Battery optimization by machine learning algorithms: Research gap via bibliometric analysis

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Abstract. Technological developments enable low-carbon transitions to be accelerated by conceptualization systems and innovations for research and development to generate clean energy. Batteries are becoming one of the essential parts of the science of electrical power sources. Lithium-ion batteries are part of the change and development factors in technologies that significantly impact the portable devices sector and the development of electric vehicles. Designing the material structure and composition of battery manufacturing with the help of engineering system design will form a much more optimal battery. Machine learning algorithms can easily optimize the battery's composition through battery experiment test data history to produce a more optimal battery configuration. This study is prepared to identify research gaps in topics related to machine learning for battery optimization. Related studies about machine learning for battery optimization are identified using bibliometric analysis and systematic literature review of the study search index through database Scopus-indexed publications. The results from this paper reveal energy management systems and strategies, hybrid vehicles, other optimization algorithms, battery electrodes, and the safety of batteries as the particular research gap according to machine learning for battery optimization. This paper expects research on battery optimization using machine learning methods will continue to be developed to maximize the potential of machine learning algorithms in helping the research process.

1. Introduction

Technological developments are enabling low-carbon transitions to be accelerated and have made the idea of clean energy disruption widespread. The transition to clean energy aims to reduce global CO_2 emissions. Through the clean energy transition, it will have an impact on around 40% of global CO_2 emissions [1]. Conceptualization systems and innovations are able to accelerate research and development to generate clean energy. Electrical energy is one of the clean energies free from carbon emissions and easily obtained today. This is due to electrical power sourced from renewable energy and does not require a combustion process that causes an increase in carbon emissions. The source of electrical energy obtained through various renewable energy is channeled and accommodated through batteries.

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Batteries are becoming one of the essential parts of the science of electrical power sources. Lithium-ion batteries are part of the change and development factors in technologies that significantly impact the portable devices sector and the development of electric vehicles [2]. Optimization of the battery is needed to increase battery life and increase the power flow channeled through the battery. Various methods have been developed to accelerate the battery optimization process in manufacturing, industrial, and electronic needs. Given that energy needs are increasing, the construction of optimal battery design is increasingly being developed using constantly evolving technology. [3]. The method of the battery optimization structure is carried out to get a battery formulation with high power resistance and energy distribution for the needs of the technology transition era. Designing the material structure and composition of battery manufacturing with the help of engineering system design will form a much more optimal battery. The purpose of the invention is to maximize the cycle in the battery to be more reliable through charging data and power distribution in the battery. Data generated from battery life trials will be used as parameters translated by machine learning to create more optimal design batteries, have a longer cycle life, deliver a high power, and are relatively affordable using environmentally friendly materials [4].

There are millions of possibilities found suitable materials to be used as electrolytes in batteries. Machine learning technology is able to help filter optimal materials for battery development. Machine learning is part of a computer system related to artificial intelligence stands out as a promising approach for research and development, especially in battery optimization. Artificial intelligence and machine learning are able to solve problem parameters effectively for a more optimal battery technologies research and development process [5]. For example, when developing electrochemical capacitors and electrolyte fluids in batteries related to experimental data. Machine learning algorithms can easily optimize the battery's composition through battery experiment test data history to produce a more optimal battery configuration. In addition, machine learning is able to expand the scale of the approach to get a more optimal battery design. Accurate data processes and able to identify errors make machine learning able to simulate experiments on a larger scale without experiments that require high costs [6]. Transparent data access makes the opportunity to adopt machine learning systems for research and development toward battery optimization even more promising. Science and technological developments make machine learning systems capable of processing data with a high level of accuracy. It is helpful for the study and future development of battery optimization [7].

