WEF 2020

The First World Energies Forum Current and Future Energy Issues 14 September – 05 October 2020 | online

A Neural Network Application for a Lithium-ion Battery Pack State-of-Charge Estimator with Enhanced Accuracy

Gabriel C. S. Almeida

A. C. Zambroni de Souza

Paulo F. Ribeiro

Federal University of Itajubá, Itajubá, Brazil



Introduction

Renewable Energy Generation taking over the world scenario

Lithium-ion being positioned as the leading technology platform for energy storage [1]

+

╋

Many known issues (accelerated aging, catastrophic device failure, hazardous incidents associated with faulty State-of-Charge estimation) [2], [3]

Advanced algorithms must be developed to predict the SOC of lithium-ion batteries accurately and effectively

In this paper, a battery model is built using Artificial Neural Network (ANN) to predict the SOC of a battery bank. The inputs do not include the previous SOC level, which makes its estimation more robust.



Theoretical Framework – State-of-Charge

SOC is the percentage of maximum possible charge in the battery [4]. The lithium-ion battery pack was cycled between 20% - 80% of the SOC in 50 cycles of charge/discharge:





Theoretical Framework – Artificial Neural Networks

ANN is a computational model formed by a set of individual processing units, the artificial neurons, interconnected by weights that can be modified according to the quality parameters that evaluate the proximity between the required response and the one obtained [5].







Methodology

FACOLTÀ DI INGEGNERIA CIVILE E

INDUSTRIALE

The figure shows the flowchart and the methodology used in this work, starting with importing and processing the data, designing and training the neural network, arriving at MSE calculation and validation of the prediction.

SAPIENZA

NIVERSITÀ DI ROMA

energies

Design of the proposed ANN

Data Acquisition and Data Pre-processing:

The input data consists of window sequences of load data extracted from the battery bank provided by the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland – EUA [6]. The data inputs must be processed to obtain a satisfactory ANN. The inputs were normalized and randomized to be separated into three sections: Training, Validation, and Test. The data in each section is different from another. The Table shows the quantitative data for each step.

Data Base	Total of Samples
Training	61971
Validation	30985
Test	30985



Design of the proposed ANN

Network Topology:

The ANN topology chosen was the Multi-Layer Perceptron (MLP) network. For the implementation of the proposed model, the MATLAB software was used. The structure of the neural network is represented in the figure and each circle is corresponding to a neuron.





Design of the proposed ANN

Network Training:

After several tests, the ANN training achieved an MSE of approximately 3.11e-06 and was considered satisfactory. The maximum number of training in the network was 173 Epochs due to the limit of 5 validation checks inserted.



Best Validation Performance is 3.1133e-06 at epoch 168



Results

After the training phase, validation model was performed comparing the estimated results and the real database. The figure shows that the ANN is accurate enough, achieving MSE an equivalent to 1.57e-06, obtaining and an approximate hit ratio of 99.81%.





Results

A second validation was performed also to estimate the SOC of cycles of a different month. The figure shows that the ANN-2 is also able to perform this task, obtaining MSE an equivalent 3.13e-05 and an approximate hit ratio of 99.06%.





Conclusions

This paper presented a neural network methodology to estimate the SOC of lithium-ion battery banks usage. The neural network used was an MLP with two-layer architecture. The proposed ANN outlined in this paper resulted in accurate MSE for both situations.

The results show that the ANN was able to self-learn the battery dynamics, allowing one to compete with the traditional SOC estimation techniques. Moreover, the inputs of the ANN do not include the previous SOC level, which makes its estimation more robust.

An alternative to improve this work is to use other types of neural systems, like Recurrent Neural Networks combined with Extended Kalman Filtering (EKF). Another option is to map the non-linear characteristics of different battery cell chemistries like LiFePO4, LiCoO2, and LNMC/Graphite.

energies

Thank you!

Questions?

Gabriel C. S. Almeidacaldas.sardinha@yahoo.com.brA. C. Zambroni de Souzazambroni@unifei.edu.brPaulo F. Ribeiropfribeiro@ieee.org



References

[1] K. Zaghib, A. Mauger, C. M. Julien, ``Rechargeable lithium batteries for energy storage in smart grids - From Fundamentals to Applications," Woodhead Publishing Series in Energy, pp. 319-351, 2015.

[2] Zhang W-J. ``A review of the electrochemical performance of alloy anodes for lithium-ion batteries," Journal Power Sources, vol. 196, pp. 13-24, 2011.

[3] S. Tong, Joseph H. Lacap, Jae W. Park, ``Battery state of charge estimation using a loadclassifying neural network," Journal of Energy Storage, vol. 7, pp. 236-243, 2016.

[4] V. Pop, H. J. Bergveld, P. H. L. Notten, P. P. L. Regtien, ``State-of-the-art of battery state-ofcharge determination," Measurement Science and Technology, IOP Publishing, vol. 16, pp. 93-110, 2005.

[5] Luiz F. R. Monteiro, Juliana R. Monteiro, Luís H. C. Ferreira, A. C. Zambroni de Souza, Benedito I. L. Lopes, ``Determination of Renewable Generation Operation with the Aid of the ANN," in 13th IEEE International Conference on Industry Applications, pp. 375-380, 2018.

[6] CALCE Battery Group, 2017. Available on: <u>https://web.calce.umd.edu/batteries/data.htm#INR18650-test</u> [Accessed: 01 - Sep - 2020].