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New Insights into the Emerging Trends Research of Machine and Deep Learning Applications in Energy Storage: A Bibliometric Analysis and Publication Trends

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ABSTRACT

The publication trends and bibliometric analysis of the research landscape on the applications of machine and deep learning in energy storage (MDLES) research were examined in this study based on published documents in the Elsevier Scopus database between 2012 and 2022. The PRISMA technique employed to identify, screen, and filter related publications on MDLES research recovered 969 documents comprising articles, conference papers, and reviews published in English. The results showed that the publications count on the topic increased from 3 to 385 (or a 12,733.3% increase) along with citations between 2012 and 2022. The high publications and citations rate was ascribed to the MDLES research impact, co-authorships/collaborations, as well as the source title/journals' reputation, multidisciplinary nature, and research funding. The top/most prolific researcher, institution, country, and funding body on MDLES research are; is *Yan Xu*, *Tsinghua University*, China, and the National Natural Science Foundation of China, respectively. Keywords occurrence analysis revealed three clusters or hotspots based on *machine learning*, *digital storage*, and *Energy Storage*. Further analysis of the research landscape showed that MDLES research is currently and largely focused on the application of machine/deep learning for predicting, operating, and optimising energy storage as well as the design of energy storage materials for renewable energy technologies such as wind, and PV solar. However, future research will presumably include a focus on advanced energy materials development, operational systems monitoring and control as well as techno-economic analysis to address challenges associated with energy efficiency analysis, costing of renewable energy electricity pricing, trading, and revenue prediction.

Keywords: Machine Learning, Deep Learning, Artificial Intelligence, Energy Storage, Renewable Energy Technologies, Bibliometric Analysis
JEL Classifications: C4, C5, R3

1. INTRODUCTION

Globally, energy is considered one of the most important resources required for socioeconomic growth and sustainable infrastructural development (Wysokiński et al., 2020; Antai et al., 2015). According to the United Nations (UN), 733 million people around the world still lack access to electricity, while 2.4 billion depend on harmful or polluting fuels for their cooking, lighting, or other domestic energy needs (TO, 2015). This scenario has created an energy and environmental crises, which could result in severely hamper growth and development worldwide. Consequently, the UN established the Sustainable Development Goals (SDG) in the year 2015 to among other issues tackle the lack of access to energy. Therefore, Goal 7 of the UN-SDG aims to ensure widespread access to clean, cheap, dependable, and modern-day energy services (TO, 2015). It also aims to enhance the energy efficiency,

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and substantially expand the global share of renewables in the global energy mix by the year 2030 (Timilsina and Shah, 2020). According to Paris Agreement, also proposed in 2015, humanity needs to curb greenhouse gas (GHG) emissions from the current levels of 50 billion tonnes per year to zero by 2050 in order to address global warming and climate change.

According to various analysts, the development and deployment of renewable energy technologies (RETs) are critical to curbing or mitigating the spiralling emissions of GHG (Dedinec et al., 2012). However, RETs are prone to numerous challenges ranging from the intermittency/inconsistency of RE production (Gowrisankaran et al., 2016; Aflaki and Netessine, 2017), conversion efficiencies (Wen et al., 2020; Yan et al., 2020), grid infrastructure and integration issues (Salman et al., 2019; Lin et al., 2017). Other notable challenges include costs per unit of renewable electricity (Alkaisi et al., 2017; Yaqoot et al., 2016), efficient storage (Weitemeyer et al., 2015; Gençer and Agrawal, 2016), and distribution as well as social acceptability and land use issues (Estévez et al., 2021; Ajibade et al., 2023). Despite the numerous outlined issues, many analysts posit that energy storage remains one of the biggest impediments to the widespread deployment of RETs worldwide (Rabbi et al., 2022). The lack of a consistent supply of RE resources such as sunlight, and wind require storage facilities to enable off-peak usage of RE as well as address issues of fluctuating supplies (Okafor et al., 2022). Given this necessity, numerous researchers have sought to explore and examine sustainable strategies and innovative technologies to ensure effective RE storage. In addition, there has been growing interest in the use of computation techniques to reliably predict, operate, and optimize RE production and storage as well as in the design of RE storage materials and technologies.

Over the years, there has been growing interest in the use of computational tools such as machine/deep learning (ML/DL) for energy storage research. According to the definition propounded by (Luxton, 2016), ML is a fundamental aspect of AI in which computers learn how to perform tasks without being programmed. The definition extends to software or machines that perform tasks through exposure or experience with data. Typically, the computer learns to understand the available data and subsequently uses the know-how to predict future or emerging data. However, (Bhavsar et al., 2017), defines ML as a set of techniques that allows computers to program and or build data-driven models through the logical detection of statistically important trends in the data sets. Similarly, (Vergaray et al., 2023) described ML as a field of study (that originated from traditional statistics and artificial intelligence) that explores the application of computer algorithms to transform experiential data into functional models. On the other hand, deep learning is defined as a branch of ML that utilizes multi-layered neural networks to solve complex computational problems (Gotway et al., 2016). According to (Messinger et al., 2022), DL has revolutionised the tractability and precision of ML, which has resulted in many breakthrough innovations in fields. Likewise, ML offers an integrated structure for presenting intelligent decision-making into several domains (Aguiar-Pérez et al., 2023).

Given the advantages of ML/DL, numerous researchers have sought to explore and exploit the use of such computation tools in addressing the challenges of energy storage. Likewise, various studies have examined the prospects and challenges of exploiting ML/DL in energy storage research worldwide. For example, ML/DL has been employed to design and develop energy materials and storage devices (Zahid et al., 2017; Henri and Lu, 2019; Yuan et al., 2019) such as novel ionic/nano liquids, polymer composites, and nanocomposites (Feng et al., 2022; Said et al., 2022; Yue et al., 2022). According to (Chen et al., 2020), ML has the potential to accelerate the development of materials for energy conversion and storage. Other notable studies have explored the application of ML/DL in the optimisation of smart grids (Zsembinszki et al., 2021), performance analysis of RETs (Moradi-Sepahvand et al., 2021), and transportation/vehicular systems (Fu et al., 2020; Bansal et al., 2021). The techno-economic assessment and cost analysis of RETs (Sheha and Powell, 2019; Bae et al., 2019), as well as the control, integration, and management of hybrid and large-scale energy storage systems (Gao and Lu, 2021; Ajibade and Ojeniyi, 2022).

