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Systematic Review

Machine Learning Applications in Renewable Energy (MLARE) Research: A Publication Trend and Bibliometric Analysis Study (2012–2021)

Samuel-Soma M. Ajibade [1], Festus Victor Bekun [2,3,*], Festus Fatai Adedoyin [4], Bright Akwasi Gyamfi [5] and Anthonia Oluwatosin Adediran [6]

[1] Department of Computer Engineering, Istanbul Ticaret University, Istanbul 34445, Turkey
[2] Faculty of Economics Administrative and Social Sciences, Istanbul Gelisim University, Istanbul 34310, Turkey
[3] Department of Economics, Adnan Kassar School of Business, Lebanese American University, Beirut 1102-2801, Lebanon
[4] Department of Computing and Informatics, Bournemouth University, Poole BH12 5BB, UK
[5] School of Management, Sir Padampat Singhania University, Bhatewar, Udaipur 313601, India
[6] Department of Estate Management, The Federal Polytechnic, Ado Ekiti 23401, Nigeria
* Correspondence: fbekun@gelisim.edu.tr

Abstract: This study examines the research climate on machine learning applications in renewable energy (MLARE). Therefore, the publication trends (PT) and bibliometric analysis (BA) on MLARE research published and indexed in the Elsevier Scopus database between 2012 and 2021 were examined. The PT was adopted to deduce the major stakeholders, top-cited publications, and funding organizations on MLARE, whereas BA elucidated critical insights into the research landscape, scientific developments, and technological growth. The PT revealed 1218 published documents comprising 46.9% articles, 39.7% conference papers, and 6.0% reviews on the topic. Subject area analysis revealed MLARE research spans the areas of science, technology, engineering, and mathematics among others, which indicates it is a broad, multidisciplinary, and impactful research topic. The most prolific researcher, affiliations, country, and funder are Ravinesh C. Deo, National Renewable Energy Laboratory, United States, and the National Natural Science Foundation of China, respectively. The most prominent journals on the top are Applied Energy and Energies, which indicates that journal reputation and open access are critical considerations for the author's choice of publication outlet. The high productivity of the major stakeholders in MLARE is due to collaborations and research funding support. The keyword co-occurrence analysis identified four (4) clusters or thematic areas on MLARE, which broadly describe the systems, technologies, tools/technologies, and socio-technical dynamics of MLARE research. Overall, the study showed that ML is critical to the prediction, operation, and optimization of renewable energy technologies (RET) along with the design and development of RE-related materials.

Keywords: machine learning; algorithms; supervised learning; unsupervised learning; deep learning; renewable energy; forecasting; optimization

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1. Introduction

Over the years, anthropogenic activities (such as fossil fuel consumption, land use changes, and industrial production) have resulted in the emission of tonnes of greenhouse gases (GHG) responsible for global warming (GW) and climate change (CC) [1,2]. The twin effects of these phenomena have greatly hampered socioeconomic growth and sustainable development worldwide [3,4]. To this end, scientists, researchers, and policymakers worldwide have proposed the decarburization of the global energy mix in a bid to curb and mitigate GHG emissions [5,6]. The transition from fossil fuel energy economy to renewable energy technologies (RET) is considered the panacea to the social, economic, and environmental challenges posed by GW and CC [7,8]. RETs consist of clean, abundant, renewable, and sustainable energy derived from natural sources such as solar, wind, hydropower, geothermal, and biomass, among others [9,10].

The production, utilization, and storage of RETs are hampered by numerous problems despite their reported benefits. These challenges are typically associated with the design, development, and adoption/deployment of RETs [11,12]. For example, the production of RETs is intermittent, which requires efficient storage for utilization during off-peak periods. Despite the potentially abundant recoverable energy, RETs are also considered expensive and require large investments for their research and development when compared to current energy technologies [13,14]. In addition, the adoption and utilization of RETs are dependent on geographical and political factors which include access to abundant, non-agricultural, or non-forest land required for the installation of essential infrastructure. Therefore, researchers worldwide are exploring novel techniques, innovative materials, and sustainable strategies to address the outlined challenges associated with RETs.

The utilization of machine learning (ML) algorithms is among the best strategies suggested by researchers to address the difficulties presented by RETs. ML, which is regarded as a branch of artificial intelligence (AI), studies the use of machine learning models such as supervised learning, unsupervised learning and also computational methods to convert empirical data into useful models [15,16]. In addition, ML is used to acquire a better understanding of data, as well as detect and examine anomalous behavior and predict future values of any phenomena [16]. Similarly, ML models and algorithms are used to ensure supervised or unsupervised learning of patterns in data, which can be applied to [17]. Hence, ML is described as the capacity of any system to gather and incorporate knowledge using large-scale observations. Typically, the objective of ML algorithms is to enable the system to improve and extend knowledge by self-learning as opposed to programming [18]. ML is a versatile tool that can be used to leverage novel data processing platforms [19] and provides an integrated structure for integrating intelligent decision-making into various domains [20].

The literature research revealed that ML is a useful technique for addressing RET-related difficulties as well as enhancing their efficiency, maintenance, and operations. Numerous researchers from all around the world have looked into the use of ML in RETs in light of these potentials. For instance, ML approaches have been looked into to determine whether they can enable the development and incorporation of RETS technically [21]. In addition, other studies have sought to demonstrate the capacity of ML algorithms to enhance the forecasting of RE [22]. Lu, Youngdeok et al. [22] adopted the multi-physical model blending to enhance the forecasting of RE through situation-dependent error correction. Likewise, Sogabe, Ichikawa [23] investigated the use of deep learning techniques to enhance the forecasting and optimization of a distributed RE system. ML techniques have also been used as computerized or algorithmic-based tools for the effective management of RE-based smart grids or energy districts [24]. Similarly, Rangel-Martinez et al. [25] examined the use of ML in smart grids as well as its capacity to enhance RE and RE-based storage systems.

In the context of renewable energy, ML approaches of many types have been put to use. Artificial intelligence (AI)-based forecasting models always show a more remarkable outcome over physical techniques as well as statistical methods [26] due to their potential skills for data-mining and feature-extracting. For instance, the accuracy of renewable energy forecasts is crucial to power system planning, management, and operations, hence ML techniques such as deep learning (DL) have been used to detect the inherent nonlinear patterns and high-level invariant structures in data [26].

As a promising subfield of machine learning, deep learning has received a lot of attention in the past few years [27] due to its three main attributes: unsupervised feature learning, excellent generalization capabilities, and big data training [26]. As a natural alternative to shallow models, it has seen extensive use in a variety of fields, including pattern recognition, image processing, defect detection, classification, and forecasting [28]. In [29], the authors suggested a deep stochastic architecture using a Boltzmann machine to accomplish this task automatically. The discovered attributes are useful for forecasting wind energy and provide a lot of insight. In order to improve the accuracy and computational efficiency of PV power output forecasts, Chang proposed a new integrating technique grounded in grey theory and deep belief networks [30]. In [31], the authors introduce a novel deep machine learning approach to forecast the energy of waves in the near future. Results from these forecasts aid in the efficient and effective management of wave power in real time. The simulation demonstrates that a decrease in wave energy absorption occurs as a result of the prediction error affecting the efficacy of the model predictive control. Also often described for use in renewable energy forecasting are deep convolutional neural networks [32], deep recurrent neural networks [33], and stacked extreme learning machines [34]. It is well acknowledged that the accuracy, stability, and effectiveness of deep learning-based forecasting models is appealing [35], which is useful for the planning, scheduling, and management of energy systems [36].

Other researchers have reviewed the current trends and scientific/technological developments on the topic in addition to the various published articles and conference papers on the applications of ML in RE in the literature. For example, Salcedo-Sanz et al. [37] reviewed the various ML prediction systems for RE applications, whereas Gu, Noh et al. [38] reviewed the characteristic properties of the various materials for RE. On the other hand, Lai, Chang et al. [39] presented a comprehensive review of the ML models for predicting and forecasting RE. In general, the research has emphasized the predictability and adaptability of ML methods and models, as well as the operations (such as data pre-processing methods, selection of variable techniques and evaluation of performance in prediction) employed in ML models for RE prediction.

