# Chapter 1

# Introduction

## 1.1 Background

In the modern world, the omnipresent threat of air pollution looms as a pressing concern, hurting both human health and the fragile balance of our ecosystem. The accelerating depletion of fossil fuels has intensified global concerns about energy scarcity. Simultaneously, rising carbon emissions have heightened awareness about climate change [1], [2]. Among various contributors, the transportation sector alone accounts for nearly one-third of global carbon emissions in the 21st century. The epicenter of air pollution's genesis resides primarily within the transportation sector [3]. Exploring alternative energy sources for transportation is essential to mitigate the effects of air pollution. In response, electric vehicles (EVs) have gained prominence as a sustainable alternative to mitigate these environmental challenges [4].

The growing need for sustainable energy solutions has spurred the need for effective energy storage devices (ESDs), which ensure a constant energy supply, increase grid stability, and allow the electrification of transportation and other sectors. Among the promising solutions are battery EVs and hybrid EVs. At the heart of EV technology lies lithium-ion batteries (LIBs), which play a crucial role in enhancing vehicle performance and supporting renewable-integrated energy storage systems (ESS) [5], [6]. LIBs are widely considered the top choice for storing energy in electric vehicles due to their high energy density, long cycle life, and low self-discharge rate [7], [8], [9].

To optimize the efficiency and reliability of LIBs in energy storage applications, real-time monitoring and predictive analytics have become essential. Crafting a state-of-the-art battery management system (BMS) is imperative to guarantee the secure and effective functioning of EVs. LIB packs are generally outfitted with a BMS, which comprises hardware and software responsible for managing various aspects of the battery [10]. A well-designed BMS performs critical functions such as monitoring battery health, estimating lifespan, balancing cell voltages, managing temperature, and fault diagnosis [11]. An EV battery pack typically comprises numerous cells, and each manufacturer's design possesses unique dynamic traits [12].

The overall performance of a LIB in a BMS is significantly influenced by its degradation, which is driven by chemical aging, charge-discharge cycles, and environmental factors. The battery capacity deteriorates as the battery ages from frequent charging and draining cycles, thereby increasing the internal resistance of the battery [13]. This deterioration affects the functionality of the battery pack, leading to catastrophic failure. Therefore, it is mandatory to have a health prediction of the battery, which will alert the user to take precautionary measures before system failure occurs. The lifetime of cells within the battery can be estimated using three important parameters: state of charge (SOC), state of health (SOH), and remaining useful life (RUL).

Supercapacitors (SCs), also known as electrolytic double-layer capacitors or ultracapacitors, are advanced ESDs that have received significant attention in recent years due to their unique properties and promising applications [14], [15]. SCs bridge the gap between conventional capacitors and batteries, offering high energy density compared to traditional capacitors and high power density compared to batteries. Due to these characteristics, SCs are becoming a viable substitute for conventional LIBs and capacitors [16]. Numerous sectors—including consumer electronics, automotive,

