# Review on State of Health estimation methodologies for lithium-ion batteries in the context of circular economy

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**Abstract**

The Electric vehicle (EV) batteries should be repurposed after reaching End of Life (EoL), because it could be economically and environmentally beneficial. State of Health (SoH) estimation plays an essential role in repurposing these EoL Lithium (Li)- ion batteries. The aim of this paper is to review different SoH estimation technique to present a novel feature based classification. The review also investigates the issues and challenges in estimating SoH for Li-ion battery, with possible solutions. Furthermore, the study provides proposals for the development of SoH estimation methods for EV batteries in the context of the Circular economy.

*Keywords:* Circular economy, Decision Making, Electric Vehicle, Lithium-ion battery, Prognostics, State of Health,

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## 1. Introduction

Just within the first quarter of the $21^{st}$ century, the global population has surpassed 7.5 billion, consequently leading to over-exploitation of natural resources and unprecedented levels of pollution [1]. Within the transport sector, road transport leads as a contributor to global warming. EVs have been one of the most encouraging ways to tackle the adverse environmental effect of hydrocarbon-based transport and is increasingly gaining market share [2]. Owing to their high energy density, Lithium (Li)-ion batteries have found its place as a power source in most of these electric vehicles. However, these batteries are not that green as it seems and is the main contributor to environmental impact. These batteries reach its End of Life (EoL) when capacity degrades to 80 percent of original capacity and cannot be used further in electric vehicles [3]. So, eventually the batteries are sent for recycling.

The circular economy states that the product should first be recovered for reuse, refurbishment and repair, then for re-manufacturing and only later for raw material utilization, which has been the main focus in traditional recycling [4]. This will help the product value chain and life cycle retain the maximum possible value and quality as long as possible. Clearly, instead of recycling, the remaining capacity can be repurposed as a second life in less demanding applications. Re-purposing is the process by which an object with one use value is transformed or redeployed as an object with an alternative use value. Some scientific communities [5] classifies second life applications according to the following three categories: i) Residence related application (3 - 4 kWh) ii) Commercial applications (25 kWh to 4 MWh): Telecommunication towers, Light commercial, Uninterruptible power supply

(UPS). iii) Energy-related / industrial applications (up to 50 MWh): Renewable energy storage, Grid stabilization. Since, there are several second life applications for these batteries, the right choice of the application at right time becomes necessary for efficient use of the batteries throughout their life cycle. This decision of choosing among several applications firmly rely on the State of Health (SoH) of these batteries at the time of re-purposing. Thus, efficient SoH estimation algorithms are necessary to make decisions while re-purposing.

This review explored past researches on SoH estimation techniques to classify them into suitable categories. In addition, different SoH estimation techniques are explained in detail, so that the reader will be able to choose the most relevant method. Also, this review explains the internal and external challenges posed while designing a Prognostics and Health Management system for the battery. Thus, this study aims to satisfy the following objectives.

1. Classify the various methods for estimating the SoH by presenting the advantages and disadvantages of these methods.
2. Summarize few relevant papers pertaining to each method for estimating SoH.
3. Explain the internal and external challenges posed by batteries in SoH estimation.
4. Identify possible efficient method to estimate SoH of EV batteries to make decisions on re-purposing.

In the past, very few studies have successfully provided an extensive description of approaches to estimate State of Health (SoH) for Li-ion battery in EV applications. References [6, 7, 8, 9] considered capacity degradation as the only factor affecting SoH. However, while making decisions on re-purposing, SoH should take into account both capacity and power fade. Very few researches ( [10, 11]) in the past includes degradation in both capacity and power during estimation of SoH. But, references [10, 11] failed to highlight the factors that affect SoH. We found that the references [12, 13, 14] delineated only data-driven approaches to estimate SoH. On the other hand, reference [15] only described the adaptive methods to estimate SoH of batteries. Reference [16] provided a very rich explanation of the requirement for battery management system but failed to have a broader classification for capacity estimation. Also, no researches in the past talk about SoH with the perspective of reusing or re-purposing batteries.

The outcome of this review will be fruitful for designing decision support system in the Circular economy. It will be helpful to battery engineers to create a novel method to estimate SoH and thus improving the performance of the battery. This review is divided into six sections. The detailed classification of SoH estimation methods are covered in section 2. We will talk about the internal and external challenges posed while estimating SoH in section 3, followed by a possible method to estimate SoH in context of circular economy in section 4. Finally, the paper is concluded in section 5.

## 2. State of Health estimation methods

State of Health conveys an approximate understanding of battery ageing and degradation behavior and also can be considered as an indicator of time, when the battery has to be reused, re-purposed or recycled. In the past, several methods have been explored for estimation of health ranging from purely physical models to data based models. The heart of these methods are mapping features/characteristics, which tends to have some correlation with SoH. The correlation can be established by physical equations, book-keeping, or data based relations. In the case of Li-ion battery, the majorly used features/characteristics can be classified into following three categories.

- **Model based features/characteristics :** These features and technical characteristics require mathematical or physical model which faithfully represents the different functionalities.
- **Data driven:** These features are analytically derived from partial or full charging/discharging cycle data of Lithium ion battery.
- **Battery Management System based raw features :** These are the raw features ( voltage, current, etc.), that can be easily acquired from battery management systems.

Figure 1 illustrates an at a glance view of features based classification of SoH estimation methods.

### *2.1. Model based features/characteristics*

Features like Open Circuit Voltage, Impedance, Diffusion Capacitance and Polarization time can indeed provide a very good insight about the State of Health of the battery using just some empirical equations. Even though they are quite efficient, still these features are not widely used in practical applications to estimate State of Health (SoH). The reason behind this is the requirement of complex physics based models for acquisition of these

