

Systematic Review

Smart Technologies Applied in Microgrids of Renewable Energy Sources: A Systematic Review

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Abstract: The production of electricity from renewable sources has become a global necessity due to concerns about reducing carbon dioxide (CO₂) emissions into Earth's atmosphere. The use of microgrids has emerged as a potential scenario in this production process, especially with the application of smart technologies integrated into decision making. This article used the PRISMA method to identify the intelligent techniques employed in the context of microgrids from 2015 to 2023, totaling 156 articles. The results indicate progress in the use of artificial neural networks and multi-agent systems in environments of, respectively, predictability and management, and open space for discussions involving the incorporation of new techniques aimed for future implementations.

Keywords: renewable energy; smart technologies; microgrids; artificial neural network; multi-agent system



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1. Introduction

Smart technology has become a widespread practice implemented in complex activities. Coding models utilized in software programming, with rules defined in a deterministic manner, have incorporated new strategies with concepts, or dimensions, represented by tasks that can be divided into predictive and descriptive [1,2].

The independence of these smart technologies, which rely on machine learning algorithms, enhanced by the evolution of equipment and the volume of data currently generated, has driven their use as a growing global trend in the search for solutions to the effects of climate change [3].

These technologies are part of discussions at national and international events, especially at the Conferences of the Parties (COP), which are the largest and most important annual conferences related to the planet's climate and aim to reduce negative phenomena characteristic of climate change that have become a global concern (UN, 2022) [4].

Despite the advancements made regarding the use of smart technologies in various application and functionality scenarios, the exclusion of people or groups from modern

energy services, defined as energy poverty [5], still reflects a reality, with 1.18 billion people in this situation worldwide [6]. This reality represents 2.6 billion people who still use improper and unhealthy energy sources for survival activities, such as cooking [5].

The notable transformations in global weather and their consequences manifest as warmer temperatures, more severe storms, increased drought, rising ocean temperatures, species loss, food resource scarcity, health risks, and the worsening of factors that place and keep people in poverty [7].

The various possibilities of renewable energy sources have emerged as one of the best options for generating clean electricity, with expansion capacity, especially through the integration of different regional characteristics existing around the world [8].

Considering these various possibilities and characteristics of electricity production, the use of microgrids presents a favorable scenario for utilizing renewable energy sources [9,10], with smart technologies acting as a key enabler of this production process, also aligning with the Sustainable Development Goals (SDGs) [11].

In this context, the identification of smart technologies with the potential to support microgrid projects serves as a relevant reference for understanding the integration of this topic within the current scientific framework. Additionally, mapping the applicability of these technologies in environments geared toward practical use enables the generation of strategic insights, particularly for the development of new microgrid plants based on renewable energy sources.

The analysis of successful case studies, as well as the identification of contexts in which such technologies have been implemented across different domains, can contribute to expanding knowledge and enhancing the capacity of new users. Moreover, identifying and quantifying the risks associated with the adoption of smart technologies in microgrid projects, along with recognizing potential limitations—whether technological, infrastructural, or financial—could provide valuable elements to support more informed decision-making processes.

In light of the above, this study aims to fill gaps in the literature by investigating the application of smart technologies in the production of renewable energy for microgrids (REM), focusing primarily on the following questions below:

- (Q01) What smart technologies are used in the renewable energy sector for microgrid applications?
- (Q02) How have smart technologies been used in microgeneration?
- (Q03) Where have smart technologies been applied in the microgeneration process?
- (Q04) What are the potential risks associated with the use of smart technologies in microgeneration?
- (Q05) What limitations in the application of smart technologies in microgrids have been addressed?

2. Materials and Methods

The methodological approach of the systematic literature review (SLR) was developed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method [12] with all items being available in the Supplementary Material. A mapping of the advances in academic productions focused on themes involving the use of smart technologies within the scope of the research was carried out, with a focus on trends and collaborations regarding the eligibility of the analyzed studies, aiming to contribute by identifying gaps in the literature that lead to future work aligned with sustainability challenges.

The composition of descriptors through the search string based on articles at their final publication stage resulted in a set of articles that were explored in the study (Table 1).

Table 1. Search strategy for descriptors utilized on Scopus and Web of Science Online databases.

Search String	Base
("Renewable Energy Sources" OR "Sustainable Development" OR "Net zero") AND ("Intelligent systems" OR "Machine learning" OR "Artificial neural networks" OR "Multi-agent systems" OR "Computational modeling") AND (microgrids OR "Smart grids")	Scopus
	Web of Science

Source: Elaborated by authors.

