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Artificial intelligence and machine learning in energy systems: A bibliographic perspective

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ABSTRACT

Economic development and the comfort-loving nature of human beings in recent years have resulted in increased energy demand. Since energy resources are scarce and should be preserved for future generations, optimizing energy systems is ideal. Still, due to the complexity of integrated energy systems, such a feat is by no means easy. Here is where computer-aided decision-making can be very game-changing in determining the optimum point for supply and demand. The concept of artificial intelligence (AI) and machine learning (ML) was born in the twentieth century to enable computers to simulate humans' learning and decision-making capabilities. Since then, data mining and artificial intelligence have become increasingly essential areas in many different research fields. Naturally, the energy section is one area where artificial intelligence and machine learning can be very beneficial. This paper uses the VOSviewer software to investigate and review the usage of artificial intelligence and machine learning in the energy field and proposes promising yet neglected or unexplored areas in which these concepts can be used. To achieve this, the 2000 most recent papers in addition to the 2000 most cited ones in different energy-related keywords were studied and their relationship to AI- and ML-related keywords was visualized. The results revealed different research trends in recent years from the basic to more cutting-edge topics and revealed many promising areas that are yet to be explored. Results also showed that from the commercial aspect, patents submitted for artificial intelligence and machine learning in energy-related areas had a sharp increase.

1. Introduction

Economic development and increasing welfare are always entangled with the rising consumption of energy resources. Increasing energy generation as the default answer to how to cope with this additive energy consumption may not be the best answer. From an energy justice perspective, it's not acceptable to deplete energy reservoirs that belong to the next generations [1]. Although retrofitting existing equipment and minimizing energy usage by combining (or cascading) multiple systems for increased efficiency may be an answer to this challenge, increasing efficiency may not be the ideal solution. It's valid that efficiency leads to lower consumption, but it should be noted that many of these systems might also be able to be turned off or operate on lower loads. So, a more dynamic approach may be a better solution.

Artificial intelligence and machine learning are relatively new concepts in energy that can be promising tools to operate systems by implementing past and predicted futures to increase the effectiveness of systems.

The first use of "Artificial intelligence" (AI) was by computer scientist McCarthy in 1954 [2]. In the conference organized by him and his colleagues, he stated that every aspect of learning and intelligence could be described in a way that a computer can simulate. AI is the ability to mimic the cognitive functions of humans, such as learning and problem-solving which are distinct features of the human mind [3]. AI is a vast and expanding area that is penetrating all scientific fields. It is currently being used in many areas, including marketing, banking, agriculture, healthcare, security, robots, speech recognition, chatbots, manufacturing, and many other areas [4,5]. In recent years AI applications in energy systems have gained more focus [6].

By energy systems, we mean all the small or big equipment, buildings, plants, or even smart energy (e.g. electricity) grids. In another word, any system that needs energy to operate, maintain specific conditions or transfer energy from one point to another. Whether it's consuming energy or transferring it, having a smart management system that can react to sudden changes to inputs (such as increasing/

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Nomenclature

AI	artificial intelligence
ANN	artificial neural network
COP	conferences of the parties
CPCs	cooperative patent classifications
GA	genetic algorithm
IoT	internet of things
ML	machine learning
SVM	support vector machines

Table 1
Common machine learning methods and approaches.

Machine learning methods	Machine learning approaches
Artificial neural networks [40]	Supervised machine learning [41]
Deep learning [40]	Unsupervised learning [41]
Decision trees [42]	Reinforcement learning [41]
Support vector machines [40]	Self-learning [43]
Regression analysis [42]	Feature learning [44]
Bayesian networks [45]	Sparse dictionary learning [46]
Genetic algorithm [47]	Anomaly detection [43]
Particle swarm optimization [47]	
Fuzzy logic [47]	

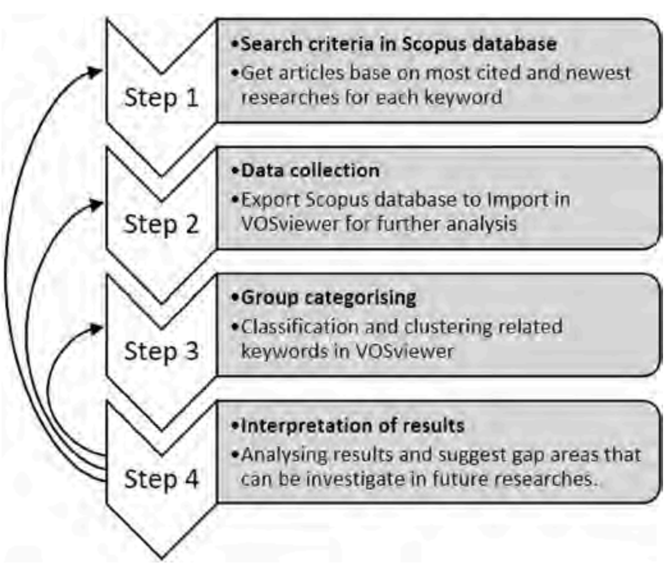

Fig. 1. Research methodology and overall procedure for each stage.

decreasing demand) or predict the future to operate the grid assets to their full potential can be very beneficial. For example, short-term predicting of the required electricity generation by fossil fuel power plants and their fuel usage by forecasting available renewable energy sources such as solar or wind and grid demand. These short-term predictions cannot be achieved by static models and need dynamic modeling with decision-making capabilities. AI can be a powerful tool to simulate human decision-making and operate smart energy systems without any interference from the operators. With ML, computers can train themselves to make better decisions and operate more accurately to the point that with enough data, computers can easily outrun humans. Below we briefly discuss the mainstream usage of AI in energy systems.

One area in AI and machine learning (ML) usage is buildings energy consumption modeling [7,8]. Building energy consumption is a challenging task since many factors such as physical properties of the

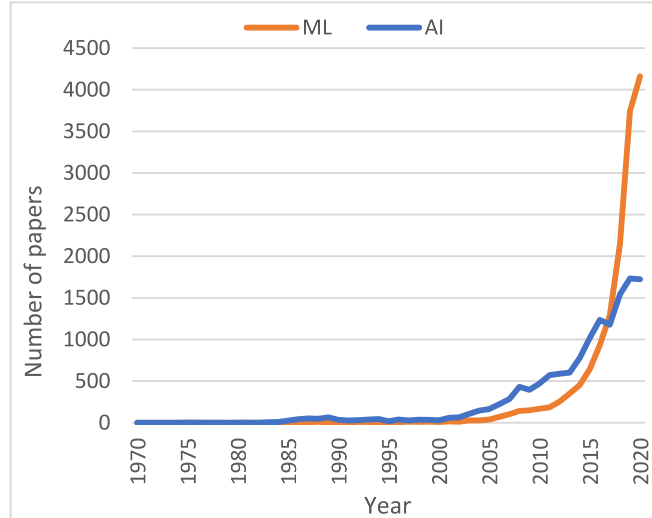

Fig. 2. The number of papers related to artificial intelligence and machine learning in the energy field (1970–2020).

building, weather conditions, equipment inside the building and energy-use behaving of the occupants are hard to predict [9]. Much research featured methods such as support vector machines (SVM) and artificial neural network (ANN),decision tree, in buildings energy consumption modeling [10]. Researches in this field also include optimization of thermal comfort control of HVAC systems [11] and absorption chiller systems [12] by genetic algorithm (GA) and ANN methods. AI and ML are also promising techniques in process control applications in the chemistry industry [13]. Much research showed that using ML methods such as GA and ANN can significantly improve energy consumption in most energy-consumption sectors, including the chemistry industry. Modeling and controlling the combustion processes [14], optimizing the distillation tower [15], or even more specific processes such as "shell" heavy oil fractionator [16] are examples of usage of AI in this industry. Generally speaking, in machine learning, a set of algorithms is employed to parsing the input data and learning from their trend/behavior while ANN, on the other hand, encompasses one set of algorithms utilized in machine learning in order to model the data using the patterns observed in Neurons. Even in complex energy sytems such as water supply system, ANN can be used to model hybrid system [17] or used to improve the manufacturing or production from the energy-consumption viewpoint [18].

Another implementation of AI and ML is in renewable energies, which have recently gained a lot of focus [19]. From this category, photovoltaic power generation is one of the promising areas. Forecasting photovoltaic power generation, and modeling and optimization [20] can significantly improve power generation by predicting the various influential variables and help the designers to improve the setup or location of the installation site. Multiple methods, including ANN, historical data, weather prediction [21–23], etc., can be used to forecast power generation. Another type of renewable energy that can be modeled by AI and ML methods is wind energy which many studies have conducted for forecasting and optimizing power generation of this renewable energy [24]. Another area that ML can be show a promising future is the management and supply of the electricity by renewable sources for the electric vehicles []. Although physical and conventional static models have an advantage in long-term energy generation predicting, such a model becomes inefficient in short-term predictions. In recent years some new models based on AI and ML, such as ANN and fuzzy logic models [26], show promising futures and have caught the attention of many researchers in this area.