Furthermore, some other ML techniques have been used to increase the performance and predictability of renewable consumption. In [40], the authors suggested a hybrid approach for solar power forecasting in the near future. The forecasting algorithm was developed on the basis of a mix of gradient-descent optimization techniques. The artificial neural network and metaheuristic optimization model are also employed alongside the gradient-descent model. Throughout the application's development process, the artificial neural network (ANN) is utilized to zero in on the best possible setting for a given parameter. Conducting the computation would be too difficult because each model performs a unique process. One key drawback is that forecasting energy use requires a new approach, which must be implemented. The result is the basis for any estimate of power generated by wind. Too much time has passed since the last update compared to other methods. By fusing the Group Method of Data Handling (GMDH) with the bootstrap approach, [41] proposes a novel input method selection procedure. The SI input layer is chosen for experimental purposes, and the support vector regression approach is utilized for short-term hourly forecasting. Both of these procedures must be carried out under identical experimental conditions. The strategy relies on a relevant dataset to contribute to the random distribution of learning. One drawback is that only one network needs to be built in order to produce a partial input result. The GMDH network evaluates possible inputs and outputs based on the non-linear relationship that is used as an input. Computation and filtering require a considerable amount of time.

In this work, the authors identify a modification to the gradient boosting technique that improves both speed and accuracy. The goal of this work is to provide a comprehensive evaluation of the various gradient boosting algorithms available on the market today [42]. This exemplifies the robust and efficient difficulties of utilizing machine learning methods. XGBoost version 1.2.1 was used and this was created by Distributed Machine Learning Community (DMLC) in washington, USA. The XGBoost method makes this possible, and its primary goal is to improve processing speed. The CatBoost method is optimized by removing the prediction and shift phases, and by adding the perfect computation property, utilizing finely tuned versions of XGBoost, LightGBM, CatBoost, random forest, and gradient boosting to achieve a high throughput. The CatBoost algorithm improves precision across the board. As a type of neural network system, it was deployed as a replacement for commonplace statistical model procedures [43].

Supervisory learning algorithms including radial basis functions (RBF), support vector regression (SVR), large scale biomedical data technology (LSBDT), and extreme learning machine (ELM) are stitched together to form a hybrid forecasting model based on machine learning. The historical dataset used to develop such prediction models might be prone to missing data and outliers as a result of data loss during grid failure events and malfunctioning monitoring sensors. This research utilized an imputation strategy based on a linear regression model to deal with the missing data issue [44]. Energy consumption in the oil and gas industry was predicted using four different forecasting models: a support vector machine, a linear regression, an extreme learning machine, and an artificial neural network. These models were trained using the training dataset and then tested using the test dataset. Using the root mean square error (RMSE) value, which is determined by averaging the outputs of two models, we evaluated the efficacy of combining all four models in order to increase the accuracy of energy consumption forecasting. The findings indicate that all four hypotheses provide reliable forecasts of future energy consumption. The hybrid model is integrated into the oil and gas industry's energy management system to control energy consumption and improve efficiency [45]. The energy was forecasted at four different stages: the data collection layer, the preprocessing layer, the prediction layer, and the performance evaluation layer. Data from each layer are processed in a unique way. To better estimate future energy use, the deep extreme learning (DELM) method was applied in the prediction layer. The DELM implements the basic structure of the ELM network and adds more hidden layers to it; it also randomly sets the weights of the input layers and the first hidden layer. The least squares approach is then used to determine the final weights for the network. Using a trial-and-error method, the optimal number of concealed layers can be discovered. The effectiveness of the proposed DELM model in estimating future energy consumption was measured with the use of an adaptive neuro-fuzzy inference system (ANFIS) and an artificial neural network (ANN) [46].

In spite of the abundance of articles, conference papers, and reviews on MLARE, not many studies exist that provide a thorough study of the research environment. As far as the author is aware, there does not currently exist a study on the bibliometric analysis and publication patterns of MLARE in the literature.

This research describes and evaluates the research environment on applications of ML in renewable energy (MLARE). The Elsevier Scopus database's published document data will be used to analyze publishing patterns on MLARE in order to determine the key players, highly cited works, and funding organizations that are actively involved in the field. On the basis of the Scopus data on the published publications indexed in the database from 2012 to 2021, bibliometric analysis is then performed.

Therefore, the objective of this research is to provide an in-depth analysis of the current state of MLARE's scientific landscape, research landscape, and publication patterns. The study's results are expected to provide academic, commercial, and policymaking experts with new understandings of the MLARE's foundations, workings, future, and obstacles. It is envisaged that this work will provide significant contributions to the study of contemporary scientific and technological developments.

2. Methodology

To achieve these abovementioned objectives, the methodology of the study, involved analysis of the publication trends using recovered data on the articles that have been published on the subject from the Elsevier Scopus database and bibliometric analysis techniques were adopted to identify, screen, and analyze all the published documents on the topic published and indexed in the Elsevier Scopus database during the time span from 2012 to 2021. The timeframe was selected to ensure comprehensive recovery and analysis of the significant developments within the ten-year period. This is similar to what was used in Ajibade, et al. [47]. The articles that were published on the subject of MLARE were first identified using an appropriately designed search string using the title keyword combinations ("machine learning" and "renewable energy"). Next, the related documents on the topic were retrieved and screened based on the keywords described in the search query executed in Scopus: >> TITLE-ABS-KEY ("machine learning" and "renewable energy") and PUBYEAR > 2011 and PUBYEAR < 2022 and PUBYEAR > 2011 and PUBYEAR < 2022 and (LIMIT-TO (DOCTYPE, "ar") or LIMIT-TO (DOCTYPE, "cp") or LIMIT-TO (DOCTYPE, "ch") or LIMIT-TO (DOCTYPE, "re") and (LIMIT-TO (Language, "English")) and (exclude (Language, "Japanese") or exclude (Language, "Polish") or exclude (Language, "Spanish") or exclude (Language, "Chinese")) and (exclude (Language, "Croatian") or exclude (Language, "Portuguese") or exclude (Language, "French") or exclude (Language, "German")) and (exclude (Language, "Korean") or exclude (Language, "Russian") or exclude (Language, "Slovenian") or exclude (Language, "Turkish")).

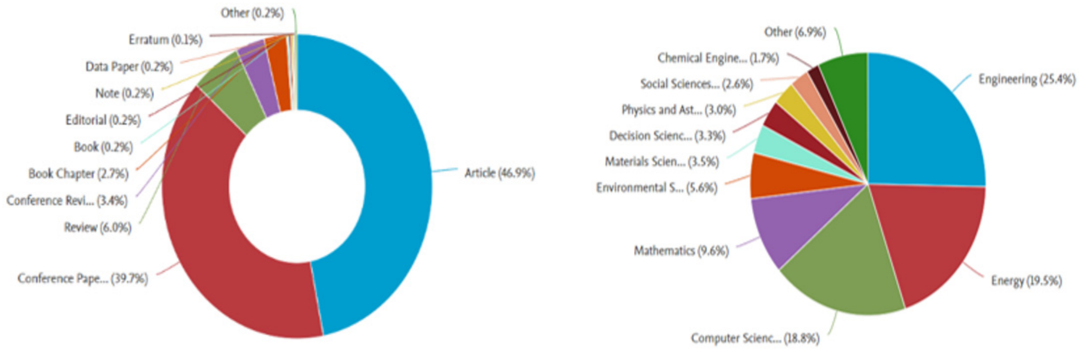
Publication information on MLARE was retrieved from Scopus in CSV (comma separated values) and RIS (Research Information Systems) formats for this study, with the latter used for its ability to better accommodate the desired time range. The recovered publications were then analyzed to reveal the most prolific authors, institutions, countries, and funding agetncies in the field, as well as the most popular document kinds, sources, subject areas, and highly cited publications. VOSviewer software (Version 1.16.17) was then used to impute the CSV file in order to conduct a co-authorship, keywords occurrence, and citations analysis of the research landscape surrounding the issue. The produced visualization maps were used to analyze global MLARE research collaborations, research hubs, and the field's potential future orientations. The VOSviewer programme was used to study the network visualization and relationship maps between the variables, with the minimal number (n) of authors, keywords, and citations per published article chosen for each investigation.

