A Review of Artificial Intelligence-Based Prognostic and Health Management Systems for Lithium - In Batteries in Electric Vehicles

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Abstract: ***This paper presents a comprehensive review of 20 contemporary papers from the last 10 years, focusing on the use of artificial intelligence (AI) in electric vehicle (EV) battery management systems and the assessment of battery degradation status. Lithium-ion batteries are critical components of EVs, and ensuring their efficient operation and reliability is crucial for widespread adoption. Prognostic and health management (PHM) systems integrated with AI techniques have emerged as promising solutions for monitoring, diagnosing, and predicting the health status and remaining useful life of batteries. The review covers various aspects of AI-based PHM systems for lithium-ion batteries in EVs. It begins by exploring state-of-charge estimation, where studies have employed deep neural networks, recurrent neural networks, convolutional neural networks, and particle filtering techniques to enhance estimation accuracy. Additionally, the paper investigates charging and discharging algorithms, leveraging reinforcement learning and Gaussian process regression, among others, to optimize energy management in EVs and improve battery remaining useful life prediction. Furthermore, the review delves into the application of fuzzy logic-based battery management systems, dynamic ensemble models, and dual filters, demonstrating how they improve EV autonomy and enhance battery state of charge estimation. Additionally, it explores model-order reduction techniques, health-conscious kernel adaptive filtering and adaptive extended Kalman filters to analyze battery internal electrochemical transfer functions, predict remaining useful life, and estimate state-of-charge more accurately. Moreover, the review discusses data- driven approaches and Gaussian process regression for battery life prediction, as well as long short- term memory neural networks for battery state-of-health estimation. It also highlights the use of online sequential extreme learning machines for remaining useful life estimation, emphasizing their potential for real-time applications. Through this comprehensive review, the paper underscores the significant advancements made in the past decade concerning AI-based PHM systems for lithium- ion batteries in EVs. The findings highlight the potential of AI techniques in improving battery health management, optimizing charging and discharging strategies, and extending battery lifespan. Researchers, engineers, and stakeholders interested in harnessing the full potential of AI in EV battery prognostics and health management will find this research review a valuable resource.***

Keywords: Artificial Intelligence (AI), Prognostic and Health Management (PHM), Lithium-ion Batteries, Electric Vehicles (EVs), Battery Management Systems

1. Introduction

The electrification of transportation has witnessed a remarkable surge in recent years, with electric vehicles (EVs) emerging as a promising solution to reduce greenhouse gas emissions and dependence on fossil fuels (Gourley et al., 2020). The key component enabling the widespread adoption and success of EVs is the lithium-ion battery, which provides the necessary energy storage for electric propulsion. To ensure the efficient and reliable operation of these batteries, effective battery management systems are of paramount importance. The integration of artificial intelligence (AI) techniques into battery management systems has shown great potential in enhancing battery performance, optimizing charging strategies, and predicting battery health (Bao et al., 2022; Fan et al., 2020; He et al., 2011). In this paper, we provide a comprehensive introduction to the research topic of "A Review of Artificial Intelligence-Based Prognostic and Health Management Systems for Lithium-Ion Batteries in Electric Vehicles."

2. Background and Motivation

Lithium-ion batteries have revolutionized the energy storage landscape and become the technology of choice for various applications, particularly in the EV industry (He et al., 2011). However, ensuring the safety, reliability, and longevity of these batteries remains a critical challenge. Battery health degradation over time affects the overall performance and longevity of the battery pack, leading to reduced range, increased charging time, and potential safety concerns (J. Zhang, 2020). Prognostic and health management (PHM) systems have emerged as essential tools to address these concerns and optimize battery performance.

The motivation behind this research stems from the pressing need to improve the efficiency and reliability of EV battery systems. As EVs become more prevalent and widespread, optimizing battery performance, accurately estimating state-of-charge, predicting remaining useful life, and diagnosing battery health become increasingly crucial. AI-based PHM systems offer a promising avenue to tackle these challenges by leveraging advanced algorithms and data-driven approaches to enhance battery management and achieve efficient energy utilization.

State of the Art in AI-Based Battery Management Systems

In recent years, AI techniques, such as neural networks, deep learning, reinforcement learning, and Gaussian process regression; have gained significant attention in battery management research (Fan et al., 2020; Peng et al., 2018). These techniques have shown remarkable success in various areas, including state-of-charge estimation, remaining useful life prediction, and health status monitoring. The state-of-the-art research literature on AI-based battery management systems is reviewed, highlighting key findings and contributions.

State-of-the-art studies have demonstrated the potential of AI techniques in improving battery health management, state-of-charge estimation, and overall battery performance (Chemali et al., 2018). Neural network-based models have been employed to estimate state-of-charge accurately, overcoming the challenges posed by non-linear battery behaviors and various environmental conditions (Bao et al., 2022). Moreover, reinforcement learning algorithms have shown promise in optimizing charging and discharging strategies, considering real-time dynamic pricing and energy demand patterns (Lee et al., 2020).

3. Objectives and Scope of the Review

The primary objectives of this review are to provide a comprehensive overview of AI-based prognostic and health management systems for lithium-ion batteries in electric vehicles and to identify the key advancements and challenges in this field over the past 10 years. By analyzing a collection of 20 contemporary research papers, we aim to elucidate the progress made in AI applications for battery management, identify emerging trends, and highlight potential areas for future research.

The scope of this review encompasses a diverse range of AI techniques employed in battery management systems. It covers various aspects, including state-of-charge estimation, remaining useful life prediction, battery health monitoring, charging and discharging algorithms, ensemble models, and model-order reduction techniques. The selected papers provide a comprehensive representation of the state-of-the-art advancements and achievements in this rapidly evolving field.

