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*Review*

# Multi-agent system implementation in demand response: A literature review and bibliometric evaluation

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**Abstract:** This research provides a comprehensive literature overview and bibliometric evaluation of multi-agent system (MAS) implementation in energy demand response (DR) to identify gaps. The review encompasses 39 relevant papers from searches in three academic databases, focusing on studies published from 2012 to the middle of 2023. The review includes MAS frameworks, optimization algorithms, communication protocols, market structures and evaluation methodologies. Bibliometric analysis of 587 documents from the search on the Scopus database identified prolific authors, influential articles and collaborative networks within the field. The findings reveal growing research interest in implementing an MAS for DR, focusing on integrating intelligent agents into electricity grids to enable effective load management and enhance grid stability. Additionally, the review outlines potential research directions, including exploring advanced MAS techniques, interoperability challenges, policy implications and the integration of renewable energy sources.

**Keywords:** distributed electricity generation; renewable energy sources; demand response; multi-agent systems; energy management; grid reliability

## 1. Introduction

The growing concerns surrounding climate change and the depletion of fossil fuel reserves have catalyzed a global transition toward sustainable and renewable energy sources [1]. Solar and wind power, two major sources of renewable electricity for distributed energy resource sources, have garnered a considerable amount of interest in recent years [2]. These distributed energy resources provide many benefits, including reduced greenhouse gas emissions, increased energy security and heightened resilience against power outages [3]. It contributes to a greener and more sustainable energy landscape, aligning with the objectives of mitigating climate change and achieving a cleaner energy future [4].

However, integrating renewable energy sources into conventional power grids introduces many technical and operational complexities [5]. Unlike traditional power plants, electricity generation from renewable sources is characterized by inherent variability and intermittency [6]. The intermittent nature of renewable energy mandates innovative strategies and mechanisms to manage and balance electricity supply and demand efficiently, ensuring the optimal utilization of available resources while mitigating the possible impacts of power fluctuations on the power grid [7]. Demand response (DR) mechanisms have emerged as indispensable tools in modern power systems to effectively address the variability and intermittency of renewable energy generation in the power grid [8]. It refers to consumers' voluntary modification of electricity consumption in response to signals or incentives to manage grid reliability, reduce peak demand and optimize energy usage, typically during periods of high demand or system stress [9].

Furthermore, DR systems involve adjusting electricity usage patterns, shifting loads or curtailing non-essential consumption to achieve more efficient and sustainable energy management [10]. However, managing all of the necessary functions and complying with all of the regulatory and technical standards takes time. An intensive engineering effort will be required to achieve the desired level of automation. Consequently, the imperative arose to deploy DR system mechanisms characterized by their intelligent and efficient nature, thus optimizing grid operations, facilitating the seamless integration of renewable energy sources, curtailing costs, fostering environmental sustainability, increasing grid flexibility and empowering consumers to contribute to decision-making in the ongoing energy transition toward an enlightened, resilient and sustainable future [11,12]. Automating, standardizing and simplifying data collection and analysis, response coordination and protocols, interfaces and information exchange, as well as restructuring complex processes and improved user-friendliness specifications, can improve existing DR solutions. These can be achieved by integrating the system with a multi-agent system (MAS) [8,13].

A MAS involves multiple agents who collaborate and perform assigned tasks [14]. The MAS properties of autonomy, sociality, reactivity and proactive behavior are powerful tools for developing complex systems [15–17]. Consumers, utility providers, market participants and devices can interact and communicate as agents in an MAS to optimize electricity consumption, coordinate load balancing and facilitate energy trading and negotiation. Agents in an MAS are intelligent entities; they can make decisions autonomously, communicate and interact with other stakeholders [18]. Designing an MAS for response to electricity demand requires the consideration of multiple conditions, such as system architecture, agent heterogeneity, communication and coordination, information exchange, decision-making algorithms, scalability, robustness and regulatory and market considerations [19]. A robust and correct communication infrastructure is imperative to facilitate seamless information exchange among participating agents. The MAS infrastructure should provide robust support for real-time data transmission, ensuring a reliable and secure connection between the agents and the central control system [20].

Moreover, the MAS requires an efficient and precise measurement and monitoring mechanism to acquire comprehensive data about the current electrical consumption across diverse sources [21,22]. This requires using smart meters and sensor devices, which give information on complex energy use patterns. Additionally, the architecture of the MAS must integrate state-of-the-art forecasting and predictive analytics methodologies to anticipate variations in electricity demand and optimize responsive strategies proactively. This process involves analyzing historical data, incorporating external factors such as weather conditions and events and using machine learning algorithms to facilitate precise predictive modeling [23,24]. Finally, the system requires a resilient decision-making framework, facilitating coordination and collaboration among participating agents. The framework should enable the seamless transmission of control signals, such as price signals or demand signals, while providing robust support for intelligent decision-making processes that align with the overarching objectives of the electricity DR program. The research gap exists in the implementation and validation of MASs for DR, and this involves encompassing varied energy ecosystems and investigating scalability and performance aspects in real-world scenarios.

This study was designed to provide a concise overview of the existing MAS frameworks used in DR systems and the prevailing challenges encountered in implementing the systems, as well as to examine a viable solution to mitigate those challenges. Additionally, we evaluate the metrics and methods used to assess the effectiveness of these solutions, which reflect the technical proficiency of the approach. Finally, we provide suggestions on design decisions that can help address common issues encountered when integrating DR with an MAS. We summarize our intentions by proposing the following research question: To what extent have MASs improved DR technology in practical implementation? These insights are essential for the development of a more sustainable and resilient electricity network.

The article follows a structured format, beginning with an introductory section that outlines the study's purpose, objectives and research question. The methodology is provided in the second section, explaining the detailed search protocols employed to identify relevant literature on MAS implementation in DR systems. Subsequently, the findings derived from the research, analysis and interpretation of these results are explained in the third section. The discussions are provided in the fourth section; lastly, the fifth section summarizes the article with conclusive remarks drawn from the findings and recommendations for future research.

## 2. Methods

This section presents a comprehensive overview of the procedural framework for systematic literature review and bibliometric analysis.

### *2.1. Systematic review analysis*

The systematic review of the literature used in this work was carried out by formulating the research question, creating a review methodology, conducting a search while choosing relevant documents using assessment criteria and extracting and analyzing data. A systematic literature review was designed to identify the critical contributions to the subject and potential research needs [25]. The objective of the systematic review was to respond to the research question of to what extent have MASs improved DR technology in practical implementation. Reputable databases are essential for a thorough and detailed systematic evaluation of the literature [26]. Due to their extensive coverage and reputable standing, we used three important databases in this study: Scopus, ScienceDirect and IEEE Xplore. The search terms utilized to answer our research question were "multi-agent systems", "demand response" and "implementation". The search was limited to articles published and authored in English over the previous 10 years (2012 to mid-2023) to guarantee the appropriateness and adequacy of the research. The search results were loaded into Mendeley reference management software to combine the results from several databases and eliminate duplicates. The papers that emerged underwent screening. The titles and abstracts were scrutinized for relevance to the study's topic. Then, using predetermined assessment criteria, full-text publications were evaluated.

The quality assessment encompasses an evaluation of article citations and journal impact to gauge the scholarly significance and relevance of the selected articles. This assessment, conducted on the selected articles, considered the number of citations received by each article in peer-reviewed literature, and it was examined as an indicator of its impact and importance within the research community. The quality assessment focuses on the most frequently cited articles from specific periods included in our content analysis. It is important to note that how often an article is cited depends on its publication and subject matter. Documents published a while ago have more chances to get cited than newer ones. So, we categorized the documents into three groups based on their publication dates, and each group was evaluated by using different criteria in our quality assessment. The resulting quality assessment is presented in Table 1, indicating the article citations and journal impact.

**Table 1.** Citation count and year of selected studies.

| S/n. | Title | Year | Citation | Ref. |
|---|---|---|---|---|
| 1. | "Reinforcement learning in local energy markets" | 2021 | 15 | [27] |
| 2. | "Energy efficient behavior modeling for demand side recommender system in solar microgrid applications using multi-agent reinforcement learning model" | 2023 | 3 | [28] |
| 3. | "Reinforcement learning-driven local transactive energy market for distributed energy resources" | 2022 | 11 | [29] |
| 4. | "Multi-agent system-based microgrid operation strategy for demand response" | 2015 | 38 | [18] |
| 5. | "Conceptual study for open energy systems: Distributed energy network using interconnected DC nanogrids" | 2015 | 190 | [30] |
| 6. | "Multi-agent deep reinforcement learning based demand response for discrete manufacturing systems energy management" | 2020 | 84 | [31] |
| 7. | "Secure automated home energy management in multi-agent smart grid architecture" | 2018 | 13 | [32] |
| 8. | "A multi-agent-based optimal control method for combined cooling and power systems with thermal energy storage" | 2021 | 14 | [33] |
| 9. | "Hardware-in-the-loop simulation of distributed intelligent energy management system for microgrids" | 2013 | 36 | [34] |
| 10. | "Optimal, dynamic and reliable demand-response via OpenADR-compliant multi-agent virtual nodes: Design, implementation & evaluation" | 2021 | 4 | [21] |
| 11. | "Optimal trading strategies for multi-energy microgrid cluster considering demand response under different trading modes: A comparison study" | 2022 | 17 | [35] |