This study is prepared to identify research gaps in topics related to machine learning for battery optimization. Related studies about machine learning for battery optimization are identified using bibliometric analysis and systematic literature review of the study search index through database Scopus-indexed publications. During the identification of various related studies, researchers use the Publish or Perish application as a corresponding study search index combined with VOSviewers to display bibliometric analysis. This study aims to explain methods or algorithms that have a strong relationship using bibliometric analysis to show the results of studies classified as high impact to help in the development process and further studies related to battery optimization using machine learning.

2. Literature Review

2.1. Data-driven machine learning approach for battery R&D

Historically, machine learning can be defined as how a machine is able to improve its performance as a machine to achieve specific goals through data and simulations. The ability to automatically conduct experimental processes from machine learning systems is one of the approaches to improving research and development performance in battery manufacturing optimization [3]. Machine learning methods are particularly relevant for material discovery or optimizing battery storage systems for battery manufacturing optimization design. Different parameter possibilities should be considered simultaneously to create an optimized battery storage system [6]. The ability of machine learning depends mainly on the quantity, quality, and veracity of the data. This makes the research and development process necessary to prepare enough data sets to expand simulations and machine thinking knowledge during the machine learning process [8]. Afterward, the architecture in machine learning algorithms needs to be trained through simulations and experiments to create supervised models in machine learning models. The training results conducted through simulations will continue to be recorded and compared to produce outputs in the form of machine learning algorithms which will then be used for design parameters in the battery optimization research and development process.

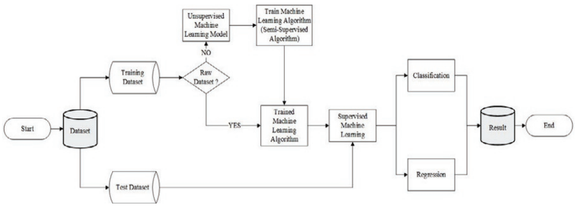

Fig.1. Working Principle of Machine Learning Algorithm

Machine learning algorithms can be classified into three levels of understanding: unsupervised, semi-supervised, and supervised (see Figure 1) [9] [10]. According to unsupervised, the machine learning approach uses raw data processed by machine learning. This approach aims to design data patterns that will be processed to form machine learning algorithms. The unsupervised machine learning approach will provide data output which will then be rerun by machine learning called the supervised machine learning approach [9]. Supervised machine learning will display the results of regression and classification used to describe and conclude data simulations carried out at the unsupervised machine learning stage [11]. The output provided from supervised machine learning is in algorithmic designs such as regression and classification as decision-making parameters in the research and development process. Meanwhile, semi-supervised approaches are a process that is located when data generated from the unsupervised stage begins to produce data that can be run at the supervised approaches stage. The multi-output method is proposed through data-driven models resulting from machine learning to create optimal battery formulation in designing battery optimization [12].

2.2. Battery Energy Storage System Optimization

Clean energy sources use renewable resources and batteries as storage systems into an innovative and environmentally friendly solution to be implemented as sustainable energy for future energy needs closely related to technological developments. A battery energy storage system is a system that supports the continuity of the transition to the use of renewable resources as a step to realizing clean and emission-free energy. The most common battery energy technology today is lithium-ion batteries. The most common type of lithium battery found is $LiMnO_2$ which is used for electronic devices [13]. The other commonly used lithium battery technology, $LiNiMnCoO_2$ and $Li_2Mn_2O_4$, are mainly used for medical devices. The main advantages of lithium-ion batteries are that they are portable, have a high energy density, and have fast charging power [14]. Besides that, the main drawbacks of lithium-ion batteries are limited energy capacity and manufacturing costs that tend to be expensive. Optimizing the battery energy storage system needs to be developed to find better battery system materials and composition. Battery energy storage systems optimization helps the flow of energy with fast response time, high reliability, and low self-discharge rate to be a promising potential for developing battery storage systems. Optimizing the design of an efficient battery storage system is essential to improve reliability and reduce net present cost (NPC) in battery manufacturing [15]. Battery optimization also helps limit the emission of ozone-depleting substances during the production process.

