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Review Article

Employment of Artificial Intelligence (AI) Techniques in Battery Management System (BMS) for Electric Vehicles (EV): Issues and Challenges

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ABSTRACT

Rechargeable Lithium-ion batteries have been widely utilized in diverse mobility applications, including electric vehicles (EVs), due to their high energy density and prolonged lifespan. However, the performance characteristics of those batteries, in terms of stability, efficiency, and life cycle, greatly affect the overall performance of the EV. Therefore, a battery management system (BMS) is required to manage, monitor and enhance the performance of the EV battery pack. For that purpose, a variety of Artificial Intelligence (AI) techniques have been proposed in the literature to enhance BMS capabilities, such as monitoring, battery state estimation, fault detection and cell balancing. This paper explores the state-of-the-art research in AI techniques applied to EV BMS. Despite the growing interest in AI-driven BMS, there are notable gaps in the existing literature. Our primary output is a comprehensive classification and analysis of these AI techniques based on their objectives, applications, and performance metrics. This analysis addresses these gaps and provides valuable insights for selecting the most suitable AI technique to develop a reliable BMS for EVs with efficient energy management.

Keywords: Artificial intelligence, battery management system, electric vehicle, lithium-ion battery, State of Charge

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INTRODUCTION

The phenomenon of global warming has evoked the concern of scholars and governments as well. Therefore, environmental protection has become a

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priority of most countries worldwide. Especially when the climate is affected by air pollutants such as carbon dioxide released from fuel burning by various vehicles. In this context, EVs have emerged as clean energy-based alternatives with numerous advantages compared to traditional vehicles. They exhibit simplicity that leads to cost-effective maintenance, lower charging costs compared to fuel expenses, and the absence of noise and harmful emissions.

Nevertheless, EVs encounter several challenges, such as the limited driving range per full charge, the relatively long charging time, the cost of degraded battery replacement, and the heavy weight of the battery packs (Sanguesa et al., 2021). Consequently, the current industry trend is towards developing EVs to overcome the gas pollution of traditional cars (Jose et al., 2022). Hence, extra attention has been paid to rechargeable batteries, especially Lithium-ion ones, which are used in EVs as an environmentally friendly alternative.

In this regard, EV batteries have been extensively discussed in numerous studies in the literature from different aspects, such as the battery charge balance and battery aging (Laadjal & Cardoso, 2021). Therefore, researchers have made noticeable efforts to improve the performance of the Battery Management System (BMS) for efficient utilization of the EV battery pack.

The journey of the BMS from a unit of merely monitoring tasks to a multi-functional integrated unit was illustrated in Shen and Gao (2019). The study's authors discussed different battery models, such as thermal, electrical, and multi-physics modeling, besides the developments in BMS functions introduced by different manufacturers in this field. The research in these fields is still ongoing, including studies on heating methods for optimal battery pack heating in cold environments (Talele et al., 2023).

However, the increasing attention and recent advancements in the realm of Artificial Intelligence (AI) and machine learning (ML) have significantly influenced research and development efforts in developing novel techniques for estimating the states of EV batteries (Vidal et al., 2020). Hence, benefiting from the development in digitalization and the availability of reliable data sources, AI technology has been employed to solve complex computational problems that used to be challenging (Nagarale & Patil, 2020). However, some other non-AI techniques may be used to reduce the online calculations, especially when simple equations are adopted, yet it may lead to less, but acceptable, accuracy (Othman et al., 2022).

On the other hand, cloud-based predictive BMS was also introduced for the estimation of various battery states, including State of Charge (SOC) and State of Health (SOH) (Tran, Panchal, Khang et al., 2022). By taking advantage of the Internet of Things (IoT) and cloud computing, a digital twin BMS has been introduced in some studies to enhance the computation power, reliability, and storage capability (Li et al., 2020; Wang et al., 2022). The digital twin BMS is a virtual copy of the physical one but is located in the cloud. The networked architecture of digital twin BMS improves its ability to perform various tasks such as fault detection, optimization and estimation of battery states. Furthermore, digital twin technology can play a crucial role in smart EVs, including autonomous navigation control, vehicle health monitoring and self-driving assistance (Bhatti et al., 2021). Hence, the utilization of online services for data training, fast computation, and model updating helps overcome the drawbacks of the traditional BMS.

In this study, the utilization of AI techniques in BMS of EV is reviewed. In particular, the study focused on the related publications in the past five years. The study provided some perspectives on the potential applications of AI techniques in the field of BMS. The study also illustrates the classification, benefits, and drawbacks of AI methods used for BMS.

OVERVIEW OF BMS

The past decades have witnessed an increased demand for batteries as reliable energy storage for various applications, such as laptops, cell phones, and EVs. Compared to other types of rechargeable batteries, lithium-ion batteries have exhibited better performance, especially in terms of battery life, which has made them the favorite for EV manufacturers. Furthermore, it is considered a clean source of energy due to its non-toxic components and high level of safety (Liu et al., 2019).

However, the chemical nature of the battery, along with frequent charging and discharging, leads to battery aging and temperature issues that need to be handled. Therefore, a BMS should be utilized for monitoring, controlling and enhancing battery performance to prolong its lifespan (Gabbar et al., 2021). An overview of BMS will be illustrated, including its main functions, as well as a brief description of the main state indicators frequently mentioned in the literature. Furthermore, as part of this overview, we present Table 1, which offers a concise summary of typical technical specifications of battery cells as obtained from the reviewed papers. Table 1 serves as a reference point to illustrate the key characteristics of battery cells in the context of BMS functionality.

