend Analysis

2.2.1. Authorship and Institution Analysis

Table 1 lists the top 10 most cited studies in the field of deep learning applied to wind energy forecasting. The most influential work is by Jiang et al. (2019), with 650 citations and an average of 130 citations per year. The second and third most cited articles are by Wang et al. (2017) and Ravuri et al. (2021), receiving 559 and 549 citations respectively.

All listed publications have been cited over 350 times, and six of them average more than 80 citations per year. These figures reflect both academic visibility and long-term relevance. Notably, each study was co-authored by multiple researchers, indicating collaborative production. The affiliations suggest strong contributions from Chinese institutions, especially in the top-ranked articles. In addition, international cooperation is evident in several entries, particularly from positions 3 to 10, where cross-country collaborations played a key role in the research output.

As seen in Table 2, the most active authors in the field of deep learning and wind energy forecasting have published between 8 and 21 articles. Jianzhou Wang leads with 21 publications and a total of 752 citations, followed by Gang Hu and Baoping Tang. The highest average citation per article (TC/TP) belongs to Hui Liu (186.75) and Xiwei Mi (166.11), highlighting the strong impact of their work. In terms of overall research influence, both citation counts and h-index values indicate that authors like Wang, Liu, and Mi play central roles in shaping the field. Their studies show not only consistency in publication output but also high visibility in the academic community.

Institutional contributions are presented in Figure 7. The Chinese Academy of Sciences ranks first with over 110 publications, followed by North China Electric Power University and Harbin Institute of Technology. All of the top 10 institutions are based in China, emphasizing the country's leading position in research combining deep learning and wind energy forecasting.

Table 1. Most Influential Articles

Rank	Authors	Year	Title	Journal	Total Citation	TC/ Year
1	Jiang, GQ; He, HB; Yan, J; Xie, P	2019	Multiscale Convolutional Neural Networks for Fault Diagnosis of Wind Turbine Gearbox	IEEE Transaction on Industrial Electronics	650	130
2	Wang, HZ; Li, GQ; Wang, GB; Peng, JC; Jiang, H; Liu, YT	2017	Deep learning based ensemble approach for probabilistic wind power forecasting	Applied Energy	559	79,86
3	Ravuri, S; Lenc, K; Willson, M; Kangin, D; Lam, R; Mirowski, P; Fitzsimons, M; Athanassiadou, M; Kashem, S; Madge, S; Prudden, R; Mandhane, A; Clark, A; Brock, A; Simonyan, K; Hadsell, R; Robinson, N; Clancy, E; Arribas, A; Mohamed, S	2021	Skilful precipitation nowcasting using deep generative models of radar	Nature	549	183
4	Huang, CJ; Kuo, PH	2018	A Deep CNN-LSTM Model for Particulate Matter ($PM_{2.5}$) Forecasting in Smart Cities	Sensors	480	80
5	Wang, F; Xuan, ZM; Zhen, Z; Li, KP; Wang, TQ; Shi, M	2020	A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework	Energy Conversion and Management	432	108
6	Wang, HZ; Wang, GB; Li, GQ; Peng, JC; Liu, YT	2016	Deep belief network based deterministic and probabilistic wind speed forecasting approach	Applied Energy	431	53,88
7	Chen, YZ; Wang, YS; Kirschen, D; Zhang, BS	2018	Model-Free Renewable Scenario Generation Using Generative Adversarial Networks	IEEE Transaction on Power Systems	419	69,83
8	Lago, J; De Ridder, F; De Schutter, B	2018	Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms	Applied Energy	410	68,33
9	Liu, H; Mi, XW; Li, YF	2018	Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM	Energy Conversion and Management	381	63,50
10	Liu, H; Mi, XW; Li, YF	2018	Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and Elman neural network	Energy Conversion and Management	358	59,67

Table 2. Most Productive Authors

Rank	Authors	TP	TC	TC/TP	h_index
1	Jianzhou Wang	21	752	35,81	18
2	Gang HU	13	285	21,92	7
3	Tang, Baoping	11	605	55,00	8
4	Zijun Zhang	10	426	42,60	8
5	Liu, Yong-Qian	10	599	59,90	7
6	Tianyu WANG	9	222	24,67	8
7	Mi, Xiwei	9	1495	166,11	9
8	Guo, Mingming	9	229	25,44	9
9	Le, Jialing	8	213	26,63	8
10	Hui Liu	8	1494	186,75	8
11	Peng, Xiaosheng	8	175	21,88	6
12	Zhang, Jincheng	8	303	37,88	7

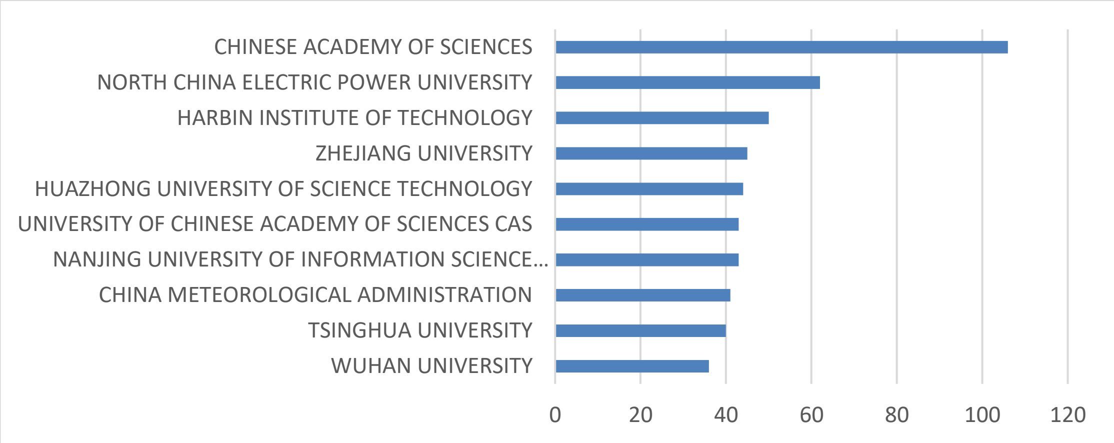

Figure 7. Most Productive Institutions

All quantitative information presented in the manuscript must adhere to the International System of Units (SI). Percentage values should be written directly following the numeral without a space (e.g., 18%). Additionally, decimal values must use a period (.) rather than a comma (,), such as 2.5 instead of 2,5, in order to maintain consistency with international scientific notation standards.

2.2.2. Country / Region Analysis

As illustrated in Figure 8, the top 10 countries contributing to deep learning in wind energy forecasting were analyzed by year. China stands out as the most dominant contributor with a total of 1,715 publications, showing a steep increase especially after 2019. In 2024, China reached its highest annual output with 427 articles, accounting for a large share of global research in the field.

