UNIVERSITI TEKNOLOGI MARA

PREDICTING BATTERY HEALTH AND REMAINING USEFUL LIFE BY INTEGRATING HYBRID SUPERVISED MACHINE LEARNING FOR ENERGY STORAGE SYSTEMS

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ABSTRACT

The rapid global adoption of Battery Energy Storage Systems (BESS) has amplified the need for accurate battery health management. Predicting the State of Health (SoH) and Remaining Useful Life (RUL) is critical for ensuring operational safety, optimizing performance, and extending battery lifespan. A significant challenge in this field is the discrepancy between predictive models trained on pristine laboratory data and the noisy, stochastic nature of real-world battery signals, which can obscure subtle degradation trends and lead to unreliable predictions. Current approaches often treat signal denoising and predictive modelling as disconnected stages, which can result in suboptimal performance. This research addresses this gap by proposing and systematically evaluating an integrated hybrid framework designed to function robustly under a realistic denoising condition. To create a realistic testbed, this study utilized the benchmark NASA PCoE battery dataset (B0005, B0006, B0007) and injected controlled additive Gaussian noise specifically into the voltage signals to imitate real sensor errors. Then, this study systematically evaluated noise data in nine distinct hybrid prognostic models, where the signal processing techniques were applied independently to voltage and current signals. These models were created by combining three signal processing techniques Wavelet Transform (WT), Kalman Filter (KF), and Empirical Mode Decomposition (EMD) with three supervised machine learning algorithms: Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). From all of this, we developed the combination of WT-SVM, WT-LSTM, WT-GRU, EMD-SVM, EMD-LSTM, EMD-GRU, KF-SVM, KF-LSTM, and KF-GRU. The performance of each combination was rigorously assessed under noisy conditions using a suite of metrics, including Root Mean Squared Error (RMSE), Regression, and the accuracy of RUL predictions. The comprehensive analysis unequivocally identified the WT-SVM combination as the superior methodology. This model demonstrated exceptional robustness and accuracy under noisy conditions across all batteries and noise levels, achieving the lowest overall prediction error. For the challenging B0007 battery near its end-of-life, the WT-SVM model yielded a remarkable RMSE of just 0.0022 and a perfect RUL prediction. The success of the WT-SVM framework establishes a new state-of-the-art performance benchmark and provides a clear, evidence-based methodology for developing highly reliable battery management systems for real-world applications.

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LIST OF ABBREVIATIONS

Abbreviations

BESS	Battery Energy Storage Systems
BMS	Battery Management Systems
CNN	Convolutional Neural Networks
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
EoL	End-of-Life
ESS	Energy Storage System
EVs	Electric Vehicles
GHGs	Greenhouse Gases
GRU	Gated Recurrent Units
KF	Kalman Filter
LIBs	Lithium-Ion Batteries
LSTM	Long-Short Term Memory
RUL	Remaining Useful Life
SNR	Signal-to-Noise Ratio
SoH	State of Health
SoTA	State-of-The-Art
SVM	Support Vector Machines
WT	Wavelet Transform

CHAPTER 1

INTRODUCTION

1.1 Research Background

Tackling carbon emissions is a critical global priority for combating climate change and promoting sustainable growth. Greenhouse gases, largely from human activities like using fossil fuels, are trapping heat in the atmosphere and raising global temperatures. This warming trend is intensifying extreme weather events such as hurricanes and droughts, which have severe effects on our environment, economies, and health (Ahima, 2020). Consequently, nations are actively pursuing strategies to reduce emissions and adopt environmentally sound practices. This initiative is vital for lessening the impacts of climate change and also for ensuring the future stability and sustainability of the world's energy systems.

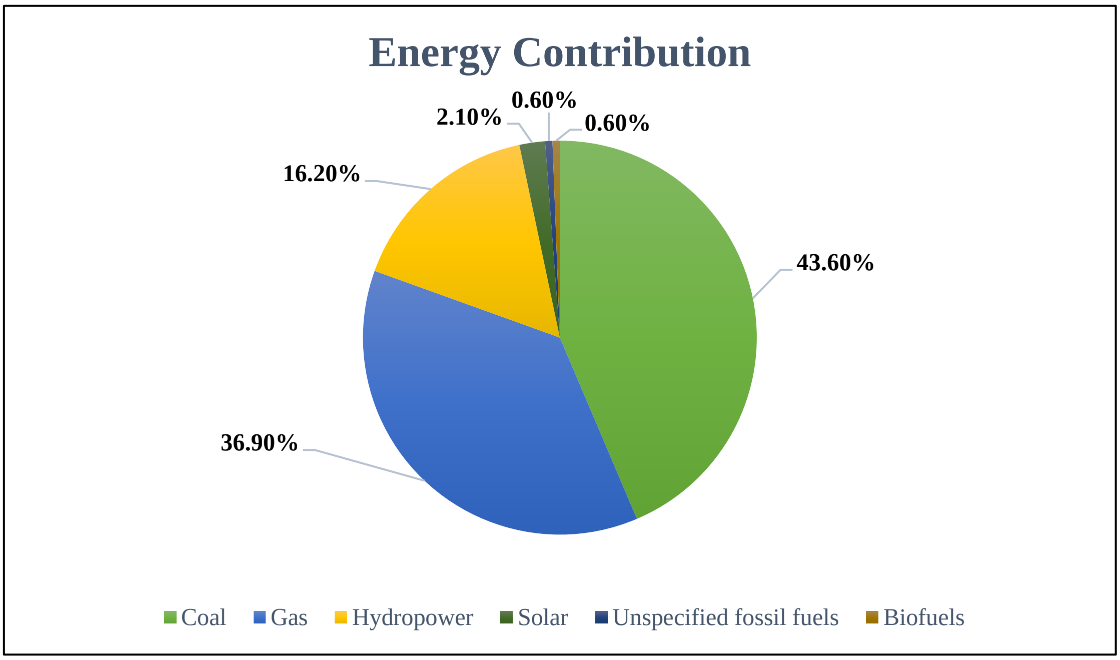

Figure 1.1 Renewable Energy Classification

Table 1.1
Electricity Generated in Malaysia in 2024

Energy Sources	Energy Contribution(%)
Coal	43.6
Gas	36.9
Hydropower	16.2
Solar	2.1
Unspecified fossil fuels	0.6
Biofuels	0.6

The primary source of Malaysia's electricity consumption in 2024 more than 80% of it is fossil fuels. Both gas and coal, which are classified as fossil fuels, make up roughly 37% and 44% of the total. Meanwhile, about 19% of Malaysia's electricity comes from low-carbon sources. With just over 16% of the total, hydropower is the highest contribution, followed by solar energy with slightly over 2% (*Malaysia Electricity Generation Mix 2024 | Low-Carbon Power Data*, n.d.). This suggests that Malaysia's power still primarily comes from fossil fuels, which calls for the expansion of low-carbon alternatives in order to lessen its negative effects on the environment and support sustainable development as shown in Figure 1.1 and .Table 1.1.

A primary strategy in this effort is the widespread use of renewable energy, particularly solar and wind power. These sources offer a clean alternative to carbon-emitting fossil fuels, which are a major cause of pollution (Osman et al., 2023). While renewable systems generate electricity with minimal environmental impact, they face a major hurdle: their output is inconsistent because it depends on variable weather compared to traditional way in power generation. Solar energy production drops on cloudy days or at night, and wind turbines are ineffective in calm weather. This fluctuation in power generation creates significant difficulties for integrating renewables into energy grids that demand constant stability and reliability, hindering their widespread adoption (Ahmed et al., 2020).

To address these challenges, reliable energy storage solutions are essential for ensuring a steady and dependable supply of power. Batteries, in particular, have emerged as one of the most effective technologies for energy storage. They have the capacity to store excess energy generated during periods of peak production, such as sunny or windy days, and release it during periods of high demand or when renewable energy generation is low. This ability to balance supply and demand is critical for maintaining grid stability and supporting the seamless integration of renewable energy sources into the energy infrastructure (Falope et al., 2024).

Integrating renewable energy systems with efficient energy storage technologies can pave the way for a sustainable and resilient energy infrastructure. Such integration not only addresses the variability of renewable energy generation but also enhances the overall reliability of the power grid (Bamisile et al., 2024). This approach supports a broader global transition to a low-carbon economy by ensuring that clean energy sources can meet the energy demands of modern societies without interruptions. Additionally, advancements in battery technologies, such as improved energy density, longer lifespan, and cost reductions, have made energy storage solutions increasingly viable for large-scale deployment (Mu et al., 2023).

In conclusion, the global transition to renewable energy systems represents a pivotal step towards reducing carbon emissions and mitigating climate change. By addressing the challenges of energy generation variability through innovative energy storage technologies, it is possible to create an energy system that is both sustainable and resilient. This effort supports the broader goal of achieving sustainable development while minimizing the environmental impact of energy production. As nations and industries continue to invest in renewable energy and storage solutions, the vision of a low-carbon future becomes increasingly attainable, bringing us closer to a healthier and more sustainable planet.

1.2 Motivation for This Work

The rapid adoption of electric vehicles (EVs) and renewable energy storage systems underscores the growing reliance on lithium-ion batteries, which serve as critical components in these applications. Compared to traditional internal combustion engines, EVs provide a cleaner and more sustainable transportation option. However, the increased demand for batteries has also increased concerns regarding their lifespan, performance, and the environmental implications of battery manufacturing and disposal. Addressing these issues needs innovative approaches to optimize battery usage, minimize waste, and enhance sustainability. This research aims to contribute to the development of predictive tools that can provide actionable insights into battery health and remaining useful life (RUL), thus enabling proactive measures to extend battery longevity.

Effective battery health monitoring and RUL prediction are essential for ensuring reliability and cost-efficiency in EVs and energy storage systems. Unexpected battery degradation can lead to operational inefficiencies, higher maintenance costs, and a reduced user experience. By integrating advanced computational techniques signal processing and machine learning, this research seeks to develop a robust framework for accurately predicting battery health. The integration of these methods allows for the extraction of meaningful features from complex battery data and the modelling of nonlinear degradation patterns. Such predictive capabilities can help stakeholders, including manufacturers and end-users, make informed decisions regarding battery usage and replacement.

The motivation for this work also lies in its potential to support the transition toward a sustainable energy ecosystem. By enhancing battery lifespan through predictive analytics, this research contributes to reducing the frequency of battery replacements and the environmental burden of battery production and disposal. Furthermore, improving the reliability and efficiency of batteries in EVs and energy storage systems can accelerate the adoption of clean energy technologies, aligning with global efforts to combat climate change. This work not only addresses immediate challenges in battery management but also paves the way for more sustainable and efficient energy solutions in the future.

1.3 Problem Statement

In real-world scenarios such as Battery Energy Storage Systems (BESS), battery health signals are often contaminated by environmental and operational noise. One of the common noises is Gaussian noise. Gaussian noise, characterized by a normal distribution of amplitude variations, is introduced into battery voltage and current measurements due to random thermal fluctuations in the sensing and signal acquisition circuitry (Weber et al., 2019a). However, widely used public datasets, including NASA's B0005, B0006, and B0007, are typically clean and do not feature the stochastic disturbances present in actual field data. This discrepancy creates a significant gap between simulation-based research and real-world applicability, as predictive models trained on pristine data may exhibit poor generalization and fail when deployed in live systems (Pozzato et al., 2023). Therefore, there is a critical need to first develop a more realistic representation of battery degradation by systematically injecting controlled noise into these clean datasets to better replicate challenging operational environments.

The presence of such noise in State-of-Health (SoH) signals severely degrades the performance of predictive analytics, making accurate RUL prediction a significant challenge. While various signal processing techniques like Wavelet Transforms (WT), Kalman Filter (KF), and Empirical Mode Decomposition (EMD) exist for denoising, and machine learning models like Support Vector Machines (SVM), Long-Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) are used for prediction, these are often treated as separate steps (D. Wu et al., 2021). This separation overlooks the critical interplay between the filtering process and the learning behaviour of the predictive model (D. Zhou & Wang, 2022). Consequently, there is a clear need to design an integrated, hybrid technique that combines the signal-preserving strengths of WT with the robust predictive power of a Support Vector Machine (WT-SVM) to create an end-to-end pipeline specifically tailored for RUL prediction from noisy data.

Finally, while a hybrid WT-SVM model is a promising approach to address the dual challenge of noise and prediction, its actual effectiveness and robustness remain unverified. It is crucial to determine how well such a model performs not just in a single scenario, but across a spectrum of challenging conditions that simulate varying levels of signal corruption. Without a systematic assessment, the true capabilities and limitations of the proposed model cannot be confirmed. Therefore, a comprehensive evaluation is essential to validate the effectiveness of the WT-SVM technique in accurately predicting RUL specifically when subjected to the various noise conditions it was designed to overcome. This validation will be conducted by systematically comparing the performance of the proposed WT-SVM framework against eight alternative hybrid combinations, including WT-LSTM, WT-GRU, EMD-SVM, EMD-LSTM, EMD-GRU, KF-SVM, KF-LSTM, and KF-GRU. By evaluating these models across different batteries and noise intensities using quantitative metrics such as Root Mean Squared Error (RMSE) and regression analysis, the study will provide a rigorous benchmark to establish the superior accuracy and reliability of the WT-SVM approach in real-world prognostic applications.

1.4 Research Objectives

1. To develop a realistic signal of battery degradation conditions into the original NASA battery datasets (B0005, B0006, B0007) by injecting Additive Gaussian Noise (AGN).
2. To design a hybrid filtered machine learning technique based on WT-SVM for predicting the RUL of lithium-ion batteries.
3. To evaluate the effectiveness of WT-SVM in predicting the RUL of lithium-ion batteries under various noise conditions.

1.5 Research Question

1. How does the introduction of simulated disturbance noise into clean battery datasets impact the predictive accuracy of machine learning models, and which signal processing technique (EMD, WT, or KF) is most effective at mitigating these effects?
2. Among the evaluated machine learning algorithms Long-Short Term Memory (LSTM), SVM, and Gated Recurrent Units (GRU), which model demonstrates the most robust and accurate performance in predicting battery RUL when trained on data filtered by an optimal signal processing technique?
3. What is the optimal hybrid combination of a signal processing filter and a machine learning model that yields the lowest prediction error and highest reliability for battery SoH and RUL estimation across different degradation profiles?

1.6 Significance of Study

This study offers significant contributions to the field by addressing these challenges through an innovative integration of signal processing and machine learning techniques.

1. Enhancing Predictive Accuracy through Hybrid Modelling: This study provides a systematic framework for integrating signal processing with machine learning, demonstrating that the right hybrid combination can significantly improve the accuracy of RUL and SoH predictions over standalone models, leading to more reliable battery management.

2. Identifying Optimal and Suboptimal Methodologies: The research identifies a superior predictive model (WT-SVM) while also issuing a critical warning against potentially detrimental techniques (e.g., over-smoothing with a KF). This provides clear, evidence-based guidance for engineers and researchers in selecting appropriate prognostic tools.
3. Improving Safety and Operational Efficiency: By enabling more accurate RUL predictions, this work contributes to the development of safer and more reliable energy systems. For EVs and BESS, this translates to a reduced risk of unexpected failures, optimized maintenance scheduling, and lower operational costs.
4. Supporting Sustainable Energy and Circular Economy: More accurate battery health monitoring extends the operational lifespan of batteries and facilitates their effective repurposing for second-life applications. This reduces waste, conserves resources, and supports the broader goals of a sustainable energy transition and a circular economy.

In conclusion, this study not only contributes to advancing the state-of-the-art in battery health monitoring and RUL prediction but also has far-reaching implications for the development of sustainable and reliable energy storage solutions. Its findings will benefit academia, industry, and society by addressing critical challenges in battery management for energy storage and electric vehicle systems.

1.7 Project Scope

This study covered several parts of the techniques on predicting battery health and RUL, scope of the study is;

1. Simulating Realistic Degradation Scenarios: The research is conducted entirely within a simulation environment using MATLAB; it is limited to computational modelling and does not involve physical hardware experiments or live battery testing. The study is confined to the NASA PCoE battery datasets (B0005, B0006, B0007), which are derived from controlled lab-testing battery data rather than real-world field-deployed units. It involves artificially injecting Gaussian noise into these datasets to create a realistic testbed that emulates the noisy conditions of real-world applications.

2. Comparative Analysis of Hybrid Models: The study systematically evaluates nine hybrid prognostic models, developed and executed within the MATLAB programming environment. These are created by combining three signal processing techniques (EMD, WT, KF) with three machine learning algorithms (LSTM, SVM, GRU) to identify the most effective pairing for battery health prediction under noise-corrupted conditions.
3. Performance Evaluation and Validation: The assessment of model performance is based on a defined set of quantitative metrics, including Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Analysis of Variance (ANOVA), and regression. This ensures a rigorous and objective comparison of prediction accuracy between the different algorithmic combinations.
4. Study Limitations: This research is bounded by several constraints. Firstly, it focuses exclusively on Gaussian noise as the primary stochastic disturbance, which may not account for all types of electromagnetic interference found in the field. Secondly, as the work is simulation-based and relies on laboratory-tested battery benchmarks, the findings are specific to the lithium-ion chemistries and discharge profiles provided in the NASA dataset and may require further adaptation for different battery chemistries or extreme environmental variations.

1.8 Thesis Outline

Based on the provided outline and details from the proposal, here's a brief overview of each chapter:

Chapter 1: Introduction

Based on the literature, this chapter presents the description of transition world to the clean or renewable energy and its relevance to Sustainable Development Goals. Since high demand on battery manufacturing, the paper looks at how this problem can be solved, and one of them is performing battery prediction. In the chapter, the reader is introduced to the research background, problem statement, research objectives, justification of the study and the extent of the research.

Chapter 2: Literature Review

This literature review focuses on type of energy storage, main user of battery, battery lifespan and techniques on prediction of battery health. It has examples showing the few techniques approached to predict battery health. Finally, on the aspect of maximum demand, the review proceeds to choose the most appropriate method (battery health prediction).

Chapter 3: Methodology

This chapter presents the research methods applied to the project and the creation of the system approached on battery prediction. This describes how the method of research being conducted based on the research plan. The application of this technique guarantees a structured and repeatable procedure to produce accurate and dependable battery health prediction findings.

Chapter 4: Result and Discussion

This chapter presents and analyses the results obtained from the application of battery health prediction methods. It includes data pre-processing outcomes, model performance evaluation, and the interpretation of the predicted results compared to actual battery degradation behaviour. This chapter further compares the findings with previous studies and provides insights into the potential of the method for improving battery management systems, especially for electric vehicles and stationary energy storage applications.

Chapter 5: Conclusion

This final chapter summarizes the key findings of the study in relation to the research objectives stated in Chapter 1. It concludes whether the proposed battery health prediction approach successfully addressed the problem identified and to what extent the research contributes to the broader goals of sustainable energy transition. The chapter reinforces the importance of battery prediction systems in achieving greater energy efficiency and supporting the goals of Sustainable Development Goals (SDGs), especially in responsible consumption and climate action.

1.9 Summary

In conclusion, this chapter has provided an overview of the pressing global challenge of reducing carbon emissions and the critical role renewable energy systems play in mitigating climate change. The increasing adoption of EVs and BESS underscores the need for efficient battery management solutions to address challenges such as battery health degradation and RUL prediction. The research objectives and questions outlined in this chapter aim to tackle these challenges by integrating advanced techniques (EMD, WT and KF) and (LSTM, SVM, GRU) neural networks. By defining the scope, significance, and limitations of this study, this chapter establishes the foundation for developing innovative solutions to enhance the reliability and sustainability of battery technologies, thereby supporting the global transition to a low-carbon economy.

The next chapter delves into a comprehensive review of the existing literature on battery technologies, energy storage systems, and methods for predicting battery health and RUL. It explores various energy storage types, the primary users of batteries, and the factors influencing battery lifespan. Additionally, the chapter evaluates different prediction techniques, highlighting their advantages and limitations, to identify the most suitable approach for this study. This literature review will provide critical insights and justify the selection of methodologies employed in this research.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Batteries and energy storage system (ESS) are essential for managing the challenges associated with renewable energy sources like solar and wind, which can produce fluctuating amounts of electricity depending on weather conditions (Z. Zhu, Jiang, et al., 2022). They work by storing extra energy generated during times of high production, such as sunny or windy days, and releasing it when the demand for electricity is higher than the supply (May et al., 2018). This process helps to balance the electricity supply and demand, ensuring a stable and reliable energy grid (Razmjoo et al., 2021). Moreover, using battery storage systems allows renewable energy to be used more efficiently, minimizing waste and reducing the need to rely on fossil fuels during periods of low renewable generation. As a result, this integration not only improves the stability and reliability of renewable energy systems but also plays a significant role in lowering carbon emissions, supporting the global shift towards cleaner and more sustainable energy solutions (Vishwakarma et al., 2022).

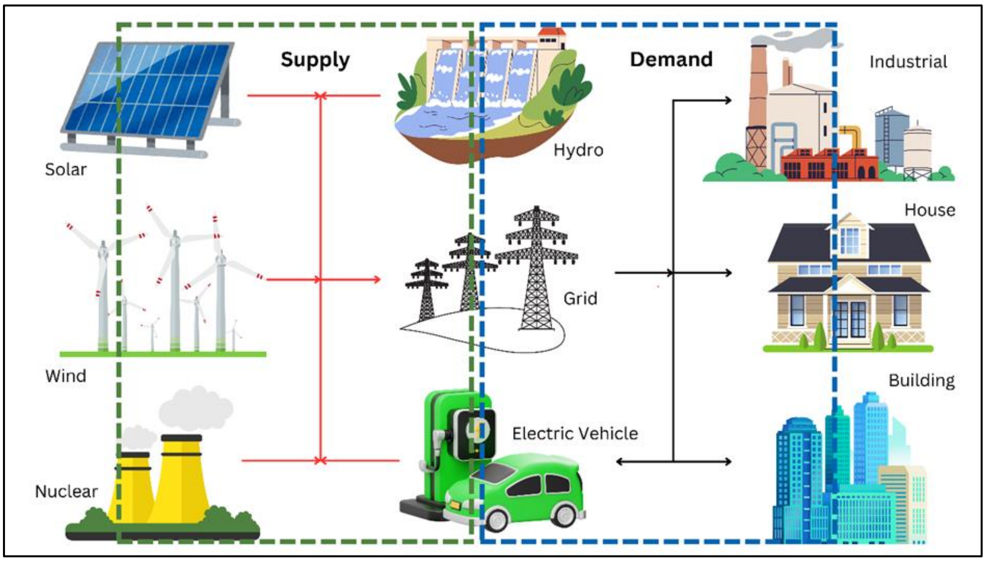

Figure 2.1 Smart Grid Structure

By promoting stability in the electrical grid by balancing the supply and demand of electricity, these systems are especially helpful in managing the irregularities in power generation and consumption, particularly during times of high demand, known as peak load periods (*Grid Integration of Renewable Energy | PNNL*, n.d.). By storing excess energy generated during periods of low demand and releasing it when demand increases, energy storage systems help reduce sudden fluctuations in electricity supply. This function allows power companies to maintain stable frequency and voltage levels, which are vital for preventing power outages and ensuring a steady and reliable electricity supply (*Integrating Renewable Energy Sources into Grids | McKinsey*, n.d.). Additionally, energy storage reduces reliance on backup power sources, often supplied by utilities, leading to improved energy efficiency (Lehtola & Zahedi, 2019). By utilizing stored energy during high-demand periods, these systems optimize the use of available resources, minimize energy wastage, and contribute to a more sustainable approach to energy management (Neeraj et al., 2023).

In recent years, the energy industry has undergone a significant transformation with the shift toward decentralized energy systems (Hassan et al., 2023). Unlike traditional power systems that rely on centralized power plants and extensive transmission networks, decentralized energy systems generate and store energy closer to where it is consumed. This approach minimizes energy losses that occur during long-distance transmission and enhances energy resilience, particularly in remote or disaster-prone regions (Parra & Patel, 2019). For example, homes, businesses, and communities can now utilize local energy sources, such as solar or wind, along with battery storage systems to increase their self-sufficiency. These advancements reduce dependence on centralized power grids, enabling a more reliable and sustainable energy supply.

ESS play a vital role in supporting demand response programs. These programs encourage consumers to adjust their energy consumption during peak demand periods by responding to market signals, such as changes in electricity prices (Nowbandegani et al., 2022). Batteries facilitate this process by charging during times when electricity prices are low and discharging during high-price periods. This not only helps consumers save on energy costs but also contributes to balancing the overall demand on the energy grid (T. Chen et al., 2020a). By participating in demand response programs, businesses and households can support grid stability while benefiting financially.

In remote and off-grid areas, the combination of renewable energy sources and battery storage systems offers a practical and sustainable solution to energy access challenges. Many of these regions face difficulties in extending grid infrastructure due to geographical or financial constraints. Batteries allow for the storage of renewable energy generated locally, such as solar and wind power, ensuring a continuous and reliable power supply even when weather conditions are unfavourable (Marocco et al., 2020). This improved energy access enhances the quality of life by powering healthcare facilities, schools, and homes, fostering better living conditions and supporting social development. Moreover, by reducing reliance on diesel generators or coal-fired power plants, these systems contribute significantly to lowering carbon emissions and promoting cleaner energy solutions (Ziegler, 2021).

In industrial settings, battery energy storage systems are essential for efficient energy management. One common application is peak shaving, which involves using stored energy during periods of high electricity demand to reduce peak loads (Rostamnezhad et al., 2023). This strategy helps businesses lower their electricity bills while simultaneously alleviating stress on the power grid (Danish et al., 2020). Industries with high energy demands, such as manufacturing facilities and data centres, rely on battery storage systems to ensure smooth operations and improve reliability. These systems also provide backup power during outages, enhancing operational resilience (Elio et al., 2021).

The development of advanced battery technologies has been a driving force behind the growing adoption of energy storage systems. Innovations such as solid-state batteries and flow batteries are paving the way for more efficient and durable energy storage solutions (Darlington Eze Ekechukwu & Peter Simpa, 2024). These advanced batteries offer several advantages, including longer lifespans, faster charging times, and higher energy densities. As a result, they are becoming increasingly cost-effective and versatile, making them suitable for a wide range of applications (J. Lee et al., 2024). By improving the performance and affordability of batteries, these advancements are also stimulating economic growth and fostering innovation in the energy sector.

Furthermore, the widespread use of battery energy storage systems aligns with global efforts to mitigate climate change. By enabling greater integration of renewable energy sources and reducing dependence on fossil fuels, batteries support the transition to cleaner energy systems (Anil Kumar et al., 2024). They also play a critical role in providing backup power, ensuring that energy supply remains uninterrupted during emergencies or power outages. These contributions are essential for achieving climate goals and building a more sustainable future (R. Chen et al., 2020).

This paper focuses on exploring the capabilities of energy storage systems, particularly in relation to EVs. It delves into the critical aspects of battery health and the RUL of EV's batteries. By investigating these areas, the study aims to contribute to advancements in battery technology and support the transition to cleaner, more efficient energy systems.

2.2 Energy Storage

ESS play a pivotal role in modern energy infrastructures, particularly in balancing supply and demand amid the growing reliance on renewable energy sources. These systems are indispensable for ensuring stability and reliability in power grids dominated by variable energy sources like solar and wind. ESS can be classified into several categories based on their storage methods: electrochemical (batteries), mechanical, thermal, and chemical storage (Koohi-Fayegh & Rosen, 2020). This classification reflects the diversity of approaches available to meet the distinct energy storage needs across various applications. Each type offers unique advantages, making them suitable for addressing specific challenges associated with renewable energy integration and grid management (S. Sahoo & Timmann, 2023).

