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Lithium-ion battery charge-discharge cycle forecasting using LSTM neural networks

Vimala Channapatana Srikantappa, Seshachalam Devarakonda
Department of Electronics and Communication Engineering, BMS College of Engineering, Bangalore, India

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ABSTRACT

An important component for the dependable and safe utilization of lithium-ion batteries is the ability to accurately and efficiently predict their remaining useful life (RUL). In this research, a long short-term memory recurrent neural network (LSTM RNN) model is trained to learn from sequential data on discharge capacities across different cycles and voltages. The model is also designed to function as a cycle life predictor for battery cells that have been cycled under varying conditions. By leveraging experimental data from the NASA battery dataset, the model achieves a promising level of prediction accuracy on test sets consisting of approximately 200 samples.

Corresponding Author:

Vimala Channapatana Srikantappa
Department of Electronics and Communication Engineering, BMS College of Engineering
Bangalore, India
Email: vimalasrikantappa@gmail.com

1. INTRODUCTION

Lithium-ion batteries are widely employed in electronic devices due to their high energy density, affordability, and longevity. Measuring the remaining useful life (RUL) of these batteries is essential to understand their lifespan, and this is accomplished by a battery management system (BMS). The BMS provides a future forecast of the battery's life. However, this task is challenging because battery mathematical models are not standardized. Each manufacturer develops their own model based on varying physical properties.

A substantial number of exemplary research studies have been conducted to predict the RUL of batteries. This study focuses on forecasting the battery charge-discharge cycle, which may contribute to more accurate RUL predictions. The objective of model-based approaches is to develop mathematical or semi-empirical models that elucidate the relationships among internal processes, operating conditions, and battery capacity degradation.

Previous studies discussing battery life and neural networks are reviewed further. The works in [1]-[4] explore battery models, examining the decrease in electrolyte volume percentage and the depletion of cyclable lithium. The particle filter [5] is a fundamental method commonly employed and integrated with various theories and strategies for enhancement. Examples include the Dempster-Shafer Theory [6] and the Akaike information criterion [7]. However, model-based solutions consistently face challenges due to the lack of reliable aging models and the issue of particle degeneracy.

Data-driven approaches, unlike model-based methods, do not require a mathematical or semi-empirical model. Instead, they rely on experimental data from battery cycling. To develop accurate life predictions, it is essential to extract relevant features from the data.

Severson and colleagues [8] examine a novel characteristic that shows a strong correlation with cycle life, based on variations in discharge capacities as functions of cycles and voltages. Alongside conventional linear regression methods, this approach yields promising results for predicting cycle life before noticeable capacity degradation—using only data from the first 100 cycles. The trait discussed in [8] only considers the change between cycles 100 and 10. When additional cycles (e.g., cycle 20, cycle 30, etc.) are included, one might wonder whether the model's predictive accuracy improves. Discharge capacities at different voltages can be represented across cycles, where each time step corresponds to a cycle, and the discharge capacities during that cycle represent the time step. It is possible to organize discharge capacities of different voltages in a specific sequence. Therefore, it is crucial to use a dataset of battery discharge capacities (as a function of voltage and cycle) to determine how long each capacity value will last across cycles.

Using the right model to learn from sequential data on capacity loss is vital. Given the presence of internal states that convey information about capacity degradation, recurrent neural networks (RNNs) may be a suitable choice. This topic has been explored in [9], [10]. Additionally, long short-term memory (LSTM) RNNs are effective in capturing long-term dependencies, which are essential for modelling capacity degradation over time, as they address the "gradient vanishing" problem. Researchers in [11]–[15] discuss the application of LSTM RNNs for predicting battery RUL. Their performance surpasses that of support vector machines (SVMs) and standard RNNs. While model-based methods offer interpretability and are grounded in physical principles, they often struggle with adapting to complex and varying battery aging behaviors. Data-driven approaches, such as LSTM RNNs, excel at capturing nonlinear patterns and handling diverse conditions but require large, high-quality datasets. This study leverages the strengths of data-driven modeling to achieve accurate cycle life predictions using sequential discharge data. Recent literature on regression and battery modelling includes:

- The novel auto-regression nested sequence (ARNS) method [16].
- Extraction of indirect health indicators (IHIs) [17].
- Active charge balancing (ACB) [18].
- Random forest (RF) regression estimator [19].
- Complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) [20]–[22].
- Effective battery SOH prediction [22].
- Particle filtering (PF) [23].
- A review study [24] examining the feasibility and economics of "Big Data" analytics-based battery health estimation.
- Bayesian non-parametric Gaussian process regression [25], which presents an extensible health estimation model.

This study aims to integrate several key features identified in previous research by inputting sequential data of charge and discharge capacities at different voltages and cycles into an LSTM RNN model. This approach shows potential for further improvements by:

- Eliminating the need for manual feature extraction.
- Analysing future charge and discharge cycle data for up to 200 samples.
- Predicting cycle durations with satisfactory accuracy using fewer inputs.
- Reducing associated costs.