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| S/n. | Title | Year | Citation | Ref. |
|---|---|---|---|---|
| 12. | "IoT-based stochastic EMS using multi-agent system for coordination of grid-connected multi-microgrids" | 2023 | 1 | [36] |
| 13. | "Implementation of a novel multi-agent system for demand response management in low-voltage distribution networks" | 2019 | 36 | [37] |
| 14. | "Combined DR pricing and voltage control using reinforcement learning based multi-agents and load forecasting" | 2022 | 0 | [38] |
| 15. | "Energy trading and control of islanded DC microgrid using multi-agent systems" | 2021 | 0 | [39] |
| 16. | "Synthesis of an intelligent rural village microgrid control strategy based on smart-grid multi-agent modeling and transactive energy management principles" | 2018 | 57 | [40] |
| 17. | "Micro-grid grid outage management using multi-agent systems" | 2017 | 32 | [41] |
| 18. | "MARLA-SG: Multi-agent reinforcement learning algorithm for efficient demand response in smart grid" | 2020 | 33 | [22] |
| 19. | "Intelligent implementation of residential demand response using multi-agent system and deep neural networks" | 2021 | 6 | [12] |
| 20. | "Optimising residential electric vehicle charging under renewable energy: Multi-agent learning in software simulation and hardware-in-the-loop evaluation" | 2019 | 7 | [42] |
| 21. | "Reinforcement learning for demand response: A review of algorithms and modeling techniques" | 2019 | 544 | [43] |
| 22. | "Multi-agent reinforcement learning for energy management in residential buildings" | 2020 | 76 | [44] |
| 23. | "A multi-agent-based optimization of residential and industrial demand response aggregators" | 2019 | 96 | [14] |
| 24. | "A multi-agent model of urban microgrids: Assessing the effects of energy-market shocks using real-world data" | 2023 | 4 | [45] |
| 25. | "Simulation of smart factory processes applying multi-agent-systems—a knowledge management perspective" | 2020 | 11 | [46] |
| 26. | "A conceptual microgrid management framework based on adaptive and autonomous multi-agent systems" | 2022 | 2 | [47] |
| 27. | "Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review" | 2020 | 323 | [48] |
| 28. | "A reinforcement learning approach to home energy management for modulating heat pumps and photovoltaic systems" | 2022 | 5 | [49] |
| 29. | "Multi-agent reinforcement mechanism design for dynamic pricing-based demand response in charging network" | 2023 | 2 | [50] |

*Continued on next page*

| S/n. | Title | Year | Citation | Ref. |
|---|---|---|---|---|
| 30. | "Reinforcement learning-based composite differential evolution for integrated demand response scheme in industrial microgrids" | 2023 | 1 | [6] |
| 31. | "A multi-agent and internet of things framework of a digital twin for optimized manufacturing control" | 2022 | 6 | [51] |
| 32. | "Optimal planning of hybrid energy conversion systems for annual energy cost minimization in Indian residential buildings" | 2019 | 12 | [52] |
| 33. | "Development and implementation of multi-agent systems for demand response aggregators in an industrial context" | 2022 | 8 | [8] |
| 34. | "An energy internet DERMS platform using a multi-level Stackelberg game" | 2020 | 9 | [53] |
| 35. | "Trading platform for cooperation and sharing based on blockchain within multi-agent energy internet" | 2021 | 11 | [54] |
| 36. | "Multi-agent architecture for peer-to-peer electricity trading based on blockchain technology" | 2019 | 49 | [55] |
| 37. | "Distributed subgradient-based coordination of multiple renewable generators in a microgrid" | 2013 | 123 | [56] |
| 38. | "A multi-agent system based coordinated multi-objective optimal load scheduling strategy using marginal emission factors for building cluster demand response" | 2023 | 7 | [57] |
| 39. | "Three-level hierarchical management of active distribution system with multimicrogrid" | 2022 | 1 | [58] |

While articles were primarily selected based on predefined inclusion and exclusion criteria, their relevance to the research question was also considered alongside the journal impact and citation counts. This assessment helps to ensure that the review is grounded in high-quality, influential sources and informs the evaluation of the strength of evidence in subsequent sections of this review. The resulting selection of 39 articles served as the analysis sample. These procedures are shown in Figure 1.

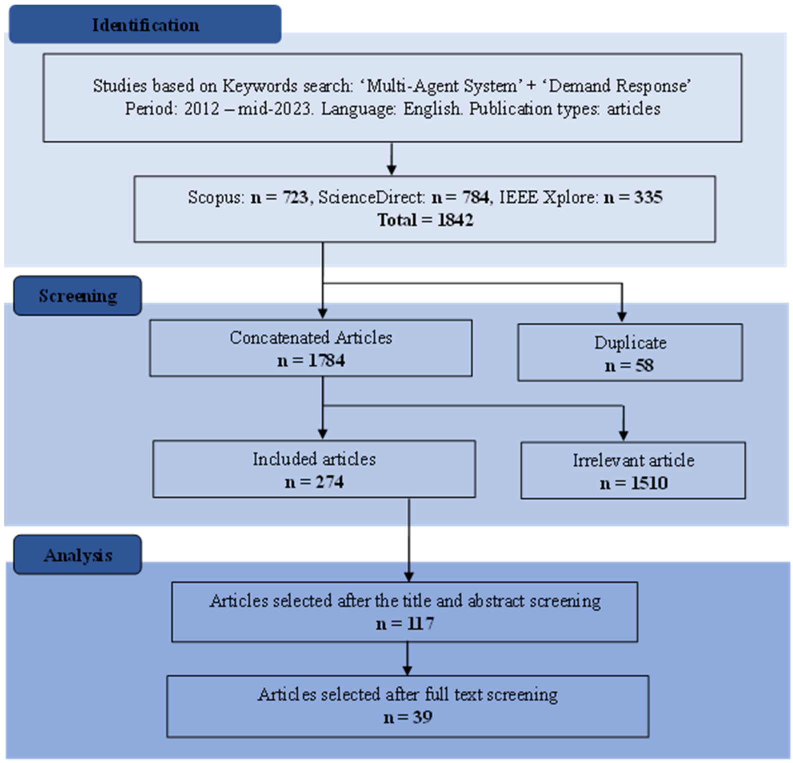


**Figure 1.** Systematic review data search and screening process.

*2.2. Bibliometric analysis*

Bibliometric analyses are generally used because they offer objective quantitative validity and reliability that compensate for subjectivity, even if systematic literature reviews attempt to eliminate subjective bias to increase the quality of the review. Performance analysis and scientific mapping are two applications of the bibliometric technique [59]. Science mapping strives to categorize and illustrate the structure and development of scientific areas, in contrast to performance analysis, which assesses the effect of research by institutions, authors or nations.

In total, 587 articles were extracted for the bibliometric analysis from the search on Scopus, as shown in Figure 2. Relevant information from the chosen articles was carefully extracted. This information included titles, author names, publication year, study objectives, methodology, conclusions, system designs and assessment techniques to understand the current state of research. Thematic analysis was used to arrange and examine the retrieved data. Based on reoccurring ideas and patterns in the articles, themes and subthemes were found. In deploying an MAS for DR, this technique made identifying common strategies, knowledge gaps and emerging trends easier.

Bibliographic information from the chosen publications was analyzed by using a bibliometric analysis tool. The VOSviewer software effectively visualizes and explores networks that involve co-authorship, co-citation and keyword co-occurrence [60]. To depict the interconnections among authors, keywords, and citation patterns, network diagrams were generated to investigate these networks. The thematic analysis and bibliometric study findings presented a comprehensive overview of the current research landscape on implementing an MAS for DR. The deployment of MASs in various methods, as related to energy DR, was considered while performing the bibliometric study in the following parts.

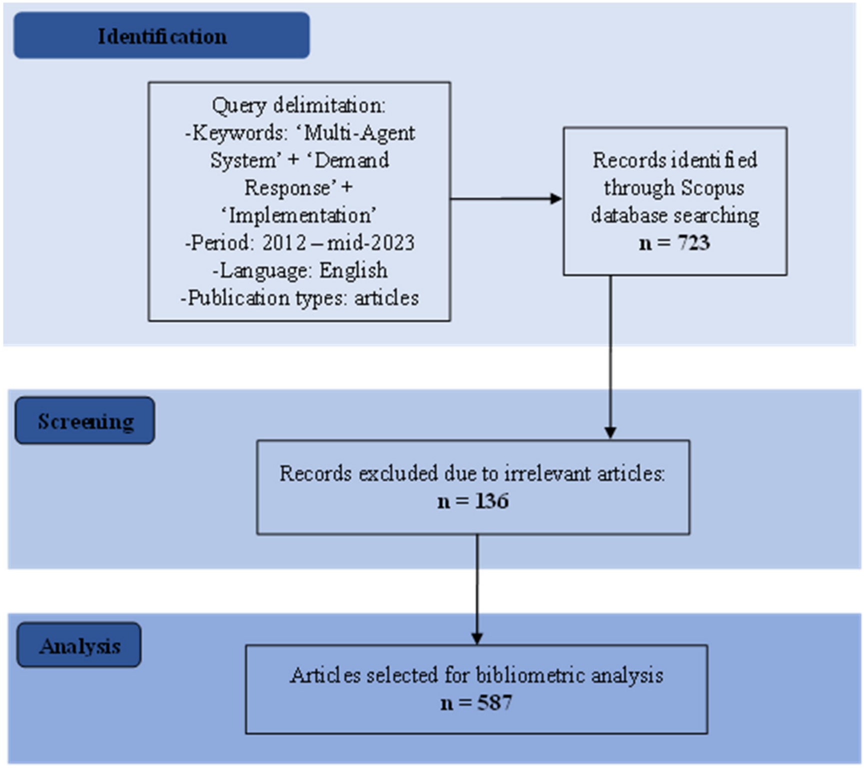


**Figure 2.** Bibliometric review data retrieval and analytical process.

## 3. Results

The analysis identified the research gap described in the systematic review analysis to carry out a thorough and critical review of the gathered material. Evaluations highlighted the gaps in the research and the potential of implementing MASs for DR. By highlighting the connections between the most significant publications, researchers, organizations, subjects and other elements of the subject, the bibliometric analysis enables the mapping and expansion of knowledge in the field of study [61]. Although bibliometric tools may be used for various analyses, this study focused on the following keywords: methodology, year of publication, country searches and article citation.

