Chapter 7

Conclusion and Future Directions

7.1 Conclusion

This thesis comprises a hybrid deep learning approach for health prognostics in energy storage systems. The primary focus is on developing state-of-the-art algorithms for capturing sophisticated and temporal dependencies in energy storage devices. These novel hybrid architectures capture short-term fluctuations and long-term degradation trends in the battery and supercapacitor data. The deep learning algorithms use transformer, gated recurrent unit, and variants of temporal convolutional networks to effectively estimate the state of charge, state of health, and remaining useful life in varying operating conditions. The integration of explainable artificial intelligence into the developed model enhances the interpretability and transparency of the model. The methodologies that are used to built these prognostic frameworks help tackle a multitude of computational challenges, such as (a) Improved life estimation in energy storage devices with lower mean absolute error and root mean square error values in different operating conditions across varied driving cycles, (b) Compact parameter footprint for the developed models, making it highly suitable for resource-constrained environments, (c) Using dynamic weight adaptation in the model to learn the evolving nature of the degradation pattern in lithium-ion battery and supercapacitor, (d) Employing a multi-branch architecture to learn the multi-scale degradation pattern, (e) Using XAI technique to understand the influence of feature localy and globaly and to increase the trust among the stakeholders.

The major findings of the overall research are as follows: (a) Deep learning frameworks using variants of temporal convolutional networks with its multi-head architecture and custom dilated convolutions capture short-term, mid-term and long-term dependencies in energy storage devices, thereby increasing the estimation accuracy; (b) Parameter efficient hybrid models combining temporal and sequence modeling developed for SOC, SOH and RUL estimation, making it computationally efficient in real-world applications; (c) The developed model is highly efficient and reliable under varying battery chemistry and supercapacitor configurations in multiple datasets. These models also show remarkable early prediction capabilities that accurately forecast battery degradation patterns from minimal capacity data. This overcomes the limitation of existing methods that require extensive degradation history for reliable predictions; (d) XAI integrated technique into the hybrid framework provides interpretable insights into significant features for life prediction. This interpretable technique also enhances trustworthiness needed in safety-critical applications using these energy storage devices; and (e) the proposed framework and techniques can be easily extended to predict the degradation pattern of any energy storage device with minor modification and fine-tuning.

Despite the proposed models demonstrating superior performance in controlled experimental settings, several critical deployment challenges must be addressed for real-world energy storage applications. The models were validated primarily on laboratory-collected data under controlled conditions, which may not adequately represent the dynamic operating environments of electric vehicles, grid-scale energy storage, or renewable energy systems where temperature fluctuations, variable load patterns, and aggressive driving cycles introduce significant variability in degradation patterns. For batteries, the validation was limited to specific chemistries from NASA, CALCE, and HNEI datasets, while the supercapacitor experiments were conducted exclusively at room temperature on a single 18V, 61.7F module, raising concerns about generalizability across different capacities, manufacturers, and environmental conditions. Safety-critical applications demand robust failure detection mechanisms and uncertainty quantification techniques such as Bayesian neural networks to provide confidence intervals alongside point estimates. Furthermore, regulatory compliance, certification requirements for automotive applications, and long-term field validation across thousands of cycles under varying environmental conditions present significant barriers to commercial adoption, requiring collaborative efforts between researchers, industry stakeholders, and regulatory bodies to establish trusted deployment frameworks.

7.2 Future Directions

In the future, several potential avenues can be explored regarding the research presented in this thesis. Some of the most promising are as follows:

- Incorporate uncertainty quantification techniques such as Bayesian neural networks and ensemble learning into the proposed framework for generating confidence intervals in life prediction applications employed in safety-critical cases.
- Embed physics-informed neural network into the developed hybrid framework to enforce electrochemical constraints and for increasing generalizability across different battery chemistries and supercapacitor technologies.
- Online learning and adaptive model approaches can be employed for refining the state estimation model using real-time operational data without the need to retrain the deep learning architectures completely.
- XAI technique such as SHAP could be augmented with causal inference methods to not only determine feature significance but also define causal relationships between operational conditions and degradation patterns in energy storage devices.
- Experiment with multi-modal sensor fusion techniques where different sources of

data, such as thermal imaging, acoustic emissions and electrochemical impedance spectroscopy, are combined with available sources of current-voltage measurements, leading to an improved prediction accuracy.

- Compressed sensing and model quantisation techniques may be explored to decrease even more the computational resources of the proposed frameworks for deployment in ultra-low power IoT devices.
- Hierarchical multi-resolution temporal convolutional architectures can be explored by stacking customized dilated temporal convolutional networks with progressively increasing receptive fields to capture the sophisticated patterns in energy storage systems.