Table 1
Key technical specifications of battery cells in BMS applications

Study	Battery Chemistry	Capacity	Nominal Voltage	Cut-Off Voltage	Maximum Discharging Current	Operating Temperature
Liu et al., 2020	Lithium-Nickel-Manganese-Cobalt-Oxide ($LiNiMnCoO_2$)	2 Ah	3.6 V	2.5/ 4.2 V	20 A	-20°– 60°
Tran, Panchal, Chauhan et al., 2022	Lithium-Iron- Manganese-Phosphate ($LiFeMnPO_4$)	25 Ah	3.2 V	2.2/ 3.65 V	75 A	-20°– 65°

Table 1 *(continue)*

Study	Battery Chemistry	Capacity	Nominal Voltage	Cut-Off Voltage	Maximum Discharging Current	Operating Temperature
Liu et al., 2018	Lithium-Iron- Phosphate (LiFePO4)	3.8 Ah	3.3 V	2.5/3.8 V	3.8 A	-20°– 60°
Kaur et al., 2021	Lithium Nickel Cobalt Manganese Oxide (LiNiCoMnO2)	3 Ah	3.7 V	2.7/4.2 V	3 Ah	-20°– 65°
Li et al., 2020	Lithium-Nickel-Cobalt-Aluminum-Oxide (Li-NCA)	3.4 Ah	3.6 V	2.65/4.2 V	8 Ah	-10°– 60°
Meng et al., 2019	Lithium-Nickel-Manganese-Cobalt (Li-NMC)	63 Ah	3.7 V	3/ 4.15 V	63 Ah	-20°– 60°
Baveja et al., 2023	Lithium-Iron-Phosphate (LiFePO4)	1.1 Ah	3.2 V	2/ 3.65 V	1.1 Ah	-20°– 60°

BMS Functions

Different types of BMS may have various functions according to their complexity and functionality. However, BMS functions typically include monitoring, protection and optimization of battery performance (Andrea, 2010). For example, BMS can monitor different measurements of the battery cells, such as voltage, current and temperature. Those measurements are essential for another vital BMS function, which is the estimation of battery states, such as SOC, SOH and State of Power (SOP). Such information can be used to perform cell balancing tasks to protect the battery cells, maximize their performance, and control the system temperature.

Moreover, BMS needs to establish good communication with the battery pack and other related devices, as seen in Figure 1, which illustrates the general functions of BMS. However, the architecture of BMS may include other tasks based on its complexity.

Cell Balancing

The battery pack of an EV is composed of several connected cells of similar characteristics. Nevertheless, different cells may have different behavior in terms of impedance, self-discharge, and temperature, which leads to an unbalanced charging situation. Hence, to handle this situation, BMS can use onboard or external components to control the charging flow so that cell balancing is achieved. Therefore, cell balancing is a vital function of MBS that helps to extend the battery life by controlling the charging process (Duraisamy & Kaliyaperumal, 2021).

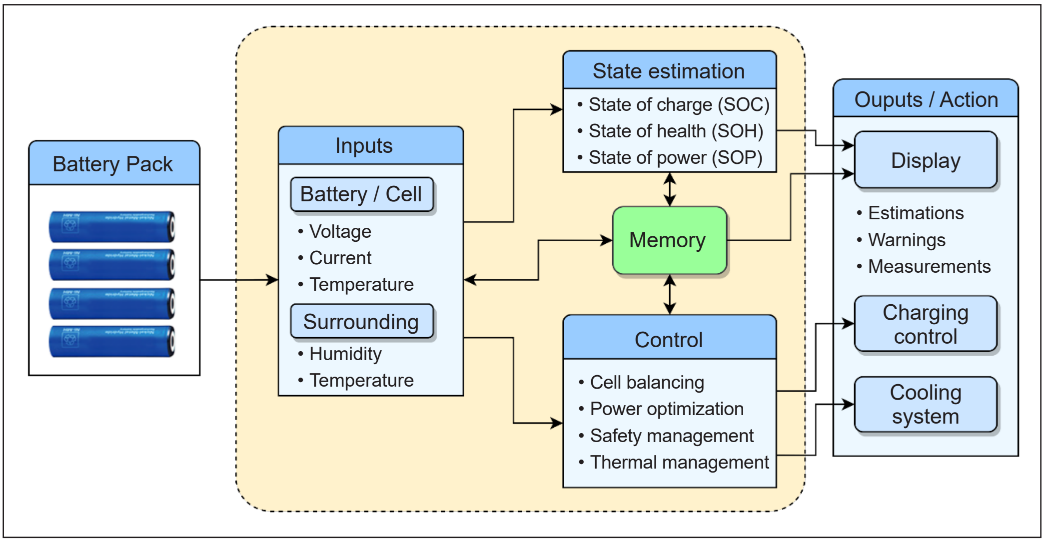

Figure 1. General functions of BMS (Zhang & Fan, 2020)

Cell balancing includes active and passive balancing, while the latter is more popular due to its low cost and simplicity. Theoretically, passive cell balancing can be achieved by a simple resistor or a power transistor, which dissipates the balancing energy as heat. On the other hand, energy is not wasted in active cell balancing; instead, it is transferred to the other cells within the battery pack (Andrea, 2010). However, the design of the cell balancing module can take a more complicated form, where it can provide thermal predictions for optimal battery thermal management systems (Baveja et al., 2023).

