2024 Tenth Indian Control Conference (ICC)
9 - 11 December, 2024
IISER Bhopal, India

DATA-DRIVEN MODEL FOR ESTIMATION OF SoH AND INTERNAL RESISTANCE OF LITHIUM ION BATTERY BASED ON DEEP NEURAL NETWORK

Mehanthika SV
Dept of Instrumentation Engg, MIT Campus, Anna University Chennai
mehanthivishu92@gmail.com

Rishi D
Dept of Instrumentation Engg, MIT Campus, Anna University Chennai
rishideivanayagamm@gmailcom

S Sutha
Dept of Instrumentation Engg,, MIT Campus, Anna University Chennai
sutha@annauniv.edu

N Pappa
Dept of Instrumentation Engg, MIT Campus, Anna University Chennai
npappa@annauniv.edu

***Abstract*— Accurate estimation of State of Health (SoH) and Internal Resistance (IR) is essential for optimized performance and longevity, particularly in the new-era of electric vehicles and renewable energy storage devices. The traditional methods struggle with battery data complexity in dynamic situations to enhance the above parameters. This paper presents a data-driven model with hybrid architecture that combines CNN and LSTM models which revolutionize the battery management and focusing on the SoH and IR estimation in dynamic environments, CNN-LSTM models excel by extracting spatial features and learning temporal dependencies within the battery datasets. This increases accuracy and enables real-time monitoring, diagnosis, and optimization of battery health. This paper also shows the execution of LSTM with and without sampling of the datasets for efficient runtime and produces accurate results, this marks a significant leap in the battery management and enabling smarter resource utilization for sustainable energy solutions.**

Keywords—CNN-LSTM, SoH, Lithium- ion Battery, Data Driven Model

I INTRODUCTION

The State-of-Health (SoH) and Internal Resistance (IR) of Lithium-ion batteries is vital for ensuring safety, performance and extending battery lifespan. Accurate estimations help detect potential failures earlier, preventing safety hazards like overheating and fires. The global interest in data-driven approaches to estimate SoH and IR of Lithium-ion batteries has increased, primarily due to the growth of EV and renewable energy markets. BMS market is projected to expand from USD 9.27 billion in 2023 to USD 10.53 billion by the end of 2024 to USD 38.13 billion by 2032, exhibiting a CAGR of 17.5% during the forecast period has shown that Deep Neural Network (DNN)-based SoH and IR estimation can achieve a 15-20% improvement compared to other methods, with an error of less than 1% [1].

Many models employing DNN have emerged for the prediction of SoH and IR in battery systems. Hybrid architectures combining CNNs, and LSTMs leverage the strengths of both approaches, offering a comprehensive understanding of battery behavior by integrating spatial and temporal dependencies. An innovative approach has been proposed based on Long Short Term Memory (LSTM) networks to estimate both SoH and IR, offering a promising method for accurate prediction [2]. A comprehensive overview of power electronics interfaced electrochemical impedance spectroscopy is provided, highlighting the potential of this technique for SoH estimation in energy storage systems [3]. A data-driven approach is introduced for estimating SoH while considering internal resistance expanding the range of methods available for accurate evaluation [4]. For battery health monitoring, a deep learning approach is proposed that combines direct current internal resistance with SoH estimation [5]. Additionally, a data- driven model that combines Independent Component Analysis (ICA) and Bidirectional LSTM for SoH estimation is presented, further diversifying the range of approaches available [6].

The prediction of SoH and IR is performed using a novel approach that combines Meta-Learning with CNN-LSTM algorithms, showcasing the potential of leveraging meta-learning techniques to enhance the accuracy of SoH estimation [7]. An online SoH estimation method based on the fusion of improved ICA and LSTM is proposed emphasizing real-time monitoring capabilities [8]. An improved CNN-LSTM is proposed by highlighting the efficacy of integrating CNN with LSTM for accurate SoH prediction [9]. Additionally, combined CNN-LSTM-GRU model is proposed to extract health feature parameters for precise SoH estimation, demonstrating the potential of hybrid neural network architectures [10]. An innovative approach is proposed using historical state and future load information for robust SoH prediction [11].

