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Review

Review of the Li-Ion Battery, Thermal Management, and AI-Based Battery Management System for EV Application

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Abstract: With the large-scale commercialization and growing market share of electric vehicles (EVs), many studies have been dedicated to battery systems design and development. Their focus has been on higher energy efficiency, improved thermal performance and optimized multi-material battery enclosure designs. The integration of simulation-based design optimization of the battery pack and Battery Management System (BMS) is evolving and has expanded to include novelties such as artificial intelligence/machine learning (AI/ML) to improve efficiencies in design, manufacturing, and operations for their application in electric vehicles and energy storage systems. Specific to BMS, these advanced concepts enable a more accurate prediction of battery performance such as its State of Health (SOH), State of Charge (SOC), and State of Power (SOP). This study presents a comprehensive review of the latest developments and technologies in battery design, thermal management, and the application of AI in Battery Management Systems (BMS) for Electric Vehicles (EV).

Keywords: lithium-ion batteries; battery management systems; AI-based monitoring systems; electric vehicle

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1. Introduction

1.1. A Brief History of EVs

The first EVs were built around the mid to late 19th century but conceded their commercial footprint to cars powered by Internal Combustion Engines (ICE) [1]. Today's transportation sector primarily uses ICE, contributing to almost a quarter of all energy-related greenhouse gas emissions. This issue initiated the demand for replacing ICE vehicles with advanced technology vehicles such as EVs. Although EVs can reduce fuel costs significantly because of the high efficiency of electric-drive systems compared to internal combustion engines, EVs suffer much greater constraints in terms of their limited driving range, scarcity of charging stations, charging times, and higher initial costs as compared to ICE vehicles [2–4]. As such, an integrative review would be suitable to understand the development of this emerging topic by providing a clear understanding of what are the key barriers and motivators of EV adoption on the sustainability dimensions.

1.2. A Brief History of LIBs

For the past 3 decades major commercial and academic progress has been made in the development of Li-based battery technologies. This has been driven by the market demand for high-performance rechargeable batteries to reduce the cost and weight of EVs while increasing their range and longevity.

Around 30 years ago Sony Co. commercialized the world's first lithium-ion battery (LIB) which led to a large increase in research in battery technologies. The research was fueled by environmental concerns and the impact of fossil fuels on greenhouse gas emissions Governments around the world subsequently have invested considerably in support of green technologies (solar, wind, etc.) and electric vehicles [5].

Lithium-ion batteries (LIBs) store energy through the storage of charge through the motion of lithium ions between positive and negative electrodes via a liquid electrolyte.

The cathode is usually made of graphite while the anode can be made of various types of lithium oxides. Many studies provide a comprehensive review of the properties of different LIB chemistries such as the lithium Iron Phosphate cell ($LiFePO_4$), lithium manganese oxide ($LiMn_2O_4$), lithium manganese oxide, or Lithium Cobalt Oxide ($LiCoO_2$) [6–10].

While LIBs provide an increased energy density and cycle life from the previous generation of batteries, with continuous technological advancements, they are operating increasingly closer to their theoretical limit [11]. Therefore, in addition to further improving the design and manufacturing process of current LIBs, research efforts have focused on developing next-generation lithium batteries, such as solid-state and metal-air batteries.

LIBs are typically made of four major parts: cathode, anode, separator, and electrolyte. Figure 1 provides a schematic of a battery cell during the charge/discharge process. The battery is filled with an electrolyte to help the movement of lithium ions between the electrodes. The arrows indicate the direction and magnitude of the current flowing into the current collectors. The current from the external circuit flows into the cell, through the tabs and then flows into all the local regions containing active materials distributed on the entire current collectors [7].

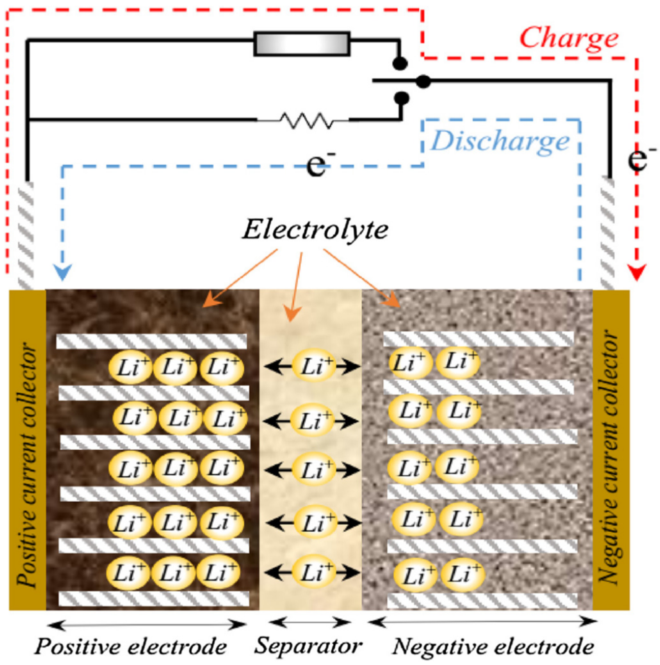

Figure 1. Schematic of a unit cell of the battery including positive and negative porous electrodes, a porous separator, and current collectors during the charge and discharge process [7].

