

THE VIEWS EXPRESSED ARE THOSE OF THE AUTHOR AND DO NOT REFLECT THE OFFICIAL POLICY OR POSITION OF THE
DEPARTMENT OF DEFENSE OR THE U.S. GOVERNMENT.

INFERRING BATTERY STATE OF CHARGE USING STRAIN SENSING AND MACHINE LEARNING

George Anthony¹, Ryan Yount¹, Austin R.J. Downey^{1,2,*}, and Kerry Sado^{1,3}

¹University of South Carolina, Department of Mechanical Engineering, Columbia, South Carolina

²University of South Carolina, Department of Civil Engineering, Columbia, South Carolina

³University of South Carolina, Department of Electrical Engineering, Columbia, South Carolina

ABSTRACT

State of charge (SOC) is a key parameter that provides information about a battery's stored energy. Knowing state of charge is essential for developing accurate models to predict battery behavior within a system and for next-generation battery control schemes. This research investigates the use of strain monitoring and machine learning to estimate a cell's state of charge. To do this, hoop strain measurements at the middle of a 18650 Nickel-Manganese-Cobalt Oxide (NMC) cell (Samsung 30Q cell) are collected, parameterized, and fed into a neural network to predict the state of charge. Experimental results obtained in this work show that a simple multi-layer perceptron model that can predict the SOC of a cell during discharge with an RMSE of 0.0886. The strain measurement modality adds a mechanical aspect to the typical approach of measuring the cell's voltage and current flow. By leveraging the repeatable deformation of the battery that occurs during charge and discharge cycles, the proposed method offers a non-invasive and simplified approach for state of charge estimation. This technique has the potential to enhance battery management systems and improve the efficiency and reliability of complex battery-powered applications. Even a slight extension of a lithium-ion battery's remaining useful life can lead to significant cost savings across various applications.

Keywords: Deep neural networks, battery modeling, battery strain, machine learning, energy storage, battery safety

1. INTRODUCTION

Battery management systems (BMS) are essential electronic control units designed to ensure the safe, reliable, and efficient operation of lithium-ion batteries [1]. These systems monitor parameters such as voltage, current, and temperature to estimate State of Charge (SOC). While current and voltage measurements are the dominating method of determining SOC, there can be inaccuracies if measurements are not calibrated [2]. Adding

another measurement would be beneficial to more complex BMS systems. While there are other works looking at the expansion of pouch cells, the study of strain gauges on 18650 cylindrical cells is a novel concept that should be explored further. This work explores using the multi-layer perceptron (MLP) neural network (NN) to estimate SOC based on strain rather than traditional measurements. This method of calculating SOC could expand our understanding of batteries and allow for more advanced control of battery systems. The work aims to prove that a MLP NN can utilize strain alone as a valid means to predict SOC.

Artificial neural networks are computational systems modeled after the way biological neurons work in the brains of animals and humans. They consist of a number of simple units called neurons which are working in parallel to send information along directed connections to each other [3]. The best-known and most widely used form is the multi-layer perceptron (MLP), which is a type of feed-forward NN that consists of an input layer, one or more hidden layers, and an output layer. Each hidden layer applies weighted linear combinations of its inputs followed by non-linear activation functions. During training, the network learns to adjust these weights to minimize the difference between its predictions and the actual target values [4]. MLPs are well-suited for problems involving low-dimensional feature sets with a non-linear relationship between inputs and outputs.

The MLP can be trained using strain because lithium-ion batteries undergo complex electrochemical and mechanical changes as it charges and discharges. Lithium ions enter the graphite anode and through intercalation fill the structure causing reversible expansion. Figure 1 shows the stages of the lithium ions as they leave the graphite anode through discharge. However there is also non-reversible expansion in the battery due to growth of the solid electrolyte interface (SEI) and other factors. This work aims to train an MLP to estimate SOC using only strain data. Strain on the battery is primarily caused by the intercalation and non-reversible expansion [5]. Using a wide assortment of discharge data, the model aims to overcome the non-reversible strain by identifying

