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AI-Based Estimation of Lithium-Ion Battery Management System: A Review of AI Integration in Electric Vehicle

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***Abstract*— Lithium-ion (Li-ion) batteries have gained considerable attention in the Electric Vehicle (EV) industry due to their high energy density, better lifespan, and higher nominal voltage. However, accurately estimating the State of Charge (SOC) and State of Health (SOH) for Li-ion batteries remains challenging due to its aging and nonlinear behaviour. This paper explores Battery Management System (BMS) models potential incorporating Artificial Intelligence (AI) estimation techniques, particularly Deep Learning (DL), to improve SOC and SOH model estimations. This research paper summarized and analyzed current BMS approaches by identify the potential gaps in existing research focus and propose another technique for further exploration in the EV Li-ion battery. Currently, there is a research gap in the existing studies, especially in the application of DL for SOC and SOH estimation. and underscores the need for more comprehensive exploration and refinement of DL methods. Future research should address these gaps to advance the integration of DL into BMS to ensure robust and reliable SOC and SOH estimations. Because of its features and capacity to improve SOC and SOH estimating health models accurately, deep learning has a lot of potential for studying SOC & SOH in BMS. As a result, there is opportunity to investigate the DL technique further in order to thoroughly and clearly examine the correctness of SOC & SOH model estimations in BMS.**

***Index Terms*— Battery management system (BMS), lithium-ion, artificial intelligence, state of charge (SOC), state of health (SOH)**

I. INTRODUCTION

Due to rising concerns about environmental pollution and global warming, modern society has made sustainability one of its top priorities. To ease these worries and move forward to a sustainable future, global energy strategies emphasise the switch from fossil fuels to renewable energy (RE) sources. The ability of RE to be efficiently used to manage energy consumption and cut carbon emissions makes it essential in the commercial, industrial, and residential sectors [1]. Major contributors to carbon emissions include electricity and heat production, transport, manufacturing and construction, as well as agriculture [2]. The transportation sector is among the leading causes of environmental pollution, contributing over one-third carbon dioxide emissions, of which vehicle transportation accounts for over 70% [3].

Technological disruptions in the transportation sector facilitate decarbonisation because of rising environmental pollution and concerns about global warming. This transformation includes a move toward adopting electric vehicles (EVs), which have several benefits, such as shorter payback period and longer lifespan, helping to reduce CO_2 emissions and change the way transportation will be in the future [4]. With the promise of lower emissions and less reliance on oil, EVs have drawn much interest as a leading the way for environmental sustainability and emissions-free mobility [4], [5].

Artificial intelligence (AI) is the most fascinating and discussed technology in the current decade for its nature to mimic human intelligence. The field of AI has shown an upward trend of growth in the 21st century (from 2000 to 2015) [6]. Artificial Intelligence (AI) is the study of creating machines that can perceive, analyze, comprehend, and react like humans. Simply said, the ultimate goal of artificial intelligence (AI) is to extend and argue humanity's capacity and efficiency in the work of changing nature and regulating society through intelligent machines. Simultaneously, artificial intelligence technologies that enhance the system's overall capabilities have significant importance. The legal standing of AI technology is examined in this study. In the current societal development stage, AI is rapidly developing its capabilities as a future technology.

This research study aims to provide an overview of AI and explain how it relates to the concepts of SOC and SOH. A difficulty at the junction of AI is data integration. AI finds extensive application in the automotive, logistics, healthcare, stock trading, robotics, finance, transportation, and educational domains. AI techniques provide promise for the vehicle, the infrastructure, the driver, or the transport user—and especially for the interactions among them. Transportation is changing as a result of the EV industry's adoption of AI, particularly deep learning (DL) and machine learning (ML), which enhances user experience, efficiency, sustainability, and safety.

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Li-ion batteries are primarily used in EVs because of their exceptional qualities [7]. Li-ion batteries provide high power and energy density, increased voltage, prolonged life cycles, and low self-discharge rates. These qualities make them the ideal option for EVs, further supported by their widespread use in portable electronics, automotive applications, and stationary energy storage systems compared to earlier battery technologies [8]. Li-ion batteries have shown rapid growth as the fastest-growing technology among different energy storage solutions [9]. However, Li-ion batteries have difficulties and disadvantages despite their dominance and countless benefits. Limited range, lengthy charging times, high costs, and reliability and safety concerns are a few of these problems. Their sensitivity to ageing and temperature requires careful management to avoid deterioration, ageing, and thermal runaways [10].

A crucial component of EVs is battery management system (BMS). Its used for controlling temperature, evaluating charge and health, and monitoring essential battery parameters. It offers priceless insight into battery health, monitors key indicators, and guards against overcharging and over-discharging situations [8], [11]. It is essential to improve EV safety to understand the battery's status, including the SOC, SOH, temperature, current rate, and charging/discharge conditions [12].