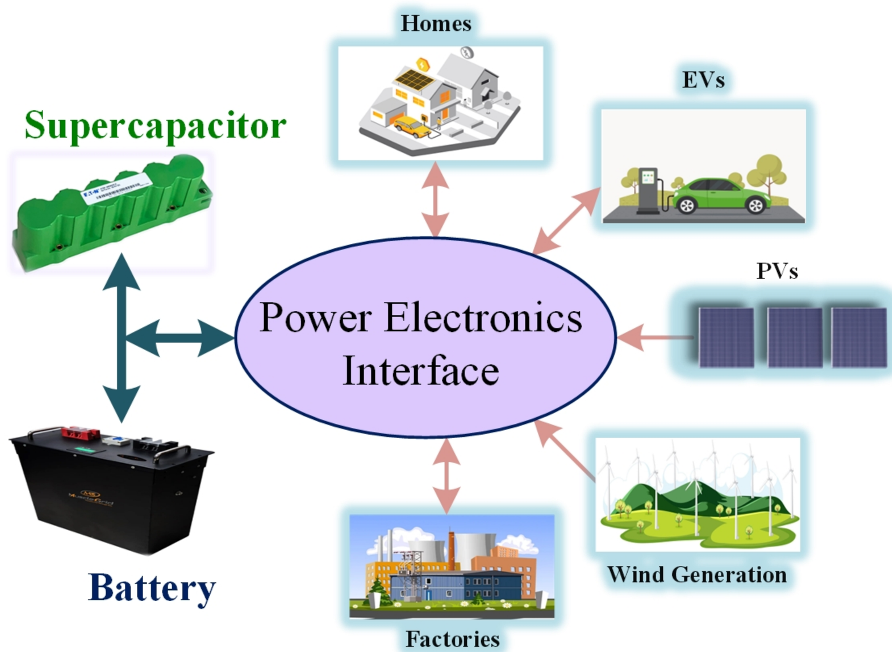


**Figure 1.1**: Applications of supercapacitors.

smart grids, renewable energy systems, and aerospace—rely on battery-integrated ESS utilizing SCs. These systems offer high power density, quick charging times, and long cycle life. Additionally, they can handle transient surge current requirements [17], [18], [19], as illustrated in Fig. 1.1. In hybrid storage systems, SCs can be paired with other energy storage components to increase the system's total current (I) and voltage (V), thereby improving the efficiency of energy usage.

The percentage of delivered energy to stored energy, or specific energy, indicates an SC's efficiency. Integrating the charging or discharging curve, respectively, yields the electrical energy that is either stored in or discharged from the SC device. An SC's efficiency is characterized by its specific energy, which represents the ratio of delivered energy to stored energy. The relationship between specific energy and specific power can be analyzed from the Ragone chart in Fig. 1.2. However, the electrochemical stability window of electrolytes sets a limit on the SC cell voltage. Therefore, to achieve the industrial application voltage level, it must be connected in series with other modules

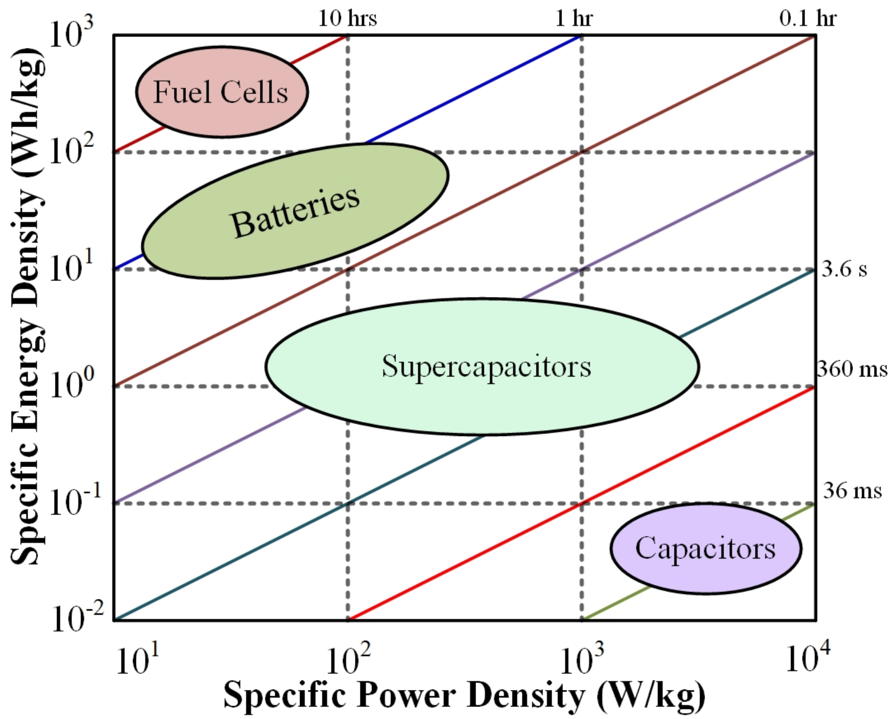


**Figure 1.2**: Ragone chart for different energy storage devices.

[20]. SCs are the favored component for many applications because of their long lifespan and minimal maintenance costs. Sensor nodes' lifespans can be increased by up to 20 years with SCs [21].

