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Machine learning driven digital twin model of Li-ion batteries in electric vehicles: a review

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Abstract: Electric Vehicles (EVs) have transformed the automotive industry and are becoming a more reliable and consistent mode of public transportation. The development of a pollution-free environment and improved ecological surroundings is being significantly assisted by battery-powered vehicles. Lithium-ion (Li-ion) batteries are the most widely used type of batteries in EVs because of their superior performance as compared to their counterparts. The core of EVs is their battery management systems (BMS), which can unarguably improve a battery's performance, operation, safety, and lifespan. Li-ion battery state estimation is one of the most important parts of the implementation of BMS, as it serves an important role in safe and reliable battery operation. Recently, researchers are working on the development of digital twin models to automate and optimize the BMS state estimation process by utilizing machine learning (ML) algorithms and cloud computing. The objective of this study is to review, characterize, and compare various ML-based approaches for the state estimation of different Li-ion battery states. Firstly, this study describes and characterizes several Li-ion battery state estimation approaches proposed in recent years. Secondly, the battery state estimation of electric vehicles is discussed. In addition, the challenges and prospects of Li-ion battery state estimation are put forward.

Keywords: battery management system; cloud computing; digital twin; electric vehicles; li-ion battery; machine learning; state estimation

1. Introduction

Electric Vehicles (EVs) have experienced remarkable growth in recent years. The necessity for such vehicles that are less polluting, environmentally friendly, and bring fewer ecological problems has greatly increased due to the catastrophic effects of global warming and green-house gas emissions. Petrol and diesel-powered vehicles emit large amounts of CO2 gas, which pollutes the air and harms both humans and other living beings [1]. EVs are considered a promising technology for limiting road transport emissions. This is a critical component in bringing down CO2 emissions, and air and noise pollution from public transportation vehicles.

The backbone of any EV is its energy storage system, which is primarily powered by rechargeable batteries. In recent times, Li-ion batteries have emerged as the leading energy storage technology in EVs, leaving behind other conventional batteries. This is due to their exceptional energy density, long cycle life, low self-discharge rate, and ability to deliver high power [2]. Despite the promising aspects of Li-ion batteries, there are certain limitations that persist such as limited range, prolonged charging times, elevated costs, and reliability and safety concerns [3].

To tackle the various challenges faced by batteries, Battery Management Systems (BMS) come into play. These systems keep an eye on the internal workings of the battery by monitoring its voltage, current and temperature levels. Based on these readings, the BMS calculates important parameters such as State-of-Charge (SoC), State-of-Health (SoH), State-of-Power (SoP), and State-of-Temperature (SoT) to keep the battery running at its optimal performance. The BMS is equipped with a significant number of voltage, current, and temperature sensors to measure the battery states. However, the physical sensors are prone to failure and result in the incorrect measurement of battery states which ultimately impacts the state estimation of BMS [4].

The research on BMS has attracted attention on a global scale to assure the effective implementation of EVs and to have a safe and reliable battery. The important factors of the BMS are the battery states. Numerous studies are being carried out to estimate the SoC, SoH, SoP, and SoT in this regard. The state estimation approaches are divided into 2 main types i.e. model-driven and data-driven approaches. The model-driven approaches try to simulate battery behavior by combining many variables into sophisticated mathematical equations that provide an accurate estimation of the battery states [5]. Due to their reliance on a comprehensive understanding of the system, model-driven state estimation methods have the potential to be very effective and precise. However, there are practical and theoretical issues to consider when attempting to obtain the perfect model of any system. Data-driven approaches to estimate the battery states do not necessarily involve the comprehension of battery working principles or the use of a particular battery model; instead, they rely solely on collected data and a statistical method to estimate battery states. The issue with statistical methods is that all statistical models are inaccurate or at least imperfect in a sense. They are employed to simulate reality. The model's underlying assumptions are sometimes far too restrictive and unrepresentative of reality. For instance, the non-linear relationship between the battery variables could not be taken into account using statistical approaches [6].

The shortcomings of the above-mentioned approaches are overcome by utilizing machine learning (ML) to develop digital twin models for battery state estimation and prediction. Machine learning is a branch of Artificial Intelligence (AI) that specializes in creating algorithms and statistical models capable of executing tasks without any direct human programming. It's an exciting area that focuses on teaching machines to learn from data and make decisions on their own [7]. The idea behind machine learning is to give computers the ability to "learn" from data, allowing them to improve their performance on a specific task over time. ML-driven approaches have gained popularity among researchers in recent years and various methods and algorithms have been proposed to estimate the battery states with maximum accuracy and minimum effort as compared to other approaches. The aim of this study is to review, classify, and compare different ML-based methods for the estimation of different battery states.

The remainder of this paper is organized as follows. The BMS of EVs is introduced in Section 2. In Section 3, the ML approaches to estimate the different battery states are discussed. We focused on the battery state estimation of electric vehicles in Section 3. In Section 4, the challenges and future research prospects of battery estimation technology are discussed. The paper is concluded in Section 5.