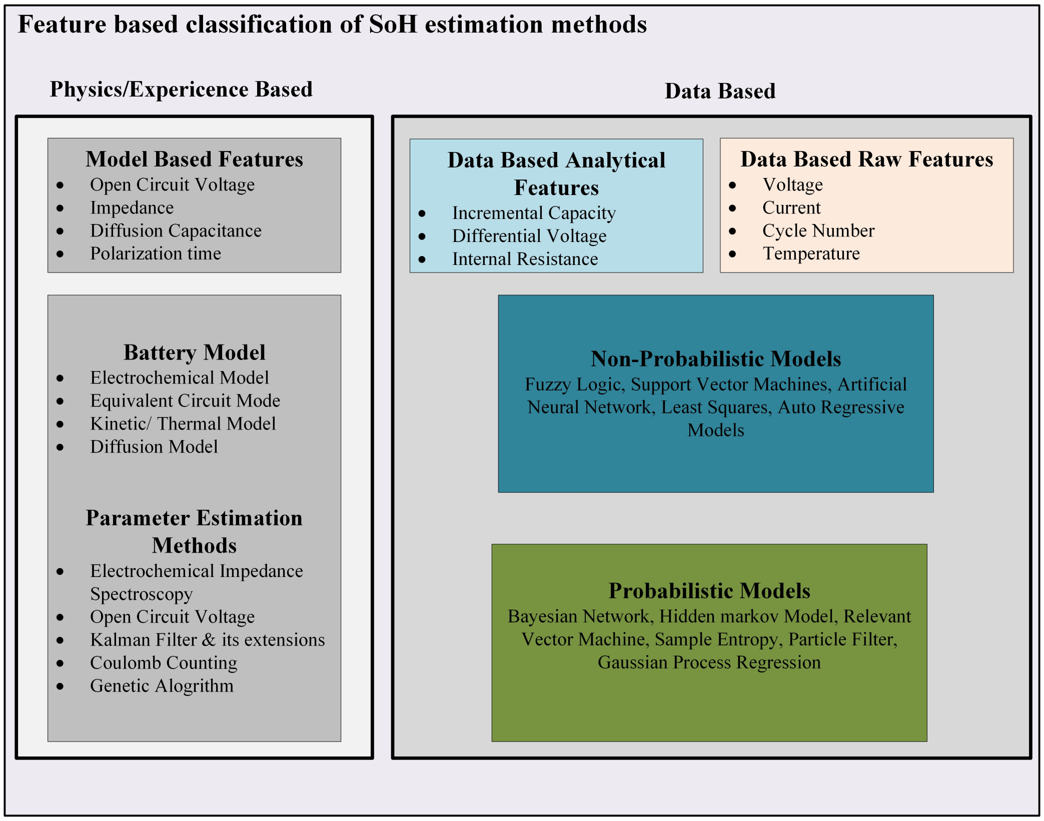


Figure 1: Feature based classification of SoH estimation methods

features. These models, namely Electrical Circuit model, Electrochemical model, Kinetic /thermal model or Diffusion model, consider physical, chemical, electrical or thermal phenomena in batteries. The parameters of these models are learned through experiments on degradation behavior or laboratorial data acquisition which is an arduous process and poses a substantial amount of complexity. Also, what adds more difficulty is that the model is not generic and tends to be different for different types of batteries.

Figure 2 delineates the models in use for obtaining different mapping features and algorithms required for correlating these features with State of

Health. A basic framework for utilizing model based feature is illustrated in Figure 3. Model selection requires an expertise in particular domain and also depends on the choice of feature. For instance, if we want to use Impedance as a feature, then a better understanding of Electrochemical modeling of battery will be needed. Further, the parameters of chosen model has to be estimated, which relies on historical data or laboratorial experiments. Once, the model has been updated, empirical correlation is established to keep track of State of Health.

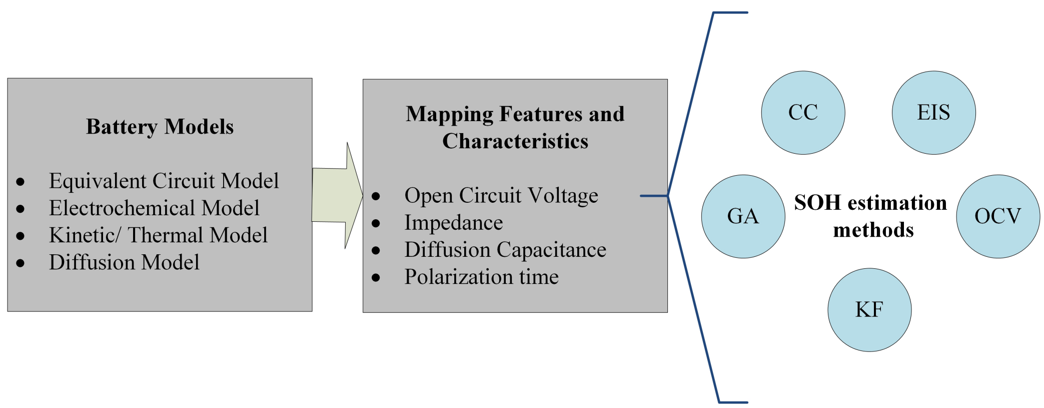


Figure 2: SoH estimation methods for features which are retrieved from Physics based battery models. The abbreviated terms for the techniques are Coulomb Counting (CC), Electrochemical Impedance Spectroscopy (EIS), Open Circuit Voltage (OCV), Kalman Filter and its extensions (KF) and Genetic Algorithm (GA).

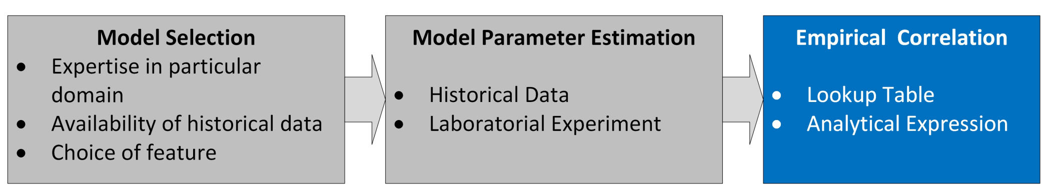


Figure 3: A framework for using Model extracted features for SoH estimation

The SoH estimation algorithms or methods stated in Figure 2 are described below.

### 2.1.1. *Electrochemical Impedance Spectroscopy (EIS)*

Electrochemical Impedance Spectroscopy gives a non-destructive measurement of a battery's internal impedance over a large spectrum of frequencies at low currents. Since, battery impedance increases with ageing and different battery dynamics affect different frequency ranges on the EIS measurement, impedance spectroscopy can be used to monitor the State of Health (SoH) of the battery.