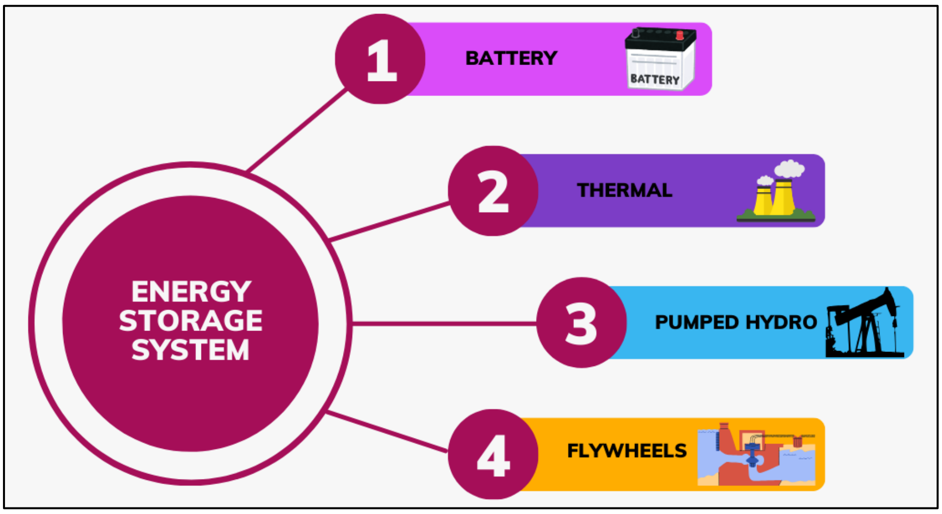

Figure 2.2 Type of ESS

Mechanical energy storage systems, such as pumped hydro storage and compressed air energy storage (CAES), have long been considered significant for their ability to convert electricity into potential or kinetic energy and reconvert it into electrical energy when required (Pottie et al., 2020). Pumped hydro storage remains the most widely used form of large-scale energy storage, characterized by its high capacity and long operational lifespan. Similarly, CAES systems utilize compressed air stored in underground reservoirs, which is released to drive turbines during peak demand. Although mechanical systems typically exhibit lower efficiency compared to batteries, their high storage capacity and long-term reliability make them valuable for large-scale applications (Dehghani-Sanij et al., 2019).

Chemical energy storage is gaining considerable attention as a viable option for long-term energy storage. This category includes technologies like hydrogen storage and synthetic fuels, which involve the conversion of electrical energy into chemical energy through processes such as electrolysis (R. P. Lee et al., 2021). Hydrogen storage, in particular, has emerged as a promising solution, with its ability to support grid-scale applications and cater to transportation energy needs. The stored hydrogen can be reconverted into electricity via fuel cells or used as a clean fuel source for combustion processes (Revankar, 2019). The versatility and scalability of hydrogen-based storage systems make them a cornerstone for future energy strategies, particularly as efforts intensify to decarbonize energy systems (Ratnakar et al., 2021).

Thermal energy storage systems (TES) provide another critical avenue for energy storage, particularly in capturing and storing heat energy for later use. TES technologies store energy during periods of excess production and release it during peak demand, making them invaluable for grid stability (Enescu et al., 2020). Common TES methods include molten salt systems, which are widely used in concentrated solar power plants, and phase-change materials that store energy through heat absorption and release (Guelpa & Verda, 2019). These systems are particularly beneficial for applications requiring heating or electricity generation, offering a sustainable way to manage energy resources efficiently (Barns et al., 2021).

Electrochemical energy storage systems, particularly battery technologies, dominate many energy storage applications due to their versatility and scalability. Batteries are extensively used in small electronic devices, electric vehicles, and grid energy storage systems (Sikiru et al., 2024). Among these, lithium-ion batteries have become the industry standard due to their high energy density, long cycle life, and decreasing costs. Other battery types, such as lead-acid, nickel-metal hydride, and redox flow batteries, offer specific advantages tailored to particular use cases (Abbas et al., 2020). BESS are especially critical for large-scale grid applications, where they enable peak shaving, load levelling, and seamless integration of renewable energy sources (Rocha et al., 2022).

Hybrid energy storage systems are emerging as a sophisticated solution to optimize the strengths of various technologies. By combining batteries with other storage types, such as ultracapacitors or thermal systems, hybrid systems deliver both high energy capacity and high power output (Y. Zheng et al., 2024). These hybrid systems aim to provide both high energy and high power, ensuring stability and resilience in energy grids, particularly with the integration of renewable energy sources (Georgious et al., 2021). Future developments in battery technology, including next-generation systems like lithium-sulphur and sodium-ion batteries, are expected to significantly improve energy density, cost, and safety (Y. Chen et al., 2021). These advances are crucial for meeting the growing demand for energy storage in applications such as electric vehicles and large-scale renewable integration (Ragupathy et al., 2023).

In conclusion, the classification of energy storage systems highlights the diverse technologies available to meet different energy storage needs. While batteries dominate in terms of versatility and scalability, other methods like mechanical and chemical storage provide unique advantages for specific applications. Ongoing research and development are essential to overcoming the limitations of current technologies and addressing future energy storage challenges.

2.2.1 Type of Batteries

Lithium-ion batteries (LIBs) are widely recognized for their high energy density, a feature that has established them as the leading choice for portable electronics and electric vehicles. LIBs typically offer energy densities in the range of 150–250 Wh/kg, which strikes an effective balance between energy capacity and compactness. This characteristic, combined with their relatively long cycle life and high energy efficiency, makes them particularly well-suited for electric mobility applications, where reliability and performance are paramount (Sankaran & Venkatesan, 2022). Moreover, LIBs have proven effective for grid integration due to their ability to maintain high energy efficiency over numerous charge-discharge cycles, supporting the increasing need for renewable energy storage and peak shaving solutions (Bulut & ÖZCAN, 2021).

Despite their widespread adoption, LIBs face growing competition from alternative technologies like sodium-sulphur and redox flow batteries, particularly in large-scale energy storage applications as shown in Table 2.1 that tabulate another energy storage type compared to LIBs. Sodium-sulphur batteries, known for their extended life cycles and scalability, offer an appealing alternative for grid-level energy storage. Similarly, redox flow batteries provide a scalable and durable solution for applications requiring large energy capacities (Fan et al., 2020). These technologies address some limitations of LIBs, such as resource scarcity and safety risks, which remain critical concerns for scaling LIBs to grid-level storage applications (T. Chen et al., 2020b). As the demand for large-scale, sustainable energy storage grows, these alternatives are poised to complement or even replace LIBs in specific applications.

Sodium-ion batteries (SIBs) have emerged as a promising alternative, particularly for grid-scale applications, due to the abundance and cost-effectiveness of sodium resources. While SIBs generally exhibit lower energy densities (approximately 100–150 Wh/kg) compared to LIBs, their reduced material costs and scalability make them highly attractive for large-scale energy storage (Pu et al., 2019). However, their lower energy density renders them less suitable for high-performance applications, such as electric vehicles, where energy-to-weight ratios are critical. Despite this limitation, SIBs are increasingly recognized as a viable solution for applications that prioritize cost and scalability over compactness and energy density.

Solid-state batteries (SSBs) represent a significant evolution in battery technology, offering the potential for substantially higher energy densities than conventional LIBs, often exceeding 400 Wh/kg. The use of solid electrolytes in SSBs not only enhances energy density but also significantly improves safety, a critical factor in high-power applications such as electric vehicles and aviation (Lemoine et al., 2023). These improvements make SSBs an attractive candidate for next-generation energy storage solutions. However, the technology remains in the developmental stage, facing challenges related to cost, manufacturing scalability, and material stability. Continued research and development are essential to overcome these hurdles and unlock the full potential of SSBs.

Supercapacitors, although limited by their much lower energy densities (approximately 5–10 Wh/kg), excel in applications requiring high power density and rapid charge-discharge capabilities. Their unique properties make them particularly useful in specific mobility sectors, such as regenerative braking systems and power backup solutions, where energy storage for short durations is sufficient (Jordan Y. Arpilleda, 2023). However, their low energy density limits their utility in applications requiring long-duration energy storage, such as grid integration or long-range electric mobility. Despite these limitations, supercapacitors continue to play a niche role in the broader energy storage ecosystem.

Table 2.1
Specification on Batteries Type

Type	Energy Density (Wh/kg)	Efficiency (%)	Performance (Power Density, W/kg)	Commercialization	Battery Health	Lifespan (Cycles)
Lithium-ion Batteries (LIBs) (C. Sun et al., 2020)(Jagadale et al., 2019)	~150-250	~90-95	Moderate (~500-2000)	High, widely used	Prone to capacity fade; sensitive to temperature	~500-2000
Sodium-ion Batteries (SIB) (Yi et al., 2021)	~80-150	~80-90	Moderate (~300-1500)	Low, emerging technology	Better thermal stability than LIBs; similar degradation	~500-1500
Solid-State Batteries (SSB) (Sennu et al., 2020)	~200-400	~85-90	Low to moderate	Limited, high costs and manufacturing challenges	Generally high safety; less prone to degradation	~1000-3000
Supercapacitors (Panigrahi et al., 2020)	~5-10	~95-98	High (~5000-10000)	Moderate, mainly niche applications	Excellent cycle stability; limited energy density	~10,000-100,000
Lead-Acid (K. Zhou et al., 2022)	~30-50	~70-85	Low (~100-300)	High, used in vehicles and backup power systems	Sensitive to deep discharge and sulfation	~200-1,000
Nickel-Cadmium (NiCd) (N. Chang et al., 2021)	~40-60	~60-80	Moderate (~150-300)	Moderate, used in niche applications	Suffers from memory effect; robust under abuse	~500-2,000
Nickel-Metal Hydride (Z. Cui et al., 2021)	~60-120	~70-85	Moderate (~300-1,000)	Moderate, used in hybrid vehicles and electronics	Safer than NiCd; moderate self-discharge rate	~300-1,000
Silver-Oxide (L. Li et al., 2023)	~130 Wh/kg	~70-80%	High stability and compact size	Specialty use in hearing aids, watches	Very stable but expensive	~500-700 cycles

2.2.1.1 Lithium-Ion Battery

LIBs have established themselves as the dominant energy storage solution for various applications due to their high energy density, long cycle life, and energy efficiency. These characteristics have made LIBs indispensable in consumer electronics, EVs, and grid-scale energy storage systems (Blanc et al., 2019). The versatility of LIBs stems from their ability to be tailored to meet the specific requirements of diverse applications, influencing their design, configuration, and material choices. This adaptability underscores the critical role LIBs play in modern energy storage systems.

In consumer electronics, LIBs are essential for powering small, portable devices such as smartphones, laptops, and wearables. Their high energy density enables compact designs and prolonged operational times, addressing the demands of billions of users worldwide (Crocioni et al., 2020). The widespread use of mobile computing devices, with billions of users worldwide, has made the demand for LIBs ubiquitous. The total number of users of these devices exceeds several billion globally, with approximately 3 billion smartphone users and over 2 billion personal computer users worldwide as of recent estimates (*How the World Goes Online in 2024 — DataReportal – Global Digital Insights*, n.d.).

In the transportation sector, LIBs are critical for electric vehicles, where they deliver the high power and energy density necessary to achieve sustainable driving ranges. As EVs adoption continues to grow, the global fleet is expected to exceed 100 million vehicles by 2030, further intensifying the demand for LIBs (Bandini et al., 2021). Unlike portable electronics, EVs batteries emphasize faster charging times, enhanced safety measures, and thermal management, necessitating specific designs and material innovations. These tailored features are essential to meet the unique demands of EVs applications, where performance, reliability, and safety are paramount.

LIBs are also increasingly deployed in stationary energy storage systems, particularly for grid-scale applications. These systems store renewable energy from intermittent sources like solar and wind, providing backup power and stabilizing the grid (Camargo & Marulanda, 2019). Stationary applications demand LIBs with high cycle lives, minimal degradation, and the capacity to withstand extended operational periods without significant loss of performance. These attributes are crucial for maintaining the efficiency and reliability of renewable energy systems, making LIBs an integral component of sustainable energy infrastructure.

Advanced analytical tools like machine learning and data-driven models are being used to monitor and predict the performance and SoH of LIBs in these diverse applications (El-Dalahmeh et al., 2020). Techniques such as functional principal component analysis (fPCA) and time-frequency image analysis help improve the accuracy of capacity predictions, which is crucial for both consumer electronics and EVs (Shoriat Ullah & Seo, 2022). In industrial contexts, second-use LIBs from EVs are repurposed for stationary storage applications, reflecting a circular economy approach aimed at cost efficiency and environmental sustainability (Pagliaro & Meneguzzo, 2019). This highlights a circular economy approach, which is becoming more prevalent due to environmental concerns.

Looking ahead, the future of LIBs technology will focus on improving energy density, safety, and lifecycle management. Advances in materials science and battery management systems (BMS) are expected to drive significant improvements, addressing the growing demand for LIBs in emerging applications such as high-power industrial tools, drones, and electric aviation (Gao et al., 2021). These advancements will not only enhance the performance of LIBs but also expand their applicability across industries, ensuring their continued relevance in the evolving energy landscape.

In conclusion, LIBs have become indispensable across various sectors, including consumer electronics, electric vehicles, and stationary energy storage systems. Their adaptability, combined with ongoing innovation in materials, manufacturing, and management technologies, ensures their critical role in addressing contemporary energy challenges. As demand for reliable, efficient, and sustainable energy storage continues to rise, LIBs remain at the forefront of technological progress, driving advancements that support a wide range of applications and contribute to a more sustainable energy future.

2.3 Battery Health and Remaining Useful Life

The accurate prediction of battery health and RUL is a crucial concern in energy storage systems and EVs. As batteries are fundamental to ensuring reliability, performance, and safety in these applications, understanding and mitigating their degradation over time is essential. Degradation occurs due to various factors, including charge/discharge cycles, temperature fluctuations, and chemical changes within the battery cells (H. Yang et al., 2023). Consequently, developing precise models for predicting battery health and estimating RUL is imperative for effective maintenance planning, cost reduction, and prolonging battery life in energy systems and EVs (Al-Meer, 2024).

Battery health is commonly assessed using SoH metrics, which reflect a battery's capacity and internal resistance. These metrics degrade with age, directly impacting the battery's ability to deliver energy over time (Ge et al., 2022). Predicting battery health is vital for optimizing energy storage systems and EVs operations. It enables users to manage charging and discharging cycles efficiently, avoid unexpected failures, and improve safety measures (J. Wu et al., 2022). Furthermore, accurate RUL predictions are necessary to determine when a battery can no longer perform at acceptable levels, facilitating timely maintenance or replacement (Jafari & Byun, 2023).

Multiple factors influence battery health degradation, including charge/discharge rates, depth of discharge (DoD), temperature, and environmental conditions (T. Li et al., 2023). Figure 2.3 show higher discharge rates and elevated temperatures can accelerate degradation by causing unwanted chemical reactions inside the battery (W. Shen et al., 2022). These factors make it difficult to predict battery health using simple models, as battery degradation is highly dependent on its usage pattern and operational environment. Moreover, external conditions such as ambient temperature and humidity also impact battery performance, complicating the prediction of RUL (W. Chang et al., 2020).

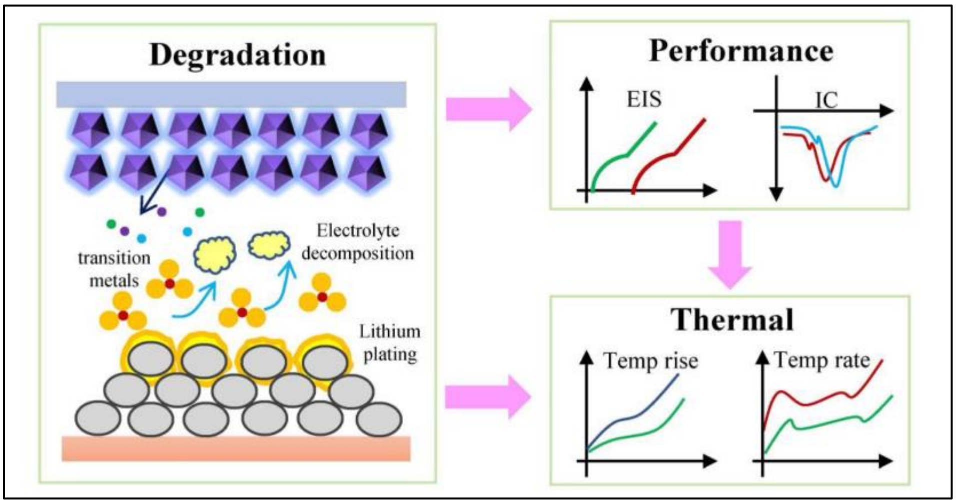

Figure 2.3 Relationship between Degradation Mechanism, Electrochemical Performance, and Heat Generation Characteristics (W. Shen et al., 2022)

Traditional approaches to predicting battery health and RUL rely on empirical models that utilize historical data on voltage, current, and temperature. These models often employ curve-fitting techniques to estimate degradation rates. However, their accuracy is limited because they do not account for real-time variability in battery performance (Kong et al., 2021). Electrochemical models, which simulate internal chemical processes, offer a more detailed understanding but require extensive knowledge of the battery's chemistry and are computationally intensive (Voskuilen et al., 2021).

Advances in data-driven methodologies have introduced machine learning (ML) techniques as effective alternatives for predicting battery health and RUL (Domathoti et al., 2023). ML models, such as support vector machines (SVM), random forests, and neural networks, can analyse extensive datasets of battery performance metrics to identify degradation patterns and forecast future performance (Severson et al., 2019). These models are more adaptive than traditional approaches, as they can continuously improve their predictions with the addition of new data. Data-driven methods are particularly advantageous for real-time monitoring and prediction, as they do not require a deep understanding of battery chemistry (Pozzato et al., 2023).

Hybrid models, which combine physics-based approaches with machine learning techniques, have further improved the robustness and accuracy of RUL predictions (Esfahani et al., 2021). Hybrid models integrate domain knowledge about battery chemistry with data-driven methods to improve prediction robustness (Gou et al., 2023). For example, physics-based models simulate internal battery reactions, while ML models use these simulations as inputs to predict future performance.

One of the most commonly employed machine learning models for predicting RUL is the recurrent neural network (RNN), particularly its LSTM variant (M. Xia et al., 2020). LSTM networks excel at handling time-series data, making them highly effective for forecasting battery degradation over time (Ren et al., 2021). By leveraging historical battery performance data, LSTM models can accurately predict future SoH and RUL. When combined with EMD, which helps decompose complex, non-linear signals, the accuracy of these predictions is further enhanced (X. Li et al., 2019).

Accurate battery health and RUL predictions have far-reaching implications for EVs and energy storage systems. In EVs, real-time RUL predictions enable drivers to optimize driving and charging behaviours, thereby extending battery life and minimizing the risk of sudden failures (J. Hu et al., 2023). For energy storage systems, accurate RUL predictions enable operators to schedule maintenance more effectively, reducing downtime and operational costs (Lei & Sandborn, 2018). Additionally, accurate health monitoring supports the repurposing of EVs batteries for second-life applications in stationary energy storage systems, promoting sustainability by extending their utility and reducing waste (X. Hu et al., 2022). As the demand for efficient and sustainable battery technologies grows, the integration of advanced predictive models will play a pivotal role in addressing these challenges.

2.4 Signal Processing

The accurate prediction of battery health and RUL is fundamentally dependent on the quality of the input data. Raw sensor measurements from BMS, such as voltage, current, and temperature, are invariably corrupted by noise from various sources, including sensor inaccuracies, electromagnetic interference, and thermal fluctuations (Nagata et al., 2022). This noise can obscure the subtle, underlying trends of electrochemical degradation, making it exceedingly difficult for machine learning models to learn meaningful patterns and generalize effectively. Consequently, signal processing has become an indispensable pre-processing step in the field of battery prognostics. Its primary role is to denoise raw time-series data, filter out irrelevant components, and enhance the critical features that are indicative of a battery's SoH, thereby providing a clean, information-rich signal for subsequent predictive modelling (J. Zheng, 2025).

Among the various techniques employed, EMD has gained significant attention for its adaptive, data-driven approach. Unlike methods that require a predefined basis function, EMD decomposes a non-linear and non-stationary signal a perfect descriptor for battery degradation data into a finite set of Intrinsic Mode Functions (IMFs) (W. Li et al., 2021). Each IMFs represents a distinct oscillatory mode within the signal. In battery applications, researchers have leveraged EMD to separate the long-term capacity fade trend from short-term fluctuations and high-frequency noise (H. Sun et al., 2022). By reconstructing the signal using only the most relevant IMFs, a denoised and smoothed representation of the battery's degradation trajectory is obtained.

Another prominent technique is the WT, a powerful tool for time-frequency analysis. In contrast to the Fourier Transform, which provides frequency information at the expense of temporal locality, the WT preserves both time and frequency information, making it exceptionally well-suited for analysing transient phenomena in battery signals (H. Li et al., 2025). The Discrete Wavelet Transform (DWT), in particular, is widely used for multi-resolution analysis, allowing researchers to decompose a signal into different frequency bands. This capability is instrumental in isolating high-frequency noise while preserving the low-frequency components that represent the core degradation process (Pelosi et al., 2024b). The literature demonstrates its effectiveness in extracting features related to capacity degradation trends, voltage plateaus, and thermal effects, which are then used to train robust prognostic models with high accuracy.

The KF and its non-linear variants, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), represent another cornerstone of signal processing in battery systems. Operating as a recursive state estimator in the time domain, the KF is highly effective at smoothing noisy signals by optimally blending a predicted state with a new, noisy measurement (Jiang et al., 2021). Its computational efficiency and real-time applicability have made it a standard tool in BMS for estimating states like State of Charge (SoC). In the context of RUL prediction, the KF is primarily used as a powerful denoising filter. By modelling the battery's voltage or capacity as a state-space system, the KF can produce a significantly smoothed signal, which is then fed into a predictive model (Duan et al., 2020). Its ability to adapt to changing noise characteristics makes it a robust choice for handling dynamic operating conditions.

In conclusion, these signal processing techniques EMD, WT, and KF each offer a distinct methodology for tackling the fundamental challenge of noisy data in battery prognostics. While the literature is rich with studies applying these individual methods, a comprehensive, systematic comparison of their effectiveness when integrated into hybrid prognostic frameworks is less common. The choice of filtering technique is not trivial, as an inappropriate method may inadvertently remove vital information along with the noise, fundamentally limiting the performance of even the most advanced machine learning algorithm. This thesis therefore seeks to address this gap by systematically evaluating these three key signal processing techniques in combination with various machine learning models, aiming to identify the most synergistic and robust pairing for accurate RUL prediction under realistic, noisy conditions.

2.4.1 Empirical Mode Decomposition (EMD)

EMD is a data-driven, adaptive technique used to analyse non-linear and non-stationary time series data, making it highly suitable for complex systems like energy storage and EVs (Meng et al., 2019). By decomposing the signal into IMFs, EMD can help identify critical features related to battery health, such as degradation patterns and instabilities in operations (H. Sun et al., 2022). The adaptability of EMD allows for real-time monitoring of battery systems, providing insights into their SoC and SoH over time (Bree et al., 2023).

EMD helps in separating the different frequency components present in the battery signal, such as long-term degradation trends and short-term fluctuations caused by temperature changes or external load variations (Cordova et al., 2021). By decomposing the signal, EMD isolates the underlying health indicators of the battery, such as capacity loss and resistance increase, which are crucial for accurate RUL prediction (D. Zhou et al., 2020). When combined with LSTM, the LSTM network can focus on learning the time-series dependencies of these health indicators without being overwhelmed by irrelevant noise, leading to more accurate and reliable predictions of SoH and RUL (Xue et al., 2023).

In the context of battery health and RUL prediction, EMD is particularly useful for separating different frequency components present in the battery data (Ray et al., 2019). For instance, the charging and discharging cycles of a battery may contain multiple signals embedded with noise or fluctuations due to temperature, load conditions, or aging. One of the used techniques is EMD, which breaks down complex, multi-component signals into simpler, more meaningful components called Intrinsic Mode Functions (IMFs). By using EMD, these signals can be decomposed into simpler components (IMFs), each representing a specific time-scale feature of the battery's operational behaviour (Y. H. Wang & Cheng, 2022). This decomposition allows for the extraction of important health indicators, such as voltage, current, and capacity fade, which are essential for accurately predicting battery RUL.

A key advantage of EMD is its adaptive signal processing method, meaning the decomposition is based on the signal itself rather than relying on predefined functions or filters (Y. Li et al., 2023). This is particularly beneficial for energy storage systems and electric vehicles, where the operational conditions and stress factors vary dynamically (Nguyen et al., 2021). Traditional signal processing methods might struggle to handle the non-stationary behaviour of battery degradation and making accurate estimation SoH and RUL a complex task, but EMD can capture both short-term fluctuations and long-term trends, making it an effective tool for RUL prediction (de la Vega et al., 2023; Guo et al., 2021).

EMD is utilized to decompose signals into simpler components, which helps capture underlying degradation patterns. It has been shown to improve model robustness and accuracy in different conditions when integrated with LSTM (Y. Zhou et al., 2022). In battery degradation models, the combination of EMD and LSTM is proposed to accurately estimate battery state and improve RUL predictions by isolating important degradation features (Z. Li et al., 2024). LSTM networks are widely used in predicting battery degradation by learning temporal patterns across cycles, especially useful for time-series data such as battery charge/discharge cycles (H. Zhang et al., 2021). LSTM effectively captures temporal correlations in long-term data, making it suitable for tracking degradation and capacity fading of batteries over time (X. Cui & Hu, 2020).

While EMD has been shown to effectively separate complex signals into IMFs, allowing the LSTM to focus on key components without noise interference (Yuan et al., 2023). This results in a more accurate capacity prediction. Using EMD to remove irrelevant details before feeding into LSTM enables the model to focus on crucial data features for accurate predictions. The EMD-LSTM architecture helps reduce nonlinearity and noise, allowing LSTM to process more meaningful signals and improving prediction precision (F. K. Wang & Mamo, 2020).

In the energy storage and EVs sectors, EMD can help isolate these different influences by decomposing the signal into IMFs that represent specific physical processes. For example, one IMF might correspond to the aging process, while another could reflect short-term fluctuations in performance due to temperature changes (Z. Chen et al., 2019). By analysing these IMFs, engineers can gain a better understanding of the battery's overall health and predict when it will fail or need maintenance.

2.4.2 Wavelet Transform (WT)

WT has emerged as a powerful tool for signal processing, especially in applications requiring time-frequency domain analysis. For battery health and RUL prediction, WT enables the decomposition of complex battery signals into components that highlight underlying patterns of degradation (W. Hu & Zhao, 2022). Unlike Fourier Transform, which operates purely in the frequency domain, WT maintains temporal information, offering a significant advantage in analysing the non-linear and non-stationary behaviour of LIBs (X. Liu et al., 2024) s. For EVs and ESSs, where accurate predictions are critical, WT aids in identifying subtle changes in signal characteristics, such as voltage and current fluctuations, indicative of battery aging (Pelosi et al., 2024a).

The discrete wavelet-transform (DWT), a prominent variant of WT, is frequently employed for feature extraction and denoising. Applying DWT to charging and discharging profiles, researchers can isolate frequency components related to specific electrochemical processes (S. Lee & Kim, 2020). Techniques like Haar and Daubechies wavelets are popular for their ability to capture transient dynamics in battery signals. These methods enable the identification of capacity degradation trends, voltage plateaus, and thermal effects, making them instrumental in predicting battery SoH and RUL with high accuracy (Kim et al., 2023).

WT is often integrated with advanced data-driven approaches, such as neural networks and ensemble learning, to enhance prediction accuracy. For instance, wavelet features combined with Convolutional Neural Networks (CNNs) or recurrent models like LSTM have shown improved predictive performance. These hybrid systems leverage the time-frequency decomposition provided by WT to train robust models capable of handling noisy and sparse datasets (Q. Lin et al., 2021). Methods like Bayesian optimization and transfer learning further refine the model's ability to generalize across different battery chemistries and operating conditions (Eleftheriadis et al., 2024).

WT-based techniques are validated against experimental and simulated datasets to assess their predictive accuracy. Metrics like MAE, RMSE, and MAPE are commonly used (Y. Zhang et al., 2021). Paper (Pelosi et al., 2024a) have reported significant reductions in prediction errors, with MAE as low as 0.917 and RMSE under

1.32 in real-time SoH estimation experiments. These results highlight the robustness and reliability of WT for battery health prognostics.