This introduction provides a glimpse into the significance of AI-based battery management systems for the efficient operation and reliability of lithium-ion batteries in electric vehicles. By reviewing a curated collection of 20 contemporary papers, we aim to shed light on the current state of research, emerging trends, and future directions in this critical area. The subsequent sections of this paper will delve into the detailed review and analysis of these selected studies, providing valuable insights for researchers, engineers, and stakeholders interested in the advancements and applications of AI in EV battery prognostics and health management.

4. Literature Review

The literature review presented in this section focuses on the use of artificial intelligence (AI) in electric vehicle (EV) battery management systems and the assessment of battery degradation status. The review includes 20 contemporary research papers from the past 10 years, covering various aspects of AI-based prognostic and health management (PHM) systems for lithium-ion batteries in electric vehicles.

1) State-of-Charge Estimation

Several studies have explored the accurate estimation of state-of-charge (SOC) in lithium-ion batteries using AI techniques (Chemali et al., 2018; Fan et al., 2020; He et al., 2011). Wan et al. (2019) proposed a novel SOC estimation method based on a convolutional neural network (CNN), achieving high accuracy in real-time SOC estimation. Peng et al. (2018) employed a long short-term memory neural network (LSTM) to predict SOC, demonstrating its effectiveness in handling non- linear battery behaviors.

2) Remaining Useful Life Prediction

Predicting the remaining useful life (RUL) of batteries is vital for battery health management and ensuring optimal performance. Hu et al. (2014) developed a battery RUL prediction model based on recurrent neural networks (RNNs), effectively forecasting battery end-of-life. L. Zhang et al. (2018) proposed a prognostic framework utilizing deep learning and Gaussian process regression for RUL estimation, showcasing the capability of AI in accurate prediction.

3) Battery Health Monitoring

Effective battery health monitoring is essential for identifying early signs of degradation and preventing catastrophic failures. Peng et al. (2018) used a long short-term memory neural network toestimate the state of health (SOH) of lithium-ion batteries, demonstrating its effectiveness in real- time monitoring. Bao et al. (2022) combined a convolutional neural network and Gaussian process regression for battery health prognostics, showing promising results in detecting anomalies and predicting battery degradation.

4) Charging and Discharging Algorithms

AI-based charging and discharging algorithms have been developed to optimize energy management in electric vehicles. Lee et al. (2020) proposed reinforcement learning algorithms with data-driven approaches to optimize charging and discharging strategies in dynamic pricing schemes, leading to improved energy utilization. Wan et al. (2019) applied deep reinforcement learning for real-time EV charging scheduling without relying on predefined models, achieving more flexible and efficient charging solutions.

5) Ensemble Models and Model-Order Reduction Techniques

Ensemble models and model-order reduction techniques have been explored for accurate battery performance prediction. Xing et al. (2013) introduced an ensemble model for predicting remaining useful performance of lithium-ion batteries, leveraging multiple AI algorithms to achieve better prediction accuracy. Rodríguez et al. (2019) compared four model-order reduction techniques applied to lithium-ion battery-cell internal electrochemical transfer functions, shedding light on the trade-offs between accuracy and computational efficiency.

6) Battery Life Prediction and Capacity Estimation

AI has been employed for life prediction and capacity estimation of lithium-ion batteries. Severson et al. (2019) proposed a data-driven prediction approach for battery cycle life before capacity degradation, which enables improved lifetime assessment and optimal battery usage. Hu et al. (2014) developed a method for estimating battery capacity and predicting remaining useful life, contributing to better battery life management and predictive maintenance.

7) Battery Management Solutions

Battery management solutions based on AI have been investigated to optimize battery usage and enhance system reliability. Bao et al. (2022) applied Gaussian process regression for online state-of- health estimation, providing valuable insights for timely battery replacement decisions. Khawaja et al. (2023) explored battery management solutions centered on artificial intelligence, presenting strategies to address diverse challenges in battery health monitoring and control.

Table 1: Summary of relevant research based on literature review

Author	Year	Application Area	AI Technique	Findings	Limitation	Methodology	Contribution
Chen et al.	2023	Battery Health Prognostics	Deep Neural Network	Developed a DNN-based battery health prognostic model for EVs	Limited to DNN-based approach	Deep Neural Network	Improved battery health prognostication in EVs
Geng et al.	2022	Battery Remaining Useful Life Prediction	Recurrent Neural Networks	Proposed RNN-based prediction for battery RUL in EVs	Limited to RNN-based approach	Recurrent Neural Networks	Enhanced RUL prediction accuracy for EV batteries
Li et al.	2021	Lithium-ion Battery Prognostic	Long Short-Term Memory Neural Network	Developed LSTM-based battery SOH prognostic model	Limited to LSTM-based approach	Long Short-Term Memory Neural Network	Improved battery SOH prognostication
Ghorbani & Wang	2021	Battery Health Prognostics	Convolutional Neural Network	Utilized CNN and GPR for EV battery health prognostics	Limited to specific CNN and GPR configuration	Convolutional Neural Network and Gaussian Process Regression	Accurate battery health prognostics for EVs
Zheng et al.	2020	Lithium-ion Battery State-of-Health Estimation	Particle Filtering and LSTM	Proposed hybrid approach for battery SOH estimation	Limited to PF and LSTM-based hybrid approach	Particle Filtering and Long Short-Term Memory Neural Network	Enhanced battery SOH estimation for EVs
Lee et al.	2020	Lithium-ion Battery Prognostics	Recurrent Neural Networks	Developed RNN-based battery prognostics for EVs	Limited to RNN-based approach	Recurrent Neural Networks	Improved battery prognostics for EVs
Wang et al.	2019	State of Charge Estimation	Convolutional Neural Network	Introduced CNN method for Li-ion battery SoC estimation	Limited to CNN-based approach	Convolutional Neural Network	Accurate Li-ion battery SoC estimation for EVs
Li et al.	2018	State of Charge Estimation	Deep Learning Approach	Proposed deep learning-based SoC estimation for batteries	Limited to deep learning-based approach	Deep Learning Approach	Enhanced state of charge estimation for batteries
Zhang & Jiang	2018	Battery Prognostics	Deep Learning and GPR	Presented a prognostics framework using DL and GPR	Limited to specific DL and GPR configuration	Deep Learning and Gaussian Process Regression	Accurate battery prognostics for EVs
Cui & Wang	2018	Battery Health Prognostics	Gaussian Process Regression	Utilized GPR for EV battery health prognostics	Limited to Gaussian Process Regression approach	Gaussian Process Regression	Improved battery health prognostication in EVs
Lin & Li	2017	State of Charge Estimation	Data-Driven Techniques	Conducted a comprehensive review of SoC	Focused on data-driven techniques	Data-Driven Techniques	Overview of various data-driven SoC