2.1. Eligibility Criteria and Data Collection

The starting point for this milestone was considered to be the year 2015, represented by the COP21, which brought the Paris Agreement [13]. This agreement is a universal representation for the development of policies that limit global warming to below 2 °C or 1.5 °C above pre-industrial levels, requiring coordination among countries in their priorities and ambitions regarding climate actions [14], with the temporal scope ending in the year 2023.

The online databases Scopus and Web of Science were limited to the publication of original articles, excluding duplicates from the compilation of both databases, within the defined temporal scope.

The descriptors from the Institute of Electrical and Electronics Engineers (IEEE) Taxonomy [15] were adopted, which align with the areas of knowledge of the study (Table 2), with the search conducted on 23 January 2024.

Table 2. Demonstration of the descriptors used by area based on the IEEE Taxonomy. The main area corresponds to the first level in the hierarchy of the IEEE Taxonomy, and the sub-area represents levels below that branch out from the major areas identified by the first level of the hierarchy.

Principal Area	Sub-Area
Industrial electronics	Renewable energy sources Sustainable development Net zero
Computational and artificial intelligence	Intelligent systems Machine learning Artificial neural networks
Systems engineering and theory	Multi-agent systems Computational modeling
Power engineering and energy	Microgrids Smart grids

Source: Elaborated by Authors.

2.2. Automation Tools Used in the Bibliometric Data Collection and Analysis Process

The automated construction of the results was composed by a set of functions that enabled statistical and computational treatment for bibliometric and scientometric research [16]. The choice of software was supported by a comparative study conducted by Moreira et al. [17], which features Bibliometrix in all items researched, with the criteria described in the cited article.

The identification of duplicates and unification of the databases were carried out using the mergeDbSources function from the Bibliometrix library and the export of results was done using the saveRDS function from the base library of the R programming language. The entire set of elements used in the above process can be consulted in the R documentation.

The complementary analysis of the result of the initial automation in the files exported from the online databases Scopus and Web of Science was conducted using Zotero software, with the primary purpose being the organization of the collections and insertion of metadata into the records of the articles researched [18]. All the software used in this study is open-source [19], with the versions listed below:

- Bibliometrix: 4.1.1;
- R: 4.0.4;
- RStudio: 2023.12.0 Build 369;
- Zotero: 6.0.30.

2.3. Selection Process

The eligibility of the articles was carried out using the content available in their respective abstracts. Inclusion in the final database was made considering only the articles that provided information directing towards the use of smart technologies and focusing exclusively on the generation of REM. All articles with the absence of smart technologies implemented in the study were excluded.

The process of identifying smart technologies for the final database was carried out by reading the abstract and inserting the metadata “technique_used,” aiming to investigate the smart technology used in the study, “desc_technique,” for a brief description of the technology used, and “eligible” for the observations identified as “Included as Eligible” (I) or “Not Included as Eligible” (E), concatenated with the number identifying the criterion (Table 3), according to the flow of the analysis process (Figure 1).

Table 3. Inclusion and exclusion criteria defined in the SLR.

Code	Description
I1	Smart Technology identified for renewable energy microgrids in the article abstract.
I2	Smart Technology not identified in code I1, but identified in the methodology of the article.
E1	Smart Technology not identified in the article.

Source: Elaborated by authors.