### *3.1. Case studies of MAS implementation for DR*

This section presents an overview of the literature on the practical implementation of MAS for DR systems. It investigates MAS utilization in controlled experimental environments, analyzing pertinent studies and offering a comprehensive overview of these implementations' crucial findings and outcomes. To ensure conciseness and deepness in our review, we have summarized selected case studies in Table 2. This table provides quick reference point, enabling readers to understand our review's objectives, methods and findings of the most pertinent case studies. However, it is important to acknowledge that not all relevant case studies could be accommodated in the table. This decision was made to balance providing a concise overview of key studies and allowing for a more thorough exploration of others that may require deeper analysis.

**Table 2.** Summary of objective, method and findings of selected case studies.

| S/n. | Objective | Methodology | Findings | Ref. |
|---|---|---|---|---|
| 1. | Automate bidding on local energy markets (LEMs) of 100 households using machine learning algorithms. | Simulation of LEM with a 15-minute merit-order market mechanism; they deployed reinforcement learning for agents. | Achieved self-sufficiency of up to 30% with trading and 41.4% with trading and DR when 45% of households installed 5kWp PV panels. | [27] |
| 3. | Enhance grid reliability to achieve self-consumption and meet DR goals. | Embedded battery energy storage system (BESS) technologies into the grid and used reinforcement learning control for operation. | Maximum peak load reduction of approximately 24.5%. | [28] |
| 4. | Examine the compatibility between specific market elements and independent learning agents in local energy markets. | Simulated autonomous local energy exchange (ALEX) as an experimental framework. | ALEX-based pricing resulted in a median reduction of 38.8% in energy bills relative to net billing. | [29] |
| 5. | Schedule strategy for distribution system operators (DSOs) that optimizes the charging/discharging of PV energy-integrated energy storage systems (PV-ESS), EV charging prices, and DR incentives. | Particle swarm optimization (PSO) was combined with Evolutionary game theory (EGT) to solve the optimization problem and determine the payoff function through self-evolutionary improvement. | Achieved the most economical decisions among agents and effectively managed the voltage profile in an IEEE 33-bus distribution system. | [62] |
| 6. | Develop a fully distributed online optimal energy management solution for smart grids. | Distributed solution based on a market-based self-interest motivation model. Each system participant is assigned an energy management agent. | Effective in maximizing social welfare and improving energy efficiency in smart grids through simulation studies. | [19] |
| 7. | Explore the feasibility and concept of a DC-based open energy system (OES) for exchanging intermittent energy between houses in a local community. | Higher-level control software, a distributed MAS that handles power exchange and a physical model of a four-node OES were used to simulate and compare power exchange strategies. | Improved solar replacement ratio and a reduction in AC grid consumption. | [30] |

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| S/n. | Objective | Methodology | Findings | Ref. |
|---|---|---|---|---|
| 8. | Propose a multi-agent deep reinforcement learning-based DR scheme for energy management in discrete manufacturing systems. | Formulated the industrial manufacturing system as a partially observable Markov game and adopted a multi-agent deep deterministic policy gradient algorithm to obtain optimal schedules for different machines. | Effectively minimized electricity costs and ensured the continuity of production tasks better than a benchmark without DR. | [31] |
| 9. | Develop a decentralized and automated DR and home energy management system. | Implemented a hierarchical agent architecture that allows stakeholders to make decisions based on energy consumption and generation changes. | It improves value for prosumers, enhances efficiency and increases market competitiveness in the low-voltage part of distribution networks. | [32] |
| 10. | Propose an MAS-based optimal control method for combined cooling, heating and power systems with thermal energy storage to minimize operation costs. | Simulated the implementation of coordinator agents, building agents, energy management agents and optimization agents. The genetic algorithm was used for the operation optimization. | Reduced operation costs by 10.0% on a typical summer day and 7.7% on a typical spring day relative to a rule-based control method. | [33] |
| 11. | Develop a distributed intelligent management system for microgrids by using a multi-agent-based control system. | Developed a hardware-in-the-loop simulation system with intelligent agents by using microcontrollers, Zigbee wireless communication and power system dynamics models in real-time simulation environments. | Demonstrates the successful development of a distributed intelligent microgrid management system and its promising application in emergency DR programs. | [34] |
| 12. | Introduce a novel, distributed MAS that optimally dispatches compliant DR requests while accounting for non-deterministic factors in practical deployments. | The distributed MAS aggregates consumers and prosumers, following virtual power plant principles, to ensure a 100% DR success rate. Agents in the MAS optimally exploit flexibility via clustering and optimization engines and use dynamic bi-directional DR matchmaking to mitigate deviations. | Ensures 100% DR success rate and delivers significant savings to aggregators and customers serving DR requests, demonstrating efficiency in ensuring technical DR fault tolerance. | [21] |

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| S/n. | Objective | Methodology | Findings | Ref. |
|---|---|---|---|---|
| 13. | Explore the cooperation of neighboring multi-energy microgrids by developing optimal trading strategies and pricing mechanisms. | A bi-level optimization model with two trading modes was utilized, employing Stackelberg game theory-based pricing for intermediary agent-based trading, and supply/demand ratio-based pricing for direct trading. | Forming a cluster of multi-energy microgrids increases the total benefits relative to individual operations. Direct trading yields higher benefits, but intermediary agent-based trading enhances self-sufficiency. | [35] |
| 14. | Develop an optimization model for interconnected multi-microgrids, considering overall system cost and utilizing a hierarchical energy management system based on the MAS. | Employed a hierarchical energy management system based on the MAS theory, where each system element is treated as an independent agent connected via the Internet of Things (IoT). | The simulation and implementation results demonstrate that the MAS-based optimization model effectively reduces operational costs in multi-microgrid systems while minimizing communication and computational burden. | [36] |
| 15. | Implement an MAS framework for flexible price-based DR in advanced distribution automation technologies to alleviate network constraints and achieve demand-supply balance. | Used a genetic algorithm-based multi-objective optimization technique to determine optimal locations and demand reduction amounts by considering probabilistic estimation of flexible demand and optimal decision-making for appliance start times based on price signals and customer willingness to participate. | Demonstrated the feasibility and effectiveness of the proposed framework in a modified IEEE 69 bus distribution network, showcasing how flexible loads can help manage network constraints and balance demand and supply. | [37] |

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| S/n. | Objective | Methodology | Findings | Ref. |
|---|---|---|---|---|
| 16. | Minimize the overall expenditure of meeting high energy demand. | It involves utilizing a long short-term memory network for predicting day-ahead load, utilizing the Q-learning algorithm for independent agent decision-making and employing a multi-agent framework overseen by a master agent to manage household agents for effective cooperation and voltage regulation. | Reduced the total average aggregated load demand from 5.23 to 3.86 kW and lowered the total average cost from 94.01 to 60.80 Rs, eliminating voltage level violations within the system. | [38] |
| 17. | Evalute the performance of load shedding by using a dynamic pricing algorithm in a multi-agent system for real-time power control in a DC microgrid with price-based DR. | Using embedded devices, relays and sensors, they designed a system by using intelligent physical agents, the Java Agent Development Framework (JADE) and an agent simulation platform to control load shedding and energy trading in residential areas. | Achieved load shedding within 600 ms, leading to an 80% cost reduction for individual houses. | [39] |
| 18. | Introduce an automated energy management system for rural off-grid communities, focusing on price-based DR and the effective integration of sustainable resources. | The paper recommends employing cascaded control abstraction, distributed market-based control and multi-agent transactive principles to implement a price-sensitive cyber-physical smart grid within rural microgrids. | The proposed smart village solution is an automated smart microgrid energy management system. | [40] |
| 19. | Create an MAS for efficiently handling micro-grid outages, improving power generation and reducing operational expenses. | Simulated the system dynamics by using the JADE to account for intermittent solar power, load variations, dynamic grid pricing and critical load discrepancies. | The simulation results illustrate that the MAS enhances microgrid efficiency, resulting in increased power generation, reduced operational costs and the optimized use of financial and environmental resources. | [41] |

