



HAL
open science

Evaluation of the State of the health of Li-ion batteries in the context of Circular Economy

Akash Basia

► **To cite this version:**

Akash Basia. Evaluation of the State of the health of Li-ion batteries in the context of Circular Economy. Automatic. Université Grenoble Alpes [2020-..], 2021. English. NNT : 2021GRALT075 . tel-03578114

HAL Id: tel-03578114

<https://theses.hal.science/tel-03578114>

Submitted on 17 Feb 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

THÈSE

Pour obtenir le grade de

DOCTEUR DE LA COMMUNAUTÉ UNIVERSITÉ GRENOBLE ALPES

Spécialité : **AUTOMATIQUE - PRODUCTIQUE**

Arrêtée ministériel : 25 mai 2016

Présentée par

Akash BASIA

Thèse dirigée par **Zineb Simeu-Abazi**
et codirigée par **Peggy Zwolinski et Eric Gascard**

préparée au sein du **Laboratoire G-SCOP**
dans **l'École Doctorale EEATS**

Evaluation of the State of the health of Li-ion batteries in the context of Circular Economy

Thèse soutenue publiquement le **17 novembre 2021**,
devant le jury composé de :

M. Nouredine Zerhouni

ENSMM, Besançon, Rapporteur

M. Benoit lung

Université de Lorraine, Rapporteur

Mme Maria Di Mascolo

CNRS, G-SCOP, Présidente

M. Kamal Medjaher

Ecole Nationale d'Ingénieurs de Tarbes, Examineur

Mme Zineb SIMEU ABAZI

Polytech'Grenoble - UGA, Directrice de thèse

Mme Peggy Zwolinski

Grenoble INP, Co-Directeur de thèse

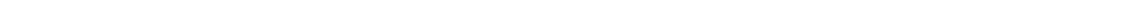
M. Eric Gascard

Polytech'Grenoble - UGA, Co-Encadrant de thèse





*"Dedicated to my parents, Deepak and Ranjana, who offered unconditional love and support, and
have always been there for me "*



Acknowledgment

This work is supported by the French National Research Agency in the framework of the "Investissements d'avenir program (ANR-15-IDEX-02) - Cross Disciplinary Program CIRCULAR"

It is a humbling experience to acknowledge those people who have, mostly out of kindness, helped along the journey of my PhD. I am indebted to so many for encouragement and support.

From the bottom of my heart I would like to say big thank you to my supervisors Prof. Zineb Simeu-Abazi, Prof. Peggy Zwolinski and Prof. Eric Gascard for their noble guidance, support with full encouragement and enthusiasm. They have supported me throughout this research project. I am extremely grateful for our friendly chats at the end of our meetings and your personal support in my academic and research endeavors.

I am extremely thankful to the whole CDP circular team for their insightful suggestions and contributions to the research project. I would like to recognize the invaluable assistance that Prof. Pierre Xavier-Thivel and his PhD. student Eddy Corron provided during my study. It is wholeheartedly appreciated that your great advice for my study proved monumental towards the success of this study.

I would like to show my gratitude to the whole G-SCOP laboratory team. It is their kind help and support that have made my study and life in the Grenoble a wonderful time. I am indebted to the administrative, human resources and informatics team of the G-SCOP lab for their assistance at every stage of the research project.

I would like to pay my special regards to Yohann Chatillon from Lancey Energy Storage for inviting me to the company for a short stint and our insightful discussion related to this research work.

To my many friends and family, you should know that your support and encouragement was worth more than I can express on paper. I would like to recognize the invaluable discussion and suggestion that my housemate Mohit provided during my study. Thank you everyone for being always there with a word of encouragement or listening ear.

Contents

Acknowledgment	i
Table of Contents	iii
Abstract	1
1 Introduction	3
1.1 Cross-disciplinary Circular Project	4
1.2 Context	5
1.3 Objective	6
1.4 Research Question	6
1.5 Thesis Outline	7
1.6 Related own publications	8
2 State of the Art	10
2.1 Prognostics Health Management	11
2.1.1 Introduction	11
2.1.2 Characteristics of PHM methods	12
2.1.2.1 Quick Prediction	12
2.1.2.2 Robustness	12
2.1.2.3 Confidence Estimation	12
2.1.2.4 Adaptability	13
2.1.2.5 Modeling and Computational complexity	13
2.1.2.6 Interpretation Clarity	13
2.1.2.7 Occurrence of Simultaneous Faults	13
2.1.3 Information and Data for PHM	13
2.1.4 Approaches to PHM	14
2.1.4.1 Reliability based PHM approach	15
2.1.4.2 Physics based PHM approach	15
2.1.4.3 Data based PHM approach	16
2.1.4.4 Fusion based PHM approach	18
2.1.5 Challenges	19
2.1.5.1 Uncertainty management	19
2.1.5.2 Validation and Verification	19
2.1.5.3 Prognostics standardization	19
2.1.5.4 Post Prognostics Reasoning	20
2.2 Lithium ion battery : Properties and Degradation	21
2.2.1 Introduction	21
2.2.2 Working Principle	22
2.2.3 Degradation mechanism	22
2.2.3.1 Chemical Degradation mechanism	23
2.2.3.2 Mechanical Degradation mechanism	23
2.2.4 Degradation modes	24

2.2.5	Effect of different parameters on cell aging	25
2.2.5.1	Effect of cycling rate and cycle number	25
2.2.5.2	Effect of Temperature	25
2.2.5.3	Effect of State of Charge	25
2.2.5.4	Effect of moisture	26
2.2.6	Li ion battery in EV : How to add sustainability to its life cycle	26
2.3	State of Health : A key indicator to decision making	28
2.3.1	SoH estimation	29
2.3.2	SOH estimation techniques and tools: State of art	29
2.3.2.1	Electrochemical Impedance Spectroscopy (EIS)	29
2.3.2.2	Open Circuit Voltage (OCV)	30
2.3.2.3	Kalman filter and its Extensions (KF)	30
2.3.2.4	Coulomb Counting (CC)	31
2.3.2.5	Genetic Algorithm (GA)	32
2.3.2.6	Fuzzy Logic (FL)	32
2.3.2.7	Support Vector Machines (SVM)	32
2.3.2.8	Autoregressive Model (ARMA)	33
2.3.2.9	Artificial Neural Network (ANN)	34
2.3.2.10	Least Square method (LS)	34
2.3.2.11	Bayesian Network (BN)	35
2.3.2.12	Hidden Markov Model (HMM)	35
2.3.2.13	Gaussian Process Regression (GPR)	36
2.3.2.14	Relevance Vector Machine (RVM)	36
2.3.2.15	Sample Entropy (SE)	37
2.3.2.16	Particle Filter (PF)	37
2.3.3	Challenges in SoH estimation	40
2.3.3.1	Internal Challenges	40
2.3.3.2	External Challenges	41
3	SoH as an indicator for Circular economy	43
3.1	Introduction	44
3.2	Global State of Health	45
3.3	Classification of SoH estimation methods	46
3.3.1	Model based features/characteristics	46
3.3.2	Data based Analytical Features	47
3.3.3	Battery Management System based raw features	48
3.4	Proposition of efficient SoH estimation methodology in the context of Circular economy	49
3.5	Overcoming the Barriers in PHM system for the Circular System by Hidden Markov Model	51
3.5.1	Introduction to HMM	51
3.5.2	Proposed Methodology	52
4	SoH estimation for Li-ion batteries in the context of CE	57
4.1	Introduction	58
4.2	Data Acquisition : An introduction to Battery Management System	58
4.3	Feature selection for Diagnosis and Prognosis	59
4.3.1	Incremental Capacity Analysis	60
4.3.2	Regional Capacity: Formulation and Calculation	61
4.3.3	Electrochemical Impedance Spectroscopy	62
4.4	Creation of Model database	64

4.4.1	Support Vector Regression : Regional Capacity correlation	65
4.5	Model selection	66
4.6	Diagnosing the current SoH	67
4.7	Time series forecasting : Applied for prognosis	67
4.7.1	The Autoregressive Moving Average (ARMA) Models	68
4.7.2	The Autoregressive Integrated Moving Average (ARIMA) Models	68
4.7.2.1	Model identification	70
4.7.2.2	Model estimation	70
4.7.2.3	Diagnostic Checking	70
4.8	ARIMA based prognosis for Future SoH estimation	70
5	SVR-ARIMA based SoH estimation : A case study on NASA AMES prognosis data	73
5.1	NASA AMES prognosis data : Details and Exploration	74
5.2	Regional capacity estimation on the given data	77
5.3	SVR model database creation	81
5.4	Diagnosis and Prognosis for an unknown battery	83
5.4.1	ARIMA model selection	83
5.4.2	Forecasting future values using ARIMA	85
5.4.3	Forecasting SoH from model database	85
5.5	Internal Resistance Forecast using ARIMA	87
5.6	Comparison of different algorithms for correlation	91
5.6.1	Model database creation	91
5.6.2	Diagnosis for SoH estimation and RMSE comparison	91
5.6.3	Comparison Results	92
6	Framework for battery repurposing : Industrial Context	96
6.1	Introduction	97
6.2	Requirements for the development of battery repurposing ecosystem	98
6.3	Stakeholder interaction	99
6.4	Policies related to battery repurposing	100
6.5	Conceptual framework for battery repurposing	101
6.6	Possible landscape for integration of second life battery in Lancey's ecosystem	103
6.6.1	Business landscape: 1	103
6.6.2	Business landscape: 2	103
	General Conclusion	107
	Bibliography	I
	List of figures	XVIII
	List of Tables	XXII
	A Annexure 1 : List of Abbreviations	XXIV
	A Resume	XXVII
A.0.1	Projet « CIRCULAR » interdisciplinaire	XXVIII
A.0.2	Le contexte	XXIX
A.0.3	Objectif	XXX
A.0.4	Question de recherche	XXX

Table of Contents

A.0.5	Aperçu de la thèse	XXX
A.0.6	Conclusion	XXXI
A.0.7	Publications propres associées	XXXII

Abstract

Electric Vehicles (EV) have been one of the most encouraging ways to tackle the adverse environmental effect of hydrocarbon-based transport. Most of the EV use Li-ion batteries as their power source, owing to their high energy density. These batteries reach its End of Life (EoL) when the capacity degrades by just twenty percent of the original capacity. A reliable circular industrial system can be developed which should be able to transform post-used EV batteries into new added-value batteries for less demanding applications, thus prolonging their life and ensuring more sustainability. Predicting the reliability of a system in its actual life cycle conditions and estimating its time to failure(State of the health estimation) is helpful in decision making for the new value chain. But the technological heterogeneity of the Li-ion batteries, as well as the dynamics of change of operating conditions, accentuates the difficulty to establish Prognostics Health Management (PHM) system for the batteries. Also, very few researches talk about State of health with the perspective of re-purposing batteries.

The objective of this thesis is to bridge the knowledge gap of diagnostics and prognostics in the context of circular economy. The results identify a contextual definition of SoH and a novel classifications for different SoH estimation methods. The thesis also investigates the issues and challenges posed while estimating SoH for Li-ion battery, with possible solutions. Furthermore, in this thesis, the ultimate goal is to provide reliable sensor networks as well as information retrieval modules to develop as accurate as possible a diagnosis and a health prognosis method for lithium-ion batteries in the context of the Circular economy.

We proposed an Incremental Capacity (IC) curve based SoH estimation system for Li-ion batteries. The model employs a Kalman filter and a finite differencing method for measurement noise attenuation. A novel method that combines Support vector regression (SVR) and the Autoregressive Integrated Moving Average (ARIMA) model is utilized to model the relationship between IC and the SoH. A use case is created on the NASA AMES open-source battery data. The case study shows that the proposed model can obtain accurate SoH prediction results without needing the State of Charge information of the battery. Finally, a framework has been proposed for establishing a repurposing based business landscape by exploring the current repurposing trends across the world.

1

Introduction

Contents

1.1	Cross-disciplinary Circular Project	4
1.2	Context	5
1.3	Objective	6
1.4	Research Question	6
1.5	Thesis Outline	7
1.6	Related own publications	8

1.1 Cross-disciplinary Circular Project

Since the beginning of the 21st century, with the exponential increase in the global population, there has been an unprecedented need to transition towards a more resource-efficient society to have a sustainable future. This has become the primary goal of governments in the European Union. The industries have to face and adapt to the primary industry of the future challenges like resource scarcity, efficient and green energy sources, customization expectations etc. Concerning this, in 2015, the European Commission adopted its first circular economy action plan. It included measures to help stimulate Europe's transition towards a circular economy, boost global competitiveness, foster sustainable economic growth and generate new jobs. To advocate the above-said shift, the Circular project began in 2017 aimed at developing reliable circular industrial systems able to transform post-used products into new added-value products.

The CDP circular is a cross-disciplinary research project which combines the skills from different domains like Industrial engineering, computer science, sustainability, management, social science and economics to design an agile circular industrial system and tackle the scientific challenges addressed by the Industry of the Future. The project's primary goal is to give the companies the ability to satisfy the requirements for transition to a circular industrial system mainly to produce high value-added products and minimize material and energy resources. The challenge was to advocate the transition towards the "take-make-consume-reuse" model instead of a classical linear "take-make-consume-dispose" model. The project is focused on batteries for electric vehicles that can be reused or repurposed after the first end of life on mobile and stationary equipment by redesigning and re-manufacturing. The project's assumptions for designing an industrial system to re-manufacture post-used products into new products were:

- The agility to the industrial systems can be provided only by an efficient and effective Human-Machine collaboration.
- There is a need to systematically redesign the industrial process and the environment to adapt to this transition.
- Specific incentives and industrial conditions are needed for the massive deployment of the reuse-oriented process.

Concerning these three hypotheses, three different work packages were deployed :

- WP1: Collaborative work for an agile re-manufacturing chain : This work package investigates the workers and their organisation as one of the key elements of the agility of the remanufacturing productive system: Human-Machine collaboration is at the core of the new working situations.
- WP2: Numerical solutions to fit agile re-manufacturing process : WP2 focuses on the numerical solutions that could help fitting the processes depending on the numerous variabilities. The agility of the productive system will be reinforced by the capacity to manage automatically regulations or reconfigurations on the operative process.
- WP3: Circularity condition and value chain : The WP3 focuses on strategies to develop for a wider adoption of industrial circular systems.

The WP1 has the following key objectives :

- define the new roles and competencies of the workers in a circular industrial system
- develop cobotic as a natural collaborative work cell
- develop diagnosis approaches to help workers deciding the product flow

Regarding the third objective, this thesis was created to develop a diagnosis and prognosis approach for li-ion batteries of EV to support decision making for second-life use of the batteries.

1.2 Context

Just within the first quarter of 21st century, the global population has crossed 7.5 billion and is expected to reach 10 billion by 2050. This substantial growth in population is leading to over-exploitation of resources and unprecedented levels of pollution. Ever-increasing demand to suffice the needs of more than seven billion people affects biodiversity, forests, wetlands, water bodies, soils, and air quality. The dilemma of a satiated present and a sustainable future has been putting pressure on the current take make waste extractive linear industrial model for an imperative change.

The environmental impact of hydrocarbon-based transport is evidently increasing, and consequently, it has become a significant contributor to global warming through the emission of Carbon dioxide. Within the transport sector, road transport leads as a contributor to global warming. EV has been one of the most encouraging ways to tackle hydrocarbon-based transport's adverse environmental effect. In regard to this, European commission has made Electrification of transport (electromobility, a priority in the Community Research Programme. Furthermore, the regulatory bodies have been constantly establishing policies to promote electric vehicle sales across the globe.

Thus, EVs are increasingly gaining market share, and companies historically embedded in the combustion-engine value chain are now experiencing a transformation of their traditional business model once a century. Although EV has no tailpipe emissions, its well-to-tank energy efficiency, coming from the electricity generation and distribution to charge the EV battery, is less performing than one of internal combustion engine vehicles. Most of the electric vehicles use Li-ion batteries as a power source because of its high energy density and low maintenance needs. These batteries are the primary contributor to the environmental impact and face recycling issues. Li-ion batteries are manufactured using exhaustible earth metals like lithium, nickel and cobalt. The extraction of these metals happens at a substantial environmental and health cost. So, to keep in check the environmental impact of EVs, it is essential to use the batteries in the most efficient way possible.

In the case of EV, due to high power and energy requirements, the battery reaches its EOL when capacity degrades to an 80 % of original capacity. Thus, the batteries are not as green as it seems. Clearly, the remaining capacity can be repurposed as a second life in less demanding applications. A substantial unused potential of the battery gets wasted, which is detrimental to the environment. However, this unused potential can also be considered an opportunity to make the EVs more affordable by applying the concept of battery second use. The second use can loop back some revenue to Original Equipment Manufacturer (OEM) that may decrease EV prices and thus make EV more competitive [Jiao2016]. According to [Melin2018], the global market of EOL Li-ion batteries is expected to grow 3.5 billion dollars by 2025. [Törkler2014] 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), etc. iii) Energy-related / industrial applications (up to 50 MWh): Renewable energy storage, Grid stabilization, etc. In this second life, the batteries can be procured at low cost, indicating new businesses opportunities.

To facilitate the reuse, re-manufacture or re-purpose of these EoL batteries, several decision has to be taken, like choosing the appropriate second life applications, identifying the right time to initiate second life use etc. However, the challenges of making efficient decisions on the aforementioned systems are still unsolved. This is primarily due to the lack of analytical methods and decision support tools, which has capability of assessing different aspects of circular manufacturing systems. For a reliable circular industrial system, it is important to predict the reliability of that system in actual life cycle condition. Research on decision-making method can be very helpful for the new value chain - e.g. predictive maintenance, re-manufactured or repurposed products. Thus, prognostics and health management plays an important role in facilitating circular economy. Having an efficient estimation of current health of the product, with a better prediction of remaining useful life, will facilitate to broaden the decision-making in Circular systems. However, the tech-

nical heterogeneity of Li-ion batteries, as well as the dynamics of change of operating condition, accentuates the difficulty to establish a PHM system for batteries. To overcome these barriers and facilitate the decision-making, we need to have an adaptive and real-time prediction strategy.

1.3 Objective

State of Health (SoH) estimation plays an essential role in taking decisions while repurposing. However, predicting accurate SoH is difficult due to the complex degradation mechanism of Li-ion batteries caused by various internal and external factors. In addition to indicators like SoH, several other factors have to be considered for establishing an industrial setup for re-manufacturing or repurposing. However, the current manufacturing system cannot curb the complexity that this circular transition will add to it. We need to have a more intelligent manufacturing system to make it more sustainable.

The objective of the thesis is to define the State of health in the context of circular economy and provide reliable sensor networks and information retrieval modules to develop as accurate as possible a diagnosis and a health prognosis system for Lithium-ion batteries. This health management system should be able to predict the state of health of the EV batteries in advance and with ease. Further, to facilitate better decision making while repurposing end of life electric vehicle batteries by using the result of developed diagnosis and a prognosis system.

1.4 Research Question

The main guiding research question of this work has been formulated as :

"How to design an efficient system that predicts and assesses the state of health of Li-ion batteries in the context of the circular economy ?"

To answer this question, the following sub-questions have been identified:

- What is the state of the art concerning the development of the PHM system for Li-ion batteries?
- What is the appropriate definition of State of health in the context of circular economy?
- How to overcome the barriers of technical heterogeneity and dynamic operating condition during SoH estimation of battery?
- What kind of tools are efficient and effective for SoH estimation of the Li-ion battery?
- What is the industrial application of the kind of model proposed?

1.5 Thesis Outline

This thesis is framed based on the outline structure shown in fig. 1.1. In chapter 1, we presented a brief discussion on the Cross-disciplinary Circular Project. The contextual problem, objective, and research questions are portrayed in this section.

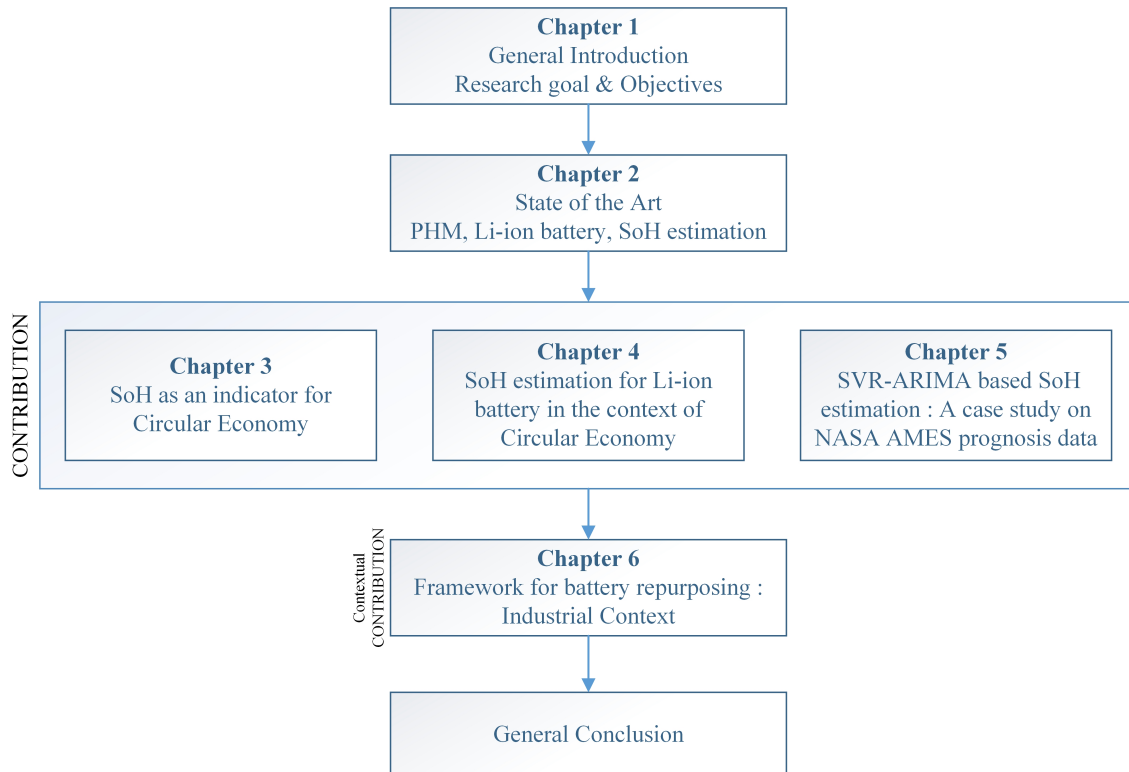


Figure 1.1: Thesis structure

In chapter 2, an overview of a conducted literature survey is presented. The domain of Prognostics Health Management, Lithium-ion batteries and State of Health estimation were discussed through a detailed study of past works.

In chapter 3, we presented a novel definition for the State of Health in the context of the Circular economy. Then, a rigid classification of SoH estimation methods is done and discussed after-by. Further, a methodology is proposed to overcome the challenges in SoH estimation for Li-ion batteries. Finally, a time series forecasting based method for SoH estimation of Li-ion battery is presented in Chapter 4. The methodology is discussed in detail, and the tools & models are also explained in this chapter.

The model discussed above was tested on NASA AMES prognosis data, and a use case was created. The detailed discussion on the case study is presented in Chapter 5.

Chapter 6 is a contextual discussion on creating a framework for battery repurposing. The repurposing requirements, stakeholder interactions, regulations & certifications were discussed, and a framework for establishing a repurposing system in an industrial context is proposed. This chapter has been written in the collaboration of a company, **Lancey Energy Storage**. Finally, the reflection is formulated in terms of the conclusion.

1.6 Related own publications

- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., “First step towards the development of a Prognosis Health Management (PHM) System for Li-ion batteries: An FMMEA based approach.”, ESREL (2019).
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., “Overcoming the Barriers in Diagnostics and Prognostics of the Circular Industrial System by Hidden Markov Model.”, ICCAD (2019).
- Basia A., Dubois F., Kurt A., (in press), “Production of the future to support circular economy- development of a dedicated platform by means of a multidisciplinary approach.”, ICCAD (2019)
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., “Review on State of Health estimation methodologies for lithium-ion batteries in the context of Circular economy”, CIRP Journal of Manufacturing Science and Technology, Accepted (11 Feb 2021)
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., (accepted), “State of Health Estimation for Lithium-ion Battery by Incremental Capacity Based ARIMA - SVR Model”, ESREL (2021).
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., (accepted), “Comparison of data driven algorithms for SoH estimation of Lithium-ion batteries”, ICCAD (2021)

2

State of the Art

Contents

2.1	Prognostics Health Management	11
2.1.1	Introduction	11
2.1.2	Characteristics of PHM methods	12
2.1.3	Information and Data for PHM	13
2.1.4	Approaches to PHM	14
2.1.5	Challenges	19
2.2	Lithium ion battery : Properties and Degradation	21
2.2.1	Introduction	21
2.2.2	Working Principle	22
2.2.3	Degradation mechanism	22
2.2.4	Degradation modes	24
2.2.5	Effect of different parameters on cell aging	25
2.2.6	Li ion battery in EV : How to add sustainability to its life cycle	26
2.3	State of Health : A key indicator to decision making	28
2.3.1	SoH estimation	29
2.3.2	SOH estimation techniques and tools: State of art	29
2.3.3	Challenges in SoH estimation	40

2.1 Prognostics Health Management

Prognostics and health management (PHM) is a research domain that aims to detect degradation, diagnose faults, and predict and proactively manage failures of a system or its components. It uses past and present information on the environmental, operational and usage conditions of a system in order to deduce its future state. This chapter reviews the state of knowledge on PHM methods, placing these in context with the different information and data available for performing the task for achieving reliable deployment in practice.

2.1.1 Introduction

In case of human health care, we make a medical analysis on the basis of parameters related to health conditions, wherein the collected measurements of these parameters are analyzed to detect anomalies, diagnose for a disease and predict its evolution. Similarly, technical procedures of health management are used to capture the functional state of industrial system from historical recordings of measurable parameters [George Vachtsevanos2006].

Suppose the problems in the industrial system can be identified at their early stages of development. In that case, it is possible to allow the equipment to run as long as it is in good condition and to schedule the maintenance interventions for the most convenient and inexpensive times. The driving objectives are maximum availability, minimum unscheduled shutdowns of production, economic maintenance [Jardine2006]. PHM systems play a pivotal role in doing just that, by supporting early problem detection and thus making it possible to allow the equipment to run as long as possible. PHM links studies of failure mechanisms to system life cycle management. PHM can be seen as the process that involves system. The main objective of creating the PHM system is to maximize return on investment (ROI) by combining different maintenance strategies (e.g., scheduled maintenance, condition-based maintenance, and predictive maintenance) to achieve optimum cost-effectiveness versus performance decisions monitoring, fault detection, isolation, and identification(fault diagnostics), failure prognostics, and action taken (e.g., required logistics, maintenance) to improve safety and reduce maintenance costs. [Bonissone2006] proposed a very elaborated representation of a PHM functional architecture which is based on knowledge and time, which has been depicted in figure 2.1. In his architecture, he combined all PHM aspects in a descriptive way which shows the relation between each PHM functional block. He also related different PHM components to the relevant decision making process based on a segmentation of decision time horizon.

The significant tasks handled by prognostics and health management systems are fault diagnostics, prognostics, and condition-based maintenance. The first task is to diagnose and identify the root causes of system failures. These root causes provide helpful information for prognostic models as well as feedback for system design improvement. The second task takes the processed data and existing system models or failure mode analysis as inputs and employs the developed library of prognosis algorithms to online update degradation models and predict failure times of the system. The third task uses prognosis results (e.g., the distribution of remaining useful life) and considers the cost versus benefits for different maintenance actions to determine when and how the preventive maintenance will be conducted to achieve minimal operating costs and risks. Before PHM development, preventive system repairs performed system maintenance through systematic inspection before breakdown. Although preventive maintenance allows manufacturers to prevent system failures or mitigate system disruptions, scheduled inspections are expensive and cannot cover unexpected shortcomings beforehand. On the contrary, condition-based maintenance based on PHM can proactively detect system failures, and can respond faster than preventive maintenance. Thus, PHM-enabled manufacturing systems can be referred to as intelligent manufacturing systems, which increase the availability and productivity of systems through condition monitoring and diagnosis or prognosis of faults.

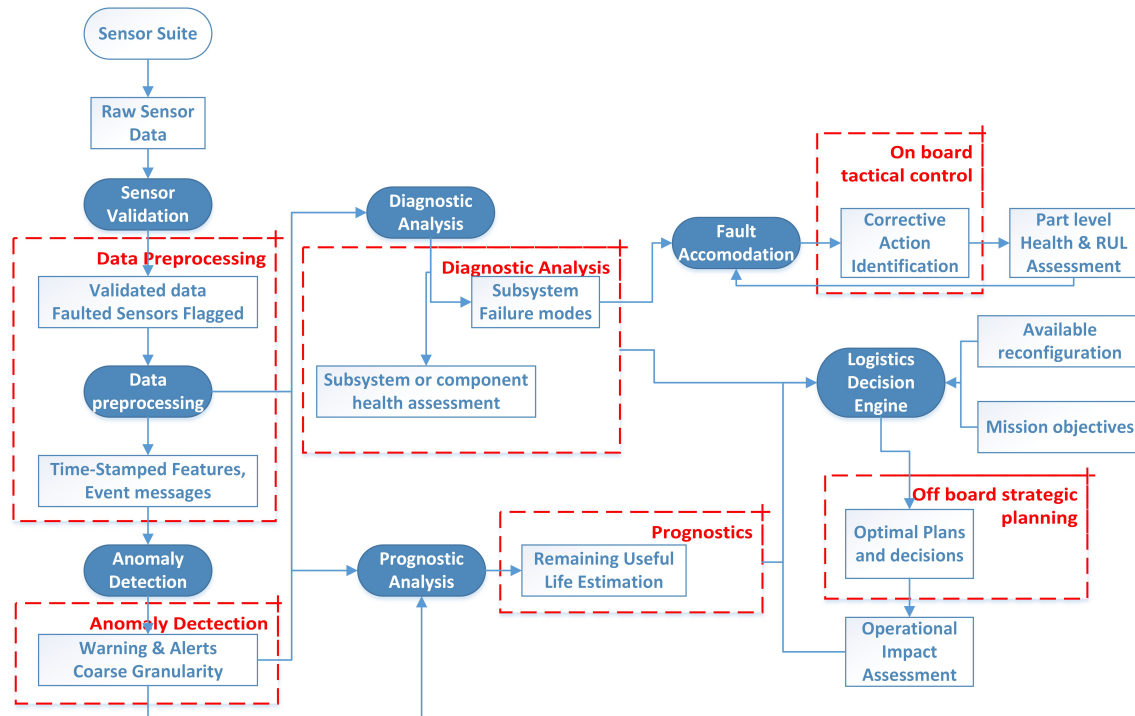


Figure 2.1: PHM functional architecture [Bonissone2006]

2.1.2 Characteristics of PHM methods

The characteristics of prognostic methods for practical application are dependent on the type of equipment and the objective of the PHM. They have been explained below in this section.

2.1.2.1 Quick Prediction

In PHM systems, the equipment's current state estimation and the prediction of its future state must be performed in a time that is compatible with the time scale of the equipment life and the time constants of the corrective actions. If failure is predicted 'too early,' more than needed lead time is used to verify the developing failure and take the preventive correction. On the contrary, if the failure is predicted too late, the time available to assess the situation will not be sufficient. Further, in the case of fast-developing conditions, e.g. of accident management, the prediction task entails the use of fast-running, approximate models; in these circumstances, a proper balance between computational rapidity and precision of the results must be sought to avoid arriving quickly at wrong decisions of intervention.

2.1.2.2 Robustness

A PHM system should have a reasonable degree of robustness. That means that the performance of the PHM systems should not degrade abruptly in the presence of noises or uncertainties. In case of novel failure situations, the PHM systems should be robust enough to promptly recognize the novel malfunctions and get adapted to recognize and handle them.

2.1.2.3 Confidence Estimation

Suppose the estimation results are to be used in decision-making. In that case, the state estimations and predictions must be accompanied by the associated error accounting for the incomplete and imprecise information available on the process. This measure also helps to project confidence in

the forecasts of the RUL. An analytical model for predicting the RUL improves the understanding of the degradation behavior.

2.1.2.4 Adaptability

The degradation processes for any system change with time due to changes in external environments. The PHM system should be adaptable enough to accommodate these changes and perform equally well in different working conditions. A distinction between stationary and transient conditions are also expected to be needed, as the correlations among the process variables may differ significantly in the two cases, and require different methods ('static' methods like Principal Component Analysis, Partial Least Squares or others for the stationary conditions, and simulation and trend analysis methods for the transient case) [Hussey2009].

2.1.2.5 Modeling and Computational complexity

A timely prognostics and clarity of interpretation demands that the amount of modeling required, and the storage and computational burden associated must be calculated appropriately for the application.

2.1.2.6 Interpretation Clarity

The PHM system must be interpretable to allow the operator to act accordingly, in full conscience of the situations and confidence in the decisions. To add more interpretability to the system, a graphical representation of the analysis outcomes and the associated uncertainty can be a good option.

2.1.2.7 Occurrence of Simultaneous Faults

A particular challenge for the PHM system can be the possibility of diagnosing multiple faults simultaneously. A codebook approach would lead to the enumeration of an exponential number of possible fault combinations and their symptoms [Kliger1995]. Possible effective approaches to multiple fault handling can be to handle the faults incrementally as they occur over time; otherwise, some approximation on the fault combinations considered is necessary [Rish2002].

2.1.3 Information and Data for PHM

For establishing an efficient PHM system, we need different forms of information and data related to the failure of equipment undergoing degradation:

- Intrinsic characteristics of the system (material, physical, chemical, etc.); These may vary from one individual equipment to another of the same type.
- Time To Failure (TTF) data of a population of similar system.
- Extrinsic parameters (environmental, operational, etc.) may vary with time during the system's life. They are not directly related to the equipment degradation state but may influence its evolution. Often, these parameters are directly observable and measured by sensors. However, in some cases, where defining operational settings of the system is complex, they are not observable or measured by sensors.
- Data corresponding to the values of observable process parameters measured by sensors during the failure of a population of identical systems. These observable process parameters are directly related to the equipment degradation state. This process parameter is like a time-dependent parameter indicating the degradation state, either because one among the observable parameters are directly measurable or can be inferred from them.

These sources of information are available alone or sometimes, in combination with other sources. The data should be acquired from the real-time field operation of the system or experimental tests conducted in the laboratory under controlled conditions.

2.1.4 Approaches to PHM

The classification of PHM systems is based on the available data and knowledge about the system or the used methodology. The prognostics system developers benefit from these classifications for algorithm selection based on available knowledge about the system and suitable forecasting techniques. Prognostics approaches classification also helps identify what techniques from other technologies can be used in prognostics algorithms development. An essential thing about prognostics approaches classification is building a way to obtain a standard methodology for prognostics application development within a standard framework. It is also necessary to identify which operating parameters are contributing to the degradation.

In general, prognostics approach can be categorized in four different classes.

- Reliability based PHM approach
- Physics based PHM approach
- Data based PHM approach
- Fusion approach

The complexity, cost, and accuracy of these prognostics techniques are inversely proportional to their applicability. The major challenge is an increase in cost & complexity with an increase in the accuracy of the approach. Fig 2.2. [Byington2002] explains this phenomena of variability of cost and complexity through different approaches very clearly.

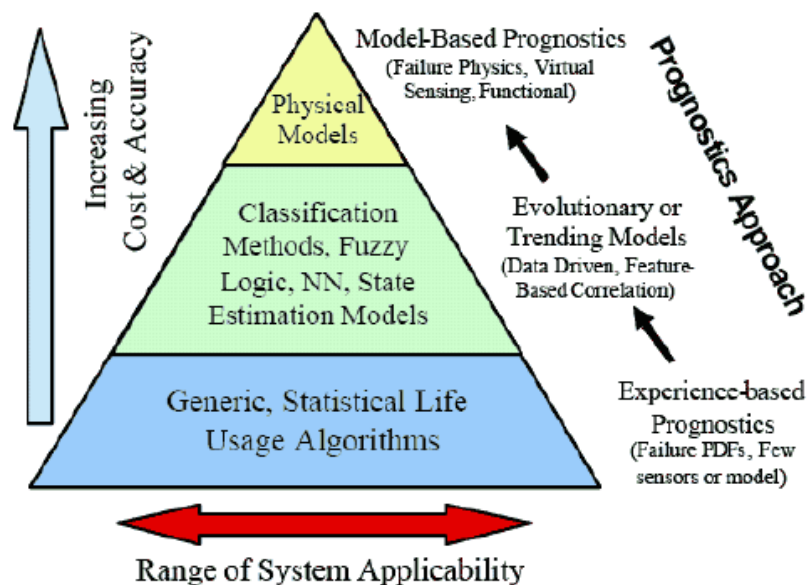


Figure 2.2: Variability of cost and complexity in PHM [Byington2002]

Now, we will discuss in details, different approach to prognostics.

2.1.4.1 Reliability based PHM approach

It is a common approach of PHM systems wherein the probability distribution is modeled based on available TTF (time to failure) data from laboratory testing and field operation. The distribution obtained allows estimating the lifetime of the average equipment under average usage conditions. This approach is also well known by the name of Experienced-based prognostics, life usage models, or statistical reliability-based approaches. A detailed review of these methods can be found in [Hu2010].

This approach is used in mass production systems where uncritical, unmonitored components are produced. These products generally do not have a physical model. In a reliability-based approach, we do not assess the product's health in real-time, so environmental conditions are not considered. It employs historical data of the components population to identify its average rate of failure. Mean time between Failure (MTBF) is obtained from the original equipment manufacturer and updated during the real-time operation.

The reliability-based approach is used to plan scheduled maintenance. For scheduled maintenance, the maintenance interval can be estimated based on the historical usage data of a large set of components. In case of insufficient data, accelerated tests can be conducted on newly used components. Statistical techniques like Weibull analysis [Nelson1985] and log-normal [Chen1995], and Poisson laws [Barbour1992] are generally used to represent this methodology.

The reliability-based approach does not require any knowledge about failure modes or system operation. These methods are simple and often very easy to implement. Even though this method is simple, it has few drawbacks as well. In a reliability-based approach, the faulty component has to be replaced at every fixed interval. In this case, the component-specific conditions are not considered causing either early replacement of working component or late replacement. Also, this approach will require a considerable amount of massive failure historical data if applied to newly developed components. Another disadvantage is the requirement of large number of degradation states and related probability distribution parameters to be fitted by data [Zille2009].

2.1.4.2 Physics based PHM approach

This approach is also known as the model-based approach. It is one of the most widely used methodologies used for prognostics and has a higher accuracy level than reliability-based approaches. This approach utilizes knowledge of a product's life-cycle loading and failure mechanisms to assess product reliability. POF methodology identifies potential failure mechanisms and failure sites for a device, product, or system. A failure mechanism is described by the relationship between the stresses and variabilities at potential failure sites. The methodology proactively assesses reliability by establishing a scientific basis for evaluating new materials, structures, and technologies.

There are two levels of modeling of the system, namely, micro level and macro level. Micro-level is modeling the effect of external stresses on the material, such as a finite element model. A macro-level model is based on the first principle knowledge about the system to model the relation between its parts. For all these models, differential or partial differential mathematical is used. Once the model is established, in-situ monitoring of the system can be conducted. The system diagnosis is used to assess its performance. The model used the knowledge about the current health of the system and the future operating scenario about the load exposure for forecasting, Remaining useful life estimation. Figure 2.3 shows a framework for PoF methodology [Pecht2009].

In the past, Physics-based prognostics has been applied to the systems where degradation phenomenon can be mathematically modeled such as in gearbox prognostic module [Byington2002], residual-based failure prognostic in dynamic systems applied to the hydraulic system [Medjaher2009], military LRU prognostics [Tuchband2007] and bearings [Medjaher2013]. Since system degradation depends on the laws of nature, the physics of the failure-based approach is very efficient. However, the accuracy and precision depend on model fidelity. It is easy to validate,

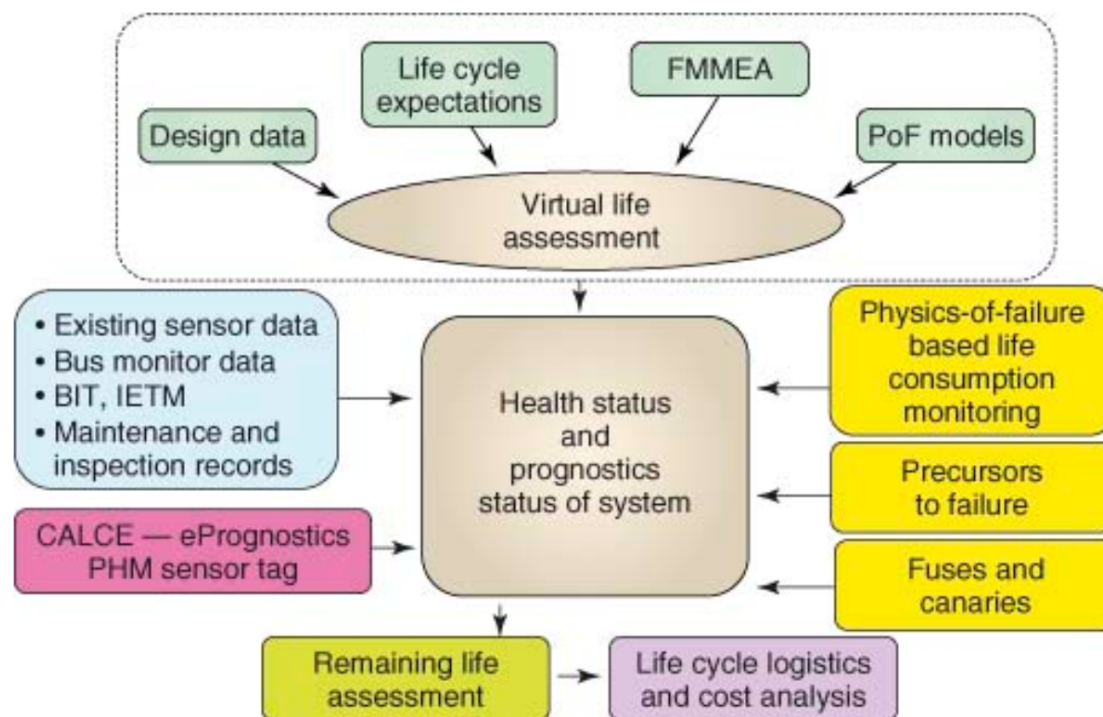


Figure 2.3: PoF framework [Pecht2009]

certificate, and verify. However, developing a highly accurate physics-based model is very expensive, time-consuming, and computationally intensive. Also, the models are system-specific, and so, reusability is very limited to other similar cases. Because of these drawbacks, often, data based approach is preferred over a physics-based approach.

2.1.4.3 Data based PHM approach

Sometimes the degradation of a system or equipment is so complex that the PoF degradation model is impossible to establish. The reason behind this complexity is the large number of external and internal factors affecting the degradation mechanism. For these kinds of systems, the Data-driven prognostics approach is the recommended technique.

Even though the physics-based approach has higher accuracy, precision, and real-time performance, the data-driven prognostics is more used than the physics-based one in the PHM community due to its quick implementation and deployment. In data-driven prognostics, we do not need to worry about the physics of degradation, so PHM system developers from cross-disciplinary domains can use it. It mainly relies on Artificial intelligence tools that can be implemented at a go with minor modifications.

This approach uses the measured performance parameters of the system, such as pressure, temperature, speed, vibration, current . . . , etc. to create a model that correlates these parameters variation to system degradation and fault progression and then use this model for RUL estimation. This model is established using statistical tools like regression analysis techniques or in a more complex scenario using the soft computing tools, e.g., ANN, fuzzy logic, neuro-fuzzy, support vector machine, RVM. . . , etc. Techniques from soft computing are preferable to statistics because of they can learn hidden relations between parameters. The data-driven approach relies on the availability of multivariate historical data about system behavior. These data should be acquired from different phases of the system: regular, faulty operation & degradation scenarios under different external operating conditions. The author in [Saxena2008] suggested different methods to acquire these data, namely : (1) data from field;(2) experimental testbeds; and (3) computer simu-

lations. For fielded applications, proprietary issues make it difficult for the data to be available for public use. Experimental testbeds are costly, dangerous, and time-consuming. Also, the absence of a real-life scenario makes it a bit unrealistic. Computer simulation is complex and challenging because building a high-fidelity simulation model is not an easy task. However, computer simulation can be considered the best way to acquire run to failure data once this model is available.

Ideally, the data-driven approach works well with the system that undergoes gradual degradation. The authors in [Pecht2008] presented an extensive methodology for data-driven algorithm development which has been depicted in figure 2.4. The methodology considers the system's function, i.e., system analysis, including its limitations, operating, and environmental conditions to perform a feasibility study for algorithm application. Further real-time data is acquired from the sensors, which represent system behavior. The acquired data is preprocessed to enhance the quality of data, which includes cleaning, normalization, and noise reduction. With the application of preprocessed data, relevant features are selected, then used to define the baseline model based on the training data. The real-time sensor-based monitoring allows identifying a variation in the system's performance, which can be interpreted as fault isolation & identification. After fault identification, the prognostics system is used for the estimation of remaining useful life.

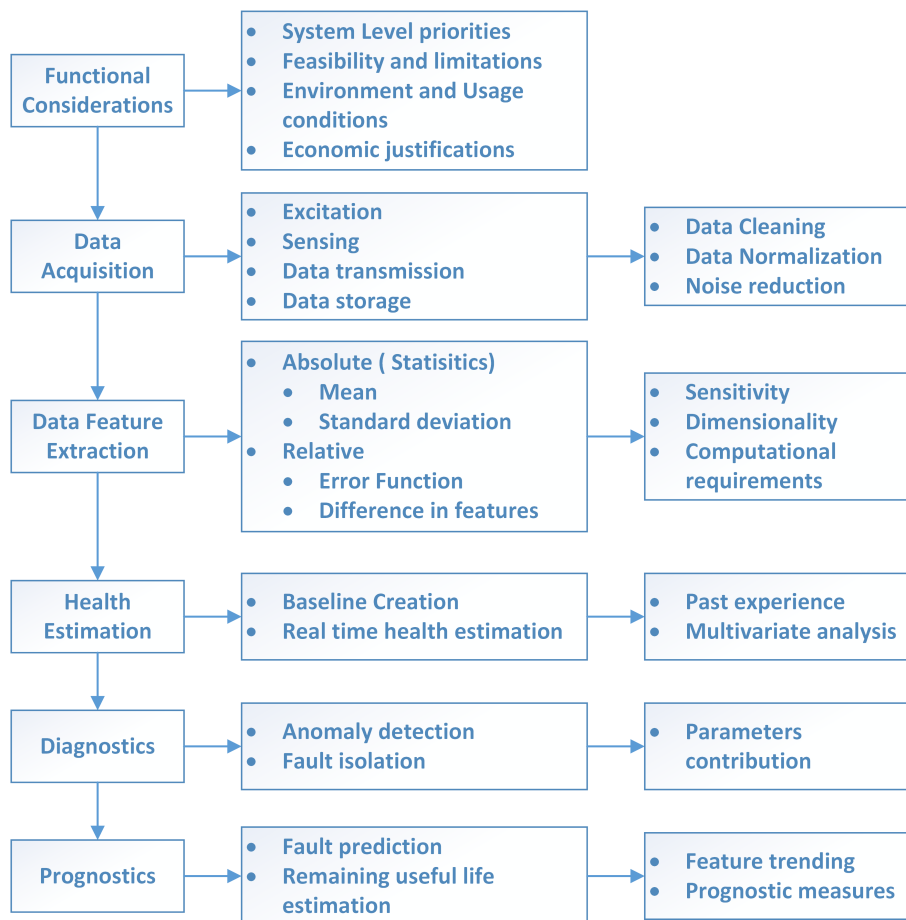


Figure 2.4: Methodology for data driven approach [Pecht2008]

The advantage of a data-driven approach is that it does not need system knowledge and is fast and easy to implement. Also, the algorithm can be tuned to be used for another system and hidden relations about the system behavior may be learned. However, there are also a few limitations of the data-driven approach. As most of the techniques are based on approximation, uncertainty management must be taken into consideration. The results are sometimes less interpretable be-

cause of the absence of physical knowledge of the system. There are some data-based issues like higher computational complexity, overfitting, or less efficient models due to the unavailability of data.

It could be an excellent solution to combine both physics-based and data-driven approach into one fusion approach to have the benefits from each and overcome their drawbacks.