The assessment of battery SOH is crucial for ensuring the safety and optimal perfrmance of batteries. Given the growing demand for batteries with longer lifespans in EVs, understanding SOH is important in optimising battery lifespan and lifecycle which are closely related in energy applications like EVs. SOH reflects performance errors but cannot be directly estimated because of the complex factors affecting battery ageing. Like all energy storage technologies, Li-ion batteries degrade over time, decreasing capacity and power output. Accurate methods for estimating the SOH of Li-ion batteries are necessary for effective monitoring and management of their degradation, ensuring optimal performance and longevity [13], [14]. Therefore, the aims of this research paper is to investigate the important issues related to BMS, SOC, and SOH aiming to provide a detail insight on BMS used in EVs. Hence, this research paper highlight the need of DL technique for SOC and SOH estimation Li-ion battery based on the previous researchers.

II. LITHIUM-ION BATTERY

The adoption of EVs as a sustainable transportation solution contributes to the simultaneous reduction of fossil fuel consumption and carbon emissions. Due to its numerous advantages, including high energy density, long lifespan, rapid charging capabilities, high operating voltage, and low self-discharge, the Li-ion battery has emerged as the preferred choice for EVs [14]. Thus, accurately estimating the state of a Li-ion battery is crucial in minimising excessive design expenses and enhancing overall vehicle efficiency, safety, and reliability. Hence, the Li-ion battery pack is one of the most expensive components in an EV, proper estimation of its states becomes essential [15].

A. *Demand of Lithium-Ion Batteries For EV, 2016-2022*

Based on the data presented in Fig. 1, it can observe the trend in demand for Li-ion batteries in EVs, measured in kilo tons, for the year of 2016 until 2022. Notably, the demand for Li-ion batteries for EVs displayed a consistent increase starting in 2018 and extending through 2020. However, a significant upsurge in demand became evident in 2021 and 2022, signifying a substantial shift towards Li-ion batteries as the preferred battery type for a significant portion of EVs. This trend emphasises the crucial role of research and development efforts focused on improving the health and efficiency of Li-ion batteries, as their impact extends beyond the EV industry to various other sectors

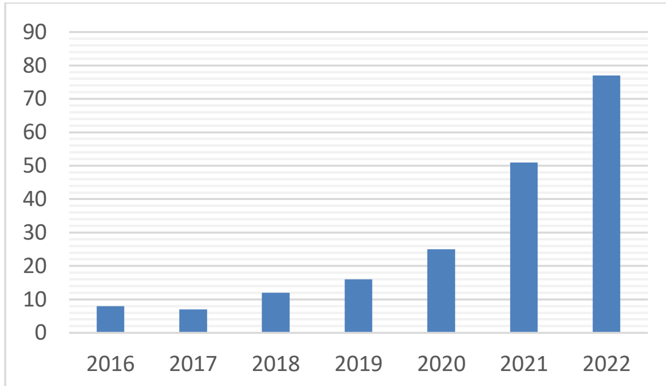

Fig. 1. The trend of lithium-ion batteries demands for EV [16]

B. *Rechargeable Batteries Type*

Table I presents a summary of various types of rechargeable batteries. The discussion focuses on a limited selection of batteries that are commonly used or have the potential to be used as alternative methods soon. Detailed properties of these batteries, along with a suitable comparison, are provided in Table I. The analysis in Table II shows that the Li-ion battery is the most suitable choice for various applications because of its helpful characteristics, such as high energy density and cell voltage. In contrast, other batteries utilising different chemistries are currently not as viable for vehicles and portable devices [17].

TABLE I. COMPARISON OF BATTERY TECHNOLOGY [17]

	Lead Acid battery	**Nickel based battery**	**Sodium ion-based battery**	**Lithium ion-based battery**
Cell Voltage	2 V	1.2 V	3.4 V	3.3 – 3.7 V
Energy density	30 – 50 WhKg−1	60 – 80 WhKg−1	100 – 115 WhKg−1	80 – 220 WhKg−1
Cost	around USD 100 per KWh	around 700 – 800 per KWh	around USD 445 – 555 per KWh	more than around USD 700 per KWh
Charging and Discharging Cycles	250 -1000	300 – 50,000	2,500 – 40,000	around 3000

C. *Electric Vehicles Currently Latest Model*

Upon reviewing the information as tabulated in Table II, the primary power source of choice for leading companies in the EVs industry is predominantly Li-ion batteries for their latest models. An analysis of the data further reveals that typical EV models exhibit energy capacities within the range of 80 kWh to 100 kWh. Vehicles that exceed this range fall into two categories: high-performance models designed for speed or larger EVs intended for extended use and enhanced capacity.

