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Intelligence Techniques in Sustainable Energy: Analysis of a Decade of Advances

Juan D. Velásquez, Lorena Cadavid and Carlos J. Franco *

Departamento de Ciencias de la Computación y la Decisión, Facultad de Minas, Universidad Nacional de Colombia, Medellín 1027, Colombia; jdvelasq@unal.edu.co (J.D.V.); dlcadavi@unal.edu.co (L.C.)
* Correspondence: cjfranco@unal.edu.co; Tel.: +57-604-425-5350

Abstract: In the last decade, many artificial intelligence (AI) techniques have been used to solve various problems in sustainable energy (SE). Consequently, an increasing volume of research has been devoted to this topic, making it difficult for researchers to keep abreast of its developments. This paper analyzes 18,715 articles—about AI techniques used for SE—indexed in Scopus and published from 2013 to 2022, which were retrieved and selected following a novel iterative methodology. Besides calculating basic bibliometric indicators, we used clustering techniques and a co-occurrence analysis of author keywords to discover and characterize dominant themes in the literature. As a result, we found eight dominant themes in SE (solar energy, smart grids and microgrids, fuel cells, hydrogen, electric vehicles, biofuels, wind energy, and energy planning) and nine dominant techniques in AI (genetic algorithms, support vector machines, particle swarm optimization, differential evolution, classical neural networks, fuzzy logic controllers, reinforcement learning, deep learning, and multi-objective optimization). Each dominant theme is discussed in detail, highlighting the most relevant work and contributions. Finally, we identified the AI techniques most widely used in each SE area to solve its specific problems.

Keywords: sustainability; renewable energy; tech mining; artificial intelligence; bibliometric analysis; machine learning

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1. Introduction

The transition from conventional fossil-fuel-based energy sources to renewable alternatives, characterized by a low environmental impact and diminished carbon emissions, has emerged as a relevant topic in the last decade [1,2]. This is a clear trend that has emerged since the 1990s, in line with the development of sustainability. Notably, various national governments have achieved significant advances in the integration of sustainable energy (SE) sources into their energy portfolios [3], but the challenges and problems related to their adequate use and popularization have grown as well [4]. On a macro level, incorporating renewable energies into planning the operation and expansion of existing electrical power systems poses essential challenges due to the inherent variability of renewable resources [5], the difficulty of forecasting [6], and their proximity to end-users. On a micro level, the adequate and optimal use of each distinct renewable technology implies solving complex technical problems associated with generic optimization, control, and forecasting issues. For example, forecasting the wind speed and subsequent energy output of wind farms is challenging due to the inherent stochastic and intermittent nature of wind velocity [2]. Similarly, forecasting the performance of fuel cells has significant complexity due to their inherent multivariate and non-linear nature [7]. This article will discuss many other similar cases in depth.

In response to this prevailing worldwide context, both practitioners and researchers have identified a suite of methodologies and tools amenable to tackling the challenges inherent to sustainable energy (SE) within the domain of artificial intelligence (AI) [8–10].

These AI approaches offer avenues for addressing extant issues and refining pre-existing solutions hitherto adapted from diverse disciplines. Notably, the past decade has been characterized by the popularization of AI techniques, which has been boosted by successful advances in methodologies such as deep learning [11,12] and the augmentation of computing capacity. Consequently, the use of AI in SE has attracted significant interest, which can be observed from the annual increase in research publications.

However, it should be noted that the domains of sustainable energy (SE) and artificial intelligence (AI) are vast fields in scope, and it is not easy to define their intersections and joint evolution to determine their history and more relevant trends over time. Considering this complexity, it is significant to profile the existing research publications using literature-based discovery techniques to identify dominant themes and development patterns in the last decade. Thus, the objective of this study is to identify, classify, and hierarchize the dominant areas using the existent literature as evidence. Previous works are focused only on subareas and do not present a comprehensive approach to this area. A small-scale attempt is presented in [13], where bibliometric methods are employed to analyze 469 documents obtained from the Web of Science. These documents were published between 1985 and 2022. The main limitation of the study presented in [13] was its search string, as it restricts the obtained documents to those having both "Artificial Intelligence" and "Renewable Energy" terms in their titles. This leads to considerable amounts of the literature being overlooked, as will be demonstrated later in this document. Another highly significant limitation of the study is that the authors do not provide details about the review and cleaning process of the keywords used in the co-word analysis. This aspect is crucial since synonyms and the duplication of terms due to the inclusion of singular and plural forms (treated as distinct text strings) can significantly impact the results, potentially leading to erroneous conclusions.

This investigative effort is thus dedicated to profiling the available data regarding the basic "4W" questions: Who? Where? When? What? To profile the research literature, we blend bibliometric and text-mining methods to map the leading players and their interconnections and discover dominant themes.

A comprehensive assembly and subsequent scrutiny of a database encompassing 18,715 scholarly articles have been undertaken to accomplish this objective. These articles collectively address the application of AI techniques in resolving the principal quandaries discerned by researchers and practitioners who are deeply engaged in the study and practice of SE.

The rest of this article is organized as follows. Section 2 presents a literature review. Section 3 describes the methodology adopted in this study and the data collection and cleaning processes employed. Section 4 presents an analysis of the results. Afterward, Section 5 details the dominant themes in the database. Finally, Section 6 draws the main conclusions.

2. Literature Review

2.1. Applications of Artificial Intelligence on Sustainable Energy

The widespread adoption of artificial intelligence has significantly impacted sustainable development, particularly in solving various issues that affect renewable energy sources. Clearly, AI is a powerful enabler of sustainable development goals, but it can also have negative impacts due to its rapid advancement without proper regulatory insight and oversight [14]. Over the last decade, AI has been applied to address various challenges in sustainable energy, and there is a significant body of literature dedicated to reviewing the progress achieved in specific and focused aspects of the application field. The published analyses are often focused on identifying and classifying the most suitable AI methods for a particular energy issue [15,16] or on examining the potential of a new AI paradigm for application to one or more energy-related problems, e.g., [17,18]. While conducting this research, a total of 378 literature reviews published between 2013 and 2022 were found. Without time restrictions in the search string, 539 review documents were obtained, covering the period between 1989 and 23 August 2023. The ten most cited reviews are listed in Table 1.

Table 1. Most cited reviews.

Authors	Year	Citations	Title
Voyant et al. [15]	2017	1034	Machine learning methods for solar radiation forecasting: A review
Vinuesa et al. [14]	2020	631	The role of artificial intelligence in achieving the Sustainable Development Goals
Raza and Khosravi [19]	2015	612	A review on artificial intelligence-based load demand forecasting techniques for smart grid and buildings
Wang et al. [18]	2019	496	A review of deep learning for renewable energy forecasting
Yadav and Chandel [20]	2014	494	Solar radiation prediction using Artificial Neural Network techniques: A review
Stetco et al. [16]	2019	460	Machine learning methods for wind turbine condition monitoring: A review
Suganthi et al. [21]	2015	387	Applications of fuzzy logic in renewable energy systems—A review
Vasquez-Cantely and Nagy [17]	2019	381	Reinforcement learning for demand response: A review of algorithms and modeling techniques
Elsheikh et al. [22]	2019	379	Modeling of solar energy systems using artificial neural network: A comprehensive review
Yarlagadda et al. [23]	2018	337	Boosting Fuel Cell Performance with Accessible Carbon Mesopores

The dataset covering the period 1989–2023 presents an annual growth rate of 19.69%. The average age of documents is 2.82 years, with an average of 51.59 citations per document. Authors work collaboratively with an average of 4.68 authors per document; international co-authorship is at 39.96%. There are 2330 unique authors, with 21 producing single-authored documents. The dataset involves 1039 organizations and 74 countries. Keywords are abundant, with 1484 author keywords and 3872 index keywords.

To analyze the published reviews between 1989 and 2023, co-word analysis was applied to all keywords (author keywords plus index keywords) to identify existing dominant thematic clusters. This type of analysis unveils the big picture of the documents, showing major emphasis areas. Only keywords appearing in five or more documents were considered for the co-word analysis. With this threshold, a coverage of 95.2% of the reviews was achieved, corresponding to 513 documents. The keywords underwent the same cleaning and standardization process used for the database analyzed in this document. This process will be discussed in more detail later.

Figure 1 presents the co-occurrence network obtained for keywords appearing in at least 15 documents. The size of text and nodes is proportional to the frequency of the keyword. The color and width of the links are proportional to the similarity measure between nodes. In this way, thicker and darker links indicate that the words in the associated nodes tend to appear together more frequently, e.g., MPPT and PHOTO_VOLTAIC_SYSTEMS, in the upper part of the network diagram. The figure shows a clear dominance of terms associated with deep learning and artificial neural networks in the reviews.

The results of the co-word analysis indicate that the published reviews can be grouped into five clusters. The first cluster discusses the use of AI in optimizing and enhancing the performance of solar and wind energy systems. Machine learning and AI techniques are used to improve the efficiency and reliability of these types of renewable energy systems. In this cluster, topics include the application of AI-enhanced Maximum Power Point Tracking (MPPT) controllers for photovoltaic (PV) systems. These controllers are essential for optimizing power extraction from solar panels, especially under fluctuating environmental scenarios such as partial shade, as addressed previously. AI and machine learning are also employed in forecasting and predicting wind and solar power, which is crucial for grid stability and efficient energy distribution.

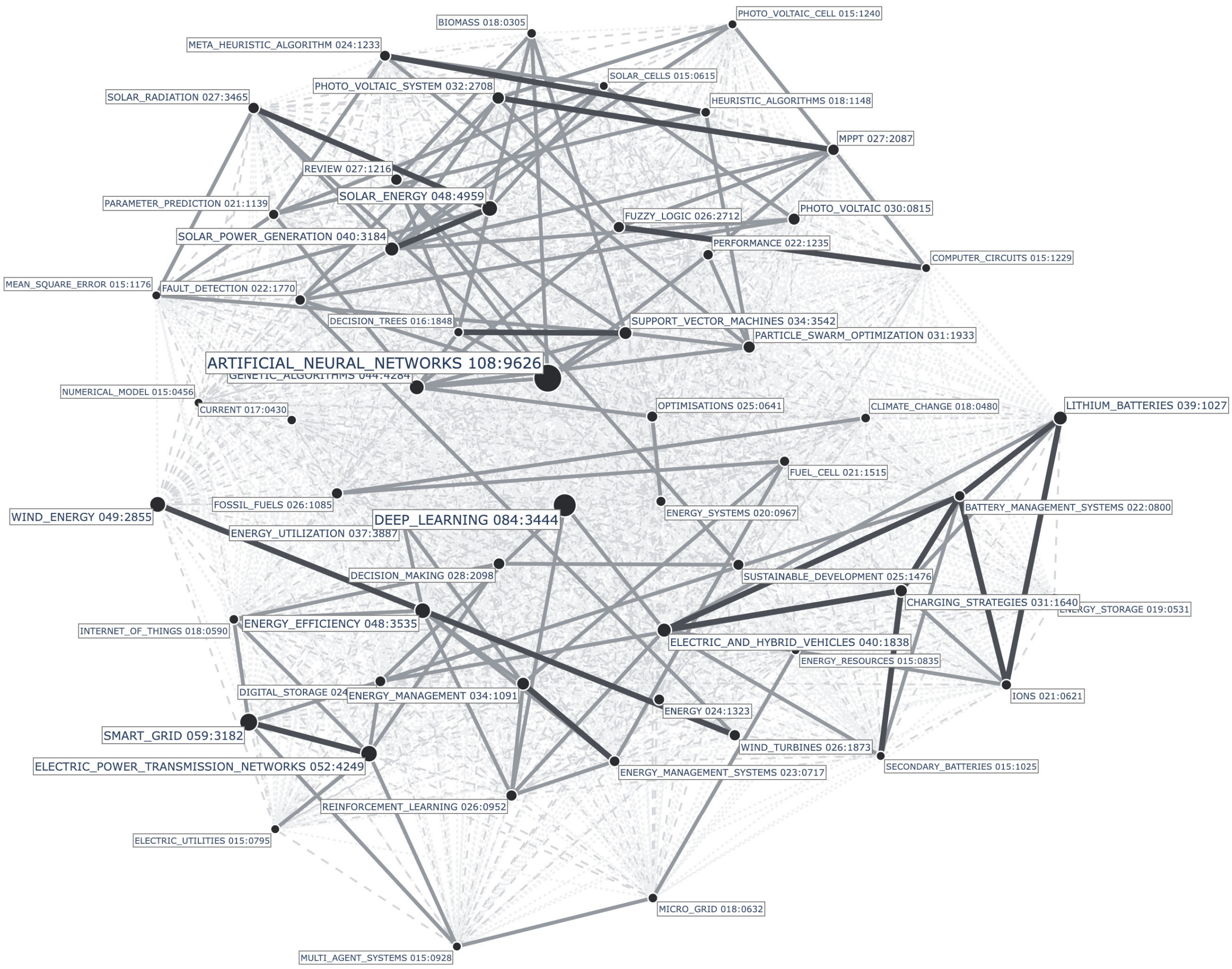

Figure 1. Keyword co-occurrence network constructed for terms with a minimum threshold of 15, considering only the literature reviews published between 1989 and 2023. The numbers following the term indicate appearances and citations, respectively. The size of the nodes is proportional to the number of appearances of the keyword. The width and darkness of links show similarity between terms, e.g., the terms tend to appear together in the documents.