2.1.4.4 Fusion based PHM approach

Fusion-based PHM approach combines data-driven and physics of failure approach to tackle the limitations of both of them. A data-driven approach can compensate for the data scarcity issues, and the PoF approach can provide knowledge about the physics of system degradation. This fusion of two methods can be conducted either before estimating remaining useful life or after RUL estimation by combining the results from each approach to obtain the global RUL called post-estimate. [Cheng2009] presented a framework for a fusion approach for RUL estimation of electronic products. The framework has been depicted in figure 2.5

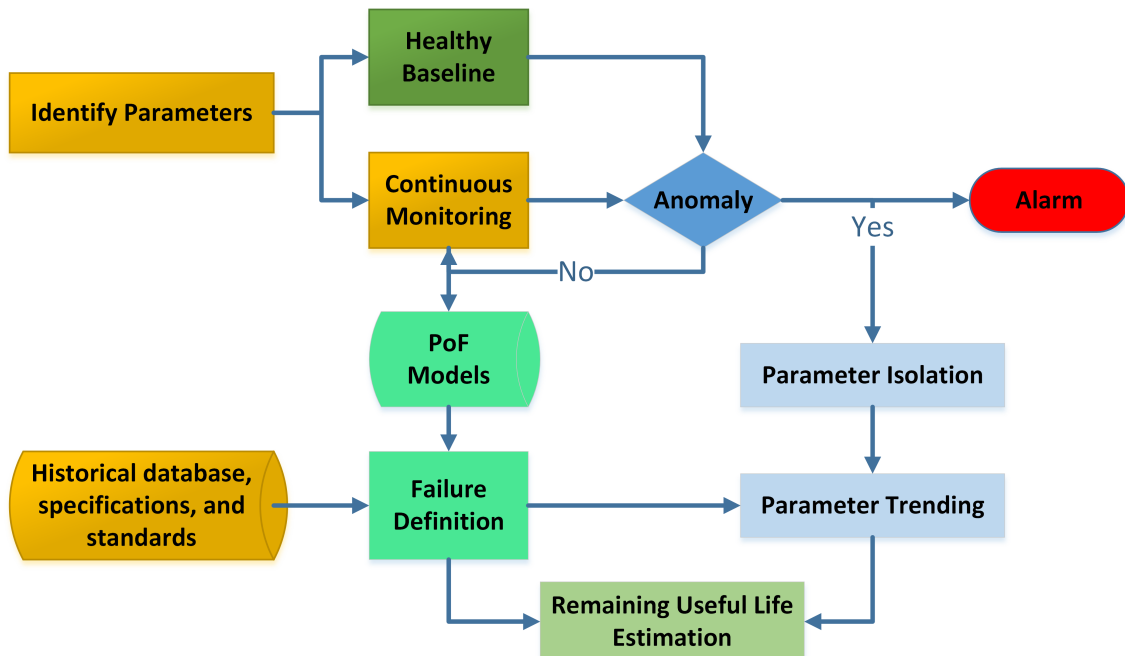


Figure 2.5: Framework for fusion based approach [Cheng2009]

POF based PHM utilizes ideologies of the products life cycle loading and failure mechanism for assessing product reliability. POF models are selected based on expected life cycle condition and FMMEA for the given system. [Pecht2009] provide deep insight into PoF model selection. Also, FMMEA helps in choosing a critical mechanism so that the PoF model will keep monitoring the life cycle environment & operating condition that propagate the mechanism. Life cycle loading data (generated from mechanical/thermal/chemical or electrical stress) can be used in the failure model to understand the extent of degradation for the given condition. The fusion approach uses data-driven techniques for anomaly detection and classification to detect the degradation of the product. Isolation of parameter that indicates anomalous behaviour is done. Time to failure is estimated based on parameter trends and failure threshold.

A fusion approach can be designed for any other application by extending the framework provided by them. [Goebel2006] applied fusion approach for aircraft engines bearing. The results justified a higher accuracy and robustness compared to using either data-driven or PoF alone. However, the fusion-based approach also carries the disadvantages of both PoF and data-driven

approaches to a certain extent. Of course, not by the same level as seen when the technique is used individually.

2.1.5 Challenges

The ability of PHM to confidently estimate the probability of failure and the Remaining Useful Life (RUL) of a system is a valuable help us for deciding when to take maintenance actions or operational decisions. However, there are several challenges and open issues in PHM [Hines2008]. Some of them are mentioned and explained here.

- Uncertainty management
- Prognostics system validation and verification
- Prognostics standardization
- Post-prognostics reasoning

Here, we will discuss in short, the above mentioned challenges.

2.1.5.1 Uncertainty management

There is always some extent of uncertainty in prognostics because it incorporates a projection of degradation mechanism into the future. Future loads and environmental conditions used in prognostics are almost impossible to predict accurately. [Sankararaman2015] presented an excellent overview of the state of the art of uncertainty quantification and management in prognostics health management.

Uncertainty in prognostics can be handled and reduced by noise modelling, avoiding overfitting, and using hybrid forecasting techniques. [Saxena2008] laid an excellent and efficient concept for considering uncertainty in the model. The amount of uncertainty in RUL estimation informs the decision-maker about the reliability of prognostics system results. So, it is also good to have a measure of uncertainty in prognostics and health management algorithms.

2.1.5.2 Validation and Verification

The deployment of the PHM system cannot be done until we have an assurance of its performance, so validation and verification of prognostics methods is essential. It also helps in evaluating the requirement specification needed for the system design. Further, it helps in identifying the weak areas in prognostics that will require more research and brainstorming. Since the beginning of applying the prognostics concept, the focus was only on prognostics algorithms development.

Recently, the PHM community is paying more attention to the importance of having prognostics metrics. The classification of PHM metrics adapted from [Saxena2010] has been represented in figure 2.6. The most important classification is based on the information these metrics provide to fulfill specific functions. In general there are four major categories, namely: (1) Algorithm performance metrics, (2) Computational performance metrics, (3) Cost-benefit metrics, and (4) Ease of Algorithm Certification. As evident from their names these metrics measure success based on entirely different criteria. The criteria have been highlighted in grey in figure 2.6.

2.1.5.3 Prognostics standardization

To have a reliable, easy and fast deployment of the PHM system, we rely on the standardization of PHM approaches. It even helps in identifying the technology gaps by unifying the concept. There are three categories of Prognostics standardization:

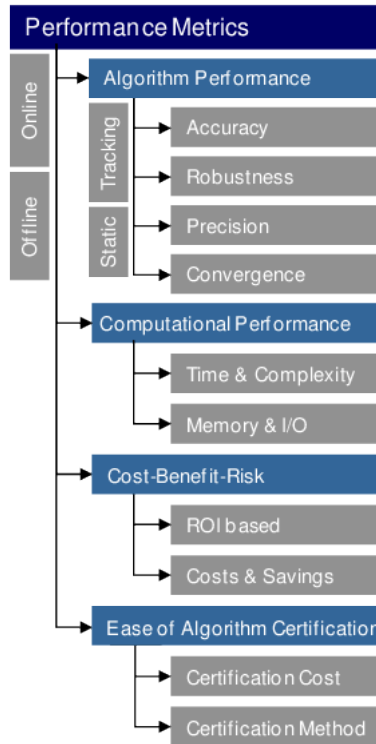


Figure 2.6: PHM metrics [Saxena2010]

- Standardization in prognostics terms and definitions
- Standardization in prognostics system development
- Standardization in prognostics metrics

Standardization in prognostics terms and definitions is done to remove ambiguity among different terminologies & lexicons used in this domain. This facilitates lucid reading and discussion on various PHM topics. Standardization in prognostics system development is done to generalize the prognostics process, information, implementation, and prognostics system design methodology. The standardization in prognostics metrics allows a standardized methodology while evaluating, validating, and comparing different prognostics algorithm. Prognostics metrics have already been discussed in the validation and verification section.

2.1.5.4 Post Prognostics Reasoning

The prognostics system provides RUL that the decision-maker uses to make appropriate decisions about the system's operation to increase its reliability, safety, and availability and reduce total life cycle cost and logistics footprint. Having valuable information is essential but using this helpful information correctly and efficiently is much more critical. Post-prognostics reasoning is a challenge because it requires developing an integrated information system that links the operation, maintenance, logistics, decision support, and decision making, all together in such a way that allows each user to benefit from the information that exists without making any interruption to the system.

Thus, depending on the application and the ability to tolerate the complexity, cost and accuracy, a PHM system can be chosen from different PHM system explained in this system. In addition, whenever a PHM system is being designed, the challenges of uncertainty management,

system validation & verification, standardization and post prognosis reasoning should also be considered and a model should be robust enough to tackle these challenges.

2.2 Lithium ion battery : Properties and Degradation

2.2.1 Introduction

Lithium is the lightest solid element with very small ionic and atomic radii and is employed to build electrochemical batteries accompanied by high voltage and high specific capacity [Chen1995]. Li-ion batteries have numerous advantages compared to the other battery chemistries because of their high gravimetric and volumetric energy densities and their low rate of self-discharge. So, it is widely utilized in small portable devices, such as Bluetooth headsets, GPS devices, cell phones, laptops, cameras, and hearing aids. In addition to portable devices, Li-ion batteries are also widely used in mobile applications, like electrical scooters, electric bicycles and electric vehicles. These batteries are fabricated using typical commercial cells (e.g., Tesla Roadster battery pack). The design consists of several parallel cells to construct blocks or elements that are connected in series. Recently, Li-ion battery is being used in the aviation industry to drive auxiliary power units (APUs), emergency lighting system, flight control electronics, and flight recorder as an independent power supply [Mikolajczak C2011]. The transport sector is one of the primary sources of greenhouse gas emissions because it uses hydrocarbon-based internal combustion engines. However, to have a sustainable future, global warming must be kept in check, and so we see an unprecedented transition to electric vehicles. Therefore, the application of electrochemical energy storage systems (EES), particularly Li-ion batteries, is rising exponentially. There is also a massive demand for Li-ion batteries in a variation of grid-scale stationary storage applications, where a significant cycle life is required. Hence, a solid understanding of the phenomena governing the degradation mechanisms of Li-ion batteries are necessary to achieve desired improvements in the cycle life and the cost as well.

Trade-off governing the power density and the energy density for several electrochemical energy storage devices such as supercapacitors, fuel cells, and batteries is illustrated in figure 2.7 [Srinivasan2008] through the Ragone plot.

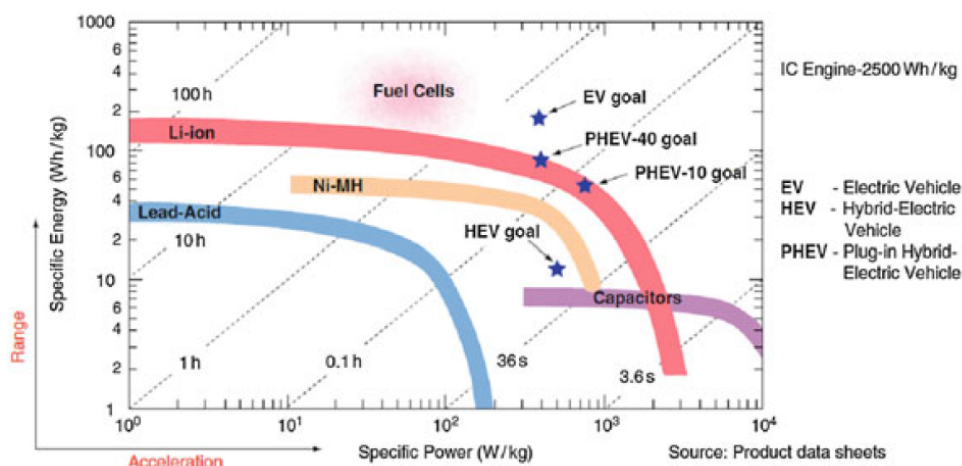


Figure 2.7: Ragone plot for different batteries [Srinivasan2008]

A Ragone plot is a plot used for comparing the energy density of various energy-storing de-

vices. On such a chart, specific energy values (in W·h/kg) are plotted versus specific power (in W/kg). The specific power and specific energy can be interpreted as the acceleration and range of the vehicle, respectively. According to figure 2.7, Li-ion batteries exhibit the highest power and energy density, among other battery chemistries.

2.2.2 Working Principle

Li-ion battery generally consists of the following components: anode, cathode, separator, and electrolyte. It has two electrodes (i.e., cathode and anode) whose chemical potentials are different to provide a potential difference. This difference in chemical potential specifies the cell's open-circuit voltage. The separator is an inactive component of a Li-ion battery that prevents physical contact between the two electrodes. The Li-ion diffused between electrodes through electrolytes during charging and discharging cycles. When an external circuit electronically connects the two electrodes, electrons are transferred from the anode (the negative electrode) to the cathode (the positive one) which balances the potential difference. The electrolyte also carries positive Li ions in the same direction. Thus, the chemical energy stored in the cell is converted to electricity in the external circuit. This is a reversible process, and so Li-ion cells can be recharged, whereby electrical energy is converted back to chemical energy.

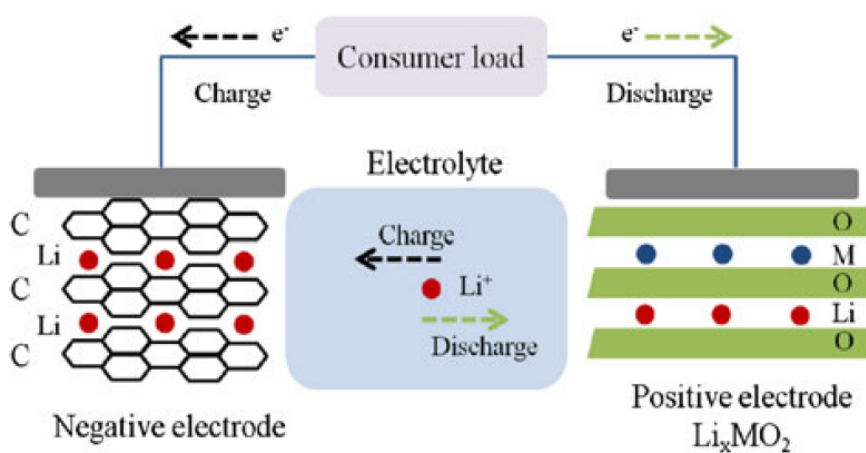


Figure 2.8: Schematic of working principle

Figure 2.8 [DD012] shows the schematic of the battery's working principle. The energy stored in a battery is obtained by multiplying the discharge power (in Watts) by discharge time (in hours). As we keep charging and discharging the cells, the battery's energy capacity gradually decreases depending on various external parameters such as charge/discharge rate and operating temperature. The respective cell voltage relies not only on the potential difference of the two electrodes but also on the reaction kinetics and the cell resistance. The rise in the cell impedance contributes to the enhanced voltage plateaus within charging and the reduced voltage plateaus within discharging, which brings about the power fade and the decline in energy conversion efficiency. Thus, the life cycle of a battery is mainly designated by the impedance rise and the capacity fade.

2.2.3 Degradation mechanism

Like any other product, lithium-ion (Li-ion) cells degrade throughout their life depending on their use (charge and discharge cycles) and their exposure to environmental conditions. Batteries contain a set of interconnected components subject to ageing, so a component ageing and its subsequent performance deterioration affect operational needs of all other elements, which will expedite the entire system ageing. This interconnection makes the degradation mechanism of the

Li-ion battery very complex. This degradation depreciates the cells energy storage ability, leading to their end of life. Since the degradation rate cannot be easily inferred from operational data, methods and models are required which utilize available parameters and measurements to generate estimates and predictions of current and future energy storage capacity and power capability.

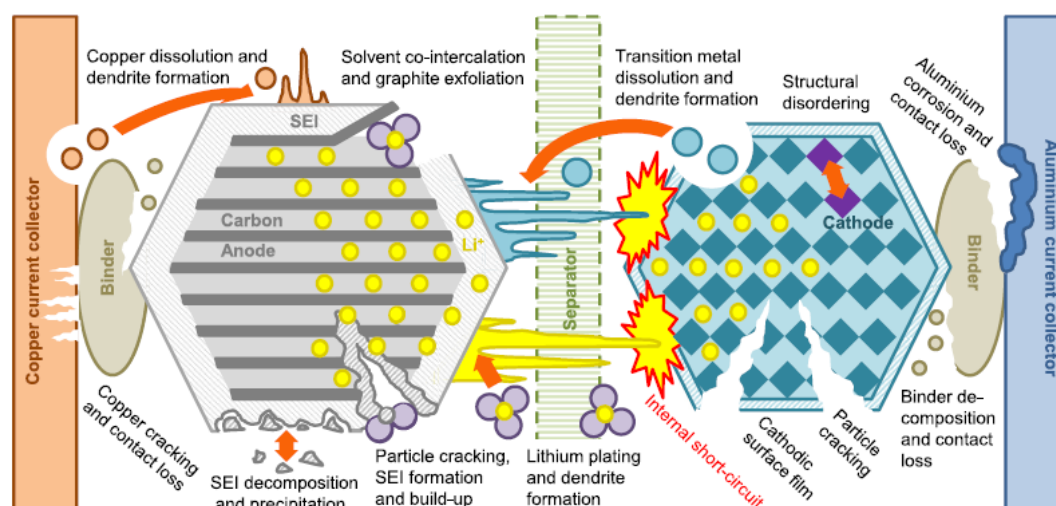


Figure 2.9: Degradation Mechanism [Birk12017]

An outline of relevant degradation mechanisms and their interactions have been depicted in figure 2.9 [Birk12017], portraying the complexity of degradation in Li-ion batteries. The interaction between different subcomponents, like anode, cathode, binder, electrolyte, separator, and current collector, reveals the overly complex degradation mechanism that include both mechanical and chemical origins which are closely interrelated [Demirocak2015]. Broadly speaking, the degradation mechanism can be classified into two categories: Chemical degradation mechanism and Mechanical degradation mechanism.

2.2.3.1 Chemical Degradation mechanism

The major causes of chemical degradation of Li-ion battery are the phenomena of electrolyte decomposition and reduction, SEI formation, binder decomposition, solvent co-intercalation, active material dissolution, gas evolution, and loss of lithium [Demirocak2015]. Lithiated negative electrode reduces the electrolyte during low potential range and is oxidized by the cathode in high potentials. There are also impurities present in the electrolyte. These impurities operate as a catalyst for the side reactions [Broussely2005]. The kinetics of side reactions varies with the change in temperature and the cell voltage. Degradation in most materials is accelerated at elevated temperatures. These side reactions bring about some changes in the materials of the electrodes. The redox reaction between the electrode and electrolyte forms an interface layer on the electrodes, further contributing to the cell's impedance increase and capacity fading. Thus, these effects often arise from various processes, and their interactions are intertwined in a complex way. The chemical degradation of battery hardware materials negatively influence the electrical performance, the cell lifespan, and safety through (i) enhanced electrical resistance (ii) corrosion products attacking (iii) exposure to the contaminants reacting with active materials, and (iv) the loss of electrolyte.

2.2.3.2 Mechanical Degradation mechanism

The movement of Li-ions from anode to cathode leads to volume expansion or shrinkage of the battery component. The change in the mechanical structure happens inhomogeneously. This process of insertion and extraction of lithium ions is called intercalation and de-intercalation,

respectively. Mechanical degradation occurs due to the volume changes and subsequent stress generated in the active material particles of anode or cathode within lithium de-/intercalation. As a consequence of tensile stress, active particles undergo cracks, loss of contact between each other or from the current collector, and isolation as well [Ramdon2014]. Furthermore, stress-induced due to cycling of a battery changes the structure of pores in the separator and reduction in Li-ion mobility [Norin2002]. Similar to the chemical degradation, mechanical degradation also accelerates by ageing, eventually compromising the cathode and anode structures.

2.2.4 Degradation modes

This section will discuss the significant chemical & mechanical degradation modes undergone by different components of Li-ion battery. These degradation modes adversely affect the performance of the battery and ultimately direct cell failure. A summarized list of degradation mechanisms, their causes, effects and links to degradation modes are depicted in Fig.2.10 [Birk12017].

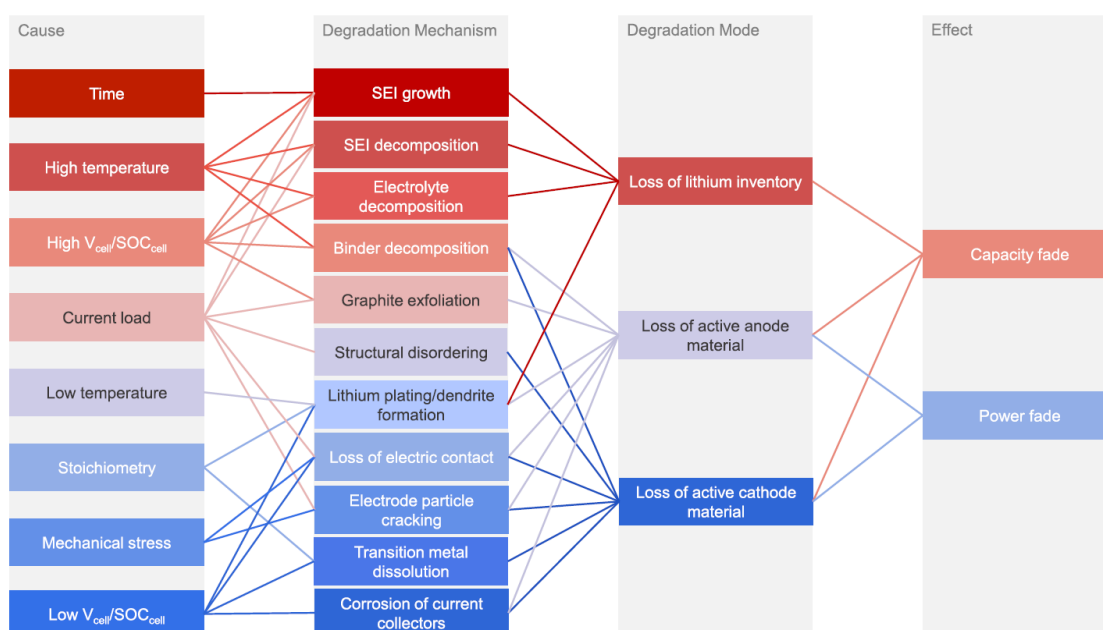


Figure 2.10: Degradation Mechanism & modes [Birk12017]

It is very clear from figure 2.10. that the degradation of Li-ion battery depends on various intertwined factors like time, temperature and mechanical stress. Eventually, these degradation modes are visible in terms of capacity or power fade. The primary effect of degradation on the cell's kinetics is an increase in internal resistance, easily measured by the voltage drop in response to a load. An increase in resistance can also lead to decreased cell capacity since cut off voltage is reached sooner in a cell with higher internal resistance. We will discuss some major degradation modes in details hereby:

- **Loss of lithium inventory (LLI):** The number of Lithium ions in the cell keeps decreasing due to parasitic reactions, like surface film formation (e.g. SEI growth), decomposition reactions, lithium plating, etc. This affects the number of Lithium ions available for cycling between the positive and negative electrode, leading to capacity fade. Surface films may also cause power fade. Lithium ions can also be lost if they are trapped inside electrically isolated particles of the active materials.
- **Loss of active material of the anode:** Certain areas of anode become unavailable for lithium insertion due to particle cracking and loss of electrical contact or blocking of active sites by

resistive surface layers. This leads to a decrease in both capacity and power capability.

- Loss of active material of the cathode: Certain areas of anode become unavailable for lithium insertion due to structural disordering, particle cracking, or electrical contact loss. This leads to a decrease in both capacity and power capability.

2.2.5 Effect of different parameters on cell aging

The degradation mechanism of the battery eventually leads to capacity or power fade, which is accelerated by high cycling rate, both low and high temperatures, both low and high SOC, both overcharge and over-discharge, high depth of discharge (DOD), and moisture. In this section, we will discuss the contribution of the following factors in battery ageing: section: cycling rate (C-rate) and the cycle number, temperature, SOC, and moisture.

2.2.5.1 Effect of cycling rate and cycle number

The authors in [Agubra2013] justified that the faster cycling rate results in higher capacity fade while the slower C-rates is related to lesser capacity fade. As we move towards a higher cycle number, the phenomena of cycle ageing occur, leading to gradual decay in the maximum storage capacity of the battery. This irreversible capacity loss occurs due to the following: electrolyte decomposition, SEI layer formation on the surfaces of the electrodes and current collectors, dissolution of active materials, phase transitions in the insertion electrode, and structural changes of the electrodes [Dubarry2011b].

The authors in [Dubarry2011b] explained that the degradation process occurs in two different steps. In the first step, the capacity fade is linear during the first 500 cycles. In this step, capacity fading happens due to the loss of lithium inventory caused by parasitic reactions, forming the SEI film on the electrode surfaces. In the second step, the capacity fading rate increases because the SEI layer grows on the electrode surfaces that restrict interfacial kinetics, causing an active material loss in the electrodes.

2.2.5.2 Effect of Temperature

Temperature significantly affects the Li-ion battery safety, performance, and cycle life [Mikolajczak C2011]. Both higher and lower temperatures negatively impact cell performance, particularly on the cell capacity. The impact of temperature and voltage on the battery failure occurs promptly. However, their influence upon the cycle life is comparatively less visible [Ji2013]. At a lower temperature than 10 degrees C or a higher temperature around 60 deg C, the cycle life gradually declines. However, if the battery is being exploited at a very high temperature of 70deg C, it can face thermal runaway.

To attain effective operation and to ensure long life, an efficient thermal management system becomes necessary. The authors in [Karimi2014] investigated different battery thermal models and analyzed the battery thermal management under different scenarios. However, there is still a dire need to address various thermal management issues like high power consumption, narrow optimum temperature range, and operation in varying climate.

2.2.5.3 Effect of State of Charge

The optimum SoC while charging or discharging plays a vital role in controlling the degradation of Li-ion battery. A lower or higher SoC enhances battery ageing in either capacity fade or power fade, or both. In the charging scenario, higher SoC leads to a risk of higher charging stress and during discharging, lower Soc might reduce the discharge efficiency. This makes the voltage

restrictions an essential steps for controlling over-charge/discharge and their corresponding problems. Figure 2.11 illustrates the SOC operating window for a typical Li-ion battery and the effects of not following this barrier.

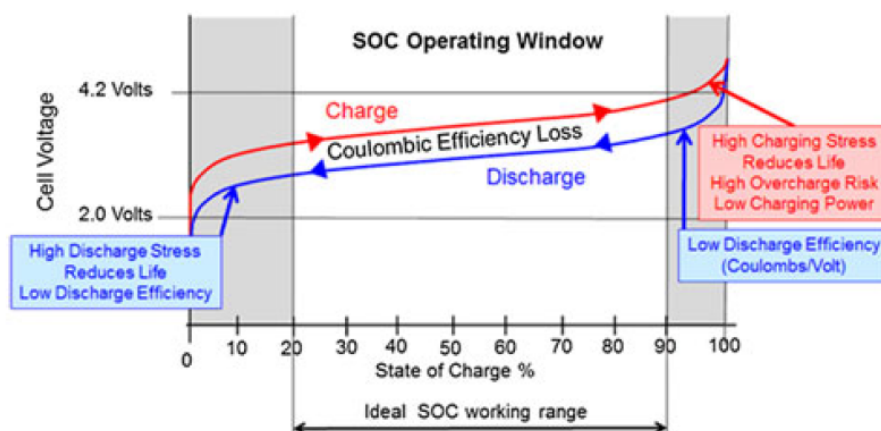


Figure 2.11: SOC operating window

2.2.5.4 Effect of moisture

The electrolytes used in Li-ion battery are susceptible to moisture because of the salt present in it and is responsible for cell degradation. The most widely used salt for the electrolyte of Li-ion batteries (i.e., LiPF₆) is highly susceptible to moisture. Due to moisture exposure, the LiPF₆ salt decomposes into hydrofluoric acid (HF), which is highly reactive and accelerated the decay in electrolyte and electrodes [J2002]. The prevention of moisture effects on cell degradation can be taken care of during the cell design process by choosing a better electrolyte.

2.2.6 Li ion battery in EV : How to add sustainability to its life cycle

In the last few decades, global warming and related resource exploitation have become the most pressing situation. The global concerns regarding the long term effect of these issues have strengthened the need to shift to approaches to ensure a more sustainable future. The transportation sector is a significant contributor to air pollution due to the unprecedented use of hydrocarbon-based fuels and dependency on internal combustion engines for over a century [Canals Casals2017].

To curb up the drawbacks of the transportation sector, we view a transition to EV Electric vehicles, which are a promising solution to restrict such emissions. EVs are increasingly gaining market share, and companies historically embedded in the combustion-engine value chain are experiencing once in a century transformation of their traditional business model. Although EV has no tailpipe emissions, its well-to-tank energy efficiency, coming from the electricity generation and distribution to charge the EV battery, is less performing than one of internal combustion engine vehicles. Owing to higher energy density and low maintenance needs, Li-ion batteries have found their place as a power source in most electric vehicles. However, global mass-market adoption of EVs is still hindered by presently high costs of lithium-ion battery (LIB) packs, which translate into highly-priced vehicles [Bonges2016]. Also, the battery is the main contributor to environmental impact and faces recycling issues. Li-ion batteries comprise exhaustible elements like Lithium, Nickel and Cobalt. The extraction of these materials come at a substantial environmental and health cost. Therefore, it is absolutely essential to use the batteries efficiently.

In addition to higher prices, these batteries are also not that green as it seems and is the main contributor to environmental impact. These batteries reach their End of Life (EoL) when capacity

degrades to 80 percent of original capacity and cannot be used further in electric vehicles. Thus, a substantial unused potential of the battery gets wasted, which is detrimental to the environment. However, this unused potential can also be considered an opportunity to make the EVs more affordable by applying the concept of battery second use. The second use can loop back some revenue to OEM that may decrease EV prices and thus make EV more competitive [Jiao2016]. According to [Melin2018], the global market of EOL Li-ion batteries is expected to grow 3.5 billion dollars by 2025. [Törkler2014] 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), etc. iii) Energy-related / industrial applications (up to 50 MWh): Renewable energy storage, Grid stabilization, etc. In this second life, the batteries can be procured at low cost, indicating new businesses opportunities.

By facilitating remanufacturing, repurposing or reuse, the circular economy principles of making the life cycle loops small are abided [Antikainen2016]. The resource cycle can be slowed down by prolonging the battery's total service life and partially closing the resource loop. The recycling phase is delayed substantially, leading towards improved sustainable resource management. [Boons2013] argue that sustainable business models (SBMs) can significantly contribute to solving economic, ecological and social problems simultaneously.

However, there is only minimal research that has analyzed sustainable business models for EV batteries. Consequently, follow-up studies in demand evaluate the increased value of reusing EV batteries [Jiao2017]. With the unprecedented increase in the number of Electric Vehicles, end-of-life (EOL) EV batteries will change the current nature of the automotive and energy industries as the electricity markets lack cost-effective ESS. Consequently, there is the opportunity for original equipment manufacturers (OEMs) and new market stakeholders such as electricity producers, grid operators, recycling companies, service providers, and final costumers, which all will be part of innovative evolving value chains. Currently, the EV business model mainly focus on economic aspects without integrating social and environmental dimensions as part of sustainable solutions [Jiao2016]. Thus, a more holistic business model is required to ensure a multidimensional sustainability in regard of Electric vehicles.

The EV batteries lifecycle mainly consists of raw material extraction (including mining and processing), battery manufacturing, the primary use in the EV (1st life), followed by end-of-life disposal [Neubauer2015, Neubauer2011, Richter2016, Ahmadi2017]. To have a sustainable lifecycle, additional loops should be added like reusing, remanufacturing or repurposing. During the first life, the EV batteries life is vastly dependent on the usage condition, characterized by driving patterns, operating temperatures and charging rates, which makes each battery age individually and makes it difficult to predict a battery's ageing behaviour. An EV battery is considered to reach EOL when it has degraded by 20%–30% of its capacity [Ahmadi2017]. As these batteries still retain around 70%–80% capacity, researchers have found that instead of recycling these EOL batteries immediately after their first use in an EV, repurposing degraded EV batteries in second life in less demanding stationary ESS is still possible and feasible from a techno-economic and environmental perspective [CREADY2003, Wolfs2011, Gaines2011, Neubauer2011, Ramoni2013, Manzetti2015].

However, since the degradation of every EV battery is unique and has its state of health depending on the previous exposure and treatment during their first life, the sorting of these batteries at the EOL is a cumbersome task. Therefore, a standard testing procedure is urgently needed so that degraded batteries can be safely characterized for use in second life application. Further, there is a lack of an accepted standard for battery reuse. Therefore, researchers are calling for battery quality standards and certification protocols to ensure safe and effective functioning in second-life applications.

The literature research in this field concluded that industrial and residential uses are the most sustainable second life application for EV batteries [Gaines2011, Neubauer2011, Standridge2015]. [Burke2010] also justified that the residential sector is the most efficient second life solution. How-

ever, from an economical point of view, [Williams2010] suggests that large-scale stationary ESS is more viable. [Richter2016], classified second life application with regards to the ESS's degree of mobility in stationary (e.g. home storage from PV panels), semi-stationary (e.g. power for construction sites), or mobile (e.g. reuse in scooters or golf cars). Thus, the battery management system has to be adjusted to the specific second life application to increase overall lifetime and economic benefits.

2.3 State of Health : A key indicator to decision making

We already conveyed that reusing the End of Life (EOL) Li-ion batteries will benefit society both economically and ecologically in the sustainability context. However, establishing a suitable infrastructure for facilitating this sustainable model is a bit challenging. During the charging and discharging process, the battery usage triggers irreversible changes in the characteristics of internal components. The main reason behind this is the complex electrochemical reactions. Such changes as solid-electrolyte inter-phase (SEI) formation undermines battery performance and are therefore seen as causes of health deterioration. In addition, the external operating condition makes the degradation even more complicated, so it is pretty challenging to foresee the health condition of batteries in the future.

The state of health conveys an approximate understanding of battery ageing and degradation behaviour. Also, it can be considered as an indicator of the time of good functioning of the battery. However, there is no consensus on the quantitative definition of SoH. Any feature that changes significantly with battery ageing, such as maximum releasable capacity or internal resistance, can be utilized to identify SoH. [Lin2015] defines SoH as a relative capacity, where relative capacity can be obtained by :

$$C_{relative} = \frac{C_{n_p}}{C_{n_o}} \quad (2.1)$$

where C_{n_p} represents the capacity of the current cells, C_{n_o} represents the initial capacity of cell before cycle test.

[Dai2009] adopted internal resistance to define SoH of batteries used in hybrid electric vehicles. In this approach, battery end of life (EOL) is reported when internal resistance rises to 160 % of initial resistance. The SoH is therefore expressed as:

$$SoH = \frac{R_{EOL} - R_{current}}{R_{EOL} - R_{new}} * 100 \quad (2.2)$$

where R_{EOL} is the internal resistance at EOL, $R_{current}$ and R_{new} are the current and original internal resistances respectively.

[Chen2013] defined SoH as the ratio of remaining capacity to nominal capacity while [Okoshi2006] used the ratio of present capacity to initial capacity to define SoH,

$$SoH = \frac{C_{current}}{C_{nominal}} * 100\% \quad (2.3)$$

$$SoH = \frac{C_{current}}{C_{initial}} * 100\% \quad (2.4)$$

Overall, capacity and internal resistance are two widely used health indicators for analyzing State of health of Li-ion batteries. The battery capacity reflects the amount of energy the battery can store, while the internal resistance or impedance are indicators of its power capability. The choice of the health indicator depends on the application of battery. When it comes to hybrid

applications, the battery's power is of great interest, compared to EV where the battery energy is more crucial.

2.3.1 SoH estimation

In case of reusing or repurposing Li-ion batteries, State of health plays an important role in taking a lot of relevant decisions. Knowing the SoH can be used to recognize an ongoing or a sudden degradation of the battery cells and to preplan a possible future use of these batteries. Even though the importance of the SoH is really high, still does not exist a consensus in the industry or in the scientific community on how exactly SoH is defined and how should be determined.

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 [Lipu2018, Omariba2018, Sarmah2019, Samadani2012] 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 ([Ungurean2017, Berecibar2016a]) in the past includes degradation in both capacity and power during estimation of SoH. But, references [Ungurean2017, Berecibar2016a] failed to highlight the factors that affect SoH. We found that the references [Wu2016, Li2019, Saha2009] delineated only data-driven approaches to estimate SoH. On the other hand, reference [Khayat2016] only described the adaptive methods to estimate SoH of batteries. Reference [Waag2014] 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.

There are numerous SoH estimation methods that has been explored in the past by different domains. We will explain each methods concisely in the section below.

2.3.2 SOH estimation techniques and tools: State of art

2.3.2.1 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.

In [Eddahech2012a], the authors proposed a method for calendar aging quantification of batteries which take in to account State of Charge (SoC) and temperature. EIS test were performed to identify the parameter for Remaining Useful life prediction. Finally authors concluded that a particular frequency range of 0.1 Hz to 1 Hz has the greatest influence on aging. The authors in [Eddahech2012b] investigated the behavior and State of Health(SoH) monitoring of Li-ion batteries. An equivalent circuit model for battery is constructed based on EIS measurements. The fundamental characteristics of this model is its simplicity and the fact that it considered dependence of internal resistance and open circuit voltage. In [Galeotti2015], the authors defined a test procedure to study the ageing of LiPO (lithium polymer) batteries through the EIS technique. The equivalent circuit model parameters were extracted from EIS spectra and a relation between the ohmic resistance of the battery and the available capacity to was established to evaluate the SoH (State of Health) through the ToE (Theory of Evidence). A modified single particle impedance model was proposed in [Li2014c]. To identify the model parameters, an optimization technique

called particle swarm optimization was employed. Further parameter variations in different stages of aging were studied.

2.3.2.2 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 State of Health and Open Circuit Voltage (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.

The authors in [Chiang2011] formulated the electrical performance of a battery into state-space representation based on an Equivalent Circuit Model. The goal was to extract OCV and internal resistance without limitation of a system input signal. A unified OCV model was proposed in [Weng2014]. This can be applied for both SoC and SoH monitoring because it captures aging information based on incremental capacity analysis. The authors also did parametric analysis and model complexity reduction to have a simplified version in the application context of SoH monitoring. In [Tong2015], the author proposed a novel SoH correlation as part of the battery equivalent circuit model. The capacity of the battery was implicitly optimized by on-line optimization of SoH. An associated state and parameter dual estimator was proposed which comprised an Extended Kalman Filter as a state observer, Recursive Least Square algorithm as an internal resistance identifier, and Parameter Varying Approach as the SoH correlation identifier. The author in [Lavigne2016] modeled a lithium ion battery by taking into consideration, the aging effects. The impact of aging on electrode stoichiometry and Open Circuit Voltage curve was analyzed. Based on the idea that for two fixed OCVs, the state of charge between two equilibrium states is unique for a given aging level, a method for state of health prediction was proposed.

2.3.2.3 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.

In case of EKF, the dimension and complexity of formed matrix could be very high. So, to further reduce the computation complexity while estimating battery SoH, the dual extended

Kalman filter can be used. It involves two Kalman filters, one filter is used to predict the SoC and the other one to predict the battery capacity.

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.

A dual filter comprising of a standard Kalman filter and an Unscented Kalman Filter was proposed in [Andre2013] to predict internal states of battery. Additionally a support vector machine algorithm was implemented and coupled with the dual filter. The authors verified and validated both the methods by cell measurements in form of cycle profiles and cycle aging tests. The authors in [Haifeng2009], designed a parameter system identification based SoH prediction method. The model parameters were estimated by Dual Extended Kalman Filter to identify internal resistance of battery. The authors in [Maletić2020] proposed a dual extended Kalman filter-based estimator for battery State of Charge, internal resistances, and parameters of open-circuit voltage. In addition, a slow time scale, sigma-point Kalman filter-based capacity estimator was designed and coupled with the DEKF. Finally, a convergence detection algorithm was proposed to ensure that the two estimators were coupled automatically only after the capacity estimate has converged. A model-based monitoring approach for the internal resistance dependent State of Health of a high power lithium-ion battery cell was proposed in [Remmlinger2013]. To cover the usual operation range of temperature, a battery cell model from the class of linear parameter-varying (LPV) models was identified from measurement data acquired from battery management system. Further, The model was used in a non-linear Kalman filter to estimate SoH on-line from on-board measurements continuously.

2.3.2.4 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.

In [Ng2009], the authors proposed a smart estimation method based on Coulomb Counting with the goal to improve the accuracy. Later, the SoH was evaluated by maximum releasable capacity. A data driven method for estimating the SoH of Li-ion battery based on charge voltage current curves was proposed in [Hu2014a]. The authors developed a non linear kernel regression model based on k-nearest neighbor regression to capture the complex dependency of capacity on several features. Further to minimize the cross validation error in estimation, the optimal combination of features weights were identified by particle swarm optimization. The authors in [Einhorn2012] presented a novel method for capacity estimation of battery. The inputs for the methods were tow different states of charge and transferred charge between these two states. In [Sepasi2015], the author proposed an inline State of Health and State of Charge estimation method for Li-ion battery packs. Inline estimated model parameters were used in a combined SoC and SoH estimator consisting of the SOC calculation based on coulomb counting method and an SoH observer using an extended Kalman filter technique to calibrate the estimate from the coulomb counting method.

2.3.2.5 Genetic Algorithm (GA)

Often Genetic Algorithm is used to estimate the parameters of non-linear model in all domains of physics. It uses huge amount data to learn parameter values. However, it is difficult to implement it online, because of high computational power.

In [Bi2016], a novel Genetic Particle Filter based method was proposed for SoH estimation to improve the accuracy of equivalent circuit model. A second-order equivalent circuit model for the battery pack was developed and the unknown parameters were identified using the recursive least-squares method. Finally, a state-space model of the GPF is developed based on the equivalent circuit model. The authors in [Zheng2013] developed an equivalent simplified approach for SoH estimation using voltage -capacity rate curve and implement Genetic Algorithm for finding the optimum transformation parameter for overlapping voltage capacity rate curve. In [Chen2013], Genetic Algorithm was employed to estimate the battery model parameters in real time using the current and voltage measurements of the battery. Parameters such as diffusion capacitance, was used to establish a correlation with SoH. The authors in [Sangwan2016] estimated the second-order RC network equivalent circuit model parameters using Genetic algorithm and Particle Swarm optimization to avoid experimental methods that are time-consuming, expensive and require high computational power. Further, for proper evaluation, the mathematical model was built to include the effect of the state of charge, and temperature variations in the battery. Estimation was finally done in terms of ratio of the predicted voltage curve's closeness to the known real voltage curve.

2.3.2.6 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.

FL system can generalize any system using cycle number estimation because in some of the battery tests, it will be logical to describe the state of battery as some levels (high, low) rather than getting a discrete number. Fuzzy logic can easily be applied to the battery SoH estimation if we define several output membership functions for the SoH, such as healthy, acceptable and End of life.

In [Salkind1999], the authors used fuzzy logic to analyze data obtained by impedance spectroscopy and coulomb counting techniques. The authors claimed that the proposed method will predict the SoC and SoH of batteries without the need to know their previous discharge or cycling history. The authors in [Singh2006] developed a fuzzy logic based State of Health (SoH) meter for lithium-ion batteries. Accurate models were developed to estimate the number of pulses that the battery pack can deliver at various stages of its cycle life (SOC measure) and the number of charge/discharge cycles (SoH measure) that it had undergone. An estimation method based on fuzzy logic system was proposed in [Zenati2012]. The authors constructed the fuzzy logic system using only the temperature and the absolute value of current that the battery sustains. The model was validated by experiments on both new and aged battery.

2.3.2.7 Support Vector Machines (SVM)

Support Vector Machine analyzes data and helps in recognizing patterns for nonlinear systems. The SVMs have been widely used for classification problems in various domains of pattern recog-

dition. However, the SVM can also be applied to regression problems, although regression is inherently more difficult than classification. 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. However, this method depends on the given environmental conditions and load conditions. 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 rise in computation cost.

The authors in [Klass2014] developed a method where battery performance tests can be applied virtually to a support vector machine based battery model. The obtained results from this method demonstrated a good accuracy over different SoC and temperature and the method is suitable for on-board applications as well. In [Patil2015], a novel method for real time estimation of Remaining Useful Life(RUL) of lithium-ion batteries is proposed. The method incorporated the integration of classification and regression attributes of Support vector machine. The classification model provided a gross estimation, and the Support Vector Regression (SVR) was used to predict the accurate RUL if the battery is close to the End of life (EoL). A new data-driven approach for embedding diagnosis and prognostics of battery health was proposed in [Nuhic2013]. Support vector machine is used for estimation of SoH. As the estimation of SoH and RUL is highly influenced by environmental and load conditions, the SVM was combined with a new method for training and testing data processing based on load collectives. The author in [Meng2018] proposed a support vector machine based novel method to predict SoH using the features from the terminal voltage response of the Li-ion battery under current pulse test. The reason behind using terminal voltage is its variability with battery aging process when measured at same test condition and being a short term test , it is convenient to be obtained in real time applications.

2.3.2.8 Autoregressive Model (ARMA)

Autoregressive Model is a regression based model which takes care of noise as well. It is an efficient tool to understand the underlying pattern of a system from time series data and predicting the near future value. 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.

In [Long2013], the authors proposed a RUL estimation method using an improved autoregressive model and particle swarm optimization. The autoregressive model is based on the capacity fade trends of lithium-ion batteries and the root mean square error (RMSE) was proposed as the new method for AR model order determination. The particle swarm optimization was used to search the optimal AR model order. The authors in [Zhou2016a] proposed a novel approach for RUL prognostics that combines autoregressive integrated moving average (ARIMA) and empirical mode decomposition (EMD). The EMD was utilized to decouple the overall degradation trend and capacity regeneration from SoH time series, which were then used in ARIMA model to predict the future SoH. A fusion model based on autoregressive moving average and Elman neural network was proposed in [Chen2019] to predict SoH accurately. The authors also incorporate the empirical mode decomposition (EMD) to process the capacity degradation data and eliminate the phenomenon of tiny capacity recovery while data processing.

2.3.2.9 Artificial Neural Network (ANN)

Recent studies in time-series forecasting have focused more on the using of versatile techniques such as neural networks (NN). The main advantage of NN methods is that they are established automatically by training, without the need for the detection of model parameters and coefficients. It is a fully data driven method that maps input to output. 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 its 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. However, because of the ability of handling a large amount of data of a complex nonlinear system, a lot of research in the past [Bai2014, Wang2017a, Lee2012] has been done to predict SoH with NN.

The authors in [Bai2014] proposed a data driven approach that combines artificial neural network with a dual extended Kalman filter (DEKF) algorithm for SoH estimation of lithium ion battery. The terminal voltages were modeled by training the neural network offline and DEKF algorithm was further employed online for SoC and SoH estimation. The author claimed the pros of this method is being a model-free approach. In [Wang2017a], a unified artificial neural network based thermo coupled equivalent circuit model was proposed with the motive of capturing electrical and thermal dynamics of lithium ion batteries. The ANN was used to establish a quantitative relationship between circuit parameters and temperature or state of charge in equivalent circuit model. This method can be easily extended to more complicated models such as first principle Electrochemical thermal model. The authors in [Lee2012] proposed two methods namely, linear prediction and neural network algorithm for estimating the remaining useful life of battery. To make this method feasible for real time operations, the model has to be scaled from cell level to the battery level. The authors in [Lin2013] proposed a probabilistic neural network to estimate the State of Health of Li-ion batteries. The data was acquired from the recharging and discharging electric characteristics as well as the life-cycle test of the battery. The test data showed that the constant current charging time, the instantaneous voltage drop at the start of discharging, and the open circuit voltage are the most important characteristics for estimating the SoH of the battery. The authors claimed that this method can accurately estimate the State of Health in short period.

2.3.2.10 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.

The authors in [Prasad2013] used offline least square method to estimate parameters of Electrochemical model of lithium ion battery. These parameters can further be correlated with the battery age since they are consistent with degradation mechanisms like solid electrolyte interface layer growth and contact loss. In [Zhang2018], the authors used the method of particle swarm optimization and genetic algorithm for battery pack model parameters identification. Also, a particle filter was employed in battery SOC and OCV estimation to avoid the noise influence occurring in battery terminal voltage measurement and current drift. In the end a recursive least square method was used to update cells' capacity. This update capacity can be compared to initial rate capacity to estimate SoH. Finally, the proposed method was verified by the New European Driving Cycle and dynamic test profiles. A model-based condition monitoring strategy was developed in [Kim2015]

for lithium-ion batteries based on electrical circuit model incorporating hysteresis effect. Recursive least squares algorithm was used for parameter identification of the battery model and a smooth variable structure filter was used for SOC estimation. The SoH estimation was established by using a recursive total least squares algorithm.