Several review papers on battery safety have been recently published, covering topics such as cathode and anode materials, electrolytes, advanced safety batteries, and battery thermal runaway issues [12,13]. Amongst all the known battery failure modes, the internal short is one of the major safety concerns for the lithium-ion battery industry. Another important consideration is temperature variation leading to thermal runaways. The cell temperature is affected by the number and thickness of electrode layers and generally the battery size. Therefore, controlling heat generation is extremely important for high-power devices, such as electric vehicle batteries, where excessive heat can cause damage and reduce the battery's longevity lifetime [7].

Thermal runaway is a continuous, temperature increase inside a Li-ion battery that can be precipitated by manufacturing defects within the battery or by overheating, over-charging, or short circuit. When internal heating extends to a maximum temperature, it causes the generation of gases, and the increase in internal pressure that leads to battery rupture, fire, and explosion [14,15]. The maximum surface temperature can rise to 943° for a fully charged 18,650 battery [16].

1.3. Batteries for EVs

There are currently three main types of anode materials used in modern electric vehicles (EVs) batteries, namely Lithium Iron Phosphate (LFP), Lithium Nickel Cobalt Aluminum Oxide (NCA), and lithium nickel manganese cobalt oxide (NMC) [6,7,17]. LIBs have had a considerable impact on the EV industry in terms of high energy density, lifespan, nominal voltage, power density, and cost. While they provide an increased energy density and cycle life from the previous generation of batteries, with continuous technological advancements, they are operating increasingly closer to their theoretical limit [11]. The different chemistries vary in energy density, power capability, cost, and cycle life among other areas. A hybrid battery pack consists of two or more chemistries so it can combine the advantages of different chemistries to improve the overall pack performance. Therefore, in addition to further improving the design and manufacturing process of current LIBs, research efforts have focused on developing next-generation batteries, such as solid-state batteries, metal-air, and lithium-sulphur cell chemistries. Solid-state batteries (SSBs) replace the liquid electrolyte used in LIBs with a solid compound that allows the movement of lithium ions. Compared to LIBs, they have the potential to provide much higher energy densities and therefore longer driving ranges for EVs. The solid electrolyte is also less flammable than the liquid electrolytes used in LIBs, which helps prevent thermal runaway in battery cells. The current challenges in SSB developments include the interfacing of various layers and costs. The current consensus is that SSBs will likely become the leading direction of the next-generation EV batteries [18]. Indeed, many leading automotive manufacturers, such as Toyota, Volkswagen, BMW, Ford, General Motors, Stellates, Mercedes-Benz and Hyundai, have invested in solid-state battery technologies [19,20].

Lithium-sulfur (Li-S) battery is another type of battery with the potential to become the next generation of cells to be used in energy storage systems because of their extremely high theoretical energy density. Li-S cells use lithium metal as the anode and sulphur as the cathode. During the charge/discharge process, a reversible redox reaction occurs between the lithium and sulphur instead of the intercalation that occurs in LIBs, offering a much higher theoretical energy density of 2500 Wh/kg. A breakthrough in 2009 that achieved stable cycling of over 20 cycles in Li-S cells was followed by extensive research to improve their specific capacity and cycle life [21]. In March 2022, American battery manufacturer Sion Power announced that they have achieved more than 2500 cycles with their 17 Ah Licerion Electric Vehicle cells which target the automotive market [22]. The German battery start-up Theion featured in a recent Forbes article [23] also has plans to deliver Li-S batteries suitable for automotive applications by 2024. While the technology is still in the prototyping phase, with the extremely high theoretical energy density and low dependence on rare earth metals, Li-S batteries have the potential to become the future generation cells after or combined with SSBs.

In addition to various types and generations of Li-ion batteries, metal-air batteries are also considered by some to be a viable future alternative for their high capacity and energy density [24,25]. The anode is made of a metal, such as lithium, aluminum-magnesium, etc., and the external air acts as the cathode. Compared to Li-ion batteries, metal-air batteries are still in a relatively early stage of development and may not see large-scale commercialization before the next iteration of Li-ion batteries.

To develop high energy density battery chemistries, combing different cell chemistries is another way to improve the overall performance or reduce the cost of the battery pack without significantly increasing its mass and volume. The different chemistries vary in energy density, power capability, cost, and cycle life. A hybrid battery pack consists of two or more chemistries so it can combine the advantages of different chemistries to improve the overall pack performance.

Several small-to-medium-scale companies have been trying to commercialize hybrid battery packs for use in EVs. UK start-up Chimera Energy [26] or Upgrade Technology Engineering [27], the same team under different company names aims to develop a multi-chemistry battery system to leverage the advantages of different chemicals and improve overall performance. They also own a patent on the control strategy of such battery packs [28].

In 2019, the UK company Williams Advanced Engineering developed an "Adaptive Multi-Chem" technology that combines high-energy-density Nickel Manganese Cobalt (NMC) pouch cells and high-power-density NMC cylindrical cells in one pack to improve the overall performance [29,30]. Finally, Italian sports car start-up Automobile Estrema announced their Fulminea project, which uses a hybrid battery pack combining supercapacitors and solid-state Li-ion cells to provide the best sports performance. The vehicles are expected to be delivered to customers in 2023 [31].