*Corresponding author: austindowney@sc.edu

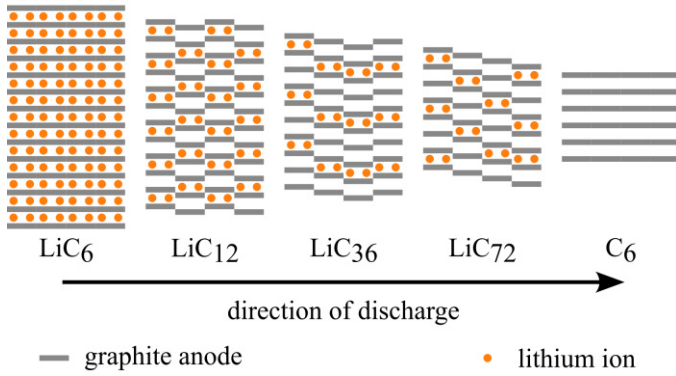


FIGURE 1: Intercalation stages of the lithium-ion battery discharging.

the shape of the strain curve using only the data given to it. By showing the MLP can function only using strain it can verify that strain would be a potential vector to enhancing other models that use more traditional methods of SOC prediction with voltage and current.

The contributions of this work are twofold, 1: propose an ML framework that estimates SOC from hoop strain data and 2 present experimental data that correlates the non-linear relationship between strain and SOC due to the delithiation of the graphite anode.

2. METHODOLOGY

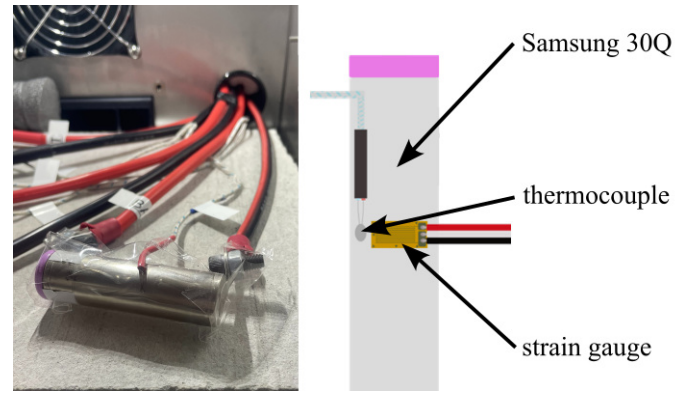
This section discusses the experimental setup of the battery discharge data collection and the model design of the MLP.

2.1 Experimental Data Collection

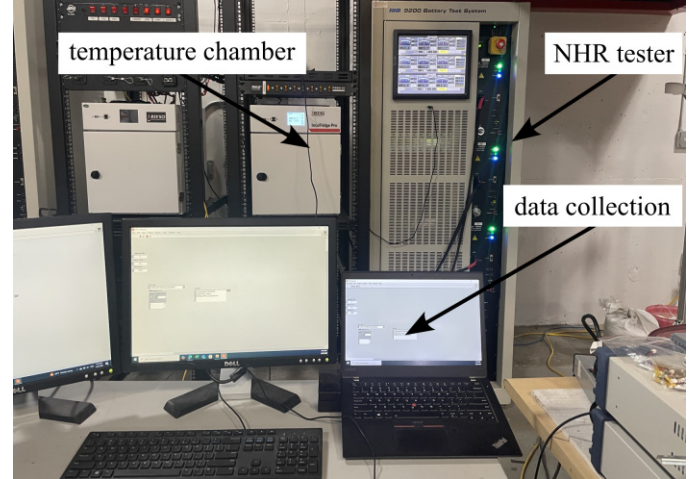
To train the model, a dataset of a NMC cell under charge and discharge cycles was collected [6]. The cell was cycled at 1C (3 A) charge and discharge while voltage, current, temperature, and strain were collected at a sampling frequency of 1Hz for approximately 650 cycles. A rate of 1C was decided due to the interference above 2C where lithium plating can cause excessive strain [7]. As seen in figure 2a, the strain gauge and thermocouple were both fastened to the center of the battery. To charge and discharge the cells we used an NHR 9200 battery test system to control the tests seen in figure 2b. From the data, capacity was determined enabling an accurate baseline estimate of SOC for training. Each battery was cycled at a 100% depth of discharge (DoD). Batteries were charged at 1C to 4.2 V with a constant voltage (CV) section down to 0.15 A. Then the discharge was a constant current 1C discharge of 3 A to a voltage of 2.5 V. There was no CV section for the discharge because we wanted a consistent rate of discharge for our tests. Tests were performed in a temperature chamber that maintained a constant 20°C to minimize the effect of temperature.