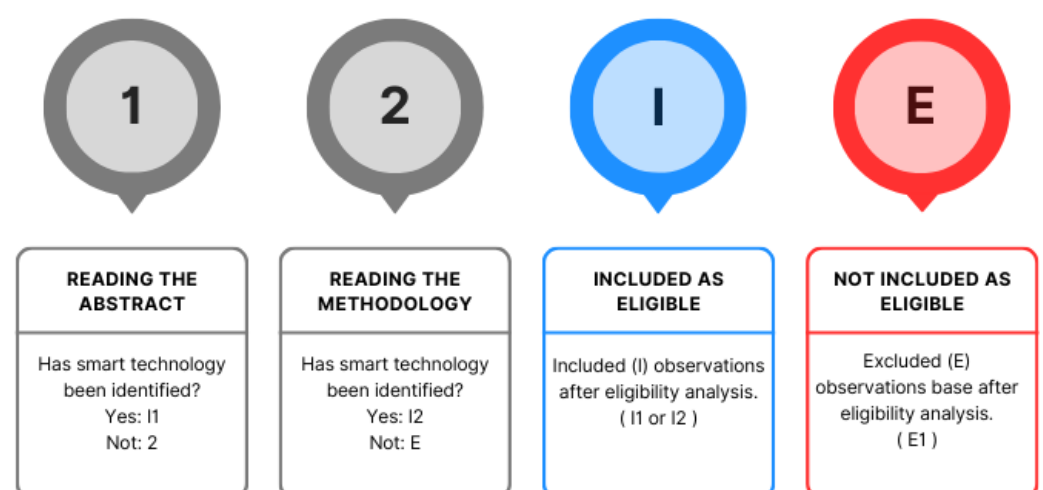


Figure 1. Inclusion and exclusion criteria flow for observations in the final database of the SLR.

2.4. Assessment of Study Bias Risk

The study was developed in two phases. The first phase was conditioned to an automated process, utilizing the computational environment for the analysis of the results.

In the second phase, the analysis is observational, aiming to identify the smart technologies and their applicability in the microgrid scenario, with a focus on renewable energy generation (Figure 2), which may bring elements of influence into the study.

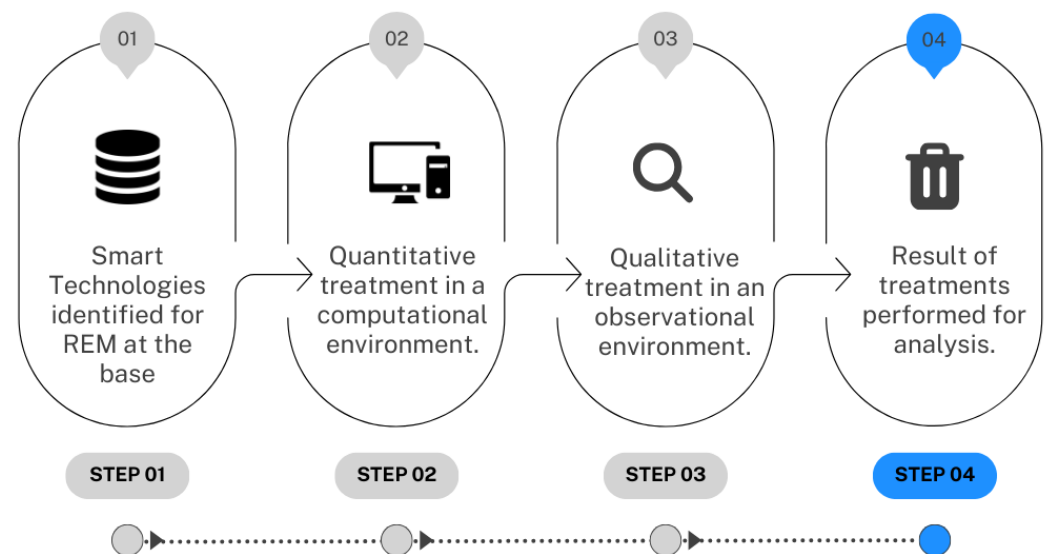


Figure 2. Flowchart of the process for handling the articles found in the database.

3. Results

A set of technologies was applied with characteristics that enhance electricity production. The combination of these technologies is presented as a potential model integration into the current scenario (Table 4).

Table 4. Demonstration of smart techniques used in the microgrid scenario.

Techniques	2015	2016	2017	2018	2019	2020	2021	2022	2023
Artificial Neural Network	[20]	[21,22]	[23–25]	[26–30]	[31–37]	[38–41]	[42–60]	[61–73]	[74–98]
Multi-Agent System	[99–101]	[102]	[103–105]	[106–109]	[110–115]	[116–123]	[124–128]	[129–137]	[138–151]
Clustering	-	-	[152]	-	-	-	[153–156]	[157–160]	-
Multiple Model	[161,162]	-	[163]	-	[164]	-	-	[165–168]	[169,170]
Regression Models	-	-	-	-	-	[171]	-	[172–175]	-

Source: Elaborated by authors.

3.1. Selection of Studies and Flow of the Methodological Process

The compilation of the data collected from Scopus and Web of Science online databases resulted, through the automation process, in a total of 56 duplicate observations, which were unified, totaling 271 observations with 30 variables in the database after the merge.