It should be noted that since the smart grid has become one of the milestones in the future energy network, the complexity of the energy

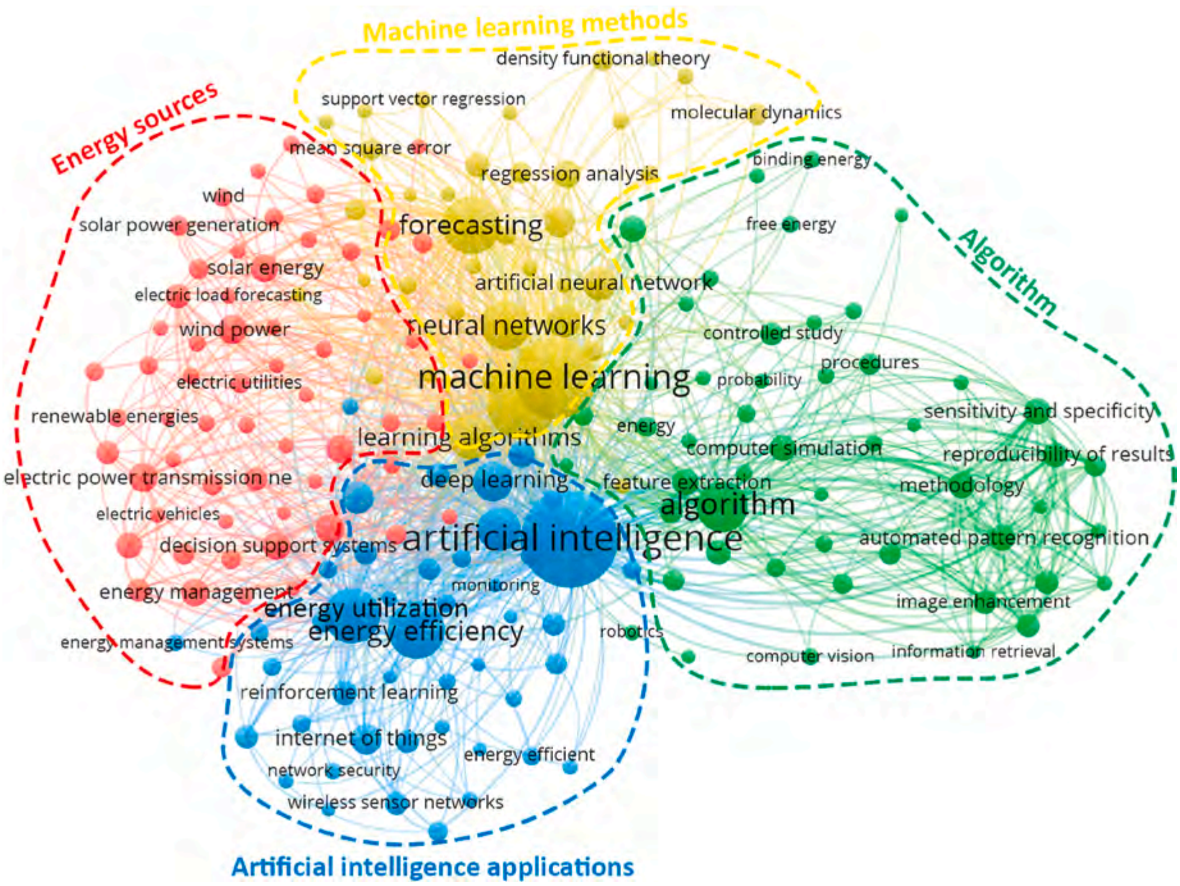

Fig. 3. A comprehensive network of energy, artificial intelligence and machine learning.

Table 2
Primary applications of artificial intelligence and machine learning in the energy field.

Goals	Systems & Section	Techniques & Models
Decision making	Solar power	Numerical model
Forecasting	Wind power	Time series analysis
Sustainable development	Stochastic systems	Uncertainty analysis
Energy management	Air conditioning	Fuzzy analysis
Environmental impact	Smart power grid	Genetic algorithm
Performance assessment	Electric vehicle	Support vector
Impact assessment (Social, technical, economic, etc.)	Power transmission network	Multi-objective optimization
	Renewable energy	Random forest
	Energy storage	Decision tree
	Buildings	Artificial neural network
	Internet of things	Pattern recognition
	Energy consumption	Ant colony optimization
		Regression analysis
		Particle swarm optimization
		Data mining
		Deep learning

grid will be skyrocketed to the point that conventional models would no longer be able to model it []. With the rapid growth of energy usage and development of the renewable energies such as PV [28–30], high forecast accuracy is required in multiple time horizons to achieve better energy management and power system planning. Since such systems consist of regulations, schedules, dispatching, and unit commitment, an intelligent system is unavoidable, which can handle complex inputs and outputs [31]. Effective planning of energy systems is vital to assist in policymaking and save millions of dollars [32]. Effective planning becomes even more critical since new integrated energy systems use electricity as the primary energy source. These intelligent systems should predict energy generation from renewable sources and energy demand to generate the deficit energy demand near the demand location to minimize losses.

Another implementation of AI is in energy storage. ML is very capable in data classification and regression, and other related tasks. AI and ML can efficiently utilize energy storage in the energy grid to shave peaks or use the stored energy when these sources are not available. ML methods have recently been used to describe the performance, properties and architecture of Li-ion batteries [33], even proposing new materials for improving energy storage capacity [34]. One of the new concepts that have gained a lot of focus in recent years is the Internet of Things (IoT). IoT imparts network and Internet connectivity to everyday objects. In IoT, every physical entity can be considered a “thing,” such as vehicles, buildings, appliances, humans, etc. [35,36]. These systems aim to minimize energy consumption, costs, and emissions by optimizing electricity flow in the grid by reducing power drawn and increasing power supply [37].

In this study, the interaction between the energy-related areas with ML and how AI can be implemented in these areas is investigated; identifying the existing network between authors and topics, journals and finally, determining the gaps in which ML can be implemented. A bibliographic review of AI, ML, and the most common energy-related terms to achieve this goal is performed.

2. Common machine learning methods and approaches

ML as a branch of AI focuses on learning and modifying the process

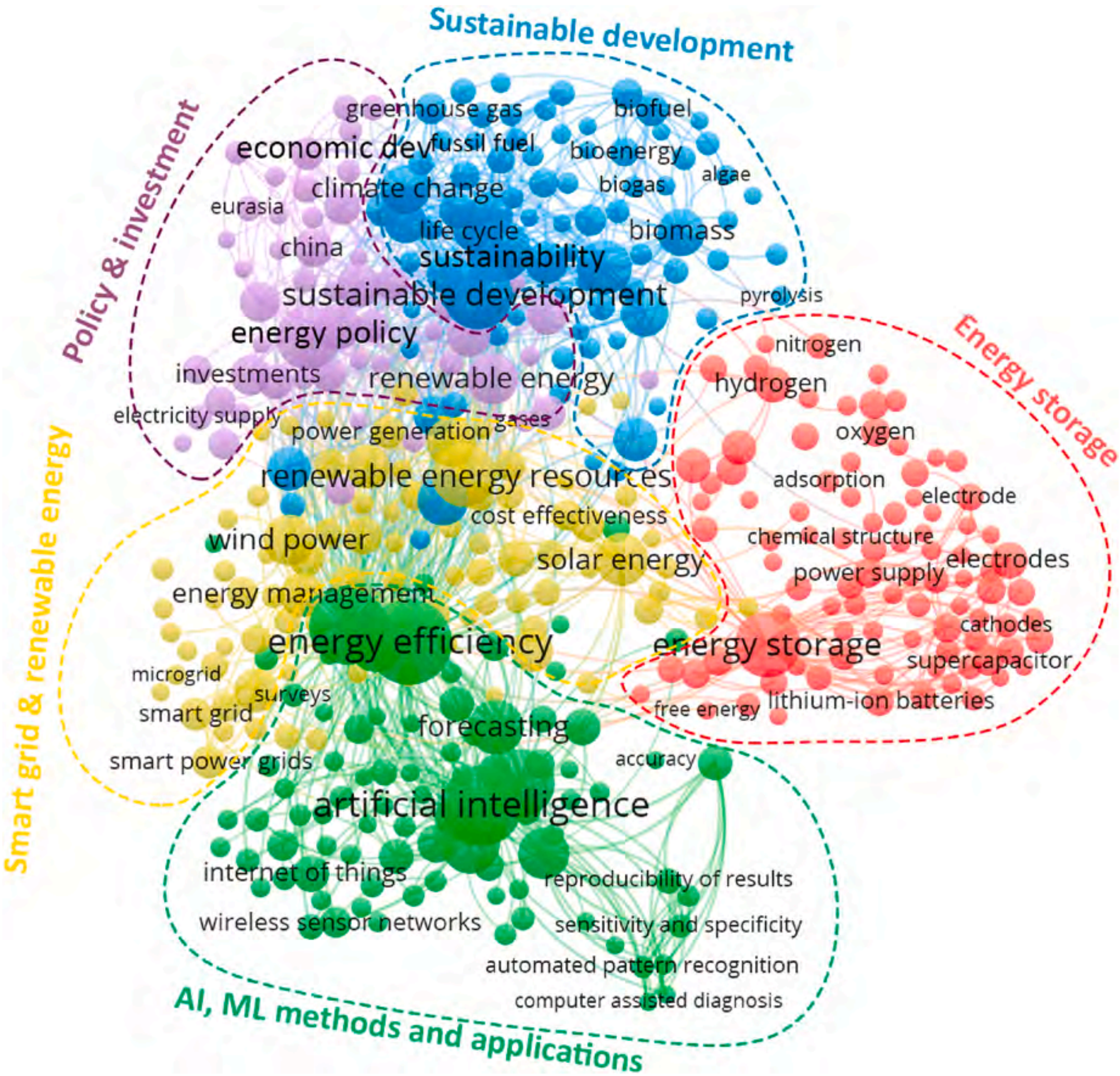

Fig. 4. A comprehensive network of energy, artificial intelligence and machine learning with other energy-related areas such as energy storage, security, reliability, supply, sustainability, policy and renewable energy.

or making new decisions based on newly acquired data [38]. In recent years, ML techniques and big data methods have significantly improved the modeling of systems by deciding complex factors or even physical properties such as material, etc. ML models can now easily outperform humans in terms of both speed and accuracy [39]. The most used ML methods and approaches are listed in Table 1.

We contend that AI and ML have become an inseparable part of energy systems; the results from numerous pieces of research are the seal of approval on this claim.

3. Methodology

A bibliographic review is a research field that finds the traces between topics, keywords and authors to map a connection between them to identify trends and focuses in publication activities. These types of reviews guide researchers on how previous works progressed over time and where they might lead in the future. A bibliographic review is important since it will illuminate their connections and show which areas are more entangled while others are without any connections. This reveals areas that have received less attention and have the potential to be explored.

Many softwares are designed for bibliometric analysis [48]. However, VOSviewer software is one of the most suitable software used to create network maps and data. This software was developed by Nees van Eck and Ludo Waltman (2009). Maps extracted by this software contain items (such as keywords, publications and researchers) that are of interest of the user. Each map contains only one type of item. There can be a link between each pair of terms that expresses the relationship between the two. This connection is marked by bows. Items and links together form a network. Items are grouped into clusters that usually have related topics.