Some factors and aspects considered as system constraints in optimizing the battery storage system are battery cell life, cost efficiency, charging and discharging operation, power oscillations, sudden load changes, disruption of the transmission system, and battery energy distribution [16]. The lifetime of a battery depends on the cell structure used, energy channeling operations, and thermal environment battery placement which is also affected by the charging-discharging cycle [17]. Sometimes the life of a battery also depends on the production cost. In addition, battery capacity and state of health (SoH) are parameters for forming a battery management system [1]. The battery management system using data-driven methods has successfully projected the SoH of Li-ion batteries through algorithms; it shows that the battery management system using machine learning algorithm is able to do battery optimization such as improve battery quality, reduce battery degradation for better capacity, and increase the lifespan of the battery [18].

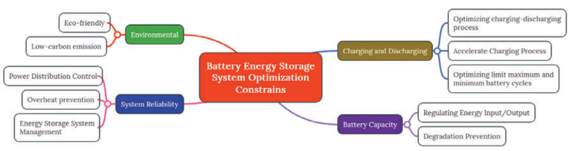

Fig.2. Optimization constraints for battery energy storage system [14]

If inferred from various factors and considerations, battery energy storage system optimization has four constraints: charging and discharging, capacity, reliable system, and environmental (see Figure 2) [14]. Charging and discharging are constraints that refer to optimizing maximum limits and minimum battery cycles, intending to extend the battery's calendric cycle. Capacity constraint refers to reducing battery degradation due to the charging-discharging process and regulating energy distribution at a specific capacity to prevent damage to the battery cell. System reliability constraints guide controlling the battery system's reliability that needs to be ensured to limit overall power and energy to avoid damage to battery cells or life-shortening. Battery system optimization can determine the operational level of the battery energy storage system when there is a direct change in power output during the charge-discharge process. Environmental constraints are related to the materials used in batteries. The materials need to be optimized to maximize the usefulness of the storage system battery and ensure to use of materials that are not harmful to the environment. Identification of all constraint systems in conducting battery optimization can be traced through simulation and data analysis. Parameters and data constraints will be efficiently processed using a machine learning approach to solve battery optimization problems [4]. Machine learning could be a promising approach to optimizing the battery storage system.

2.3. Bibliometric analysis & Study Search Engine Indexing

Bibliometric analysis is a popular method of analyzing large amounts of scientific data. The bibliometric analysis uses quantitative methods to measure specific indicators in scientific data, studies, and papers. Bibliometric analysis techniques are divided into two types, namely performance analysis and science mapping based on research papers [19] show the goal of the bibliometric analysis is to summarize large amounts of bibliometric data to find emerging trends of research topics in structured network visualization. The analysis technique performed using the bibliometric method is used when a broad scope of research in a particular field requires large scientific data sets. From the point of view of scientists and researchers, the benefit of conducting bibliometric research is the bibliometric method can easily classify and make the identification of the relationship between trending research topics with other research topics that have been frequently researched, so the results of bibliometric research can be an initial picture and study literature for a research study in a particular field [20]. Whereas from the point of view of the community and practitioners, the benefits provided by bibliometric research can offer indirect benefits to expand understanding of a particular field. Thus, bibliometric study helps practitioners make decisions from bibliometric results and networks [21]. Bibliometric methods are increasingly used, making some application developers create software to perform bibliometric analysis [19]. The bibliometric tools used in this study are VOSviewer as bibliometric network visualization and Publish or Perish as search engine indexing for citation analysis on academic metadata from academic databases such as Scopus and Google Scholar. Literature analysis from bibliometric analysis combined with bibliometric mapping through network visualization with the VOSviewer application produces an overview of the interrelationships between scientific research using network approaches, areas (nodes), and levels of interaction [22]. In addition, search engine indexing from academic databases through the Publish or Perish application supports scientific data indexing as a parameter to bibliometric mapping. Researchers can see the relationship between keywords from scientific data and sorted research about machine learning for battery optimization based on several criteria discussed in the methodology of this study.