The second cluster addresses the application of AI in solving different problems in smart grids and microgrids, which include aspects such as energy efficiency, energy utilization, and energy management. This cluster emerges because smart grids represent a transformative shift in electric power transmission networks, evolving as a direct response to the growing intricacies and demands of contemporary energy needs. Smart grids aim to elevate energy efficiency and optimize energy utilization substantially, converging these efforts towards the overarching goal of adept energy management [24]. As indicated in the analyzed reviews, AI plays a prominent role in diverse aspects of the operation of energy systems [25,26].

The third cluster addresses the application of traditional models of neural networks, support vector machines, and genetic algorithms to different problems in renewable energy. Artificial neural networks (ANNs) emulate the human brain's structure and function to process data, making them adept at modeling complex systems with non-linear relationships. This adaptability has rendered ANNs invaluable in renewable energy research. The reviews indicated that ANNs have shown proficiency in solving tasks of modeling, forecasting, and optimizing. In addition, there is a synergistic integration of ANNs with genetic algorithms (GAs). These techniques have been applied to improve the efficiency of biodiesel production [27], to forecast energy for renewable sources including solar, wind, and hydro [28], to develop novel renewable energy materials [29], and to augment the heat transfer efficiency in nanofluid systems [30]. Support vector machines (SVMs) are another technique commonly used in energy systems; SVM has been used, for example, to identify prime locations for electric vehicle charging stations [31] and to architect energy distribution frameworks [32].

The fourth cluster discusses the application of diverse deep learning models in sustainable energy. The reviews mainly focus on solving problems related to electric and hybrid vehicles and different aspects of batteries, such as estimating the state of charge and remaining useful life. This emphasis in the most relevant literature is because of the rising use of lithium-ion batteries in applications such as portable electronics and electric vehicles, and there is an increasing interest in optimizing their performance and predicting their state [33]. Lithium-ion batteries are categorized as secondary batteries and are fundamental to energy storage systems, particularly for powering electric and hybrid vehicles due to their high energy densities [34]. Ensuring the consistent and reliable performance of these batteries is paramount. As vehicles transition to being powered by these batteries, predicting their lifespan and the remaining energy they can offer has become crucial [35]. Deep learning's capacity for nonlinear modeling, a skill highlighted by its ability to handle complex tasks and historical data, provides a robust tool for accurately estimating the State of Charge (SOC) of batteries, a crucial factor for their health [36]. This accurate SOC estimation is indispensable for creating advanced battery management systems and formulating effective charging strategies [37]. Similarly, the global tilt towards electric and hybrid vehicles is also driven by environmental imperatives. The transportation sector substantially contributes to greenhouse gas emissions and consumes a significant portion of global energy [35]. With the pressing need to curtail greenhouse gases due to their role in climate change, electric and hybrid vehicles have emerged as potential game-changers. They substantially reduce dependency on fossil fuels, decreasing greenhouse gas emissions [38]. Advanced battery management systems, enhanced by deep learning capabilities, play a critical role in this transition. By boosting vehicle reliability, these systems facilitate the broader adoption of electric and hybrid vehicles, underscoring our commitment to a sustainable future [38].

Finally, the fifth cluster groups reviews discussing the use of AI in proton exchange membrane fuel cells and other devices for energy storage and conversion like rechargeable electric batteries. This cluster also includes works related to hydrogen production. Fuel cells, particularly proton exchange membrane fuel cells (PEMFCs), are electrochemical devices that convert chemical energy directly into electrical energy using specific chemical reactions [39]. PEMFCs have become increasingly prominent in the energy domain owing to their versatile properties, such as high power density and quick startup. They can achieve notable conversion efficiencies, with some models reaching up to 65% [40,41]. The scope of energy storage and conversion extends beyond just fuel cells. It encapsulates devices such as rechargeable electric batteries. With the advent of artificial intelligence and machine learning, there has been a rapid advancement in the design and development of essential battery materials, especially electrode materials and solid electrolytes [42]. Machine learning stands out as a transformative tool in this domain, unveiling and predicting novel battery systems, thus propelling the evolution of battery research [43,44]. Moreover, combining imaging techniques with machine learning has enriched our understanding of battery materials. This synergistic approach has revealed intricate details about electrode microstructures and their consequential influence on overall battery performance [45].

To analyze the evolution of the topics addressed by the literature reviews, the dominant clusters were analyzed for each year in the period 2011–2023. With the clusters of each year, a Sankey diagram was prepared that shows the migration of keywords from one cluster to another. This diagram is presented in Figure 2.

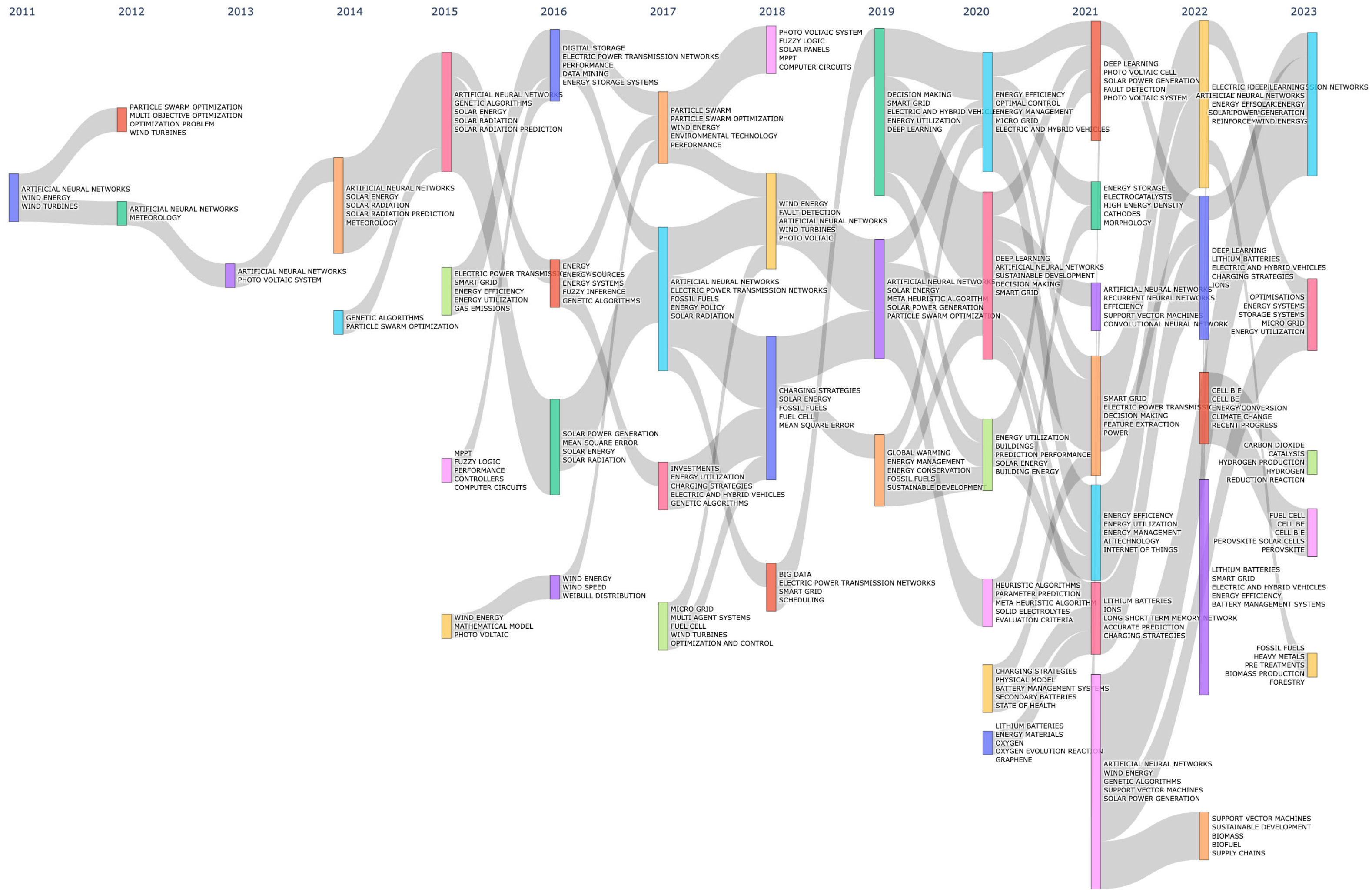

Figure 2. Thematic clusters per year for the reviews published from 2011 to 2023.

In the oldest review found, Nilsson, in 1989, analyzes the application of expert systems in utility electrical power plant systems [46]. In 1998, Li et al. [47] presented a comparative analysis of regression and ANNs for the prediction of wind turbine power. Next, in 2000, Kalogirou [48] reviewed the application of ANNs in renewable energy systems. In 2008, Mellit and Kalogirou [49] analyzed the application of AI in photovoltaic systems. In 2009, Mellit et al. [50] discussed using AI for sizing photovoltaic systems. Starting in 2011, literature reviews on the topic of study began to be consistently produced.

As seen in Figure 2, between 2011 and 2014, reviews focused on the applications of ANN, PSO, and GA in solar and wind energy. For 2015, the reviews on smart grids, energy efficiency, and the use of fuzzy logic in MPPT, are consolidated. For 2016, reviews on energy storage take a central role. For 2017, hybrid and electric vehicles and microgrids stand out as new focuses of interest. In 2018, the use of big data appears as one of the central themes. Subsequently, in 2019, a significant number of reviews on deep learning were published. In 2020, topics related to lithium batteries, charging strategies, electric vehicles, and deep learning occupy the attention of reviews. These topics continue to be valid during the years 2021 and 2022. Finally, for 2023, hydrogen stands out as one of the most relevant topics.

2.2. Dominant Theme Identification and Co-Word Analysis

Profiling large volumes of the literature is a challenge that needs to be addressed using bibliometric and text mining methods [51–53]. Bibliometrics involves applying quantitative techniques to bibliographic databases to determine performance indicators for authors, institutions, countries, and sources [54]. It also aims to elucidate the analyzed field's social, intellectual, and conceptual structure [55]. However, the techniques vary based on the quantity of documents to be analyzed and the available software. Specifically, for large volumes of information, it is necessary to employ text mining techniques that enable preprocessing and highlighting of the most essential information before analyzing the available data.

The identification of relevant themes in a body of literature is primarily based on the analysis of keywords or noun phrases extracted from the text of the documents. Keyword analysis is commonly used to uncover the intellectual structure (major dominant themes), while noun phrases are used to discover emerging topics. Particularly in the latter case, there is a significant effort to develop methodologies that enable the detection of technological emergence through the analysis of the scientific literature and patents [56].

Determining thematic areas using co-word analysis is based on clustering techniques on the matrix or network of keyword co-occurrences. This technique is well known and widely used in the most relevant literature. For example, in [57], co-word analysis is used to obtain the research clusters to analyze business models in green buildings. Chen et al. [58] deduced the characteristics of an energy policy in China using this technique.

3. Materials and Methods

3.1. Workflow Overview

This study followed the standard workflow proposed in [54,55], which includes the following stages:

1. Study design.
2. Data collection and preparation.
3. Data analysis.
4. Data visualization.
5. Interpretation.

3.2. Study Design

The parameters of the study are presented in Table 2. The study was restricted to the last ten complete years to discover the recent evolution of the field.

Table 2. Parameters of the study.

Parameter	Value
Database	Scopus
Years of Analysis	From 2013 to 2022
Data Retrieval	23 August 2023
Search String	It is derived using an iterative construction method, which will be elaborated upon in the subsequent section.
Inclusion Criteria	Articles published in peer-reviewed journals and conference proceedings, specifically those in English.
Exclusion Criteria	None

To define the analysis period, the articles retrieved by the search string designed in this research were analyzed without considering any time restrictions. The analysis of the keywords (not discussed here) shows that the research published during the period 1979–2012 is concentrated on the use of classic ANN models (back-propagation feed-forward networks, radial basis function networks, SVM), GA, PSO, expert systems, and fuzzy systems to solve problems related to solar and wind energy and batteries. During that period, there was not a variety of techniques and issues in the area similar to those that have arisen in recent years, as seen in Figure 2. In this way, it was decided to use the last ten years in this analysis to capture the temporal evolution of the different thematic focuses that have been presented. In addition, Ref. [13] covers the initial period.

Constructing the search string posed a substantial challenge in the context of this research. Designing search strings to collect publications in a field of knowledge is a central activity in bibliometric analysis, meta-analysis, and systematic literature reviews. One of the main functions of search strings is identifying relevant documents in a specific area while discarding non-relevant content. Nevertheless, the wider the field of knowledge, the more challenging the identification of keywords. Such is the case for AI and SE.