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| S/n. | Objective | Methodology | Findings | Ref. |
|---|---|---|---|---|
| 20. | Investigate the interplay between financial autonomy, service provision and stakeholder engagement within the context of implementing a distributed energy resource management system (DERMS) in an Energy Internet framework. | They employed a transparent decision support system and a reverse Stackelberg game-theoretic approach to determine a fair distribution of financial resources among transactive energy participants by utilizing interconnected sub-games and utility functions to model the price response at different levels. | The study confirms the existence and uniqueness of the Nash equilibrium and offers precise solutions for stakeholder energy contributions. | [53] |
| 21 | Present an energy management framework that fosters efficient decision-making and coordination among operating agents, including distribution utilities, microgrid operators and end-user aggregators. | It introduced a game-theoretic dynamic pricing scheme that facilitates interactions between distribution utilities, microgrid operators and end-user aggregators. | The results validate that the participatory strategy leads to improved economic benefits and technical aspects by reducing peak demand and enhancing voltage profiles in the power trading model. | [58] |

We will briefly describe each case study not included in Table 1 to ensure a comprehensive overview of the available literature. In [22], an effective energy management system employing an MAS was implemented to model distributed energy resources in a neighborhood grid alongside multiple green residential buildings. The proposed model computes the price at which the supply and demand for electricity reach equilibrium in a home microgrid. The model was demonstrated to improve overall energy efficiency and individual residential green building profits and optimally manage devices in green residential buildings. Consequently, in [12], a system based on intelligent multi-agents was proposed to optimize the response to residential demand in distributed networks. The model portrays retailers and smart home devices as multifunctional and intelligent agents. Smart home devices forecast and schedule energy loads, while a retail agent informs home agents of energy prices. Simulation accurately predicted electricity loads and energy prices through the use of coupled convolutional neural network - a long short-term memory model.

Furthermore, in [42] discusses prediction-based multi-agent reinforcement learning for decentralized electric vehicles, and it addresses the optimum charging challenge concerning intermittent wind power and variable base load demands. GridLAB-D, a software power network simulator, was used in [42] to train and test the algorithm in a residential load management scenario. The simulation agents learned the optimal charging behavior for electricity, effectively circumventing high-power demand instances and attaining a peak-to-average ratio of 1.67, which represented a significant improvement from the baseline scenario's 2.24 ratio. The DR approach maximizes renewable energy utilization and avoids peak power use to meet DR objectives [43]. A multi-agent reinforcement learning approach was also explored in [44] for energy management. Real data and probability density functions were used in the proposed method to address uncertainties. The method involves using training scenarios to facilitate the training of Q functions for agents. Upon examination of the results, it was observed that the overall disparity in energy costs between the scenarios that incorporate trained Q values and those that employ the no-regret learning method was minimal, amounting to 0.4%. This outcome underlines the agents' commendable adaptation to the environment. The reinforcement learning-based method leads to more cost-effective consumer schemes than conventional mathematical optimization-based energy management programs.

A novel agent-based framework was proposed in [14]; incorporate flexibility in industrial and residential demand. A central DR provider was proposed to coordinate responses from industrial and residential DR aggregators. These aggregators allow entire production lines to be flexible for energy-intensive industries such as cement production and metal smelting. In their framework, thermostatically controlled appliances and electrical storage systems are also utilized by residential DR aggregators to store thermal and electrical energy. Additionally, electricity markets use integrated flexibility to maximize profits for market participants, eliminating the need for supportive regulations to subsidize responsive consumers. A test of the proposed structure was conducted in the Danish sector of the Nordic electricity market to demonstrate its applicability and efficiency. They found that integrating flexibility into power systems may improve their ability to handle intermittent power sources.

A model based on an MAS was developed to analyze microgrid capacity using real-world data [45]. A full simulation of microgrid performance was carried out by applying economic, technical and environmental metrics. This model included autonomous agents with specific load profiles, renewable energy generation sources and DR potential. A peer-to-peer e-commerce marketplace can be simulated by using the model, where agents trade electricity. Using data from a medium-sized German city on the performance of Europe's microgrids in 2022 and 2019, the model was validated to examine the effects of the energy market shocks. The study results prove that microgrids with peer-to-peer trading can reduce electricity costs and greenhouse gas emissions.

When designing the MAS, industrial consumers' operational constraints and preferences were considered to ensure effective implementation. The production schedules, process continuity and specific functional requirements of industrial facilities were considered during the negotiation process [46]. Considering these factors, DR actions were carried out without disrupting critical operations, and while achieving substantial reductions in peak demand. During the implementation of the MAS for DR, various approaches were employed to stimulate consumer engagement. Financial incentives, personalized energy consumption feedback and time-of-use pricing alternatives were strategically deployed [37]. By providing actionable information and attractive incentives, consumers were empowered to modulate their energy consumption responsively. The actions achieved through these implementations provide information on the detailed design and seamless deployment of the MAS in residential and integrated DR initiatives. Within residential feeder 7, the implementation of DR yielded a remarkable reduction in load, i.e., 69.30%. This substantial load reduction serves as compelling evidence for the practical viability and effectiveness of the proposed framework. These visions pave the way for a wider acceptance and utilization of such systems in practical, real-world settings.

The studies analyzed reveal the diverse methodologies and findings in the context of MAS implementation for DR. These studies leverage techniques such as reinforcement learning, optimization algorithms and intelligent agents to address various challenges in DR. The findings underscore the effectiveness of MASs in reducing electricity costs, enhancing grid stability and optimizing energy management. They highlight successful applications in scenarios ranging from microgrid control to household demand management. These studies demonstrate the versatility and promise of MASs as essential tools for tackling contemporary energy management issues, offering solutions that contribute to cost savings and improved operational efficiency across different contexts in the energy sector.

### *3.2. Recent MASs framework for DR*

This section presents a comprehensive overview of the advances in implementing MASs for DR, highlighting the latest strides in this field. It encompasses emerging trends and novel methodologies that have enhanced the effectiveness and efficiency of MAS installations, illuminates notable breakthroughs in the domain and accentuates pivotal progress made in this discipline. Recent scholarly investigations have explored the perspective of MASs for DR programs by integrating advanced machine learning and artificial intelligence methodologies [28,47–49]. The authors of [50] introduced an innovative design framework for multi-agent reinforcement mechanisms that simultaneously determines the optimal charging rates for a subset of charging stations over a specific period. This framework considers the power output restrictions, unexpected incoming requests and unforeseen charging requirements of self-interested users who strive to maximize utility. Utilizing Markov game theory effectively captured the essence of cooperation between stations [6]. At the same time, the complex challenge was addressed through the implementation of a multi-agent deep deterministic policy gradient. The primary objective entailed the augmentation of network revenue over the long term while simultaneously considering the social welfare of all users. An experimental evaluation assessed the framework's efficacy, revealing superior performance compared to the time-of-use pricing system and the noncooperative deep deterministic policy gradient method.

Furthermore, the integration of Internet-of-Things (IoT) technology has facilitated the collection and transmission of data in real time with enhanced stability within MASs for DR [36,51]. Smart meters and IoT sensors provide continuous and valuable insights into environmental parameters, grid conditions and energy consumption patterns [8,52]. In [36], a novel optimization model is introduced for interconnected multi-microgrids, and it considers the total cost of the entire system. A hierarchical energy management system was employed to achieve optimal system performance, drawing on the principles of the MAS concept. Within the framework of the IoT platform, every individual element of the system engages in autonomous agent-based interactions with other components. A primary advantage of this structure is its ability to be partitioned into multiple layers, which presents a significant benefit of effectively managing the overall complexity.

Similarly, the introduction of multiple management stages has reduced the communication costs incurred by the system. The simulation and implementation outcomes demonstrated the effectiveness of the proposed MAS-based optimization model in significantly curbing the operating expenses of the multi-microgrid system. In particular, this achievement was achieved while maintaining minimal communication expenses and computational burden.

Other notable progress is evident in blockchain research, which has paved the way for establishing trust among agents, thus enabling secure data exchange and facilitating automated transactions within DR programs. In [54], an innovative blockchain-based trading system was devised to promote multi-agent collaboration and facilitate energy sharing. The simulation of nodes in market transactions was accomplished by integrating power system modeling at the physical layer with a transaction consensus approach at the cyber layer. This framework captured the complex dynamics of the power system while ensuring seamless and secure market interactions. An ingenious integration of smart contracts with blockchain technology was introduced to enable autonomous peer-to-peer power trading within a microgrid setting without human intervention [55]. This pioneering approach leveraged an MAS to facilitate secure and efficient power transactions seamlessly. Utilizing blockchain technology allows the proposed market to facilitate microtransactions while reducing transaction costs. Moreover, incorporating blockchain technology has significantly sustained the platform's security by establishing a verifiable record of information origin, instilling confidence among all participating parties. Incorporating an MAS alongside the potential for agent negotiations further facilitates the attainment of an optimal system state that is characterized by low energy costs and rewarding local energy production.