The lifetime of an SC is determined by a number of variables, including charging and discharging cycles, voltage and temperature (T) [22]. A SC can operate through thousands to millions of charge-discharge cycles before reaching its end of life. Cell degradation in an SC is characterized by either an increase in internal resistance or a decrease in capacitance [23]. Once it reaches its end of life, its performance deteriorates, which can negatively affect the efficiency and reliability of ESS [24]. Therefore, accurately estimating the RUL of SCs is essential for ensuring the secure and reliable operation of ESS across various applications [25].

The LIBs and SCs are energy storage elements with varying characteristic features, but both these storage elements face challenges in life estimation concerning ageing, degradation trends, and environmental conditions. Traditional approaches use lookup table-based methods [26], which have a direct mapping from various parameters to the output SOC, SOH, and RUL. Real-time parameter collection is challenging, and these tables can't capture the complex degradation characteristics of the ESS. One of the most widely used approaches for life estimation is model-based methods, where mathematical or physical models are defined to characterise the degradation pattern of these ESDs [27]. These methods often rely on predefined models and require significant domain knowledge. Furthermore, they struggle to capture the unseen complex, nonlinear relationships inherent in battery degradation processes. These conventional techniques for life estimation struggle to handle the multidimensional nature of degradation behaviour in ESS. They also cannot adequately account for environmental variabilities and the intricate interactions between electrochemical, thermal, and mechanical factors. Deep learning is now a potent tool that can automatically extract intricate patterns from high-dimensional data, adjust to nonlinear degradation behaviours, and produce more accurate predictions under a variety of operating conditions without the need for explicit feature engineering, thanks to the development of intelligent sensing and the availability of data [28]. Because of this feature, deep learning is especially well-suited to forecast ESD lifespan behaviour in situations when conventional techniques are ineffective.

A three-layer framework for real-time battery health analysis is shown in Fig. 1.3 [29]. The first layer comprises a photovoltaic unit, power electronics interface, battery, grid connection, and DC loads. This layer enables battery charging, grid connectivity, and power supply to DC loads. The second layer integrates an Internet of Things-based sensor for gathering data and monitoring essential parameters to ensure an accurate assessment of battery performance. The top layer employs artificial intelligence (AI)-powered algorithms to predict crucial battery metrics, including SOC, SOH, and RUL, leveraging both historical and current data.

These advanced AI-based techniques using hybrid deep learning models have advanced

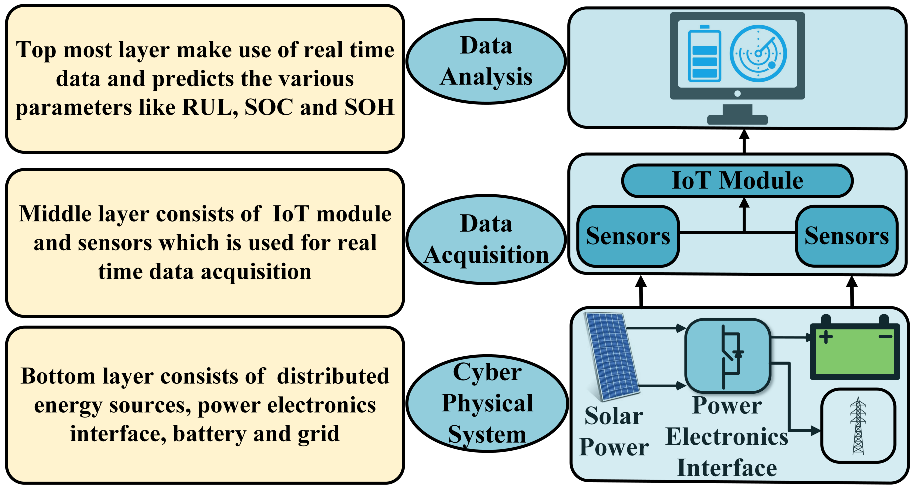


**Figure 1.3**: Three-layered framework for battery health analysis.

the life estimation in ESSs, but their inherent black-box nature poses a significant challenge to users and developers [30]. These models fail to give insights into the inner workings of the system and how these input features, like voltage variations, temperature conditions, charge, and discharge currents, affect the predicted final output. This non-transparent prediction makes it difficult for stakeholders to interpret, trust and understand the predictions in these energy storage applications.