2. METHOD

The LSTMRNN model is designed for the appropriate battery data set. This section details the LSTMRNN model MSE equation. Then the results section details the actual implementation. In the LSTM RNN model, the number of LSTM layers and the input sequence length (e.g., 100–300 cycles) determine how well the model captures temporal dependencies in battery degradation. The tanh activation function is commonly used in LSTM cells to regulate the flow of information, while dropout regularization (typically 0.2–0.5) helps prevent overfitting by randomly deactivating neurons during training. Together, these components enhance the model’s ability to generalize across varying battery conditions and cycle patterns.

2.1. LSTMRNN model

In this LSTMRNN [12], the input layer is fed into the LSTM layer. This RNN LSTM is better in convergence and accuracy. In this, the MSE is minimized, and the algorithm always tries to minimize the MSE.

$$MSE = \frac{1}{N}\sum\left(\overline{\overline{S_i}} - S_i\right)^2 \quad (1)$$

The rate of learning is 1e-3, and the Adam optimizer is used here for the training. The training and testing of the LSTMRNN is done in the MATLAB software 2023b. The system used here is AMD Ryzen 4000 series, with 16 GB RAM and NVIDIA RTX 1080 graphics card. The flow chart of the LSTM RNN implementation procedure is stated as shown in Figure 1.

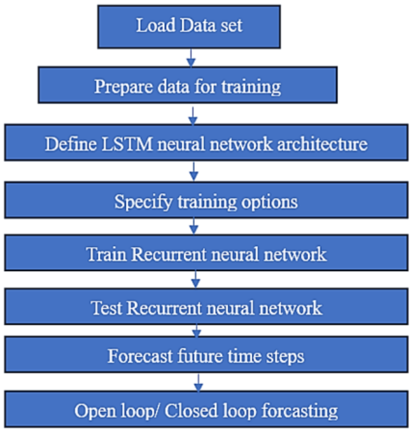

Figure 1. Flow chart of the LSTM RNN implementation procedure

3. RESULTS AND DISCUSSION

By iterating over time steps and changing the RNN state, an LSTM network processes incoming data sequentially. All previous time steps are stored in the RNN state. An LSTMRNN may predict future values of a time series or sequence using previous time steps. Create a regression LSTMRNN with sequence output to train an LSTMRNN for time series forecasting. The replies (targets) are the training sequences with values displaced by one time step. At each input sequence time step, the LSTMRNN learns to predict the next time step.

Two forecasting methods exist: open loop and closed loop. Open-loop forecasting predicts the next time step using just input data. Actual values from your data source are used to predict future time steps. Closed-loop forecasting uses past forecasts to predict future time steps. Actual values are not needed for the model to predict. The Waveform dataset contains 2000 synthetic waveforms of various lengths across three channels used by this software. The example uses closed-loop and open-loop forecasting to let an LSTM neural network predict future waveform values from past time step values.

3.1. Load data

Figure 2 shows the structure of the data used in the analysis. This data is taken from the NASADATA set. It has four mat files in it. They are B0005, B0006, B0007 and B0018. In this B0018 is a totally impedance dataset which is not similar to others. So, we neglected the B0008 in the training.

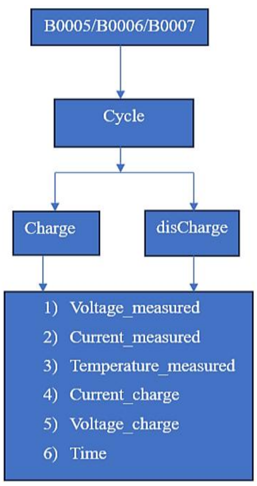

Figure 2. The structure of the DATA for the battery used in this analysis

3.2. Define LSTMRNN architecture

An LSTMRNN layer consisting of 128 hidden units should be implemented. A sequence input layer should be used, and the size of the input should be determined by the number of channels present in the input data. The quantity of hidden units is the determining factor in the amount of information that the layer is able to gather. The use of more hidden units has the potential to improve accuracy, but it also raises the possibility of excessive fitting to the dataset that was used for training. Incorporating an entirely connected layer with an output size that matches the number of input channels is necessary in order to generate sequences that contain the same number of channels as the data that is being entered. Additionally, a regression layer should be incorporated.

In practical applications such as BMS in electric vehicles EVs, the distinction between closed-loop and open-loop prediction results is critical. Open-loop prediction involves estimating battery health or RUL based solely on initial data inputs, without incorporating feedback from ongoing battery performance. This approach is computationally efficient and suitable for early diagnostics or offline analysis but may become inaccurate over time as battery conditions evolve due to factors like temperature, load, and aging. In contrast, closed-loop prediction continuously updates its forecasts using real-time data, making it highly adaptive and robust. This dynamic feedback mechanism is essential for real-time BMS operations, enabling proactive maintenance, fault detection, and optimized charging strategies. Closed-loop systems enhance safety by identifying anomalies early, improve efficiency by extending battery life, and contribute to cost savings and better user experience through reliable range estimation. From a machine learning perspective, open-loop resembles one-shot prediction, while closed-loop aligns with sequence-to-sequence learning with feedback, often implemented using recursive forecasting or online retraining in models like LSTM. Cases: i) Case 1: Dataset: B0005; ii) Case 2: Dataset: B0006; and Case 3: Dataset: B0007. Case 1 deals with the B0005 dataset, case 2 deals with the B0006 dataset, and case 3 deals with the B0007 dataset.