However, to use impedance spectroscopy as a diagnostic tool, there will be a need for an electrochemical model of a battery, which tends to be unique for every battery. Thus, it is quite infeasible to use EIS for SoH estimation because of the cost and complexity of on board implementation. In fact, this method is efficient for laboratory experiments.

### 2.1.2. *Open Circuit Voltage (OCV)*

When a battery is charged or discharged, its voltage generally increases or decreases, respectively. For a battery with higher capacity, the discharging or charging leads to a lower voltage change as compared to the battery with lower capacity. Thus, this relation between ampere hours charged or discharged from the battery and the difference in voltage before and after the respective charging and discharging can be used for capacity estimation. However, laboratorial experiments are needed to model a relationship between SoH and OCV. Also, a very accurate battery model with parameters adaptable to ageing state is required for an efficient OCV estimation from the battery voltage measured under the load.

### *2.1.3. Kalman filter and its Extensions (KF)*

Kalman filter uses a series of measurements taken over time, and estimate the output variable that tends to be more precise. The main assumption in Kalman filtering is that the measuring noise and process noise are Gaussian, independent of each other, and have a mean of zero. It is a two-step method.

- Prediction Phase: Kalman filter estimates the current output variable.
- Updating Phase: Kalman filter updates the estimated state variables by minimizing the difference between estimated and observed state variables.

However to use Kalman filter, the degradation model of system should be available. The Kalman filter was initially intended for the use in linear systems. In case of batteries, the degradation model is complex enough and so non-linear. For nonlinear systems, such as those used for the battery State of Health (SoH) estimation, an extended versions of the Kalman filter can be used.

The Extended Kalman filter (EKF) uses the expansion of the Taylor series with the function of predicting and updating estimates of current state variables. Also, when KF is applied to linear systems it can be analytically shown that the resulting state estimator is stable. However, EKF is a heuristic extension of KF, stability cannot be analyzed. Still, EKF is widely used for developing model using State of Charge (SoC) as internal state of non-linear model.

Unscented Kalman filter adapts perfectly to the non-linearity of the battery cell characteristics. It uses a series observed over time in order to obtain the most accurate result. Also, it estimates the result from different unknown variable than those based on single measurement to make it more precise. However, too much computational effort makes it difficult to implement in real life applications.

### *2.1.4. Coulomb Counting (CC)*

It is a book-keeping method where the charge transferred through the battery during full charge-discharge process is counted by monitoring the input and output current continuously. Thus, the transferred amount of ampere hours are tracked and consequently the remaining capacity is known.

Since, this method continuously needs to keep track of the charge transfer, it is a time consuming process and requires a high storage capacity. Also, if the initial value of ampere hour is given wrong, then all estimation tends to be incorrect. So, frequent calibration are often needed to prevent accumulated errors in charge integration. Thus even though, Coulomb Counting is a simple method, but it usually needs another methods in order to update the parameter and eliminate possible errors.

### *2.1.5. Genetic Algorithm (GA)*

Often Genetic Algorithm is used to estimate the parameters of the non-linear model in all domains of physics. GA can also work as a good prediction algorithm if BMS raw data, like the voltage, is used as a feature. However, it uses a huge amount of data to learn parameter values and is difficult to implement online because of high computational power.

write few lines about genetic algorithm

### *2.2. Data driven Analytical Features*

Features like Incremental Capacity (IC), Differential Voltage (DV) or Internal Resistance (IR) are analytically derived from partial or full charging/discharging cycle data of Lithium (Li)- ion battery. It not only captures some physics about degradation but also eliminates the needs of physical models for acquisition of these features. These features can be correlated to State of Health (SoH) using large number of probabilistic and non-probabilistic algorithms. These features work quite well with online implementation of SoH, considering there will always be a trade-off between algorithm efficiency and computational complexity.

Figure 4 describes the probabilistic and non-probabilistic models that can be used for correlating the mapping features or characteristics with State of Health. Majorly used analytical features are Incremental Capacity (IC), Differential Voltage (DV) and Internal Resistance (IR).

A basic framework for utilizing Incremental Capacity [19] as analytical feature is illustrated in Figure 5. Full or partial cycle data is acquired from battery through Battery Management System (BMS). This database is then pre-processed for eliminating unnecessary measurement noise. Further, Analytical extraction of Incremental Capacity peaks are done which can be correlated to State of Health using the probabilistic and non-probabilistic algorithms illustrated in Figure 4.

The algorithms or models for correlating analytical features to State of Health are mentioned below.

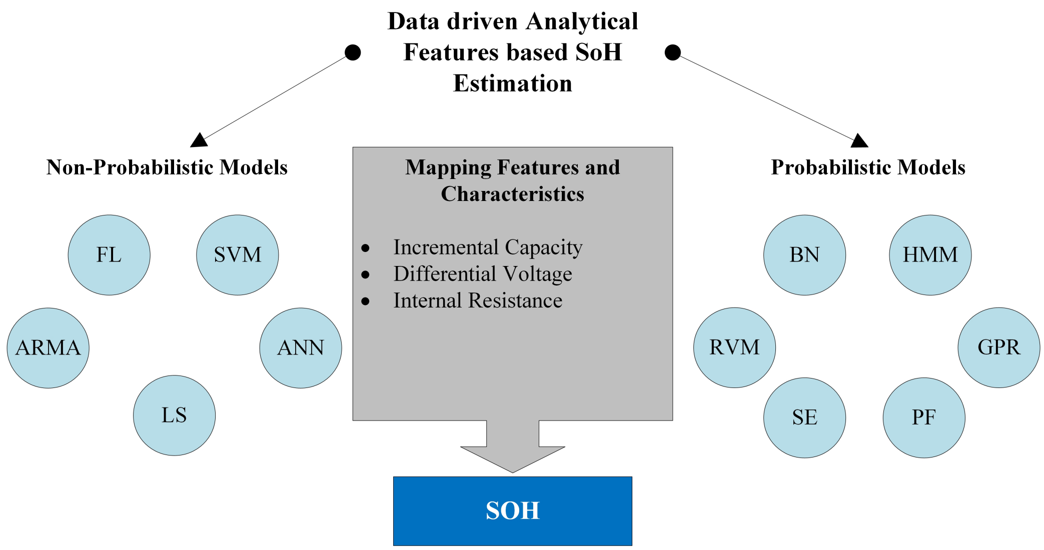


Figure 4: Data driven probabilistic and non probabilistic algorithms for analytically derived features to estimate State-of-Health (SoH). Probabilistic models gives the measure of uncertainty in prediction while non probabilistic models can be used to get definite result. The abbreviated terms for the techniques are Fuzzy Logic (FL), Support Vector Machine (SVM), Auto regressive Model (ARMA), Least Square (LS), Artificial Neural Network (ANN), Bayesian Network (BN), Hidden Markov Model (HMM), Gaussian Process Regression (GPR), Particle Filter (PF), Sample Entropy (SE) and Relevance Vector Machine (RVM)