Figure 3 details the methodology adopted in this study to design the search string and retrieve the publications. Note that some stages could be similar to those in other methodologies to select publications in literature reviews, e.g., PRISMA [59]. However, the methodology implemented here was different because its goal was to develop an adequate search string by tracking keywords instead of filtering the results retrieved by a search string that was established a priori.

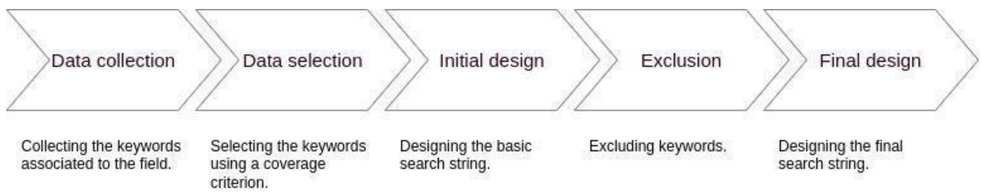

Figure 3. Methodology implemented to design the search string.

3.3. Design of the Search String

The search string was designed in late 2022 during the preliminary formulation of the research project. The design process is discussed in the following sections.

3.3.1. Data Collection

The objective of the first step was to find the keywords associated with the categories of sustainable energy (SE) and artificial intelligence (AI). To do this, all Q1 and Q2 journals belonging to these categories were identified in Scimago Journal and Country Rank. A total of 103 journals were found in the SE category and 100 in the IA category. Then, the author's keywords were downloaded for each journal article from 2013 to 2022. For this period, 274,764 articles and 334,527 keywords were found in the SE category, and 123,362 articles and 203,443 keywords in the AI category. This equates to a total of 398,126 articles and 516,244 author keywords. Table 3 summarizes these figures.

Table 3. Collected keywords to design the search string.

	Sustainable Energy (SE)	Artificial Intelligence (AI)	Total
Journals classified in quartiles Q1 and Q2.	103	100	203
Publications between 2013 and 2022	274,764	123,362	398,126
Keywords	334,527	203,443	516,244

Of the total keywords, 191,662 author keywords in AI and 158,849 author keywords in SE appear in six or fewer documents. These could be considered rare terms. On the other hand, if basic text mining techniques were used to homogenize the text, such as unifying plurals and singulars, it was found that of the totals of 334,527 and 203,443, there are 311,316 and 247,848 different keywords.

3.3.2. Data Selection

A manual analysis was conducted to identify the most significant keywords within each field (i.e., SE and AI). For this purpose, the terms that ranked among the top 1000 most frequently used keywords each year and had a minimum frequency of eight were subject to manual examination. The resulting keywords obtained from this process were incorporated into the initial search string.

3.3.3. Initial Design

The keywords selected in the preceding phase were employed in formulating an initial search query within the Scopus database. That preliminary string specified that the title of the documents should include at least one relevant SE keyword and one relevant AI keyword. No restrictions were imposed concerning the field of knowledge or publication year. This initial query retrieved a total of 12,428 documents.

3.3.4. Exclusion

The titles of the top 2000 most cited publications obtained through the initial search query were subject to manual review to identify those that did not align with the objectives of this study. These words were deleted from the search string. This review led to identifying keywords that, owing to their general nature, failed to retrieve pertinent documents for this investigation.

3.3.5. Final Design

As a result of the previous step, the final search string included only keywords that allow the target documents to be retrieved for analysis. The final search string is detailed in Appendix A.

3.4. Data Collection and Preparation

All information from the documents retrieved by the search string was extracted from the Scopus database. The downloaded fields encompassed article title, authors' names, authors' Scopus identifiers, source title, citation count, references, abstract content, author keywords, and index keywords. All this information was downloaded in CSV format to facilitate subsequent processing.

Multiple procedures were employed to extract, clean, and consolidate the data in the dataset. These procedures encompass a combination of computational operations complemented by manual refinements. The comprehensive process involved:

- Removing accents to normalize textual representation.
- Standardizing the formatting of author names.

- Disambiguating author names based on Scopus Author ID.
- Removing parts of titles in languages other than English.
- Extracting and refining geographic regions and affiliations from the affiliation field.
- Applying text string transformations such as case conversion, whitespace removal, concatenation, and character substitution as required.
- Eliminating occurrences of <NA>, substituting where applicable.
- Homogenizing author and index keywords. Within this phase, a thesaurus was systematically constructed through an iterative approach. Initially, text mining techniques were used to group terms differing in spelling (American and British) or plural and singular forms. After this, a manual computer-assisted validation process was undertaken. The primary objective of this manual verification was to establish uniformity among synonyms and textual variations not encompassed within the preliminary phase.

3.5. Data Analysis, Visualization, and Interpretation

This study used several performance metrics to characterize the contributions of journals, authors, organizations, and countries in the field. The performance metrics for productivity and impact include the number of publications and citations per year, and citations per year and document.

Co-word analysis was used to examine the content of the documents. In this case, it was assumed that words frequently appear together and have a thematic relationship. In this research, the relationships between terms are represented using a co-occurrence network, where the nodes represent the terms and the links represent co-occurrence. The number of co-occurrences between the words in the corresponding nodes weights the links.

The co-occurrence network derived from the author's keywords was clustered to identify the dominant themes, applying community detection algorithms. Each resulting cluster corresponds to one dominant theme. Documents with one or more author keywords belonging to the cluster were examined to analyze each dominant theme.

4. Results

4.1. Performance Metrics

4.1.1. General Performance Metrics

The employed dataset encompasses documents published from 2013 to 2022, comprising 18,715 documents. This yields an annual growth rate of 41.71%, with an average document age of 3.63 years and 19.56 citations per document. Notably, each document receives an approximate annual citation count of 1.96. The dataset involves contributions from 4467 distinct source titles, with an average of 4.19 documents per source. The dataset contains 11,614 articles, 7100 conference papers, and 1 retracted document (which was ignored in the analysis). The 54,884 authors collectively yield an average of 4.14 authors per document, alongside an average of 4.24 co-authors. Around 23.81% of authors partake in international co-authorship, contributing to 77,571 author appearances. Furthermore, the dataset encompasses 13,450 organizations across 138 countries. There are 28,487 author keywords and 46,920 index keywords.

4.1.2. Performance Trend Metrics

Figure 4 depicts the annual publication count, while Table 4 outlines the primary yearly performance metrics. The plotted curve shows a distinct upward trajectory, reflecting an increasing interest in the research domain. However, it is noteworthy that the average citations per document and the mean citations per document per year reveal a consistent downward pattern, as can be seen in Table 4. This trend can be attributed to the tendency for older documents to accumulate more citations. Particularly interesting is the anomaly in 2018; despite a surge in publication volume, there was an abrupt drop in both the average citations per document and the mean citations per document per year.

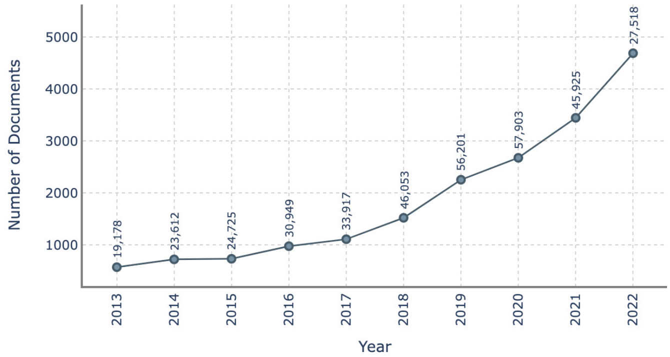

Figure 4. Number of documents per year. The number above each marker indicates the total citations per year.

Table 4. Annual performance metrics.

Year	Documents	Citations	Average Citations per Document	Average Citations per Document per Year
2013	573	19,178	33.47	3.35
2014	723	23,612	32.66	3.63
2015	734	24,725	33.69	4.21
2016	977	30,949	31.68	4.53
2017	1111	33,917	30.53	5.09
2018	1523	46,053	30.24	6.05
2019	2256	56,201	24.91	6.23
2020	2678	57,903	21.62	7.21
2021	3448	45,925	13.32	6.66
2022	4692	27,518	5.86	5.86

4.1.3. Authors' Performance Metrics

There are 54,884 authors and 242 authors with ten or more publications. Table 5 details the performance indicators, ordered by the number of documents, for the top 20 authors with more documents or more total citations (GCS). Seven authors belong in both groups. Javaid N. ranks first with 50 publications, while Xiong R. is the most cited author. In addition, the number of local citations (citations among the documents in the database or local citation score (LCS)) was calculated; this value was used to compute the h-, g-, and m-index presented in the table. As a result, Mekhilef S., with an h-index of 21, is the most relevant author considering local citations and the number of published documents.

Table 5. Performance metrics for the top 20 most productive and top 20 most cited authors.

Author	Rank OCC	Rank GCS	OCC	GCS	LCS	H-Index	G-Index	M-Index
Javaid N *	1	18	50	1290	129	18	7	2.25
Vale Z	2	82	37	690	38	14	5	1.4
Mekhilef S *	3	5	32	1673	283	21	8	2.1
Hannan MA *	4	17	30	1263	227	19	7	2.11
Ismail B/1	5	1807	30	174	25	7	3	0.7
Chen Z/26 *	6	9	25	1395	182	17	7	1.7
Blaabjerg F	7	30	24	1048	99	16	7	3.2
Lipu MSH	8	33	23	977	192	13	7	2.17
HongWen H *	9	4	22	1701	376	14	7	2.33
Wang J/107 *	10	12	22	1381	205	15	7	1.67
Rezk H	11	64	22	755	95	13	6	2.17
Dash PK	12	73	22	718	106	12	6	1.71
Catalao JPS	13	78	22	695	120	12	5	1.5

Table 5. *Cont.*

Author	Rank OCC	Rank GCS	OCC	GCS	LCS	H-Index	G-Index	M-Index
Chen Z/72	14	124	22	602	71	11	5	1.1
Yang Q/20	15	376	22	400	64	10	4	1.67
Hu X/8 *	16	10	21	1393	208	16	7	1.78
Khatib T	17	67	21	746	113	13	6	1.44
Wang F/30	18	34	20	969	200	11	7	1.38
Hussain A/3	19	44	20	870	165	13	6	2.17
Salcedo-Sanz S	20	57	20	812	12	16	6	1.5
Xiong R	24	1	19	2280	335	17	8	1.89
Liu H/60	25	2	19	2036	467	15	9	1.88
He H/6	34	6	17	1628	155	13	7	1.3
Shamshirband S/1	42	8	16	1475	226	15	8	1.67
Wang Z/45	43	20	16	1238	223	12	7	1.33
Liu T/2	56	15	15	1354	287	13	8	1.62
Li Y-F/2	113	3	12	1823	424	11	9	1.38
Dong ZY	114	11	12	1388	216	12	7	1.33
Wang HZ	175	7	10	1588	350	9	6	1.29
Chen Z/55	243	19	9	1241	184	8	6	1
Mi X-W	410	16	7	1272	300	7	7	1.17
Peng JC	598	13	6	1378	299	6	6	0.86
Liu YT	872	14	5	1366	299	5	5	0.71

OCC: occurrences; GCS: global citation score; LCS: local citation score. * Authors simultaneously belong to the top 20 most frequent and top 20 most cited authors.

A correlation map for exploring the co-authorship relationships among the authors in Table 5 is presented in Figure 5. The size of the nodes is proportional to the number of documents of the author, whereas the width of the links is proportional to the number of co-authored publications. The figure shows six clusters of authors and nine isolated authors.

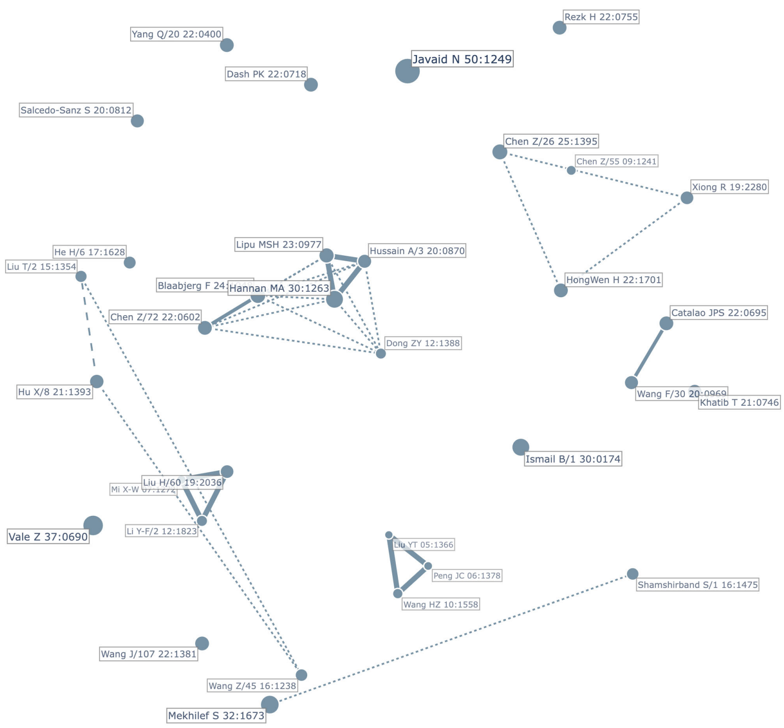

Figure 5. Co-authorship among the top 20 authors with more documents or more citations. Numbers following the name indicate the total number of documents and citations.

