

CHAPTER I

INTRODUCTION

1.1 General Introduction

In today's rapidly advancing technological era, Li-ion batteries have emerged as the heart of global energy storage systems. It is undeniable that these batteries serve as the foundation for numerous innovations driving our daily lives, ranging from small portable devices like smartphones and tablets to large-scale industries such as EVs and smart grid systems. The preference for Li-ion batteries over other types stems from their superior characteristics, including high energy density, lightweight properties, and long operational lifespan, which perfectly meet the high-efficiency energy demands of the modern world.

However, despite their high performance, Li-ion batteries remain electrochemical devices with inherent natural limitations. As they undergo repeated usage and charging cycles over extended periods, degradation is inevitable. Internal chemical reactions gradually shift, leading to a decrease in energy storage capacity and an inability to deliver power as efficiently as when they were new. If this degradation is left unmonitored, it can lead to various risks, such as unexpected device shutdowns or, in severe cases, thermal runaway, which poses a safety hazard to users. For this reason, the BMS was developed to act as a controller and safety guardian. One of the most critical functions of the BMS is to estimate the SOH. Knowing the SOH is analogous to a health check-up, informing us of how much remaining life the battery has or what percentage of its efficiency remains. This information is vital for decision-making regarding maintenance planning, replacing batteries before failure, and ensuring that systems operate with maximum safety and cost-effectiveness.

1.2 Problem Statement

Currently, global warming and climate change have become urgent agendas prioritized by governments worldwide. Nations are collaborating through global initiatives such as the Paris Agreement and the United Nations' Sustainable Development Goals (SDGs) to reduce greenhouse gas emissions. These efforts are the primary drivers shifting the world from fossil fuels to clean energy, leading to an exponential rise in the demand for renewable energy and EVs. Consequently, the role of LIBs has become increasingly significant as the key enabler of this transition.

As battery usage creates a surge in demand, a consequential challenge arises regarding the management of aging batteries. Generally, when an EV battery's SOH falls below 80%, it is considered unsuitable for vehicle propulsion. However, these batteries still retain sufficient energy capacity to be utilized for other purposes, such as stationary energy storage for homes or buildings (Second-life applications). The problem lies in determining which batteries are still of good quality for reuse. Accurate SOH estimation is, therefore, essential to ensure that battery resources are utilized to their maximum economic potential while minimizing electronic waste.

Nevertheless, a major technical barrier existing today is "data complexity and volume." In real-world applications, modern battery systems continuously monitor and record status parameters such as voltage, current, and temperature at very high frequencies, generating massive amounts of Big Data. Processing all this raw data instantaneously to estimate SOH requires immense computational resources, which often exceeds the capabilities of the standard embedded chips found in vehicles or general devices. This leads to latency and excessive power consumption. This thesis aims to directly address this problem by introducing a resampling technique to reduce data size and complexity while preserving critical details. This approach allows for the effective application of Deep Learning technologies to estimate SOH quickly, accurately, and practically within resource-constrained systems.

1.3 Research Objectives

Building upon the challenges and limitations discussed previously, particularly regarding data complexity and computational constraints in battery management systems, this research aims to develop a robust and efficient framework for SOH estimation. The primary goal is to bridge the gap between high-accuracy theoretical models and practical implementation by integrating effective data management strategies with advanced deep learning techniques.

The main objectives of this thesis are as follows,

- 1) To apply a resampling technique to reduce the size and complexity of battery measurement data while preserving critical information necessary for accurate SOH estimation
- 2) To apply deep learning techniques for estimating the SOH of LIBs using multiple open-source datasets

1.4 Scope and limitations

1.4.1 Scope

The scope of this research is defined by the specific methodologies, datasets, and parameters selected for investigation, as detailed below:

1) Algorithms and Models: The study employs Deep Learning techniques, specifically LSTM, Bi-LSTM, GRU, and AM-LSTM. Additionally, GPR is utilized as a statistical baseline method (non-Deep Learning) to compare estimation performance.

2) Resampling Technique: A resampling approach is applied to reduce data size and complexity. The investigation covers specific resampling intervals for each dataset: 13 distinct intervals for the Oxford dataset and 8 distinct intervals for the NASA dataset.

3) Data Inputs: The study utilizes two open-source datasets (Oxford and NASA). The input features for all models are strictly derived from Voltage and Current measurements obtained during the charging and discharging cycles.

1.4.2 Limitations

The primary limitation of this research stems from its exclusive reliance on pre-existing open-source datasets rather than primary data generated through controlled laboratory experiments. Consequently, the researcher cannot control or modify the experimental conditions, such as ambient temperature, aging protocols, or discharge rates, as these factors were fixed during the original data collection. This implies that the findings and the developed models are inherently constrained by the specific physical characteristics and operational environments of the batteries in the Oxford and NASA datasets. Therefore, the models may not be directly generalizable to other battery chemistries or usage scenarios that differ significantly from the conditions recorded in these datasets without further retraining or adaptation.

1.5 Conception

The conception of this thesis is established upon a data-driven framework designed to optimize the SOH estimation process for LIBs. The core concept integrates Deep Learning techniques with a strategic Resampling approach. The fundamental idea is that by systematically reducing the sampling rate of raw voltage and current data, the computational complexity and data volume can be minimized without losing the critical electrochemical features such as ICA and AUC required for accurate health assessment. To realize this concept, the study utilizes reliable open-source datasets (Oxford and NASA) to simulate real-world degradation scenarios across different battery chemistries. The technical implementation and verification are conducted within the MATLAB environment, which serves as the primary platform for data preprocessing, model training, and performance evaluation. The overall conception aims to demonstrate that a simplified data structure, when processed by advanced neural networks, can achieve high estimation accuracy comparable to models using raw, high-resolution data. To realize this concept, the study utilizes reliable open-source datasets (Oxford and NASA) to simulate real-world degradation scenarios across different battery chemistries. The technical implementation and verification are conducted within the MATLAB environment, which serves as the primary platform for data preprocessing, model training, and performance evaluation. The overall conception aims to

demonstrate that a simplified data structure, when processed by advanced neural networks, can achieve high estimation accuracy comparable to models using raw, high-resolution data.

1.6 Research Benefits

Accurate estimation of battery SOH can significantly enhance the efficiency, reliability, and safety of battery management systems, contributing to the optimization of system performance and lifecycle management. By applying a resampling technique to simplify input data while preserving essential features, the proposed method is expected to reduce model complexity, improve computational efficiency, and facilitate the deployment of SOH estimation models in practical applications.

1.7 Structure of thesis

This thesis is organized into five chapters, outlining the progression from theoretical background to experimental validation and conclusion. The structure is defined as follows:

Chapter I: Introduction presents the general background, problem statement, research objectives, scope, limitations, and the conceptual framework of the study.

Chapter II: Literature Review and Theoretical Background provides a review of related literature and fundamental theories regarding LIBs and their degradation mechanisms. It also covers the basic principles of the deep learning algorithms used in this study and defines the evaluation metrics for performance assessment.

Chapter III: Impact of OCV Features on SOH Estimation investigates the effect of integrating OCV features into the estimation process. This chapter focuses on utilizing AUC and charging duration as input features for a LSTM model.

Chapter IV: SOH Estimation using Resampling Technique and Deep Learning details the core methodology of this thesis. It presents the application of the resampling technique to reduce data complexity and evaluates the performance of multiple deep learning models (LSTM, Bi-LSTM, GRU, AM-LSTM) and GPR using Oxford and NASA datasets.

Chapter V: summarizes the research findings, discusses the key contributions.