

A Digital Twin Approach For Battery Management Systems For Electric Vehicles

Realizing the digital twin concept for electric vehicle battery management systems through multi-physis, multi-scale simulation and machine learning.

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Abstract

The digital twin concept enables the integration of complex multiphysics and multidimensional models and simpler reduced order models (ROM). Our approach to developing a digital twin simulation of lithium-ion batteries for electric vehicles utilized a dataset generated from the COMSOL[®] Multiphysics simulation of the Cahn-Hilliard equation for a single particle model (SPM) of a lithium iron phosphate (LiFePO4) cathode. The ROM was then developed by utilizing experimental data for an A123 Systems 26650 2.3 Ah cylindrical battery to train a self-normalizing neural network (SNN). Finally, the ROM was verified as an on-board battery management system (BMS) for ambient temperatures ranging from 253 to 298 K and discharge rates ranging from 1 C to 20.5 C.



Methodology

We applied the 3D Cahn-Hilliard phase field SPM for LiFePO4 nanoparticles to serve as a test-bed for the development and verification of the SNN. The diffusional chemical potential based on the regular solution model and acquired from the Cahn– Hilliard free energy functional is

FIGURE 1. Left: Depiction of our Multi-Physics, Multi-Scale Lithium-Ion Battery Model and Simulation. Right: Visualization of the Implementation of the On-board Self Normalizing Neural Network Model.

$$\bar{\mu} = -k_b T \ln \left[\frac{\bar{c}}{1-c_m} \right] + \frac{\bar{\Omega}(c_m - \bar{c})}{c_m} - \frac{KV_S}{c_m} \bar{\nabla}^2 \bar{c}$$

Results

We tested and verified the SNN for a 1 C discharge rate for ambient temperatures ranging from 253 to 298 K. The model results were also compared to experimental results for discharge rates ranging from 1.0 to 10.6 C for an ambient temperature of 298 K. Finally, we validated the trained SNN using the harsh road test dataset: Up Mount Sano in Huntsville, AL as shown in Figure 2.



FIGURE 2. Validation Of the Self Normalizing Neural Network Model for Harsh Drive-Cycle Data.

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