

## Mathworks Microgrant Research Proposal: Battery State of Health Machine Learning Prognostics

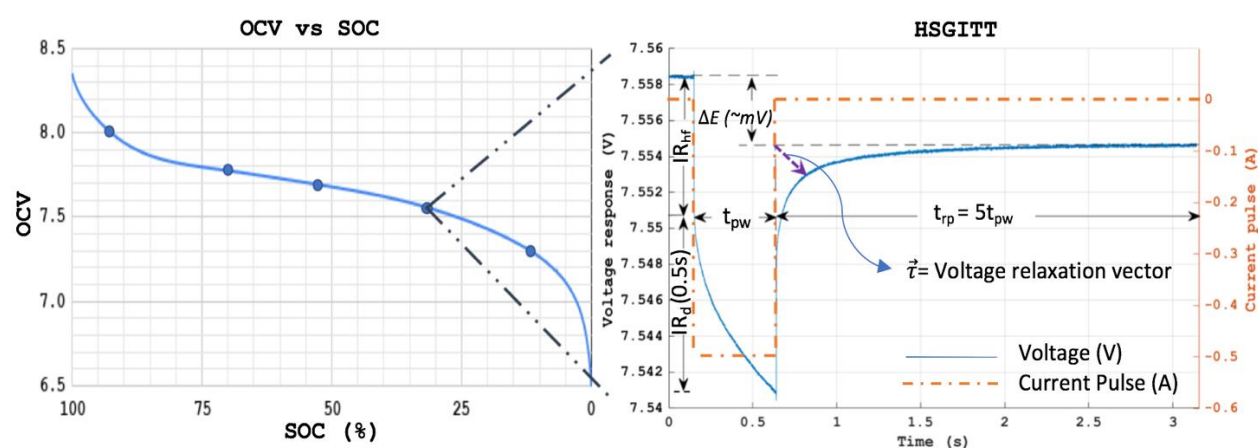
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Period of funding for one CCIS and one COS student: April 15 – October 14, 2019 (6 months)

NU and NuVant Systems (NU spin-off) recondition used nickel-metal-hydride hybrid vehicle battery modules. Reconditioned modules are inventoried until assembled into aftermarket battery packs. However, inventories can be on the order of thousands of modules, and shelved modules will self-discharge at varying rates. Currently, *reliable* state-of-charge (SOC), amp-hour (Ah) capacity, and internal resistance prognostics for a Prius pack (28 modules) demands tens of hours of data acquisition and analysis. This time must be reduced to tens of minutes. Knowledge of the above parameters, summarily called state-of-health (SOH), is critical for optimal pack re-assembly and vehicle replacement scheduling.

Figure 1 (left) is a used Prius module open circuit voltage (OCV) vs. SOC curve (i.e., performance curve) obtained at NU. Smotkin/COS has developed the use of High-Speed Galvanostatic Intermittent Titration Technique (HSGITT), involving a coulombic discharge pulse of tens of milliseconds, that yields 5 parameters coupled to a point (blue dots) on the performance curve. The Smotkin group will team with a machine learning group (Yu/CCIS) to map predictor variables to SOH parameters.



**Figure 1: Left:** OCV vs. SOC. Blue dots are HSGITT points along the discharge curve. **Right:** HSGITT performance parameters: **(i)** Current pulse width ( $t_{pw}$ ): 0.5 s; **(ii)** Peak current ( $i_p$ ): 0.5 A. Convert s to Ah: Multiply s by  $i_p$ . **HSGITT predictor variables:** **1)** OCV: 7.56 V; **2)** High frequency resistance ( $R_{hf}$ ): 0.016  $\Omega$ ; **3)** Time dependent diffusional resistance ( $R_d(0.5s)$ ): 0.019  $\Omega$ ; **4)**  $\Delta E$ : 4 mV; **5)**  $(\frac{dE}{dQ})$ : 0.25 V/C; **6)** Voltage relaxation vector ( $\vec{\tau}$ ): 0.0572.

With thousands of NiMH batteries generating millions of coulombic discharge pulses, it becomes increasingly difficult to manually map predictor variables to SOH. OCV vs SOC curves exhibit large variations across batteries, which are hard to model accurately with physical equations. We will take a machine learning approach to develop battery prognostics for automated battery SOH determination. To achieve this goal, we will leverage massive time series data from HSGITT and develop the mapping from raw coulombic discharge pulses to the SOC and SOH.

We propose to use recurrent neural networks (RNNs), which are flexible deep learning models that can automatically extract features from a time series. RNNs have shown to be highly successful for analyzing sequential data such as speech waveforms and language sentences.

Two students will be partially funding for 6 months. The COS student will acquire performance curves and HSGITT using a library of hundreds of Prius battery modules. The student will also correlate predictor variables to fundamental processes occurring within battery modules. The CCIS student will use COS data for RNNs analysis. The CCIS/COS team will demonstrate the application of RNNs to electrochemical problems, which will result in new computing software for MathWorks. The machine learning algorithms will have broad applications in chemistry, chemical engineering, and for commercial licensing. NuVant, keen to integrate SOH algorithms into EVc-30 software packages for reconditioning units deployed worldwide, has donated several units for research at NU.