The applied methodology resulted in a total of 156 publications that used smart technologies focused on the descriptors and excluded 115 publications that were outside the scope of implementation or applied techniques not considered as smart systems within the scope of the research (Figure 3).

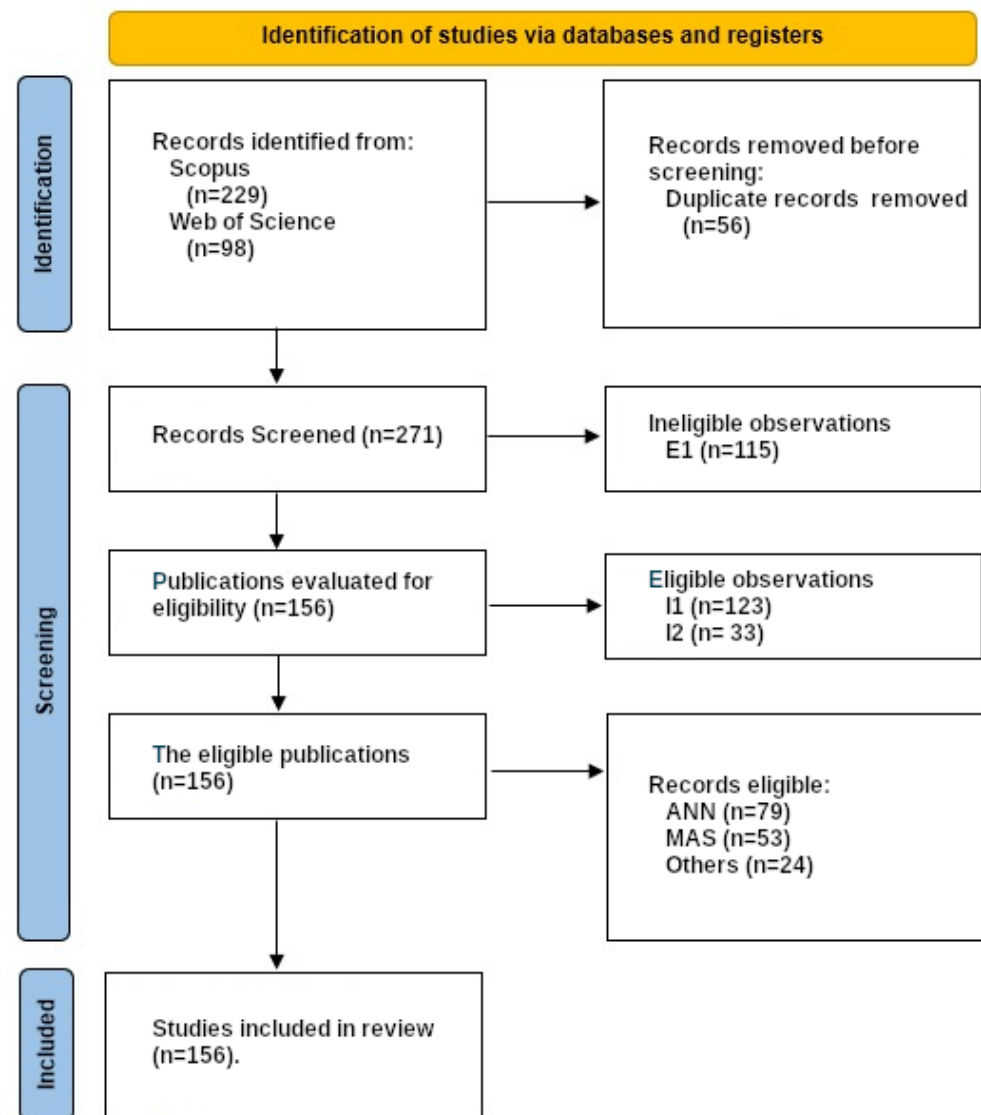


Figure 3. Process flow for handling the articles found in the database.

3.2. Bibliometric Analysis of the Eligible Studies

Bibliometric analysis is considered as the data generated from Scopus and Web of Science databases, discarding duplicates and non-eligible observations. This database contains a set of 30 variables, with their identification available in the developer's documentation [176], and all bibliometric analysis graphs were generated through the Bibliometrix software, based on the set of information formed by the importation process.

4. Discussion

The study shows that the increased perception of electricity production from renewable sources has sparked academic interest from a multidisciplinary perspective. Based on the results obtained from the elements explored in the methodological process, it forms the foundation to answer the questions proposed in the introduction.