Apart from their use in EVs, hybrid battery packs can also be useful in microgrid applications. They not only allow the combination of different battery chemistries as in EVs but their combination with recycled second-life automotive batteries. In 2020, Japanese battery manufacturer GS Yuasa built an energy storage system combining lead-acid and Li-ion batteries to reduce costs [32].

The Li-ion batteries are used to provide high energy output for EV charging and the lead-acid batteries are used to capture the renewable energy generated from nearby photovoltaic arrays [33]. Retired EV batteries can still be used in other applications where the power capability is not as critical as in the automotive sector. A group from the University of Oxford is exploring the possibility of combining different chemistry batteries to provide a low-cost energy storage solution in sub-Saharan countries [34]. This topic was also studied by a group from Oak Ridge National Laboratory, where a system architecture for a multi-chemistry second-life battery system was proposed to integrate BMS and power electronic converters from multiple manufacturers [35].

While hybrid battery packs have the potential to provide cost reduction and moderate improvement in the overall energy and power performance, they cannot provide the significant improvement offered by SSBs and Li-S batteries. Therefore, major EV manufacturers are more interested in using novel cell chemistries than SSbs [36].

2. Battery Thermal Conditioning

The battery thermal management system is one of the main aspects of an EV. Therefore, a major focus area for research is the optimal working temperature range of batteries during charging/discharging mode and the associated thermal management.

Since thermal runaway leads to fire in battery packs [37], regulating the battery temperature within a safe range of 25 °C to 40 °C during charging and discharging cycles in EVs is essential for the battery's longevity and safety [38]. A 10 Ah pouch Li-ion cell has been tested at various C-rates to measure the time-dependent temperature behaviour constant current charge/discharge. The battery was placed in a small chamber with a fixed temperature of 14 °C. Figure 2a–c demonstrates the temperature variation of the battery surface versus time at 0.1, 0.5 and 0.8 C rates, respectively. Figure 2d displays the positions of thermocouples (T1–T4) on the battery surface. These results show the growth of surface temperature close to the positive tab for T1 about 0.6 °C, 6.4 °C and 10.9 °C above the initial temperature after one charge/discharge cycle at 0.1 C, 0.5 C, and 0.8 C, respectively [7,17].

The study was expanded at a higher C rate to validate the battery thermal behaviour, and the simulation results are compared with the experimental measurements at 0.5 C, 1 C, 2 C and 4 C discharge rates as reported in Figure 3. The results suggest that an electrochemical-thermal model can reliably estimate the thermal behaviour of an NCA Li-ion cell batteries, enabling a rapid strategy to investigate the temperature distribution of the cell under different C-rates [7,17]. The temperature increase at the end of 0.5 C discharge is about 3.8 °C, and the cell temperature significantly rises above the ambient temperature as the C-rate grows.

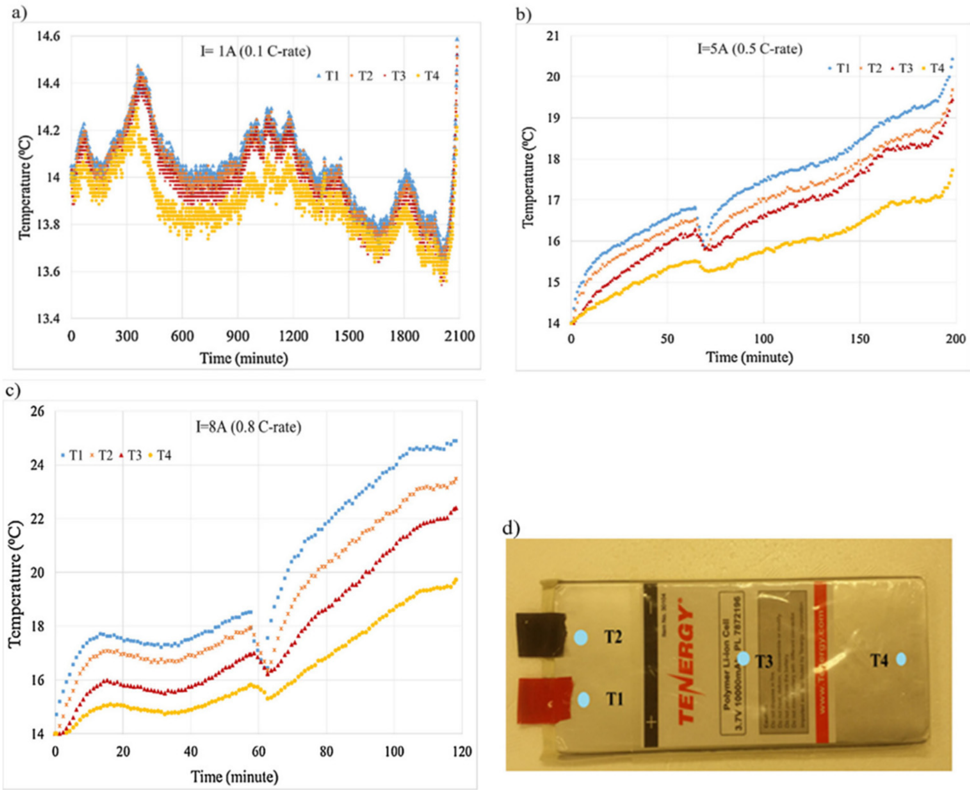

Figure 2. Surface temperature profiles at (**a**) 0.1 C-rate, (**b**) 0.5 C-rate and (**c**) 0.8 C-rate. (**d**) Temperature is measured close to the positive tab (T1, blue lines), close to the negative tab (T2, orange lines), center (T3, red lines) and at the bottom of the battery (T4, yellow lines) [7].