2.3.2.11 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.

The authors in [Ng2014] proposed a naive Bayesian model for remaining useful life prediction of batteries under different operating conditions. The authors concluded that if the discharge environment is constant, then remaining useful life of a battery can be predicted using Naive Bayesian model irrespective of the operating condition. Another interesting conclusion portrayed that the operating condition of lithium ion battery poses more challenges than the environmental condition while predicting SoH. In [He2014], the authors proposed a novel online method for SoH estimation of lithium ion battery based on Dynamic Bayesian Network (DBN). In this network, State of Charge is used as hidden states and the terminal voltages have been used as an observation symbols. Further, a forward algorithm was applied in order to estimate the SoH in real-time. The authors in [Hu2015a] presented a sparse Bayesian learning method that utilized charge voltage and current measurement from a lithium ion battery to estimate the SoH. Relevance Vector Machine (RVM) was employed as a probabilistic kernel regression method to learn the complex correlation between battery's capacity and identified characteristics features.

2.3.2.12 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. This tool is widely used because it allows to handle complex emission Probability Density Functions (PDFs) generated by a set of continuous features extracted from raw monitoring signals.

In [Min Zhu2016], the authors proposed a novel SoH estimation based on Grey-Markov Chain which takes into account the internal resistance of battery. They also designed the real-time internal measurement equipment to calculate internal resistance data automatically. SoH was considered as hidden states of the model and internal resistance was used as the observance sequences for the Markov chain. The authors in [Yu2013] proposed a hidden Markov model based method to distinguish the degradation modes of electric vehicles batteries. A cluster analysis of charge and discharge curve was done to identify the degradation modes of the battery. Then, HMM was applied to understand the dynamic changes of degradation modes and to predict future degradation mode sequences. A hidden Markov model based SoH estimation method was proposed in [Piao2016]. The correlation of battery's degradation to SoH was done by the parameter of internal resistance. Different driving patterns were also considered during model implementation. The author claimed that this method can be used for online prediction as well. The authors in [Lee2020] proposed capacity-fading behavior analysis for the early detection of unhealthy Li-ion batteries against the capacity-fading behaviors of healthy batteries. The proposed model consisted of a local outlier

factor for calculating the anomaly scores of the capacity-fading behaviors of test batteries at a certain cycle, kernel density estimation for normalizing the range of anomaly scores over cycles, and a hidden Markov model for estimating the probability of a battery to be in particular state.

2.3.2.13 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. However, there have been a limited number of studies in this aspect.

The authors in [Yang2018] proposed a novel Gaussian process regression (GPR) model based on charging curve. Four specific parameters were extracted from charging curves and were used as inputs of the GPR model. Further, the grey relational analysis method is applied to analyze the relational grade between selected features and SoH. The paper also experimented on a battery with dynamic discharging profile to verify the robustness and reliability of the proposed method. In [Wang2017a], the authors proposed a novel ICA-based method for battery SoH estimation to identify the most effective characteristic parameters of IC curves. The peak value and position was extracted as health factors (HFs) from IC curves. Then, SoH and HFs were correlated through the grey correlation analysis. The SoH model was established using Gaussian process regression (GPR), in which the optimal hyper parameters were calculated by the multi-island genetic algorithm (MIGA). A systematic multi scale Gaussian process regression (GPR) modeling method was proposed in [He2015] to estimate SoH. Wavelet analysis method was used to avoid fluctuations in SOH time series. GPR was utilized to fit the extracted global degradation trend, and GPR with the input of lag vector was modeled to recursively predict local regeneration and fluctuations. In [Liu2013], the authors proposed a data driven approach based on GPR to describe the uncertainty in evaluation and prediction. To realize future SoH, they used an improved GPR method—combination Gaussian Process Functional Regression (GPFR)—to capture the actual trend of SoH, including global capacity degradation and local regeneration.

2.3.2.14 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.

The lithium-ion battery RUL prediction is a regression prediction problem. 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.

In [Saha2007], the authors used relevance vector machine for diagnosis as well as for model development. Further, a Particle Filter framework was proposed which uses this model and statistical estimates of the noise in the system and anticipated operational conditions to provide estimates of SOC and SoH. The authors in [Zhou2016b] extracted a novel health indicator (HI) from the operating parameters of lithium-ion batteries for degradation modeling and RUL prediction. The authors utilized Pearson and Spearman correlation analyses to evaluate the similarity between real capacity and the estimated capacity derived from the HI. Relevance vector machine was employed to predict the RUL based on the presented HI. In [Wang2013], the capacity prognostic method proposed by the authors consist of a relevance vector machine and a conditional three parameter

capacity degradation model. The relevance vector machine was employed to derive the relevance vectors that can be used to find the representative training vectors containing the cycles of the relevance vectors and the predictive values at the cycles of the relevance vectors. In [Li2014a], the authors proposed a multi step-ahead prediction model based on the mean entropy and relevance vector machine to predict State of Health and remaining useful life of the battery. A wavelet denoising approach was introduced into the RVM model to decrease the uncertainty. The mean entropy based method was then employed to choose the optimal embedding dimension for correct time series reconstruction. Finally, RVM was employed as a novel nonlinear time-series prediction model to predict the State of Health and remaining useful life of the battery.

2.3.2.15 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.

The authors in [Hu2014b] discussed a sample entropy based capacity estimator for lithium ion batteries. The sample entropy of cell voltage sequence under hybrid pulse power characterization profile was used as the input of the health estimator. The calculated sample entropy and capacity of a reference Li-ion cell (randomly selected from the eight cells) at three different ambient temperatures were used as the training data to design the model by using the least-squares optimization. In [Li2014b], the authors presented a remaining capacity estimation method for a single lithium ion battery. Sample Entropy was used to calculate the surface temperature during charging process and the correlation between Sample Entropy and capacity fading was set up. The authors in [Hu2015b] proposed a machine learning based battery State of Health indication and prognosis system. The sample entropy of short voltage sequence was used as an effective signature of capacity loss. Further, Advanced sparse Bayesian predictive modeling (SBPM) methodology was incorporated to capture the underlying correspondence between the capacity loss and sample entropy. The proposed approach allowed for an integration of temperature effects in the model as well.

2.3.2.16 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.

The particle filter can be used on a battery model with unknown parameters. The output of the method is an estimation of the PDF based on a set of points (particles). Particle filter can be used to develop a statistical estimation of State of Health. However, for particle filter, the amount of defined samples imposes an 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.

In [Schwunk2013], the authors presented a particle filter based estimation method. The model overcomes the problem of flat and ambiguous characteristic curves by using Monte Carlo sampling methods which are able to represent any probability density function. The ambiguities were modeled stochastically to avoid the complexity dealing with hysteresis. The same framework was

employed for SoH estimation which took the estimated state of charge as input for estimating the battery's state of health. The authors in [Dong2014] proposed a Support vector regression-Particle filter based method for SoH and RUL estimation. Novel capacity degradation parameters were also proposed in this paper. The author claimed that the combined Support vector regression-particle filter has better performances than the classical particle filter based estimation. The authors in [Samadi2012] presents a particle filter based algorithm to estimate health states and for condition monitoring of the Li-ion battery which can effectively handle the nonlinear and complex nature of the partial derivative equations describing the dynamics of the battery. The author claimed that accurate estimation of the average as well as spatial distribution of health concentration in the battery can be done using this method.

Table 2.1 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 the next chapter.

Table 2.1: List of relevant papers for SoH estimation

Citation	Corresponding Author	Algorithms / Methods Used	Mode of Operation	Category
[Bai2014]	Pinfeng Wang	Artificial Neural Network & Dual Extended Kalman Filter	Offline / Online	Raw data based features
[Wang2017b]	Yi-Jun He	Artificial Neural Network & Equivalent Circuit Model	Offline	Model based features
[Lee2012]	Seungchul Lee	Artificial Neural Network	Offline	Analytical features based
[Ng2009]	Kong Soon Ng	Coulomb counting	Offline	Model based features
[Einhorn2012]	Markus Einhorn	Coulomb counting	Online	Model based features
[Hu2014a]	Chao Hu	Coulomb counting & K means & Particle Swarm Optimization	Offline / Online	Analytical features based
[Tang2011]	Xidong Tang	Equivalent Circuit Model	Online	Model based features
[Wei2018]	Jingwen Wei	Particle Filter & Support vector regression	Online	Analytical features based
[Klass2014]	Verena Klass	Support Vector Machines	Online	Raw data based features
[Patil2015]	K. S. Hariharan	Support Vector Machines	Offline / Online	Raw data based features
[Nuhic2013]	Adnan Nuhic	Support Vector Machines	Online	Raw data based features
[MinZhu2016]	Min Zhu	Grey Markov Chain	Online	Analytical features based
[Yu2013]	Gang Yu	Hidden Markov Model	Offline / Online	Raw features based
[Piao2016]	Sheng Lu	Hidden Markov Model	Offline / Online	Raw data based features
[Hu2014b]	Xiaosong Hu	Sample Entropy & Least squares optimization	Offline / Online	Raw data based features
[Li2014b]	Chao Lyu	Sample Entropy & Particle Filter	Offline / Online	Analytical features based
[Zou2015]	Yuan Zou	Kalman Filter & Recursive Least square & Equivalent Circuit Model	Offline	Model based features
[Long2013]	Bing Long	Autoregressive Model & Particle Swarm Optimization	Offline / Online	Analytical features based
[Zhou2016a]	Yapeng Zhou	Autoregressive integrated moving average (ARIMA) model	Offline / Online	Analytical features based

Continued on next page

2.3. State of Health : A key indicator to decision making

Table 2.1 – continued from previous page

Citation	Corresponding Author	Algorithms / Methods Used	Mode of Operation	Category
[Chen2019]	Zheng Chen	Autoregressive moving average model & Elman Neural network	Offline	Analytical features based
[Ng2014]	Selina S.Y. Ng	Naive Bayesian model	Online	Analytical features based
[He2014]	Mingyu Gao	Dynamic bayesian Network	Online	Analytical features based
[Hu2015a]	Chao Hu	Sparse bayesian learning & Relevance Vector Machine	Online	Analytical features based
[Saha2007]	Bhaskar Saha	Relevance Vector Machine & Particle Filter	Online	Analytical features based
[Zhou2016b]	Yapeng Zhou	Relevance Vector Machine	Online	Analytical features based
[Wang2013]	Qiang Miao	Relevance Vector Machine	Online	Analytical features based
[Li2014c]	Baojin Wang	Electrochemistry based Impedance model	Offline	Model based features
[Ed-da-hech2012a]	A. Eddahech	Electrochemical Impedance Spectroscopy	Offline	Model based features
[Ed-da-hech2012b]	Akram Eddahech	Electrochemical Impedance Spectroscopy & Neural Network	Offline / Online	Model based features
[Gale-otti2015]	Matteo Galeotti	Electrochemical Impedance spectroscopy	Offline	Model based features
[Salkind1999]	Alvin J. Salkind	Fuzzy Logic	Online	Analytical features based
[Singh2006]	Pritpal Singh	Fuzzy Logic & Electrochemical Impedance Spectroscopy	Offline / Online	Analytical features based
[Zenati2012]	Ali Zenati	Fuzzy Logic	Online	Analytical features based
[Bi2016]	Haiyang Yu	Genetic Re sampling Particle Filter	Offline / Online	Model based features
[Zheng2013]	Minggao Ouyang	Genetic Algorithm	Offline	Analytical features based
[Chen2013]	Chunting Chris Mi	Genetic Algorithm	Online	Analytical features based
[Yang2018]	Zonghai Chen	Gaussian Process Regression	Offline / Online	Analytical features based
[Wang2017a]	Lei Zhang	Gaussian Process regression & Genetic Algorithm	Offline / Online	Analytical features based
[He2015]	Yi Jun He	Multiscale Gaussian Process Regression	Online	Analytical features based
[Liu2013]	Datong Liu	Gaussian Process Functional Regression	Online	Analytical features based
[Andre2013]	Dave Andre	Dual Kalman Filter & Support Vector Machines	Offline / Online	Model based Approach
[Haifeng2009]	Dai Haifeng	Kalman Filter & Open Circuit Voltage	Offline	Model based features
[Kim2013]	Taesic Kim	Recursive Least square	Online	Model based features
[Miao2013]	Qiang Miao	Unscented Particle Filter	Offline / Online	Analytical features based
[Prasad2013]	Githin K. Prasad	Recursive Least square	Offline	Model based features
[Zhang2018]	Zonghai Chen	Particle Swarm Optimization & Genetic Algorithm	Offline / Online	Raw data based features

Continued on next page

Table 2.1 – continued from previous page

Citation	Corresponding Author	Algorithms / Methods Used	Mode of Operation	Category
[Kim2015]	Taesic Kim	Recursive Least square	Online	Model based features
[Schwunk2013]	Simon Schwunk	Particle Filter	Offline / Online	Model based features
[Dong2014]	Hancheng Dong	Particle Filter & Support Vector Regression	Offline / Online	Model based features
[Samadi2012]	M.F. Samadi	Particle Filter & Electrochemical Model	Offline	Model based features
[Chi-ang2011]	Yi-Hsien Chiang	Equivalent Circuit Model & Open Circuit Voltage	Online	Model based features
[Weng2014]	Caihao Weng	Open Circuit Voltage model	Offline	Model based features

2.3.3 Challenges in SoH estimation

Right from the advent of Lithium ion battery for vehicular application, efficient estimation of State of Health (SoH) has been one of the fundamental research fields. 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 [Basia2019]. 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.

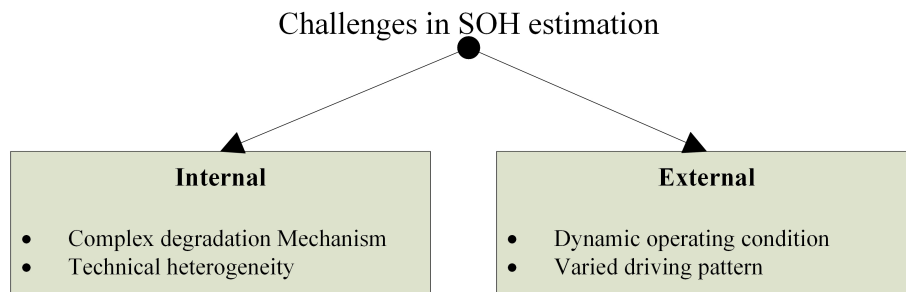


Figure 2.12: Classification of challenges in State of Health (SoH) estimation

2.3.3.1 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.

a. 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. It can have both chemical and mechanical origins. The reason behind this complexity is the nature of interdependence of various internal and external causes that leads to this degradation [Kabir2017]. 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 makes the study of degradation mechanism and consequently the estimation of state of health challenging. In addition, most of these factors [Birk2017] are nonlinear and that only current, voltage and external cell temperature with no internal state variables can be measured in real time makes state estimation even more challenging.

b. Technical heterogeneity

In the 21st 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. Thus, it is often challenging to have a global estimation model to predict the state of health of Lithium (Li) - ion batteries that are manufactured by different industries across the globe.

2.3.3.2 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.

a. 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 authors in [Leng2015] concluded that increase in the operating temperature increases the degradation rates of all components in the Lithium ion battery which include maximum charge storage capacity, the effectiveness of the electrode in storing Li-ions, charge transfer rate constant, effectiveness of the graphite electrode in providing its stored Li-ions, electrode and electrolyte resistance. 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.

b. 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. Driver's personal driving behavior is usually quite distinctive and can be recognized by means of driving patterns after some driving cycles. 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.

3

SoH as an indicator for Circular economy

Contents

3.1	Introduction	44
3.2	Global State of Health	45
3.3	Classification of SoH estimation methods	46
3.3.1	Model based features/characteristics	46
3.3.2	Data based Analytical Features	47
3.3.3	Battery Management System based raw features	48
3.4	Proposition of efficient SoH estimation methodology in the context of Circular economy	49
3.5	Overcoming the Barriers in PHM system for the Circular System by Hidden Markov Model	51
3.5.1	Introduction to HMM	51
3.5.2	Proposed Methodology	52

3.1 Introduction

State of Health (SoH) is an important measure of battery's life. In fact, it reflects the general condition of a battery and its ability to deliver the specified performance compared with a new battery. Being one of the prominent technologies in the battery management system (BMS), SoH, which reflects the degradation degree of energy/capacity and power/resistance for a battery during the whole life, is a foundation for SoC estimation, pack technology and secondary use. Also, SoH estimation plays an important role in ensuring safety and reliability of battery operation. SoH is not an absolute measurement but an indication of how much of the available "lifetime energy throughput" of the battery has been consumed, and how much is still left. In the case of Lithium (Li)-ion batteries, the capability to store energy and to provide a certain power decreases over the battery lifetime because of ageing or conditions of use. The capability to store energy can be indicated by battery capacity and likewise power providing capability can be indicated by internal resistance. The internal ageing mechanisms of different battery types convey loss of lithium inventory, active material decomposition, and structural changes as the common reasons for capacity loss and the increase in internal resistance is mainly contributed by Solid Electrolyte Interface (SEI) layer growth [Kabir2017].

Most of the battery manuals test procedures define that after 20 percent decrease in the initial rated capacity, the battery is considered not appropriate for vehicle application and need to be replaced [Podias2018]. Because, the battery might not be available to provide sufficient power under peak load. However, in many cases, the increase of the internal resistance resulting in power decrease leads to battery failure in advance. It is not only the capacity that deters the use of battery for long time but also, the degradation in power. So, SoH should indicate both capacity and power fade. In the past a lot of research work on SoH has taken into account either decreasing capacity or power degradation.

There are numerous second-life applications of Li-ion battery such as stationary energy storage system, less demanding mobile applications or power source for consumer electronics. These applications can utilize the remaining potential of EoL EV Li-ion batteries with a proper setup of a sustainable business model wherein diagnostics of the EOL batteries plays an important role. For a reliable circular industrial system, it is important to predict the reliability of that system in actual life cycle condition and the estimation of time to failure. Diagnosis aims to monitor the health state in real time while prognostics predicts the evolution of health state and remaining useful life. A prognostics health management system takes sensor measured values as input and ideally performs fault detection, diagnosis and prognosis.

Figure 3.1 illustrates the block diagram for diagnosis and prognostics applied to the circular economy. We have identified three kinds of dependencies. Bold arrows represent the sequence of processes that has to be followed for diagnostics and prognostics in the circular economy. The first task is setting up of a data acquisition system. The data collected will have to be cleaned, processed and then used for identifying relevant health indicators that will probe in State of health of Li-ion batteries. Once, we ave identified health indicators or features, an efficient diagnostics and prognostics algorithm will be chosen accordingly. The thin arrows represent the sub-processes of each process. The dashed arrows indicate the inputs for establishing the decision support system in context to the circular economy. The health indicators and results from diagnostics and prognostics process is important for setting up the decision support system. Eventually this decision support system can help in providing insights on Re-manufacturing and repurposing planning, predictive maintenance etc.

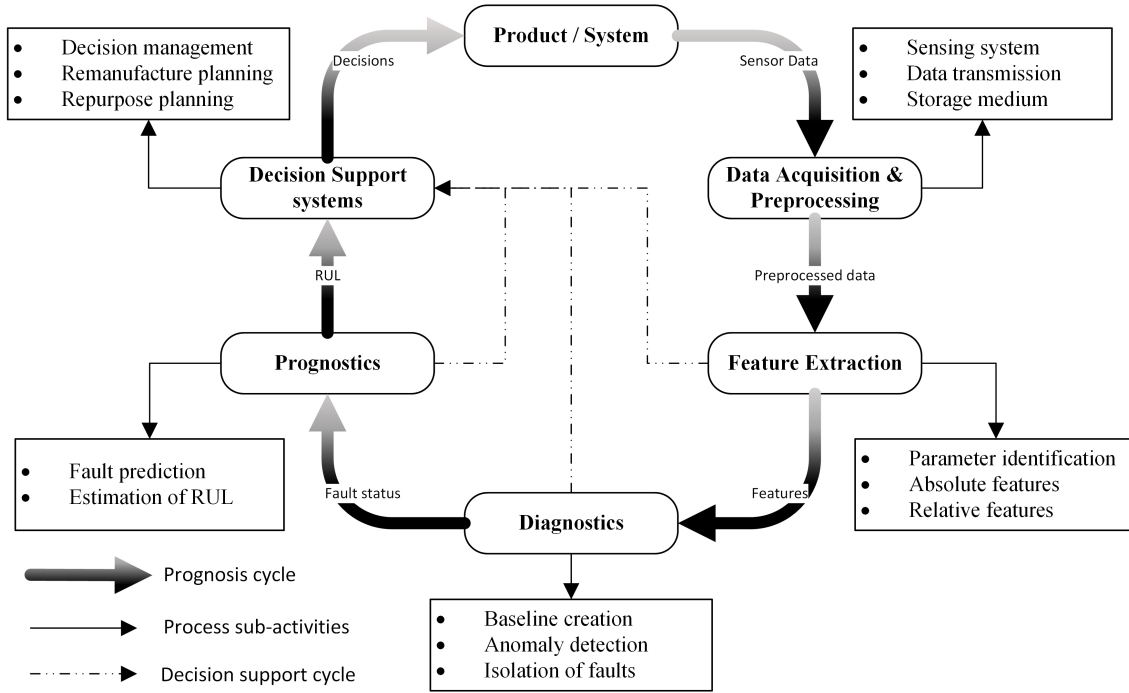


Figure 3.1: PHM system for Circular economy

3.2 Global State of Health

In context to the Circular economy, the principal motive of estimating SoH is to make better decisions while choosing re-purposing applications after the end of first life. In some applications (mobile - hover boards, electric bikes), power capability might have the same degree of importance as that of capacity. There are applications like inverters, which does not require same level of capacity as that of EV battery but better power capability might be needed. We propose a novel definition of State of health explained below.

$$\text{Global State of Health} = \frac{\alpha * SoH_C + \beta * SoH_P}{\alpha + \beta} \quad (3.1)$$

SoH_C = State of health corresponding to degradation in capacity of the battery.

SoH_P = State of health corresponding to degradation in power of the battery.

α = Weighing factor for degree of importance for capacity related to second life applications.

β = Weighing factor for degree of importance for power related to second life applications.

The parameters α and β can be established on the basis of second life applications. If power capability is more important than capacity for a particular application, then beta should be greater than alpha and vice versa. Thus for any SoH estimation system, it is advisable to have two estimation indicators, one for capacity fade and other for power fade respectively. Further, depending upon the second life manufactures, these indicators can be weighed to achieve a global value of State of Health.

3.3 Classification of SoH estimation methods

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 based** : 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 3.2 illustrates an at a glance view of features based classification of SoH estimation methods.

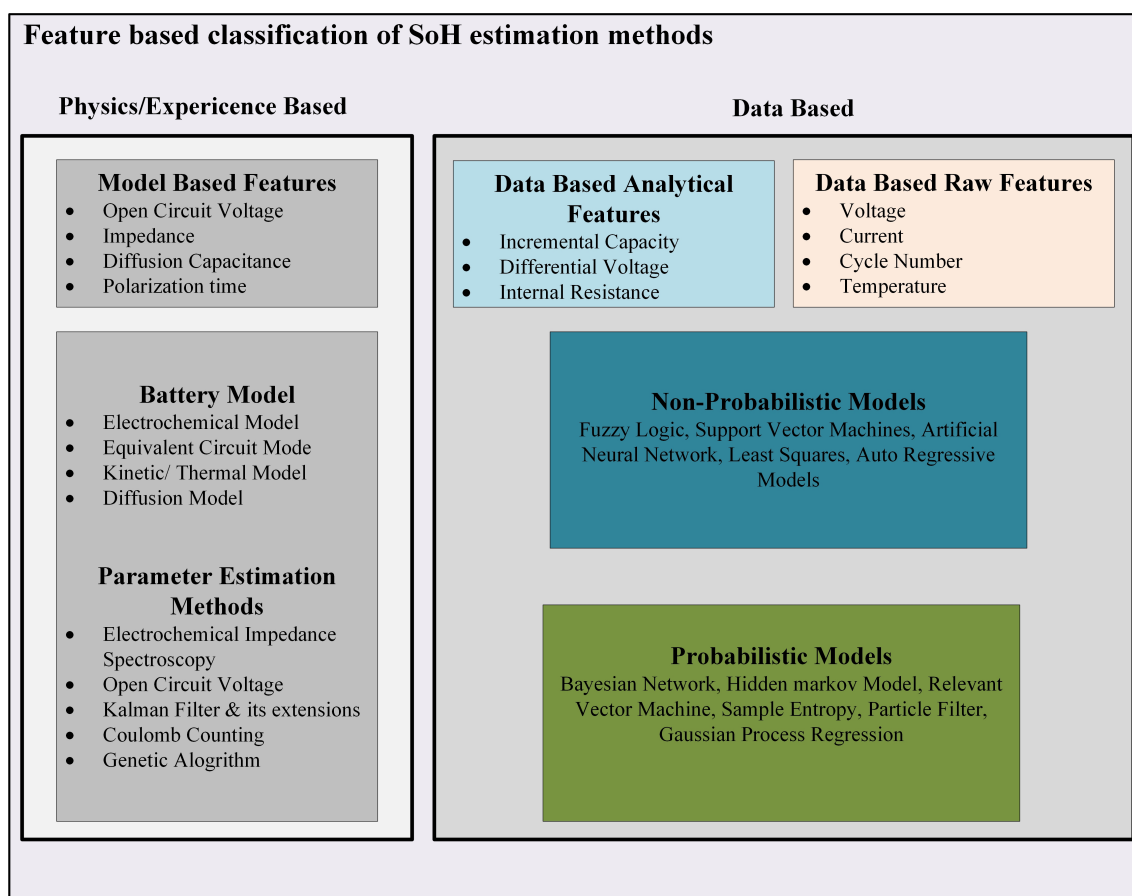


Figure 3.2: Feature based classification of SoH estimation methods

3.3.1 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 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 3.3 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 3.4. 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.

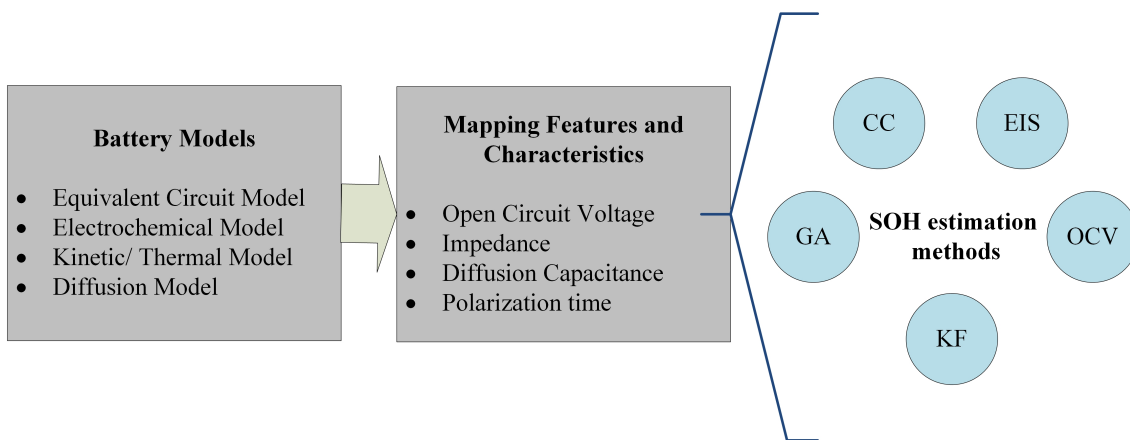


Figure 3.3: SoH estimation methods for features which are retrieved from Physics based battery models. The abbreviated terms for the techniques are Coulomb Counting (CC), Electrochemical Impedance Spectroscopy (EIS), Open Circuit Voltage (OCV), Kalman Filter and its extensions (KF) and Genetic Algorithm (GA).

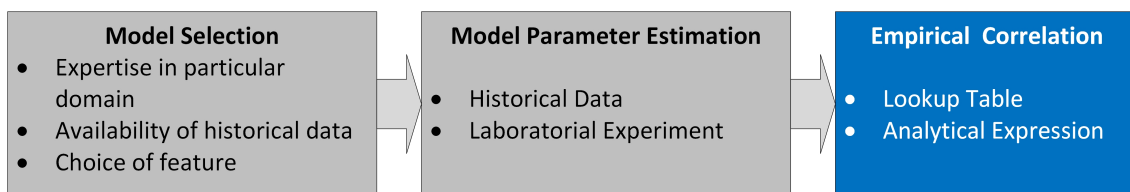


Figure 3.4: A framework for using Model extracted features for SoH estimation

3.3.2 Data based 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 3.5 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 [Weng2013] as analytical feature is illustrated in Figure 3.6. 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 3.5.

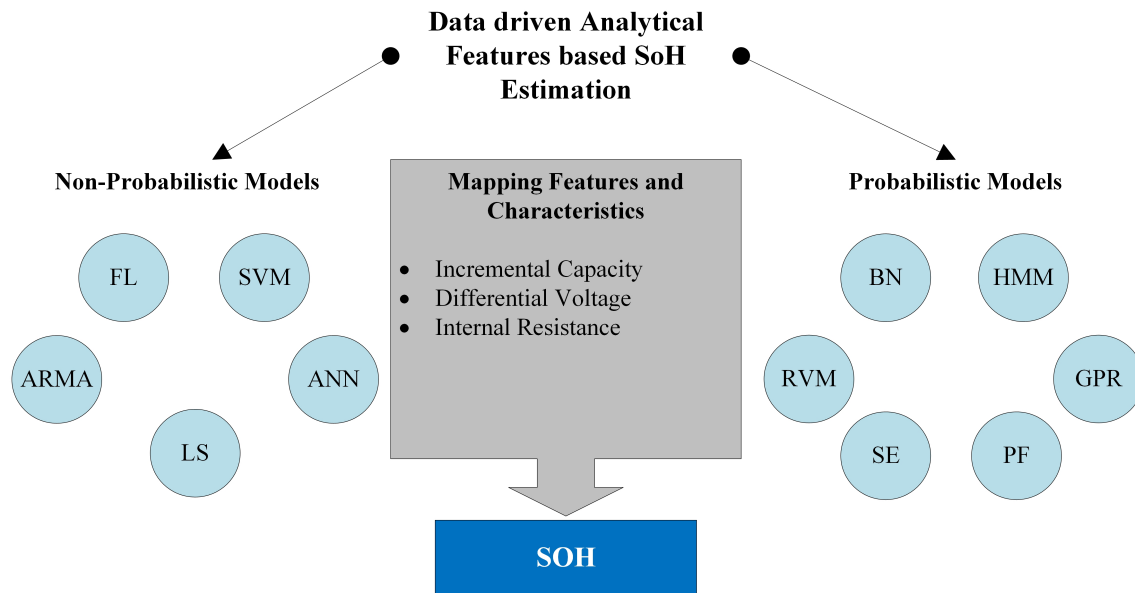


Figure 3.5: Data driven probabilistic and non probabilistic algorithms for analytically derived features to estimate State-of-Health (SoH). Probabilistic models gives the measure of uncertainty in prediction while non probabilistic models can be used to get definite result. The abbreviated terms for 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)

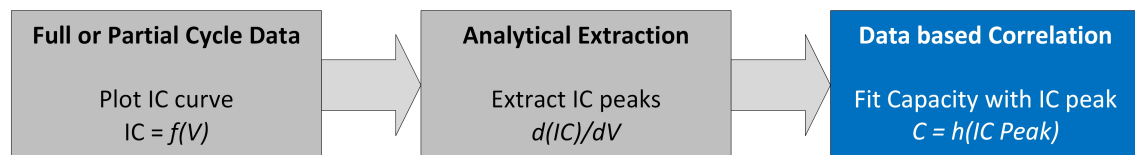


Figure 3.6: Illustration of data driven analytical feature based State of Health (SoH) modeling: A framework for using Incremental Capacity Analysis (ICA) to predict SoH.

3.3.3 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

3.4. Proposition of efficient SoH estimation methodology in the context of Circular economy

discussed in previous subsection can also be used for these features to set up a correlation between features and the State of Health. However, often it is recommended to use algorithms with higher computations like Artificial Neural network for this kind of features.

A basic framework for utilizing battery management system based raw feature is illustrated in Figure 3.7. 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 and non-probabilistic algorithms discussed in Chapter 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.

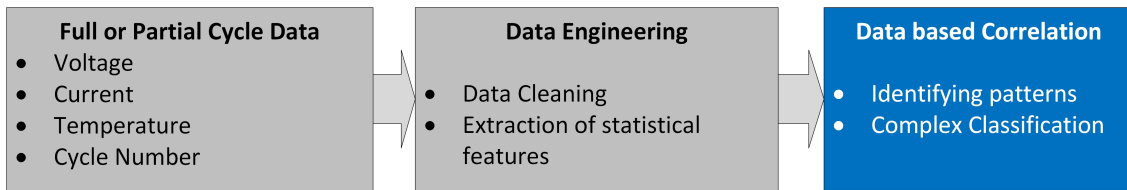


Figure 3.7: A framework for using battery management system based raw features to predict State of Health (SoH).

To summarize this section, Table 3.1 illustrates the advantages and disadvantages of utilizing different State of Health (SoH) estimation category.

3.4 Proposition of efficient SoH estimation methodology in the context of Circular economy

In the context of Circular economy, the purpose of estimating State of Health of the lithium ion battery is to support the decision making while reusing or re-purposing the battery for second life application. Since, there are several second life application, choosing the right application for the End of Life batteries is very important to keep the resource in use for long. Health indicators which quantifies factors like capacity and power capability plays an important role in deciding the type of application that will be suitable for a particular battery in second life. Since, Global State of Health gives a good idea about these factors and so, it is an important indicator for decision making.

Also, the motive of SoH estimation in the context of circular economy is to make decisions. If an estimation result is used for decision making, it is always recommended to consider some extent of uncertainty in the prediction. Since, these decisions firmly relies on the estimation results, it is highly probable to have true negative or false positive results if uncertainties are not taken care of. To have a measure of uncertainty while prediction, use of probabilistic models are highly recommended.

Having an overly complex degradation mechanism and high sensitivity to the operating conditions, every battery degrades differently, even if they are physically similar. Often, model based estimation considers a better understanding of physics of degradation while estimating SoH. However, these degradation mechanisms are complex and depends 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 these kind of models. To support decision making in circular economy, and to ensure industrial feasibility of the re-purposing model, the prediction of SoH has to be

Table 3.1: Summary of State of Health (SoH) estimation category.

SoH estimation category	Advantages	Disadvantages
Model based features for SoH estimation	<ul style="list-style-type: none"> • Very efficient for laboratorial analysis of battery. • Easy to implement for offline application. • Dynamic performance of battery can be taken care of. 	<ul style="list-style-type: none"> • Identification of model parameters are computationally expensive for online applications. • Self-updating of model parameters are difficult. • Cannot measure uncertainty in prediction. • Expertise in physical domain is necessary. • Destructive methods will damage the battery permanently.
Data based analytical features for SoH estimation	<ul style="list-style-type: none"> • Small number of input features are required for model training. • Low computational effort. • Vast set of algorithms can be used. • Understanding of battery physics can be avoided. • Can consider uncertainty in prediction. 	<ul style="list-style-type: none"> • Some of the features can be hard to obtain during operation due to limited capability of BMS. • Either Charging or discharging condition should be uniform. • Requires efficient filtering, as analytical derivation of features amplifies the measurement noise. • Complexity in algorithm increases while considering dynamic operating condition.
Battery Management System based raw features for SoH estimation	<ul style="list-style-type: none"> • Suitable for online application. • Data is easy to obtain. • Understanding of battery physics is not required. • Can consider uncertainty in prediction. • Less pretest required. 	<ul style="list-style-type: none"> • Correlation between the feature and SoH requires higher computational load and so the cost increases. • Estimation accuracy is highly sensitive to quality and quantity of training data. • High requirement on efficiency and portability of algorithm.

done accurately in real time. On the other hand, data based methods, which eliminates the need of understanding the physics of degradation, can be a better choice of estimation tool. Even though, it does not give 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, the battery is operated in a varying operational condition imbuing a lot of uncertainties. These uncertainties will make these models underperform. So, models which can be trained from a larger set of real time data is also important to consider. Also, to make a more robust model, it is important to apply realistic load patterns which deal with the driving patterns of different geographical regions.

To summarize this section, an efficient SoH estimation method that can suffice the need of 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.

3.5 Overcoming the Barriers in PHM system for the Circular System by Hidden Markov Model

3.5.1 Introduction to HMM

In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In an HMM, the active current state is hidden, but the observed information from monitoring and tests, dependent on the state, is visible. Each state has a probability distribution over the possible output observation. Therefore, the sequence of observation generated by an HMM gives some information about the sequence of states. HMMs are very versatile and is widely used in temporal pattern recognition such as speech, handwriting, gesture recognition, score following, partial discharges, and bioinformatics. A discrete-time finite state space HMM $\mathcal{H} = \langle S, V, A, B, \Pi \rangle$ is defined as follows ([Rabiner1989]):

- S is a finite set of N states, with $S = \{S_1, S_2, S_3, \dots, S_N\}$. In the latter, we denote the active state at time t as q_t . We assume a discrete time domain with $t \geq 1$.
- V is a finite set of M distinct observation symbols per state, with $V = \{v_1, v_2, v_3, \dots, v_M\}$. When the HMM is in state q_t , only one observation symbol is emitted. We denote the symbol observed at time t is o_t .
- $A = [a_{ij}]$ is the state transition probability distribution matrix. The matrix element a_{ij} is the transition probability from state S_i to state S_j and is defined as $a_{ij} = P(q_{t+1} = S_j | q_t = S_i)$, given $i, j \in [1, N]$. The probability matrix A ensures the following property: $\forall i \in [1, N], \sum_{j=1}^N a_{ij} = 1$ and the coefficient of a_{ij} are non negative and equal to zero if there is no direct switching from state S_i to state S_j .
- $B = [b_{jm}]$ is the observation symbol probability distribution matrix. The matrix element b_{jm} is the emission probability for state S_j of observation symbol v_m and is defined as $b_{jm} = P(o_t = v_m | q_t = S_j)$, given $m \in [1, M], j \in [1, N]$.
- $\Pi = [\pi_i]$ is the initial probability distribution vector line. The vector element π_i is the probability that the HMM will start at time 1 in state S_i and is defined as $\pi_i = P(q_1 = S_i)$, given $i \in [1, N]$. Also, the probability vector Π ensure the following property, $\sum_{i=1}^N \pi_i = 1$.

The above HMM model is illustrated in figure 3.8.

The simulation of an HMM during T time steps is carried out by following steps ([Rabiner1989]):

1. Choose an initial state $q_1 = S_k$ according to the initial state distribution Π .
2. Set $t = 1$.
3. Choose $O_t = v_k$ according to the symbol probability distribution matrix B .
4. Transit to a new state q_{t+1} according to the state transition probability distribution matrix A .

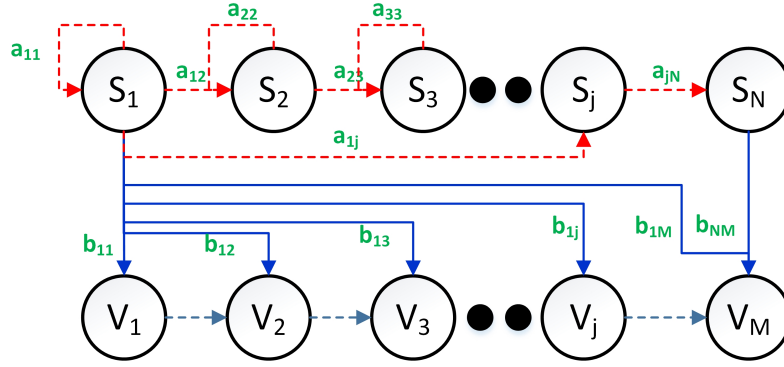


Figure 3.8: Basic structure of a HMM model

5. Set $t = t + 1$; return to step (3) if $t < T$, else terminate the simulation procedure.

Hidden Markov models are bounded by two very strong assumptions ([Rabiner1989]):

(I) Markov assumption.

With a first-order Markov chain, the probability of a particular state depends only on the previous state:

$$P(q_t = a | q_1, \dots, q_{t-1}) = P(q_t = a | q_{t-1}) \quad (3.2)$$

(II) Output independence.

The probability of an output observation o_t depends only on the state that produced the observation q_t and not on any other states or any other observations:

$$P(o_t | q_1, \dots, q_t, \dots, q_T, o_1, \dots, o_t, \dots, o_T) = P(o_t | q_t) \quad (3.3)$$

HMM should be characterized by three fundamental problems ([Rabiner1989]):

- i. Evaluation: Given an HMM $\mathcal{H} = \langle S, V, A, B, \Pi \rangle$ and an observation sequence $\mathcal{O} = \langle o_1, \dots, o_T \rangle$ build upon V , determine the probability of the observation sequence, i.e. $P(\mathcal{O} | \mathcal{H})$. The solution to this problem is obtained by using the *forward-backward algorithm* ([Baum1972, Bishop2006]). In failure prognostic, this is considered as detection or a diagnostic problem.
- ii. Decoding: Given an observation sequence \mathcal{O} and an HMM \mathcal{H} , discover the hidden state sequence $\mathcal{Q} = \langle q_1, \dots, q_T \rangle$ that is optimal in some sense (i.e., best explains the observations). This problem is solved by using the *Viterbi algorithm* ([Forney1973, Bishop2006]).
- iii. Learning: Given an observation sequence \mathcal{O} build upon the set V and S the set of states in the HMM \mathcal{H} , learn the HMM parameters A , B and Π to maximize $P(\mathcal{O} | \mathcal{H})$. This problem is solved by using the *Baum-Welch algorithm* ([Welch2003, Bishop2006]) which is a particular instantiation of the *expectation-maximization algorithm* suited for HMMs.

The above-explained stochastic model is used as an estimation and prediction tool in our proposed methodology.

3.5.2 Proposed Methodology

In circular industrial systems, due to technological heterogeneity in products, it is quite difficult to make decisions on re-manufacturing or re-purposing. Health degradation of these type of products is very dynamic and the degradation behavior changes in different geographical regions due to

varying environmental & operating condition. To overcome this barrier of dynamics of change in prognostics, we hereby propose a real time stochastic method based on hidden Markov model.

As discussed in the previous section, 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. First and foremost thing is to identify the parameters that have to be monitored for generating a set of observation sequence. An experience-based selection of monitored parameters will accelerate the diagnosis and prognosis. For example, in Li-ion batteries, state of health depreciates with loss of capacity or increase in internal resistance. It will be prudent to choose these parameters, instead of selecting parameters to which health is independent.

The proposed method will be implemented in three steps:

1. Offline step: Setting up a model database and continuous parameters learning using the Baum-Welch algorithm ([Welch2003, Bishop2006]).
2. Online step: Choosing the right model using the forward algorithm ([Baum1972, Bishop2006]) for real-time diagnosis and analyzing the current state of health of the product by using Viterbi algorithm ([Forney1973, Bishop2006]).
3. Online step: Prognosis for remaining useful life estimation, using the model selected in step 2.

Below we describe our approach step-by-step.

1st step of our approach

Since the degradation of product varies differently in different geographical region, a single hidden Markov model will not be sufficient to handle the dynamics of change in the degradation. It is plausible to create a database of models, where each model represents a chosen geographical region. We suppose that we have X distinct geographical region. Initially, we define X hidden Markov models ($\mathcal{H}_1, \mathcal{H}_2, \dots, \mathcal{H}_X$) corresponding to region R_1, R_2, \dots, R_X . The hidden Markov model \mathcal{H}_i can be expressed as the tuple $\langle S, V, A_i, B_i, \Pi_i \rangle$. The set of states S and the set of distinct observation symbols V are common to all HMMs. The state transition matrix A_i , the observation symbol matrix B_i and the initial probability vector Π_i are specialized to each region R_i . Initial values of A_i , B_i and Π_i can be assumed randomly but having an experienced based random values initialization will accelerate the diagnostic and estimation step.

Models for each region has to be updated from the learning data sets. Larger the size of data sets, better will be the learning. For each region, Baum-Welch algorithm takes the initial values of probability density function A_i , B_i and Π_i with generated observation sequence as input and provides us the updated values of parameters of hidden Markov models. Continuous learning enhance the prediction process because the observation sequences change very dynamically depending on the operating condition of given region. Mathematically the goal is to adjust the model parameters A_i, B_i, Π_i to maximize the probability of the observation sequence O given the model. $\mathcal{H}_i = \langle S, V, A_i, B_i, \Pi_i \rangle$ is chosen, such that $P(O | \mathcal{H}_i)$ is locally maximized using an iterative procedure such as the Baum-Welch method (or equivalently the EM (expectation-modification) method). Figure 3.9 illustrates the basic block diagram of the model learning process.

2nd step of our approach

Given an observation sequence O , it is utterly important to use the correct model for diagnosing the health of status of a product relating to this sequence O . This phase is performed online,

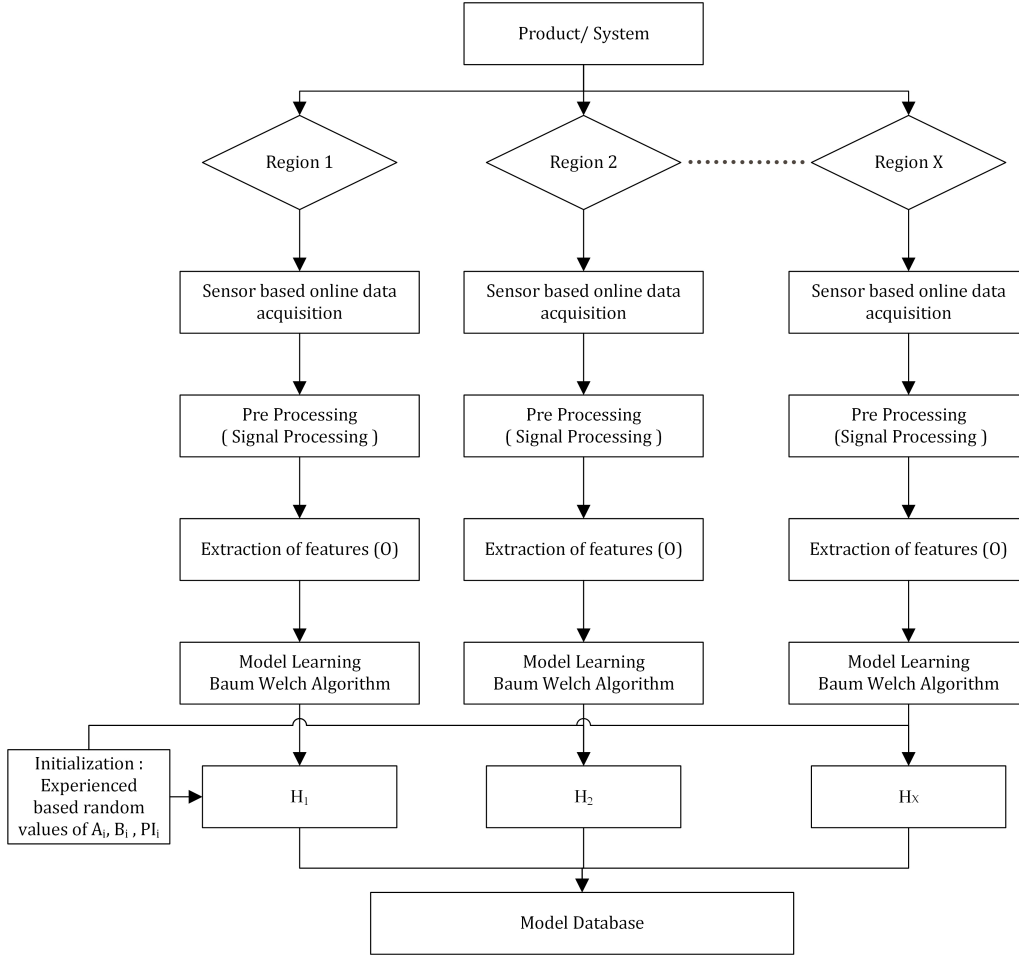


Figure 3.9: Model Learning

we choose the most reliable model from the model database created in the first step. Forward probability algorithm for maximum likelihood estimation is applied to find the best fit \mathcal{H}_i . The selection process is based on the calculation for each region R_i of the probability that model \mathcal{H}_i has generated the sequence O ($P(O | \mathcal{H}_i)$). We define the region R_{rel} , as the region which gives us the most reliable model associated with the observation sequence. R_{rel} satisfies the following property:

$$P(O | \mathcal{H}_i) \leq P(O | \mathcal{H}_{rel}), \forall i \in [1, X].$$

We associate with the selected region R_{rel} , its confidence value C , defined as $C = P(O | \mathcal{H}_{rel})$. Further, \mathcal{H}_{rel} is used to diagnose the current health status of the product.