TABLE II SPECIFICATIONS OF CURRENTLY LATEST EV MODEL THAT USE LI-ION BATTERY[18]

Car Type	**Manufacturing year**	**Brand**	**Battery Capacity**
	2018	Jaguar I-PACE	90 kWh
	2019	Mercedes Benz EQC	80 kWh
	2017	Tesla model 3	82 kWh
	2021	Tesla model S	100 kWh
	2015	Tesla model X	100 kWh
	2020	Tesla Model Y	79.2 kWh

III. BATTERY MANAGEMENT SYSTEM

A. *Battery Management System (BMS) Function*

BMS plays a vital role in various industries, particularly the automotive sector, by ensuring battery components' safety, dependability, and efficiency. Its primary function is to regulate key operating parameters of the battery, such as current, voltage, and power, to optimise its lifespan. The BMS can calculate the SOC and SOH of the battery, making it suitable for innovative applications [19].

In EVs, including battery-operated and hybrid EVs, it is crucial to have a monitoring system in place to prevent potential tragedies caused by the unpredictable behaviour of the battery. From a safety perspective, the BMS is vital in alerting the user about unforeseen conditions and taking appropriate corrective measures. In automotive systems, the BMS monitors the temperature of the coolant surrounding the battery pack. This helps optimise the distribution of power to individual components more efficiently [20].

Here are several essential functions that a BMS possess [21], [22]:

1) *Data Acquisition*
The BMS collects data from multiple sensors, such as voltage, current, and temperature, to monitor the battery system.
2) *Battery Health Monitoring*
The BMS ensures the battery is in optimal condition by continuously assessing its performance and detecting any abnormalities or degradation.
3) *State Estimation*
The BMS estimates the battery's state, including SOC and SOH, providing crucial information about its energy level and overall condition.
4) *Cell Balancing*
The BMS implements a cell balancing procedure to equalise the charge levels among individual battery cells, enhancing their longevity and optimising performance.
5) *Charge Control*
The BMS regulates the charging process of the battery, ensuring that it is performed safely and efficiently.
6) *Thermal Management*
The BMS actively manages the battery's temperature, utilising various techniques to prevent overheating or extreme temperature fluctuations.
7) *Communication*
The BMS establishes communication with different components of the battery system, enabling coordinated operation and exchanging important information.
8) *Alerting and Reporting*
The BMS promptly notifies relevant controllers or systems about the battery's state, allowing for timely actions or interventions when necessary.

B. *Electrical Vehicle Construction*

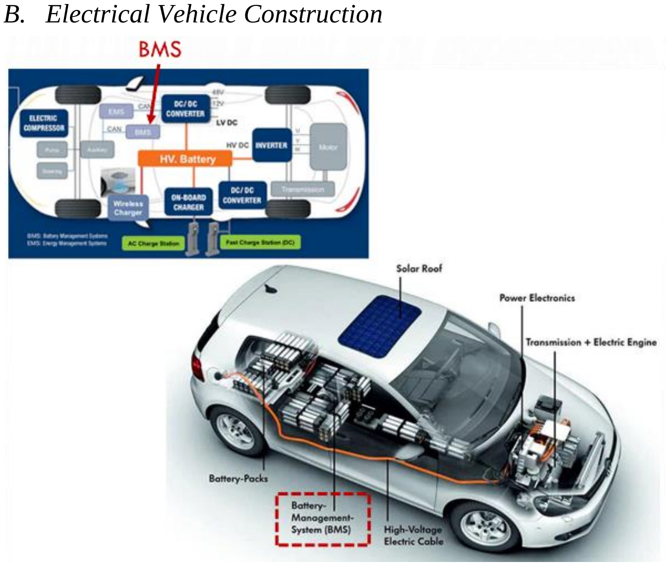

Fig. 2. The basic construction of EV [23]

Diagram depicted in Fig. 2 clearly illustrates an EVs structure. The diagram shows that the battery is at the vehicle's rear. The BMS is interconnected with the battery, serving the critical role of monitoring the battery's condition and overseeing all components that can potentially affect the battery's overall health and performance.

C. *Battery Management System (BMS) Operation*

In BMS, there are three types of parameters involved. Fig. 3 explains the interrelation and significance of SOC, SOH, and SOP parameters in battery systems and their influence on the overall performance and behaviour of the battery.

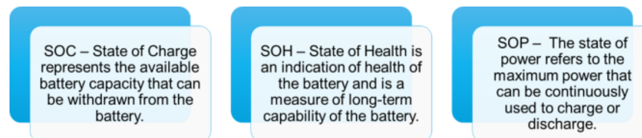

Fig. 3. The battery conditions of SOC, SOH and SOP

BMS technology controls and maintains batteries through sensors, controllers, actuators, and algorithms. Its primary aim is to ensure battery safety and reliability while providing essential data for vehicle control, energy management, and intervention in case of abnormal battery conditions. In addition, the BMS collects real-time data on individual cell parameters, such as temperature, terminal voltage, and current, to estimate SOC, SOP, and SOH using embedded algorithms and strategies. The estimation results are then relayed to the vehicle control unit (VCU) to manage energy and power distribution in EVs [24].