To achieve the goal, VOSviewer software [49] is used to perform the bibliographic analysis and investigate the connection between different research areas. VOSviewer is free software developed by N.J.V. Ech and L. Waltman with the help of the University of Leiden. This software constructs the network and bibliometric maps on the co-occurrence of data based on keywords, authors, journals, etc. For the initial stage, we limited our search terms to "artificial intelligence," "machine learning," and "energy" keywords to identify studies in this area. In the next stage, we added additional keywords related to the energy section to explore neglected fields and identify gap areas. The following keywords were used in the second stage to attain the results: Artificial intelligence;

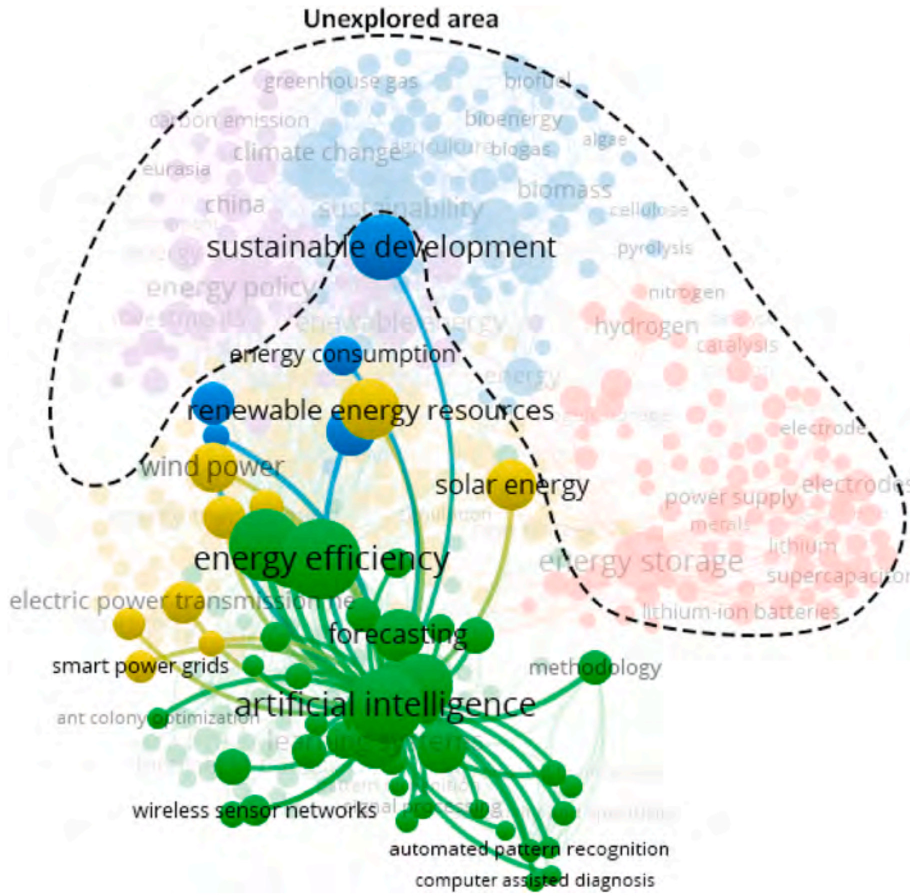

Fig. 5. Network connections of artificial intelligence and unresearched gap areas.

Machine learning; Data mining; Energy; Storage; Security; Reliability; Supply; Sustainability; Policy; Renewable energy. In both stages, each keyword is searched separately and the results of all keywords are imported into the VOSviewer simultaneously.

We used the Scopus database to identify the 2000 most cited and 2000 newest articles for each keyword in each stage. This is important since it grants us the ability to investigate the most influential research and recent trends in this field. These data were extracted from the Scopus database in December 2020. Fig. 1 shows the overall procedure (4 steps) for stages 1 and 2, from selecting keywords and extracting data from the Scopus database to classification and mapping the results.

In the third stage, we compare the results from the two previous stages to identify the gap areas. And in the final stage, we run an additional study on journals that the research results in the field are published into.

4. Results and discussion

Although artificial intelligence (AI) and machine learning (ML) are not new concepts and have been around since the mid-fifties, the first paper in the energy-related field was published in 1969; however, due to various reasons, namely insufficient computational power, such a method weren't very attractive. From 2000, with advances in computer technology, AI gains more focus, and papers in this area increased by incredible growth. ML-related papers showed a slower increase from 2000 to 2014, but after 2014 there was a virtual explosion in studies; the number of papers sharply increased to the point it became ten times the number in 2014 in 6 years. Fig. 2 shows the number of papers related to artificial intelligence and machine learning in the energy field.

4.1. *Co-occurrence analysis*

This analysis identifies the most frequently used keywords in the title, author's keywords, and abstract of the papers to create a map to connect keywords used in the paper. The strength of this link measures the number of papers that have these two keywords in them. In other words, generated network map demonstrates the repentance of a keyword in the papers and the like hood of other link keywords with that keyword in the paper.

Fig. 3 shows the connections between artificial intelligence and machine learning in the energy field. Four major clusters, each referring to a specific field of research, build up the entire map for this network. These sections are artificial intelligence and its applications in energy efficiency and utilization (Blue); Machine learning and its related methods for Forecasting (Yellow); Algorithms and pattern recognition for learning systems (Green); Energy sources and users, transportation and management (Red). Table 2 shows the most effective implementation of AI and ML in energy, identifying target systems, using techniques and goals.

By including important energy fields such as energy storage, security, reliability, supply sustainability, policy and renewable energy, Fig. 3 can be expanded to cover all aspects of energy in our modern society. As we see in Fig. 4, the upscaled network consists of 5 main sectors including: AI, ML and their methods and applications (Green); Smart grid management, renewable energy and electricity consumers (Yellow); Energy policy, investment, economic development and social aspects (purple); Sustainable development, fossil fuels, greenhouse gasses, carbon dioxide and environmental impact (Blue); Energy storage, batteries and hydrogen (Red). As can be seen in Figs. 3 and 4, mapping a network of AI and ML with important energy fields provides an opportunity to identify unexplored and neglected areas that has the

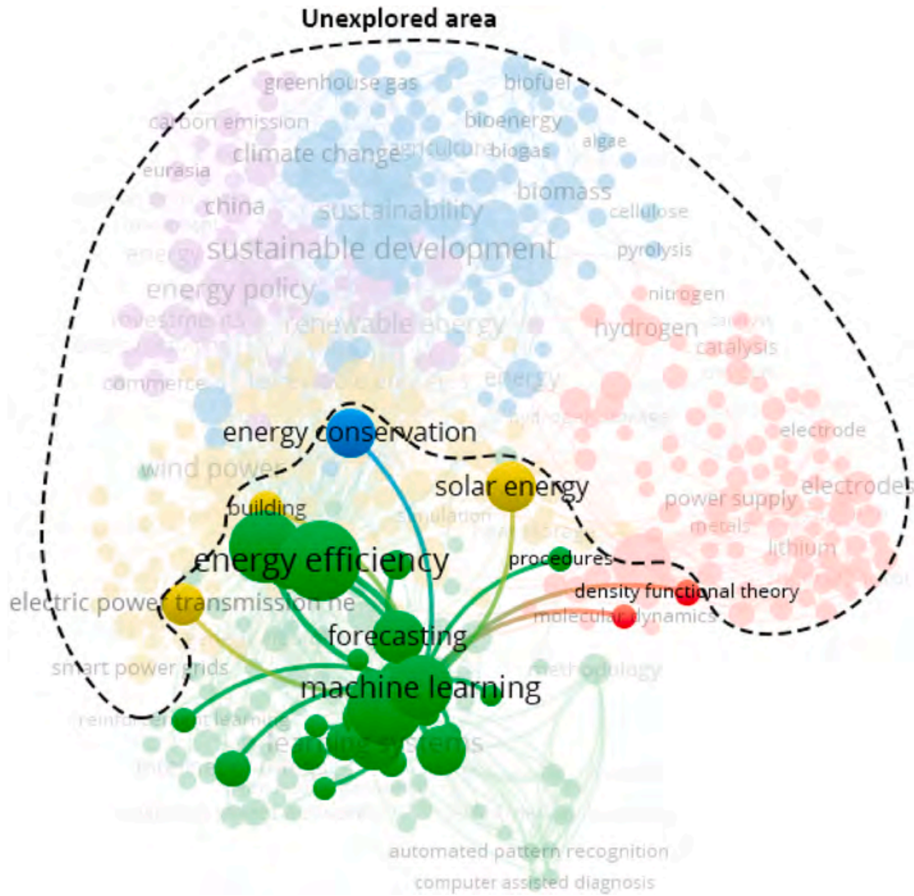

Fig. 6. Network connections of machine learning and unresearched gap areas.

potential to explore in the future.

Network connections of AI in Fig. 5 demonstrate the potential of expanding research in unexplored areas. The unexplored researched area mainly consists of topics related to energy storage, batteries, hydrogen-related areas like fuel cell, environmental assessments, biofuel, fossil fuels, climate change, carbon, policy and investment. As for ML, as demonstrated in Fig. 6, a smaller network can be seen compared to AI. The existence of the unexplored researched area maybe because, as we saw in Fig. 2, although articles in ML are virtually exploding, however, since it is a relatively new field, it hasn't expanded to other areas yet. The potential area for expanding the usage of ML in addition to the areas mentioned in the AI section can be listed as Heat storage; Thermal energy; Molecular and crystal structures, for example in batteries; Agriculture; Carbon capture techniques like those with the help of algae; Life cycle assessments; Environmental management; Economic and investment; Energy planning; Renewable energies like the wind; Uncertainties analysis; and many other usages.

4.2. Research trend

To study the research trend in energy-related topics, specifically AI and ML, we used VOSviewer software to feature a timetable related to the researched papers. Figs. 7 and 8 show the research trend in all energy fields and AI- and ML-related energy fields, respectively. Since trend analyzing requires reviewing the newly submitted papers, as mentioned before, we included both the highest citation and recent papers to perform a comprehensive analysis to map an accurate timetable.

Regarding the most important topics in the energy field, as demonstrated in Fig. 7, our findings pointed out that in the 2012 to 2014 period, most of the research was investigating different fuel technologies such as hydrogen, ethanol, biofuels, etc. From 2014 to 2016, as we see in Fig. 7, concepts like sustainability and sustainable development was dominating most of the research. Naturally, sustainability-related topics such as environmental impact, global warming, greenhouse gasses, carbon dioxide, life cycle assessment, and climate change also gained a lot of attention. Furthermore, clean energy sources, namely wind and solar, gained focus. This research could be traced back to the united nations climate change conferences (UNCCC) and conferences of the parties (COP). The COP18 to 20, which coincides with the period of 2012–2014, was trying to reach an agreement on adopting programs like the "Green Climate Fund" and "Climate Technology Centre" by the states' parties; and the second period of the Kyoto Protocol commitment [50–52]. It is entirely plausible that during this period, researchers tried to introduce new technologies to reduce carbon dioxide emissions either by reducing the consumption of fossil fuels or introducing alternative fuels. From 2014 to 2016, coinciding with COP 20 to 22, researchers were trying to propose new technologies and improvements to adapt to the goals of the Paris agreement [53].