3. Methodology

3.1. Bibliometric Analysis & Mapping

This study's bibliometric analysis and mapping were performed through the Scopus database by searching through search engine indexing available on the Scopus database to find scientific literature from keywords about machine learning associated with battery optimization. Scientific literature searches are carried out using Scopus's database because it has a significant enough data completeness about books, journals, conference papers, thesis, abstracts, and citations. In addition, Scopus is also one of the largest digital platforms that present a variety of science literacy and has a user-friendly interface. The searching process for relevant scientific literature data that will be taken as parameters in bibliometric analysis and mapping will be focused on narrowing the discussion scope through several keywords. The elimination of study results that are less relevant to the scope of discussions related to machine learning for battery optimization is also carried out to get more focused mapping and analysis results. Keywords inputted on Scopus search engine indexing include "Machine Learning", "Battery", "Optimization", and "Design" with input query on Scopus database in the form of boolean logic written as TITLE-ABS-KEY (machine AND learning AND battery AND optimization AND algorithm). Publish or Perish is used to find scientific literature related to machine learning for battery optimization that has a high impact on providing several recommended studies about machine learning for battery optimization. The results of recommendations and discussions from bibliometric analysis and mapping will be aimed for continuity of studies and further research that discusses more comprehensively related to machine learning for battery optimization. Additional query was added to narrow the scope to more detailed and relevant based on inclusion and exclusion criteria (see Table 1). Additional input in the form of boolean logic written as TITLE-ABS-KEY (machine AND learning AND battery AND optimization AND algorithm) AND (LIMIT-TO (DOCTYPE, "ar") AND (LIMIT-TO (LANGUAGE, "English ")) AND PUBYEAR > 2015.

Table 1. Inclusion & Exclusion Criteria

Inclusion Paper	Exclusion Paper
The scope of the analysis from scientific literature must be focused on machine learning for battery optimization	Outside the scope of research on battery optimization study were excluded
Scientific literature must be journal article	Review journal article were excluded
Selected scientific literature must be published from 2015 to 2022	Articles that were published under 2015 were excluded
Selected scientific literature must be written in English	Other languanges were excluded

The detailed systematic literature searching process using PRISMA method is shown in Figure 3. In the first step, when the keyword input "machine learning," there were 424,158 studies that appeared. Then the search continued to be done by adding more keywords "battery" and "optimization" to get related studies and displayed 465 studies. The screening process of 465 study documents is filtered with the criteria in Table 1, showing that there are 133 scientific articles after filtering by criteria process. The last screening is done with the help of Publish or Perish and several stages of manual identification to find scientific literature identified with high impact to get 17 articles that will be used for bibliometric analysis and systematic literature review. Selected scientific literature studies through several screening stages and software screening will be analyzed using VOSviewer software. The result will show a visualization of associated keywords from selected papers. The network of the related keywords will be used to identify research or publication gaps referring to machine learning for battery optimization.

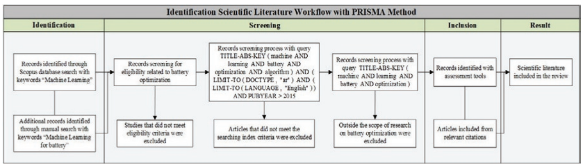

Fig.3. Scientific literature screening workflow with PRISMA method

4. Result and Discussion

4.1. Systematic literature review

Systematic literature reviews from 17 selected papers using the Scopus database for the topic of machine learning for battery management are shown in Table 2. Through the 17 selected articles, it can be seen that the use of machine learning algorithms in optimizing and helping systematic experiments on battery optimization. Problems often encountered in the battery optimization process are battery degradation, short life cycles, and malfunction in the internal part of the battery composition that causes heat in the battery during the charging-discharging process. These battery issues encourage battery optimization research to improve battery performance and optimal safety battery design through experiments and data processed through machine learning technology optimization algorithms