3. Results and Discussion

3.1. Published Documents Analysis

The Scopus database search recovered 1218 publications comprising various document types. Figure 1a shows the distribution of the various document types that have been employed by various authors to disseminate their research findings on the MLARE. As can be seen, the major document types on the topic comprise Articles (572), Conference Papers (485), Reviews (72), Conference Reviews (42), and Book Chapters (35), among others. While Figure 1b shows the distribution of documents on MLARE research by subject area, which provides insights into the depth and scope of the topic. As can be seen, the top five subject areas for MLARE are Engineering (714), Energy (547), Computer Science (531), Mathematics (267), and Environmental Science (157), which cuts across the fields of science, technology, engineering, social sciences, and humanities. The other subjects are Material Science, Decision Science, Physics and Astronomy, Social Science and Chemical Engineering. Based on the above, it can be surmised with reasonable certainty that MLARE is a broad, interconnected, and multidisciplinary area of research.

It is widely reported that multidisciplinary research provides multiple approaches to problem-solving, which is crucial for the growth and development of scientific research. In addition, the multidisciplinary approach to science reportedly eliminates the likelihood of repetitive or biased outcomes, which enhances the reliability and accuracy of research on the whole [47]. However, this has prompted questions such as whether or not interdisciplinary research teams ensure higher output in science, as examined by Abramo, D'Angelo et al. [48]. In a separate study, Abramo, D'Angelo et al. [49] examined the impact of multidisciplinary collaborations on the diversification of research. Their results revealed that research diversification through collaborations with multidisciplinary teams enhances researchers' output particularly when this occurs in larger differentiated groups. Therefore, the high variation in subject areas of the studies on MLARE indicates high rates of collaboration among the various engaged in this topical area of research. The considerable expansion in the number of published documents and citations on the subject over the 10-year period investigated in this study may also be attributed to the high frequency of multidisciplinary studies and collaborations indicated for MLARE investigations. Figure 2 displays the publication growth trends for published documents on MLARE research from 2012 to 2021. The plot of published documents against the year of publication showed an incremental trend, from 1 to 479 published documents between 2012 and 2021, which indicates an immense growth rate of 47,800%. However, the apparent growth in scientific interest in MLARE was slow in the first five years from 2012 to 2016 with <50 documents per year (i.e., 6.65% of the total publications) published compared to the years from 2017 to 2021. The findings indicate significant growth as well as interest in the area which may be due to an increase in the socio-economic and environmental impacts of the topic.



(**a**) (**b**)

Figure 1. Distribution of document types and subject areas of the published documents on MLARE research (2012–2021). (**a**) Distribution of various document types used by various authors on MLARE (**b**) Distribution of various subject areas in the research of MLARE.

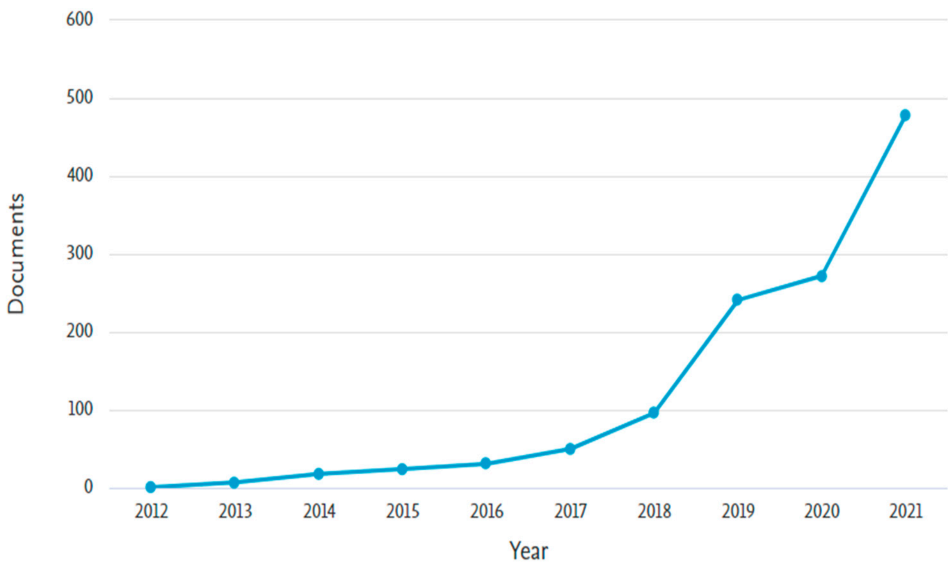


Figure 2. Publication growth trend on MLARE research (2012–2021).

Renewable energy is considered an important subject worldwide due to humanity's quest to address the challenges of global warming and climate change [50]. With the ratification of the Paris Climate Agreement in 2015, nations have pledged to curb their greenhouse gas emissions from current levels of 50 billion to zero by the year 2050 [51]. One approach to achieve this lofty goal is the transition from fossil fuel economy to renewable energy technologies (RET) [52]. However, RETs are currently prone to various challenges ranging from intermittent power generation [53] and expensive installation infrastructure [54] to grid-related challenges and high energy production costs particularly in the absence of subsidies and carbon lock-in [55]. To address these challenges, scientists are exploring various algorithmic or numerical tools such as artificial intelligence (AI), neural networks (NN), and deep/machine learning (D-/ML) to explore and examine sustainable solutions. Hence, it can be reasonably hypothesized that the field of MLARE research has grown out of the need to identify, examine, and address the challenges of RETs using ML. Over the years, numerous researchers have actively become involved in the area producing numerous highly cited documents published in various source titles including journals and conference proceedings. Table 1 displays the most highly cited published documents on MLARE indexed in the Scopus database from 2012 to 2021.

Table 1. Top 10 most highly cited published documents on MLARE (2012–2021).

References	Title	Year	Source Title	Cited by	Document Type
Gu G.H., Noh J., Kim I., Jung Y. [38]	Machine learning for renewable energy materials	2019	Journal of Materials Chemistry A	118	Review
Salcedo-Sanz S., Cornejo-Bueno L., [37]	Feature selection in machine learning prediction systems for renewable energy applications	2018	Renewable and Sustainable Energy Reviews	67	Review
Perera K.S., Aung Z., Woon W.L. [21]	Machine Learning Techniques for Supporting Renewable Energy Generation and Integration: A Survey	2014	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	45	Article
Lu S., Youngdeok H., Khabibrakhmanov I., [22]	Machine learning-based multi-physical-model blending for enhancing renewable energy forecast—Improvement via situation-dependent error correction	2015	2015 European Control Conference, ECC 2015	39	Conference Paper
Lai J.-P., Chang Y.-M., Chen C.-H., Pai [39]	A survey of machine learning models in renewable energy predictions	2020	Applied Sciences (Switzerland)	35	Review
Magazzino C., Mele M., Morelli G. [56]	The relationship between renewable energy and economic growth in a time of COVID-19: A machine learning experiment on the Brazilian economy	2021	Sustainability (Switzerland)	34	Article
Ma T., Guo Z., Lin M., Wang Q. [57]	Recent trends on nanofluid heat transfer machine learning research applied to renewable energy	2021	Renewable and Sustainable Energy Reviews	33	Article
Rangel-Martinez D., Nigam K.D.P., [25]	Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage	2021	Chemical Engineering Research and Design	25	Article
Ahmed W., Ansari H., Khan B., Ullah Z., Ali [24]	Machine learning-based energy management model for smart grid and renewable energy districts	2020	IEEE Access	16	Article
Sogabe T., Ichikawa H., Sakamoto K., [23]	Optimization of the decentralized renewable energy system by weather forecasting and deep machine learning techniques	2016	IEEE PES Innovative Smart Grid Technologies Conference Europe	15	Conference Paper

The most highly cited document type is Articles (5) followed by Reviews (3) and lastly Conference Proceedings (2). The most cited publication is the review paper "Machine learning for renewable energy materials" by Gu, Noh et al. [38] published in the Journal of Materials Chemistry A which has been cited 118 times. The paper highlighted the potential of ML as an important framework tool for the design, development, and performance prediction of RE materials. The synthesized materials have widespread applications in the areas of RETs, batteries, catalysts, fuel cells, and photovoltaics, among others. The second most cited publication (which has been cited 67 times) is "Feature selection in machine learning prediction systems for renewable energy applications" by Salcedo-Sanz et al. [37], which is also a review paper published in Renewable and Sustainable Energy Reviews. The study demonstrated the application of the feature selection problem of ML in prediction systems for RETs such as solar and wind energy technologies. On the other hand, the article "Machine Learning Techniques for Supporting Renewable Energy Generation and Integration: A Survey" by [21] published in the Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) which has been cited 45 times is the third most cited published document on the topic. The study examined the impact of ML on RE integration and utilization. Other notable studies on MLARE research have examined the application of ML in forecasting [22,39], optimization [23], and feature selection [26] of decentralized RE systems as well as the operational management of smart grids [24,25]. In addition, ML has been applied in materials science applications of RE.