Finally, there have been notable enhancements in decentralized control and coordination techniques, and they have resulted in the increased effectiveness and scalability of DR solutions based on MASs. Decentralized techniques expand the realm of decision-making and coordination beyond the dependence on a single control unit, distributing these responsibilities among multiple agents [56]. In response to the concurrent change in electricity prices and marginal emission factors, the authors of [57] developed an MAS-based coordinated optimum load scheduling technique for building cluster load management. To address the dynamic fluctuations of electricity prices and marginal emission factors, an innovative, coordinated optimum load scheduling technique for building cluster load management was developed by the authors of [57], who employed the MAS framework. The proposed approach effectively mitigates conflicts arising from multiple optimization objectives by concurrently minimizing power costs, carbon emissions and peak loads while ensuring high user satisfaction with electricity consumption. Assessment of user satisfaction was quantified through a utility function, signifying its careful consideration within the optimization framework. The findings demonstrate that the implementation of hybrid DR can effectively reduce peak power by 5.54% without inducing any increase in energy prices or carbon emissions. This outcome highlights the potential of hybrid-based DR to achieve substantial peak power reduction while maintaining economic and environmental equilibrium.

### *3.3. Analysis of influential authors and research organizations*

This section examines the patterns of research cooperation that have arisen in the literature while highlighting some of these prominent authors. The bibliometric study has found 159 authors with 160 affiliations linked to research publications on MASs for DR. The reports on the main concepts, techniques and real-world applications of MASs for DR have benefited from the contributions of these scholars. Their knowledge and groundbreaking work have influenced the industry and stimulated innovation. Figures 3 and 4 display the top authors and institutions published on MASs for DR.

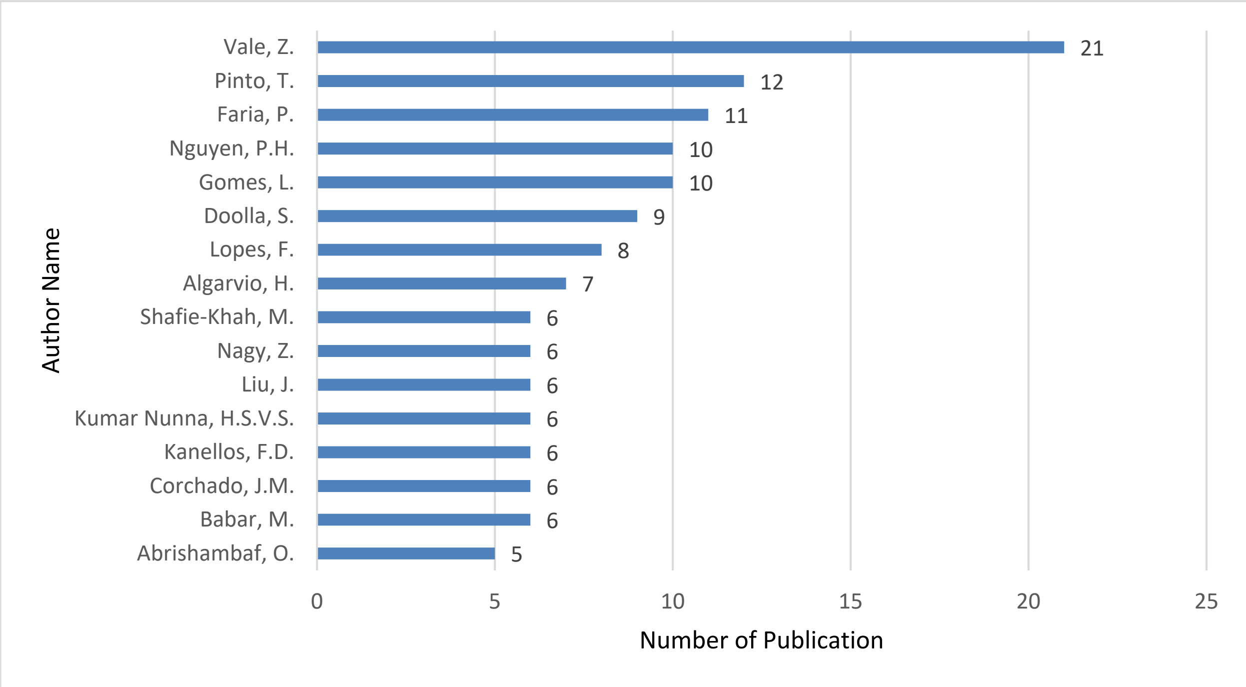


**Figure 3.** List of authors with the most publications.

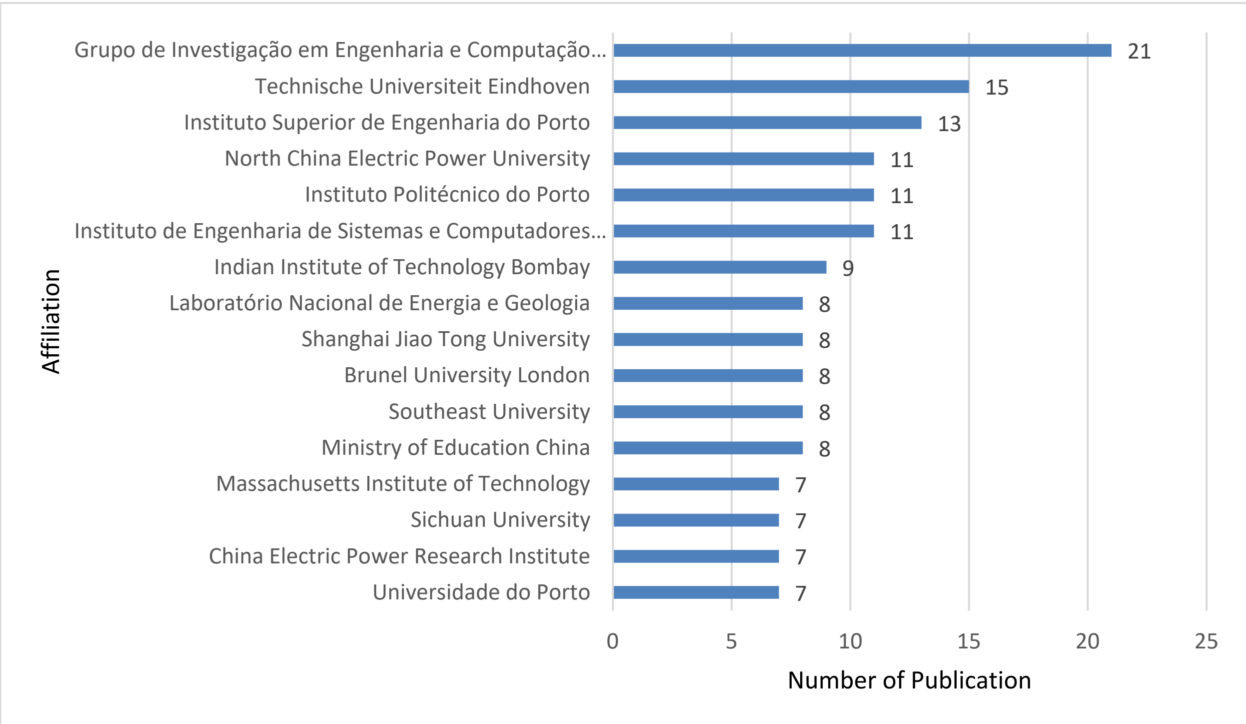


**Figure 4.** The affiliations for the most cited publications.

The most prominent authors in the field of MASs for DR include the authors of [28,29,55,63–68]. Other notable authors are the authors of [14,36,37,66,72,73,68–70]. Their research contributions cover various topics, including market-based strategies, agent coordination and decision-making algorithms.

Their papers have received numerous citations and significantly influenced how MASs are understood and used in response to demand.

Through a spatial representation of the research collaborations, a density visualization analysis yielded 12 distinct clusters, as illustrated in Figure 5. The intensity of the colors in the visualization serves as an indicator of the density of author collaborations. Darker regions signify heightened densities, signifying a greater magnitude of collaborative efforts among authors. Visualization shows the clusters of authors who exhibit robust collaboration within their respective research domains. Notable areas encompass the implementation of MASs for DR in microgrid and smart home contexts.

Moreover, the visualization effectively highlights areas characterized by lower density, indicating relatively sparse author collaborations. Prominent areas characterized by a low collaboration density include the implementation of MASs for DR in urban and industrial transformers. These areas of lower density present promising avenues for future research and exploration, offering novel opportunities to advance the field.