The United States follows with 477 publications, showing consistent growth since its first contribution in 2015. Other notable countries include India (176 articles), England (243), South Korea (210), and Iran (138), all showing moderate but steady progress over the years.

Countries such as Canada, Australia, Saudi Arabia, and Germany also contribute actively, although at a lower volume. Most countries in the top 10 began contributing regularly after 2018, marking the beginning of global interest in applying deep learning to wind energy.

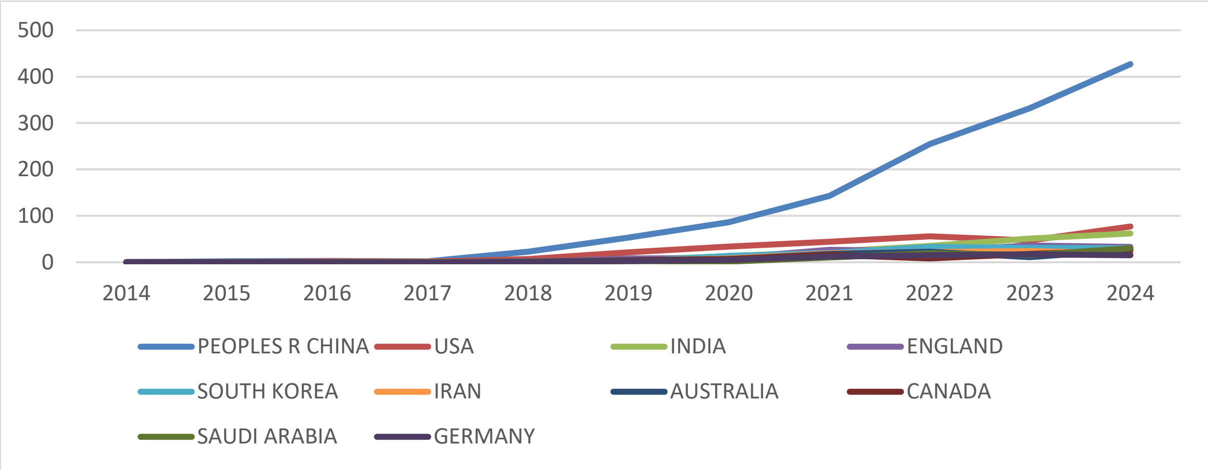

Figure 8. Most Productive Countries

2.2.3. Document Sources and Funding Agencies Analysis

The top 10 journals publishing studies on deep learning applications in wind energy forecasting are presented in Figure 9. Among them, Energy ranks first with 116 articles, followed by Energies (103) and IEEE Access (86). Other key journals include Renewable Energy, Applied Energy, and Energy Conversion and Management, each contributing over 50 publications. These sources have played a crucial role in disseminating research within the field, particularly on AI-supported forecasting systems.

Figure 10 shows the funding institutions that most frequently support studies in this domain. The National Natural Science Foundation of China (NSFC) stands out, supporting over 700 publications, far exceeding other agencies. It is followed by the National Key Research and Development Program of China and the Fundamental Research Funds for the Central Universities, each backing over 100 publications.

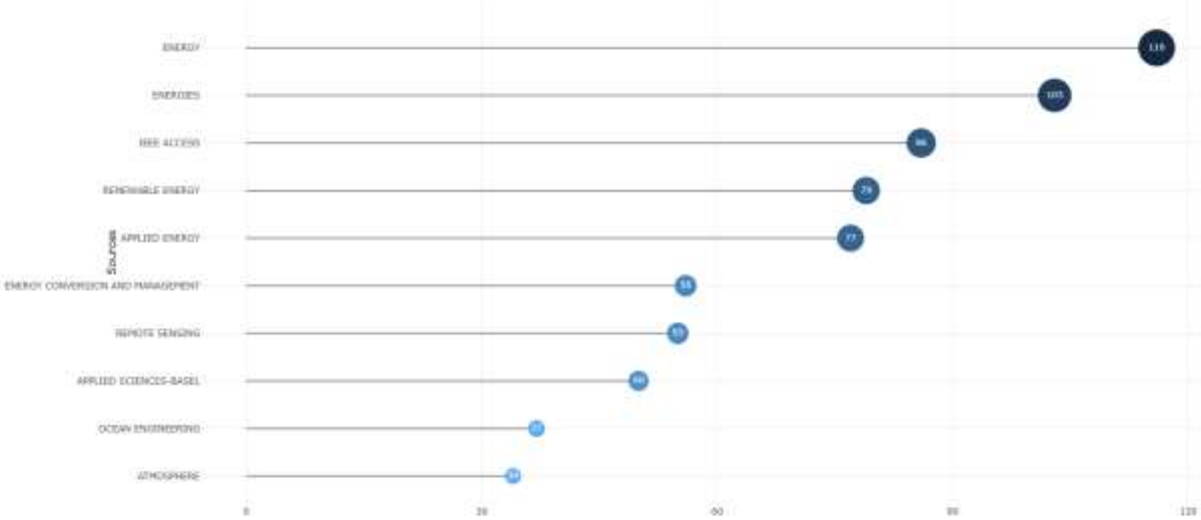

Figure 9. List of The Top 10 Contributing Journals

Other notable contributors include the National Science Foundation (NSF) in the United States, European Union (EU), and the Ministry of Science and ICT (MSIT) from South Korea. These organizations represent the key financial pillars behind the growth of deep learning research in renewable energy forecasting across different regions.