Given the impact of the topic, some researchers have conducted reviews on the various developments on the topic. Most notably (Artrith, 2019) reviewed the current status of researches on the application of ML in the modelling of materials and interfaces for energy conversion and storage. Likewise, (Qian et al., 2022) reviewed the recent advances in ML studies on MXenes for energy conversion and storage. In the review by (Barrett and Haruna, 2020), the potential of ML as a practical tool for computing the physico-chemical properties and time scales of energy materials was identified and highlighted. The authors also underscored the current capability of ML in comparison to computational quantum mechanical modelling methods such as density functional theory for application in data analysis. Other studies have reviewed the current developments on ML applications in energy storage from a computation angle compared to the materials aspect earlier presented. The review paper by (Abualigah et al., 2022) reviewed the applications of ML in the optimisation of energy storage from wind and PV solar renewable energy systems.

Further reviews of the literature on the applications of machine/deep learning on energy storage (MDLES) research show that over 1201 documents including articles, conference papers and reviews have been published on the subject over the years. Despite the numerous publications on MDLES research, there is currently no study that has examined the research landscape, publications trends, and stakeholders' analysis of the topic. Therefore, this study presents a bibliometric analysis and literature review of the current developments in MDLES research based on published documents indexed in the Elsevier Scopus database between 2012 and 2022. The paper also aims to provide crucial insights into the current publication trends, and benchmark publications, as well as the most prolific authors, affiliations, countries, and funding organisations actively engaged in the research topic. The presented anthology of materials will avail current and future researchers with critical information on the current status and future directions of MDLES research.

2. METHODOLOGY

The objective of the paper is to examine the research trends and publications landscape on the application of machine/deep learning in energy storage. The analyses were performed based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique, which is used to identify, and screen published documents from selected scientific databases. In this study, the Elsevier Scopus database was selected for the identification of the published documents on machine/deep learning in energy storage research (abbreviated hereafter as MDLES research).

The published documents or publications on the MDLES research were identified using the "TITLE-ABS-KEY" search criteria: ("machine learning" OR "deep learning" AND "energy storage") AND PUBYEAR >2011 AND PUBYEAR <2023 which was executed in Scopus to recover related documents published on the topic between 2012 and 2022. The search was executed on 24th January 2023 and recovered 1122 results comprising numerous document types (e.g., notes, erratum, letters, and data papers, etc.) and source types (trade journals, book series, and books, etc.) published in various languages (e.g., Chinese, Korean).

Consequently, the document screening process was performed to eliminate the non-peer reviewed, duplicates, and unrelated as well as non-English publications from the recovered list of documents. The screening process was performed using the "LIMIT-TO" and "EXCLUDE" refine functions of Scopus, which resulted in 969 published documents after eliminating 153 documents from the list. The resulting document types were articles, conference papers, and reviews, whereas the source types are journals and conference proceedings, all published in the English language.

The analysis stage involved examining the publication's trends and research landscape on MDLES studies using the recovered publications data from Scopus and Bibliometric analysis (BA). The publication's trends analysis involved examining the publication's output, as well as the productivity of the top authors, affiliations, institutions, and countries. The impact of research funding and the top funding agencies on the topic were also analysed. Lastly, the research landscape was analysed through the co-authorship, keywords co-occurrence, and citation analyses features of the BA software VOS viewer (version 1.6.17). The BA analysis was used to examine the impact of collaborations on the productivity of the major research actors, as well as determine the current hotspots and future directions on MDLES.

3. RESULTS AND DISCUSSION

3.1. General Publication Trends

Figure 1 illustrates the plot of the total publications and citations on MDLES research against the year of publication. The analysis of the general publication trends shows that the number of published documents increased from 3 to 385 (or a 12,733.3% increase) between 2012 and 2022.

Based on the data, the rate of publications on the topic translates into 88.09 publications or 9.09% of the total publications (TP) per annum. Similarly, the total number of citations (TC) was found to increase over the years from 989 in 2012 to 1061 citations in 2022, although the highest number of TC = 3928 was recorded in the year 2020. Based on the metrics, MDLES has an *h*-index of 59 based on TC = 15,256, which indicates it is a topic that has a very high research impact. High citation rates are normally ascribed to factors such as the type/quality of the publications, the reputation of the scientific journals, and or the multidisciplinary nature of both publication and journal (Bordons et al., 2013; Ajibade et al., 2022; Carroll, 2016). To examine the impact of this submission on MDLES research, the distribution of document types, source types, and subject areas was examined in detail. Table 1 shows the distribution of document types on the MDLES research as recovered from the Scopus database on the topic between 2012 and 2022. As can be seen, the most predominant document type commonly used for publication is "articles," which accounts for 61.4%, whereas "conference papers" account for 29.9% and lastly "reviews" at 8.7%. The preference for articles is often attributed to the prestige or influence attached to this form of publication, particularly when allied with high-impact journals (Suber, 2008; González-Pereira et al., 2009).

Conference papers provide authors (particularly early career types) with the opportunity to present their findings at meetings or seminars and learn about progress in their field [50]. It also provides a social environment for academics and other scientific actors to network, interact and receive instant or immediate feedback, which serves as a launch pad for future collaborations or publications in top-tier journals (Van Teijlingen and Hundley, 2022; Pan and Lee, 2011; Rowley, 2012). Typically, the highest research impact or scholarly prestige is reserved for publication in high-impact journals. Hence, the analysis of the top journals on MDLES research was examined as shown in Figure 2.