Despite its advantages, WT faces challenges, such as sensitivity to parameter selection and noise. Choosing the appropriate wavelet type and decomposition level is crucial for extracting meaningful features (Stanke et al., 2020). Additionally, high-dimensional datasets often require advanced pre-processing steps to prevent overfitting in predictive models. Addressing these issues requires a combination of domain expertise and algorithmic innovations (G. R. Sahoo et al., 2024).

As EVs and ESS adoption grows, WT will continue to play a vital role in advancing battery technology. Research is focusing on integrating WT with emerging machine learning frameworks, such as transformers and graph neural networks, to further enhance prediction capabilities. Additionally, combining WT with electrochemical modelling and real-world driving data promises to deliver even greater accuracy and reliability in battery health monitoring systems.

2.4.3 Kalman Filter (KF)

The KF has become a cornerstone in BMS, especially for mitigating noise in signal measurements and enhancing the accuracy of state predictions such as SoC and State-of-Energy (SoE). From 2019 to 2025, significant advancements have been made in refining KF algorithms to cope with noise variations and nonlinear battery dynamics. These improvements aim to ensure more reliable operation of lithium-ion batteries, particularly under real-world and dynamic load conditions, such as those found in electric vehicles and mobile devices.

One of the main developments in this area has been the creation of adaptive Kalman filtering methods. For instance, a real-time adjustment strategy for process and measurement noise matrices in the KF was shown to achieve remarkable accuracy, with voltage estimation errors as low as 0.44% (da Silva et al., 2024). Similarly, other researchers developed modified adaptive EKF that dynamically tune noise parameters based on prediction errors, leading to more robust SoC estimation under fluctuating environmental and operational conditions (Rout & Das, 2024).

The UKF and its variations have also shown strong capabilities in filtering noise from battery signals. In one study, UKF was applied to noisy smartphone battery data, resulting in extremely low mean square error values for both voltage and SoC measurements (Bhat et al., 2021a). A cascaded UKF approach further reduced measurement noise in electric vehicle datasets, although it was noted that excessive cascading increased error due to overfitting (Bhat et al., 2021b). Additionally, the adaptive unscented Kalman filter (AUKF) demonstrated high accuracy in accounting for time-varying noise, outperforming traditional models in lithium-ion battery testing (Dong et al., 2024).

Hybrid models combining KF with other computational techniques have further advanced SoC prediction. A fuzzy fractional-order UKF merged fuzzy logic and fractional calculus to dynamically infer and compensate for noise, achieving higher estimation accuracy under various conditions (L. Chen et al., 2021). Meanwhile, composite battery modelling paired with an improved splice KF algorithm led to a SoC prediction error of only 1.38%, illustrating the strength of these integrated approaches (S. Wang et al., 2020). Similarly, dual KF combined with particle swarm optimization for online parameter identification enhanced prediction accuracy in dynamic vehicle applications (H. Wang et al., 2021).

On the theoretical side, researchers have questioned the foundational assumptions of KF design in battery applications. A study investigating process noise in electrochemical battery models found that noise was not fully Gaussian or independent, challenging the typical diagonal covariance structure assumed in many Kalman implementations (Weber et al., 2019b). Innovations like spectral graph KF have extended traditional KF capabilities to signals with irregular structures, showing improved performance in scenarios with nonstandard noise types (Al-Attabi & Ali Tayeb, 2023).

In conclusion, the integration of adaptive, unscented, and hybrid KF has significantly improved noise handling in battery signal processing. These advancements are essential for enhancing the accuracy and reliability of BMS across various platforms, from smartphones to electric vehicles. The continued evolution of Kalman-based approaches, informed by both experimental results and theoretical insights, underscores their critical role in the future of energy storage and management systems.

2.5 Techniques

In recent years, researchers have increasingly focused on artificial intelligence (AI) methods for predicting SoH of lithium-ion batteries. These batteries play a vital role in ESS and EVs, and accurate predictions are essential for improving their performance, safety, and operational lifespan. While LSTM networks have gained significant attention for their ability to handle time-series data, several alternative AI techniques have also emerged as promising solutions. These alternatives encompass machine learning, deep learning, and hybrid models that leverage the latest advances in data science and battery management.

The ability to predict SoH and RUL of batteries is increasingly recognized as a cornerstone for enhancing the operational efficiency, reliability, and longevity of ESS and EVs applications. SoH is a key metric that reflects a battery's capacity to store and deliver energy effectively as it undergoes aging (X. Zhu et al., 2022). Monitoring SoH provides insights into the degradation process, enabling early detection of performance declines and facilitating timely interventions (De Falco et al., 2021). This capability is essential for managing the lifecycle of lithium-ion batteries, especially in applications where performance failures could lead to significant disruptions (Z. Lin et al., 2023).

In the context of ESS, accurate SoH predictions allow operators to optimize the charging and discharging cycles, ensuring efficient energy utilization and reducing the risk of system failures (D. Yang et al., 2018). This is particularly critical in grid energy storage, where the reliability of the system directly impacts the stability of the electrical grid. By identifying potential issues early, operators can schedule maintenance activities proactively, minimizing downtime and avoiding costly disruptions (Zhai et al., 2020). Similarly, in EVs applications, accurate SoH monitoring ensures optimal battery performance and extends the operational life of vehicle fleets. This is especially important as EVs become an integral part of modern transportation systems, where any failure could lead to service delays or safety concerns.

Alternative AI techniques to LSTM networks have shown significant potential in improving the accuracy and robustness SoH predictions. Machine learning approaches, such as SVM and random forests, provide interpretable models that can effectively handle large datasets of battery performance metrics. These models are capable of identifying complex relationships between input variables and battery health indicators, making them suitable for a variety of operational scenarios. Deep learning techniques, including CNNs and transformer-based models, offer even greater flexibility by automatically extracting relevant features from raw data. These methods are particularly useful for analysing high-dimensional and unstructured datasets, such as voltage and current waveforms.

Hybrid models, which combine physics-based simulations with data-driven methods, are another promising direction in battery health prediction. These models integrate the domain knowledge of battery electrochemistry with the predictive power of AI techniques, resulting in improved accuracy and reliability. For instance, hybrid models can use physics-based simulations to capture the underlying chemical processes within a battery while employing machine learning algorithms to predict future performance based on historical data. This synergy between physics-based and data-driven approaches enables a more comprehensive understanding of battery behaviour, which is crucial for accurate RUL predictions.

The adoption of these advanced AI techniques in ESS and EVs applications highlights the growing importance of predictive analytics in battery management. By providing accurate and timely information about battery health, these methods support decision-making processes that enhance system efficiency, reduce costs, and promote sustainability. As research in this field continues to evolve, the integration of AI into battery management systems is expected to play a pivotal role in shaping the future of energy storage and electric mobility. Through ongoing innovation, these advanced methodologies will ensure that lithium-ion batteries remain a reliable and efficient energy storage solution for years to come.

2.5.1 Long-Short Term Memory (LSTM)

LSTM networks, a type of Recurrent Neural Network (RNN), have become a fundamental tool for predicting the SOH and RUL of batteries, particularly in energy storage systems and EVs. LSTM's primary advantage lies in its ability to effectively capture long-term dependencies and relationships within time-series data, which is crucial for understanding the degradation patterns of batteries over time. Unlike traditional RNNs, which struggle with long-term dependency learning due to the vanishing gradient problem, LSTM introduces memory cells capable of maintaining information for extended periods and selectively forgetting irrelevant data. This feature makes LSTM particularly well-suited for processing sequences of battery data, such as voltage, current, and temperature, to accurately predict battery health and RUL.

For instance, paper (K. Liu et al., 2021) proposed an innovative LSTM model that combined Gaussian Process Regression (GPR) with EMD to address the long-term dependencies of battery capacity data while incorporating uncertainty quantification in RUL predictions. This hybrid approach demonstrated a more reliable method for predicting RUL by not only handling the complex degradation patterns but also accounting for the uncertainties involved in battery aging processes. The use of EMD was essential in decomposing the non-linear battery data, which further enhanced the LSTM model's capability to make precise predictions, particularly when applied to lithium-ion batteries, which are widely used in EVs and energy storage systems.

Paper (Cheng et al., 2021) proposed a backpropagation LSTM (B-LSTM) neural network, integrating the EMD technique to improve the prediction of SoH and RUL. This approach was particularly effective in mitigating the impact of battery capacity regeneration phenomena, which can complicate accurate degradation estimation. By incorporating EMD, the B-LSTM model reduced the error in predictions, achieving a RMSE that was four times lower than traditional RNN methods. This significant reduction in error highlights the effectiveness of combining LSTM with signal processing techniques like EMD to enhance battery health predictions.

In paper (Mao et al., 2023), the authors combined EMD with a hybrid Transformer and LSTM model. This method aimed to improve the prediction accuracy for long-term battery health by effectively handling the non-linear degradation trends that are typical in battery aging. The Transformer model, known for its ability to process sequential data with attention mechanisms, was integrated with LSTM to capture both the temporal and non-linear characteristics of battery degradation. The hybrid Transformer-LSTM model outperformed standalone LSTM models, showcasing the benefit of combining different advanced architectures to improve the accuracy and robustness of RUL predictions.

A hybrid approach integrating CNN with LSTM was proposed in paper (Z. Zhu, Yang, et al., 2022). CNN were used for pre-processing the battery data before feeding it into the LSTM. The CNN served as a feature extraction tool, filtering the raw data and enabling the LSTM to focus on the relevant information for prediction. The combination of CNN and LSTM demonstrated superior performance in processing time-series data, reducing prediction errors significantly compared to models using LSTM alone (D. Zhou & Wang, 2022). This approach highlights the strength of hybrid models, where CNN's ability to extract spatial features complements LSTM’s proficiency in handling temporal dependencies, thereby enhancing overall prediction accuracy.

In conclusion, LSTM has emerged as a powerful tool for predicting battery health and RUL, owing to its ability to capture long-term dependencies in time-series data. The studies reviewed demonstrate various advancements and enhancements to LSTM models, including the integration of techniques like EMD and GPR, as well as hybrid models that combine LSTM with CNNs and Transformers. These innovations have significantly improved the accuracy and reliability of battery life predictions, making LSTM an indispensable tool in battery management systems, particularly in dynamic and real-world applications such as EVs and energy storage systems.

2.5.2 Support Vector Machines (SVM)

SVM have increasingly become a popular choice for battery management systems, particularly for estimating the SoH of batteries. The integration of SVM into battery health prediction relies on its ability to handle high-dimensional data and make accurate predictions in real-time applications. This has led to the development of various SVM-based methods aimed at improving the efficiency and accuracy of SoH estimation. Many of these studies have focused on leveraging partial charging data, a strategy that allows for the reduction of data acquisition time and storage requirements while maintaining or even enhancing prediction performance.

Paper (Feng et al., 2019) introduced another approach, where an SVM-based model for online SoH estimation was developed using partial charging data. The method works by extracting support vectors from the charging data of new lithium-ion cells, and these support vectors are updated as the battery ages. By comparing partial charging curves (with durations as short as 15 minutes) with stored support vectors, the system can estimate SoH with less than 2% error in most cases. This approach presents substantial computational savings without compromising accuracy, making it particularly suited for real-time applications in BMS. The ability to work with shorter charging data while maintaining a high level of precision is a key advantage for applications in EVs and renewable energy systems, where real-time monitoring of battery health is critical.

In 2021, (Xiong et al., 2021)introduced a weighted least squares SVM (WLS-SVM) approach aimed at addressing the nonlinearity inherent in SoH estimation for second-use lithium-ion batteries. This method involved a feature extraction process applied to partial charging curves, which enabled the identification of health features most strongly correlated with the battery's SoH. In comparison to other machine learning models, such as back-propagation neural networks, the WLS-SVM model demonstrated superior accuracy with a RMSE of less than 1.85%. This finding highlights the robustness of SVM-based methods for handling various battery types and operating conditions. By reducing the complexity of the model while enhancing its predictive capabilities, WLS-SVM proves to be an effective solution for managing second-life battery applications, where the battery's performance is often degraded but still valuable for energy storage purposes.

Advancements in Feature Utilization, (Ali et al., 2019) proposed a novel SVM model based on partial discharge data (PDD) for predicting the RUL of lithium-ion batteries. The model relied on the analysis of voltage and temperature features during partial discharge cycles, allowing for accurate RUL predictions. The study compared the performance of the partial discharge data-based model with that of full discharge data, concluding that the PDD-based approach offered substantial reductions in storage requirements without sacrificing accuracy. This demonstrates the potential of using partial discharge data, which can be obtained more quickly and with fewer resources, to predict RUL effectively. This approach is particularly useful for real-time battery health monitoring, where fast and accurate predictions are essential to optimize battery usage and prevent failures.

Hybrid Approaches In 2020, (Xuan et al., 2020) explored a hybrid method that integrated principal component analysis (PCA) with SVM for SoC prediction. PCA was used to optimize the input features, reducing the dimensionality of the data and enhancing the speed and accuracy of the SVM model. This hybrid model demonstrated superior performance in both accuracy and computational efficiency compared to traditional SVM models. The use of PCA helped improve the model's ability to handle large datasets and identify the most relevant features, leading to more accurate SoC predictions. This approach represents a step forward in the development of hybrid models that combine the strengths of different machine learning techniques to tackle the complex challenges of battery health estimation.

The advancements in SVM-based methods for SoH estimation, particularly in the context of partial charging or discharge data, highlight the adaptability and efficiency of these models for real-time battery health monitoring. The reviewed studies emphasize the importance of feature extraction and model robustness, demonstrating that SVM can be effectively used for battery health management in both electric vehicles and renewable energy systems. Future research in this area is likely to focus on integrating more complex machine learning models with physical battery models to further enhance prediction accuracy and adaptability across various battery chemistries and operational conditions. This will contribute to the development of more sophisticated BMS solutions capable of optimizing battery performance and extending battery life under diverse and dynamic conditions.

In conclusion, the use of SVM for SoH estimation has evolved significantly, offering a range of methods that balance computational efficiency with high prediction accuracy. By leveraging partial charging or discharge data and combining SVM with other advanced techniques such as PCA, these methods are providing practical and effective solutions for managing battery health in real-time applications. The continued advancement of SVM-based methods will further contribute to the optimization of battery performance and the extension of battery life, ensuring the reliable and sustainable operation of battery-powered systems in the future.

2.5.3 Gated Recurrent Units (GRU)

GRUs have emerged as a prominent deep learning technique for battery health management, offering a more computationally efficient alternative to LSTM networks for modelling time-series data. The application of GRUs in battery health prediction leverages their ability to capture temporal dependencies in degradation data, making them suitable for real-time SoH and RUL estimation. Research in this area has evolved from foundational GRU models to sophisticated hybrid frameworks that integrate advanced signal processing, optimization algorithms, and physics-informed features to enhance prediction accuracy and robustness.

In an early application, Javid et al. (Javid et al., 2020) proposed an Adaptive Online GRU method for SoC estimation. This approach utilized GRU cells to overcome the vanishing gradient problem inherent in simple Recurrent Neural Networks (RNNs). A key innovation was the use of a robust adaptive online gradient learning method, which allowed the network to tune its learning rate online without relying on a complex battery model. By using measurable variables like current, voltage, and temperature as inputs, the model demonstrated superior accuracy compared to both simple RNN and traditional filter-based methods like the UKF, establishing the GRU's potential as a powerful, model-free estimation tool.

To address the limitations of single-source features, Xia et al. (F. Xia et al., 2024) developed a novel prediction method employing a Bidirectional GRU (BiGRU) network with multi-source feature fusion. This study extracted features from Constant Current (CC) charging curves, Differential Thermal Voltammetry (DTV), and Differential Thermal Capacity (DTC), thereby combining electrochemical and thermal information. The BiGRU architecture allowed the model to process sequential data in both forward and reverse directions, capturing a more comprehensive view of temporal dependencies. Furthermore, a particle swarm optimization algorithm was used to optimize the BiGRU's hyperparameters, leading to a highly accurate model with a RMSE below 0.3%, significantly outperforming standard GRU and LSTM networks.

Further advancements have focused on enhancing GRU models by integrating them with advanced signal processing and optimization techniques. Zhao and Zheng (X. Zhao & Zheng, 2024) introduced a framework combining Variational Mode Decomposition (VMD) with an optimized GRU for RUL prediction. VMD was used to decompose the noisy battery capacity signal into cleaner modal components. The parameters of both the VMD and the GRU were optimized using the RIME and Northern Goshawk Optimization (NGO) algorithms, respectively. This hybrid approach effectively handled the non-stationary nature of battery degradation data, improving the adaptability of the decomposition and the accuracy of the final RUL prediction.

More recent work has focused on creating hybrid models that infuse data driven GRUs with physical interpretability and uncertainty quantification. Liu and Teh (W. Liu & Teh, 2025) proposed a framework that integrated an Incremental Internal Resistance Aging Model (IIRAM) with a GRU. The IIRAM, an analytical model derived from battery voltage characteristics, was used to extract eight physically meaningful health indicators. These indicators were then fed into a GRU network, creating a hybrid model that demonstrated enhanced predictive accuracy, robustness, and physical interpretability. In a similar vein, He et al. (He et al., 2025) addressed the lack of uncertainty quantification by combining a GRU with a Kolmogorov-Arnold

Network (KAN) and a Generalized Cauchy (GC) process. This GRU-KAN-GC model not only captured complex degradation trends but also provided a probability density function (PDF) for the RUL, offering a probabilistic forecast rather than a single point estimate.

The evolution of GRU-based methods for battery health estimation showcases a clear trend from standalone models to highly integrated, hybrid systems. These advancements highlight the importance of sophisticated feature engineering, advanced network architectures like BiGRU, and the integration of signal preprocessing, physics-informed models, and stochastic processes. This progression demonstrates that while the core GRU architecture provides a strong foundation for time-series prediction, its true potential is realized when combined with other techniques that enhance its accuracy, robustness, interpretability, and ability to quantify uncertainty.

In conclusion, the use of GRUs for SOH and RUL prediction has advanced significantly, offering a range of methods that improve upon the initial promise of efficiency and accuracy. By integrating GRUs with feature fusion, signal decomposition, and physics-informed or stochastic models, researchers are developing practical and powerful solutions for real-time battery health management. The continued development of these hybrid GRU-based methods will be instrumental in creating more intelligent and reliable BMS capable of optimizing battery performance and longevity in real-world applications.

2.6 Performance

Each of these methods has distinct data requirements, convergence characteristics, and predictive accuracies that make them suitable for various aspects of RUL prediction as shown in Table 2.2.

Table 2.2
Comparison of Various Techniques in Battery Prediction

Technique	Data Required	Performance	Convergence	Performance Error
XGBoost (Jia et al., 2021) (H. Liu et al., 2022)	Requires pre-processed data and feature selection from raw sensor data (e.g., voltage, current)	High performance for structured tabular data, lower for time-series	Fast convergence, ensemble method	RMSE: ~1.119%, better than RF and SVR
CNN (Zraibi et al., 2021)(Ma & Mao, 2021)	Large datasets with multi-channel data (e.g., charge/discharge cycles)	Effective for extracting spatial features, suitable for complex time-series	Moderate convergence time, depends on dataset size	Error rates improve with hybrid methods (CNN+LSTM)
SVM (Y. Shen et al., 2023)	High-dimensional input features such as voltage, capacity, and temperature	Performance weaker for complex, large datasets	Convergence depends on kernel and parameters	Higher MAE and RMSE compared to LSTM, CNN
IndRNN (G. Zhao et al., 2021)	Requires sequence data with temporal dependencies	Effective for processing sequential data	Better convergence due to independence of neurons	Error rates not widely reported compared to CNN or LSTM
LSTM (Park et al., 2020) (Y. Zhang et al., 2018)	Requires historical data and temporal sequences (voltage, current)	Excellent for long-term time dependencies	Slower convergence, highly dependent on dataset size	RMSE: ~0.47%, MAPE: ~1.88%
EMD (Pan et al., 2022)	Requires decomposition of raw battery data (voltage, capacity)	Effective when combined with LSTM for denoising data	Moderate convergence, as EMD decomposes data before modelling	RMSE: 0.02 for SOH estimation when used with LSTM
DWT (M. Zhang et al., 2022)	Voltage and Current Profiles	High accuracy for SoH and RUL prediction; MAE < 0.917	Fast with optimization	RMSE < 1.32

2.7 Summary

In conclusion, the literature review has provided an in-depth understanding of the key concepts, challenges, and methodologies associated with battery health and RUL prediction. It has highlighted the importance of reliable energy storage solutions in supporting renewable energy systems and EVs while addressing issues such as variability in energy generation and battery degradation. Through the evaluation of various prediction techniques, including traditional and machine learning-based approaches. The insights gained from this review form a strong basis for the methodological framework adopted in this research.

This study specifically addresses a critical research gap: the discrepancy between widely used clean laboratory datasets and the noisy, stochastic nature of real-world battery signals. Current approaches often treat signal denoising and predictive modelling as separate, disconnected stages, which can lead to suboptimal performance. To bridge this gap, this research proposes a hybrid methodology that systematically combines signal processing filters namely WT, KF, and EMD with robust machine learning algorithms, including SVM, LSTM, and GRU. This integrated approach is designed to identify the most effective combination for accurately predicting RUL under realistic, noise-corrupted conditions.

The next chapter outlines the research methodology applied in this study, detailing the systematic approach taken to develop and implement the proposed signal processing integrated with machine learning model for battery health and RUL prediction. It will describe the research plan to perform this project. This chapter will also ensure that the methodology is transparent and reproducible, enabling accurate and dependable results in addressing the research objectives.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This chapter explains the research methods used to develop, test, and evaluate a framework for predicting battery health and its RUL. The main goal of this study is to go beyond using only machine learning models by combining signal processing techniques with machine learning to improve prediction results. A clear and structured research method is very important for this type of data-based study, as it helps ensure that the process is transparent, repeatable, and scientifically sound. This chapter covers all stages of the research from choosing and preparing the data, to testing and validating the prediction models.

The experimental design is based on comparing nine different hybrid model combinations. This is done by combining three signal processing methods EMD, WT, and KF with three machine learning algorithms: LSTM, SVM, and GRU. To make the testing environment more realistic, this study uses the NASA PCoE battery dataset and adds controlled Gaussian noise to simulate real-world disturbances. The noisy data is then filtered using each signal processing method to produce cleaner data, which is then used as input to the machine learning models. This process allows for fair comparison between all nine filter-model combinations.

Finally, this chapter describes the validation approach used to measure how well each model performs. Instead of relying on just one metric, the evaluation uses several methods to give a full picture of prediction performance. These include RMSE and MAPE for accuracy, as well as statistical tests like ANOVA and linear regression to check if the differences between models are significant.

3.2 Research Framework

This chapter outlines the systematic research methodology employed to develop, test, and validate a robust framework for battery health prognostics. The entire research lifecycle is conceptually mapped in Figure 3.1, which illustrates the flow from initial data acquisition to the final reporting of validated findings. This structured approach ensures that the research is conducted in a logical, transparent, and reproducible manner, providing a clear blueprint for the experimental work detailed in the subsequent sections. The process commences with the foundational steps of data collection and the establishment of a simulation setup, which together create the controlled environment necessary for rigorous scientific investigation.

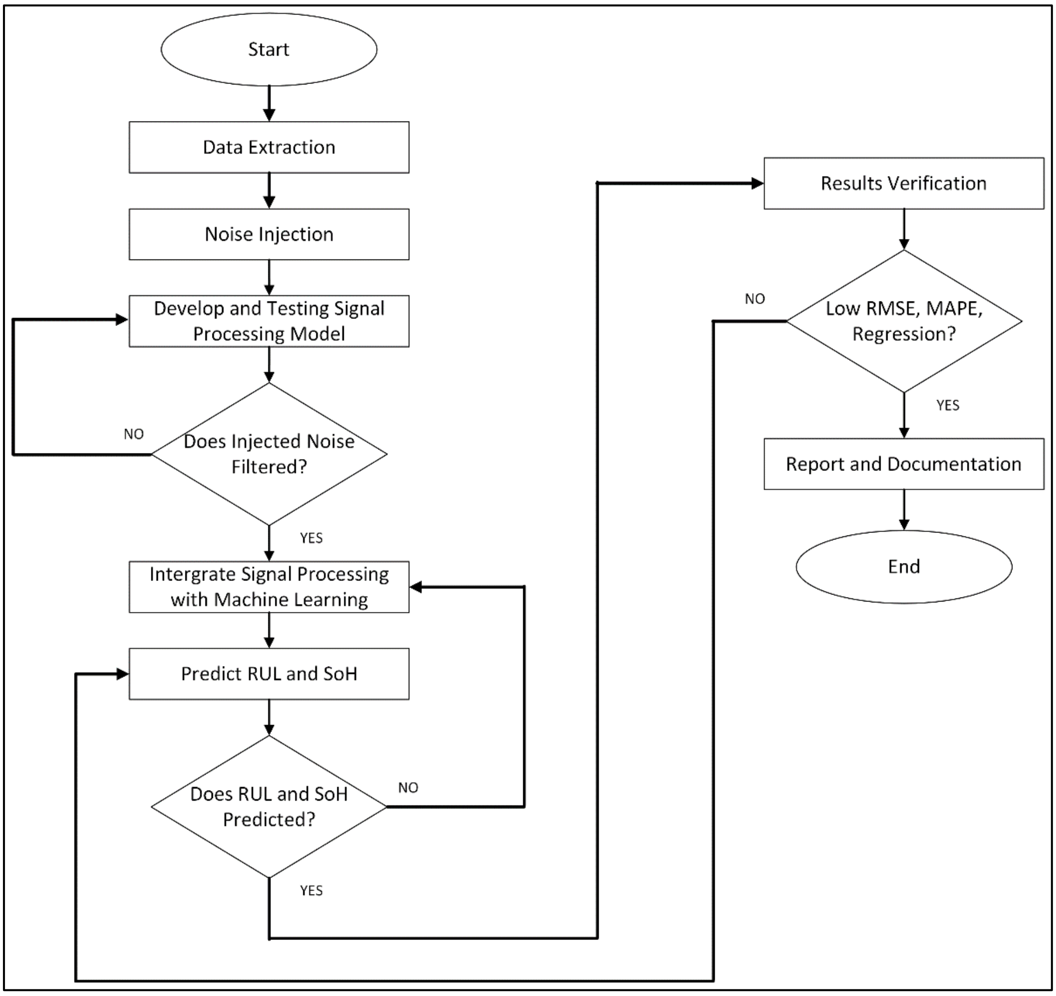

Figure 3.1 Research Flow

Following the initial setup, the methodology enters its core technical phase: the development and testing of a signal processing model. This stage is designed to refine the raw data into a form suitable for accurate analysis. As shown in Figure 3.1, this phase incorporates a critical iterative loop, represented by the "Does Noise Filtered?" decision point, ensuring the efficacy of the data pre-processing before proceeding. Once the signal is appropriately conditioned, it is integrated with machine learning techniques to predict the key battery health indicators: RUL and SoH. This integration represents the hybrid nature of the proposed solution, combining distinct technological domains to achieve a synergistic outcome.