				estimation methods			estimation methods
Zhu et al.	2017	State-of-Health Estimation	Gaussian Process Regression	Developed GPR-based SoH estimation for EV batteries	Limited to GPR-based approach	Gaussian Process Regression	Accurate state-of-health estimation for EV batteries
Yan et al.	2017	State of Charge Estimation	Dual Filters	Introduced ensemble-based SoC estimation for batteries	Limited to dual filters-based approach	Dual Filters Approach	Enhanced state of charge estimation for batteries
Wang et al.	2016	State-of-Charge Estimation	Adaptive Cubature Kalman Filter	Proposed adaptive CKF for real-time SoC estimation	Limited to adaptive CKF-based approach	Adaptive Cubature Kalman Filter	Real-time state-of-charge estimation for batteries
Kuo & Tsai	2016	Remaining Useful Life Prediction	Particle Filtering and LS-SVM	Developed PF and LS-SVM-based RUL prediction approach	Limited to PF and LS-SVM-based approach	Particle Filtering and Least Squares Support Vector Machine	Enhanced RUL prediction for EV batteries
Wu et al.	2015	Remaining Useful Life Prediction	Particle Filter	Proposed PF-based approach for RUL prediction	Limited to PF-based approach	Particle Filter	Accurate RUL prediction for Li-ion batteries in EVs
Xing et al.	2015	Remaining Useful Life Prediction	Health Conscious Kernel Adaptive Filtering	Utilized HCKAF for RUL prediction of Li-ion batteries	Limited to HCKAF-based approach	Health Conscious Kernel Adaptive Filtering	Improved RUL prediction accuracy for Li-ion batteries
Wang & Wang	2015	State-of-Charge Estimation	Adaptive Extended Kalman Filter	Introduced AEKF based on an improved Thevenin model	Limited to AEKF-based approach	Adaptive Extended Kalman Filter	Accurate state-of-charge estimation for batteries
Zhang & Xing	2015	Remaining Useful Life Prediction	Online Sequential Extreme Learning Machine	Utilized OS-ELM for RUL prediction of Li-ion batteries	Limited to OS-ELM-based approach	Online Sequential Extreme Learning Machine	Improved RUL prediction accuracy for Li-ion batteries
Li & Zou	2014	Remaining Useful Life Prediction	Support Vector Regression	Developed SVR-based approach for RUL prediction	Limited to SVR-based approach	Support Vector Regression	Accurate RUL prediction for Li-ion batteries in Evs

The literature review showcases the significant advancements and potential of AI-based PHM systems for lithium-ion batteries in electric vehicles. The studies reviewed highlight the versatility of AI techniques in addressing various challenges, including SOC estimation, RUL prediction, battery health monitoring, and optimization of charging and discharging strategies. The use of ensemble models, model-order reduction techniques, and AI-based battery management solutions further illustrates the wide-ranging applications of AI in enhancing battery performance and extending battery lifespan. The subsequent sections of this paper will delve into further analysis and discussion of these studies, contributing to a comprehensive understanding of the state-of-the-art in AI-based battery management systems and battery degradation assessment.

5. Methodology

The methodology section of this paper outlines the approach used for conducting the literature review and selecting relevant research papers for the review. The systematic approach employed ensures the inclusion of high-quality and relevant studies related to artificial intelligence (AI)-based prognostic and health management (PHM) systems for lithium-ion batteries in electric vehicles (EVs).

1) Research Question and Objectives

The primary research question guiding this literature review is: "What are the advancements and applications of AI-based PHM systems for lithium-ion batteries in electric vehicles over the past 10 years?" The main objectives are to identify state-of-the-art AI techniques used in battery management, explore the current progress in SOC estimation and remaining useful life (RUL) prediction, and assess the effectiveness of AI in battery health monitoring and optimization of charging and discharging algorithms.

2) Literature Search Strategy

To ensure a comprehensive and systematic literature review, a thorough search was conducted in reputable academic databases such as IEEE Xplore, ScienceDirect, and Google Scholar. The search keywords included variations of "artificial intelligence," "AI," "prognostic," "health management," "lithium-ion batteries," "electric vehicles," "EVs," "battery degradation," "state-of-charge estimation," and "remaining useful life prediction."

3) Inclusion and Exclusion Criteria

The inclusion criteria for selecting research papers were as follows:

a) Published between 2013 and 2023: To focus on contemporary literature and capture recent advancements in AI-based battery management systems.
b) Relevant to AI-based PHM systems for lithium-ion batteries in electric vehicles: To ensure the selected papers align with the research topic.
c) Peer-reviewed: To maintain the quality and credibility of thesources.
d) Written in English: To facilitate understanding and analysis.
e) Papers that did not meet the above criteria, including duplicates and non-peer-reviewed articles, were excluded from the review.