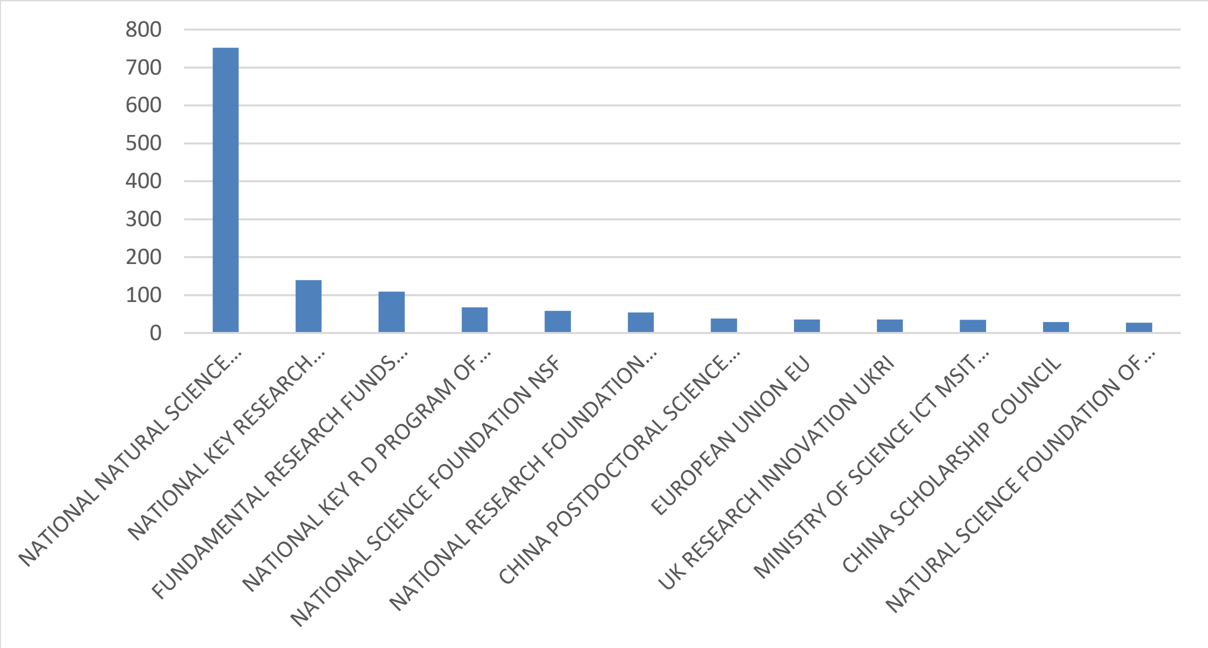

Figure 10. List of Top Contributing Funding Agencies

2.2.4. Timeline Analysis

The temporal evolution of research content in the field of deep learning-based wind energy forecasting was examined through keyword usage, as shown in Figure 11. The figure highlights the most frequently used terms in article titles between 2022 and 2024. Unsurprisingly, the phrase “deep learning” dominated all years, reaching 230 mentions in 2024 alone.

Other frequently appearing terms include “wind speed”, “wind power”, and “wind turbine”, which showed consistent growth across all three years. In particular, “wind power” increased notably from 52 mentions in 2023 to 92 in 2024, reflecting growing emphasis on generation-related forecasting.

Terms such as “neural network”, “fault diagnosis”, and “power forecasting” also remained prominent, each being used 30 or more times annually. Meanwhile, concepts like “short-term wind”, “machine learning”, and “learning model” demonstrated moderate but steady usage, suggesting sustained relevance.

Overall, the data suggest that while core terms like “deep learning” maintain dominance, related concepts such as predictive modeling, turbine diagnostics, and renewable integration have become more visible in recent literature.

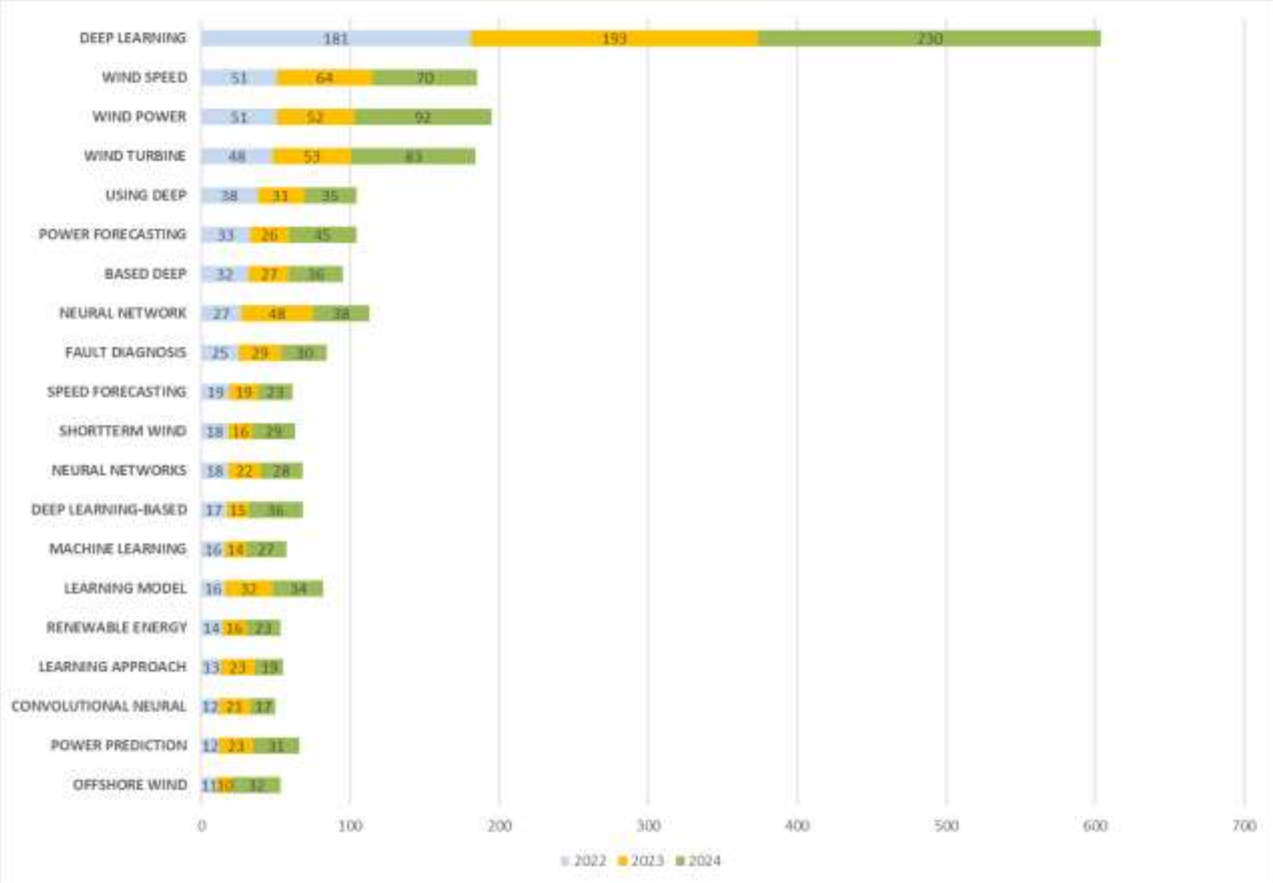

Figure 11. The Most Common Bigrams in Article Titles

RANK	KEYWORDS	STRENGTH
1	DEEP LEARNING	481
2	WIND TURBİNE	56
3	MACHINE LEARNING	55
4	WIND SPEED FORECASTING	55
5	DEEP LEARNING	53
6	WIND SPEED	50
7	WIND ENERGY	43
8	WIND POWER FORECASTING	43
9	FORECASTING	39
10	WIND TURBİNES	35
11	CONVOLUTIONAL NEURAL NETWORK	35
12	WIND POWER	32
13	FAULT DIAGNOSIS	31
14	WIND POWER PREDICTION	30
15	RENEWABLE ENERGY	30
16	WIND SPEED PREDICTION	29
17	WIND POWER GENERATION	26
18	LSTM	25
19	LONG SHORT-TERM MEMORY	25
20	ATTENTION MECHANISM	25