4.1.4. Organizations' Performance Metrics

Table 6 presents the performance metrics for the authors' institutions of affiliation. Notable trends include the dominance of Chinese institutions such as North China Electric Power University, Tsinghua University, and Huazhong University of Science and Technology, indicating China's robust contribution to the research landscape. However, organizations like Islamic Azad University, the University of Tehran in Iran, and the National Institutes of Technology in India demonstrate a significant impact despite lower publication counts. A prominent outlier is the University of California (USA), with a high global citation count but a relatively lower number of documents published, underscoring its research quality.

Table 6. Performance metrics for the top 20 most productive and top 20 most cited affiliations.

Affiliation	Rank OCC	Rank GCS	OCC	GCS	LCS	H Index	G Index	M Index
North China Electric Power Univ (CHN) *	1	2	296	7904	1064	44	11	4.4
Islamic Azad Univ (IRN) *	2	3	206	6613	370	43	11	4.3
Tsinghua Univ (CHN) *	3	4	203	6582	649	42	11	4.2
Min of Education (CHN) *	4	6	187	5760	548	41	10	4.1
Huazhong Univ of Sci and Technol (CHN) *	5	5	176	6216	707	47	11	4.7
Beijing Inst of Tech (CHN) *	6	1	162	7200	1180	45	11	4.5
N Inst of Technol (IND) *	7	15	156	2895	285	29	8	2.9
Zhejiang Univ (CHN) *	8	16	147	2875	229	30	8	3.
Chongqing Univ (CHN) *	9	9	130	4812	595	42	10	4.2
Southeast Univ (CHN)	10	32	111	2116	247	25	8	2.5
Shanghai Jiao Tong Univ (CHN) *	11	17	106	2837	196	31	8	3.
Univ of Chinese Acad of Sciences (CHN) *	12	13	105	3052	229	27	9	3.38
Aalborg Univ (DNK) *	13	18	104	2778	206	28	9	2.8
Shandong Univ (CHN)	14	96	99	1160	81	20	6	2.
Wuhan Univ of Technol (CHN)	15	36	98	2028	137	28	7	3.11
Tianjin Univ (CHN) *	16	20	96	2558	305	25	8	2.5
Univ of Tehran (IRN) *	17	11	95	3701	254	35	9	3.5
Univ of California (USA)	18	23	94	2424	210	25	8	2.5
Nanyang Technological Univ (SGP) *	19	10	93	4098	352	34	11	3.4
N Univ of Singapore (SGP) *	20	12	86	3146	394	27	9	2.7
Univ of Malaya (MYS)	22	8	84	4873	598	40	11	4.
Univ of Sci and Technol of China (CHN)	23	7	83	5330	310	34	11	4.25
City Univ of Hong Kong (HKG)	31	14	72	2972	534	28	10	2.8
Shenzhen Univ (CHN)	65	19	49	2571	453	21	8	3.

OCC: occurrences; GCS: global citation score; LCS: local citation score. * Affiliations simultaneously belonging to the groups of top 20 most frequent affiliations and top 20 most cited affiliations.

4.1.5. Countries' Performance Metrics

Table 7 provides insights into performance indicators for the countries of affiliation of the authors, sorted by the number of documents. China holds a prominent position, with the highest number of documents and total citations, indicating a dominant research output. Significantly, it should be emphasized that China's production is 2.5 times that of the country ranking second in the list. India and the United States follow with substantial publication counts and citations. Despite fewer published documents, Iran showcases a relatively high global citation count, underscoring impactful research. The United Kingdom, South Korea, and other countries also demonstrate substantial contributions. Notably, Singapore and Hong Kong stand out with a high global citation count compared to their scientific production, reflecting their research excellence.

Figure 6 presents the auto-correlation map for the countries appearing in Table 7. There are no strong links between countries, and this figure shows a moderate level of collaboration among countries. There are no strong links, and notably, there are no isolated nodes.

Table 7. Performance metrics for the top 20 most productive and top 20 most cited countries.

Country	Rank OCC	Rank GCS	OCC	GCS	LCS	H Index	G Index	M Index
China*	1	1	6221	144,197	18,238	149	18	14.9
India*	2	3	2488	31,678	2595	75	12	7.5
United States*	3	2	1805	50,078	5329	105	16	10.5
Iran*	4	4	847	23,672	1787	77	13	7.7
United Kingdom*	5	5	803	21,037	2037	73	13	7.3
South Korea*	6	6	723	18,017	1871	63	13	6.3
Malaysia*	7	9	582	14,828	1603	63	12	6.3
Canada*	8	8	557	15,984	1772	63	13	6.3
Australia*	9	7	498	17,394	1673	65	13	6.5
Saudi Arabia*	10	12	485	10,112	748	49	11	4.9
Spain*	11	10	481	12,598	867	58	12	5.8
Turkey*	12	19	468	8159	909	45	9	4.5
Taiwan*	13	13	440	9351	1028	48	10	4.8
Italy*	14	11	437	11,022	1175	55	12	5.5
Egypt*	15	18	424	8566	616	47	10	4.7
Germany*	16	15	418	8945	749	47	12	4.7
France*	17	14	399	9146	902	49	13	4.9
Algeria*	18	20	380	7660	930	44	11	4.4
Morocco	19	29	378	3475	382	27	7	2.7
Indonesia	20	30	330	3009	281	23	7	2.3
Singapore	24	17	235	8761	897	51	12	5.1
Hong Kong	25	16	210	8800	1057	52	11	5.2

OCC: occurrences; GCS: global citation score; LCS: local citation score. * Countries simultaneously belonging to the groups of top 20 most frequent countries and top 20 most cited countries.

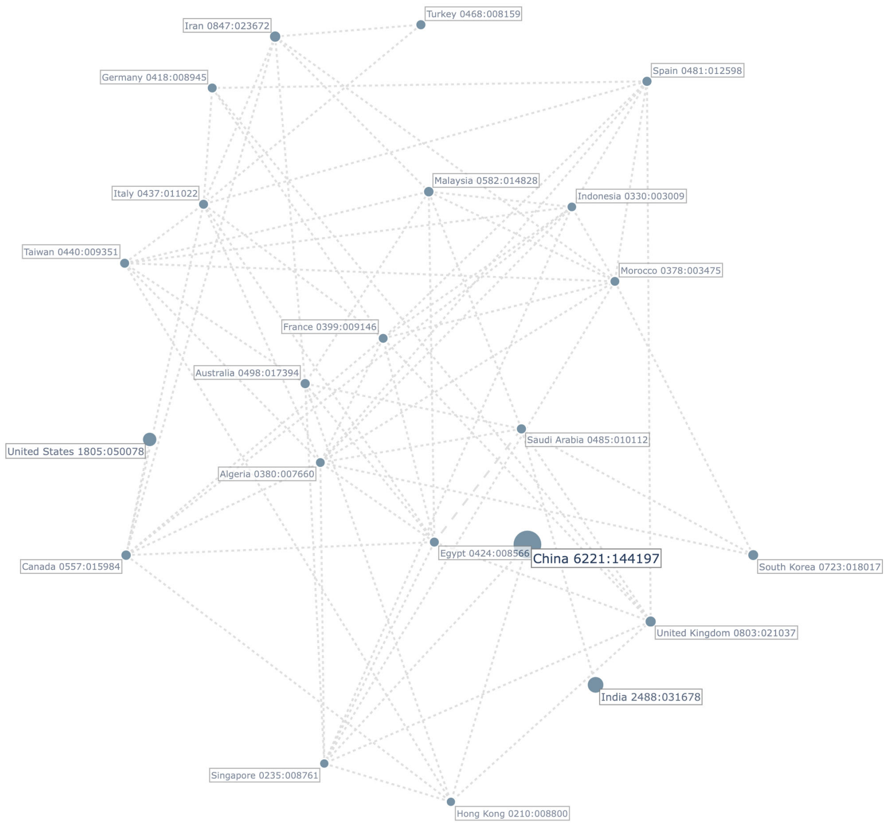

Figure 6. Co-authorship among the top 20 countries with more documents or more citations. Numbers following the name indicate the total number of documents and citations.

4.1.6. Sources' Performance Metrics

Table 8 presents the performance indicators for the top 20 most frequent and the top 20 most cited publication sources in the analyzed dataset, sorted by the number of occurrences (OCC). Of the 26 publications sources in the table, 14 belong simultaneously to the two groups, indicating high quality and productivity. Prominent sources like *Energies* and *Energy* demonstrate high frequency and global citations, indicating influential platforms. Journals like *Applied energy* (*APPL ENERGY*) and *Energy Conversion and Management* (*ENERGY CONVERS MANAGE*) also display high global citations, highlighting their impact. Notably, some sources exhibit high local citations relative to global citations, suggesting a concentrated impact within the field; this is the case of *ACS Applied Materials & Interfaces* (*ACS APPL MATER INTERFACES*), with a local citation score (LCS) of 3493, appearing in the 25th position in the frequency ranking. Regarding the impact and frequency, the most important source is *Applied Energy*, with an h-index of 83. However, *Applied Energy* is the most influential document source within the field of applications of AI in SE, with an h-index of 87. Additionally, specific sources like the *Journal of Physics: Conference Sseries* (*J PHYS CONF SER*) have a lower global impact despite the higher number of publications. All the journals listed in the table fall within the energy domain, except for *Applied Soft Computing Journal* (*APPL SOFT COMPUT J*), which pertains to the field of artificial intelligence.

Table 8. Performance metrics for the top 20 most frequent and top 20 most cited sources.

Affiliation	Rank OCC	Rank GCS	OCC	GCS	LCS	H Index	G Index	M Index
ENERGIES *	1	5	713	15,379	1748	57	11	5.7
ENERGY *	2	2	408	22,846	2672	83	13	8.3
IEEE ACCESS *	3	6	404	11,586	1621	54	11	9
APPL ENERGY *	4	1	332	23,675	3354	87	15	8.7
RENEW ENERGY *	5	4	266	16,080	2195	74	13	7.4
J PHYS CONF SER	6	118	248	406	42	7	3	0.78
ENERGY CONVERS MANAGE *	7	3	222	16,997	2665	81	14	8.1
ENERGY REP	8	34	163	1853	130	21	6	5.25
APPL SCI *	9	20	162	2848	395	25	7	3.12
INT J HYDROGEN ENERGY *	10	14	147	4643	427	39	9	3.9
J ENERGY STORAGE *	11	18	129	3151	456	27	8	3.86
IOP CONF SER EARTH ENVIRON SC	12	145	126	307	53	8	3	0.8
J CLEAN PROD *	13	10	117	5530	639	45	10	5.62
INT J ENERGY RES	14	41	113	1545	171	23	7	2.3
SOL ENERGY *	15	7	110	6230	725	47	11	4.7
INT J ELECTR POWER ENERGY SYS *	16	11	107	5410	517	44	10	4.4
J POWER SOURCES *	17	9	105	5899	749	42	12	4.2
J MATER CHEM A *	18	17	90	3190	26	34	9	3.78
J RENEWABLE SUSTAINABLE ENERG	19	47	88	1313	214	21	6	2.1
IEEE POWER ENERGY SOC GEN MEE	20	81	88	667	97	15	5	1.5
IEEE TRANS SMART GRID	30	8	72	5939	601	42	12	4.2
ENERGY BUILD	31	12	72	5178	454	41	11	4.1
IEEE TRANS IND INF	37	15	66	4087	368	33	10	3.3
APPL SOFT COMPUT J	52	19	47	2991	333	30	9	3
IEEE TRANS IND ELECTRON	58	13	43	4883	514	30	11	3
IEEE TRANS SUSTAINABLE ENERGY	61	16	43	3511	365	26	11	2.89

OCC: occurrences; GCS: global citation score; LCS: local citation score. * Affiliations simultaneously belonging to the groups of top 20 most frequent affiliations and top 20 most cited affiliations.

4.2. Determination of the Dominant Themes Using Co-Word Analysis

This section discusses the process for obtaining the dominant themes using the Author keywords (AKs). For this research, the author keywords were selected. AKs refer to a set of words or phrases that authors themselves choose to represent the primary themes, concepts, and topics addressed in their research article. These keywords aim to reflect the content and focus of the research paper accurately. Authors often select keywords that are not only relevant to their work but also are words that potential readers might use when searching for related articles. Author keywords provide direct insight into the subject matter of the research article. In contrast, index keywords (IK) come from a standardized list or taxonomy maintained by the database or indexing service. Consequently, AKs are more precise than IKs to capture the essence of the documents.