To overcome this limitation, Explainable AI (XAI) methods are being integrated into ESS life prediction frameworks [31]. Of them, SHapley Additive exPlanations (SHAP) has become a potent instrument for improving the interpretability of models [32]. In order to help users comprehend which features influence the model's predictions for every unique energy storage case, SHAP offers both global and instance-level explanations. In addition to increasing trust in the model's dependability, this interpretability makes it possible to conduct in-depth feature impact analyses, allow focused debugging, and improve decision-making for ESS management and maintenance tasks.

## 1.2 Problem Formulation

The safe and reliable operation of ESS, including LIBs and SCs, requires accurate health prognostics and life estimation under varying operational and environmental conditions. The existing techniques have significant challenges in capturing complex multi-scale temporal deterioration patterns while retaining real-time performance under a variety of environmental conditions, charge/discharge rates, and aging mechanisms. Furthermore, typical black-box deep learning techniques are unable to offer clear insights into prognostic conclusions. As a result, the safety-critical nature of ESS necessitates not only excellent prediction accuracy but also model interpretability and trustworthiness. To address the practical requirements of model transparency in ESS and to confront the technical challenges associated with accurate prediction, this thesis aims to develop advanced, interpretable modeling frameworks. These frameworks are designed to effectively capture multi-scale temporal dependencies within degradation data while providing clear, explainable insights to support health prognostics and decision-making processes.

## 1.3 Scope of the Work

This thesis aims to enhance the dependability, safety, and intelligence of ESS through the development of precise and interpretable models for assessing the health of batteries and SCs. With the ever-growing demand for effective energy management in EVs, portable electronics, and in smart grid, robust and accurate life estimation of these ESS has become critical. This thesis focuses on three important health indicators in ESS, such as SOC, SOH AND RUL. The life estimation of these indicators is critical for ensuring optimal performance, avoiding unexpected failures, and extending the lifespan of these ESS. The scope of the thesis encompasses varying operating conditions for life estimation, including fluctuations in temperature, charge-discharge cycles, and load profiles, to ensure the proposed model's generalizability and suitability in real-world settings.

Another important dimension is the emphasis on the interpretability of the model. The transparency as well as the understanding of the inner process of the estimation of life in ESS are essential, as they are key components in so many safety-critical applications. By integrating the XAI-based interpretable techniques, the stakeholders can obtain valuable insights into the prediction process, as well as how the input parameters affect the predicted output value.

The datasets employed contain publicly available datasets and a lab-generated dataset under controlled conditions using hall sensors. The proposed model, along with the state-of-the-art works, is evaluated not only on the means of prediction accuracy, but also on the robustness, computational efficiency, and generalizability across various scenarios. Ultimately, the scope of this work encompasses the development and implementation of novel interpretable algorithms for intelligent ESS that provide scalable, reliable, and highly effective solutions for modern energy infrastructures.

## 1.4 Objectives

- Apply advanced novel hybrid deep learning models for robust and accurate SOC, SOH, and RUL prediction across varying operating conditions.
- Developing memory-efficient models with parameter efficiency, specifically designed for deployment in real-time datasets.
- Integrate XAI techniques to deliver transparent and reliable insights, thereby supporting critical decision-making processes in the management of ESS.
- Ensure cross-platform compatibility by validating the model's performance across diverse datasets, encompassing different battery types, manufacturers, and chemistry, thereby supporting scalability and generalization.