The diagnosis of the product is performed on-line in real time. The chosen model \mathcal{H}_{rel} is exploited to detect the products current condition using a method of dynamic programming called the Viterbi algorithm. The observation sequences generated from monitored signals are thus continuously fed to the model \mathcal{H}_{rel} in order to calculate $P(S | O, \mathcal{H}_{rel})$. The state sequence S , having the highest value of $P(S | O, \mathcal{H}_{rel})$ can be interpreted as the sequence of health that generated the acquired signals from the component. Figure 3.10 illustrates the diagnostic process for the system.

3rd step of our approach

To make a better decision on the application of the product in second life, knowing the future state of health and transition points are important. The prognosis should generally answer the question

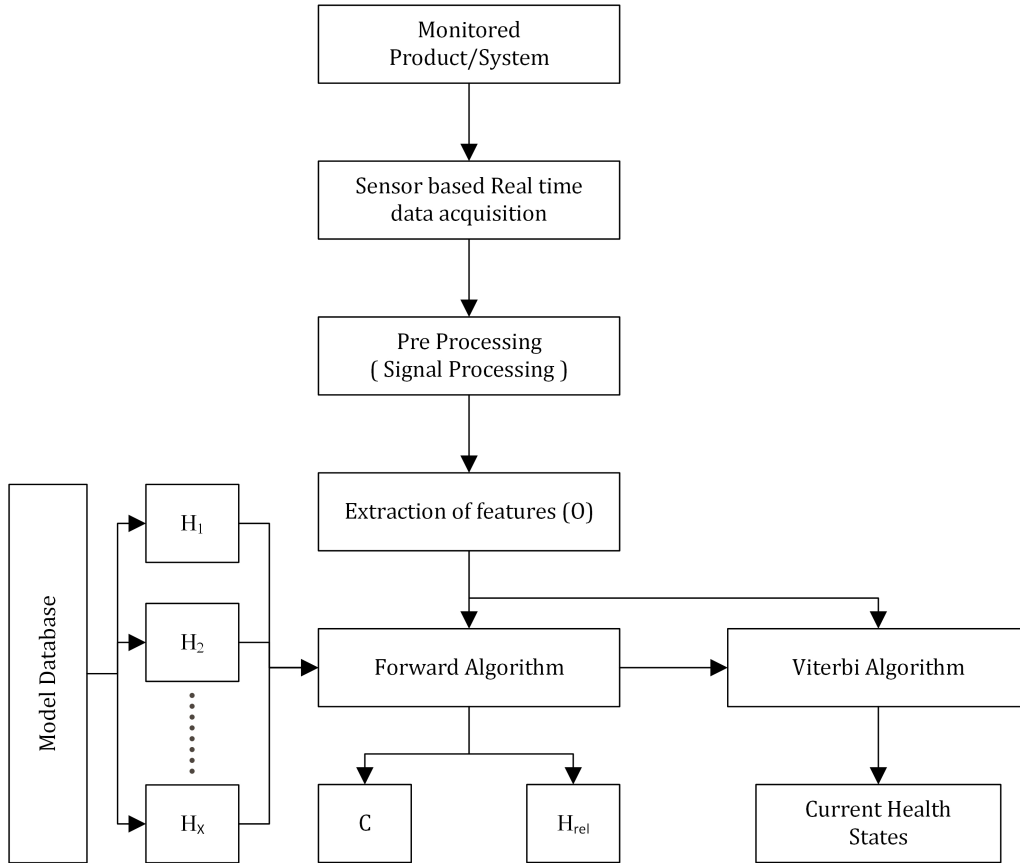


Figure 3.10: Model Identification and Diagnosis

of time period after which the state of health of product makes a transition and the time to end of life. We realize the prognostics framework as follows: We use the current identified state, the final state (the failure state) and the probability transition matrix A_{rel} of the selected hidden Markov model \mathcal{H}_{rel} to find the critical path, which goes from the current state to the end state. Potential transitions can be identified by all the non-zero probabilities in the transition matrix, and then the minimal paths chosen among all the the possible transitions. The stay duration of every state has to be summed up over all the transitions to find the remaining useful life.

It is interesting to note that region based estimation can also be extended to technical heterogeneity. Sometimes, two product of same kind being operated in the same operating condition behaves differently. This is because of the different kind of components used while manufacturing (same product, manufactured by a different company) degrades differently in same operating condition. Extending the model database for different product-make, can take care of this anomaly as well.

4

SoH estimation for Li-ion batteries in the context of CE

Contents

4.1	Introduction	58
4.2	Data Acquisition : An introduction to Battery Management System	58
4.3	Feature selection for Diagnosis and Prognosis	59
4.3.1	Incremental Capacity Analysis	60
4.3.2	Regional Capacity: Formulation and Calculation	61
4.3.3	Electrochemical Impedance Spectroscopy	62
4.4	Creation of Model database	64
4.4.1	Support Vector Regression : Regional Capacity correlation	65
4.5	Model selection	66
4.6	Diagnosing the current SoH	67
4.7	Time series forecasting : Applied for prognosis	67
4.7.1	The Autoregressive Moving Average (ARMA) Models	68
4.7.2	The Autoregressive Integrated Moving Average (ARIMA) Models	68
4.8	ARIMA based prognosis for Future SoH estimation	70

4.1 Introduction

As discussed in the previous section, in the circular economy context, the principal purpose of SoH estimation is to support decision making for choosing the second life applications. For repurposing, remaining capacity is the most important indicator to decide on appropriate second life application. However, in some applications (mobile - hover boards, electric bikes), power capability might have the same degree of importance as that of capacity. There are applications like inverters, which does not require same level of capacity as that of EV battery but better power capability might be needed. So, there must be two different insights on battery's health, capacity fading insight and power fading insight, to evaluate the global state of health. This section aims to establish an efficient method to predict SoH_c and SoH_p for a lithium-ion battery in advance. The proposed methodology can be divided into five major tasks :

- Data Acquisition
- Feature selection
- Model database creation
- Model selection
- Diagnosis & Prognosis

4.2 Data Acquisition : An introduction to Battery Management System

The U.S. Council for Automotive Research (USCAR) and the U.S. Advanced Battery Consortium (USABC) have set minimum goals for battery characteristics for the long-term commercialization of advanced batteries in EVs and hybrid electric vehicles (HEVs) [USC2006]. Safety and reliability should be given the highest priority to enlarge the market share of EVs and HEVs. Battery management system plays a vital role in ensuring safety and in improving battery performance.

The battery management system is the electronic protection circuitry needed to measure cell temperatures, voltages, and current to ensure the reliable operation of the Li-ion battery. It works in a very similar way like an engine management system in a hydrocarbon based vehicles. A comprehensive Battery management system (BMS) takes care of the following functions:

- Data Acquisition
- Ensuring safety & protection
- Battery charge & discharge control
- Cell Balancing
- Thermal Management
- Prolongation of battery life

The generic structure of BMS is portrayed in Figure 4.1 [Xing2011]. The general architecture of a battery management system comprises (1) the power module (to charge the battery), either a separate or an integrated device, (2) a protection IC connected in series with the battery (to

ensure that the battery is never operated in an unsafe region), (3) if required, a dc/dc converter to efficiently condition the unregulated battery voltage (3–4.2V), (4) the load, which converts the battery power into other energy forms, and (5) the SoC indicator, e.g., a light emitting diode or a liquid-crystal display. The battery pack is installed with various sensor for acquiring data at the monitoring layer. The acquired data is used to maintain the system’s safety and ensure optimal battery operation. The data collected by sensors are usually stored in the BMS. However, to have real-time monitoring, an external data logger (telemetry) can be installed additionally in the vehicle.

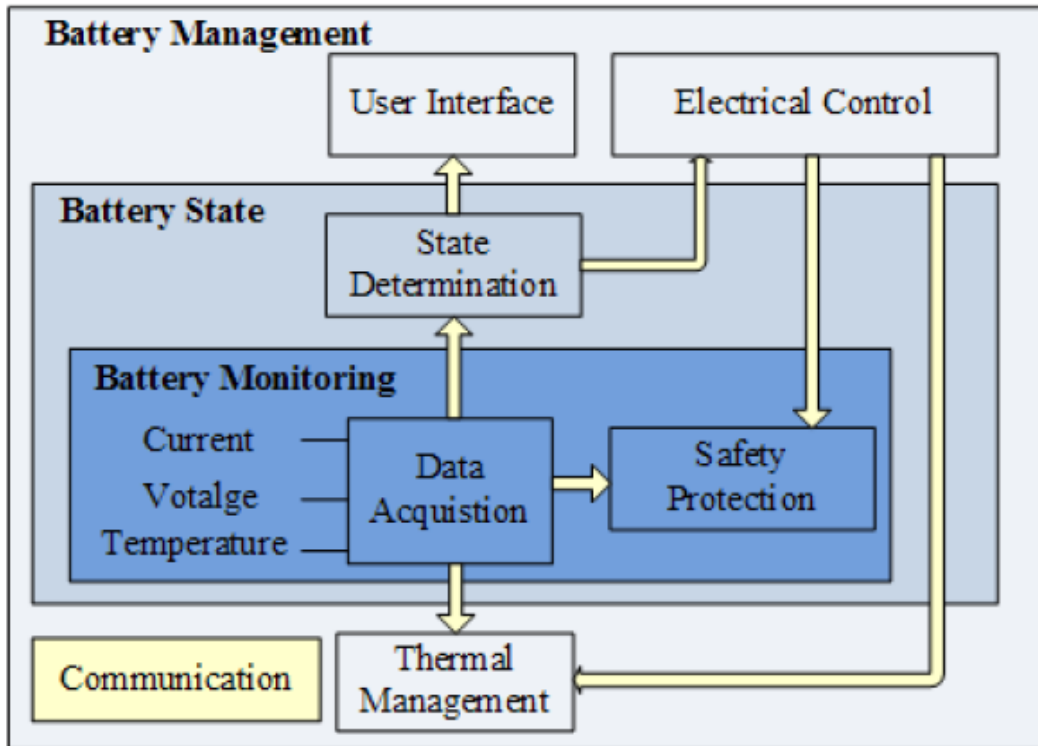


Figure 4.1: BMS: Generic Structure [Xing2011]

As illustrated in Figure 4.1, the voltage, current and temperature readings are constantly monitored and stored in the BMS for its efficient operation. Tracking these sensor signals and real-time processing data from a BMS can help us design the battery SoH prediction system. If there is a lack of sufficient online data acquired from BMS, one can also create an experimental setup for data acquisition. The lithium-ion battery’s constant current charging process in the laboratory environment is similar to the real EV applications in the charging current and mode. The availability of the climatic chamber even makes it possible to simulate some real-time operating conditions. Hence, we can also apply the cyclic data from the experimental platform to model the battery degradation process and estimate the SoH for real EV applications.

4.3 Feature selection for Diagnosis and Prognosis

Several different features have been explored in the past to depict the degradation mechanism of the battery and to model the aging parameters. Normally features are detected from the raw/

charging data to build the aging model and to estimate SoH of the battery. Higher the correlation of a feature with the health of the battery, higher is the reliability of that particular feature. In addition to correlation, ease of acquiring or analytically calculating the feature should also be given a priority. A feature selection method generally consists of C-curve extraction, feature generation, and choosing the most appropriate features for SoH estimation.

Different geometric analysis were used to select the feature from battery terminal voltage in constant current charging process [Wu2016]. The author in [Wang2019], employed a similar methodology for feature extraction and health estimation. Although, in most of the cases, the acquisition of feature is real time scenario has not been considered. Since, the data is affected by the EV driving's behavior, so the feature selected from some particular SoC or specific voltages will make it challenging to accurately estimate SoH. The frequencies of these SOC and voltages' occurrence are different regardless of the charging or discharging process. This arises a question : Which features can easily be obtained in real EV applications? Furthermore, as stated in [Casari2018], "bad features may require a much more complicated model to achieve the same level of performance." Thus, features influence the complexity of the model and the accuracy of the estimation results.

An experience-based selection of monitored parameters will accelerate the diagnosis and prognosis. For example, in Li-ion batteries, state of health depreciates with loss of capacity or increase in internal resistance. It will be prudent to choose these parameters, instead of selecting parameters to which health is independent. 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.

4.3.1 Incremental Capacity Analysis

The incremental capacity analysis is an Electrochemical technique that gives insight into the internal cell state using only the cell voltage and current data. It depicts the change in the capacity associated with a voltage step. The concept of ICA originates from the study of the lithium intercalation process and the corresponding staging phenomenon. Numerous papers use ICA as a tool to analyze cell capacity degradation [Dubarry2011a, Dubarry2014, Stroe2020] or even degradation mechanisms [Han2014, Dubarry2012]. The constant-current-constant-voltage (CC-CV) charging curves are used to generate the IC curves through differentiation. It has been demonstrated in the literature that the incremental capacity $\delta Q/\delta V$ is more indicative of the underlying Electrochemical changes during battery aging than the conventional charging/discharging curves themselves.

[Weng2013] and [Feng2013] applied ICA for SoH monitoring, [Berecibar2016b] compared three different regression models for battery SoH estimation based on ICA use. ICA transform voltage plateaus of a charging/discharging voltage curve into peaks of the corresponding incremental capacity (IC) curve by differentiating the charged battery capacity versus the terminal voltage. It has the advantages of insensitivity to battery types and efficacy in identifying capacity loss mechanisms. It has enormous potential for online battery degradation diagnosis since only a low-rate the constant charging process is required to derive the IC curve.

Owing to constant current, the capacity and voltage can be calculated as:

$$Q = I * t \tag{4.1}$$

$$V = f(Q), Q = f^{-1}(V) \tag{4.2}$$

where t is charging time and I refers to charging current. Based on the Eq. (4.1), the IC curve can be expressed as follows,

$$(f^{-1})' = \frac{dQ}{dV} = \frac{I \cdot dt}{dV} = I \cdot \frac{dt}{dV} \quad (4.3)$$

The slope dQ/dV can be re-written as a function of V according to Eq. (4.3)

$$(f^{-1})' = \frac{dQ}{dV} = \frac{I}{dV/dt} = g(V) \quad (4.4)$$

In discrete space, dV and dQ can be replaced by δV and δQ . So when δV is tending to 0,

$$\frac{dQ}{dV} = \frac{\delta Q}{\delta V} \quad (4.5)$$

The voltage sequence V and current sequence I correspond to the voltage and current at the time sequence T , respectively.

$$\begin{aligned} V &= (V_1, V_2, V_3, V_n) \\ I &= (I_1, I_2, I_3, I_n) \\ T &= (T_1, T_2, T_3, T_n) \end{aligned} \quad (4.6)$$

The Incremental capacity from V_k to V_{k+1} can be expressed as,

$$Q_{(V_k \rightarrow V_{k+1})} = I_k(t_{k+1} - t_k) \quad (4.7)$$

Once the Incremental capacity is calculated from the voltage and current charging data, relevant features has to be extracted from the curve. In the past, researchers have justified that the value of different IC peaks [Dubarry2012], corresponding peak voltages [Li2018] and peak areas [Jiang2017] can be used to estimate battery SoH. Moreover, due to the derivative nature, the ICA results can be sensitive to noise and need a filtering approach.

4.3.2 Regional Capacity: Formulation and Calculation

In terms of capacity, the SoH of a Li-ion battery can be defined as the ratio of current capacity and the battery rated capacity (mentioned in the specification sheet).

For EVs, the current capacity is impossible to obtain during operation without conducting laboratorial tests because it needs the battery to be fully charged or discharged. However, several features can be extracted from IC curve and then correlated to capacity. The author in [Tang2018] presented a method to derive SoH from some regional current trajectory within a charging/ discharging operation. The integral of the regional current trajectory along time t is termed as regional capacity denoted by C_n . This regional capacity can be correlated to SoH of a battery using some probabilistic or non-probabilistic algorithms.

The procedure to calculate the regional capacity for each cycle is summarized here as follows.

1. Measure the current and voltage trajectories of battery cells.
2. Plot the Incremental Capacity curve and locate its peak point. The peak value of an IC curve is the maximum value of $dQ(t)/dV(t)$ for all $t \geq 0$ in the charging operation. The terminal voltage corresponding to the IC peak is denoted by V_{peak} .
3. To reduce the noise due to derivative, calculate the IC curve using the finite difference method over N steps.

$$\frac{dQ(t)}{dV(t)} \approx \frac{\Delta Q(k)}{\Delta V(k)} = \frac{Q(k) - Q(k-N)}{V(k) - V(k-N)} \quad (4.8)$$

4. To further reduce the noise and filter, Kalman filter can be employed [Hargrave1989], where the evolution of the IC curve can be modeled as a random walk with additive Gaussian process noise and measurement noise.

$$x_k = x_{k-1} + w_k \quad (4.9)$$

$$y_k = x_k + v_k \quad (4.10)$$

where y_k represents the noise polluted measurement of x_k . We define Q and R as the covariance of process noise and measurement noise, K as the Kalman Gain, and P as the covariance of estimate \hat{x} . Then the filtering algorithm can be described as :

$$\bar{x}_k = \hat{x}_{k-1} \quad (4.11)$$

$$\bar{P}_k = \hat{P}_{k-1} + Q \quad (4.12)$$

$$K_k = \bar{P}_k(\bar{P}_k + R)^{-1} \quad (4.13)$$

$$\hat{x}_k = \bar{x}_k + K_k(y_k - \bar{x}_k) \quad (4.14)$$

$$\hat{P}_k = (1 - K_k)\bar{P}_k \quad (4.15)$$

5. Specify a regional voltage ΔV_{reg} whose middle point is the IC curve's peak. ΔV_{reg} can be chosen in the neighborhood of the peak voltage. It is worth noting that ΔV_{reg} has a significant impact on regional capacity, which may influence the relationship between regional capacity and real capacity. Higher the regional voltage, higher will be the accuracy of regional capacity calculation. This regional voltage is used to determine the initial and end time points (t_0 and t_1) for counting the regional capacity. Mathematically, there exist:

$$V(t_0) = V_{peak} - \Delta V_{reg}/2 \quad (4.16)$$

$$V(t_1) = V_{peak} + \Delta V_{reg}/2 \quad (4.17)$$

6. Calculate the regional capacity C_n , which is the capacity change over the time interval (t_0 and t_1), with the form of

$$C_n(\tau) = Q(t_1) - Q(t_0) \quad (4.18)$$

7. Repeat these steps for all the cycles of battery data so that at the end, we will have the regional capacity for every cycle.

4.3.3 Electrochemical Impedance Spectroscopy

In the case of a Li-ion battery, Impedance can be referred as the opposition to current flow through the battery. This leads to over-potential while charging or discharging. The impedance increases over time because of the aging caused by degradation of the electrode materials, electrolyte, and electrical contacts within the cell. Thus, with a proper impedance characterization we can track the power capability of the battery. Electrochemical impedance spectroscopy (EIS) is a powerful and widely used non-destructive test method for characterization of LIBs through impedance measurement. Being a non-destructive tool, EIS can be used from time to time throughout the battery lifetime as a diagnostic tool for health estimation or second life application characterization [Coron2020]. EIS analyses the electrochemical system by applying low amplitude sinusoidal current or voltage signals excitations over a wide range of frequencies. The method relies on voltage and current measurements acquisition which can be handled by BMS. This makes EIS a fast, non-invasive and reliable technique able to identify the origin of cell degradation processes.

The EIS approach typically needs to apply a sinusoidal current or voltage of a certain amplitude and frequency. The observed amplitude and phase shift of the output voltage or current

is measured. The process is repeated for a range of frequency, typically in kHz to mHz range to generate a characteristic impedance spectrum. The result is plotted using either Nyquist plot (imaginary part of impedance vs real part of impedance) or Bode plot (real and imaginary part of impedance vs frequency), which enables estimation of resistance, capacitance, and inductance of the cell at given time stamp. The EIS approach typically needs to apply a sinusoidal current or voltage of a certain amplitude and frequency. The observed amplitude and phase shift of the output voltage or current is measured. The process is repeated for a range of frequency, typically in kHz to mHz range to generate a characteristic impedance spectrum. The result is plotted using either Nyquist plot (imaginary part of impedance vs real part of impedance) or Bode plot (real and imaginary part of impedance vs frequency), which enables estimation of resistance, capacitance, and inductance of the cell at given time stamp. The typical EIS spectrum of a Li-ion cell composes of a unique semiarch or two semiarches in the Mid-frequency region. The representation of the frequency regions on a Nyquist plot is depicted in the figure 4.2 [Jurilli2021] below. EIS spectrum can be divided in 3 regions:

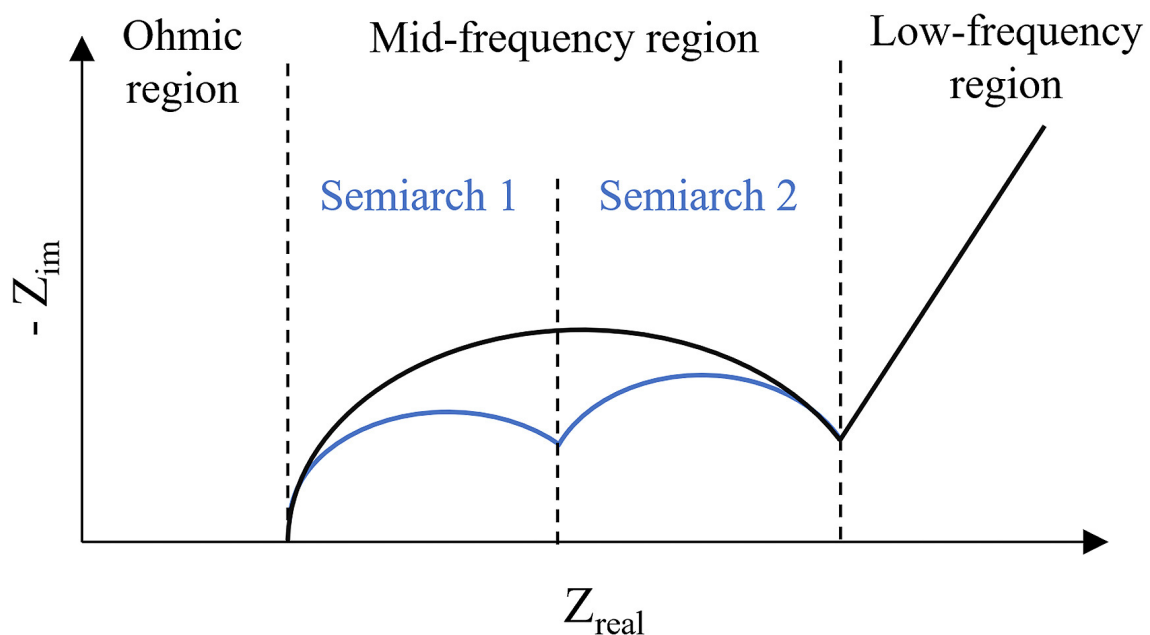


Figure 4.2: Representation of EIS through Nyquist plot [Jurilli2021]

- Ohmic region (frequency higher than 1000 Hz): which represents the internal resistance of the cell measured, where the cell impedance switch from an inductive to capacitive behaviour.
- Mid-frequency region (frequency interval between 1000 Hz and 0.1 Hz): which represents the charge-transfer processes, both from electrolyte to electrodes surface and from electrodes surface into the bulk active material of the electrodes. The arcs appearing in the mid-frequency range are primarily due to the electrochemical processes occurring at the electrode/electrolyte interfaces inside the cell, which combine resistive and capacitive effects.
- Low-frequency region (frequency lower than 0.1 Hz): which represents the diffusion processes at the two electrodes. This region is often neglected because it takes too long to measure impedance at lower frequency.

After obtaining reliable EIS measurements, interpretation has been a big challenge. The most widely used approach is Equivalent Circuit Modelling, wherein the EIS response of the cell is

analytically parameterized in terms of electrical circuit elements that represents different physical and chemical process of the battery. Features extracted from sensor data of voltage, current, power, impedance, frequency, and temperature readings are used to estimate the internal parameters in the lumped-parameter battery model shown in Figure 4.3. The parameters of interest are the double layer capacitance C_{DL} , the charge transfer resistance R_{CT} , the Warburg impedance R_W , and the electrolyte resistance R_E . The values of these internal parameters is depended on intertwined electrochemical degradation processes.

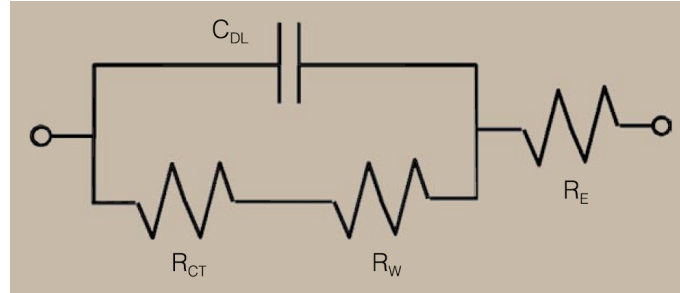


Figure 4.3: Lumped parameter battery model

R_E is quantified as the horizontal distance between the zero and the point where the EIS spectrum crosses the real axis (high frequencies); and, R_{CT} and R_W are calculated as the horizontal distances of the each depressed semicircle, respectively. R_E can be used to model the resistance in the current collectors, connectors and electrolyte Corrosion of current collectors and connectors as well as changes in the electrolyte composites due to side reactions caused by conductivity loss. Increase in R_{CT} is a notion of reduction of charge-transfer Li-ion intercalation and de-intercalation reactions. In other words, Loss of Li ion inventory can be interpreted in terms of increase in R_{CT} Tracking the resistance is beneficial as the resistance increase is an indicator of power fade which is used to define *SoHp*.

In the past, researchers have experimentally validated that R_E and R_{CT} values changes significantly [Goebel2008] due to battery degradation. For setting up an EIS based prognosis, from now on , we will refer summation of R_E and R_{CT} as internal resistance of battery. So the feature relevant to capacity fade is regional capacity and for power fade is internal resistance.

In the next section, we will discuss about creating a model database by employing the above said features.

4.4 Creation of Model database

The barriers of technical heterogeneity and dynamic operating condition demands a robust model for efficient SoH prediction. The degradation of Li-ion battery depends on the way, a user is driving his vehicle and also the external environmental condition, especially the temperature. In a broader perspective, the environmental condition and driving pattern can be related to the particular geography, wherein the vehicle is being operated. This means that an estimation model created using degradation of a battery used in a particular region might not work as expected in other geographical region. A single SoH prediction model will lack the robustness to handle this uncertainty. So, we will create a model database for different geographical locations [Basia2019]. To diagnose an unknown battery for SoH estimation and forecasting, we will identify the best model out of the model database and then use the chosen best model for diagnosis. Model learning will be done using a sufficient amount of data from the batteries with known state of health for

every region.

The steps to create a model database is as follows :

1. Given cycle wise charging/discharging data (V, I, t) with its corresponding capacity based SoH.
2. As explained previously, in section, use the charging or discharging data to calculate the feature values for each cycle.
3. Create a correlation model for having a regional capacity and SoH correlation. Any probabilistic or non probabilistic algorithms can be used for establishing correlation between the features and State of health.
4. Repeat the previous steps for batteries from x different region R_1, R_2, \dots, R_x to have models M_1, M_2, \dots, M_x respectively.

4.4.1 Support Vector Regression : Regional Capacity correlation

SVR is a very efficient algorithm for describing the nonlinear relationship between inputs and outputs, and it is perfectly suitable for SoH estimation. The basic idea of SVR for regression is to use a nonlinear mapping function to map the training data into higher dimensional space and then perform linear regression in higher dimensional space in order to separate the data. Predetermined kernel function is used for data mapping while the data separation is done by finding the optimal hyperplane (called the Support Vectors) with the maximum margin from the separated classes. Suppose we have a battery dataset,

$(x_1, y_1), \dots, (x_i, y_i)$, where $x_i \in R^n$ is the regional capacity for i^{th} cycle and y_i is the SoH value or target output. An SVR function for the given case can be defined as :

$$f(x_i) = w^T \phi(x_i) + b \quad (4.19)$$

where $f(x_i)$ denotes the output values, $\phi(x_i)$ is a nonlinear mapping function, and w and b are the parameters to be determined. The regression's objective is to make the output of the model as similar as possible to y_i . The standard form of support vector regression can be written as :

$$\min \frac{1}{2} w^T w + C \sum_{i=1}^n (\xi_i + \xi_i^*) \quad (4.20)$$

with the constraints:

1. $w^T f(x_i) + b - y_i \leq \varepsilon + \xi_i$
2. $y_i - w^T f(x_i) - b \leq \varepsilon + \xi_i^*$
3. $\xi_i, \xi_i^* \geq 0, i = 1, 2, 3, \dots, n$

where C denotes the penalty parameter, ε denotes a soft margin that is specified by the user, ξ_i denotes the training error below ε and ξ_i^* denotes the training error above ε . Thus, the SVR function gets transformed to :

$$f(x_i) = \frac{1}{2} \sum_{i=1, j=1}^n (\beta_i - \beta_i^*) * K(x_i, x_j) + b \quad (4.21)$$

where β_i and β_i^* are Lagrange multipliers and $K(x_i, x_j) = \exp(-\|x_i - x_j\|_2)$ is the gaussian radial basis function kernel.

The advantages of SVR is that its computational complexity does not depend on the dimensionality of the input space. Additionally, it has excellent generalization capability, with high prediction accuracy and robust to the outliers.

The generic block diagram for setting up of model databases for different geographical region using the feature of regional capacity and SVR as a correlation algorithm is depicted in the figure 4.4 below.

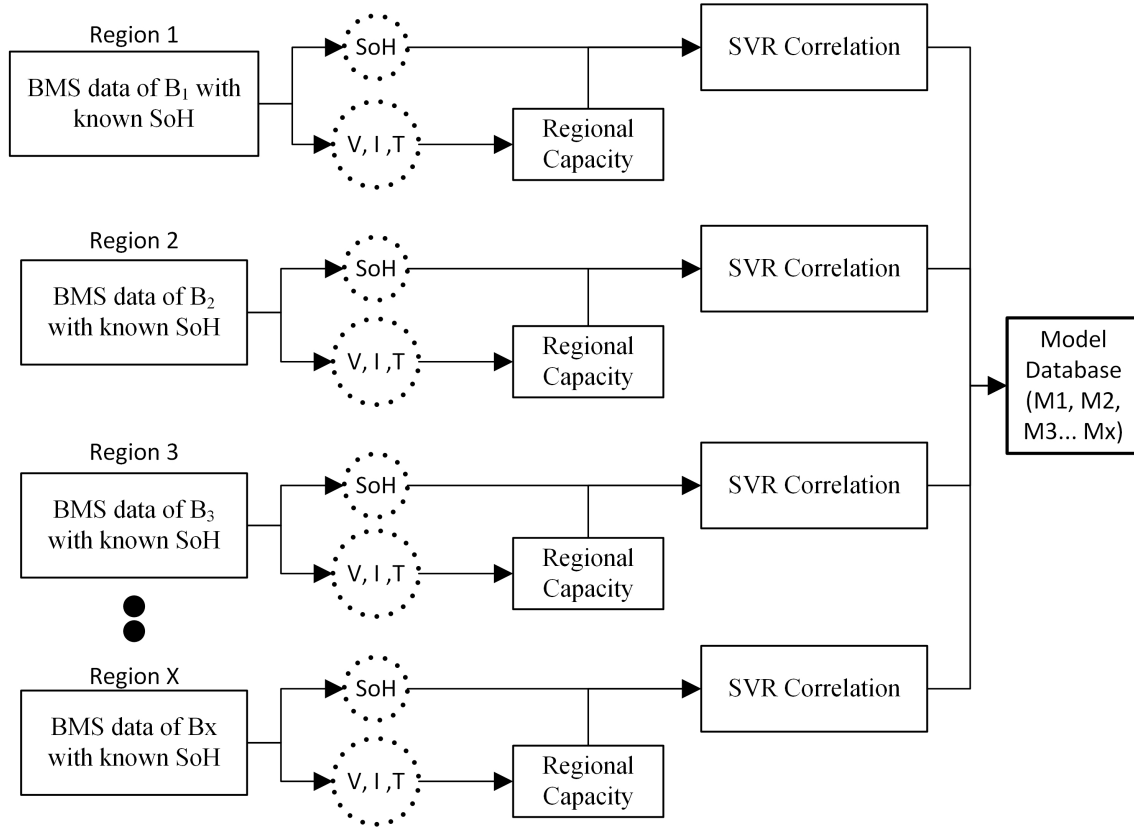


Figure 4.4: Creation of Model database

4.5 Model selection

When a battery with unknown SoH is to be diagnosed, first we need to identify the best model from the model database (M_1, M_2, \dots, M_x). The overall process is illustrated in figure 4.5. We first extract the historical data from the BMS of this battery and use it for calculating regional capacity for each cycle. The regional capacity for corresponding cycles are then converted to a time series where cycle number represents the time stamp. We compare this time series to the Incremental capacity time series used to create each model from the database. To compare, a measure of root mean square error is used.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_i - \hat{x}_i)^2}{N}} \quad (4.22)$$

where x_i is the actual value and \hat{x}_i is the predicted value of the target variable. The model, for which the root means square error is minimum is chosen as our best fit model denoted by M_{best} .

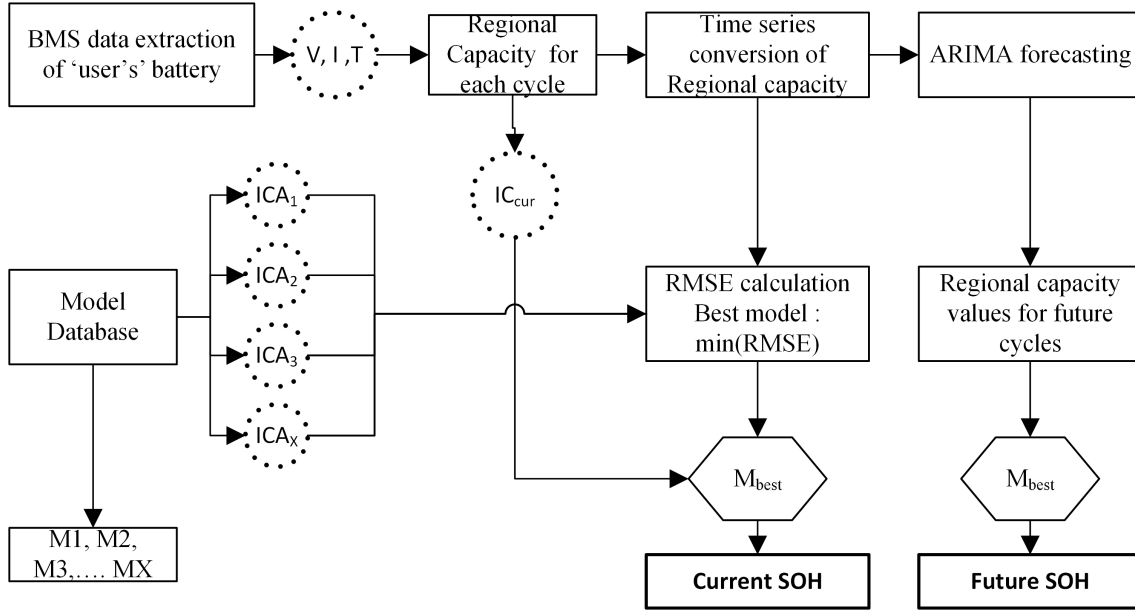


Figure 4.5: Identification of best model

4.6 Diagnosing the current SoH

For diagnosing a battery with unknown State of Health, the BMS data is extracted first. Then using the BMS data (V,I,t), features are analytically calculated for each cycle. In the case of capacity based estimation, regional capacity is the feature of our interest. Let us represent the regional capacity of the current cycle (the cycle at which battery is being diagnosed) as IC_{cur} . We will use IC_{cur} as an input to the best fit model M_{best} identified in the previous section for current SoH estimation. Thus the SVR correlation will generate the current SoH. Figure 4.5 depicts the simple process of diagnosing the current SoH of a battery.

4.7 Time series forecasting : Applied for prognosis

Time series forecasting is a method to analyze data changes across equally spaced time intervals. It has been used in various domains, like geology, econometrics, healthcare, and production systems. It involves developing models that can capture or describe an observed time series to understand the underlying causes of the system's behavior by making assumptions on the data structure and decomposing the time series into constitution components. In addition, the purpose of time series forecasting is to predict or forecast the future values of a series based on the history of that series. An efficient time series forecasting depends on an appropriate model fitting. Researchers have put up much effort into developing several efficient models to improve forecasting accuracy. So, various significant time series forecasting models have been evolved in the literature.

One of the most popular and frequently used stochastic time series models is the Autoregressive Integrated Moving Average (ARIMA) model [Ho1998]. ARIMA model comprises subclasses from other models, such as the Autoregressive (AR) [Lewis1985], Moving Average (MA) [Huang1984], and Autoregressive Moving Average (ARMA) models [Benjamin2003]. ARIMA can even be used for season time-series data. Box and Jenkins [Box2013] had proposed an interesting variation of the ARIMA model, viz. the Seasonal ARIMA (SARIMA). The ARIMA model is widely used because of its flexibility to represent several varieties of time series with simplicity

and the applicability of the Box-Jenkins methodology [Box2013] for the optimal model building process.

Very few researches have explored the applicability of ARIMA as a tool for prognostics in the domain of Li-ion batteries. We have discussed some of the studies in the section 2.3.2.8. Our SoH prediction methodology will incorporate ARIMA as a prognostics algorithm by converting the battery-acquired features into time series.

4.7.1 The Autoregressive Moving Average (ARMA) Models

Auto regressive moving average model is a combination of AR(p) and MA(q) models used for univariate time series modelling. For an AR(p) model the forecasted value of the variable is obtained by a linear combination of p past observations and a random error together with a constant term. Mathematically the AR(p) model can be expressed as:

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \varepsilon_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t \quad (4.23)$$

Where y_t is the actual value and ε_t is the random error at time period t , ϕ_i is a model parameter and c is a constant. The order of the model is denoted by p . An MA(q) model uses past errors as the explanatory variables. The model can be represented by the equation mentioned below.

$$y_t = \mu + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t = \mu + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-p} + \varepsilon_t \quad (4.24)$$

Where μ is the mean of the series, θ_j is the model parameter and q is the order of the model. However fitting a moving average model is more complicated than an AR model because the random error is not foreseeable in MA model.

Autoregressive Moving Average model, a more efficient time series model can be implemented by combining the Autoregressive and Moving average models. Mathematically an ARMA(p,q) model is represented as :

$$y_t = c + \varepsilon_t + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} \quad (4.25)$$

Where p is the order of autoregressive terms and q is the order of moving average terms. The manipulation of ARMA models can be done using the lag / backshift operator notation, which is defined as $Ly_t = y_{t-1}$. The conversion of time series models to the polynomials of lag operator is as follows :

$$AR(p) \text{ model : } \varepsilon_t = \varphi(L)y_t \quad (4.26)$$

$$MA(q) \text{ model : } y_t = \theta(L)\varepsilon_t \quad (4.27)$$

$$ARMA(p,q) \text{ model : } \varphi(L)y_t = \theta(L)\varepsilon_t \quad (4.28)$$

Where,

$$\varphi(L) = 1 - \sum_{i=1}^p \phi_i L^i \text{ and } \theta(L) = 1 + \sum_{j=1}^q \theta_j L^j \quad (4.29)$$

4.7.2 The Autoregressive Integrated Moving Average (ARIMA) Models

ARIMA model is a generalized model of an ARMA model to perform forecasting from non-stationary data. Often, sensor-acquired time-series data show non-stationary behavior because of the prevailing trend and seasonal patterns. Since, ARMA models are inefficient to describe non-stationary time series, ARIMA models have wider range of applications compared to the former. ARIMA model converts the non stationary time series data into stationary by finite differencing of

the data points. Mathematically ARIMA(p,d,q) model can be represented using lag polynomials in the form:

$$\varphi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \quad (4.30)$$

where, p, d and q are whole number representing the order of autoregressive, integrated and moving average part of model respectively. Since d represents the order of differencing, so if $d = 0$, the ARIMA model reduces to an ARMA(p,q) model. The parameter identification and estimation of the ARIMA model are the preliminary steps in conducting ARIMA based forecasting. Box and Jenkins (cite) presented a practical methodology to build ARIMA models. Figure 4.6 [Jamil2020] shows a schematic diagram of the box and Jenkins methodology for ARIMA modeling. The Box-Jenkins methodology (ARIMA model) is conducted in three phases: identification, estimation and testing, and application. We will discuss in detail each of the three phases.

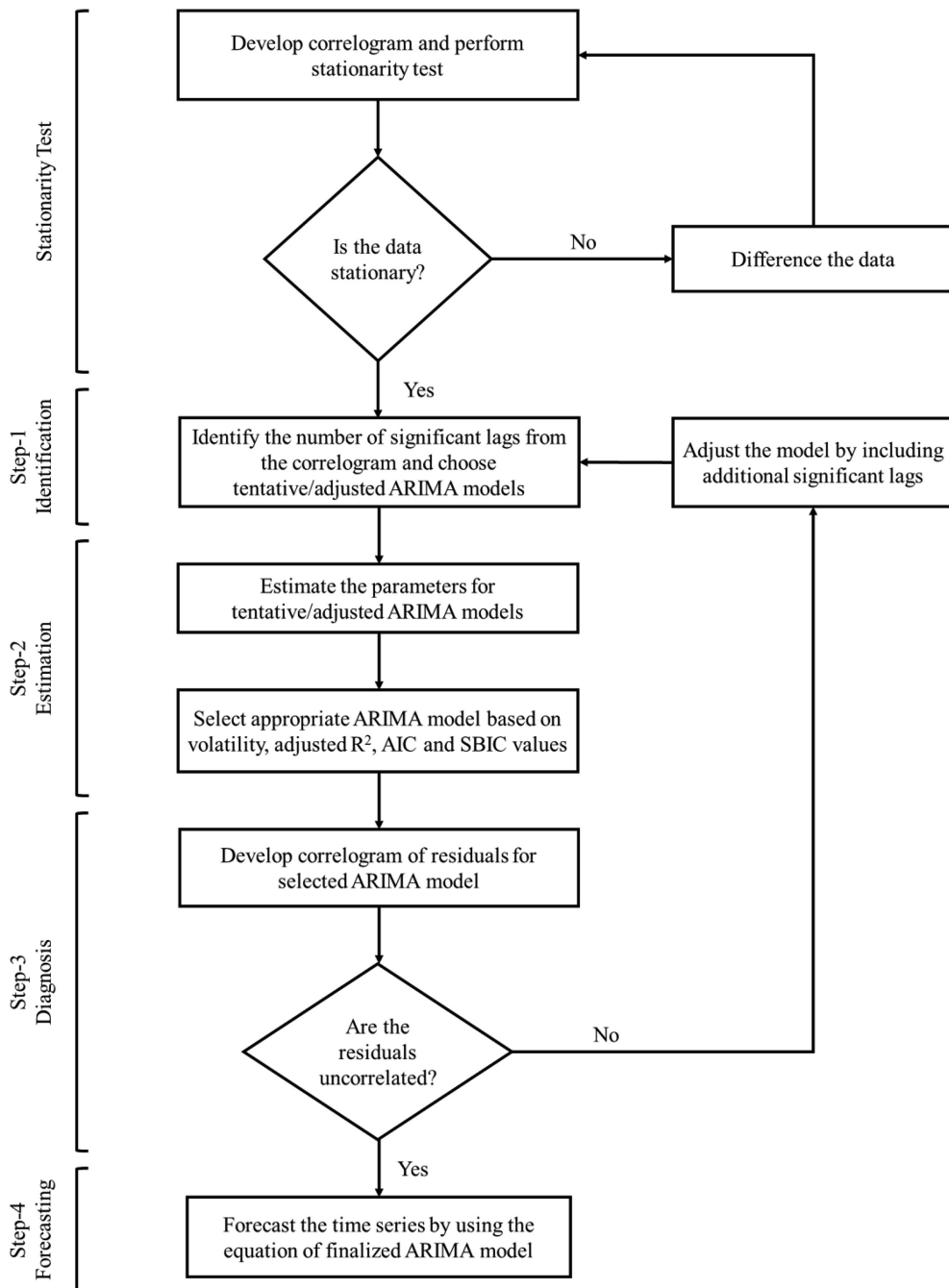


Figure 4.6: Box & Jenkins methodology schematic [Jamil2020]

4.7.2.1 Model identification

Assuming the absence of seasonal variation, the model identification steps involve the methodology to select the values of p , d and q in the ARIMA(p,d,q) model. The first and foremost thing to do is trend removal, either by differencing or by deterministic trend removal. The auto-correlation and partial auto-correlation plot gives interesting insights about the existence of trend in data. The level of differencing can be identified by observing the auto-correlation plots. The time series should be differenced upto the order where auto-correlation plots die out quickly. Once the series is appropriately differenced, the partial auto-correlations of the differenced series can be used to determine the value of p . In the case, where partial auto-correlations cut off after a few lags, the last lag with a large value would be the estimated value of p . If partial auto-correlations do not cut off, either the value of p equals to zero or the ARIMA model has a positive p and q . The auto-correlations of the differenced series can be used to estimate the value of q . If the auto-correlations cut off after a few lags, the last lag with a large value would be the estimated value of q . In case, the auto-correlations do not cut off, the value of q equals to zero or the ARIMA model has a positive p and q . If neither auto-correlations or the partial auto-correlations cut off, a mixed model is suitable. However, in that case, trial and error is used to find the right model until the residuals stop showing large auto-correlations.

4.7.2.2 Model estimation

After accurately identifying the order of ARIMA models, i.e. values of p,d and q , the next step is to estimate the parameter θ and ϕ for the identified order. Box Jenkins [George E. P. Box2015] proposed the method of Maximum likelihood for conducting the same. The maximum likelihood equation is solved by nonlinear function maximization. Back propagation can be used to estimate the initial residuals.

4.7.2.3 Diagnostic Checking

After model fitting, the final step is to do a diagnostic of the model. This can be done by observing the auto-correlation plots of the residuals to check if large correlation values still exists. In case, the auto-correlations and partial auto-correlations are large, an adjustment in p and q values are required followed by re-estimation of the parameter θ and ϕ . Once a suitable model is identified with lower correlations in the residuals, the model can be stated as a good model and can be used for forecasting.

4.8 ARIMA based prognosis for Future SoH estimation

For prognosis, we will use the regional capacity time series acquired from the “to be diagnosed” battery. Using this acquired time series and the box-Jenkins methodology explained in previous section, the order and model parameter of an ARIMA forecasting model can be estimated. The regional capacity of future charging/discharging cycles is predicted using the ARIMA model and stored as an another time series. This time series is then used as an input to the SVR model M_{best} for finding the correlated future capacity based SoH. The root mean square error can be calculated to check prediction efficiency. The above said methodology is illustrated in figure 4.5.

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

4.8. ARIMA based prognosis for Future SoH estimation

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.