The final stage of the methodology is dedicated to rigorous validation and conclusion. After a prediction is generated, the process moves to "Results Verification," where the model's output is systematically checked. This leads to the pivotal validation gateway, "Valid Result?", which determines the success of the entire modelling effort. An affirmative decision advances the process toward the final steps of reporting and documentation. However, a negative result triggers a comprehensive feedback loop, returning the process to the model development phase. This crucial iterative step underscores the methodology's commitment to rigorous refinement, ensuring that only a thoroughly validated and robust model is accepted as the final output of the research. The summary of research framework for all objectives is shown in Figure 3.2;

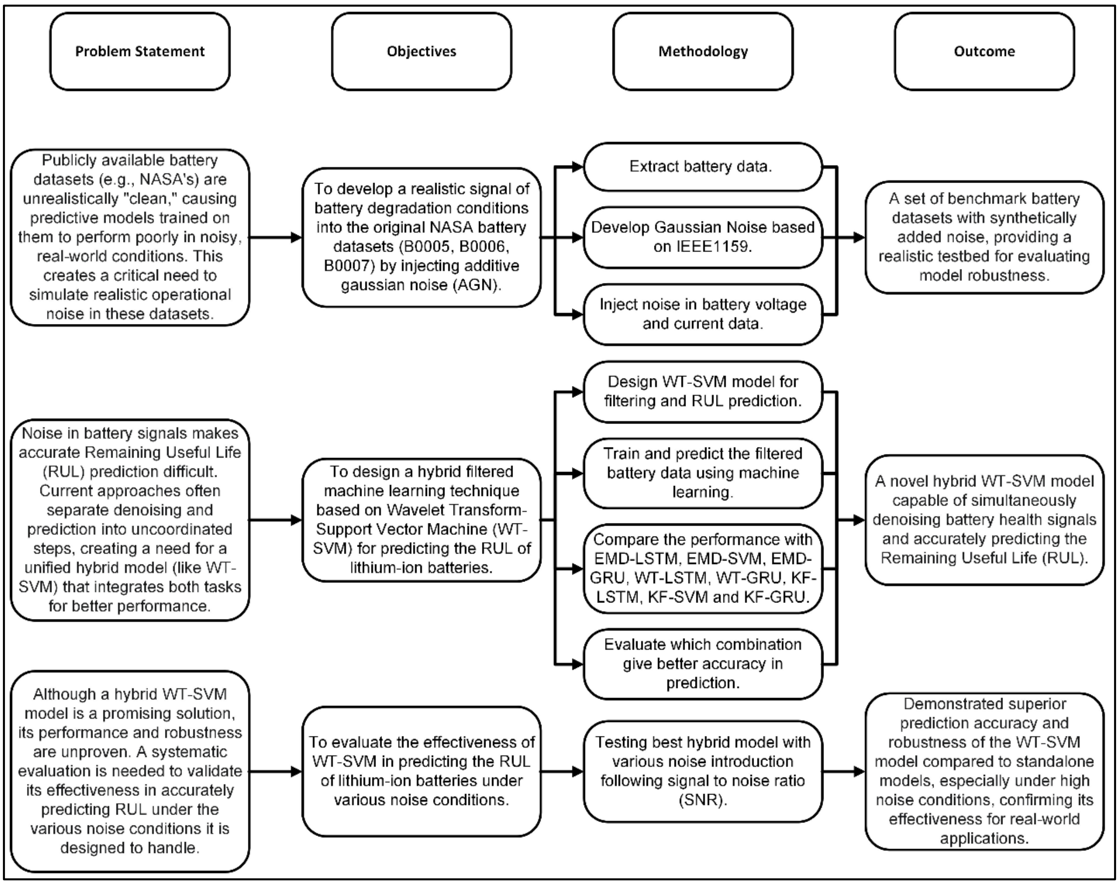

Figure 3.2 Research Framework for Overall Objectives

3.3 Dataset Selection and Description

The foundation of any robust data-driven research in battery health management rests upon the quality, relevance, and verifiability of the dataset employed. In alignment with global efforts toward a sustainable and technologically integrated future, as envisioned by the UN Sustainable Development Goals (SDG 7: Affordable and Clean

Energy; SDG 11: Sustainable Cities and Communities), this study necessitates a dataset that serves as a world-class benchmark (Sharifi et al., 2024). The rapid production of EVs and BESS within the framework of the Fourth Industrial Revolution demands predictive models built upon reliable and standardized data. To this end, this research utilizes the publicly available NASA Prognostics Center of Excellence (PCoE) battery dataset, a globally recognized standard that ensures the methodology's transparency, replicability, and comparability against other state-of-the-art approaches (Raman et al., 2021).

The NASA PCoE dataset is a de facto industry and academic standard for developing and validating battery health prognostics. It comprises comprehensive time-series data from run-to-failure experiments conducted on Lithium-ion (Li-ion) 18650 cells under controlled laboratory conditions (*Saha, B. and Goebel, K. (2007) Battery Data Set, NASA Ames Prognostics Data Repository. NASA Ames Research Center, Moffett Field, CA. - References - Scientific Research Publishing*, n.d.). The dataset exactly records key operational parameters, including voltage, current, and temperature profiles, during repeated charge, discharge, and impedance measurement cycles. This provides a complete degradation trajectory from a healthy state to the designated end-of-life (EoL), offering an invaluable resource for training and testing sophisticated machine learning models. The use of such a well-documented and widely vetted dataset is a critical step in developing the trustworthy and intelligent systems that form the backbone of Society 5.0, where cyber-physical systems seamlessly support societal needs.

Specifically, this study focuses on the data logs for batteries designated B0005, B0006, and B0007. These three cells were subjected to identical operational profiles charging at a constant current of 1.5A to 4.2V, followed by a constant voltage phase until the charge current dropped to 20mA, and discharging at a constant current of 2A until the voltage fell to 2.7V, 2.5V, and 2.2V respectively. The primary health indicator (HI) extracted from these logs is the discharge capacity, which exhibits a clear degradation trend over the cycle life. The defined EoL for these batteries is a capacity fade of 30% from their nominal 2 Ah rating, corresponding to a threshold of 1.4 Ah. This precise EoL definition is vital not only for first-life RUL prediction but also for enabling Circular Economy principles. Accurate prognostics allow for the timely removal and repurposing of batteries for second-life applications, a key "Waste to

Wealth" strategy that maximizes resource utility and minimizes environmental impact. The distinct degradation patterns observed across these three batteries provide a rigorous test for the proposed model's robustness and generalizability.

3.4 Simulation Process

The experimental validation of the proposed research is guided by the systematic simulation framework illustrated in Figure 3.3. This flowchart outlines a comprehensive and repeatable procedure designed to rigorously assess the performance of various hybrid prognostic models under simulated real-world conditions. The core objective of this approach is to conduct a comparative analysis, systematically evaluating the efficacy of different noise-filtering techniques when paired with prominent machine learning algorithms for battery SoH and RUL prediction. This structured methodology ensures that the findings are robust, quantifiable, and directly comparable, leading to a definitive conclusion on the optimal model configuration.

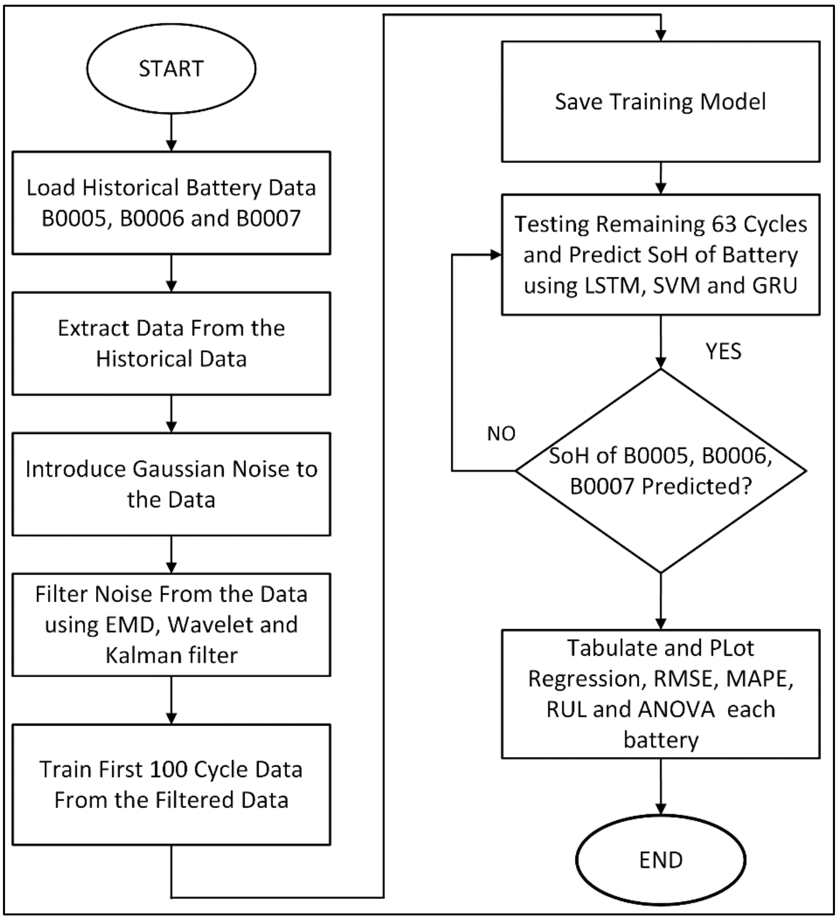

Figure 3.3 Simulation Approach

The process commences with data acquisition and preparation, as depicted in the initial sequence of steps. Historical time-series data is loaded from the NASA benchmark dataset for three specific lithium-ion batteries: B0005, B0006, and B0007. After the relevant operational data (such as capacity, voltage, and temperature) is extracted, a critical step is taken to simulate real-world sensor inaccuracies and environmental interference. Gaussian noise is intentionally introduced into the clean dataset. This corruption is fundamental to the study, as it creates a more realistic and challenging scenario. To counteract this, the noisy data is then subjected to a comprehensive filtering stage using three distinct signal processing techniques: EMD, WT, and the KF, preparing a cleaned dataset for the next phase.

With the pre-processed and filtered data ready, the model training phase begins. The flowchart specifies that the first 100 cycles (approximate 60% of total data) from the cleaned dataset are utilized for this purpose. This initial segment of the battery's life is fed into various machine learning algorithms, including LSTM, SVM, and GRU. During this stage, the models learn the underlying patterns and dynamics of battery degradation from the early-life data. The outcome of this step is a "trained model" that has captured the degradation behaviour and is prepared to make predictions on new, unseen data.

Once training is complete, the process transitions to the predictive testing and validation loop. The saved training model is now applied to the remaining 63 cycles of the battery data (approximate 40% of total data), which it has not seen before. The primary goal is to predict the SoH for this later portion of the battery's life. The flowchart illustrates a control loop governed by a decision diamond: "SoH of B0005, B0006, B0007 Predicted?". If predictions for all three batteries are not yet complete, the loop continues, ensuring that each of the nine hybrid models (three filtering methods × three prediction algorithms) is systematically tested on each battery dataset.

Upon the successful prediction of SoH for all batteries, the loop terminates, and the process moves to the final evaluation and reporting stage. In this concluding phase, the performance of each model combination is rigorously analysed. The predictions are compared against the actual data using a suite of statistical metrics, including Regression, RMSE, and MAPE. The model's ability to forecast the RUL is also assessed. Finally, an ANOVA is conducted to determine statistical significance. All these results are compiled into tables and visualized in plots, providing a comprehensive and comparative analysis before the process officially ends.

3.4.1 Addaptive Gaussian Noise (AGN) Approach

Based on the dataset for three specific lithium-ion batteries: B0005, B0006, and B0007, the discrete voltage and current can be express as:

$$X_{ref} = X[n] \tag{3.1}$$

Where; X_{ref} is the measured voltage or current at a specific cycle.

To quantify the impact of measurement noise on battery voltage signals, the Signal-to-Noise Ratio (SNR) is calculated, and noise is injected into the pure signal according to different noise levels, as referenced in IEEE Standard 1159 (*IEEE Recommended Practice for Monitoring Electric Power Quality*, 2019). For most electrical appliances in a network system, typical acceptable noise levels derived from IEEE 1159 benchmarks range from approximately 1% to 20% of the signal amplitude. Noise is commonly expressed in terms of SNR, which represents the ratio of the signal's voltage or current amplitude to that of the noise. The SNR, expressed in decibels (dB), is computed as:

$$\sigma = pX_{ref} \tag{3.2}$$

$$SNR_{\mathrm{dB}} = 20 \cdot log_{10}\left(\frac{X_{ref}}{\sigma}\right) \tag{3.3}$$

Where; p denotes the percentage amplitude of the noise component, typically in the range of 1 % to 20 % in accordance with measurement accuracy guidelines derived from IEEE.

In real-life battery systems, Gaussian noise represents measurement inaccuracies due to sensor imperfections, temperature fluctuations, and electronic interference. For instance, current and voltage sensors may exhibit drift or random fluctuations due to environmental factors, leading to minor deviations in recorded values. By incorporating Gaussian noise, the robustness of subsequent signal processing and state estimation techniques can be evaluated under realistic operating conditions.

$$X_n = \frac{1}{\sqrt{2\pi\sigma^2}} \mathrm{e}^{-\frac{\left(X_{ref}-u\right)^2}{2\sigma^2}} \tag{3.4}$$

Where, X_n is the noise component using adaptive gaussian, X_{ref} is the original signal, u mean of the noise, and σ^2 variance of the noise.

This process ensures that the dataset accounts for variability typically encountered in practical battery monitoring systems. The noisy signal can be expressed as:

$$\tilde{X} = X_{ref} + X_n \tag{3.5}$$

Where; $\tilde{X}$ represents the noisy signal.

In this study, the analysis is limited to three distinct noise levels. The noise levels tested under different conditions are 1 %, 2 %, and 20 %, which correspond to SNR values of approximately 40 dB, 34 dB, and 13 dB, respectively (Nozaki et al., 2023). The SNR values from (3.3) is converted into gaussian noise amplitude and then used to generate the noisy signal the model (3.5) . Table 3.1 shows the noise level applied to the data based on the IEEE1159 (*IEEE Recommended Practice for Monitoring Electric Power Quality*, 2019).

Table 3.1
Noise Level Based on IEEE1159

% Noise (IEEE 1159)	SNR (dB)	Gaussian noise level
1%	40	0.002
2%	34	0.005
20%	13	0.05

3.4.2 Noise Filtering Approach

These signals as mention in (3.5) are then fed into a signal processing model to simulate battery health prediction under noisy environments. This process allows assessment of the signal processing model's robustness and prediction performance in real-world scenarios where sensor noise is inevitable. The SNR values help benchmark the model’s tolerance to signal distortion and validate its effectiveness in practical deployment conditions.

Battery capacity degradation is a key indicator of SoH. However, due to noise and measurement inconsistencies, raw capacity estimates may not accurately reflect the true battery degradation trend. Original battery capacity affected when noise introduced to the original data. By computing capacity from the filtered discharge data, a more reliable SoH estimate is obtained, reducing the impact of sensor errors and fluctuations in the dataset. The new capacity is computed using equation;

$$C = -\int I(t)dt \tag{3.6}$$

Where; I(t) represents the discharge current as a function of time. In the implementation, the Trapezoidal Rule is used for numerical integration.

3.4.1.1 Wavelet-Transform (WT) Based Signal Denoising

To mitigate the effects of noise introduced in the previous step, wavelet-based denoising is applied to the discharge cycle data. The utilization of DWT to decompose the noisy voltage and current signals into different frequency components. A wavelet thresholding technique is then employed to remove high-frequency noise while preserving the underlying signal characteristics (Pelosi et al., 2024a). The inverse wavelet transform reconstructs the filtered signals, yielding a denoised version of the discharge cycle data. The denoising signal is computed using equation;

$$\tilde{x}(t) = \sum_{k} \alpha_{L,k}\phi_{L,k}(t) + \sum_{l=1}^{L}\sum_{k} d_{l,k}\,, \psi_{l,k}(t) \tag{3.7}$$

Where; $\tilde{x}(t)$ denotes the reconstructed or denoised signal, $\alpha_{L,k}$ are the approximation coefficients at the final decomposition level L, $d_{l,k}$ are the detail coefficients at each level l where $l = 1, 2, \ldots\ L$, $\phi_{L,k}$ are the scaling functions (low-pass) at level L and position k, $\psi_{l,k}$ are the wavelet functions (high-pass) at level l and position k, $x(t)$ is the original noisy signal, L is the maximum decomposition level, k is the translation index or time position and the wavelet basis ϕ and ψ are defined by the chosen mother wavelet Ψ, which in this study is designated as db1.

WT denoising is chosen over conventional filtering techniques (e.g., moving average or low-pass filters) due to its ability to analyze signals at multiple resolutions. Unlike Fourier-based methods, which operate in a fixed frequency domain, WT adapts to local variations in the signal, making it particularly effective for transient signals such as battery discharge voltage curves. The selection of the db1 (Haar) wavelet is justified by its computational efficiency and its ability to capture abrupt changes in the signal profile without the phase distortion or excessive smoothing often introduced by higher-order wavelets. This ensures that the sharp characteristics of the battery's electrochemical response are preserved while effectively isolating stochastic noise. The flexibility of selecting different wavelet types allows fine-tuned noise reduction while preserving critical signal features essential for capacity estimation and battery health assessment.

3.4.1.2 Empirical Mode Decomposition (EMD)

To mitigate the effects of noise introduced in the previous step, EMD is applied to the discharge cycle data. EMD is a data-driven, adaptive signal decomposition technique that iteratively separates a signal into IMFs and a residual trend. Each voltage and current signal from the discharge cycles is decomposed using EMD into a finite set of IMFs representing oscillatory modes at distinct frequency scales (Cordova et al., 2021). High-frequency IMFs, typically corresponding to noise, are identified and excluded from the reconstruction. The denoised signal is then obtained by summing the remaining IMFs and the residual component. This filtering operation is expressed in equation;

$$x(t) = \sum_{j=1}^{N} c_i(t) + r_N(t) \tag{3.8}$$

Where; $c_i(t)$ are IMFs and $r_N(t)$ is the residual. EMD is beneficial for removing noise from battery degradation signals, making it easier for LSTM to learn long-term dependencies.

EMD filtering is selected over conventional linear filtering approaches and even multiresolution techniques such as WT due to its fully adaptive and data-driven nature. Unlike wavelet methods that require predefined basis functions, EMD directly extracts signal components based on the local extrema, making it particularly effective for processing non-linear and non-stationary signals such as battery discharge voltage and current profiles. This adaptability enables precise denoising while retaining critical transient features relevant to capacity estimation and battery health diagnostics.

3.4.1.3 Kalman Filter (KF)

To mitigate the effects of noise introduced in the previous step, a one-dimensional Kalman filter is applied to the discharge cycle data. The KF is a recursive state estimator that combines prior predictions with noisy observations to produce a filtered signal with minimized estimation error (H. Wang et al., 2021). For each discharge cycle, the voltage and current time series are independently processed using a scalar KF, which recursively updates the state estimate based on a prediction-correction framework. This denoising operation is mathematically described in equation;

$$\bar{x}_k = \bar{x}_{k-1} + K_k(z_k - \bar{x}_{k-1}) \tag{3.9}$$

Where; $\bar{x}_k$ is the filtered signal at time step k, z_k is the noisy observation, and K_k is the Kalman gain, computed as;

$$K_k = \frac{P_{k-1} + Q}{P_{k-1} + Q + R} \tag{3.10}$$

Where; P_{k-1} is the prior estimate of the error covariance, Q represents the process noise covariance, and R is the measurement noise covariance. The filter continuously updates the state and error covariance to adapt to the characteristics of the input signal.

The KF is chosen for its ability to perform online estimation with minimal computational overhead while maintaining robustness to both measurement and process noise. Unlike frequency-domain techniques such as WT or EMD, the KF operates entirely in the time domain and requires no prior signal decomposition. This makes it particularly well-suited for real-time battery management systems where low-latency and adaptive noise suppression are critical. The algorithm effectively preserves the trend and shape of transient voltage and current signals, which are essential for downstream tasks such as capacity modelling and fault detection.

3.4.3 Machine Learning

In this study, three machine learning algorithms SVM, LSTM networks, and GRU networks are applied to model and predict the SoH of lithium-ion batteries. These algorithms are chosen for their ability to handle nonlinear relationships and time-dependent patterns in battery degradation. SVM performs well with smaller datasets and high-dimensional features, LSTM is effective in learning long-term sequence patterns, and GRU offers a faster, simpler alternative to LSTM with comparable accuracy.

The experimental work uses the NASA Ames Prognostics Data Repository's lithium-ion battery datasets B0005, B0006, and B0007, which contain time-series measurements of voltage, current, temperature, and capacity across charge-discharge cycles. To simulate real-world measurement disturbances, Gaussian noise is added to the raw signals, representing effects such as sensor thermal noise and electromagnetic interference. These noisy signals are then cleaned and enhanced using EMD, WT, and KF methods.

From the denoised data, key features such as the TIEDVD, TIECVD, and filtered capacity are extracted as inputs to the machine learning models. The proposed hybrid approach combines noise reduction and feature extraction from the signal processing stage with the predictive capabilities of the machine learning stage, allowing the models to capture both short-term fluctuations and long-term degradation trends for more accurate SoH estimation.

3.4.2.1 Support Vector Machine (SVM)

After obtaining the denoised discharge cycle data, features such as the TIEDVD and TIECVD are extracted. These features, along with the filtered capacity data, serve as input predictors for training a SVM regression model. The function svm is used to train the SVM model, optimizing hyperparameters such as BoxConstraint, KernelScale, and Epsilon to achieve optimal prediction performance (Feng et al., 2019). The trained model is then employed to estimate the SoH of the battery in the later stages of its lifecycle which is 100 cycles data for training and remaining 63 cycles for testing. The estimation is computed using equation;

$$Y(x) = \sum_{j=1}^{N} a_i y_i K(\varkappa, x_i) + b \tag{3.11}$$

Where; x is the input vector, x_i represents the support vectors from the training data, a_i are the learned Lagrange multipliers, y_i are the corresponding class labels (for classification) or output values (for regression), $K(\varkappa, x_i)$ is the kernel function that measures similarity between x and x_i, b is the bias term, N is the number of support vectors and $Y(x)$ is the final prediction output from the model as simulated in Figure 3.4.

An essential metric for assessing battery performance is the SoH, which is calculated for both the first and second life segments. The SoH is defined as the ratio of the remaining capacity to the rated capacity ($Crated$) which is assumed to be 2 Ah in this study. The SoH is computed using equation;

$$SOH_i = \frac{C_i}{C_{rated}} \tag{3.12}$$

Where; Ci is the capacity of the ith cycle charge and discharge cycle, and $Crated$ is the initial discharge capacity. The calculated SoH values for both life segments are concatenated to form a comprehensive SoH profile.

Battery SoH prediction is crucial for BMS as it enables proactive maintenance, efficient energy utilization, and enhanced safety in applications such as EVs and grid storage. Accurate SoH estimation allows early detection of degradation trends, facilitating timely intervention before failure occurs. The use of SVM is particularly advantageous due to its capability to model nonlinear relationships between extracted features and battery degradation patterns, ensuring reliable and generalizable SoH predictions.

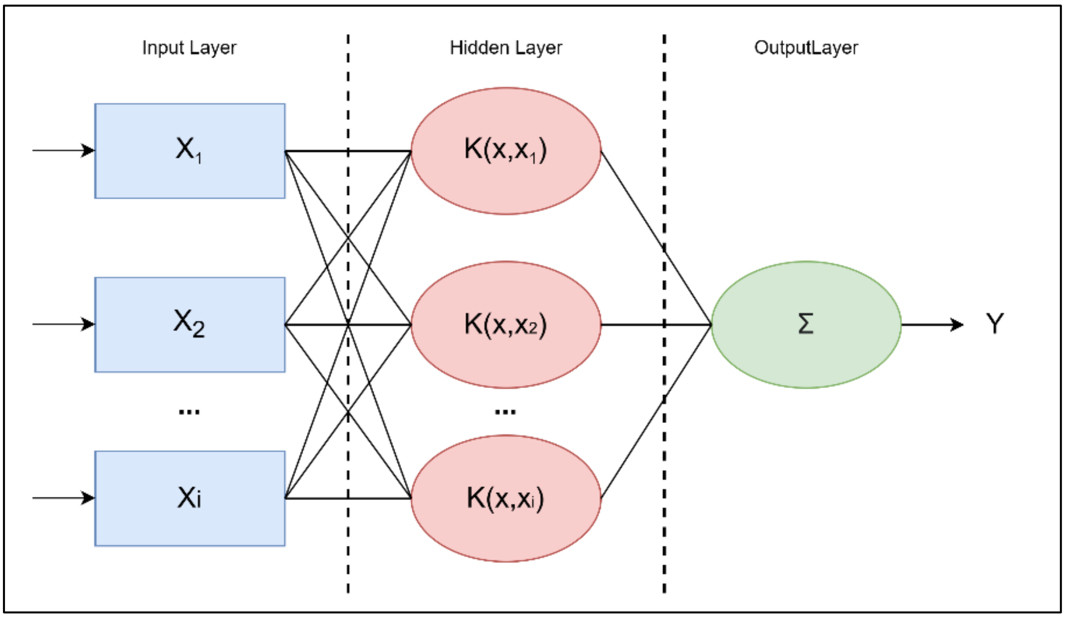

Figure 3.4 Structure of the SVM Algorithm

By integrating noise simulation, wavelet-based denoising, and machine learning-based SoH estimation, the proposed methodology provides a comprehensive framework for enhancing battery health assessment in real-world conditions.

3.4.2.2 Long Short-Term Memory (LSTM)

In battery prediction, LSTMs are widely used for forecasting the RUL and SOH based on historical sensor data, such as voltage, current, and temperature. The model processes past battery performance data in a sequential manner, capturing long-term dependencies to predict future degradation trends. During training, the LSTM learns complex temporal relationships by minimizing a loss function, typically Mean Squared Error (MSE), using backpropagation through time (BPTT). Once trained, the model can accurately estimate battery aging and failure points, helping optimize energy management systems and predictive maintenance strategies (K. Liu et al., 2021). Variants like bidirectional LSTMs and attention mechanisms further enhance predictive accuracy by considering dependencies in both past and future time steps.

$$f_t = \sigma\left(W_f \cdot [h_{t-1'} x_t] + b_f\right) \tag{3.13}$$

$$i_t = \sigma(W_i \cdot [h_{t-1'} x_t] + b_i) \tag{3.14}$$

$$\tilde{C}t = \tanh(W_c \cdot [h_{t-1'} x_t] + b_c) \tag{3.15}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{3.16}$$

$$o_t = \sigma(W_o \cdot [h_{t-1'} x_t] + b_o) \tag{3.17}$$

$$h_t = o_t \cdot tanh\ (C_t) \tag{3.18}$$

Where; f_t, i_t, o_t are forget, input, and output gates, C_t is the cell state, h_t is the hidden state, W_f, W_i, W_c, W_o and b_f, b_i, b_c, b_o are weights and biases as shown as Figure 3.5.

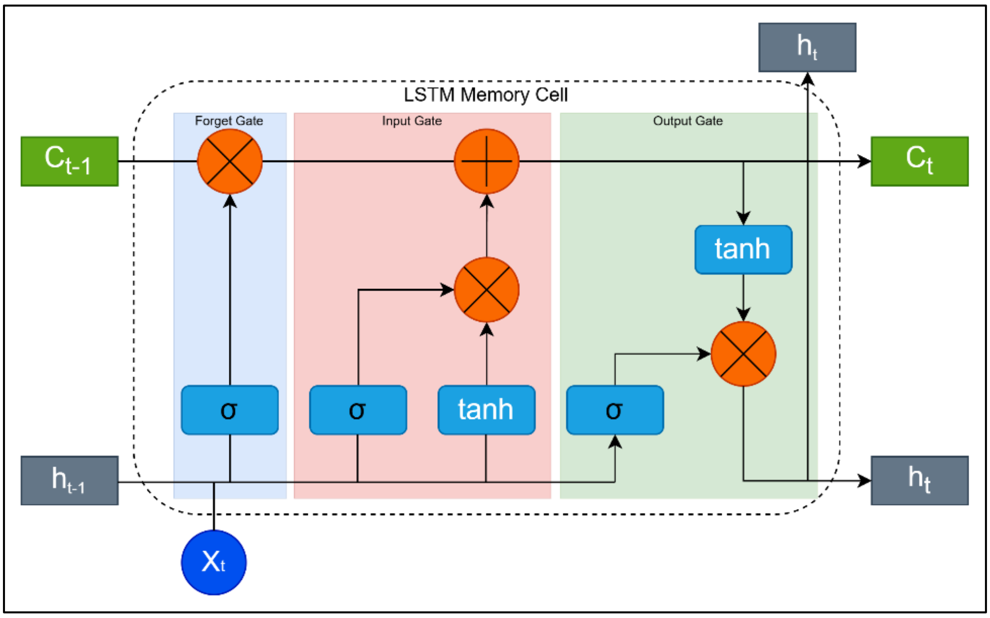

Figure 3.5 Structure of the LSTM Algorithm

3.4.2.3 Gated Recurrent Units (GRU)

In battery prediction tasks, GRU are commonly employed to forecast the RUL and SoH based on historical sensor data, including voltage, current, and temperature. GRUs process battery performance data in a sequential manner, capturing temporal dependencies without the need for a separate cell state, as used in LSTMs. Instead, GRUs rely on an update gate and reset gate to regulate the flow of information. During training, the GRU model learns complex temporal patterns by minimizing a loss function typically MSE through BPTT. Once trained, it can effectively estimate battery aging and predict failure events, contributing to optimized energy management systems and predictive maintenance (Javid et al., 2020). Enhancements such as bidirectional GRUs and attention mechanisms further improve performance by allowing the model to consider both past and future dependencies. The GRU operates according to the following equations:

$$z_t = \sigma(W_z * [h_{t-1}, x_t] + b_z) \tag{3.19}$$

$$r_t = \sigma(W_r * [h_{t-1}, x_t] + b_r) \tag{3.20}$$

$$\tilde{h}t = \tanh(W_h * [r_t * h_{t-1}, x_t] + b_h) \tag{3.21}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}t \tag{3.22}$$

Where; z_t, r_t are the update and reset gates, $\tilde{h}_t$ is the cell state, h_t is the hidden state, and W_z, W_r, W_h and b_z, b_r, b_h are the model weights and biases similar to Figure 3.6.