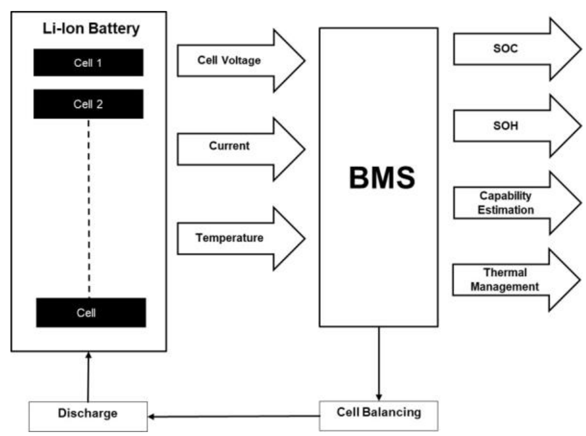

Fig. 4. Block diagram of battery management system[25]

Fig. 4 shows the basic block diagram of BMS. To achieve the desired voltage, the battery pack of an EV is formed by connecting multiple cells in series and parallel. These cells can be charged with electric current and discharged as needed. However, to mitigate cell imbalance within the battery pack and enhance cell capacity, the implementation of a BMS is essential.

Battery cell balancing can be accomplished through two methods: active and passive. Active cell balancing involves charging a low-voltage cell using a high-voltage cell, whereas passive cell balancing dissipates excess energy stored in the battery as heat. The BMS collects data such as voltage, current, and temperature from each cell to make decisions on cell balancing, thermal management, and estimate the SOC and SOH of the battery.

IV. STATE OF CHARGE AND STATE OF HEALTH

A. State of Charge (SOC)

The battery's SOC acts as a fuel gauge, similar to those in traditional gasoline vehicles. However, unlike a fuel gauge that directly shows the remaining energy, determining the percentage of usable energy left inside a battery requires an indirect measurement through estimation. This estimation relies on various methods and techniques that utilise measurable signals, including battery terminal voltage, current, and temperature [26].

Estimating the SOC accurately is a challenging task because of the non-linear and variable behaviour of batteries. In the design of BMS for EVs, SOC estimation holds utmost significance. It plays a crucial role in performing EVs. Various methods are employed to achieve precise and reliable SOC estimation, considering the unique characteristics of batteries [27].

EVs Li-Ion battery (LIB) is a dynamic and non-linear system with multiple state variables. The key to effective control and maximising LIB power is accurately predicting and understanding its dynamic behaviour.

SOC represents the measurement of the remaining energy in a battery (ψ). In physical terms, the remaining energy in a battery is defined as the average concentration of Li-ions in the cathode ($C_{s,avg}$) relative to the maximum achievable concentration [28] as shown in (1).

$$\psi = \frac{C_{s,avg}}{C_{s,max}} \tag{1}$$

In theory, it is possible for the SOC of a battery to be at $\psi = 0\%$ or $\psi = 100\%$. However, it is not feasible to fully deplete or overcharge a battery as it can damage its structure and accelerate degradation. Therefore, a range of SOC values is defined for Li-ion batteries, where the lower limit $\psi_{0\%} > 0$ and the upper limit $\psi_{100\%} < 1$. The SOC is determined based on the ratio within this defined range of SOC values as shown in (2).

$$SOC = \frac{\psi_k - \psi_{0\%}}{\psi_{100\%} - \psi_{0\%}} \tag{2}$$

The variable ψ_k represents the remaining energy in the battery at a specific time k. whereas this definition of SOC is theoretically accurate, it is not practically feasible for a BMS to directly measure ψ due to the inability to directly measure the concentration of Li-ions. Consequently, an alternative definition of SOC is necessary, one that is not reliant on directly measuring the Li-ion concentration [28].

$$SOC(t) = \left(\frac{C_r}{C_m}\right) 100\% \tag{3}$$

C_r represents the remaining capacity available to power electric devices. C_m denotes the maximum capacity the cell can store, as determined by its electrochemical characteristics. The SOC ranges from 0% to 100%, where 0% indicates a fully discharged battery, and 100% indicates a fully charged battery [29]. Conventionally, the SOC is expressed in percentage as presented in Fig. 5, where 100% and 0% represent the fully charged and fully discharged conditions of the battery, respectively.

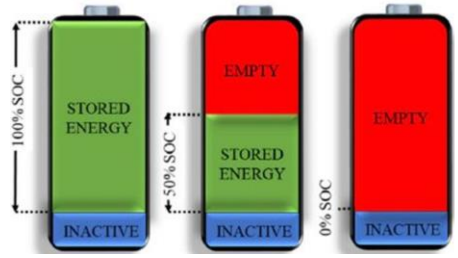

Fig. 5. The layout of SOC

B. State of Health (SOH)

The SOH of a battery describes the difference between a battery being studied battery and considers cell aging. A battery's SOH reflects its overall health condition. It directly impacts the SOC of the battery. SOH can be determined by measuring the capacity and impedance of the battery. It naturally declines as the battery ages and undergoes wear and tear. Factors such as overcharging, over-discharging, and exposure to high temperatures can contribute to a shortened lifespan and diminished SOH of the battery [30]. The lifespan of a Li-ion battery is determined by the number of cycles it can undergo before its SOH decreases to 80%. Once the SOH value reaches 80% or lower, it is typically recommended to replace the battery [31]. It is defined as the ratio of the maximum battery charge to its rated capacity. It is expressed as a percentage as seen in Fig. 6.

