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Review

Systematic Literature Review on Fuzzy Hybrid Methods in Photovoltaic Solar Energy: Opportunities, Challenges, and Guidance for Implementation

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Abstract: The application of fuzzy hybrid methods has significantly increased in recent years across various sectors. However, the application of fuzzy hybrid methods for modeling systems or processes, such as fuzzy machine learning, fuzzy simulation, and fuzzy decision-making, has been relatively limited in the energy sector. Moreover, compared to standard methods, the benefits of fuzzy-hybrid methods for capturing complex problems are not adequately explored for the solar energy sector, which is one of the most important renewable energy sources in electric grids. This paper investigates the application of fuzzy hybrid systems in the solar energy sector compared to other sectors through a systematic review of journal articles published from 2012 to 2022. Selection criteria for choosing an appropriate method in each investigated fuzzy hybrid method are also presented and discussed. This study contributes to the existing literature in the solar energy domain by providing a state-of-the-art review of existing fuzzy hybrid techniques to (1) demonstrate their capability for capturing complex problems while overcoming limitations inherent in standard modeling methods, (2) recommend criteria for selecting an appropriate fuzzy hybrid technique for applications in solar energy research, and (3) assess the applicability of fuzzy hybrid techniques for solving practical problems in the solar energy sector.

Keywords: fuzzy hybrid methods; fuzzy machine learning; fuzzy decision-making; fuzzy simulation; renewable energy; solar energy

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1. Introduction

Solar energy has been effectively used as a valuable energy source in the energy sector in response to the rising global energy demand for housing and industrial production. The advantages of solar energy use have become more pronounced because of the rising energy demand across industries and the infeasibility and environmental impact of alternative energy sources such as fuel. According to Pérez et al. [1], the photovoltaic (PV) solar system lifecycle can be divided into four main stages: evaluation/diagnosis, installation, operation, and disposal. In the evaluation/diagnosis stage, the technical and economic feasibility of the project is analyzed, and the elements that will make up the system are also decided, taking into account the technical and social needs of the project. In the installation stage, the elements chosen during evaluation are mounted. The operation stage refers mainly to the functioning of the system, considering its maintenance and monitoring. Finally, the disposal stage marks the end of the system's lifecycle. In this last stage, all elements are analyzed in terms of whether they can be reused or recycled, and those that cannot must be disposed of according to current regulations in order to guarantee correct waste management.

This breakdown of the lifecycle of PV solar systems is important in this study because, as will be demonstrated in this paper, there are fuzzy hybrid methods that can be applied for one or several specific stages. Problems studied in the solar energy literature can include (1) simulation of manufacturing processes or system modeling; (2) prediction or forecasting of elements such as energy demand, maintenance, or system output; and (3) decision-making, such as selecting a suitable energy source, assessing an energy source's or infrastructure's performance, and identifying the optimal location of the energy facility. Other challenges to the adoption of renewable energy technologies were identified by Saraji et al. [2], including financial issues, governmental support, local engagement, underdeveloped business models, land use, a lack of regulations, technical issues, and awareness and knowledge.

Zadeh first introduced fuzzy set theory in 1965 [3]. This concept transformed the perception of modeling uncertainties, as fuzzy sets extended the notion of classical sets and Boolean logic. Hence, the fuzzy logic approach is capable of handling natural language and approximate reasoning by mathematically translating linguistic variables into numeric form, allowing the user to draw definite conclusions from ambiguous information and incomplete data [3]. Fuzzy sets are represented using membership functions. In fuzzy hybrid models, it is crucial to appropriately represent linguistic variables and fuzzy rules, employ the correct fuzzy arithmetic method, and select the most suitable defuzzification methods [4].

Fuzzy hybrid systems have been applied to solve different types of problems in the literature. This is achieved by integrating fuzzy logic with standard techniques to produce hybrid systems, such as fuzzy machine learning, fuzzy simulation, and fuzzy decision-making, which combines the advantages of fuzzy and standard methods. In the renewable energy sector, fuzzy simulation methods are used to capture the behavior of systems and processes to predict or forecast critical variables such as energy load, energy usage, and so on. Moreover, fuzzy decision-making methods entail a combination of evaluating alternative policies, identifying the optimal energy source, identifying the optimal location of an energy facility, and/or selecting the optimal type of renewable energy source [5].

Despite the presence of extensive research on the use of fuzzy hybrid techniques in other sectors, the literature on fuzzy hybrid techniques in the solar energy sector is lacking. Moreover, no detailed systematic review or content analysis exists that synthesizes the existing limited literature to guide researchers in selecting appropriate fuzzy hybrid techniques to apply to their specific problems. This study has three objectives: (1) investigate the application of fuzzy hybrid systems in the solar energy sector in comparison to other sectors, and demonstrate the capability of these methods in comparison to standard modeling/simulation; (2) recommend selection criteria for applying a suitable fuzzy hybrid method in solar energy research; and (3) provide a systematic review of fuzzy hybrid methods to assess the applicability of fuzzy hybrid techniques in the solar energy sector.

This paper contributes significantly to the literature review on applying fuzzy hybrid techniques in solar PV systems. The insights provided in this paper can help advance research and development in this field and ultimately lead to more effective and efficient use of solar energy on electric grids. The main contributions are as follows:

1. State-of-the-art review of existing fuzzy hybrid techniques: This paper provides a comprehensive review of existing fuzzy hybrid techniques, including fuzzy machine learning, fuzzy simulation, and fuzzy decision-making, as they are applied in the solar energy sector. This review helps identify each technique's strengths and weaknesses and provides guidance for selecting the appropriate technique for specific applications in solar PV systems;
2. Showing the capability of fuzzy hybrid techniques: This paper shows the capability of fuzzy hybrid techniques that could be implemented to capture complex problems in solar PV systems that standard modeling methods cannot adequately address. The use of fuzzy hybrid techniques can help overcome standard methods' limitations and provide more accurate and reliable results;
3. Criteria for selecting appropriate fuzzy hybrid techniques: This paper provides criteria for selecting the appropriate fuzzy hybrid technique for specific applications in the

solar energy sector. These criteria consider factors such as the type of problem, data availability, and complexity level;

4. Assessment of the applicability of fuzzy hybrid techniques: This paper assesses the applicability of fuzzy hybrid techniques for solving practical problems in the solar energy sector. The results of this assessment can help researchers identify areas where fuzzy hybrid techniques can be most effective, and they can be used to guide future research in this field.

The rest of this paper is organized as follows: After a brief introduction to fuzzy logic and the application of fuzzy hybrid methods in the solar energy sector, an overview of fuzzy logic applications in different sectors (e.g., construction, mining, and electronics) is presented. Next, the methodology is discussed, which details the steps used to perform a systematic review of articles with fuzzy hybrid applications in the solar energy domain. Then, the results of the content analysis of the literature are presented for three main categories of fuzzy hybrid systems: fuzzy machine learning, fuzzy decision-making, and fuzzy simulation. Then, a checklist for selection criteria for fuzzy hybrid methods for solving problems in the solar energy sector is presented. The last section provides conclusions and recommendations for future work.

2. Methodology

This paper presents a systematic analysis of the extensive literature on fuzzy hybrid methods used in solar energy research that has been published in high-ranking journals. Figure 1 illustrates the methodology used, which consists of two main steps: (1) a review of the literature on fuzzy logic application across different sectors (e.g., construction, automotive, and mining), and (2) a content analysis of existing literature on the applications of fuzzy hybrid techniques to solve problems in the solar energy sector.

This study used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method to conduct the systematic review. A description of the PRISMA methodology can be synthesized into two main steps [6]:

1. Identification and screening: This step involves identifying the research question, creating a protocol, searching multiple databases and sources, and screening the titles, abstracts, and full texts of potentially relevant studies to determine inclusion or exclusion;
2. Data extraction and synthesis: This step involves extracting relevant data using a standardized data extraction form, managing and organizing the data for analysis, and synthesizing the findings across the included studies through statistical analysis, meta-analysis, or a narrative synthesis.

These two steps ensure that the systematic review or meta-analysis is conducted rigorously and transparently, focusing on identifying all relevant studies and synthesizing the findings in a reproducible and replicable way.

The research questions for the systematic review using the PRISMA methodology for this study were:

- What are the existing fuzzy hybrid techniques used in the solar energy sector for modeling systems or processes, such as fuzzy machine learning, fuzzy simulation, and fuzzy decision-making?
- How do fuzzy hybrid techniques compare to standard methods for capturing complex problems in the solar energy sector?
- What criteria can be used to select an appropriate fuzzy hybrid technique for applications in solar energy research?
- What are the practical problems in the solar energy sector that can be solved using fuzzy hybrid techniques?
- How does applying fuzzy hybrid techniques in the solar energy sector compare to their application in other sectors?

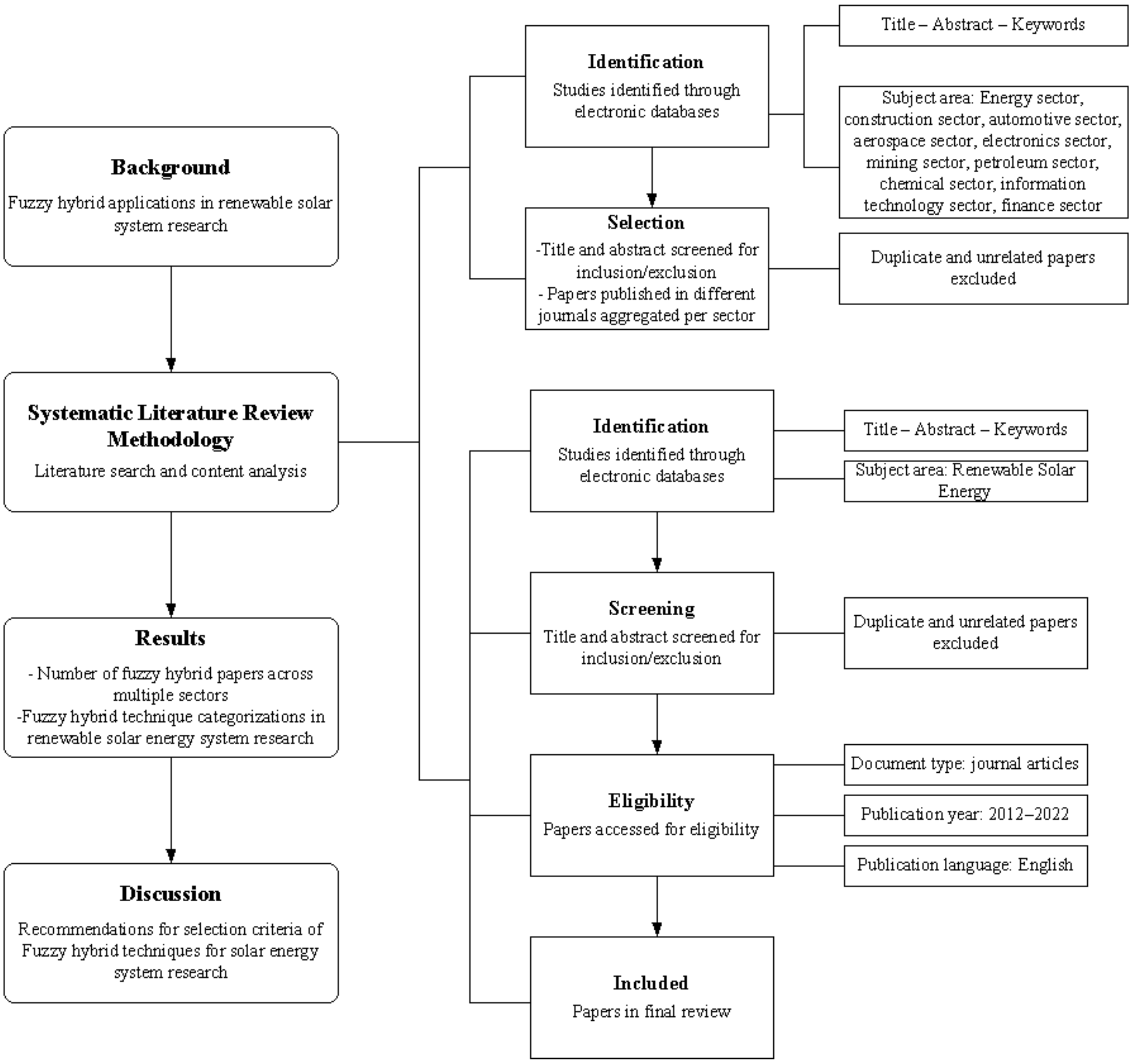

Figure 1. Methodology for the systematic literature search and content analysis used in this study.

One limitation of the methodology is that only published studies are considered, so it might not capture all relevant research in the field. Reliance on published studies can introduce a risk of publication bias, which occurs when only studies with statistically significant findings are published while non-significant findings are not reported.

2.1. Literature Review Process

The literature review began with six searches in Scopus with a filter for articles published from 2012 to 2022 (the last ten years as of this writing). Each search included the relevant set of words with *AND* as the Boolean operator. The resulting list of articles from each search was analyzed using Bibliometrix software version 4.1.2 [7]. The Bibliometrix analysis was conducted to obtain the number of fuzzy-related articles across various sectors, or specifically within the solar energy sector, for each of three areas of study: fuzzy machine learning, fuzzy decision-making, and fuzzy simulation. Each search resulted in a list of articles, and the analysis of each list gives the number of different sources (journals) and authors involved, the annual scientific production (in articles per year), the annual average growth rate in the number of articles, and the average number of times the articles were cited.

In addition, a keyword co-occurrence network (KCN) was generated for each Scopus search using VOSviewer software version 1.6.18. KCN is a method that aims to comprehend the constituents and arrangement of knowledge in scientific or technical fields through the analysis of connections between keywords in the relevant literature. In a KCN, keywords are represented as nodes and links that connect pairs of words that co-occur. The strength of the link between a pair of words is determined by the frequency with which they co-occur in multiple articles and is represented as the weight of the link. This network allows for the identification of meaningful knowledge components and insights by analyzing the patterns and strength of links between keywords that appear in the literature [8].