2.2 Model Design

A relationship between strain and SOC appears to exist given the consistency in the shape of the strain curve during constant current discharge cycles. However, this relationship is non-linear and that makes it difficult to quantify SOC given a typical linear



(a) Battery with strain gauge and thermocouple.



(b) Experimental lab setup.

FIGURE 2: Battery testing setup. (a) shows the strain gauge and thermocouple mounted on the battery; (b) shows the lab setup where testing was conducted.

regression model. Moreover, there is no known physics-based equation to find SOC from given a strain value, so a data-driven approach is appropriate. With these issues in mind, a NN was chosen as an alternative to traditional methods such as Coulomb counting or voltage measurements. With simplicity as a motivator, the type of model chosen was an MLP. The MLP contains a single input as strain, three hidden layers with 64 nodes in the first and 32 in the second and third, and one output layer for the predicted SOC value as seen in figure 3. The activation function for the model was Rectified Linear Unit (ReLU), which outputs the input if it was positive, and zero otherwise. The loss function used during training was mean squared error (MSE), and the test sets were evaluated using root mean squared error (RMSE). The NN was trained using a gradient-based algorithm called the Adam optimizer. A constant learning rate of 0.001 was used throughout training to control the step size of weight updates. To improve generalization and prevent overfitting, L2 regularization was applied with a strength of 0.0001.

An issue with using single point strain data as an input to the model is that it does not account for the non-linear deformation over time during charge and discharge. This change is also not monotonic or instantaneous, meaning the difference can vary

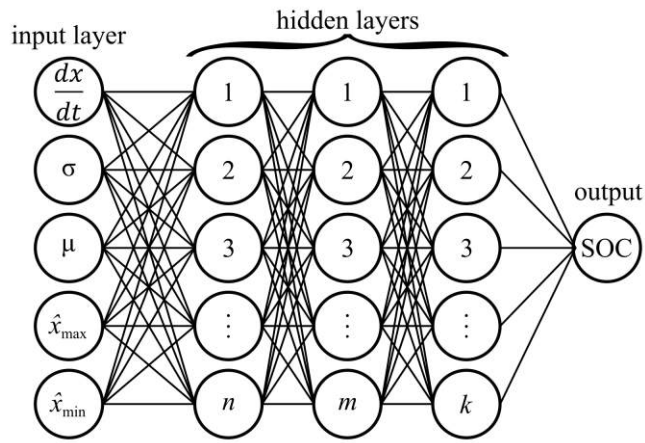


FIGURE 3: Diagram of the Neural Network being used for the SOC model.

from cycle to cycle. Rather than relying on a single point of strain, a window of strain data was used to extract descriptive statistical features. This approach captured dynamic behavior over time and reduced the effect of sensor noise in the datasets from possible issues during the experimental setup and was expected to improve generalization in the model so that overfitting would be mitigated. The features extracted included maximum, minimum, standard deviation, slope, and mean.

The dataset was split into 80% for training and 20% for testing. The training iterated through a maximum of 1000 epochs before stopping. However, if the loss improvement between epochs was less than 0.0001 for two consecutive iterations, the training stopped early. The performance of the model was monitored with a training loss curve, seen in figure 4, as well as testing RMSE per cycle. Feature importance was also recorded across the training set, showcasing the mean change in MSE if the weights and biases associated with that feature were changed.