4.2.1. Keywords Preparation

Keywords were prepared by building a thesaurus constructed using the following steps:

- A table was constructed with two columns: the "original (raw) keyword" and the "modified keyword". In this step, the two columns contain the same text. The "modified keyword" column corresponds to the cleaned author keyword used in the analysis. The following steps were applied only to the "modified keyword" column.
- British English words were rewritten in American English.
- Abbreviations were eliminated from the terms; for instance, "electric vehicles (EV)" was converted to "electric vehicles".
- Text collision techniques were employed to standardize terms that might differ in word order or usage of plurals and singulars. For instance, these techniques group phrases like "analysis of data" and "data analysis", as well as "electric vehicle" and "electric vehicles".
- Lastly, a computer-assisted review was performed. In this step, for example, the uses of common synonyms such as "forecast" and "predict", or "lithium" and "li-ion" are reviewed.

The obtained table is used to clean and standardize the AKs. Simultaneously, a compilation of stop words was generated as part of this procedure. The list encompasses terms that will be ignored during the analysis. The list includes vague terms without utility in the analysis, country names, and overly broad terms such as "sustainable energy" or "machine learning".

4.2.2. Selection of the Minimum Number of Keyword Occurrences

Due to the extensive volume of processed articles and the duration of the time span, the analysis was performed for each year within the analysis period. During this phase, it is necessary to select the minimum number of appearances that a keyword must have to be considered in the analysis. Setting this threshold too low would result in the inclusion of infrequent keywords that pertain to particular topics beyond the scope of this research. Table 8 shows the number of documents per year, the number of documents without AKs (column "Documents with N/A"), and the number of usable documents. The threshold of the minimum number of occurrences was determined as the maximum number of occurrences ensuring coverage across at least 90% of the usable documents. The calculated values appear in Table 9.

Table 9. Dataset coverage.

Year	Documents	Documents with N/A	Usable Documents	Selected Threshold	Coverage	Used Documents
2013	573	116	457	3	90.8%	415
2014	723	130	593	5	90.2%	535
2015	734	95	639	4	90.6%	579
2016	977	134	843	5	90.4%	762
2017	1111	166	945	4	91.0%	860
2018	1523	227	1296	4	91.4%	1185
2019	2256	293	1963	6	90.1%	1768
2020	2678	359	2319	4	91.3%	2116
2021	3448	434	3014	5	91.0%	2742
2022	4692	531	4161	5	90.9%	3784

4.2.3. Clusters of Author Keywords Obtained for Each Year

A co-occurrence network of author keywords was constructed for every year within the analysis period. This network uses the cleaned author keywords, as discussed previously. Subsequently, the Louvain community detection algorithm was employed to extract keyword clusters representing the prevailing subject areas. Table 10 presents the results that were obtained. For each year, the obtained clusters are accompanied by the corresponding count of author keywords and the four most frequent terms. Clusters are arranged based on their cluster size, determined by the number of keywords they encompass. This sequence can be interpreted as a ranking that reflects the significance of the subjects throughout each year.

Table 10. Clusters obtained for each year of the period of analysis.

Year	Cluster	Number of Keywords	Percentage	Main Keywords
2013	1	27	29.3%	GENETIC_ALGORITHMS; PARTICLE_SWARM_OPTIMIZATION; DISTRIBUTED_GENERATION; WIND_ENERGY; DATA_MINING
	2	23	25.0%	ARTIFICIAL_NEURAL_NETWORKS; RADIAL_BASIS_FUNCTION_NETWORK; WIND_SPEED; BIODIESEL; PEMFC
	3	18	19.6%	MPPT; FUZZY_LOGIC_CONTROL; PHOTO_VOLTAIC; FUZZY_LOGIC; PHOTO_VOLTAIC_SYSTEM
	4	17	18.5%	ELECTRIC_AND_HYBRID_VEHICLES; SUPPORT_VECTOR_MACHINES; SMART_GRID; MICRO_GRID; ENERGY_MANAGEMENT
	5	7	7.6%	WIND_TURBINES; DIFFERENTIAL_EVOLUTION; EVOLUTIONARY_ALGORITHMS; PARAMETER_PREDICTION; SOLAR_CELLS
2014	1	22	33.8%	ARTIFICIAL_NEURAL_NETWORKS; GENETIC_ALGORITHMS; WIND_ENERGY; SUPPORT_VECTOR_MACHINES; WIND_TURBINES
	2	16	24.6%	DISTRIBUTED_GENERATION; SMART_GRID; MICRO_GRID; ENERGY_EFFICIENCY; ADAPTIVE_NEURO_FUZZY_INFERENCE_SYSTEM
	3	15	23.1%	PARTICLE_SWARM_OPTIMIZATION; ELECTRIC_AND_HYBRID_VEHICLES; ENERGY_MANAGEMENT; LITHIUM_BATTERIES; STATE_OF_CHARGE
	4	12	18.5%	MPPT; FUZZY_LOGIC; FUZZY_LOGIC_CONTROL; PHOTO_VOLTAIC_SYSTEM; PHOTO_VOLTAIC
2015	1	26	31.7%	GENETIC_ALGORITHMS; FUZZY_LOGIC; SMART_GRID; MICRO_GRID; DISTRIBUTED_GENERATION
	2	21	25.6%	ARTIFICIAL_NEURAL_NETWORKS; WIND_TURBINES; WIND_ENERGY; WIND_SPEED_FORECASTING; SOLAR_RADIATION
	3	15	18.3%	ELECTRIC_AND_HYBRID_VEHICLES; SUPPORT_VECTOR_MACHINES; ENERGY_MANAGEMENT; CHARGING_STRATEGIES; Q_LEARNING
	4	14	17.1%	PARTICLE_SWARM_OPTIMIZATION; FUZZY_LOGIC_CONTROL; MPPT; PHOTO_VOLTAIC; DIFFERENTIAL_EVOLUTION
	5	6	7.3%	PHOTO_VOLTAIC_SYSTEM; PI_CONTROL; FIREFLY_ALGORITHMS; ANT_COLONY_OPTIMIZATION; INTELLIGENT_CONTROL

Table 10. *Cont.*

Year	Cluster	Number of Keywords	Percentage	Main Keywords
2016	1	30	32.6%	ARTIFICIAL_NEURAL_NETWORKS; SUPPORT_VECTOR_MACHINES; WIND_TURBINES; WIND_SPEED_FORECASTING; SOLAR_RADIATION
	2	24	26.1%	PARTICLE_SWARM_OPTIMIZATION; MICRO_GRID; SMART_GRID; ELECTRIC_AND_HYBRID_VEHICLES; ENERGY_MANAGEMENT
	3	19	20.7%	FUZZY_LOGIC_CONTROL; MPPT; PHOTO_VOLTAIC; FUZZY_LOGIC; DISTRIBUTED_GENERATION
	4	12	13.0%	GENETIC_ALGORITHMS; DIFFERENTIAL_EVOLUTION; ENERGY_EFFICIENCY; MULTI_OBJECTIVE_OPTIMIZATION; ARTIFICIAL_BEE_COLONY
	5	7	7.6%	WIND_ENERGY; EVOLUTIONARY_ALGORITHMS; PROBABILISTIC_FORECASTING; WIND_FARM; UNCERTAINTY
2017	1	43	30.1%	ARTIFICIAL_NEURAL_NETWORKS; SUPPORT_VECTOR_MACHINES; LITHIUM_BATTERIES; EXTREME_LEARNING_MACHINE; SOLAR_RADIATION
	2	33	23.1%	PARTICLE_SWARM_OPTIMIZATION; MICRO_GRID; ELECTRIC_AND_HYBRID_VEHICLES; SMART_GRID; ENERGY_MANAGEMENT
	3	28	19.6%	MPPT; FUZZY_LOGIC_CONTROL; FUZZY_LOGIC; PHOTO_VOLTAIC; PHOTO_VOLTAIC_SYSTEM
	4	18	12.6%	WIND_ENERGY; ENERGY_EFFICIENCY; DATA_MINING; DEEP_LEARNING; CLUSTERING_ALGORITHMS
	5	14	9.8%	GENETIC_ALGORITHMS; WIND_TURBINES; DISTRIBUTED_GENERATION; WIND_FARM; ENERGY
	6	7	4.9%	ARTIFICIAL_BEE_COLONY; SOLAR_CELLS; META_HEURISTIC_ALGORITHM; GRAVITATIONAL_SEARCH_ALGORITHM; PARAMETER_PREDICTION
2018	1	59	29.4%	ARTIFICIAL_NEURAL_NETWORKS; SUPPORT_VECTOR_MACHINES; DEEP_LEARNING; ADAPTIVE_NEURO_FUZZY_INFERENCE_SYSTEM; WIND_SPEED_FORECASTING
	2	39	19.4%	PARTICLE_SWARM_OPTIMIZATION; MPPT; FUZZY_LOGIC_CONTROL; PHOTO_VOLTAIC; FUZZY_LOGIC
	3	36	17.9%	GENETIC_ALGORITHMS; SMART_GRID; ENERGY_EFFICIENCY; ENERGY_CONSUMPTION; DATA_MINING
	4	30	14.9%	MICRO_GRID; ENERGY_MANAGEMENT; REINFORCEMENT_LEARNING; DISTRIBUTED_GENERATION; MULTI_OBJECTIVE_OPTIMIZATION
	5	24	11.9%	ELECTRIC_AND_HYBRID_VEHICLES; LITHIUM_BATTERIES; STATE_OF_CHARGE; ENERGY_STORAGE; STATE_OF_HEALTH
	6	13	6.5%	WIND_TURBINES; FAULT_DIAGNOSIS; ENERGY; FEATURE_EXTRACTION; CONDITION_MONITORING

Table 10. *Cont.*

Year	Cluster	Number of Keywords	Percentage	Main Keywords
2019	1	56	30.3%	SMART_GRID; GENETIC_ALGORITHMS; ELECTRIC_AND_HYBRID_VEHICLES; MICRO_GRID; ENERGY_MANAGEMENT
	2	52	28.1%	DEEP_LEARNING; LONG_SHORT_TERM_MEMORY_NETWORK; SUPPORT_VECTOR_MACHINES; CONVOLUTIONAL_NEURAL_NETWORK; LITHIUM_BATTERIES
	3	39	21.1%	ARTIFICIAL_NEURAL_NETWORKS; WIND_TURBINES; WIND_ENERGY; ENERGY_EFFICIENCY; ENERGY_CONSUMPTION
	4	38	20.5%	MPPT; PARTICLE_SWARM_OPTIMIZATION; FUZZY_LOGIC_CONTROL; PHOTO_VOLTAIC; FUZZY_LOGIC
2020	1	76	23.0%	ELECTRIC_AND_HYBRID_VEHICLES; GENETIC_ALGORITHMS; SMART_GRID; MICRO_GRID; REINFORCEMENT_LEARNING
	2	72	21.8%	DEEP_LEARNING; LONG_SHORT_TERM_MEMORY_NETWORK; CONVOLUTIONAL_NEURAL_NETWORK; WIND_ENERGY; SOLAR_RADIATION
	3	69	20.8%	PARTICLE_SWARM_OPTIMIZATION; MPPT; PHOTO_VOLTAIC; FUZZY_LOGIC_CONTROL; PHOTO_VOLTAIC_SYSTEM
	4	64	19.3%	ARTIFICIAL_NEURAL_NETWORKS; LITHIUM_BATTERIES; SUPPORT_VECTOR_MACHINES; STATE_OF_CHARGE; ENERGY_CONSUMPTION
	5	21	6.3%	MULTI_OBJECTIVE_OPTIMIZATION; SOLAR_CELLS; ARTIFICIAL_BEE_COLONY; INTEGRATED_ENERGY_SYSTEMS; SENSITIVITY_ANALYSIS
	6	20	6.0%	WIND_TURBINES; FAULT_DETECTION; DOUBLY_FED_INDUCTION_GENERATOR; CONDITION_MONITORING; ANOMALY_DETECTION
	7	9	2.7%	OXYGEN_EVOLUTION_REACTION; ELECTROCATALYSTS; METAL_ORGANIC_FRAMEWORKS; HYDROGEN_EVOLUTION_REACTION; DENSITY_FUNCTIONAL_THEORY
2021	1	95	27.6%	ELECTRIC_AND_HYBRID_VEHICLES; MICRO_GRID; REINFORCEMENT_LEARNING; SMART_GRID; ENERGY_MANAGEMENT
	2	94	27.3%	ARTIFICIAL_NEURAL_NETWORKS; GENETIC_ALGORITHMS; PARTICLE_SWARM_OPTIMIZATION; PHOTO_VOLTAIC; MPPT
	3	86	25.0%	DEEP_LEARNING; LONG_SHORT_TERM_MEMORY_NETWORK; LITHIUM_BATTERIES; CONVOLUTIONAL_NEURAL_NETWORK; RECURRENT_NEURAL_NETWORKS
	4	42	12.2%	WIND_TURBINES; SUPPORT_VECTOR_MACHINES; FAULT_DIAGNOSIS; FAULT_DETECTION; RANDOM_FOREST
	5	23	6.7%	OXYGEN_EVOLUTION_REACTION; ELECTROCATALYSTS; OXYGEN_REDUCTION_REACTION; HYDROGEN_EVOLUTION_REACTION; PEROVSKITE_SOLAR_CELLS
	6	4	1.2%	MULTI_OBJECTIVE_OPTIMIZATION; NSGA_II; BUILDING_ENERGY_CONSUMPTION; THERMAL_COMFORT

Table 10. *Cont.*

2022	1	132	27.9%	ELECTRIC_AND_HYBRID_VEHICLES; ENERGY_MANAGEMENT; GENETIC_ALGORITHMS; MICRO_GRID; SMART_GRID
	2	102	21.6%	DEEP_LEARNING; LONG_SHORT_TERM_MEMORY_NETWORK; CONVOLUTIONAL_NEURAL_NETWORK; WIND_TURBINES; WIND_ENERGY
	3	85	18.0%	PARTICLE_SWARM_OPTIMIZATION; MPPT; PHOTO_VOLTAIC; FUZZY_LOGIC_CONTROL; PHOTO_VOLTAIC_SYSTEM
	4	78	16.5%	ARTIFICIAL_NEURAL_NETWORKS; SUPPORT_VECTOR_MACHINES; PEMFC; RANDOM_FOREST; EXTREME_GRADIENT_BOOSTING
	5	50	10.6%	LITHIUM_BATTERIES; STATE_OF_CHARGE; STATE_OF_HEALTH; TRANSFER_LEARNING; REMAINING_USEFUL_LIFE
	6	26	5.5%	OXYGEN_EVOLUTION_REACTION; HYDROGEN_EVOLUTION_REACTION; OXYGEN_REDUCTION_REACTION; PEROVSKITE_SOLAR_CELLS; OXYGEN_VACANCIES

Figure 7 displays a Sankey diagram, wherein the clusters are organized by year, following the order indicated in Table 10. This diagram facilitates the observation of keyword transitions across clusters, illustrating the shifts in research focus across different years. Several patterns emerge when analyzing the evolution of clusters and the movements of keywords between clusters year by year.