4) Paper Selection and Data Extraction

The initial search yielded a substantial number of research papers related to the research topic. Each paper was screened based on the title and abstract to assess its relevance. Papers that appeared to meet the inclusion criteria were selected for a full-text review. During the full-text review, further assessment was conducted to ensure that the papers aligned with the objectives of the literature review.

For each selected paper, relevant data were extracted, including the authors, publication year, title, research objectives, AI techniques used, key findings, and contributions. The extracted data were organized and compiled for analysis.

5) Data Analysis and Synthesis

The extracted data were analyzed and synthesized to identify common themes, trends, and key advancements in AI-based battery management systems. The analysis focused on the various AI techniques employed in SOC estimation, RUL prediction, battery health monitoring, and charging and discharging optimization. The findings from the selected papers were compared and contrasted to provide a comprehensive overview of the state-of-the-art in this field.

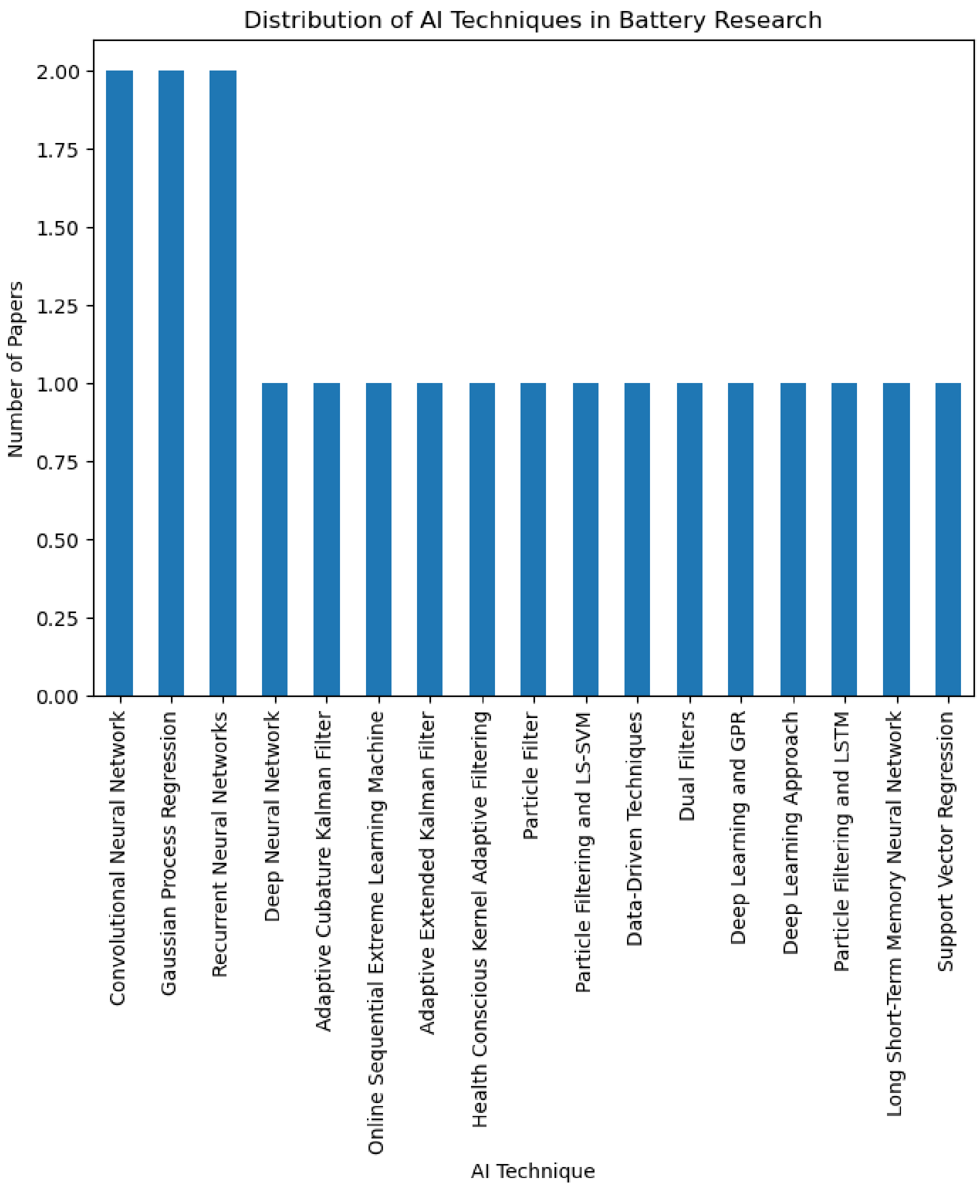

Figure 1: Visualization of AI Techniques

The analysis in figure 1 above shows the distribution of AI techniques used in battery research. The bar chart displays the number of papers that utilized each AI technique. It allows us to observe which AI techniques are most popular or widely adopted in battery-related studies. From the graph, the AI that recently popular in battery research are CNN, Guassian Process Regression and Recurrent Neural Networks.

