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Jelena Andric
Senior Researcher | Docent, PhD
Division of Vehicle Engineering and
Autonomous Systems
Phone: +46 31-772 64 40
Email: jelena.andric@chalmers.se

Stiftelsen ÅForsk
Frösundaleden 2A
169 99 Stockholm
Sweden

SCIENTIFIC REPORT

for the project 19-504

Artificial Intelligence-Based State-of-Charge Estimator for Battery Management System for Electric Vehicles

PROJECT PARTICIPANTS:

- Docent **Jelena Andric**, PhD (jelena.andric@chalmers.se), Division of Vehicle Engineering and Autonomous Systems, Chalmers University of Technology.
- Dr. **Jan Östh** (jan.osth@afry.com), Group Manager Fluid Mechanics, AFRY.
- Dr. **Amirreza Movaghar** (amirreza.movaghar@afry.com), AFRY.
- Dipl. Ing. **Mazyar Moghaddam** (mazyar.moghaddam@northvolt.com) and Dipl. Ing. **Michel Chapuis** (michel.chapuis@northvolt.com), Thermal Management Team, Northvolt AB.
- Dipl. Ing. **Peter Stopp** (p.stopp@gtisoft.com), Gamma Technologies, Vehicle & Electrification Team.

Project results

In this project, an intelligent estimator for the State-of-Charge (SOC) of a Lithium-ion (Li-ion) battery for electric off-road vehicles (for mining and tunneling applications) is developed by means of Artificial Neural Networks (ANNs). A Feed-forward Neural Network (FFNN) model is proposed to predict the SOC for a Li-ion battery pack of a mining vehicle. The suitability of the developed FFNN-based SOC estimator is analyzed for the experimentally recorded data, as well as for data that were not previously seen by the network.

FFNN-based SOC estimator training and validation

The FFNN-based SOC estimator for the Li-ion battery cell was trained in a supervised manner using the experimental measurement data provided by Northvolt AB. The experimental data sets comprise constant current (CC) discharge sequences for different C-rates and constant current - constant voltage (CC-CV) charging sequences, as well as in-between resting periods. The experimental data are randomly divided into two data sets where eighty percent (80%) of data is used for training the network and the remaining twenty percent (20%) for network validation. The mean squared error (MSE) is employed to evaluate the performance of the trained FFNN model. It is found that the best performance for the validation data set is 4.18×10^{-5} at epoch 267. The **validation results** for the developed FFNN-based SOC estimator are compared with the OCV-SOC data from the experiments. Figure 1 illustrates a very good agreement between the **predicted SOC** (FFNN-based estimator) and the **desired SOC** (experimental OCV-SOC).

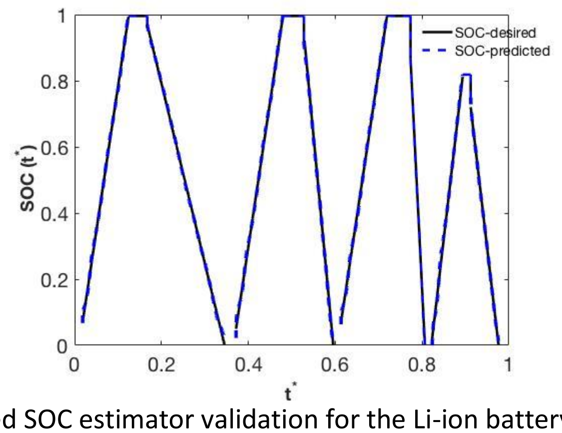

Figure 1. FFNN-based SOC estimator validation for the Li-ion battery cell; t^*denotes the dimensionless time.

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FFNN-based SOC estimation in unseen conditions

The ability of the ANN-based model to generalize and make accurate predictions on previously unseen data is crucial to model performance. The evaluation of the proposed FFNN-based SOC estimator is here accomplished by using an independent set of experimental data from the operating cycle of a mining vehicle.

The developed FFNN-based SOC estimator for the Li-ion battery cell is adopted to the battery module/pack consisting of parallel- and serial-connected cells and used to predict the SOC of a mining vehicle under its entire operating cycle.

The **desired** (OCV-SOC from the mining vehicle operation) and the **predicted** (FFNN-based SOC) outcomes for the battery pack are visually compared in Figure 2. The results illustrate a good agreement between the desired and predicted SOC for the battery pack indicating a good performance of the FFNN model.

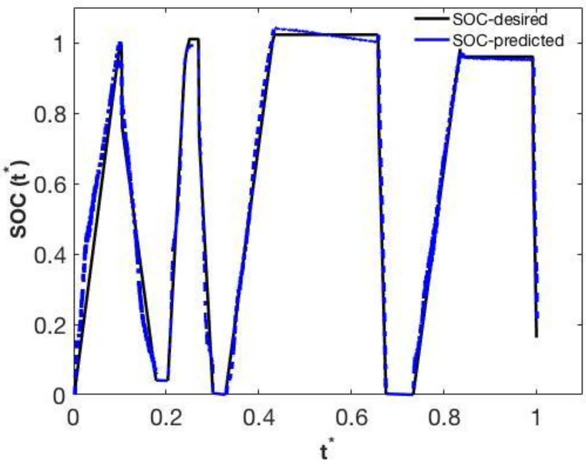

Figure 2. FFNN-based SOC prediction for the battery pack in the mining vehicle; t^*denotes the dimensionless time.

The accuracy of the proposed FFNN model is quantified by computing the average relative error between the predicted and the desired outputs as:

$$Average\ Relative\ Error = \frac{1}{N}\sum_{i=1}^{N} |SOC_{desired}(i) - SOC_{predicted}(i)|.$$

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Here N is the number of time instances, $SOC_{desired}$ is the desired output and the $SOC_{predicted}$ is the output predicted by the FFNN model.