Figure 3 shows the convergence graph for case 1, where the iteration is 400. The epochs to display are 200. The iteration per epoch is 2. The learning rate is set to 0.001. Figure 4 convergence graph for case 2, where the iteration is 400. The epochs to display are 200. The iteration per epoch is 2. The learning rate is set to 0.001. Figure 5: convergence graph for case 3, where the iteration is 400. The epochs to display are 200. The iteration per epoch is 2. The learning rate is set to 0.001.

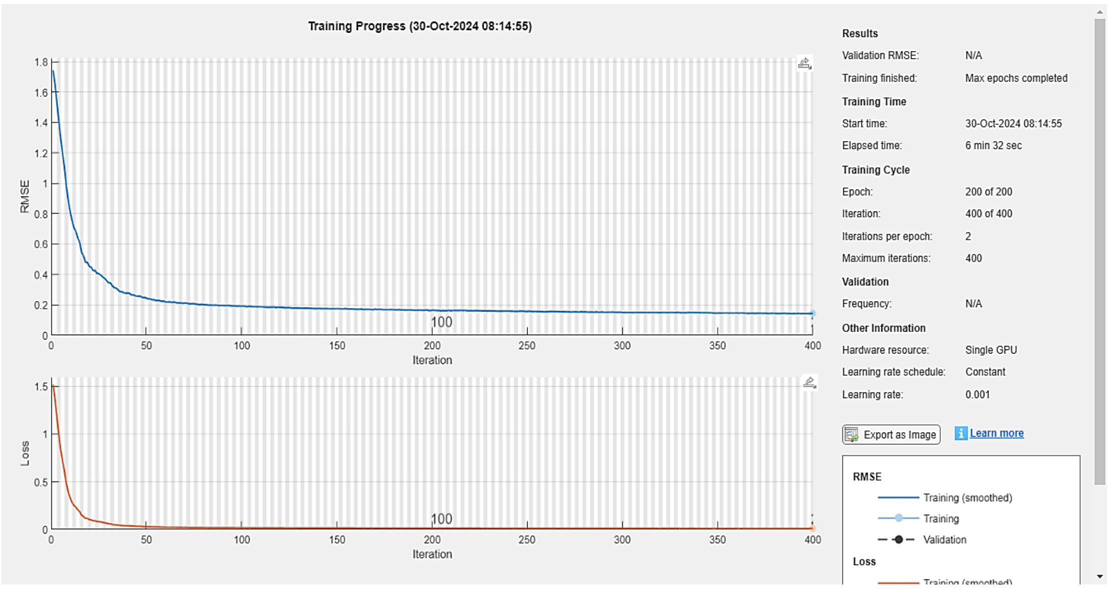

Figure 3. Convergence graph for case 1

A frequency vs. RMSE plot is typically used to evaluate the distribution of prediction errors (root mean square error) across different test samples or model runs. Here's what it means:
- X-axis (RMSE): Represents the range of RMSE values obtained from predictions—lower values indicate better accuracy.
- Y-axis (Frequency): Shows how often each RMSE value (or range) occurs across the dataset or multiple experiments.

Figure 6 shows the frequency vs RMSE value with binary bins for case 1. Here it shows that the RMSE between 0 to 1 is more compared to others. This shows the model trained is close to the original. Figure 7 shows the frequency vs RMSE value with binary bins for case 2. Here, it shows that the RMSE between 0 to 1 is higher compared to others. This shows the model trained is close to the original. Figure 8 shows the Frequency vs RMSE value with binary bins for case 3. Here, it also shows that the RMSE between 0 to 1 is higher compared to others. This shows the model trained is close to the original.