An online estimation method is introduced for SoH based on the Singular Spectrum Analysis (SSA)-Elman neural network, highlighting the importance of real-time monitoring for effective battery management [12]. The significance of Electrochemical Impedance Spectroscopy (EIS) for fast and accurate SoH estimation is emphasized, underscoring the potential of this technique for enhancing battery health diagnostics [13]. A reduced-order electrochemical model is proposed for SoH estimation in electrified vehicles, illustrating the importance of physics-based modelling for accurate prediction in real-world applications [14]. An EIS- based SoH estimation method is proposed by considering temperature and state-of-charge effects, emphasizing the necessity of accounting for environmental factors in battery health assessment. A

reliable data-driven SoH estimation model is presented for electric vehicle batteries, highlighting the importance of robust and accurate prediction algorithms for practical implementation [16]. An online SoH estimation approach based on the RVM with dynamic integration, is introduced, showcasing the potential of machine learning techniques for real-time monitoring [17]. Capacity and remaining useful life prediction using BDT learning system is proposed and LSTM neural network, underlining the importance of advanced data-driven methods for comprehensive battery health assessment [18]. Collectively, these studies highlight the diverse range of methodologies available for SoH and IR estimation.

This paper makes use of the NASA Prognostics Centre of Excellence Data Repository's battery datasets. For two Samsung 22P 18650 battery cells, data preparation was done to estimate SoH and resistance. The cells' nominal parameters included a charging cut-off voltage of 4.20 V ± 0.05 V, a maximum discharge current of 10 A, a not-to-be-discharged voltage of 2.5 V, a diameter of 18.3 mm, a height of 64.8 mm, and a weight of 43.3 g. Three scenarios of charging, discharging, and resistance measurement using the ICA methods are investigated for the battery cells. After completing 270 experimental resistance measurements in the frequency range of 1 Hz to 1kHz, the complex impedance measurement scenario was established.

This paper proposes a data-driven model which provides a better method to estimate SoH and IR accurately with shorter execution-time using deep neural networks by combining CNN- LSTM.

The main contribution of the work are as follows:- i) The input features are selected based on sensitivity analysis method to estimate SoH and battery internal resistance ii) Two-stage LSTM model is developed for internal resistance estimation, the first stage, voltage, current and temperature are used to estimate SoH using the first LSTM network. Then, using the second LSTM network, the estimated SoH, current, voltage, and temperature are used to estimate SEI resistance and charge transfer resistance. Further, input data is fed to model with and without down sampling to analyse efficiency and adhering to the previously mentioned pattern and to overcome challenges of LSTM model, iii) the CNN-LSTM model is developed for SoH and internal resistance estimation.

The paper is organized as follows: - Section 1 presents Introduction, Proposed methodology is discussed in Section 2. Results of the proposed work are discussed in Section 3 and conclusion is given in Section 4.

II.METHODOLOGY

The model uses input parameters like current, voltage, temperature to predict SoH using the model in the first stage. Capacity is estimated using a model and finally SoH is directly derived from capacity. The same input parameters along with the predicted SoH is used to predict IR [(R_e), (R_{ct})] using same model in second stage. LSTM model is fed input data with and without down sampling. Data grouping aids in lowering the total dimensionality of the input data for the LSTM model. This may result in less computational complexity during inference and training, increasing the viability of handling big datasets or deploying models in settings with limited resources. Down sampling can aid in the summary of data over time periods, which may strengthen the model's resistance to noise and extraneous details in the data. Trial and error method for optimization of parameter to down sampling is overcame by CNN-LSTM Hybrid Model including the rationale for combining CNN and LSTM networks where the convolutional layer is used to extract features from the time-series data and The LSTM layer is used to capture temporal dependencies.

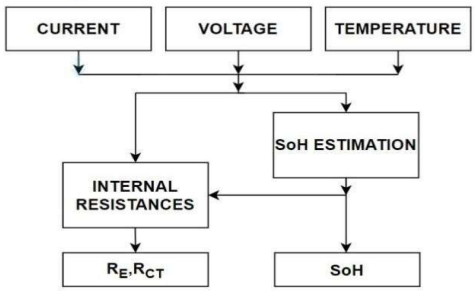


Fig.1. Workflow diagram

A. LSTM NETWORK

The topology of the LSTM neural network's as shown in Fig.2. with n nodes where $n = 1, 2, \ldots Nh$, with x_n representing the normalized input, which includes the cell's voltage, current, and temperature, c_n and h_n stands for the network node n's state output and hidden output, respectively. Three gates are present in every LSTM network node: the input gate (i_n), the output gate (O_n), and the forget gate (f_n).