As observed in Figure 2, the number of publications in the top journals on MDLES research has increased proportionally over the years. The top 5 journal sources on MDLES research account for

Figure 1: General publication trends on machine and deep learning in energy storage research (2012-2022)

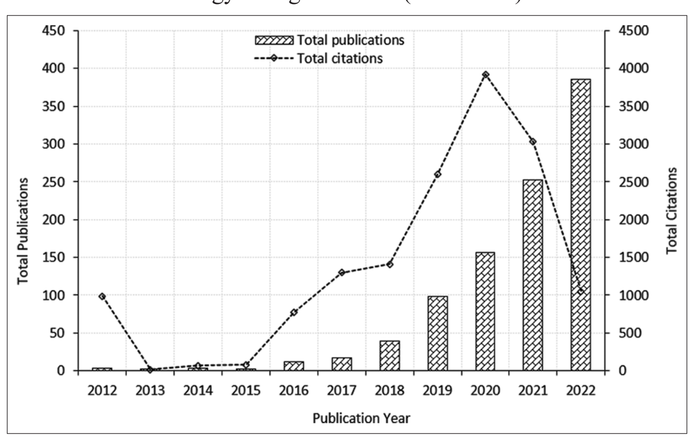


Table 1: Distribution of document types on MDLES research

Document types	Total publications (TP)	Percentage of total publications (%TP)
Article	595	61.40
Conference paper	290	29.93
Review	84	8.67

over 150 publications, 15% of TP, and 2680 citations on the topic. The top five journals and their publication counts (in brackets) on the topic are *Energies* (47), *Applied Energy* (37), *Journal of Energy Storage* (30), *IEEE Access* (22), and *Energy* (18). Further analysis shows that the most productive source title is *Energies*, which is an open-access journal published by MDPI (Multidisciplinary Digital Publishing Institute). However, the most impactful (defined as the ratio of total citations to total publications) journal on the topic is *Energy* (TC/TP = 352.07), which is followed by *Applied Energy* (TC/TP = 294.10) and *Journal of Energy Storage* (TC/TP = 114.99). It can be concluded that open access and journal reputation have been critical to the author's decision to publish their works in the MDLES research landscape.

Another factor could be the multidisciplinary nature of the journal or source titles which accommodates broad-themed papers on MDLES. The analysis of the subject areas for publications on the topic was performed to examine the interdisciplinary nature of the topic. Figure 3 shows the distribution of subject areas for publications on the topic as deduced from the Scopus database from 2012 to 2022. As can be seen, a high number of publications are indexed under the Engineering category with 591 publications, which is followed by Energy (496) and then Computer Science (303). Other notable categories include Mathematics (182), Materials Science (156), and Chemistry (110). The findings indicate that although the publications are largely within the STEM fields, the subject area analysis indicates that MDLES research is broad-themed, complementary, and interdisciplinary, which may explain the high number of publications and citations received on the topic over the years.

Figure 2: Distribution of top 5 journal/source titles on machine and deep learning in energy storage research (2012-2022)

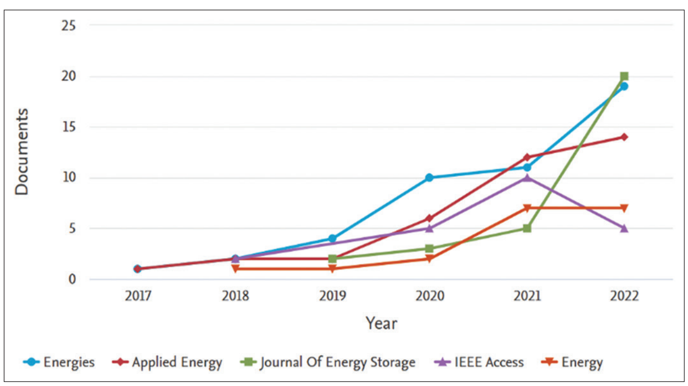
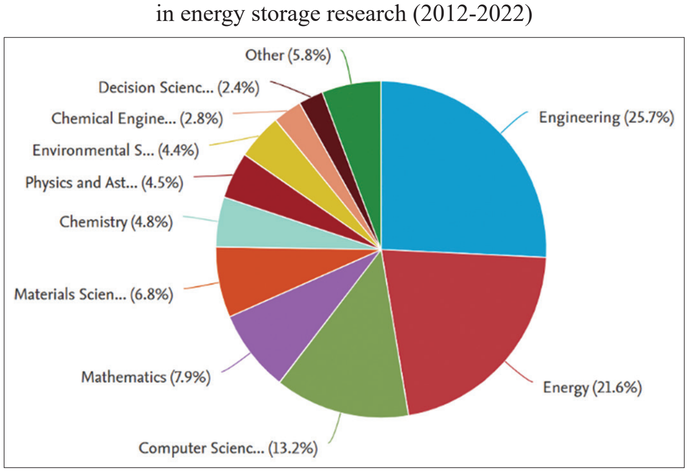


Figure 3: Distribution of subject areas for machine and deep learning in energy storage research (2012-2022)



The numerous studies on machine/deep learning algorithms in energy storage research clearly show the growing importance of the application of mathematics and computer science in addressing energy engineering challenges. One of the most notable research areas that benefitted from the interdisciplinary nature of MDLES is battery development. For example, (Hu et al., 2015) employed advanced sparse Bayesian predictive modelling to examine the life span of lithium-ion (Li-ion) batteries in electric vehicles. The study observed that ML could be potentially useful in examining and managing the health of Li-ion batteries in EVs. In another similar study, (Hu et al., 2015) also employed the ML-based State-of-Charge (SOC) estimator and novel genetic algorithm-based fuzzy C-means (FCM) clustering technique to examine Li-ion batteries in EVs. Other notable studies include the use of ML for estimating the SOC of Li-ion batteries used in EVs (Chemali et al., 2018; Feng et al., 2019; Shen et al., 2019). ML has also been applied in the design, development, and optimisation of renewable energy technologies such as biomass (Wang et al., 2020), solar (Chung et al., 2020; Karaağaç et al., 2021; Syed and Khalid, 2021; Dhanalakshmi et al., 2022), and wind energy (Cabrera et al., 2018; Moreno et al., 2018) as well as smart-and micrograds (Wang et al., 2018; Nie et al., 2020; Akpolat et al., 2021). The studies have demonstrated the prospects of utilising machine/deep learning algorithms for predicting, managing and optimising RETs for clean energy generation and storage. Lastly, the review of literature and subject area analysis shows that MDLES research is a highly influential topic with significant potential for future growth, development, and highly cited publications alike.