2. Battery management system of electric vehicles

Battery management systems measure, estimate, and regulate battery states to guarantee the safe and efficient operation of Li-ion batteries in electric vehicles. The key functions of BMS include estimation of battery states e.g. SoC, SoH, and RUL [8], regulating battery temperature within safe limits [9], cell monitoring and balancing, and fault diagnosis [10]. Figure 1 shows the diagram of typical BMS. A typical BMS consists of 5 main components *i.e.* battery pack, state measurement module, state estimation module, state management module, and communication module. Each component is described as follows:

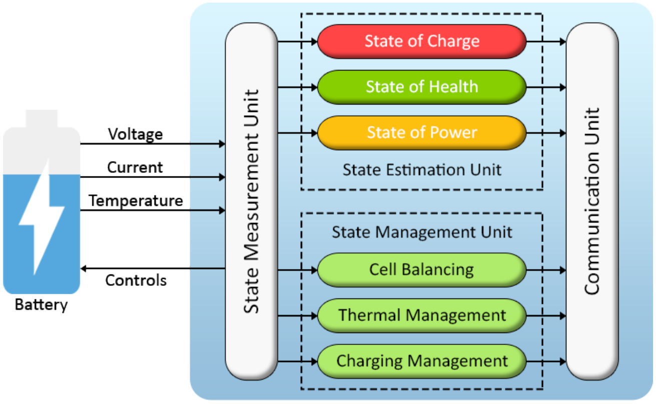

Figure 1. Block diagram of battery management systems.

2.1. *Battery pack*

EVs rely on the battery pack to fulfill their power requirements. A battery pack consists of thousands of cells which are installed as a number of modules and packs. Numerous current, voltage, and temperature sensors are also installed in the battery pack [11].

2.2. *State measurement*

The state measurement module processes the voltage, current, and temperature obtained from each cell of the battery pack through physical sensors. The measured data is then utilized in the state estimation, management, fault diagnosis, and communication modules [12].

2.3. *State estimation*

State estimation is one of the most important functions of BMS, which is carried out by the state estimation module. The internal battery states e.g. SoC, SoH, and RUL are estimated by utilizing the measured battery states [13].

2.4. *State management*

The state management module guarantees the safe and efficient operation of batteries and includes cell balancing, thermal management, and charging/discharging control functions [14]. The purpose of cell balancing is to equalize voltage through active or passive balancing techniques. Thermal management is responsible for regulating the temperature of the battery. The charging/discharging controller is responsible for improving the power factor by controlling the phase difference between voltage, and current [15].

2.5. *Communication module*

The communication module is responsible for internal as well as external communication in EVs. A controller area network (CAN) bus system is adopted for the transmission of battery states between the BMS and the vehicle control unit [16].

3. Machine learning for state estimation of Li-ion batteries

This section discusses the ML-based methods for the estimation of different battery states.

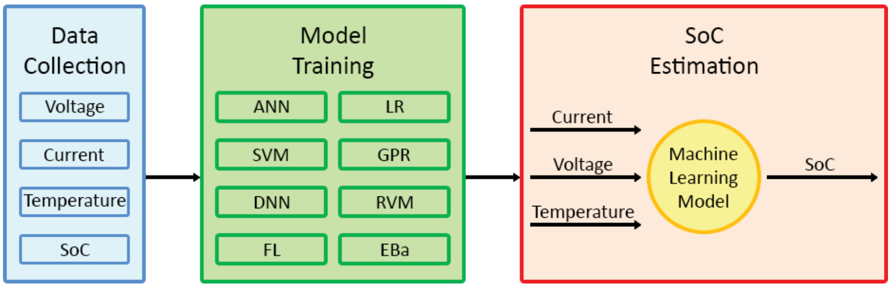

Figure 2. General diagram of SoC estimation methodology.

3.1. *SoC estimation*

SoC stands for the state of charge, and in the context of batteries, it refers to the percentage of the total energy stored in a battery that is currently available for use [17]. The SoC of a battery is an important parameter to monitor, as it affects the performance of the battery and its ability to power the devices it is connected to. A battery with a low SoC may result in reduced performance or unexpected shutdowns, while a battery with a high SoC may indicate that the battery is not being fully utilized, leading to reduced battery life. So, an accurate and reliable estimation of battery SoC is necessary for the reliable operation of a battery.

The SoC of a battery cannot be directly measured because it is an abstract concept that represents the amount of energy stored in the battery at a given moment [18]. Voltage measurement is a commonly used method for estimating the SoC of a Li-ion battery. Specifically, the open circuit voltage of the battery is measured and then compared to a look-up table or model that correlates the open circuit voltage to the SoC. However, this method can be inaccurate because the relationship between voltage and SoC is not linear and can be affected by factors such as temperature and aging [19], however, various research works are going on to estimate it indirectly by applying ML-based methods like artificial neural networks (ANN), deep learning (DL), ensemble bagging (EBa), support vector machine (SVM), and so on. Figure 2 shows the general diagram of SoC estimation methodology.

Support Vector Machine (SVM) is a type of supervised machine learning algorithm that is used for classification and regression analysis. It is a linear model that tries to find the best boundary between the different classes in the training data. This boundary, known as the maximum margin hyperplane, maximizes the distance between the nearest data points from different classes, called support vectors. The idea behind this is to make the classifier robust to the presence of outliers and noise in the data. Song *et al.* [20] introduced an SoC estimation method that relies on least-squares SVM. The forecasts were enhanced using an unscented particle filter. The factors taken into account for the estimation were battery terminal voltage, electric current, and SoH. These were also approximated using LS-SVMs by incorporating the duration of equal discharge voltage decrease as input characteristics. The suggested SoC estimation approach was evaluated using a dataset created by subjecting battery cells to dynamic stress testing and cycling profiles. The results demonstrated that the maximum error achieved by the proposed SoC estimation method was less than 2%. In [21], incorporating the extended Kalman filter (EKF) with the support vector machine, a novel approach was presented to estimate SOC for battery cells. The initial SoC estimation value was obtained using the extended kalman filter algorithm, and the filtered output data of the EKF algorithm was used to train the SVM model. This SVM model was designed to possess high regression prediction ability which helps compensate for the errors of the preliminary SoC estimation value. The end result was an improvement in the overall accuracy of SoC estimation. Li *et al.* [22] put forward an innovative method that combined the sliding window technique with LS-SVM to efficiently manage extensive datasets. The LS-SVM parameters were fine-tuned using the Grey Wolf Optimizer (GWO) to achieve a globally optimal solution.