2.2. Selecting an Appropriate Fuzzy Application

Identified criteria can be used to assess the capabilities of various fuzzy applications by identifying their advantages and disadvantages. This study followed two basic steps to select a fuzzy hybrid method for modeling solar energy processes. First, the advantages and disadvantages of each possible fuzzy hybrid method were listed. Then, detailed selection criteria were listed based on various categories (e.g., accuracy, computational complexity, and data availability). Researchers and practitioners can utilize the content analysis offered in this paper and the listed advantages, disadvantages, and criteria to choose an appropriate fuzzy hybrid machine learning, decision-making, or simulation method to resolve a particular PV solar problem. This analysis allows them to select a methodology that best meets their needs while considering the possible drawbacks associated with each one.

3. Results and Discussion

3.1. Literature Search and Content Analysis Results

3.1.1. Fuzzy Hybrid Machine Learning

A Scopus search carried out for "fuzzy AND hybrid AND machine AND learning" (*fuzzy-hybrid-machine-learning*) yielded 1409 articles. These articles were published in 678 different sources by 3253 authors. Figure 2 shows the annual scientific production (articles per year) of the articles analyzed. Significant growth in the publication of articles on this topic has occurred, with an average annual growth rate of 19.83%. The year with the most articles published was 2022, and the average number of citations per article is 12.4.

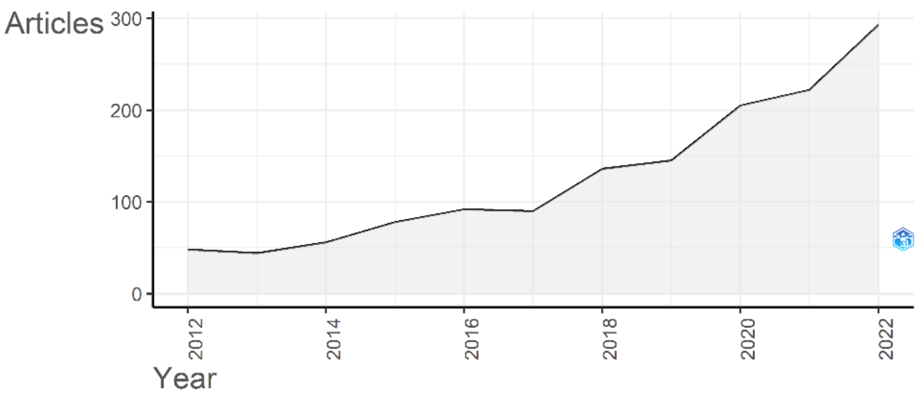

Figure 2. Annual scientific production (articles per year) for *fuzzy-hybrid-machine-learning*.

Table 1 presents the most relevant sources, according to the number of articles published on *fuzzy-hybrid-machine-learning*.

The countries with the greatest scientific production (i.e., number of articles) for *fuzzy-hybrid-machine-learning* were India (with 794 articles), China (155), Iran (95), Malaysia (38), Saudi Arabia (28), Türkiye (28), Korea (23), the United Kingdom (19), Canada (17), and the USA (17). The countries that produced articles with the most citations for *fuzzy-hybrid-machine-learning* were China (2836 citations), India (2220), Iran (1940), Norway (803), the United Kingdom (660), Malaysia (569), Australia (527), the USA (476), Canada (345), and

Korea (315). India, China, and Iran rank highest in both cases, and only three countries from the Americas appear (Canada, the USA, and Brazil).

Table 1. The most relevant sources are based on the number of articles published for *fuzzy-hybrid-machine-learning*.

Rank	Source	Publisher	No. of Articles
1	Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	Springer	72
2	Advances in Intelligent Systems and Computing	Springer Science and Business Media	67
3	Communications in Computer and Information Science	Springer Science and Business Media	35
4	IEEE Access	IEEE	25
5	Lecture Notes in Electrical Engineering	Springer	22

Table 2 presents the most globally cited articles for *fuzzy-hybrid-machine-learning*. These articles primarily focus on water, electric vehicles, and health. The most-cited article has 502 citations and was published in 2018 in the journal Water.

Table 2. Most globally cited articles for *fuzzy-hybrid-machine-learning*.

Authors, Year	Title	Total Citations	Source
Mosavi et al., 2018 [9]	Flood prediction using machine learning models: Literature review	502	Water
Liu et al., 2017 [10]	Reinforcement learning optimized look-ahead energy management of a parallel hybrid electric vehicle	249	IEEE/ASME Transactions on Mechatronics
Seera and Lim 2014 [11]	A hybrid intelligent system for medical data classification	232	Expert Systems with Applications
Mohan and Subashini 2018 [12]	MRI based medical image analysis: Survey on brain tumor grade classification	220	Biomedical Signal Processing and Control
Bui et al., 2017 [13]	A hybrid artificial intelligence approach using GIS-based neural-fuzzy inference system and particle swarm optimization for forest fire susceptibility modeling at a tropical area	203	Agricultural and Forest Meteorology

The most frequent keywords that occurred as a result of the keyword search for *fuzzy-hybrid-machine-learning* were *machine learning* (appearing in 395 articles), *fuzzy inference* (324), *learning systems* (308), *fuzzy neural networks* (289), *fuzzy systems* (267), *fuzzy logic* (240), *forecasting* (237), *learning algorithms* (183), *support vector machines* (166), and *artificial intelligence* (162). A KCN was created with these keywords in order to analyze the links between them. As Figure 3 shows, four main clusters were found for *fuzzy hybrid machine learning*, and the term *machine learning* had the most links; this node is also the largest, which means it is the term with the highest frequency. *Fuzzy inference*, *fuzzy neural networks*, and *learning systems* are terms with higher frequency, which matches the previous keyword analysis. This KCN also shows a closer relationship between some keywords, such as *machine learning*, *fuzzy systems*, *forecasting*, *fuzzy inference*, *learning*, *systems*, and *artificial intelligence*, as represented by the thicker lines joining them. On the other hand, small nodes, such as *GIS*, *groundwater*, *computer crime*, and *semantics*, represent keywords with lower frequency, and the lack of a link connecting them to other nodes indicates these keywords are in the margins of this field of research.

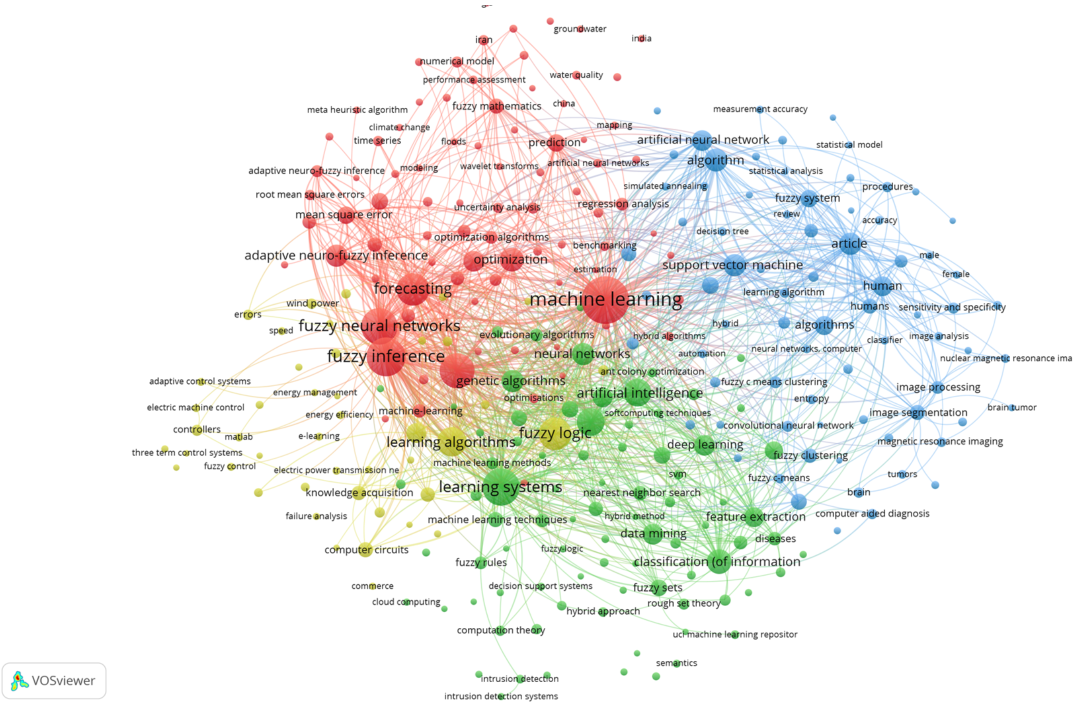

Figure 3. Keyword co-occurrence network for *fuzzy-hybrid-machine-learning*.

Table 3 shows the most frequently addressed types of problems across various sectors and the fuzzy hybrid methods applied to them.

Table 3. Fuzzy hybrid machine learning applications across industry sectors.

Industry Sector	No. of Fuzzy Articles *	Problems Addressed	Fuzzy Hybrid Method (s) Applied
Information technology	5855	Performance, decision-making, prediction, and evaluation/assessment	ANFIS
Mining	3723	Evaluation/assessment, process modeling, decision-making, and prediction	ANFIS
Electronics	3190	Prediction, optimization, system modeling, assessment, and decision-making	ANFIS, fuzzy clustering
Chemical	2442	Evaluation/assessment, planning/management, prediction, and optimization	Fuzzy ANNs
Construction	1856	Prediction, evaluation/assessment, planning/management, process and system modeling, and performance	ANFIS, fuzzy clustering, and fuzzy fault tree analysis
Finance	1420	Decision-making, prediction, evaluation/assessment, and planning/management	ANFIS, fuzzy clustering
Automotive	1250	Prediction, evaluation, process modeling, and system modeling, and optimization, decision-making	Fuzzy ANNs, ANFIS
Aerospace	1041	Planning, performance, prediction, and decision-making	ANFIS
Energy	997	Decision-making, optimization, prediction, and simulation (process/system)	Fuzzy ANNs
Petroleum	718	Process modeling, and system modeling, planning, evaluation/assessment, and decision-making	ANFIS

* Sources: SpringerLink, Wiley Online Library, Taylor & Francis Online, Elsevier, IEEE Xplore, and Emerald.

3.1.2. Fuzzy Logic in the Solar Energy Sector

A Scopus search of "fuzzy AND solar AND energy" (*fuzzy-solar-energy*) for articles related to solar energy that implement fuzzy methods yielded a total of 2934 articles published between 2012 and 2022. The average number of citations per article is 11.90. These articles were published in 1200 sources by 6830 authors. Figure 4 shows the number of articles published annually, with an average annual growth rate of 19.33%.

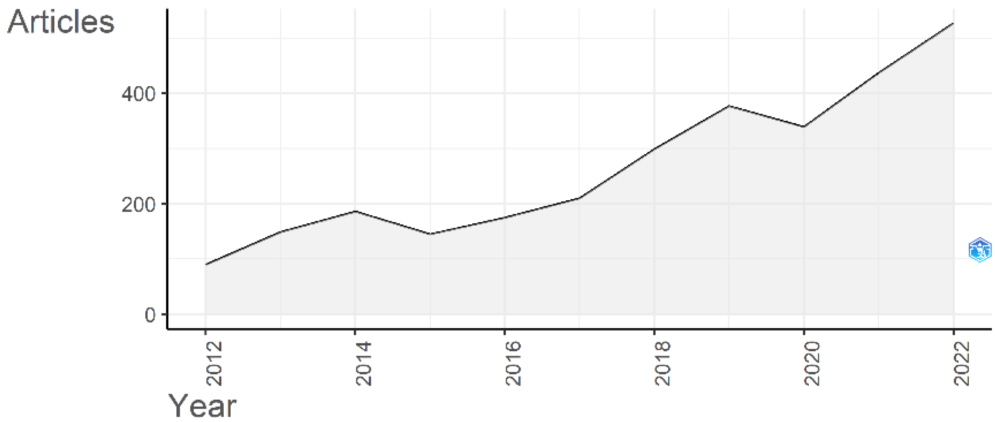

Figure 4. Annual scientific production (in articles per year) for *fuzzy-solar-energy*.

Table 4 presents the most relevant sources, according to the number of articles published on *fuzzy-solar-energy*.

Table 4. Most relevant sources are based on the number of articles published for *fuzzy-solar-energy*.

Rank	Source	Publisher	No. of Articles
1	Energies	MDPI	86
2	Lecture Notes in Electrical Engineering	Springer	64
3	IEEE Access	IEEE	55
4	Applied Mechanics and Materials	Trans Tech Publications	52
5	Advances in Intelligent Systems and Computing	Springer	44

The countries with the greatest scientific production for *fuzzy-solar-energy* were India (with 1742 articles), China (305), Iran (136), Türkiye (95), Algeria (69), Indonesia (44), Egypt (30), Malaysia (30), Morocco (27), and Saudi Arabia (26). The countries that produced articles with the most citations for *fuzzy-solar-energy* were China (4661 citations), India (4523), Iran (3544), Türkiye (1959), the USA (1406), Algeria (980), Egypt (835), Australia (663), the United Kingdom (642), and Japan (500). In short, most of the articles published and cited are from countries in the Middle East and Asia. India, China, Iran, and Türkiye are the countries with the most published articles and therefore the most citations by country for this search. India and China are by far the countries with the most articles published about fuzzy methods applied to solar energy. The USA is the only country in the Americas that appears in these two analyses.

Table 5 presents the most influential articles from 2012 to 2022 based on the number of citations they have received. The one with the most citations was published in 2013 in the journal IEEE Transactions in Industrial Electronics, with 384 citations.

Table 5. Most globally cited articles for *fuzzy-solar-energy*.

Authors, Year	Title	Total Citations	Source
Njoya Motapon et al., 2013 [14]	A comparative study of energy management schemes for a fuel-cell hybrid emergency power system of more-electric aircraft	384	IEEE Transactions in Industrial Electronics
Eltawil and Zhao 2013 [15]	MPPT techniques for photovoltaic applications	359	Renewable and Sustainable Energy Reviews
Suganthi et al., 2015 [16]	Applications of fuzzy logic in renewable energy systems—A review	353	Renewable and Sustainable Energy Reviews
Yang et al., 2014 [17]	A weather-based hybrid method for 1-day ahead hourly forecasting of PV power output	349	IEEE Transactions on Sustainable Energy

The most frequent keywords for the *fuzzy-solar-energy* search results are *fuzzy logic* (appearing in 1097 articles), *solar energy* (1077), *solar power generation* (729), *photovoltaic cells* (545), *controllers* (540), *computer circuits* (517), *maximum power point trackers* (469), *fuzzy inference* (414), *maximum power point tracking* (362), and *MATLAB* (345). Figure 5 presents the KCN for *fuzzy solar energy*, showing five main clusters. The largest nodes in this KCN, and thus the keywords with the highest frequency, are *fuzzy logic*, *solar energy*, and *solar power generation*. The terms with the closest relationship, represented by the thickest lines, are *solar energy*, *fuzzy logic*, *photovoltaic cells*, *decision-making*, *renewable energy sources*, and *fuzzy inference*. Conversely, the keywords located in the margins of this field of research, based on their size and the lack of a link connecting them to other nodes, are *press load control*, *biogas*, *carbon*, *backpropagation*, *P&O* (perturbation and observation), and *electric current control*.