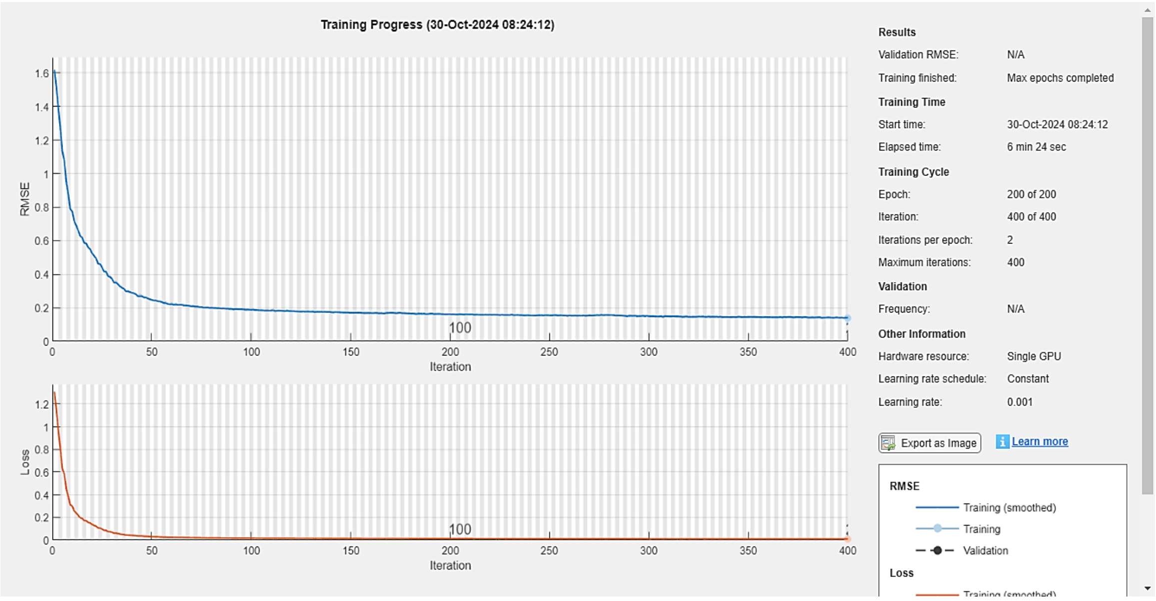

Figure 4. Convergence graph for case 2

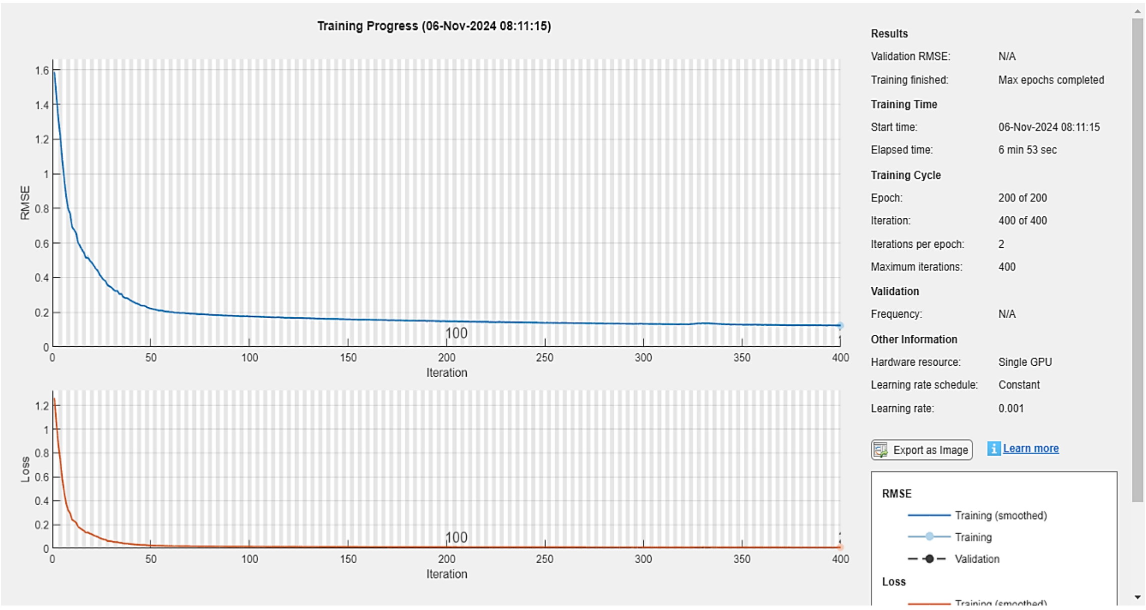

Figure 5. Convergence graph for case 3

Table 1. RMSE for all the cases

Cases	RMSE
Case 1	0.2335
Case 2	0.2376
Case 3	0.2250

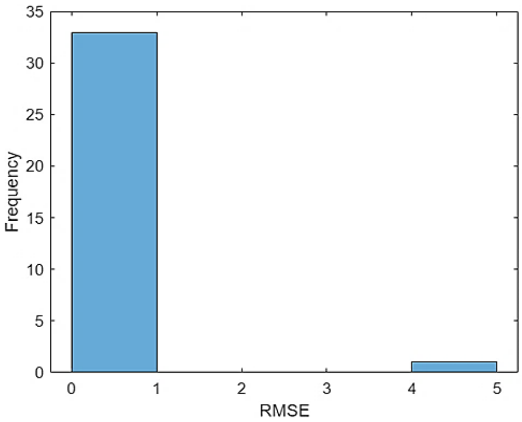

Figure 6. Frequency vs RMSE value with binary bins for case 1

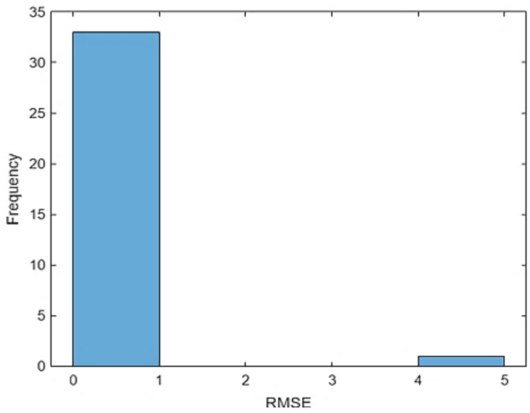

Figure 7. Frequency vs RMSE value with binary bins for case 2

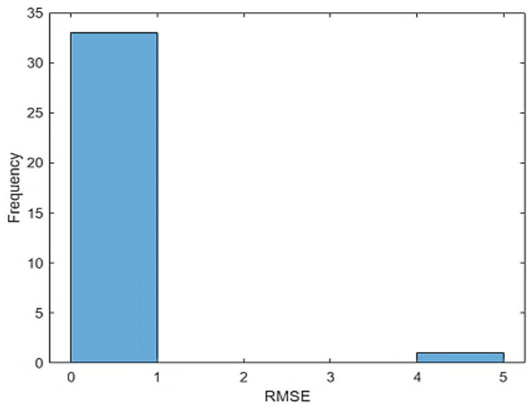

Figure 8. Frequency vs RMSE value with binary bins for case 3

The case-wise RMSE is shown in Table 1. Figures 9, 10, and 11 show the six data used for training: V measured, I measured, Temperature measured, charge current, change voltage, and time taken for case 1, case 2, and