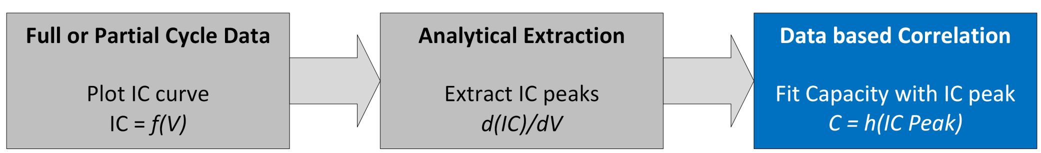


Figure 5: Illustration of data driven analytical feature based State of Health (SoH) modeling: A framework for using Incremental Capacity Analysis (ICA) to predict SoH.

### *2.2.1. Non probabilistic Models*

The non probabilistic models mentioned in figure 4 for correlating analytical features to State of Health are mentioned in this section.

#### *2.2.1.1. Fuzzy Logic (FL)*

Fuzzy logic uses a set of fuzzy rules for processing data measured from complex, non-linear systems. Then, the data must be divided into fuzzy subsets. The subsets are then categorized according to the associated uncertainties. The members of the fuzzy sets belong to a membership function, which determines the accuracy of State of Health (SoH) estimation. To apply FL, it is not needed to understand the system process and equations. However, it allows expressing a complex system using a higher level of abstraction which comes from experimental tests and real applications. Being a purely data driven method, this method possess a higher accuracy but requires higher amount of computation.

#### *2.2.1.2. Support Vector Machines (SVM)*

Support Vector Machine analyzes data and helps in recognizing patterns for non-linear systems. The SVMs have been widely used for classification problems in various domains of pattern recognition. Besides, the SVM can also be applied to regression problems. The SVM used for regression as a non-linear estimator is normally more robust than a least-squares estimator because it is insensitive to small changes. SVM is widely used because of its capability of handling small training data-sets. However, when the size of training data-set increases, the number of support vectors increase accordingly, which leads to a rise in computation cost.

#### *2.2.1.3. Autoregressive Model (ARMA)*

Autoregressive Model is a regression based model which is generally used to understand the underlying pattern of a system from time series data and predicting the near future values. The accuracy of an AR Model relies on completeness of the historical data used in training. In practical applications, usually the historical data is incomplete and so recursive model training and updating is required to make a reasonable estimation and future prediction. The AR model has the advantages of easy parameterization and low computational complexity.

However, the AR model is linear while the battery capacity fading process is often nonlinear, which leads to an under fitted model. To solve this problem, an Autoregressive Integrated Moving Average (ARIMA) framework can be used that combines the AR model and the moving average method. Instead of using past values of the forecast variable in a regression, the moving average uses the past forecast errors in a regression-like model.

#### *2.2.1.4. Artificial Neural Network (ANN)*

Artificial Neural Network (ANN) is composed of multiple processing units called neurons, which are located in multiple layers. Just like human brain, the ANN needs to learn. It uses weights and biases on each neuron for learning. To increase the accuracy, ANN needs to have more neurons, which limits it implementation on real life models. In addition, each ANN needs to be trained before it can be used; numerous cycles may be required to train it. For that reason, the trained ANN can be used for only one specific application. This makes it a little difficult to use it for predicting State of Health (SoH) of batteries with dynamic degradation.

#### *2.2.1.5. Least Square method (LS)*

The Least Square method is a statistical procedure to find the best fit for a set of data points by minimizing the sum of the offsets or residuals of points from the plotted curve. It is normally expressed in the form of regression analysis. In the past, Least Square Method has been used to study the degradation parameters of Lithium (Li) - ion battery. It has also been used to estimate the electrical model parameters of battery. Apart from model parameter learning, LS can also be used as a purely data driven method to predict capacity degradation.

### *2.2.2. Probabilistic Models*

The probabilistic models mentioned in Figure 4 for correlating analytical features to State of Health are mentioned in this section. To consider an uncertainty while estimating the State of Health of Li-ion batteries, it is recommended to use probabilistic models.

#### *2.2.2.1. Bayesian Network (BN)*

A Bayesian model calculates the probabilities of an observation belonging to a particular class according to the Bayes theorem, by assuming that each predictor is conditionally independent of every other predictor. It is well-known for its competitive performance in practical applications. Its strengths include its simplicity, efficiency, and robustness to noise and missing data. It also permits the use of more than two classes.

It manages uncertainty and complexity to regression and classification in from of Relevance Vector Machine and in State estimation through Particle Filter.

#### *2.2.2.2. Hidden Markov Model (HMM)*

The Hidden Markov Model is a dual stochastic model, which takes care of randomness in observed sequence (acquired from monitored signals) and also in the sequence of hidden states of health of the product. It is also a purely data driven method which makes it a strong tool for practical application. Given the complicated configuration parameters for battery simulation models and the accuracy of HMM in estimating results, several studies in the past has proposed methods of battery life state estimation through an HMM.

*2.2.2.3. Gaussian Process Regression (GPR)*

The Gaussian Process Regression method has been applied in many fields because of the advantages of being non-parametric and probabilistic. It is applicable to complex regression problems such as high dimension, small sample and non linearity. Compared to neural networks and SVM, GPR has the advantages of easy application. Also, since, GPR is built in the Bayesian framework, it not only evaluate the battery capacity loss but can also express the uncertainty of estimated results using the confidence interval with upper and lower bounds. Thus, it can be helpful in decision making. Since the battery ageing is a complex and nonlinear process, GPR can be applied for SoH estimation of lithium-ion batteries.