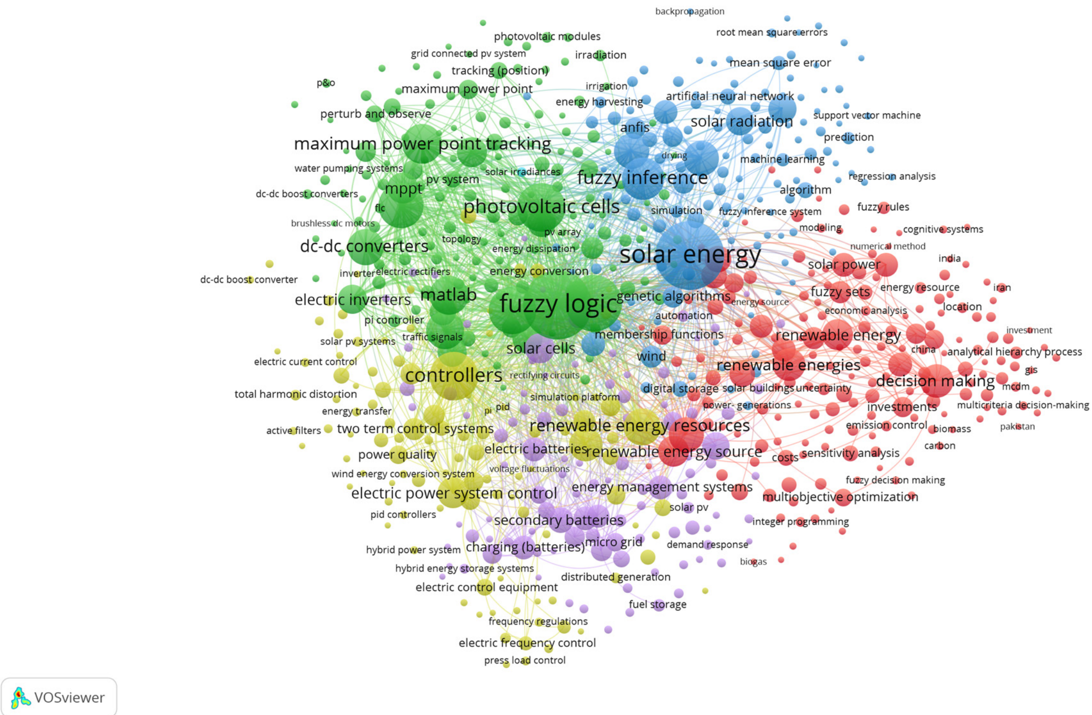

Figure 5. Keyword co-occurrence network for *fuzzy-solar-energy*.

3.1.3. Fuzzy Decision-Making in Different Sectors

According to a Scopus search carried out for "fuzzy AND decision AND making" (*fuzzy-decision-making*), a total of 30,561 articles on this topic were published between 2012 and 2022. However, Scopus only allows downloading the bibliographical information for a maximum of 20,000 items. Therefore, the analysis covers 20,000 articles on *fuzzy-decision-making fuzzy decision-making* that were published between 2017 and 2022. These articles were written by 28,872 authors and published in 3694 sources, with an annual growth rate of 19.02% and an average number of citations of 11.53 per document. Figure 6 summarizes these results and shows significant growth in the number of publications on *fuzzy-decision-making* during this period.

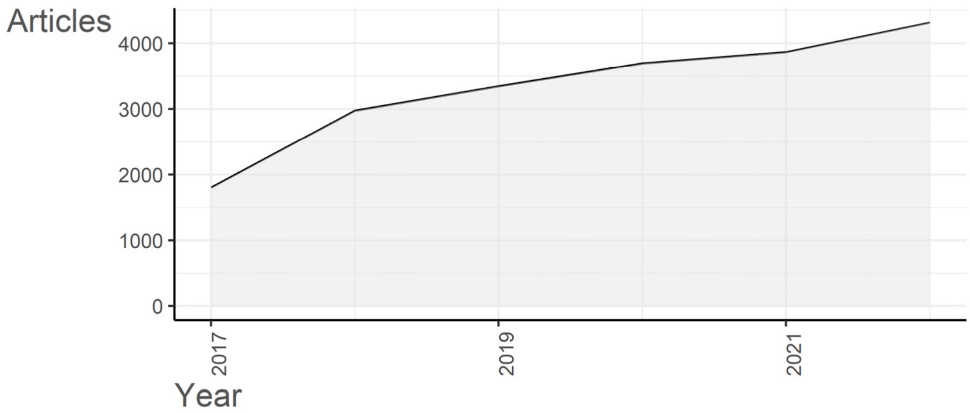

Figure 6. Annual scientific production (articles per year) for *fuzzy-decision-making*.

Table 6 shows the sources with the highest number of articles published about *fuzzy-decision-making*. The Journal of Intelligent and Fuzzy Systems is the journal with the most articles (721) published on this topic.

Table 6. Most relevant sources based on the number of articles published for *fuzzy-decision-making*.

Rank	No. of Articles	Source	Publisher
1	721	Journal of Intelligent and Fuzzy Systems	IOS Press BV
2	632	Advances in Intelligent Systems and Computing	Springer
3	433	Soft Computing	Springer
4	382	IEEE Access	IEEE
5	329	Sustainability (Switzerland)	MDPI

The countries with the greatest scientific production for *fuzzy-decision-making* were China (9672), India (2288), Iran (1189), Türkiye (1144), Pakistan (581), Spain (367), Malaysia (300), USA (287), Poland (270), and the United Kingdom (210). The countries that produced articles with the most citations for *fuzzy-decision-making* were China (87,990), India (29,144), Iran (14,614), Türkiye (14,266), Pakistan (8511), Spain (6031), the United Kingdom (3719), the USA (3670), Malaysia (3610), and Australia (2994). In both cases, China has the highest rank by far, followed by India, Iran, and Türkiye.

Table 7 contains the five articles most frequently cited worldwide for *fuzzy-decision-making*. The article with the most citations was cited 463 times and published in 2017 in the International Journal of Intelligent Systems.

Table 7. Most globally cited articles for *fuzzy-decision-making*.

Authors, Year	Title	Total Citations	Source
Liu and Wang 2018 [18]	Some q-rung orthopair fuzzy aggregation operators and their applications to multi-attribute decision-making	463	International Journal of Intelligent Systems
Guo and Zhao 2017 [19]	Fuzzy best-worst multi-criteria decision-making method and its applications	450	Knowledge-Based Systems
Qin et al., 2017 [20]	An extended TODIM multi-criteria group decision-making method for green supplier selection in interval type-2 fuzzy environment	439	European Journal of Operational Research
Si et al., 2018 [21]	DEMATEL technique: A systematic review of the state-of-the-art literature on methodologies and applications	405	Mathematical Problems in Engineering
Kutlu Gündoğdu and Kahraman 2019 [22]	Spherical fuzzy sets and spherical fuzzy TOPSIS method	351	Journal of Intelligent and Fuzzy Systems

For the fuzzy decision-making search, the keywords with the highest number of appearances are *decision-making* (13,964), *fuzzy sets* (4257), *fuzzy logic* (2965), *linguistics* (1243), *decision theory* (1223), *fuzzy mathematics* (1147), *fuzzy inference* (1145), *mathematical operators* (1082), *fuzzy rules* (1075), and *risk assessment* (1038). Figure 7 shows the KCN for the articles analyzed. There are four main clusters of words, with *decision-making* having the greatest number of appearances, followed by *fuzzy logic*, as shown by the size of their node. The thickest links indicate a closer relationship between *decision-making*, *fuzzy logic*, *fuzzy sets*, and *decision theory*. On the other hand, some of the words located in the margins of this field of research are *city*, *landfill*, *river*, *energy resource*, *image analysis*, and *diagnostic accuracy*.

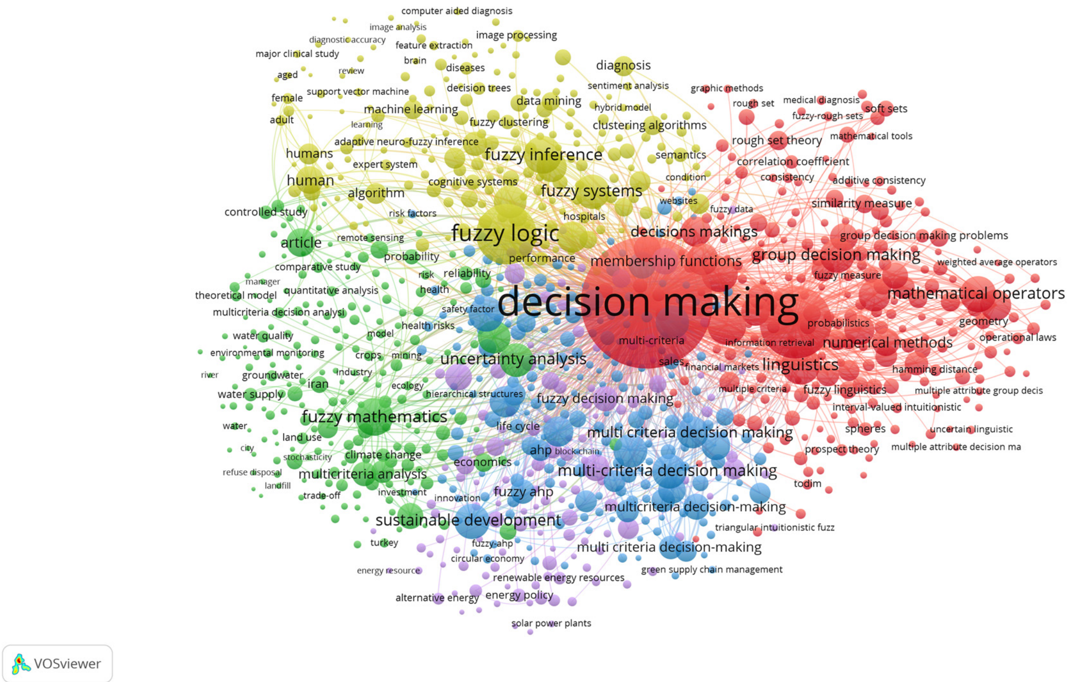

Figure 7. Keyword co-occurrence network for *fuzzy-decision-making*.

Table 8 shows the fuzzy hybrid decision-making problems addressed in the greatest number of articles across various industry sectors, including the fuzzy hybrid methods applied to solve them.

Table 8. Fuzzy hybrid decision-making applications across industry sectors.

Industry Sector	No. of Fuzzy Articles *	Problems Addressed	Fuzzy Hybrid Methods Applied
Mining	1382	Multi-objective optimization, decision support systems, and sustainability	Fuzzy AHP, fuzzy decision trees, and fuzzy expert systems
Construction	783	Construction management, planning, risk analysis, and assessment	Fuzzy AHP, fuzzy ANP, and fuzzy DEMATEL
Information technology	578	Risk evaluation	Fuzzy cognitive mapping, fuzzy AHP
Chemical	483	Environmental impact, risk assessment	Fuzzy AHP
Energy	447	Energy management, multi-objective optimization, energy policy, decision support systems, and planning	Fuzzy VIKOR, fuzzy MCDM, fuzzy AHP, and neuro fuzzy inference systems
Finance	371	Investment evaluation, risk assessment	Fuzzy AHP
Petroleum	292	Petroleum reserve evaluation, quality control, risk assessment, and cost effectiveness	Fuzzy AHP
Automotive	274	Supplier selection, material selection, supply chain management, and environmental management	Fuzzy MCDM, fuzzy TOPSIS
Electronics	217	Performance evaluation, optimization	Fuzzy AHP, fuzzy ANP
Aerospace	92	Decision support systems, performance assessment	Fuzzy MCDM, ANFIS

* Sources: SpringerLink, Wiley Online Library, Taylor & Francis Online, Elsevier, IEEE Xplore, and Emerald.

3.1.4. Fuzzy Decision-Making in the Solar Energy Sector

A Scopus search on “fuzzy AND decision AND making AND solar AND energy” (*fuzzy-decision-making-solar-energy*) and the corresponding Bibliometrix analysis yielded 346 articles published between 2012 and 2022 by 930 authors in 179 sources, with an annual growth rate of 25.25% and an average of 16.85 citations per article. Figure 8 shows the scientific production of articles over this period.

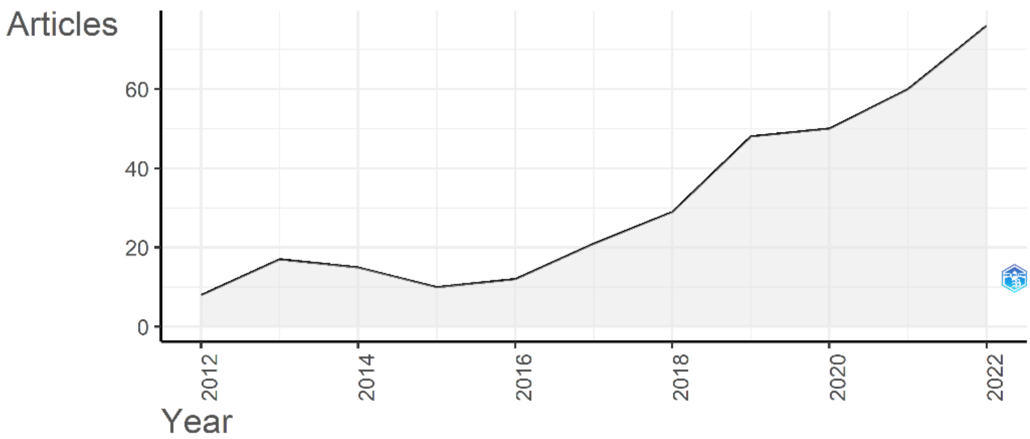

Figure 8. Annual scientific production (in articles per year) for *fuzzy-decision-making-solar-energy*.