case 3, respectively. Figure 12 shows the open-loop prediction/forecasting for case 1. Figure 13 shows the open-loop prediction/ forecasting for case 2. Figure 14 shows the open-loop prediction/forecasting for case 3.

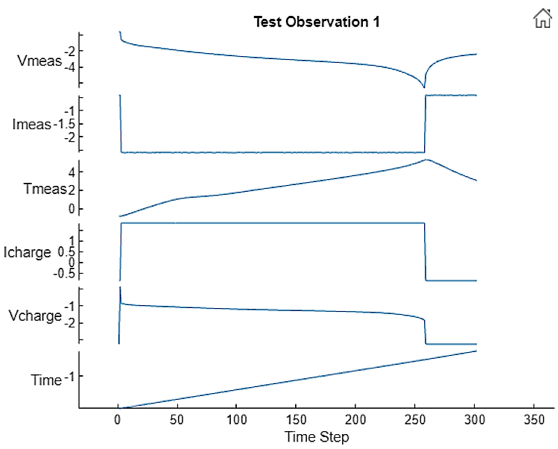

Figure 9. Case 1: the six data used for training V measured, I measured, temperature measured, charge current, change voltage, and time taken

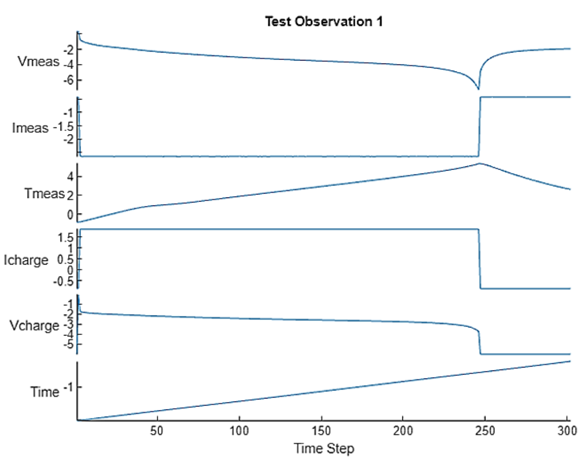

Figure 10. Case 2: the six data used for training V measured, I measured, temperature measured, charge current, change voltage, and time taken

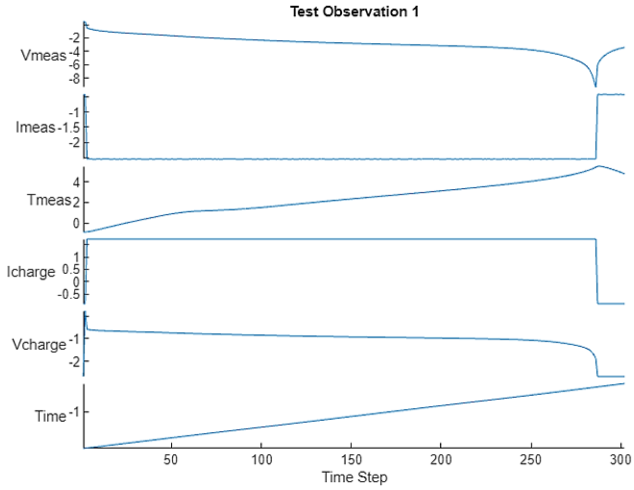

Figure 11. Case 3: the six data used for training V measured, I measured, temperature measured, charge current, change voltage, and time taken