4.1. Question 1 (Q1)

Regarding the smart technologies used in the production of renewable energy for applications in microgrids, two main approaches predominated—artificial neural networks (ANN) and multi-agent systems (MAS)—standing out as the most recurrent among the

eligible studies. In addition to these, other techniques were identified, such as clustering algorithms, multiple model, and regression models (Table 4), although their application occurs more sporadically, which justifies their joint categorization as “Other” for analysis purposes.

To illustrate the evolution of the number of studies that deal with the use of smart technologies in the production of renewable energy for microgrids and to perform analyses, Figure 4 was constructed. Regarding the behavior of eligible productions, it was identified that there was an increase in the number of publications in almost every year, with a decline in the total number of publications in the years 2016 and 2021 for MAS and 2012 and 2022 for ANN. When analyzing the other technologies, it was noticed that their behavior occurred in an inconsistent way.

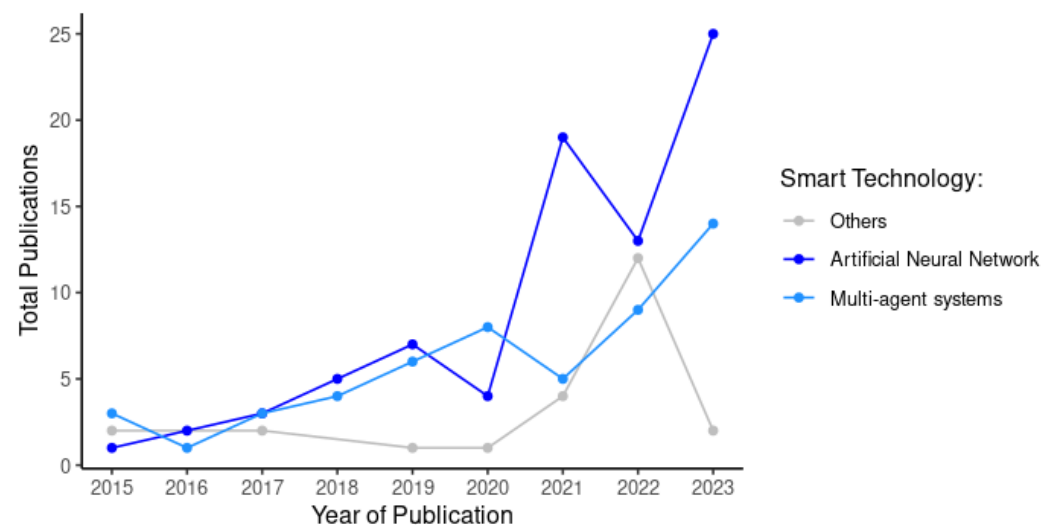


Figure 4. Evolution of eligible techniques by year.

When analyzing the behavior of technologies classified as “Others”, it was identified that one of the reasons related to the irregularity of publications is the use of tools that complement the aforementioned approaches [161,162,164,167,169]. Due to the complexity of the issues involving large volumes of data to be analyzed, these techniques could assume a more expressive role as optimizing agents in the future in renewable energy generation.

The evolution of smart technologies in microgrids points to a trend towards collaborative, hybrid, and more resilient systems [39,122]. The integration of these approaches, when empirically validated and aligned with the real context, represents a promising path for strengthening microgrids with renewable sources [177].

4.2. Question 2 (Q2)

Technologies have been mainly used as agents to make renewable energy production projects viable in the context of microgrids. At this point, the focus is on the hybrid power generation, because of the specific characteristics such as the intermittency of the energy flow from renewable sources [36,63,100,141,154,177–182]. Although the use of these technologies is predominantly associated with power generation, several studies also point to their application in the construction of scenarios involving energy storage and consumption [40,48,117,126]. The literature highlights that these technologies allow the adjustment of strategies to better meet local needs, which can result in reduced operational costs and increased energy availability [40,43,48,117,126,153].

Regarding artificial neural networks (ANN), their main use has been for the development of work and analyses with the aim of predicting and understanding load variations with high precision in renewable energy generation [53–60]. The predictability provided by

these technologies makes it possible to minimize fluctuations in energy production and contributes to greater stability in microgrid operations [177], in addition to improving resource allocation [31]. A publication that highlights the use of ANN to predict predictability due to the changing nature of renewable energy (intermittency), this strategy has the definition of weights for the network and consequently identify different climatic and fault conditions in the system, increasing its quality and adapting it when necessary [85].