[23]. The algorithm approach used can be in several forms of algorithmic techniques that have been commonly used, such as various vector machine algorithms, genetic algorithms, particle swarm optimization, etc. But inventions related to novel algorithms such as Forgetting Online Sequential Extreme Learning Machine (FOS-ELM) with the Hybrid Grey Wolf Optimizer (HGWO) algorithm can be used for the Li-ion battery prognostic process and then can be used as a basis parameterization for optimizing battery design [24]. The results of the systematic literature review also showed a link to data experiments and the use of algorithms to improve the accuracy of experimental results and reduce costs during battery optimization, especially in battery cycle life coverage, state of charge, state of health, energy management system, battery capacity, electrochemical battery, optimizing battery electrode, and battery temperature [25]. Given that energy needs and the development of electric vehicles are increasing, battery optimization and the discovery of a novel mixture of electrochemical are increasingly essential to be studied further for the advancement of battery technology [26].

Table 2. Scope of discussion and methods related to battery optimization from selected journal articles based on the search index of the Scopus database

Type(s) of Approach	**Parameters**	**Results**	**Ref**
Closed-Loop Optimization (CLO), Predicting Final Cycles, Bayesian Optimization Algorithm	Battery cycle life, battery material selection	Incorporates experimental results to assist in determining future decisions and generalized to applications in optimal battery design	(Attia et al., 2020)
Improving back-propagation neural network (BPNN) using backtracking search algorithm (BSA)	State of charge, charging-discharging limit	BSA optimization utilization has improved the robustness of BPNN to create a more optimal state of charge battery design	(Mahammad A. Hannan, Lipu, Hussain, Saad, & Ayob, 2018)
Rule-based algorithms, optimization-based control algorithms, intelligent-based control algorithms	Hybrid energy storage system optimization (HESS) on battery and ultracapacitor, energy management strategy	Machine learning utilization has improved the efficiency, performance, and lifetime of HESS through a multi-system control strategy using an energy management strategy	(Xiong, Chen, Wang, & Sun, 2018)
Deterministic policy gradient algorithm (DDPG) with expert assistance.	Battery temperature and degradation control, battery health	DDPG algorithm combined with expert assistance creates a proposed strategy that can suppress the battery temperature and reduce overall driving cost compared to existing research about the lithium-ion battery system	(Wu, Wei, Liu, Quan, & Li, 2020)

Table 3. *Cont*

Type(s) of Approach	**Parameters**	**Results**	**Ref**
Extreme learning machine, bat algorithm	State of health battery	The ELM model combined with the bat algorithm creates faster learning and high SOH estimation accuracy for optimizing the battery health management system	(Ge, Zhang, Kong, & Wan, 2022)
Machine learning framework, genetic algorithm	Optimal lithium-ion battery design	There is a high correlation between fire spread and negative cathode. Using genetic algorithms will help find optimal design conditions for improved design safety and better performance	(Yamanaka et al., 2020)
Gaussian Naives Bayes algorithm	The electrode in battery cell performance	Machine learning training algorithms can predict heterogeneity and homogeneity in electrodes and become a robust optimization method for next-generation battery electrodes in the manufacturing process	(M Duquesnoy et al., 2021)
Genetic algorithm, particle swarm optimization algorithm	Battery remaining useful life (RUL)	The particle swarm algorithm is applied to improve the performance	(Yang, Peng, Wang, Yuan, & Wu, 2018)

4.2. Bibliometric analysis & mapping

The bibliometric method analyzes critical topics related to machine learning, battery, and optimization. This method will also help strengthen the search results and analysis of the systematic literature review. Based on the 17 selected articles, several extracted keywords from abstract and titles related to machine learning for battery optimization are filtered and analyzed through VOSviewer and visualized in Figure 4.