*2.2.2.4. Relevance Vector Machine (RVM)*

The Relevance Vector Machine is a Bayesian theory based data-driven algorithm used to estimate a battery Remaining Useful Life (RUL) due to its sparse feature and uncertainty management capability. However, some of the regressive cases indicate that the RVM can obtain a better short-term prediction performance rather than long-term prediction. Also, the RVM can be simply influenced by the noise with the training data.

#### *2.2.2.5. Sample Entropy (SE)*

Sample entropy is an efficient method for monitoring the variation and complexity of voltage response of battery during ageing and therefore it is considered as one of the diagnostic tools for monitoring the battery capacity. While measuring the consistency in a data sequence, It can also analyze the probability of time series, thus it can be used as an indicator to predict the battery health performance. To get better and more accurate results, Sample entropy should be combined with some machine learning method where it is employed as the input data feature and the State of Health (usually capacity) is the target vector of learning algorithm.

#### *2.2.2.6. Particle Filter (PF)*

Particle Filters are classified under non-linear filters which combine Bayesian learning techniques and sampling to provide good state tracking performance while keeping the computational load under control. It is classified as a sequential Monte Carlo method, which estimates the state Probability Distribution Function (PDF) from a set of particles and the associated weights. The use of weight, helps in adjusting the state PDF to its most likely form. However, for particle filter, the amount of defined samples imposes and important effect on calculation speed and accuracy. So, huge amount of samples are required for practical application. Also, accuracy of particle filter based model could be easily affected by variable current and temperature.

### *2.3. Battery Management System based raw features*

Features like Voltage, Current, Temperature, Cycle number and Charging time can also be used to establish a correlation with state of health of Li-ion batteries. These features are normally acquired by battery management system in all batteries and hence easy to collect. Since, these raw signals are expected to have noise, some kind of filtering is needed to attenuate the measurement noise. All the algorithms for analytical features (probabilistic and non probabilistic) which were discussed in previous subsection 2.2 can also be used for these features to set up a correlation between features and the State of Health.

A basic framework for utilizing battery management system based raw feature is illustrated in Figure 6. Full or partial cycle data like voltage, current or cycle number is acquired from battery through Battery Management System (BMS). This database is then pre-processed for eliminating unnecessary measurement noise, using efficient filtering techniques and followed by extraction of statistical features. These features are then directly correlated to State of Health using the probabilistic & non-probabilistic algorithms discussed in Section 2.2. Battery management system based raw features can be interesting for the readers from the domain of informatics who does not have a detailed understanding of degradation mechanism of Li-ion battery.

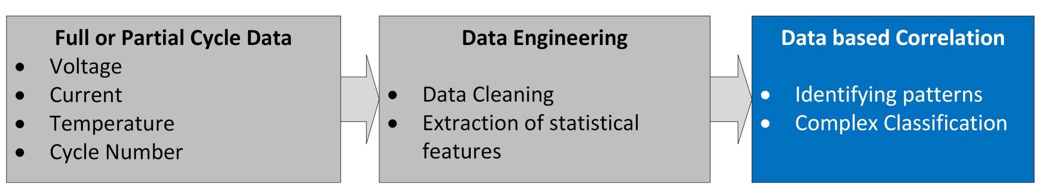


Figure 6: A framework for using battery management system based raw features to predict State of Health (SoH).

To summarize this section, we illustrate Table 1 below which depicts advantages and disadvantages of utilizing different State of Health (SoH) estimation category.

Table 1: Summary of State of Health (SoH) estimation category.

| **SoH estimation category** | **Advantages** | **Disadvantages** |
|---|---|---|
| Model based features for SoH estimation | • Very efficient for laboratorial analysis of battery.<br>• Easy to implement for offline application.<br>• Dynamic performance of battery can be taken care of. | • Identification of model parameters are computationally expensive for online applications.<br>• Self-updating of model parameters are difficult.<br>• Cannot measure uncertainty in prediction.<br>• Expertise in physical domain is necessary.<br>• Destructive methods will damage the battery permanently. |
| Data based analytical features for SoH estimation | • Small number of input features are required for model training.<br>• Low computational effort.<br>• Vast set of algorithms can be used.<br>• Understanding of battery physics can be avoided.<br>• Can consider uncertainty in prediction. | • Some of the features can be hard to obtain during operation due to limited capability of BMS.<br>• Either Charging or discharging condition should be uniform.<br>• Requires efficient filtering, as analytical derivation of features amplifies the measurement noise.<br>• Complexity in algorithm increases while considering dynamic operating condition. |
| Battery Management System based raw features for SoH estimation | • Suitable for online application.<br>• Data is easy to obtain.<br>• Understanding of battery physics is not required.<br>• Can consider uncertainty in prediction.<br>• Less pretest required. | • Correlation between the feature and SOH requires higher computational load and so the cost increases.<br>•Estimation accuracy is highly sensitive to quality and quantity of training data.<br>• High requirement on efficiency and portability of algorithm. |

Table 2 provides a comprehensive list of relevant papers which are dedicated to State of Health estimation of Lithium ion batteries. We have categorized these papers according to the classification provided by us in this review.

