Methods for state of health estimation for lithium-ion batteries: An essential review

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Abstract. Electric vehicles (EVs) are a practical and suitable choice for reducing the pollution rate caused by combustible engines of conventional cars. The lithium-ion batteries (LIB) serve as a support for energy storage in EVs owing to their benefits and advantages. To ensure their optimal performance and working under safe conditions the state of health SOH of battery has to be accurately estimated. In this paper, the main estimation techniques, namely, model-based, and data-driven approaches are explained with a brief look at their several stages. Thus, two examples are presented for each method: neural networks (NN) and support vector machines (SVM) for data-driven, the combination of variable forgetting factor recursive least squares (VFF-RLS) with adaptive unscented Kalman filter (AUKF) and particle swarm optimization (PSO), genetic algorithm (GA), particle filter (PF), recursive least squares (RLS) for model-based method to show how each method is applied. Finally, a list of advantages and drawbacks of some parameter identification and SOH estimation methods is prepared, and then some other related works are referred to.

Keywords: Lithium-ion batteries (LIB), State of Health (SOH), Neural Networks (NN), Support Vector Machines (SVM), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Recursive Least Square (RLS), Adaptive Unscented Kalman Filter (AUKF)

1 Introduction

Owing to the growth of population size, the use of combustible vehicles grows, which causes the increase of pollution rate, consequently, the battery market evaluates, especially for electric vehicles use such as Nickel Metal Hybrid, Lead-Acid, and Lithium-ion batteries [1]. Among these different kinds, the lithium-ion ones are the widely used, therefore they gain a good interest in research due to their benefits [2].

The state of health is crucial to determine how much a battery is degraded, it also enhances a reliable battery system, but unfortunately, its estimation is still a tough task due to the non-linear, dynamic, and complex characteristics [3]. Several works were published on that topic either based on previous experiments and papers or by proposing novel methods, although each represents advantages and drawbacks.

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Acronyms			
Adam	Adaptive moment estimation		
ANN	Artificial Neural Networks	**NNLS**	Non Negative Least Squares
AUKF	Adaptive Unscented Kalman Filter	**OCM**	Off-board Capacity Measurements
BMS	Battery Management System	**OCV**	Open Circuit Voltage
CNN	Convolutional Neural Networks	**PF**	Particle Filter
DARNN	Dual stage Attention mechanism based Recurrent Neural Networks	**PHEV**	Plug-in Hybrid Electric Vehicle
DEKF	Dual Extended Kalman Filter	**PSO**	Particle Swarm Optimization
DNN	Deep Neural Networks	**Relu**	Rectified linear unit
ECM	Electrochemical Model	**RLS**	Recursive Least Squares
EECM	Electrical Equivalent Circuit Model	**RMSE**	Root Mean Squared Error
EKF	Extended Kalman Filter	**RMSPE**	Root Mean Squared Percentage Error
EM	Empirical Model	**SDFF – RLS**	Recursive Least Squares with Sliding window Difference Forgetting Factor
GA	Genetic Algorithm	**SOC**	State Of Charge
GPR – LSTM	Gaussian Process Regression Long Short-Term Memory	**SOH**	State Of Health
KF	Kalman Filter	**SVM**	Support Vector Machines
LIB	Lithium-Ion Batteries	**UDDS**	Urban Dynamometer Driving Schedule
LSSVM	Least Squares Support Vector Machines	**UKF**	Unscented Kalman Filter
MAE	Mean Absolute Error	**VFF – LMRLS**	Variable Forgetting Factor Limited Memory Recursive Least Squares
MAX	Maximum Relative Error	**VFF – RLS**	Variable Forgetting Factor Recursive Least Squares
MCPSO	Mixed Swarm Based Cooperative Particle Swarm Optimization	**WNN**	Wavelet Neural Networks
MSE	Mean Squared Error		