3.2. Highly Cited Publications (HCP)

Numerous studies have highlighted the correlation between high citation rates and research impact (Antelman, 2004; Meijaard et al., 2015). Hence, the assessment of the research landscape in any field requires analysis of the top-cited publications. In this study, the HCP is defined by the number of publications with 100 or more citations in the Scopus database to date. Table 2 shows the top 30 most highly cited publications on MDLES research from 2012 to 2022. The data analysis shows that the top 30 most HCP consists of 66.67% articles and 33.33% review papers, which have cumulatively gained between 104 and 892 citations (5971 in total or 199.03 on average) over the period examined in this study. The most HCP is the review paper "Current methods and advances in the forecasting of wind power generation" by (Foley et al., 2012). The authors described the use of ML in the benchmarking and forecasting of wind energy. The 2nd most HCP is "Perovskites in catalysis and electrocatalysis" by (Ajibade et al., 2022), (792 citations) which highlighted the potential of ML in catalysis. The authors reported that ML is a vital tool for the targeted design of catalysts as well as for detecting the key descriptors used to predict and justify the activity of such catalysts. ML can also be used for computing the basic properties and high-throughput screening of materials using computational tools such as density functional theory (DFT). The 3rd most HCP is "Battery health prognosis

Table 2: Top 30 most highly cited publications on MDLES research (2012-2022)

Authors/references	Paper title	Source title	Citations	Document Type
(Foley et al., 2012)	Current methods and advances in forecasting of wind power generation	Renewable Energy	892	Review
(Ajibade et al., 2022)	Perovskites in catalysis and electro catalysis	Science	792	Review
(Hu et al., 2015)	Battery health prognosis for electric vehicles using sample entropy and sparse Bayesian predictive modelling	IEEE Transactions on Industrial Electronics	340	Article
(Chemali et al., 2018)	State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach	Journal of Power Sources	308	Article
(Chen et al., 2019)	Combining theory and experiment in lithium-sulphur batteries: Current progress and future perspectives	Materials Today	235	Review
(Hu et al., 2015)	Advanced Machine Learning Approach for Lithium-Ion Battery State Estimation in Electric Vehicles	IEEE Transactions on Transportation Electrification	219	Article
(Ojeniyi and Ajibade, 2022)	A review of composite solid-state electrolytes for lithium batteries: Fundamentals, key materials, and advanced structures	Chemical Society Reviews	208	Review
(Wang et al., 2020)	Recent progress of biomass-derived carbon materials for super capacitors	Journal of Power Sources	196	Review
(Ng et al., 2020)	Predicting the state of charge and health of batteries using data-driven machine learning	Nature Machine Intelligence	190	Review
(Feng et al., 2019)	Online State-of-Health Estimation for Li-Ion Battery Using Partial Charging Segment Based on Support Vector Machine	IEEE Transactions on Vehicular Technology	155	Article
(Wen et al., 2019)	Optimal load dispatch of community microgrid with deep learning-based solar power and load forecasting	Energy	149	Article
(Shen et al., 2019)	A deep learning method for online capacity estimation of lithium-ion batteries	Journal of Energy Storage	143	Article
(Wang and Hong, 2020)	Reinforcement learning for building controls: The opportunities and challenges	Applied Energy	141	Article
(Trahey et al., 2020)	Energy storage emerging: A perspective from the Joint Centre for Energy Storage Research	Proceedings of the National Academy of Sciences of the United States of America	137	Article
(Ding et al., 2019)	Transforming Energy with Single-Atom Catalysts	Joule	134	Review
(Yu et al., 2020)	Deep Reinforcement Learning for Smart Home Energy Management	IEEE Internet of Things Journal	128	Article
(Shen et al., 2019)	Phase-field modelling and machine learning of electric-thermal-mechanical breakdown of polymer-based dielectrics	Nature Communications	125	Article
(Liu et al., 2020)	Machine learning assisted materials design and discovery for rechargeable batteries	Energy Storage Materials	120	Review
(Zeng et al., 2018)	Dynamic Energy Management of a Microgrid Using Approximate Dynamic Programming and Deep Recurrent Neural Network Learning	IEEE Transactions on Smart Grid	118	Article
(Kim et al., 2016)	Machine Learning Assisted Predictions of Intrinsic Dielectric Breakdown Strength of ABX3 Perovskites	Journal of Physical Chemistry C	116	Article
(Chen et al., 2020)	Machine learning: Accelerating materials development for energy storage and conversion	InfoMat	115	Article
(Ajibade et al., 2021)	Exceptional piezoelectricity, high thermal conductivity, and stiffness and promising photocatalysis in two-dimensional MoSi2N4 family confirmed by first-principles	Nano Energy	114	Article
(Sharifzadeh et al., 2019)	Machine-learning methods for integrated renewable power generation: A comparative study of artificial neural networks, support vector regression, and Gaussian Process Regression	Renewable and Sustainable Energy Reviews	112	Article
(Moghadam et al., 2019)	Structure-Mechanical Stability Relations of Metal-Organic Frameworks via Machine Learning	Matter	111	Article
(Jiang et al., 2018)	Machine-learning-revealed statistics of the particle-carbon/binder detachment in lithium-ion battery cathodes	Nature Communications	110	Article
(Mannodi-Kanakkithodi et al., 2018)	Scoping the polymer genome: A roadmap for rational polymer dielectrics design and beyond	Materials Today	109	Review
(Xiong et al., 2018)	Towards a smarter hybrid energy storage system based on battery and ultracapacitor - A critical review on topology and energy management	Journal of Cleaner Production	107	Article
(Schopfer et al., 2018)	Economic assessment of photovoltaic battery systems based on household load profiles	Applied Energy	107	Article
(Aslam et al., 2021)	A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids	Renewable and Sustainable Energy Reviews	104	Review
(Wu et al., 2020)	Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems	Energy and AI	104	Article
(Li et al., 2019)	Constrained EV Charging Scheduling Based on Safe Deep Reinforcement Learning	IEEE Transactions on Smart Grid	100	Article

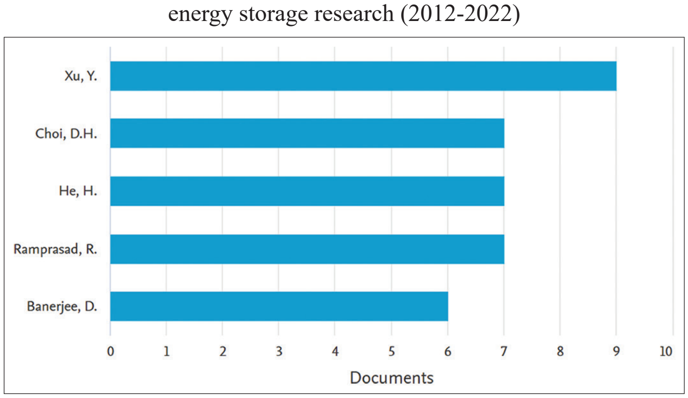
for electric vehicles using sample entropy and sparse Bayesian predictive modelling" by (Hu et al., 2015), with 340 citations. Lastly, "State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach" by (Chemali et al., 2018) is another HCP on the topic with 308 citations. The HCP analysis shows that the MDLES research landscape is characterized by highly influential publications which have identified, examined, and highlighted various potential areas for the application of computational tools such as ML/DL in tackling renewables and energy engineering challenges.