Generally, both passive and active cell balancing schemes have advantages and drawbacks, yet both techniques lead to a remarkable enhancement in battery performance (Omariba et al., 2019). However, optimal cell balancing can be achieved by adopting intelligent techniques, such as machine learning. This approach leads to extra advantages such as achieving higher SOC, reducing cell degradation, improving battery safety, and extending lifespan (Andrea, 2010). Furthermore, AI techniques can also be employed in other BMS functions to enhance performance.

Battery States

Batteries have attracted the concern of developers and researchers due to their features as a clean source of energy that can be recharged and requires minimal maintenance. However, batteries are degradable products that wear out over time as a result of aging and repeated charging and discharging, which affect their efficiency and performance. Therefore, the battery state should always be monitored to ensure its safety and efficiency and to keep the EV under control. However, the battery states cannot be measured directly; instead, they can be estimated by utilizing other acquired measurements such as current, voltage and temperature.

With regard to BMS, there are several battery states to be considered, such as SOC, SOH and state of life. Such states have been widely utilized to avoid battery overcharging and over-discharging and, consequently, to prolong the battery life (Park et al., 2020). The following is a brief discussion of the most important battery state indicators, namely, SOC, SOH and SOP.

State of Charge (SOC). Like the fuel gauge in traditional vehicles, SOC is the battery state gauge of the remaining amount of energy inside a battery, which can be used to obtain other states of the battery, such as the state of safety and the state of function (Sanguesa et al., 2021). SOC indicator is mathematically defined as the ratio of battery charge level to its rated capacity and can be expressed as Equation 1 (Murnane & Ghazel, 2017):

$$SOC = \frac{C_{releasable}}{C_{rated}} \times 100\% \qquad [1]$$

where, $C_{releasable}$ is the amount of capacity that can be discharged when the battery is fully depleted, while C_{rated} is the measurement of charge and discharge currents with respect to the nominal capacity of the battery.

It can be noticed that many approaches for the enhancement of SOC prediction have been proposed by several studies related to BMS in the literature. However, it is noteworthy that apart from SOC prediction, the value of SOC can be improved during the driving process using different technologies, such as the Regenerative Braking System (RBS) (Ghazali et al., 2020).

State of Health (SOH). For a fully charged new battery, the maximum releasable capacity is almost the same as its rated capacity. However, as the battery degrades over time, its maximum capacity declines. This concept can serve as an indicator of the overall health of the battery; hence, the SOH indicator is defined as the ratio of maximum battery charge level to its rated capacity and can be expressed as Equation 2 (Murnane & Ghazel, 2017):

$$SOH = \frac{C_{max}}{C_{rated}} \times 100\% \qquad [2]$$

where, C_{max} is the maximum capacity that can be discharged from a fully charged battery.

It should be noted that the value of C_{max} naturally decreases over time due to several factors, such as ambient temperature, cycle aging, and charging rate. Monitoring these factors is crucial for enhancing the SOH and prolonging battery life.

State of Power (SOP). For safety purposes, it is important to know how much power can be delivered by the battery at a specific time. That purpose can be achieved by the SOP indicator, which is defined as the ratio of battery peak power to its rated power and can be expressed as Equation 3 (Rahimifard et al., 2021):

$$SOP = \frac{P_{max}}{P_{rated}} \times 100\% \qquad [3]$$

where, P_{max} is the maximum power that can be continually delivered by the battery over a given duration, while P_{rated} is the rated power as specified by the manufacturer.

The main advantage of SOP is that it helps to bind the charge or discharge power within certain limits; thus, the lifespan of the battery can be prolonged. However, SOP is highly dependent on the SOC in addition to other factors such as battery capacity, voltage, chemistry, and initial features.

AI TECHNIQUES APPLIED IN BMS

AI has significantly influenced the advancement of EV technology in the past decade. Therefore, several AI techniques, such as Deep Learning (DL), have been applied in the technology of EVs for different purposes, including the control of self-driving vehicles and charging system optimization, as illustrated in Figure 2.

An analytical study by Lee (2020) demonstrates the effect of AI on EV technology based on patent data over more than three decades. The study concluded that AI has been