Numerical investigations in the literature showed that the conductivity of the electrolyte increases with temperature, causing more current to be directed to hotter sections of the battery [17,39,40]. A range of thermal management strategies are commonly used in battery packs to ensure temperature uniformity amongst cells and for maintaining the temperature within the range [41]:

- Air cooling
- Liquid cooling
- Phase change materials (PCM)
- Heat pipes
- and a combination of the above strategies.

The liquid and air cooling systems are considered active cooling systems since they include external pumps, fans, and other auxiliary systems [42]. Active cooling systems demand more space and power, while PCMs are known as passive thermal management systems and do not generally require additional components for their operation [43]. Key considerations in the selection of thermal management systems include energy efficiency, cell temperature uniformity, and overall weight and volume.

Mengliang et al. proposed a heat pipe and refrigerant-based BTMS coupled with an air-conditioning system for a battery module to investigate the battery temperature distribution, and energy efficiency of the BTMS [44]. The results reveal that once the initial temperature is increased from 25 °C to 30 °C and 35 °C, the average coefficient of performance increased by 16.95% and 38.41%, respectively; and the average exergy efficiency of the BTMS improved by 2.63% and 5.07%, respectively [38].

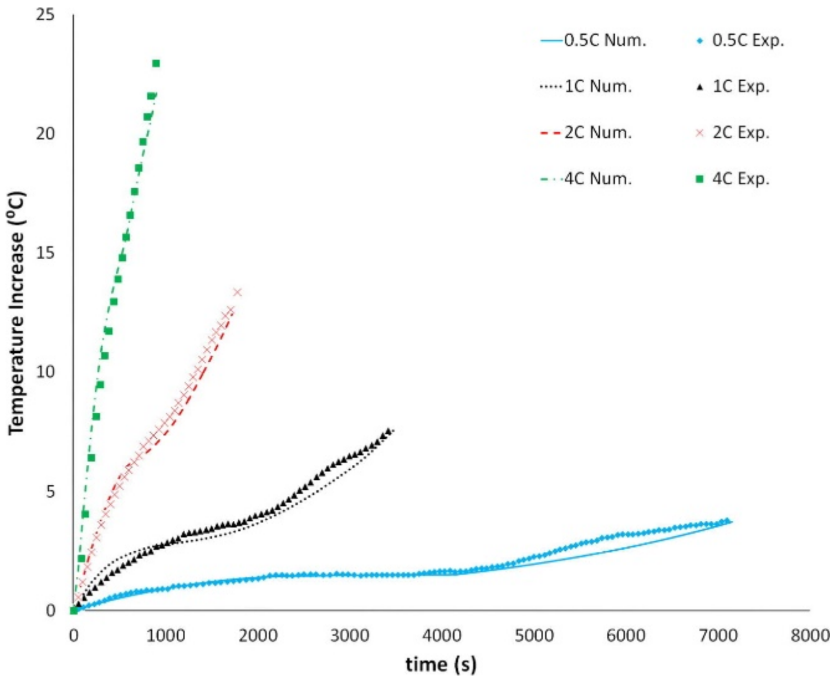

Figure 3. Numerical and experimental validation of average surface temperature during various discharge rates [17].

Kokkula et al. investigated the thermal management of pouch-type lithium-ion batteries with a straight mini-channel-based cold plate sandwiched between two consecutive pouch-type $LiFePO_4$ cells to form a module coolant pass through the plate. The results revealed that a cold plate including an even number of channels has a higher pressure drop than an odd number of channels due to the flow resistance. Additionally, the average temperature of the battery module decreased with an increase in coolant flow rate at the expense of a more considerable pressure drop and increased power consumption [45].

A three-dimensional numerical model is developed by Peng et al. to study the PCM process and its effect on battery thermal behaviour at different C-rate discharge processes (0.5 C, 1 C and 2 C), and different PCM properties (different mass fractions of expandable graphite) of the battery module. The results suggest a non-uniform PCM liquid fraction distribution during the discharge process since the outer layer and top portion of PCM melted first. Alternatively, by adding high thermal conductivity nanoparticles to a composite PCM of 12 wt% EG (expanded graphite), the results showed that the heat dissipation of the battery pack responded well to the increased flow rate than that of pure PCM. Additionally, they experimentally observed the good effects of composite PCM for battery thermal management systems [46].

Based on the above analysis and perception few important future research perspectives are highlighted. From the literature, thermal fins are mostly created of copper, bronze, steel, nickel, stainless steel, and aluminum alloy. Although the integration of metal plates with the fins can effectively improve the cooling performance, the weight of the system is still a concern and, exploring novel designs of fins using advanced manufacturing techniques still requires more attention. Moreover, to efficiently dissipate heat generated during battery operation at a higher temperature and during a faster-charging rate, the use of evaporative fluid as a potential added technique can significantly improve the performance of existing air-cooled battery management systems.

In addition, the prediction of lithium-ion battery temperature performance in different operating conditions, for different values of PCM material, thicknesses, and discharge rates would be beneficial for accelerating the industrialization of this innovative cooling strategy.