With the formation of governments' policies regarding sustainable development and the emergence of new technology in harvesting energy, from 2016 to 2018, the scientific society focused on concepts like energy efficiency, energy utilization and proposing alternative energy sources [54]. In this period, the smart power grid was the leading topic followed by energy storage technologies either for mobile or stationary uses. As discussed previously, although the AI concept emerged in the mid-fifties, energy-related usage of this concept is very new. Fig. 8 shows the trend of AI- and ML-related topics in energy fields. The oldest researches in this field are related to methodologies, algorithms, pattern recognition and image processing circa 2012 to 2014. In the following period, from 2014 to 2016, energy-related topics like optimization gained focus. Also, decision support and energy management were some other popular researched topics. Finally, 2016 to 2018 can be named the

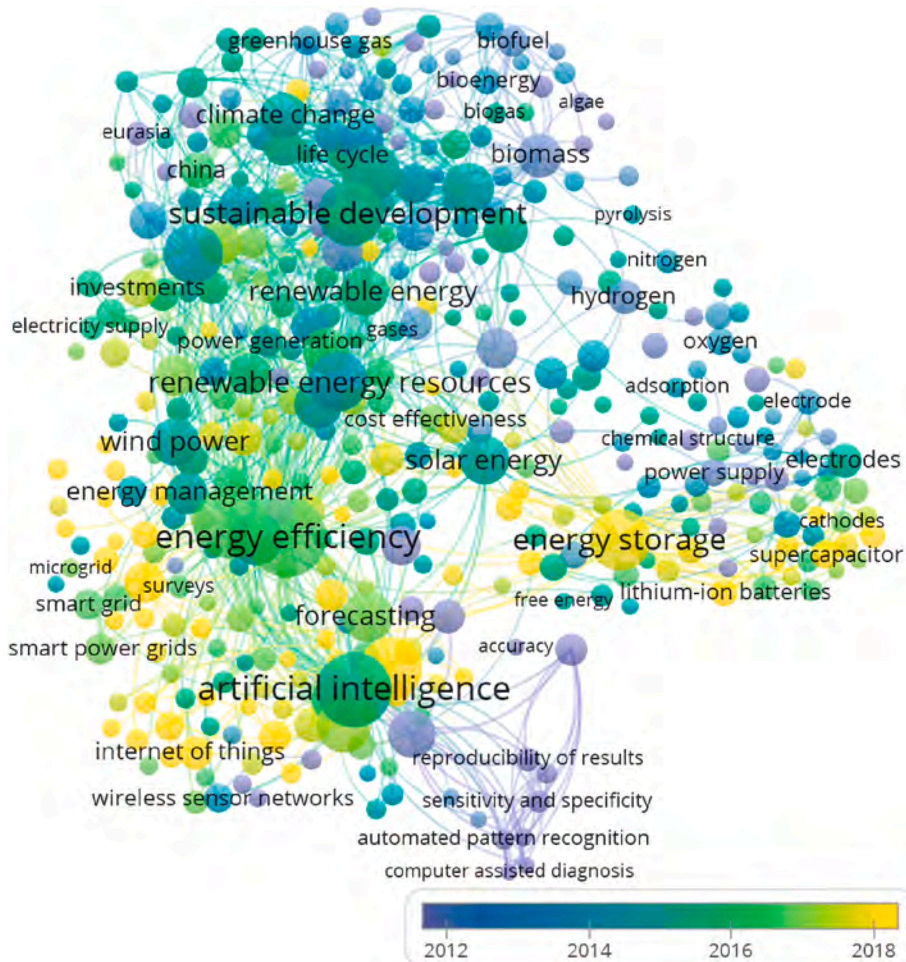

Fig. 7. Research trends of most essential topics in the energy field.

start of the AI and ML era. In early 2016, neural networks and learning systems gained lots of focus, followed by learning algorithms, forecasting, decision-making, and smart grids circa 2017. In 2018, ML and many related topics, namely energy efficiency and energy utilization, decision tree, solar power and wind power, were popular. Finally, in 2019 and 2020, concepts such as predictive analysis, deep learning and the Internet of things emerged.

It should be noted that the data used for all the figures cover the data that includes the 2000 most cited and 2000 most recent papers for each of the energy-related topics from 2010 to 2020. Although the scaling of the timetable in these figures is till 2018, indeed these figures also include research from 2018 to 2020. Since the number of research till 2018 is more significant than the following period, scaling the timetable from 2012 to 2020 couldn't demonstrate a distinctive contrast between different years. For better visualization and to project a better color gradient for time table in some figures we have changed the coloring setting to focus on 2012–2018. Any research conducted after 2018 has been shown the same color as those of 2018 (i.e., yellow).

Finally, we should conclude that, as shown in Fig. 9, topics like sustainable development, energy policy, energy efficiency, utilization and storage and renewable energy resources are the main topics in the energy field, which can be integrated with ML to further create new possibilities.

4.3. Research gaps

Based on our findings, we propose a list of research gaps in the AI and ML field in Table 3. This list consists of many challenges that are trending among researchers in recent years. We suggest that using ML-provided tools will significantly assist future research in these areas to reach a comprehensive result.

As we can see in Table 3, some of these topics have been covered in more detail and some were less noticed such as Uncertainty analysis, Risk assessment and Demand response. The lack of connection between the topics may be due to the lack of research, or the weak strength of the connection line which indicates the small number of studies on the desired topic.

4.4. Journals in the energy field

To better understand the research in the energy field, we also analyzed the publications in top journals in this field. Fig. 10 shows the journals in that most of the research in energy fields is published. This figure also shows the research trend based on research submitted to different journals. It can be seen that research about any topic is firstly published in journals that feature innovation, such as Nature and Science; After introducing the ideas in these journals, specialized journals will publish research results on these topics in more specific usages. Most recent publications in the energy field have been published in journals such as energy storage, advances in intelligent systems and chemical engineering journals. Based on this figure, we can conclude that intelligent systems with the ability to store electricity are being approached from different aspects.

Fig. 11 also shows the number of research submitted in different journals from 2010 to 2020. As can be seen, renewable energy, cleaner production and energy policy has published most of these research.

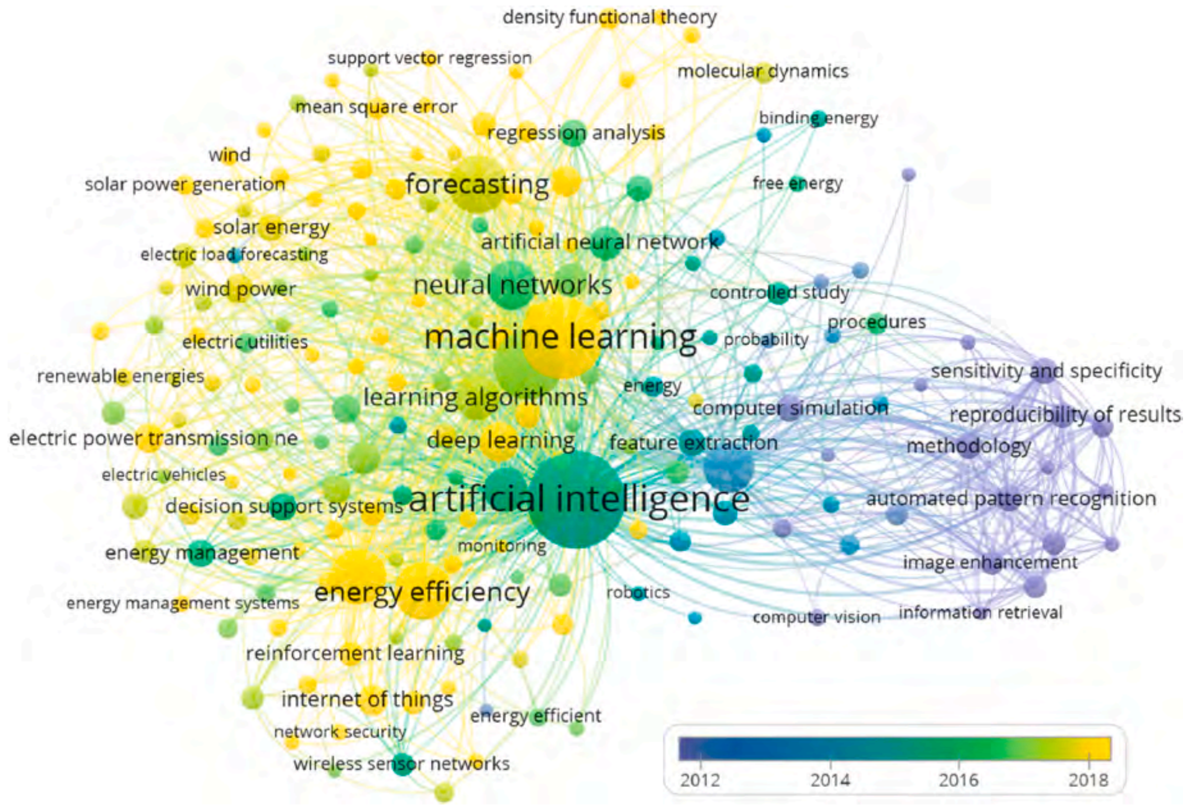

Fig. 8. Research trends of artificial intelligence and machine learning related topics in the energy field.

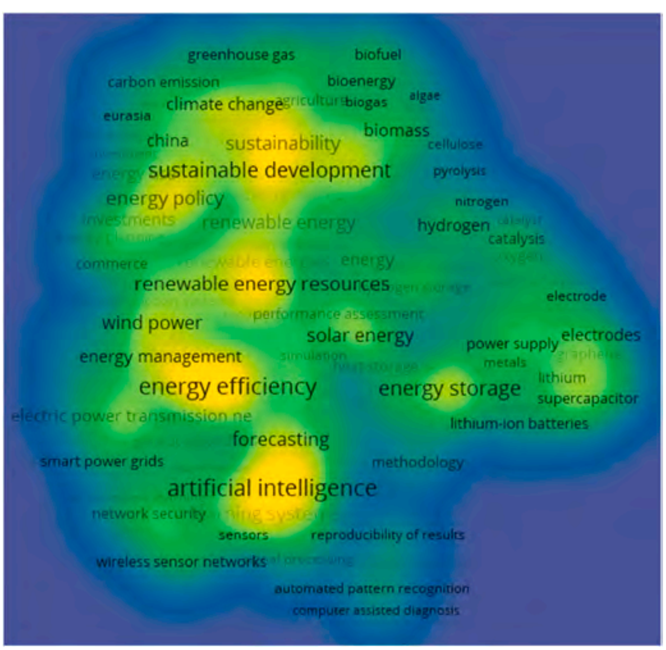

Fig. 9. The main focus of research topics in the energy field.