SOH is not a directly measured quantity like voltage or current, but it can be estimated using distinct techniques. In general, there are two types of work, the first one is about estimating the state of health of a single cell of the battery, and the second one is dedicated to the estimation in the battery pack. What makes a difference in estimation between single cell and battery pack is the working temperature and characteristics of cells [4].
[5] explained both types of application, in terms of individual cells, the SOH estimation is divided into three categories, the first category is based on **capacity** using voltage, temperature, expansion or ultrasound, the second one is based on **impedance** using time domain or frequency domain, and the last one is based on **aging mechanism parameters**. In terms of a battery pack that contains many individual cells, the SOH is estimated by either model-based or data-driven methods.
The model-based method uses the battery model as a starting point, it describes as much as possible the behavior of the battery and contains a specific number of resistances and ca-

pacitors, and from which some equations are extracted, after identifying their parameters the SOH is estimated.
Contrary to model-based, data-driven method estimates SOH without the knowledge of battery features, using a trained model by machine learning founded on real battery data, details are explained in this article. The content of this paper is arranged as follows:
Section 2 defines the state of health of the battery.
Section 3 gives an overview of recent SOH estimation methods, here the model-based and data-driven methods are explained briefly, thus the procedure of their use is represented, also two examples of each method are defined to provide a concise idea about how each method is applied.
Section 4 outlines the advantages and limitations of different SOH estimation methods and different battery model parameters identification methods in case of the use of a model-based method, then some works using diverse techniques are cited.
Section 5 gives the conclusion.

2 Definition of SOH

The state of health of a battery evaluates its actual performance compared with its fresh initial state. It can be expressed in terms of capacity as displayed in **Eq. 1**, here C_{fresh} and C_{aged} are the nominal and the aged capacity respectively [5].
SOH alerts when the battery has to be substituted and when it becomes unusable anymore for vehicles [6]. It can't be directly measured [7] so many methods are proposed to estimate it with high accuracy.

$$SOH_E = \frac{C_{aged}}{C_{fresh}} \times 100\ (\%) \tag{1}$$

3 Overview of recent SOH estimation methods

The state of health of the battery can be estimated using model-based or data-driven methods through different approaches as shown in **Figure 1** and which are explained in the two following subsections.

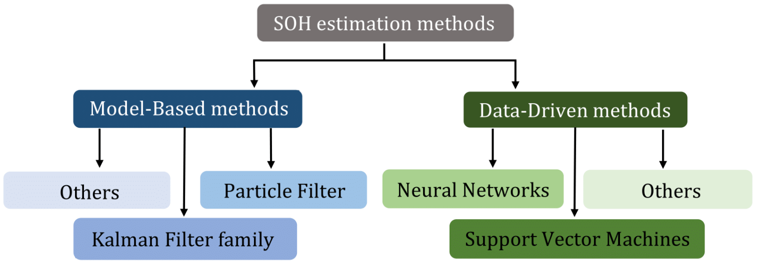

Figure 1: Different methods of SOH estimation

3.1 Model based methods

Model-based methods involve five procedures: Selection of battery model, Discretization, parameter identification, State space representation, and SOH estimation as depicted in **Figure 2**. [8] discuss various battery models that can be employed, including EM, ECM, and

EECM. Details regarding each model are provided in **Table 1**. An example illustrating the application of these methods is detailed in **Section 3.1.1**.

Figure 2: Workflow for model-based methods

Table 1: Types of battery models

Model	Features
EECM	• Considers electrical characteristics of the battery • Trade-off between computational efficiency and accuracy • Simplicity • 1RC and 2RC are the most popular used EECM models
ECM	• Considers electrochemical characteristics of the battery • Causes large computational loads
EM	• Does not consider physical characteristics • Large Estimation error

The state of health of the battery can be estimated by applying various methods, as highlighted in **Figure 1**, such as particle filter, Kalman filter family (Unscented Kalman Filter (UKF), Extended Kalman Filter (EKF), Adaptive Unscented Kalman Filter (AUKF)), or other techniques, like least squares, recursive least squares, and H infinity filter.

3.1.1 VFF-RLS and AUKF method

[9] estimated state of health of the battery through the steps illustrated in **Figure 2**, the description of the process is as follows :

Selection of battery model : Several model types can be used, [9] opted for the 2RC EECM model.

Discretization : The model equations are obtained through Kirchchoff voltage laws and OCV-SOC relationship [8]. Discretization serves to create a mapping from s-plan to z-plan to get final equations which lead to capacitor and resistance determination [9].