5

SVR-ARIMA based SoH estimation : A case study on NASA AMES prognosis data

Contents

5.1	NASA AMES prognosis data : Details and Exploration	74
5.2	Regional capacity estimation on the given data	77
5.3	SVR model database creation	81
5.4	Diagnosis and Prognosis for an unknown battery	83
5.4.1	ARIMA model selection	83
5.4.2	Forecasting future values using ARIMA	85
5.4.3	Forecasting SoH from model database	85
5.5	Internal Resistance Forecast using ARIMA	87
5.6	Comparison of different algorithms for correlation	91
5.6.1	Model database creation	91
5.6.2	Diagnosis for SoH estimation and RMSE comparison	91
5.6.3	Comparison Results	92

5.1 NASA AMES prognosis data : Details and Exploration

In this chapter, we will implement the SoH estimation methodology discussed in Chapter 4. We have used the Li-ion battery data obtained from data repository of NASA Ames Prognostics Center of Excellence (PCoE). This data set has been sampled from a battery prognostics test bed in NASA which comprises of commercially available Li-ion 1850 sized rechargeable batteries, power supply and programmable DC electronic load, voltmeter, thermocouple sensor, environmental chamber, electrochemical impedance spectrometry (EIS), PXI chassis based on DAQ and experiment control condition. The experimental scenario allows to control the charging, discharging and operating conditions of the battery. The Li-ion batteries were run through 3 different operational profiles (charge, discharge and impedance) at room temperature. The dataset consisted of database collected from experiments on 37 different scenarios. The dataset description suggested that batteries No.5, No.6, No.7 and No.18 have higher order of relevance for PHM design. So, in this chapter, the datasets from these four batteries have been explored to create an efficient PHM system in the context of Circular economy. Charging was carried out in a constant current (CC) mode at 1.5A until the battery voltage reached 4.2V and then continued in a constant voltage (CV) mode until the charge current dropped to 20mA. Discharge was carried out at a constant current (CC) level of 2A until the battery voltage fell to 2.7V, 2.5V, 2.2V and 2.5V respectively for batteries No.5, No.6, NO.7 and No.18. Impedance measurement was carried out through an electrochemical impedance spectroscopy (EIS) frequency sweep from 0.1Hz to 5kHz. Repeated charging and discharging cycles result in accelerated aging of the batteries. The experiments were stopped when the batteries reached end-of-life (EOL) criteria, which was a 30% fade in rated capacity (from 2Ahr to 1.4 Ahr).

The charging current and voltage curve for Battery B0005, B0006, B0007 and B00018 has been plotted below.

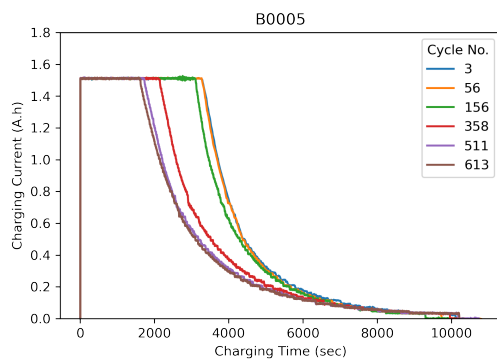


Figure 5.1: Charging current curve

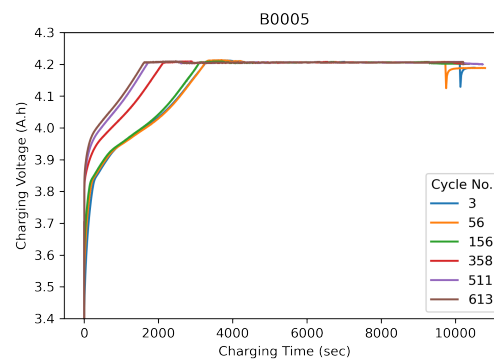


Figure 5.2: Charging voltage curve

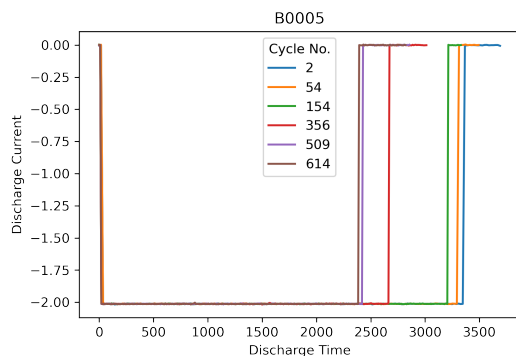


Figure 5.3: Discharging current curve

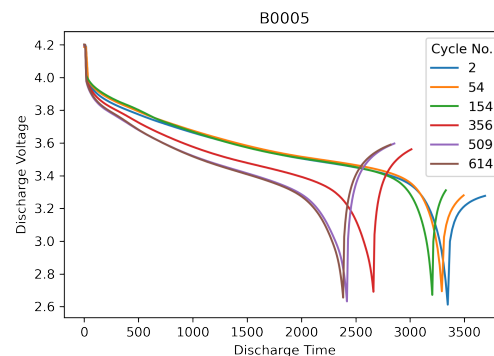


Figure 5.4: Discharging voltage curve

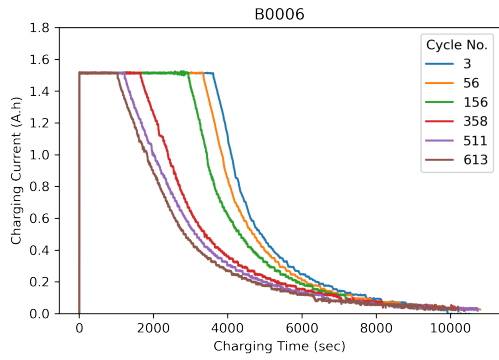


Figure 5.5: Charging current curve

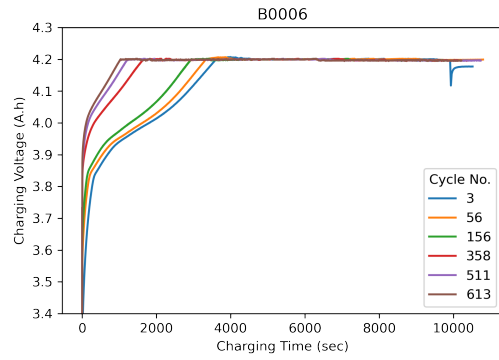


Figure 5.6: Charging voltage curve

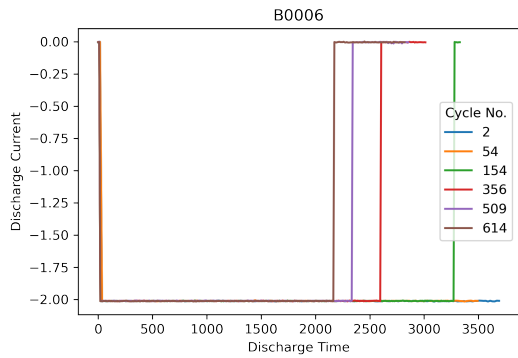


Figure 5.7: Discharging current curve

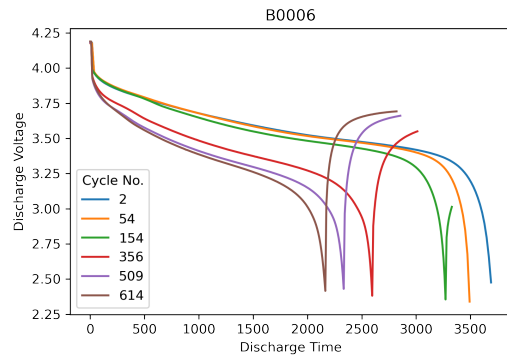


Figure 5.8: Discharging voltage curve

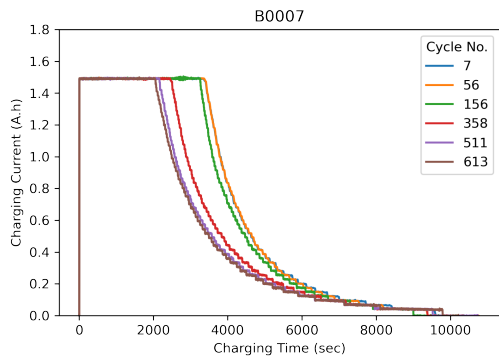


Figure 5.9: Charging current curve

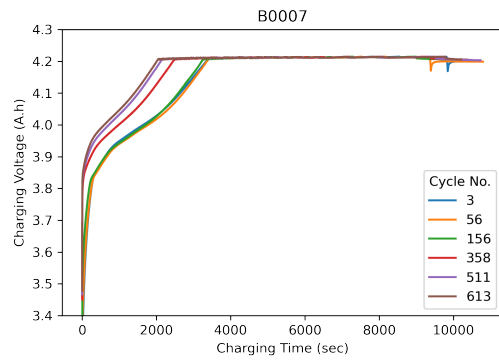


Figure 5.10: Charging voltage curve

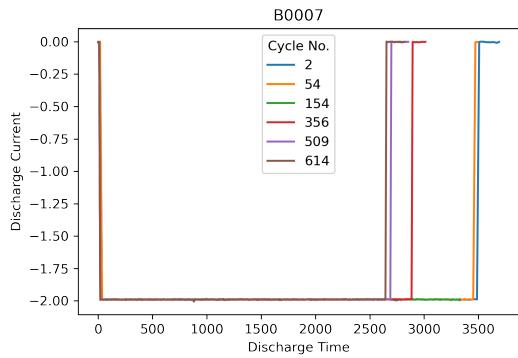


Figure 5.11: Discharging current curve

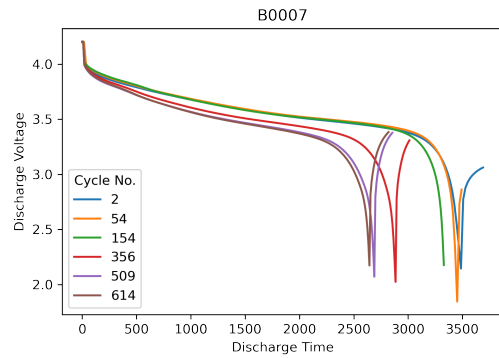


Figure 5.12: Discharging voltage curve

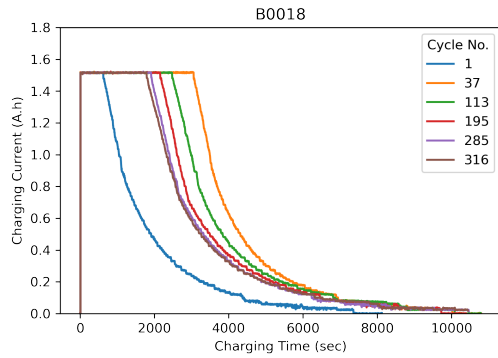


Figure 5.13: Charging current curve

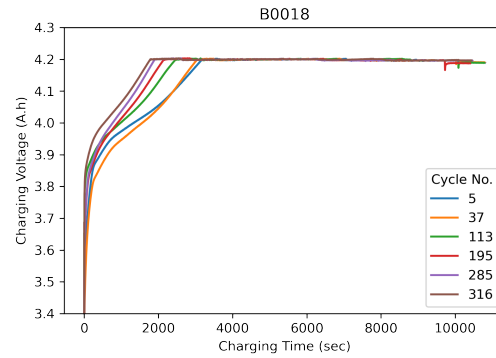


Figure 5.14: Charging voltage curve

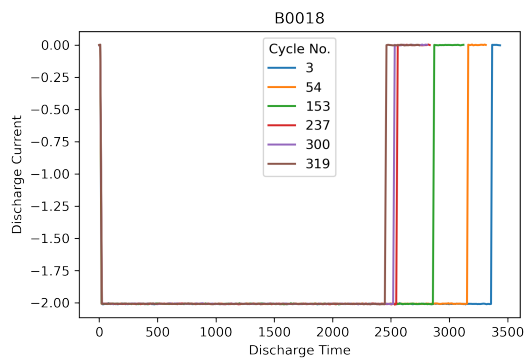


Figure 5.15: Discharging current curve

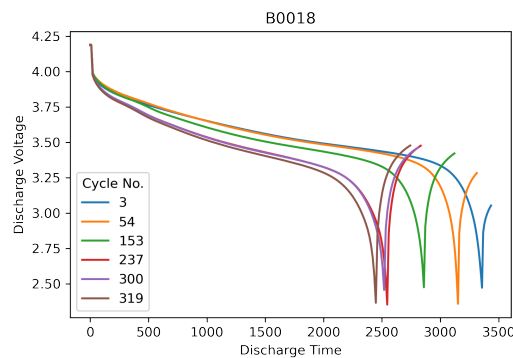


Figure 5.16: Discharging voltage curve

By observing the charging and discharging voltage and current curve, some conclusions can be directly drawn.

In figure 5.1, figure 5.5, figure 5.9 and figure 5.13, the charging current has been plotted against the charging time for different cycle number across the life of batteries B0005, B0006, B0007 and B0018 respectively. The charging scenario for all the batteries was constant current - constant voltage (CCCV) operation. The plots show that as the battery gets older, the shift from constant current to constant voltage appears earlier. In other words, charging current starts to decrease more quickly. Also, there is a slight increase in the slope of current decay. Similarly in figure 5.2, figure 5.6, figure 5.10 and figure 5.14, during the constant current charging period, the slope of charging voltage curve increase as we move toward the end of life of the batteries. These changes can also be used as a health indicator for SoH estimation of battery. However, the varying SoC during charging makes it a bit challenging to estimate SoH using these raw features. The discharging current curve in figure 5.3, figure 5.7, figure 5.11 and figure 5.15 justifies that as the batteries degrade over time, it discharges more quickly. There is an approximately thirty percent of decrease in discharge time between a new battery and a battery close to the end of life. Similarly in figure 5.4, figure 5.8, figure 5.12 and figure 5.16, the slope of discharge voltage curve increase as we move toward the end of life of the batteries. The measured and actual capacity over different cycles for the batteries have been depicted in figure 5.17 and 5.18. Capacity can be calculated by integrating the current over full charging cycles to identify the amount of charge. We have also plotted a comparison of the variation in measured temperature of the cell during charging at beginning of life and at end of life of the batteries in figure 5.19. After several charging and discharging cycles, the temperature while charging rises more quickly than a new battery.

SoH estimation can be employed using the features generated from these raw data. However, since the computational complexity will be higher in this case, so we will analytically generate the feature of regional capacity from the above mentioned data for SoH estimation.

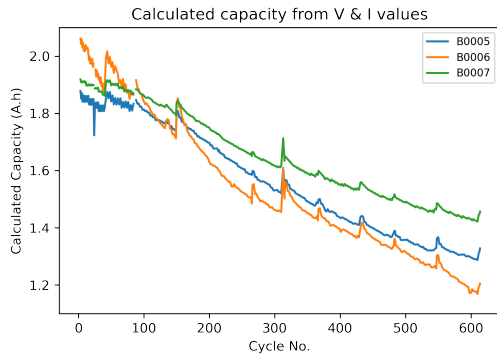


Figure 5.17: Calculated Capacity

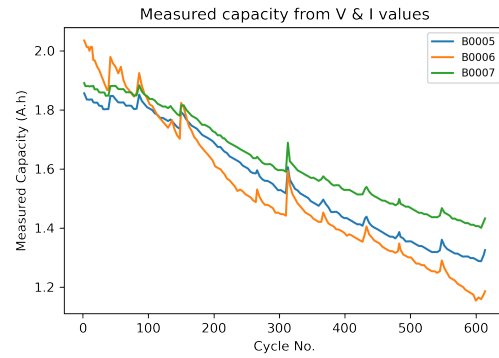


Figure 5.18: Measured Capacity

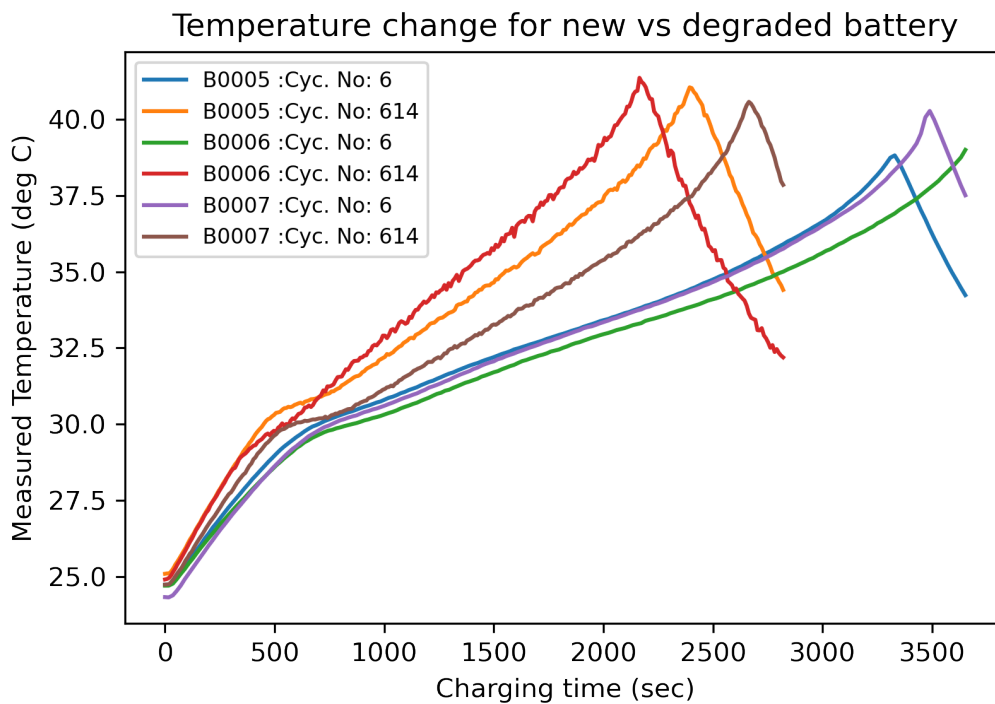


Figure 5.19: Variation in temperature during charging

5.2 Regional capacity estimation on the given data

To calculate the regional capacity for each cycle for different batteries, we will follow the methodology explained in Chapter 3. The voltage and current measurement data were used to plot the incremental capacity curve for different cycles of all the batteries. The incremental capacity curve for second discharging cycle of battery B0007 has been depicted in the figure 5.20. The terminal voltage corresponding to the peak of the curve can be called as V_{peak} . To reduce the noise in the IC curve, we employed a Kalman filter with a process noise covariance of 0.0002 and measurement noise covariance of 1. The calculated Kalman gain was approximately 0.50 and the noise was attenuated significantly. The filtered incremental capacity curve for second discharging cycle of battery B0007 has been depicted in figure 5.21.

Insights about aging mechanisms can be extracted from the peak amplitude and position of the IC curve. In the past researchers have used the area, position and gradient of IC curve as well for understanding the degradation mechanism of the battery. The peak position, slope and amplitude

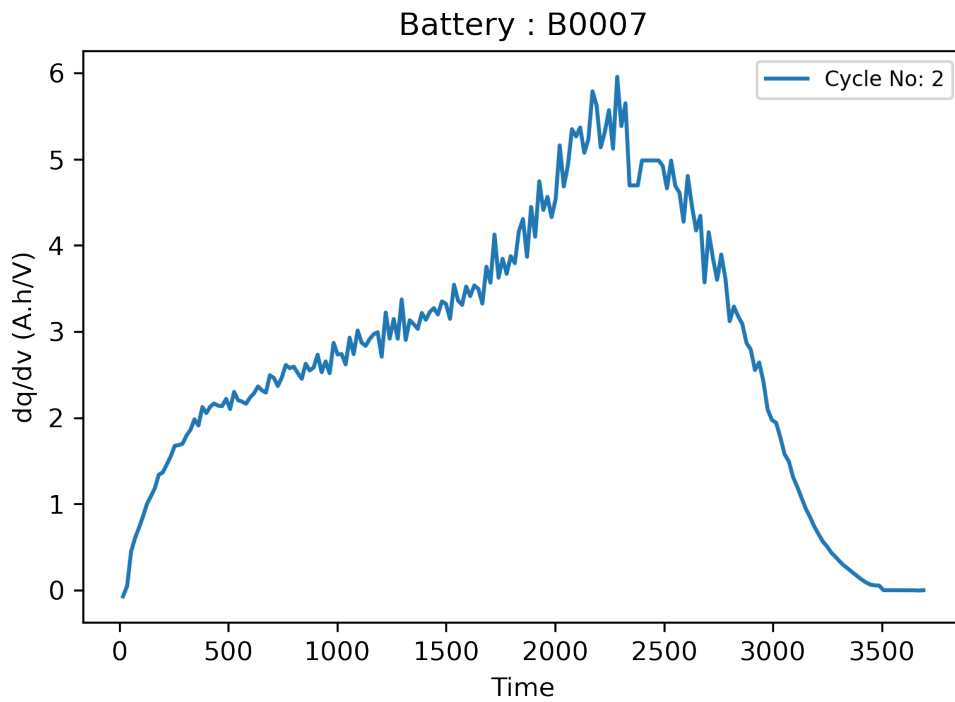


Figure 5.20: Incremental Capacity curve: B0007

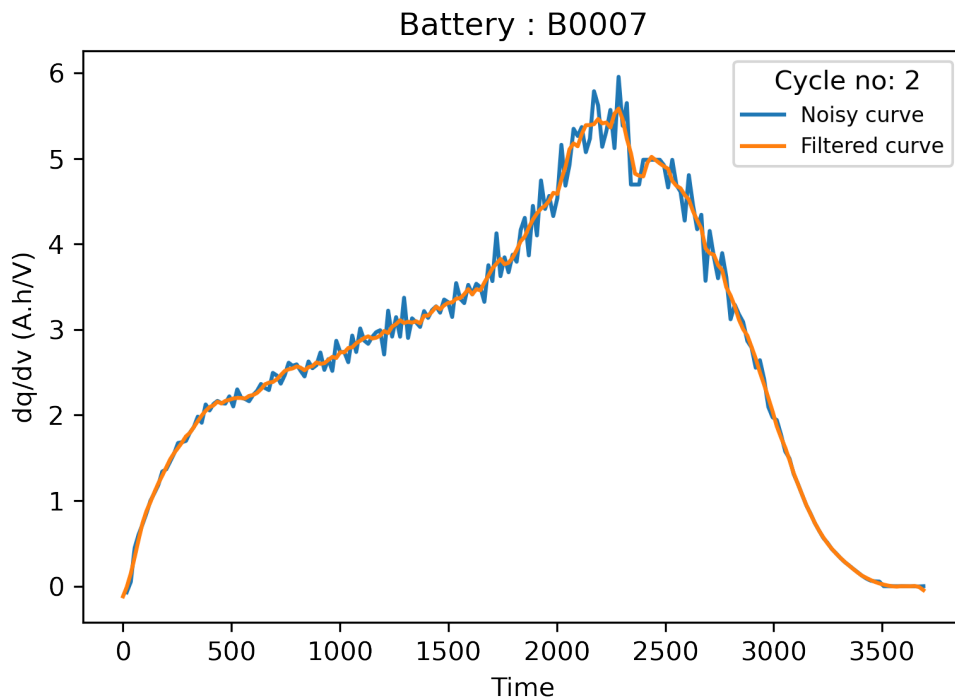


Figure 5.21: Filtered Incremental Capacity curve: B0007

of the IC curve changes as the battery undergoes cycling. A comparison of IC curve for different cycles of battery B0007 is plotted in figure 5.22. It is evident from the figure that the peak of IC curve shifts with degradation of battery.

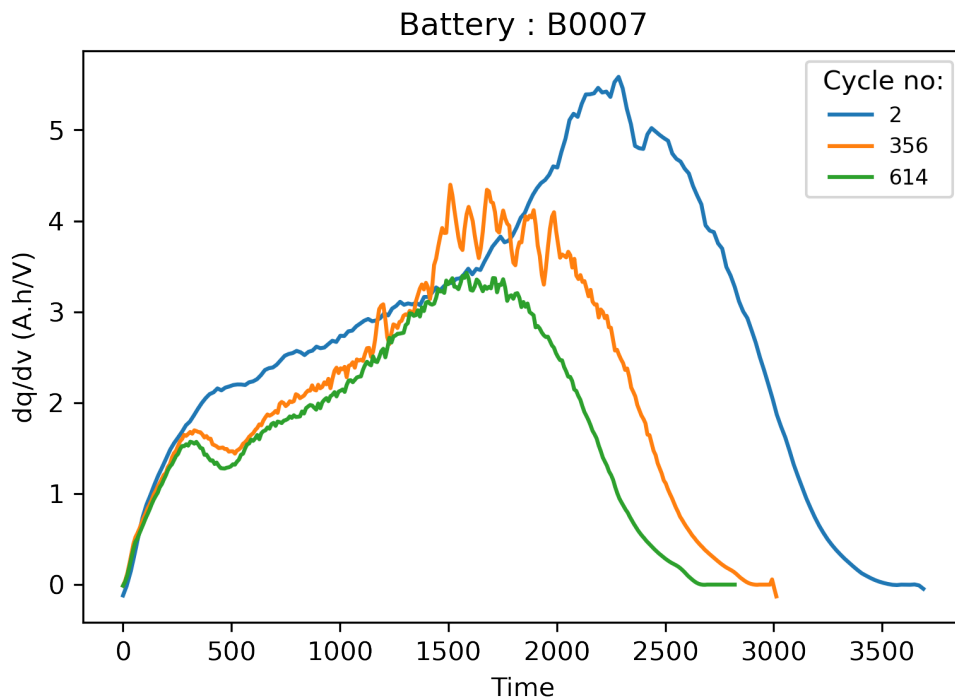


Figure 5.22: Cyclewise IC curve: B0007

To calculate the feature of regional capacity, we specified the ΔV_{reg} as 100 millivolts. The value of ΔV_{reg} decides the accuracy of calculation. Higher the ΔV_{reg} , higher will be the correlation of regional capacity with real capacity. However, using a smaller value of ΔV_{reg} allows the fast estimation of regional capacity. The regional capacity was calculated for each cycle of the batteries B0005, B0006, B0007 & B0018 which has been depicted in figure 5.23, figure 5.24, figure 5.25 and figure 5.26, respectively. It can be interpreted from the figures that the feature of regional capacity is highly correlated to the real capacity of the batteries. The correlation plot for the battery B0007 has been depicted in figure 5.27

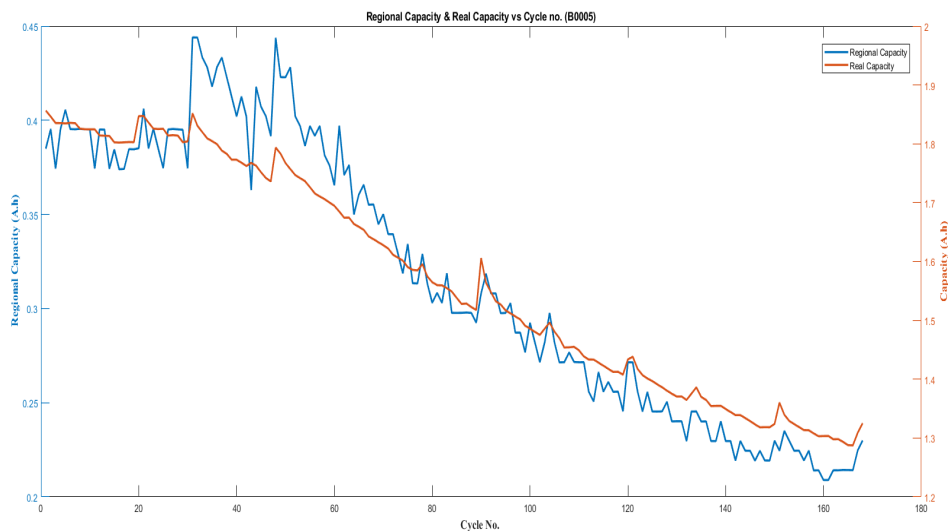


Figure 5.23: Cyclewise Regional capacity plot: B0005

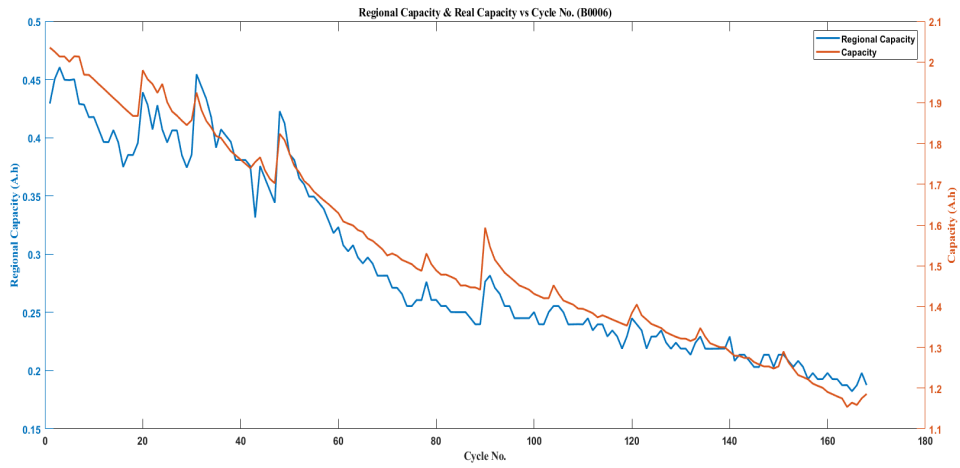


Figure 5.24: Cyclewise Regional capacity plot: B0006

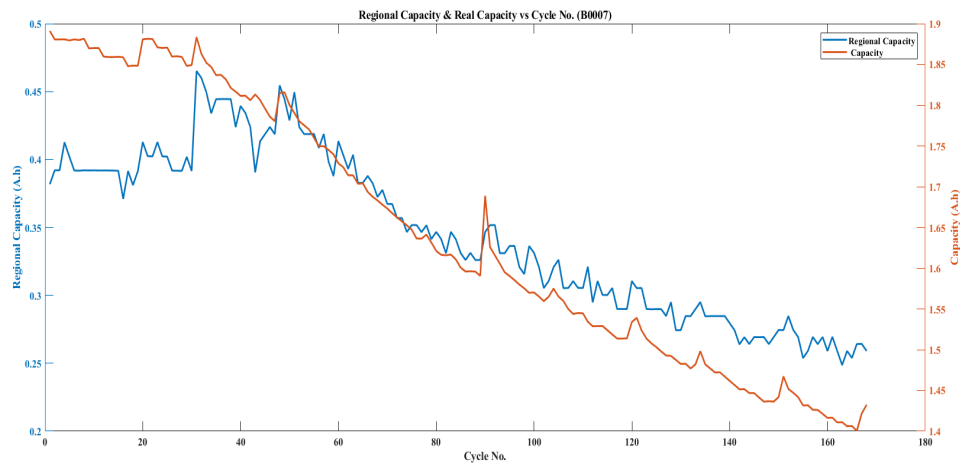


Figure 5.25: Cyclewise Regional capacity plot: B0007

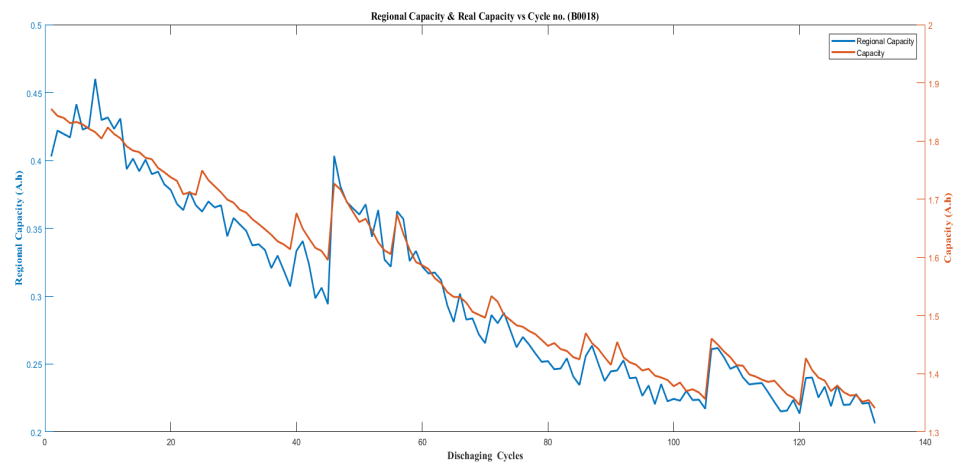


Figure 5.26: Cyclewise Regional capacity plot: B0018

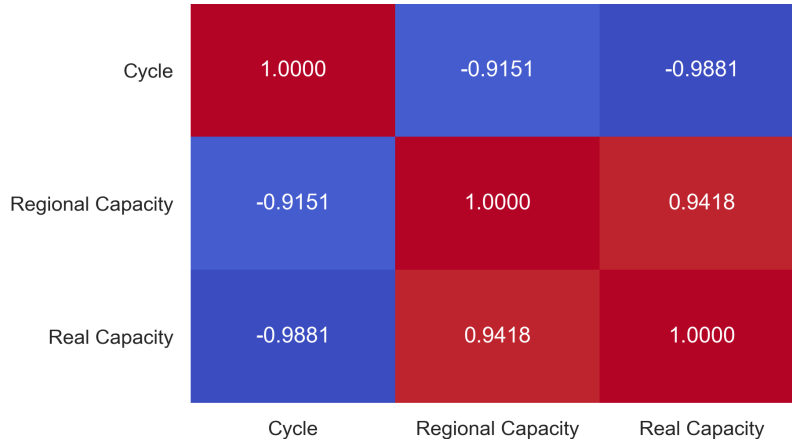


Figure 5.27: Feature correlation plot: B0007

5.3 SVR model database creation

The Support vector regression was used to create a correlation model for each of the battery. Analytically generated feature of regional capacity was used as an independent variable. The Regional capacity vs real capacity data was divided into training and testing data (ratio 7 : 3). The SVR model was trained and tuned by grid search with tenfold cross validation technique and then model efficiency was estimated for the test set. The methodology employed has been depicted in figure 5.28

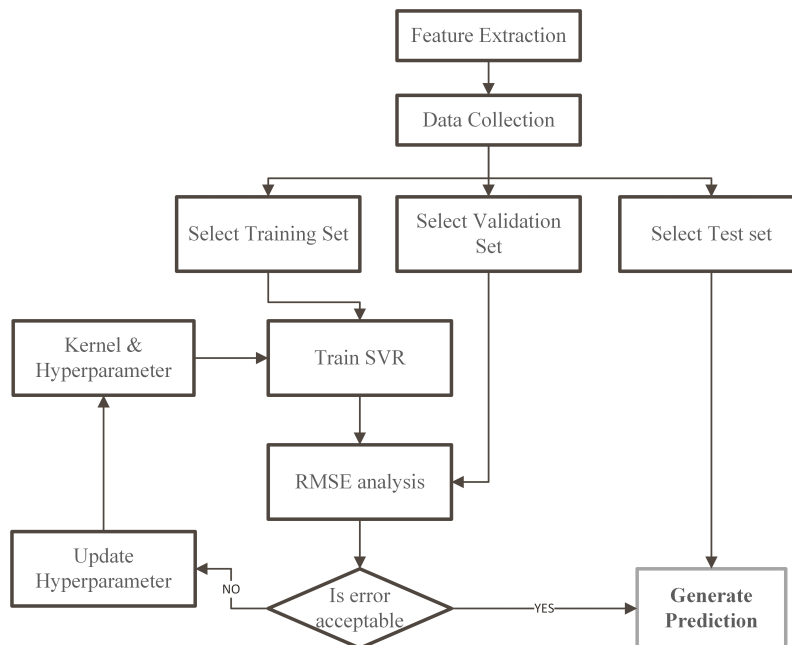


Figure 5.28: SVR model creation procedure

The SVR correlation model results for battery B0005 has been depicted in Fig 5.29 and is represented as M_1 . The black cross are the actual data, the red ones are pre-tuned model prediction and the green cross are post tuning prediction results. Our model database comprises of the three model, represented by M_1 , M_2 and M_3 for battery B0005, B0006 and B0007 respectively.

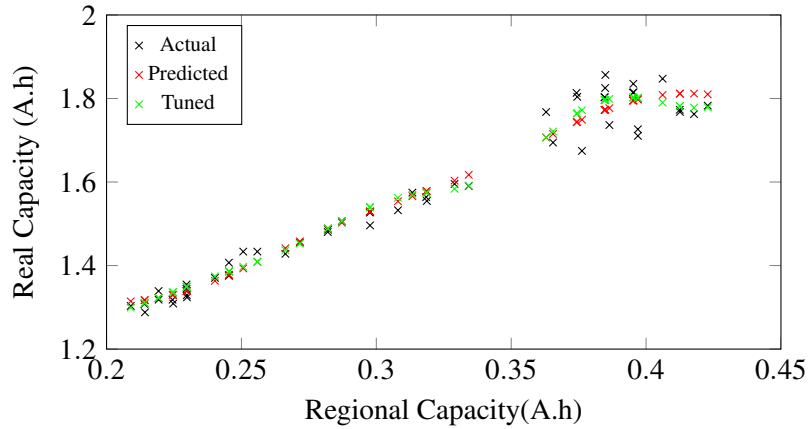


Figure 5.29: SVR model results for battery B0005

Similarly, the model M_2 and M_3 for battery B0006 and B0007 has been presented below.

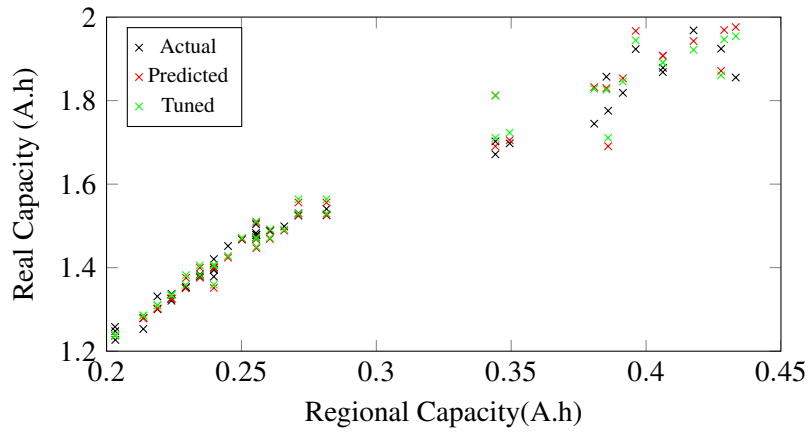


Figure 5.30: SVR model results for battery B0006

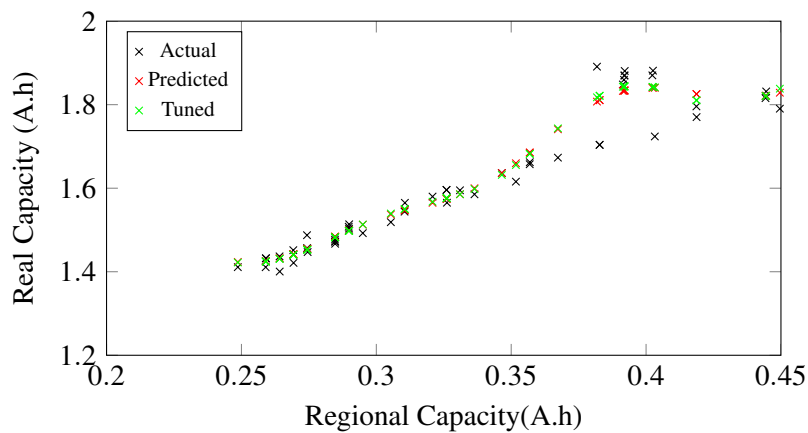


Figure 5.31: SVR model results for battery B0007

5.4 Diagnosis and Prognosis for an unknown battery

In this section, we will take a battery with unknown state of health and predict its future capacity using the correlation model established in the previous section.

5.4.1 ARIMA model selection

We first extract the BMS acquired data of voltage, current and time upto the current cycle. Then, these raw data was used to calculate the regional capacity of each cycle upto the current cycle. The regional capacity data was converted to a time series and has been depicted in figure 5.32.

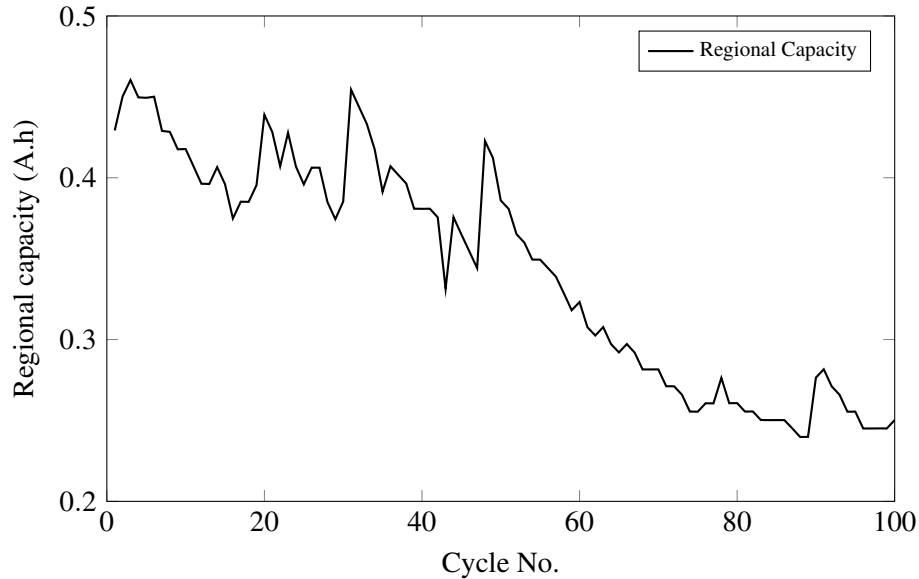


Figure 5.32: Feature extraction of to be diagnosed battery

To obtain the future values of regional capacity, we employed a time series forecasting ARIMA model using Box Jenkins methodology. The auto-correlation and partial auto-correlation function was plotted in figure 5.33 and figure 5.34 for the given data for making observations on stationarity. The auto-correlations were significant for a large number of lags but perhaps the auto-correlations at lag-2 and above are merely due to the propagation of the auto-correlation at lag-1. Also, the PACF plot has a significant spike only at lag-1, meaning that all the higher-order auto-correlations are effectively explained by the lag-1 auto-correlation. This shows that the given time series is non stationary.

To convert the series into a stationary series, first order differencing was employed. The differencing result has been portrayed in figure 5.35

Once the signal have been made stationary, order of Auto-regression and moving average has to be identified. The best model was chosen on the basis of Akaike Information Criterion. The model with higher negative AIC value can be considered as the best model. We also added a factor of seasonality in the model. There are two main reason behind adding the notion of seasonality. First, there is a phenomena of regenerative capacity with the EV batteries where the capacity of the battery increases sometimes during the course of usage. Second, since the degradation of the battery depends on the user's behaviors of using the equipment, adding seasonality can help us to decide the amount of reliance to the user's behavior. The comparison of AIC values for different ARIMA model has been depicted in the table 5.1 below.

Thus, for the given data-set an ARIMA model with an order of 0,1,1 can be deemed as the most efficient model.

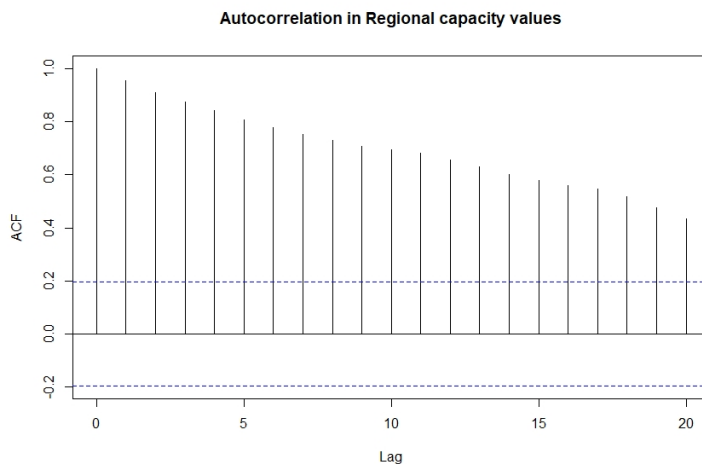


Figure 5.33: ACF plot

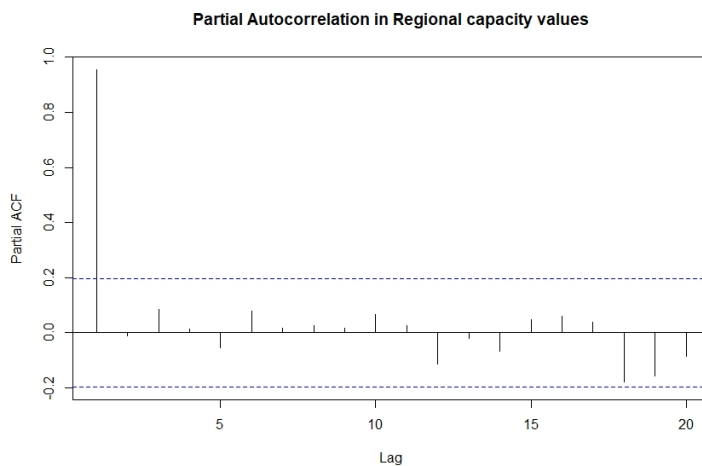


Figure 5.34: PACF plot

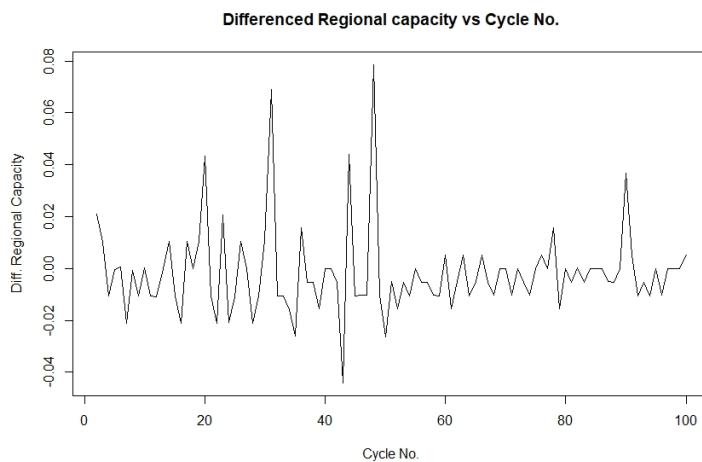


Figure 5.35: Differenced Regional capacity

ARIMA structure	AIC
ARIMA(2,1,2)(0,1,0)[35]	-17.42889
ARIMA(0,1,0)(0,1,0)[35]	-20.99261
ARIMA(1,1,0)(0,1,0)[35]	-22.04329
ARIMA(0,1,1)(0,1,0)[35]	-22.78156
ARIMA(1,1,1)(0,1,0)[35]	-21.70482
ARIMA(0,1,2)(0,1,0)[35]	-20.81055
ARIMA(1,1,2)(0,1,0)[35]	-19.52355

Table 5.1: AIC value comparison for different ARIMA models

5.4.2 Forecasting future values using ARIMA

The ARIMA model identified in the previous sub section can now be used to predict the future values of Regional capacity. ARIMA(0,1,1)(0,1,0)[35] was used on the data-set shown in figure 5.32. The prediction result has been plotted below in figure 5.36. The comparison of predicted and actual value of regional capacity for the next 68 cycles is shown in figure 5.37. The Root mean square error noted was 0.0208, which is well under acceptable limit of 5 percent.