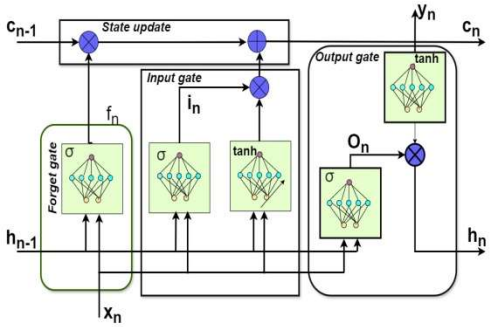


Fig.2. Single LSTM cell internal architecture

Cell State (c_n): $c_n = tanh\,(Wc\,[h\,, x_n] + b_c)$

Hidden State (h_n): $h_n = o_n * tanh\,(c_n)$

Input Gate (i_n): $i_n = W_f\,[h_{n-1}\,,\, x_n] + b_f$

Forget Gate (f_n): $f_n = \sigma\,(W_o\,[h_{n-1}\,,\, x_n] + b_f)$

Cell Update (g_n): $g_n = f_n * c_{n-1} + i_n * c_n$

Output Gate (o_n): $o_n = \sigma([h_{n-1}, x_n] + b_o$

Completely Networked Layers: There are completely connected layers for further processing and prediction-making after the LSTM layers.

a) DOWN SAMPLING OF DATA TO LSTM MODEL:

For the data to accurately track the trend of deterioration in capacity, it is necessary to give special consideration to data preparation [1] for SoH estimation. Accordingly the experimental data collected in the discharge scenario is used as input to network. M reasonable ranges are created from the input parameter data that are gathered by experiment. $N_c \times 3M$ is shape of input matrix where N_c is no of cycles and M is reasonable range and taken as 30 and $3M$ is due to three input parameters of voltage, current, temperature. Shape of output matrix is of $Nc \times 1$, one column here is capacity over discharge cycles. As with establishing a network for SoH estimation, the network's input size for R_e and R_{ct} estimation is $3M + 1$, and the input data consists of capacity, voltage, current, and temperature. The charge transfer resistance R_{ct} with a size of $N_c \times 1$ and the equivalent series resistance R_e are included in the output data. Normalization of the data series X is $X = \{(1), (2) \dots (N)\}$, where N is the number of sampled data points. x can be current, voltage, temperature, or resistance is done. Since time series data is large in number, without data reduction complexity of model increases.

To avoid the mentioned disadvantage, data reduction is aimed by choosing reasonable range by manual trial and error method. Information loss may occur from the aggregation of data that is part of the grouping process. This may result in less computational complexity during inference and training since data set is reduced and accuracy decreases. Data grouping aids in lowering the total dimensionality of the input data for the LSTM model as shown in Fig.3 with the hyper parameters as given in Table I.

a) COMPLETE TREND OF DATA WITHOUT SAMPLING TO LSTM MODEL:

To overcome the above challenges with down sampled dataset, giving complete trend of dataset as input to model is depicted. In this case instead of taking M reasonable ranges, complete trend of data without sampling is given to model. $N_c \times 3M$ is the shape of an input matrix where N_c is number of cycles and M is complete range of data without sampling and it is nearly 300 and $3M$ is due to three input parameters of voltage, current, temperature. The shape of the output matrix is of $N_c \times 1$, one column here is capacity over discharge cycles. As with establishing a network for SoH estimation, the network's input size for R_e and R_{ct} estimation is $3M + 1$, and the input data consists of capacity, voltage, current, and temperature. The charge transfer resistance R_{ct} with a size of $N_c \times 1$ and the equivalent series resistance R_e are included in the output data. Normalization of the data series X is $X = \{(1), (2), \dots x(N)\}$, where N is the number of sampled data points. X can be current, voltage, temperature, or resistance is done.