Various types of PCMs can absorb and release a large quantity of thermal energy through the phase change procedure from solid–liquid, solid–solid and then liquid–gas.

Although paraffin wax (PW) is the most favoured PCM due to its high energy density, nontoxicity and low vapour pressures, the disadvantage of PW is low thermal conductivity and the risk of liquid leakage during the phase change procedure.

From the literature to increase the thermal conductivity of PW, different thermally conductive fillers, such as ceramic fillers Al2O3 AlN and metal nanoparticles Cu, Al and Ag can be added to PW [47–49]. Additionally, the liquid leakage issue of PW can be avoided by mixing polymer and PW since the polymeric matrix can fix PW by a strong intermolecular force [50,51].

Y. Zhang et al., used graphite/paraffin/silicone rubber composite PCMs to control the temperature and improve the safety performance and service life in heat energy storage, battery management and thermal interface materials for electronic devices. In this study, the expanded graphite (EG), paraffin wax (PW) and silicone rubber (SR) matrix are blended with the mixture EG/PW/SR composite shown in Figure 4. Further analysis proved that the fusion latent heat and the crystallization latent heat of the composite PCM were 43.6 J/g and 41.8 J/g, respectively. Moreover, The shape stable test indicates that the EG/PW/SR composite PCM may well resist baking at 150 °C for 24 h with no shift [52].

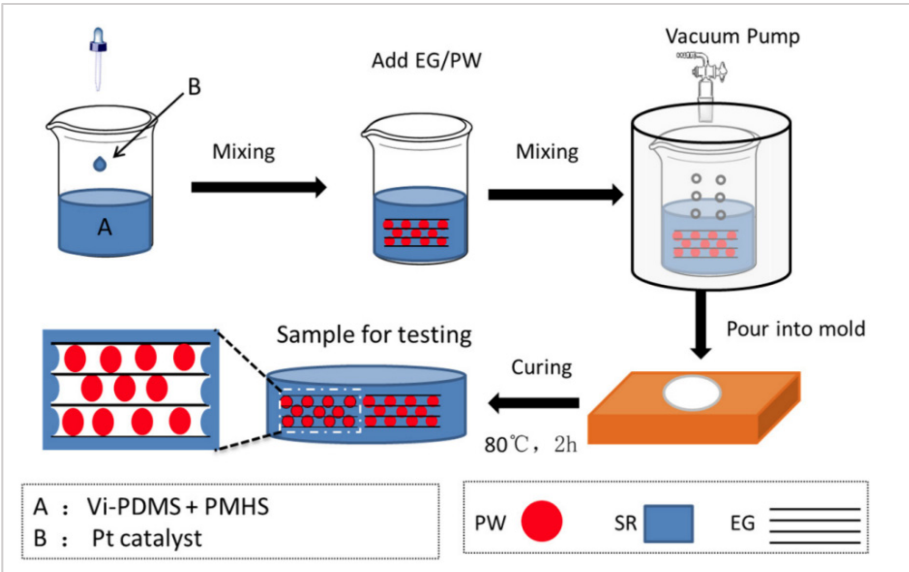

Figure 4. The preparation process of expanded graphite (EG)/paraffin wax [52].

3. Battery Management System

A battery-management system (BMS) detects unusual circumstances and validates the proper method for controlling the temperature behaviour of the battery to avoid any negative impact on the power-intake profile. BMS plays a critical role in the safe and efficient operation of batteries. It uses state estimation which is a broad field of research.

BMS should be designed to mitigate the effects of operations at different states, power demands, temperatures, and states of health. It generally employs model base estimation that requires an accurate battery model and a robust estimation strategy to work efficiently. Since LIBs charge faster than conventional battery technologies, a well-designed BMS is essential to help with the safety, dependability, and overall performance of lithium-ion battery systems.

Since LIBs charge faster than conventional battery technologies, a well-designed BMS is essential to help with the safety, dependability, and overall performance of lithium-ion battery systems. The accurate estimation of the SOC of a Li-ion battery is challenging because the Li-ion battery is a highly time-variant, non-linear, and complex electrochemical system. The SOC estimation methods have been classified into four main categories, namely the direct measurement method, bookkeeping estimation method, model-based method, and computer intelligence method. A critical explanation, including their merits, limitations, and estimation errors from other studies, is provided. Some recommendations depending on the development of technology are suggested to improve online estimation [53].

The BMS is responsible for monitoring the SOC, SOH, SOP, and the remaining useful life (RUL) of the battery pack as well as for cell balancing, thermal management, and safety. Figure 5 demonstrates the global market for battery-management systems for different applications [54].