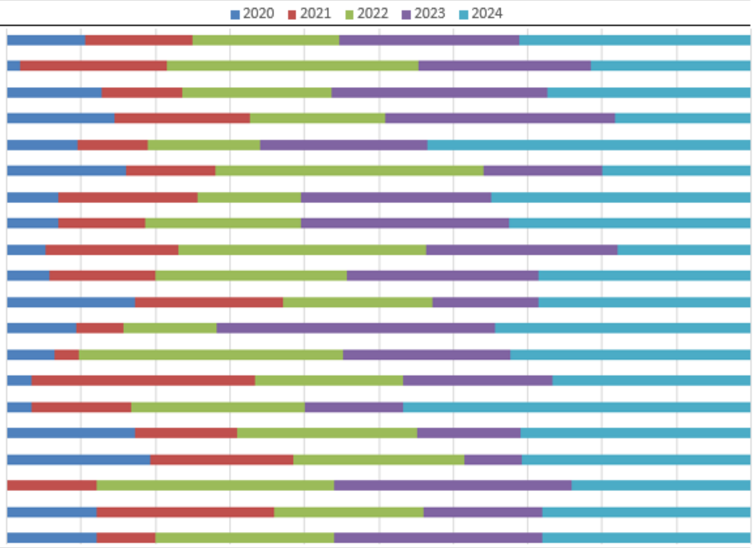

Figure 12. The Most Frequently Used Keywords in Articles

As illustrated in Figure 12, the term "deep learning" has been the most frequently used keyword from 2020 to 2024, followed by concepts such as "wind turbine," "machine learning," and "wind speed forecasting." A steady rise is observed in advanced model-related terms like "LSTM," "attention mechanism," and "neural network," indicating an increasing focus on complex learning architectures. In addition, keywords such as "fault diagnosis," "renewable energy," and "wind power prediction" have gained visibility, pointing to expanding interest in system reliability and sustainable forecasting approaches.

Figure 13 reveals that most publications are aligned with the Affordable and Clean Energy goal, followed by Climate Action and Sustainable Cities and Communities. This highlights the field's strong orientation toward global energy and environmental priorities. However, certain SDGs such as Innovation and Infrastructure, Life on Land, and Good Health and Well-Being remain underrepresented. These findings suggest a growing but still uneven connection between deep learning-based wind forecasting research and broader sustainability targets.

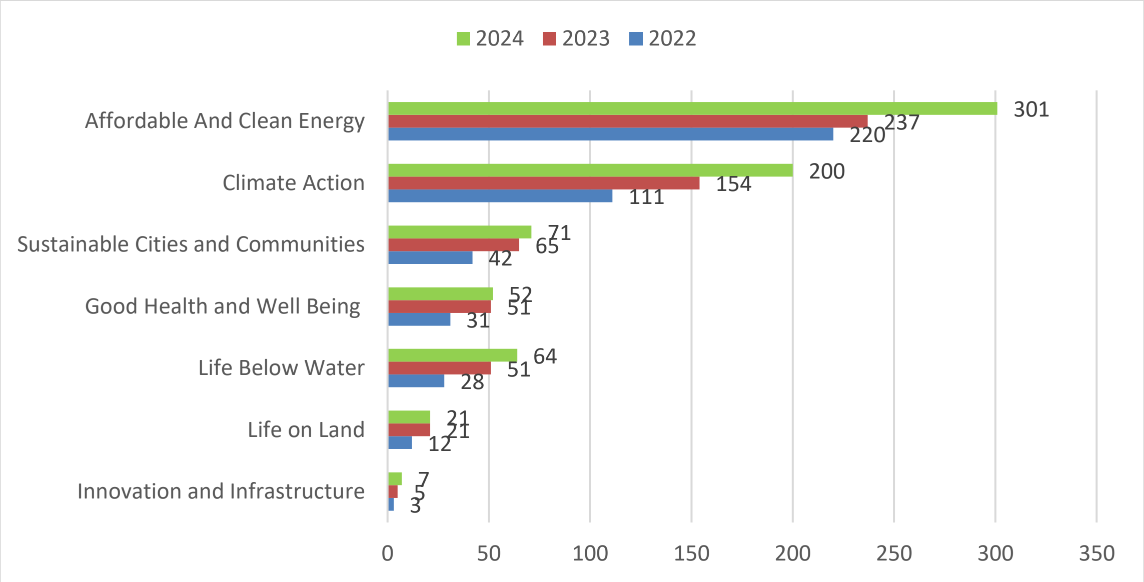

Figure 13. Sustainable Development Goals Analysis

2.2.5. Social Network Analysis

The collaboration structure among authors in the field of deep learning-based wind energy forecasting is presented in Figure 14. The network, generated using the bibliometrix package in R, highlights key contributors such as Wang J, Li Y, and Liu Y, who appear at the center of highly connected clusters. These researchers exhibit strong total link strength (TLS), reflecting frequent co-authorship and influence within their academic circles. The visual separation of author clusters by color also indicates the presence of tight-knit collaboration groups, likely affiliated with shared institutions or national research initiatives.

Figure 16 displays the international collaboration network among countries. China stands out as the most central actor, with strong bilateral ties to countries such as the United States, United Kingdom, and Australia. The size of China's node and the thickness of its connecting lines emphasize its dominant role both in research output and in fostering cross-border scientific cooperation. The network suggests that China not only leads in volume but also acts as a strategic bridge in the global research landscape surrounding artificial intelligence and renewable energy.