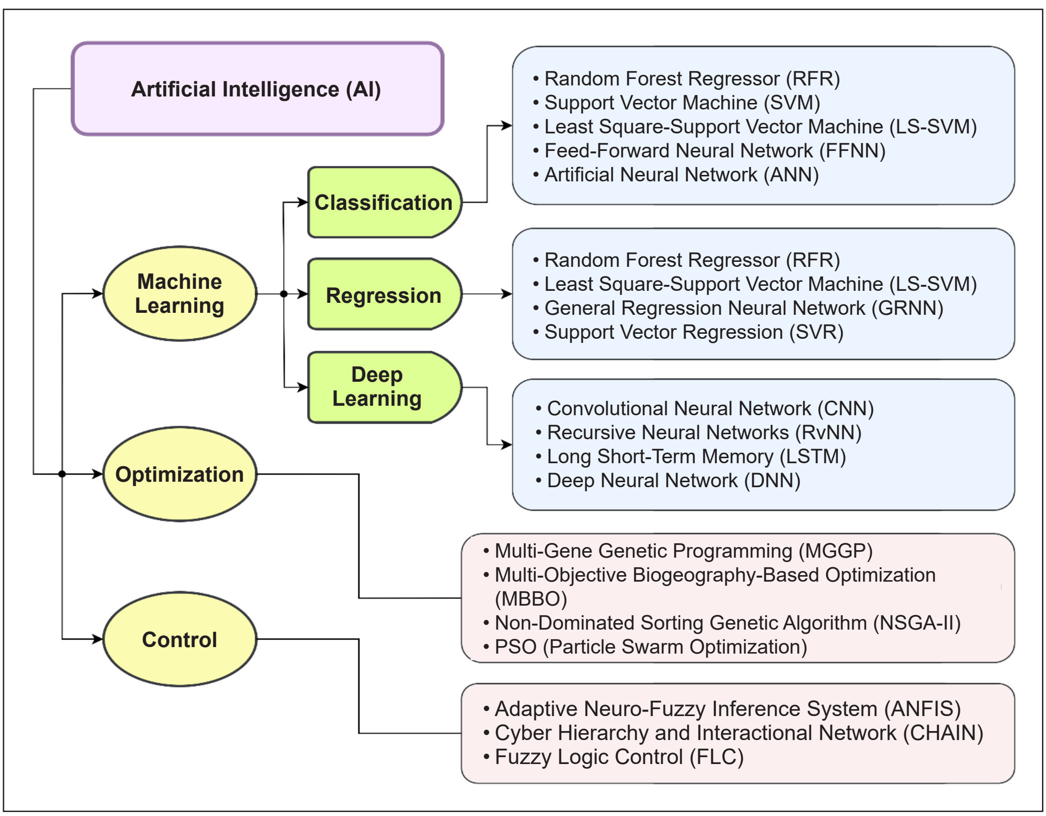

Figure 2. AI techniques in BMS applications (Ardeshiri et al., 2020)

employed to increase the driving range of EVs, enhance the automation of EVs, and encourage clean energy by adopting battery-based EVs. Furthermore, the study found that fuzzy and Neural Networks (NN) have been the most used AI algorithms in EV technology, which have influenced the charging time, the battery state prediction, and the optimization of the energy management system.

Recent research efforts on battery management technology have paid extra attention to AI algorithms aiming for smarter and more effective BMS. Therefore, various types of AI techniques have been proposed in the literature to enhance the efficiency and functionality of the BMS.

Neural Networks

Neural Network (NN) is a biologically inspired algorithm that has been used for solving a variety of problems. In general, NN is composed of three layers: the input layer that accepts the initial data, a hidden layer that includes the computations, and the output layer that produces the result. However, the NN may contain one hidden layer or more, as illustrated in Figure 3.

Further insights into the diversity of neural network architectures can be obtained from Table 2, which summarizes key attributes of neural networks as observed in some relevant studies from our reviewed papers. These studies provide valuable examples of different configurations, including variations in inputs, hidden layers, and outputs.

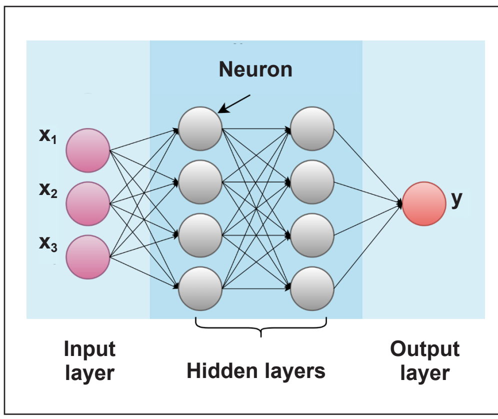

Figure 3. Neural network architecture (Karahoca, 2012)

In battery management, NN exhibited an accurate SOC estimation. Therefore, different NN methods were utilized in the

Table 2
Key attributes of Neural Networks applied in BMS

Study	Inputs	Hidden Layers	Output
Liang et al., 2018	Current and Temperature	9	Discharge Priority
Bonfitto, 2020	Current, Voltage and Temperature	2	SOC
How et al., 2020	Current, Voltage and Temperature	4	SOC
Zhao et al., 2020	Current, Voltage and Temperature	6	SOC
Purohit et al., 2021	Current and Time	1	SOC/ SOE/ PL
Chandran et al., 2021	Time, Current and Voltage	1	SOC
Duraisamy and Kaliyaperumal, 2021	Current, Voltage and Temperature	1	Resistor Switch

literature for SOC estimation under two main categories: Feed-Forward Neural Network (FFNN) and DL methods. The first has the advantage of a simple structure, while the latter has the ability to handle time-series data. Thus, a hybrid method of FFNN and DL may have the advantages of both methods. However, battery aging, temperature, and operating conditions should be considered to enhance the accuracy of SOC estimation when NN is applied (Cui et al., 2022).

In recent research, various types of Neural Networks have been utilized to improve the performance of BMS. The following is a brief demonstration of the researchers' efforts in that field.

Feed-Forward Neural Network. FFNN algorithm is the conventional type of NNs, which consists of three layers with several neurons in each one. This algorithm has been used to solve a wide range of problems using different optimization techniques. However, the efficiency of FFNN is affected by the quality of the trained data in terms of accuracy, precision, and flexibility. Therefore, prior data cleaning should be applied to the trained data to improve its quality (Hemeida et al., 2020).