- The use of fuzzy controllers for tracking the maximum power point in photovoltaic systems is a topic that has remained relevant during the last decade.
- Research on electric vehicles has been a dominant area in all years, particularly concerning topics related to their impact on the electrical grid, the corresponding energy source management, and subjects related to electric batteries. In 2019, batteries became a central research topic with their own cluster in the diagram.
- The use of deep learning techniques has been a dominant topic since 2019, and with these techniques, various issues related to wind and solar energy, as well as electric batteries, have been addressed.
- The utilization of heuristic optimization techniques, such as genetic algorithms, particle swarm optimization, and ant colony optimization, has been a prevalent theme throughout the decade. These techniques have been applied to optimization problems in energy, such as distribution planning and issues related to other artificial intelligence models when used in renewable energy contexts. An example of this is parameter identification in models.
- Artificial neural networks, support vector machines, and neuro-fuzzy systems have been applied to a wide range of problems and have served as benchmarks for evaluating newer models like deep learning.

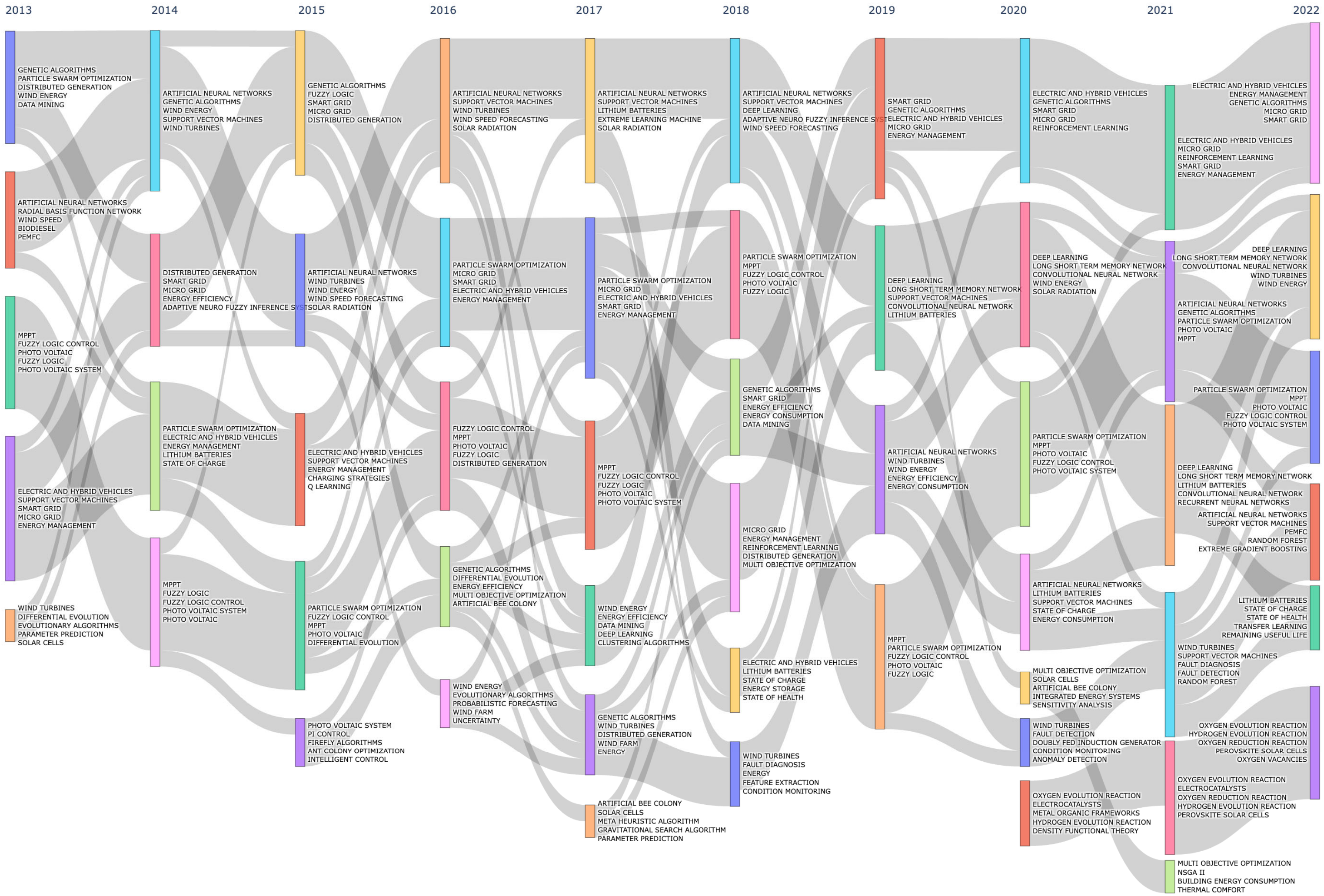

Figure 7. Clusters per year ordered by the number of terms in each cluster.

Figures 2 and 8 can be compared to establish a parallel with previous works. As shown year-by-year, Figure 8 captures many details about the research emphasis in each year. For example, DEEP_LEARNING appears in Figure 2 in the year 2019, and this term is associated with the keywords DECISION_MAKING, SMART_GRID, and ELECTRIC_AND_HYBRID_VEHICLES; however, Figure 8 shows the same keyword (DEEP_LEARNING) in the years 2017 and 2018 associated with WIND_ENERGY. On the other hand, the works discussed in Section 2 are focused on narrow themes; in this sense, they are not comparable with our research.

Figure 8. Trending keywords per year.

Figure 8 presents the trending words per year. In the figure, the width of the lines is proportional to the total number of occurrences of the corresponding keyword. The analysis of the graph enables the identification of the most important words per year. Complementing the previous figure, it also helps establish the relevance of the themes. For example, deep learning is the most significant topic for 2020, 2021, and 2022. It is crucial to note at this point that Figure 7 presents clusters ordered by the number of keywords they contain, not by the total occurrences of the keywords.

5. Discussion

A detailed analysis of the underlying themes was conducted for each cluster obtained each year. This process is necessary because, by definition, clusters are derived from co-word analysis group keywords that frequently appear together in documents. However, each cluster can encompass more than one dominant area. For instance, if support vector machines and artificial neural networks are employed to predict a battery's charge state and the wind turbine's output power, the clustering algorithm tends to create a cluster containing the keywords related to these topics. This situation can go unnoticed when individual keywords are analyzed in isolation using numerical techniques without attempting to interpret their interrelationship within a cluster. This is a well-known situation in practice (for example, in customer analytics). As a result, there is a desire for clusters to be interpretable or explainable based on expert knowledge in the field.

This work conducted a computer-assisted manual analysis of each cluster's 50 most cited articles annually. This analysis was supported by using text-mining techniques to uncover the underlying structure of the clusters. This analysis allowed for the discovery of the underlying dominant thematic areas. These areas can be categorized as belonging to artificial intelligence or sustainable energy. Addressing both classifications can lead to redundancies, so it was decided to conduct the analysis using a classification based on dominant themes in sustainable energy. This section discusses the emerging areas identified as dominant in detail.

5.1. Analysis of Dominant Themes

This section details the dominant themes that were found in the database. As this analysis was classified by SE theme, the following subsections briefly describe the problems found in diverse SE subfields and how they have been addressed using AI.

5.1.1. Solar Energy

Photovoltaic (PV) generation systems are particularly attractive renewable energy sources because they do not entail fuel costs and require minimum maintenance [60]. Nevertheless, they pose complex problems, which have been addressed using several AI techniques:

- Maximum Power Point Tracking (MPPT) in solar power systems under variable conditions of solar radiation, shading, and ambient temperature [61]. This kind of tracking is challenging in extreme environments [62] due to the problems of traditional control techniques (in terms of accuracy, flexibility, and efficiency), as well as the presence of multiple local maxima in the power–voltage curve [63] when PV systems are partially shaded. MPPT has been implemented using traditional control systems, e.g., perturb-and-observe [64], fuzzy logic [65], and neuro-fuzzy systems [66]. Other heuristic mechanisms have been incorporated to optimize control systems: ant colony optimization [61,67–69], artificial bee colony optimization [69–71], particle swarm optimization or PSO [72,73], and differential evolution and genetic algorithms [74]. Likewise, adaptive mechanisms have been used in controllers [75], e.g., based on Hopfield networks [76,77].
- Modelling and forecasting solar radiation at different scales: monthly [78,79], daily [80,81], and hourly [82]. One of the biggest problems of this type of SE is that solar radiation depends on climatic factors that are difficult to forecast accurately, such as temperature, humidity, wind speed, and daylight duration [83]. In addition, there is a lack of accurate data about climatic variables [80]. The literature has reported experiences of solar radiation forecasting using multi-layer perceptrons [78–80], radial basis function networks [79–81], fuzzy linear regression [84], SVMs [84], and hybrid models [82]. Some

studies have proposed training neural network models using evolutionary algorithms, such as PSO [78].
- Identifying solar photovoltaic (PV) system parameters is challenging due to their nonlinear, multimodal, and multivariate characteristics. The efficiency of converting solar energy into electricity largely hinges on the precision of these parameters. Traditional methods often grapple with issues such as immature convergence and falling into local optima, as they cannot effectively navigate the complex landscape of PV system models [85]. Diverse techniques have been used for parameter identification, including genetic algorithms (GAs) and other metaheuristic techniques, such as PSO [86], the Firefly algorithm [87], and differential evolution [88,89].

5.1.2. Smart Grids and Microgrids

Smart grids and microgrids are essential for managing power transmission systems efficiently and safely [90]. However, designing and operating them pose significant challenges, i.e., the decentralized control of these distributed sources, real-time electricity pricing, price sensitivity, using Energy Storage Systems (ESSs), and incorporating variable-operation renewable sources [91,92]. The following are some of the problems of these types of grids and the solutions that have been proposed:

- Operation planning, efficient management, and determining optimal policies. Solving these problems is more complicated due to variable renewable sources. Some authors have proposed using multi-agent systems to manage microgrids [92,93] and smart grids [91]. For instance, Cha et al. [93] used smart agents to improve the management of microgrids, which are subjected to variable loads (i.e., refrigerated containers, electric vehicles, and loading stations for ships) and meet their own demand using wind power. Kuznetsova et al. [94] used reinforcement learning to plan the use of a battery in a system composed of a microgrid, a consumer, a renewable source, and a storage battery. The same methodology was adopted by Mbuwir et al. [95] to find optimal policies that can maximize solar self-consumption in microgrids. Intelligent agents have been employed to operate grids optimally using a decentralized management scheme [93,96].
- Estimating electricity prices. Forecasting electricity prices in deregulated markets presents significant challenges due to the inherent volatility and dynamic interaction between consumers and real-time prices within smart grid systems. The unpredictable nature of these interactions can lead to deviations from initial forecasts, underscoring the importance of accurate prediction tools [97]. In response to these complexities, sophisticated artificial intelligence methodologies have been developed. These methodologies include fuzzy systems such as ANFIS [98], SVR [98,99], reinforcement learning [100], recurrent neural networks [101], and deep learning models [102] such as LSTM [103] and GRU [104].
- Determining the optimal size and location of energy storage systems. Kerdphol et al. [105] and Baghaee, Mirsalim, and Gharehpetian et al. [106] proposed the use of radial basis function networks to determine (1) the optimal size and location of energy storage systems using batteries in microgrids and (2) the electricity that distributed sources should supply to the transmission network.
- Expansion planning. One of the main challenges in the planning and operation of the modern transmission infrastructure (smart grids and microgrids) is locating and sizing sustainable generation sources [107,108]. This is because it is necessary to simultaneously optimize multiple objectives, which involves minimizing system losses and voltage deviations and maximizing voltage stability indices [109–112]. In addition, this kind of optimization should consider different technical and economic constraints, such as fluctuations in sustainable generation and demand [113]. This is a complex optimization problem that, in radial basis function networks, is usually addressed using modified versions of GAs [109,114,115], such as self-adaptive algorithms [113], those based on chaos or quantic computing [108], and their hybrids with techniques

such as PSO [107]. However, to a lesser extent, other heuristic algorithms have been implemented for this purpose in the literature, such as the bat algorithm [112] and PSO [111,116–118].

