Sensor System Integration through AI
(AI-Powered Data-Driven Digital Twin for Electric Vehicle Battery Systems)

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I. INTRODUCTION

Battery technology innovation is pivotal for electric vehicles (EVs) to flourish. Battery DTs offer an unprecedented vantage point into battery behavior, empowering advanced decision-making for optimal EV operation. We present a customized DT architecture that facilitates precise estimation of SoC, SoH, and SoE, which are paramount for effective battery management [1]. We delve into an ingenious strategy that harmoniously amalgamates cloud and edge platforms, achieving the dual objectives of real-time insights and resilience against unpredictable cloud disruptions. This PhD research presents a comprehensive approach for battery DTs, introducing a customized architecture, novel edge-cloud partitioning, and validation using synthetic and real datasets.

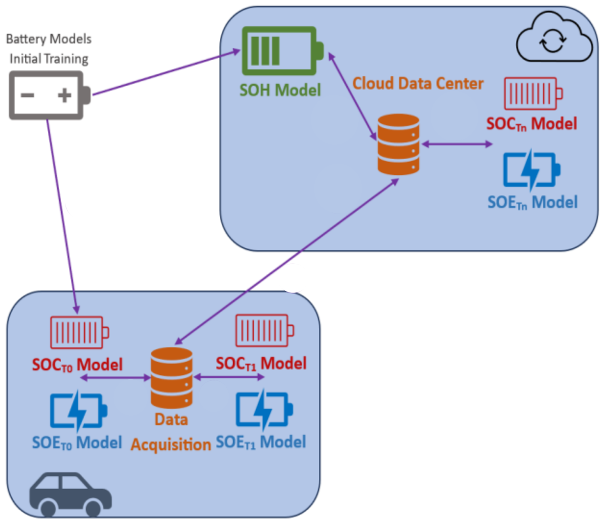


Figure I: Digital Twin Architecture

II. DIGITAL TWIN ENHANCEMENT FOR MODERN BMSs

While BMSs traditionally manage batteries, integrating Battery DTs extends their capabilities. Real-time insights into battery dynamics empower BMSs to make judicious decisions that go beyond immediate management. Battery DTs augment core BMS functions, accurately estimating State-of-Charge (SoC), State-of-Health (SoH), and State-of-Energy (SoE). These insights facilitate proactive maintenance, adaptive controls, optimized charging, extensive scenario analysis, and predictive efficiency enhancements.

a) DT Architecture: The typical DT architecture consists of three main layers:

1. Hardware and Connectivity Layer: collects sensor data for preprocessing, permitting localized data usage or cloud forwarding.
2. Twin Layer: Represents the virtual copy of the battery and is in the cloud. It includes a time-series database for storing battery data and running models to estimate SoX variables.
3. Service Layer: Exports information to third parties, providing services like visualization and predictive maintenance.

b) Accurate Battery Modeling: In the Twin Layer, battery models are vital to elucidate the interrelation of SoC, SoH, and SoE. While circuit-equivalent models and algorithmic approaches have limitations [2], data-driven strategies like machine learning overcome these by learning from historical data. Continuous training is essential to adapt to battery dynamics. Our proposed digital twin constructs SoX models through historical battery and discharge data, employing a data-driven approach. The EV collects measurements continuously, uploaded to the cloud. The cloud updates SoH and periodically retrains the SoC & SoE model, deployed to the EV. This iterative process ensures accurate SoX estimation and effective adaptation.

c) Edge-Cloud Architecture: The combination of edge computing and cloud services presents an opportunity to enhance traditional BMS limitations. However, maintaining battery state models both in the cloud and at the edge is a challenge. This research introduces an edge-cloud architecture that efficiently collects edge data while utilizing cloud storage and services. It employs fixed time intervals for partitioning, adapting the threshold based on battery dynamics and characteristics. This architecture addresses precise SoC and SoE estimation and resilience against cloud disruptions. Continuous cloud SoH updates ensure accurate estimation, and the edge retains a recent model copy for estimation during cloud outages. The model synchronizes upon cloud reconnection for up-to-date insights.