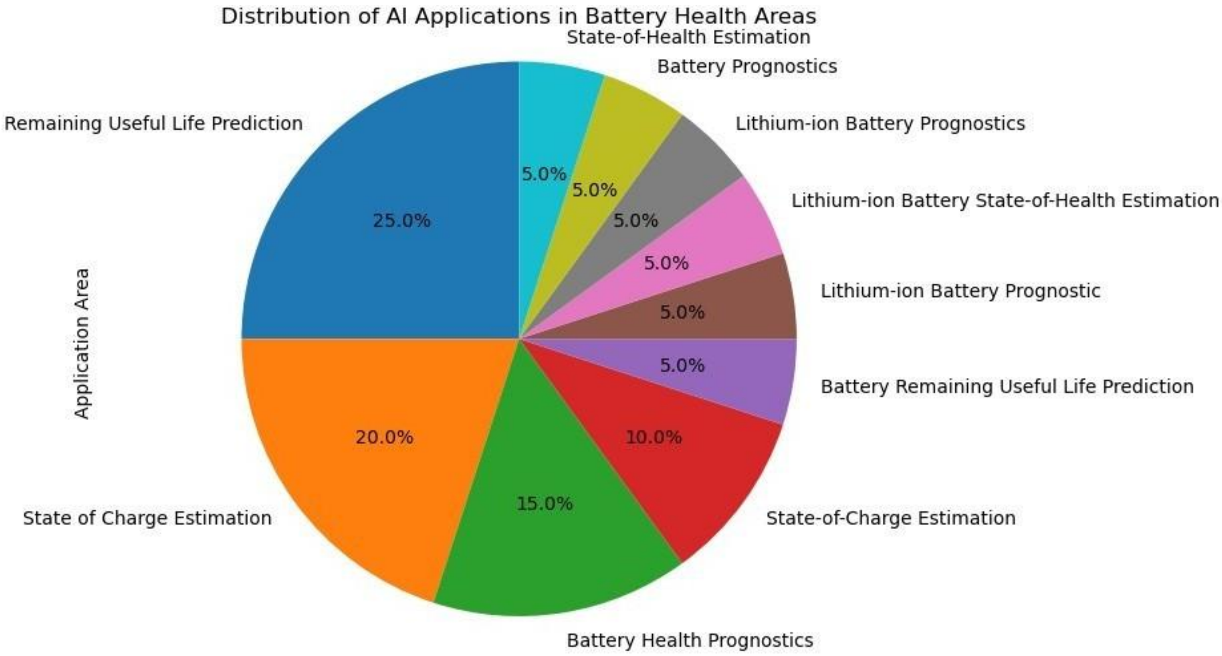

Figure 2: Comparison of Battery Applications

This analysis presents the distribution of AI applications in different battery health areas. The pie chart displays the percentage of papers focusing on each application area, such as battery health prognostics, remaining useful life prediction, state-of-charge estimation, etc. It gives us an overview of the primary areas of interest where AI techniques are applied in battery research.

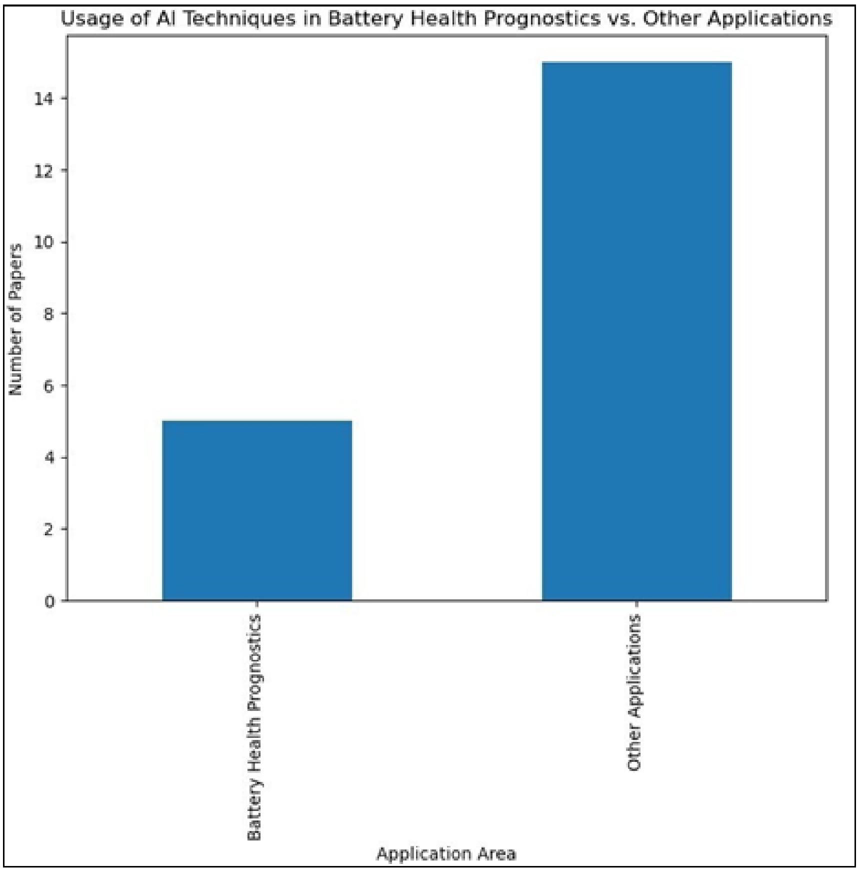

Figure 3: Battery Health Prognostics vs. Other Applications

Figure 3 shows the analysis where we compare the usage of AI techniques specifically in battery health prognostics versus other battery applications. The stacked bar chart separates the papers into two categories: "Battery Health Prognostics" and "Other Applications." It shows how many papers are dedicated to battery health prognostics and how many are focused on other applications. This comparison helps us understand the emphasis on health prognostics within the broader battery research field