Model parameters identification : The model parameters are recognized using different methods such as PSO-GA algorithm [4], VFF-LMRLS algorithm [10], VFF-RLS [9], in case of negative parameters NNLS algorithm can be applied [11].

State space representation : This representation is made based on model parameters obtained in the previous step.

SOH estimation : Many methods can be used to estimate the state of health of a battery e.g. Kalman filter family. [9] opted for the use of AUKF in their work.

[9] estimated the internal resistance which corresponds to the state of health of the battery through applying the VFF-RLS algorithm and AUKF, they performed the constant current and UDDS tests and it was revealed that the internal resistance was predicted with high accuracy, therefore the proposed method was able to predict SOH accurately and consistently.

3.1.2 The combined PSO, GA, PF and RLS method

A genetic algorithm (GA) can estimate the parameters of a nonlinear system, such as a battery, through encoding, selection, crossover, and mutation. It requires a population and a fitness function to evaluate each solution [12]. In Particle Swarm Optimization (PSO), each candidate solution is specified as a particle [13], this method identifies the optimal solution by initializing with random solutions and reproducing the behavior of particles within a multidimensional search space. The particles are characterized by their position which defines the solution, and their velocity which represents direction and speed. PSO algorithm is well-regarded for its rapid convergence and is widely used across many fields [14]. The combination of GA and PSO increases the accuracy of model parameters identification [8]

To estimate the state of health (SOH) of the battery [4] put forward the use of an nRC battery model and identify its parameters by applying GA-PSO combination, followed by the application of Particle Filter (PF) and RLS algorithm for SOH estimation. The PSO-GA involves creating a population of pop_sz particles, each characterized by random positions X and velocities V, which are updated in each iteration based on specific equations. The particles are then ranked according to their fitness value to define L particles with the lowest fitness value. The L particles are then combined with pop_sz - L particles generated by GA to form a new generation for the next iteration. The process continues until the best fitness value is attained as shown in **Figure 3**. Here, max_a and max_b designate the number of generations for PSO-GA and PSO algorithms respectively. Once the parameters are identified, the SOC is estimated using the particle filter to avoid measurement noise. Finally, the capacity is updated using the RLS algorithm. Experiments indicate that this method reaches high accuracy and robustness in estimating SOH [4].

3.2 Data driven methods

Data-driven methods are carried out by the four stages presented in **Figure 4**, the data is extracted from measurement and divided into two folds, one for training and one for testing the model which predicts the state of health of the battery. The methods used while training the model are declared in **Figure 1** such as neural networks NN, support vector machines SVM, and others like GPR-LSTM etc...

3.2.1 Neural networks method

Neural networks can estimate an accurate SOH under different conditions without prior knowledge of battery characteristics [6], it learns the behavior of the system based on data received.
[15] Estimated the state of health of the battery using neural networks through several steps.

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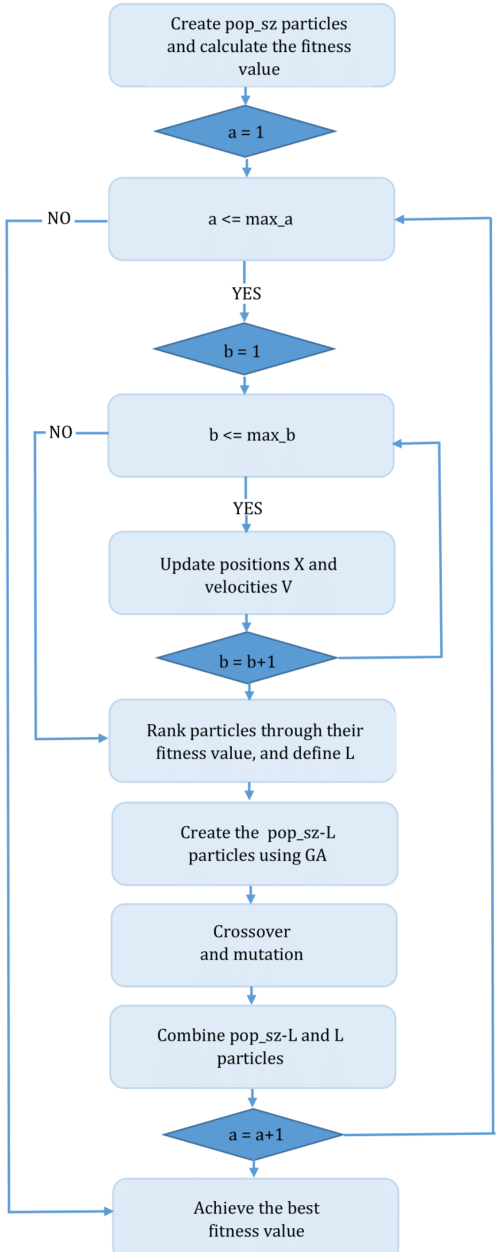

