In the first part, this dissertation introduces a novel cell balancing strategy for reconfigurable battery packs. We focus on answering these two questions: 1) How can we use reconfiguration of lithium-ion battery packs to achieve better state of charge (SoC) balancing? 2) How can we design an intelligent algorithm that uses advanced artificial intelligence/machine learning (AI/ML) models for real-time adaptive SoC balancing? Here, we introduce a novel cell balancing algorithm for reconfigurable lithium-ion battery packs, which outperforms traditional active and passive balancing approaches. These packs have dynamic switching networks that can form various series-parallel topologies. The proposed balancing method uses multiple AI/ML models to predict optimal switching configurations that minimize the SoC imbalance inside the battery pack during discharging. Extensive simulation experiments on a 16-cell battery pack demonstrate that this topology-aware approach can improve battery runtime by up to 22.4% compared to a fixed and non-topology-switching battery pack. Additionally, the AI/ML framework offers greater adaptability and simplicity than traditional control-based solutions, simplifying the need for complex mathematical control strategies.

In the second part of this dissertation, we introduce a multi-variable AI/ML prediction model, which can simultaneously predict two critical battery cell health indicators: remaining useful life (RUL) and cell temperature. We focus on answering the following questions: 1) How can we develop efficient AI models to estimate multiple battery health-related attributes simultaneously? 2) How can we optimize and deploy such AI models using existing optimization frameworks on resource-constrained devices and preserve similar performance while being more energy efficient? The proposed AI/ML model is a combination of a temporal convolution network (TCN) and an attention layer. The model is trained on publicly available datasets from Sandia National Laboratories and validated across three different battery datasets. The model is optimized using TinyML techniques and deployed on a Raspberry Pi 4 using three quantization methods: 8-bit integer, dynamic range, and 16-bit float quantization. Among them, dynamic range quantization achieves the best model prediction accuracy, minimal performance degradation, smallest model size, and fastest inference time.

Together, these contributions showcase that an innovative SoC balancing algorithm using a reconfigurable battery pack can extend the runtime per charge for electric vehicles (EVs) and hybrid electric vehicles (HEVs). At the same time, battery cells can be better monitored by using a multi-variable AI/ML model for RUL and cell temperature prediction on energy-efficient and resource-constrained internet of thing (IoT) devices. Thus, the proposed algorithms in this dissertation can enhance the performance of EV technology and other energy storage systems, towards achieving a more sustainable future.