Comparing Figs. 10 and 11 shows that although renewable energies had a lot of focus in the past (circa 2016), there is a possibility that this focus can be shifted in the near future, and ML can play a significant part in it.

Figs. 12 and 13 also illustrate the trend and important journals in AI and ML-related topics in the energy field and the number of researches submitted compared to other journals. As we see, early publications are related to computer science. The journals with the most published in this field from highest to lowest based on the papers we analyzed are advances in intelligent system, applied energy, energies, energy, energy and buildings, renewable and sustainable energy reviews, journal of cleaner production, energy conversion and management, sensors and renewable energy.

4.5. Patents in machine learning

At the end of this report, we intend to review the number of patents in ML in the energy field to determine how much the concept of ML is integrated into the industry. To achieve this purpose, we used Google Patents to investigate the patents submitted in this field. We limited the patents by filtering the keywords “Energy” and “Machine Learning” between 1985 and 2020. Fig. 14 compares the number of submitted patents with the number of submitted papers with the exact keywords. As we see, a significant number of patents are submitted in this period, summing up to 255,551, which is 17 times the paper submission with a total of 15,028 in the same period. However, the increasing trend of paper submission can also be seen in the number of patents submitted which sharply increased from 2010 and reached its max number in 2018 before dropping to a number similar to that of 2012. Decreasing the number of patents submitted in 2020 could be due to the Covid-19 pandemonium; nevertheless, there is no reason to justify a significant reduction in the number of submitted patents in 2019 after a period of sharp increase. To examine more closely and find the cause of this decline, we examined the number of patents filed in 10 widely used areas of machine learning separately. The result of this study is demonstrated in Fig. 15. It can be said that in 2018, a change in the growth trend of the number of submitted patents can be observed. As we see in Fig. 15, solar, energy storage, wearable and air conditioning sections show a decline in submitted patents after a peak in 2017; Wind, buildings, Internet of things and energy consumption and management, sections show a decline in submitted patents after a peak in 2018; Also, smart grid and electric vehicles have a peak in 2019.

Table 3
Research gaps in AI and ML.

<table>
<tr><th>Research gap</th><th>Connections</th></tr>
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Energy storage

There are many possibilities to employ AI and ML to create a smart energy storage system, such as:

- Household PV battery storage system [55]
- Cutting down the electricity bill with smart management [56]
- Battery management in electric vehicles [57]
- Prognosis of battery health [58]
- Optimizing renewable energy generation at different hours of the day [59]
- Prediction of the online capacity of Li-ion batteries [60]

•Heat storage systems [61]

- Phase change materials or systems [62]
- Creating new materials for storage [63]
- Management, optimization, material development, the prognosis of status, or predicting the demand.

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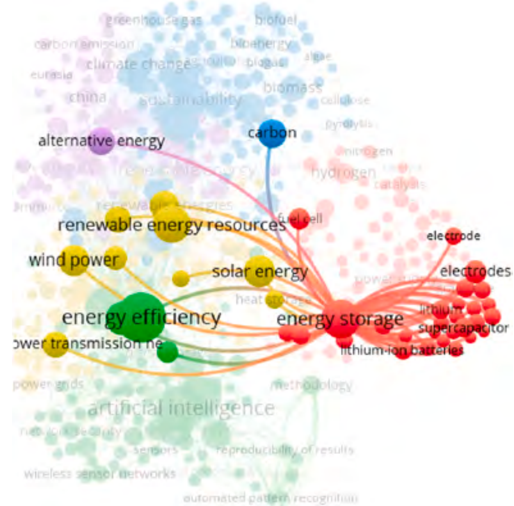

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Uncertainty analysis

Undoubtedly uncertainties are one of the major challenges in the forecasting of many energy systems such as:

- Forecasting energy load in smart grids [64]
- Considering energy scheduling and uncertainties in supply and demand in microgrids [65].
- Forecasting renewable energy generation like wind [66] and solar [67].
- Uncertainty quantification of Heat storage from short-term sources [61]
- Maintenance prediction for manufacturing plants [68] or other faculties.
- Improving the performance of low-cost sensors [69].

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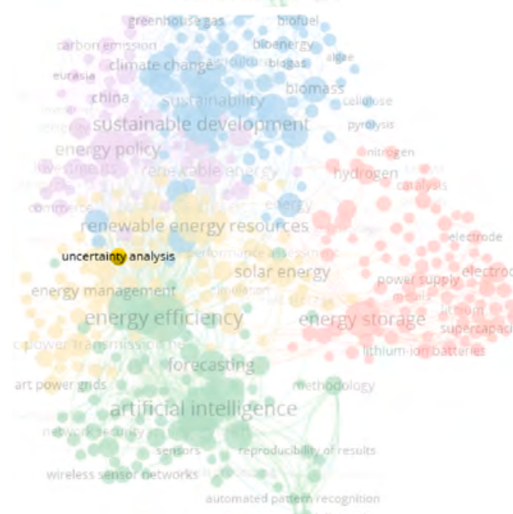

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Wastewater management

Wastewater is one of the areas that depend on many different factors, and optimizing these factors to manage wastewater efficiently is a challenging task. Some of the promising applications in this field are:

- Improving wastewater treatment with ML methods [70]
- Predicting the amount of waste based on ML methods to create a smart system in water treatment plants to create a real-time predictive control of wastewater treatment [71]
- Creating a smart waste management microgrid [72]
- Using the Internet of things to manage household wastes [73].

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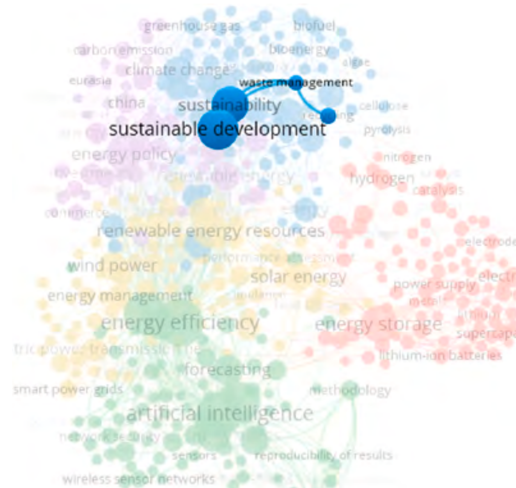

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Emission control

Reducing or controlling greenhouse gas emissions, especially carbon dioxide or other harmful pollutants, is one of the challenges in sustainable development and global warming. ML methods can be used to:

- Accurately predict the CO_2 emission [74]
- Predicting cooling and heating loads for energy-efficient design of office buildings based on occupancy behavior [75] or other public buildings such as convenience stores [76].
- Forecasting carbon trading volume and price [77].
- Or other applications like smart monitoring to control combustion based on powerplant loads to reduce the emission rate of pollutants [78].

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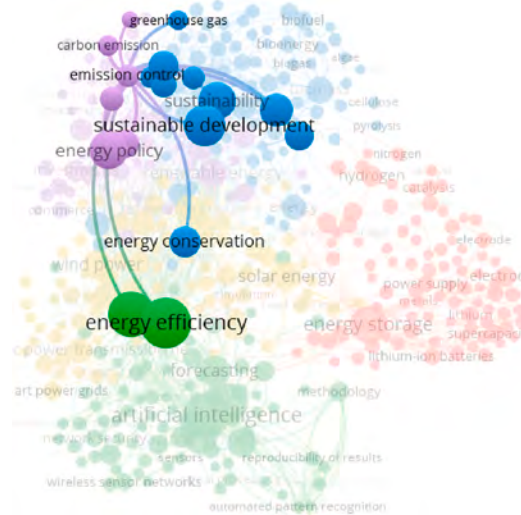

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Biofuel

ML methods can be very beneficial for optimizing biofuel production and forecasting. This method can be used to:

- Explore critical factors in algal biomass and lipid production in renewable fuels production [79]
- Forecasting future biomass yield from crops [80].
- Studying climate change's effect on carbon flux [81] as one of the main factors in algal biofuel production.

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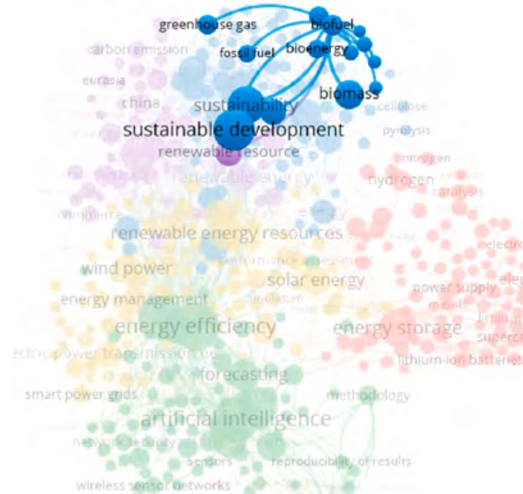

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Supply chain

Some of the applications in this section are:

- Enhancing the resiliency and sustainability of energy, food, or water [82]
- Integrating ML methods in the feedstock supplier selection process [83], for example, biomass fuel production or other fuels [84].
- Creating a smart supply chain and energy grid to predict energy usage and operate power plants to meet demand [85] to minimize fuel consumption.
- Predicting the weather and ambient conditions for energy peak shaving in smart grids [86].