This optimization considerably improved SoC estimation, leading to an RMSE of under 3%.

In several recent studies, neural networks (NN) have been a widely used method. Kang *et al*. [23] developed an RBFNN (Radial Basis Function Neural Network)-based model to determine SoC under the impact of aging, temperature, and driving operating cycles. The model's mean absolute error (MAE) was reported to be under 5% after being tested on a 6 Ah Li-ion battery. Tong *et al*. [24] estimated SoC in three operational states idle, charge, and discharge and utilized an NN-based model to do the estimations. The pulse test was utilized for model validation, whereas the US06 driving cycle was used for model training. The proposed model outperforms other NN models with an average SoC error of 3.8%. In [25], an SoC estimation model based on recurrent neural network (RNN) for Li-ion batteries was evaluated under circulating current and temperatures. When compared to the multilayer perceptron NN approach, the model has a higher execution time and lower RMSE. Cui *et al*. [26] developed a smart SoC estimate mode for Li-ion batteries by utilizing Wavelet NN. The model has been shown to be successful in lowering the MAE of the SoC estimation model.

The application of deep learning (DL) techniques in battery-related research is still highly underdeveloped as of now. The DL methods have primarily been used to predict SoH and remaining useful life (RUL) [27]. However, there are not many well-established works on the subject of SoC estimation. A work by Chemali *et al*. [28] has provided some insight into the potential application of DL in SoC estimation. To calculate the SoC of Li-ion batteries, the authors employed the long short-term memory (LSTM) DL architecture. Using a fixed temperature and an MAE of 0.573%, the method can predict SoC values with high accuracy. By putting the method to the test on a dataset that differs from the training dataset in surrounding temperature, the authors go one step further. The MAE for the LSTM network was 1.606%. In [29], an SoC estimation method for Li-ion battery was developed using the LSTM algorithm. Different EV drive cycles are used to evaluate the proposed method's robustness. When the results of SoC estimation are compared with a model-based approach, LSTM displays better performance with lower RMSE and higher estimation accuracy. Another study [30] by Chemali *et al*. explored the use of DNN to estimate the SoC of a Li-ion battery. A single input layer, multiple hidden layers, and a single output layer make up the DNN proposed in this study. When tested against several datasets, the authors found the lowest MAE to be 1.10%. In [31], to evaluate SoC for Li-ion battery, a gated recurrent unit based on RNN was established. To improve the training operation and determine the optimal parameters, Nadam and AdaMax optimizers were utilized to develop an ensemble optimization method. The efficiency of the proposed method was tested using various dynamic variables. The developed model outperforms others in terms of reducing data training time and increasing accuracy. In [32], to investigate the battery SoC under various load profiles, an algorithm based on deep belief network was proposed. The average SoC error for the proposed approach was less than 2.2%, and the results were adequate.

Fuzzy logic (FL) is a mathematical framework for dealing with uncertainty and imprecision in reasoning. It is an extension of classical (Boolean) logic, which deals with binary values of true or false. In contrast, fuzzy logic allows for intermediate values between true and false, referred to as "fuzzy" values [33]. Several studies have used FL to calculate SoC. Li *et al*. [34] developed a strong tracking adaptive UKF technique to estimate SoC. The fuzzy adaptive forgetting factor was utilized to update the model parameters. When tested against an unseen baseline SoC and voltage data, the proposed model outperformed the traditional UKF method in terms of accuracy, robustness, and convergence speed. In [35], to forecast the SoC of a Li-ion battery pack used in EV, the authors put forward a method by combining FL with SVM. In comparison to NN and standard Support Vector Regression (SVR) models, an improvement in SoC estimation accuracy was observed in the proposed method. Saji *et al*. [36] discussed the importance of battery management systems and proposed a Coulomb counting and fuzzy logic method for optimal State of Charge (SoC) estimation of Li-ion batteries. The simulation using Matlab Simulink showed that this method achieved reliable operation and prolonged lifespan, with accurate SoC estimation preventing deep discharge and overcharging. Table 1 provides the comparison of different ML-based SoC estimation methods.

Table 1. Comparison of machine learning-based SoC estimation methods.

Method	Advantages	Disadvantages
LR	Simple and easy to implement; provides clear understanding of relationship.	Assumes linear relationship; may not capture nonlinear effects; sensitive to outliers.
ANN	Can handle complex relationships; can account for temperature and aging effects.	Requires large amount of data for training; difficult to interpret; computationally expensive.
DNN	Can handle complex relationships; can learn features from raw data; can generalize well.	Computationally expensive; requires large amount of data for training; difficult to interpret.
SVM	Can handle nonlinear relationships; effective with high-dimensional data.	Sensitive to kernel function and hyperparameters; may not perform well with noisy or unseparated data; computationally expensive.
RVM	Handles high-dimensional data; provides sparse solution; estimates uncertainty.	Computationally expensive; requires careful selection of kernel function and hyperparameters; may not perform well with noisy data.
GPR	Provides probabilistic framework; models uncertainty; handles nonlinear relationships.	Computationally expensive; requires careful selection of kernel function and hyperparameters; may not perform well with noisy data.
FL	Handles imprecise and uncertain information; captures nonlinear relationships.	Requires careful selection of fuzzy rules and membership functions; computationally expensive; may not perform well with noisy data.
EBa	Handles nonlinear relationships; handles missing and noisy data well; provides feature importance.	Requires large amount of data for training; computationally expensive; difficult to interpret.