3.3. Top Authors

Figure 4 shows the top 5 most prolific authors on MDLES research from 2012 to 2022. As can be seen, the authors have published 6 or more publications on the topic over the years. The top author is Yan Xu who is based at the Nanyang Technological University (Singapore) with 9 publications, which have gained a total of 100 citations (*h*-index = 6). The author's most notable publication is "Data-Driven Game-Based Pricing for Sharing Rooftop Photovoltaic Generation and Energy Storage in the Residential Building Cluster under Uncertainties" published in the IEEE Transactions on Industrial Informatics, which has been cited 21 times. In the article, Yan Xu and co-workers proposed an innovative data-driven approach for rooftop PV electricity pricing using ML. The findings showed that the ML-based approach could be potentially deployed to address energy-sharing challenges using partial or uncertain information. Another notable contribution of Yan Xu is the article, "Proactive frequency control based on ultra-short-term power fluctuation forecasting for high renewables penetrated power systems" published in IET Renewable Power Generation with 21 citations to date. The authors proposed and examined the use of an ML-based ensemble-forecasting model to forecast extreme short-range power instabilities. The objective was to create an automatic generation control model/system to mitigate the frequency deviations typically observed in highly intermittent and uncertain power output sources such as renewables. The findings showed that the ML-based approach has potential to the reduce the charging and discharging frequencies and efficiently prolong the lifespan of energy storage systems.

The research landscape of MDLES has also been significantly influenced by the contributions of *Dae-hyun Choi* (Chung-Ang University, South Korea), *Hongwen He* (Beijing Institute of Technology, China), and *Ramamurthy Ramprasad* (Georgia

Figure 4: Top 5 most prolific authors on machine and deep learning in energy storage research (2012-2022)



Institute of Technology, United States) who have 7 publications each on the topic. The productivity of researchers in any given field of research is typically attributed to various factors, one of which is collaborations and partnerships that foster various forms of knowledge sharing or exchange. The impact of collaborations on MDLES research can be examined through the co-authorship feature of VOS viewer.

Figure 5 shows the network visualisation map (NVM) for co-authorship on MDLES research from 2012 to 2022. The map is based on a minimum of 5 documents and 50 citations per author. The results showed that 61 authors out of the possible 3166 have 5 or more publications that have gained over 50 citations during the timeframe examined in the study. Furthermore, 57 out of the 61 i.e., 93.44% of the top authors on MDLES have co-authored papers on the topic. In addition, the cluster analysis shows that there are 8 clusters comprising 3-13 authors along with 244 links with a TLS of 334. As such, it could be judiciously deduced that co-authorship has had a significant impact on the productivity of the authors on the topic.

3.4. Affiliations

Figure 6 shows the plot of the top 5 most prolific affiliations on MDLES research (2012-2022). As can be seen, the top 5 most prolific affiliations have published 15 or more publications on the topic over the timeframe examined in this study. The top affiliations and their publication counts (in brackets) are *Tsinghua University* (32), Chinese Academy of Sciences (28), Ministry of Education China (27), *Nanyang* Technological University (NTU, 21), and *Shanghai Jiao Tong* University (18). Except for NTU Singapore, the other four most prolific affiliations are based in China, which indicates that Chinese-based institutions are dominant actors or stakeholders in the application of ML/DL in energy storage.

The dominance of China and its institutions is largely due to the nation's long-term plan for scientific growth and technological development. As stated in the nation's AI roadmap of 2017, China has developed a three-pronged AI roadmap policy which aims to "keep pace with leading AI technology and applications in general by 2020, make breakthroughs by 2025, and be the world leader in the field 5 years thereafter" (Ajibade et al., 2022). According to (Lee, 2017), China also has a long-term plan to overtake the United States to become the worldwide global leader in the field by 2030. However, (O'Meara, 2019) notes that China can only achieve these goals through research into fundamental theories and innovative technologies such as artificial intelligence (AI). It is envisaged that research into AI and computational tools such as ML/DL could provide the breakthroughs required. Consequently, the nation's quest has opened up investments in the sector providing ample funding for advanced research and development (R&D) in the sector across industry and academia. The impact of research funding and the leading bodies sponsoring R&D in the sector are identified and examined in section V.

3.5. Funding Bodies

Figure 7 shows the top 5 most prolific funding bodies for MDLES research from 2012 to 2022 based on Scopus data. As can be seen, the top 5 funders have sponsored 20 more publications on the

Figure 5: NVM for co-authorship among authors on machine and deep learning in energy storage (2012-2022)