## 1.5 Preliminaries

This section provides a concise description of the fundamental health indicators used in ESS, such as SOC, SOH, and RUL; the XAI strategy for model interpretability; and the temporal modelling architectures employed in life estimation within ESS, which collectively form the foundation of the proposed prognostic systems.

### 1.5.1 Battery Health Metrics

The accurate life estimation in batteries and SC is critical for ensuring the safety, reliability, and longevity of the ESS. Three key metrics related to the life of these ESS are SOC, SOH, and RUL, and are discussed below.

#### 1.5.1.1 State of Charge

The SOC indicates the proportion of energy currently available in a battery relative to its total charge capacity [33]. It is commonly expressed as a percentage and serves a similar role to a fuel gauge in conventional vehicles, reflecting how much charge remains before the battery/supercapacitor needs recharging.

$$\text{SOC } (\%) = \left( \frac{Q_{\text{current}}}{Q_{\text{max}}} \right) \times 100\% \tag{1.1}$$

- $Q_{\text{current}}$ denotes the present amount of charge stored in the battery (Ah).
- $Q_{\text{max}}$ represents the maximum possible charge the battery can hold (Ah).

The SOC estimation being non-linear and dynamic, it is typically estimated through algorithms such as coulomb counting, model-based methods, or advanced data-driven methods [34].

#### 1.5.1.2 State of Health

The SOH provides an estimate of a battery's overall condition compared to its original, unused state [35]. It shows how much the battery has deteriorated as a result of aging, cycles of charge and discharge, or environmental conditions. SOH is crucial for assessing a battery's long-term safety and viability.

$$\text{SOH (\%)} = \left(\frac{Q_{\text{full}}}{Q_{\text{rated}}}\right) \times 100\% \tag{1.2}$$

- $Q_{\text{full}}$ is the battery's current full charge capacity (Ah).
- $Q_{\text{rated}}$ is the manufacturer's rated capacity when the battery was new (Ah).

A diminishing SOH implies decreased storage capacity and efficiency, making it an important statistic for maintenance planning and warranty considerations.

#### 1.5.1.3 Remaining Useful Life

The RUL estimates the number of cycles a LIB or SC can continue to operate before reaching its end-of-life (EOL) condition [36]. EOL is typically defined as the point at which the battery or SCs' SOH drops below a critical threshold.

$$\text{RUL} = N_{\text{EOL}} - N_{\text{current}} \tag{1.3}$$

- $N_{\text{EOL}}$ is the number of cycles to reach EOL.
- $N_{\text{current}}$ is the number of cycles already completed.

Predicting the RUL effectively allows for proactive maintenance and replacement plans, lowering the risk of abrupt failures and increasing the operational efficiency of ESS.