Figure 3: The combined PSO and GA algorithm for parameters identification

Initially, data samples from 704 vehicles were collected, including traveled distance, state of charge, current throughput, and discharge/charge C-rate. The OCM procedure was then carried out to predict capacity. In order to define the necessary inputs to build the neural networks, the awareness of the variables that correlate with predicted capacity is required using the Pearson correlation coefficient, which ultimately highlights age, temperature, and

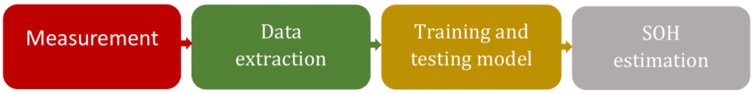

Figure 4: Workflow for data-driven methods

traveled distance as the most associated variables with capacity.
The model was developed in Keras, with one input and one hidden layer, a Relu activation function was used for the non-linearity purpose, a dropout layer was introduced as a regularization means to reduce overfitting, and Adam was used as an optimizer.
They conclude finally that the neural network has a high accuracy for prediction and is able to detect different complex mutual dependencies of input variables but it is still poor in estimation in the case of small datasets.

3.2.2 Support vector machines method

Support vector machines are applied to predict the SOH of batteries through regression analysis. This method is adept at detecting patterns in nonlinear systems by analyzing data and can be employed in offline and online mode [6]. This method is highly effective for solving high-dimensional problems while requiring a small amount of data [16]. There are many types of batteries, such as LIBs which are widely used in the automotive field and are given significant attention. According to [8], SVMs are a great choice for the estimation of LIBs's SOH due to their fast computational speed. The main purpose is to learn the behavior of the battery using the available dataset to create a model that accurately describes it. [17] applied SVM to data extracted from a PHEV battery without prior knowledge of its features. **Figure 5** illustrates how SVM can be employed across various stages [18].

In this case, the SVM implementation was done in C using SVMLight functions (svm_Learn, svm_classify). Based on the explanations by [18] and [17] the steps depicted in **Figure 5** can be described as follows:

Data Selection : The extracted measured current and voltage, along with the estimated State of Charge (SOC) from the Battery Management System (BMS) are split into train and test sub-datasets.

Training Run: Create the SVM model using the svm_Learn function with the data from the first sub-dataset.

Test Run : Apply the svm_classify function using data from the second sub-dataset to test the model.

SVM Performance Estimation : Evaluate the model's performance by calculating the Root Mean Squared Percentage Error (RMSPE). RMSPE measures forecast accuracy by taking the square root of the average of squared percentage errors between predicted and actual values.

Figure 6 illustrates how SVM generally works, the model receives the State Of Charge and current to estimate the voltage which will be compared to the real measured one corresponding to the given inputs. RMSPE error between real and estimated values is calculated in parallel. This operation is performed in each iteration using different data until the minimal error is reached. Consequently, the trained model is ready to predict the voltage that is going