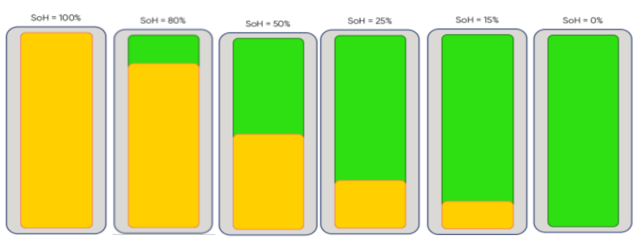

Fig. 6. The SOH illustration of health condition

Two commonly used definitions of SOH are based on different performance characteristic parameters. One definition is based on capacity, whereas the other is internal resistance. The specific details of these two definitions can be described using (4) and (5):

$$SOH = \frac{Q_c}{Q_{new}} \times 100\% \quad (4)$$

$$SOH = \frac{R_{EOL} - R}{R_{EOL} - R_{new}} \times 100\% \quad (5)$$

In the given (4), Q_c represents the maximum usable capacity of the battery, Q_{new} represents the initial rated capacity of a new battery under the current cycle C. R represents the actual internal resistance during the current cycle, R_{new} represents the initial internal resistance of the new battery. R_{EOL} represents the internal resistance at the end of the battery's life.

With an increasing number of battery cycles, the maximum available capacity of the battery tends to decrease, whereas the internal resistance tends to increase. Battery failure is commonly observed when the internal impedance reaches twice the initial impedance ($R = 2 \times R_{new}$). Similarly, when capacity is used as a performance characteristic parameter, it is considered that the battery needs to be replaced when the maximum usable capacity decays to 80% of the rated capacity ($Q = 80\% \times Q_{new}$) [32].

C. *SOH Measurement Method*

1) *Direct Measurement Methods*
   These methods involve measuring various parameters of the battery, including impedance, internal resistance, open-circuit voltage (OCV), and charge/discharge current. A notable observation is the strong inverse relationship between battery capacity loss and internal resistance. In simpler terms, as the internal resistance of the battery increases, its capacity tends to degrade. This relationship is widely utilised in estimating the SOH of the battery [33].
2) *Model-Based Method*
   Battery models are created to evaluate the ageing process of batteries, and two common types of models are used: the electrochemical model (EChM) and the equivalent circuit model (ECM). The ECM model is constructed using electrical components, such as resistors, capacitors, and voltage sources [33], [34].
3) *Adaptive Filter Methods*
   Adaptive filter methods, such as the Kalman filter, particle filter, and the fewest squares, are frequently employed for battery parameter estimation. In the Kalman filter method, battery parameters are measured over a specific period to calculate the SOH of the battery [35].
4) *Data-Driven Method*
   Currently, data-driven methods have emerged as the preferred approach for calculating the SOH of batteries. This shift is primarily attributed to advancements in computing devices such as high-speed CPUs, graphical processing units (GPUs), and sophisticated learning algorithms. In the data-driven method, a significant amount of battery parameters is continuously collected until the battery reaches failure. SOH estimation is accomplished using various techniques, such as fuzzy logic (FL), support vector machine (SVM), artificial neural network (ANN), and DL methods [36].

V. AI-BASED ESTIMATION TECHNIQUES

A. *Artificial Intelligence In BMS*

The method based on AI can applied to both SOC estimation and SOH estimation [36], [37]. Machine Learning (ML) and DL are subsets of AI. They form part of the broader AI field, as depicted in the Venn diagram in Fig. 7, which illustrates the subdivisions within AI, including ML and its subsequent branches, such as representation learning and DL. In the context of estimating the SOC and SOH for EVs, innovative techniques in ML are incorporated within the AI domain. These methods encompass various subfields of ML and have significant relevance in the field of EVs [38].

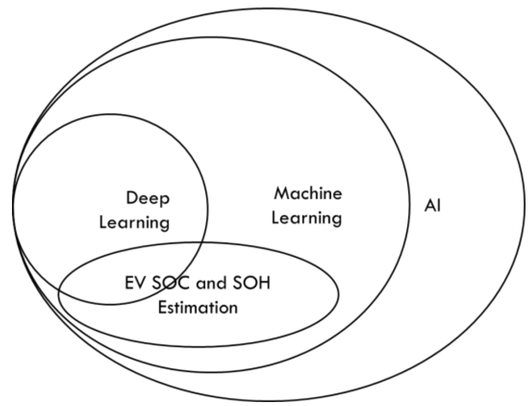

Fig. 7. Venn diagram SOC and SOH Estimation [38]

B. *BMS Machine Learning*

ML techniques have emerged as prominent methods for estimating crucial battery performance indicators, including SOH and SOC. These approaches leverage the advancements in computational power and the increasing availability of battery data, enabling more accurate and reliable estimations of battery parameters [39].