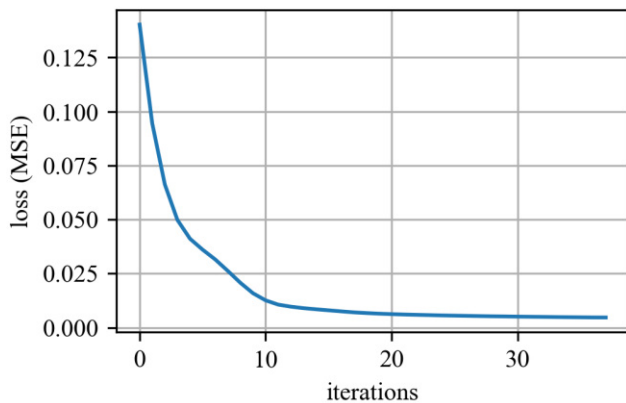


FIGURE 4: Loss value obtained through the training of the NN measured in MSE.

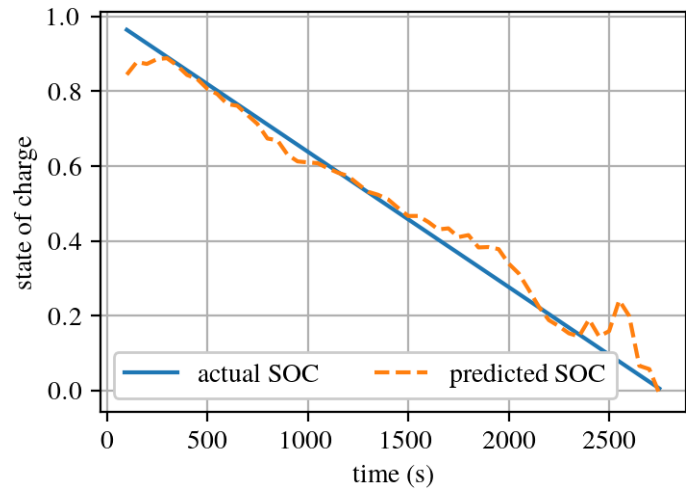


FIGURE 5: Result of MLP after training on dataset of 631 files for cycle 578 RMSE=0.0475.

TABLE 1: Error metrics between actual and predicted SOC for cycle 578

Metric	Value
MSE	0.002254
RMSE	0.047477
MAE	0.033308

3. RESULTS

Preliminary investigations show that due to the unique nature of the battery strain as the cell degrades, the MLP model will be able to create a correlation between SOC and strain successfully. Initial data appears to show that using different features of the strain measurement can relate to the intercalation stages of a lithium-ion battery and predict SOC.

To start the verification of the MLP a trivial dataset of 10 random discharge cycles was fed into the model. The MLP successfully executed using 8 cycles for training and 2 for testing. The two tests resulted in a RMSE of 0.1291 an acceptable start for such a low amount of data. After verifying the model was functioning as intended another test was performed with 100 random cycles. This test trained on 80 cycles and tested on 20 with an average RMSE of 0.1008. This improvement showed that the MLP was improving with more data. Finally, the MLP received all the data, roughly 631 cycles, this resulted in a final RMSE of 0.0886. This showed additional improvement with more data and some tests had an error as low as 0.0478. The best performing data is shown in figure 5.

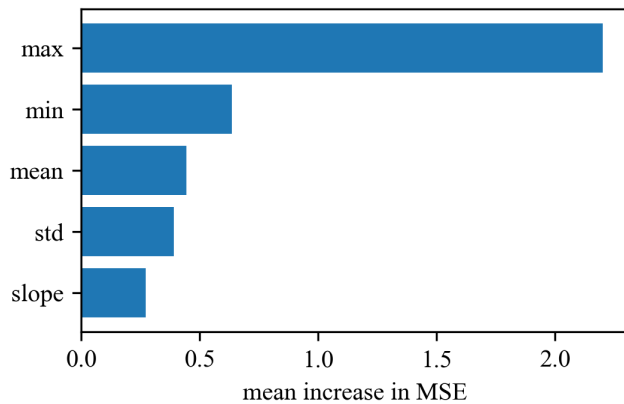


FIGURE 6: Feature importance values of the different features from the window.