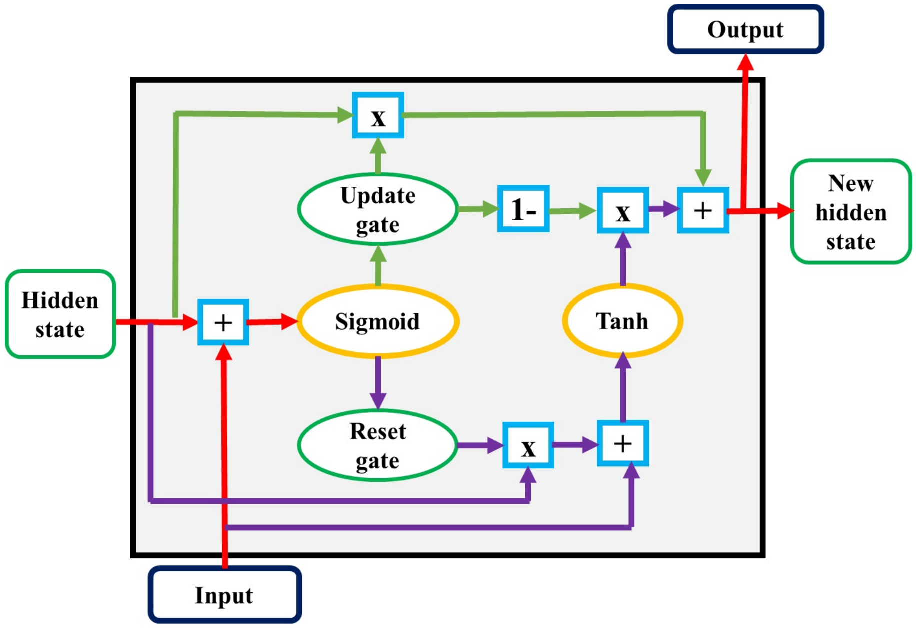


**Figure 1.4**: The structure of GRU cell.

### 1.5.2 Deep Learning Architectures employed for life prediction

#### 1.5.2.1 Gated Recurrent Unit

The gated recurrent unit (GRU) is a variant of the recurrent neural network (RNN) architecture that effectively captures the temporal dependencies in the degradation data within ESS. GRU with its gating mechanism effectively resolve the vanishing gradient issues in RNN architectures [37]. The architecture of GRU is shown in Fig. 1.4. The update gate decides how much past information is to be kept; meanwhile reset gate decides the information from previous memory that is to be forgotten. With this gating structure, GRU learn temporal dependencies from varying time scales, suited for time-series modeling in health prediction tasks. The architecture of the GRU is more compact compared to the long short-term memory (LSTM) network [38]. It uses fewer gates, resulting in a reduced number of parameters, while still achieving comparable performance in many applications.

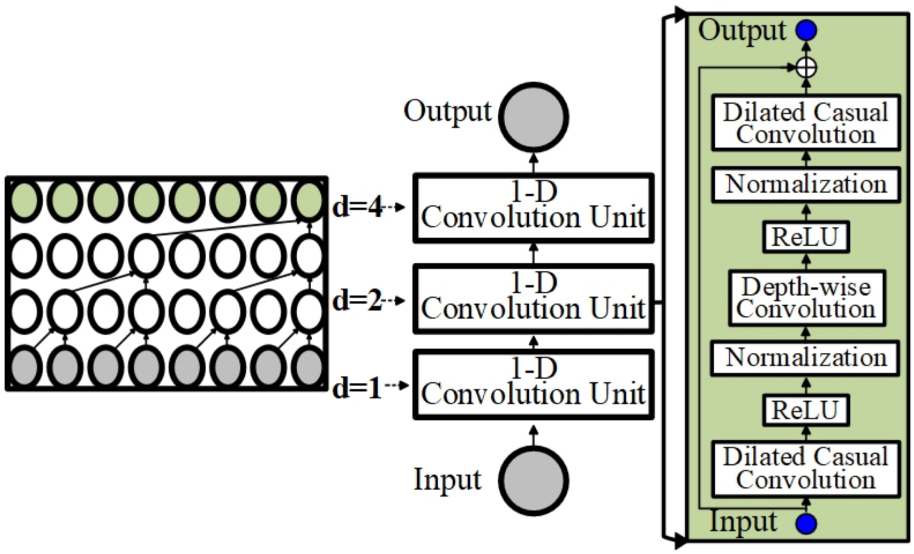


**Figure 1.5**: The architecture of dilated TCN.

#### 1.5.2.2 Temporal Convolutional Network

Temporal convolutional network (TCN) is a deep learning architecture highly suited for temporal modeling tasks [39]. TCN is not a memory-based model like GRU; rather, it serves as a pattern detector over time. The TCN scans over the input data sequence using the filters to detect the short-term and long-term patterns in the data. The architecture employs one-dimensional causal convolutions, which ensure current input at a given time step depends only on current and past input, not on the future. This prevents the leakage of data from the future [40]. The TCN architecture also has dilated convolutions, which allow the model to effectively capture long-range temporal dependencies by enabling the receptive field to expand exponentially with network depth. The residual connections in TCN help the model to train deeper without loss of critical information. A schematic representation of a typical TCN architecture is shown in Fig. 1.5. TCNs have demonstrated remarkable efficacy in time-series forecasting, anomaly detection, and life estimation applications because of their parallelism, stable gradients, and capacity to handle sequences of different lengths.