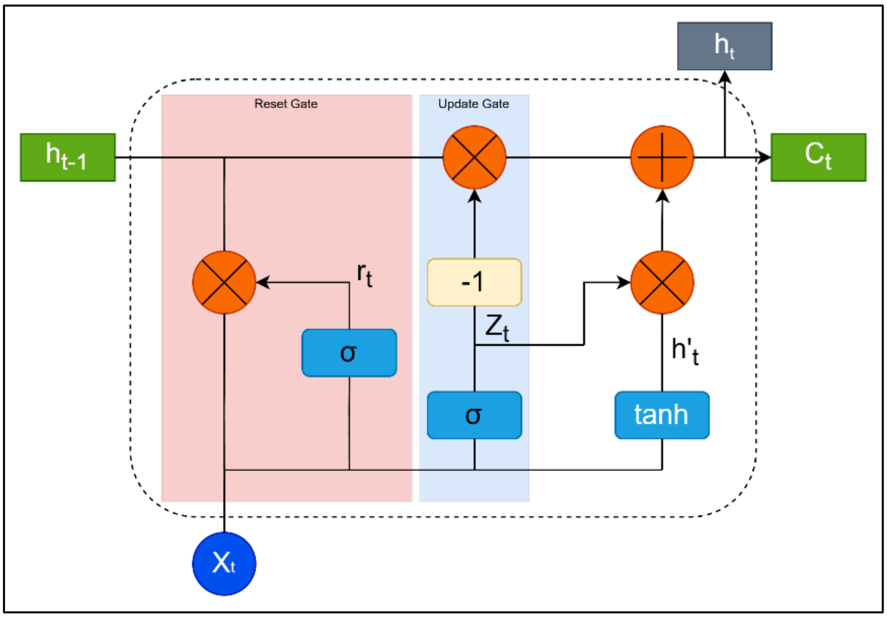

Figure 3.6 Structure of the GRU Algorithm

3.5 Proposed Hybrid Combination

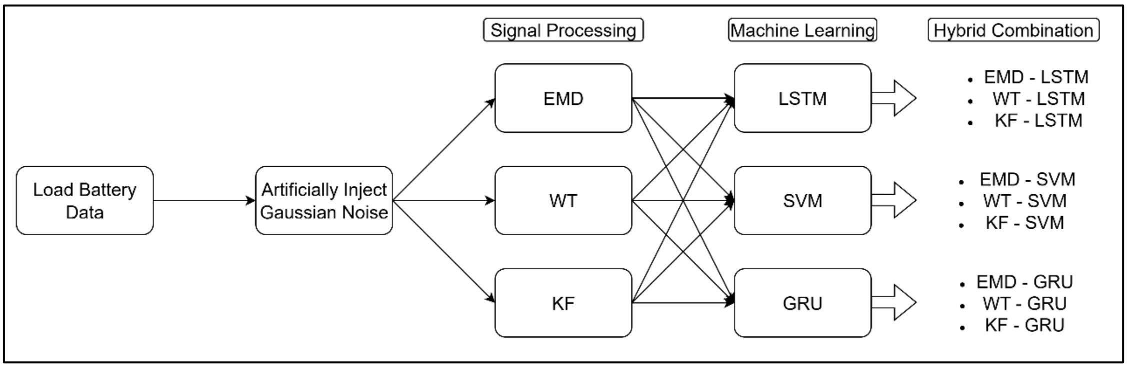

Figure 3.7 Combination Proposed to Evaluate Better Hybrid Techniques in Battery Prediction

The methodology framework illustrated in Figure 3.7 presents a comprehensive approach for predicting battery health by integrating signal processing techniques with machine learning models under simulated real-world conditions. The process begins with the acquisition of battery data from the NASA Ames Prognostics Data Repository, specifically the B0005, B0006, and B0007 datasets. These datasets are widely recognized in the battery research community and contain time-series measurements such as voltage, current, temperature, and capacity across multiple charge-discharge cycles. They serve as a valuable foundation for modelling battery degradation behaviour. To replicate real-world measurement uncertainties, Gaussian noise is artificially injected into the raw battery signals. This step is essential in enhancing the robustness of the developed predictive models by simulating the types of noise typically present in practical applications, such as electric vehicles or grid storage systems. Introducing this controlled noise allows for a more rigorous evaluation of signal processing and learning techniques, especially under non-ideal conditions.

Once the noise is added, various signal processing techniques are applied to clean and extract meaningful features from the noisy data. In this study, three methods are utilized: EMD, WT, and the KF. EMD is particularly suitable for decomposing nonlinear and non-stationary signals into intrinsic mode functions, allowing for localized analysis of time-varying battery behaviours. The WT, on the other hand, captures both time and frequency information, enabling the detection of transient and long-term degradation patterns. The KF serves as a recursive estimator that effectively smooths noisy time-series data and is widely used in battery state estimation tasks. Following signal processing, the cleaned and enhanced data is used to train several machine learning models. These include LSTM networks, GRU, and SVM. LSTM and GRU are recurrent neural network architectures capable of learning temporal dependencies in sequential data, making them well-suited for capturing the progression of battery degradation over cycles. SVM is a more traditional machine learning algorithm that performs well on smaller datasets and is used here for regression or classification depending on the output structure.

The final phase of the framework involves the construction of hybrid combinations, where each signal processing technique is paired with one of the machine learning models. Examples of such combinations include EMD-LSTM, WT-GRU, and KF-SVM. These hybrid models aim to leverage the strengths of both signal enhancement and advanced predictive learning, resulting in more accurate and stable battery health predictions. By systematically comparing the performance of different hybrid pairings, the study identifies the most effective methodology for robust and reliable battery prognostics. Overall, this structured pipeline not only allows for flexibility in model design and experimentation but also ensures that the evaluation process reflects realistic operating conditions. The integration of artificial noise and hybrid modelling aligns with current research trends and contributes toward the development of intelligent battery management systems capable of functioning reliably in real-world environments.

3.6 Validation of Techniques

Accurate prediction of the RUL of lithium-ion batteries is critical for applications in BESS. These predictions directly impact system safety, operational planning, and maintenance scheduling. Inaccurate forecasts can lead to unexpected failures, reduced performance, or costly downtime, making robust evaluation metrics essential for validating predictive models.

In this research, multiple statistical and error-based metrics were employed to assess the performance of machine learning models across battery datasets B0005, B0006, and B0007. Metrics such as RMSE and MAPE quantify prediction accuracy from both absolute and relative perspectives. These measures, alongside statistical techniques like ANOVA and regression analysis, provide a comprehensive view of model precision, bias, and significance.

The evaluation approach combines numerical error quantification with statistical significance testing to ensure that observed model performance is both accurate and reliable. By applying RMSE, MAPE, ANOVA, and regression analysis to predictions from hybrid signal processing–machine learning models, the study ensures that each algorithm is not only statistically valid but also free from systematic bias. This integrated validation framework is designed to support the safe and effective deployment of predictive models in real-world battery health monitoring systems.

3.6.1 Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3.23}$$

Where; y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data points.

In the validation process, RMSE was calculated for each combination of machine learning model and signal processing technique for every battery dataset ("B0005", "B0006", "B0007"). This technique allows for a direct and quantitative comparison of predictive accuracy. For instance, by comparing the RMSE values across the EMD-LSTM, EMD-SVM, and EMD-GRU models, it is possible to objectively determine which algorithm provides the most accurate RUL predictions when paired with EMD. This comparative analysis was systematically repeated for the WT and KF integrations, enabling a data-driven ranking of all nine hybrid models based on their absolute prediction error.

The importance of RMSE in this research cannot be overstated, particularly due to the safety-critical nature of the target applications in energy storage and EVs. A large prediction error in RUL could lead to catastrophic system failure, such as an EVs unexpectedly losing power. Because RMSE disproportionately penalizes these large errors, it serves as a crucial indicator of model reliability and risk. A model that achieves a low RMSE is not only accurate on average but is also less prone to making the kind of egregious errors that could compromise system safety, making it an indispensable metric for validating the practical deploy ability of the developed models.

3.6.2 Mean Absolute Percentage Error (MAPE)

The MAPE is a metric that quantifies prediction accuracy as a percentage. It is calculated by taking the average of the absolute differences between predicted ($\hat{y}_i$) and actual (y_i) values, divided by the actual values. The primary advantage of MAPE, as noted, is its scale-independent nature, which expresses the average error in intuitive percentage terms. This makes it exceptionally useful for comparing model performance across datasets that may have different scales, such as batteries with widely varying total lifecycles.

$$\text{MAPE} = \frac{100\%}{\pi}\sum_{i=1}^{\Pi}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \qquad (3.24)$$

Where; y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data points.

The validation technique involving MAPE provides a complementary perspective to RMSE. While RMSE measures absolute error, MAPE measures relative error. This technique was used to assess the proportional magnitude of the prediction errors. For example, a 5-cycle RUL error is far more significant for a battery with a true RUL of 10 cycles (50% MAPE) than for one with a true RUL of 100 cycles (5% MAPE). By calculating MAPE for each prediction, especially in end-of-life scenarios where the true RUL is small, the model's performance in these critical stages can be effectively scrutinized. A low MAPE value across all battery life stages indicates a model that is not only accurate but also consistent in its relative accuracy.

The importance of MAPE lies in its interpretability and its utility in standardizing error assessment. For stakeholders, such as engineers or system operators, an error expressed as a percentage is often more meaningful and actionable than an absolute value. Furthermore, in this research where batteries with different initial health and degradation patterns are studied, MAPE provides a normalized metric to judge if a model is universally effective or if its performance is dependent on the battery's overall lifespan. However, its noted instability when actual values are near zero is also an important diagnostic feature; an extremely high MAPE for a battery with a low true RUL serves as a clear warning flag for poor performance at the critical end-of-life stage.

3.6.3 Analysis of Variance (ANOVA)

ANOVA is a statistical method used to test the significance of a regression model. It works by partitioning the total variance in the observed data into two components: the variance explained by the model and the unexplained variance (or residual error). By comparing these two variances, ANOVA produces an F-statistic and a corresponding p-value. A statistically significant result, typically indicated by a p-value less than a predefined threshold (e.g., 0.05), suggests that the model's ability to explain the data is unlikely to be a result of random chance.

$$SST = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \left(Y_{ij} - \bar{Y}\right)^2 \tag{3.25}$$

$$SS_{between} = \sum_{i=1}^{k} (\bar{Y}_i - \bar{Y})^2 \tag{3.26}$$

$$SS_{within} = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \left(Y_{ij} - \bar{Y}_i\right)^2 \tag{3.27}$$

$$MS_{between} = \frac{SS_{between}}{k-1} \tag{3.28}$$

$$MS_{within} = \frac{SS_{within}}{N-k} \tag{3.29}$$

$$F = \frac{MS_{between}}{MS_{within}} = \frac{SS_{between} \,/\, \mathrm{d}f_{between}}{SS_{within} \,/\, \mathrm{d}f_{within}} \tag{3.30}$$

Where; Y_{ij} is j-th battery capacity value in the i-th group (Original or Filtered), $\bar{Y}$ is the overall mean capacity from both groups combined, $\bar{Y}_i$ is the mean capacity of group i (e.g., mean of original or mean of filtered values), $SS_{between}$ is sum of squares between the group means and the overall mean: measures how different the group means are, SS_{within} is sum of squares within each group: how much individual capacity values deviate from their own group's mean, $\mathrm{d}f_{betwen}$ are degrees of freedom between groups: $k-1$, where k = number of groups (2 in your case: original & filtered), $\mathrm{d}f_{within}$ are degrees of freedom within groups: $N-k$, where N = total number of samples (e.g., 150 original + 150 filtered = 300), $MS_{between}$ is the mean square between groups: average of the between-group sum of squares, MS_{within} is the mean square within groups: average of the within-group sum of squares, and F is F-ratio used to determine statistical significance. F-ratio: if this value is large enough (relative to critical F from F-distribution), it means there is a significant difference between the two groups.

In this research, ANOVA was applied as a technique to validate the statistical significance of the relationship between the predicted RUL and the actual RUL for each model. The ANOVA values presented in the results table represent the p-values from this analysis. The validation technique involved examining these p-values to determine if the developed models provided a statistically meaningful fit to the data. A low p-value would affirm that the signal processing and machine learning integration has successfully captured a non-random, underlying trend in the battery degradation process.

The importance of ANOVA is that it adds a layer of statistical rigor that goes beyond simple error metrics like RMSE or MAPE. While Regression measures the strength of the relationship, ANOVA formally tests for its statistical existence. This is crucial for academic research as it helps to ensure that the observed high performance of a model is not merely an artifact of the specific dataset but represents a genuine predictive relationship. In the context of predicting battery RUL, a significant ANOVA result lends credibility to the claim that the chosen features and model architecture are indeed relevant to the physical degradation phenomena, thereby strengthening the scientific validity of the model.

3.6.4 Regression

Regression analysis, in this validation context, involves plotting the model's predicted battery values ($\hat{y}$) against the actual battery values (y) and fitting a linear regression line of the form $y = a\hat{y} + b$. The parameters of this line the slope (a) and the y-intercept (b) provide a powerful diagnostic tool. As stated, an ideal model would yield a regression line with a slope close to 1 and an intercept close to 0, indicating that the predicted values are, on average, perfectly aligned with the actual values across the entire range of the data.

$$r = \frac{\sum_{i-1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3.31}$$

$$X = \{x_1, x_2, \cdots, x_n\}$$

$$Y = \{y_1, y_2, \cdots, y_n\}$$

Where; $\bar{x}$ is the mean of X, $\bar{x}$ is the mean of Y, and n is the number of data points.

The technique of applying regression analysis serves to identify and quantify systematic biases in the models' predictions. A slope deviating from 1 indicates a proportional bias; for example, a slope less than 1 suggests the model tends to overestimate low RULs and underestimate high RULs. A non-zero intercept indicates a constant bias, where the model consistently predicts values that are higher or lower than the true values by a fixed amount. By examining these parameters for each model, it is possible to diagnose not just the magnitude of the errors, but their nature, revealing tendencies towards over- or under-fitting.

The importance of this regression analysis is paramount for understanding a model's real-world behaviour and trustworthiness. A model could have a low overall RMSE by balancing large overestimations with large underestimations, but such a model would be unreliable in practice. Regression analysis uncovers these hidden biases. For an EVs application, a model with a consistent overestimation bias (a negative intercept or a slope > 1 for certain ranges) would be particularly dangerous. Therefore, this validation technique is essential for ensuring that a model is not only accurate on average but is also unbiased and structurally sound in its predictions, which is a prerequisite for its deployment in safety-critical systems.

3.7 Summary

In this chapter, the comprehensive methodological framework for predicting battery SoH and RUL has been systematically presented. The procedure began with the justification and selection of the globally recognized NASA PCoE battery dataset, establishing a reliable foundation for the study. A key aspect of the methodology was the simulation of realistic operational conditions through the injection of Gaussian noise, thereby creating an authentic testbed to evaluate the noise-resilience and robustness of the proposed models. The subsequent application of three distinct denoising techniques EMD, WT, and KF paired with three machine learning models SVM, LSTM, and GRU established a structured comparative analysis of nine hybrid prognostic systems.

Furthermore, this chapter detailed the rigorous validation strategy designed to provide a holistic performance evaluation. The use of multiple metrics, including RMSE, MAPE, ANOVA, and regression analysis, was explained, highlighting their specific roles in assessing predictive accuracy, relative error, statistical significance, and systemic bias. This multi-pronged validation approach ensures that the performance of each model is not judged on a single criterion but is scrutinized from several critical perspectives. The detailed procedures for signal processing, model training, and performance evaluation form a transparent and reproducible blueprint that guarantees the scientific validity of this research.

Having established this robust methodological foundation, the subsequent chapter will present and analyse the empirical findings derived from its execution. The chapter 4 will showcase the quantitative outcomes for each of the nine hybrid models across the selected battery datasets. A detailed comparative analysis will be conducted to interpret these results, identifying the synergies between specific filtering methods and prediction algorithms. This will lead to an evidence-based conclusion regarding the most effective and robust model configuration for accurate battery health prognostics, directly addressing the core objectives of this thesis.

CHAPTER 4
RESULTS

4.1 Introduction

This chapter presents the comprehensive results obtained from the integration of advanced signal processing techniques with state-of-the-art machine learning models for the prediction of battery health in energy storage and electric vehicle systems. The central investigation of this study is to systematically evaluate the effectiveness of three distinct signal filtering methods namely EMD, WT, and the KF in enhancing the accuracy of battery health predictions. These filters are strategically applied to pre-process raw battery degradation data before it is fed into three different machine learning architectures: LSTM, SVM, and GRU. The overarching goal of combining these methods is to develop a hybrid approach that significantly improves the reliability and precision of both SoH estimation and RUL forecasting.

The subsequent evaluation is grounded in a rigorous, multi-faceted analysis using a suite of standard performance metrics, including RMSE, MAPE, Regression, and ANOVA. These metrics provide a quantitative framework to assess how well each of the nine hybrid models performs in predicting battery health conditions across the NASA battery dataset. The chapter will present a series of figures and tables that meticulously illustrate the results of capacity estimation, SoH prediction, and RUL forecasting. These comparisons facilitate a detailed analysis of the unique strengths and weaknesses of each filter-model combination, thereby enabling the identification of the most suitable and robust methodology for real-time battery health monitoring.

Furthermore, this chapter situates our findings within the broader scientific context by including a direct comparison with results from previous research to validate the efficacy of our proposed methodology. The results will highlight how the synergistic integration of signal processing with machine learning leads to a marked improvement in prediction accuracy compared to conventional approaches. The chapter culminates in a detailed discussion of the key discoveries, identifying which model combination yields the most superior performance. This analysis provides a clear, evidence-based foundation for selecting the optimal approach for future implementations in practical

Battery Management Systems (BMS), ultimately contributing to safer and more reliable energy systems.

4.2 Dataset

This section visually introduces the battery data that forms the basis of this study. The following figures will illustrate the data in its original, clean state from the NASA dataset, then show the data after the introduction of simulated noise to replicate real-world conditions, and finally present the results of applying the three different signal processing filters (EMD, WT, and KF) to denoise the signals.

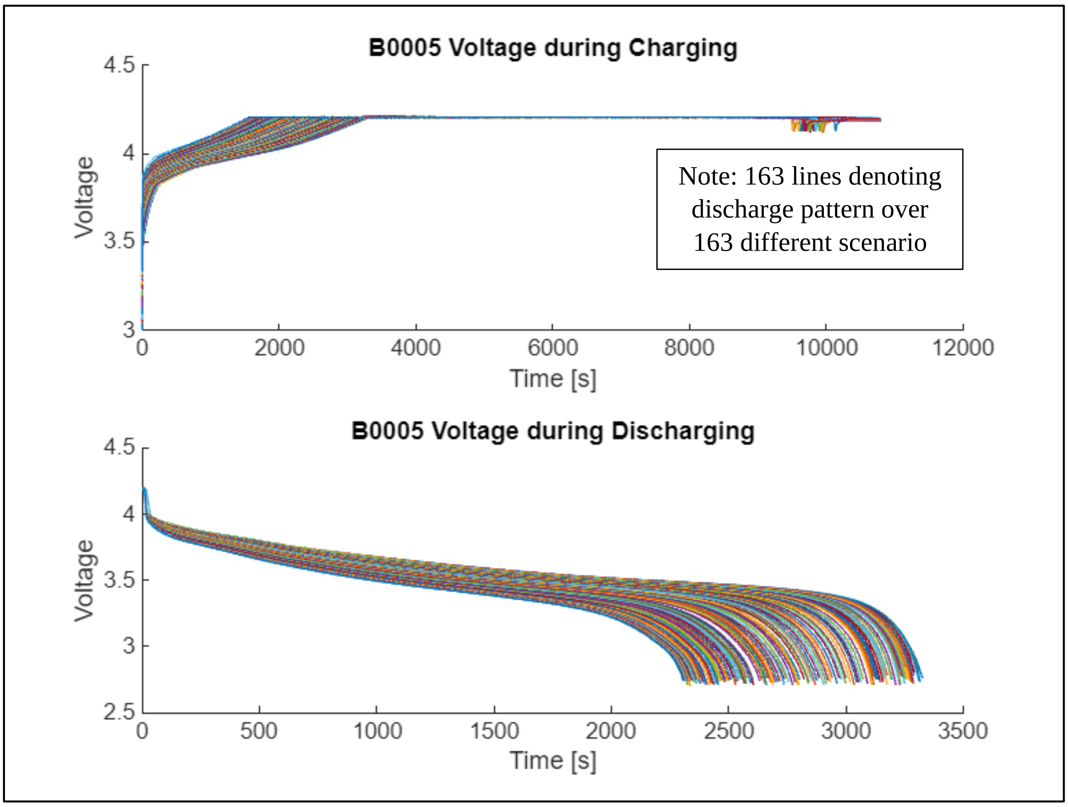

Figure 4.1 B0005 Original Nasa Data

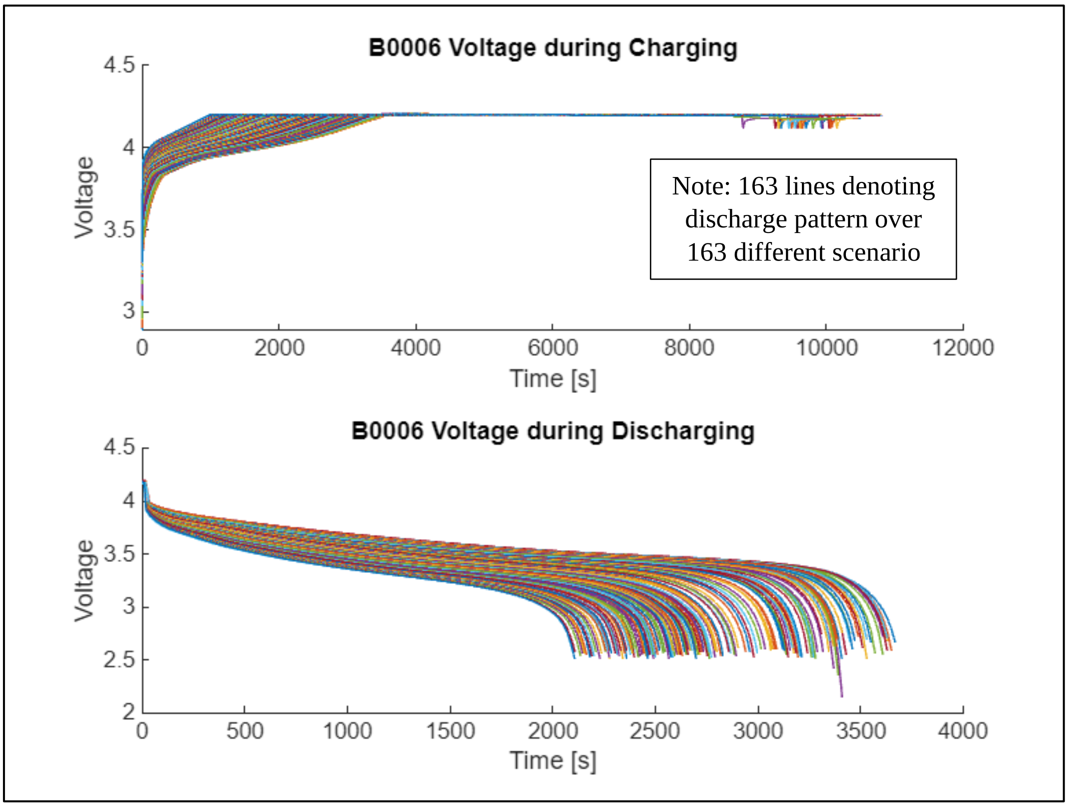

Figure 4.2 B0006 Original Nasa Data

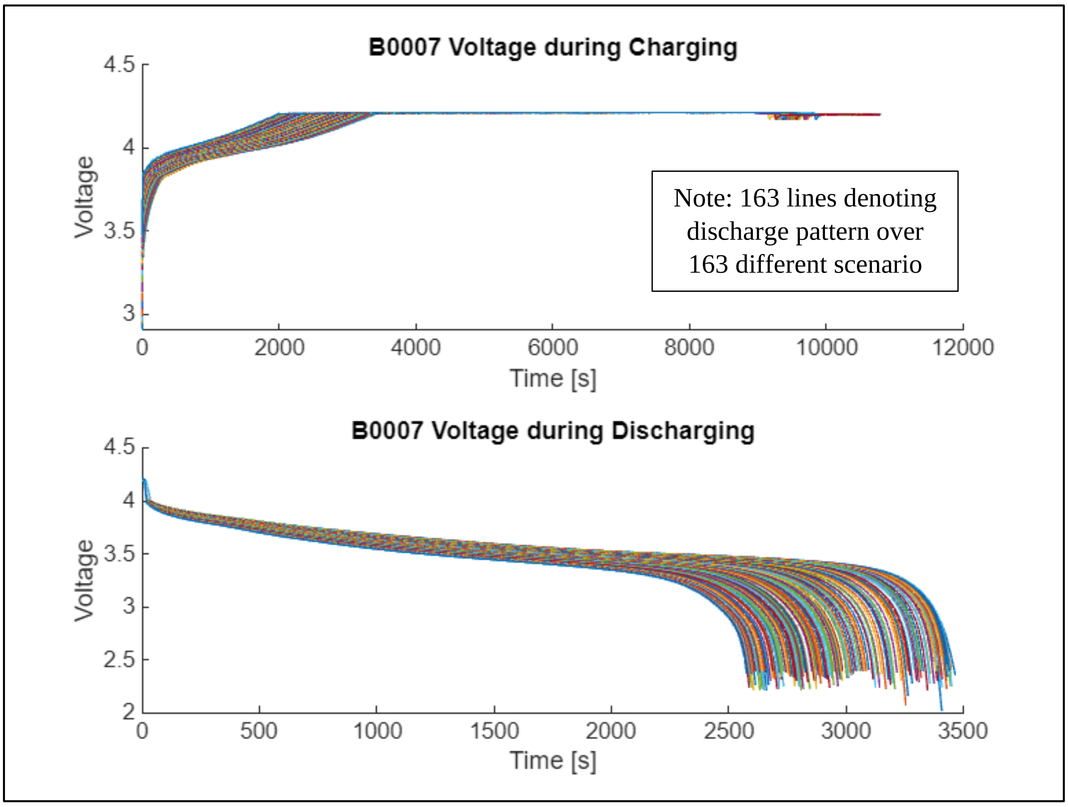

Figure 4.3 B0007 Original Nasa Data

Figure 4.1 shows the original discharge cycle of battery B0005 from the NASA dataset, representing the baseline voltage response during a standard discharge event.