3.2. SoH estimation

The SoH of a battery measures how well it is performing right now in comparison to how well it performed under ideal conditions and when it was new [37]. It is important to monitor the SoH of a battery because it can affect the performance of the device that the battery is powering. Due to the significance of battery SoH in EVs, research on this topic has garnered a lot of interest. Theoretically, the SoH can be determined by monitoring the battery capacity during charging and discharging with the described method at a specific temperature.

There are two main approaches for SoH estimation: model-driven and data-driven methods. Model-driven methods for SoH estimation involve using mathematical models to estimate the SoH of a battery based on its performance characteristics, such as voltage, current, and temperature. These models can be based on empirical data or physics-based models, and they are typically designed to account for the effects of aging and other factors that can impact battery performance over time. Model-driven methods are limited in their ability to capture complex and non-linear behavior. Data-driven methods, on the other hand, can be more flexible and can capture complex patterns. They involve using machine learning algorithms to estimate the SoH of a battery based on its historical performance data. This approach is based on the idea that the behavior of a battery over time can be used to determine its SoH. Data-driven methods can be trained on large amounts of data collected from batteries over time, and they can be used to make real-time SoH predictions based on current performance data.

The ML-based approach uses neural networks (NN), support vector machine (SVM), and fuzzy logic (FL) to map complex relationships between the battery features and their SoH. Then the estimated SoH is extrapolated using these methods. Figure 3 shows the general diagram of SoH estimation methodology.

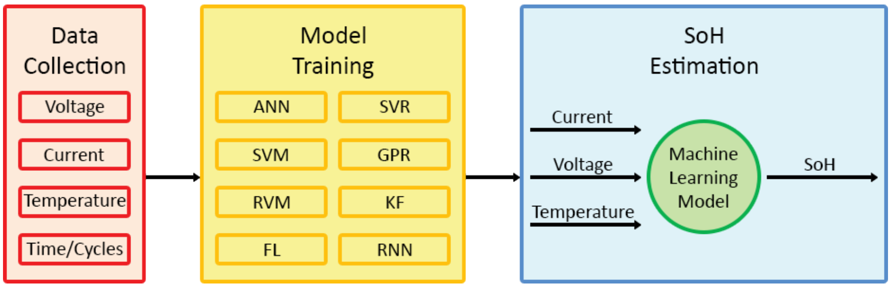

Figure 3. General diagram of SoH estimation methodology.

The capability of self-organization and self-adaptation in ANNs allows them to automatically learn complex relationships between inputs and outputs and adjust to new data without relying on the underlying electrochemical principles of batteries. Yang *et al.* [38] utilized a BPNN algorithm to forecast the battery's SoH based on the maximum capacity. The BPNN was trained using the first-order ECM parameters and SoC as inputs and SoH as the output. As per literature [39], batteries operate differently based on cycle numbers and parameters such as platform voltage, duration, voltage boost points, and number of data points in the charge/discharge curve. Therefore, the equivalent circle life of the battery is predicted as the output of a feedforward NN, with the inputs being the battery terminal voltages during the constant current charging subprocess. This approach allows for the prediction of SoH by modifying the model's output. Zhang *et al.* [40] estimated the SoH of a battery based on RNN and LSTM structures, taking into account the variable input dimension and enabling adaptive time series prediction.

Ali *et al.* [41] proposed a PDD-based SVM model for accurate RUL prediction of lithium-ion batteries in BMS. The SVM model utilized critical PDD features to classify and predict RUL with high accuracy, which was compared with full discharge data. Results showed that the PDD-based SVM model can be used for online RUL estimation in electric vehicles with low storage pressure on BMS. Gao *et al.* [42] suggested a multi-kernel SVM model to enhance RUL prediction accuracy for Li-ion batteries in BMS. The model employed polynomial and radial basis kernel functions alongside the particle swarm optimization algorithm to boost prediction precision and generalization capacity while decreasing training duration and computational complexity. The proposed algorithm demonstrated encouraging outcomes using the NASA battery dataset. Chen *et al.* [43] presented a novel method for estimating the SoH of batteries by employing a fixed-size least squares SVM model. This groundbreaking model, developed using arbitrary entropy, aimed to predict SoH based on the discharge duration within a chosen voltage range. The input variable consisted of the discharge time of the voltage interval, with SoH as the output. They utilized the Bayesian framework to compute the model parameters with accuracy and efficiency, further improving prediction performance.

Kim *et al.* [44] put forth a novel approach for online prediction of SoH utilizing FL. This technique places emphasis on two critical elements, the battery's maximum capacity, and resistance. These parameters were determined by measuring voltage, current, time, and temperature under certain conditions. Then, utilizing the existing FL reasoning framework, the optimal membership function was selected to predict the SoH. On the other, hand Landi *et al.*. [45] harnessed the power of FL to precisely calculate a battery's health index by fitting a curve that mirrors capacity decay and features in various operating and environmental conditions. Table 2 provides the comparison of different ML-based SoH estimation methods.

Table 2. Comparison of machine learning-based SoH estimation methods.