III. RESULT

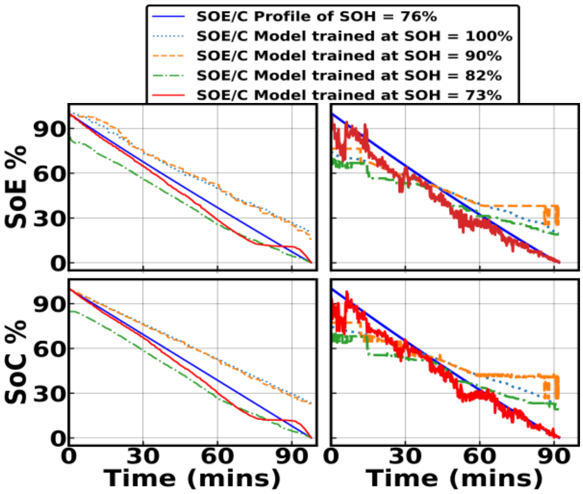
The study evaluated initial outcomes using three datasets: Sandia Battery Dataset [3], NASA Ames Prognostics Center of Excellence Randomized Battery Dataset [4], and a simulated dataset [6]. The Sandia dataset examined commercial cells, exploring factors like temperature, depth of discharge, and discharge current up to 70% capacity. The NASA Ames dataset involved lithium-cobalt-oxide batteries subjected to varying charging and discharging currents. The simulated dataset was created using a battery model with diverse temperature and current profiles. Data underwent Coulomb Counting for determining SoC, SoE, and SoH. After refining, the dataset contained current, voltage, temperature, relative time, SoC, SoE, and SoH columns. Models, including Gradient Boosting Models (GBM) and Neural Networks Models (MLP, CNN, LSTM), were employed. Accuracy was gauged using metrics like root mean square error (RMSE) and mean absolute error (MAE).

The efficacy of the proposed DT architecture was demonstrated by estimating SoH as seen in table I, SoC and SoE using models trained at varying SoH levels for the NASA and Sandia datasets. Figure II shows the result where a red solid line, trained at 73% SoH, closely mirrored the actual discharge profile with RMSE of 0.809% and 4.363% for NASA and Sandia, respectively. Outdated models exhibited significant errors, underscoring the need for periodic retraining, and updating. This validates the importance of recurrent model adaptation and confirms the validity of the proposed architecture.

Dataset	Time(s) [Train + Inference]	RMSE (%)	MAE (%)	R2
NASA	0.579 + 0.090	0.0219	0.811	0.997
Sandia	5.166 + 0.022	0.113	2.096	0.7825
Simulated-Data	3.713 + 0.040	0.960	7.15	0.729

Table I: SOH Model Performance

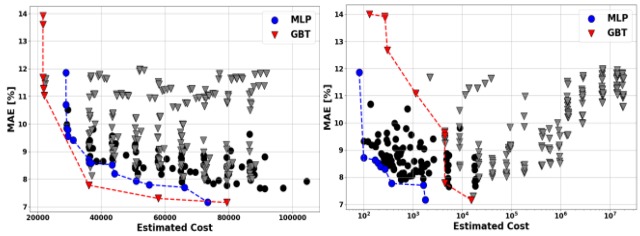
Then a further approach conducting a Pareto analysis of the data-driven models [6], exploring various hyperparameters and input feature configurations. The analysis considers the trade-offs between error, time/energy, and memory to optimize the models to be deployed in both cloud and edge.



a) NASA dataset b) Sandia dataset

Figure II: SoC and SoE discharge profiles comparison among SoC and SoE models trained in different SoH levels.

Figure III presents the results demonstrating the flexibility of the data-driven approach to estimate SoX, with configurations varying approximately by a factor of 3 in latency, energy, and memory.



a) Time/Energy **b) Memory**

Figure III: Pareto-fronts obtained from the hyper-parameters' exploration of data-driven models.

IV. Conclusion & Future Works

The EV market requires advancements in battery technology. Battery Digital Twins (DTs) accurately replicate battery dynamics, enabling intelligent management, predictive maintenance, and exploratory analyses. This thesis presents a customized architecture for precise estimation of SoX variables. A novel division of DT tasks between cloud and edge platforms is proposed, supported by evidence from real-world datasets. Future work will include an in-depth detail about edge-cloud partitioning, connectivity, security & computing that will leverage the capabilities of Digital Twins to establish a robust foundation for a digital ecosystem that enhances battery performance and ensures long-term durability.

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