- Detecting malicious attacks in smart grids. Integrating advanced information and communication technologies (ICTs) in developing smart grids has undeniably amplified the efficiency and resilience of power distribution and management [119]. However, as the smart grid architecture becomes more centralized and reliant on software-defined networking (SDN) that captures data in real time, it also ushers in new vulnerabilities [120]. A significant concern is the susceptibility of smart grids to false data injection attacks. Such attacks cunningly sidestep conventional bad data detection systems within energy management systems, leading to distorted state estimations. The repercussions can vary from minor operational mishaps to large-scale blackouts [121,122]. To counteract these cyber threats, diverse artificial intelligence techniques have been used. Machine learning models, including those employing support vector machines (SVMs) and hybrid models integrating SVMs with random forest (RF), have displayed promising outcomes in recognizing various cyber threats [120]. Deep learning, too, has shown commendable progress in this arena. LSTM autoencoders are employed to discern false data injection attacks by extracting spatial and spectral features from state estimations, showcasing significant simulation accuracy [123]. Concurrently, convolutional neural network (CNN)-based strategies offer continuous recognition of areas affected by such attacks, integrating well with existing frameworks and providing rapid detection even on standard computing platforms [124]. Distinct research introduced an anomaly detection technique using CNNs to identify denial of charge (DoC) attacks on electric vehicle charging stations, leveraging the station's energy demand patterns [125]. Additionally, wavelet convolutional neural networks have been highlighted as especially proficient at pinpointing distributed denial of service (DDoS) attacks in smart grid systems, combining high detection rates with minimal false alarms [126]. Deep convolutional neural networks (DCNNs) push the boundaries further in curtailing false data injection attack effects, surpassing traditional techniques [127,128].
- Islanding detection in microgrids. For several reasons, islanding detection in grid-linked photovoltaic-based distributed power generation (PVDPG) systems is critical. This includes ensuring the safety of line workers and the general public, protecting consumer and utility equipment, preventing malfunctions of power system protective equipment, maintaining power quality, and strengthening the overarching security of the power system [129,130]. A significant challenge in devising reliable detection mechanisms lies in the inconsistent power output often associated with renewable energy sources like PVDPG, which can lead to voltage disturbances and unforeseen blackouts [131]. Recent innovations merging the Internet of Things (IoT) with cloud computing and machine learning have paved the way for enhanced microgrid controls [132]. IoT devices are pivotal in this technological nexus, providing superior measurement and control functionalities, vital for the microgrid environment. Moreover, cloud-based artificial neural networks (ANNs) have proven effective in islanding detection, especially when utilizing data from islanding simulations [132]. Numerous AI methodologies exhibit promise in islanding detection. For instance, ANFIS is an advanced technique for islanding detection, capitalizing on passive detection parameters such as voltage, frequency rate changes, and power variations [129,133]. Additionally, the synergy of LSTM networks with the empirical wavelet transform boosts the reliability of smart islanding detection [134]. Finally, Kermany et al. [135] used fuzzy neural networks for this purpose.

5.1.3. Fuel Cells

Fuel cells continuously convert chemical energy from fuel into electricity. Accurately predicting different variables associated with these devices (e.g., service life) is essential to reduce costs and improve durability [136]. AI applications for fuel cells include:

- Estimating optimal operating parameters. One of the fundamental problems that should be solved to improve the performance of these systems is modeling and precisely identifying the parameters that characterize the cells. However, to do that, complex nonlinear multimodal functions should be solved so that optimization algorithms are not trapped in local optima. This problem has been addressed using GAs and their variants [137–139], Elman networks [140,141], and metaheuristic techniques such as the artificial bee colony algorithm [142].
- Performance prediction. Predicting the performance of fuel cells is essential for improving their operational parameters and ensuring accurate long-term projections, especially given the challenges presented by factors such as degradation mechanisms and aging processes [143,144]. Various artificial intelligence (AI) techniques have been employed to tackle these complexities. The neural network autoregressive with external input (NNARX) method was utilized to forecast the performance of solid oxide fuel cells (SOFCs) [144]. In contrast, deep belief networks (DBN) offer heightened accuracy in the realm of proton exchange membrane fuel cells (PEMFCs) [145]. Echo-state neural networks have also emerged as an effective tool for predicting degradation [143]. Specialized neural network models, such as the wavelet transform combined with long short-term memory (LSTM) and gradient boosting decision tree (GBDT), have achieved exceptional results in various facets of fuel cell prediction [146–148]. Techniques like merging convolutional neural networks (CNNs) with random forest feature selection and spatiotemporal vision-based deep neural networks with 3D inception LSTM have shown significant advances in fuel cell vehicle speed predictions [145,149]. LSTMs, especially when combined with techniques like electrochemical impedance spectroscopy and Savitzky Golay filters, have displayed superiority in forecasting fuel cell degradation and performance [150–152].
- Failure diagnosis. Proton exchange membrane (PEM) fuel cells are garnering attention due to their potential in sectors like fuel cell vehicles [153,154]. However, the complexity of PEM fuel cells and the variety of potential faults they can exhibit make their reliability and durability a concern, highlighting the significance of fault diagnosis. Various artificial intelligence (AI) techniques have been developed to address these challenges. Fuzzy logic has been instrumental in diagnosing common PEM fuel cell issues such as flooding and dehydration [154]. Another method merges a probabilistic neural network with a differential evolution algorithm designed for impedance identification [155]. Siamese artificial neural networks, tailored to PEM fuel cells, distinguish features from impedance spectra [156]. Additionally, support vector machines combined with binary trees have been utilized to hasten fault categorization [153], and a novel deep learning approach marries a backpropagation neural network with an inception-based convolutional network, targeting fault identification in fuel cell tram systems [157]. In recent advancements, long short-term memory (LSTM) networks, acclaimed for processing time series data, have been pivotal for diagnosing issues like flooding in vehicle-based systems [158]. This proficiency was augmented by integrating LSTM networks with empirical mode decomposition (EMD), achieving high levels of fault classification accuracy [159]. Other approaches include using ensembles of neural network models [160].
- Optimizing the micro-structure design [161,162]. The intricate dynamics of fuel cells, governed by numerous factors, emphasize the essential nature of their design. One of the primary design challenges revolves around the cathode, where tweaking channel structures, such as integrating blocks in the cathode flow fields, can enhance oxygen delivery to the catalyst layer, subsequently optimizing fuel cell efficiency [163]. Solid oxide fuel cells come with challenges driven by inherent nonlinearities, delays in

operation, and unique operational boundaries [164]. Innovatively, designs inspired by natural patterns, like the wave-like structures reminiscent of cuttlefish fins, exhibit promising performance enhancement advancements [162]. Artificial intelligence (AI) is a formidable ally when navigating this intricate landscape. For instance, genetic algorithms have proven instrumental in refining fuel cell channel designs [162] and conceptualizing bio-inspired structures [162]. In fuel cell electric vehicles, AI, armed with advanced optimization techniques such as the elephant herding optimization algorithm, has made noteworthy progress [165]. This showcases AI's vast potential in conceptualizing sophisticated hybrid systems [166]. Extending its role further, AI employs innovative algorithms like the modified NSGA II to fine-tune aerodynamic attributes of fuel cell parts for peak performance [167]. Augmenting this, the fusion of machine learning and traditional techniques, especially in solid oxide fuel cell systems, signifies a transformative pathway to a greener and more efficient energy horizon [168].

5.1.4. Hydrogen

Clean renewable hydrogen (produced from different domestic resources) is used in energy storage, energy generation, fuel mixtures, and industrial processes. In this context, AI techniques have been used for several purposes:

- Managing islanded energy systems (with clean, renewable energy sources) that use hydrogen to store energy. García et al. [169] and Zahedi and Ardehali [170] investigated the use of fuzzy control systems to satisfy the energy demand in these systems. Chen et al. [171] used a predictive control model for the optimal dispatch of a system composed of a wind farm, a hydrogen/oxygen storage system, and several fuel cells.
- Modelling and forecasting hydrogen production. Nasr et al. [172] used models of artificial neural networks to estimate the hydrogen production profile based on biomass and considering variables such as temperature, time, and pH. Ozbas et al. [173] used different machine learning algorithms to predict hydrogen production based on biomass gasification. Nasrudin et al. [174] investigated the effect of different algorithms (used to train neural networks) on the accuracy of the models in terms of their hydrogen and biochar production predictions.
- Analyzing the behavior of fuel cells. Bicer, Dincer, and Aydin [175] developed a model that represents the behavior of a fuel cell connected to a smart cell, which is used to forecast the parameters of the actual cell.

This cluster includes other studies on synthesizing gas (or syngas) production. Similar to the case of hydrogen, the most relevant research in this area is about predicting syngas production [176], simulating the syngas production process [177], and predicting syngas composition (Shenbagaraj et al. [178] and Li et al. [179] used artificial neural networks for this purpose).

5.1.5. Electric Vehicles

The search for sustainable, low-carbon footprint transportation has found a promising solution in plug-in hybrid and all-electric vehicles due to their low fuel consumption and reduced emissions [180]. Nevertheless, their use and operation inside electricity generation and transmission systems pose important challenges:

- Developing and operating a power supply infrastructure for EVs. Optimizing the charging state of EVs is a complex nonlinear problem because it should consider network conditions, charging time, and battery capacity [180], as well as the intermittent and disorganized nature of the demand [181]. In this case, the goals are to minimize the total operating cost of the vehicle, which is the sum of the fuel and electricity costs [182], provide optimal scheduling [181], and establish the optimal location and size of renewable energy sources and charging stations [183–186]. In general, these goals have been addressed using adaptations of heuristic algorithms, such as particle swarms [180–182] and artificial immune algorithms [187]. Additionally, some studies have used PSO algorithms to determine the charging and discharging patterns of systems that integrate (simultaneously) charging stations for EVs, solar PV microgeneration, and energy storage batteries. Intelligent agents have been used for this purpose as well [188].

- Estimating and forecasting different characteristics of batteries—such as their optimal parameters [180], charging state, remaining service life, or degradation—under multiple temperature and voltage conditions to maximize their service life [189–195]. Different types of neural networks have been used for this purpose: RBF networks [196,197], SVMs [198–200], Elman networks [201], and time-delay neural networks [202]. Recently, deep learning techniques have also been applied to this end, e.g., LSTM networks [203–207], GRU networks [208], ensembles [209], and autoencoders [210].
- Optimizing EV operation. To improve fuel consumption, Qu et al. [211] used reinforcement learning to minimize automatic plug-in EVs' start and stop cycles.
- Managing the power in the electric system and electricity storage cells of EVs. This challenge has been addressed using metaheuristic techniques [212] and fuzzy logic.

5.1.6. Biofuels

Several studies have applied AI techniques to biodiesel, an organic, renewable synthetic fuel obtained from vegetal oils and animal fat. Biodiesel can be used in internal combustion engines to replace the fuel obtained from petroleum. The following are some of the main problems in this field that have been addressed using AI:

- Determining the optimal parameters for biofuel production. Multiple studies have compared neural networks with response surface methodology for modeling and optimizing biofuel production under different conditions [213–216]. Other articles have compared fuzzy logic models [217], neuro-fuzzy interference models, and response surface methodology [218].
- Estimating the cetane number of biodiesel as an indicator of its quality. Piloto-Rodríguez et al. [219,220] concluded that, for this purpose, neural networks were more accurate than linear regression. Miraboutalebi, Kazemi, and Bahrami [221] compared neural networks and random forests.
- Modeling and optimizing biodiesel engines. Wong et al. [222] used cuckoo search and extreme learning machines (ELMs) to reduce emissions and fuel costs and improve engine performance.
- Determining the performance of diesel engines when they use biodiesel [223,224].
- Determining the amount of biodiesel in mixtures with diesel [225] or their components [226].
- Forecasting biofuel properties [227]. Biodiesel's importance as an environmentally friendly alternative to conventional fuels cannot be overstated. Its fatty acid composition profoundly influences its physicochemical attributes. These attributes, including kinematic viscosity, flash point, cloud point, pour point, and many more, profoundly determine its performance when used in engines [227]. Yet, predicting these properties from their fatty acid constituents remains a formidable challenge. In efforts to surmount this hurdle, advanced artificial intelligence methodologies have been leveraged. Gene expression programming (GEP) is one such technique. For example, it has been effectively employed in modeling the performance and emission characteristics of engines running on biodiesel blends like linseed oil methyl ester [228]. Compared to traditional multiple linear regression (MLR) approaches, GEP offers superior accuracy in predicting biodiesel properties [227]. Furthermore, artificial neural networks (ANNs) and their hybrids, like the adaptive neuro-fuzzy inference system (ANFIS) combined with genetic algorithms (GA), have shown promising results in predicting biodiesel engine characteristics [229].