As observed, the top 10 most cited published documents on MLARE research accrued between 15 and 118 citations (or 42.7 on average per document). The high rate of citations observed for the documents could be attributed to the research impact of the topic as well as the author reputation, which typically results in collaborations, co-authorships, and co-citations with their peers. To examine this viewpoint, the most cited papers on MLARE were examined using the co-citation analysis feature of VOSviewer, as depicted in Figure 3. The network visualization of co-citations among the most cited publications on MLARE research was performed based on the minimum occurrence of 25 citations per document. The map shows that the highest set of connected publications is 61 out of 169 or 36.09%, which indicates a high rate of co-citations among the most cited published documents on the topic. The most cited published document on the topic with the highest TLS is [29] with 17 links, followed by Das (2018) with 8 links and lastly Persson (2017) with 6 links. The network analysis revealed 12 clusters comprising two to eight published documents with the highest cluster comprising the works of Chen A (2020), Chen C (2020) and Tabor DP (2018), whereas the smallest cluster is made up of Demolli H (2019) and Najeebullah (2015).

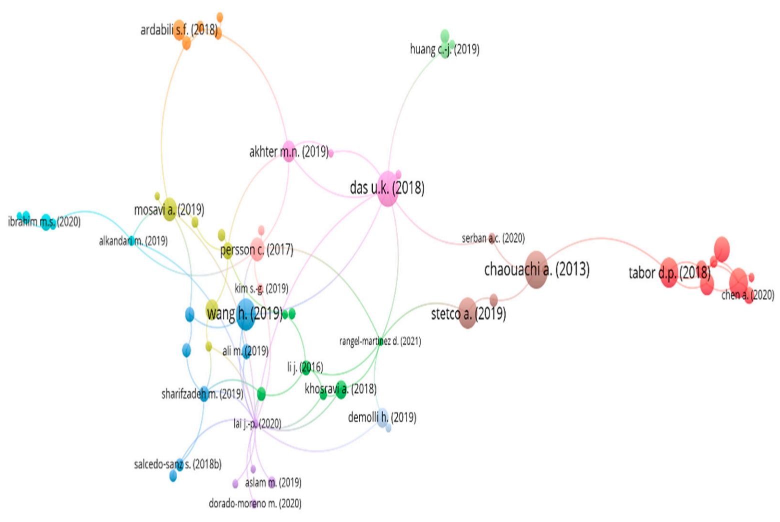


Figure 3. Network visualization of co-citations among published documents on MLARE research.

The high citation rates of the top cited published documents may be due to the research impact of the respective studies but also the reputation of the sources that have published them. To validate this submission, the top source titles that have published works on MLARE research were recovered from the Scopus database. Figure 4 shows the top source titles for publications on MLARE research in the literature, whereas the network visualization of co-citations among the topic is presented in Figure 5.

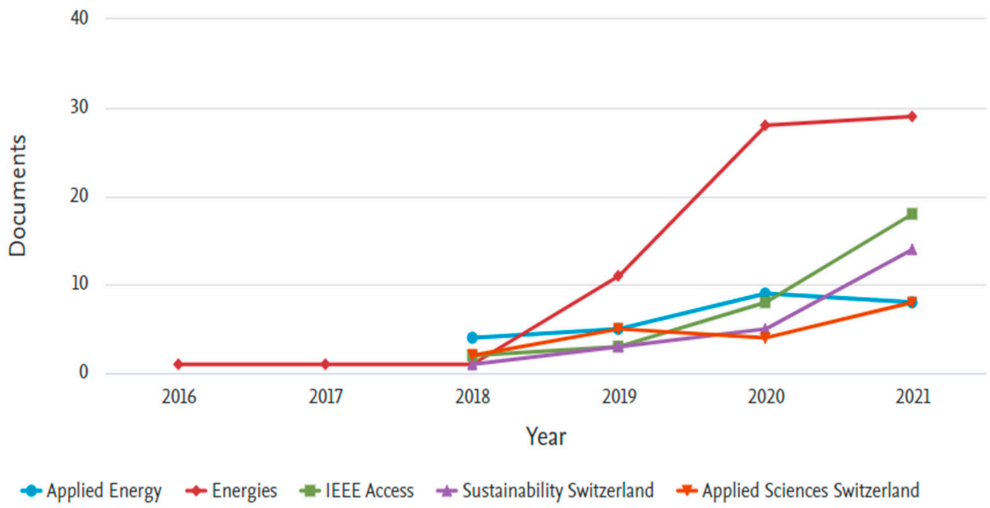


Figure 4. Top source titles for publications on MLARE research.

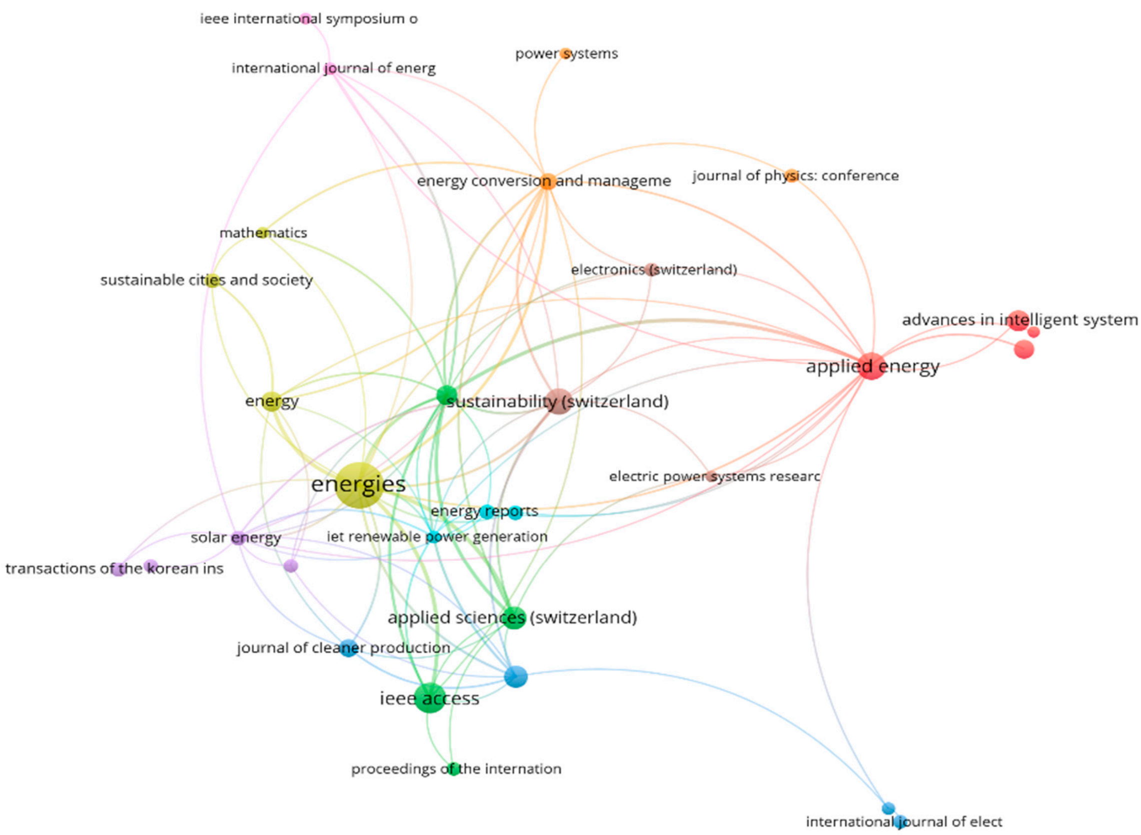


Figure 5. Network visualization of co-citations among the source titles on MLARE research.