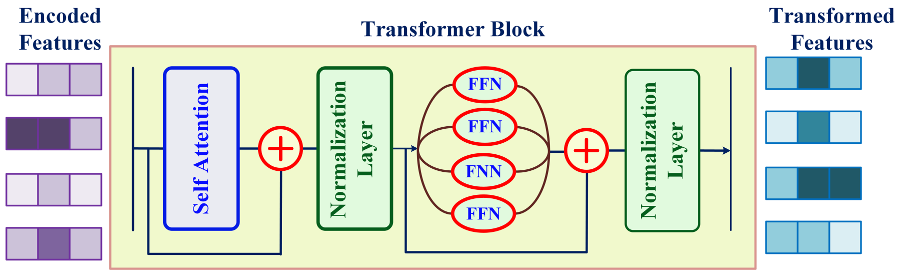


**Figure 1.6**: Transformer architecture.

#### 1.5.2.3 Transformers

The transformer is a neural network architecture that relies on attention mechanisms for modeling complex dependencies in time-series [41]. The Transformer block, which processes encoded input information through a number of layers, is the central component of the design, as shown in Fig. 1.6. In order for the model to assess the significance of each component in the sequence, a self-attention mechanism first records the contextual associations between input tokens. After passing through a normalization layer, the output is subjected to an independent feed-forward neural network for every point. In order to increase gradient flow and retain information, residual connections are introduced after both primary stages. The transformed features are output by a normalization layer at the end. The flexible design and parallel processing capabilities of the transformer make it a powerful tool for handling tasks such as time-series forecasting, natural language processing, and life prediction in ESS.

### 1.5.3 Explainable Artificial Intelligence

The AI-based models using deep learning excel in capturing the sophisticated degradation trends in ESDs. Still, the inner workings of these models are not clear to end-users as well as manufacturers. This is a serious problem in health monitoring, as a wrong decision could lead to a catastrophic failure of the application using these ESS. This is where XAI plays a key role in making these models transparent and understandable to end users. XAI describes techniques that make machine learning models' judgments more transparent and intelligible by assisting us in interpreting and explaining their behaviour [42].

In this dissertation, two common techniques for XAI are employed: SHAP and local interpretable model-agnostic explanations (LIME). SHAP shows the influence of the individual input feature on the model's final output prediction [43]. This indicates how the features such as voltage, current, temperature, or charge-discharge cycles contribute to the predicted life of these batteries or SC and by how much. By displaying the aggregate impact of each feature across the entire dataset, SHAP not only explains individual predictions but also offers global interpretability, which aids in determining the most important factors in the model's learning process. Meanwhile, the XAI technique-LIME works by varying the input timeseries data and observing how the output prediction for the model changes with this variation [44]. This gives an understanding of prediction for an individual instance, without having an understanding of the complex deep learning models.

By using SHAP and LIME, the user as well as the developers can gain insights into the inner workings of the model by making the prediction process understandable and interpretable.

## 1.6 Contributions

The overall structure of this thesis is presented in Fig. 1.7. It consists of an introduction, a literature review, four contributing chapters, and a section on conclusion and future enhancements, each of which is briefly outlined below.

**Chapter 1** presents an introduction to life estimation in ESD, along with the background, scope of the thesis, methodologies employed for life estimation in energy storage elements, research objectives, and a summary of the significant contributions.