The average relative error is 0.5% meaning that the developed FFNN-based SOC estimator performs with 99.5% average accuracy. This result strongly indicates that the designed FFNN-based SOC estimator can capture the SOC behavior for this type of mining application.

Project Methodology

The SOC estimator is a crucial part for vehicle batteries where accurate SOC estimations in real time are required by the battery management system (BMS) to utilize the battery to its full capability [1]. The SOC must be accurately predicted under different vehicle operating conditions and account for changes in temperature, different charging and discharging currents, and cell aging to:

- Forecast with great certainty the remaining driving/operating range of a vehicle to avoid the so-called "range anxiety" since the users need to know when and how long the battery needs to be charged.
- Perform active cell balancing in battery modules and packs to minimize cell-to-cell differences in capacity and temperature.
- Monitor cell degradation to determine when batteries need replacement.

Definition and estimation of the SOC

The SOC of a battery is typically defined as the ratio of the battery's present capacity to its nominal capacity (i.e. the maximum amount of charge that can stored in the battery specified by the manufacturer). Several direct measurement methods can be used for the SOC estimation [2,3]. The Coulomb counting method is a well-known technique to predict the SOC from its previously estimated values and by integrating the measured discharging/charging currents over the operating periods of time. The drawback is that the method does not account for losses during charging/discharging nor for the self-discharge leading to error accumulation with time. Hence, periodic measurement recalibration is needed to account for these errors. One possible to perform this recalibration is to use the voltage method that converts the voltage value to the equivalent SOC value using the known Open Circuit Voltage (OCV) curve. The method, however, requires stable voltage range which make is challenging for implementation.

With the development of artificial intelligence, new adaptive systems for the SOC estimation are being developed to predict internal cell dynamics. Given that batteries are complex mechanical-chemical systems that when in operation are affected by different external and internal factors, their SOCs are profoundly nonlinear. Therefore, ANN-based multi-layer architectures emerge as suitable tools for modelling battery packs due to its known ability of nonlinear input-output mapping [4,5,6].

FFNN-BASED INTELLIGENT SOC ESTIMATOR

The FFNN model was created using MATLAB. The architecture of the FFNN to predict the battery SOC is shown in Figure 3.

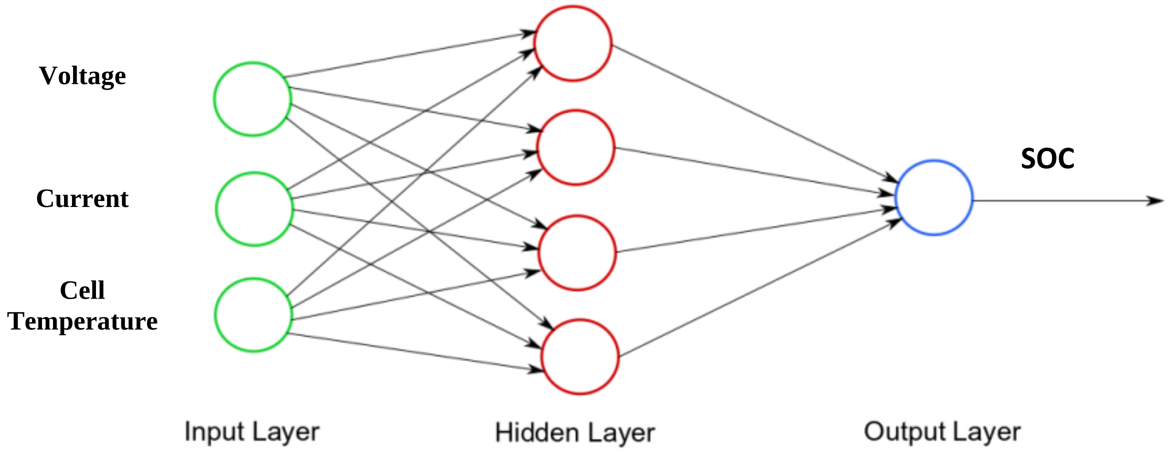

Figure 3. Feed-forward Neural Network (FFNN) architecture for this project. The input data are vectors representing the recorded signals for voltage, current and cell temperature and the output is the estimated SoC for the battery.

The architecture consists of three (3) input layers, one (1) hidden layer, and one (1) output layer. The input data are vectors representing the experimentally recorded values for voltage, current, temperature and the OCV-SOC of the battery cell. The output of the FFNN model is the battery SOC.

The number of hidden layers was determined by trial and error and it was found that one hidden layer was enough to achieve good results. The developed FFNN model outputs the value of the SOC of the battery cell at the current time t based on the resent three measurement histories (e.g. at the time steps t, $t-1$ and $t-2$) for voltage, current and cell temperature.

Concluding remarks

This report presents the development of an intelligent Feed-forward Neural Network (FFFN)-based estimator for the State-of-Charge (SOC) of a Lithium-ion (Li-ion) battery module/pack. The developed estimator performs well in real-time SOC estimation for a mining vehicle.

The present study constitutes an excellent basis for further development of the FFNN-based SOC estimator for electric road vehicles with highly transient operating cycles. The approach is particularly suitable for developing control algorithms and system-level models for real-time simulations.

Result dissemination and utilization

During the project, the four parties (Chalmers, AFRY, Northvolt AB and Gamma Technologies LLC) had several technical meetings, as well as two steering group meetings at Northvolt AB in Stockholm.

The dissemination of the project findings will be carried out in accordance with the Non-Disclosure Agreement (NDA) mutually agreed and signed by all four parties. The following are in the process:

- A scientific article is under preparation and will be submitted for journal publication.
- Transferring the developed FFNN models to Northvolt AB and Gamma Technologies LLC.

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