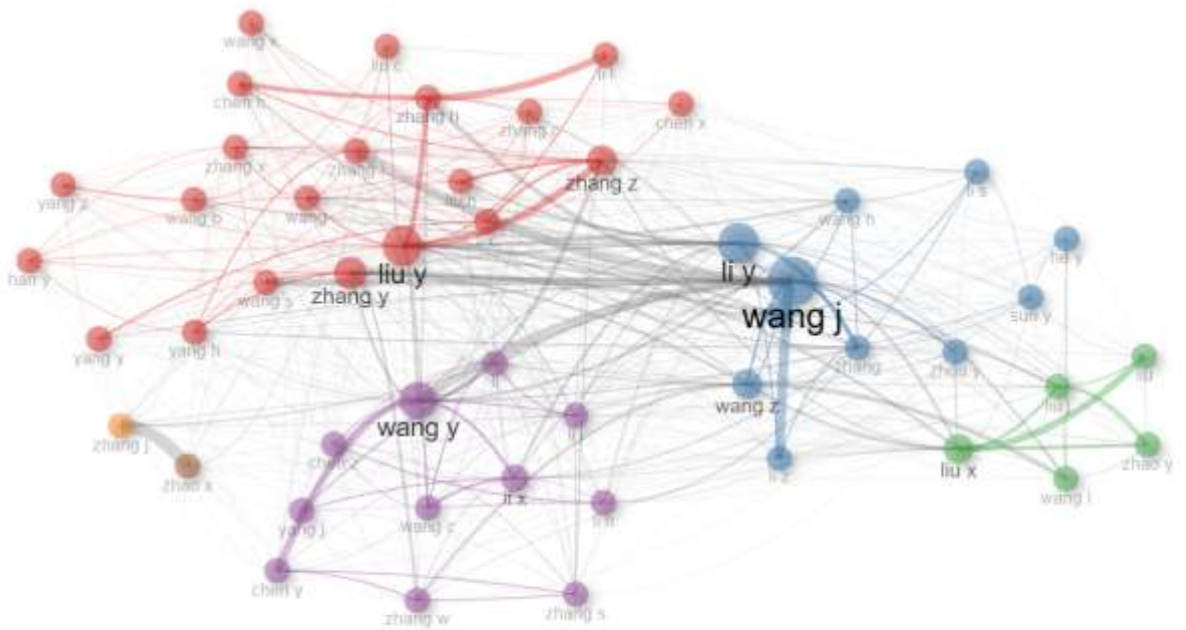

Figure 14. The Collaboration Network of Authors

Figure 15 presents the institutional collaboration network for studies on deep learning in wind energy forecasting. The most central and influential institution is North China Electric Power University, distinguished by its large node size and strong connection density. Close behind are Huazhong University of Science and Technology, Wuhan University, and Harbin Institute of Technology, which form their own dense clusters with frequent co-authorship links. The collaboration between Wuhan University and Harbin Institute appears particularly significant, suggesting a focused research partnership. The network is divided into color-coded clusters, each representing groups of institutions that tend to collaborate more intensely with each other. These clusters reflect regional and institutional research alliances. Overall, the figure confirms the central role of Chinese universities and reveals a well-structured academic ecosystem with clearly defined collaboration hubs.

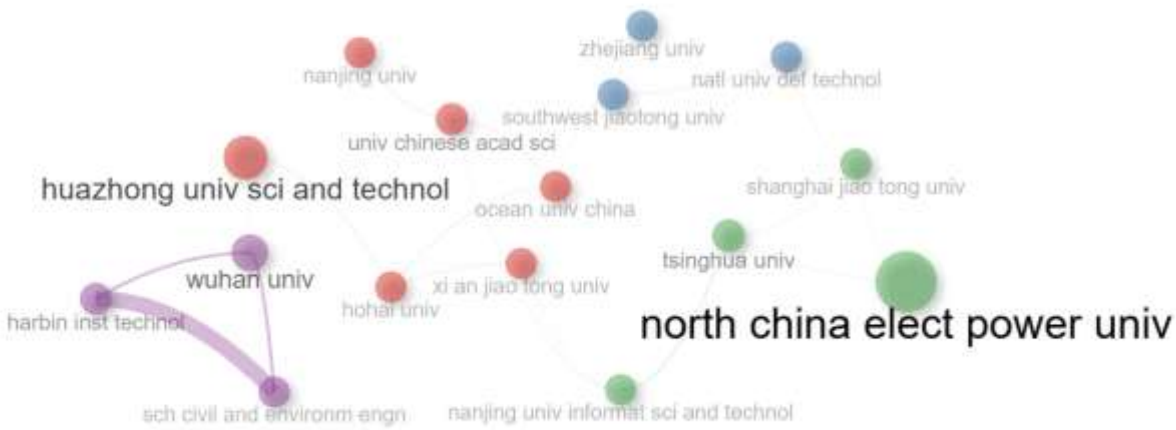

Figure 15. The Collaboration Network of Institutions

Figure 16 illustrates the international collaboration network in deep learning–based wind energy research, where China emerges as the most influential hub. With over 1300 collaborative links, China dominates the field, followed by the United States (around 740 links), the United Kingdom (approximately 480 links), and Australia (over 400 links). Notably, China and the U.S. have co-authored 279 studies, representing 16% of China's and 58% of the U.S.'s publications in this domain. China has also maintained more than 100 joint publications each with the United Kingdom, Australia, Canada, and Singapore, reflecting its central role in connecting global research communities. The density and thickness of the connecting lines highlight not only the quantity of China's collaborations but also its bridging role in fostering international scientific exchange. Additionally, USA–Australia and USA–South Korea partnerships have made notable contributions, with 56 and 55 joint publications respectively, shaping a diverse yet China-centered global collaboration structure in deep learning–driven wind energy studies

Figure 16. The Collaboration Network of Countries

2.2.6. Keywords Detection

Figure 17 and Figure 18 illustrate the bibliometric mapping of frequently used terms derived respectively from Keywords Plus and article abstracts. According to the Keywords Plus analysis, the most recurring terms in publications were "model", "prediction", "neural-network", and "algorithm", each exceeding significant usage thresholds. The visual prominence of these terms is reflected in their frequencies, with "model" and "prediction" each appearing over 2300 times across the corpus. In particular, terms like "optimization", "ensemble", and "decomposition" also held noticeable weight, suggesting a strong research focus on computational efficiency and hybrid methodologies in wind energy forecasting studies.

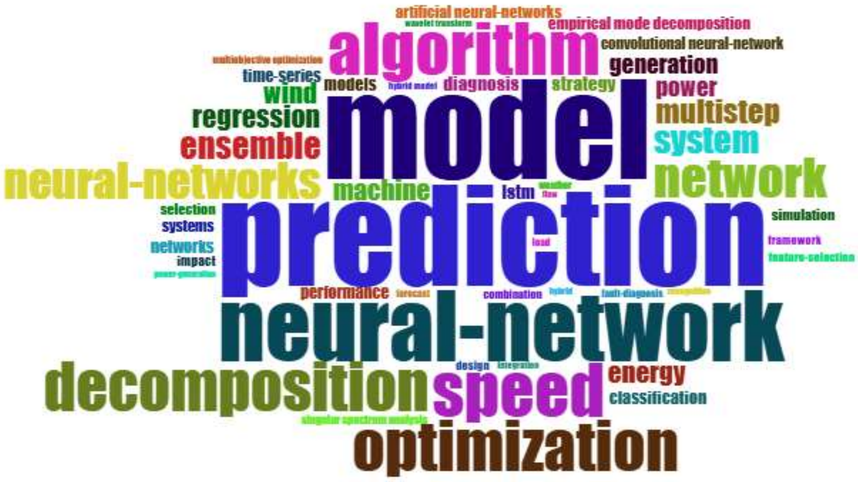

Figure 17. Keywords Plus with The Highest Frequency

In parallel, Figure 18 displays the trigram frequency distribution derived from article abstracts, highlighting dominant expressions such as “wind speed forecasting”, “deep learning model”, and “convolutional neural network”. The trigram “wind speed forecasting” alone appeared in more than 4700 instances, while “deep learning” and “machine learning” followed closely, cited in over 1600 and 1800 occurrences, respectively. This reflects a rising academic emphasis on AI-driven methods in predictive modeling, particularly within the wind energy domain. Overall, the combination of these findings confirms the centrality of deep learning and neural architectures in current research trends, especially in domains requiring precision forecasting and robust energy modeling.