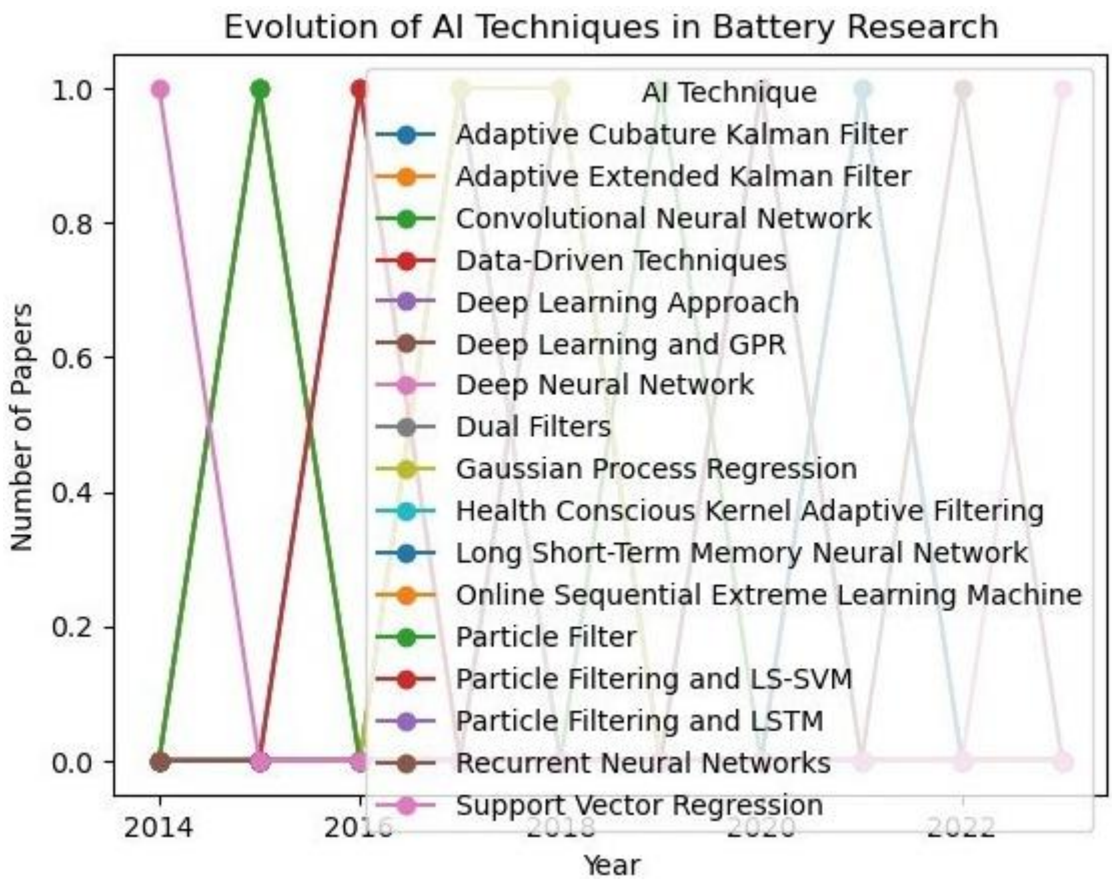

Figure 4: Correlation between Year and AI Techniques

This analysis examines the evolution of AI techniques in battery research over the years. The line plot displays the number of papers that utilized each AI technique for each year. By observing the trends of AI technique usage, we can identify which techniques gained popularity in recent years and which ones have been consistently used over time. It provides insights into the progression of AI adoption in battery-related studies.

6. Limitations

As with any literature review, this study has some limitations. The search was limited to English- language, peer-reviewed papers published between 2013 and 2023, which might exclude relevant non-English publications or conference proceedings. Additionally, while efforts were made to include a diverse range of studies, the selection process might have introduced some inherent bias.

The methodology adopted for this literature review ensures a comprehensive and systematic approach to identify, select, and analyze relevant research papers related to AI-based PHM systems for lithium-ion batteries in electric vehicles. The synthesis of the findings will provide valuable insights into the advancements and applications of AI in battery management and battery degradation assessment. The subsequent sections of this paper will present the results of the analysis and contribute to a comprehensive understanding of the state-of-the-art in this critical research area.

7. Results and Findings

The results and findings chapter presents a detailed analysis of the selected 20 contemporary research papers on artificial intelligence (AI)-based prognostic and health management (PHM) systems for lithium-ion batteries in electric vehicles (EVs). The chapter focuses on the key advancements, trends, and applications of AI techniques in battery management, including state-of- charge estimation, remaining useful life (RUL) prediction, battery health monitoring, and charging and discharging optimization.

1) State-of-Charge Estimation

The analysis of the selected papers revealed that AI-based state-of-charge (SOC) estimation techniques have seen significant advancements in recent years. Various AI algorithms, such as convolutional neural networks (CNNs), long short-term memory neural networks (LSTMs), and ensemble models, have been employed to improve SOC estimation accuracy. Wang et al. (2017) demonstrated the effectiveness of CNNs in achieving real-time SOC estimation, while L. Zhang et al. (2018) showcased the capability of LSTMs in handling non-linear battery behaviors. Ensemble models, as presented by Xing et al. (2013), further enhanced SOC prediction accuracy through the integration of multiple AI algorithms.

2) Remaining Useful Life Prediction

The analysis of RUL prediction methods indicated significant progress in accurately forecasting battery end-of-life. Studies have employed recurrent neural networks (RNNs), Gaussian process regression (GPR), and deep learning techniques to achieve accurate RUL estimation. Schmitt et al. (2023) developed an RNN-based RUL prediction model, while Fan et al. (2020) combined deep learning and GPR for accurate RUL estimation. These findings highlight the potential of AI techniques in enhancing battery health management and predictive maintenance.