Table 9 shows the five journals with the highest number of publications. The journal Renewable Energy published the most articles related to *fuzzy-decision-making-solar-energy*. It is essential to mention that no substantial difference exists between the number of publications in the journals shown in the ranking, with a three-way tie for second place.

Table 9. Most relevant sources based on the number of articles published for *fuzzy-decision-making-solar-energy*.

Rank	Source	Publisher	No. of Articles
1	Renewable Energy	Elsevier	16
2	Energies	MDPI	15
2	Energy	Elsevier	15
2	Journal of Cleaner Production	Elsevier	15
5	Sustainability (Switzerland)	MDPI	11

The countries with the greatest scientific production for *fuzzy-decision-making-solar-energy* were China (160), Türkiye (40), Iran (35), India (28), Spain (6), the USA (6), Italy (5), Morocco (5), Thailand (5), and Australia (4). The countries that produced articles with the most citations for *fuzzy-decision-making-solar-energy* were China (1676 citations), Türkiye (1008), Iran (841), India (269), France (154), Spain (112), Australia (103), Denmark (88), Colombia (82), and Italy (66). Note that China leads by far in both groups, with 160 articles published and more than 1670 citations.

Table 10 shows the five articles most cited worldwide for *fuzzy-decision-making-solar-energy*. The article with the most citations was published in 2013 in the journal Energy Conversion and Management and was cited 216 times.

Table 10. Most globally cited articles for *fuzzy-decision-making-solar-energy*.

Authors, Year	Title	Total Citations	Source
Ahmadi et al., 2013 [23]	Designing a solar powered Stirling heat engine based on multiple criteria: Maximized thermal efficiency and power	216	Energy Conversion and Management
Aydin et al., 2013 [24]	GIS-based site selection methodology for hybrid renewable energy systems: A case study from western Turkey	206	Energy Conversion and Management
Wu et al., 2018 [25]	Evaluation of renewable power sources using a fuzzy MCDM based on cumulative prospect theory: A case in China	166	Energy
Ahmadi et al., 2013 [26]	Multi-objective thermodynamic-based optimization of output power of Solar Dish-Stirling engine by implementing an evolutionary algorithm	154	Energy Conversion and Management
Zoghi et al., 2017 [27]	Optimization solar site selection by fuzzy logic model and weighted linear combination method in arid and semi-arid region: A case study Isfahan-IRAN	119	Renewable and Sustainable Energy Reviews

The most frequent keywords of the articles analyzed for *fuzzy-decision-making-solar-energy* are *decision-making* (in 286 articles), *solar energy* (144), *solar power generation* (73), *fuzzy logic* (68), *renewable energies* (60), *sustainable development* (60), *energy policy* (56), *investments* (51), *fuzzy sets* (47), and *wind power* (46). Figure 9 presents the KCN and the four main clusters of words for this search, which show that the nodes with the greatest number of occurrences are *decision-making* and *solar energy*. There is a closer relationship between the terms *decision-making*, *solar energy*, and *solar power generation*, as represented by the thicker link that joins them. In this case, there are no terms in the margins of this field of research, since all the words are connected between them, but the less frequent terms can be identified by the smallest nodes.

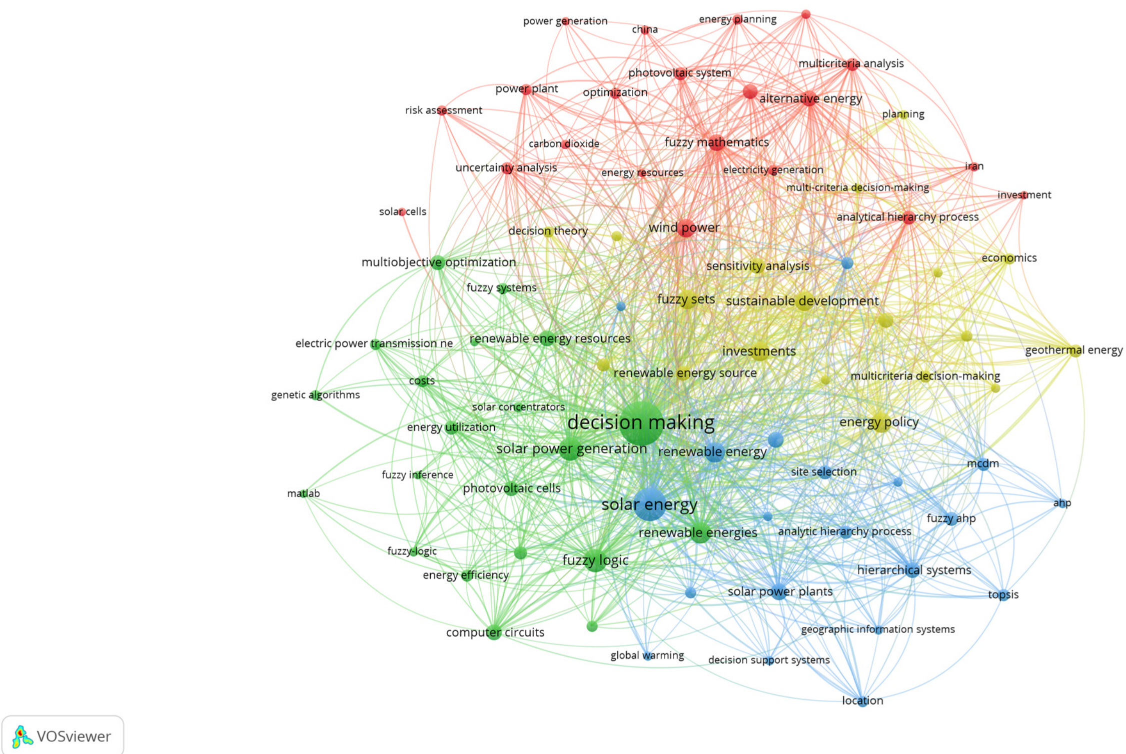

Figure 9. Keyword co-occurrence network for *fuzzy-decision-making-solar-energy*.

3.1.5. Fuzzy Simulation in Different Sectors

A Scopus search using the words "fuzzy AND simulation" (*fuzzy-simulation*) yielded a list of 42,585 articles published between 2012 and 2022. As noted previously, because of

Scopus limitations, bibliographic information was downloaded and analyzed for 20,000 articles. The articles analyzed were published from 2018 to 2022, written by 29,301 authors, published in 4120 sources, and had an annual publication growth rate of 18.59%, as shown in Figure 10. The average number of citations per document is 6.57.

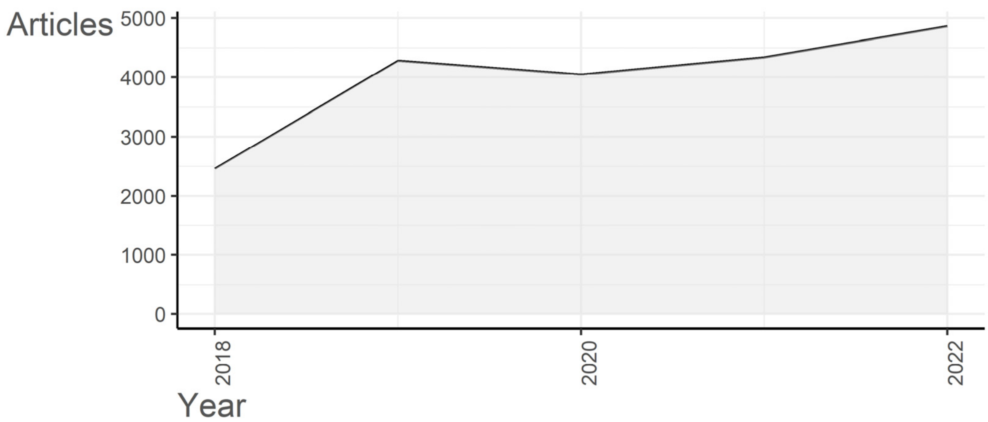

Figure 10. Annual scientific production (in articles per year) for *fuzzy-simulation*.

The countries with the greatest scientific production for *fuzzy-simulation* were China (12,986), India (1663), Iran (1001), Algeria (315), Korea (303), the USA (193), Morocco (192), Türkiye (183), Egypt (182), and Malaysia (174). The countries that produced articles with the most citations for *fuzzy-simulation* were China (57,172), Iran (10,305), India (10,266), Korea (3217), the USA (2248), the United Kingdom (1909), Algeria (1820), Canada (1779), Egypt (1778), and Türkiye (1586).

Table 11 shows the most relevant sources that have published the greatest number of articles related to *fuzzy-simulation*.

Table 11. Most relevant sources based on the number of articles published for *fuzzy-simulation*.

Rank	No. of Articles	Source	Publisher
1	496	IEEE Transactions on Fuzzy Systems	IEEE
2	482	IEEE Access	IEEE
3	308	Journal of Physics: Conference Series	IOP Publishing
4	270	Advances in Intelligent Systems and Computing	Springer Science and Business Media
5	262	Lecture Notes in Electrical Engineering	Springer

Table 12 shows the five articles most frequently cited worldwide for *fuzzy-simulation*. The article with the most citations has 527 and was published in 2018 in the journal Water.

Table 12. Most globally cited articles for *fuzzy-simulation*.

Authors, Year	Title	Total Citations	Source
Mosavi et al., 2018 [9]	Flood prediction using machine learning models: Literature review	527	Water (MDPI)
He and Dong 2017 [28]	Adaptative fuzzy neural network control for a constrained robot using impedance learning	446	IEEE Transactions on Neural Networks and Learning Systems
Qiu et al., 2019 [29]	Observer-based fuzzy adaptative event-triggered control for pure-feedback nonlinear systems with prescribed performance	367	IEEE Transaction on Fuzzy Systems
Tong et al., 2020 [30]	Observer-based adaptive fuzzy tracking control for strict-feedback nonlinear systems with unknown control gain functions	312	IEEE Transactions on Cybernetics
Bai et al., 2020 [31]	Industry 4.0 technologies assessment: A sustainability perspective	302	International Journal of Production Economics

The keywords with the greatest number of appearances are *fuzzy logic* (5886), *controllers* (4210), *fuzzy inference* (2863), *fuzzy control* (2855), *computer circuits* (2585), *MATLAB* (2386), *adaptative control systems* (2113), *fuzzy systems* (2101), *fuzzy neural networks* (1849), and *three-term control systems* (1297). Figure 11 presents the KCN of the keywords from the articles analyzed for this search. As shown, there are four main clusters, and the largest nodes match the most frequent keywords of *fuzzy logic*, *controllers*, *fuzzy inference*, *fuzzy control*, and *computer circuits*. In this case, the words with the thickest link, and thus the closest relationship, are *fuzzy logic*, *computer circuits*, *controllers*, *MATLAB*, and *adaptative control systems*. On the other hand, the keywords in the margin of this field of research, because they are not connected to other words and have the smallest nodes, are *diagnostic imaging*, *female*, *stochastic model*, *validity*, *chattering phenomenon*, and *smart grid*.

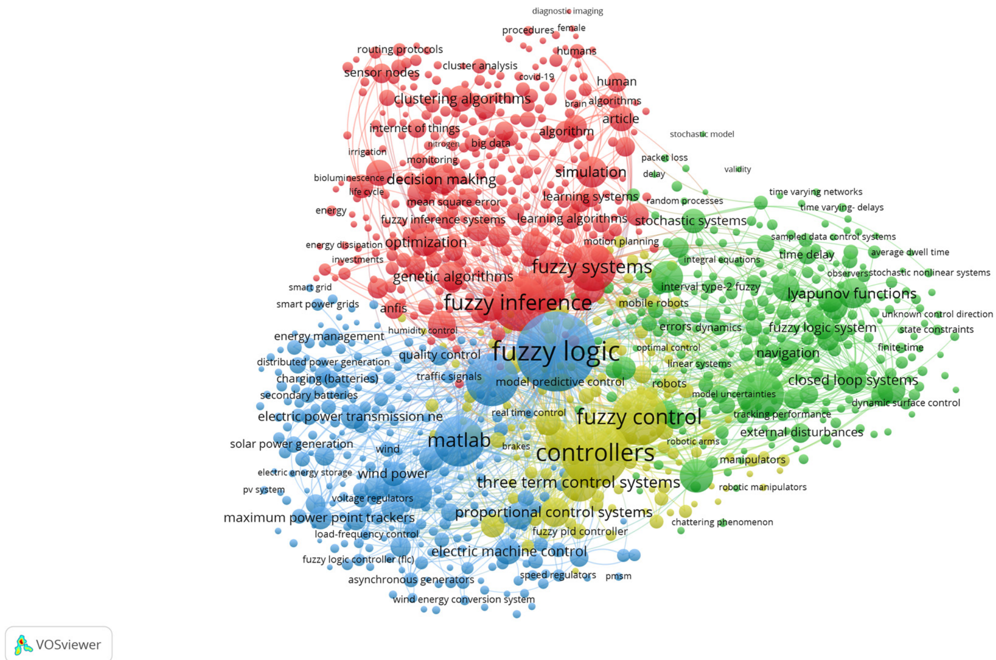

Figure 11. Keyword co-occurrence network for *fuzzy-simulation*.

Table 13 shows the types of problems most frequently addressed across various industry sectors and the fuzzy methods applied to solve them.

Table 13. Fuzzy hybrid simulation applications across industry sectors.

Industry Sector	No. of Fuzzy Articles *	Problems Addressed	Fuzzy Hybrid Methods Applied
Energy	2150	Energy efficiency, energy management, and system modeling	AI-fuzzy controllers
Electronics	1753	System control, process modeling, and system modeling	Fuzzy controllers, NN
Construction	1746	Process modeling, system modeling	Fuzzy system dynamics, FCM-SD
Mining	1403	Planning and scheduling, process modeling, and system modeling	Fuzzy inference systems, neural networks
Chemical	1039	Process modeling, process engineering	Fuzzy control systems, neural network
Information technology	606	System control, process modeling	Fuzzy control systems, neural networks, and fuzzy PID
Automotive	584	Process modeling, system modeling	Fuzzy controllers, NN
Petroleum	391	Process modeling, process engineering	Fuzzy control systems, neural network
Aerospace	328	Process modeling, system modeling	Fuzzy controllers, NN
Finance	149	Process modeling, budget control	Fuzzy simulation, ANFIS

* Sources: SpringerLink, Wiley Online Library, Taylor & Francis Online, Elsevier, IEEE Xplore, and Emerald.