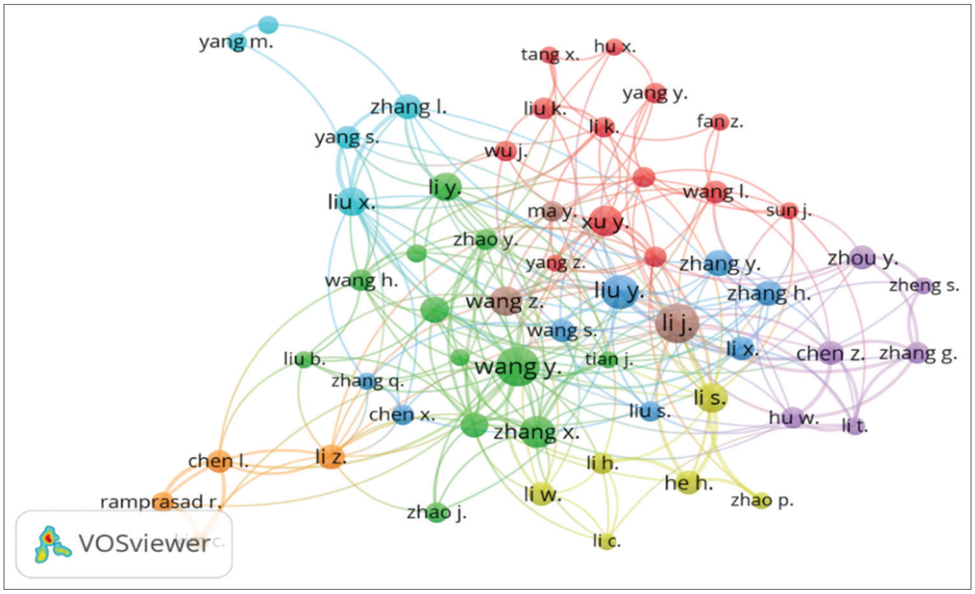


Figure 6: Top 5 most prolific affiliations on machine and deep learning in energy storage research (2012-2022)

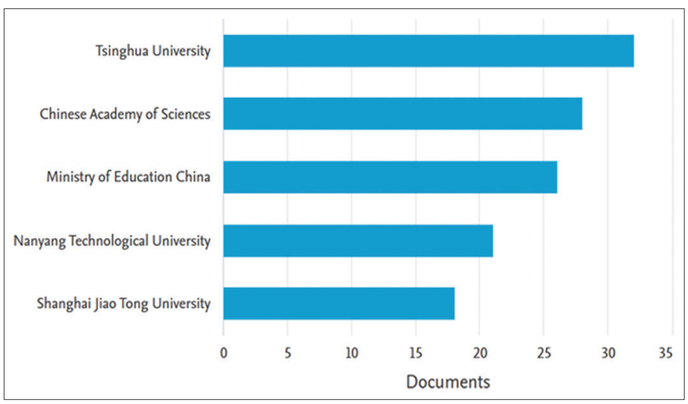
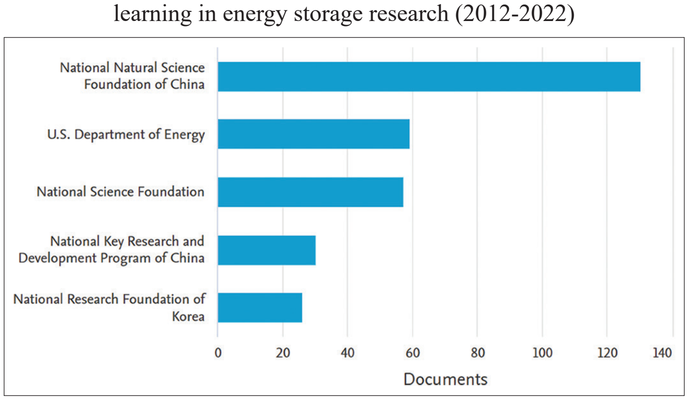


Figure 7: Top 5 most prolific funding bodies for machine and deep learning in energy storage research (2012-2022)



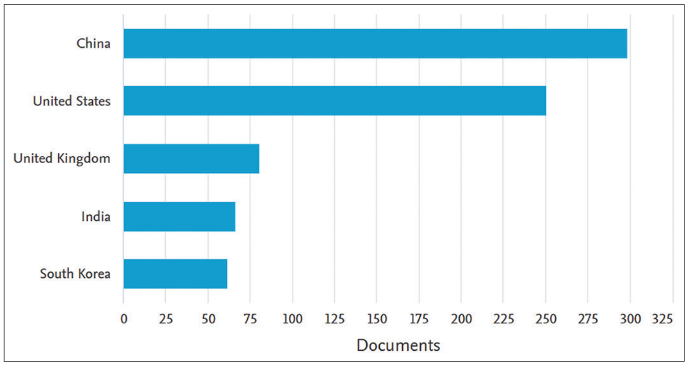
topic over time. The most active funder is the National Natural Science Foundation of China (NSFC) with 130 publications that have gained 3,445 citations (*h*-index 31; TC/TP = 26.5) over time. Notably, the NSFC has been critical in funding the research works of *Hongwen He* and *Shuangqi Li* who are both based at the Beijing Institute of Technology (BIT, China). The NSFC has also funded research collaborations between Yan Xu (the most prolific author on MDLES) based at NTU Singapore and other researchers based in Chinese institutions such as *Hong Kong* Polytechnic University*, Hunan University,* and *Shanghai Jiao Tong University*. This confirms that funding as in the case of the duo at BIT and the works NTU with others show that funding supports collaborations among researchers worldwide.

The United States Department of Energy (US-DoE) is also another major funder of MDLES research. To date, the US-DoE has funded research resulting in 59 publications that have amassed 1620 citations (*h*-index 17; TC/TP=27.45). The agency has been critical to the research endeavours of *Tianzhen Hong* (Lawrence Berkeley National Laboratory, Berkeley), *Badri Narayanan* (University of Louisville, Louisville), and *Rajeev S. Assary* (Argonne National Laboratory, Lemont), which have produced 8 publications in total. The funds from the agency have also enabled collaborations between US-based researchers and others in institutions in China (6), Germany (3), Canada (2), France (2), and the United Kingdom (2). The third major funder of MDLES research is also another US-based agency the National Science Foundation (NSF) with 57 publications, which have accumulated 1,013 citations with an *h*-index of 15. The NSF has been influential to the works of the collaborative works of *Abdullah Al Hadi*, *Rosemary E. Alden*, and *Huangjie Gong* based at the University of Kentucky, Lexington. Overall, the funding body analysis shows that the US and China-based institutions dominate the funding landscape for MDLES research, which is largely due to their quests to not only make breakthroughs in ML/DL/AI research but also dominate the sector globally. Further analysis of the influence of the two nations along with others is presented in Section VI.

3.6. Countries

Figure 8 shows the top 5 most prolific countries involved in MDLES research worldwide. The data shows that China, the US, the UK, India, and South Korea are the most active research nations when it comes to the topic between 2012 and 2022. The findings show that all 5 nations have published 50 or more publications on the topic.