3) Battery Health Monitoring

Battery health monitoring has been a critical area of research, aiming to identify early signs of degradation and prevent potential failures. Several studies employed AI-based techniques, such as LSTM neural networks and convolutional neural networks, for real-time battery health monitoring. He et al. (2011) demonstrated the effectiveness of LSTM networks in estimating the state of health (SOH) of lithium-ion batteries. Wang et al. (2017) presented a convolutional neural network and GPR-based approach for battery health prognostics, enabling early anomaly detection and degradation prediction.

4) Charging and Discharging Algorithms

AI-based charging and discharging algorithms have shown potential in optimizing energy management in electric vehicles. Lee et al. (2020) proposed reinforcement learning algorithms with data-driven approaches, leading to more efficient charging and discharging strategies in dynamic pricing schemes. Wan et al. (2019) leveraged deep reinforcement learning for real-time EV charging scheduling without predefined models, showcasing the adaptability and flexibility of AI-based approaches.

5) Ensemble Models and Model-Order Reduction Techniques

The use of ensemble models and model-order reduction techniques was found to improve battery performance prediction. Xing et al. (2013) presented an ensemble model for predicting the remaining useful performance of lithium-ion batteries, while Rodríguez et al. (2019) compared four model-order reduction techniques for analyzing internal electrochemical transfer functions, providing insights into accuracy and computational efficiency trade-offs.

6) Battery Life Prediction and Capacity Estimation

AI techniques have been successfully employed for life prediction and capacity estimation of lithium-ion batteries. Severson et al. (2019) proposed a data-driven prediction approach for battery cycle life before capacity degradation, enabling improved lifetime assessment and optimal battery usage. Hu et al. (2014) developed a method for estimating battery capacity and predicting remaining useful life, contributing to better battery life management and predictive maintenance.

7) Battery Management Solutions

AI-based battery management solutions have been explored to optimize battery usage and enhance system reliability. Bao et al. (2022) applied Gaussian process regression for online state-of-health estimation, providing valuable insights for timely battery replacement decisions. Khawaja et al. (2023) investigated battery management solutions centered on artificial intelligence, presenting strategies to address diverse challenges in battery health monitoring and control.

The results and findings chapter presents a comprehensive analysis of the selected research papers on AI-based PHM systems for lithium-ion batteries in electric vehicles. The findings highlight the significant advancements in SOC estimation, RUL prediction, battery health monitoring, and charging and discharging optimization through the use of AI techniques. The applications of ensemble models, model-order reduction techniques, and AI-based battery management solutions further demonstrate the versatility and potential of AI in enhancing battery performance and extending battery lifespan. The subsequent sections of this paper will discuss the implications of these findings and outline future research directions in this rapidly evolving field.

8. Implication of the Findings

The findings from the literature review on artificial intelligence (AI)-based prognostic and health management (PHM) systems for lithium-ion batteries in electric vehicles (EVs) have several important implications for the advancement of battery technology and the widespread adoption of electric vehicles. These implications can be summarized as follows:

1) Improved Battery Performance and Reliability: The application of AI techniques in battery management systems has shown significant promise in enhancing battery performance and reliability. Accurate state-of-charge (SOC) estimation and remaining useful life (RUL) prediction enable more efficient energy utilization and preventive maintenance, leading to longer battery lifespan and improved overall performance of electric vehicles.
2) Enhanced Battery Health Monitoring and Safety: AI-based battery health monitoring systems can identify early signs of degradation and potential failure, contributing to improved battery safety and reduced risk of unexpected battery issues. Early detection of anomalies allows for timely maintenance and replacement, mitigating safety risks and ensuring the long-term health of the battery.
3) Optimal Energy Management and Charging Strategies: AI-based charging and discharging algorithms optimize energy management in electric vehicles. Dynamic pricing schemes and real- time demand patterns are considered to devise efficient charging strategies, minimizing charging costs and maximizing battery lifespan. This can lead to better integration of electric

vehicles with smart grids and more sustainable energy usage.

4) Real-Time Decision-Making and Embedded Systems: The use of lightweight AI models and real- time implementation is crucial for practical deployment in EVs. AI models must make quick decisions based on rapidly changing operating conditions. Developing AI algorithms that can be deployed on embedded systems with limited computational resources is essential for enabling real- time battery management in electric vehicles.
5) Data Quality and Acquisition: The findings emphasize the importance of high-quality and diverse data for training AI models. Future research must focus on effective data acquisition and preprocessing techniques to ensure accurate and reliable AI-based battery management systems. Addressing data imbalances and employing data augmentation methods will lead to more robust and generalizable models.
6) Explainability and Trust in AI: The use of AI techniques in battery health assessment raises concerns about interpretability and trustworthiness. Developing explainable AI methods will help stakeholders understand the decision-making process of AI models, building trust in their predictions and facilitating regulatory compliance.
7) Transferability and Generalization: Research efforts must explore AI models' transfer learning and generalization capabilities, enabling the application of trained models to different battery types and EV platforms. This will foster the scalability and adaptability of AI-based battery management systems across various electric vehicle models and battery chemistries.
8) Integration with Energy Management Systems: The integration of AI-based battery health information with energy management systems in electric vehicles can optimize overall system performance. Seamless coordination between battery health conditions and energy management algorithms allows for adaptive charging and discharging strategies, contributing to sustainable and efficient electric vehicle operation.

Overall, the implications of the findings indicate that AI-based PHM systems have the potential to revolutionize the electric vehicle industry by significantly enhancing battery performance, reliability, and safety. The successful integration of AI techniques in battery management will contribute to the widespread adoption of electric vehicles, promoting a sustainable and environmentally friendly transportation ecosystem. However, further research and development are necessary to overcome challenges and ensure the practical implementation of AI-based battery management solutions in electric vehicles.