While in [40], it focuses on predicting the SOC of a battery using six different machine-learning algorithms. These algorithms include artificial neural network (ANN), support vector machine (SVM), linear regression (LR), Gaussian process regression (GPR), ensemble bagging, and ensemble boosting. By utilising these ML models, the researchers analyse the non-linear relationship between input features such as voltage and current and the estimation of SOC. ML algorithms are chosen for SOC estimation because of their ability to handle non-linear data effectively. The proposed method can be applied for real-time SOC estimation by optimising the hyperparameters of the GPR-linear model.

The use of ML techniques to estimate the SOH parameters in EV applications under various scenarios was explored and studied by [41]. By conducting a comprehensive analysis of cell ageing in different storage conditions, a new approach is developed that utilises impedance data for SOH estimation. A fully connected feed-forward neural network (FC-FNN) is utilised to estimate the battery's maximum available capacity based on a limited number of impedance measurements. The proposed method is tested using real EV battery data, considering long-term scenarios and diverse degradation procedures.

This research paper [42], focuses on predicting the SOC of Li-ion batteries under dynamic loads. The study compares the performance of various SOC ML models in predicting the SOC of an 18650 cell. These models are developed using measurement data got from dynamic load tests. To account for the impact of realistic operational conditions, a multi-sine load profile consisting of five charge/discharge load patterns applies to the cell. The results of the performance analysis indicate that Long Short-Term Memory (LSTM) Neural Network and Prophet models exhibit high efficiency in SOC prediction and are considered suitable options for real-time applications.

C. BMS Deep Learning

The accuracy and stability of battery models can be significantly enhanced using state estimation methods based on DL algorithms. However, a major obstacle to implementing these methods is the requirement for a large amount of training data. To overcome this challenge, a deep transfer learning method is developed to expedite the training process of the battery model. This approach enables the utilisation of operation data from various types of EVs to establish state estimators. By leveraging this deep transfer learning technique, the training of the battery model can be accelerated, leading to improved performance and efficiency [43].

A method utilising a deep neural network (DNN) is introduced to estimate the SOC of LiFeO4 batteries accurately was investigated in [44]. By analysing the charging current and voltage data, the DNN provides an initial SOC value that improves the accuracy of the Ampere-hour (Ah) counting method. The DNN achieves impressive SOC estimation results, with an error rate below 2.03% across the entire SOC range, even when encountering flat open circuit voltage (OCV) plateaus. This method can be adapted for different charging protocols beyond the constant current constant voltage (CCCV) approach. To enhance the method's robustness, a linear Kalman filter is incorporated, forming a closed-loop estimation framework that combines the DNN with the Ah counting method. Validation tests confirm the framework's ability to improve resistance against random noises and error spikes.

While [45], investigates the estimation of SOC using both a deep neural network (DNN) and an artificial neural network (ANN) based on data collected from laboratory experiments and simulations. The DNN exhibited exceptional efficiency, delivering accurate and reliable estimation performance for both battery types. The average error value was less than 0.5%, with a maximum error value of less than 2.5%. By showing a strong correlation between the estimated SOC and the reference SOC, the validation test results confirmed a successful match between the two. In conclusion, the proposed algorithm provides robust and precise SOC estimation for the batteries under study.

The input data comprises electrochemical impedance spectroscopy (EIS) measurements at different temperatures collected from batteries with a SOC of 100% where a DL architecture was introduced for SOC Li-ion batteries estimation. A key contribution of this method is the conversion of EIS data into a 2D image, which is then used for unsupervised feature learning using a convolutional auto-encoder (CAE). The extracted features are then fed into a deep neural network (DNN) to estimate the charge capacity and SOH of the batteries at various temperatures. The proposed method shows its effectiveness in training multi-temperature SOH estimation models using DL [46].

1) *Estimating SOH Using Deep Learning Method*

Data-driven approaches include ML and DL strategies that take advantage of the relationships that hide in large datasets and do not require a mathematical model of the batteries. It is crucial to note that each of these models has a unique set of challenges. They require extensive computing resources, such as massive memory devices and cutting-edge CPU units, as well as complicated training procedures [47]. DL highlights being "deep" by utilising several hidden layers in neural networks to a large extent. In the domain of DL, there are a few common algorithms. Recurrent Neural Networks (RNNs), for instance, include a context unit that considers historical ageing information. Fully connected hidden layers characterise Deep Neural Networks (DNNs). Convolutional Neural Networks (CNNs) integrate convolutional and pooling layers ahead of the hidden layers, and these convolutional and pooling layers are employed to reduce the dimensionality of the input data effectively. This hierarchical structure is a key aspect of DL, allowing for sophisticated data processing and feature extraction [48].