Benefitting from its capabilities, Purohit et al. (2021) employed the FFNN algorithm in the realm of battery management to predict SOC, state of energy (SOE), and power loss (PL) of EV battery packs. The training algorithm was simulated using two-layer FFNN to estimate the battery pack states. The results showed higher accuracy of the proposed estimation method compared to other regression models. FFNN algorithm was also employed by Bonfitto (2020) to obtain a combined estimation of SOC and SOH battery states. FFNN was designed by training the collected datasets from laboratory environment experiments while real driving profiles were used for validation. The study results showed high accuracy in both SOC and SOH estimation.

While most researchers focused on the battery states at the individual battery level, Liang et al. (2018) considered the state of the battery module as a whole. The study proposed a methodology to evaluate the state of the battery module using its current and temperature values as inputs to overcome the difficulty of SOH estimation on the module level. For that purpose, Artificial Neural Network (ANN) models were used with three training algorithms, namely, Levenberg, Bayesian Regularization and Scaled Conjugate. The findings of the study indicated that the model with the best performance was obtained using the Levenberg algorithm.

General Regression Neural Network. The General Regression Neural Network (GRNN) method is a single-pass NN algorithm that can be used for solving regression problems. GRNN consists of four layers: input, hidden, summation, and division layer. Instead of iterative training, GRNN uses input and output data to approximate an arbitrary function between them (Azzeh et al., 2018).

Li and Zhao (2021) employed the GRNN algorithm to enhance the performance of EV BMS. The study proposed a cloud-based framework for battery management by utilizing big data and cyber-physical system technologies. The study used GRNN and a data cleaning technique to restore the missing data in the battery's cloud database under varying temperature conditions. The outcomes of the experiments revealed that the proposed method was stable and adaptable to the changes in battery temperature. The results also showed a minimum error in data restoring and SOC estimation. However, the proposed method is highly dependent on the quality and the speed of communication with the data in the cloud, which may not always be stable.

Deep Neural Network. Nowadays, Deep Neural Network (DNN) plays a main role in data modeling and analysis; thus, it can be used in BMS technology to enhance the prediction of the battery states. For example, data-driven modeling can use battery signals to achieve a reliable estimation of battery capacity without the need to know its internal features.

A data-driven DNN approach was utilized by Kara (2021) to predict the Remaining Useful Life (RUL) of lithium-ion batteries, which helps reduce maintenance costs and increase system efficiency and reliability. The proposed method combined Convolutional neural networks (CNN), Fully Connected Layer (FCL), and Long Short-Term Memory (LSTM) algorithms, while Particle Swarm Optimization (PSO) was applied to obtain the optimal parameters, such as a number of epochs and NN layers, to extract the spatial-temporal relationship from historical degradation data. The proposed model, which was tested on NASA's battery dataset, showed accurate results in terms of SOH and RUL prediction compared to the benchmark models. However, the proposed model may introduce high computational demand due to the hyperparameter optimization procedure, especially in the case of using a large training set.

DNN was also used by How et al. (2020) to develop a SOC estimation model, which was trained using the drive cycle of Dynamic Stress Test (DST). The study results revealed that increasing the number of hidden layers in the DNN model can noticeably improve the SOC estimation. However, the study found that four hidden layers were the optimal number that, if exceeded, would increase the error rate. According to the study results, the proposed model was found capable of estimating SOC values of various unseen drive cycles, including the Federal Urban Driving Schedule (FUDS), Beijing Dynamic Stress Test (BDST), and Supplemental Federal Test Procedure (SFTP) US06.

Recursive Neural Network. A Recursive Neural Network (RvNN) is a kind of deep learning network with an architecture in which the same weights are applied recursively on a structured input to get a structured prediction. RvNN can be seen as a generalized version of the Recurrent Neural Network (RNN) with a specific tree structure. It is a useful technique for pattern recognition in a data set and for the prediction of structured outputs (Irsoy & Cardie, 2014).

A SOC prediction model for Lithium-ion Batteries was proposed by Zhao et al. (2020) based on RvNN. The proposed model aims to improve the representation of battery data and obtain hidden feature information in the battery vector. Consequently, the prediction performance of SOC will be improved. The study also proposed a prediction model based on CNNs and fed it with trained battery vectors. Simulation results of the study showed that the integration of the trained vectors with CNNs enhanced the performance of SOC prediction by a noticeable margin compared to the traditional estimation methods.

Evolutionary Methods

In some cases, it is difficult to use conventional methods for developing the EV battery model, especially in the presence of nonlinear relations, complicated computations, or multi-objective optimization. In this case, evolutionary computation techniques can be considered a good alternative to deal with those challenges.

Multi-Objective Biogeography-based Optimization. When two or more objectives are needed to be achieved, Multi-Objective Optimization (MOO) is a good option for optimal solutions. The main advantage of the MOO algorithm is that it helps find a balance between contradictory objective functions and optimal trade-off solutions.

An example of the employment of an evolutionary algorithm in the field of BMS has been proposed by Liu et al. (2018), where a Multi-objective Biogeography-Based Optimization (M-BBO) algorithm was applied to derive the charging patterns that suit Lithium-ion batteries. The optimization technique in that study was fed with the following objectives: charging time, battery health and efficiency of energy conversion. On the other hand, the constraints were defined as voltage, current, temperature, and SOC of the battery. The authors used Pareto frontiers to find a trade-off between the charging speed and the efficiency of energy conversion so that a suitable charging pattern can be selected for different priorities.