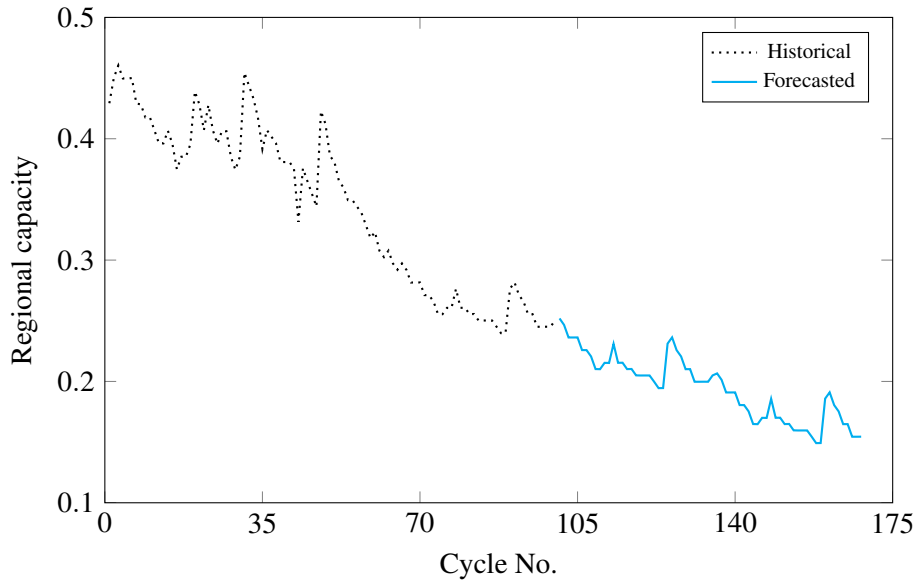


Figure 5.36: ARIMA model forecasting

5.4.3 Forecasting SoH from model database

First, we need to identify the best model from the model database (M_1, M_2, \dots, M_x) created in section 5.3. The overall process is illustrated in figure 4.5. The data-set shown in figure 5.32 was compared to the regional capacity time series used to create each model from the database. To compare, a measure of root mean square error is used.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_i - \hat{x}_i)^2}{N}} \quad (5.1)$$

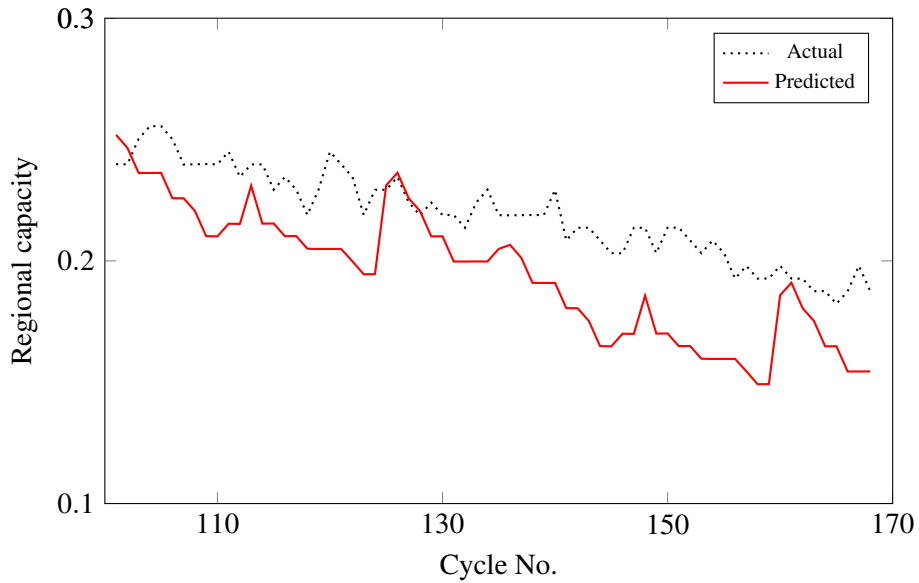


Figure 5.37: Comparison of predicted vs actual regional capacity

where x_i is the actual value and \hat{x}_i is the predicted value of the target variable. The model, for which the root means square error is minimum is chosen as our best fit model denoted by M_{best} . The RMSE value for M1, M2 and M3 were 0.044, 0.001, 0.063 respectively. Thus for the given battery, M2 can be considered as a best model. The model M2 was used for SoH correlation, for which the result has been shown in figure 5.38. The RMSE noted was 0.079, which is acceptable.

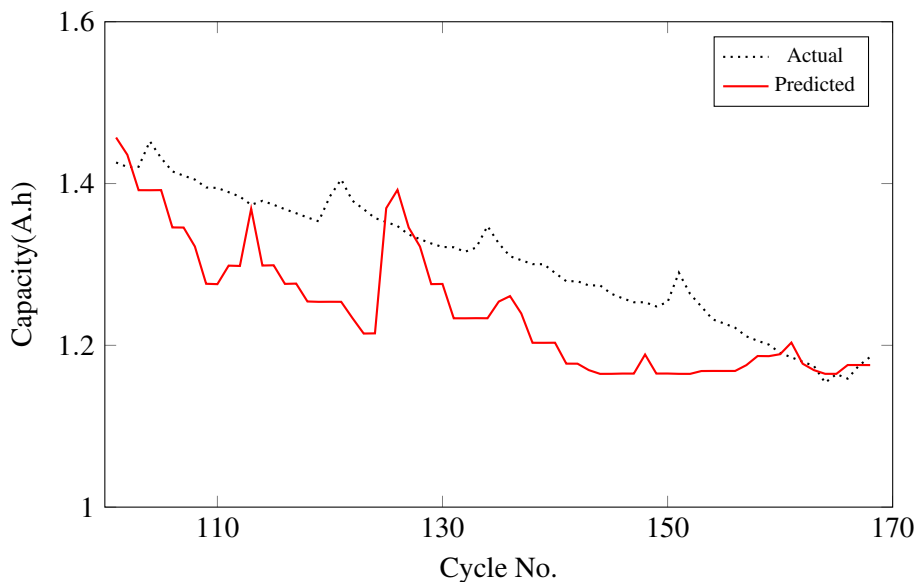


Figure 5.38: Actual ve predicted capacity

Thus, for any battery with unknown State of Health, regional capacity based estimation can be done for predicting future state of health. The model robustness depends on the model database. The very same ARIMA model can be used for internal resistance forecasting. In the next section, we will portray the prediction of internal resistance prediction for the given battery data.

5.5 Internal Resistance Forecast using ARIMA

As discussed before, the SoH in context of circular economy should give insights about both capacity and power fade. The degradation in power capability of Li-ion batteries is majorly related to increase in the internal resistance of the battery. Knowing the future values of Internal resistance can help the decision makers to choose the right application for the End of Life batteries. We presented the method of Electrochemical Impedance spectroscopy in section 4.3.3, where a sinusoidal current or voltage of a certain amplitude and frequency to the cell and observed amplitude and phase shift of the output voltage or current is measured. We also discussed the importance of summation of R_E and R_{CT} as internal resistance of battery.

In this section, we will use the summation of R_E and R_{CT} values as an indicator for internal resistance. The R_E and R_{CT} values for the testing cycle was extracted from NASA AMES open source data and has been explored here to forecast the future value of itself using time series forecasting algorithms. Normally to calculate the values of R_E and R_{CT} , either Nyquist plot (imaginary part of impedance vs real part of impedance) or Bode plot (real and imaginary part of impedance vs frequency) can be used. The representation of the frequency regions on a Nyquist plot was depicted in the figure 4.2 [Turilli2021].

The filtered $R_E + R_{CT}$ values acquired from NASA AMES open source data for battery B0005, B0006 and B0007 has been plotted in figure 5.39. It is evident from the plot that as the cycle number increases, the internal resistance of the battery keeps increasing as well. Thus, affecting the power capability.

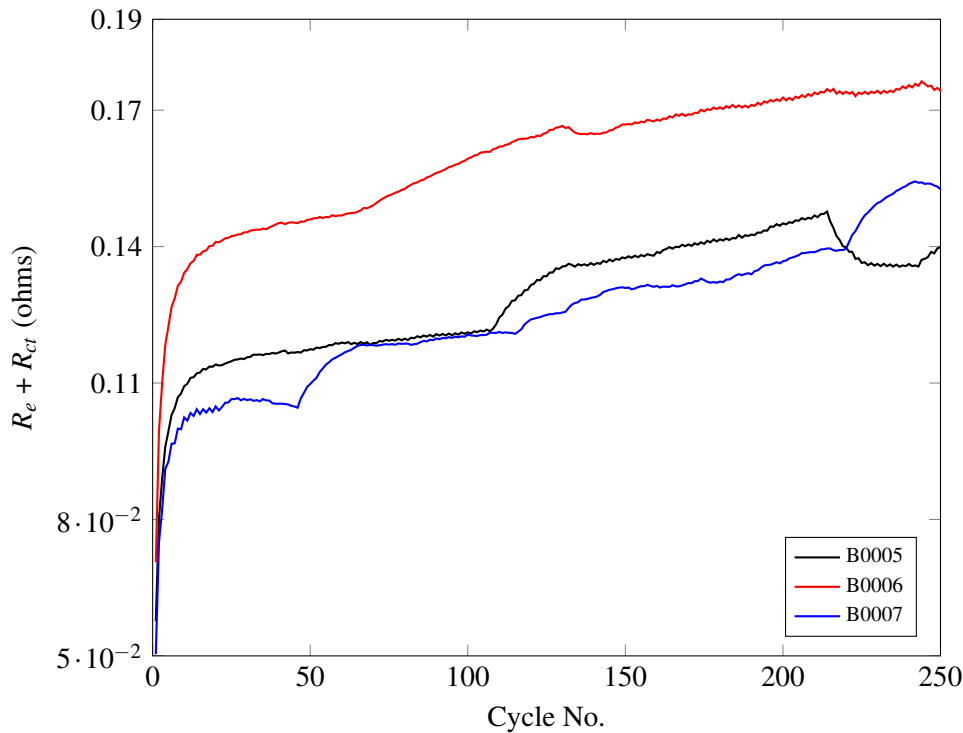


Figure 5.39: Internal Resistance data

We explored the data of battery B0006 to check the applicability of ARIMA for internal resistance forecasting. The IR data (R_E and R_{CT}) was first divided into training and testing set. The training data was used as an input to identify the appropriate ARIMA model and to obtain the model parameters using Box-Jenkins methodology. The training data-set has been plotted below in figure 5.40.

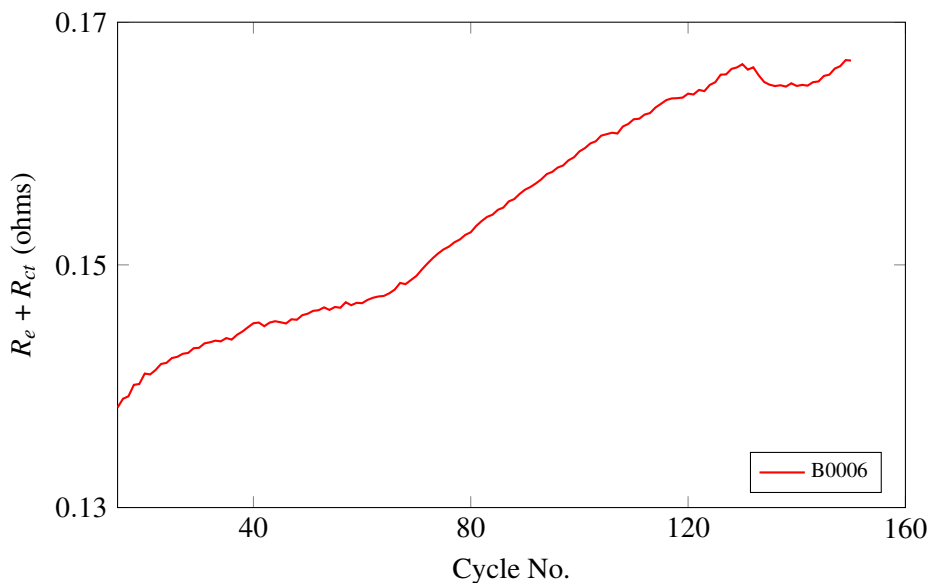


Figure 5.40: ARIMA based IR training data

The training data was converted into time series and stationary check was employed. Further, first order differencing of the data was employed and ACF/PACF plot of the differenced series were mapped. The ACF/PACF plot justified that the first order differencing works well enough for IR data. The differenced series and ACF/PACF plot has been depicted in figure 5.41 and figure 5.42 respectively.

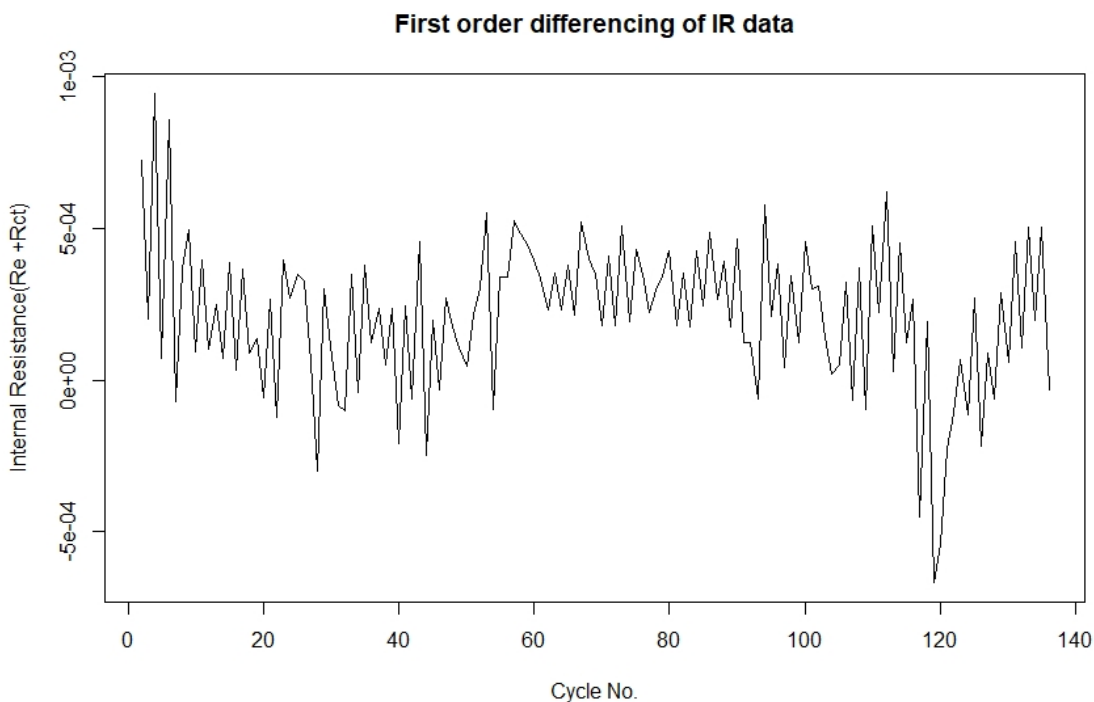


Figure 5.41: Differenced Internal Resistance training data

Once the signal have been made stationary, order of Auto-regression and moving average has

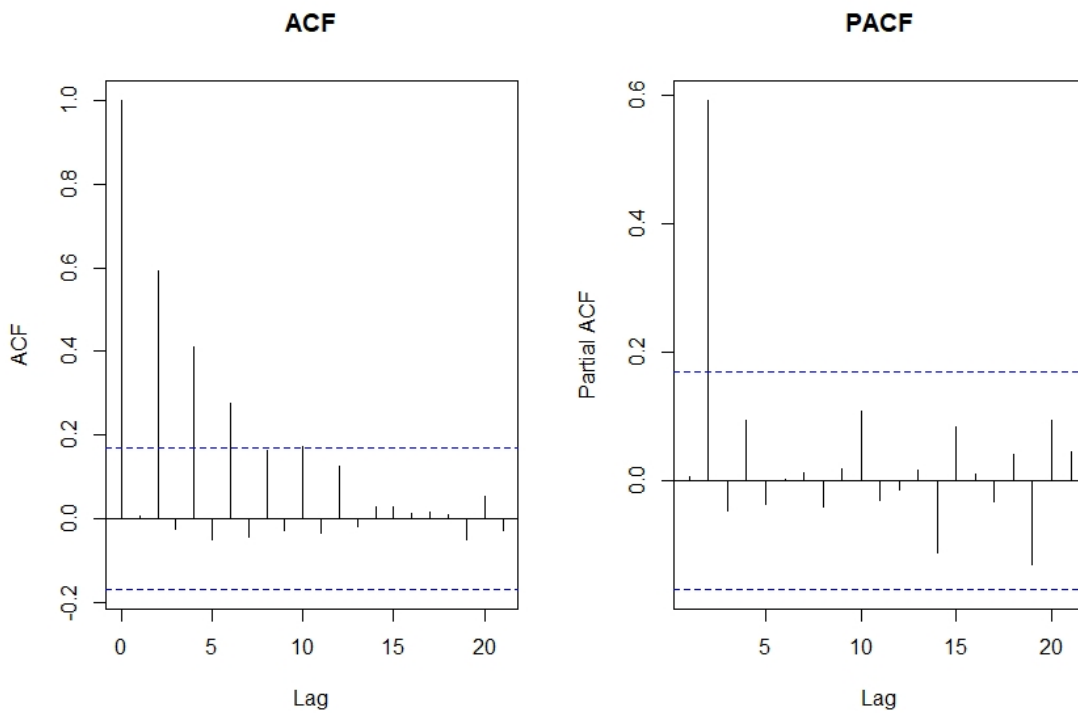


Figure 5.42: ACF and PACF plot for differenced IR data

to be identified. The best model was chosen on the basis of Akaike Information Criterion. The model with higher negative AIC value can be considered as the best model. The comparison of AIC values for different ARIMA model has been depicted in the table 5.2 below.

ARIMA structure	AIC
ARIMA(2,1,2) with drift	-1911.738
ARIMA(0,1,0) with drift	-1856.228
ARIMA(1,1,0) with drift	-1854.142
ARIMA(1,1,2) with drift	-1890.847
ARIMA(2,1,1) with drift	-1911.626
ARIMA(2,1,3) with drift	-1909.555
ARIMA(1,1,3) with drift	-1899.131
ARIMA(3,1,1) with drift	-1910.875
ARIMA(2,1,2)	-1905.864

Table 5.2: AIC value comparison for different ARIMA models for IR forecasting

Thus, for the given data-set an ARIMA model with an order of 2,1,2 can be deemed as the most efficient model. The model parameters have been presented in the table 5.3 below.

The ARIMA model identified from the table 5.2 can now be used to predict the future values of Internal Resistance. ARIMA(2,1,2 with drift) was used on the data-set shown in figure 5.40. The prediction result has been plotted below in figure 5.43. The comparison of predicted and actual value of Internal resistance for the next 100 cycles is shown in figure 5.44. The Root mean square

Parameters	AR1	AR2	MA1	MA2	Drift
Coefficients	-0.0776	0.7445	0.1259	-0.2065	2e-04
Standard error	0.0969	0.0945	0.1372	0.1300	1e-04

Table 5.3: ARIMA model parameters

error noted was 0.0097, which is well under acceptable limit of 5 percent.

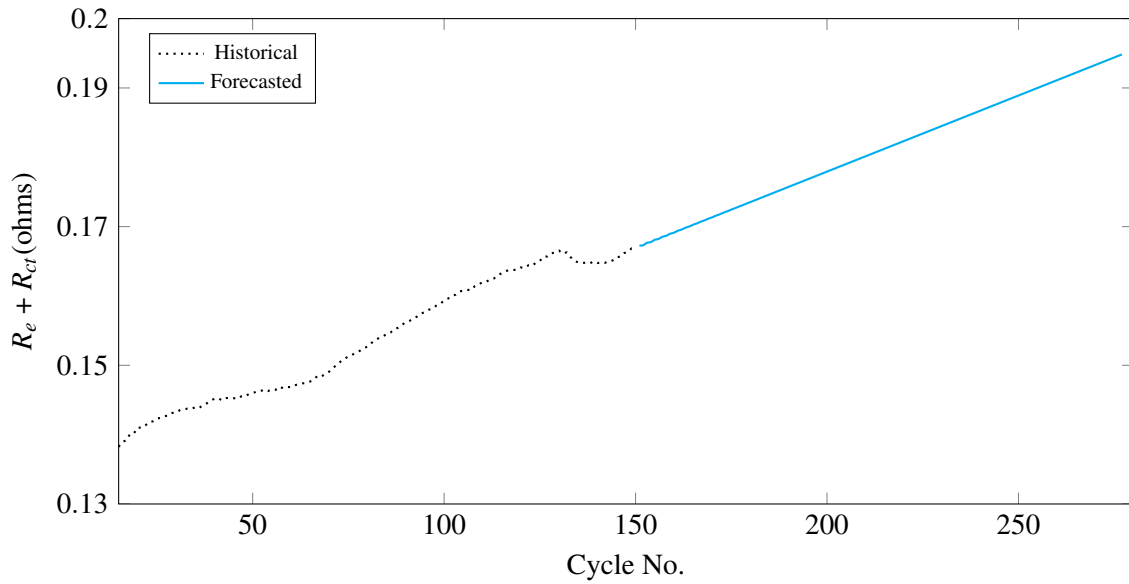


Figure 5.43: ARIMA model forecasting for IR

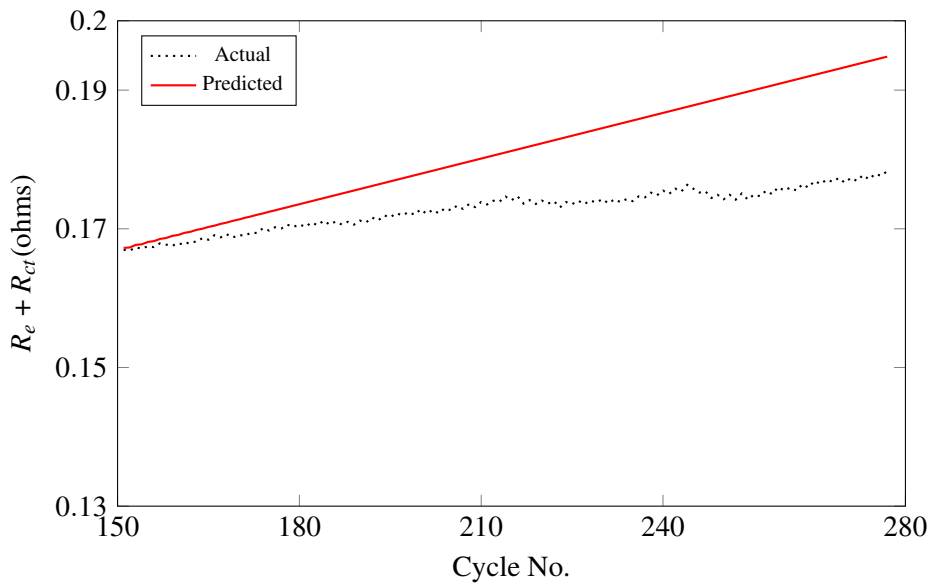


Figure 5.44: Comparison of predicted vs actual Internal Resistance

Thus for any battery the historical Electrochemical impedance spectroscopy data can be ex-

ploited to forecast the future internal resistance. However, industrially it is still challenging to measure the impedance data of the battery at pack level.

5.6 Comparison of different algorithms for correlation

In this section, we have explored different machine learning methods to correlate the regional capacity to State of Health of Li-ion batteries. The correlation was learnt using three different machine learning model namely Linear Regression, Support vector regression and Feed forward Neural network. We have used the data-set of battery B0006 and B0007 from NASA AMES used in the previous section. The accuracy of different model has been compared using the indicator of Root mean square error.

The proposed comparison of prediction model comprised of two major steps. Mainly,

1. Model database creation
2. Diagnosis for SoH estimation and RMSE comparison

The detailed explanation is as follows:

5.6.1 Model database creation

We used labeled battery data with known SoH to create a correlation model for SoH estimation. Raw data from BMS is extracted and further preprocessed before using it to create the model database. The steps to create a model database is as follows :

1. Given cycle wise charging/discharging data (V, I, t) with its corresponding capacity based SoH.
2. As explained previously, use the charging or discharging data to calculate regional capacity for each cycle.
3. First, create a Linear Regression(LR) correlation model for having a regional capacity and SoH correlation. The LR model is denoted as M_1
4. Followed by LR, a Support Vector regression correlation model is made between regional capacity and original capacity. This SVR model is denoted as M_2 .
5. Further, to improve the model accuracy, a feed forward neural network based correlation model is created, which is denoted as M_3 .

The above-said process is illustrated in the block diagram shown in figure [5.45](#)

5.6.2 Diagnosis for SoH estimation and RMSE comparison

When a battery with unknown SoH is to be diagnosed, first we need to extract the historical data from the BMS of this battery. Then, using the analytical calculation, we calculate the regional capacity for each cycle. The regional capacity for corresponding cycles are then converted to a time series where cycle number represents the time stamp for the series. Let us represent the regional capacity of the current cycle(the cycle at which battery is being diagnosed) as Reg_{cur} . We will use Reg_{cur} as an input to the model M_1 , M_2 , M_3 for finding the correlated value of SoH corresponding to different models. In addition, to check the model accuracy, we will calculate SoH for each regional capacity value and then compare RMSE for different models. The above said methodology is illustrated in figure [5.46](#)

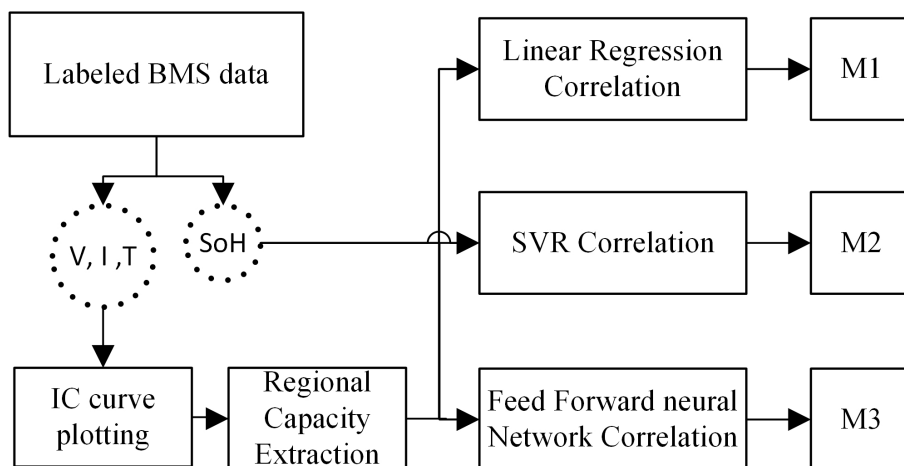


Figure 5.45: Model database for accuracy comparison

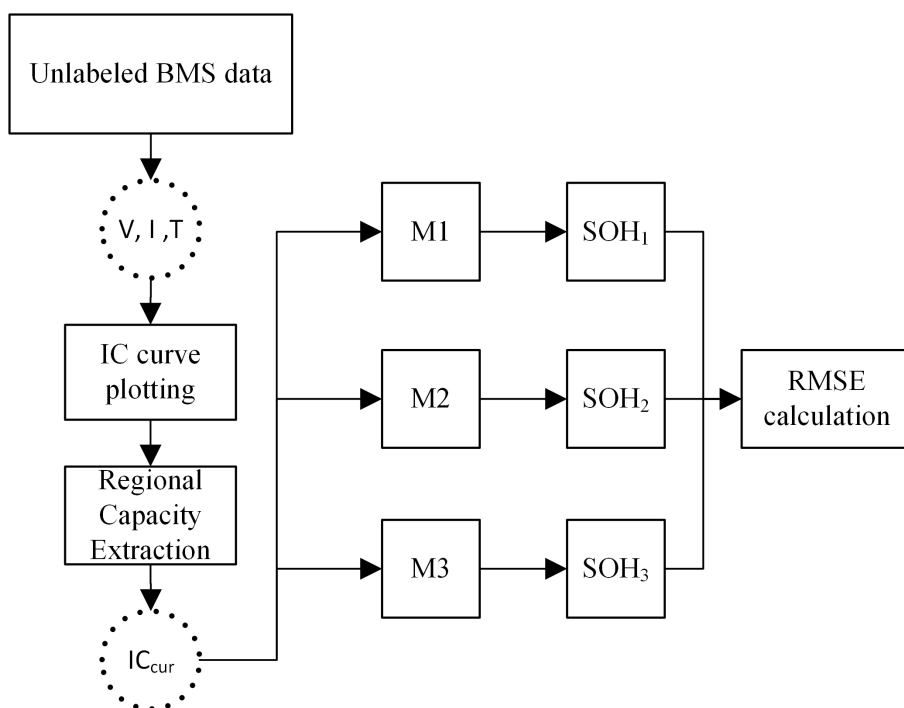


Figure 5.46: Model database for accuracy comparison

5.6.3 Comparison Results

Figure 5.24 & figure 5.25 shows the cycle-wise regional capacity extraction for battery B0006 and B0007 respectively. These dataset were used to create different correlation model and further compared with an indicator of RMSE. The regional capacity vs real capacity data was divided into training and testing data (ratio 7:3). SoH was predicted using the above model, and the predicted vs actual SoH for B0006 and B0007 has been shown in figure 5.47 and figure 5.48. The Root mean square error noted for B0006 and B0007 were 0.069 and 0.052 respectively.

Then we created a SVR correlation model, using the same training data used for LR. The SVR model was trained and tuned by grid search with ten fold cross validation technique and then model efficiency was tested on test set. SoH was predicted by using the above SVR model, and the predicted vs actual SoH for B0006 and B0007 has been shown in figure 5.49 and figure 5.50. The RMS error noted for B0006 and B0007 using SVR were 0.30 and 0.037. The RMSE of 0.30

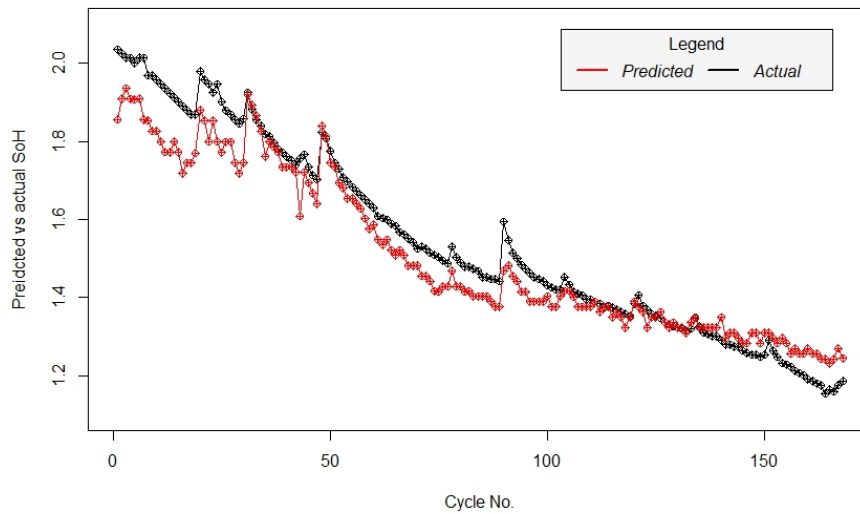


Figure 5.47: Predicted vs Actual SoH (Linear Regression): B0006

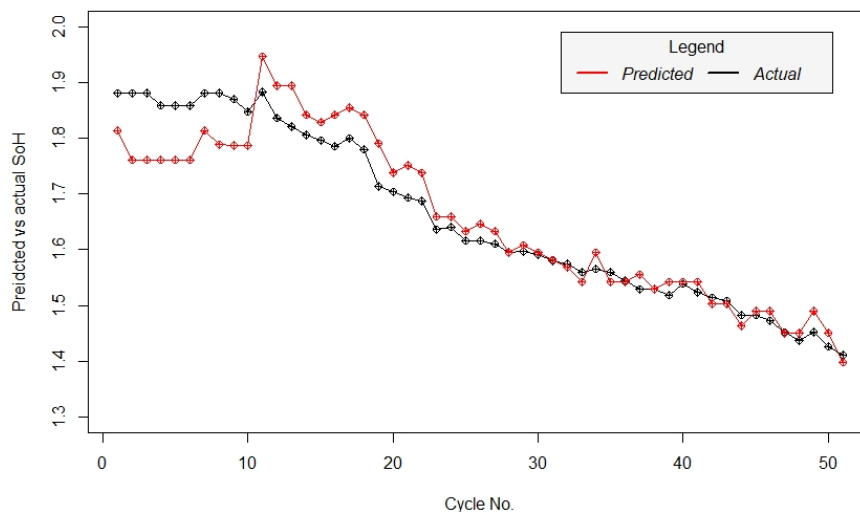


Figure 5.48: Predicted vs Actual SoH (Linear Regression): B0007

is very high, and thus, SVR model for one battery does not work well for other battery.

Similarly, we created feed-forward neural network based correlation using the same training data used for LR. The model structure is shown in figure 5.51.

We then used this model for SoH prediction for battery B0006. The predicted vs actual SoH for B0006 has been shown in figure 5.52. The RMSE noted for B0006 was 0.037, which is well under acceptable limit. However, when the very same model was applied to other batteries, the RMSE was very high, and thus NN model for one battery does not work well for the other battery. Thus, for the same battery, Neural network is more efficient than SVR and LR. However, if a single model has to be used for different batteries, Linear regression performed better. This is generally because neural network needs larger dataset than available here.

To summarize, the feature of regional capacity is highly correlated to the state of health of the Li-ion battery. In that case, all the tested algorithms performed well. Linear regression is

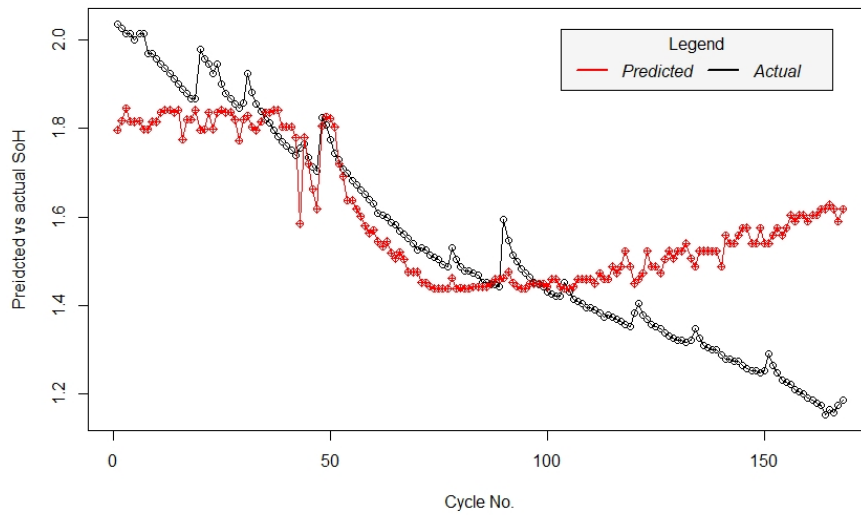


Figure 5.49: Predicted vs Actual SoH (Support Vector Regression): B0006

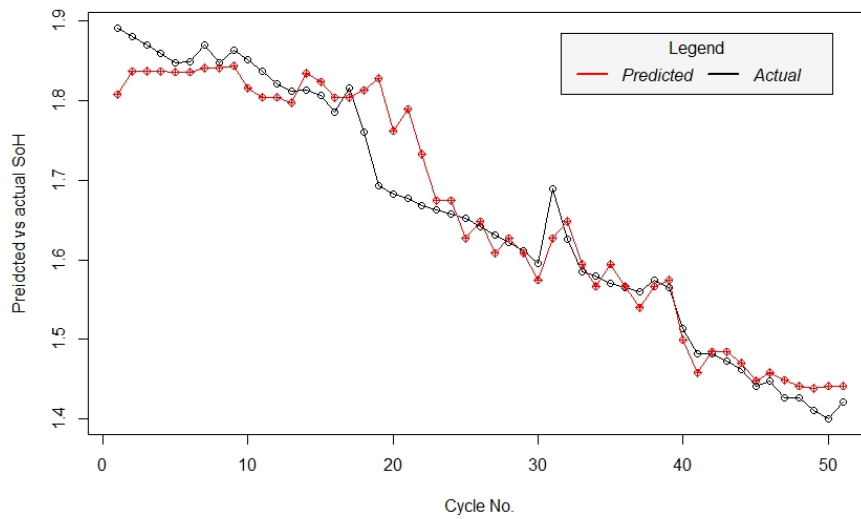


Figure 5.50: Predicted vs Actual SoH (Support Vector Regression): B0007

simple and easy to implement and has a very low computational complexity. On the other hand, Neural network performed good as well. However, it will need large amount of data for increasing robustness. Support vector regression is well suited for this kind of dataset, where the number of data points are lesser.

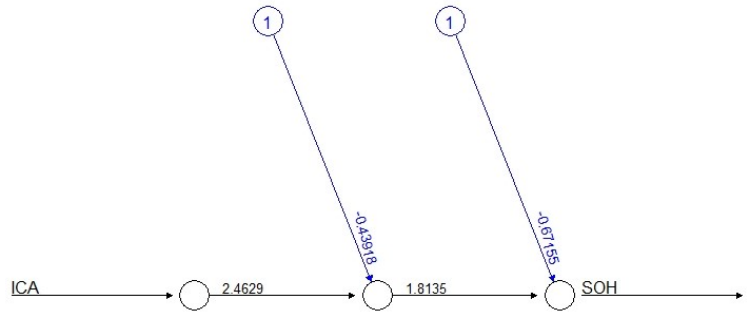


Figure 5.51: Neural Network Structure

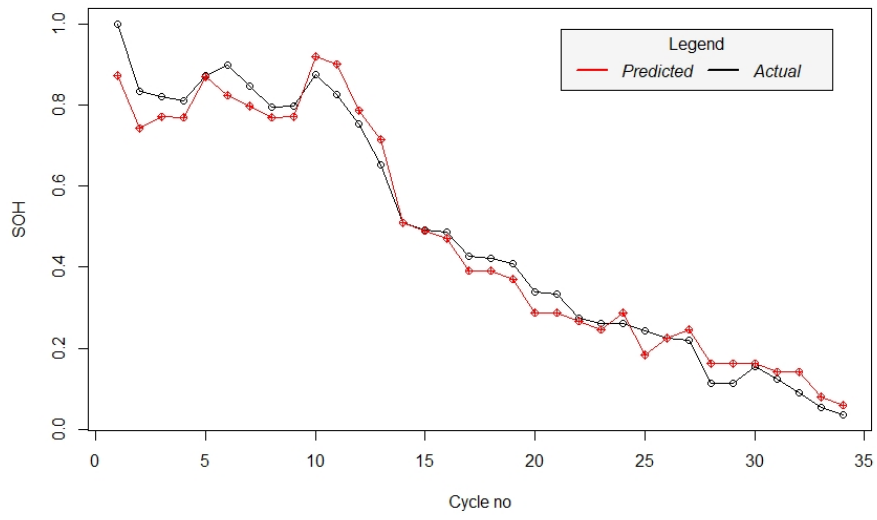


Figure 5.52: Predicted vs Actual SoH (Neural network): B0006

6

Framework for battery repurposing : Industrial Context

Contents

6.1	Introduction	97
6.2	Requirements for the development of battery repurposing ecosystem	98
6.3	Stakeholder interaction	99
6.4	Policies related to battery repurposing	100
6.5	Conceptual framework for battery repurposing	101
6.6	Possible landscape for integration of second life battery in Lancey's ecosystem	103
6.6.1	Business landscape: 1	103
6.6.2	Business landscape: 2	103

6.1 Introduction

There are different terminologies used for repurposing business model, like product life extension, cascading and repurposing [Lüdeke-Freund2019], second life or second use [Albertsen2021]. However, all these terminologies are used to describe the scenario of giving the product a second life after the product reaches its end of first life. According to [Melin2018], the global market of EOL Li-ion batteries is expected to grow 3.5 billion dollars by 2025. [Törkler2014] 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), etc. iii) Energy-related / industrial applications (up to 50 MWh): Renewable energy storage, Grid stabilization, etc. In this second life, the batteries can be procured at low cost, indicating new businesses opportunities.

Repurposing of the EoL Li-ion battery have been discussed quite a lot in academia since last decades [Bräuer2016, Jiao2017, Neubauer2015, Narula2011, Williams2010]. However, there is not a lot of real life application of repurposing in industrial scenario. Until today, very few OEM and battery manufacturing companies have explored the possibility of repurposing of their batteries. We have synthesized the current second life industrial collaboration happening around the world in table 6.1. Even though technically repurposing has been proven viable and have assured efficient operation in second life application, for creating a business application out of repurposing, the financial and ecological feasibility plays an important role.

OEM	2nd life battery buyer	Date of collaboration	Details
Tier Mobility	Nunam: Specialize in LIB reuse technology	28 June 2021	Turn used batteries into new energy storage systems which will then power small devices such as smartphones, fans or lamps.
SKODA AUTO	IBG Cesko : Create energy related innovative solution	27 May 2021	Smart energy storage system using second-life batteries from electric vehicles
Nissan	Beeplanet	2018	Manufactures low, medium and large-scale energy storage equipment from second life batteries of electric vehicle
Irizar E mobility	Ibil : Designer Repsol : Commissioner	30 Oct 2019	50 kW charging station for electric vehicles with an energy storage system from Irizar e-mobility second-life batteries
Nissan (Leaf)	Relectrify	Feb 2021	Combines repurposed batteries from Nissan Leaf vehicles with Relectrify's BMS and Inverter technology to create a battery system that has exceeded expectations.
BMW UK	OffGrid Energy	19 Oct 2020	BMW Group UK will supply OffGrid Energy, market leaders in energy storage, with battery modules for them to adapt to create mobile power units, giving retired BMW and MINI EV batteries a useful second life when they can no longer efficiently be used in cars.
FCA Italy S.P.A	Engie EPS	13 Dec 2020	First large-scale industrial application of V2G integrated with second-life batteries.
Volvo bus	Stena's Batteryloop	13 Sep 2020	Give old batteries a second life in static energy storage projects for a number of years

Table 6.1: Second life battery collaboration

[Zheng2020] estimated that repurposed EV batteries can save upto 80 percent of energy storage cost. Thus, it helps in creating substantial financial benefits for energy storage operators. According to [Reinhardt2019], the second-life EVB market will be driven by the storage solution

demand. The U.S. Department of Energy (2020) has given a prediction for the global energy storage market that could grow to more than 2,500 GWh by 2020. Repurposing the end of life li-ion batteries have a significant impact on reducing the environment impact [Reinhardt2019]. In fact, the environmental impact of a repurposed battery can be less than ten percent of new Li-ion battery [Zheng2020]. So, the repurposing business model will help to keep the environmental impact of batteries in check.

In this chapter, we have explored the repurposing requirements, stakeholder interactions, regulations and certifications, and have provided a framework for establishing a repurposing system in an industrial context. This chapter has been written in the collaboration of a company, **Lancey Energy Storage**.

6.2 Requirements for the development of battery repurposing ecosystem

[Bowler2014] identified that the feasibility of battery second use ecosystem is dependent on the following requirements:

- If EV batteries are capable of being mechanically and electrically integrated into second life application in a safe and a cost effective way.
- The availability of the infrastructure to disassemble the battery from vehicle, diagnosing the battery for second life application, integration of battery into new system, bringing the system to the market and maintaining the new system throughout its life time.
- End of life battery with better performance characteristics which should allow the used battery to be economically favorable or competitive to new battery market.

In regard to this, [Neubauer2010] proposed to ask the following questions before deciding on second life use of EoL EV batteries.

- What is the performance of EoL batteries when subjected to second use application profile?
- What will be the cost implication of this application and how much revenue can be expected?
- Does the performance, cost and life of a second use battery is beneficial compared to those of competing technologies?
- Are there any regulatory issues or barriers specific to a particular second life application?
- Is there sufficient availability of retired EV batteries to suffice the need of second life market?

To answer these questions, there is a need for efficient diagnosing system for EoL Li-ion batteries. This diagnosing system should also analyze the performance of the EoL batteries with respect to the second life use profile. In addition, firm regulations and standards are important to ensure safety and reliability of battery in second life use. Economically, a definite indicator is required, which can give a clear comparison of second life use and other alternatives for second life applications. Levelized Cost of Storage (LCOS) is an interesting indicator for quantifying the second life storage solution's cost in relation to energy or service delivered. The author in [Steckel2021] developed a model for estimating the Levelized Cost of Storage for second-life BESS and develops a harmonized approach to compare second life battery energy storage system to new battery energy storage system.

6.3 Stakeholder interaction

[Neubauer2010] proposed a detailed timeline about the life cycle of battery going through a repurposing process, which has been represented in the figure 6.1.

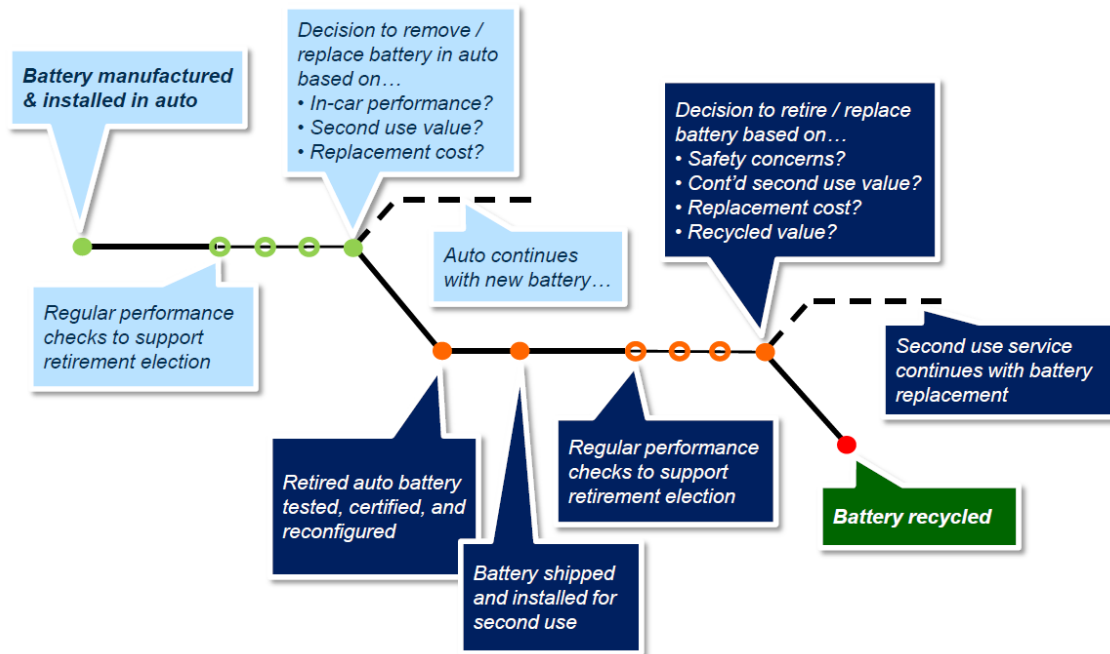


Figure 6.1: Timeline for repurposing

It is clear from the above timeline, that a single actor cannot handle the process of repurposing. There are several stakeholders who have to work together to facilitate repurposing. The major stakeholders who will be involved in battery repurposing infrastructure and their primal duties have been discussed below in the table 6.2.

The battery manufacturer can ensure the manufacturing of the battery in such a way that reuse, recycling and repurposing can be simplified. Methods like battery tagging can help to keep track of the battery source. Further OEMs play a significant role in creating a repurposing landscape. OEMs decide when the battery can be ejected from the first life, propose collecting these batteries, and identify the suitable repurposing agents for these EoL batteries. The other major player in repurposing infrastructure is the repurposers, who gives the battery second life. Their prominent role is to collect and sort the battery according to the degraded state, identify the proper application for the battery, integrate the battery in the second life system, and ensure smooth second life operation.

Further, they are also responsible for making decisions on battery handling after the end of their second life. In addition, there are third party stakeholders like data-based service provider who supports OEM and repurposer in setting up an intelligent technical infrastructure for battery handling by providing artificial intelligence-based solutions. The recyclers ensure that the unusable battery does not go to landfill and extract the maximum possible resources from End of Life batteries. This whole infrastructure is directed and regulated by governmental regulatory bodies through regulations and standardization of the battery repurposing process. All these stakeholders have to work in harmony for making the repurposing business a success.

Stakeholder	Responsibility
Battery Manufacturer	<ol style="list-style-type: none"> 1. Ecodesign of battery 2. Push the repurposing regulations
Battery based equipment manufacturer a) Electric Vehicle b) Two wheeler E-mobility c) ESS developer	<ol style="list-style-type: none"> 1. Ensure efficient operation of battery to increase battery life 2. Timely collection of EOL battery from the equipment 3. Push the repurposing regulations
Charging Infrastructure companies	<ol style="list-style-type: none"> 1. Ensure optimal charging of battery to increase battery life 2. Can also create repurposed charging infrastructure
Data based Diagnostics as a Service provider	<ol style="list-style-type: none"> 1. Provide battery diagnostics insights to facilitate decision making 2. Create second life use models using EOL battery data
Repurposing Companies a) ESS developers b) Offgrid power generators c) Small scale consumer electronics manufacturer	<ol style="list-style-type: none"> 1. Collection of the EOL batteries from OEM 2. Testing and sorting 3. Integration into new system 4. Lifecycle monitoring
Recyclers	<ol style="list-style-type: none"> 1. Collection of batteries after second EOL for recycling
R&D labs	<ol style="list-style-type: none"> 1. Support the repurposers to have state of the art systems for diagnosis & battery sorting
Governmental Regulatory bodies	<ol style="list-style-type: none"> 1. Push the regulations to industrial market for ensuring safety repurposing business landscape 2. Create standards and certification procedures for battery repurposing

Table 6.2: Stakeholders involved in battery repurposing

6.4 Policies related to battery repurposing

In December 2020, a Proposal for regulation of the European Parliament and of the Council concerning batteries and waste batteries, repealing Directive 2006/66/EC and amending Regulation (EU) No 2019/1020 [Commission2020] was introduced in European Union.