3.1.6. Fuzzy Simulation in the Solar Energy Sector

The bibliographic information of 1025 articles based on the Scopus search for "fuzzy AND simulation AND solar AND energy" (*fuzzy-simulation-solar-energy*) listed 2586 authors. These articles were published in 534 sources, had an average annual publication growth rate of 22.29% (see Figure 12), and had an average of 9.82 citations per article. The publication of articles on this topic has grown significantly over the period investigated, with decreases in 2015 and 2020.

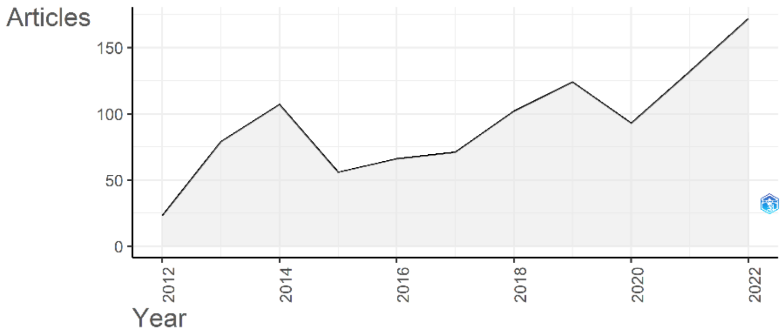

Figure 12. Annual scientific production (in articles per year) for *fuzzy-simulation-solar-energy*.

Table 14 presents the five sources with the largest number of articles published related to *fuzzy-simulation-solar-energy*. The journal Applied Mechanics and Materials had the most articles published related to this topic.

Table 14. Most relevant sources based on the number of articles published for *fuzzy-simulation-solar-energy*.

Rank	No. of Articles	Source	Publisher
1	47	Applied Mechanics and Materials	Trans Tech Publications
2	34	Advanced Materials Research	Trans Tech Publications
3	31	Energies	MDPI
4	21	IEEE Access	IEEE
5	18	Lecture Notes in Electrical Engineering	Springer

The countries with the greatest scientific production for *fuzzy-simulation-solar-energy* were India (599), China (109), Algeria (45), Iran (38), Tunisia (19), Indonesia (17), Türkiye (17), Egypt (15), Morocco (14), and Saudi Arabia (13). The countries that produced articles with the most citations for *fuzzy-simulation-solar-energy* were India (1170), China (1158), Iran (1103), Algeria (608), Türkiye (395), Japan (353), Egypt (247), Saudi Arabia (218), Denmark (181), and Spain (174). India and China had the greatest number of articles published and citations by country for this topic.

The five articles most cited worldwide for *fuzzy-simulation-solar-energy* are presented in Table 15. The top article has been cited 382 times and was published in 2013 in the journal IEEE Transactions on Industrial Electronics.

The most frequently appearing keywords for fuzzy simulation solar energy are *fuzzy logic* (396 articles), *solar energy* (336), *MATLAB* (268), *solar power generation* (268), *controllers* (240), *photovoltaic cells* (234), *maximum power point trackers* (228), *computer circuits* (209), *maximum power point tracking* (172), and *DC–DC converters* (159). The KCN for these articles is presented in Figure 13, which shows that the most frequent keywords for this search are *fuzzy logic*, *solar energy*, and *MATLAB*, since they have the biggest nodes. The thickest links show that the closest relationship is between *fuzzy logic*, *fuzzy logic controllers*, *MATLAB*, *computer circuits*, and *solar energy*. The lack of links indicates that the keywords in the margin of this field of research are *harmonic distortion*, *efficiency*, *P&O*, *FLC*, *DC motors*, *neural networks*, *Monte Carlo methods*, and *scheduling*.

Table 15. Most globally cited articles for *fuzzy-simulation-solar-energy*.

Authors, Date	Title	Total Citations	Source
Njoya Motapon et al., 2013 [14]	A comparative study of energy management schemes for a fuel-cell hybrid emergency power system of more-electric aircraft	382	IEEE Transactions on Industrial Electronics
García et al., 2013 [32]	ANFIS-based control of a grid-connected hybrid system integrating renewable energies, hydrogen, and batteries	192	IEEE Transactions on Industrial Informatics
Yin et al., 2016 [33]	An adaptative fuzzy logic-based energy management strategy on battery/ultracapacitor hybrid electric vehicles	163	IEEE Transactions on Transportation Electrification
García et al., 2013 [34]	Optimal energy management system for stand-alone wind turbine/photovoltaic/hydrogen/battery hybrid system with supervisory control based on fuzzy logic	155	International Journal of Hydrogen Energy
Yi and Etemadi, 2017 [35]	Fault detection for photovoltaic systems based on multi-resolution signal decomposition and fuzzy inference systems	145	IEEE Transactions on Smart Grid

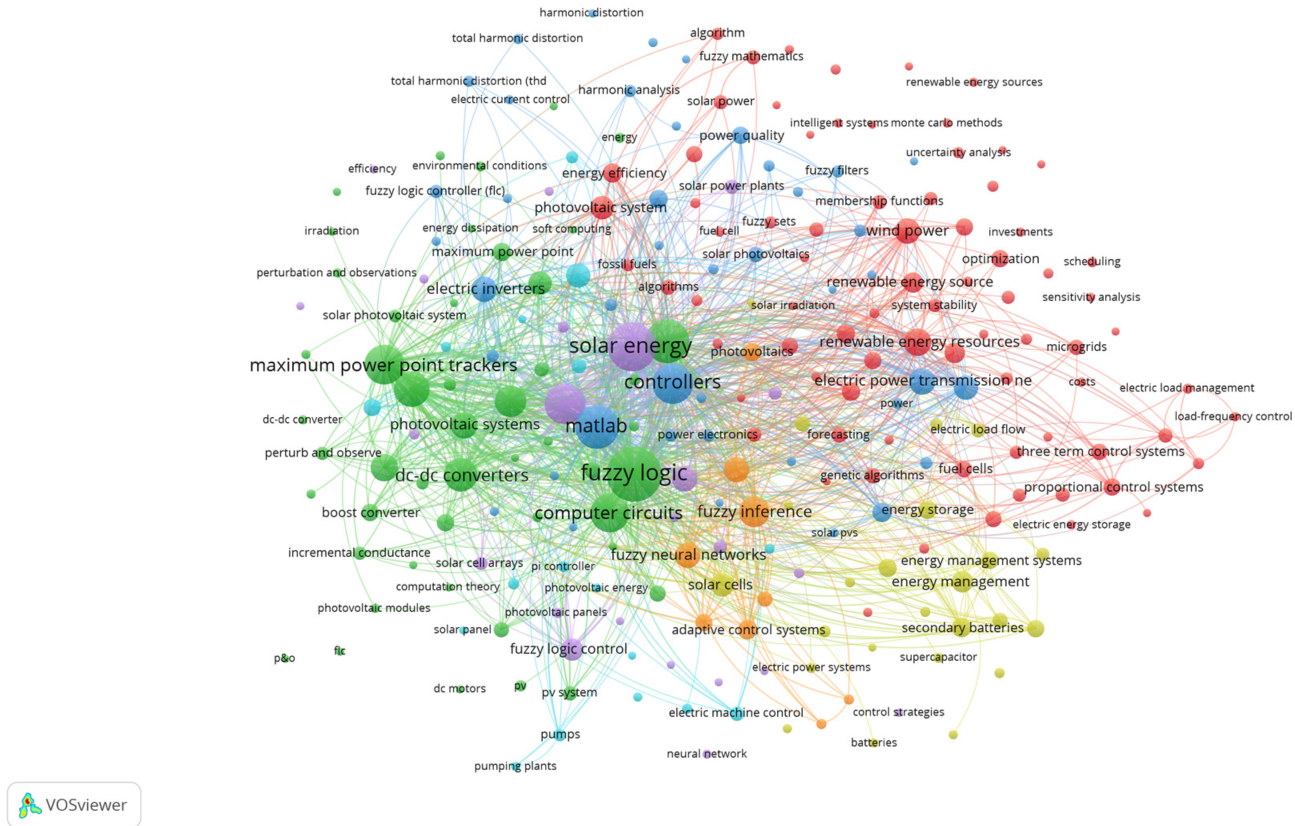

Figure 13. Keyword co-occurrence network for *fuzzy-simulation-solar-energy*.

3.1.7. Content Analysis and Discussion

Table 16 presents the total number of publications analyzed and their classification per application category of the articles published in 2012–2022 that were analyzed for the applications of fuzzy hybrid machine learning, decision-making, and simulation in the solar energy sector. Table 17 gives more details on these articles.

Table 16. Application of *fuzzy hybrid machine learning*, *decision-making*, and *simulation* categories (2012–2022).

Rank	Application Category	Fuzzy Hybrid Machine Learning	Decision-Making	Simulation
1	Prediction/forecasting	32	8	4
2	System modeling	4	2	50
3	Evaluation/assessment	5	55	8
4	Maintenance	3	0	0
	Total	44	65	62

Table 17. Application categories for fuzzy hybrid method articles (2012–2022).

Application Category	Year	Author (s)	Application Area	Method	Journal/Book
Machine learning					
System modeling	2022	Fahim and Vaezi [36]	Systems operation	Fuzzy ANN	Handbook of Smart Energy Systems
Maintenance	2022	Gao et al. [37]	Operational optimization	Deep learning, reinforcement learning	Applied Energy
Prediction/forecasting	2022	Mostafa et al. [38]	Renewable energy, smart grid	Fuzzy clustering, random forest, and decision tree	Machine Learning with Applications
Evaluation/assessment	2021	Ahmad et al. [39]	Renewable energy demand and digitalization	Neuro-fuzzy models	Journal of Cleaner Production
Prediction/forecasting	2021	Alkhayat and Mehmood [40]	Renewable energy forecasting	Deep learning	Energy and AI
Prediction/forecasting	2021	Bakay et al. [41]	Electricity production	Deep learning, SVM, and ANN	Journal of Cleaner Production
Evaluation/assessment	2021	Chen et al. [42]	Energy management	Reinforcement learning	arXiv
Prediction/forecasting	2021	Devaraj et al. [43]	Energy demand	Deep learning	International Journal of Energy Research
System modeling	2021	Garud et al. [44]	Photovoltaic systems	Fuzzy ANN, genetic algorithm	International Journal of Energy Research
Prediction/forecasting	2021	Jamil et al. [45]	Energy prediction	ANN	IEEE Systems Journal
Prediction/forecasting	2021	Jebli et al. [46]	Solar energy prediction	Linear regression, random forest, support vector regression, and ANN	Energy
Prediction/forecasting	2021	Malik et al. [47]	Energy prediction	Fuzzy reinforcement learning	Sustainable Energy Technologies and Assessments
Prediction/forecasting	2021	Perera et al. [48]	Building energy systems	Reinforcement learning, fuzzy logic	Renewable and Sustainable Energy Reviews
Evaluation/assessment	2021	Rangel-Martinez et al. [49]	Energy efficiency	ANFIS, ANN	Chemical Engineering Research and Design
Prediction/forecasting	2021	Severiano et al. [50]	Solar energy forecasting	Fuzzy time series	Renewable Energy
Prediction/forecasting	2021	Zhou et al. [51]	Energy forecasting	Deep learning, long-short-term memory	Wireless Communications and Mobile Computing
Prediction/forecasting	2021	Zulkifly et al. [52]	Energy forecasting	SVM, GPR, linear regression, and decision tree	International Journal of Renewable Energy Research
Prediction/forecasting	2020	Ahmad et al. [53]	Energy planning and forecasting	Fuzzy ANN	Sustainable Cities and Society
Maintenance	2020	Ali and Choi. [54]	Distributed energy resources, demand response	ANFIS, ANN	Electronics
Evaluation/assessment	2020	Antonopoulos et al. [55]	Demand response	Fuzzy ANN	Renewable and Sustainable Energy Reviews
Prediction/forecasting	2020	Çınar et al. [56]	Maintenance	Fuzzy c-means	Sustainability
Prediction/forecasting	2020	Ibrahim et al. [57]	Smart energy systems	Deep learning, ANN	Applied Energy
Prediction/forecasting	2020	Lai et al. [58]	Renewable energy	Adaptive neuro-fuzzy inference system	Applied Sciences
Prediction/forecasting	2020	Li et al. [59]	PV power forecasting	Deep learning, long short-term memory networks	Applied Energy
Prediction/forecasting	2020	Nam et al. [60]	Renewable energy forecasting	Deep learning	Renewable and Sustainable Energy Reviews
Prediction/forecasting	2020	Solyali [61]	Energy forecasting	ANFIS, ANN, SVM	Sustainability
Prediction/forecasting	2020	Stefenon et al. [62]	Solar trackers	Deep learning, long-short-term memory	IET Generation, Transmission and Distribution
Prediction/forecasting	2020	Xu et al. [63]	Demand response	Reinforcement learning, ANN	IEEE Systems Journal