Method	Advantages	Disadvantages
ANN	Can handle complex nonlinear relationships; can learn features from raw data; can generalize well.	Requires large amount of data for training; may overfit; computationally expensive.
RNN	Can handle temporal dependencies and nonlinear dynamics; can learn from long sequences of data; provides good generalization performance.	Computationally expensive; requires large amount of data for training; can be sensitive to vanishing or exploding gradients.
SVR	Can handle nonlinear relationships; handles high-dimensional data well; effective with small to medium-sized datasets.	Sensitive to kernel function and hyperparameters; computationally expensive; may not perform well with noisy or unseparated data.
SVM	Can handle nonlinear relationships; handles high-dimensional data well; provides good generalization performance.	Sensitive to kernel function and hyperparameters; computationally expensive; may not perform well with noisy or unseparated data.
RVM	Provides a sparse solution; handles high-dimensional data well; estimates uncertainty.	Computationally expensive; requires careful selection of kernel function and hyperparameters; may not perform well with noisy data.
GPR	Provides a probabilistic framework; handles nonlinear relationships; provides good performance with small datasets.	Computationally expensive; requires careful selection of kernel function and hyperparameters; may not perform well with noisy data.
KF	Provides a state estimation framework; can incorporate prior knowledge and measurements; provides a recursive and efficient solution.	Assumes linear and Gaussian models; requires a good model of the system dynamics and measurement noise; may be sensitive to initialization and tuning of parameters.
FL	Can handle imprecise and uncertain information; captures nonlinear relationships; provides a transparent and interpretable framework.	Requires careful selection of fuzzy rules and membership functions; computationally expensive; may not perform well with noisy data.

3.2.1. Remaining Useful Life Prediction

The remaining useful life (RUL) of a battery refers to the estimated amount of time a battery can continue to perform its intended function before it needs to be replaced or recharged [46]. The RUL is an important metric for various applications, such as electric vehicles and renewable energy systems, where the ability to predict the remaining life of the battery is crucial for planning and maintenance purposes.

The RUL prediction methods are often classified as model-driven and data-driven. Because Li-ion battery degradation is a non-linear and time-varying dynamic electrochemical process, it is challenging to develop an effective prediction model for Li-ion battery degradation [47]. Therefore, data-driven methods for RUL have emerged as a research hotspot in recent years mainly due to the developments in artificial intelligence and machine learning. The most commonly utilized ML approaches for RUL prediction are neural networks, support vector machines, and deep learning. Figure 4 shows the general diagram of RUL estimation methodology.

In order to intelligently estimate RUL while recursively updating model parameters, Wu *et al.* [48] introduced a novel method for accurately predicting the RUL of batteries by combining a neural network degradation model with a bat particle filter to create a powerful system for intelligent RUL estimation. In 500 prediction cycles, the proposed model had an

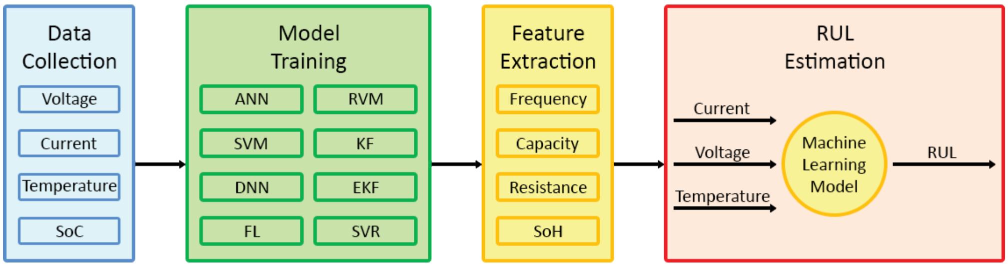

Figure 4. General diagram of RUL estimation methodology.

RUL prediction error of only 2 cycles. Zhou *et al.* [49] took a different approach, creating a framework based on a temporal convolutional network for SoH monitoring and RUL prediction. By using empirical mode decomposition to denoise the offline data and incorporating online data to refine the model, the model was able to produce highly precise RUL predictions. The average error was nearly 8 cycles smaller than that of other commonly used models. Zhang *et al.* [50] developed an online RUL estimation system using ANN and partial incremental capacity under continuous current discharge. The Spearman correlation analysis was utilized to extract the training and validation sets for the model, and the results showed a MAE and RMSE of less than 4 and 6 cycles respectively. The model was able to generalize well and make accurate predictions.

The DL or DNN model has several hidden layers as opposed to the single-layer feed-forward NN structure of the traditional ANN model. The DNN algorithm uses nonlinear calculations to construct a functional connection between the input vector and the output vector. The function parameters are computed using a specific manner during the calculating procedure. Qu *et al.* [51] utilized a combination of NN approach, particle swarm optimization, and an attention method to improve the LSTM network's prediction of battery RUL and SoH. Zhu *et al.* [52] proposed a novel method for RUL prediction in Li-ion batteries known as DGWO-ELM which combines extreme machine learning, gray wolf optimization, and differential evolution, The input weights and bias were improved using this technique, producing an MRMSE of 0.43%. Zhang *et al.* [53] proposed an LSTM-RNN-based battery RUL prediction method. The elastic mean square backpropagation technology was utilized to optimize LSTM-RNN, and the overfitting problem was solved using a dropout technique. Table 3 provides the comparison of different ML-based RUL estimation methods.