2) *Category of Deep Learning Methods*

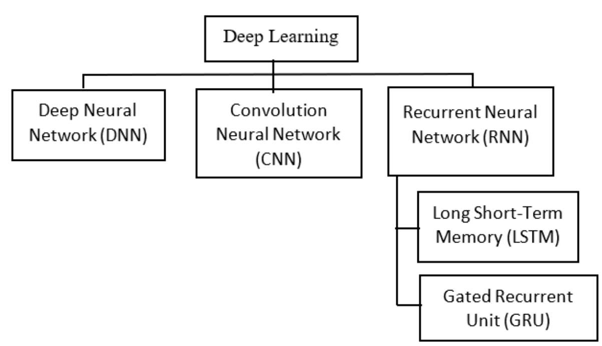

Fig. 8. The architecture of DL methods

Fig. 8 illustrates common used methods employed and studied by previous researchers for estimating the SOC and SOH. The accompanying Table III will provide brief explanations of each model's operation, along with their respective advantages and disadvantages.

TABLE III . EXPLANATION OF DEEP LEARNING (DL) MODEL AND ITS ADVANTAGE AND DISADVANTAGE

Model	Operation	Advantage	Disadvantage
DNN[49]	DNNs consist of multiple hidden layers.Information is passed through the hidden layers.These layers are activated by one or more activation functions.	DNN's deep architecture enables SOH estimation using sensor data such as V, I, T, and time-series data, without requiring extensive feature extraction.	Despite its higher accuracy in SOH estimation, has drawbacks including increased computational time and greater computing resource requirements.
CNN[49]	CNN models, commonly used for image recognition and classification, have also been successful in battery SOH estimation. CNN models have the advantage of low computational training time, reducing the human effort needed to develop their functionalities.	CNN can automatically extract and select features from raw data. This feature extraction is enabled using convolutional and pooling layers in CNN.	Data integration during the pooling process can result in the loss of some features. Due to its structural variability, it requires multiple parameter adjustments for confirmation. Many samples are needed for training.
RNN[49]	RNNs store historical information in the context unit and allow feedback from hidden layers to the previous layer's input. This addition of the context unit makes RNNs uniquely suited for handling sequential data.	RNNs excel in modelling time-dependent behaviour. RNNs incorporate the dependence on previous states within the network. This allows the consideration of the battery's behaviour up to the training point when predicting its future State of Health (SOH).	RNNs' strength in modelling time-dependent behaviour can be a drawback in certain applications. Predicting future behaviour with RNNs necessitates knowledge of the battery's past behaviour.
LSTM[50], [51]	The LSTM model is a highly effective DL technique for estimating the SOH of lithium-ion batteries. It is commonly used because it can resolve the vanishing gradient problem and improve model training accuracy in SOH estimation.	LSTM calculates dependencies in time series data. It excels in handling time-related data. It addresses gradient vanishing problem during training. Demonstrates strong generalization capabilities.	High hardware resource requirements. Demands a large amount of supporting data. Computational efficiency is lower compared to simple neural networks or data-driven algorithms.
GRU[50], [51]	GRU models are well-suited for SOH estimations in lithium-ion batteries. They effectively address the vanishing gradient problem and require less memory space for model training.	GRUs, like other recurrent neural networks, are capable of learning long-term dependencies, which is beneficial for time-series data like battery usage data. GRUs have fewer parameters than LSTMs, making them more computationally efficient and still maintaining a similar performance level.	Like other DL methods, GRUs require a large amount of data for training. GRUs, like other DL methods, lack interpretability which can be problematic in certain applications.

TABLE IV . ANALYSIS OF PREVIOUS RESEARCH PAPERS

Author	Title	Objective	Method
Dong-Ji Xuan et al. 2020[51]	Real-time estimation of state-of-charge in ***lithium-ion batteries*** using improved central difference transform method	• Real-time ***SOC*** estimation.	• Improved central difference transform Kalman filter. • Square root second-order central difference transform Kalman filter (SRCDKF).
Prakash Venugopal et al. 2019[35]	State-of-Health Estimation of ***Li-ion Batteries*** in Electric Vehicle Using IndRNN under Variable Load Condition	• ***SOH*** estimation.	• SOH estimation method using an independently recurrent neural network (IndRNN) • Compares IndRNN with other recurrent neural network (RNN) architectures like long short-term memory (LSTM) and gated recurrent unit (GRU).
Xiaosong Hu et al. 2020[52]	An enhanced multi-state estimation hierarchy for advanced ***lithium-ion battery*** management	• Co-estimation hierarchy for the ***State of Charge (SOC), State of Health (SOH)***, and State of Power (SOP).	• Multi-Time-Scale Estimation Framework. • Online, model-based SOC estimation using modified moving horizon estimation (mMHE).
Ran Li et al. 2021[53]	On-Line Estimation Method of ***Lithium-Ion Battery*** Health Status Based on PSO-SVM	• Online estimation method for ***LI battery health***. • Using the Particle Swarm Support Vector Machine algorithm.	• Particle Swarm Optimization-Support Vector Machine (PSO-SVM). • Joint SOC-SOH estimation within a battery management system.
Kangwei Dai et al. 2019[54]	An Improved ***SOC*** Estimator Using Time-Varying Discrete Sliding Mode Observer	• Time-varying-model-based discrete sliding mode observer (TVDSMO) for ***SOC*** estimation.	• Recursive fitting technology to update battery parameters automatically. • validated using LiFePO4 (LFP) and Ni-Mn-Co (NMC) lithium-ion cells across various temperatures and operating conditions.
Shulin Liu et al. 2022[55]	A method for state of charge and state of health estimation of ***lithium-ion battery*** based on adaptive unscented Kalman filter	• Joint estimation of **SOC** and **SOH** • Using AUKF algorithm in lithium-ion batteries.	• Adaptive Unscented Kalman Filter (AUKF) algorithm. • Simultaneous estimation of SOC and SOH.
Ran Li et al. 2022[56]	State of Health and Charge Estimation Based on Adaptive Boosting integrated with particle swarm optimization/support vector machine (AdaBoost-PSO-SVM) Model for ***Lithium-ion Batteries***	• Estimated battery ***SOH*** using the PSO-SVM algorithm.	• SOC-SOH online estimation method based on the PSO-SVM algorithm. • Learning AdaBoost algorithm to enhance the PSO-SVM regression model.