The top source title or journal for MLARE research is the open-access journal Energies (Switzerland) published by (MDPI) with 71 published documents. In second place is IEEE Access which has published 31 documents, followed by Applied Energy with 26.

In fourth and fifth places are Sustainability and Applied Sciences (both published by MDPI) with 23 and 19 published documents, respectively. The results reveal that three (Energies, Sustainability and Applied Sciences) out of the top five source titles are open-access, whereas two are subscription-based titles. The findings confirm the widely held notion that open access enhances visibility, impact and citation rates. As a result, numerous researchers across the globe now opt for open-access journals to increase the visibility and impact of their research. Nonetheless, it is important to state that publishing in open-access journals has also become a funding requirement, particularly for researchers with United States, United Kingdom, or European Union grants such as national institutes of health (NIH), engineering and physical sciences research council (EPSRC), and H2020, to mention but a few. Given this, the top researchers in the field of MLARE and others have resorted to publication in open-access journals. The top researchers on the MLARE are presented in the Authors and Affiliations section.

As observed in Figure 5, co-citations among the source titles on the topic are high, as shown in the high rate of linked sources, i.e., 31 out of 39 or 79.49%. Based on the findings, a total of nine clusters comprising two to four sources with the largest containing Applied Energy, Advances in Intelligent Systems, and Energy and AI, whereas the smallest has IEEE Int Symposium and International Journal of Energy. The highest TLS of 52 was observed for Energies, which is followed by Renewable and Sustainable Energy Reviews (RSER) (43), and lastly Applied Energy (26). These findings indicate the most influential journals based on the citation analysis are Energies, RSER, and Applied Energy, which indicates that the journal's reputation, impact factor and prestige play an important role in the citation rate and the author's preference for presenting their findings in these source titles.

3.2. Authors and Affiliations

Figure 6 displays the top authors/researchers on MLARE research based on data recovered from the Scopus database. The analysis of the top researchers provides an indication of the most prominent and promising stakeholders in any given field of research [38]. As observed, the most prolific researcher, as defined by several published documents, is Ravinesh C. Deo based at the University of Southern Queensland (Australia) with eight publications. In second and third places are Joshuva A. Dhanraj of the Hindustan Institute of Technology and Science (India) and Amir Mosavi of the Technische Universität Dresden (Germany), each with seven publications. Lastly, the duo of Tanveer Ahmad (Kyushu University, Japan) and Jean Scartezzini (Ecole Polytechnique Fédérale de Lausanne, Switzerland) are in fourth and fifth places, respectively, with six published documents each. Furthermore, it was observed that the top 10 most prolific authors on the topic have published a total of 59 documents or ~4.84% of the total publications on MLARE research over the 10 years. Based on the high productivity of these select authors, these are the most prominent authors in the field. High research productivity, as measured by high publication rates, is often recognized as the product of numerous favorable factors such as the availability or access to scientific resources such as grants, equipment, or infrastructure that supports intellectual growth and technological development. As observed, the top five most prolific researchers are based on organization for economic cooperation and development (OECD) or Western nations such as Australia, Japan, Germany, and Switzerland, which are traditionally significant funders of research. The research and scientific climate in these regions may also be an important dynamic in the productivity of the researchers through collaborations with their peers. The extent or degree of collaborations can be examined through co-authorship analysis using bibliometric analysis. In this research work, the co-authorship among authors who are passively engaged in MLARE research was investigated using VOSViewer software (Version 1.16.17). The VOSViewer was released by Nees Jan van Eck and Ludo Waltman from Leiden University, Netherlands.

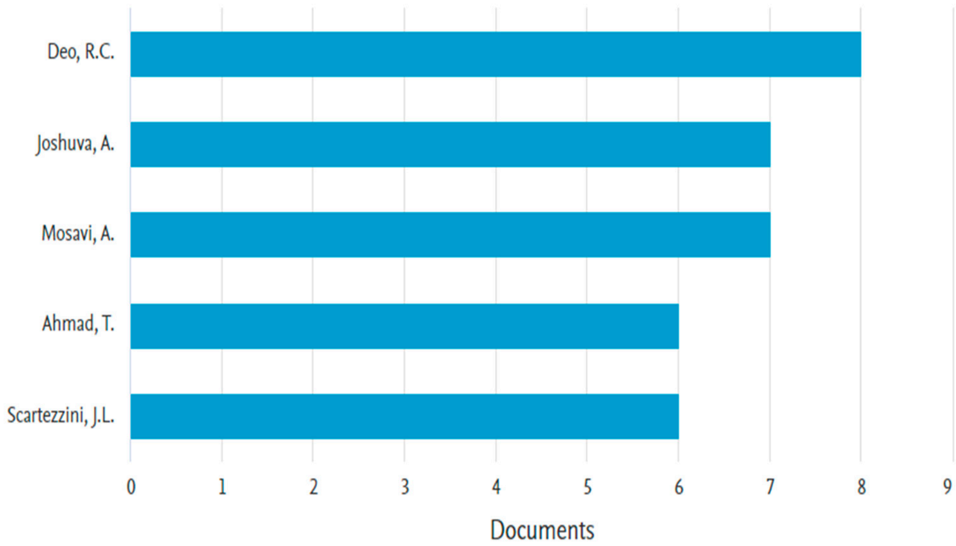


Figure 6. Top authors/researchers on MLARE research.

Figure 7 displays the network visualization map of the co-authorship on MLARE research based on data from the Scopus database. The analysis is based on a minimum of three documents that have been cited at least three times. The findings indicate that the total number of authors that are connected is 85 out of 166, which resulted in 12 clusters comprising 3 to 14 authors. The largest cluster consists of Chen Y; Chen Z; and Li X, among others, whereas the smallest consists of Zhukov A, Sidorov D, and Li Y. Based on the findings, it can be reasonably surmised that there is a high degree of collaboration between the authors as shown by the high percentage of linked authors (51.20%). Collaborations are critical to the growth and development of research, and, as such, many authors explore the option to enhance their publication's output, citations, and prestige. Other benefits of collaborations include increasing the changes. According to the study by Abramo, D'Angelo et al. [58], it is critical to create collaborations with peers within and outside the researchers' institutions to build their careers. Likewise, Shagrir et al. [59] proposed that collaboration among colleagues is an integral part of academic and professional development at institutions of higher learning. Subramanyam et al. [60] also affirmed that scientific research has become a collaborative undertaking aimed at finding multidisciplinary solutions to problems, increasing research output, and gaining financial support.

The degree or extent of collaborations between authors is also influenced by institutional policies. Ye, Song et al. [61] reported that research networks across institutions can significantly influence researchers' performance. Likewise, Adams et al. [62] discovered evidence that institutional collaborations strongly influence scientific output as well as reputation. Hence, the impact of institutions on the productivity of researchers in the field of MLARE was examined as depicted in Figure 8. As can be seen, the top research affiliation on MLARE research is the National Renewable Energy Laboratory (NREL) with 18 published documents. Based in the United States, NREL is a federal government-sponsored research and development facility that focuses on the exploration and advancement of energy efficiency, renewable energy, energy systems integration, and sustainable transport research. The center also specializes in ML applications for the development of energy technologies and processes. For example, the ARPA program aims to design new battery materials through the USD 1,800,000 initiative termed "End-to-End Optimization for Battery Materials and Molecules by Combining Graph Neural Networks and Reinforcement Learning" [63]. Another application of ML in RE initiative spearheaded by the NREL is ALFABET (A Machine-Learning-derived, Fast, Accurate Bond dissociation Enthalpy Tool) which helps researchers identify the most promising, lower emission, and high engine efficiency biofuels [64].