The objective of this New Battery Regulation Proposal is to set a standardized rules and instructions to enhance the functioning of the battery market, alleviate social and environmental impact, and promote circular economy. The article 59 of this regulations was rigidly made for facilitating battery repurposing. Its main key points related to repurposing include:

- Right to access the BMS data of EV batteries and industrial batteries to repurposers.
- Repurposers are obliged to ensure adequate quality control and safety during the performance testing, packing and shipment of batteries and their components.
- Repurposers shall ensure that the repurposed or re-manufactured battery complies with this regulations related to environmental and human health protection requirements in other legislation and technical requirements for its specific purpose of use when placed on the market.
- There would be an Electronic exchange system, which stores characteristic information and data of each EVB's type and model, "shall be sortable and searchable, respecting open standards for third party use".
- Battery passport is expected to support second-life EVB operators to have better used EVB classification decisions, and support recyclers to better plan their operations.

In addition, there are several standards that have been established by different regulatory bodies for ensuring adequate quality control and safety during battery repurposing.

The International Electrotechnical Commission, which is an international standards organization that prepares and publishes international standards for electrotechnology have provided the following standards related to LIB reuse.

- **IEC 62619** : This Standard specifies requirements and tests for the safe operation of secondary lithium cells and batteries, for use in industrial applications. The standards also includes a detailed list of LIB second life applications like telecoms, uninterruptible power supplies (UPS), utility switching, emergency power and similar applications.
- **IEC 63330** :This standard specifies the requirements for repurposing of secondary cells, modules, battery packs and battery systems. It also specifies the procedure to evaluate the performance and safety of used battery for repurposing.

The Energy Storage and Stationary Battery Committee under the society of IEEE power and energy has developed a standard called **P2993 - Recommended Practices for Energy Storage System Design using Second-life Electric Vehicle Batteries**. This standard describes the selection and repurposing (including design, operation and maintenance) of second-life electric vehicle batteries in energy storage systems with voltage levels of 10kV and below.

Thus, there are well defined standards set by different governing organization to facilitate repurposing of EV batteries.

6.5 Conceptual framework for battery repurposing

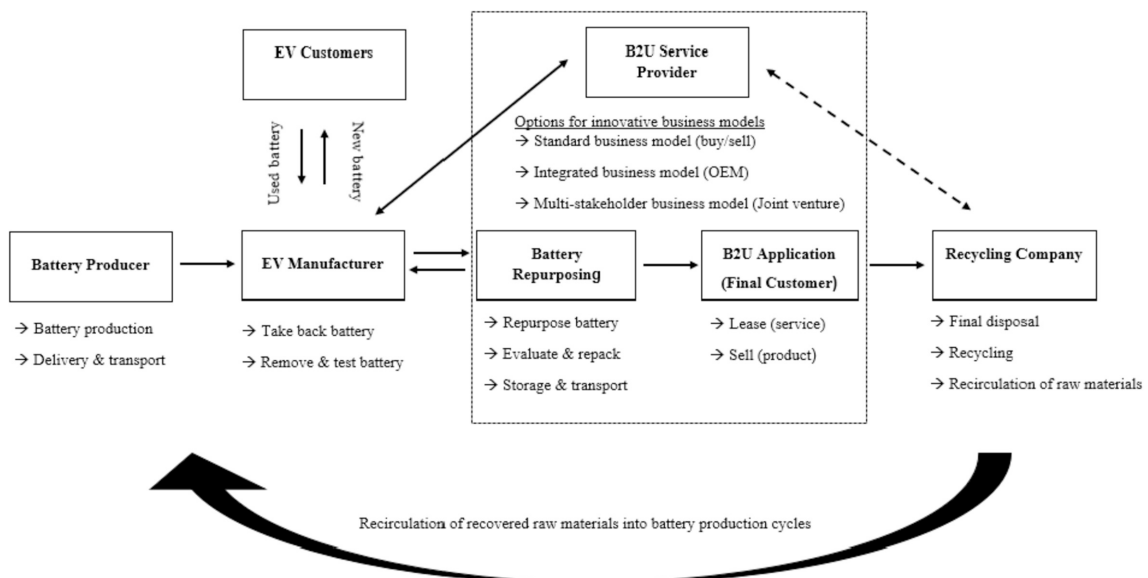


Figure 6.2: Conceptual battery second use innovative business model framework. [Reinhardt2019]

In order to support the repurposing business, there is a need of a rigid framework which should portray the interactions of process and products among different stakeholders involved in repurposing. [Reinhardt2019] proposed a conceptual battery second use innovative business model framework based on the findings of [B. Klör2015] and [M. Rehme2016]. The framework has been

represented in figure 6.2. [B. Klör2015] came up with a concept of intermediary market where intermediary agents will be responsible for battery collection, repurposing and finally selling second life batteries to final customers on behalf of an EV manufacturer. [M. Rehme2016]. proposed two concepts: the integrated business model in a closed battery market whereby the OEM implements the B2U process into existing organizational structures and the multi-agent business model in an open market that allows trading and resale of second life batteries and therefore opens competition among several agents.

However, with the arrival of new battery regulation proposal [Commision2020], new actors like third party data based service provider will come into play. Also with the standard being set up, these framework has to be revamped. Here, we have proposed a detailed framework for setting up a repurposing business model in figure 6.3.

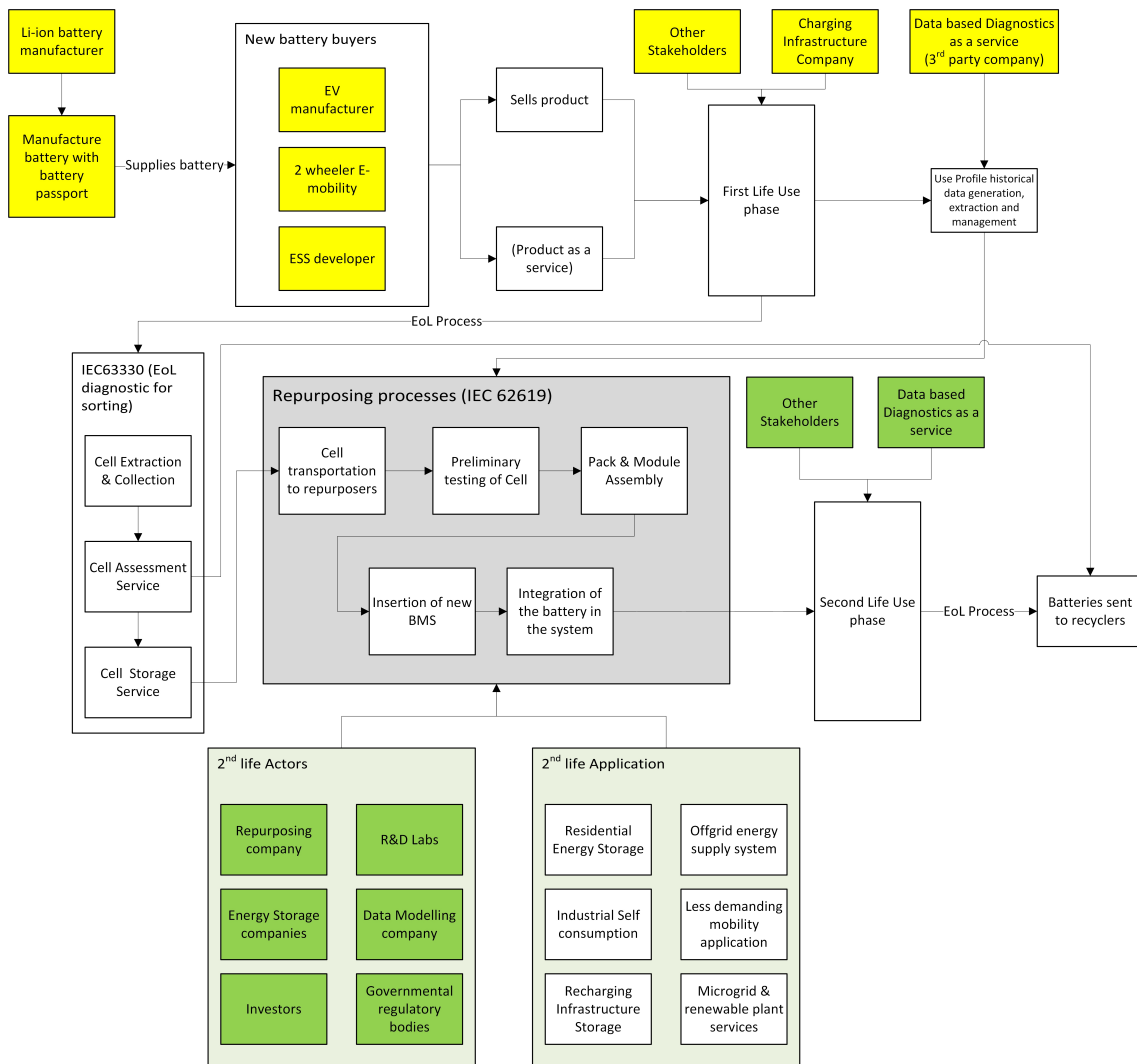


Figure 6.3: Proposed framework for battery repurposing

The yellow highlighted cells are indirect stakeholders who are mostly responsible for first life operation of batteries and the green highlighted cells are direct stakeholder who actively take part in repurposing landscape. The major inputs are the inclusion of battery passport which should support second-life EVB operators to have better used EVB classification decisions, and support recyclers to better plan their operations. In addition, the repurposers should strictly follow the IEC directive of IEC62619 and IEC63330 while battery sorting, diagnosis and integrating it into second life applications.

It is clear form the above discussion that efficient diagnosis and prognosis with a reliable

decision support system is the key to facilitate repurposing business ecosystem. In regard to this, evaluation of state of health of the Li-ion battery is an important process and there is a need of development of an efficient PHM system. This requirement of an intelligent PHM system is not limited to the battery, but for any repurposable modular product.

6.6 Possible landscape for integration of second life battery in Lancey's ecosystem

Lancey Energy Storage designs and produces Lancey, a battery and a native energy management system (EMS) based the smart electric heater. It is both ecologically and economically beneficial to the customers and environment. The battery charges during off peak hours to power the radiator during peak hours, making sure that the heater almost never consumes electricity during peak demand, when its production releases more CO₂. In case of a rooftop photovoltaic installation, the EMS and battery of Lancey heaters enable to maximize its auto-consumption rate.

Lancey uses the Li-ion battery consisting of premium battery cells, with a storage capacity of 800 Wh. These batteries come at a substantial cost leading to a higher capital expenses. Lancey Energy Storage is looking forward to explore a possibility of using second life batteries from a two wheeler mobility solution providing company, La Poste in France.

In regards to this, we explored two possible business landscape for this collaboration to use repurposed batteries.

6.6.1 Business landscape: 1

In the first proposed landscape, La Poste is responsible for collection of end of life batteries and creating an inventory of EoL batteries. Once there is sufficient amount of batteries in the inventory, the batteries will be sent to Lancey Energy Storage in accordance with proper transport regulations. During the first life of batteries in bikes, a 3rd party data acquisition service provider, Orange, will create an infrastructure for scheduled sharing of battery usage data to Lancey Energy storage. This will help in creating data based insights for battery sorting.

When Lancey receives a stock of battery, it will follow the standards of IEC63330 and IEC62619 to assess the EoL battery and integrate it to their energy storage and heating system applications. Further, at the end of second life, these batteries will be sent to recyclers for material extraction. The detailed block diagram is depicted in figure. 6.4.

6.6.2 Business landscape: 2

In the second proposed landscape, La Poste is responsible for collection of end of life batteries and creating an inventory of EoL batteries. Once there is sufficient amount of batteries in the inventory, the batteries will be sent to a Recycler in accordance with proper transport regulations. It is assumed that this Recycler will have a well established system for battery sorting and creating cell that can be reused in second life in accordance to IEC63330 and IEC62619 standards. The advantage of this landscape is that the recyclers can directly recycle the batteries which are not good enough for second life applications. During the first life of batteries in bikes, a 3rd party data acquisition service provider, Orange, will create an infrastructure for scheduled sharing of battery usage data to Recycler and Lancey Energy storage. This will help in creating data based insights for battery sorting and also it will help Lancey to make decisions on second life applications.

Lancey can directly procure the repurposed batteries from this recyclers to use in second life

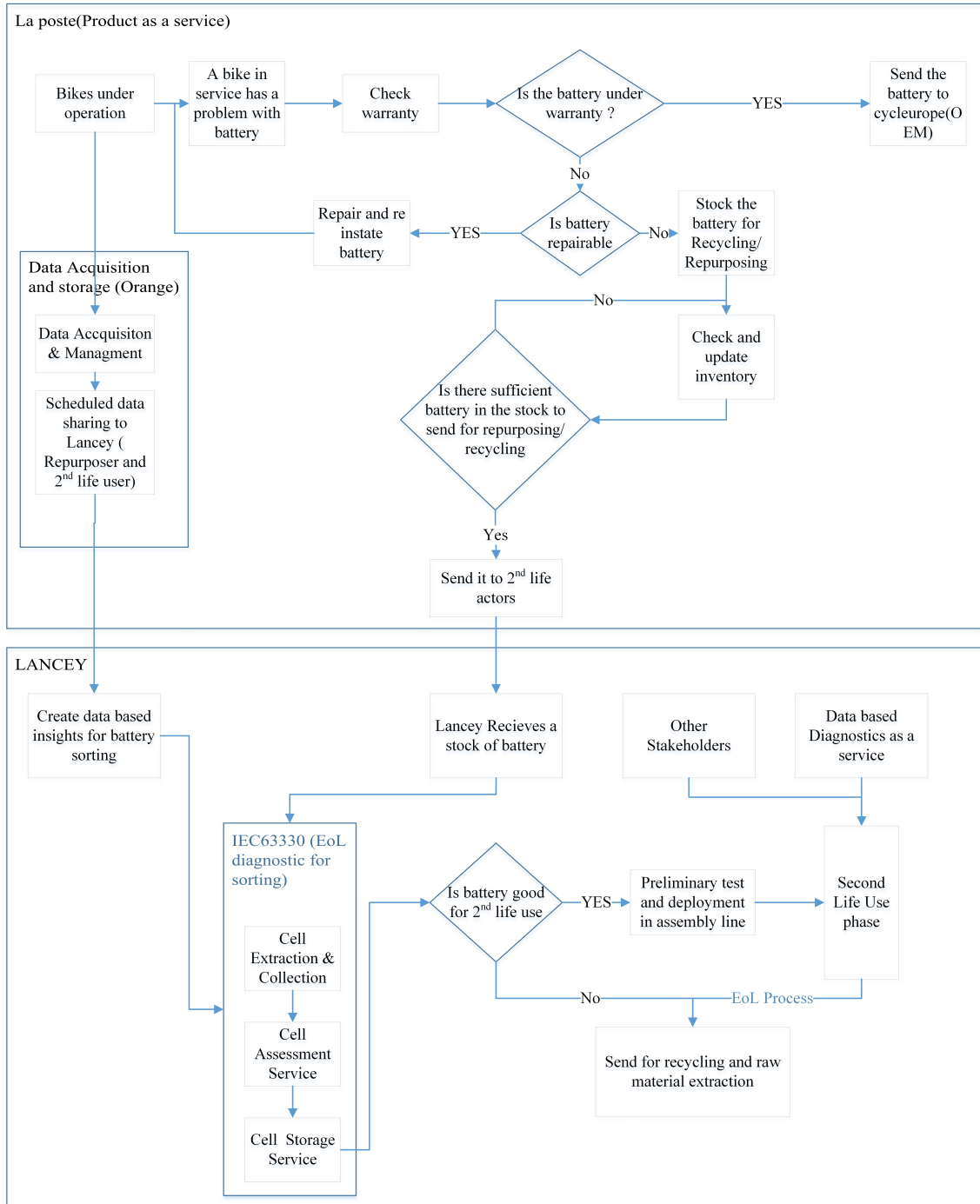


Figure 6.4: Proposed framework for battery repurposing (Business landscape: 1)

application. After the end of second life, Lancey can return the battery to same recycler for material extraction. The detailed block diagram is depicted in figure. 6.5.

Thus, for any repurposing landscape, the most important step is battery diagnosis and sorting. This steps is guided by the standards of IEC62619 and IEC63330. Efficient battery diagnosis is a key to battery repurposing landscape and so it necessary to predict the state of health of the Li-ion battery.

In this chapter, we presented an industrial perspective of the application of tools developed in the thesis. For a reliable implementation of the repurposing framework in electric mobility industries, state of health estimation plays a major role both in first life and the subsequent life of

6.6. Possible landscape for integration of second life battery in Lancey's ecosystem

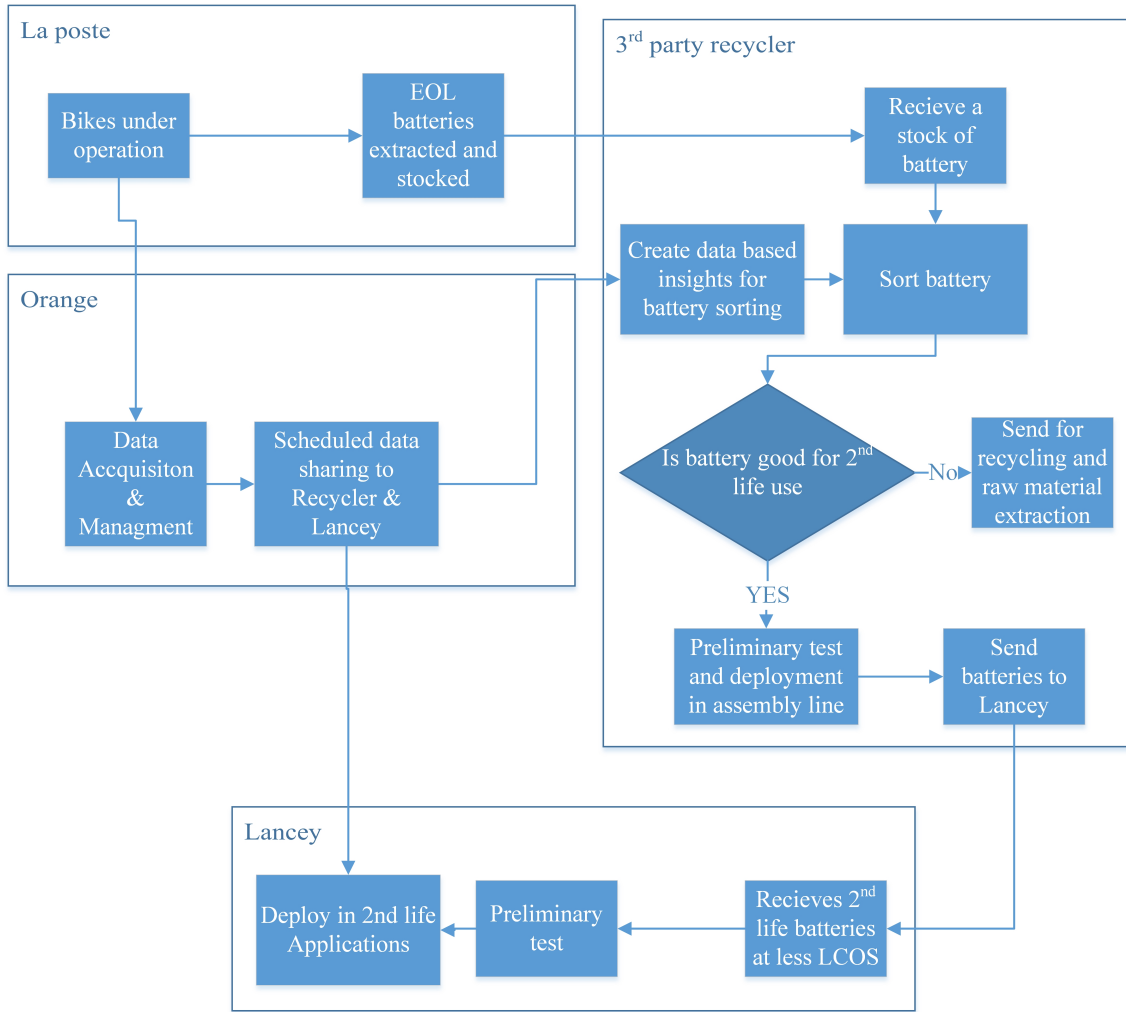


Figure 6.5: Proposed framework for battery repurposing (Business landscape: 2)

the batteries.

General Conclusion

Electric Vehicles (EV) have been one of the most encouraging ways to tackle the adverse environmental effect of hydrocarbon-based transport. Most of the EV use Li-ion batteries as their power source, owing to their high energy density. These batteries reach its End of Life (EoL) when the capacity degrades by just twenty percent of the original capacity. A reliable circular industrial system can be developed which should be able to transform post-used EV batteries into new added-value batteries for less demanding applications, thus prolonging their life and ensuring more sustainability. Predicting the reliability of a system in its actual life cycle conditions and estimating its time to failure(State of the health estimation) is helpful in decision making for the new value chain. But the technological heterogeneity of the Li-ion batteries, as well as the dynamics of change of operating conditions, accentuates the difficulty to establish Prognostics Health Management (PHM) system for the batteries. The objective of this thesis was to bridge the knowledge gap of diagnostics and prognostics in the context of the circular economy. The results identified a contextual definition of the State of health and a novel classification for different SoH estimation methods. The thesis also investigated the issues and challenges posed while estimating SoH for Li-ion batteries, with possible solutions. Furthermore, in this thesis, the ultimate goal was to provide reliable sensor networks and information retrieval modules to develop as accurate as possible a diagnosis and a health prognosis method for lithium-ion batteries in the context of the Circular economy. Finally, a framework has been proposed for establishing a repurposing based business landscape by exploring the current repurposing trends across the world.

The first contribution focused on the contextual problem to facilitate the repurposing of end of life EV batteries by efficiently predicting the State of health. Concerning this, we proposed a contextual definition of the Global State of Health, which considers the factor of both capacity and power fade. We also classified the different SoH estimation methods available in the literature into rigid categories based on the features used. These categories are model-based features, data-based analytical features and battery management system based raw features.

The second contribution investigated the issues and challenges posed while estimating SoH for Li-ion battery: complex degradation mechanism, technical heterogeneity, dynamic operating condition, and varied driving pattern. We proposed a Hidden Markov model-based methodology to overcome these barriers for designing a PHM system for a circular industrial model.

The third contribution was an Incremental Capacity (IC) curve based SoH estimation system for Li-ion batteries. The model employed a Kalman filter and a finite differencing method for measurement noise attenuation. A novel approach that combines Support vector regression (SVR) and the Autoregressive Integrated Moving Average (ARIMA) model was utilized to model the relationship between IC and the SoH. A use case was created on the NASA AMES open-source battery data. The case study shows that the proposed model can obtain accurate SoH prediction results without needing the State of Charge information of the battery. This model was also compared to the Linear regression and feed-forward neural network-based correlation models.

The final contribution was based on the requirements for establishing a battery repurposing system. We explored the repurposing requirements, stakeholder interactions, regulations & cer-

tifications and have proposed a framework for establishing a repurposing system in an industrial context.

The outcome of this thesis will be fruitful for designing a decision support system in the Circular economy. Furthermore, it will be helpful to battery engineers to create a novel method to estimate SoH and thus improve the battery's performance. Efficient SoH estimation will also help in setting up a battery repurposing system. In addition, a model like this can even be extended to other electronic modular products like washing machine, heating system etc.

This work, which identifies the lock to be lifted in the field of the prognosis of the state of health of batteries, is a first step in the framework of the circular economy. It reveals a vast area of research that is both ambitious and credible. We can cite those which are part of the continuity of these activities by using the proposed methods and others on large fields of application. First, the implementation of a decision support system in the circular economy will bring added value to the results obtained in this thesis. It is a work that could be done in the short-term by the use of health data and battery performance developed in the thesis.

Bibliography

- [Agubra2013] Victor Agubra et Jeffrey Fergus. *Lithium Ion Battery Anode Aging Mechanisms*. *Materials*, vol. 6, pages 1310–1325, 03 2013.
- [Ahmadi2017] Young S.B. Fowler M. Ahmadi L. *A cascaded life cycle: reuse of electric vehicle lithium-ion battery packs in energy storage systems*. *Int J Life Cycle Assess*, vol. 22, page 111–124, January 2017.
- [Albertsen2021] Levke Albertsen, Jessika Luth Richter, Philip Peck, Carl Dalhammar et Andrius Plepys. *Circular business models for electric vehicle lithium-ion batteries: An analysis of current practices of vehicle manufacturers and policies in the EU*. *Resources, Conservation and Recycling*, vol. 172, page 105658, 2021.
- [Andre2013] Dave Andre, Christian Appel, Thomas Soczka-Guth et Dirk Uwe Sauer. *Advanced mathematical methods of SOC and SOH estimation for lithium-ion batteries*. *Journal of Power Sources*, vol. 224, pages 20 – 27, 2013.
- [Antikainen2016] Maria Antikainen et Katri Valkokari. *A Framework for Sustainable Circular Business Model Innovation*. *Technology Innovation Management Review*, vol. 6, pages 5–12, 07 2016.
- [B. Klör2015] S. Bräuer F. Plenter M. Monhof B. Klör D. Beverungen. *A market for trading used electric vehicle batteries – theoretical foundations and information systems*. pages 1–18. 23rd European Conference on Information System (ECIS), May 2015.
- [Bai2014] Guangxing Bai, Pingfeng Wang, Chao Hu et Michael Pecht. *A generic model-free approach for lithium-ion battery health management*. *Applied Energy*, vol. 135, pages 247 – 260, 2014.
- [Barbour1992] A D Barbour, L Holst et S Janson. *Poisson approximation*, volume 2 of *Oxford Studies in Probability*. The Clarendon Press Oxford University Press, New York, 1992. Oxford Science Publications.
- [Basia2019] Akash Basia, E. Gascard, Zineb Simeu-Abazi et Peggy Zwolinski. *Overcoming the Barriers in Diagnostics and Prognostics of the Circular Industrial System by Hidden Markov Model*. In 3rd International Conference on Control, Automation and Diagnosis (ICCAD'19), Proceedings of the 3rd International Conference on Control, Automation and Diagnosis (ICCAD'19), IEEE Press, 2019, Grenoble, France, July 2019.
- [Baum1972] Leonard Baum. *An inequality and associated maximization technique in statistical estimation of probabilistic functions of a Markov process*. *Inequalities*, vol. 3, pages 1–8, 1972.

Bibliography

- [Benjamin2003] Michael A Benjamin, Robert A Rigby et D Mikis Stasinopoulos. *Generalized Autoregressive Moving Average Models*. Journal of the American Statistical Association, vol. 98, no. 461, pages 214–223, 2003.
- [Berecibar2016a] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo et P. Van den Bossche. *Critical review of state of health estimation methods of Li-ion batteries for real applications*. Renewable and Sustainable Energy Reviews, vol. 56, pages 572 – 587, 2016.
- [Berecibar2016b] Maitane Berecibar, Floris Devriendt, Matthieu Dubarry, Igor Villarreal, Noshin Omar, Wouter Verbeke et Joeri Van Mierlo. *Online state of health estimation on NMC cells based on predictive analytics*. Journal of Power Sources, vol. 320, pages 239–250, 07 2016.
- [Bi2016] Jun Bi, Ting Zhang, Haiyang Yu et Yanqiong Kang. *State-of-health estimation of lithium-ion battery packs in electric vehicles based on genetic resampling particle filter*. Applied Energy, vol. 182, pages 558 – 568, 2016.
- [Birk12017] Christoph R. Birkl, Matthew R. Roberts, Euan McTurk, Peter G. Bruce et David A. Howey. *Degradation diagnostics for lithium ion cells*. Journal of Power Sources, vol. 341, pages 373–386, 2017.
- [Bishop2006] Christopher M Bishop. *Pattern recognition and machine learning*, chapitre 13, pages 605–652. springer, 2006.
- [Bonges2016] Henry A. Bonges et Anne C. Lusk. *Addressing electric vehicle (EV) sales and range anxiety through parking layout, policy and regulation*. Transportation Research Part A: Policy and Practice, vol. 83, no. C, pages 63–73, 2016.
- [Bonissone2006] P. Bonissone. *Knowledge and Time: A Framework for Soft Computing Applications in Prognostics and Health Management (PHM)*. 01 2006.
- [Boons2013] Frank Boons et Florian Lüdeke-Freund. *Business Models for Sustainable Innovation: State of the Art and Steps Towards a Research Agenda*. Journal of Cleaner Production, vol. 45, pages 9–19, 04 2013.
- [Bowler2014] Melissa Bowler. *Battery Second Use: A Framework for Evaluating the Combination of Two Value Chains*. Thèse de Doctorat, Clemson University, 2014.
- [Box2013] George Box. *Box and jenkins: Time series analysis, forecasting and control*, pages 161–215. Palgrave Macmillan UK, London, 2013.
- [Broussely2005] M. Broussely, Ph. Biensan, F. Bonhomme, Ph. Blanchard, S. Herreyre, K. Nechev et R.J. Staniewicz. *Main aging mechanisms in Li ion batteries*. Journal of Power Sources, vol. 146, no. 1, pages 90–96, 2005. Selected papers presented at the 12th International Meeting on Lithium Batteries.

-
- [Bräuer2016] Sebastian Bräuer, Markus Monhof, Benjamin Klör, Florian Plenter, Daniel Beverungen et Christian Siemen. *Residential Energy Storage from Repurposed Electric Vehicle Batteries: Market Overview and Development of a Service-Centered Business Model*. In 2016 IEEE 18th Conference on Business Informatics (CBI), volume 01, pages 143–152, 2016.
- [Burke2010] Andrew Burke, Marshall Miller et Hengbing Zhao. *Lithium batteries and ultracapacitors alone and in combination in hybrid vehicles: Fuel economy and battery stress reduction advantages*. JSR, vol. 21, 01 2010.
- [Byington2002] C.S. Byington, M.J. Roemer et T. Galie. *Prognostic enhancements to diagnostic systems for improved condition-based maintenance [military aircraft]*. In Proceedings, IEEE Aerospace Conference, volume 6, pages 6–6, 2002.
- [Canals Casals2017] Lluc Canals Casals, Beatriz García et María González Benítez. *Ag-ing model for re-used electric vehicle batteries in second life stationary applications*, pages 139–151. 03 2017.
- [Casari2018] A. Casari et A. Zheng. *Feature engineering for machine learning*. O’Reilly Media, Inc., 2018.
- [Chen1995] Gemai Chen. *Generalized log-normal distributions with reliability application*. Computational Statistics & Data Analysis, vol. 19, no. 3, pages 309–319, 1995.
- [Chen2013] Zheng Chen, Chunting Chris Mi, Yuhong Fu, Jun Xu et Xianzhi Gong. *Online battery state of health estimation based on Genetic Algorithm for electric and hybrid vehicle applications*. Journal of Power Sources, vol. 240, pages 184–192, 2013.
- [Chen2019] Z. Chen, Q. Xue, R. Xiao, Y. Liu et J. Shen. *State of Health Estimation for Lithium-ion Batteries Based on Fusion of Autoregressive Moving Average Model and Elman Neural Network*. IEEE Access, vol. 7, pages 102662–102678, 2019.
- [Cheng2009] Shunfeng Cheng et Michael Pecht. *A fusion prognostics method for remaining useful life prediction of electronic products*. In 2009 IEEE International Conference on Automation Science and Engineering, pages 102–107, 2009.
- [Chiang2011] Yi-Hsien Chiang, Wu-Yang Sean et Jia-Cheng Ke. *Online estimation of internal resistance and open-circuit voltage of lithium-ion batteries in electric vehicles*. Journal of Power Sources, vol. 196, no. 8, pages 3921 – 3932, 2011.
- [Commision2020] European Commision. *Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL concerning batteries and waste batteries, repealing Directive 2006/66/EC and amending Regulation (EU) No 2019/1020*, December 2020.
- [Coron2020] Eddy Coron, Sylvie Genies, Mikael Cugnet et Pierre Xavier Thivel. *Impact of Lithium-Ion Cell Condition on Its Second Life Viability*. Journal of the Electrochemical Society, vol. 167, 07 2020.
-

- [CREADY2003] ERIN CREADY, JOHN LIPPERT, JOSH PIHL, IRWIN WEINSTOCK et PHILIP SYMONS. *Technical and Economic Feasibility of Applying Used EV Batteries in Stationary Applications*. 03 2003.
- [Dai2009] Haifeng Dai, Wei Xuezhe et Sun Zechang. *A new SOH prediction concept for the power lithium-ion battery used on HEVs*. pages 1649 – 1653, 10 2009.
- [DD012] Chen DD. *Microscopic investigations of degradation in lithium-ion batteries*. Thèse de Doctorat, Karlsruher Institut für Technologie (KIT), June (2012).
- [Demirocak2015] Dervis Emre Demirocak et Bharat Bhushan. *Probing the aging effects on nanomechanical properties of a LiFePO₄ cathode in a large format prismatic cell*. *Journal of Power Sources*, vol. 280, pages 256–262, 2015.
- [Dong2014] Hancheng Dong, Xiaoning Jin, Yangbing Lou et Changhong Wang. *Lithium-ion battery state of health monitoring and remaining useful life prediction based on support vector regression-particle filter*. *Journal of Power Sources*, vol. 271, pages 114 – 123, 2014.
- [Dubarry2011a] Matthieu Dubarry, Bor Yann Liaw, Mao-Sung Chen, Sain-Syan Chyan, Kuo-Chang Han, Wun-Tong Sie et She-Huang Wu. *Identifying battery aging mechanisms in large format Li ion cells*. *Journal of Power Sources*, vol. 196, no. 7, pages 3420–3425, 2011.
- [Dubarry2011b] Matthieu Dubarry, Cyril Truchot, Bor Yann Liaw, Kevin Gering, Sergiy Sazhin, David Jamison et Christopher Michelbacher. *Evaluation of commercial lithium-ion cells based on composite positive electrode for plug-in hybrid electric vehicle applications. Part II. Degradation mechanism under 2C cycle aging*. *Journal of Power Sources*, vol. 196, pages 10336–10343, 12 2011.
- [Dubarry2012] Matthieu Dubarry, Cyril Truchot et Bor Yann Liaw. *Synthesize battery degradation modes via a diagnostic and prognostic model*. *Journal of Power Sources*, vol. 219, pages 204–216, 2012.
- [Dubarry2014] Matthieu Dubarry, Cyril Truchot et Bor Yann Liaw. *Cell degradation in commercial LiFePO₄ cells with high-power and high-energy designs*. *Journal of Power Sources*, vol. 258, pages 408–419, 2014.
- [Eddahech2012a] A. Eddahech, O. Briat, E. Woïrgard et J.M. Vinassa. *Remaining useful life prediction of lithium batteries in calendar ageing for automotive applications*. *Microelectronics Reliability*, vol. 52, no. 9, pages 2438 – 2442, 2012. SPECIAL ISSUE 23rd EUROPEAN SYMPOSIUM ON THE RELIABILITY OF ELECTRON DEVICES, FAILURE PHYSICS AND ANALYSIS.
- [Eddahech2012b] Akram Eddahech, Olivier Briat, Nicolas Bertrand, Jean-Yves Deléage et Jean-Michel Vinassa. *Behavior and state-of-health monitoring of Li-ion batteries using impedance spectroscopy and recurrent neural networks*. *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pages 487 – 494, 2012.

-
- [Einhorn2012] M. Einhorn, F. V. Conte, C. Kral et J. Fleig. *A Method for Online Capacity Estimation of Lithium Ion Battery Cells Using the State of Charge and the Transferred Charge*. IEEE Transactions on Industry Applications, vol. 48, no. 2, pages 736–741, March 2012.
- [Feng2013] Xuning Feng, Li Jianqiu, Minggao Ouyang, Languang Lu, Jianjun Li et Xiangming He. *Using probability density function to evaluate the state of health of lithium-ion batteries*. Journal of Power Sources, vol. 232, page 209–218, 06 2013.
- [Forney1973] G David Forney. *The Viterbi algorithm*. Proceedings of the IEEE, vol. 61, no. 3, pages 268–278, 1973.
- [Gaines2011] Linda Gaines, John Sullivan et Andrew Burnham. *Paper No. 11-3891 Life-Cycle Analysis for Lithium-Ion Battery Production and Recycling*. Transportation Research Board 90th Annual Meeting, Washington, DC, 01 2011.
- [Galeotti2015] Matteo Galeotti, Lucio Cinà, Corrado Giammanco, Stefano Cordiner et Aldo Di Carlo. *Performance analysis and SOH (state of health) evaluation of lithium polymer batteries through electrochemical impedance spectroscopy*. Energy, vol. 89, pages 678 – 686, 2015.
- [George E. P. Box2015] Gregory C. Reinsel Greta M. Ljung George E. P. Box Gwilym M. Jenkins. *Time series analysis: Forecasting and control*, 5th edition. John Wiley and Sons, 2015.
- [George Vachtsevanos2006] Michael Roemer Andrew Hess Biqing Wu George Vachtsevanos Frank Lewis. *Fault diagnosis*, chapitre 5, pages 172–283. John Wiley & Sons, Ltd, 2006.
- [Goebel2006] K. Goebel, N. Eklund et P. Bonanni. *Fusing competing prediction algorithms for prognostics*. In 2006 IEEE Aerospace Conference, pages 10 pp.–, 2006.
- [Goebel2008] Kai Goebel, Bhaskar Saha, Abhinav Saxena, Jose Celaya et Jon Christophersen. *Prognostics in Battery Health Management*. Instrumentation & Measurement Magazine, IEEE, vol. 11, pages 33 – 40, 09 2008.
- [Haifeng2009] D. Haifeng, W. Xuezhe et S. Zechang. *A new SOH prediction concept for the power lithium-ion battery used on HEVs*. In 2009 IEEE Vehicle Power and Propulsion Conference, pages 1649–1653, Sep. 2009.
- [Han2014] Xuebing Han, Minggao Ouyang, Languang Lu, Jianqiu Li, Yuejiu Zheng et Zhe Li. *A comparative study of commercial lithium ion battery cycle life in electrical vehicle: Aging mechanism identification*. Journal of Power Sources, vol. 251, pages 38–54, 2014.
- [Hargrave1989] P. J. Hargrave. *A tutorial introduction to Kalman filtering*. In IEE Colloquium on Kalman Filters: Introduction, Applications and Future Developments, pages 1/1–1/6, 1989.
-

- [He2014] Zhiwei He, Mingyu Gao, Guojin Ma, Yuanyuan Liu et Sanxin Chen. *Online state-of-health estimation of lithium-ion batteries using Dynamic Bayesian Networks*. Journal of Power Sources, vol. 267, pages 576 – 583, 2014.
- [He2015] Yi-Jun He, Jia-Ni Shen, Ji-Fu Shen et Zi-Feng Ma. *State of health estimation of lithium-ion batteries: A multiscale Gaussian process regression modeling approach*. AIChE Journal, vol. 61, no. 5, pages 1589–1600, 2015.
- [Hines2008] J. Wesley Hines et Alexander Usynin. *Current Computational Trends in Equipment Prognostics*. International Journal of Computational Intelligence Systems, vol. 1, no. 1, pages 94–102, 2008.
- [Ho1998] S.L. Ho et M. Xie. *The use of ARIMA models for reliability forecasting and analysis*. Computers & Industrial Engineering, vol. 35, no. 1, pages 213–216, 1998.
- [Hu2010] Chang-Hua Hu, Xiao-Sheng Si et Jian-Bo Yang. *System reliability prediction model based on evidential reasoning algorithm with nonlinear optimization*. Expert Systems with Applications, vol. 37, no. 3, pages 2550–2562, 2010.
- [Hu2014a] Chao Hu, Gaurav Jain, Puqiang Zhang, Craig Schmidt, Parthasarathy Gomadam et Tom Gorka. *Data-driven method based on particle swarm optimization and k-nearest neighbor regression for estimating capacity of lithium-ion battery*. Applied Energy, vol. 129, pages 49 – 55, 2014.
- [Hu2014b] Xiaosong Hu, Shengbo Eben Li, Zhenzhong Jia et Bo Egardt. *Enhanced sample entropy-based health management of Li-ion battery for electrified vehicles*. Energy, vol. 64, pages 953 – 960, 2014.
- [Hu2015a] Chao Hu, Gaurav Jain, Craig Schmidt, Carrie Strief et Melani Sullivan. *Online estimation of lithium-ion battery capacity using sparse Bayesian learning*. Journal of Power Sources, vol. 289, pages 105 – 113, 2015.
- [Hu2015b] Xiaosong Hu, Jiuchun Jiang, Dongpu Cao et Bo Egardt. *Battery Health Prognosis for Electric Vehicles Using Sample Entropy and Sparse Bayesian Predictive Modeling*. IEEE Transactions on Industrial Electronics, vol. 63, pages 1–1, 01 2015.
- [Huang1984] Jun S. Huang. *THE AUTOREGRESSIVE MOVING AVERAGE MODEL FOR SPATIAL ANALYSIS*. Australian Journal of Statistics, vol. 26, no. 2, pages 169–178, 1984.
- [Hussey2009] Lu B. & Bickford R. Hussey A. *Performance Enhancement of On-Line Monitoring through Plant Data Classification*. In 6th American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Controls and Human Machine Interface Technology, April 2009.
- [Iurilli2021] Pietro Iurilli, Claudio Brivio et Vanessa Wood. *On the use of electrochemical impedance spectroscopy to characterize and model the*

-
- aging phenomena of lithium-ion batteries: a critical review*. Journal of Power Sources, vol. 505, page 229860, 2021.
- [J2002] Yamaki J. Advances in lithium-ion batteries, chapitre Liquid electrolytes, chapter 5, page 155–183. Springer Science & Business Media New York, 2002.
- [Jamil2020] Rehan Jamil. *Hydroelectricity consumption forecast for Pakistan using ARIMA modeling and supply-demand analysis for the year 2030*. Renewable Energy, vol. 154, pages 1–10, 2020.
- [Jardine2006] Andrew K.S. Jardine, Daming Lin et Dragan Banjevic. *A review on machinery diagnostics and prognostics implementing condition-based maintenance*. Mechanical Systems and Signal Processing, vol. 20, no. 7, pages 1483–1510, 2006.
- [Ji2013] Y. Ji, Y. Zhang et Chao-Yang Wang. *Li-Ion Cell Operation at Low Temperatures*. Journal of The Electrochemical Society, vol. 160, 2013.
- [Jiang2017] Yan Jiang, Jiuchun Jiang, Caiping Zhang, Weige Zhang, Yang Gao et Qipei Guo. *Recognition of battery aging variations for LiFePO₄ batteries in 2nd use applications combining incremental capacity analysis and statistical approaches*. Journal of Power Sources, vol. 360, pages 180–188, 2017.
- [Jiao2016] Na Jiao et Steve Evans. *Secondary use of Electric Vehicle Batteries and Potential Impacts on Business Models*. Journal of Industrial and Production Engineering, vol. 33, pages 1–7, 04 2016.
- [Jiao2017] Na Jiao et Steve Evans. *Business Models for Sustainability: The Case of Repurposing a Second-Life for Electric Vehicle Batteries*. pages 537–545, 04 2017.
- [Kabir2017] M. M. Kabir et Dervis Emre Demirocak. *Degradation mechanisms in Li-ion batteries: a state-of-the-art review*. International Journal of Energy Research, vol. 41, no. 14, pages 1963–1986, 2017.
- [Karimi2014] G. Karimi et A. R. Dehghan. *Thermal analysis of high-power lithium-ion battery packs using flow network approach*. International Journal of Energy Research, vol. 38, no. 14, pages 1793–1811, 2014.
- [Khayat2016] N. Khayat et N. Karami. *Adaptive techniques used for lifetime estimation of lithium-ion batteries*. In 2016 Third International Conference on Electrical, Electronics, Computer Engineering and their Applications (EECEA), pages 98–103, April 2016.
- [Kim2013] T. Kim, W. Qiao et L. Qu. *Online SOC and SOH estimation for multicell lithium-ion batteries based on an adaptive hybrid battery model and sliding-mode observer*. In 2013 IEEE Energy Conversion Congress and Exposition, pages 292–298, Sep. 2013.
- [Kim2015] Taesic Kim, Yebin Wang, Huazhen Fang, Zafer Sahinoglu, Toshihiro Wada, Satoshi Hara et Wei Qiao. *Model-based condition monitoring for lithium-ion batteries*. Journal of Power Sources, vol. 295, pages 16 – 27, 2015.
-

- [Klass2014] Verena Klass, Mårten Behm et Göran Lindbergh. *A support vector machine-based state-of-health estimation method for lithium-ion batteries under electric vehicle operation*. Journal of Power Sources, vol. 270, pages 262 – 272, 2014.
- [Kliger1995] S. Kliger, S. Yemini, Y. Yemini, D. Ohsie et S. Stolfo. *A coding approach to event correlation*. In Integrated Network Management, 1995.
- [Lavigne2016] Loic Lavigne, Jocelyn Sabatier, J. Francisco, Franck Guillemard et A. Noury. *Lithium-ion Open Circuit Voltage (OCV) curve modelling and its ageing adjustment*. Journal of Power Sources, vol. 324, pages 694–703, 08 2016.
- [Lüdeke-Freund2019] Florian Lüdeke-Freund, Stefan Gold et Nancy M. P. Bocken. *A Review and Typology of Circular Economy Business Model Patterns*. Journal of Industrial Ecology, vol. 23, no. 1, pages 36–61, 2019.
- [Lee2012] Battery Prognostics: SoC and SoH Prediction, volume ASME 2012 International Manufacturing Science and Engineering Conference of *International Manufacturing Science and Engineering Conference*, 06 2012.
- [Lee2020] Changyong Lee, Sugyeong Jo, Daeil Kwon et Michael Pecht. *Capacity-fading Behavior Analysis for Early Detection of Unhealthy Li-ion Batteries*. IEEE Transactions on Industrial Electronics, vol. PP, pages 1–1, 02 2020.
- [Leng2015] Feng Leng, Cher Ming Tan et Michael Pecht. *Effect of Temperature on the Aging rate of Li Ion Battery Operating above Room Temperature*. Scientific reports, vol. 5, page 12967, Aug 2015.
- [Lewis1985] Richard Lewis et Gregory C Reinsel. *Prediction of multivariate time series by autoregressive model fitting*. Journal of Multivariate Analysis, vol. 16, no. 3, pages 393–411, 1985.
- [Li2014a] H. Li, D. Pan et C. L. P. Chen. *Intelligent Prognostics for Battery Health Monitoring Using the Mean Entropy and Relevance Vector Machine*. IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 44, no. 7, pages 851–862, July 2014.
- [Li2014b] Junfu Li, Chao Lyu, Lixin Wang, Liqiang Zhang et Chenhui Li. *Remaining capacity estimation of Li-ion batteries based on temperature sample entropy and particle filter*. Journal of Power Sources, vol. 268, pages 895 – 903, 2014.
- [Li2014c] Shengbo Eben Li, Baojin Wang, Huei Peng et Xiaosong Hu. *An electrochemistry-based impedance model for lithium-ion batteries*. Journal of Power Sources, vol. 258, pages 9 – 18, 2014.
- [Li2018] Yi Li, Mohamed Abdel-Monem, Rahul Gopalakrishnan, Maitane Berecibar, Elise Nanini-Maury, Noshin Omar, Peter van den Bossche et Joeri Van Mierlo. *A quick on-line state of health estimation method for Li-ion battery with incremental capacity curves processed by Gaussian filter*. Journal of Power Sources, vol. 373, pages 40–53, 2018.

