

CHAPTER V

CONCLUSION

5.1 Conclusion

This thesis presents a comprehensive study on SOH estimation for LIBs by integrating effective data management strategies with advanced deep learning techniques. The experimental results lead to the following conclusions:

First, the application of the resampling technique proved effective in reducing the size and complexity of battery measurement data. This reduction directly correlated with a significant decrease in computational load and model training time compared to using raw data. Crucially, this process preserved the essential information required for accurate estimation. By selecting a resampling interval aligned with the physical characteristics of the specific dataset, the method successfully filtered out noise in high-fluctuation scenarios while retaining the fine-grained details of complex electrochemical behaviors.

Second, the evaluation across multiple open-source datasets (Oxford and NASA) demonstrated the robustness of the proposed approach under distinct operating conditions. The findings indicate that deep learning models, particularly the developed architecture, possess the capability to learn and adapt to diverse degradation patterns, ranging from monotonic decay to highly fluctuating trends. When compared to traditional statistical methods like GPR, deep learning techniques exhibited superior accuracy and stability in handling large-scale, complex datasets. These outcomes suggest that the proposed approach serves as a viable and efficient solution for practical implementation in battery management systems constrained by limited computational resources.

5.2 Suggestions

Based on the findings and limitations of this study, several recommendations are proposed for future research to further enhance the reliability and applicability of SOH estimation models:

1) **Validation with Real-world Driving Profiles:** While this study utilized standard laboratory datasets, future work should verify the proposed method using data collected from real-world electric vehicle operations. Real-world conditions often involve highly dynamic current loads, irregular charging habits, and varying ambient temperatures, which could test the robustness of the resampling and estimation algorithms more rigorously.

2) **Integration of Additional Health Indicators:** To improve estimation accuracy, particularly for different battery chemistries, future research could incorporate additional input features beyond voltage and current. Integrating temperature data or integrating mechanical stress sensors (e.g., expansion/strain measurements) could provide a more holistic view of the battery's health status.

3) **Spatial Representation in Large-Scale Systems:** For practical deployment in large-scale energy storage systems, environmental factors such as temperature distribution often vary significantly depending on the physical location of the battery cells. Relying on training data from a single localized cluster may fail to capture these environmental heterogeneities. Therefore, future implementations should adopt a spatially stratified sampling strategy, selecting representative cells from diverse physical locations across the entire battery pack to ensure the model generalizes well to all environmental conditions within the system.

4) **Model Retraining and Lifecycle Adaptability:** Since battery degradation is a non-linear and time-varying process, a static model trained solely on historical data may eventually experience performance degradation due to concept drift where the underlying data distribution shifts as the battery ages. To maintain estimation accuracy throughout the entire lifespan, it is recommended to implement a periodic retraining strategy. Future implementations should consider triggering model updates based on usage intensity or performance degradation metrics for instance, recalibrating the model every 50–100 cycles or whenever the prediction error exceeds a user-defined

threshold (e.g., $\text{RMSE} > 3\%$). Establishing these optimal triggers is a critical area for further investigation.

Therefore, while this research confirms the technical efficacy of the proposed framework, its transition to practical application requires addressing the dual challenges of interpretability and adaptability. As deep learning models inherently lack transparency, ensuring explainable outcomes is crucial for meeting rigorous safety standards. Simultaneously, the rapid evolution of energy storage demands a system capable of adapting to emerging battery chemistries and novel degradation mechanisms. Addressing these factors is essential to guarantee that the estimation framework remains both robust and relevant in a continuously advancing technological landscape.