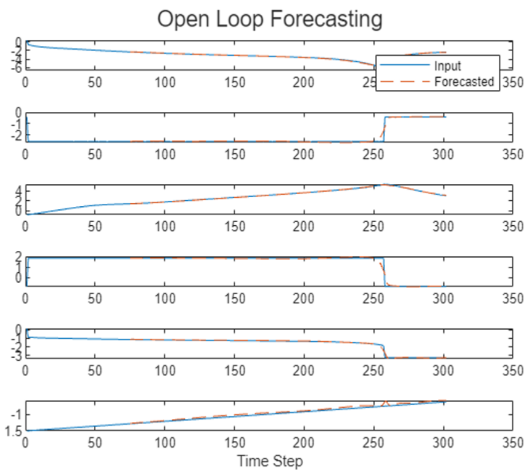

Figure 12. Open-loop prediction/forecasting for case 1

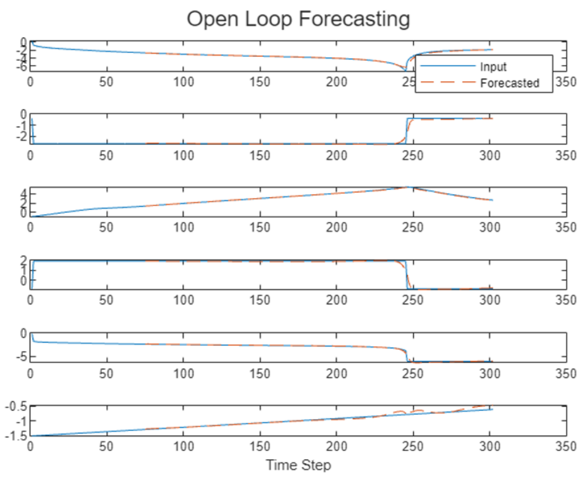

Figure 13. Open-loop prediction/forecasting for case 2

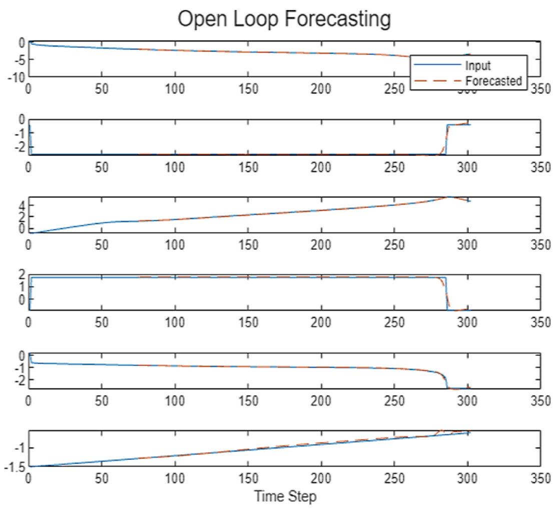

Figure 14. Open-loop prediction/forecasting for case 3

This shows that the open-loop prediction is close enough to the original data. The blue line shows the original data. The dotted orange line shows the predicted data. The orange line falls on the blue. Which means the open-loop forecast is accurate.

Figure 15 shows the closed-loop prediction/forecasting for case 1. Figure 16 shows the closed-loop prediction/forecasting for case 2. Figure 17 shows the open-loop prediction/forecasting for case 3. This shows that the closed-loop prediction for 200 samples shows the future of the cell behavior for the next 200 sample times. The blue line solid one shows the actual values, and the dotted orange line shows the forecasted ones. In the article [26], the authors report the following performance metrics: The multi-channel LSTM model achieves a root mean square error (RMSE) ranging from 0.47% to 1.88%. In our case, we got 0.2% approx.