Table 2: List of relevant papers for SoH estimation

| Sl. No | Corresponding Author | Algorithms / Methods Used | Mode of Operation | Category |
|---|---|---|---|---|
| [20] | Pinfeng Wang | Artificial Neural Network & Dual Extended Kalman Filter | Offline / Online | Raw data based features |
| [21] | Yi-Jun He | Artificial Neural Network & Equivalent Circuit Model | Offline | Model based features |
| [22] | Seungchul Lee | Artificial Neural Network | Offline | Analytical features based |
| [23] | Kong Soon Ng | Coulomb counting | Offline | Model based features |
| [24] | Markus Einhorn | Coulomb counting | Online | Model based features |
| [25] | Chao Hu | Coulomb counting & K means & Particle Swarm Optimization | Offline / Online | Analytical features based |
| [26] | Xidong Tang | Equivalent Circuit Model | Online | Model based features |
| [27] | Jingwen Wei | Particle Filter & Support vector regression | Online | Analytical features based |
| [28] | Verena Klass | Support Vector Machines | Online | Raw data based features |
| [29] | K. S. Hariharan | Support Vector Machines | Offline / Online | Raw data based features |
| [30] | Adnan Nuhic | Support Vector Machines | Online | Raw data based features |
| [31] | Min Zhu | Grey Markov Chain | Online | Analytical features based |
| [32] | Gang Yu | Hidden Markov Model | Offline / Online | Raw features based |
| [33] | Sheng Lu | Hidden Markov Model | Offline / Online | Raw data based features |
| [34] | Xiaosong Hu | Sample Entropy & Least squares optimization | Offline / Online | Raw data based features |
| [35] | Chao Lyu | Sample Entropy & Particle Filter | Offline / Online | Analytical features based |
| [36] | Yuan Zou | Kalman Filter & Recursive Least square & Equivalent Circuit Model | Offline | Model based features |
| [37] | Bing Long | Autoregressive Model & Particle Swarm Optimization | Offline / Online | Analytical features based |
| [38] | Yapeng Zhou | Autoregressive integrated moving average (ARIMA) model | Offline / Online | Analytical features based |
| [39] | Zheng Chen | Autoregressive moving average model & Elman Neural network | Offline | Analytical features based |
| [40] | Selina S.Y. Ng | Naive Bayesian model | Online | Analytical features based |
| [41] | Mingyu Gao | Dynamic bayesian Network | Online | Analytical features based |
| [42] | Chao Hu | Sparse bayesian learning & Relevance Vector Machine | Online | Analytical features based |
| [43] | Bhaskar Saha | Relevance Vector Machine & Particle Filter | Online | Analytical features based |

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**Table 2 – continued from previous page**

| Sl. No | Corresponding Author | Algorithms / Methods Used | Mode of Operation | Category |
|---|---|---|---|---|
| [44] | Yapeng Zhou | Relevance Vector Machine | Online | Analytical features based |
| [45] | Qiang Miao | Relevance Vector Machine | Online | Analytical features based |
| [46] | Baojin Wang | Electrochemistry based Impedance model | Offline | Model based features |
| [47] | A. Eddahech | Electrochemical Impedance Spectroscopy | Offline | Model based features |
| [48] | Akram Eddahech | Electrochemical Impedance Spectroscopy & Neural Network | Offline / Online | Model based features |
| [49] | Matteo Galeotti | Electrochemical Impedance spectroscopy | Offline | Model based features |
| [50] | Alvin J. Salkind | Fuzzy Logic | Online | Analytical features based |
| [51] | Pritpal Singh | Fuzzy Logic & Electrochemical Impedance Spectroscopy | Offline / Online | Analytical features based |
| [52] | Ali Zenati | Fuzzy Logic | Online | Analytical features based |
| [53] | Haiyang Yu | Genetic Re sampling Particle Filter | Offline / Online | Model based features |
| [54] | Minggao Ouyang | Genetic Algorithm | Offline | Analytical features based |
| [55] | Chunting Chris Mi | Genetic Algorithm | Online | Analytical features based |
| [56] | Zonghai Chen | Gaussian Process Regression | Offline / Online | Analytical features based |
| [57] | Lei Zhang | Gaussian Process regression & Genetic Algorithm | Offline / Online | Analytical features based |
| [58] | Yi Jun He | Multiscale Gaussian Process Regression | Online | Analytical features based |
| [59] | Datong Liu | Gaussian Process Functional Regression | Online | Analytical features based |
| [60] | Dave Andre | Dual Kalman Filter & Support Vector Machines | Offline / Online | Model based Approach |
| [61] | Dai Haifeng | Kalman Filter & Open Circuit Voltage | Offline | Model based features |
| [62] | Taesic Kim | Recursive Least square | Online | Model based features |
| [63] | Qiang Miao | Unscented Particle Filter | Offline / Online | Analytical features based |
| [64] | Githin K. Prasad | Recursive Least square | Offline | Model based features |
| [65] | Zonghai Chen | Particle Swarm Optimization & Genetic Algorithm | Offline / Online | Raw data based features |
| [66] | Taesic Kim | Recursive Least square | Online | Model based features |
| [67] | Simon Schwunk | Particle Filter | Offline / Online | Model based features |
| [68] | Hancheng Dong | Particle Filter & Support Vector Regression | Offline / Online | Model based features |

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**Table 2 – continued from previous page**

| Sl. No | Corresponding Author | Algorithms / Methods Used | Mode of Operation | Category |
|---|---|---|---|---|
| [69] | M.F. Samadi | Particle Filter & Electrochemical Model | Offline | Model based features |
| [70] | Yi-Hsien Chiang | Equivalent Circuit Model & Open Circuit Voltage | Online | Model based features |
| [71] | Caihao Weng | Open Circuit Voltage model | Offline | Model based features |
| [72] | Lingjun Song | Artificial Neural Network | Online | Raw data based features |
| [73] | M. Maures | Linear Regression | Offline | Analytical features based |
| [74] | Xing Shu | Least square | Online | Raw data based features |
| [75] | Daniel-Ioan Stroe | Linear Regression | Offline | Analytical features based |
| [76] | Zhongbao Wei | Linear Regression | Offline | Analytical features based |
| [77] | Bin Gou | Non linear autoregressive structure | Online | Analytical features based |
| [78] | Jianfang Jia | Gaussian Process Regression | Online | Analytical features based |
| [79] | Hao Ji | Monte carlo simulation | Online / Offline | Analytical features based |
| [80] | Kirandeep Kaur | Deep learning algorithm | Online / Offline | Raw data based feature |
| [81] | Shunli Wang | Kalman filter | Online / Offline | Model based features |

## 3. Challenges in State of Health estimation for Li-ion batteries

The performance of battery degrades over time because of various intertwined factors which makes the study of degradation mechanism quite complex. The complex degradation mechanism and sensitivity to the operating condition is still a barrier while estimating SoH of the battery [82]. In addition to this, there are other factors like technical heterogeneity (the availability of same kind of products manufactured by different companies in the market), which makes the prediction difficult.

In this section , we will discuss these challenges in brief. The challenges while predicting SoH of the Lithium (Li) - ion battery can be classified into internal and external challenges.

### *3.1. Internal Challenges*

The challenges posed due to the internal structure of the lithium ion battery has been stated as internal challenges. These are the challenges pertaining to the different kind of materials used while manufacturing the batteries.