Multi-Gene Genetic Programming. Multi-Gene Genetic Programming (MGGP) is a nonlinear system modeling technique that combines the advantages of Genetic Programming (GP) and classical regression and, thus, can be used to generate prediction models. Taking advantage of this feature, MGGP has been employed by Cui et al. (2020) to model the EV battery. The study has two objectives: to create a model for battery capacity and to find the optimized design of the battery enclosure. For that purpose, the study used a modified MGGP approach for training the experimental data to obtain the model of EV battery capacity. Then, the battery pack enclosure was optimized using the Non-dominated

Sorting Genetic Algorithm (NSGA-II) algorithm to achieve the study objectives, such as minimizing the mass and improving the performance of the heat dissipation of the battery packs. However, the optimum design of the battery pack encloser cannot be generalized, as it is influenced by other factors such as vehicle design, size, and weight.

Non-dominated Sorting Genetic Algorithm. As mentioned, multi-objective optimization deals with problems of conflicting objectives, where a set of solutions is obtained, which may contain a non-dominated set of solutions. In this case, NSGA-II, the succeeding version of the NSGA algorithm, can be used to solve this multi-objective optimization problem. NSGA-II offers an enhanced mating mechanism based on crowding distance and uses an adapted dominance explanation without penalty functions to build the constraints (Hojjati et al., 2018).

The mentioned advantage of NSGA-II has been utilized by Meng et al. (2019) to improve the accuracy of battery SOH estimation. Considering the accuracy of SOH estimation and the measurement efficiency, multiple voltage ranges were optimized in the said study using the NSGA-II algorithm. The non-dominated solutions helped to increase the flexibility of the proposed method. Consequently, more choices would be available for SOH estimation at different stages of battery charging. The results of that study showed an accurate estimation of battery capacity using an optimal single voltage range. However, the proposed method cannot be generalized for different battery types since the optimal voltage ranges require prior information about the degradation process of the battery. Furthermore, the cycle aging of the battery was not considered in the study.

Particle Swarm Optimization. In addition to the wide range of applications, the well-known Particle Swarm Optimization (PSO) algorithm can also be used for battery SOH prediction, as introduced by Li et al. (2021). The authors performed data cleaning on real driving data before the data was optimized using PSO. The obtained results showed an accurate model of SOH prediction. However, battery aging has not been considered in that study, which may affect its performance when applied in reality.

Genetic Particle Filter. Particle Filter (PF) algorithm is a type of Monte Carlo method and recursive Bayesian estimation. In recent years, researchers have shown increasing interest in the ability of this algorithm to estimate the state of non-linear and non-Gaussian problems. However, using PF leads to a particle degeneracy problem, which can be solved by involving a Genetic Algorithm (GA) to change the small-weight particles into offspring particles (Qiu & Qian, 2018).

A prediction method based on Genetic Particle Filter (GPF) was introduced by Liu et al. (2020) for SOC and SOP estimation. The advantages of GA and PF were combined by the proposed method to enhance the diversity of particles. The incremental current test was used in the study to identify the parameters of the proposed battery model, which was tested on the FUDS driving cycle. The outcomes of the experiments showed that the proposed genetic PF algorithm achieved better accuracy in SOC and SOP estimation compared to the traditional PF method.

Regression Algorithms

Regression algorithms, such as Decision Trees (DT), are a type of supervised machine learning algorithm for classification and prediction applicable in a wide range of fields. The nodes in the decision tree perform a comparison test between independent variables and a constant in a top-down process to achieve the best attribute for solving the classification problems (López et al., 2022). The employment of different types of regression algorithms in BMS technology, as discussed in the reviewed papers, is illustrated in the following points:

Least Square-Support Vector Machine. Support Vector Machine (SVM) is an effective technique for solving problems such as non-linear classification and density estimation. Therefore, the SVM algorithm has been effectively used for classification purposes, such as image classification in OCR applications (Tan et al., 2022). On the other hand, the Least-Square Support Vector Machine (LS-SVM) is a variant of the traditional SVM technique, which can be used for classification, regression, and clustering, besides exhibiting high accuracy in solving optimization problems (Mitra et al., 2007).

Shu et al. (2020) proposed a uniform framework for SOH estimation and healthy features optimization of the Lithium-ion battery in EVs. The study utilized a fixed-size LS-SVM for SOH estimation, while GA was applied to determine the optimal charging voltage range and the optimal parameters of fixed-size LS-SVM. The experimental results showed that the proposed framework was robust and more accurate in terms of SOH estimation compared to traditional ML algorithms. However, the experiments in the study have been conducted at a fixed temperature, which is not the case in real life. Therefore, the proposed method in the study can be enhanced by considering the change in the surrounding temperature.

Support Vector Regression. Support Vector Regression (SVR) is a supervised ML technique that can solve regression problems by analyzing the relationship between a continuous dependent variable and the predictor variables. Furthermore, SVR has the ability to handle high-dimensional data as its optimization is represented by support vectors rather than the dimension of input data (Zhang & O'Donnell, 2020).

Xuan et al. (2020) employed the Principal Component Analysis (PCA) of battery features to study the effect of external factors, such as voltage, current, and temperature, on the accuracy of SOC estimation. The study also proposed an SVR-based SOC prediction method with a classification of collected data and optimization of the training set size. The experimental results showed that the enhanced SVR algorithm outperformed the original SVR algorithm in terms of accuracy and computational speed. However, the evaluation of the proposed method did not include more complicated driving conditions.