However, the literature also highlights that the quality of forecasts may be inaccurate or limited, mainly due to the conditions and data provided [39,41–43,50,51]. One work that emphasizes the quality of forecasts was that of Madler et al. (2023) [138], which presented a comparison of the performance of microgrids in 2022, during the energy crisis in Europe. In this study, data from 2019 were used to make the comparison in order to present the efficiency of the results in reducing electricity costs and CO₂ emissions through a peer to peer review.

Other parameters that affect the quality of forecasts correspond to resource intermittency and failure events [127,138,156,171]. Due to the complexity of generating the forecast, some authors limit themselves to studying one type of energy [38]. Furthermore, the model's forecast when using historical data may have a limitation or not represent the behavior of the system, which may lead to a generalization, and its accuracy may be compromised in another context, in addition to making the model non-dynamic [45–48]. Regarding ANN, some studies indicate that it stands out in relation to other machine learning algorithms due to its generalization capacity and adaptability to different contexts [56,117,118,125,154].

The use of multi-agent systems (MAS) has focused on simulating interactions between autonomous agents and decisions within the context of microgrids, allowing coordination and management analyses in decentralized systems [114,116–128]. However, the literature suggests that the use of MAS may be insufficient to accurately model and evaluate contexts that involve both social and technological aspects, and may lead to a simplification of reality, especially regarding interactions between agents [60,116,117,125,126]. On the other hand, due to its flexibility, MAS can be integrated with other complementary technologies, such as ANN [167], clustering [161] and fuzzy logic [164]. Furthermore, studies indicate that SMA can contribute to optimizing the balance between supply and demand in the allocation of resources, favoring the success of decentralized management [110].

Regarding the other techniques, they have been used to identify patterns, allowing the development of strategies to reduce costs and increase efficiency in energy use [153–156,171]. Among these techniques, clustering stands out, which, in addition to identifying patterns of energy consumption and generation, allows the construction of strategies to reduce costs and optimize energy use [67]. The literature highlights questions about its ability to generalize to different regions, especially in places with different climatic conditions and energy patterns [58,117,118,125]. The exclusive use of historical data can also compromise the effectiveness of the model, especially if there are sudden changes in the consumption pattern [50,153,154].

Finally, the literature highlights ANN as a tool to perform analyses of the predictability of renewable energy microgrids, the use of clustering techniques and other regression techniques to identify patterns, and the adoption of MAS to manage and coordinate agent interactions [39,60,123,153–155]. However, after identifying the main applications of these technologies in the renewable energy production process, technical barriers related to the specific characteristics of the technologies were identified, in addition to the challenges imposed by the intermittency of energy sources, such as the intermittency of sources [54–56,118,120,125–127].

Among the main barriers identified, the fact that the techniques are not suitable for real-time analysis stands out, in addition to not being effective in dealing with extreme situations or events, such as system failures [43,45–48,53,54]. Another barrier when creating the model was the simplification of reality, due to the social and technological context, as they may not capture the complexities and unpredictable variables of the real world and may have difficulty dealing with the dynamicity of the environment or dependence on software [57,116,124,153,154]. Another point identified was that the models may not be robust enough for another generation scale [51,58,118–122,156]. Another factor that may contribute to this was the lack of adequate processing power to handle the necessary analysis [60,114,125–128,153]. Finally, in relation to simulation, it was identified that computational complexity tends to increase as the number of devices in the microgrid grows, making the process more costly and time consuming [38,50,116,124].

4.3. Question 3 (Q3)

The cutout defined on the RSL eligibility criteria in relation to global scientific production focuses on the countries: Italy with 25 publications, China with 20 publications, and India with 17 publications. The remaining countries do not exceed a total of 15 publications. This scenario is also reflected in the most cited countries, with China presenting a total of 959 citations, followed by Italy with 651 citations, and the Netherlands with 335 citations. When looking at the collaboration network between countries, the largest collaboration occurs between Saudi Arabia and the United Kingdom, with a total of 3 collaborations.

These countries—Italy, China, and India—are leading the implementation of these technologies, standing out in solutions for energy efficiency and integration of renewable sources [129]. Other studies focused on the energy management model for grid-interconnected microgrid systems have also been conducted in Hainan Province, China [82]. In this study, the authors explore the interactivity of electric vehicles with the grid during their charging periods, as well as the different periods in which these charges occur considering different user profiles.