Richard Bustos et al. 2023[57]	***Lithium-Ion Battery*** Health Estimation Using an Adaptive Dual Interacting Model Algorithm for Electric Vehicles	• Estimating ***state of charge (SOC).*** • Battery capacity of ***lithium-ion batteries*** (LiBs).	• Dual-filter approach incorporates standard Kalman filter (KF). • sliding innovation filter (SIF) to estimate SOC. • capacity (dual-KF and dual-SIF).
Zhansheng Nin et al. 2022[58]	Co-estimation of ***state of charge and state of health*** for 48 V battery system based on cubature Kalman filter and H-infinity	• Multi-scale co-estimation approach for ***SOC*** and ***SOH*** estimation.	• Cubature Kalman filter (CKF), forgetting factor-recursive least squares (FF-RLS), and H-infinity algorithms.
Chaolong Zhang et al. 2022[59]	A reliable data-driven state-of-health estimation model for ***lithium-ion batteries*** in electric vehicles	• deep-ion battery SOH estimation.	• Incremental capacity analysis (ICA) combined with an improved broad learning system (BLS) network. • broad learning system (BLS) network optimized. • particle swarm optimization (PSO) algorithm.

D. Research Gaps

From Table IV, it summarizes the latest and most influential research in the realm of enhancing the health of Li-ion batteries. Most of the research endeavours in this field have been directed towards the development of more precise methods for calculating the SOH of these batteries. Notably, some studies have a specific focus on SOC estimation, whereas others only address SOH estimation. This distinction can be observed in several of the research papers. However, it is important to note that SOC estimation plays a pivotal role in refining the SOH estimation model. The joint estimation of SOC and SOH has emerged as a highly popular strategy in recent years. Table IV shows that most of the methodologies used are RNN, SVM, EKF, PSO, SMO, H-infinity, ICA and BLS. However, there are gaps in AI techniques for SOC and SOH estimation involving DL and ML technique. In terms of the methodologies adopted, AI methods, encompassing ML and DL, have acquired significant traction. In terms of AI methods, covering ML and DL has gained significant traction. However, DL model estimation is less prevalent than ML model estimation, although it has the potential to improve accuracy and sophistication in battery health assessment. Therefore, this research will focus on DL techniques for SOC and SOH estimation as part of future research work as shown in Fig. 9.

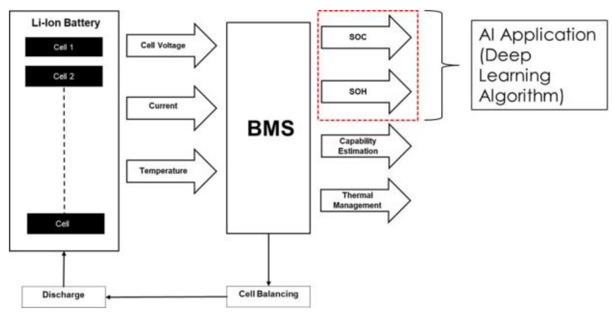

Fig. 9. AI application employed in this research

VI. Conclusion

This study focuses on the research needs and completed projects related to EV BMS systems. Critical remarks from this study, however, point to gaps in the existing research, particularly with regard to the use of DL in Li-ion battery SOC and SOH modeling. As a result, DL has been proposed as a future study topic for the estimate of SOC and SOH models in Li-ion EV batteries. Because of its features and capacity to improve SOC and SOH estimating health models accurately, deep learning has a lot of potential for studying SOC & SOH in BMS. As a result, there is opportunity to investigate the DL technique further in order to thoroughly and clearly examine the correctness of SOC & SOH model estimations in BMS.

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