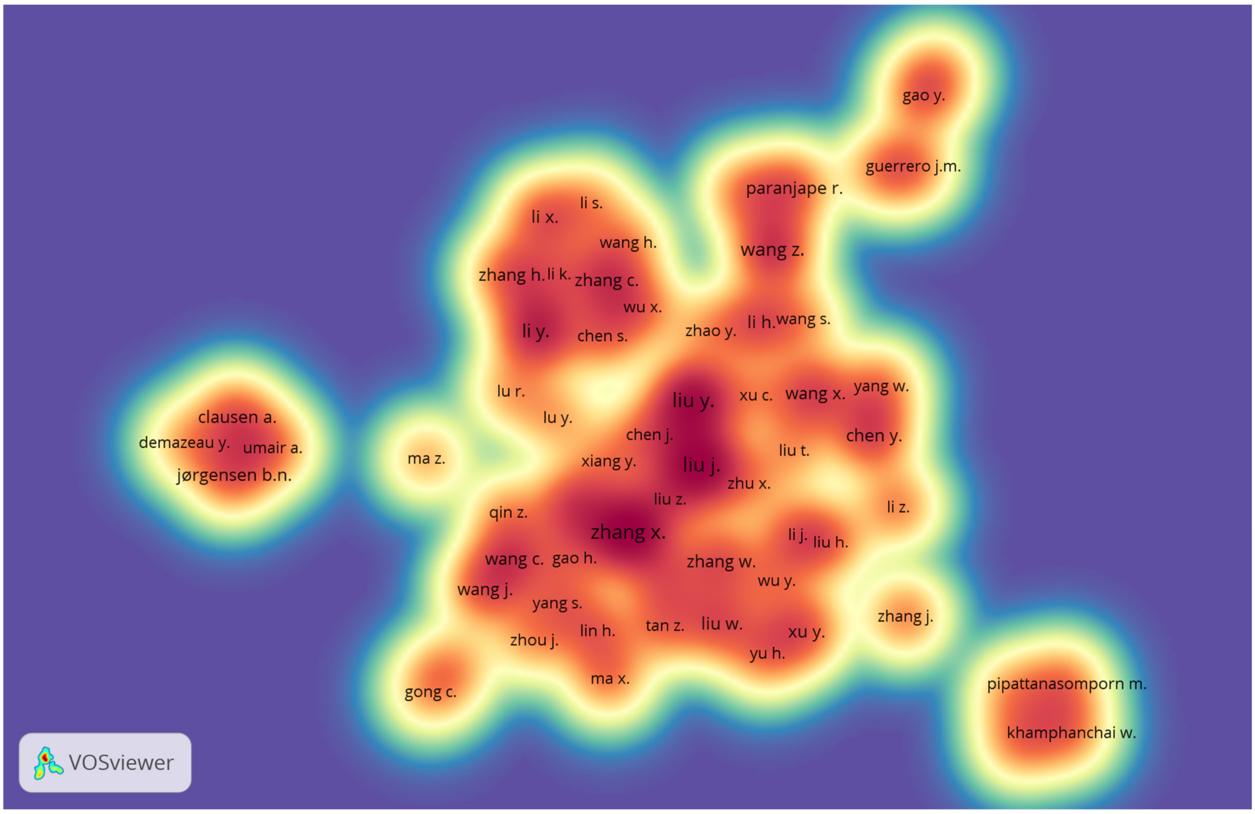


**Figure 5.** Density visualization of author collaboration produced by VOSviewer.

Collaboration is necessary to promote interdisciplinary research and combine skills from many fields to produce more thorough and significant studies. Collaborative research activities have been observed among 11 subjects on implementing MASs for DR. Experts from various fields, including energy, engineering and computer science, participate in these collaborations; see Figure 6. The combined efforts have produced unique applications of MASs for, particularly in terms of creative ideas and improved methodologies.

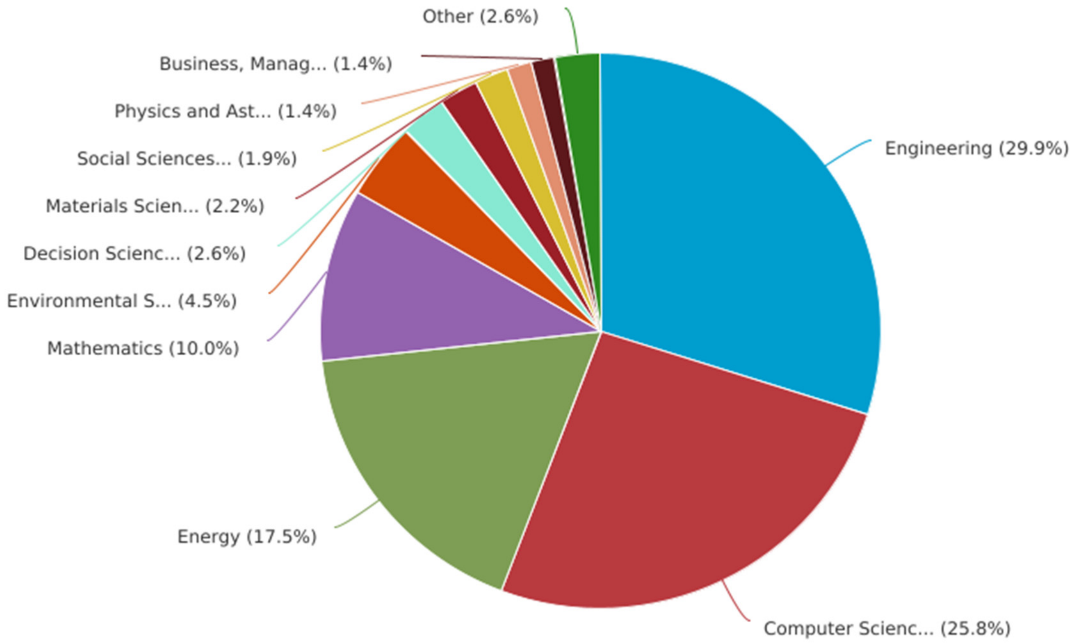


**Figure 6.** Analysis of publications according to subject.

The collaboration patterns in the Scopus search illustrate the significance of knowledge sharing and the cross-pollination of ideas in furthering the subject; they also show the value of multidisciplinary teamwork. Such partnerships support a thriving research community, offer a forum for tackling difficult problems and push the limits of MAS implementation to respond to energy demand.

*3.4. Analysis of keyword co-occurrence*

The study of keyword co-occurrence in the literature is presented in this subsection. The MAS implementation for DR identifies and analyzes the new research issues that have gained popularity. Here, we investigate how many themes are related and what it means for future studies. Figure 7 displays the co-occurrence of the terms from documents relating to the deployment of MAS-in-DR programs created using the VOSviewer software.

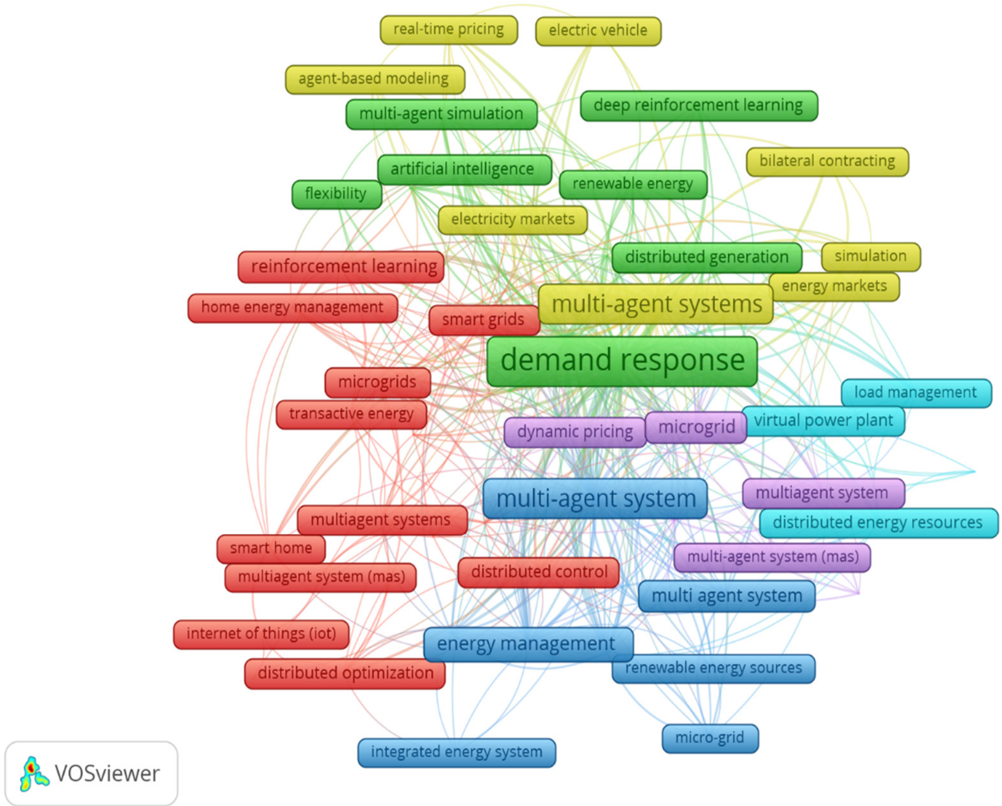


**Figure 7.** Analysis of keyword co-occurrence in VOSviewer.

Keywords with a minimum incidence of five times were filtered to get the results displayed in the figure. The network visualization results presented in Figure 7 show that the largest cluster (i.e., the green cluster) is strongly related to the use of an MAS for DR, and it encompasses terms such as "multi-agent simulation", "distributed generation", "renewable energy" and "deep reinforcement learning". The red keyword cluster "smart grids" is linked to other keywords generally related to the grid and residential optimization of distributed energy. The other two major groups (i.e., blue and yellow) are associated with the technical approaches of the DR projects. Furthermore, Figure 8 includes an overlay visualization for further analysis of the relevant keywords in the literature.