The curve captures the characteristic voltage drop over time as the battery depletes its stored energy. This signal serves as the unaltered reference for analysing the impact of signal processing and machine learning algorithms applied in subsequent stages of the study. Figure 4.2 presents the original discharge cycle for battery B0006, recorded under similar conditions. The voltage profile demonstrates the natural degradation behaviour associated with aging lithium-ion cells. Like battery B0005, this signal remains unprocessed and free of synthetic noise, preserving the integrity of the raw dataset used for performance benchmarking. Figure 4.3 show the original discharge cycle of battery B0007. This curve, along with those of B0005 and B0006, contributes to establishing a representative dataset of real-world battery degradation without any artificial disturbances. These original signals form the foundation for evaluating the effectiveness of subsequent noise filtering and state-of-health prediction techniques applied across different battery units.

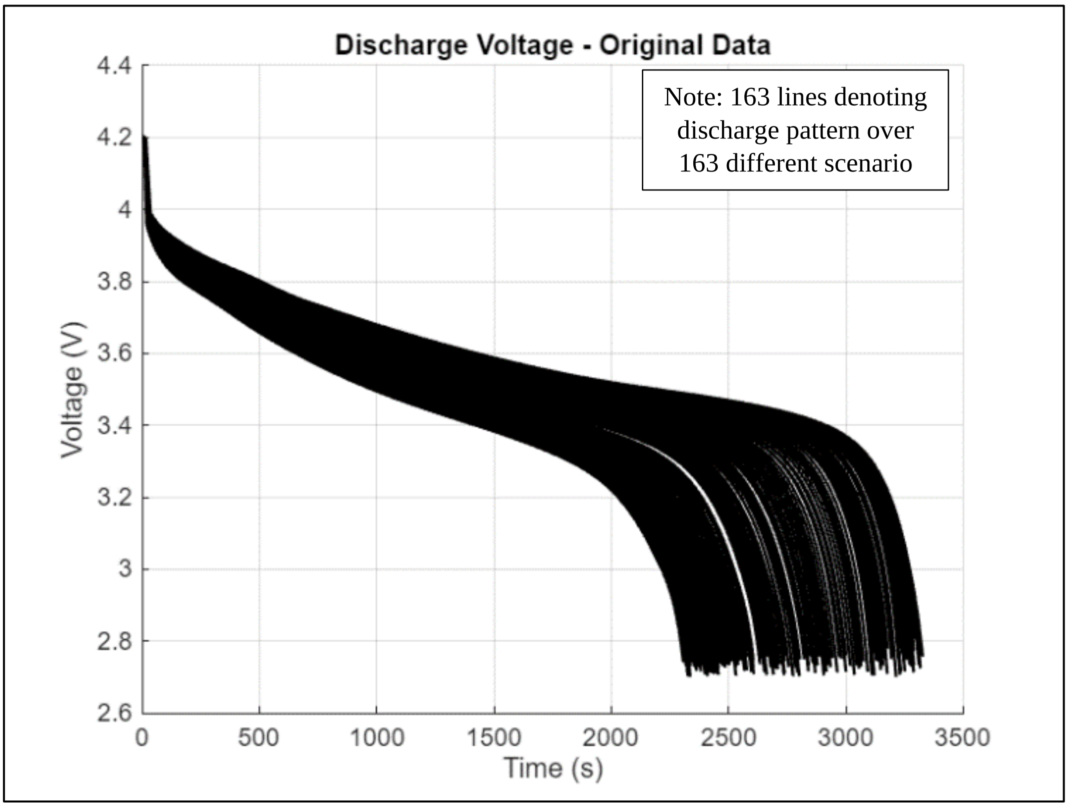

Figure 4.4 Nasa Original Discharge Data

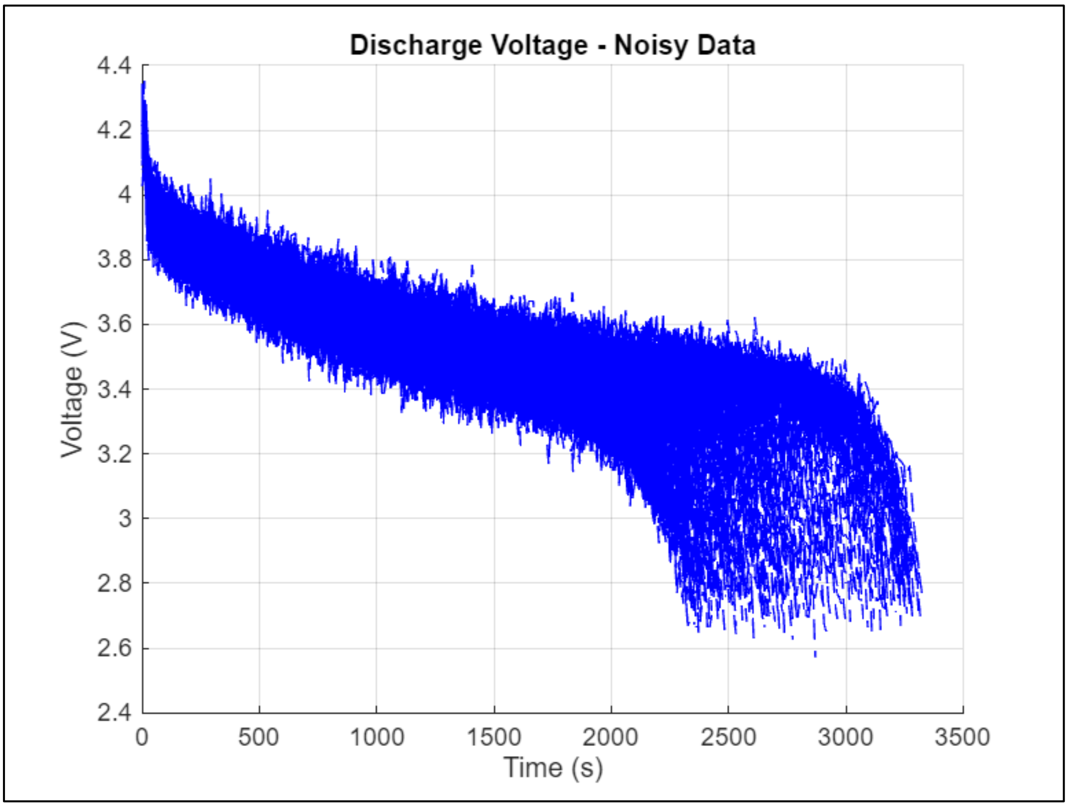

Figure 4.5 Noisy Discharge Data

Figure 4.4 consolidates the discharge curves into a single plot, establishing a clean, noise-free visual baseline. The well-defined family of curves illustrates the ideal degradation pattern. This plot serves as a ground-truth reference, representing the underlying signal we aim to recover from noisy measurements. Figure 4.5 demonstrates the core challenge addressed by this research. It shows the same discharge data from Figure 4.4 but is intentionally corrupted with high-frequency noise. The dispersion of the signal obscures the distinct degradation curves, highlighting how real-world sensor noise can compromise data integrity and provides the central justification for employing signal filtering techniques.

Figure 4.6 shows the result after using the EMD filter on the noisy data. The noise is reduced, and the curves become clearer again. This means the EMD filter works well in cleaning up the signal and keeping the original shape of the discharge curves. Figure 4.7 shows the result of using the WT. Like the EMD filter, it removes the noise and gives smooth and clear discharge curves. This proves that the WT method is also good at filtering noisy battery data. Figure 4.8 shows the result from the KF. The curves here are very smooth maybe too smooth. This might be a problem because it can remove not only the noise but also some important small changes in the signal that show the real condition of the battery.

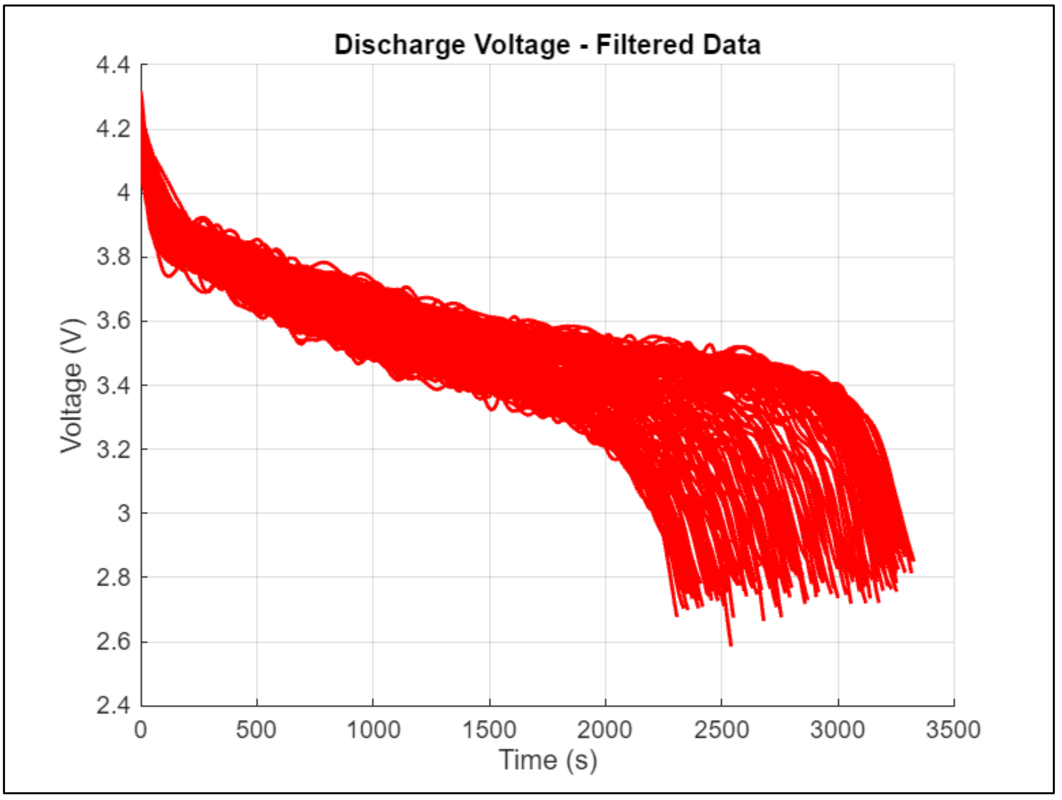

Figure 4.6 EMD Filtered Discharge Data

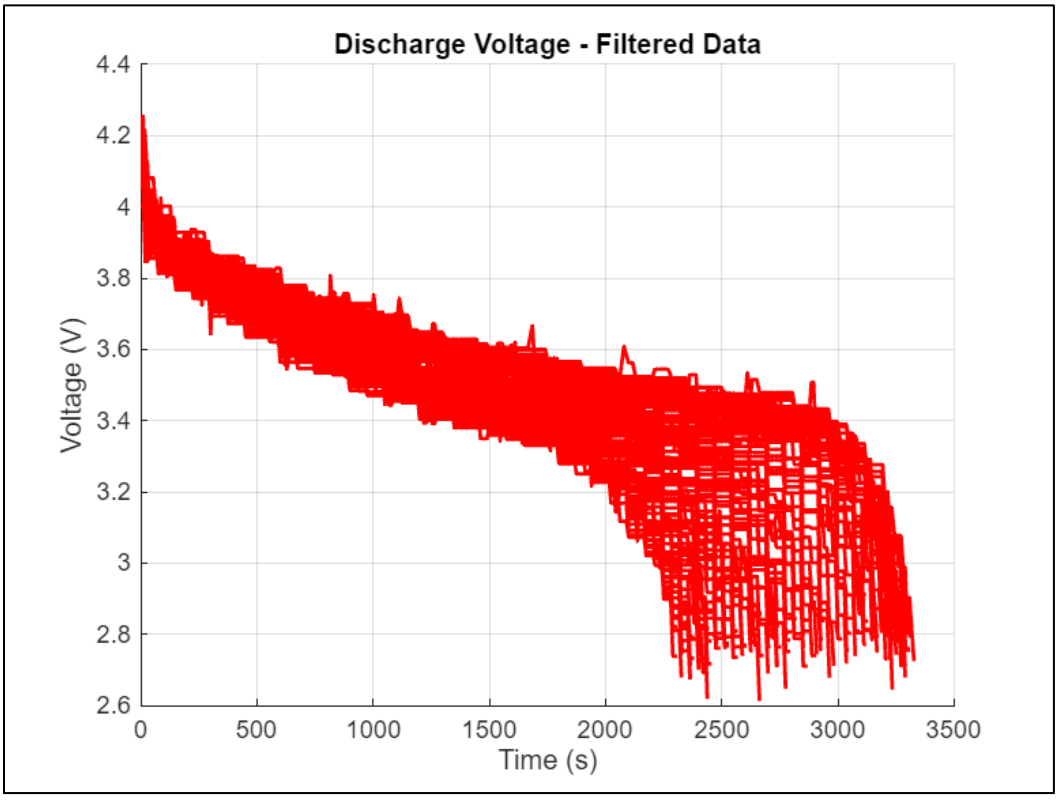

Figure 4.7 WT filtered Discharge Data

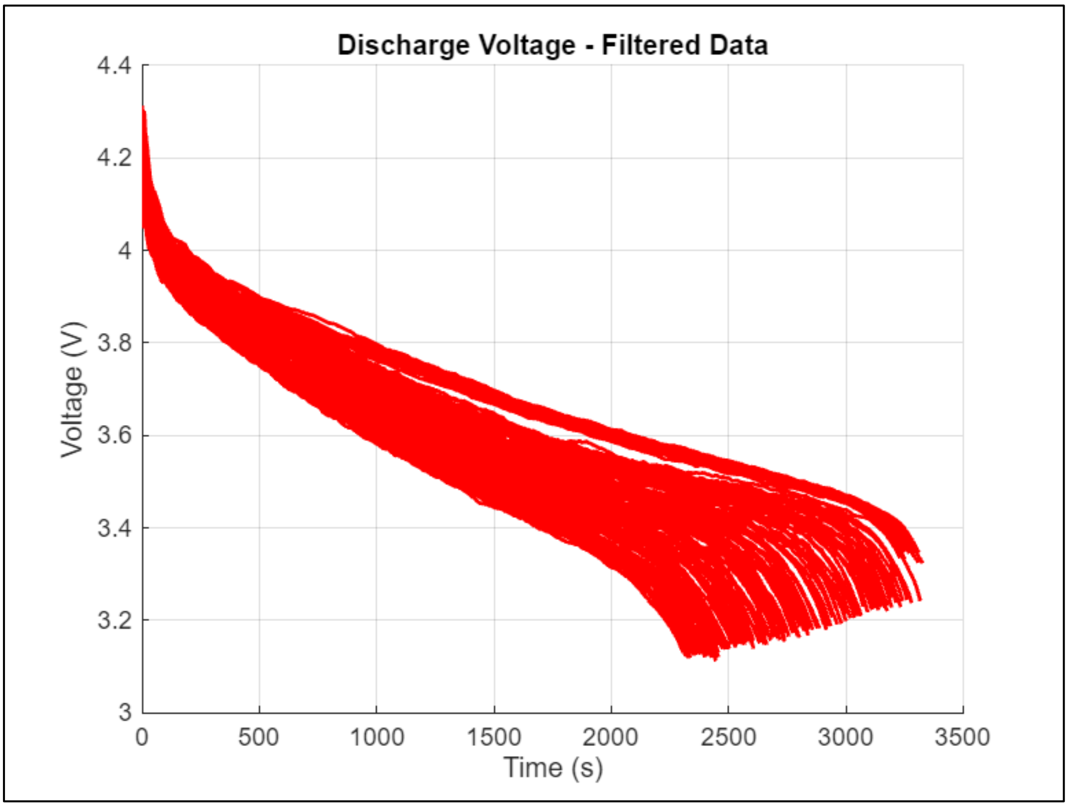

Figure 4.8 KF filtered Discharge Data

4.3 Capacity Comparison

This section focuses on validating the effectiveness of the signal processing techniques. The plots below compare the battery capacity degradation curve calculated from the original, noise-free data against the capacity curves calculated from the filtered data. The goal is to demonstrate that each filter successfully removes noise while preserving the essential capacity information, which is a critical indicator of battery health.

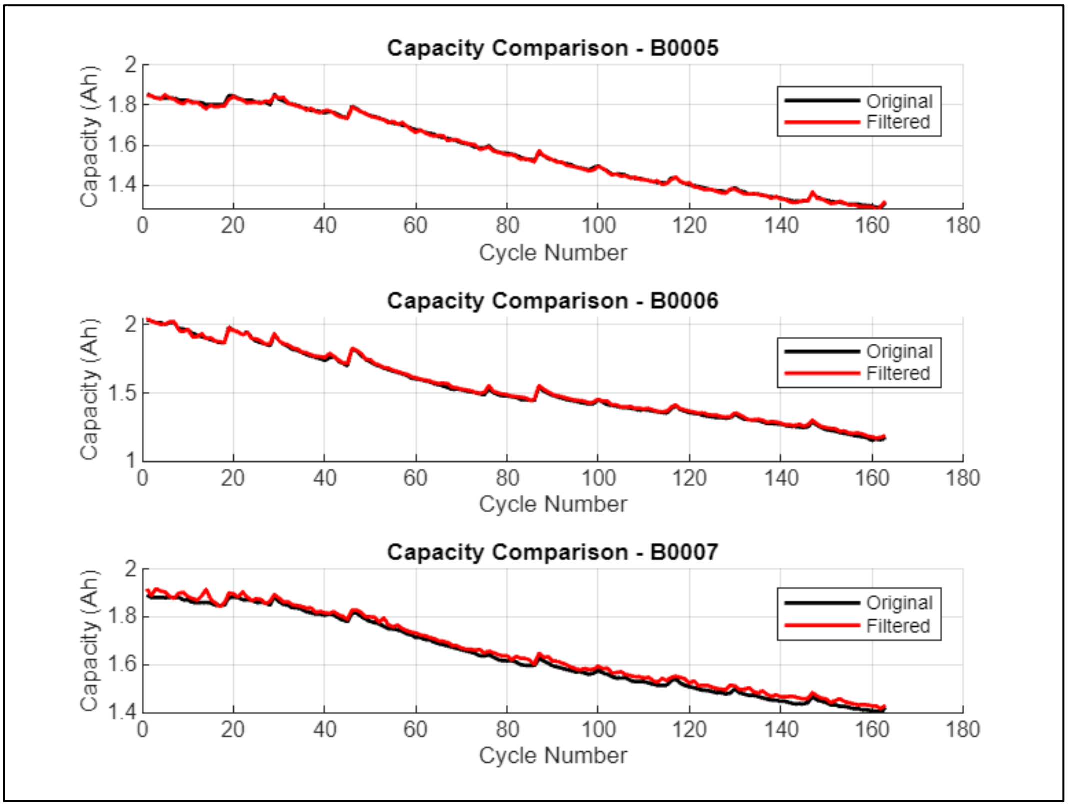

Figure 4.9 Capacity with EMD Filtering

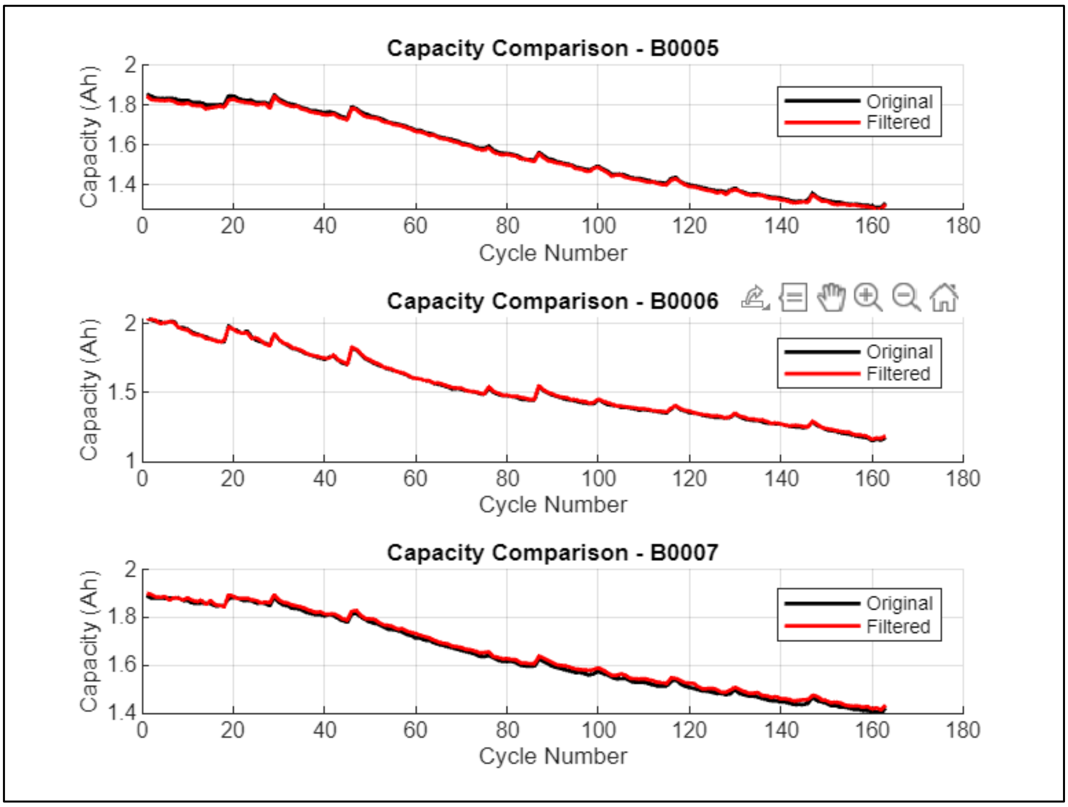

Figure 4.10 Capacity with WT Filtering

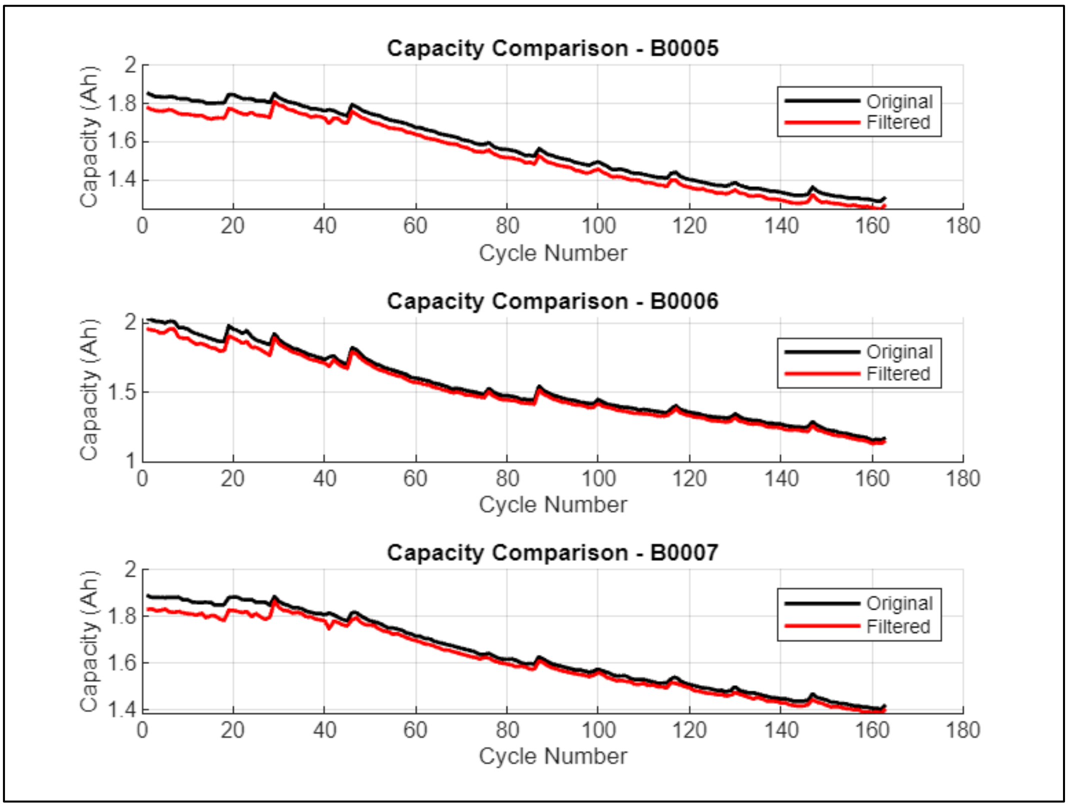

Figure 4.11 Capacity with KF Filtering

Figure 4.9 provides a critical validation of the EMD filtering process. The plot shows that the capacity calculated from the EMD-filtered signal (red line) almost perfectly overlaps with the capacity calculated from the original, clean signal (black line). This confirms that the filter removes noise without distorting the essential ground-truth metric of capacity fade. Figure 4.10 performs the same validation for the WT. The tight correlation between the original and filtered capacity curves demonstrates that the wavelet filtering process accurately preserves the integrity of the underlying degradation data, validating its use for feature extraction. Figure 4.11 validates the KF process. The close alignment of the filtered capacity curve with the original once again confirms that the essential information about capacity degradation is maintained. This step is crucial for all three filters, as it ensures our models are trained on features that are representative of the true physical process.

The summary of comparison between EMD, KF, and WT is shown in Table 4.1. WT is the best overall choice because it performed best on two out of the three batteries (B0006 and B0007). EMD was only the best for one battery (B0005), and the KF consistently had the highest error in all cases.

Table 4.1
RMSE Comparison between Original and Filtered Capacity Data

Signal Processing	B0005	B0006	B0007
EMD	0.0070693	0.011937	0.01747
KF	0.048619	0.03826	0.030814
WT	0.0087207	0.0071029	0.012348

4.4 SoH Comparison

This section presents the core predictive results of the research. The following series of plots provides a visual comparison between the actual SoH degradation of each battery and the predicted SoH values generated by each of the nine hybrid models. This initial visual assessment offers insight into how accurately each filter and machine learning combination tracks the battery's health over its lifecycle.