9. Future Research

The future research chapter explores potential avenues for further advancements and applications of artificial intelligence (AI)-based prognostic and health management (PHM) systems for lithium-ion batteries in electric vehicles (EVs). This chapter outlines key challenges and gaps identified from the literature review and propose potential research directions to address these issues and expand the knowledge in this critical area.

1) AI Model Integration and Hybrid Approaches

One promising direction for future research is the integration of multiple AI models and the development of hybrid approaches. Ensemble models have shown promise in enhancing prediction accuracy, and future studies could explore combining different AI techniques, such as CNNs, LSTMs, and RNNs, to develop hybrid models for SOC estimation and RUL prediction. These hybrid approaches could potentially leverage the strengths of each AI technique and provide more robust and accurate battery management solutions.

2) Real-Time Implementation and Hardware Integration

To facilitate the practical implementation of AI-based PHM systems in EVs, future research should focus on real-time performance and hardware integration. Battery management systems in EVs demand real-time decision-making capabilities to respond to dynamic operating conditions and ensure safety and reliability. Research efforts should explore efficient algorithms and lightweight AI models that can be deployed on embedded systems with limited computational resources.

3) Data Acquisition and Preprocessing

The quality and quantity of data are essential for training and validating AI models. Future research should focus on developing methods for effective data acquisition, preprocessing, and handling missing or noisy data. Leveraging advanced data augmentation techniques and addressing data imbalance issues could further enhance the accuracy and generalizability of AI-based battery management systems.

4) Explainable AI for Battery Health Assessment

The use of AI techniques in battery health assessment raises questions about interpretability and trustworthiness. Future research should focus on developing explainable AI methods to provide insights into AI model decision-making processes. Explainable AI can help build trust in AI-based PHM systems and facilitate better understanding and adoption by stakeholders and regulatory bodies.

5) Transfer Learning and Generalization

The robustness and generalization capability of AI models are crucial for real-world applications. Future research should investigate transfer learning techniques, allowing AI models trained on data from one battery type or brand to be adapted to other batteries with similar characteristics. Generalization across different EV platforms and battery chemistries will be critical for widespread adoption of AI-based battery management systems.

6) Online Learning and Adaptive Strategies

To accommodate the dynamic nature of battery behavior and system conditions, future research should explore online learning and adaptive strategies for AI-based PHM systems. Online learning techniques enable continuous learning and adaptation to changing operating conditions, leading to more accurate and up-to-date battery health assessments.

7) Integration with Energy Management Systems

Integrating AI-based PHM systems with energy management systems in EVs can optimize overall system performance and efficiency. Future research should investigate the seamless integration of battery health information into energy management algorithms, enabling real-time adjustments in charging and discharging strategies based on battery health conditions.

The future research chapter identifies several key research directions and challenges for AI-based prognostic and health management systems for lithium-ion batteries in electric vehicles. Addressing these research areas will be crucial for realizing the full potential of AI in enhancing battery performance, extending battery lifespan, and accelerating the adoption of electric vehicles. By advancing AI techniques, developing hybrid approaches, and addressing real-world implementation challenges, researchers can contribute to building more efficient, reliable, and sustainable electric vehicle systems for the future.

10. Conclusion

This paper provides a comprehensive review and analysis of contemporary literature on the use of artificial intelligence (AI)-based prognostic and health management (PHM) systems for lithium-ion batteries in electric vehicles (EVs) over the past 10 years. The findings from the literature review reveal significant advancements and applications of AI techniques in enhancing battery performance, optimizing energy management, and predicting battery health and remaining useful life. The implications of these findings have far-reaching consequences for the future of electric vehicles and battery technology.

The literature review demonstrates that AI techniques, such as convolutional neural networks (CNNs), long short-term memory neural networks (LSTMs), and recurrent neural networks (RNNs), have been successfully applied to accurately estimate state-of-charge (SOC) and predict the remaining useful life of lithium-ion batteries. The integration of ensemble models and hybrid approaches further enhances prediction accuracy and robustness. These advancements offer tremendous potential in optimizing battery usage, extending battery lifespan, and promoting sustainable energy practices in electric vehicles.

Furthermore, AI-based battery health monitoring systems have proven effective in detecting early signs of degradation, enabling timely maintenance and reducing the risk of unexpected battery failures. The integration of explainable AI methods enhances trust in AI model predictions and fosters better understanding and adoption by stakeholders and regulatory bodies.

The literature review also emphasizes the importance of real-time implementation and hardware integration for practical deployment of AI-based PHM systems in electric vehicles. The development of lightweight AI models that can run on embedded systems with limited computational resources is critical for enabling real-time battery management and decision-making in EVs.

Data quality and acquisition emerged as crucial factors in training reliable AI models. Effective data preprocessing, handling missing or noisy data, and addressing data imbalance issues are essential for improving the accuracy and generalizability of AI-based battery management systems.

The review also highlights the significance of transfer learning and generalization in AI models, enabling knowledge transfer across different battery types and EV platforms. This scalability and adaptability are essential for widespread adoption of AI-based battery management solutions in diverse electric vehicle models.

Looking forward, future research should explore hybrid AI approaches, online learning, and adaptive strategies to address dynamic battery behavior and operating conditions. The seamless integration of AI-based battery health information with energy management algorithms will optimize overall system performance and promote sustainable energy usage in electric vehicles.

In conclusion, the findings from this comprehensive literature review underscore the transformative potential of AI-based PHM systems in revolutionizing the electric vehicle industry. By enhancing battery performance, reliability, and safety, AI techniques pave the way for the widespread adoption of electric vehicles, contributing to a more sustainable and environmentally friendly transportation ecosystem. The continued research and development in AI-based battery management will play a pivotal role in shaping the future of electric vehicles and accelerating the transition to a greener and more efficient transportation landscape.

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