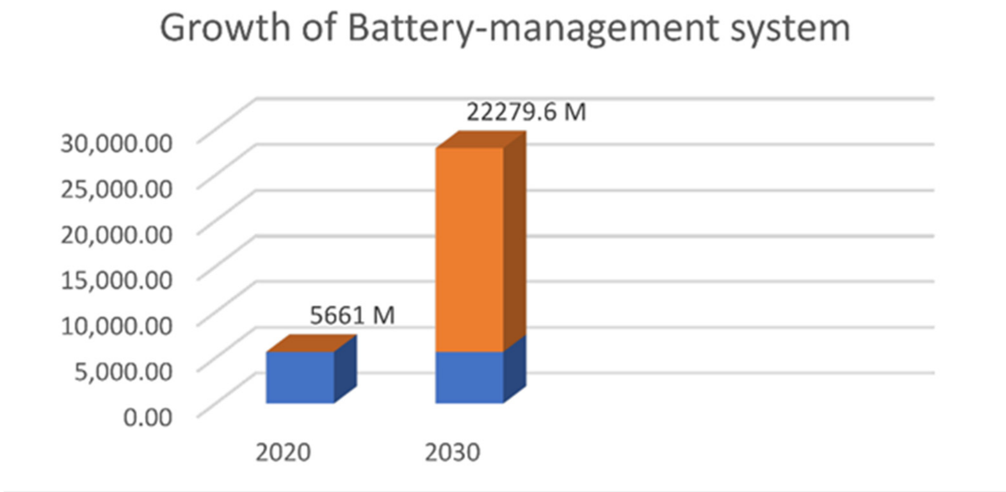

Figure 5. Growth of Battery-management systems from 2020 to 2030 [54].

Battery packs are the most expensive components in EVs and the largest factor contributing to the price differential between EVs and conventional ICE-powered vehicles [7]. In the small and midsize car segments, the average EV costs $12,000 more to produce than comparable ICE-powered vehicles. The reason behind this cost is that most original equipment manufacturers over-engineer battery packs by 10–14% in terms of capacity to slow down the battery degradation rate due to SBMS limitations. This over-engineering could be mitigated by implementing accurate and robust SOC, SOH, and SOP estimation strategies onboard the BMS.

Multiple models can be considered or learned for SOC and SOH estimation. These models are used in combination with an AI-empowered filter [55]. However, a combination of linear and nonlinear filters can be deployed for estimating the states whose time evolutions are governed by linear and nonlinear dynamics, respectively. In this way, the computational burden can be reduced [56].

Next-generation management will serve as the vital link between EVs and the energy society, which consists of numerous EVs, charging stations, and power plants. It is essential to have an accurate estimation of battery voltage, heat generation rate, and state of health under different conditions to maintain the safe and efficient operations of the BMS for EV application.

With the increasing number of onboard batteries, advanced management is needed for battery modules. Advanced management systems take different forms, including centralized systems and distributed. The advanced management system focuses on improving the battery performance and the user's driving experience and enables the monitoring of battery dynamics. Battery modelling and state estimation, thermal management, battery equalization, charging control, and fault diagnosis are the required functions [57].

While AI technology would improve and transform the implementation of LIBs for EV applications, the deployment of AI/ML algorithms into real-world scenarios for predicting and discovering battery materials and estimating the state of the battery system is challenging [58].

ML techniques can be used to link data, by creating a new dataset construction and/or existing dataset development where a critical correlation in material science is the structure-property relation. A predictive AI/ML approach helps to extract complicated and nonlinear patterns from training datasets and translate the meta-data into statistical models. Therefore, fault prognosis as an additional function to the local fault detection function of the BMS would use historical data and machine learning to predict or prevent the occurrence of a fault in the battery system [59–61].

The SOH estimation based on ML technologies is shown in Figure 6. The overall framework is based on two parts, the offline training process, and the estimation process which could be either offline or online. Sui et al. analyzed the impact of entropy as a feature for capacity estimation of the battery by monitoring the variation of voltage, current, and temperature during the aging process. The performance of these sample entropy (SE)-based estimators, revealed that the entropy-based SOH estimation method will be improved once the battery SOC gets to the polarization zone [62].

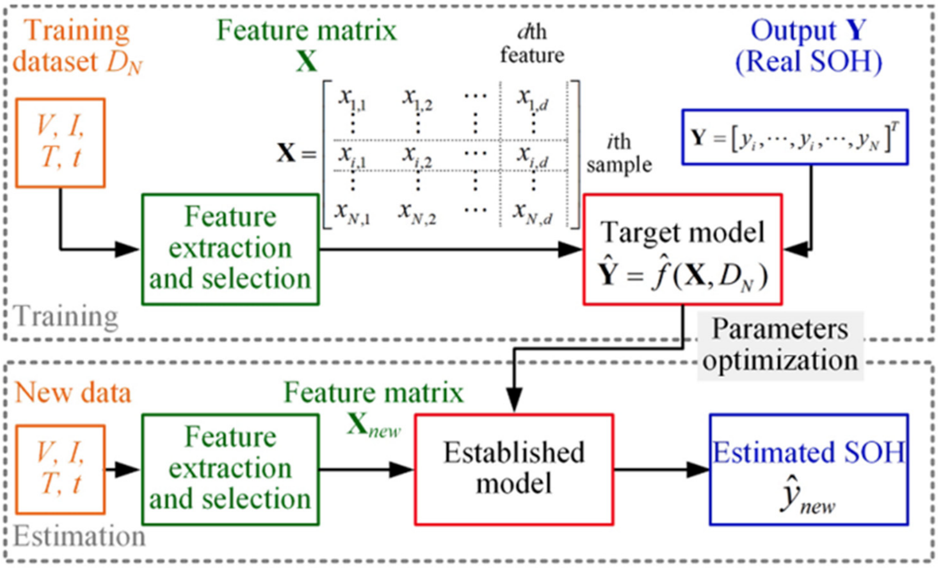

Figure 6. The battery SOH estimation structure using ML algorithms [61].