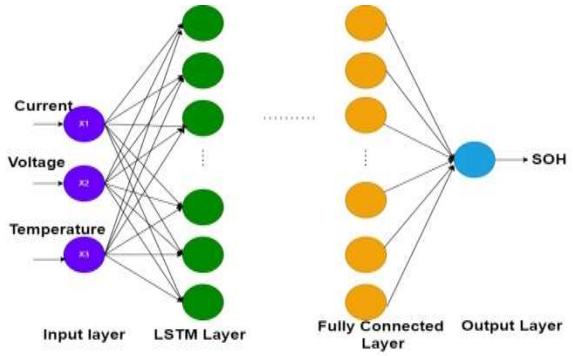


Fig.3. Proposed LSTM model's structure with data reduction

TABLE I HYPERPARAMETERS FOR LSTM MODEL

HYPERPARAMET	VALUES
Number of hidden	2
Number of hidden neurons in each	100
Loss function	RMSE,MAE
Activation Function	ReLU
Number of epochs	10(with data reduction) 100(without data reduction)

Normalization of the whole dataset within range of 0 to 1 is done before feeding to model. This model's computational efficiency is less since the data set is large and accuracy increases compared to giving down sampled data set as input to model. It is possible to overlook minute details and transient patterns that are essential for accuracy. The same hyper parameters as given in Table I are used.

B. CNN-LSTM MODEL

A hybrid CNN-LSTM model as shown in Fig.4 is a kind of neural network design that combines the advantages of LSTM networks with CNNs which predict time series data involving both temporal and spatial dependencies in the data. CNN- LSTM hybrid model can take advantage of CNNs' capacity to extract spatial features and LSTMs' capacity to record temporal dependencies by merging two architectures. Neural network model using Keras with a combination of CNN which make up the model's initial layers to extract spatial information from the input data and LSTM layers for time series data is used.

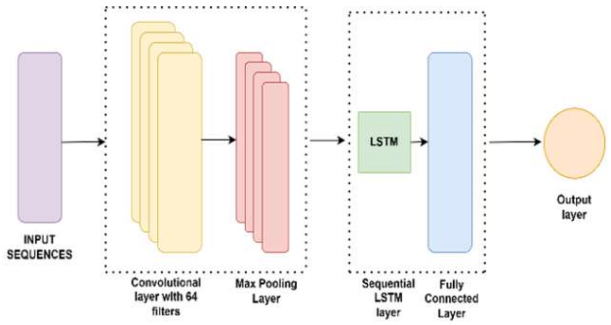


Fig .4. CNN-LSTM Execution of flow

This architecture is suitable for processing multi-variate time series data where both temporal dependencies and spatial patterns are across features. The input shape for the time distributed layer is a variable-length sequence, 2 is the number of features at each time step.

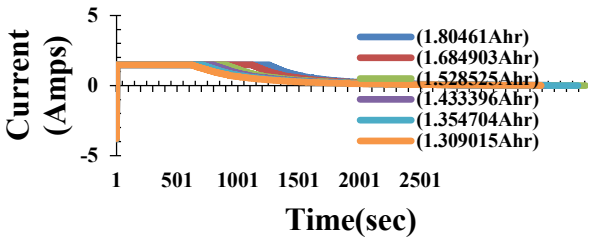
TABLE II HYPERPARAMETERS USED FOR CNN-LSTM MODEL

HYPERPARAMETERS	VALUES
Kernel size	1
1D convolutional layer with No. of Filters	64
Number of LSTM layer	1
Pooling size	2
Number of hidden neurons in each layer	50
Loss function	RMSE, MAE
Activation Function	ReLU
Number of epochs	500

III. RESULTS AND DISCUSSIONS

The battery's charging and discharging data from NASA(https://data.nasa.gov/dataset/ Li-ion-BatteryAging- Datasets /uj5r-zjdb) as in Fig.5 and Table III shows changes that correlate to the capacity degradation of the cell throughout charge and discharge cycles. The capacity reduces with an increase in cycles, and the amount of time required to fully charge a cell at 1.5 constant current until the voltage reaches 4.2 V drops. When cell capacity drops, it takes less time for the discharge current to reach 2 A. Similarly, when cell voltage drops to 2.7 V, it takes less time for the discharge current to reach 2 A.