Due to its significant advantages in processing limited training data sets, SVR has drawn a lot of interest. SVR is a non-parametric regression ML technique that uses support vectors to create a hyperplane that best fits the data, and the number of support vectors grows with the size of the training data set. A prediction model based on SVR was built by Patil *et al.* [54]. The model was built using feature vectors generated from voltage and temperature curves, with an RMSE of 0.357%. At a confidence interval of 95%, the upper and lower errors were 7.87% and 10.75% respectively. Du *et al.* [55] used SVR to develop an RUL prediction model for lithium-ion batteries, utilizing six sets of coupled stress experimental data. The relative error of the model was less than 5% for 600 cycles. Wang *et al.*. [56] aimed to improve the accuracy of RUL prediction model based on SVR by utilizing the ABC algorithm. They optimized the core parameters of their SVR-based RUL prediction model using the ABC algorithm. The results were impressive - the average value of all units was below 27%, and the RMSE of the ABC-SVR approach was under 0.05. These results demonstrate the potential of combining SVR and ABC for highly precise RUL predictions.

4. Battery state estimation of electric vehicles

Due to the existing constraints linked to BMS design, it is more difficult to integrate large-scale Li-ion battery systems, which is hindering the widespread adoption of EVs [57]. The limitations of the current locally integrated battery management system (BMS) design have resulted in computing and data storage challenges [58]. Despite extensive research efforts, the complexity of battery algorithms makes them impractical for improving real-world BMS performance. To address these limitations, battery algorithms have been developed with a focus on balancing accuracy and complexity. However, a new solution has been proposed in the form of a cloud-based smart BMS, which takes advantage of cloud storage and computing to overcome these challenges [59]. This innovative design offers a way to effectively manage the complexities of BMS and enhance its performance.

Table 3. Comparison of machine learning-based RUL estimation methods.

Method	Advantages	Disadvantages
ANN	Can handle complex nonlinear relationships; can learn features from raw data; can generalize well.	Requires large amount of data for training; may overfit; computationally expensive.
DNN	Can handle complex nonlinear relationships; can learn features from raw data; can handle large datasets; provides good generalization performance.	Requires large amount of data for training; computationally expensive; may overfit.
SVR	Can handle nonlinear relationships; handles high-dimensional data well; provides good generalization performance.	Sensitive to kernel function and hyperparameters; computationally expensive; may not perform well with noisy or unseparated data.
SVM	Can handle nonlinear relationships; handles high-dimensional data well; provides good generalization performance.	Sensitive to kernel function and hyperparameters; computationally expensive; may not perform well with noisy or unseparated data.
RVM	Provides a sparse solution; handles high-dimensional data well; estimates uncertainty.	Computationally expensive; requires careful selection of kernel function and hyperparameters; may not perform well with noisy data.
KF	Provides a state estimation framework; can incorporate prior knowledge and measurements; provides a recursive and efficient solution.	Assumes linear and Gaussian models; requires a good model of the system dynamics and measurement noise; may be sensitive to initialization and tuning of parameters.
EKF	Provides a state estimation framework; can incorporate prior knowledge and measurements; can handle nonlinearities; provides a recursive and efficient solution.	Assumes linear Gaussian process and may have convergence issues in highly nonlinear models; requires a good model of the system dynamics and measurement noise; may be sensitive to initialization and tuning of parameters.
FL	Can handle imprecise and uncertain information; captures nonlinear relationships; provides a transparent and interpretable framework.	Requires careful selection of fuzzy rules and membership functions; computationally expensive; may not perform well with noisy data.

4.1. Cloud data platform

Cloud computing takes the state estimation of EV batteries to new heights by enabling the accurate and reliable estimation of the current state of charge, health, and other parameters of the battery. By leveraging the power of cloud computing, storage, and big data, intelligent algorithms, and BMS controllers can perform more efficiently and effectively in real-world scenarios. With big data technology, large memory devices, computing power, and analytics are combined with smart approaches to provide more precise results. By continuously transmitting voltage, current, temperature, and other data to a big data platform, intelligent algorithms can be trained on real-time data, leading to more accurate predictions of battery state parameters such as SoC, SoH, and RUL, as well as the detection of thermal runaway and defects. The data is stored and monitored in the cloud throughout the battery's lifespan and processed to provide valuable insights for future performance enhancements. Studies such as Haldar *et al.* [60] and Sivaraman *et al.* [61] have investigated the use of IoT for real-time battery monitoring and management in EVs, while Kim *et al.* [62] introduced a cloud-based battery monitoring solution for EV applications. cyber-physical analysis and data mining techniques were used to evaluate the proposed solutions, and the results showed that the algorithms accurately estimated SoC and diagnosed the faults.

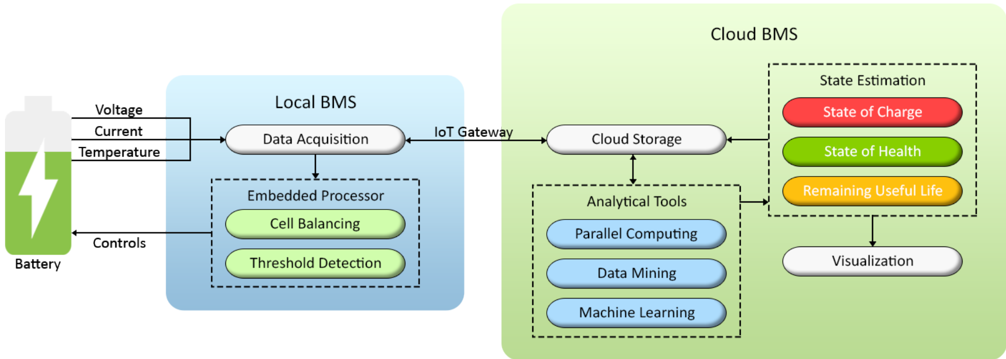

Figure 5. Cloud-based BMS. Adapted from [58] under CC-BY 4.0.