The electric vehicle charging scenario has several layers in relation to interactivity, not only due to the different charging methods and characteristics of the specifications of each electric vehicle, but also considering the possibilities that charging brings in terms of interaction with the grid. Generally, in the most conventional process, electric vehicles are charged by receiving energy sources from the grid. However, because of the different architectures that these vehicles can have, interaction with the grid can be done in different ways, even with the vehicle supplying energy to the grid, doing the reverse process, known as vehicle-to-grid (V2G) [82,104].

Based on this context, the study carried out by the authors, mentioned above, sought to understand how smart technologies could perform better control, aiming at sustainability and efficiency throughout this interactive process, in addition to predicting behaviors according to users and loading events.

More recent studies, in 2023, used experimental data from Austria, Belgium, and Slovenia with a one-hour sampling interval for total electricity consumption [96], focusing on the efficiency, cost, and robustness of the proposed model. Historical data from 2019 were used to compare the performance of microgrids in 2022 during the energy crisis in Europe, with the aim of presenting the efficiency of the results in reducing electricity costs and CO₂ emissions through peer to peer (P2P) networks [138].

Also in 2023, another case study in the Zafarana region of the Gulf of Suez in Egypt was proposed, considering the changing nature of renewable energy in relation to climate. This study suggests an intelligent system based on artificial neural networks (ANN) to adjust the grid weights to identify different weather and fault conditions [85].

Another study conducted by [149] in 2023 proposes the use of intelligent systems based on reinforcement learning to maximize the energy management system for renewable sources in pelagic island grid microgrids.

The combination of energy sources enables diverse applications in the most diverse locations, such as the North and Northeast regions of Brazil, which are regions with high poverty rates and which face economic and infrastructure challenges, but which constitute alternatives to the country's energy matrix due to their renewable energy potential [8].

4.4. Question 4 (Q4)

The potential risks associated with the use of smart technologies in microgeneration point to two important scenarios. First, data quality is a challenge, and this difficulty presents itself in several ways, among which we can highlight the variation in environmental parameters, resulting from the intermittent process of renewable energy sources. This unpredictability constitutes an important element in discussions that direct this topic.

This variability found in renewable energy generation models, resulting from this inability to produce continuous energy, such as solar and wind power, can negatively affect the accuracy of the models used in the predictability process, especially when combined with historical data [60,123].

In this scenario, several techniques have been used to minimize the risks of unpredictability using clusters [153,154] or using hierarchical distributed agent systems [118,125–127] to coordinate and control energy generation and consumption units or even through neural network techniques [39,54] based on hybrid models aiming at network balance.

In addition to the inaccuracies generated by the inability to produce energy continuously, unexpected changes in energy consumption patterns also pose a significant challenge for forecasting models. The excessive increase in energy use due to constant and notable climate changes, whether due to extreme weather conditions that are becoming increasingly frequent and intense, or due to the sudden adoption of equipment that minimizes the effects caused by these changes, has consequences for the data analyzed.

These environmental and social consequences directly affect the ability of models to anticipate these energy needs based on discrepancies in historical data, compromising the effectiveness of the models [50,153,154], since the relationship between the accuracy and quality of the data used for training represents a strong dependence for the models used in the analysis of this information [38,41,42,46,55,156,171].

A second important aspect of the use of smart technologies in micro-energy generation is the volume of data generated. This characteristic is necessary to ensure the effectiveness of the model; in addition, the production of a large volume of historical data is necessary for a validation process [47,53,57,58,117].

However, this characteristic is directly related to the capacity to process this information. Computational complexity in the relationship between large volumes of data and computing power requires an infrastructure with the production capacity and processing level necessary to transform this dataset into information that guarantees effective results, but without overloading systems, thus ensuring a safe experience in the intelligent use of computing resources [43,45,50,51,120].

With the increasing complexity of distribution networks and the implementation of technologies such as microgeneration and energy storage, the ability to predict and manage energy demand becomes increasingly crucial. However, this prediction can also be compromised if the available data are of insufficient quality [38,54–56].

Although it is possible to perform variation with a more limited set of data, faster model construction and the combination of data and techniques can result in overfitting, compromising the robustness of the models [50,56–58,154–156]; therefore, the balance

between a dataset and the limitation of the scope of the analysis is a crucial factor in creating forecasting solutions that are as efficient as they are assertive.