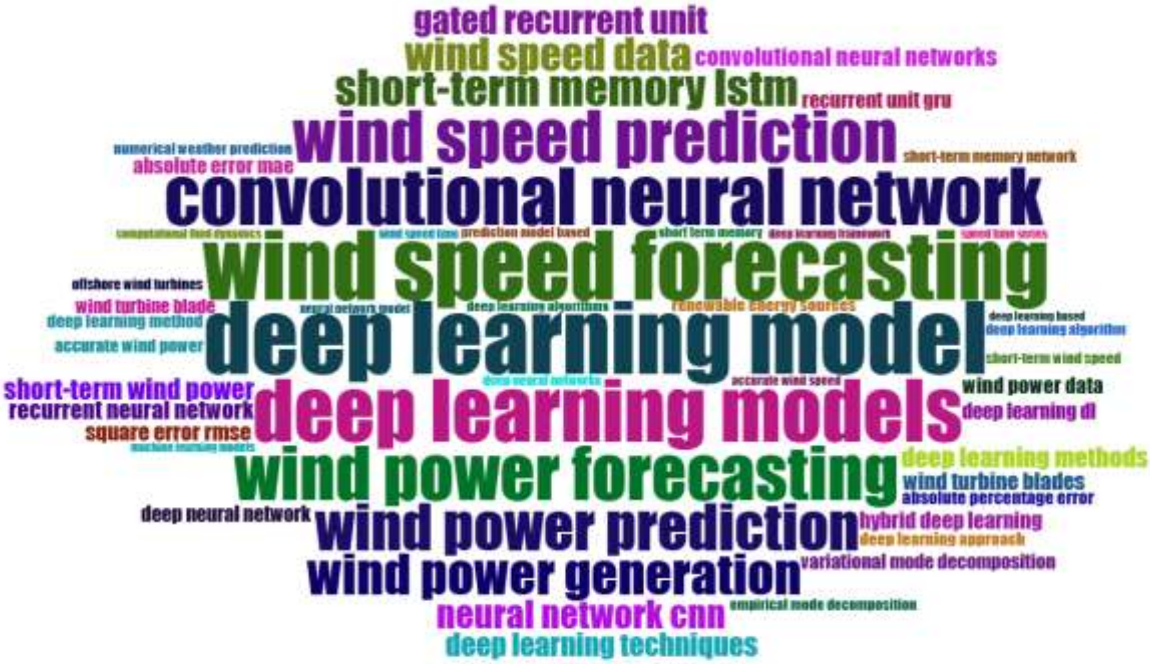

Figure 18. The Most Frequently Used Trigrams in Article Abstract

2.2.7. Conceptual Structure

Figure 19 presents the thematic structure of research trends in the domain of wind energy forecasting, using conceptual mapping of keywords based on centrality and density. The most prominent area in the motor themes quadrant—defined by high centrality and high density—includes topics such as “wind speed forecasting,” “deep learning,” “machine learning,” and “fault diagnosis.” These themes indicate well-established and rapidly evolving research directions with strong connectivity across publications and high developmental depth.

The basic themes quadrant, identified by high centrality but low density, reveals topics like “convolutional neural networks,” “transfer learning,” and “fault detection,” which serve as fundamental building blocks in current studies. Their central position highlights their importance, even if their internal development is still growing. In contrast, niche themes such as “multi-objective optimization” and “tropical cyclones” appear in the high-density but low-centrality area, signaling specialized yet isolated discussions.

Finally, themes like “decomposition” and “deep learning model” located in the low-density and low-centrality quadrant are considered emerging or potentially declining, suggesting either underexplored potential or fading relevance. This thematic configuration shows that deep learning remains a foundational and integrative component, while fault analysis and transfer methods are critical for advancing wind energy prediction systems.