4.2. *Digital twin EV BMS*

A digital twin is a virtual replica or representation of a physical object, system, or process. It is created using data from sensors, IoT devices, and other sources to model the object, system, or process in real-time [63]. The digital twin enables the monitoring, analysis, and optimization of the physical object or process, often using machine learning and artificial intelligence algorithms to provide insights and predictions. Aheleroff *et al.* [64] highlighted the applications and capabilities of the digital twin in the context of industry 4.0 by using IoT, cyber-physical systems, cloud computing, and big data. The authors also provided an insight into the digital twin layers *i.e.* application, cyber, digital, communication, and physical layers through a reference architecture model. In the context of an EV battery, it serves as a virtual representation of the battery, providing real-time state estimation. This innovative technology enhances the precision of battery state estimation by using sensor data and machine learning algorithms to anticipate the battery's behavior under varying conditions and identify any potential problems before they arise. This leads to optimized battery performance and a prolonged lifespan. Recent research on battery digital twins has focused on improving the accuracy and reliability of battery state estimation, as well as optimizing battery performance and extending its lifespan. Li *et al.* [65] introduced a cloud-based BMS that transmits all essential battery information to the cloud through IoT components, using the data to create a digital twin. The digital twin, powered by battery diagnostic algorithms, provides an in-depth analysis of the battery's SoC and aging. Additionally, two methods were developed specifically for cloud-based BMS - an adaptive extended H-infinity filter for SoC estimation and particle swarm optimization for SoH estimation. Wang *et al.* [66] presented an intelligent BMS system that fuses digital twin technology with cloud computing. The BMS, acting as a bridge between the physical and digital realms, sends data from the battery to the cloud, building digital twin models, and then transmits the results of state estimation and health predictions back to the vehicle. In a groundbreaking study, Li *et al.* [67] presented a cutting-edge digital twin model that seamlessly integrates with the BMS. This model leverages the power of a multi-linear regression algorithm to accurately estimate and predict a range of crucial battery pack states. By utilizing this innovative approach, the proposed model was capable of providing valuable insights into the real-time performance of battery packs. Sancarlos *et al.* [68] proposed a digital twin model for the real-time monitoring of EV battery and BMS. Firstly, sparse-Proper Generalized Decomposition method was employed to build the regression model, which enabled the real-time monitoring of overall EV system performance. The data gathered from real-time simulations were utilized to test the effectiveness and accuracy of the proposed method. Secondly, a data-driven model base on Dynamic Mode Decomposition techniques was utilized to develop an online hybrid twin to bridge the gap between the digital twin estimations and the physically measured data. Li *et al.* [69] improved their existing model for battery management systems (BMS) in electric vehicles by proposing an intelligent digital twin model that utilizes historical battery data obtained from real driving scenarios to measure, estimate, predict, and diagnose the battery pack states. The proposed model consists of two parts, state estimation based on a regression model using a backpropagation neural network (BPNN) and fault diagnosis using a threshold-based method. Additionally, a whale optimization algorithm (WOA) was utilized to optimize the parameters of the regression model. The authors evaluated the proposed method using a dataset gathered from an electric vehicle over one year and found that it achieved over 95% prediction accuracy and can effectively diagnose faults in the BMS. This model can potentially overcome the problems of high cost, reduced space, low efficiency, and high failure rates that BMS typically experience. Kortman *et al.* [70] proposed a digital twin model to anticipate future failures and continuous SoH monitoring. A Low Power Wide Area Network was employed to monitor and assess the battery's overall health. Data from the Intelligent Battery Sensor, a data collection component built into the real system, was used to build the digital twin cloud. Figure 5 illustrates the functioning of a cloud-based BMS.

Although digital twin technology is currently used primarily in the context of Industry 4.0, its applications could potentially expand significantly with the emergence of Industry 5.0. Aheleroff *et al.* [71] highlighted the importance of mass personalization for sustainability at scale and proposed a Reference Architecture Model to achieve it through a human-centric approach. According to their study, Industry 5.0 can enhance Industry 4.0 for higher resilience and sustainability by focusing on collaboration between human capabilities, machines, and technologies. Applying this approach in the context of digital twin can enable the creation of virtual models that facilitate collaboration between humans and machines, leading to the production of more sustainable and value-added products. For example, digital twins can facilitate more efficient resource utilization by providing real-time monitoring and optimization of EV BMS operations [72]. This, in turn, can contribute to the adoption of circular economy principles, extending the life of batteries, reducing waste and maximizing resource efficiency. Additionally, digital twins can enhance the flexibility and adaptability of EV BMS, enabling them to adjust to changing conditions and respond to unforeseen events. This can support the development of resilient EVs that can continue to operate effectively even in challenging conditions. Therefore, exploring the potential applications of digital twin technology in EV BMS with Industry 5.0 can open up exciting opportunities for research and contribute to the development of sustainable and resilient EVs in the future.

5. Challenges and prospects

This section discusses the challenges and prospects related to the cloud-based battery state estimation of EVs.

5.1. Challenges

Challenges related to cloud-based state estimation of batteries of electric vehicles include:

(1) Data privacy and security concerns: Sensitive data such as battery state information must be transmitted to and stored on cloud servers, which raises concerns about data privacy and security. It includes confidentiality of battery information, such as the state of charge, voltage, and temperature, which may reveal sensitive information about the vehicle and its usage patterns; Protection of data transmission, which could be intercepted during transmission to or from the cloud; Data storage and accessibility, as data stored in the cloud may be vulnerable to unauthorized access or manipulation; Data ownership, as the ownership and control of the data may be disputed; Data retention and deletion, as the data stored in the cloud may persist even after the vehicle owner deletes it from their local device.