Random Forest Regressor. Random Forest (RF) is an ensemble learning algorithm that can be used for solving classification and regression problems. In RF, a group of decisions is made to classify the dataset, while the final decision is taken based on the majority. Therefore, RF demonstrates better accuracy when applied to large datasets. Besides, it is an effective technique for estimating missing data (Awad & Khanna, 2015).

Utilizing RF advantages, Mawonou et al. (2021) employed the Random Forest Regressor (RFR) for data-driven aging prediction of EV lithium-ion batteries. The RF algorithm was trained on real-life EV data collected over several years to develop an aging predictor to accurately estimate the battery SOH.

Multi ML Techniques. Machine Learning (ML) is a general topic that includes numerous techniques with a wide range of applications. Many types of those techniques have been successfully implemented by several studies in BMS applications. In general, ML methods can be classified into three categories: supervised, unsupervised and reinforcement learning.

Basically, ML methods have been used in BMS for battery modeling; thus, the exact chemical process of the battery is not needed. Moreover, ML techniques have been used to perform other functions of BMS, such as estimating the battery states and predicting the battery aging and degradation (Ahmed et al., 2021). The following is a brief demonstration of several studies where multiple ML techniques have been employed in BMS applications.

Kaur et al. (2021) proposed three models of battery capacity estimation based on three network architectures: FFNN, CNN and LSTM. The evaluation of battery capacity estimation considered the impact of different variables, such as the model complexity and the sampling rate. The study results showed that LSTM was more accurate and flexible compared to FNN and CNN methods. Results also proved that using sparsely sampled signals as model input was more efficient than using densely sampled signals and reduced the computational cost. However, the study considered measurements from a set of two batteries to evaluate the model performance, while the validation could be more accurate if larger battery datasets were considered. Furthermore, the study did not consider the effect of other parameters, such as the ambient temperature, on SOH estimation.

Tran, Panchal, Chauhan, et al. (2022) included a comparison of four ML models, namely, Linear Regression, RF, K-Nearest Neighbors, and DT, for predicting thermal and electrical behaviors of Lithium-ion batteries under different ambient temperatures. The training, validation, and testing of the models used the following input features: battery capacity, ambient temperature, battery current, historical battery voltage, and temperature to predict the battery voltage and temperature. Simulation results showed that the DL-based model was the most accurate of all models.

Another comparison of six ML models for Lithium-ion battery SOC estimation was presented by Chandran et al. (2021). The comparison included several ML algorithms, such as SVM, ANN, and Gaussian Process Regression (GPR). The study results showed that among the proposed ML methods, ANN and GPR demonstrated the best performance in terms of SOC estimation according to Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics. Moreover, the study denoted that the proposed method is valid for real-time SOC estimation after optimizing the hyperparameters of the GPR-linear model.

Other AI Techniques

In addition to the previously mentioned AI techniques, several other techniques have been proposed in related literature studies on EV BMS, which will be described in this subsection.

Fuzzy Logic Control. Fuzzy Logic Control (FLC) is an intelligent algorithm that can be useful, especially when it is difficult to build a mathematical model of the system. The robust FLC is very useful for nonlinear and time-varying systems. Besides, it has the advantage of adaptation due to flexibility and easiness of changing the fuzzy rules (Ma et al., 2018).

Benefiting from its capability of dealing with such nonlinear systems, FLC was employed by Abulifa et al. (2019) to control the energy consumption of EV batteries. The study aimed to increase driving time by minimizing energy consumption, namely, when the Heating, Ventilation, and Air-Conditioning (HVAC) system is on. The proposed FLC was tested on NEDC and Japan10-15 driving cycles. The results showed that applying FLC increased the battery driving range between 10% and 20% compared to the uncontrolled strategy. However, the proposed design in the study is limited to a specific configuration and needs to be tested using different specifications and driving cycles.

Similarly, Kamal and Adouane (2018) applied FLC to minimize total energy consumption and reduce battery aging. The parameters of the fuzzy membership function were tuned using NNs to control power distribution between the internal combustion engine and the electric motor. FLC was employed to detect battery faults and to compensate for the faults of the voltage sensor and current actuator. Simulation results confirmed the ability of the proposed approach to achieve a suboptimal energy consumption when applied to vehicles of unknown driving cycles and its ability to compensate for the effects of battery faults.

However, fuzzy logic is dependent on human intelligence and expertise, which may vary from one person to another. Therefore, fuzzy membership functions of FLC usually need tuning for better performance.

Cyber Hierarchy and Interactional Network. Cyber Hierarchy and Interactional Network (CHAIN) is a framework that can provide multi-scale insights; thus, it is a suitable environment to develop efficient algorithms for battery state estimation, fault diagnosis, cell balancing, and other functions of BMS. In that context, a CHAIN framework of end-edge-cloud architecture was proposed by Yang et al. (2020) for developing a cloud-based BMS. The proposed framework included several functions, such as SOX estimation, cell balancing, and fault diagnosis. Such a cloud-based BMS provides multi-scale perceptions and allows the application of advanced algorithms to perform the system functions efficiently. The CHAIN framework was also proposed by Yang et al. (2021) to certify the stability and security of full battery lifespan to achieve optimal battery performance.