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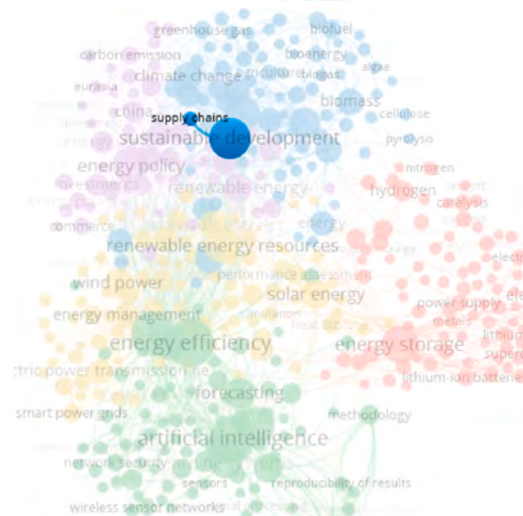

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Table 3 (*continued*)

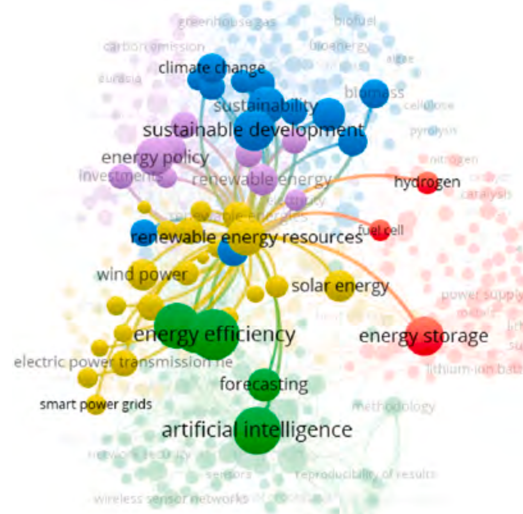
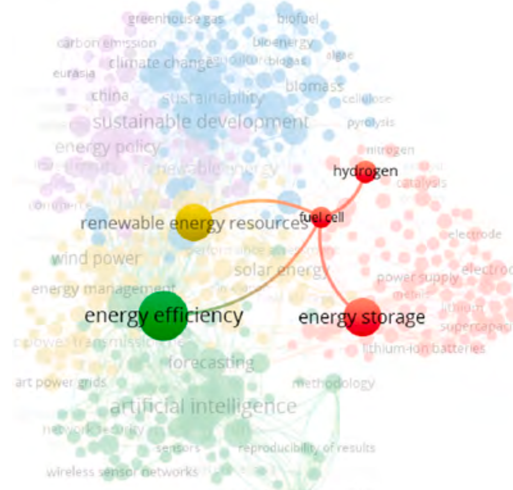
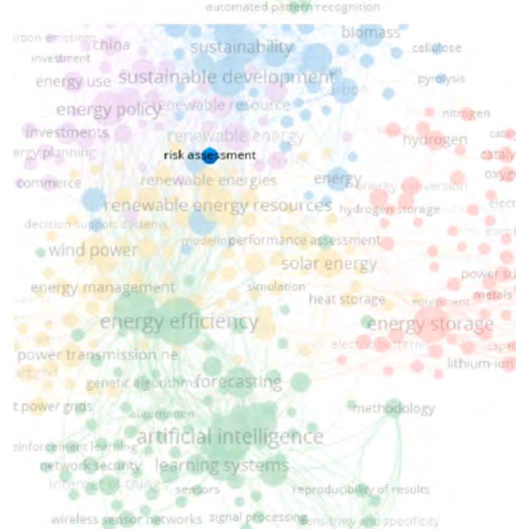
Research gap	Connections
Renewable energies Due to the instability of renewable energy production, having an accurate prediction of how much renewable energy is available is very important. ML methods can be employed to: • Perform a very short-term probabilistic prediction of renewable energies [87] • Forecasting daily solar irradiance for power generation [88] • Calculate power generation forecasting based on wind speed [89] • Accelerating the discovery of new materials in developing clean energy [90]	
Fuel cells Optimizing the efficiency of fuel cells and hydrogen generation are some of the ML applications in this area. Here are some of the possible applications: • Guiding high-temperature PEM fuel cells for operating in higher power density [91] • Predicting SOFC voltage [92] • Modeling hydrogen production [93] • Predicting degradation of PEM fuel cell membrane [94] • Designing new materials for hydrogen storage [95]	
Risk assessment Human behavior and other technical factors play a significant role in systems performance. One of the applications of ML is in risk assessment proposes, such as: • Risk analysis for the demand side [96] • Developing assisting tools for safety and decision-making in nuclear power plants [97] or other risk areas • Safety assessment in the exploration and exploitation of oil and gas [98] • Network reliability by probabilistic day-ahead forecasting [99]	

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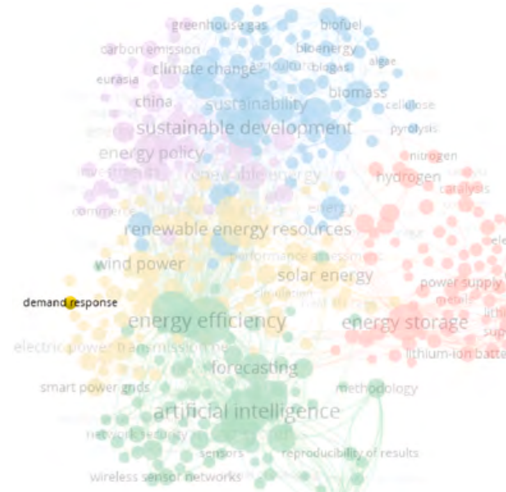
Table 3 (*continued*)

Research gap	Connections
Demand response Predicting demand is one of the challenges in energy management. One of the tools that can be used for this proposal is ML. Some of the ML applications are: • Decision-making in demand response management [100] • Forecasting power consumption in residential and commercial buildings [101] • Occupancy modeling in buildings [102] • Retail electrical markets modeling with demand response [103] • Demand response algorithms for smart-grid-ready residential buildings using machine learning models [104]	

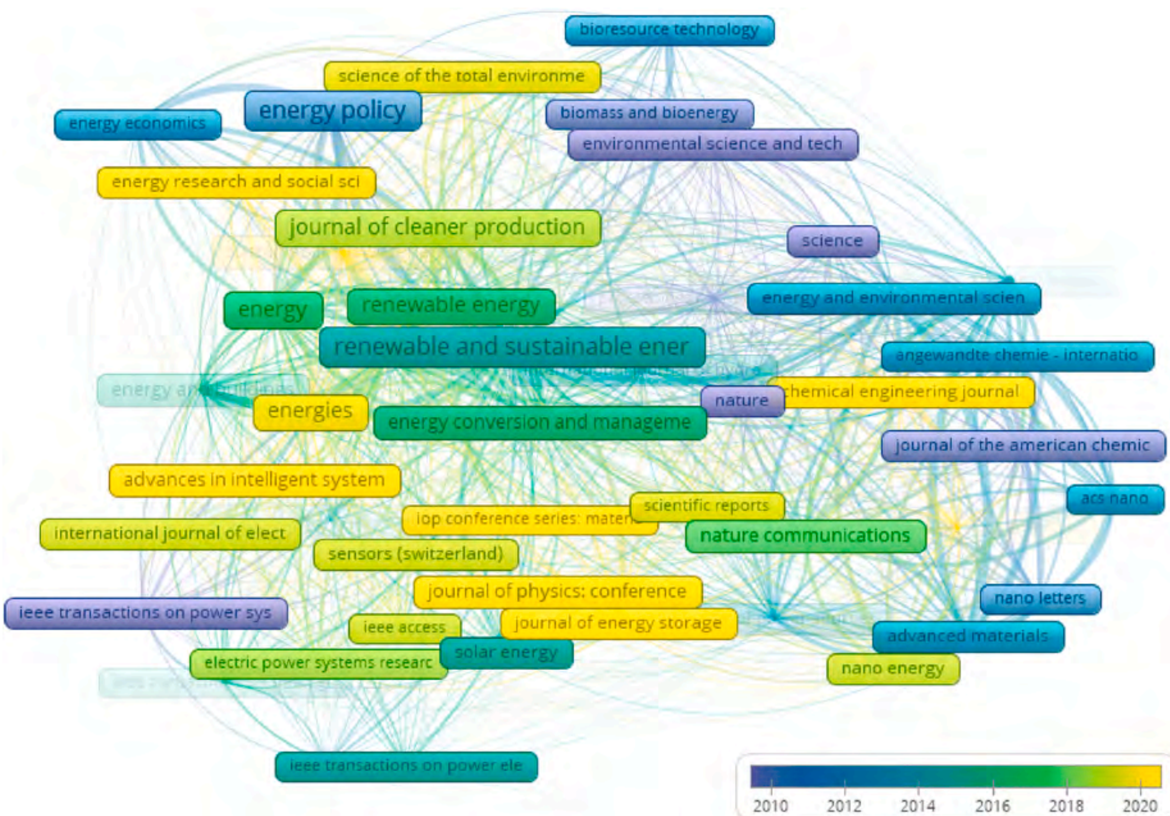


Fig. 10. Most important journals in the energy field and trend of research submitted in different journals.

If we consider the growing trend of a technology, after the growth and development stage, there is usually a period of stability, after which the technology may grow again or decline due to the inefficiency of technology. However, a sharp decline after a sharp rise is very irrational and unrealistic.

Since the data is insufficient for a definitive statement, the future of ML may not be entirely clear. This declining trend may show that ML has not been able to compete with static models and demonstrate its superiority in this area, resulting in this technology experiencing a declining trend in the coming years. Nevertheless, we argue that this drop in patent submission might be temporary; since papers in ML are exploring new fields, we should expect another increase in the number of patents in the following years.