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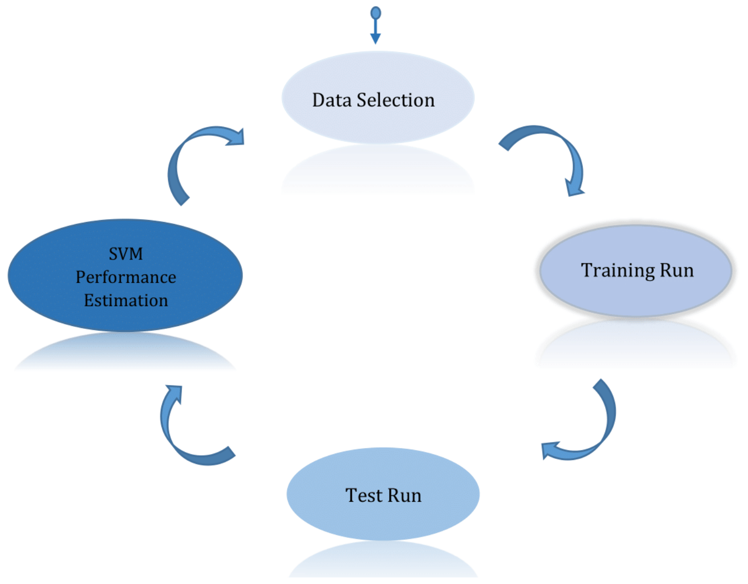

Figure 5: Several steps of the use of support vector machines SVM.

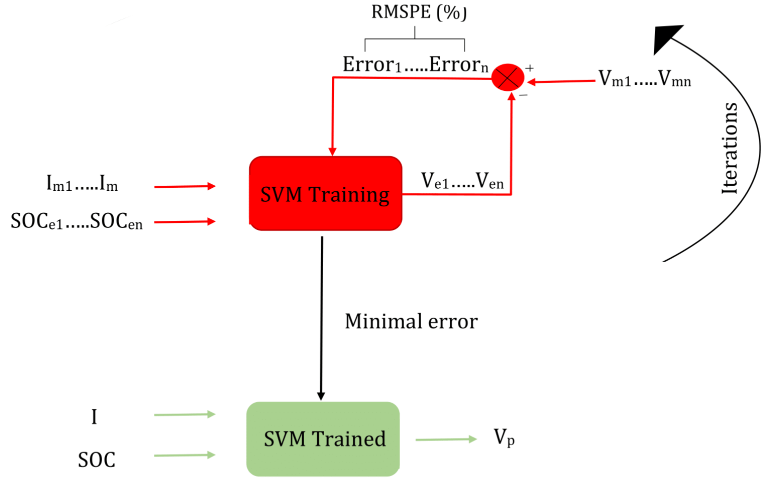

Figure 6: Shematic overview of SVM, I_m is the measured current, $\mathrm{SOC_e}$ is the estimated State Of Charge from BMS, V_e, V_m and V_p are the estimated, measured and predicted voltage respectively.

to be used for SOH estimation.
State of Health (SOH) can be estimated based on two main indicators: resistance and capacitance. SOH decreases as resistance increases and capacitance decreases.
[18] developed an SVM model based on State of Charge (SOC), current, and voltage. This model, tested with hypothetical inputs, served as a look-up table for voltage prediction under

constant temperature. By calculating discharge resistance from January to December based on predicted voltage by the SVM model, they determined that temperature significantly affected resistance variability, more than aging. To improve prediction accuracy, they recommend including temperature and time dependencies. That's what [17] introduced in their work, as a result, the estimated SOH indicators align well with experimentally measured results. The SVM model can be implemented in vehicle Battery Management Systems (BMS) to provide real-time performance updates and predictions [18].

4 Discussion

While using RLS, GA, or PSO for battery model parameters identification as mentioned in **Section 3.1**, other works incorporate the use of MCPSO [19], VFF-RLS [9], SDFF-RLS [20], and hybrid methods like PSO-GA as explained in **Section 3.1.2**. Each one represents advantages and drawbacks as shown in **Table 2**.
Regarding SOH estimation, in terms of model-based, many methods are used such as the least squares, particle filter, Luenberger-based and sliding mode observers [21], thus Kalman family, for example, KF, or their improved versions like DEKF [22] or AUKF [9].
The H infinity filter is also applied due to its robustness against errors [23]. Each one of them has its strengths and weaknesses including time execution, convergence, algorithm complexity, etc... as shown in **Table 3**.
In terms of data-driven methods transfer learning and sample entropy are applied [21], also machine learning algorithms like GPR-LSTM [24], SVM [18], [17] or NN [15], or developed techniques based on NN such as DNN, ANN, and WNN. Many works were published in connection with state of health estimation based on SVM like LSSVM [25], and based on neural networks, such as the incremental capacity and wavelet neural networks WNN with genetic algorithm [26], convolutional neural networks CNN and bidirectional gated recurrent unit [27], convolutional neural networks and transformer model [28], or novel dual-stage attention mechanism based recurrent neural networks DARNN [29]. The advantages and limitations of some of the above-mentioned approaches are detailed in **Table 4**.
To evaluate the error between real SOH and estimated SOH by each method, some metrics are commonly used such as (RMSE, MAE, MAX, MSE) [8], or RMSPE as seen in **Section 3.2.2**. The RMSE and MAE are calculated according to **Eq. 2** and **Eq. 3** respectively [30], MSE is derived as described in **Eq. 4** [31], while RMSPE is computed as shown in **Eq. 5** [17]. Here y_i and $\hat{y}_i$ represent the actual value and the predicted value, thus n is the number of estimations. The different works cited previously in **Section 3.1.1**, **Section 3.1.2**, **Section 3.2.1** and **Section 3.2.2** are compared using various evaluation's metrics and shown in **Table 5**.