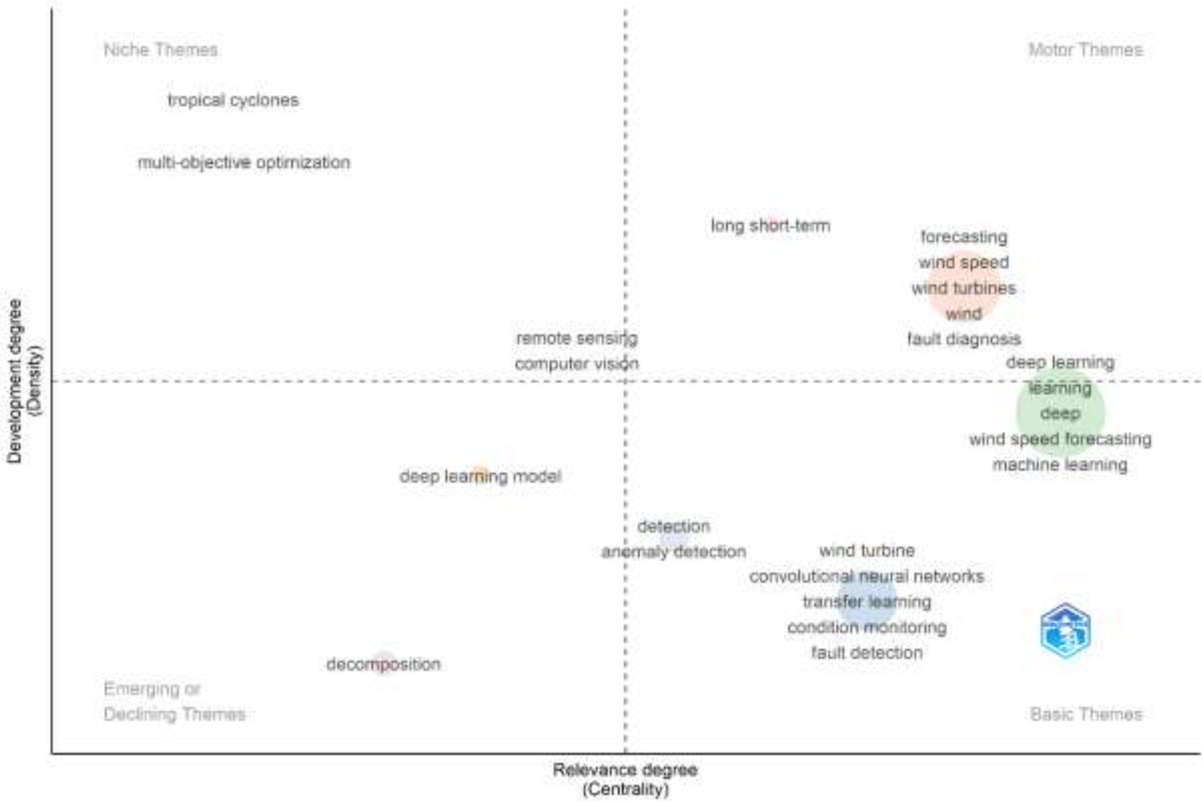

Figure 19. Author’s Keywords Thematic Map

Figures 20 and 21 illustrate the thematic and conceptual structures within the wind energy forecasting research domain. In Figure 20, themes like "wind speed," "deep learning," and "wind turbine" are classified as basic themes, showing high centrality but moderate development. "Fault diagnosis" and "wave height" appear as motor themes, reflecting both high relevance and strong development. In contrast, topics such as "remote sensing," "air quality," and "particulate matter" lie in the emerging or declining quadrant, indicating either fading interest or early-stage exploration. Niche themes like "smart grids" and "green hydrogen" suggest specialized but relatively isolated research areas.

Figure 21 presents a conceptual structure map based on Multiple Correspondence Analysis. The purple cluster forms the densest area, encompassing a wide range of techniques and concepts like "neural networks," "time-series," and "fault detection." The turquoise cluster groups terms such as "wind power generation" and "predictive models," representing a strategic layer focused on output optimization. The red and green clusters—focusing on "forecasting methods" and "signal decomposition" techniques like "wavelet" and "transform"—highlight specific methodological paths within the field.

Overall, both maps reveal a research environment where algorithmic development, deep learning applications, and predictive modeling are central. The findings emphasize the increasing integration of advanced AI techniques with traditional forecasting, while also pointing to emerging frontiers such as sustainability metrics and high-resolution data integration.