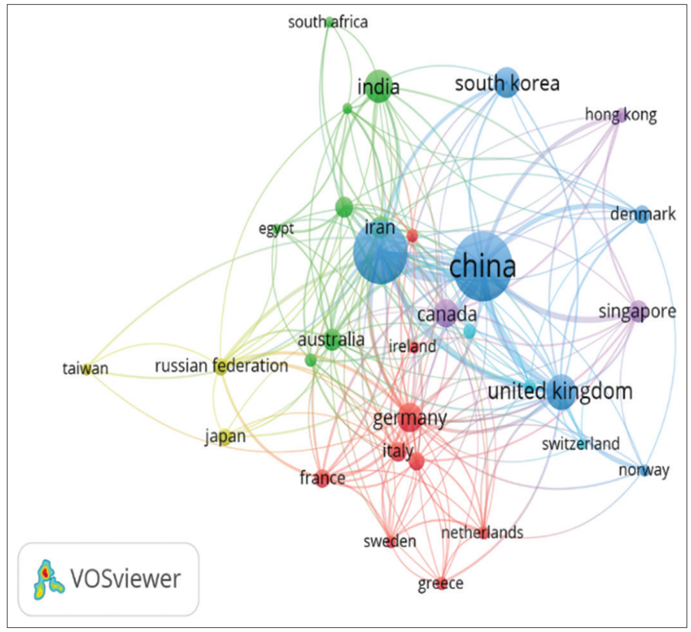
Figure 8: Top 5 most prolific countries in machine and deep learning in energy storage research (2012-2022)



As can be seen, the most prolific nation involved in MDLES research is China with 298 publications, which have gained 5249 citations with an h-index of 38 over the years. The productivity of China could be attributed to the works of *Hongwen He* (7), and *Shuangqi Li* (5) who are based at the Beijing Institute of Technology as well as Tsinghua University researchers such as *Xiang Chen* (3), and *Longqing Chen* (2). The productivity of China is also due to the collaborations between the nation's researchers and others abroad such as *Xinhua Liu* (5) of Imperial College London, London (UK), *Yan Xu* (Nanyang Technological University, Singapore), *Zhe Chen* (Aalborg University, Denmark) among others. The United States with 250 publications is the second most prolific country involved in MDLES research. The nation's productivity is largely due to the works of *Ramamurthy Ramprasad* (7), *Debjyoti Banerjee* (6), and *Chiho Kim* (5) who are based at various institutions including the Argonne National Laboratory, Massachusetts Institute of Technology, and Pacific Northwest National Laboratory. Other significant contributors to the research and development of MDLES are the United Kingdom (80), India (66), and South Korea (61). Overall, the findings indicate that the research landscape on MDLES has been largely influenced by national interests, which has fuelled not only high research activities and productivity but also collaborations between national/international researchers and institutions based in various countries. To further examine this submission, the visualisation map showing the network of countries actively involved in MDLES research was created using the co-authorship feature of the VOSviewer software, as illustrated in Figure 9.

The map shows that 32 out of 88 countries have published at least 5 documents that have received 50 citations on MDLES research. The countries with the highest number of co-authored publications (P) and citations (C) are China (P=306, C=5173), the US (251, 5,790), and the UK (81, 1,999), whereas the highest TLS observed for the nations are China (179), US (122), and UK (94). The data indicate that the three nations are the most dominant in the field, which, as earlier stated, is due to their quest to gain first-mover advantage and dominate the field so as to promote their national interests. Cluster analysis of the NVM shows that there are 6 major clusters comprising 3-9 countries with 206 links and a TLS of 520. The largest cluster comprises France, Greece, and Germany among others, whereas the smallest has Belgium, Switzerland, and Turkey. Overall, it can be inferred that collaborations between these nations have played an active

Figure 9: Network visualisation map for co-authorship among nations on machine and deep learning in energy storage (2012-2022)



part in the development of MDLES research over the years. The existence of clusters also suggests that MDLES research has evolved from hotspots or thematic-based research in the various institutions and countries actively involved in the field across the world. The various hotspots and thematic areas of MDLES research are identified and analysed as presented in Section VII.

3.7. Hotspots/Thematic Areas

Figure 10 shows the NVM of keywords co-occurrences on MDLES research, and clusters generated from the analysis using VOSviewer. The findings indicate that out of the possible 7,630 keywords identified for the topic, 41 keywords satisfied the set criteria of a minimum occurrence of 50 times. The top 3 occurring keywords on the topic are digital storage (447), machine learning (438), and Energy Storage (407), whereas the highest TLS was observed for digital storage (2326), machine learning (1870), and deep learning (1859). This finding indicates MDLES research is largely focused on the use of machine/deep learning for energy and digital storage. Cluster analysis revealed three (3) clusters comprising 7-19 keywords, which are denoted by different colours (red, green, and blue) as shown in Figure 10. The largest cluster consists of deep learning, energy utilisation, microgrids, and storage systems among others, whereas the smallest comprises energy efficiency, solar energy, optimisation, and forecasting. Based on the findings the research and development in the field have evolved in three pathways with the highest occurrences observed between 2020 and 2021 (Figure 11), as characterised by the clusters deduced from the analysis.

Cluster 1 (red) specifically highlights the application of DL technologies and systems for electrical/energy storage, management, and utilisation in applications such as smart grids. Cluster 2 (green) shows the use of ML and neural networks for digital/energy storage or applications such as battery charging. Lastly, cluster 3 on MDLES research highlights the application

Figure 10: Network visualisation map of keywords co-occurrences on machine and deep learning in energy storage research