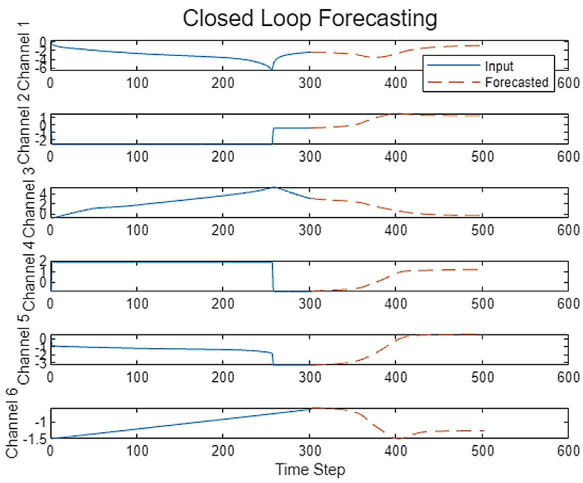

Figure 15. Case 1: closed loop forecast for 200 data

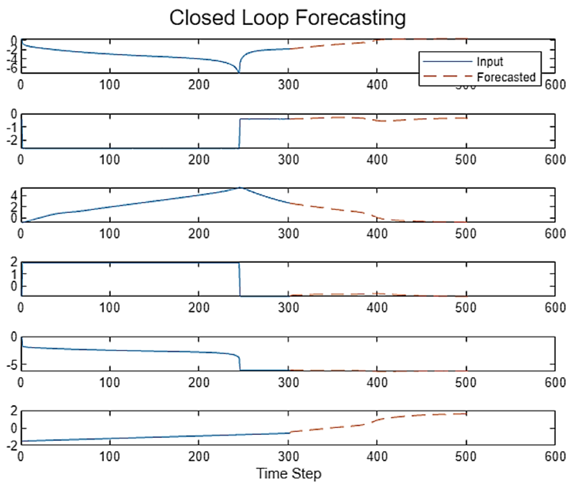

Figure 16. Case 2: closed loop forecast for 200 data

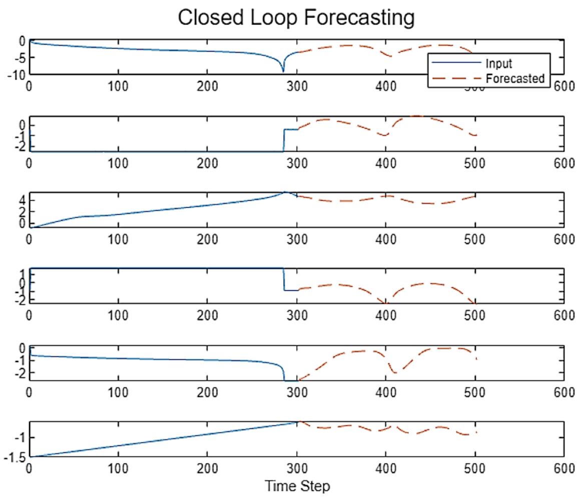

Figure 17. Case 3: closed loop forecast for 200 data

4. CONCLUSION

The purpose of this work is to construct an LSTM RNN model for the early prediction of the cycle life time of battery cells. The input data consists of cycle sequences of capacities within charge and discharge windows. This feature is closely associated with cycle lifetime. Within the first 300 samples of data, our model achieves root mean square error (RMSE) values that are satisfactory on the primary test set. Additionally, the model demonstrates acceptable prediction performance on the secondary test set by utilizing fewer cycles of data, made possible through the application of data augmentation during training. In summary, this work aims to explore an LSTM RNN model that leverages a novel input format of sequential data. The model shows potential to reduce the number of early cycles required for accurate cycle life predictions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Vimala Channapatana Srikantappa	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Seshachalam Devarakonda		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest.

DATA AVAILABILITY

Publicly available datasets were analyzed in this study. The Li-ion Battery Aging Datasets can be found at the NASA Open Data Portal: https://data.nasa.gov/dataset/li-ion-battery-aging-datasets.

REFERENCES

[1] S. Richard, W. Ralf, H. Gerhard, P. Tobias, and W. Martin, "Performance and cost of materials for lithium-based rechargeable automotive batteries," *Nature Energy*, vol. 3, no. April, pp. 267–278, 2018, [Online]. Available: http://dx.doi.org/10.1038/s41560-018-0107-2

[2] Ramadass P., Haran Bala, Gomadam M. Parthasarathy, White Ralph, and Popov N. Branko, "Development of first principles capacity fade model for Li-ion cells," *Journal of The Electrochemical Society*, vol. 151, no. 2, pp. A196–A203, 2004.

[3] G. Ning, R. E. White, and B. N. Popov, "A generalized cycle life model of rechargeable Li-ion batteries," *Electrochimica Acta*, vol. 51, no. 10, pp. 2012–2022, 2006, doi: 10.1016/j.electacta.2005.06.033.

[4] H. Ekström and G. Lindbergh, " A model for predicting capacity fade due to SEI formation in a commercial graphite/LiFePO 4 cell ," *Journal of The Electrochemical Society*, vol. 162, no. 6, pp. A1003–A1007, 2015, doi: 10.1149/2.0641506jes.

[5] X. Su, S. Wang, M. Pecht, L. Zhao, and Z. Ye, "Interacting multiple model particle filter for prognostics of lithium-ion batteries," *Microelectronics Reliability*, vol. 70, pp. 59–69, 2017, doi: 10.1016/j.microrel.2017.02.003.

[6] W. He, N. Williard, M. Osterman, and M. Pecht, "Prognostics of lithium-ion batteries based on dempster-shafer theory and the bayesian monte carlo method," *Journal of Power Sources*, vol. 196, no. 23, pp. 10314–10321, 2011, doi: 10.1016/j.jpowsour.2011.08.040.

[7] Y. Xing, E. W. M. Ma, K. L. Tsui, and M. Pecht, "An ensemble model for predicting the remaining useful performance of lithium-ion batteries," *Microelectronics Reliability*, vol. 53, no. 6, pp. 811–820, 2013, doi: 10.1016/j.microrel.2012.12.003.

[8] K. A. Severson *et al.*, "Data-driven prediction of battery cycle life before capacity degradation," *Nature Energy*, vol. 4, no. 5, pp. 383–391, 2019, doi: 10.1038/s41560-019-0356-8.

[9] J. Liu, A. Saxena, K. Goebel, B. Saha, and W. Wang, "An adaptive recurrent neural network for remaining useful life prediction of lithium-ion batteries," *Annual Conference of the Prognostics and Health Management Society, PHM 2010*, 2010, doi: 10.36001/phmconf.2010.v2i1.1896.

[10] M. Rezvani, M. Abuali, S. Lee, J. Lee, and J. Ni, "A comparative analysis of techniques for electric vehicle battery prognostics and health management (PHM)," *SAE Technical Papers*, 2011, doi: 10.4271/2011-01-2247.

[11] Y. Zhang, R. Xiong, H. He, and M. G. Pecht, "Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 5695–5705, 2018, doi: 10.1109/TVT.2018.2805189.

[12] J. Brownlee, "Deep learning with python: Develop deep learning models on theano and tensorflow," *Machine Learning Mastery*, pp. 1–17, 2017.

[13] S. Braun, "LSTM benchmarks for deep learning frameworks," Jun. 2018.