Currently, with the rapid development of AI in every industry, AI is finding its way into our everyday lives. Generative AI has been determined as a strategic AI technology by Gartner [63]. Additionally, in an earlier report, it was predicted that AI would lead to breakthroughs in key areas such as [64]:

- Augmented workforce
- Cybersecurity
- Metaverse
- Autonomous vehicles

Energy management, climate, healthcare, drug discovery, and robotics are among other fields where AI can make a difference.

The learning architectures and transformer-based models that benefit from an attention mechanism have been playing a critical role in different AI applications, especially in natural language processing. Putting language models aside, regarding the previously mentioned trends, the following state-of-the-art algorithms represent the recent top AI achievements for different application domains:

- Computer vision:
  - Time-Space Transformer has been developed by Meta AI (Facebook AI) for video understanding through action recognition. Compared to a 3D convolutional neural network (CNN), TimeSformer is faster to train and requires less computing power. Hence, it is more suitable for real-time or on-demand video-processing applications [63].

- Perceiver has been developed by Google DeepMind based on transformers to be compatible across various modalities including image, video, and point cloud. Using an asymmetric attention mechanism, it can handle large inputs by iteratively distilling inputs into a latent information bottleneck [65].

- Generative AI:
  - DALL-E has been developed by OpenAI to create images from text descriptions, which applies to a wide range of concepts that can be expressed using natural language. Building on transformers, DALL-E models the text and image tokens as one data stream in an autoregressive manner [66].
  - Google DeepMind has proposed an AI framework to play the role of an assistant for mathematicians helping them in discovering new conjectures and theorems. The algorithm relies on seeking potential patterns and relations between mathematical objects [67].
- Deep reinforcement learning:
  - AlphaFold has been developed by Google DeepMind for predicting the protein structures in the human proteome [68].
  - A deep reinforcement learning algorithm has been proposed by Google DeepMind for high-dimensional and high-frequency control of tokamak, which is a nuclear fusion reactor. The proposed controller autonomously learns to command the magnetic actuator coils in a way to satisfy a diverse set of requirements over a wide range of plasma configurations [65].
- Multimodal learning:
  - To cope with the insufficiency of multimodal training data, a transformer-based multimodal learning architecture has been proposed [69]. In this architecture, a set of unimodal pre-trained transformer models are used to encode different modal inputs. Then, representations, which are provided by these encoders, are fused by another set of transformer layers.
  - In multimodal learning, some modalities likely face issues such as missing data, noisy data, lack of annotated data, unreliable labels, and scarcity of training data. To cope with such issues, the notion of multimodal co-learning has been proposed for performing knowledge transfer from resource-rich modalities to resource-poor ones [70].
  - Since data plays an important role in the learning process, recently, in the AI community, a campaign has been started by Andrew Ng to promote data-centric AI as opposed to model-centric AI [71]. According to Andrew Ng, "data-centric AI is the discipline of systematically engineering the data needed to successfully build an AI system". The main idea is to have smart-size learning models instead of overly complex ones. However, the model quality should not be compensated for simplicity. To obtain a high-quality AI system, such simpler models must be trained on datasets, which are carefully collected smartly. In this regard, observability deserves special attention.

Observability plays a key role in estimation, control, and decision-making. Regarding condition monitoring as well as fault diagnosis and prognosis, the notion of observability has been recently extended from the system level to the data level. Aiming for high-quality data, the following five pillars have been proposed for data observability [72]:

- Freshness refers to the availability of up-to-date data.
- Distribution refers to whether data is in the acceptable range.
- Volume refers to the completeness of data.
- Schema is concerned with structure change for the data.
- Lineage is concerned with both upstream and downstream negative impacts of data downtime.

To build an automated end-to-end data pipeline, AI must be part and parcel of each one of these pillars. AI can handle partial observability and compensate for missing data through data imputation [73]. Furthermore, deploying a cognitive controller alongside the physical controller in the system will pave the way for improving observability [74]. While the physical controller controls the flow of energy in the system, the cognitive controller is responsible for controlling the flow of information toward minimizing risk in the decision-making process [75].

The sequential data collected as time series reflects the dynamic state of the system under study, and the fusion of features associated with different modalities into an industrial knowledge graph will facilitate condition monitoring and prognostics [76]. Graph neural networks [77] and tools from graph signal processing [78] can be deployed to develop such a framework. Furthermore, graph neural networks allow for handling unstructured data [79]. Using such a knowledge graph allows the AI-empowered decision-making process to move beyond robustness and aim at achieving antifragility through learning and system reconfiguration. While a robust or resilient system is supposed to resist shocks and stay the same, an antifragile system must improve. Antifragile systems should be immune to prediction errors. Moreover, in case of an adverse event, the antifragile system must be able to quickly restore its normal status and recover its normal performance [80].

For condition monitoring and prognostics, state/parameter estimation would be a key element. Through shifting from a model-centric to a data-centric approach, a large spectrum of AI-empowered filters can be developed and used for state/parameter estimation regarding the deployed models and learning methods [56]. In this regard, multiple-linear, adaptive, kernel-based, and deep-learning models can be tailored to and learned for the application at hand. For training such models, supervised, semi-supervised, unsupervised, weakly supervised, self-supervised, noise-robust, and reinforcement learning can be used [81]. Such models can then be used in combination with different filtering algorithms as the required state-space models. For instance, to handle partially known dynamics, recurrent neural networks (RNNs), as well as a combination of RNNs and time-varying state-space models, were used to aid the Kalman filter [82]. Alternatively, the filtering procedure can also be viewed as a learning process as well. In this regard, for time-series analysis, probabilistic transformers combine a state-space model with the transformer architecture to benefit from an attention mechanism [83].