Although the use of data involves predictability and management in relation to the use of smart technologies in microgeneration, the security of sensitive data also represents a significant concern [43,153]. This concern is heightened if we consider that digitalization and connectivity are increasingly present in energy systems. The increase in data collection, whether residential or industrial, creates greater concern about the networks that enable this communication.

Whether these data come from a renewable source or not, a set of measures is required to guarantee the security of this information so that cyber criminals do not use it for improper manipulation. Given this scenario, the implementation of security measures is necessary to guarantee the integrity and privacy of sensitive data, preventing these risks from affecting both consumers and energy suppliers. Therefore, the protection of information related to energy consumption and generation is also a concern.

4.5. Question 5 (Q5)

The need for high computational power for large volumes of data represents high energy consumption. The energy demand for processing this information makes it impossible for small businesses and researchers who work, specifically, in regions where financial, technological, and social resources for building these environments are limited [45,51,120,153–156].

In this scenario, some models are reducing the demand for processing this information for mobile devices, acting at the edge of the network to ensure low latency [43]. Other predictability scenarios seek to meet different time horizons, with different forecasting methodologies [41,50].

In addition to the computational power highlighted above, the production of large volumes of data also demands resources. The unavailability of data, especially in regions with low investment resources, similarly impacts the computational complexity in building environments that enable the local capture of this information, aiming at the validation of models. This impossibility of acquiring data represents a limitation, since such data are not always available [47,53,56–58,117,125].

Even considering that computational complexity and the dataset are available, when targeting the variability of renewable energy production models, the absence of an energy storage process that guarantees the continuity of the processing of training algorithms that support decision making on the data obtained constitutes a limiting factor for its usability, especially when we observe the growth shown in the use of ANN and the focus on energy microgrids.

Given this dichotomy between the need for high energy capacity to meet the demands of data centers and cooling systems that guarantee an infrastructure that enables the continuous operation of computational power and the pressure on renewable energy generation and distribution systems, it is clear that the need to optimize algorithms and the demand for processors with low energy consumption constitute a limiting factor for the implementation of robust processing techniques. Given this scenario, other studies have focused on model optimization, especially considering the intermittency of renewable energy sources [183–186].

When considering the transfer of this environmental information to an infrastructure that allows processing without compromising energy as a possibility, it is necessary to design the privacy of these data onto these communication channels [43,153].

Models based on a learning approach have been explored to obtain data from different parts of the world [42]. Other studies have focused on network isolation, also using learning-based intrusion detection techniques to ensure data security [60].

However, when the process occurs without adequate management of the sensitive data, with the absence of an adequate communication protocol between systems and agents, the security is compromised for the transfer of these data [121]; therefore, the security infrastructure that allows communication is an important requirement, having in its absence a limiting agent on this possibility.

It is also worth noting that this entire technological framework is dependent on specific techniques. This dependence on the flexibility and adaptability of computational resources has repercussions on the use of smart technologies, especially in a context of rapid evolution of tools and methodologies [54,123,126,127].

5. Conclusions

This study aims to contribute to the improvement of solutions that represent the state of the art in research focusing on microgrids powered by sustainable sources of electrical energy. A total of 156 articles on technologies related to intelligent systems were analyzed.

By considering various possibilities of renewable energy sources tied to territorial dimensions and local characteristics that define different countries, it is evident that the techniques are directed without clear indication of the most relevant points in this network-building process, which is linked to the production of renewable energy from microgrids (EFRM).

The direction of the research explored here serves as a starting point for deepening topics involving environmentally correct actions, but with a gap in the need to advance in the intersection with social justice. It thus highlights the need for a networked production process capable of measuring the relevance of locations and relationships that represent this network, considering local specificities in relation to the whole, in order to achieve a better understanding of how these technologies are operationalized.

The study suggests the need to explore regional characteristics for the use of renewable energy in microgrids. Such characteristics would support the expansion of the scope of the models presented, thus allowing new research to focus on this scope. These proposals have a direct impact on the use of these resources in the microgrid scenario and can be addressed in future work.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Network
CO ₂	Carbon Dioxide
COP	Conferences of the Parties
IEEE	Institute of Electrical and Electronics Engineers
MAS	Multi-Agent System
P2P	Peer to Peer
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RDS	R Data Serialization
REM	Renewable Energy for Microgrids
SDG	Sustainable Development Goal
SLR	Systematic Literature Review

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