-
- [Li2019] Yi Li, Kailong Liu, Aoife M. Foley, Alana Zülke, Maitane Berecibar, Elise Nanini-Maury, Joeri Van Mierlo et Harry E. Hoster. *Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review*. Renewable and Sustainable Energy Reviews, vol. 113, page 109254, 2019.
- [Lin2013] H. Lin, T. Liang et S. Chen. *Estimation of Battery State of Health Using Probabilistic Neural Network*. IEEE Transactions on Industrial Informatics, vol. 9, no. 2, pages 679–685, May 2013.
- [Lin2015] Cheng Lin, Aihua Tang et Wenwei Wang. *A Review of SOH Estimation Methods in Lithium-ion Batteries for Electric Vehicle Applications*. Energy Procedia, vol. 75, pages 1920–1925, 08 2015.
- [Lipu2018] M. S. Hossain Lipu, M. A. Hannan, Aini Hussain, M. M. Hoque, Pin J. Ker, M. H. M. Saad et Afida Ayob. *A review of state of health and remaining useful life estimation methods for lithium-ion battery in electric vehicles: Challenges and recommendations*. Journal of Cleaner Production, vol. 205, pages 115 – 133, 2018.
- [Liu2013] Datong Liu, Jingyue Pang, Jianbao Zhou, Yu Peng et Michael Pecht. *Prognostics for state of health estimation of lithium-ion batteries based on combination Gaussian process functional regression*. Microelectronics Reliability, vol. 53, no. 6, pages 832 – 839, 2013.
- [Long2013] Bing Long, Weiming Xian, Lin Jiang et Zhen Liu. *An improved autoregressive model by particle swarm optimization for prognostics of lithium-ion batteries*. Microelectronics Reliability, vol. 53, no. 6, pages 821 – 831, 2013.
- [M. Rehme2016] A. Temmler U. Götze M. Rehme S. Richter. *Second-Life battery applications - market potentials and contribution to the cost effectiveness of electric vehicles*. 5th Conference on Future Automotive Technology (COFAT), May 2016.
- [Maletić2020] Maletić, Hrgetić et Deur. *Dual Nonlinear Kalman Filter-Based SoC and Remaining Capacity Estimation for an Electric Scooter Li-NMC Battery Pack*. Energies, vol. 13, page 540, 01 2020.
- [Manzetti2015] Sergio Manzetti et Florin Mariasiu. *Electric vehicle battery technologies: From present state to future systems*. Renewable and Sustainable Energy Reviews, vol. 51, pages 1004–1012, 2015.
- [Medjaher2009] Kamal Medjaher et Noureddine Zerhouni. *Residual-based failure prognostic in dynamic systems*. In T. Escobet, B. Morcego, V. Puig et J. Quevedo, éditeurs, 7th IFAC International Symposium on Fault Detection, Supervision and Safety of Technical Processes, SAFE PROCESS'09., page 6 pages, Barcelone, Spain, June 2009. IFAC.
- [Medjaher2013] Kamal Medjaher, Noureddine Zerhouni et Jihène Baklouti. *Data-Driven prognostics based on health indicator construction : Application to PRONOSTIA's Data*. pages 1451–1456, 07 2013.
- [Melin2018] H. E. Melin. *The lithium-ion battery end-of-life market 2018-2025*. Rapport technique, Circular Energy Storage, Research and Consulting, July 2018.
-

- [Meng2018] Jinhao Meng, Lei Cai, Guangzhao Luo, Daniel-Ioan Stroe et Remus Teodorescu. *Lithium-ion battery state of health estimation with short-term current pulse test and support vector machine*. Microelectronics Reliability, vol. 88-90, pages 1216 – 1220, 2018. 29th European Symposium on Reliability of Electron Devices, Failure Physics and Analysis (ESREF 2018).
- [Miao2013] Qiang Miao, Lei Xie, Hengjuan Cui, Wei Liang et Michael Pecht. *Remaining useful life prediction of lithium-ion battery with unscented particle filter technique*. Microelectronics Reliability, vol. 53, no. 6, pages 805 – 810, 2013.
- [Mikolajczak C2011] White K Thomas Long R Mikolajczak C Kahn M. *Lithium-ion batteries hazard and use assessment*. Rapport technique, Fire Protection Research Foundation,, July 2011.
- [Min Zhu2016] Min Zhu, Wensong Hu et N. C. Kar. *The SOH estimation of LiFePO4 battery based on internal resistance with Grey Markov Chain*. In 2016 IEEE Transportation Electrification Conference and Expo (ITEC), pages 1–6, June 2016.
- [Narula2011] Chaitanya K. Narula. *Economic Analysis of Deploying Used Batteries in Power Systems*. Rapport technique, Oak Ridge National Laboratory, 2011.
- [Nelson1985] Wayne Nelson. *Weibull Analysis of Reliability Data with Few or No Failures*. Journal of Quality Technology, vol. 17, no. 3, pages 140–146, 1985.
- [Neubauer2010] Jeremy Neubauer et Ahmad Pesaran. *PHEV/EV Li-Ion Battery Second-Use Project*. Rapport technique, National Renewable Energy Laboratory, April 2010.
- [Neubauer2011] Jeremy Neubauer et Ahmad Pesaran. *The ability of battery second use strategies to impact plug-in electric vehicle prices and serve utility energy storage applications*. Lancet, vol. 196, pages 10351–10358, 12 2011.
- [Neubauer2015] Jeremy Neubauer, Eric Wood et Ahmad Pesaran. *A Second Life for Electric Vehicle Batteries: Answering Questions on Battery Degradation and Value*. SAE International Journal of Materials and Manufacturing, vol. 8, 01 2015.
- [Ng2009] Kong Soon Ng, Chin-Sien Moo, Yi-Ping Chen et Yao-Ching Hsieh. *Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries*. Applied Energy, vol. 86, no. 9, pages 1506 – 1511, 2009.
- [Ng2014] Selina S.Y. Ng, Yinjiao Xing et Kwok L. Tsui. *A naive Bayes model for robust remaining useful life prediction of lithium-ion battery*. Applied Energy, vol. 118, pages 114 – 123, 2014.
- [Norin2002] Laura Norin, Robert Kosteccki et Frank McLarnon. *Study of Membrane Degradation in High-Power Lithium-Ion Cells*. Electrochemical and Solid-State Letters, vol. 5, no. 4, page A67, 2002.

-
- [Nuhic2013] Adnan Nuhic, Tarik Terzimehic, Thomas Soczka-Guth, Michael Buchholz et Klaus Dietmayer. *Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods*. Journal of Power Sources, vol. 239, pages 680 – 688, 2013.
- [Okoshi2006] Tetsuro Okoshi, Keizo Yamada, Tokiyoshi Hirasawa et Akihiko Emori. *Battery condition monitoring (BCM) technologies about lead–acid batteries*. Journal of Power Sources, vol. 158, pages 874–878, 08 2006.
- [Omariba2018] Zachary Bosire Omariba, Lijun Zhang et Dongbai Sun. *Review on Health Management System for Lithium-Ion Batteries of Electric Vehicles*. Electronics, vol. 7, no. 5, 2018.
- [Patil2015] Meru A. Patil, Piyush Tagade, Krishnan S. Hariharan, Subramanya M. Kolake, Taewon Song, Taejung Yeo et Seokgwang Doo. *A novel multistage Support Vector Machine based approach for Li ion battery remaining useful life estimation*. Applied Energy, vol. 159, pages 285 – 297, 2015.
- [Pecht2008] Michael Pecht et Sachin Kumar. *Data Analysis Approach for System Reliability, Diagnostics and Prognostics*. In Pan pacific microelectronics symposium,, 2008.
- [Pecht2009] Michael Pecht et Jie Gu. *Physics-of-failure-based prognostics for electronic products*. Transactions of the Institute of Measurement and Control, vol. 31, no. 3-4, pages 309–322, 2009.
- [Piao2016] Changhao Piao, Zuncheng Li, Sheng Lu, Zhekui Jin et Chongdu Cho. *Analysis of Real-Time Estimation Method Based on Hidden Markov Models for Battery System States of Health*. Journal of Power Electronics, vol. 16, pages 217–226, 01 2016.
- [Podias2018] Andreas Podias, Andreas Pfrang, Franco Di Persio, Akos Kriston, Silvia Bobba, Fabrice Mathieux, Maarten Messagie et Lois Boon-Brett. *Sustainability Assessment of Second Use Applications of Automotive Batteries: Ageing of Li-Ion Battery Cells in Automotive and Grid-Scale Applications*. World Electric Vehicle Journal, vol. 9, no. 2, 2018.
- [Prasad2013] Githin K. Prasad et Christopher D. Rahn. *Model based identification of aging parameters in lithium ion batteries*. Journal of Power Sources, vol. 232, pages 79 – 85, 2013.
- [Rabiner1989] Lawrence R Rabiner. *A tutorial on hidden Markov models and selected applications in speech recognition*. Proceedings of the IEEE, vol. 77, no. 2, pages 257–286, 1989.
- [Ramdon2014] Sanjay Ramdon et Bharat Bhushan. *Short communication*. Journal of Power Sources, vol. 246, no. C, pages 219–224, 2014.
- [Ramoni2013] Monsuru Ramoni et Hong-Chao Zhang. *End-of-life (EOL) issues and options for electric vehicle batteries*. Clean Technologies and Environmental Policy, vol. 15, 12 2013.
-

- [Reinhardt2019] Robert Reinhardt, Ioannis Christodoulou, Santiago Gassó-Domingo et Beatriz Amante García. *Towards sustainable business models for electric vehicle battery second use: A critical review*. Journal of Environmental Management, vol. 245, pages 432–446, 2019.
- [Remmlinger2013] Jürgen Remmlinger, Michael Buchholz, Thomas Soczka-Guth et Klaus Dietmayer. *On-board state-of-health monitoring of lithium-ion batteries using linear parameter-varying models*. Journal of Power Sources, vol. 239, pages 689 – 695, 2013.
- [Richter2016] Stefan Richter, Marco Rehme, Aniko Temmler et Uwe Götze. *Second-Life Battery Applications - Market potentials and contribution to the cost effectiveness of electric vehicles*, 05 2016.
- [Rish2002] Irina Rish, Mark Brodie et Sheng Ma. *Accuracy vs. Efficiency Trade-offs in Probabilistic Diagnosis*. pages 560–566, 01 2002.
- [Saha2007] B. Saha, S. Poll, K. Goebel et J. Christophersen. *An integrated approach to battery health monitoring using bayesian regression and state estimation*. In 2007 IEEE Autotestcon, pages 646–653, Sep. 2007.
- [Saha2009] Bhaskar Saha, Kai Goebel et Jon Christophersen. *Comparison of prognostic algorithms for estimating remaining useful life of batteries*. Transactions of the Institute of Measurement and Control, vol. 31, no. 3-4, pages 293–308, 2009.
- [Salkind1999] Alvin J Salkind, Craig Fennie, Pritpal Singh, Terrill Atwater et David E Reisner. *Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology*. Journal of Power Sources, vol. 80, no. 1, pages 293 – 300, 1999.
- [Samadani2012] Seyed Ehsan Samadani, Roydon A. Fraser et Michael Fowler. *A Review Study of Methods for Lithium-ion Battery Health Monitoring and Remaining Life Estimation in Hybrid Electric Vehicles*. In SAE Technical Paper. SAE International, 04 2012.
- [Samadi2012] M. F. Samadi, S. M. M. Alavi et M. Saif. *An electrochemical model-based particle filter approach for Lithium-ion battery estimation*. In 2012 IEEE 51st IEEE Conference on Decision and Control (CDC), pages 3074–3079, Dec 2012.
- [Sangwan2016] Venu Sangwan, Avinash Sharma, Rajesh Kumar et Akshay Rathore. *Equivalent circuit model parameters estimation of Li-ion battery: C-rate, SOC and Temperature effects*. 12 2016.
- [Sankararaman2015] Shankar Sankararaman et Kai Goebel. *Uncertainty in Prognostics and Systems Health Management*. International Journal of Prognostics and Health Management, vol. 6, 07 2015.
- [Sarmah2019] Sudipta Bijoy Sarmah, Pankaj Kalita, Akhil Garg, Xiao-dong Niu, Xing-Wei Zhang, Xiongbin Peng et Dipanwita Bhattacharjee. *A Review of State of Health Estimation of Energy Storage Systems: Challenges and Possible Solutions for Futuristic Applications of Li-Ion Battery Packs in Electric Vehicles*. Journal of Electrochemical Energy Conversion and Storage, vol. 16, no. 4, 03 2019. 040801.

-
- [Saxena2008] Abhinav Saxena, Kai Goebel, Don Simon et Neil Eklund. *Damage propagation modeling for aircraft engine run-to-failure simulation*. In 2008 International Conference on Prognostics and Health Management, pages 1–9, 2008.
- [Saxena2010] Abhinav Saxena, Jose Celaya, Bhaskar Saha, Sankalita Saha et Kai Goebel. *Metrics for Offline Evaluation of Prognostic Performance*. International Journal of Prognostics and Health Management, vol. 1, pages 2153–2648, 01 2010.
- [Schwunk2013] Simon Schwunk, Nils Armbruster, Sebastian Straub, Johannes Kehl et Matthias Vetter. *Particle filter for state of charge and state of health estimation for lithium–iron phosphate batteries*. Journal of Power Sources, vol. 239, pages 705 – 710, 2013.
- [Sepasi2015] Saeed Sepasi, Reza Ghorbani et Bor Yann Liaw. *Inline state of health estimation of lithium-ion batteries using state of charge calculation*. Journal of Power Sources, vol. 299, pages 246 – 254, 2015.
- [Singh2006] Pritpal Singh, Ramana Vinjamuri, Xiquan Wang et David Reisner. *Fuzzy logic modeling of EIS measurements on lithium-ion batteries*. Electrochimica Acta, vol. 51, no. 8, pages 1673 – 1679, 2006. Electrochemical Impedance Spectroscopy.
- [Srinivasan2008] Venkat Srinivasan. *Batteries for Vehicular Applications*. AIP Conference Proceedings, vol. 1044, no. 1, pages 283–296, 2008.
- [Standridge2015] Charles Standridge et Md Hasan. *Post-vehicle-application lithium-ion battery remanufacturing, repurposing and recycling capacity: Modeling and analysis*. Journal of Industrial Engineering and Management, vol. 8, 06 2015.
- [Steckel2021] Tobiah Steckel, Alissa Kendall et Hanjiro Ambrose. *Applying levelized cost of storage methodology to utility-scale second-life lithium-ion battery energy storage systems*. Applied Energy, vol. 300, page 117309, 2021.
- [Stroe2020] Daniel-Ioan Stroe et Erik Schaltz. *Lithium-Ion Battery State-of-Health Estimation Using the Incremental Capacity Analysis Technique*. IEEE Transactions on Industry Applications, vol. 56, no. 1, pages 678–685, 2020.
- [Tang2011] X. Tang, X. Mao, J. Lin et B. Koch. *Capacity estimation for Li-ion batteries*. In Proceedings of the 2011 American Control Conference, pages 947–952, June 2011.
- [Tang2018] Xiaopeng Tang, Changfu Zou, Ke Yao, Guohua Chen, Boyang Liu, Zhenwei He et Furong Gao. *A fast estimation algorithm for lithium-ion battery state of health*. Journal of Power Sources, vol. 396, pages 453–458, 2018.
- [Tong2015] Shijie Tong, Matthew P. Klein et Jae Wan Park. *On-line optimization of battery open circuit voltage for improved state-of-charge and state-of-health estimation*. Journal of Power Sources, vol. 293, pages 416 – 428, 2015.
-

Bibliography

- [Törkler2014] A. Törkler. *Batteries Refurbishing & Reuse*. ELIBAMA Projet: European Li-Ion Battery Advanced Manufacturing for Electric Vehicles, 2014. available at <https://elibama.files.wordpress.com/2014/10/v-c-batteries-reuse.pdf>.
- [Tuchband2007] B. Tuchband et M. Pecht. *The Use of Prognostics in Military Electronic Systems*. 2007.
- [Ungurean2017] Lucian Ungurean, Gabriel Cârstoiu, Mihai V. Micea et Voicu Groza. *Battery state of health estimation: a structured review of models, methods and commercial devices*. International Journal of Energy Research, vol. 41, no. 2, pages 151–181, 2017.
- [USC2006] *Energy Storage System Goals: USABC Goals for Advanced Batteries for EVs*. UNITED STATES COUNCIL FOR AUTOMOTIVE RESEARCH LLC, August 2006.
- [Waag2014] Wladislaw Waag, Christian Fleischer et Dirk Uwe Sauer. *Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles*. Journal of Power Sources, vol. 258, pages 321 – 339, 2014.
- [Wang2013] Dong Wang, Qiang Miao et Michael Pecht. *Prognostics of lithium-ion batteries based on relevance vectors and a conditional three-parameter capacity degradation model*. Journal of Power Sources, vol. 239, pages 253 – 264, 2013.
- [Wang2017a] Z. Wang, J. Ma et L. Zhang. *State-of-Health Estimation for Lithium-Ion Batteries Based on the Multi-Island Genetic Algorithm and the Gaussian Process Regression*. IEEE Access, vol. 5, pages 21286–21295, 2017.
- [Wang2017b] Z. Wang, J. Ma et L. Zhang. *State-of-Health Estimation for Lithium-Ion Batteries Based on the Multi-Island Genetic Algorithm and the Gaussian Process Regression*. IEEE Access, vol. 5, pages 21286–21295, 2017.
- [Wang2019] Zengkai Wang, Shengkui Zeng, Jianbin Guo et Taichun Qin. *State of health estimation of lithium-ion batteries based on the constant voltage charging curve*. Energy, vol. 167, no. C, pages 661–669, 2019.
- [Wei2018] J. Wei, G. Dong et Z. Chen. *Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression*. IEEE Transactions on Industrial Electronics, vol. 65, no. 7, pages 5634–5643, July 2018.
- [Welch2003] Lloyd R Welch. *Hidden Markov models and the Baum-Welch algorithm*. IEEE Information Theory Society Newsletter, vol. 53, no. 4, pages 10–13, 2003.
- [Weng2013] Caihao Weng, Yujia Cui, Jing Sun et Huei Peng. *On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression*. Journal of Power Sources, vol. 235, page 36–44, 08 2013.

-
- [Weng2014] Caihao Weng, Jing Sun et Huei Peng. *A unified open-circuit-voltage model of lithium-ion batteries for state-of-charge estimation and state-of-health monitoring*. Journal of Power Sources, vol. 258, pages 228 – 237, 2014.
- [Williams2010] Brett Williams et Timothy Lipman. *Strategy for Overcoming Cost Hurdles of Plug-In-Hybrid Battery in California: Integrating Post-Vehicle Secondary Use Values*. Transportation Research Record: Journal of the Transportation Research Board, vol. 2191, pages 59–66, 12 2010.
- [Wolfs2011] Peter Wolfs. *An economic assessment of “second use” lithium-ion batteries for grid support*. pages 1 – 6, 01 2011.
- [Wu2016] Ji Wu, Yujie Wang, Xu Zhang et Zonghai Chen. *A novel state of health estimation method of Li-ion battery using group method of data handling*. Journal of Power Sources, vol. 327, pages 457–464, 2016.
- [Xing2011] Yinjiao Xing, Eden W. M. Ma, Kwok L. Tsui et Michael Pecht. *Battery Management Systems in Electric and Hybrid Vehicles*. Energies, vol. 4, no. 11, pages 1840–1857, 2011.
- [Yang2018] Duo Yang, Xu Zhang, Rui Pan, Yujie Wang et Zonghai Chen. *A novel Gaussian process regression model for state-of-health estimation of lithium-ion battery using charging curve*. Journal of Power Sources, vol. 384, pages 387 – 395, 2018.
- [Yu2013] Gang Yu, Lu Ying Sheng et Mi Mi Guo. *Degradation Model Prediction for Battery of Electric Vehicle Based on Hidden Markov Model*. In Applied Mechanics, Materials and Manufacturing, volume 378 of *Applied Mechanics and Materials*, pages 492–495. Trans Tech Publications Ltd, 11 2013.
- [Zenati2012] A. Zenati, P. Desprez, H. Razik et S. Rael. *A methodology to assess the State of Health of lithium-ion batteries based on the battery’s parameters and a Fuzzy Logic System*. In 2012 IEEE International Electric Vehicle Conference, pages 1–6, March 2012.
- [Zhang2018] Xu Zhang, Yujie Wang, Chang Liu et Zonghai Chen. *A novel approach of battery pack state of health estimation using artificial intelligence optimization algorithm*. Journal of Power Sources, vol. 376, pages 191 – 199, 2018.
- [Zheng2013] Yuejiu Zheng, Languang Lu, Xuebing Han, Jianqiu Li et Minggao Ouyang. *LiFePO₄ battery pack capacity estimation for electric vehicles based on charging cell voltage curve transformation*. Journal of Power Sources, vol. 226, pages 33 – 41, 2013.
- [Zheng2020] Yu Zheng, Yue Song, Andy Huang et David J. Hill. *Hierarchical Optimal Allocation of Battery Energy Storage Systems for Multiple Services in Distribution Systems*. IEEE Transactions on Sustainable Energy, vol. 11, no. 3, pages 1911–1921, 2020.
-

Bibliography

- [Zhou2016a] Yapeng Zhou et Miaohua Huang. *Lithium-ion batteries remaining useful life prediction based on a mixture of empirical mode decomposition and ARIMA model*. *Microelectronics Reliability*, vol. 65, pages 265 – 273, 2016.
- [Zhou2016b] Yapeng Zhou, Miaohua Huang, Yupu Chen et Ye Tao. *A novel health indicator for on-line lithium-ion batteries remaining useful life prediction*. *Journal of Power Sources*, vol. 321, pages 1 – 10, 2016.
- [Zille2009] V. Zille, A. Despujols, P. Baraldi, G. Rossetti et E. Zio. *A framework for the Monte Carlo simulation of degradation and failure processes in the assessment of maintenance programs performance*. 2009.
- [Zou2015] Yuan Zou, Xiaosong Hu, Hongmin Ma et Shengbo Eben Li. *Combined State of Charge and State of Health estimation over lithium-ion battery cell cycle lifespan for electric vehicles*. *Journal of Power Sources*, vol. 273, pages 793 – 803, 2015.

List of Figures

1.1	Thesis structure	7
2.1	PHM functional architecture [Bonissone2006]	12
2.2	Variability of cost and complexity in PHM [Byington2002]	14
2.3	PoF framework [Pecht2009]	16
2.4	Methodology for data driven approach [Pecht2008]	17
2.5	Framework for fusion based approach [Cheng2009]	18
2.6	PHM metrics [Saxena2010]	20
2.7	Ragone plot for different batteries [Srinivasan2008]	21
2.8	Schematic of working principle	22
2.9	Degradation Mechanism [Birk12017]	23
2.10	Degradation Mechanism & modes [Birk12017]	24
2.11	SOC operating window	26
2.12	Classification of challenges in State of Health (SoH) estimation	40
3.1	PHM system for Circular economy	45
3.2	Feature based classification of SoH estimation methods	46
3.3	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).	47
3.4	A framework for using Model extracted features for SoH estimation	47
3.5	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)	48
3.6	Illustration of data driven analytical feature based State of Health (SoH) modeling: A framework for using Incremental Capacity Analysis (ICA) to predict SoH.	48
3.7	A framework for using battery management system based raw features to predict State of Health (SoH).	49
3.8	Basic structure of a HMM model	52
3.9	Model Learning	54
3.10	Model Identification and Diagnosis	55
4.1	BMS: Generic Structure [Xing2011]	59
4.2	Representation of EIS through Nyquist plot [Iurilli2021]	63
4.3	Lumped parameter battery model	64
4.4	Creation of Model database	66
4.5	Identification of best model	67

4.6	Box & Jenkins methodology schematic [Jamil2020]	69
5.1	Charging current curve	74
5.2	Charging voltage curve	74
5.3	Discharging current curve	74
5.4	Discharging voltage curve	74
5.5	Charging current curve	75
5.6	Charging voltage curve	75
5.7	Discharging current curve	75
5.8	Discharging voltage curve	75
5.9	Charging current curve	75
5.10	Charging voltage curve	75
5.11	Discharging current curve	75
5.12	Discharging voltage curve	75
5.13	Charging current curve	76
5.14	Charging voltage curve	76
5.15	Discharging current curve	76
5.16	Discharging voltage curve	76
5.17	Calculated Capacity	77
5.18	Measured Capacity	77
5.19	Variation in temperature during charging	77
5.20	Incremental Capacity curve: B0007	78
5.21	Filtered Incremental Capacity curve: B0007	78
5.22	Cyclewise IC curve: B0007	79
5.23	Cyclewise Regional capacity plot: B0005	79
5.24	Cyclewise Regional capacity plot: B0006	80
5.25	Cyclewise Regional capacity plot: B0007	80
5.26	Cyclewise Regional capacity plot: B0018	80
5.27	Feature correlation plot: B0007	81
5.28	SVR model creation procedure	81
5.29	SVR model results for battery B0005	82
5.30	SVR model results for battery B0006	82
5.31	SVR model results for battery B0007	82
5.32	Feature extraction of to be diagnosed battery	83
5.33	ACF plot	84
5.34	PACF plot	84
5.35	Differenced Regional capacity	84
5.36	ARIMA model forecasting	85
5.37	Comparison of predicted vs actual regional capacity	86
5.38	Actual vs predicted capacity	86
5.39	Internal Resistance data	87
5.40	ARIMA based IR training data	88
5.41	Differenced Internal Resistance training data	88
5.42	ACF and PACF plot for differenced IR data	89
5.43	ARIMA model forecasting for IR	90
5.44	Comparison of predicted vs actual Internal Resistance	90
5.45	Model database for accuracy comparison	92
5.46	Model database for accuracy comparison	92
5.47	Predicted vs Actual SoH (Linear Regression): B0006	93
5.48	Predicted vs Actual SoH (Linear Regression): B0007	93
5.49	Predicted vs Actual SoH (Support Vector Regression): B0006	94

List of figures

5.50	Predicted vs Actual SoH (Support Vector Regression): B0007	94
5.51	Neural Network Structure	95
5.52	Predicted vs Actual SoH (Neural network): B0006	95
6.1	Timeline for repurposing	99
6.2	Conceptual battery second use innovative business model framework. [Reinhardt2019]	101
6.3	Proposed framework for battery repurposing	102
6.4	Proposed framework for battery repurposing (Business landscape: 1)	104
6.5	Proposed framework for battery repurposing (Business landscape: 2)	105

List of Tables

2.1	List of relevant papers for SoH estimation	38
3.1	Summary of State of Health (SoH) estimation category.	50
5.1	AIC value comparison for different ARIMA models	85
5.2	AIC value comparison for different ARIMA models for IR forecasting	89
5.3	ARIMA model parameters	90
6.1	Second life battery collaboration	97
6.2	Stakeholders involved in battery repurposing	100



Annexure 1 : List of Abbreviations

ACF	AutoCorrelation Function
AIC	Akaike information criterion
ANN	Artificial Neural Network
APU	Auxiliary Power Unit
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BMS	Battery Management System
BESS	Battery Energy Storage System
BN	Bayesian Network
CC	Coulomb Counting
CCCV	Constant Current Constant Voltage
CDP	Cross Disciplinary Project
CE	Circular Economy
C-rate	Charge-rate
DoD	Depth of Discharge
DV	Differential Voltage
EES	Electrochemical Energy Storage
EIS	Electrochemical Impedance Spectroscopy
EMS	Energy management System
EoL	End of Life
EV	Electric Vehicles
FL	Fuzzy Logic

FMMEA	Failure Modes, Mechanisms, and Effects Analysis
GA	Genetic Algorithm
GPR	Gaussian Process Regression
HMM	Hidden markov Model
IC	Incremental Capacity
IEC	International Electrotechnical Commission
IR	Internal Resistance
KF	Kalman Filter
LCOS	Levelized Cost of Storage
Li	Lithium
LIB	Lithium-ion Battery
LiPO	Lithium Polymer
LLI	Loss of Lithium Inventory
LS	Least Square
MA	Moving Average
MTBF	Mean Time between Failure
OCV	Open Circuit Voltage
OEM	Original Equipment Manufacturer
PACF	Partial AutoCorrelation Function
PCA	Principal Component Analysis
PF	Particle Filter
PHM	Prognostics Health Management
PoF	Physics of Failure
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
RVM	Relevance Vector Machines
SEI	Solid Electrolyte Interphase
SoC	State of Charge
SoH	State of Health
SVM	Support Vector Machine
SVR	Support Vector Regression
UPS	Uninterrupted Power Supply
WP	Work Package



Resume

Dans le domaine du transport, les véhicules électriques (VE) font partie des moyens les plus encourageants pour lutter contre l'impact environnemental lié à l'utilisation des hydrocarbures. La plupart des véhicules électriques utilisent des batteries Li-ion comme source d'alimentation, en raison de leur haute densité énergétique. Cependant, ces batteries atteignent leur fin de vie (EoL) lorsque leur capacité se dégrade de seulement vingt pour cent de la capacité d'origine. Une solution qui rentre dans le cadre de l'économie circulaire serait de transformer les batteries des VE post-utilisées en de nouvelles batteries à valeur ajoutée pour des applications moins exigeantes, prolongeant ainsi leur durée de vie. Il est donc nécessaire de prédire l'état de santé des batteries considérées en fin de vie en tenant compte des conditions réelles d'utilisation et en estimant leur durée de vie restante (RUL : Remaining Useful Life). Cependant, l'hétérogénéité technologique des batteries Li-ion, ainsi que la dynamique de changement des conditions d'exploitation, accentue la difficulté à établir un pronostic sur l'état de santé des batteries (PHM). De plus, peu de recherches s'intéressent aux méthodes d'évaluation de l'état de santé des équipements dans une perspective de réutilisation.

L'objectif de cette thèse est de combler le fossé des connaissances sur le diagnostic et le pronostic dans un contexte d'économie circulaire. Les travaux proposés identifient une définition contextuelle de l'état de santé (SoH : State of Health) et une classification de différentes méthodes d'estimation de SoH. La thèse étudie également les problèmes et défis posés lors de l'estimation du SoH pour la batterie Li-ion, avec des propositions de solutions comme de fournir des réseaux de capteurs fiables ainsi que la recherche d'informations pour développer au plus juste une méthode de diagnostic et de pronostic de santé des batteries Li-ion dans le contexte de l'économie circulaire qui correspond au but ultime de cette thèse.

Nous avons proposé un système d'estimation SoH basé sur une courbe de capacité incrémentale (IC) pour les batteries Li-ion. Le modèle utilise un filtre de Kalman et une méthode permettant de mesurer l'atténuation du bruit. Afin de modéliser la relation entre IC et le SoH, une nouvelle méthode est proposée. Elle combine une technique d'apprentissage supervisé et un modèle statistique pour analyser ou prédire les données de séries temporelles. C'est ainsi que la régression de support vectorielle (SVR) associée à la méthode d'Autoregression (ARIMA) nous donne des résultats satisfaisants. Un cas d'utilisation sur les données de batterie open source NASA AMES est créé. Il nous permet de valider les approches proposées. L'étude de cas montre que le modèle proposé peut obtenir des résultats de prédiction SoH précis sans avoir besoin des informations sur l'état de charge de la batterie. Enfin, un cadre a été proposé pour établir un paysage économique basé sur la réaffectation des batteries en explorant les tendances actuelles de réaffectation à travers

le monde.

A.0.1 Projet « CIRCULAR » interdisciplinaire

Depuis le début du 21^{ème} siècle, avec l'augmentation exponentielle de la population mondiale, un besoin sans précédent de transition vers une société plus efficace et durable des ressources s'est fait sentir. C'est devenu l'objectif principal des gouvernements des pays européens et Syndicats. Les industries doivent faire face et s'adapter à l'industrie primaire des défis futurs comme la rareté des ressources, les sources d'énergie efficaces et vertes, les attentes de personnalisation, etc. En 2015, la Commission européenne a adopté son premier plan d'action pour l'économie circulaire. Il comprenait les mesures pour aider à stimuler la transition de l'Europe vers une économie circulaire, à stimuler la concurrence mondiale, à favoriser une croissance économique durable et à générer de nouveaux emplois. C'est ainsi que le projet « CIRCULAR » a débuté en 2017. Il vise à développer des systèmes industriels circulaires fiables capable de transformer des produits post-utilisés en nouveaux produits à valeur ajoutée. C'est un projet de recherche transdisciplinaire qui associe les compétences de différents domaines comme le génie industriel, l'informatique, la sûreté de fonctionnement, la gestion, les sciences sociales et l'économie dans le but de concevoir un système industriel circulaire agile permettant de relever le défi scientifique et les enjeux de l'Industrie du Futur. L'objectif premier du projet est de donner aux entreprises la capacité à satisfaire les exigences de transition vers un système industriel circulaire et principalement à produire des équipements à haute valeur ajoutée tout en minimisant les ressources matérielles et énergétiques. Le défi était de prôner la transition vers le modèle "prendre-faire-consommer-utiliser" à la place du modèle « prendre-faire-consommer-éliminer ». Le projet est axé sur les batteries pour véhicules électriques qui peuvent être réutilisés ou remanufacturés après une première fin de vie. Les hypothèses du projet pour la conception d'un système industriel pour remanufacturer des produits post-utilisés en nouveaux produits sont:

- L'agilité aux systèmes industriels ne peut être fournie que par une collaboration Homme-Machine.
- Il est nécessaire de repenser systématiquement le processus industriel et environnemental pour s'adapter à cette transition.
- Des incitations spécifiques et des conditions industrielles sont nécessaires pour le déploiement massif du processus orienté vers la réutilisation.

Concernant ces trois hypothèses, trois lots de travaux différents ont été déployés :

- Travail collaboratif pour une chaîne de remanufacturing agile : Ce work package permet d'investiguer les travailleurs et leur organisation comme l'un des éléments clés de l'agilité du remanufacturing comme système productif : la collaboration Homme-Machine est au cœur de la nouvelle situation de travail.
- WP2 : Solutions numériques pour s'adapter au processus de remanufacturing agile : WP2 se concentre sur des solutions métriques qui pourraient aider à adapter les processus en fonction des nombreuses variable sites. L'agilité du système productif sera renforcée par la capacité à gérer automatiquement des régulations ou reconfigurations sur le processus opératoire.
- WP3 : Condition de circularité et chaîne de valeur : Le WP3 se concentre sur les stratégies à développer pour une adoption plus large des systèmes circulaires industriels.

Le WP1 a les objectifs clés suivants :

-
- définir les nouveaux rôles et compétences des travailleurs dans un système industriel circulaire
 - développer la cobotique comme cellule de travail collaborative naturelle
 - développer des approches de diagnostic pour aider les travailleurs à décider du flux de produits.

Cette thèse rentre dans le cadre du troisième point du WP1, à savoir, développer une approche de diagnostic et pronostic pour les batteries Li-ion des VE afin de soutenir la prise de décision et donner une seconde vie aux batteries.

A.0.2 Le contexte

L'impact environnemental du transport à base d'hydrocarbures est manifestement en augmentation, et par conséquent, il est devenu un contributeur important au réchauffement climatique par l'émission de dioxyde de carbone. Dans le secteur des transports, et particulièrement le transport routier, il est en tête en tant que contributeur au réchauffement climatique. Les VE sont l'un des moyens les plus encourageants pour lutter contre les émissions de dioxyde de carbone. À cet égard, la Commission européenne a fait de l'électrification des transports (électromobilité), une priorité du programme communautaire de recherche. Par ailleurs, les organismes ont constamment mis en place des politiques pour promouvoir les ventes de véhicules électriques à travers le monde. Ainsi, les véhicules électriques gagnent de plus en plus de parts de marché et les entreprises historiquement ancrées dans la chaîne de valeur des moteurs thermiques vivent aujourd'hui une transformation de leur business model traditionnel. La plupart des véhicules électriques utilisent des batteries Li-ion comme source d'énergie en raison de sa densité énergétique élevée et de ses faibles besoins d'entretien. Ces piles sont les principaux contributeurs à l'impact environnemental et sont confrontés à des problèmes de recyclage. Les batteries Li-ion sont fabriquées à partir de métaux terrestres épuisables comme le lithium, le nickel et le cobalt. L'extraction de ces métaux se produit à un coût environnemental et sanitaire substantiel. Donc, pour garder le contrôle sur l'impact environnemental des VE, il est essentiel d'utiliser les batteries de la manière la plus efficace possible. Dans le cas des véhicules électriques, en raison des besoins élevés en puissance et en énergie, la batterie atteint sa fin de vie lorsque la capacité se dégrade à 80 % de la capacité d'origine.

Ainsi, les batteries ne sont pas aussi vertes qu'il semble. De toute évidence, la capacité restante peut être réutilisée comme une seconde vie dans des environnements moins exigeants. Un potentiel substantiel inutilisé de la batterie est gaspillé, ce qui est préjudiciable à l'environnement. Cependant, ce potentiel inexploité peut aussi être considéré comme une opportunité de faire des VE plus abordables en appliquant le concept de seconde utilisation de la batterie. La seconde utilisation peut rapporter une partie des revenus au fabricant d'équipement d'origine (OEM) et réduire les prix des véhicules électriques et rendre ainsi les VE plus compétitifs [Jiao2016]. Selon [Melin2018], le marché mondial des batteries Li-ion en fin de vie devraient croître de 3,5 milliards de dollars d'ici 2025. Dans cette seconde vie, les batteries peuvent être achetées à faible coût, indiquant de nouvelles opportunités commerciales. Pour faciliter la réutilisation, le remanufacturing de ces batteries en fin de vie, plusieurs décisions doivent être prises, comme choisir les applications de seconde vie appropriées ou identifier le bon moment pour initier une seconde vie. Cependant, les défis des prises de décisions efficaces sur les systèmes mentionnés ne sont toujours pas résolus. Ceci est principalement dû au manque de méthodes analytiques et des outils d'aide à la décision, capables d'évaluer différents aspects de la fabrication circulaire et les systèmes de gestion des équipements en fin de vie. Pour un système industriel circulaire fiable, il est important de prédire la fiabilité de ce système en état de cycle de vie réel. La recherche sur la méthode de prise de décision peut être très utile pour la nouvelle chaîne de valeur comme l'intégration de la maintenance prédictive des produits manufacturés ou réutilisés. Ainsi, le pronostic, la gestion et l'estimation de

l'état de santé des équipements (PHM) jouent un rôle important dans le soutien de l'économie circulaire. Une estimation efficace de la santé actuelle du produit, avec une meilleure prédiction de la durée de vie utile, permettra l'élargissement de la prise de décision dans les systèmes circulaires. Cependant, l'hétérogénéité des batteries Li-ion, ainsi que la dynamique de changement d'état de fonctionnement, accentue la difficulté d'établir un système PHM pour les batteries. Pour surmonter ces obstacles et faciliter la prise de décision, nous devons avoir une stratégie de prédiction adaptative et en temps réel.

A.0.3 Objectif

L'estimation de l'état de santé (SoH) joue un rôle essentiel dans la prise de décisions lors de la réorientation. Cependant, il est difficile de prédire un SoH précis en raison du mécanisme de dégradation complexe du Li-batteries ioniques causées par divers facteurs internes et externes. En plus des indicateurs comme SoH, plusieurs autres facteurs doivent être pris en compte pour établir une configuration industrielle pour le remanufacturing ou réaffectation. Nous avons besoin d'un système de fabrication plus intelligent et plus durable. L'objectif de la thèse est de définir l'état de santé dans le contexte de l'économie circulaire. Il s'agit donc de fournir des réseaux de capteurs fiables avec des modules de recherche d'informations pour développer aussi précisément que possible un diagnostic et un pronostic de l'état de santé pour les batteries Li-ion. Ce développement de PHM doit être capable de prédire l'état de santé des batteries de VE.

A.0.4 Question de recherche

La principale question de recherche directrice de ce travail a été formulée comme suit :

"Comment concevoir un système efficace qui prédit et évalue l'état de santé du Li-ion batteries dans le contexte de l'économie circulaire ?"

Pour répondre à cette question, les développements suivants ont été identifiés :

- Quel est l'état de l'art concernant le développement du système PHM pour les batteries Li-ion ?
- Quelle est la définition la plus appropriée sur l'état de santé dans le contexte de l'économie circulaire ?
- Comment surmonter les difficultés liées à l'hétérogénéité technique, les conditions d'utilisation variés et le fonctionnement dynamiques dans l'estimation SoH des batteries ?
- Quels types d'outils sont efficaces pour l'estimation du SoH de la batterie Li-ion ?
- Quelle est l'application industrielle du type du modèle proposé ?

A.0.5 Aperçu de la thèse

Dans le chapitre 1, le lecteur trouvera une brève présentation du projet interdisciplinaire « CIRCULAR » ainsi que son contexte et ses objectifs. Le chapitre 1 posera les questions de recherche traitées dans cette thèse.

Dans le chapitre 2, une vue d'ensemble d'une étude bibliographique est présentée. Le domaine de Pronostics Heath Management, les batteries lithium-ion et l'estimation de l'état de santé sont présentés à travers une étude détaillée des travaux existants.

Le chapitre 3 est dédié à la nouvelle définition de l'état de santé dans le contexte de l'économie circulaire. De plus, une classification des méthodes d'estimation de SoH est proposée. Ce chapitre est complété par la méthodologie proposée pour répondre aux défis de l'estimation de SoH pour Li-batteries.

Le chapitre 4 est consacré au développement de la méthode basée sur la prévision de séries chronologiques pour l'estimation de SoH de la batterie Li-ion. La méthodologie est détaillée ainsi que les modèles et outils utilisés. L'approche proposée a été testée sur les données de pronostic AMES de la NASA, et un cas d'utilisation a été créé. La discussion détaillée de l'étude de cas est présentée au chapitre 5.

Le chapitre 6 est une discussion contextuelle sur la création d'un cadre pour la réutilisation des batteries. Les exigences de réorientation, les interactions avec les parties prenantes, les réglementations et les certifications ont été discutées. Un cadre pour l'établissement d'un système de reconversion dans un contexte industriel est proposé. Cette chapitre a été réalisé en collaboration avec l'entreprise, Lancey Energie Storage qui s'intéresse à la seconde vie des batteries. Finalement, une réflexion sur le travail réalisé et les perspectives est formulée en termes de conclusion.

A.0.6 Conclusion

Ce travail de thèse apporte une contribution significative sur l'étude du PHM des batteries en fin de vie dédiées à une seconde vie. Les résultats identifient une définition contextuelle de leur état de santé ainsi qu'une nouvelle classification pour différentes méthodes d'estimation du SoH. Les travaux de cette thèse ont également permis de trouver une solution aux problèmes et aux défis posés lors de l'estimation SoH pour les batteries Li-ion.

La première contribution s'est concentrée sur le problème contextuel pour faciliter la réorientation de la fin de vie des batteries des VE en prédisant efficacement l'état de santé. A ce propos, nous avons proposé une définition contextuelle de l'état de santé mondial, qui tient compte à la fois de la capacité et la variation de puissance. Nous avons également proposé une classification des différentes méthodes d'estimation de SoH disponibles dans la littérature.

La deuxième contribution concerne les problèmes et les défis posés lors de l'estimation de SoH pour batterie Li-ion : le mécanisme de dégradation complexe, l'hétérogénéité technique, les conditions fonctionnement dynamique, et le modèle de conduite varié. Nous avons proposé une méthodologie basée sur un modèle de Markov caché pour surmonter ces obstacles et concevoir ainsi un PHM pour un modèle industriel dans le contexte d'économie circulaire.

La troisième contribution était un système d'estimation de SoH basé sur une courbe de capacité incrémentielle (IC) pour les batteries Li-ion. Le modèle a utilisé un filtre de Kalman et une méthode de différenciation finie pour atténuation du bruit de mesure. Une nouvelle approche qui combine la régression vectorielle de support (SVR) et le modèle de moyenne mobile intégrée autorégressive (ARIMA) a été utilisé pour modéliser la relation entre IC et SoH. Un cas d'utilisation a été créé sur l'open-source NASA AMES données de la batterie. L'étude de cas montre que le modèle proposé peut obtenir une prédiction précise du SoH sans avoir besoin des informations sur l'état de charge de la batterie. Ce modèle a également été comparé aux modèles de corrélation basés sur les réseaux neuronaux de régression linéaire et d'anticipation.

La contribution finale est basée sur les exigences relatives à l'établissement d'une batterie de seconde vie. Nous avons exploré les exigences de réaffectation, les interactions avec les parties prenantes, les réglementations et les certifications pour proposer un cadre pour la mise en place d'un système de reconversion dans un contexte d'économie circulaire.

Le résultat de cette thèse sera fructueux pour la conception d'un système d'aide à la décision dans l'Économie circulaire. De plus, il sera utile aux ingénieurs de batteries pour développer une nouvelle méthode d'estimation du SoH et ainsi améliorer les performances de la batterie. Une estimation SoH efficace aidera également dans la mise en place d'un système de réutilisation des batteries. De plus, un modèle comme celui-ci peut même être étendu à d'autres produits modulaires électroniques comme la machine à laver, le système de chauffage, etc.

Ce travail, qui identifie le verrou à lever dans le domaine du pronostic de l'état de la santé des batteries, est une première étape dans le cadre de l'économie circulaire. Il révèle une vaste domaine recherche à la fois ambitieuse et crédible. On peut citer ceux qui s'inscrivent dans la

continuité de ces travaux en utilisant les méthodes proposées et d'autres sur de vastes domaines d'application. D'abord, la mise en place d'un système d'aide à la décision dans l'économie circulaire apportera de la valeur ajoutée aux résultats obtenus dans cette thèse. C'est un travail qui pourrait être fait à court terme par l'utilisation de données de santé et performances développées pour les batteries dans la thèse.

A.0.7 Publications propres associées

- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., "First step towards the development of a Prognosis Health Management (PHM) System for Li-ion batteries: An FMMEA based approach.", ESREL (2019).
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., "Overcoming the Barriers in Diagnostics and Prognostics of the Circular Industrial System by Hidden Markov Model.", ICCAD (2019).
- Basia A., Dubois F., Kurt A., (in press), "Production of the future to support circular economy- development of a dedicated platform by means of a multidisciplinary approach.", ICCAD (2019)
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., "Review on State of Health estimation methodologies for lithium-ion batteries in the context of Circular economy", CIRP Journal of Manufacturing Science and Technology, Accepted (11 Feb 2021)
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., (accepted), "State of Health Estimation for Lithium-ion Battery by Incremental Capacity Based ARIMA - SVR Model", ESREL (2021).
- Basia A., Simeu-Abazi Z., Zwolinski P. & Gascard E., (accepted), "Comparison of data driven algorithms for SoH estimation of Lithium-ion batteries", ICCAD (2021)

"Evaluation of the State of the health of Li-ion batteries in the context of Circular Economy"

Résumé

Les batteries de véhicules électriques atteignent leur fin de vie (FdV) lorsque la capacité se dégrade de seulement vingt pour cent de la capacité d'origine. Un système industriel circulaire fiable peut être développé qui devrait être capable de transformer les batteries EV post-utilisées en de nouvelles batteries à valeur ajoutée pour des applications moins exigeantes. Prédire la fiabilité d'un système dans ses conditions réelles de cycle de vie et estimer son temps de défaillance (estimation de l'état de santé) est utile dans la prise de décision pour la nouvelle chaîne de valeur. L'objectif de cette thèse est de fournir des réseaux de capteurs fiables ainsi que des modules de recherche d'informations pour développer le plus précisément possible une méthode de diagnostic et de pronostic de santé des batteries lithium-ion dans le contexte de l'économie circulaire. Les résultats identifient une définition contextuelle de SoH et de nouvelles classifications pour différentes méthodes d'estimation de SoH. La thèse étudie également les problèmes et les défis posés lors de l'estimation du SoH pour la batterie Li-ion, avec des solutions possibles. Nous avons proposé un système d'estimation de SoH basé sur une courbe de capacité incrémentielle (IC) pour les batteries Li-ion. Une nouvelle méthode qui combine la régression vectorielle de support (SVR) et le modèle de moyenne mobile intégrée autorégressive (ARIMA) est utilisée pour modéliser la relation entre IC et SoH. Un cas d'utilisation est créé sur les données de batterie open source NASA AMES. Enfin, un cadre a été proposé pour établir un paysage commercial basé sur la réaffectation en explorant les tendances actuelles de réaffectation à travers le monde. Ce cadre a été créé sous la collaboration d'une société, Lancey Energy Storage.

Mots-clés : Économie circulaire, Diagnostic, Véhicules électriques, Batterie lithium-ion, Pronostic, État de santé

Abstract

The Electric Vehicle batteries reach its End of Life (EoL) when the capacity degrades by just twenty percent of the original capacity. A reliable circular industrial system can be developed which should be able to transform post-used EV batteries into new added-value batteries for less demanding applications. Predicting the reliability of a system in its actual life cycle conditions and estimating its time to failure (State of the health estimation) is helpful in decision making for the new value chain.

The objective of this thesis is to provide reliable sensor networks as well as information retrieval modules to develop as accurate as possible a diagnosis and a health prognosis method for lithium-ion batteries in the context of the Circular economy. The results identify a contextual definition of SoH and a novel classifications for different SoH estimation methods. The thesis also investigates the issues and challenges posed while estimating SoH for Li-ion battery, with possible solutions. We proposed an Incremental Capacity (IC) curve based SoH estimation system for Li-ion batteries. A novel method that combines Support vector regression (SVR) and the Autoregressive Integrated Moving Average (ARIMA) model is utilized to model the relationship between IC and the SoH. A use case is created on the NASA AMES open-source battery data. Finally, a framework has been proposed for establishing a repurposing based business landscape by exploring the current repurposing trends across the world. This framework has been created under the collaboration of a company, Lancey Energy Storage.

Keywords : Circular Economy, Diagnosis, Electric Vehicles, Lithium-ion battery, Prognosis, State of Health