It can be noted that the CHAIN framework is a promising technology as it utilizes the high computing capabilities of the platform to solve complex algorithms. Thus, the performance of BMS is enhanced. However, like other cloud-based technologies, it is dependent on wireless communication and online services; thus, it is highly dependent on and affected by network availability and conditions. Therefore, an onboard control module may be considered as a backup solution for outage conditions.

In conclusion, the investigated AI techniques in this paper have been used for different purposes in BMS, such as regression, optimization, and state estimation. However, each technique may be more suitable for a particular application. Therefore, a summary of those techniques, including their advantages, disadvantages, and applications in BMS, is illustrated in Table 3.

Table 3
Advantages and disadvantages of various AI techniques used in EV BMS

AI Technique	Application in BMS	Advantages	Disadvantages
• **Neural Networks (FFNN, GRNN) (Hemeida et al., 2020; Purohit et al., 2021; Bonfitto, 2020; Liang et al., 2018; Azzeh et al., 2018; Li & Zhao, 2021)**	• SOC, SOH & PL prediction • To estimate the orders of cell balancing. • To obtain the optimal charging current profile to decrease temperature and charging time. • To recover lost data in the battery's cloud database	• Ability to handle unorganized data • Its adaptive structure makes it applicable for different purposes	• Heavily relies on the size of training data • Affected by data suitability
• **Deep Learning (CNN, RvNN, LSTM) (Zhao et al., 2020; Kaur et al., 2021; Tran, Panchal, Chauhan et al., 2022)**	• SOC prediction • RUL prediction	• Ability to handle complex data and relationships • Suiting parallel and distributed modes for fast training	• Requires high computational power • Requirement of huge amount of trained data

Table 3 *(continue)*

AI Technique	Application in BMS	Advantages	Disadvantages
• **Evolutionary Methods (MGGP, M-BBO, NSGA-II, PSO) (Cui et al., 2020; Liu et al., 2018; Meng et al., 2019; Li et al., 2021)**	• To obtain the model of EV battery capacity by training the experimental data • To derive the charging patterns that suit Lithium-ion batteries • To enhance SOH estimation via optimal charge voltage range • To identify optimal battery pack features for better heat dissipation	• Reducing the search time for the optimal solution • Supporting multi-objective optimization	• Do not always achieve the best answer • Sometimes they get stuck in local optima • Require well-defined objective and constraint functions
• **Regression Algorithms (LS-SVM, SVR, RFR) (Shu et al., 2020; Xuan et al., 2020; Mawonou et al., 2021)**	• SOC prediction • SOH estimation	• Better performance in higher dimensions • Optimal choice for linear/non-linear classes • No need for data normalization or scaling • The impact of missing values is negligible • Reduced error through aggregated tree inputs	• Slow when dealing with a larger dataset • Poor performance with overlapped classes • Sensitive to data change • Training decision trees is time-consuming
• **CHAIN (Yang et al., 2020)**	• SOC, SOH prediction • Cell balancing • Thermal control	• Powerful computational performance • Offers multi-disciplinary digital solutions	• Requires a continuous internet connection • High-performance cloud computing increases the cost
• **FLC (Abulifa et al., 2019; Kamal & Adouane, 2018)**	• To minimize the energy consumption of EV battery	• Effective tool for solving nonlinear problems • Can be easily constructed and modified	• Limited to human knowledge and expertise • Membership functions require tuning to increase accuracy
• **PCA (Xuan et al., 2020)**	• To study the effect of current, voltage and temperature on SOC estimation	• Saving time by removing correlated features in a dataset • Improves visualization by transforming data from high to low dimensions	• Data normalization is required before performing • Combination of features makes it difficult to understand the major components

A critical review of BMS research reveals significant gaps. While AI, especially Neural Networks, is widely used for SOC estimation, more robustness testing is needed under dynamic conditions, like varying temperatures and real-world driving profiles. Integration with advanced battery tech, e.g., solid-state batteries, lacks attention. Adapting AI to these technologies is unexplored. Additionally, BMS and IoT integration for real-time monitoring and predictive maintenance remains underexplored.

Lastly, assessing AI-driven BMS scalability across diverse applications needs more research. A holistic approach, encompassing cybersecurity, materials science, and data analytics, is essential for evolving battery management.

CONCLUSION

In this paper, the employment of AI techniques in EV BMS was reviewed. The study explored the state of the art in the field of AI-based BMS as indicated in the literature over the past few years. Various types of AI techniques, such as neural networks, regression algorithms, and evolutionary methods, were demonstrated in this study, with more focus on their applications in BMS development.

It was noted that most reviewed papers employed supervised machine learning methods, either for classification or regression purposes. Meanwhile, a smaller number of researchers applied AI techniques for optimization or control purposes. It was also observed that recent studies have given more attention to the fast-growing technologies in the fields of IoT, communications, and cloud computing. Therefore, several studies have proposed cloud-based approaches to enhance the efficiency of BMS and obtain faster and more accurate results.

Finally, here are key recommendations to improve BMS performance and identify further research opportunities:

- Enhance Lithium-ion battery performance simulation by incorporating factors like temperature, humidity, and noise during data acquisition.
- Consider onboard control modules as a robust alternative to cloud-based technology, particularly in areas with unstable internet connections.
- Continue researching the physical optimization of battery pack topology for improved power consumption, cell balancing, and ease of control.

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