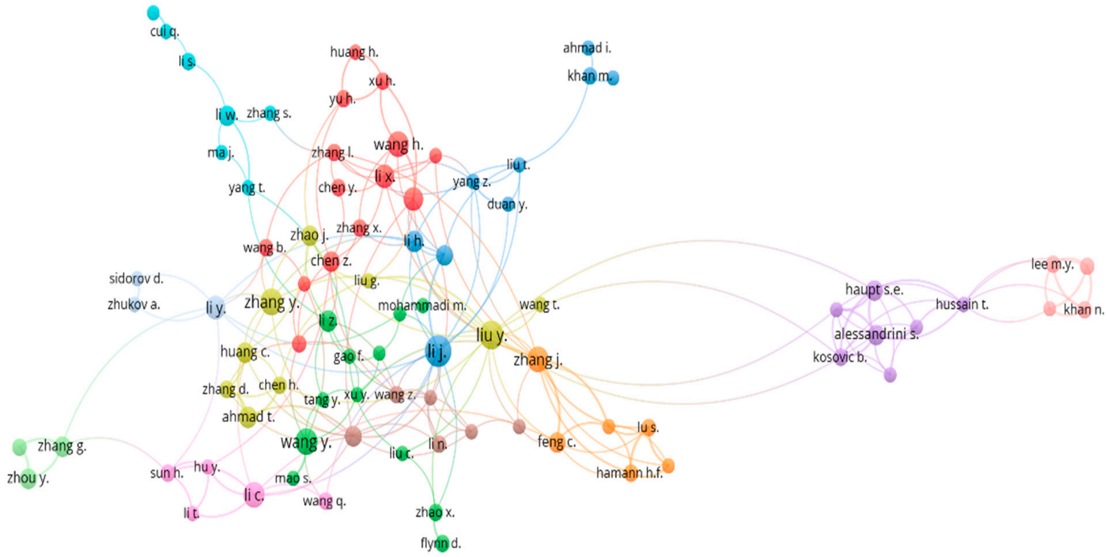


Figure 7. Network visualization of co-authorship among authors on MLARE research.

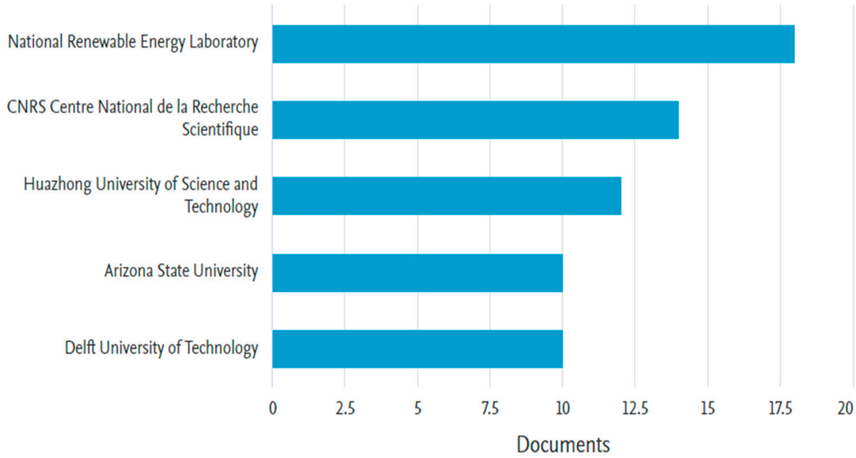


Figure 8. Top research affiliations on MLARE research.

The second most productive affiliation on MLARE research is the Centre National de la Recherche Scientifique (CNRS) in France with 14 published documents, whereas Huazhong University of Science and Technology China has 12. Other notably active institutions are the Arizona State University (USA) and Delft University of Technology (Netherlands) with 11 and 10 publications, respectively. Based on the findings, the top five most active affiliations have produced a total of 65 published documents (13 on average or 5.34% of the total publications) on the topic. This indicates a high rate of research productivity which could be attributed to various factors. One such factor is collaborations among the authors based at these institutions, as earlier surmised.

Figure 9 displays the visualization of network of co-authorship links among institutions on MLARE research. The analysis of the inter-institutional collaborations is based on the minimum set criteria of one document per organization, which has received at least one citation. As observed in Figure 1, a total of 49 institutions actively engaged in MLARE research have collaborated, which has given rise to seven clusters comprising between 4 and 10 organizations. While the most prolific institution is the NREL, the most influential in terms of collaboration is the Institute of Research and Development (Duy Tan University DTU, Viet Nam) which has the highest total link strength (TLS). Further analysis reveals that the top three most influential organizations (namely DTU, the Department for Management of Science and Technology Development, and the Faculty of

Information Technology based at Ton Duc Thang University) are all based in Vietnam. The results showed a high rate of collaboration between these organizations as well as with others based abroad, which accounts for the high productivity in terms of publications and citations over the years.

The productivity rate of authors and organizations is strongly influenced by the research policy and developmental focus of their host countries. Typically, the countries provide the necessary enabling environment for authors and organizations to perform their research. In turn, the nation benefits from the discoveries, publications, patents, and citations resulting from such research efforts. Figure 10 shows the top five countries actively involved in MLARE research based on the total number of published documents over the 12 years. The findings indicate that the top five countries have produced 660 published documents (54.19% of TP or 132 on average). The most prolific country is the United States with 189 published documents, followed by India and China with 162 and 158, respectively. The United Kingdom and Germany come in fourth and fifth places with 151 published documents cumulatively. The high productivity of these nations could be attributed to the growing importance and applications of the ML and RE sector of the global energy economy. Many studies have emphasized the importance of ML in the growth and development of RETs, particularly in the areas of energy materials design, parametric optimization, and performance prediction, among others. The applications of ML in RE are thus expected to grow in the coming years, resulting in an even higher number of publications, citations, collaborations, products, and patents in MLARE research.

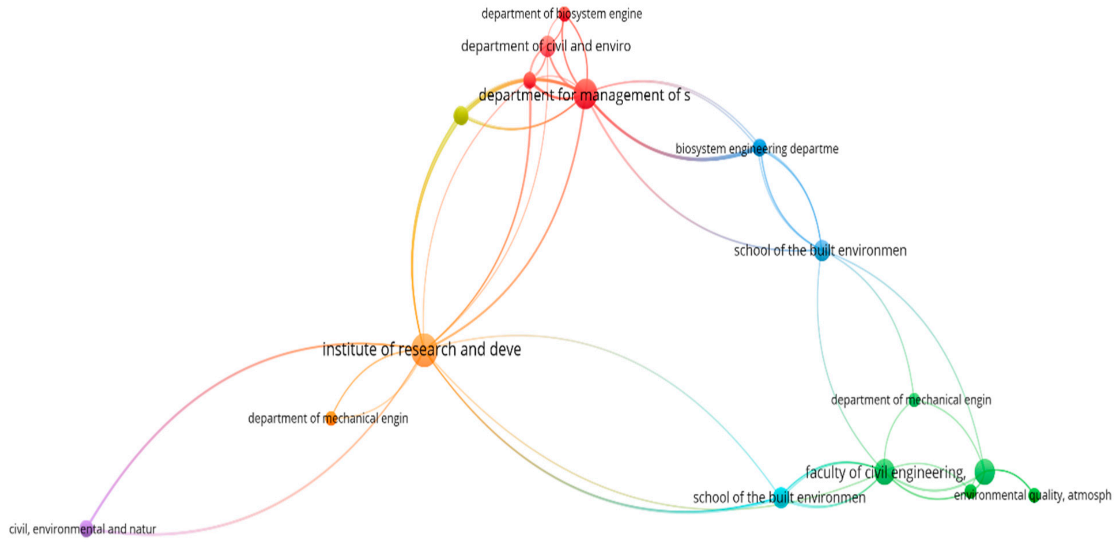


Figure 9. Network visualization of co-authorship links among institutions on MLARE research.

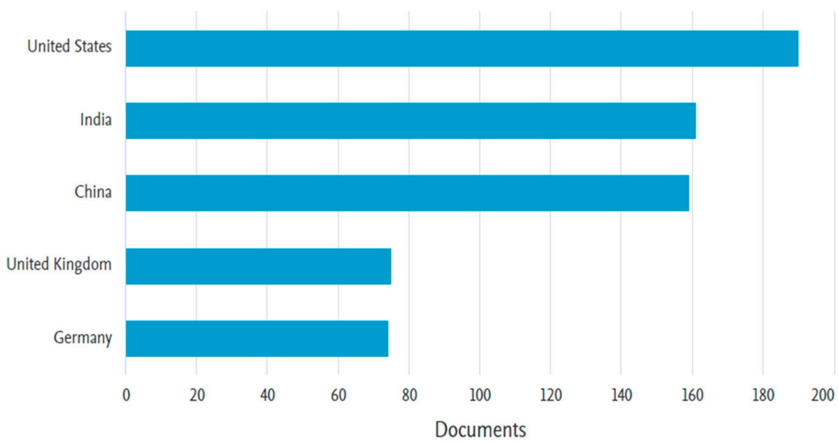


Figure 10. Top countries actively involved in MLARE research.