**Chapter 2** provides a detailed overview of various techniques used for estimating

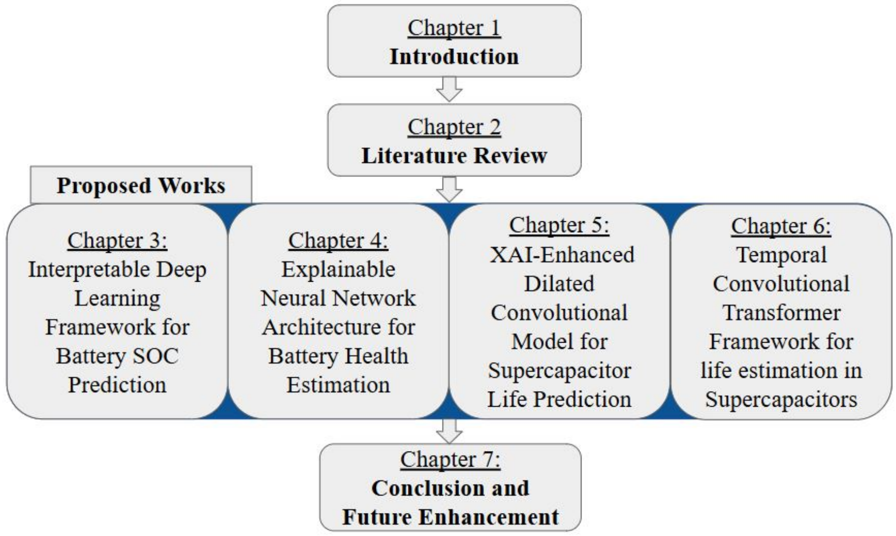


**Figure 1.7**: Layout of the Thesis.

SOC, SOH, and RUL, including a literature survey of existing deep learning and machine learning approaches. The chapter concludes by identifying key research gaps in the current body of work.

**Chapter 3** presents a novel multi-head dilated temporal convolutional network (MHDTCN) architecture that effectively captures multiscale temporal features through multiple heads with varied dilation rates. By integrating a GRU layer, the model further captures sequential dependencies in battery data, resulting in a hybrid MHDTCN-GRU framework that delivers reliable and accurate SOC estimation. Additionally, SHAP-based interpretability is employed to identify influential features under varying temperature conditions, enhancing transparency and trust in the model's predictions

**Chapter 4** introduces a multi-faceted temporal convolutional network with dynamic weight adaptation (MFDWA) along with GRU, that captures short-term fluctuations as well as long-term degradation trends in LIB data, enabling robust and accurate SOH prediction, even from early-stage capacity fade data. This memory-efficient hybrid model performs well in varying prediction scenarios across diverse battery types. The addition of SHAP in the proposed model enhances interpretability and transparency and also highlights the key input features for health prediction in batteries.

**Chapter 5** proposes a novel customized dilated temporal convolutional network (CDTCN) that captures multiscale temporal patterns in SC data through branches with varied customized dilation rates. The proposed hybrid CDTCN-GRU model demonstrates superior predictive accuracy for RUL estimation, while the integration of SHAP-based explainability—applied for the first time in supercapacitor analysis—enhances model transparency by identifying key features influencing degradation behavior.

**Chapter 6** presents a hybrid temporal convolutional transformer (TCT) architecture that combines the localized pattern learning of TCN with the global attention capabilities of transformers for robust SC degradation modeling under varying conditions. The framework demonstrates improved predictive accuracy and training stability through adaptive attention, residual connections, and parallelized computation, outperforming traditional hybrid models.

**Chapter 7** concludes the research findings and outlines the possible directions to expand the work to more challenging dimensions in the future.

In summary, Chapter 1 highlights the critical importance of accurate life estimation in energy storage systems, emphasizing SOC, SOH, and RUL as key indicators for safe and efficient operation of batteries and supercapacitors. It underscores the limitations of traditional approaches in capturing complex, nonlinear degradation patterns and motivates the adoption of advanced deep learning models, complemented by XAI techniques such as SHAP and LIME to ensure transparency and trust. The chapter also outlines the objectives and contributions of the thesis, focusing on developing robust, interpretable, and memory-efficient prognostic frameworks applicable to real-world conditions. Building on this foundation, Chapter 2 presents a comprehensive literature review of existing life estimation methods, critically evaluating current machine learning and deep learning approaches while identifying the research gaps addressed in this work.