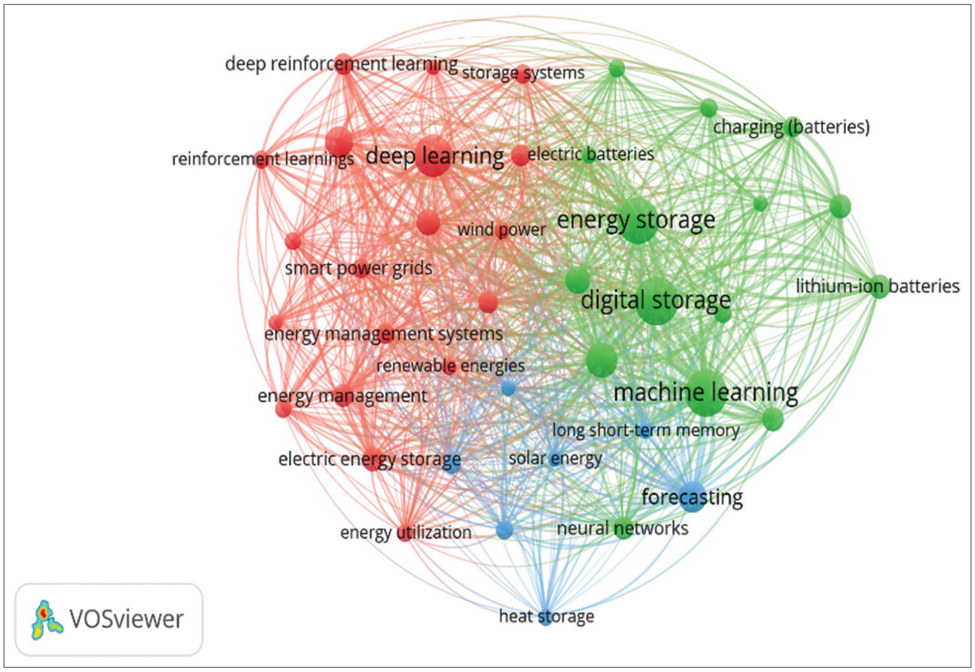
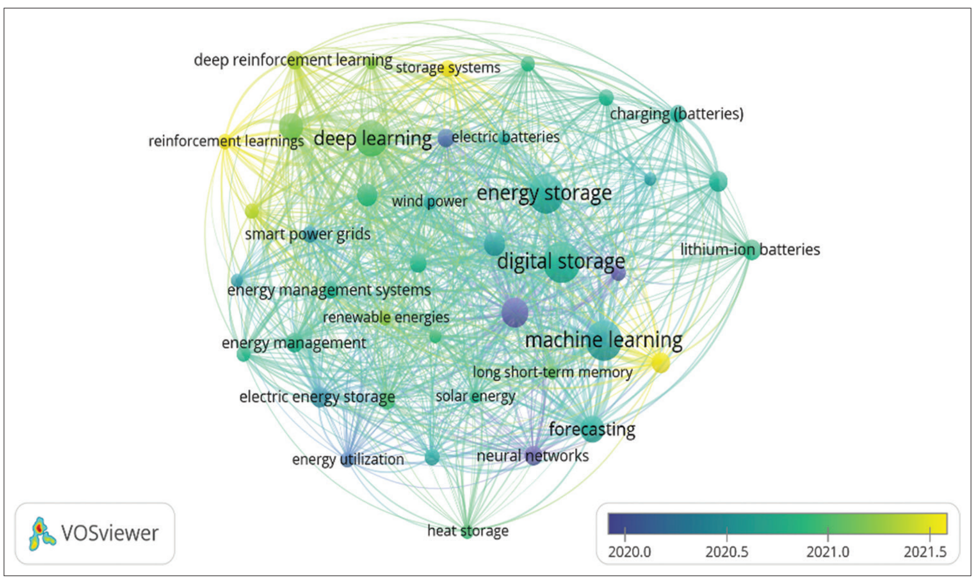


Figure 11: Overlay visualisation map of keywords co-occurrences on machine and deep learning in energy storage research



of ML/DL for forecasting, operating, and optimisation of energy storage. Based on the cluster analysis, MDLES research has been largely focused on the use of ML/DL technologies for forecasting and optimising energy/digital storage in batteries, heat storage as well as other storage devices.

Future research will likely focus on the ML/DL and computational applications for the design and development of more efficient energy storage materials such as nanofluids, polymer composites, and polymeric nanocomposites. Such materials or interfaces could greatly enhance large-scale energy/electrical storage, particularly at low fields as well as the optimal control of such complex energy storage systems. The design, development, utilisation, and optimisation of phase change materials using ML/DL could also take centre stage in the near future. Furthermore, advances in MDLES could enhance smart grid efficiencies as well as the real-time pricing, revenue prediction, or trading of electricity particularly intermittent sources such as renewable wind or solar energy storage systems. Other studies could also provide a framework to address current issues such as SOC in batteries, as well as the performance and reliability of such complex storage systems.

4. CONCLUSION

The paper examined the publication trends and bibliometric analysis trends on machine/deep learning applications for energy storage. The PRISMA technique employed to identify, screen, and filter published documents MDLES research from the Elsevier Scopus database revealed 969 published documents after the elimination of 153 unrelated documents. The distribution of published documents revealed various English language-based articles, conference papers, and reviews published in various high-impact journals such as *Energies*, *Applied Energy*, and *Journal of Energy Storage*. Subject area analysis revealed MDLES research publications are indexed under various categories such as *Engineering*, *Energy* and, *Computer Science*, which indicate MDLES research is broad-themed and interdisciplinary. The multidisciplinary nature and research funding for MDLES have been adjudged as the reasons for the high publication and citation rate of the topic. The publication trends also revealed that the most prolific researcher is *Yan Xu* (Nanyang Technological University), whereas for institutions it is *Tsinghua University* (China).

The funding landscape revealed that institutions in China and US are the largest funders of MDLES research, which accounts for their high rate of publications, citations, and stakeholders on the topic worldwide. Hotspot analysis revealed that the growth and development of MDLES research can be explained by the three clusters or themes derived from keywords co-occurrence analysis. The top 3 occurring keywords on the topic are digital storage (447), machine learning (438), and energy storage (407), which indicates MDLES research has been largely focused on the application of machine/deep learning for the prediction, operation, and optimisation of energy storage particularly renewable energy technologies such as wind, and solar. Based on the findings, the authors opine that future directions on the topic will most likely include a focus on ML/DL and computational applications for energy materials synthesis, energy efficiency analysis, operational systems monitoring and control as well as techno-economic analysis for electricity pricing, trading, and revenue prediction. Overall, the paper provided comprehensive insights into the publication's trends, and research landscape on MDLES using the PRISMA technique, Scopus database, and Bibliometric analysis.

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