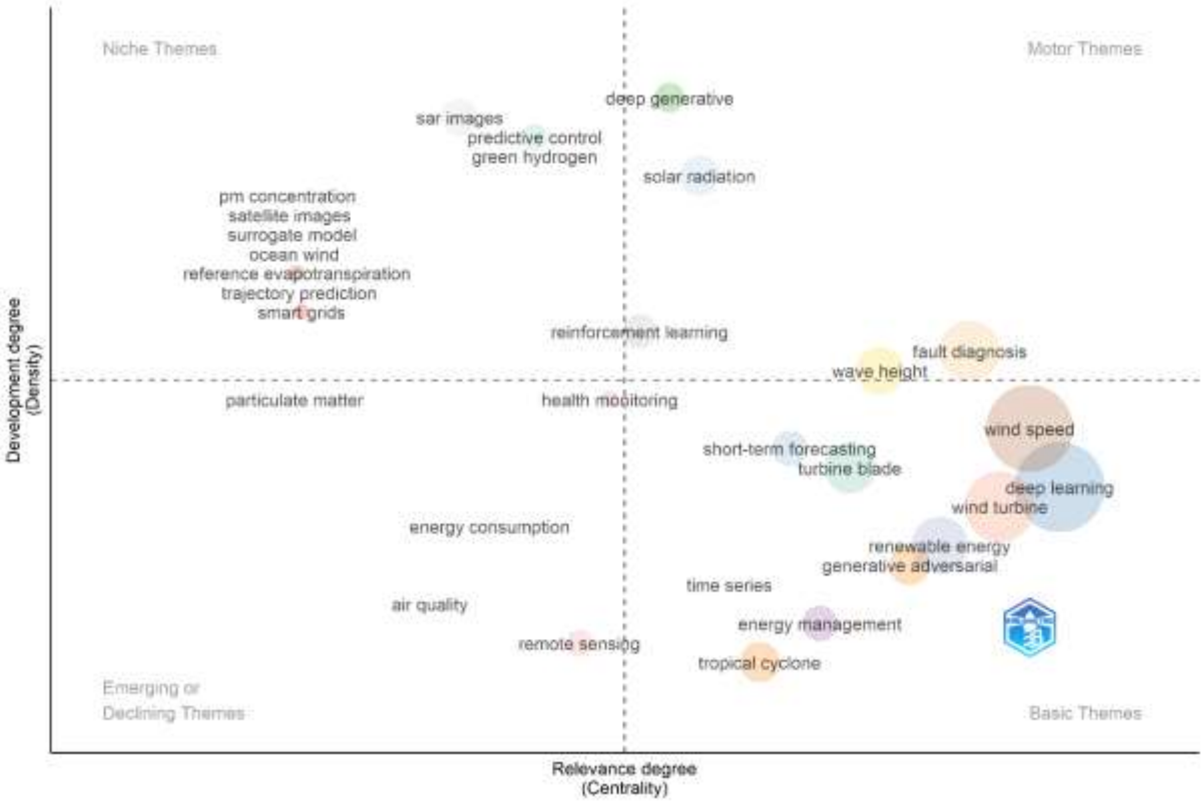

Figure 20. Article Title Bigrams Thematic Map

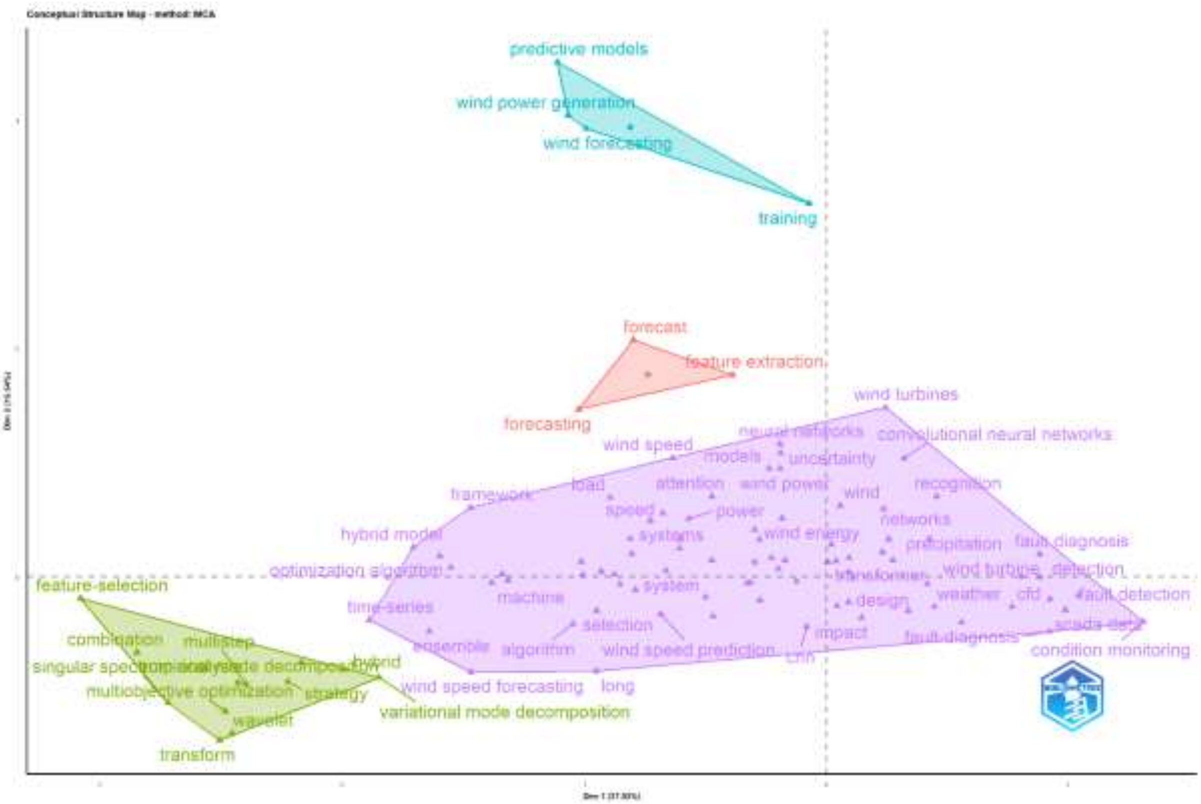

Figure 21. Keywords Conceptual Structure Map

3. Result and Discussion

The bibliometric analysis of deep learning applications in wind energy forecasting reveals a rapidly growing research area marked by increased scholarly interest and international collaboration. From 2013 to 2024, publication trends show exponential growth, particularly after 2019. The number of annual publications rose from fewer than 20 before 2018 to a peak of 866 articles in 2024, indicating a sharp acceleration in both technological advances and academic engagement in this field. This surge reflects broader global efforts toward sustainable energy forecasting using AI-driven models.

The distribution of publications across disciplines and journals underscores the interdisciplinary character of the domain. Journals such as Energy, Energies, and IEEE Access emerged as dominant publication venues, each contributing significantly to the dissemination of research findings. The categorization of articles revealed that most studies fell under the domains of engineering (24.6%), energy fuels (14.4%), and computer science (11.4%), with notable overlaps in environmental sciences and thermodynamics. These results highlight how deep learning serves as a bridge between computational modeling and real-world energy challenges.

Citations patterns reveal both academic relevance and intellectual influence. The total citation count has grown steadily since 2019, culminating in a peak TC/TP ratio exceeding 25 in 2024, which suggests that recent publications are gaining rapid traction. The most cited works, such as Jiang et al. (2019) and Ravuri et al. (2021), emphasize fault diagnosis, convolutional neural networks, and ensemble modeling. Many of these studies were the product of multi-author, cross-national collaborations—further underscoring the field's collaborative ethos. Notably, Chinese institutions dominate both in volume and citation impact, with the Chinese Academy of Sciences and North China Electric Power University consistently appearing at the top of institutional rankings.

A significant finding from the social network analysis is China's central role in international collaboration. China not only produced the largest number of articles (1,715) but also established strong bilateral research ties with countries such as the United States, the United Kingdom, and Australia. This demonstrates China's strategic leadership in renewable energy research and its capability to act as a global connector in the dissemination of AI-based forecasting models.

Keyword and thematic mapping offer further insight into research priorities and trends. The most frequently used keywords include "deep learning," "wind speed forecasting," "fault diagnosis," and "LSTM." These terms suggest that while the field is deeply rooted in predictive analytics, there is also a strong emphasis on model reliability and system optimization. Advanced architectures such as convolutional and recurrent neural networks (e.g., LSTM, GRU) have gained prominence, pointing to an ongoing evolution toward more nuanced, hybrid modeling approaches. Thematic maps identified "deep learning," "machine learning," and "wind turbine" as core and motor themes—representing both the foundational pillars and the most developed areas of research.

Finally, the alignment of publications with Sustainable Development Goals (SDGs) indicates a focused contribution to global energy and climate objectives. Most research aligns with SDG 7 (Affordable and Clean Energy), followed by SDG 13 (Climate Action). However, themes such as SDG 9 (Industry, Innovation, and Infrastructure) and SDG 11 (Sustainable Cities and Communities) remain underrepresented, suggesting opportunities for expanding the societal impact of future research.

In summary, the field of deep learning-based wind energy forecasting is rapidly maturing, characterized by interdisciplinary innovation, global cooperation, and an increasing emphasis on sustainability. The data presented in this study underscore the importance of collaborative research frameworks and advanced neural models in driving the next generation of energy forecasting solutions.

4. Conclusion

This bibliometric analysis has provided a comprehensive overview of the academic landscape surrounding the application of deep learning techniques in wind energy forecasting between 2013 and 2024. The steady increase in publication output—particularly after 2019—demonstrates the escalating relevance of AI-powered forecasting tools within the context of global energy transformation. The prevalence of article-type publications highlights the field's scientific maturity, while the surge in citation metrics indicates growing academic influence and practical significance.

The dominance of Chinese institutions and scholars—both in terms of productivity and citation impact—points to a geographic concentration of research leadership. However, the expanding network of international collaborations signals a broader, more integrated global research community that is increasingly united around sustainability-driven technological advancement. Through social network analyses and keyword mapping, this study has revealed that model complexity, fault diagnosis, and hybrid deep learning architectures are at the heart of the research focus.

In addition to academic growth, the thematic evolution of keywords and SDG alignment suggest a maturing awareness of the socio-environmental dimensions of renewable energy forecasting. Despite the strong presence of topics related to clean energy and climate action, certain sustainability goals remain underexplored, indicating potential avenues for interdisciplinary expansion. The findings emphasize that future research should not only push the boundaries of algorithmic accuracy but also broaden its scope to encompass emerging societal and ecological challenges.

Ultimately, this study offers a foundational framework for researchers, practitioners, and policymakers aiming to navigate and contribute to the fast-evolving intersection of artificial intelligence and renewable energy systems. By mapping the intellectual structure, collaboration networks, and thematic trends of the field, it lays the groundwork for more strategic and impactful future investigations into deep learning-based hybrid models for wind energy forecasting.

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