#### *3.1.1. Complex degradation mechanism*

The degradation mechanism of Lithium(Li) - ion battery is a very complex phenomena which often manifests itself by loss in capacity and power fade. The reason behind this complexity is the nature of interdependence of various internal and external causes that leads to this degradation [17]. The measurable effects of these degradation mechanisms on the battery can be concise in the form three degradation modes, namely loss of lithium inventory, loss of active positive electrode material and loss of active negative electrode material. Each of these degradation modes are assumed to have unique and measurable effects on the health of Li-ion cells. The presumptive nature and extent of these effects is often based on logical arguments rather than experimental proof. This make the study of degradation mechanism and consequently the estimation of state of health challenging.

#### *3.1.2. Technical heterogeneity*

In the $21^{st}$ century, we are already seeing a virtuous circle of Industrial development: creating income, diversifying demand and massifying consumption. This has led to a sudden increase in the industries working on the same kind of product. There are several companies who, manufacture Lithium (Li)-ion batteries of similar kind but uses different sub products or raw materials. Thus, even though the chemical composition of a same kind of Li-ion battery is same, these batteries are structurally and physically different. This leads to aberration in the degradation patterns of Li-ion batteries manufactured by different companies. A single estimation model to estimate State of Health (SoH) with such robustness is quite incomprehensible.

### *3.2. External Challenges*

The challenges posed by external environmental factors in estimating State of Health (SoH) has been stated as external challenges. The physical environment, where the vehicle is being used and the user's behavior (driving pattern, frequency of driving) adds heterogeneity to the degradation mechanism of Li-ion batteries consequently limiting the robustness during SoH prediction.

#### *3.2.1. Dynamic Operating condition*

Environmental factors mainly temperature and humidity significantly impacts on the performance of Lithium (Li)-ion batteries and also limits the application of Li-ion batteries. The increase in the operating temperature increases the degradation rates of all components in the Lithium ion battery which include maximum charge storage capacity and the effectiveness of the electrode in storing Li-ions. Moreover, different operating conditions result in different adverse effects. Modeling a physics based or data based method which works accurately in a wide range of temperature has been a major concern among the battery health prognostics domain.

#### 3.2.2. Varied Driving Pattern

In case of an Electric Vehicle (EV), the battery load profiles largely differ from the standard laboratory test procedures, which typically apply constant currents for discharging. Due to the acceleration and deceleration of the vehicle, the battery load is highly dynamic and also, driving is not a pure discharging process because regenerative braking leads to recurring recharging periods. To have a more global classification, driving patterns can be classified according to different geographical region. However, inclusion of these driving patterns for different geographical region will further increase the computational complexity of the estimation model, and so, indeed it is very challenging.

## 4. Choosing an efficient SoH estimation methodology in the context of Circular economy

In the context of Circular economy, since the estimation result is being used for decision making, it is recommended to consider some extent of uncertainty in the prediction. Having an overly complex degradation mechanism and high sensitivity to the operating conditions, every battery degrades differently. Often, model-based estimation considers a better understanding of the physics of degradation while estimating SoH. Nevertheless, as stated before in section 3.1.1, these degradation mechanisms are complex and depend on numerous intertwined factors. So, having such extensive robustness to estimate SoH accurately for different batteries in real-time is quite difficult to attain using this kind of models. On the other hand, data-based methods, which eliminates the need for understanding the physics of degradation, can be a better choice of estimation tool. Even though it does not gives too much comprehension about degradation physics, it can estimate SoH quite accurately. Also, it is more convenient to implement data-driven methods in real-time.

A major problem with the existing data-driven models is that modeling battery degradation is based on the data, which was collected at a constant discharge rate and a constant ambient temperature. In practice, as explained in section 3.2, the battery is operated in a varying operational condition imbibing many uncertainties. These uncertainties will make these models under-performing. So, models have to be created for different operating conditions. Also, to make a more robust model, it is important to apply realistic load patterns which deal with the driving patterns of different geographical region. In short, an efficient SoH estimation method that can suffice the need for indicators for decision making in Circular economy should be robust, data-driven, probabilistic and real-time feasible. In addition to this, it is recommended to use analytical features instead of raw features, since it makes the computational load little lesser. To set up a prognostics health management system for Li-ion battery, following things has to be taken care of

- Choosing an appropriate feature.
- Selecting the most efficient correlation algorithm.
- Model learning and model database creation.
- Model selection and diagnosis.

- Prognostics to estimate the remaining useful life.

Concerning capacity fade, features like Incremental capacity can be taken into use for estimating SoH. Let us say; the electric vehicles are operated in X different geographical region. Since the dynamic operating condition varies differently in a different geographical region, so, a model for every distinct geographical region should be created. Model learning will be done using a sufficient amount of data from the batteries with known state of health for every region. As illustrated in Figure.7 , full or partial cycle data is acquired from the battery through the Battery Management System (BMS). This database is then pre-processed for eliminating unnecessary measurement noise. Further, Analytical extraction of Incremental Capacity peaks should be done, which can be correlated to the State of Health using the probabilistic and non-probabilistic algorithms described in section 3.1. The choice of the algorithm should depend on the amount of data available for model training and of course, correlation efficiency.

When a battery is to be diagnosed, the best fit model from the model database should be identified first as illustrated in Fig. 8. The historical data from BMS of the to be diagnosed battery will be extracted, and Incremental Capacity is calculated for each cycle. It will be converted to a time series where cycle number represents the time stamp for the series. To choose the best fit model, this time series is compared to the Incremental capacity time series of each model from the database. The model which will emit minimum root means square error can be considered our best fit model denoted by $M_{best}$. The Incremental capacity of the current cycle( the cycle at which the battery is being diagnosed) represented by $IC_{cur}$ will then be used as input