Table 17. *Cont.*

Application Category	Year	Author (s)	Application Area	Method	Journal/Book
Prediction/forecasting	2020	Zhang et al. [64]	Smart grids	Deep learning, reinforcement learning	CSEE Journal of Power and Energy Systems
Prediction/forecasting	2019	Carvalho et al. [65]	Maintenance	Fuzzy c-means	Computers and Industrial Engineering
Prediction/forecasting	2019	Chou et al. [66]	Electricity consumption	Hybrid ARIMA–MetaFA–LSSVR	IEEE Systems Journal
Prediction/forecasting	2019	Hong and Riofloride [67]	Power forecasting	Deep learning	Applied Energy
Prediction/forecasting	2019	Mosavi et al. [68]	Energy demand and forecasting	Deep learning, ANFIS, ANN, and decision tree	Energies
Prediction/forecasting	2019	Phan et al. [69]	Energy prediction	Reinforcement learning, fuzzy logic	Applied Sciences
Prediction/forecasting	2019	Shamshirband et al. [70]	Solar energy optimizing	Deep learning	IEEE Systems Journal
Prediction/forecasting	2019	Sharifzadeh et al. [71]	Electricity demand	ANFIS, ANN, SVR, and GPR	Renewable and Sustainable Energy Reviews
Prediction/forecasting	2019	Wang et al. [72]	Renewable energy forecasting	ANFIS, fuzzy time series	Energy Conversion and Management
Maintenance	2019	Weichert et al. [73]	Manufacturing optimization	ANFIS, fuzzy clustering	International Journal of Advanced Manufacturing Technology
Prediction/forecasting	2018	Cheng and Yu. [74]	Smart energy and electric power systems	Reinforcement learning, deep learning	International Journal of Energy Research
Prediction/forecasting	2018	Fallah et al. [75]	Demand response, load forecasting	Deep learning and fuzzy rule-based	Energies
Prediction/forecasting	2017	Voyant et al. [76]	Energy forecasting	ANFIS, ANN, SVM, and regression	Renewable Energy
System modeling	2016	Zahraee et al. [77]	Hybrid energy system	ANFIS	Renewable and Sustainable Energy Reviews
Prediction/forecasting	2015	Faquir et al. [78]	Energy forecasting	Fuzzy logic control	International Journal of Fuzzy System Applications
Prediction/forecasting	2015	Jurado et al. [79]	Building electricity forecasting	Fuzzy inductive reasoning, ANN, and random forest	Energy
Prediction/forecasting	2015	Osório et al. [80]	Energy prediction	Neuro-fuzzy system, evolutionary PSO	Renewable Energy
Evaluation/assessment	2015	Suganthi et al. [16]	Renewable energy	Fuzzy logic, neural networks, and genetic algorithms	Renewable and Sustainable Energy Reviews
Decision-making					
Evaluation/assessment	2022	Akram et al. [81]	Performance evaluation	Fuzzy sets, multi-attribute group decision-making	Energies
Evaluation/assessment	2022	Asakereh et al. [82]	Renewable energy selection/ranking of alternatives	MCDM, FAHP	Sustainable Energy Technologies and Assessments
Evaluation/assessment	2022	Atwongyeire et al. [83]	Optimal site selection	GIS, FAHP, and MCDM	Energies
Evaluation/assessment	2022	Azmi et al. [84]	Financial analysis and sustainability	MCDM, FAHP	International Journal of Energy Research
Evaluation/assessment	2022	Fard et al. [85]	Financial analysis and sustainability	Hybrid fuzzy best-worst method, geographic information system	Renewable and Sustainable Energy Reviews
Evaluation/assessment	2022	Bilgili et al. [86]	Renewable energy selection/ranking of alternatives	Intuitionistic fuzzy TOPSIS	Renewable Energy
Evaluation/assessment	2022	Dinçer et al. [87]	Cost management	Pythagorean fuzzy DEMATEL, TOPSIS, and Shapley value	Energy Reports
Evaluation/assessment	2022	Guo and Gong [88]	Optimal energy management	Deep reinforcement learning	International Journal of Electrical Power and Energy Systems
Evaluation/assessment	2022	Khorshidi et al. [89]	Optimal site selection	Hybrid fuzzy DEMATEL, fuzzy MOORA	International Journal of Ambient Energy
Evaluation/assessment	2022	Li et al. [90]	Multi-objective optimization	Scenario-based stochastic optimization	Sustainable Cities and Society
Evaluation/assessment	2022	Memari and Mohammadi [91]	Optimal site selection	Fuzzy ANP, Z-number VIKOR	International Journal of Information and Decision Sciences
Evaluation/assessment	2022	Naeem and Ali [92]	Criteria evaluation and selection	MCGDM, Aczel–Alsina spherical fuzzy aggregation	Physica Scripta
Evaluation/assessment	2022	Narayanamoorthy et al. [93]	Renewable energy selection	MEREC, MULTIMOORA	Sustainable Energy Technologies and Assessments
Evaluation/assessment	2022	Nhi et al. [94]	Optimal site selection	FANP, TOPSIS, and FMCDM	Computers, Materials and Continua
Evaluation/assessment	2022	Noorollahi et al. [95]	Optimal location selection	GIS, fuzzy Boolean logic, AHP, and MCDM	Renewable Energy

Table 17. *Cont.*

Application Category	Year	Author (s)	Application Area	Method	Journal/Book
Evaluation/assessment	2022	Pandya and Jariwala [96]	Multi-objective optimization	Moth flame optimization algorithm	Smart Science
Evaluation/assessment	2022	Ponce et al. [5]	Systems operation	Multi-criteria decision-making fuzzy TOPSIS and S4 framework	Energies
Evaluation/assessment	2022	Shah and Longsheng [97]	Sustainability analysis	Fuzzy Delphi, grey AHP	Sustainable Energy Technologies and Assessments
Evaluation/assessment	2022	Singh [98]	Optimal site selection	MADM, DHFs	Granular Computing
Evaluation/assessment	2022	Subba and Shabbiruddin [99]	Optimal material selection	Fuzzy COPRAS	International Journal of Management Science and Engineering Management
Evaluation/assessment	2022	Sun et al. [100]	Renewable energy selection	q-ROF DEMATEL	Energy
Evaluation/assessment	2022	Thanh and Lan [101]	Optimal site selection	SWOC-FAHP-WASPAS analysis	Energies
Evaluation/assessment	2022	Tufail and Shabir [102]	Optimal site selection	VIKOR, MCDM	Journal of Intelligent and Fuzzy Systems
Evaluation/assessment	2022	Xu et al. [103]	Financial analysis	Fuzzy, ELECTRE	International Journal of Fuzzy Systems
Prediction/forecasting	2021	Behera et al. [104]	Multi-objective optimization	PSO	World Journal of Engineering
Evaluation/assessment	2021	Ezbakhe and Pérez-Foguet [105]	Renewable energy selection/ranking of alternatives	MCDA, ELECTRE III	European Journal of Operational Research
Evaluation/assessment	2021	Hsueh et al. [106]	Criteria identification and selection/sustainable system development	AI-MCDM, analytic hierarchy process, and Delphi method	Sustainability (Switzerland)
Evaluation/assessment	2021	Mostafaeipour et al. [107]	Criteria identification and selection/sustainable system development	Fuzzy best-worst method	Energy
Evaluation/assessment	2021	Pang et al. [108]	Criteria identification and selection, sustainable system development	Fuzzy MCDM, intuitionistic uncertain language Choquet ordered weighted aggregation operator (IULCWA)	IEEE Access
Evaluation/assessment	2021	Pour et al. [109]	Optimal site selection	GIS-FFDEA	Journal of Renewable Energy and Environment
Evaluation/assessment	2021	Ramezanzade et al. [110]	Renewable energy selection/ranking of alternatives	Fuzzy MCDM, fuzzy Shannon's entropy	Sustainability (Switzerland)
Evaluation/assessment	2021	Saraswat and Digalwar [111]	Renewable energy selection/ranking of alternatives	Integrated Shannon's entropy, FMCDM	Renewable Energy
Evaluation/assessment	2021	Türk et al. [112]	Optimal site selection	GIS-intuitionistic fuzzy based approach	Scientific Reports
Evaluation/assessment	2020	Chen et al. [113]	Renewable energy selection/ranking of criteria and alternatives	MCDM, PROMETHEE II	International Journal of Fuzzy Systems
Evaluation/assessment	2020	Çoban [114]	Renewable energy selection/ranking of alternatives	MCDM, FAHP	Complex and Intelligent Systems
Evaluation/assessment	2020	Mokarram et al. [115]	Optimal site selection	Fuzzy AHP, fuzzy ANP, and GIS	Journal of Cleaner Production
Prediction/forecasting	2020	Papageorgiou et al. [116]	Scenario analysis	Fuzzy cognitive maps	Energies
Evaluation/assessment	2020	Rani et al. [117]	Performance evaluation	Pythagorean fuzzy SWARA-VIKOR	Sustainability (Switzerland)
Evaluation/assessment	2020	Sitorus and Brito-Parada [118]	Renewable energy selection/ranking of criteria and alternatives	Integrated constrained fuzzy Shannon entropy (IC-FSE)	Renewable and Sustainable Energy Reviews
Evaluation/assessment	2019	Aktas and Kabak [119]	Optimal site selection	AHP-hesitant fuzzy sets	Arabian Journal for Science and Engineering
Evaluation/assessment	2019	Dinçer and Yüksel [120]	Criteria identification and selection/evaluation of alternatives	Hesitant fuzzy DEMATEL, hesitant fuzzy TOPSIS	International Journal of Energy Research
Evaluation/assessment	2019	Gnanasekaran and Venkatachalam [121]	Solar panel selection/evaluation of alternatives	Analytical hierarchy process, fuzzy AHP, solar panel, TOPSIS, and VIKOR	International Journal of Mechanical and Production Engineering Research and Development
Evaluation/assessment	2019	Issa et al. [122]	Evaluation of alternatives	Fuzzy TOPSIS, AHP, and MCDM	Journal of Civil Engineering and Management
Evaluation/assessment	2019	Mohamad et al. [123]	Multi-objective optimization	Monte Carlo, GA, and fuzzy	IEEE Access
Prediction/forecasting	2019	Ren et al. [124]	Multi-objective optimization	Non-dominated sorting genetic algorithm-II (NSGA-II), random walk, directional exploitation (RWDE) algorithm	Journal of Cleaner Production

Table 17. *Cont.*

Application Category	Year	Author (s)	Application Area	Method	Journal/Book
Evaluation/assessment	2019	Sasikumar and Ayyappan [125]	Solar panel selection/evaluation of alternatives	FAHP-TOPSIS	Journal of The Institution of Engineers (India): Series C
Prediction/forecasting	2019	Serrano-Gomez and Munoz-Hernandez [126]	Risk analysis	Monte Carlo-FAHP	PLoS ONE
Evaluation/assessment	2019	Solangi et al. [127]	Optimal site selection	AHP-fuzzy VIKOR	Environmental Science and Pollution Research
Evaluation/assessment	2019	Wu et al. [128]	Optimal site selection	PROMETHEE	Renewable Energy
Evaluation/assessment	2019	Xie et al. [129]	Criteria identification and selection/evaluation of alternatives	Interval fuzzy programming	Energies
Evaluation/assessment	2019	Zeng et al. [130]	Selection of solar cells	FMADM	Energies
Prediction/forecasting	2018	Çoban and Onar [131]	Financial analysis	Fuzzy logic	Soft Computing
System modeling	2018	Dettori et al. [132]	System control	Fuzzy logic	Applied Energy
Evaluation/assessment	2018	Otay and Kahraman [133]	Optimal site selection	Fuzzy AHP	International Journal of the Analytic Hierarchy Process
Evaluation/assessment	2018	Wang et al. [134]	Optimal site selection	DEA, FAHP, and FMCDM	Energies
Evaluation/assessment	2018	Wang and Tsai [135]	Criteria identification and selection/evaluation of alternatives	DEA, FAHP, and FMCDM	Energies
Evaluation/assessment	2018	Yuan et al. [136]	Renewable energy selection/ranking of criteria and alternatives	Fuzzy logic	Journal of Cleaner Production
Evaluation/assessment	2017	Abdullah and Najib [137]	Sustainable energy sources selection	FAHP	International Journal of Fuzzy System Applications
Prediction/forecasting	2017	Ahmadi et al. [138]	Multi-objective optimization	Fuzzy TOPSIS, fuzzy LINMAP	Thermal Science and Engineering Progress
System modeling	2017	Gangothri and Kiranmayi [139]	System control	Fuzzy logic	Journal of Advanced Research in Dynamical and Control Systems
Evaluation/assessment	2017	Lee et al. [140]	Optimal site selection	Fuzzy analytic network process (FANP), interpretive structural modeling (ISM)	Sustainability (Switzerland)
Evaluation/assessment	2015	Lee et al. [141]	Optimal site selection	Analytic hierarchy process (AHP), data envelopment analysis (DEA), and fuzzy logic	Sustainability (Switzerland)
Evaluation/assessment	2017	Samanlioglu and Aya [142]	Optimal site selection	AHP, fuzzy logic, multiple-criteria decision-making, and PROMETHEE II	Journal of Intelligent and Fuzzy Systems
Prediction/forecasting	2013	Ahmadi et al. [23]	Multi-objective optimization	Evolutionary algorithms	Energy Conversion and Management
Prediction/forecasting	2013	Ahmadi et al. [26]	Multi-objective optimization	Evolutionary algorithms	Energy Conversion and Management
Evaluation/assessment	2012	Boran et al. [143]	Policy evaluation and analysis	Multi-criteria axiomatic design	Energy Sources, Part B: Economics, Planning and Policy
Fuzzy Simulation					
System modeling	2022	Kader et al. [144]	Renewable energy grid, systems control	Type-2 fuzzy logic system, PSO	Energies
System modeling	2022	Bouhouta et al. [145]	Renewable energy grid	Fuzzy M5P, fuzzy logic controller	Energy Sources, Part A: Recovery, Utilization and Environmental Effects
Prediction/forecasting	2022	Cao et al. [146]	Energy management	Deep learned type-2 (T2) fuzzy logic system (FLS), singular-value decomposition (SVD)	Energy Reports
System modeling	2022	Zhu and Chen [147]	Renewable energy grid	Fuzzy logic controller	Frontiers in Energy Research
Evaluation/assessment	2022	Giurgi et al. [148]	Energy management	Fuzzy logic controller	Applied Sciences (Switzerland)
System modeling	2022	Guo and Gong [88]	Energy management	Deep reinforcement learning, fuzzy logic controller	International Journal of Electrical Power and Energy Systems
System modeling	2022	Hemalatha and Seyezhai [149]	Systems operation	Fuzzy MPPT controller	Applied Nanoscience (Switzerland)
System modeling	2022	Kurian et al. [150]	Renewable energy performance	Fuzzy logic controller	Sustainable Energy Technologies and Assessments
Evaluation/assessment	2022	Salman et al. [151]	Renewable energy performance	Fuzzy logic controller	Bulletin of Electrical Engineering and Informatics
System modeling	2022	Septiarini et al. [152]	Systems operation	Fuzzy logic controller	International Journal of Computational Vision and Robotics