The impact of collaboration on the productivity rate of the top five countries on the topic was examined using the co-authorship analysis feature of VOSviewer. Figure 11 shows the network visualization of co-authorship links among countries actively engaged in MLARE research globally. The map shows that 62 out of the 110 countries that fulfilled the set criteria of a minimum of three documents that have been cited three times have active collaborations or links with each other. The findings indicate a high rate of co-authorship (>60%) and collaboration among nations involved in MLARE research.

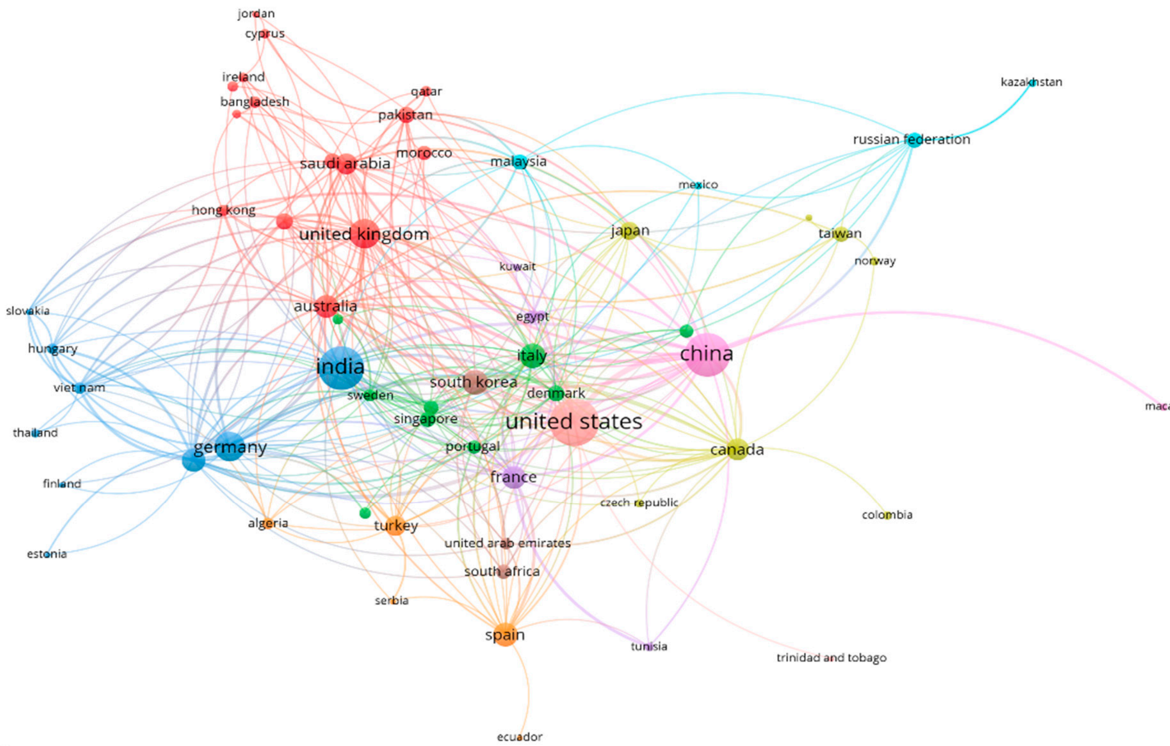


Figure 11. Network visualization map of collaborating countries in MLARE research.

The highest TLS was observed for China (109) followed by the US (91) and the UK (74). In contrast, the US has the highest number of published documents (191) and citations (3507) compared to China (161 and 3349, respectively). The findings indicate that China is the most influential country involved in MLARE research based on its high TC/TP ratio = 20.80, whereas the US is the most prolific country (TC/TP = 18.36). The enormous interest of China-based researchers in MLARE research could be linked to the nation's growing interest in decarbonizing its fossil fuel-dominated energy mix by transiting to cleaner sources of energy [65,66]. According to the World Research Institute (WRI), China is the largest global emitter of greenhouse gases with emissions estimated to be 11,886.8 million tonnes of CO_{2e} (carbon dioxide equivalent) or 25.76% of the global total, which is followed by the USA with 5907.3 million tonnes of CO_{2e} or 12.8% [67]. With the ratification of the Paris Agreement in 2015, the top two emitters along with 192 other nations pledged to reduce GHGs emissions by the year 2050 [68,69]. Given this, the signatory nations along with the US and China have devoted significant financial, technological, and capacity-building resources to address the challenges of global warming and climate change. Hence, machine learning is expected to promote the growth and development of strategies and technologies aimed at the realization of these goals.

3.3. Funding Organisations

The availability/access to funding is the bedrock of successful research endeavors. Research funding helps researchers to acquire all the necessary resources to successfully carry out research, publish papers, travel, and equip their institutions with the tools necessary to compete with their peers globally. Hence, the growth and development of any research discipline are largely influenced by financial support from funding agencies [70]. The top funding agencies actively financing MLARE research are presented in Figure 12. As can be seen, the top five funding agencies on the topic have produced 209 (or 41.8 on average) published documents accounting for 17.16% of the total over the years. The most productive funder is the National Natural Science Foundation of China (NSFC) with 68 (or 5.58% on average) published documents on the topic. The funding activities of the NSFC have greatly aided in positioning Chinese authors and institutions at the forefront of MLARE research. In the second and third places are the US-based funders National Science Foundation (44 or 3.61% of TP), and the Department of Energy (42 or 3.45% of TP). Other notable funders are the Horizon 2020 Framework Programme of the European Union and the National Research Foundation of Korea with 30 and 25 published documents, respectively.

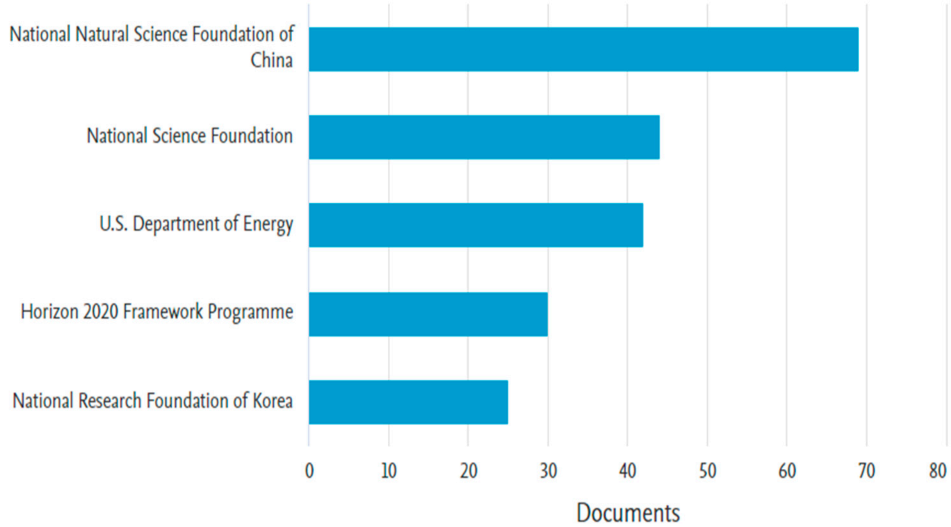


Figure 12. Top funding agencies actively financing MLARE research.

In addition to providing financial support to researchers and their institutions, the research provided by funding organizations offers an environment for fostering collaborations. The availability of funding also helps researchers to attend conferences, seminars, meetings, and symposia where connections are established with their peers across the globe. According to the study by Davies, Gush et al. [71], research funding promotes collaboration among researchers, which ultimately results in higher productivity. Likewise, Shin et al. [72] observed that research funding significantly and positively influences collaboration, which, according to Confraria et al. [73], can greatly enhance the abilities and performance of researchers particularly those from less developed nations. Lastly, research funding helps to nurture and foster research and the creation of academic clusters, which typically aim to enhance scholarly prestige and international recognition [74].