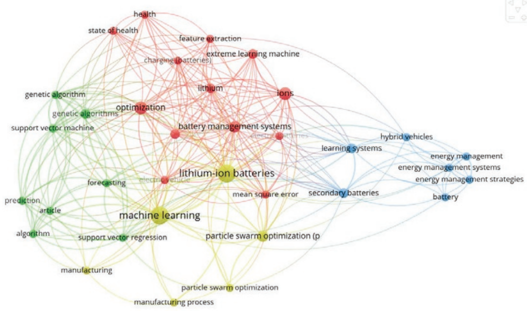

Fig.4. Bibliometric analysis & mapping of machine learning related to battery optimization

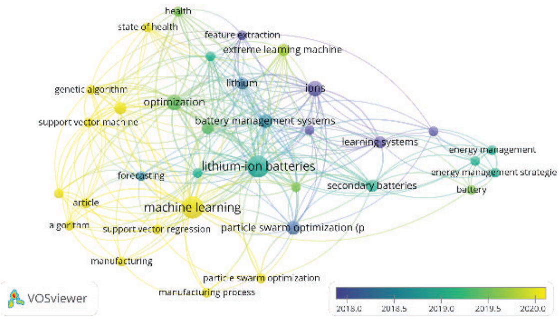

Fig.5. Density and overlay visualization of machine learning related to battery optimization

Visualization results from the bibliometric mapping of 17 articles with critical topics in machine learning for battery optimization are shown in Figure 4. Critical issues related to machine learning, battery optimization, and algorithms are divided into four types of clusters. Cluster 1 is marked in red with 13 critical topics about parameters closely associated with the battery optimization process. Cluster 2 is marked in green with eight critical topics related to approach algorithms carried out during machine learning-related research and experiment. Cluster 3 is marked in blue with seven critical topics related to energy management that closely correlate with energy control and battery function. Cluster 4 is observed in yellow with six crucial topics related to machine learning algorithm approaches and optimization methods for lithium-ion battery optimization. It can be seen that cluster 4 has the most substantial link strength with another cluster. Cluster 4 contains critical topics such as machine learning and lithium-ion batteries with solid relationship link scores above 50 link strengths compared to other essential topics of the red and green clusters. The connections show that algorithmic approaches, optimization methods, and parameters are related to lithium-ion batteries and the machine learning approach. In addition, all kinds of optimization systems and algorithms in conducting research methodologies have a strong relationship with machine learning for lithium-ion battery optimization research and experiment. The study focused on machine learning and optimization in lithium-ion batteries is increasing. Research on optimization algorithms and machine learning is expanding in 2020 as the world's energy needs increase (see Figure 5). The statement was supported by the emergence of the lithium-ion battery industry to fulfill the demand for electric vehicles to reduce world carbon emissions [4]. The strong link between optimization, machine learning, and lithium-ion batteries suggests that machine learning can increase accuracy in estimating experimental data for battery optimization and reduce research costs. This prompted many researchers to continue to develop new machine learning algorithms to expand the discovery of composition and design formulations on more optimal batteries in accordance with the discussion of optimization constraints in Figure 2 and the network of optimization parameters connected to lithium-ion batteries and machine learning in Figure 4.

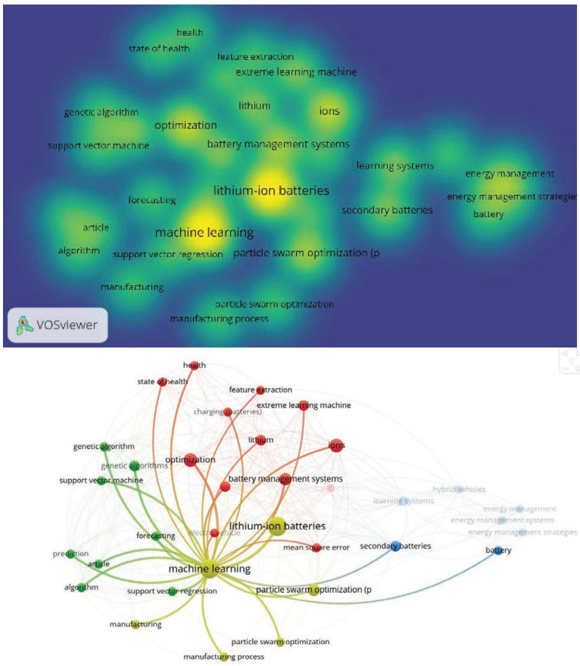

Fig.6. The research gap related to machine learning, optimization, and lithium-ion batteries