Habibi presented a new hybrid filter-based method for state estimation as the smooth variable structure filter (SVSF). The SVSF method is model-based and applies to smooth nonlinear dynamic systems. It allows for the explicit definition of the source of uncertainty and can guarantee stability given an upper bound for uncertainties and noise levels. The performance of the SVSF improves with the more refined definition of upper bounds on parameter variations or uncertainties. By combining SVSF) with different models and learning methods, a large spectrum of novel AI-empowered filtering algorithms will be derived and used for condition monitoring and prognostics, especially in energy management systems (EMS). To be more specific, such filters will be used as part and parcel of a BMS for battery state estimation. Then, these estimates will be used for diagnosing and prognosing electrical faults or cell failures as well as improving battery efficiency [84]. The combination of the SVSF with deep learning, reinforcement learning, and graph neural networks to derive novel filtering algorithms is uncharted territory to improve the overall accuracy and stability of the estimates. Therefore, there is great potential from both theoretical and practical perspectives to make a difference in the literature. Moreover, using the main idea behind the SVSF may contribute to AI research in the sense of deriving novel learning algorithms [85].

Regarding the advantages of SVSF over the Kalman filter such as robustness against model uncertainty and the existence of a secondary set of indicators in addition to the innovation vector, it is expected that the AI-empowered SVSF algorithms will come out as winners in competitions against the available deep learning-based filters that are built on Kalman filter. Moreover, it is expected that the AI-empowered SVSF algorithms find applications beyond the domain of applicability of current deep learning-based filters.

Data collection is an essential aspect of developing and training AI models. This proposal will generate extensive and high-quality data for various battery chemistry and cell types. These data will become an asset for researchers to conduct further analysis, use for training and modelling, and benchmark against. The datasets will enable more researchers to start innovating without building up facilities first, accelerating the pace of battery research.

4. Conclusions

The climate change concern and other environmental issues due to the immense exploitation of fossil fuels and the emission of greenhouse gases result in increased consumption of rechargeable batteries. Although there are various types of primary batteries and rechargeable batteries available in the market, lithium-ion LIBs are the most common energy storage systems due to their high specific capacity, high energy density and good cycling stability especially for EV applications [7].

In the current study, different cooling methods were investigated to improve the temperature performance of LIBs have been summarized including air cooling, liquid cooling, PCM cooling, and heat pipes. It is noticed that the air-cooling system has advantageous features such as safe, consistent, and simple design, but the lower heat capacity and thermal efficiency of the air as a cooling method. Liquid-cooled is a very effective cooling technique with greater thermal conductivity and greater heat capacities compared to air cooling in which a liquid is used as a coolant to eliminate the heat generated by a battery. To increase thermal conductivity, PCM cooling allows simple cooling designs to wrap batteries, with graphite sheets between batteries, increasing the heat loss and improving the temperature uniformity of the battery pack. To achieve better cooling performance PCM cooling can also be combined with liquid cooling or heat pipes.

Moreover, a BMS is an essential device for charging and discharging the batteries, overcoming many challenges, and improving the operating performance of battery modules. On the other hand, using AI-based predictive algorithms in BMS can improve the availability of testing datasets and robust processing of data in real-time for EV applications.

According to the above analysis, a future investigation using a Kalman Filter Algorithm is necessary to improve the existing algorithms by including both SOH and SOC estimators to calculate the ageing of the battery in terms of power management during long periods of use. This response to the demand side of safety challenges in packing lithium-ion battery energy management.

Moreover, from the perspective of theory and application, ML technologies possess play a major role in battery SOH estimation. Therefore, the outlook of the research on future research should focus on implementing advanced battery models and algorithms onto the cloud-based BMS and the difficulty of onboard implementation. In particular, an EMS system that runs optimally under harsh weather can significantly improve the mileage and usability of electric vehicles in Canada and similar regions with cold climates. This will encourage customer acceptance of electric vehicles and accelerate the pace toward carbon peak and carbon neutrality goals.

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Abbreviations

The following abbreviations are used in this manuscript:

EVs	Electric Vehicles
BMS	Battery Management System
AI	Artificial Intelligence
ML	Machine Learning
SOC	State of Health
SOH	State of Charge
EV	Electric Vehicle
LIBs	Lithium-ion batteries
$LiFePO_4$	Lithium Iron Phosphate
$LiCoO_2$	Lithium Cobalt Oxide
NCA	Lithium Nickel Cobalt Aluminum Oxide
LFP	Lithium Iron Phosphate
SSB	Solid-state batteries
Li-S	Lithium-sulfur
NRC	National Research Council Canada
NMC	Nickel Manganese Cobalt
PCM	Phase change materials
PW	Paraffin Wax
EG	Expanded Graphite
SR	Silicone Rubber
RUL	Remaining Useful Life
CNN	Convolutional Neural Network
RNNs	recurrent neural networks
SVSF	smooth variable structure filter
EMS	energy management systems

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