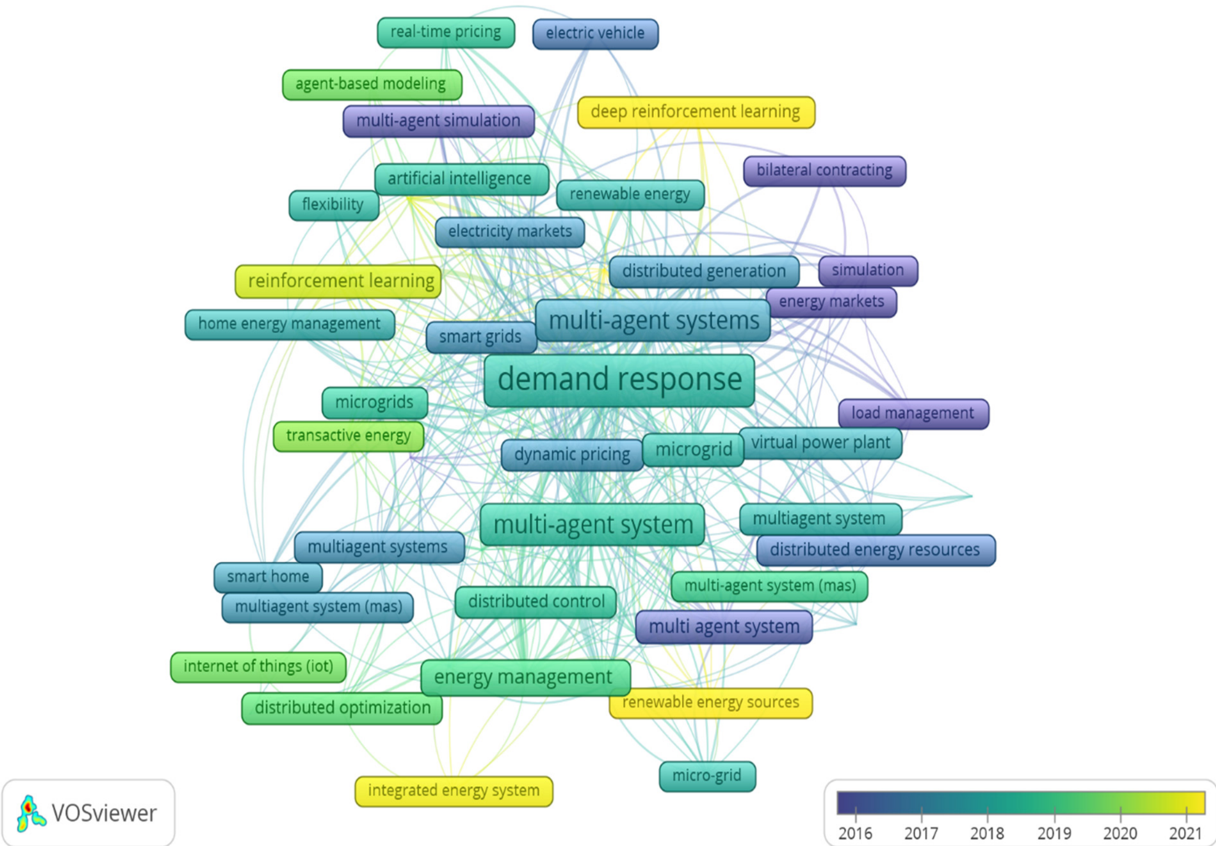


**Figure 8.** Overlay visualization of keyword occurrence on VOSviewer.

Recent publications included studies based mainly on MASs for intelligent energy management [23,47,50,74–77]. The recent co-occurrence of the keywords “deep reinforcement learning”, “renewable energy sources”, “integrated energy systems” and “transactive energy” is shown in Figure 8. The terms are primarily associated with 2021 and later.

*3.5. Visualisation of publication trends*

Figure 9 presents a graphical representation of the annual publication count of the utilization of an MAS in DR. The data reveal substantial publication growth from 2012 onward, with a notable surge to more than 73 publications in 2021.

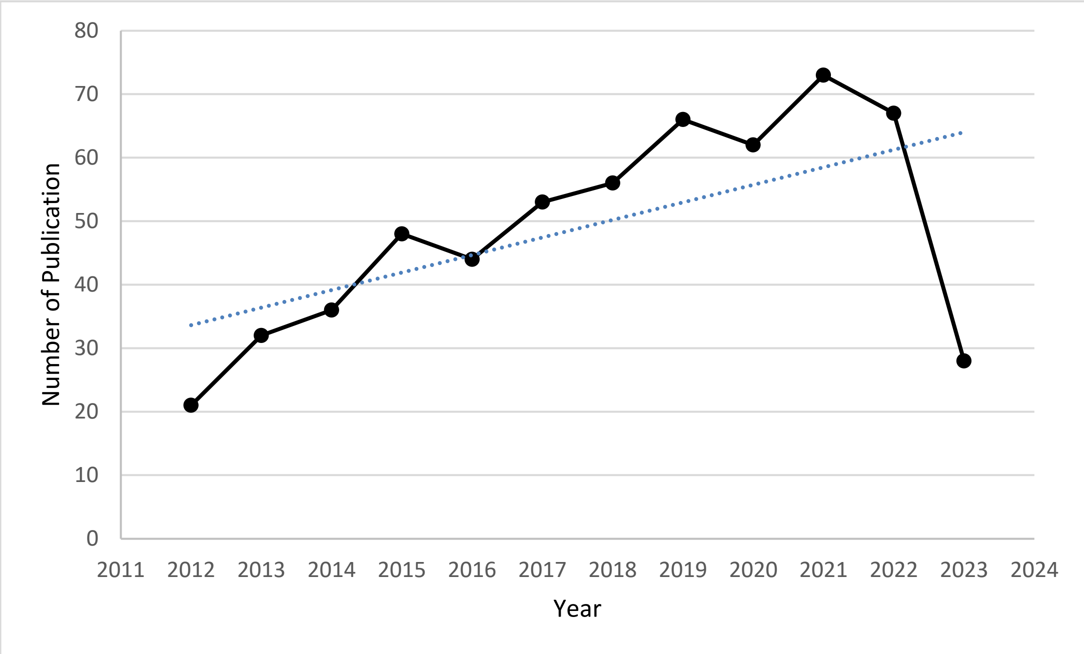


**Figure 9.** Analysis of scientific output by year of publication.

The combination of technological developments, increased interest in DR, interdisciplinary collaboration, supporting regulations and funding opportunities can be attributed to the increase in publications on the application of MASs for DR. These reasons have helped the scientific community to concentrate on creating novel methods to optimize energy consumption and load demand using MASs.

Also, along with the number of publications, the citation overview of the selected documents is discussed, including the mean total citation per year of the papers selected, as shown in Figure 10. The results show that the highest number of mean citations per year was reached in 2022. In total, 2010 citations were received that year. Though the number of publications was less in the early years, the numbers began to rise gradually in 2013.

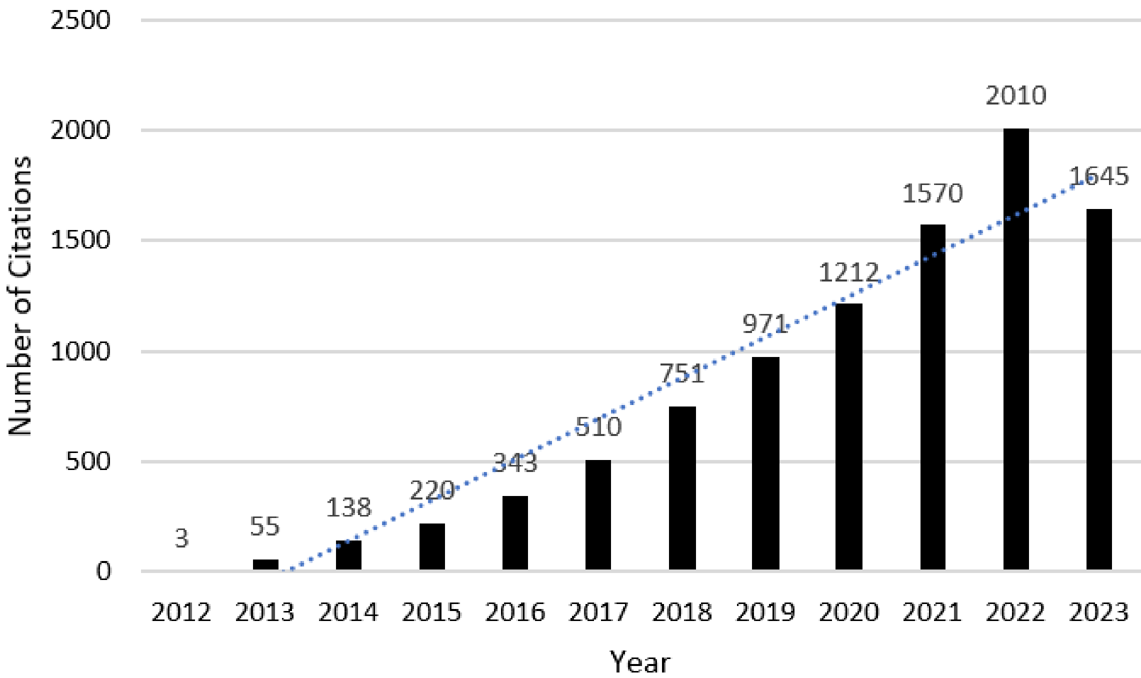


**Figure 10.** Analysis of article citation by year of publication.

The trend of publications in the top territories that published papers on MAS implementation for DR is shown in Figure 11 to demonstrate significant patterns.