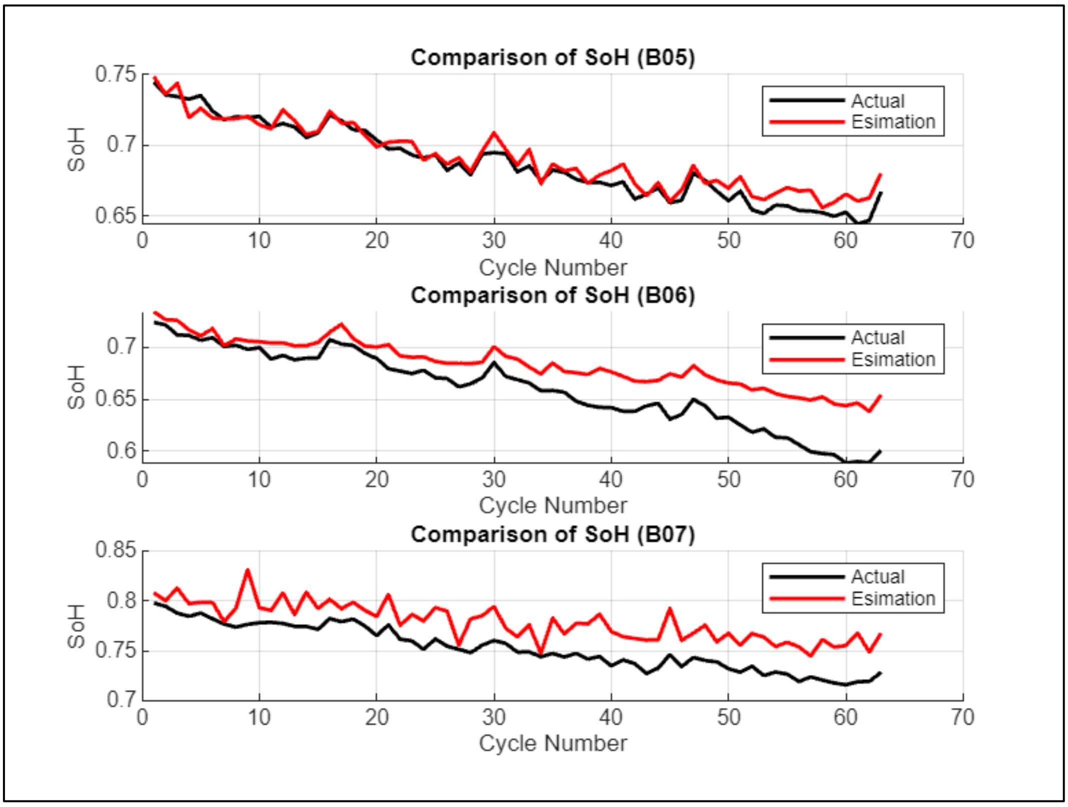

Figure 4.12 SoH with Hybrid Approach EMD-LSTM

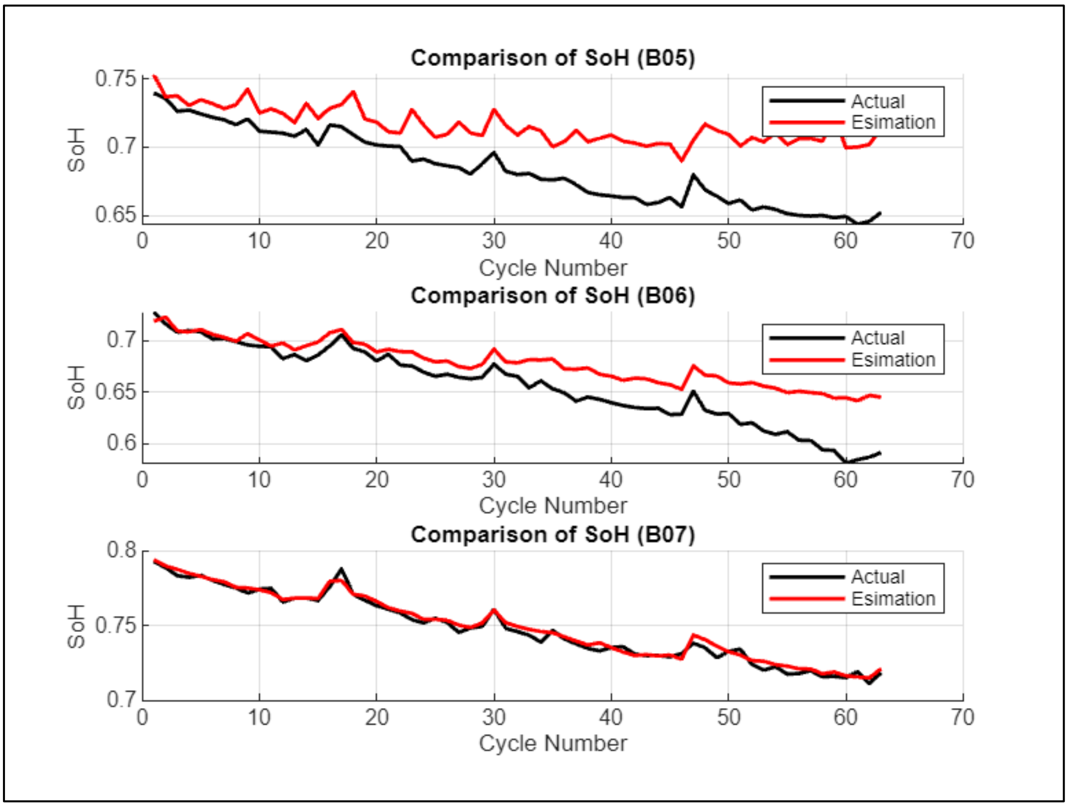

Figure 4.13 SoH with Hybrid Approach EMD-SVM

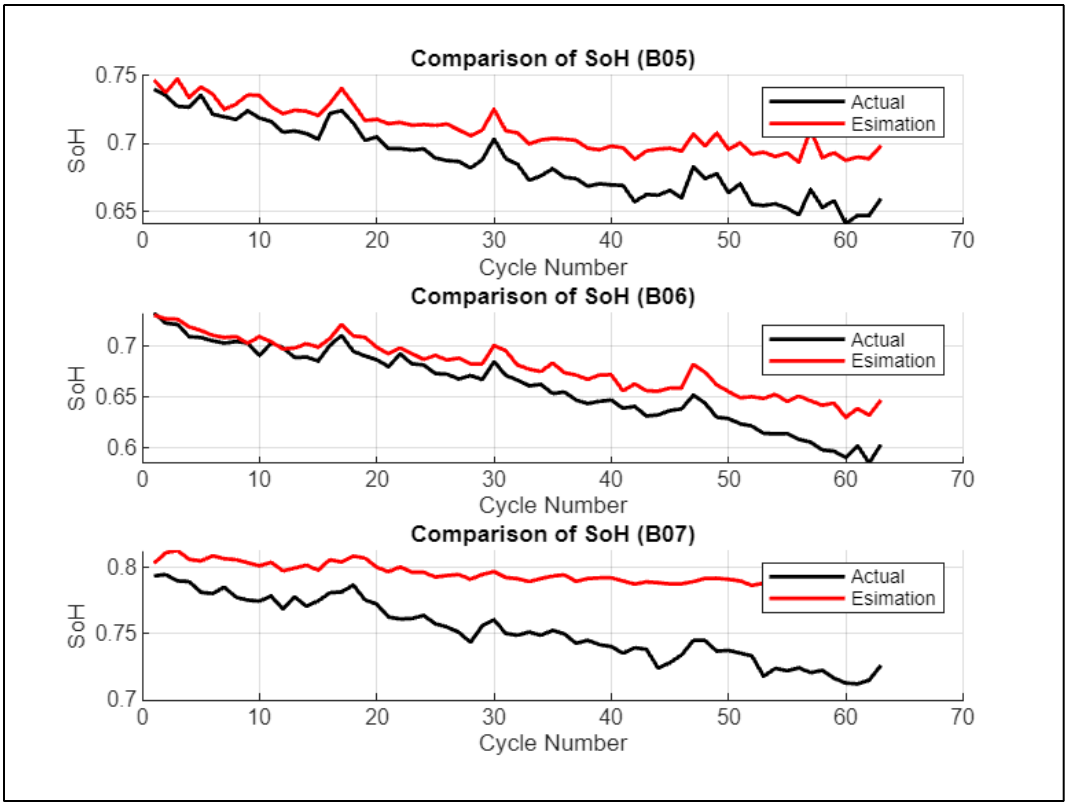

Figure 4.14 SoH with Hybrid Approach EMD-GRU

Figure 4.12 shows the SoH prediction results for the EMD-LSTM model. The close tracking between the predicted (red) and actual (black) SoH values for batteries

B0005 and B0007 indicates strong predictive accuracy. However, a visible gap for battery B0006 suggests the model has a higher prediction error for that specific degradation pattern. Figure 4.13 presents the prediction results for the EMD- SVM model. A significant deviation is observed for battery B0005, indicating the model struggles with earlier-stage prediction. Conversely, the exceptionally tight fit for B0006 and B0007 suggests a high degree of accuracy for batteries in their later stages of life. Figure 4.14 displays the results for the EMD-GRU model. The model demonstrates a balanced and consistent performance across all three batteries. The predicted SoH values closely follow the actual degradation curves, suggesting this combination offers robust generalizability without the specialization seen in the EMD-SVM model.

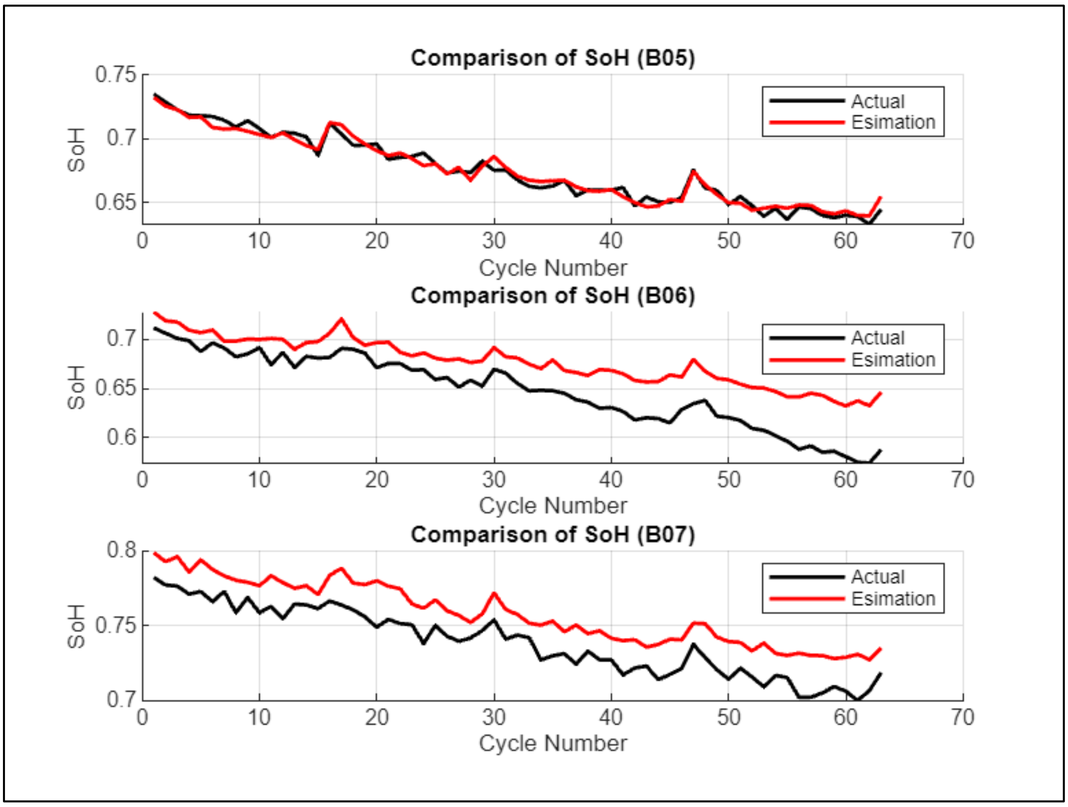

Figure 4.15 SoH with Hybrid Approach WT-LSTM

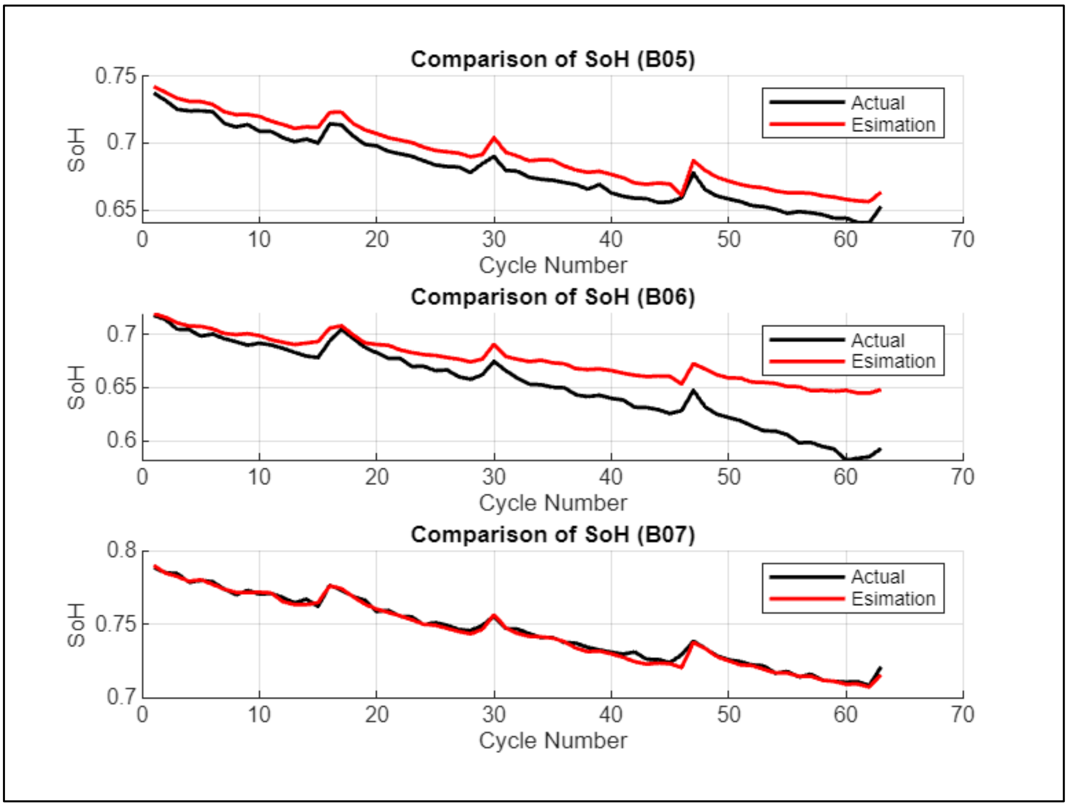

Figure 4.16 SoH with Hybrid Approach WT-SVM

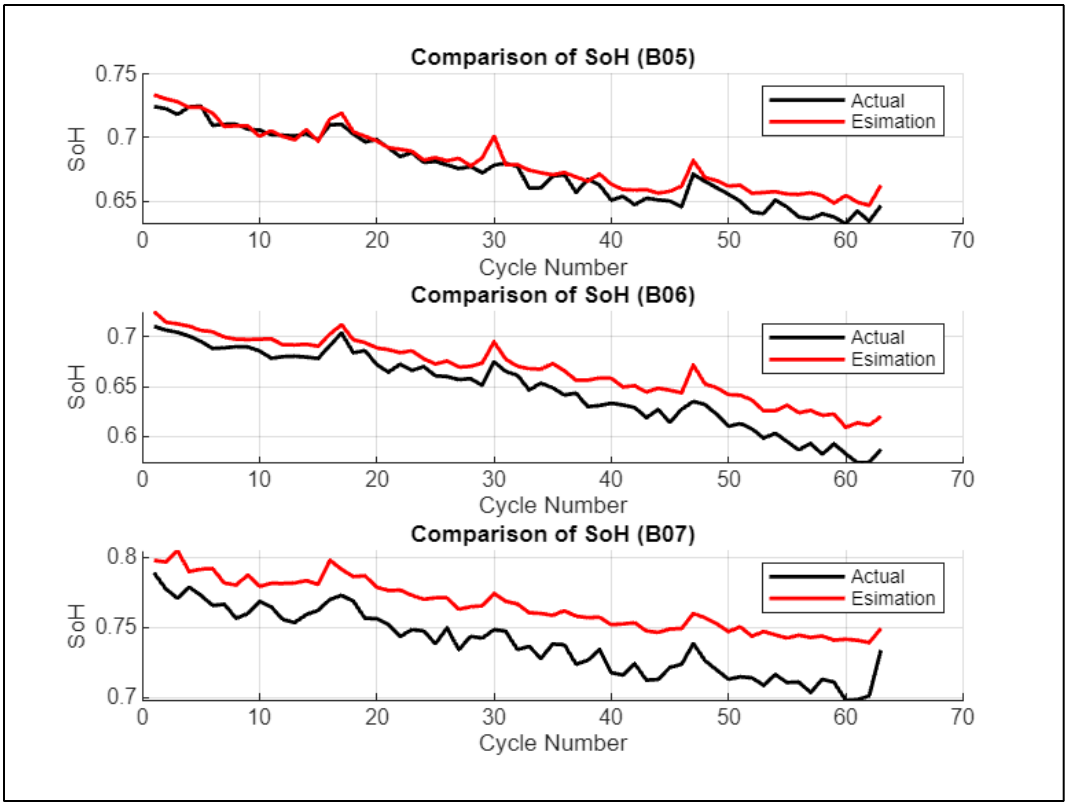

Figure 4.17 SoH with Hybrid Approach WT-GRU

Figure 4.15 shows the SoH prediction for the WT-LSTM model. The plots for B0005 and B0006 indicate a good fit. However, the apparent accuracy for B0007 is misleading, as this visual representation of SoH tracking does not capture the model's significant failure in predicting the final RUL, which is a key finding detailed in the quantitative tables. Figure 4.16 presents the results for the WT-SVM model. The exceptionally tight correlation between the predicted and actual SoH across all three battery plots provides strong visual evidence of this combination's superior and highly consistent predictive accuracy, which aligns with its top performance in the quantitative analysis. Figure 4.17, showing the WT-GRU results, mirrors the performance of the WT-LSTM model. It demonstrates a recurring failure mode for RNN-based architectures with wavelet features, where apparent SoH tracking accuracy masks a critical inability to correctly predict the RUL for a battery near its end-of-life.

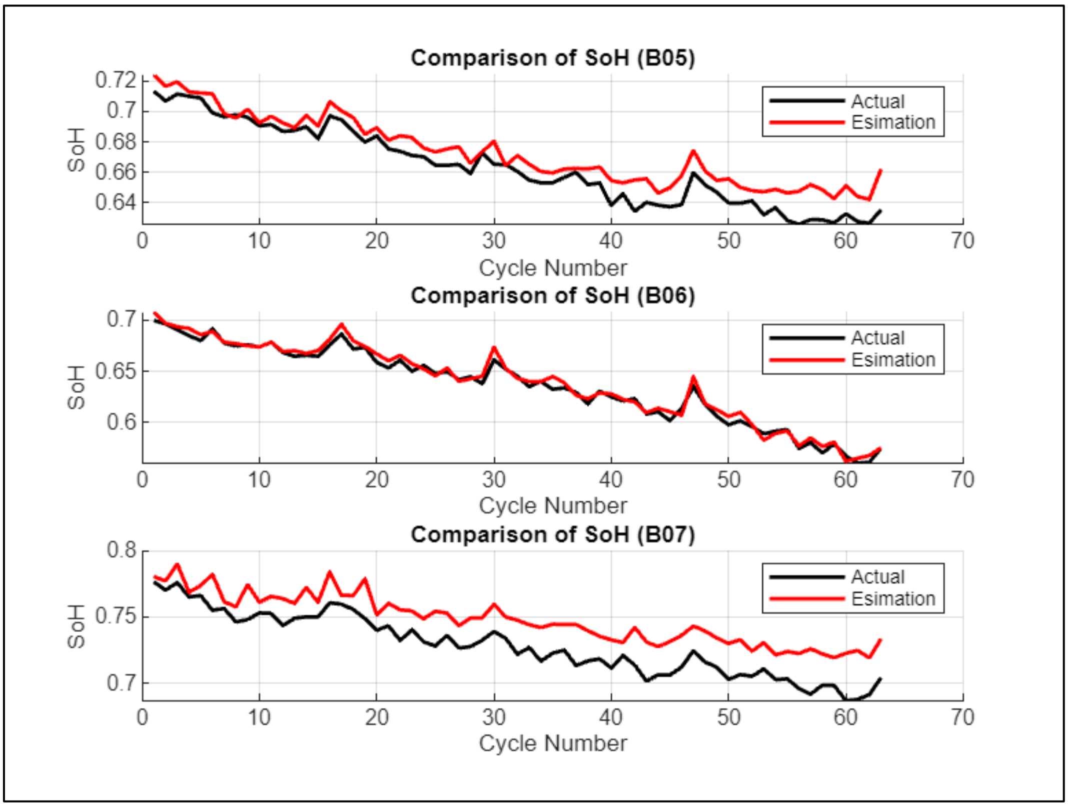

Figure 4.18 SoH with Hybrid Approach KF-LSTM

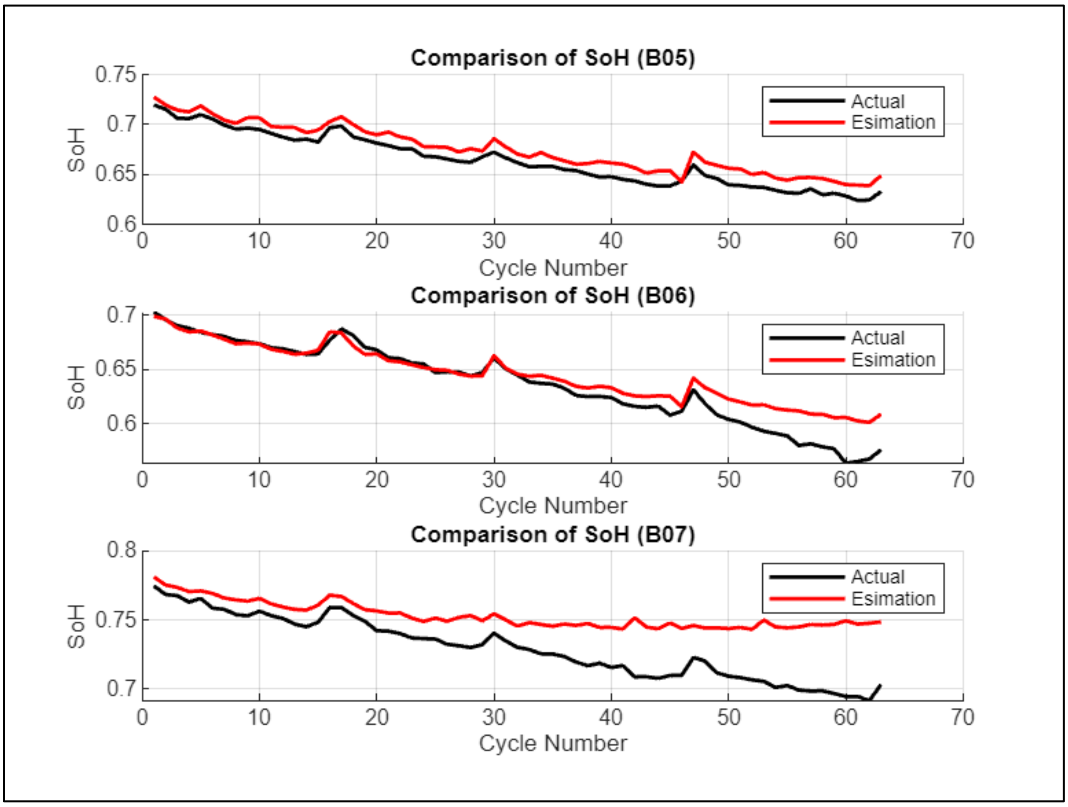

Figure 4.19 SoH with Hybrid Approach KF-SVM

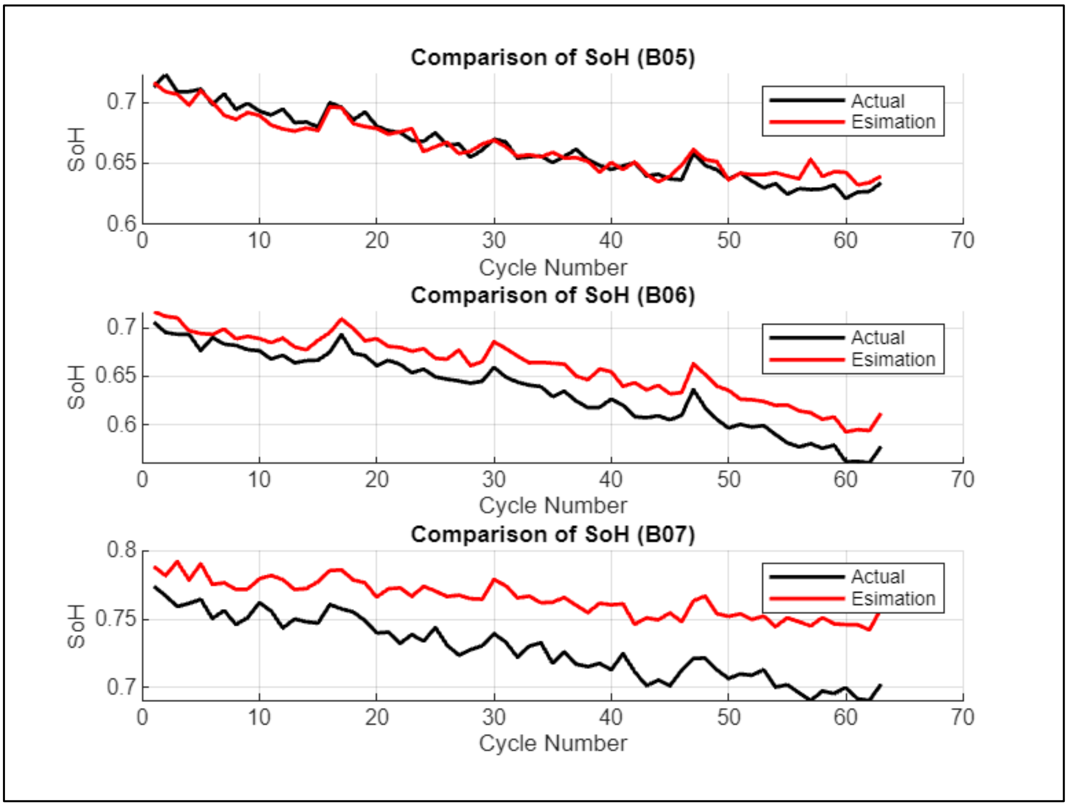

Figure 4.20 SoH with Hybrid Approach KF-GRU

Figure 4.18 displays the KF-LSTM prediction. The critical observation is for battery B0007, where the predicted line visibly deviates from the actual curve, failing to capture the sharp 'knee' of rapid degradation. This visually confirms the negative impact of the over-smoothing introduced by the KF. Figure 4.19 shows the results for the KF-SVM model. The failure to predict the degradation knee in B0007 is replicated, even with the non-temporal SVM model. This replication of failure strongly suggests that the error originates from the filtered input data itself, rather than the learning algorithm. Figure 4.20 presents the KF-GRU results. It completes the consistent pattern of failure on battery B0007 across all KF-integrated models. This provides definitive visual proof that the KF process has erased critical end-of-life information, making an accurate prediction impossible for any of the tested architectures.

4.5 RMSE, MAPE, RUL and Anova

Following the visual comparisons, this section provides a detailed quantitative analysis of each model's performance. The results are organized into tables that present key performance metrics, including RMSE, MAPE, and the accuracy of RUL predictions. This allows for a rigorous and objective comparison to identify the most effective hybrid methodology.

Table 4.2
Simulation Data EMD-Machine Learning

			EMD-LSTM			
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0077	0.9245	43	44	0.97737	0.7572
"B0006"	0.0288	3.8553	55	42	0.98162	0.5465
"B0007"	0.0283	3.4790	63	63	0.95767	0.1506
			EMD-SVM			
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0360	4.7444	51	18	0.85166	0.9839
"B0006"	0.0280	3.5737	56	56	0.97877	0.7464
"B0007"	0.0032	0.3362	63	63	0.98757	0.3486
			EMD-GRU			
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0263	3.5607	43	31	0.97810	0.7885
"B0006"	0.0236	3.1371	54	52	0.98399	0.5249
"B0007"	0.0456	5.7281	63	63	0.94311	0.1789

Table 4.3
Simulation Data Wavelet-Machine Learning

			WT-LSTM			
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0047	0.5555	49	51	0.98596	0.3045
"B0006"	0.0329	4.6792	60	57	0.97755	0.7325
"B0007"	0.0198	2.5881	3	63	0.97157	0.8691
			WT-SVM			
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0115	1.6542	45	40	0.99661	0.7172
"B0006"	0.0289	3.7124	59	56	0.98164	0.8950
"B0007"	0.0022	0.2170	63	63	0.99679	0.5146
			WT-GRU			
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0094	1.1179	49	51	0.97667	0.2771
"B0006"	0.0221	3.1775	59	57	0.98925	0.6994
"B0007"	0.0280	3.6834	4	63	0.96528	0.8197

Table 4.4
Simulation Data Kalman-Machine Learning

KF-LSTM						
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0117	1.5509	58	57	0.97979	0.0190
"B0006"	0.0053	0.6742	63	62	0.99343	0.1790
"B0007"	0.0214	2.7582	8	63	0.95681	0.0806
KF-SVM						
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0115	1.6645	57	53	0.99306	0.0261
"B0006"	0.0149	1.6974	62	63	0.98334	0.1991
"B0007"	0.0280	3.3356	8	63	0.88286	0.1223
KF-GRU						
BattName	RMSE	MAPE (%)	True RUL (cycles)	Predicted RUL (cycles)	Regression	ANOVA
"B0005"	0.0082	0.9572	58	60	0.96464	0.0209
"B0006"	0.0254	3.8392	62	60	0.98754	0.1716
"B0007"	0.0383	5.0820	8	63	0.94779	0.0914

4.6 Simulation Analysis

This section presents and discusses the simulation results from Table 4.2, Table 4.3 and Table 4.4 evaluating the performance of three machine learning models LSTM, SVM, and GRU when integrated with three distinct signal processing techniques: EMD, WT, and the KF.