Table 17. *Cont.*

Application Category	Year	Author (s)	Application Area	Method	Journal/Book
System modeling	2022	Vaibhav and Srikanthan [153]	Hybrid renewable energy systems	Fuzzy logic-based GPSO PR Controller	International Journal of Renewable Energy Research
System modeling	2022	Yahiaoui et al. [154]	Renewable energy conversion	AI, fuzzy logic controller	Frontiers in Energy Research
System modeling	2021	Abdellatif et al. [155]	Energy management	Fuzzy logic controller	International Journal on Electrical Engineering and Informatics
System modeling	2021	Ali et al. [156]	Renewable energy grid	Fuzzy logic controller	IEEE Access
System modeling	2021	Cioccolanti et al. [157]	Energy management	Fuzzy logic controller	Applied Sciences (Switzerland)
System modeling	2021	Palacios et al. [158]	Systems control	Fuzzy logic controller, PSO	International Review of Automatic Control
System modeling	2021	Ramakrishna et al. [159]	Systems operation	Fuzzy logic controller	Journal of Green Engineering
System modeling	2021	Şahin and Okumuş [160]	Systems control	Fuzzy logic controller	Electric Power Components and Systems
System modeling	2021	Yussif et al. [161]	Systems control	Fuzzy logic controller	Energies
System modeling	2020	Thakur et al. [162]	Systems control, renewable energy	Fuzzy set theory, fuzzy logic, neural networks, ANN, ANFIS, FES, RSM, and SVM	Applied Soft Computing Techniques for Renewable Energy
System modeling	2020	Chouksey et al. [163]	Operational optimization	Fuzzy logic controller, ANN-based PSO	Fuzzy Sets and Systems
Evaluation/assessment	2020	El Hichami et al. [164]	Systems control	Fuzzy logic controller	Journal of Advanced Research in Dynamical and Control Systems
System modeling	2020	Hamdi et al. [165]	Systems control	Adaptive neuro-fuzzy inference systems (ANFIS), fuzzy logic controller	Protection and Control of Modern Power Systems
System modeling	2020	Mohapatra et al. [166]	Systems operation	Adaptive fuzzy MPPT	Journal of The Institution of Engineers (India): Series B
Evaluation/assessment	2020	Ontiveros et al. [167]	Systems control	Fuzzy logic controller	International Journal of Photoenergy
System modeling	2019	Choudhury and Rout [168]	Photovoltaic system, systems control	Mamdani-based fuzzy logic controller	International Journal of Intelligent Systems Technologies and Applications
System modeling	2019	Bansal [169]	Renewable energy grid	Fuzzy logic controller	International Journal of Engineering and Advanced Technology
System modeling	2019	Farajdadian and Hosseini [170]	Systems control	Firefly algorithm, fuzzy logic controller, and PSO	Solar Energy
Prediction/forecasting	2019	Perveen et al. [171]	Energy forecasting	Fuzzy logic, ANN, and ANFIS	IET Energy Systems Integration
System modeling	2019	Ramya et al. [172]	Demand response	Fuzzy logic controller	Journal of Intelligent and Fuzzy Systems
System modeling	2019	Sutar and Butale [173]	Systems control	Fuzzy logic controller	International Journal of Engineering and Advanced Technology
System modeling	2018	Assahout et al. [174]	Photovoltaic system	Fuzzy logic, ANN	International Journal of Power Electronics and Drive Systems
System modeling	2018	Benaissa et al. [175]	Operational optimization	ANFIS	Revue Roumaine des Sciences Techniques Serie Electrotechnique et Energetique
System modeling	2018	Jemaa et al. [176]	Systems control	Fuzzy logic controller	International Journal of Photoenergy
System modeling	2018	Kanagasakthivel et al. [177]	Systems control	ANFIS-based MPPT controller	Journal of Intelligent and Fuzzy Systems
Prediction/forecasting	2018	Perveen et al. [178]	Energy forecasting	Fuzzy logic	Journal of Renewable and Sustainable Energy
System modeling	2018	Shah et al. [179]	Operational optimization	Fuzzy logic-based FOGI-FLL algorithm	IEEE Transactions on Industrial Informatics
Prediction/forecasting	2017	Almaraashi [180]	Energy demand	Fuzzy logic	PLoS ONE
System modeling	2017	Andigounder et al. [181]	Systems control	ANFIS controller	Ecology, Environment and Conservation
System modeling	2017	Gangothri and Kiranmayi [139]	Renewable energy	Fuzzy logic, MPPT	Journal of Advanced Research in Dynamical and Control Systems
System modeling	2017	Goh et al. [182]	Photovoltaic systems	Fuzzy logic controller	Journal of Telecommunication, Electronic and Computer Engineering
System modeling	2017	Hariprabhu and Sundararaju [183]	Renewable energy grid	Sophisticated fuzzy rule set (SFRS) based MPPT	Journal of Advanced Research in Dynamical and Control Systems
System modeling	2017	Mayilvahanan et al. [184]	Performance enhancement	Dynamic rule soft switching algorithm, fuzzy logic	Journal of Computational and Theoretical Nanoscience

Table 17. *Cont.*

Application Category	Year	Author (s)	Application Area	Method	Journal/Book
System modeling	2017	Sukumar et al. [185]	Systems control	Fuzzy logic controller	Energies
Evaluation/assessment	2016	Ben Smida and Sakly [186]	Renewable energy grid	Fuzzy logic controller, MLI, and MPPT	International Journal of Renewable Energy Research
System modeling	2016	Bouzeria et al. [187]	Systems control	Fuzzy logic controller	International Journal of Simulation and Process Modelling
System modeling	2016	El Filali et al. [188]	Photovoltaic systems	Fuzzy logic, MPPT	Journal of Theoretical and Applied Information Technology
System modeling	2016	Nader and Abderrahmane [189]	Renewable energy grid	Electrical grid, fuzzy logic control; MPPT	Revue Roumaine des Sciences Techniques Serie Electrotechnique et Energetique
System modeling	2016	Wang et al. [190]	Renewable energy grid	Fuzzy logic	KSII Transactions on Internet and Information Systems
System modeling	2015	Arulmurugan and Suthanthiravanitha [191]	Photovoltaic systems	Hopfield neural network, MPPT, and optimized fuzzy rule	Electric Power Systems Research
System modeling	2015	Kang et al. [192]	Systems control	Fuzzy logic controller	Applied Energy
Evaluation/assessment	2015	Muthuramalingam and Manoharan [193]	Photovoltaic systems	Fuzzy logic controller, genetic algorithm	World Journal of Modelling and Simulation
System modeling	2015	Prakash and Sahoo [194]	Photovoltaic systems	Fuzzy logic controller	Research Journal of Applied Sciences, Engineering and Technology
Evaluation/assessment	2015	Shiau et al. [195]	Energy demand	Fuzzy MPPT algorithms	Algorithms
System modeling	2015	Shiau et al. [196]	Systems control	Fuzzy logic controller	Energies
System modeling	2014	Chakraborty et al. [197]	Photovoltaic systems	Fuzzy logic, advanced quantum evolutionary method	IET Generation, Transmission and Distribution
System modeling	2014	Othman et al. [198]	Systems operation	Fuzzy logic controller, MPPT	WSEAS Transactions on Power Systems
System modeling	2014	Shiau et al. [199]	Systems operation	Fuzzy logic controller	Energies
System modeling	2013	Chakraborty et al. [200]	Systems operation, renewable energy smart grid	Fuzzy logic, advanced quantum evolutionary method	IEEE Transactions on Sustainable Energy

The results of the literature review and analysis illustrate a lack of scientific production based on designing, implementing, and deploying hybrid fuzzy logic methods in the solar energy sector, which is extremely important in the effort to reduce CO_2 and greenhouse emissions worldwide.

The analysis of articles indicated that between 2012 and 2022, more than 2900 articles related to fuzzy solar energy were published in 1200 different sources. Moreover, two countries dominate the scientific production on this topic: India and China. The data presented in this paper support the possibility of implementing hybrid fuzzy logic systems in solar energy because the countries leading PV solar energy installations are also leading research in hybrid fuzzy logic systems [201].

On the topic of fuzzy hybrid machine learning, the publication of articles increased substantially during 2012–2022, with 1409 articles in all. The greatest number of these articles are from India and are primarily focused on the information technology, mining, electronics, chemical, and construction sectors. In contrast, the application of fuzzy hybrid machine learning in the energy sector is still low and mainly centered on decision-making, optimization, prediction, and simulation problems.

With respect to fuzzy decision-making, more extensive scientific production is observed for 2012–2022, with more than 30,500 articles published. This analysis considered 20,000 articles published from 3694 different sources for 2017–2022, of which almost 30% were from China and focused on the mining sector. With respect to the energy sector, fuzzy hybrid decision-making is mainly applied in energy management, multi-objective optimization, energy policy, decision support systems, and planning problems. Focusing only on solar energy and decision-making, only 346 articles were published, most of them in China.

During 2012–2022, more than 42,500 articles were published related to fuzzy simulation, although this study analyzed only 20,000 articles published in 2018–2022 due to

Scopus's limitation of only being able to download bibliographical information for that maximum number of articles. For this topic, scientific production has remained almost linear since 2019, with China publishing 65% of the total articles published, and more articles were published on the energy sector, focusing on energy efficiency, energy management, and system modeling. Other sectors dominating the fuzzy simulation articles publication are electronics, construction, and mining. Between 2012 and 2022, 1025 articles related to "fuzzy simulation and solar energy" were published in 534 sources. India led the publication of these works, followed by China.

As Figure 14 and Table 17 show, out of the four stages of solar system lifecycles (evaluation/diagnosis, installation, operation, and disposal), most applications of fuzzy hybrid machine learning, decision-making, and simulation focused on prediction/forecasting, manufacturing process/system modeling, and evaluation/assessment, and therefore addressed the evaluation/diagnosis stage. Just a few focus on the operation stage, and thus all focus on maintenance.

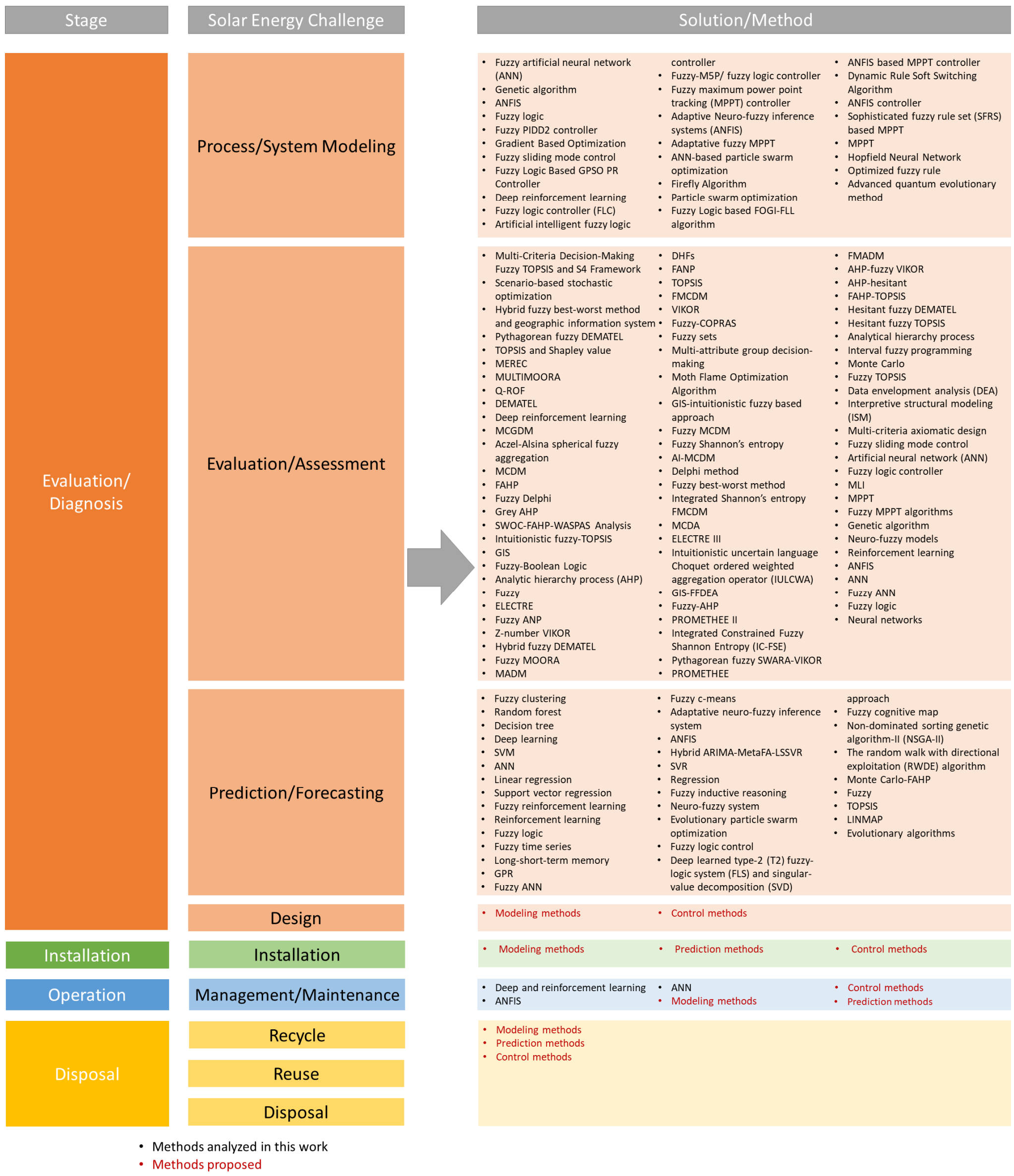

Figure 14. Challenges for solar energy systems and possible methods for their solution.

3.2. Selecting Fuzzy Hybrid Applications

As discussed above, there is a considerable lack of applications of fuzzy hybrid machine learning, decision-making, and simulation in research on the installation, operation, and disposal stages of solar energy systems. No application has been explored for solving problems in the installation and disposal stages, and just a few applications have been explored for the operation stage. For these three stages, methods of modeling, prediction, and control are proposed here.

Numerous hybrid fuzzy logic methods have been effectively designed and implemented in several areas, but hybrid fuzzy logic methods regarding solar energy are poorly implemented. Hybrid fuzzy logic methods can be used to help improve solar energy generation and operation at specific stages. This review presents how methodologies using fuzzy logic can be deployed in the solar energy sector, especially when combined with some conventional methodologies to improve their performance. Table 18 presents the advantages (pros) and disadvantages (cons) of fuzzy hybrid machine learning, decision-making, and simulation methods.