5.1.7. Wind Power

In the last decade, wind farms have been integrated into interconnected electricity generation systems and global electricity markets [230]. In this subfield, AI has been mainly used for:

- Wind speed forecasting. Accurate wind speed forecasting is essential for managing wind systems regarding safety, stability, and quality [231]. Nevertheless, this task is hard due to turbine operation [232] and the effect of weather conditions [230]. It is even more complex because wind series present wide fluctuations, autocorrelation, and stochastic volatility [191]. Therefore, efforts have been made to develop AI-based methodologies to forecast wind speeds. In many relevant studies, decomposition techniques have been used to extract significant information from wind data [233,234] and later feed that information to forecasting models. Other studies have combined traditional time series model forecasts with machine learning techniques such as ELMs and SVMs [2]. Different kinds of SVMs, Elman neural networks [235], neuro-fuzzy systems, and ELMs have been used to forecast wind speed as the output variable [230,234,236–238], or as part of systems that combine forecasts. For example, Wang and Hu [2] analyzed a combined forecast system that predicts wind speed in the short term. Their system combines individual forecasts obtained by an ARIMA model, ELMs, and two different types of SVM. In most articles reviewed here, the parameters of the SVMs were estimated using several techniques, including variants of the PSO algorithm [236,239], evolutionary algorithms [240], cuckoo search [241], and differential evolution [242].
- Optimal selection and location of generators for wind farms. Most of the time, this problem has been solved using PSO [243–245], neural networks [246], and different evolutionary algorithms such as the firefly algorithm [247].
- Maximum Power Point Tracking (MPPT). This type of tracking has been performed using fuzzy logic [248] and other AI techniques [249], which include PSO [250].
- Power output forecasting. This challenge has been addressed using neural networks [251], neuro-fuzzy systems [252], and machine learning algorithms [253].
- Failure diagnosis. This area has been investigated using ELMs [254] and SVMs [255,256].
- Turbine angle control. Fuzzy logic has been implemented to investigate this topic [257–259].
- Optimal dispatch. Usually, the goal is reducing CO2 emissions [260].
- Locating capacitors in wind power systems [261].

5.1.8. Management, Planning, and Operation of Energy Systems

This cluster covers other energy system management, planning, and operation themes. The following are the main topics discussed in this cluster:

- Integrating the energy consumption of buildings. As Naji et al. [262] claim, buildings' electricity consumption represents a significant percentage of the total electricity consumption. Therefore, maximizing their energy efficiency is an essential task in terms of sustainability. Ferreira et al. [263] and Yu et al. [264] used a multi-objective genetic algorithm to minimize the energy consumption of buildings while maintaining thermal comfort for their occupants. Similarly, Yang et al. [265] employed nondominated sorting genetic algorithms to optimally locate renewable sources on the roofs of buildings at a university campus. Taking another approach to this problem, Naji et al. [262] implemented ELMs to optimize the building materials of construction projects to minimize their electricity demand.
- Predicting energy consumption. T.-Y. Kim and Cho [100] implemented the CNN-LSTM model to capture the space and time characteristics of the time series of residential electricity consumption to produce better forecasts. Other authors have used SVMs to forecast the electricity consumption of buildings [266,267].

- Forecasting demand response to save energy. Demand response has been simulated using intelligent agents [268]. Wen, O'Neill, and Maei [269] investigated using reinforcement learning to provide an optimal demand response.
- Solving multi-objective problems. Heuristic optimization techniques, such as GAs, have been employed to solve multi-objective problems in combined heat and power systems commonly used in buildings [270]. In this case, the goal is to minimize the production costs while meeting heating and electricity requirements [271]. As in the case of multi-objective optimization of distributed generation, most of the time, these problems have been successfully solved using variants of GAs [270–274].

5.2. Current Dominant Themes

The analysis presented represents the dominant thematic areas over the past decade. However, this analysis does not necessarily reflect the most relevant topics currently. To uncover the currently relevant topics of interest, a co-occurrence analysis of keywords was conducted under the following parameters:

- The analysis period was restricted to 2020, 2021, and 2022. For this period, there are 9494 documents with author keywords.
- Keywords that appear in at least five documents were considered. Additionally, only keywords that appear twice as many times in the period 2020–2022 compared to the base period of 2013–2019 were considered. In other words, if a keyword appears 100 times in the base period, it must appear 200 times in the period 2020–2022 to be considered. This restriction ensures its novelty.

The obtained results reveal the following themes of interest.

- The application of deep learning techniques, such as LSTM networks, convolutional networks, and recurrent networks, for time series forecasting in wind energy and electricity consumption.
- The use of reinforcement learning techniques and Q-learning addresses various issues related to integrated energy systems, virtual power plants, and power regulation.
- The use of various AI techniques in problems related to hydrogen, cells, and biochar.
- The estimation of the state of charge, remaining useful life, and health status in lithium batteries.
- The use of metaheuristics like Gray Wolf Optimization in power systems.

6. Conclusions, Limitations, and Future Work

6.1. Conclusions

This article analyzed the evolution of the most relevant themes in publications on AI applications for SE, which were represented using keyword clusters. The methodology adopted here employed text mining techniques, co-occurrence analysis, and clustering to determine the clusters of keywords that appeared together most often. In addition, it implemented a novel technique to construct the search string, which can be helpful in exploring the literature in various fields of knowledge. Data cleaning, homogenization, and text mining were used to transform the keywords, identify and cluster terms with the same meaning, and disambiguate them by analyzing the context where they appeared. Likewise, text analysis techniques and expert opinion were utilized to interpret each identified cluster.

This analysis established eight dominant themes in the literature about SE: (1) solar energy; (2) smart grids and microgrids; (3) fuel cells; (4) hydrogen; (5) electric vehicles; (6) biofuels; (7) wind power; and (8) management, planning, and operation of energy systems. The analysis also revealed eight AI techniques that have been predominantly used to solve SE problems: (1) genetic algorithms, (2) support vector machines, (3) particle swarm optimization, (4) differential evolution, (5) backpropagation neural networks, (6) fuzzy logic controllers, (7) reinforcement learning, and (8) deep learning.

It was found that although some AI techniques (e.g., SVMs, genetic algorithms, and PSO) are widely used for multiple SE topics, not all techniques are suitable to solve all the major problems in SE. A vast collection of AI tools has been used in some SE subfields (e.g., solar energy or electric vehicles). In contrast, research has focused on a single AI tool in some others (e.g., fuel cells or hydrogen).

The results presented the evolution of international authors' interests in different AI and SE topics over the period examined here. In addition, a thematic evolution can be observed regarding the popularization of different AI techniques and advances in SE. This analysis determined the most important SE clusters in recent years (2020–2021): (1) energy consumption, (2) smart grids, (3) wind turbines, (4) solar irradiance, and (5) wind power. It also revealed the most commonly used AI techniques in the same subperiod: (1) swarm optimization, (2) genetic algorithms, (3) long short-term memory, (4) support vector machines, (5) back propagation, (6) neural networks, and (7) differential evolution algorithms.

6.2. Limitations

There are several limitations to this study. First, there may be new dominant areas emerging today. As of this document's review date, more than 3900 documents have already been published for the year 2023. Given the high volume of new documents, reviewing the progress made during this year is important. On the other hand, only Scopus has been considered as the source of information. In this sense, including other documentary bases, such as Dimensions, could be interesting.

Another aspect concerns the kind of keywords chosen and their refinement process. In this study, only the author's keywords were considered. However, it is essential to investigate whether adding or using index keywords or nominal phrases extracted from the document titles and abstracts could help identify other issues or methodologies that the field's community should consider.

Other limitations are related to the use of a co-word analysis. This technique is based on the principle that the co-occurrence of two terms in a set of documents reflects a meaningful relationship. However, co-occurrence does not always mean a substantive or causal relationship. Additionally, the strength of connections based on frequency might overlook less frequent but significant relationships. Other techniques, such as document classification, topic modeling, or emergency indicators, could provide new insights.

6.3. Future Work

Looking back at the work, we can identify several potential directions for future research:

- Crafting specialized techniques to automate the cleanup of keywords and noun phrases extracted from documents. This facet is vital for any subsequent analysis.
- Formulating or employing methodologies that identify the emergence of new themes and convergence in methodological approaches.
- It is essential to contrast outcomes between various methodologies that depict the field's progression, such as topic modeling or document classification.
- Detailed examination of the primary dominant areas discovered.

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Abbreviations

APPL ENERGY	*Applied Energy*
APPL SCI	*Applied Sciences (Switzerland)*
APPL SOFT COMPUT J	*Applied Soft Computing Journal*
ENERGIES	*Energies*
ENERGY	*Energy*
ENERGY CONVERS MANAGE	*Energy Conversion and Management*
ENERGY REP	*Energy Reports*
ENERGY BUILD	*Energy and Buildings*
IEEE ACCESS	*IEEE Access*
IEEE POWER ENERGY SOC GEN MEE	*IEEE Power and Energy Society General Meeting*
IEEE TRANS IND ELECTRON	*IEEE Transactions on Industrial Electronics*
IEEE TRANS IND INF	*IEEE Transactions on Industrial Informatics*
IEEE TRANS SMART GRID	*IEEE Transactions on Smart Grid*
IEEE TRANS SUSTAINABLE ENERGY	*IEEE Transactions on Sustainable Energy*
IOP CONF SER EARTH ENVIRON SC	*IOP Conference Series: Earth and Environmental Science*
INT J ELECTR POWER ENERGY SYS	*International Journal of Electrical Power and Energy Systems*
INT J ENERGY RES	*International Journal of Energy Research*
INT J HYDROGEN ENERGY	*International Journal of Hydrogen Energy*
J CLEAN PROD	*Journal of Cleaner Production*
J ENERGY STORAGE	*Journal of Energy Storage*
J MATER CHEM A	*Journal of Materials Chemistry A*
J PHYS CONF SER	*Journal of Physics: Conference Series*
J POWER SOURCES	*Journal of Power Sources*
J RENEWABLE SUSTAINABLE ENERG	*Journal of Renewable and Sustainable Energy*
RENEW ENERGY	*Renewable Energy*
SOL ENERGY	*Solar Energy*

Appendix A

The subsequent text represents the search string employed for document retrieval.

(
TITLE({adabost} OR {adaptive fuzzy control} OR {adaptive learning} OR {adaptive system} OR {adaptive systems} OR {adversarial learning} OR {adversarial machine learning} OR {adversarial training} OR {ant colony optimization} OR {artificial bee colony} OR {artificial bee colony algorithm} OR {artificial intelligence} OR {artificial neural network} OR {artificial neural networks} OR {associative memory} OR {autoencoder} OR {autoencoders} OR {automl} OR {bat algorithm} OR {bayesian network} OR {bayesian networks} OR {bayesian neural networks} OR {big data analytics} OR {boosting} OR {bp neural network})
) OR (
TITLE({cellular automata} OR {cellular neural networks} OR {collaborative filtering} OR {collaborative learning} OR {computational intelligence} OR {convolution neural network} OR {convolutional neural network} OR {convolutional neural networks} OR {data mining} OR {deep belief network} OR {deep belief networks} OR {deep convolutional network} OR {deep convolutional neural networks} OR {deep generative models} OR {deep learning} OR {deep learning method} OR {deep learning methods} OR {deep neural network} OR {deep neural networks} OR {deep reinforcement learning} OR {differential evolution} OR {differential evolution algorithm} OR {distributed learning} OR {encoder-decoder} OR {ensemble classifier})
) OR (
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) OR (
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) OR (
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) OR (
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) OR (
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) OR (
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) OR (
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) OR (
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) OR (
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) OR (
TITLE({sodium ion batteries} OR {sodium ion battery} OR {sodium-ion batteries} OR {sodium-ion battery} OR {solar air heater} OR {solar cell} OR {solar cells} OR {solar collector} OR {solar collectors} OR {solar cooling} OR {solar energy} OR {solar forecasting} OR {solar hydrogen} OR {solar irradiance} OR {solar irradiation} OR {solar photovoltaic} OR {solar photovoltaics} OR {solar pond} OR {solar power} OR {solar pv} OR {solar radiation} OR {solar thermal} OR {solar thermal energy} OR {solar water heater} OR {solid oxide electrolysis cells})
) OR (
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AND
(LIMIT-TO (LANGUAGE,"English"))

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