It should also be noted that, as shown in Fig. 16, based on the results of the Google Trend, over the past five years, there is a slow increase in the interest rate of search terms that include both “Machine learning” and “energy.” Indicating that a drop in the number of submitted patents might be due to the saturation of the patent conceptualization phase and moving to the manufacturing phase. Or simple might be due to the increasing number of searches in the academic section and related

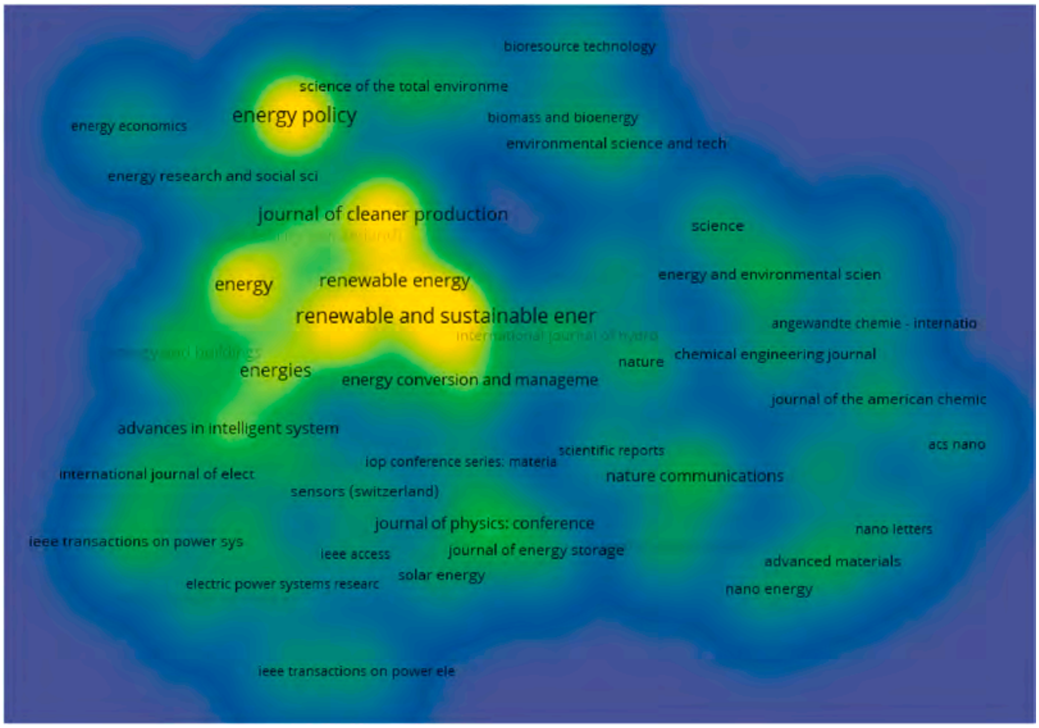


Fig. 11. The number of research submitted in different journals.

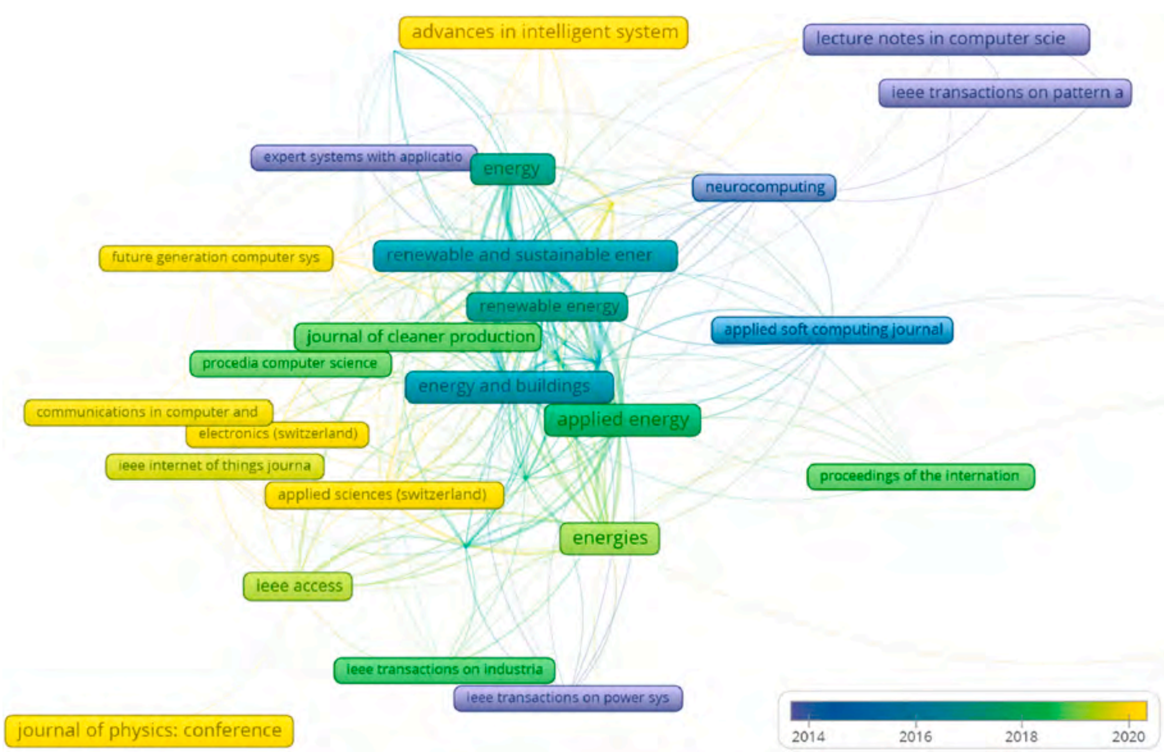


Fig. 12. Most important journals in AI- and ML-related topics in the energy field and the trend of research submitted in different journals.

scientific papers.

Another matter that can be considered a confirmation of this statement is equality in the number of patents submitted by inventors and assignees, indicating that new technologies in this field are emerging. Fig. 17 illustrates the top 5 assignees, inventors and Cooperative Patent Classifications (CPCs) in the top 1000 results by filing date in machine learning in the main sections of the energy field (sections specified in Fig. 15). Usually, patent submission has many inventors and few assigners initially; but with the maturity of the technology, this ratio reverses and assigners dominant the patent submission. As we see in Fig. 17-A&B, the number of assigners and inventors are comparably similar, indicating that this field is new and individuals and corporations

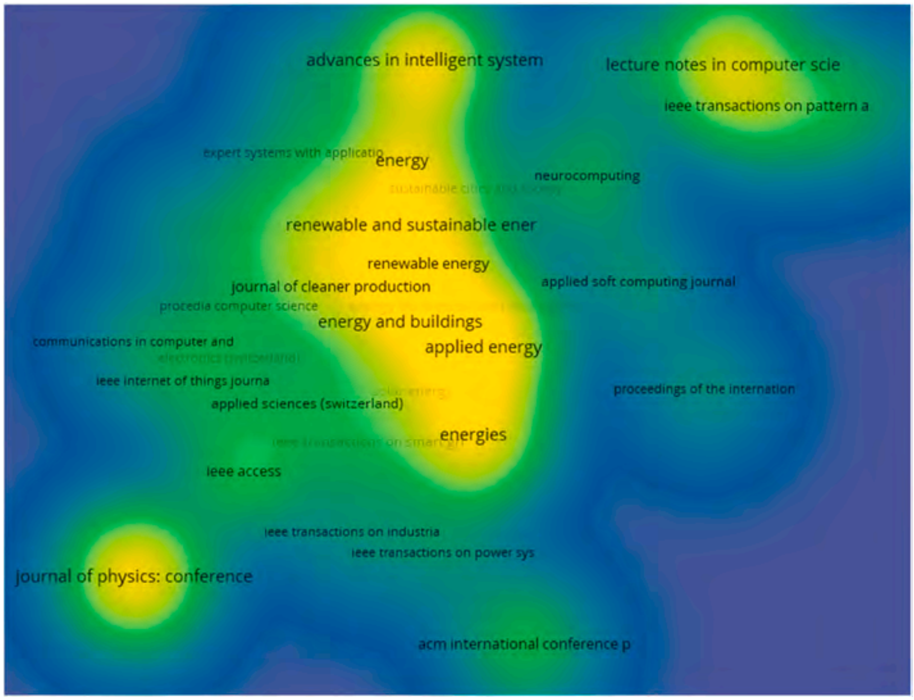


Fig. 13. The number of research submitted in different journals in AI and ML-related fields.

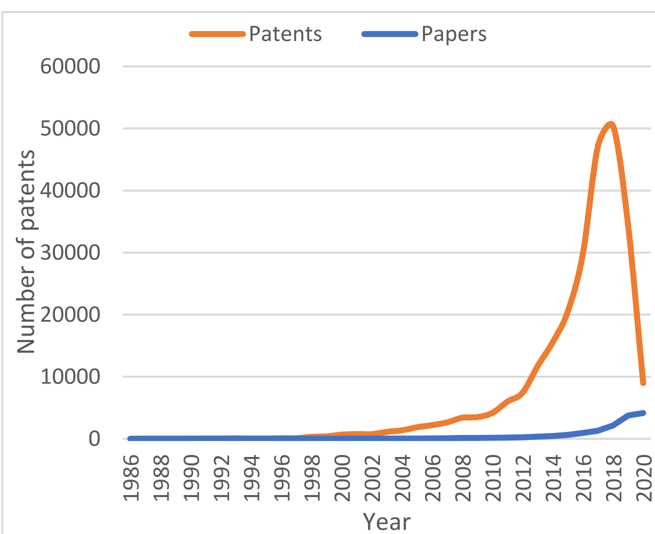


Fig. 14. The number of patents in machine learning in the energy field (1985–2020).

both submit new patents.

For a better understanding of which section these patents belong to, CPCs can be very useful. CPC is a patent classification jointly developed by the United States patent and trademark office and the European patent office. Table 4 listed the top 5 C PCs and what section and class they are related to.

5. Conclusion

The concept of artificial intelligence (AI) and machine learning (ML) is for computers to simulate humans' learning and decision-making capabilities. With advances in computing systems, AI and ML have become increasingly important areas in many different branches of science and industry. The energy section is also one of the areas that can benefit from AI and ML. To investigate the current standing point of AI and ML in energy-related areas, we used VOSviewer software to investigate and review the relatively new usage of AI and ML in the energy field and propose promising or neglected areas in which these concepts can be used.

The results showed that from 2000 AI gains an increasing focus, especially after 2014 when the number of articles in ML skyrocketed. And in 6 years become 10 times more compared to 2014. Although there have been many papers in different fields of energy that introduced new usages of AI and ML in that section, due to the vastness of energy usage and respected fields of it, obviously, in no way the available articles could cover all these areas.

By analyzing the occurrence of the AI and ML energy-related keywords in the articles, we find out that the current literature can be divided into 4 major groups: (1) AI applications in efficiency and utilization; (2) ML for forecasting; (3) Algorithm and pattern recognitions for learning systems; (4) management and transportation of energy sources. Including important energy fields in our analysis showed that AI and ML currently are employed in a small section of all the energy-related field and has promising potential to integrate into other sections. Our study revealed many promising and neglected areas where AI can be implemented. Some of these sections are energy storage, uncertainty analysis, wastewater treatment, emission control, biofuel production, energy supply chain, renewable energies, risk assessment and demand response. As for the ML, in addition to the unexplored areas mentioned in the above sections, heat storage, thermal energy, carbon capture techniques, environment management, economic and investment, renewable energies and uncertainty analysis can be identified.

Researchers in these areas are suggested to explore the benefits of AI and ML in their respective research field to explore new possibilities.