[14] G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, and N. Srivastava, "Dropout: a simple way to prevent neural networks from overfitting," *Journal of Machine Learning Research*, vol. 15, no. 1, pp. 1929–1958, 2014.
[15] D. P. Kingma and J. Ba, "Adam: a method for stochastic optimization," Jan. 2017.
[16] T. Pham *et al.*, "ARNS: a data-driven approach for SoH estimation of Lithium-ion battery using nested sequence models with considering relaxation effect," *IEEE Access*, vol. 10, pp. 117067–117083, 2022, doi: 10.1109/ACCESS.2022.3217478.
[17] D. Y. Reddy, B. Routh, A. Patra, and S. Mukhopadhyay, "Gaussian process regression based state of health estimation of Lithium-ion batteries using indirect battery health indicators," in *2021 IEEE International Conference on Prognostics and Health Management (ICPHM)*, Jun. 2021, pp. 1–7. doi: 10.1109/ICPHM51084.2021.9486519.
[18] A. Lamprecht, M. Riesterer, and S. Steinhorst, "Random forest regression of charge balancing data: a state of health estimation method for electric vehicle batteries," in *2020 International Conference on Omni-layer Intelligent Systems (COINS)*, Aug. 2020, pp. 1–6. doi: 10.1109/COINS49042.2020.9191421.
[19] L. Mao, H. Hu, J. Chen, J. Zhao, K. Qu, and L. Jiang, "Online state-of-health estimation method for Lithium-ion battery based on CEEMDAN for feature analysis and RBF neural network," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 11, no. 1, pp. 187–200, Feb. 2023, doi: 10.1109/JESTPE.2021.3106708.
[20] K. A. Severson *et al.*, "Data-driven prediction of battery cycle life before capacity degradation," *Nature Energy*, vol. 4, no. 5, pp. 383–391, Mar. 2019, doi: 10.1038/s41560-019-0356-8.
[21] J. Yang, B. Xia, W. Huang, Y. Fu, and C. Mi, "Online state-of-health estimation for lithium-ion batteries using constant-voltage charging current analysis," *Applied Energy*, vol. 212, pp. 1589–1600, 2018, doi: 10.1016/j.apenergy.2018.01.010.
[22] P. Leijen, D. A. Steyn-Ross, and N. Kularatna, "Use of effective capacitance variation as a measure of state-of-health in a series-connected automotive battery pack," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 3, pp. 1961–1968, 2018, doi: 10.1109/TVT.2017.2733002.
[23] G. Dong, Z. Chen, J. Wei, and Q. Ling, "Battery health prognosis using brownian motion modeling and particle filtering," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 11, pp. 8646–8655, Nov. 2018, doi: 10.1109/TIE.2018.2813964.
[24] Y. Li *et al.*, "Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review," *Renewable and Sustainable Energy Reviews*, vol. 113, p. 109254, Oct. 2019, doi: 10.1016/j.rser.2019.109254.
[25] R. R. Richardson, M. A. Osborne, and D. A. Howey, "Battery health prediction under generalized conditions using a Gaussian process transition model," *Journal of Energy Storage*, vol. 23, pp. 320–328, Jun. 2019, doi: 10.1016/j.est.2019.03.022.
[26] K. Park, Y. Choi, W. J. Choi, H.-Y. Ryu, and H. Kim, "LSTM-based battery remaining useful life prediction with multi-channel charging profiles," *IEEE Access*, vol. 8, pp. 20786–20798, 2020, doi: 10.1109/ACCESS.2020.2968939.

BIOGRAPHIES OF AUTHORS

Vimala Channapatana Srikantappa has completed her graduation in B.E. electrical and electronics communication engineering from K.V.G College of Engineering, Mangalore University. MBA a distant education from Sikkim Manipal University and M.Tech. in power systems from Ghousia College of Engineering, Ramanagram. At present a research scholar at BMS College of Engineering, Bangalore, India, and also working as an assistant professor at the Department of Electrical and Electronics Engineering, SJB Institute of Technology, Bangalore. Member of MIE (M- 612799). She has 9+ years of industry experience in abroad as well as in India and 10+ years of teaching experience. Her area of expertise is in power systems, electrical machines, and battery management systems in EV. She can be contacted at email: vimalasrikantappa@gmail.com.

Dr. Seshachalam Devarakonda is a professor and Vice Principal at the Department of Electronics and Communication Engineering, BMS College of Engineering, Bangalore, India. He holds a Ph.D. degree in Electrical Engineering-Control Engineering, and Power Electronics, Motilal Nehru National Institute of Technology, Allahabad, U.P His Research Interests are Model order reduction, Power Electronics, Non-Linear control engineering, and battery management systems in EHV. He has played a major role in establishing a Centre of Excellence along with the Skill Sector Council of India (ESSCI) in VLSI design. Member of several boards of studies (BOS) such as Dayananda Sagar College of Engineering, New Horizon College of Engineering, Dr AIT Bangalore, Kongu College of Engineering Erode, Adhiamman College of Engineering Hosur, and proposed innovative curricula. He also played a key role in starting a third PG program, M.Tech. in VLSI Design and Embedded Systems, in 2014, which is successfully running in the department now. He is a member of the evaluation committee for the National Board of Accreditation and AICTE. He has received funds under the MODROBS scheme from AICTE & has conducted several workshops on outcome-based education (OBE). A member of professional societies such as IEEE and ISTE. Has supervised four Ph.D. scholars and several M.Tech. students and now guiding three research scholars. He can be contacted at email: dschalam.ece@bmsce.ac.in.