A.DATA ANALYSES AND INFERENCE



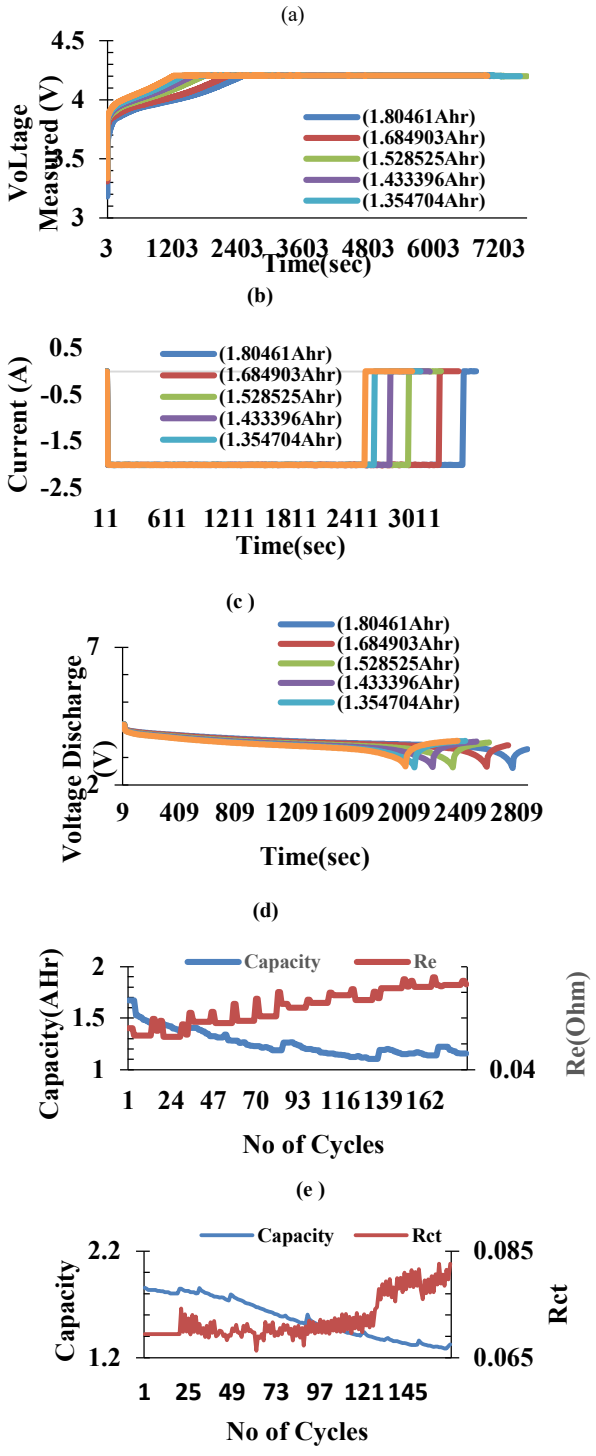


Fig.5. Dynamic profile of various parameters for capacity degradation

TABLE III DESCRIPTION OF BATTERY DATA

Constant Current Charging mode	1.5 A (until cell voltage reaching 4.2V)
Constant Voltage Charging mode	4.2V (until current drops to 20mA)
Discharging Current	2 A (constant)
Discharging Voltage	From 4.2 V to 2.7 V
Operating Temperature	24°C

The difficulty experienced when shifting an electron from one atom or compound to another is measured by R_{ct}. R_e is the SEI film's resistance. Based on the current research, two parameters that are most impacted resistances aging are R_e and R_{ct}. Correlations between capacity and IR (R_{ct} and R_e) of the cell are illustrated in Fig 5.