3.4. Keyword Co-Occurrence

The analysis of the occurrence of related keywords is an important feature of the bibliometric analysis of any given area of research [75]. It is considered an integral indicator of the research themes, hotspots, or clusters peculiar to that research area [76,77]. In this study, the co-occurrence of keywords on MLARE research was examined using VOSviewer software according to the following criteria. Figure 13 shows the network visualization map of collaborating countries in MLARE research. The search term was based on the minimum of 25 occurrences per keyword, which resulted in 107 keywords out of the possible 8131 keywords. The network map shows MLARE consists of four clusters (comprising 7 to 41 keywords) that denote the various research themes or hotspots on the topic. As can be observed, the highest occurring keywords are machine learning (770), learning systems

(373), and forecasting (360). The highest TLS was observed for machine learning (5095), followed by forecasting (3057) and learning systems (2917), which indicates that these are the most influential keywords on the topic. Further analysis shows that the largest (red) cluster consists of KWs such as Big Data, Mircogrids, and Power markets, among others, whereas the smallest cluster (lime green) has Climate Change, Fossil fuels, Global warming, and Investments, among others.

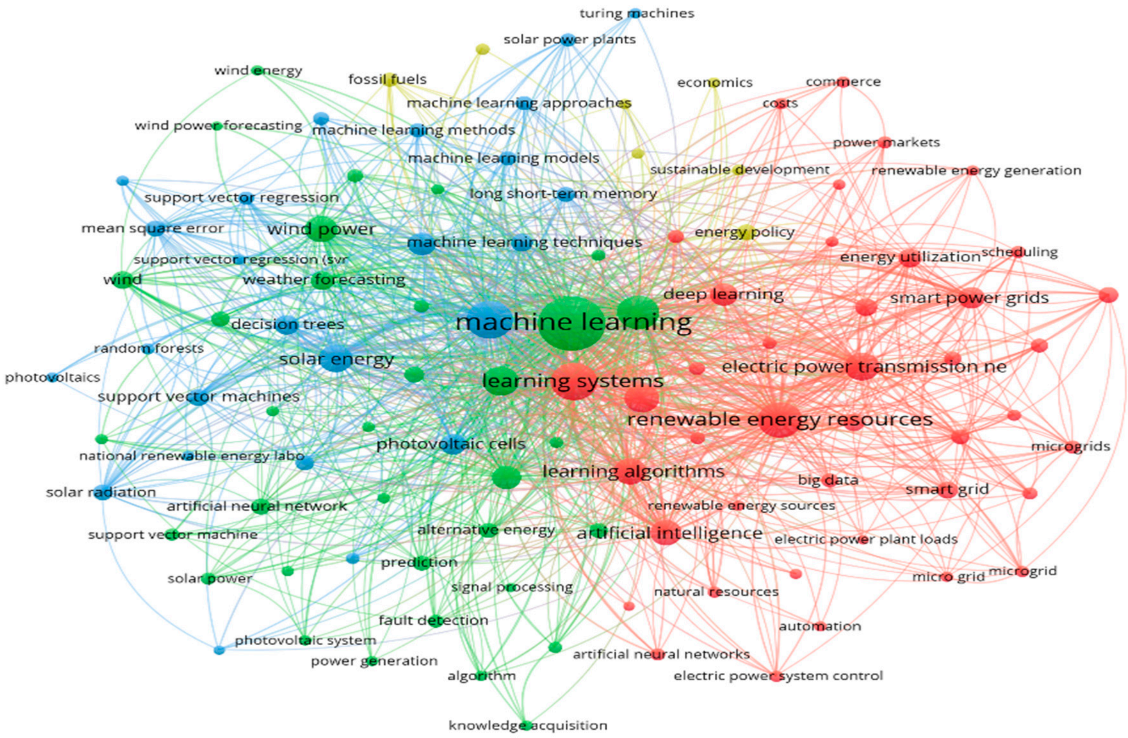


Figure 13. Network visualization map of collaborating countries in MLARE research.

The keywords (KWs) and cluster analysis indicate that four major themes or hotspots exist for research on the topic. The largest (red) cluster on MLARE research describes the various networks, systems, and tools operating with ML. For example, Microgrids, electric power system control, and artificial neural networks are systems and tools that utilize ML in their operations, maintenance, and control. Other keywords in this cluster include energy utilization, electric power transmission, and deep learning, which describe the use of ML algorithms and tools. The second largest cluster (green cluster) consists of KWs such as alternative energy solar power, photovoltaic system, power generation, and wind power, which describe the specific renewable energy technologies that utilize ML. The third cluster (blue) consists of machine learning techniques, solar radiation, support vector machines, decision trees, and machine learning models, among others. This cluster describes the equipment and algorithms of ML used for RETs observation, optimization, and operations. The last cluster (lime green) describes the socio-economic and socio-technical aspects of ML applications in RE. The KWs economics, energy policy, fossil fuels, and sustainable development are indicators of the social aspect of the research area. With the growing importance of ML, various researchers have also sought to examine the socio-economic and socio-technical aspects of its application in RETs. The KW co-occurrence analysis also reveals that MLARE is a broad, impactful, and multi-disciplinary area of research with investigations spanning social sciences, humanities, computer sciences and engineering, as well as aeronautics, materials, and energy engineering sectors. The interdisciplinary nature of MLARE research may also account for the high rates of publications, and citations of the authors along with the organizations and countries actively engaged in the area.

4. Conclusions

The paper examined the publication trends and research landscape on the applications of MLARE. Therefore, publication trends on MLARE were investigated based on the published document data obtained from the Elsevier Scopus database from 2012 to 2021. The bibliometric analysis of the published documents was carried out to investigate the research climate on the subject. The findings reveal that 1218 publications, comprising Articles (572), Conference Papers (485), and Reviews (72), among others, have been published on the topic over 10 years. The findings revealed that MLARE is a broad, multidisciplinary, and impactful research topic that spans science, technology, engineering, and mathematics, among others, based on the various thematic areas indexed in the Scopus database. The high rate of multidisciplinary research and collaboration observed for MLARE studies may also account for the high growth in the number of published documents and citations on the topic over the 10 years examined in this study. The findings have also shown that the MLARE research field has grown out of the need to identify, examine, and address the challenges of RETs using ML. The most prolific researcher on the topic is Ravinesh C. Deo (University of Southern Queensland, Australia) with 8 published documents, whereas the most productive affiliation is the NREL with 18 published documents. The high productivity and citations of the researchers and affiliations on MLARE are attributed to the collaborations as deduced by bibliometric analysis using VOSviewer software.

Another important factor responsible for the high productivity of the stakeholders is research funding support as shown by the high output of MLARE funders. The top five funding agencies on the topic have produced 209 (or 41.8 on average) published documents accounting for 17.16% of the total over the years. The most productive funder is the National Natural Science Foundation of China (NSFC) with 68 (or 5.58% on average) published documents on the topic. Keyword occurrence analyses revealed four clusters or thematic areas on MLARE that describe the network systems, renewable energy technologies, machine learning tools/technologies, and, lastly, socio-technical aspects of ML applications in RE. Therefore, the study showed that machine learning is an important tool/technique for the predicting, operating, and optimizing of renewable energy technologies as well as the design and development of renewable energy materials. The paper presented insights into the research landscape on the application of ML in RETs, which could be beneficial to current and future researchers interested in venturing into this broad, multidisciplinary, and impactful field.

The article can also help future researchers choose crucial collaborators, funding agencies, journals for publications, and uncharted research horizons as they design their own research programs. However, the study is subject to the same restrictions as other bibliometric analyses. Since the findings and conclusions of bibliometric studies are time-sensitive, they will change if the publications are generated at different times or if the analysis is conducted at a time different from July 2021. Similarly, the addition of other article types, especially reviews, will affect the outcome of the analysis. Scopus literature is used exclusively in this bibliometric analysis; however, the potential impact of the chosen scholar database on the analysis outcome is intriguing, and future research could benefit from examining the use of alternative databases such as WOS. A similar analysis based on the literature extracted from NREL may reveal more recent progress and breakthroughs on this topic by researchers in the United States, as the leading research affiliation on MLARE research is based in the United States and the United States is also identified as the top productive and active country in MLARE research. WRI also reports that China accounts for 25.76 percent of global greenhouse gas emissions and that the United States accounts for 12.80 percent [48]. This suggests that machine learning could be used to help combat climate change and global warming in future research.

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