(2) Latency: Cloud-based state estimation algorithms require data to be transmitted to the cloud for processing, which can result in significant latency. Latency can be caused by network delays in transmitting data from the electric vehicle to the cloud. It can also occur if too much data is aggregated before it is transmitted to the cloud, leading to a delay in processing. Latency can occur if cloud resources are not allocated efficiently, leading to longer processing times for state estimation. This can be a problem for real-time applications, such as monitoring the state of a battery during charging or discharging.

(3) Network reliability: The reliability of the network connection between the vehicle and the cloud can greatly affect the performance of cloud-based state estimation algorithms. Interruptions or outages in the network connection can result in inaccurate predictions or even cause the system to fail. Limited bandwidth can result in slow data transmission, causing delays in state estimation. Interference from other devices or networks can affect the reliability of data transmission in cloud-based state estimation.

(4) Algorithm issues: Cloud-based state estimation algorithms may require regular updates to improve performance or address bugs. This can be challenging, as it requires coordination between the vehicle manufacturer, the algorithm developer, and the cloud service provider. The accuracy of the state estimation algorithms can be affected by various factors, including measurement errors, battery aging, and temperature changes. Cloud-based state estimation algorithms often require a subscription or usage-based fee, which can be costly for vehicle manufacturers and consumers. They can also be computationally intensive, leading to high processing costs and slow response times.

(5) Cost: There are several cost factors associated with cloud-based state estimation including data transmission costs, storage costs, infrastructure costs, computation costs, maintenance costs, etc. Overall, the costs associated with cloud-based state estimation of EV batteries can add up quickly, and careful consideration of the costs should be done before implementing such a system.

5.2. Prospects

Prospects related to cloud-based state estimation of batteries of electric vehicles include:

(1) Improved battery management: Cloud-based state estimation has the potential to significantly improve the battery management of electric vehicles. By using cloud computing, real-time data from the battery system of an electric vehicle can be processed and analyzed, providing more accurate information about the battery's SoC, SoC, and overall performance. This information can then be used to optimize the charging and discharging patterns of the battery, extending its lifespan and ensuring maximum performance.

(2) Increased scalability: One of the key advantages of cloud-based state estimation is that it enables central monitoring and control of battery systems across a large fleet of electric vehicles. This is particularly relevant for electric vehicle fleets used in ride-sharing and

delivery services, where a large number of vehicles need to be managed efficiently. The central monitoring and control provided by cloud-based state estimation can help to ensure that all vehicles are charged efficiently, reducing the cost of electricity and extending the lifespan of the batteries.

(3) Remote monitoring and management: The prospect of cloud-based battery state estimation in remote monitoring of electric vehicles has the potential to greatly improve the efficiency, reliability, and performance of these vehicles, making them a more attractive option for consumers and fleet operators. The technology is still in its early stages, but it is expected to become increasingly widespread as electric vehicles become more popular and more widely adopted. Another benefit of remote monitoring and management is that it enables predictive maintenance. Predictive maintenance uses data from the battery system to identify potential issues before they become critical, reducing the need for costly repairs and replacements and reducing the total cost of ownership for electric vehicle owners.

(4) Cost reduction: The use of cloud-based battery state estimation in electric vehicles has the potential to greatly reduce the cost of ownership, making these vehicles a more attractive option for consumers and fleet operators. By improving the efficiency, reliability, and performance of the battery system, cloud-based battery state estimation has the potential to play a significant role in the widespread adoption of electric vehicles.

(5) Better decision making: Cloud-based battery state estimation helps in better decision making by providing more accurate and real-time information about the battery system of an electric vehicle. This information can be used to make informed decisions about the management and maintenance of the battery, leading to more efficient and cost-effective management of electric vehicles.

6. Conclusion

A review of the use of machine learning in the state estimation of batteries of electric vehicles (EVs) was conducted in this paper. It can be seen from the recent research that ML-driven digital twin-based state estimation of batteries of EVs suggests that utilizing machine learning techniques and cloud-based systems can improve the accuracy and efficiency of battery state estimation for EVs. This can include using methods such as neural networks, support vector machines, fuzzy logic, and deep learning to process and analyze data from the battery of EVs. The review also discusses the benefits of using cloud-based resources, such as the ability to process large amounts of data in real-time and the ability to share data among different EVs. The challenges linked to the use of these methods were also discussed, such as the need for large amounts of training data, and the need for effective data management and communication protocols. Overall, it can be concluded that ML-driven digital twin-based state estimation is a promising approach for improving the performance of EV batteries. Additionally, using cloud-based systems allows for the sharing and updating of data and models across multiple vehicles and remote monitoring and management of the battery state. However, there are also challenges to be addressed such as handling the large amount of data generated by EVs and ensuring data privacy and security.

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Conflicts of Interests

All authors declare that there is no conflict of interest.

Authors contribution

Conceptualization, M.B.K., W.H., and H.L.; Writing—original draft preparation, M.B.K., and W.H.; Writing—review and editing, M.B.K., W.H., and H.L.; Visualization, M.B.K., and W.H.; Supervision, H.L.; Funding acquisition, H.L.; Resources, H.L.; Project administration, H.L. All authors have read and agreed to the published version of the manuscript.

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