Table 18. Advantages and disadvantages of fuzzy hybrid machine learning, decision-making, and simulation methods.

Category/Method	Advantages	Disadvantages	References
Fuzzy Machine Learning			
ANFIS, ANN, and deep learning	• Provides accelerated learning capacity and adaptive interpretation capabilities to model complex patterns and apprehend nonlinear relationships; • Knowledge representation and automated learning; • Ability to use linguistic variables to model the input–output relationships of a given system; • Represent qualitative, vague, and imprecise concepts; • Learning capabilities and pattern matching; • Ability to solve both linear and nonlinear problems.	• High computational expense and complexity depend on algorithm mathematics and the number of iterations; • Loss of interpretability in larger inputs; • Curse of dimensionality; • Need to select appropriate membership functions; • Can easily converge to local minima; • Trade-off between interpretability and accuracy; • High processing time for large neural networks, and highly relying on the training process.	[202–209]
Fuzzy clustering	• Flexibility to express that data points can belong to more than one cluster; • Clusters can be characterized by a small number of parameters.	• Computationally expensive and high likelihood of complexity; • Need large data sets; • Sensitive to initialization of the weight matrix.	[16,204–206]
Fuzzy inductive reasoning	• Handle subjective variables and judgements; • Allow to make an observation and then apply it to a variety of similar and sometimes unlike instances with probability; • Deal with dynamical systems.	• Inferences are limited in scope and are inaccurate.	[207,208,210]
Fuzzy reinforcement learning	• Does not require large labeled datasets; • Highly adaptable and goal-oriented; • Can correct the errors that occurred during the training process; • Achieves the ideal behavior of a model within a specific context, to maximize its performance.	• Can lead to an overload of states if too many iterations; • Needs a lot of data and a lot of computation; • Curse of dimensionality limits reinforcement learning heavily for real physical systems.	[211–214]
Fuzzy Decision-making			
Fuzzy AHP	• Can be easily understood; • Easy to use compared to other methods; • Easier to structure problems systematically.	• Consistency of results with expert judgements can depend on the way the problem is structured (e.g., one-level hierarchy vs two-level hierarchy); • Some methods in the fuzzy component of the method are not straightforward to use for establishing priorities or weights; • Interdependence between criteria and alternatives; • Can be subject to inconsistencies in judgement and ranking criteria; • Addition of alternatives at the end could cause reversal of final rankings.	[215,216]

Table 18. *Cont.*

Category/Method	Advantages	Disadvantages	References
Fuzzy ANP	• Is capable of capturing relationships belonging to different categories; • Can capture subjective and objective measurements of variables; • Can be easily understood.	• Can become computationally complex to implement; • Involves pairwise comparison process, which can become cumbersome; • Problem with updating the system if (when) new information arises.	[217–219]
Fuzzy ELECTRE	• Takes into account vagueness and uncertainty; • More stable as it is less sensitive to changes in data as compared to other methods.	• More difficult to comprehend; • Strength and weakness of alternatives cannot be directly identified; • Verification of results and impacts is difficult; • Threshold needs to be defined, whose size impacts ranking of alternatives.	[216,220,221]
Fuzzy genetic algorithms	• Successfully applied to a range of problems; • No specific requirement on the problem before using GA, can be used to solve any problem; • Cover larger space of the search space per iteration (as compared with other comparative approaches); • Uses operators which enable it to mix good attributes from different solutions (subsequent exploitation enables finding of optimal solutions); • No definite mathematical restrictions on properties of fitness function; • Can handle noisy functions well; • More resistant to becoming trapped in local optimum solutions.	• Selection of initial population affects quality of solution; • Solution may take more computational time if large population is considered; and small population may lead to poor solution; • Premature convergence can lead to suboptimal solution; • Selection of efficient fitness functions; • No general method for selection of particular encoding scheme for specific problems; • Needs to be coupled with a local search technique; • Can have issues with finding exact global minimum; • Identifying fitness function can be a problem.	[222–225]
Fuzzy PSO	• There are few parameters to adjust; • Can work for applications with both specific and wide range of applications; • Good for multi-objective optimization.	• Solution can become of low quality; • Needs memory to update; • Possibility of early coverage.	[226,227]
Fuzzy PROMETHEE	• Easy to use; • Normalization of scores not needed; • Does not require the assumption of proportionate criteria; • More powerful in different problem contexts.	• No clear method for weight assignment.	[216,220]
Fuzzy TOPSIS	• Basic idea behind its formulation is simple and intuitive; • Easy and useful method with extensive applications; • The methodology is easily programmable; • Number of steps is same irrespective of number of attributes	• Distance function does not consider correlation between attributes.	[216,219,228]
Fuzzy VIKOR	• Can solve discrete decision problems that are conflicting and with criteria consisting of different units; • Can process problems with higher number of alternatives and attributes; • Can be used for complex systems; • Has fewer factors to consider and is relatively simpler to implement; • Can rank alternatives to determine best solution accurately.	• Cannot elicit the weights and check the consistency of the decision-making.	[216,219,229,230]
Fuzzy Simulation			
Fuzzy discrete event simulation	• Capable of modeling processes that involve number of activities; • Capable of simulating a process to predict the duration of an activity or performance of resources; • Can process fuzzy numbers, deterministic and probabilistic values; • Allows users to interact with the model and observe the model's changes as the simulation clock advances; • Useful for performing processes-based simulation.	• Difficulty in implementing classical arithmetic operations when fuzzy numbers are involved; • Time paradox phenomenon can occur, where time decreases instead of increasing; • More details are necessary to represent the system; • Cannot capture dynamic feedback relationships between system variables [204].	[204,231–234]

Table 18. *Cont.*

Category/Method	Advantages	Disadvantages	References
Fuzzy system dynamics	• Ideal for simulating systems that are continuous in behavior, broad in details, and qualitative and quantitative in nature; • Captures the system at a higher level to identify variables that affect the state of the system; • Can capture interdependencies between variables, that also involve non-linear relationships with multiple feedback processes that are able to change through time.	• Proper system representation, including defining model boundaries and aggregation level can become difficult; • Identifying causal relationships can become difficult in some systems; • Identifying feedback loops can become difficult; • Capturing system variables having qualitative data can make the model computationally cumbersome; • Verification and validation process can become difficult.	[232–239]
Fuzzy agent-based modeling	• Can capture complex systems and emerging behaviors (i.e., where the system can be abstracted interacting objects whose behavior lead to a global behavior); • Can model systems even when the overall behavior of the system is not known initially; • Can handle large amount of goal-driven, autonomous, and adapting agents; • Can easily capture behaviors of numerous activities, each with differing attributes and complex interrelationships, and changing conditions during simulation.	• Not best suited for modeling high-level aggregated systems; • Not suited for investigating which processes dominate in aggregated systems; • Not suited for modeling systems with feedback relationships.	[233,234,240,241]
Fuzzy Monte Carlo simulation	• Is able to account for both random uncertainty and subjective uncertainty of the system; • Can account for both variability and uncertainty of information; • Has the ability to generate multiple scenarios while sampling of each probability distribution of the input variables exhibiting uncertainty.	• Requires intensive computation; • Requires known probability density functions for input parameters; • Ignores time dependency of systems behavior.	[242–245]

After the advantages and disadvantages of each method are reviewed, criteria for selecting an appropriate method must be considered. Table 19 summarizes the criteria for selecting fuzzy hybrid techniques and the characteristics of each based on the literature review and content analysis.

This study offers a wider view of all the fuzzy hybrid methods available in the literature, with their advantages, disadvantages, and applications in fuzzy machine learning, fuzzy decision-making, and fuzzy simulation. The goal of this study is to enable practitioners to make more informed and complete decisions about what method to use, and they must also consider appropriate selection criteria depending on the solar energy problem to be solved. This method can be applied to problems presented at any stage of the PV system lifecycle, from analysis to installation, operation, and disposal. The method selected will depend on the complexity of the problem and the selected category criteria.

After the fuzzy hybrid methods available in the solar energy literature were reviewed, it was observed that there are several areas in which the performance of solar PV panels could be improved so the main and local grids can provide a better quality of energy. Hybrid fuzzy systems can be implemented in the following areas:

- Fault Detection and Diagnosis: This is an area in which hybrid fuzzy systems can be deployed to detect and diagnose faults in solar PV systems. The information from sensors and hybrid fuzzy systems can detect potential fault conditions and recommend maintenance or repairs;
- System Controls: Hybrid fuzzy systems can also be implemented to enhance the performance of MPPT control techniques in solar PV systems through the analysis of data from sensors and other sources. Hybrid fuzzy systems can be employed to adjust the voltage and current of a PV system to increase efficiency;
- Energy Management: This is an important area in which hybrid fuzzy systems can be used to incrementally improve the efficiency of electric systems, reduce CO_2 emissions, and thus enhance the energy management of solar PV systems. Since hybrid fuzzy

systems can adjust the system's energy consumption to maximize its efficiency and reduce costs, they are an excellent alternative to be implemented in solar PV systems;

- Prediction and Forecasting Systems: In systems used to predict and forecast the performance of solar PV systems and weather conditions, hybrid fuzzy systems can be used to analyze data from weather patterns, solar irradiance, and other factors. They can generate an accurate prediction of the amount of energy produced by the solar PV system. Thus, fuzzy hybrid systems can help utilities better manage the main and local grids.

Table 19. Selection criteria for fuzzy hybrid techniques in solar energy systems research.

Selection Criteria Category	Specified Selection Criteria	Application Category			
		Evaluation/Assessment	Maintenance	Prediction/Forecasting	System Modeling
Accuracy	• Ability to achieve high optimization effectiveness and efficiency; • Ability to capture uncertainty and vagueness of model outputs; • Ability to obtain high validity; • Ability to produce low training and testing errors (classification accuracy); • Ability to produce the least root-mean-square error and/or mean absolute error between the target values and the values predicted by fuzzy hybrid model (prediction accuracy).	Fuzzy machine learning	Fuzzy machine learning	Fuzzy machine learning	Fuzzy simulation
Computational complexity	• Ability to avoid local minima trapping; • Ability to capture dynamic systems and relationships; • Ability to model a large number of parameters (high dimensionality); • Ability to perform need analysis; • Ability to perform trend analysis and pattern recognition in predictive models (e.g., time series); • Ability to perform scenario and sensitivity analyses.	Fuzzy simulation	Fuzzy simulation	Fuzzy simulation	Fuzzy simulation
Data availability	• Ability to accommodate a mix of quantitative and qualitative inputs; • Ability to capture subjectivity and vagueness; • Ability to model highly dimensional and complex data.	Fuzzy decision-making	Fuzzy decision-making	Fuzzy decision-making	Fuzzy machine learning
Implementation complexity	• Availability of commercial software packages, open-source coding, and self-coding.	Fuzzy simulation	Fuzzy simulation	Fuzzy simulation	Fuzzy simulation
Interpretability	• Ability to prioritize available alternatives for determining the optimal option; • Transparency.	Fuzzy decision-making	Fuzzy decision-making	Fuzzy decision-making	Fuzzy decision-making
Processing ability	• Fast convergence and computational speeds.	Fuzzy machine learning	Fuzzy machine learning	Fuzzy machine learning	Fuzzy machine learning

The results of this study highlight the potential benefits of adopting fuzzy hybrid systems in the PV solar energy sector. The implementation of such systems could lead to improvements in the analysis, installation, operation, and disposal stages of solar energy projects. In light of these findings, it is recommended that development policies be put in place to promote the adoption of fuzzy hybrid systems in the sector.

One proposed policy is the development of pilot projects to demonstrate the effectiveness and feasibility of fuzzy hybrid systems in the PV solar energy sector. These projects could be funded by the government or industries and involve collaborations between researchers, industry professionals, and end users. Another policy proposal is the establishment of standards and guidelines to guide the implementation of fuzzy hybrid systems in the sector. These guidelines could cover various areas, such as the evaluation, operation, installation, and disposal stages of solar energy projects. Additionally, standards could be established for performance metrics of fuzzy hybrid systems and best practices for selecting appropriate systems. Incentives such as tax credits or subsidies could be provided to encourage the adoption of fuzzy hybrid systems in the PV solar energy sector. This could include incentives for research and development, pilot projects, and the implementation of these systems in commercial projects. Furthermore, public-private partnerships could be fostered by the government to promote the adoption of fuzzy hybrid systems in the sector. Such partnerships could involve collaborations between academic researchers, industry professionals, and government agencies to develop and implement these systems in the field.

Training programs should be established to educate stakeholders in the PV solar energy sector about the benefits of fuzzy hybrid systems. These programs could target policymakers, industry professionals, and end users, covering areas such as fuzzy machine learning, fuzzy simulation, and fuzzy decision-making. In addition, it is recommended that the government and industry fund research and development to promote the use of fuzzy hybrid systems in the PV solar energy sector. This could include funding for academic research and industry-academic collaborations.

Finally, the results of studies on fuzzy hybrid systems in the PV solar energy sector should be disseminated to stakeholders such as installers, operators, and disposal teams to promote the adoption of these systems. Workshops and training programs could also be organized to educate stakeholders about the benefits of these systems. These proposed policies could accelerate the adoption of fuzzy hybrid systems in the PV solar energy sector and help improve solar energy projects' efficiency and effectiveness.

4. Conclusions

This paper presents a review of fuzzy hybrid systems implemented in several sectors as well as the possibility of using them in PV systems. Additionally, this paper describes the trends in using hybrid fuzzy logic in PV solar energy applications, including the low number of published research papers using hybrid fuzzy logic methods in PV solar energy compared to other sectors. Thus, it promotes the use of well-known hybrid fuzzy logic methodologies in solar energy. Since fuzzy hybrid systems have been designed and deployed successfully in several applications, an excellent opportunity exists for implementing those methodologies in the PV solar sector. Further, by presenting the main advantages and disadvantages of several fuzzy logic hybrid systems, the information provided in this paper can be used as a guide for selecting and implementing hybrid fuzzy logic systems in the solar energy sector to improve the analysis, installation, operation, and disposal stages of solar energy projects. This paper also demonstrates that hybrid fuzzy logic systems could be used in the solar energy sector to improve performance by applying specific fuzzy techniques in the evaluation, operation, installation, and disposal stages. Finally, the methodology presented in this study can be used to support research on other renewable energy sources, such as wind energy.

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