Studying the timetable of the literature revealed that from 2012 to 2014 most studies were about different fuel technologies such as hydrogen, ethanol, and biofuels. Later in the next two years, concepts like sustainability and sustainable development was dominating most of the literature. Topics such as environmental impact, global warming, greenhouse gasses, carbon dioxide, life cycle assessment, and climate change also gained a lot of attention. Furthermore, clean energy sources, namely wind and solar, gained focus. In early 2016, AI concepts began to

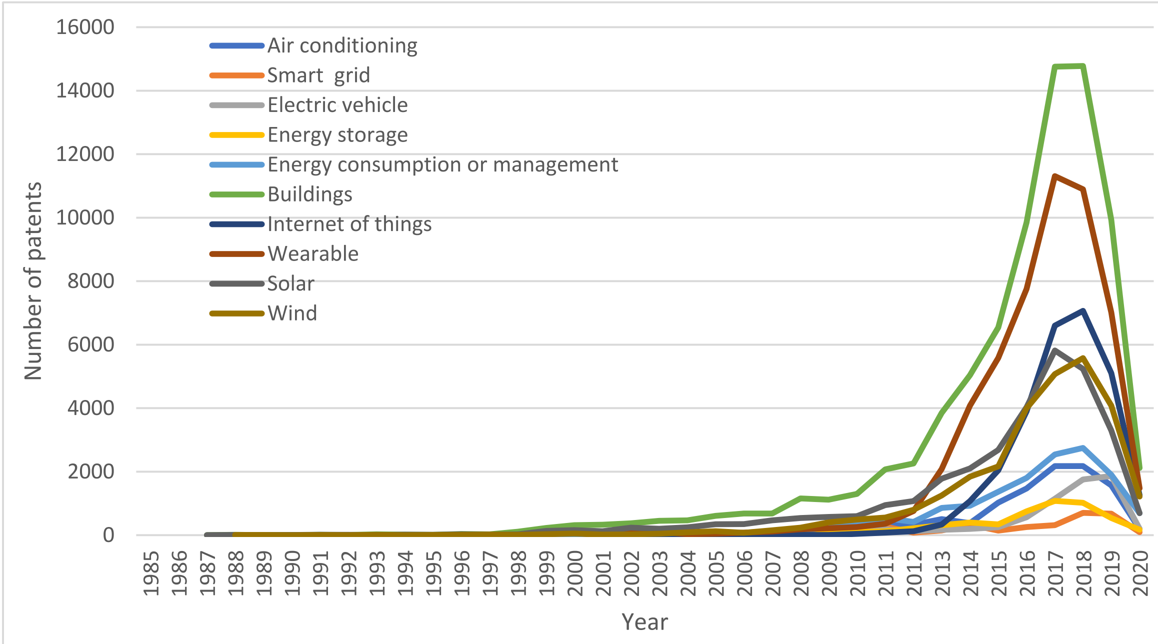


Fig. 15. The number of patents in machine learning in the selected energy field (1985–2020) [105].

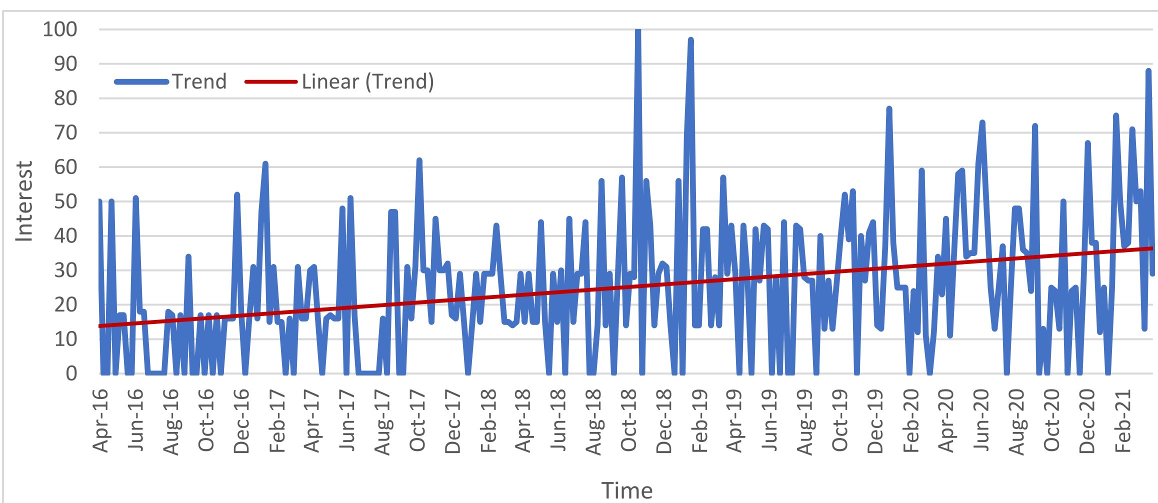


Fig. 16. The interest rate of search terms that include both "Machine learning" and "energy" in the past five years [106].

emerge. In 2017, research focused on forecasting, decision-making and smart grids. Later, ML concepts of energy utilization and renewable energy emerged in 2018. Predictive analysis and deep learning studies are more focused on in 2019 and 2020. The Internet of things is one of the latest trends in this field that has gained lots of attention.

We also conducted a detailed study on the journals that have published studies. We observed that as research progressed over the years the new articles in ML are mostly published in new specialized journals. Although, energy, renewable energy, renewable and sustainable energy and journal of cleaner production are journals that hold most of the publications regarding energy-related AI and ML articles.

We also investigated the number of patents submitted for AI and ML in energy-related areas to determine how much this technology has been implemented in the industry, which revealed a submission number 17 times the number of papers in scientific journals. This fact alone shows how highly AI and ML are regarded in the industry and how scientists and companies are racing to introduce new technologies. Nonetheless, the number of submitted patents shows a declining trend since 2018, after a sharp increase, making the future of ML unclear since this pattern is very unusual. This pattern could be due to the Covid-19 as sudden decrease after sudden increase in not very routine. Also, it should be noted that Google Trend shows an increase in search terms related to ML and energy so we could expect another rise in the number of submitted articles and pattents in future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

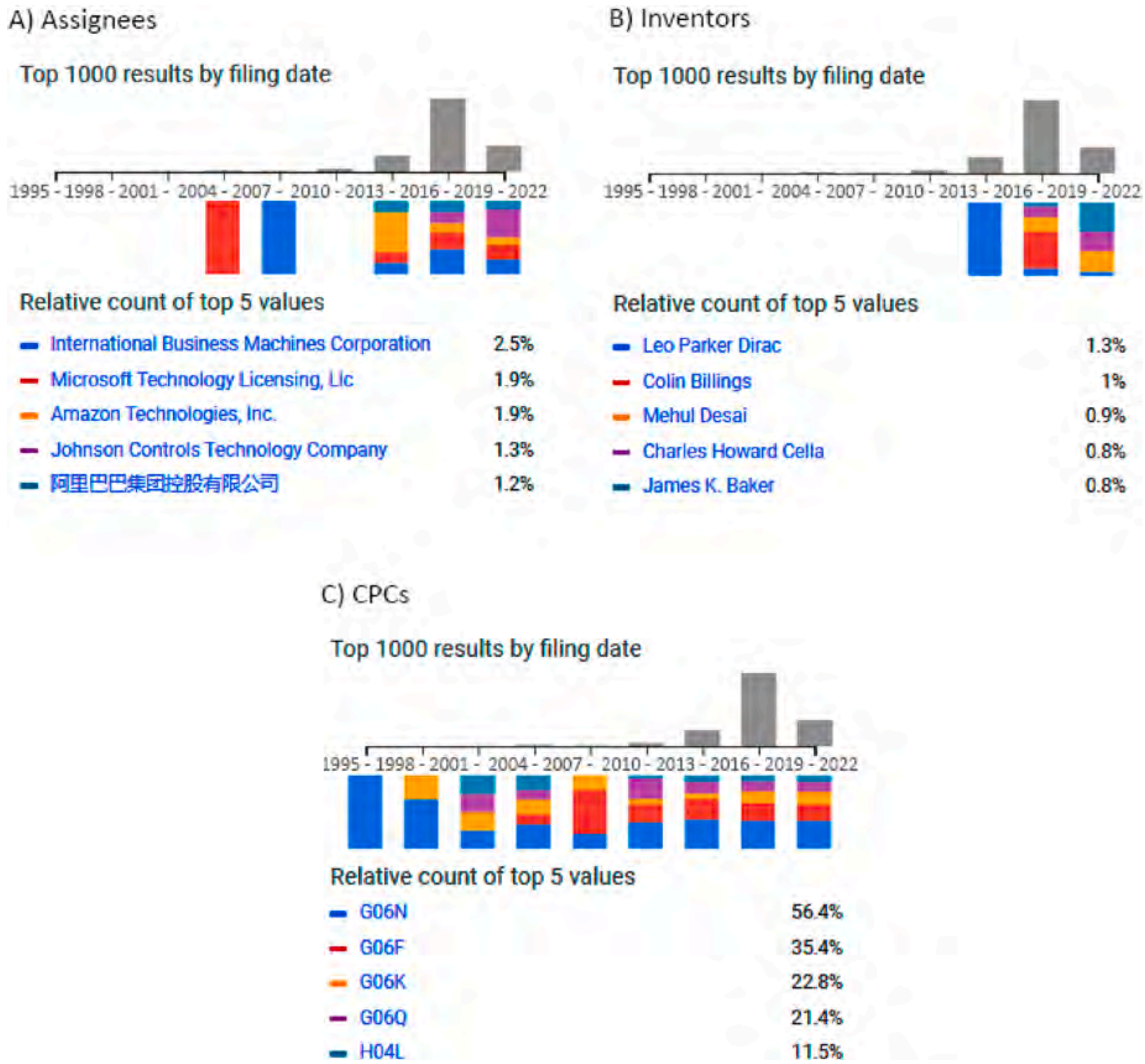


Fig. 17. Top 5 assignees, inventors and CPCs in the top 1000 results by filing date in machine learning in the energy field [105].

Table 4
Top 5 cooperative patent classifications (CPCs) of machine learning in the energy field [107].

CPC	Description
G06 N	Computer systems based on specific computational models
G06F	Electric digital data processing
G06K	Recognition of data; Presentation of data; Record carriers; Handling record carriers
G06Q	data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes; Systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes, not otherwise provided for
H04L	Transmission of digital information, e.g., telegraphic communication

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