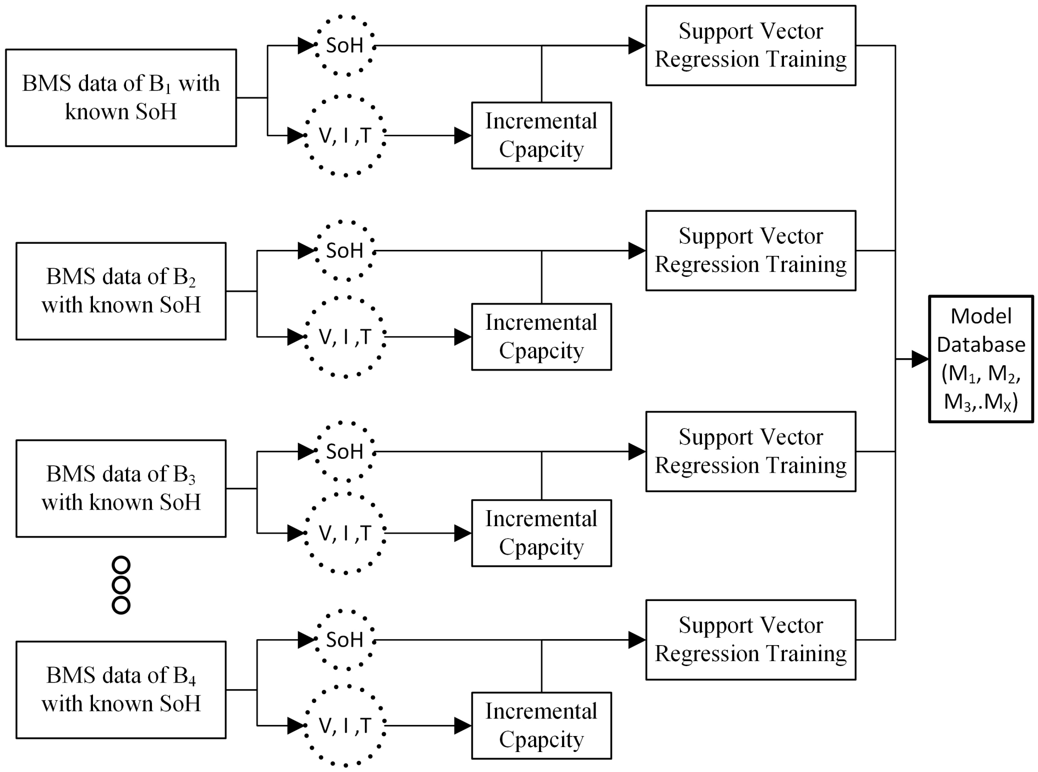


Figure 7: Model database creation.

to $M_{best}$ for estimating Current SoH.

For prognosis, we first do a time series forecasting of the future values of Incremental capacity series. Further, we use the same $M_{best}$ model to predict the future SoH of the battery and so the RUL. Similarly, for power fade, features like Internal resistance can be used for estimating SoH. Internal resistance can be measured by the non-destructive method of Electrochemical impedance spectroscopy and the values for every cycle can be stored in BMS. The diagnosis and prognosis are made in the same ways as it will be done for capacity based SoH. Once SoH is known, the choice of second life application can be anticipated beforehand. The reason being, capacity and power

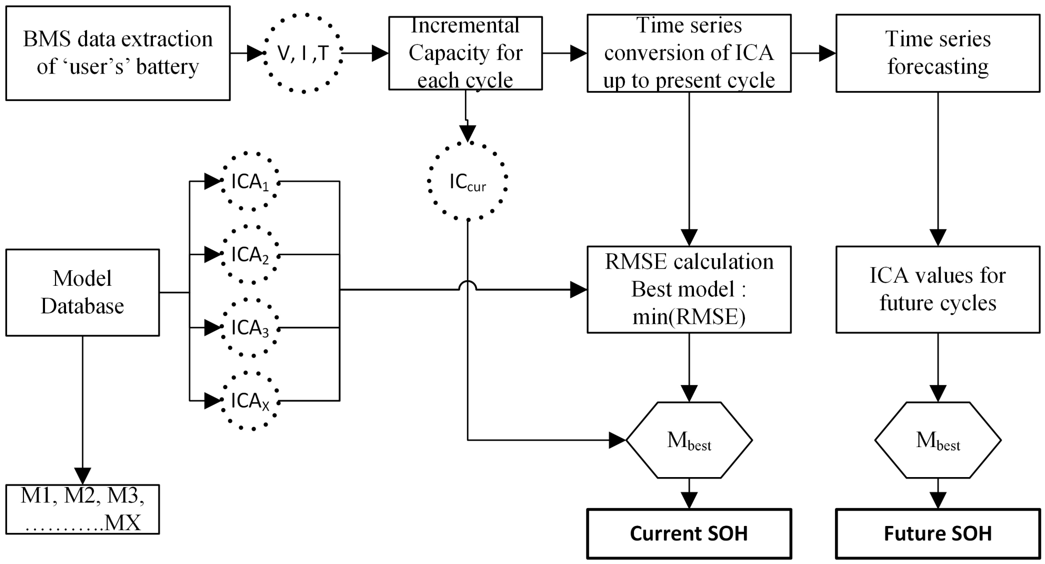


Figure 8: Model selection and PHM system set up.

requirements are the major indicators for choosing second life application. Apart from these two indicators, indicators like battery size, weight, and other aesthetical aspects would also be considered during decision making.

## 5. Conclusion

Accurate estimation of the SoH of Li-ion batteries is imperative for decision making in the context of a circular economy. We systematically classified the existing SoH estimation methods into firm categories. Every SoH estimation method has its own drawbacks and possibilities for improvement. Model-based features are efficient for laboratorial analysis of battery and take care of the dynamic performance of the battery. Nevertheless, it fails to measure uncertainty in prediction and lacks robustness. On the other hand, data-driven analytical features need low computational effort and can consider the uncertainty in prediction, but it required efficient filtering. The battery management system based raw features are suitable for online prediction, but it puts much computational load on the system. Comprehensively, it can be concluded that researchers from different domain should choose the estimation method based on their expertise in a particular field and the amount of data available.

The internal and external challenges in designing a Prognostics and Health Management system for the Electric vehicle batteries were discussed in detail. Setting up a prognostics health management system includes identifying appropriate feature and an efficient correlation algorithm. To cope up with the problem of dynamic operating condition and technical heterogeneity, we recommend creating a model database, consisting of estimation models for the different geographical region. Diagnosis of any battery is made after selecting the best model from the model database. Once SoH is known, the second life application of EV batteries can be anticipated beforehand. Besides, indicators like battery size, weight, and other aesthetic aspects should also be considered during decision making.

In future, the primal objective should be to develop an SoH estimation tool without constraints on chemistry variations. Ideally, an SoH estimation algorithm which can work for vehicles operated at a different place with the distinct environmental condition and driving pattern. Thus, intensive research based on realistic situations will give a new dimension toward great invention in battery research.

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