The bibliometric mapping results show a research gap related to battery optimization through machine learning algorithms. The research gap is about energy management systems and strategies, hybrid vehicles, other optimization algorithms, battery electrodes, and the safety of batteries (see Figure 6). Further research related to energy management systems, hybrid vehicles, electrochemical mixtures, and novel optimization algorithms is essential to expand novel research related to battery optimization using machine learning. The limitations of this paper are searches that are carried out only using Scopus's database. The data extracted is only in the form of keywords from titles and abstracts, bibliometric data, and author keywords.

4.3. Future Recommendations

Based on the systematic literature review and bibliometric analysis, there are several recommendations for further studies about machine learning for battery optimization. Considering the development of technology and the increasing demand for batteries, we need to expand and develop battery technology, especially lithium-ion batteries that are commonly used. Problems related to temperature, battery performance, and battery optimization constraints can still be explored more deeply in designing a more optimal and reliable battery. Then the electrochemical components in the battery can still be traced to get the right composition design to produce a more reliable battery with high performance. Further explanation and research about the topics related to research gap can be found in several papers from previous section. The results of the literature review and previous discussion also showed that several researchers have optimized the battery using machine learning algorithms with research parameters contained in the bibliometric analysis, namely Teo Lombardo, Alejandro A. Franco, Marc Duquesnoy, and Emiliano N. Primo (see Table 2). From the point of view of research and experimentation using machine learning, the algorithms used in optimizing by machine learning can still be improved. Research and inventions related to algorithms can still be done to maximize the potential of machine learning as an approach to conducting battery optimization research by discovering novel optimization algorithms. A deeper study on optimization using machine learning can be started with research related to genetic algorithms or particle swarm optimization algorithms (see Table 2). Both optimization algorithms can improve accuracy in conducting further research related to batteries. In addition, analysis with new algorithms can also be developed to expand exploration and maximize machine learning performance for future research on battery optimization. Other research related to energy management systems, hybrid vehicles, electrochemical mixtures, energy optimization cases, and novel optimization algorithms will be vital literature to close the research gap to further research related to machine learning for battery optimization.

5. Conclusion

Systematic Literature Review and Bibliometric Analysis are conducted in this paper. Searching process for scientific literature is carried out by looking for studies related to machine learning on the Scopus database with the keywords “Machine Learning”, “Battery Optimization”, and “Algorithms”. From the 424,158 studies about machine learning, it was successfully filtered into 17 selected articles related to optimization, machine learning, and lithium-ion batteries. Keyword data extracted from abstracts and titles of 17 selected papers and bibliometric data are used as parameters for conducting bibliometric analysis. Systematic literature review results and bibliometric analysis show a strong relationship between machine learning and lithium-ion battery optimization research. The results of visualization through bibliometric analysis show a research gap and strong relationships related to machine learning for battery optimization as a foundation for developing research related to battery optimization that will affect the advancement of battery technology. The results from this paper reveal energy management systems and strategies, hybrid vehicles, other optimization algorithms, battery electrodes, and the safety of batteries as the particular research gap according to machine learning for battery optimization. In addition, several key papers and researchers who discuss machine learning algorithms for battery optimization have been shown through systematic literature reviews and their relationship through bibliometric analysis. This paper expects research on battery optimization using machine learning methods will continue to be developed to maximize the potential of machine learning algorithms in helping the research process. Machine learning can provide more accurate results and expand the discovery of algorithms and battery designs that are more optimal for future energy needs.

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