The model is able to train relatively quickly as seen in figure 4 with less than 40 iterations before finishing training. Looking at figure 6 the maximum of the window is the most important training feature with other features having similar relative importance. It is interesting to note that in general the model works better for later data and spikes in error for cycles between 50 and 350 cycles. Further investigation of this trend could identify if there is a problem with the MLP or if more data is needed to be consistent.

4. CONCLUSION

This paper presented an approach to using strain measurements from a single strain gauge on a 18650 cell to predict SOC using an MLP with windowed data. By correlating battery casing strain directly with the lithium intercalation processes, the MLP model effectively captured the underlying electro-chemical-mechanical relationships inherent to battery operation. The findings show that not only is SOC able to be predicted by the MLP but that the accuracy increases with more data showcasing the potential of this approach to be expanded with a larger dataset. By adding this method with other traditional approaches modern BMSs could further mitigate error in SOC calculation.

Future work should investigate more cells to verify that this method is not isolated to a single cell. Additionally, this work could be expanded to use other more traditional methods of SOC measurement and potentially provide additional resolution for more complex models.

ACKNOWLEDGMENTS

This work was supported by the Office of Naval Research under contract NOs. N00014-24-C-1301, and N00014-23-C-1012. The support of the ONR is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the United States Navy.

REFERENCES

- [1] Rahimi-Eichi, Habiballah, Ojha, Unnati, Baronti, Federico and Chow, Mo-Yuen. "Battery Management System: An Overview of Its Application in the Smart Grid and Electric Vehicles." *IEEE Industrial Electronics Magazine* Vol. 7 No. 2 (2013): pp. 4–16. DOI [10.1109/mie.2013.2250351](https://doi.org/10.1109/mie.2013.2250351).
- [2] Hendricks, Christopher, Sood, Bhanu and Pecht, Michael. "Lithium-Ion Battery Strain Gauge Monitoring and Depth of Discharge Estimation." *Journal of Electrochemical Energy Conversion and Storage* Vol. 20 No. 1 (2022). DOI [10.1115/1.4054340](https://doi.org/10.1115/1.4054340).
- [3] Kruse, Rudolf, Mostaghim, Sanaz, Borgelt, Christian, Braune, Christian and Steinbrecher, Matthias. *Multi-layer Perceptrons*. Springer International Publishing (2022): pp. 53–124. DOI [10.1007/978-3-030-42227-1_5](https://doi.org/10.1007/978-3-030-42227-1_5).
- [4] Riedmiller, Martin. "Advanced supervised learning in multi-layer perceptrons — From backpropagation to adaptive learning algorithms." *Computer Standards and Interfaces* Vol. 16 No. 3 (1994): pp. 265–278. DOI [10.1016/0920-5489\(94\)90017-5](https://doi.org/10.1016/0920-5489(94)90017-5).
- [5] Ren, Wenju, Zheng, Taixiong, Piao, Changhao, Benson, Daryn Eugene, Wang, Xin, Li, Haiqing and Lu, Shen. "Characterization of commercial 18,650 Li-ion batteries using strain gauges." *Journal of Materials Science* Vol. 57 No. 28 (2022): pp. 13560–13569. DOI [10.1007/s10853-022-07490-4](https://doi.org/10.1007/s10853-022-07490-4).
- [6] ARTS-Lab. "Dataset cycling with strain monitoring for Samsung 30Q cell." GitHub. URL <https://github.com/ARTS-Laboratory/dataset-cycling-with-strain-monitoring-for-samsung-30Q-cell>.
- [7] Song, Jifeng, Li, Yuanlong, Ren, Tao, Wang, Juntao and Yang, Zhengye. "Two Strain Modes and Transition Point of 18650 Lithium-Ion Battery at Different Charging Rates." (2023) DOI [10.2139/ssrn.4526882](https://doi.org/10.2139/ssrn.4526882).