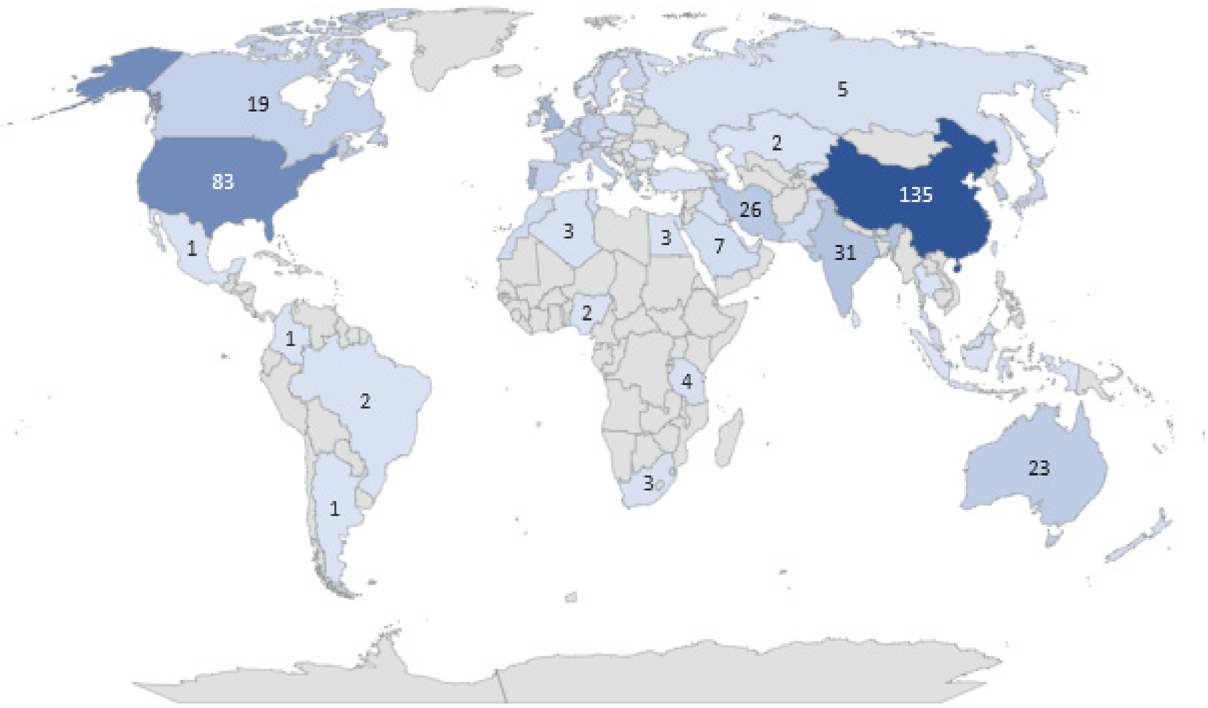


**Figure 11.** Number of publication records by country.

Countries such as China, the USA, Germany and Japan have emerged as significant contributors. The number of papers on MAS implementation for DR has steadily increased in these regions, reflecting an increasing interest and research focus on maximizing energy usage through decentralized control and coordination. Figure 11 illustrates the research productivity of different countries in the field of MASs for DR. China has emerged as the leading contributor, with 135 published documents, followed by the USA, with 83 documents, and the United Kingdom with 43 documents. In particular, an analysis of African nations reveals a limited publication count, with each nation having published fewer than five articles on MASs for DR. Recognizing the historical success of DR in curbing peak demand within emerging markets, several developed nations, including the USA, Germany and Australia, are now actively exploring DR mechanisms to facilitate grid frequency-balancing services and increase the flexible capacity of the electricity market [78,79]. According to a report in [1], by 2030, Europe and China will have cut their carbon emissions by 60 to 65 percent from 2005 levels. Consequently, this reasonable goal can indicate a rise in research institutions' interest in studying distributed energy source optimization.

## 4. Discussion

Although the systematic and bibliometric review on the use of MASs for DR offers useful insights into the body of literature, it is important to recognize some limitations that might have affected the scope and implications of this work. The availability and accessibility of publications in scholarly databases are essential for the review process. Due to publication bias or the exclusion of papers written in languages other than English, some pertinent studies were not included in the analysis. Therefore, the results might only fully represent a portion of the literature on the subject. The research included in the study also covers a variety of approaches, themes and experiments. The heterogeneity of the research may constrain the clear correlation and generalizability of the results. The reported results can differ significantly depending on several variables, including the simulation model, the market structure and the implementation strategy. Despite these limitations, the systematic and bibliometric investigation of MAS deployment for DR represents an essential synthesis of the existing research corpus. It offers an overview of the current state of knowledge of academics, professionals and decision-makers in this field, identifies knowledge gaps and highlights potential directions for further research in this area.

Various methodologies and techniques have been employed to implement MASs for DR. A centralized MAS [80], which utilizes a central agent, provides simplicity but may suffer from single points of failure. In contrast, distributed MASs [6], which are without central agents, exhibit greater robustness but require more intricate management. Hybrid MASs [6] combine elements of both, seeking a balance between simplicity, resilience and performance. These approaches can be enhanced with specific techniques, such as game theory [6,63,72], which facilitates negotiation and cooperation in competitive environments; machine learning [81], which allows for adaptation to change grids and consumer behavior; and optimization [82], which finds optimal energy consumption schedules. This research finding suggests that certain MAS methods, such as multi-agent reinforcement learning [71], price-based DR [78] and decentralized energy management systems [83], exhibit exceptional performance when applied for energy DR. The most suitable MAS approach should consider program requirements, consumer characteristics, scalability, robustness and efficiency.

Integrating MASs with the IoT and AI technologies has revealed the unexploited perspective for improved performance and efficiency. However, scholarly work has documented several challenges in this domain. These challenges include establishing well-defined protocols, efficient data management, seamless system compatibility and preserving privacy. Among the prominent concerns highlighted in the literature is the scalability of MASs in the context of DR. As the number of agents and devices within the system increases, the complexity of coordination and communication increases. Thus, ensuring the proficient handling of numerous users and devices through the MAS without compromising performance becomes an imperative priority.

Furthermore, gathering, distributing and analyzing private customer energy usage data is a necessary component of MAS implementation for DR. Privacy concerns are brought about by the dangers resulting from unlawful access, use or disclosure of personal information. Gaining consumer trust and promoting active participation in the DR program depends on how privacy is protected and whether strong security measures are implemented. Furthermore, there are many difficulties in managing and analyzing the massive amounts of data produced by and MAS for DR. For decision-making, system optimization and overall performance, efficient data collection, storage, integration and analysis are essential. Developing improved data management methods, through techniques such as data fusion, aggregation and analytics, is necessary to support efficient DR plans and extract valuable discoveries. System interoperability is another mentioned drawback. Interoperability is necessary to integrate MASs with infrastructure, energy management systems and smart grid components. However, providing smooth interoperability between various systems, protocols and communication standards is challenging. It means developing standardized interfaces, protocols and structures for efficient data flow, interoperability and collaboration involving heterogeneous components. The lack of widely accepted and established protocols for MAS implementation for DR highlights the necessity for standardized protocols, which complicates efforts to improve interoperability, scalability and integration. The absence of standards makes it difficult to create MASs that are interoperable with one another, share data and enable inter-agent communication. The effectiveness of the implementation of MASs in practical DR applications depends on the solution to these difficulties. Researchers and practitioners must develop scalable MAS architectures, reliable privacy-preserving methods, effective data management strategies and standard protocols. The potential of MASs to facilitate the transition to sustainable and smart energy grids and enable effective responses to demand can be fully realized by addressing these difficulties.

## 5. Conclusions

In conclusion, this review of the literature was designed to analyze MAS implementation for DR applications. We investigated this field's current body of research through a systematic and bibliometric evaluation, highlighting significant trends, approaches and difficulties. The analysis revealed a significant growth in the application of MASs for DR, indicating the increasing recognition of its potential to optimize energy consumption and enhance the grid's reliability. The reviewed studies demonstrated the effectiveness of MASs in addressing the complexities of DR, including coordination, communication and decision-making among multiple entities.

Based on the analysis, it is evident that MASs hold great promise for future DR applications in home and industrial energy. The reviewed studies demonstrated their potential to enable dynamic, responsive and efficient energy management, contributing to the integration of renewable energy sources, reduction of peak loads and overall grid stability. MAS implementation for DR can help consumers by allowing them to actively engage in energy markets and make smart decisions regarding their energy consumption. Future research should address the identified challenges and limitations and explore novel approaches for MAS implementation in response to demand to further advance the field. Furthermore, more attention should be paid to real-world case studies and practical deployments to assess MAS-based DR systems' scalability, reliability and economic viability.

This systematic and bibliometric review provides comprehensive overview of current research on MAS implementation for DR. By synthesizing the existing literature, we have contributed to understanding the key trends, methodologies and challenges in this field. Researchers, practitioners and policymakers who seek to advance and implement MAS-based DR systems will find the data provided here to be valuable, ultimately promoting a more sustainable and effective energy future.

## Use of AI tools declaration

The authors declare that they have used the ChatGPT artificial intelligence tool in the creation of this article. The tool was used for the paraphrasing purpose in the **Introduction** of the manuscript.

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## Conflict of interest

The authors declare no conflict of interest.

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