Table 2: Types of battery model parameters identification

Method	Advantages	Drawbacks
RLS	Fast convergence [32]	Affected by the presence of outliers [32]
GA	Adaptive optimization [26]	computational redundancy [4]
PSO	Better convergence speed [14]	Can get stuck in local optima [4]

Table 3: Types of SOH estimation techniques related to model-based methods

Method	Advantages	Drawbacks
Least squares	Low complexity of algorithm [6]	Need time to improve the controller[6]
PF	Less processing time [6] and reduce system error [8]	High mathematical complexity [6] and suffers from the curse of dimensionality problem [33]
KF	Filter high degree of noise [6]	High computational complexity [6]
UKF	Able to deal with uncertainty [3]	Low calculation complexity [3]
AUKF	Faster convergence and higher accuracy [9]	The error covariance matrix needs to be a positive definite matrix [8]

Table 4: Types of SOH estimation techniques related to data-driven methods

Method	Advantages	Drawbacks
NN	High accuracy and Self-learning ability [15]	High computational cost [6]
SVM	The accuracy in high dimensional systems is acceptable [16]	Lack of sparseness [16]
WNN	Better learning ability [26]	The network fall into oscillations and local minimum [26]
DNN	Single network offer accurate strategy [34]	Represents challenges including energy consumption and data security [35]

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{4}$$

$$\text{RMSPE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\frac{\hat{y}_i - y_i}{y_i})^2} \times 100\ (\%) \tag{5}$$

Table 5: Comparison of estimation using different methods based on various evaluation's metrics

Method	**RMSE**	**RMSPE**	**MAE**
NN	0.03 [15]	-	-
SVM	-	0.0028 [18]	-
PSO,GA,PF and PF	0.0037 [4]	-	0.0027 [4]
VFF-RLS and AUKF	0.0022 [9]	-	-

5 Conclusion

This study aims to provide a general overview of SOH estimation approaches including model-based and data-driven methods. It focuses on their workflows, advantages, drawbacks, and works built on top of these techniques. Based on the furnished information in this paper the derived conclusions are as follows :

- The model-based methods consist briefly of battery model selection (EM, ECM, ECCM), followed by parameters identification (RLS, PSO, GA, etc…), then SOH estimation (Kalman filter family, PF, LS, H infinity filter, etc…)
- Most parameter identification methods are improved and are founded on RLS like VFF-RLS, SDFF-RLS, VFF-LMRLS, or a combination of techniques that are currently employed such as PSO-GA. The same concept is applied to SOH estimation where the Kalman filter family (KF, EKF, AUKF, DEKF) is widely used.
- The data-driven methods consist of building a model that describes the behavior of a system without prior knowledge of its features, based on its available inputs and outputs, such as SVM, LSSVM, GPR-LSTM, NN, and its improved versions like DNN, ANN, WNN, RNN or CNN, etc…

An accurate SOH forecast is crucial for batteries to work under safe conditions, each proposed technique has its own benefits and drawbacks including convergence speed, accuracy, precision, computational load, self-learning, and cost, that's why a great deal of effort has been supplied to find the best trade-off between all these characteristics for better estimation, consequently, this topic is still a hot research field.

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