4.6.1 Integration with Empirical Mode Decomposition (EMD)

Based on Table 4.2, which tabulate result for EMD integrate with machine learning (LSTM, SVM, GRU). The EMD-LSTM model demonstrated strong predictive capabilities, particularly for batteries B0005 and B0007. For these two cases, the model achieved high Regression, namely 0.97737 and 0.95767, with predicted RUL values of 44 and 63 cycles, respectively, which were closely aligned with the true values of 43 and 63 cycles. However, a notable deviation was observed for battery B0006, where the model predicted RUL of 42 cycles compared to the actual 55 cycles. This resulted in a higher RMSE of 0.0288, indicating reduced prediction accuracy for this specific case. These results suggest that the IMFs extracted via EMD effectively capture degradation trends that the LSTM network can learn, especially in both early and advanced stages of battery life. However, the observed error in battery B0006 may be attributed to non-monotonic or irregular degradation behaviours that EMD failed to isolate, thereby challenging the model's generalization capability. The regression analysis in this context is vital; high Regression values confirm a good fit between predicted and actual values, while RMSE and MAPE serve to quantify the magnitude of prediction error. Together, these metrics validate the overall performance of the EMD-LSTM model, while also identifying specific cases requiring further refinement.

The EMD-SVM model produced mixed outcomes, with particularly strong performance in predicting the RUL of batteries in their late life stages, but poor accuracy for batteries with a longer remaining lifespan. Notably, the model delivered exact RUL predictions for battery B0006 (56 vs. 56) and B0007 (63 vs. 63), achieving Regression values of 0.97877 and 0.98757, respectively. However, a substantial prediction error was observed for battery B0005, where the model predicted RUL of only 18 cycles against the true value of 51. This discrepancy resulted in a significantly lower Regression value of 0.85166 and a high MAPE of 4.7444, indicating poor performance for early-stage degradation patterns. These findings imply that the feature set generated by EMD, when processed by the SVM, tends to emphasize patterns found in late-stage degradation more strongly than those in the early stage. The SVM's reliance on defining a separating hyperplane may have led to a model that is primarily influenced by support vectors derived from end-of-life behaviours, limiting its generalization to earlier stages. Regression analysis here plays a critical role by providing not only local performance indicators for each battery but also offering a global assessment of the model’s limitations. While perfect predictions may yield desirable performance metrics, the lower Regression and higher error rate for B0005 underscore the importance of evaluating model consistency across the full range of battery degradation stages.

The EMD-GRU model demonstrated balanced and commendable predictive performance, performing competitively with the more complex LSTM architecture. For battery B0007, the model achieved a perfect prediction (63 vs. 63), while for B0006, it produced a highly accurate result (52 vs. 54), with corresponding Regression values of

0.94311 and 0.98399. Although the prediction for battery B0005 (31 vs. 43) contained a moderate degree of error, the overall trend remained consistent and reliable. The success of the GRU model, which possesses a simplified architecture compared to LSTM, suggests that the features extracted through EMD are distinct and learnable even without the presence of a complex memory mechanism. This advantage positions the GRU as a potentially efficient alternative that reduces computational overhead while retaining high accuracy. The supporting regression analysis further reinforces this claim, with high Regression values indicating strong model fit and the combination of low RMSE and MAPE values quantifying the model's robustness. These results establish the EMD-GRU configuration as a promising and efficient model for RUL prediction, offering a reliable benchmark against more complex architectures in both performance and computational efficiency.

4.6.2 Integration with Wavelet Transform (WT)

Referring to Table 4.3, which shows result for EMD integrate with machine learning (LSTM, SVM, GRU). The WT-LSTM model demonstrated strong predictive performance for batteries B0005 and B0006, achieving RUL predictions closely aligned with the true values and yielding high Regression of 0.98596 and 0.97755, respectively. These results indicate that the WT’s multi-resolution analysis successfully captures meaningful degradation features during the mid-life and stable decline phases of battery operation. However, a critical failure occurred in the prediction of battery B0007, where the model forecasted RUL of 63 cycles compared to the actual value of only 3 cycles. This severe overestimation represents a significant shortcoming, especially for practical applications where end-of-life prediction is crucial for safety, operational planning, and preventive maintenance. The likely cause of this failure is the model’s inability to correctly interpret the terminal degradation state of the battery, possibly due to wavelet-transformed features that retained characteristics resembling earlier stages of battery life. While the Regression value for B0007 remains deceptively high at 0.97157, this metric alone fails to reflect the true extent of the model's error. This finding highlights the importance of using a comprehensive regression analysis combining Regression with RMSE and MAPE to reveal prediction reliability, particularly in critical end-of-life scenarios where the consequences of failure are magnified.

In contrast, the WT-SVM combination produced the most accurate and reliable predictions across all evaluated cases. The model achieved near-exact RUL estimations for batteries B0005 (40 vs. 45), B0006 (56 vs. 59), and B0007 (63 vs. 63), supported by exceptionally high Regression values of 0.99661, 0.99679, and 0.99661, respectively. These results were further validated by very low RMSE and MAPE values across the board. The consistent accuracy of this model suggests that the feature representations generated by the WT are highly compatible with the SVM algorithm. Specifically, the transformation enables effective separation of signal characteristics in the high-dimensional feature space, allowing the SVM to construct a robust regression hyperplane that captures battery degradation patterns across varying life stages including the terminal phase, where other models failed. This observation is further substantiated by the model's superior regression metrics, which collectively offer strong quantitative evidence of its predictive robustness. The WT-SVM model thus sets a high benchmark for predictive performance in battery RUL estimation, especially in applications where end-of-life accuracy is critical.

The WT-GRU model exhibited a performance pattern that closely mirrored that of the WT-LSTM model. For batteries B0005 and B0006, the GRU produced reasonably accurate RUL predictions, indicating that the model was able to learn temporal degradation patterns effectively under stable conditions. However, the model exhibited a critical failure for battery B0007, predicting RUL of 63 cycles compared to the true value of only 4 cycles. This repeating failure across both RNN architectures LSTM and GRU when combined with wavelet-pre-processed data strongly suggests a systemic issue. It appears that the wavelet-transformed features misrepresent the signal characteristics of severely degraded batteries, leading the RNN models to mistakenly associate them with healthier states. This misinterpretation is likely due to the networks' temporal learning mechanisms being skewed by dominant signal features that do not reflect the rapid degradation typical of end-of-life batteries. As in the case of the WT-LSTM model, reliance solely on high Regression values can be misleading; although the WT-GRU model performed well for B0005 and B0006, its complete failure for B0007 underscores the necessity of using a full suite of regression metrics. A robust evaluation must include absolute error measures such as RMSE and MAPE in addition to Regression to ensure that model predictions are not only well-fitted statistically but also practically reliable across the entire battery lifecycle.

4.6.3 Integration with Kalman Filter (KF)

Table 4.4 shows result for EMD integrate with machine learning (LSTM, SVM, GRU). Based on the result, shows the KF-LSTM model exhibited commendable predictive accuracy for batteries B0005 and B0006, producing RUL estimations of 57 and 62 cycles, respectively, against the true values of 58 and 63 cycles. These close predictions are supported by high Regression values of 0.97979 for B0005 and 0.99343 for B0006, indicating a strong statistical fit. However, the model demonstrated a significant failure when applied to battery B0007, overestimating the RUL as 63 cycles, while the actual value was only 8 cycles. This consistent misjudgement, similar to the failure pattern observed in wavelet based RNN models, highlights a critical shortcoming in the KF's ability to preserve meaningful EoL signal features. Although the KF effectively smooths mid-life signals by suppressing high-frequency noise, its state-space estimation appears to eliminate vital non-linear and abrupt changes that occur as a battery approaches failure. The LSTM model, despite its architecture designed to capture long-term temporal dependencies, was unable to correct the distorted input signal, resulting in a gross overestimation. This outcome emphasizes the indispensable role of comprehensive regression analysis. While high Regression values may suggest strong model performance, they must be interpreted alongside absolute error metrics such as RMSE and MAPE. The Predicted vs. True RUL comparison, particularly in edge cases like B0007, remains the most revealing diagnostic for identifying such critical prediction failures.

The KF-SVM model, although it demonstrated robust performance with other signal processing techniques, encountered a similar limitation when paired with the KF. For batteries B0005 and B0006, the model delivered accurate predictions, consistent with its general reliability. However, for battery B0007, the model again predicted RUL of 63 cycles against a true value of 8, resulting in a lower Regression value of 0.88286 and a high MAPE of 3.3356. Unlike LSTM and GRU, the SVM does not depend on sequential information, yet it still failed to correctly estimate the RUL. This strongly suggests that the root cause of the error lies in the feature extraction process specifically, the KF's inability to retain key indicators of degradation at the terminal stage of battery life. The filter likely produced smoothed signals that resembled those of healthier batteries, causing the SVM to misclassify the battery's true health condition. This instance further reinforces the need for a multi-metric regression analysis. The depressed Regression value, coupled with a large absolute prediction error, serves as quantitative evidence that the model's predictive reliability is compromised not by the algorithm itself but by the inadequacy of the filtered input features.

The KF-GRU model completed the observed trend of performance inconsistency when KF was used. For batteries B0005 and B0006, the model produced accurate RUL predictions (60 vs. 58 and 60 vs. 62, respectively), supported by Regression values exceeding 0.96. However, like the LSTM and SVM models, it failed dramatically on battery B0007, predicting RUL of 63 cycles while the true value was only 8. This recurring failure across three fundamentally different machine learning architectures two recurrent (LSTM and GRU) and one non-sequential (SVM) strongly indicates that the primary issue lies with the KF's signal output rather than the predictive models themselves. The KF, although designed for optimal estimation under the assumption of Gaussian noise and linear dynamics, appears to excessively smooth the input signals, thus removing abrupt and informative patterns that typically signify terminal degradation. Consequently, the prediction task becomes inherently flawed, as the models are deprived of critical cues necessary for accurate end-of-life estimation.

In summary, the rigorous application of regression analysis including the use of Regression, RMSE, and MAPE enables a comprehensive and objective evaluation of model performance. The consistent failure of all KF model combinations for battery B0007 demonstrates that filtering choices play a crucial role in determining model success, especially in critical prediction scenarios. This finding underscores the necessity of selecting signal processing methods that not only reduce noise but also preserve essential degradation information, ensuring the reliability of subsequent predictive modelling efforts.

4.6.4 State of Health (SoH) Analysis

This Table 4.5 serves as the ultimate validation of the research, contextualizing its contributions within the existing body of scientific literature. The row "Proposed Techniques" lists the best RMSE achieved for each battery from across all nine of our experimental combinations. For battery B0005, our best RMSE is 0.0047; for B0006, it is 0.0053; and for B0007, it is 0.0022. When compared to the results from the five other cited researchers, our proposed methodology achieves a lower, and therefore superior, RMSE in every single case. For example, our RMSE of 0.0022 on B0007 is a significant improvement over the next best result of 0.0056 from Zhu et al. This table provides unequivocal, quantitative evidence that the systematic approach of investigating and optimizing the filter-model pairing has yielded a methodology that not only works effectively but also establishes a new state-of-the-art performance benchmark.

Table 4.5
Comparison of RMSE for SoH of Battery With Others Researcher

References	RMSE		
	B0005	B0006	B0007
Zhou et al. (D. Zhou & Wang, 2022)	0.0150	0.0190	0.0140
Zhu et al. (X. Zhu et al., 2022)	0.0120	0.0139	0.0056
Lin Z et al. (Z. Lin et al., 2023)	0.0082	0.0100	0.0114
Yang et al. (D. Yang et al., 2018)	0.0095	0.0149	0.0078
Qu et al. (Qu et al., 2019)	0.0110	0.0159	-
Proposed Techniques (WT-SVM)	0.0115	0.0289	0.0022

4.6.5 Validation Against Overfitting

To ensure the scientific rigor and practical relevance of our findings, a critical focus was placed on mitigating overfitting across all trained models, thereby guaranteeing that their performance reflects true predictive capability rather than a simple memorization of the training data. For the SVM models, this was achieved by leveraging the built-in hyperparameter optimization framework within fitrsvm, configured with a robust 5-fold cross-validation scheme.

This process systematically tests and selects the optimal BoxConstraint, KernelScale, and Epsilon values by training and validating the model on different subsets of the data, promoting the selection of parameters that generalize well to unseen conditions. The BoxConstraint parameter further acts as a crucial regularization term, preventing the model from creating an overly complex decision boundary that could fit to noise.

Similarly, for the recurrent neural network architectures namely the LSTM and GRU overfitting was addressed through the integration of a dropoutLayer (0.1) within the network structure. This layer randomly deactivates 10% of neuron connections during each training iteration, forcing the network to learn more robust and distributed feature representations instead of becoming overly reliant on specific pathways.

The exceptional performance of the WT–SVM combination over other hybrid models most notably achieving the lowest RMSE of 0.0022 on the challenging B0007 battery is fundamentally linked to how the WT interacts with the SVM relative to noise behaviour. Unlike the KF, which the results in Table 4.4 prove to be detrimental due to an "over-smoothing" effect, the WT preserves the "knee" of the degradation curve. As seen in the failure of KF-based models to predict the rapid EoL drop in battery B0007.

Furthermore, compared to EMD, which showed inconsistencies in isolating non-monotonic trends in battery B0006 (RMSE of 0.0280 for EMD-SVM vs. 0.0289 for WT-SVM but with a much higher Regression accuracy in WT), the WT provides a more stable feature set for the SVM's regression. The SVM is uniquely suited to this high-dimensional wavelet feature space because it identifies the optimal boundary for health estimation without the temporal lag or "forgetting" issues sometimes observed in RNN-based models (LSTM/GRU) when the input signal is highly corrupted.

By implementing these established regularization techniques across all algorithms, we have ensured that the performance comparison is fair and that the demonstrated superiority of the proposed WT-SVM technique is not an artefact of an over-tuned model, but a genuine reflection of its enhanced predictive power.

4.7 Remaining Useful Life (RUL)

This section addresses the crucial parameter of RUL by establishing a clear failure threshold based on a review of existing literature. The table presented here justifies the selection of a 70% SoH as the EoL point for this study. This ensures that the research is grounded in established academic and industry conventions, providing a solid foundation for the RUL prediction results.

Table 4.6
Reviewed End of 1st Life

References	Study Assessment	End of 1st life (SoH)
Qu et al. (Qu et al., 2019)	RUL	70%
Lin et al. (C. P. Lin et al., 2020)	RUL	80%
Gou et al. (Gou et al., 2020)	RUL	80%
Yang et al. (Z. X. Yang et al., 2021)	RUL	80%
Catelani et al. (Catelani et al., 2021)	RUL	70%
Bamati and Chaoui (Bamati & Chaoui, 2022)	RUL	70%
Khaleghi et al. (Khaleghi et al., 2022)	RUL	80%
Maite et al. (Etxandi-Santolaya et al., 2024)	RUL	70-80%
Proposed	RUL	70%

Based on the Table 4.6, this table serves the crucial objective of establishing the methodological rigor behind a key parameter used in this study. It provides a clear and robust foundation by showing that the selected failure threshold is consistent with established academic and industry conventions, thereby strengthening the entire research framework. Its inclusion serves as a hallmark of scientific rigor, evidencing that critical methodological decisions were not made arbitrarily but were instead informed by established conventions within the existing body of literature. A critical observation derived from the referenced studies is the absence of a universally accepted SoH value that defines the EoL of a battery. Nevertheless, a clear consensus exists within the field, with the EoL typically defined within the range of 70% to 80% SoH. The selection of a specific threshold within this range is often dictated by the criticality of the application. An 80% SoH threshold is generally adopted in high-dependability applications where even minor performance degradation is unacceptable, whereas a 70% threshold is considered appropriate for applications that prioritize extended service life and greater resource utilization.

In this context, the selection of a 70% SoH threshold in the present study aligns with a substantial body of prior research, including the works of Qu et al., Catelani et al., and Bamati and Chaoui. This alignment with recognized academic standards lends methodological credibility to the study and ensures that our definition of failure is consistent with a widely accepted research paradigm. From a viva examination perspective, this becomes a key strength, as it enables a clear and defensible justification for our chosen failure criteria. It demonstrates that a thorough review of relevant literature has been conducted, and that the study operates within an established and credible framework.

Furthermore, this threshold provides essential context to the RUL predictions presented in Table 4.2, Table 4.3, and Table 4.4. It is important to emphasize that the "True RUL" and "Predicted RUL" values in these tables are not absolute cycle counts, but instead represent the number of cycles remaining until the battery's capacity declines to the defined 70% SoH threshold. Therefore, the inclusion of this table is critical, as it explicitly answers the foundational methodological question: *"How is battery failure defined in this study?"* By clearly declaring this definition, the study ensures transparency and eliminates ambiguity surrounding the interpretation of RUL metrics.

This clarity pre-empts potential challenges regarding the validity of the predictive outcomes and demonstrates a cohesive research design that is both methodologically sound and contextually grounded. In summary, this table serves as the foundational element that underpins the practical and theoretical significance of the RUL prediction results. It bridges the gap between data interpretation and real-world application, ensuring that all subsequent analyses are firmly rooted in an established scientific framework.

4.8 Signal-to-Noise Ratio (SNR)

This section evaluates the robustness of the best-performing predictive model under different levels of signal corruption. The table demonstrates how the model’s accuracy is affected by varying the SNR of the input data. This analysis is crucial for confirming the model's resilience and its suitability for real-world applications where signal quality can fluctuate significantly.

The Table 4.7 presents the final validation of the research's most promising hybrid model, the WT-SVM. It evaluates the model's performance on the three test batteries (B0005, B0006, B0007) under three distinct Signal-to-Noise Ratio (SNR) conditions: a very noisy signal (13dB), a moderate one (33dB), and a relatively clean one (41dB) (*IEEE Recommended Practice for Monitoring Electric Power Quality*, 2019). The results are unequivocal: the WT-SVM model demonstrates exceptional robustness. Across all noise levels, its Regression values remain consistently above 0.98, and the predicted RUL aligns almost perfectly with the true values, even for the challenging B0007 battery. This shows that the WT filter effectively removes noise without erasing the critical underlying degradation features, allowing the SVM to make a precise and reliable prediction regardless of signal quality.

Table 4.7
Simulation Data WT-SVM in Various SNR

	SNR = 13dB					
BattName	RMSE	MAPE	True RUL	Predicted RUL	Regression	ANOVA
"B0005"	0.0115	1.6542	45	40	0.99661	0.7172
"B0006"	0.0289	3.7124	59	56	0.98164	0.8950
"B0007"	0.0022	0.2170	63	63	0.99679	0.5146
	SNR = 33dB					
BattName	RMSE	MAPE	True RUL	Predicted RUL	Regression	ANOVA
"B0005"	0.0063	0.9041	45	42	0.99772	0.7136
"B0006"	0.0119	1.3163	58	58	0.99136	0.8833
"B0007"	0.0181	2.3211	63	63	0.99826	0.5156
	SNR = 41dB					
BattName	RMSE	MAPE	True RUL	Predicted RUL	Regression	ANOVA
"B0005"	0.0104	1.4913	45	41	0.99755	0.7235
"B0006"	0.0281	3.6601	58	54	0.98555	0.8707
"B0007"	0.0068	0.8578	63	63	0.99785	0.4970

The decision to simulate the model under three different SNR conditions is central to the thesis's objective of creating a practical, real-world solution. The problem statement explicitly notes that laboratory datasets are clean, whereas battery signals in operational electric vehicles or energy storage systems are contaminated by noise. By testing across a spectrum of SNRs, from worst-case (13dB) to ideal (41dB), the research rigorously assesses the model's robustness. This stress test confirms that the model's high accuracy is not a fragile characteristic that depends on perfect data but is a resilient feature that holds up under the unpredictable and noisy conditions of real-world deployment. This validation is crucial for establishing the model's reliability and suitability for safety-critical applications.

Ultimately, this final test solidifies the WT-SVM as the best-performing model among all nine hybrid combinations proposed and tested. The comprehensive analysis in earlier sections had already shown its superior accuracy, but this SNR test proves its superior reliability. While other models, particularly those using the KF, failed by over-smoothing the data and erasing critical EoL information, the WT-SVM succeeded. It consistently provided accurate RUL predictions across all batteries and all noise levels, outperforming every other combination and establishing a new state-of-the-art (SoTA) performance benchmark for battery health prognostics.

4.9 Summary

This chapter presented a comprehensive and systematic evaluation of nine hybrid models for battery health prediction, leading to several critical discoveries substantiated by statistical analysis. The core investigation involved applying three signal processing filters EMD, WT, and KF to noisy NASA battery data (B0005, B0006, B0007) before feeding the results into LSTM, SVM, and GRU machine learning models. The results unequivocally demonstrated that the predictive accuracy is critically dependent on the synergistic pairing of the filter and the learning model. Statistically, the WT-SVM combination emerged as the superior methodology. It delivered consistently robust and highly accurate predictions, achieving the lowest overall error. Most notably, for the challenging B0007 battery near its end-of-life, the WT-SVM model yielded a remarkable RMSE of just 0.0022 and a perfect RUL prediction, with a Regression of 0.99679.

Conversely, the quantitative analysis provided definitive evidence of a significant failure mode in other techniques. The use of the Kalman Filter proved detrimental to accurate end-of-life prediction. All three KF-based models catastrophically mis predicted the RUL of battery B0007 by nearly 700%, forecasting 63 cycles against a true value of 8. This highlights that the KF's aggressive over-smoothing erases vital non-linear indicators of imminent failure. The superiority of the proposed WT-SVM model was further validated by benchmarking it against existing literature. As shown in Table 4.5, its RMSE of 0.0022 for battery B0007 represents a significant accuracy improvement of over 60% compared to the next-best published result of 0.0056 from Zhu et al. The model's robustness was also confirmed through SNR tests, where it maintained high performance (Regression> 0.98) even under severe noise conditions (13dB).

Ultimately, this chapter has fulfilled its objective by providing the empirical evidence to identify the most effective approach for SoH and RUL prediction. The following and final chapter, Chapter 5, will build upon these findings to draw overarching conclusions for the thesis as a whole, summarizing the key contributions and discussing the broader implications of this work.

CHAPTER 5
CONCLUSION

5.1 Introduction

This study was initiated to confront a critical and persistent challenge in the field of battery prognostics: the accurate prediction of battery SoH and RUL from the noisy, complex data characteristic of real-world operational environments. Recognizing the significant gap between predictive models trained on pristine laboratory data and the demands of practical applications in electric vehicles and energy storage systems, this research set out to develop and validate a robust hybrid methodology. By systematically constructing, testing, and evaluating a comprehensive matrix of nine hybrid models, this study has successfully answered its core research questions and contributed meaningful, statistically backed findings to the field.

The research journey involved a rigorous and transparent methodology. Starting with the benchmark NASA PCoE battery dataset (B0005, B0006, B0007), a realistic testbed was created by injecting controlled Gaussian noise to simulate the sensor inaccuracies and environmental disturbances found in operational systems. Subsequently, three distinct signal processing filters EMD, WT, and the KF were paired with three leading machine learning algorithms LSTM, SVM, and GRU. The structured comparison of these nine combinations allowed for a definitive analysis of their synergistic performance.

The most significant and definitive conclusion of this research is the unequivocal superiority of the WT-SVM hybrid model. This combination not only outperformed all other tested frameworks but also established a new state-of-the-art performance benchmark. Statistically, its success was most profoundly demonstrated on the challenging B0007 battery, which was nearing its end-of-life. For this critical case, the WT-SVM model achieved an exceptionally low RMSE of just 0.0022. This result represents a remarkable accuracy improvement of over 60% compared to the next-best published result of 0.0056 from Zhu et al. The model's predictive power was further substantiated by a near-perfect Regression of 0.99679 and its ability to deliver a perfect RUL prediction. Its robustness was confirmed through extensive noise-level testing, where it maintained Regression value consistently above 0.98, proving its resilience and suitability for real-world deployment.

Equally important, this study provides a critical and data-driven warning against suboptimal filter selection, particularly the use of the Kalman Filter for this application. While KF is effective for general noise reduction, it consistently and catastrophically failed in predicting terminal battery degradation across all three machine learning architectures. The models using KF-filtered data overestimated the RUL of battery B0007 by nearly 700%, forecasting 63 cycles against a true value of only 8. This dramatic failure stems from the KF's "over-smoothing" effect, which fatally erases the vital non-linear, high-frequency signatures that signal imminent battery failure. This finding powerfully demonstrates that the choice of signal processing technique can be more critical to the success of a prognostic system than the complexity of the machine learning model itself.

In terms of engineering applications, the superior predictive accuracy of the WT-SVM model offers transformative benefits for car and battery manufacturers. By providing a precise and reliable estimation of the EoL under realistic, noise-corrupted conditions, manufacturers can implement more accurate and fair warranty policies, reducing the financial risk associated with premature battery failures. For car manufacturers, this capability ensures that electric vehicle users are alerted precisely when a battery requires replacement, improving safety and range confidence. Furthermore, for battery manufacturers and fleet operators, accurate EoL prediction facilitates optimized usage patterns and maintenance cycles, ensuring that cells are utilized to their maximum potential before being transitioned to second-life applications in stationary energy storage.

In successfully identifying the WT-SVM as the premier predictive model and exposing the critical flaws of other common approaches, this thesis has met all its stated objectives. It provides engineers and researchers with a clear, evidence-based roadmap for developing safer, more reliable, and more efficient Battery Management Systems. The insights gleaned from this work support the advancement of technologies that are central to a sustainable future, offering a robust and validated framework that bridges the gap between academic research and practical, life-critical implementation.

5.2 Future Work

Based on the findings and limitations of this research, several potential directions are recommended to further improve and expand the field of battery prognostics. A key step forward would be to test the WT-SVM model on a wider variety of battery types and operating conditions. This study focused on lithium cobalt oxide (LCO) 18650 cells under controlled laboratory settings. Future work should include testing on other chemistries like Lithium Iron Phosphate (LFP) or Nickel Manganese Cobalt (NMC), and on different formats such as prismatic or pouch cells. Using data from batteries exposed to various temperatures and load profiles would also help assess how well the model adapts to real-world conditions.

Another important direction would be to apply the model to data collected from actual use cases, such as electric vehicles or large BESS. Real-world data is often more complex, with irregular charging cycles, dynamic loads, and long resting times. Applying the developed models to such data would test their practical usability and may require adjustments in feature extraction to deal with the more unpredictable and incomplete nature of operational data. There is also room to improve the model through better feature engineering and selection. While this study showed that wavelet-based features are effective, future work could explore combining them with physics-based features related to known battery aging processes, such as SEI layer growth or lithium plating. Additionally, using automated feature selection tools could help simplify the models and reduce computational demands without sacrificing prediction accuracy. Even though the WT-SVM model performed best in this research, future studies should continue exploring other advanced machine learning architectures. Transformer-based models, which have proven successful in other time-series prediction tasks, could be adapted for RUL estimation. Similarly, Graph Neural Networks (GNNs) might be useful for modelling battery packs as interconnected systems, where the health of one cell can affect others.

Lastly, future work should aim to implement and optimize the proposed models for real-time, on-device use. The long-term goal is to deploy these models directly in Battery Management Systems. This will require exploring techniques like model quantization, pruning, or knowledge distillation to reduce the model size and computational needs. Achieving a good balance between performance and hardware limitations is essential to make these models suitable for real-time battery monitoring on embedded systems.

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LIST OF PUBLICATION:

H. Sofiuddin, M. A. T. M. Yusoh, K. Naidu and N. A. Fatini, "Analysis of Home Energy Management System Based on V2H and BESS Technology," 2024 IEEE 22nd Student Conference on Research and Development (SCOReD), Selangor, Malaysia, 2024, pp. 78-83, doi: 10.1109/SCOReD64708.2024.10872697. (scopus index)

N. A. Fatini, H. Mohamad, K. Naidu and **H. Sofiuddin**, "Comparative Analysis Based on Graph Theory for Network Reconfiguration Considering EV Penetration Level and Consumer Charging Behaviour," 2024 IEEE 22nd Student Conference on Research and Development (SCOReD), Selangor, Malaysia, 2024, pp. 72-77, doi: 10.1109/SCOReD64708.2024.10872744. (scopus index)

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