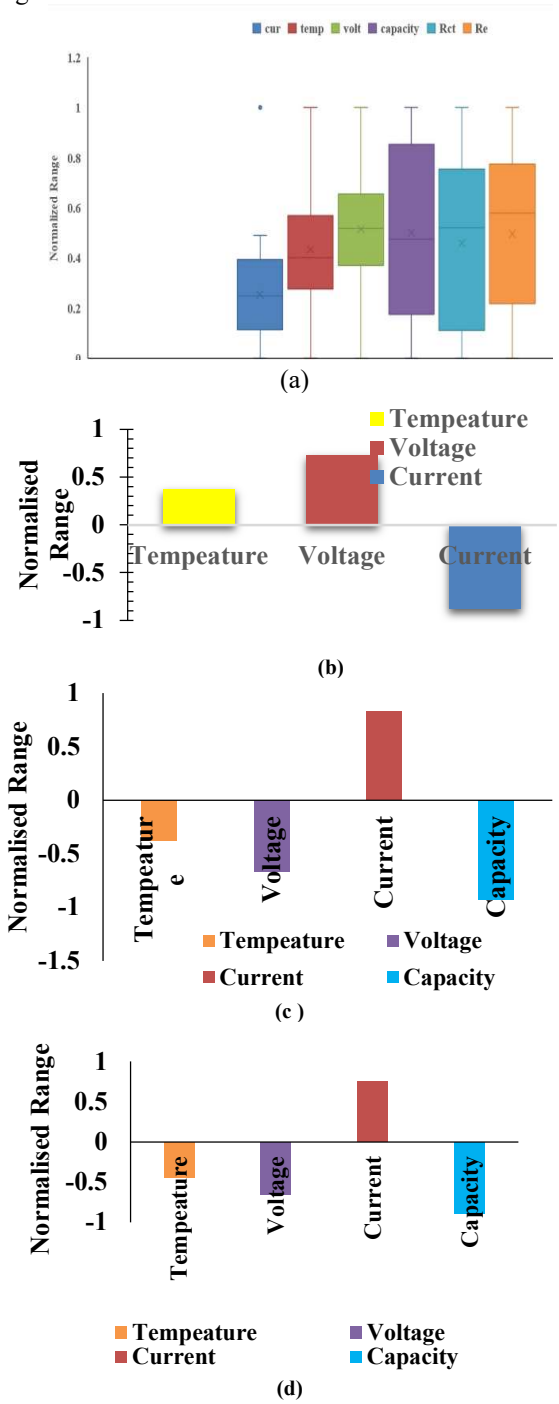


Fig.6. Box plot to depict normalized range of various parameters Capacity, R_{ct}, R_e respectively vs (Input parameters,) temperature, voltage, current

Fig 6 shows a quick visual summary of the variability of values in a current, voltage, temperature, capacity, and internal resistance dataset. They show the median, upper and lower quartiles, minimum and maximum values, and any outliers in the dataset. Correlation analysis helps uncover the strength and direction of the association between R_e and temperature, voltage, current, capacity. This quantifies the extent to which changes in one variable are paired with changes in the other.

B. R_{ct}, R_e, SoH ESTIMATION

CNN-LSTM model accurately tracks true value compared to all the other models as depicted in Fig. 7. SoH estimation using the CNN-LSTM network has smaller RMSE than those using the LSTM network using real data without sampling and LSTM using sampled data. Similarly, the above trend follows for R_e, R_{ct} estimation. From Table IV, it is observed that hybrid CNN-LSTM has highest accuracy, followed by LSTM with manual data sampling and LSTM network without sampling has the least accuracy.

The computational speed of CNN- LSTM is larger than computational speed of LSTM. LSTM network learning process has a learning rate of 0.001, 10 epochs, a ReLU activation function performed on a computer with 8 GB RAM and a Core I5 processor speed takes a learning time of 3 minutes. Optimal epoch value is obtained using GridSearch CV method. The CNN- LSTM network learning process with a learning rate of 0.001, 500 epochs, ReLU activation function takes a learning time of 1 min when performed on a computer with 8 GB RAM, Core I5 processor speed.

TABLE IV PERFORMANCE OF LSTM WITH /WITHOUT SAMPLING AND THE HYBRID CNN-LSTM MODEL

	LSTM WITHOUT SAMPLING		LSTM USING DATA WITH SAMPLING		CNN-LSTM	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
SoH	0.087	0.087	0.065	0.043	0.053	0.045
R_e	0.006	0.006	0.002	0.002	0.002	0.001
R_{ct}	0.008	0.008	0.004	0.002	0.003	0.002

IV. CONCLUSION AND FUTURE WORKS

In this paper, the proposed robust data-driven model based on CNN-LSTM architecture for accurate estimation of SoH and IR of Lithium-ion Battery has been successfully developed and validated. The integration of CNNs for spatial feature extraction and LSTM for capturing temporal dependencies has proven effective in handling the complexities of battery behavior and degradation patterns. Through extensive testing with real-world data, the proposed model consistently demonstrated superior performance and significant step forward in leveraging deep learning techniques for enhancing the reliability and longevity of battery systems.

Investigating methods to integrate uncertainty estimation into the model's predictions can provide valuable insights into prediction reliability and facilitate informed decision-making in real-time applications. Lastly,

exploring opportunities to optimize the computational efficiency of the CNN-LSTM architecture and adapting the model for deployment in edge computing environments will support real-time monitoring and proactive management of lithium-ion battery systems.

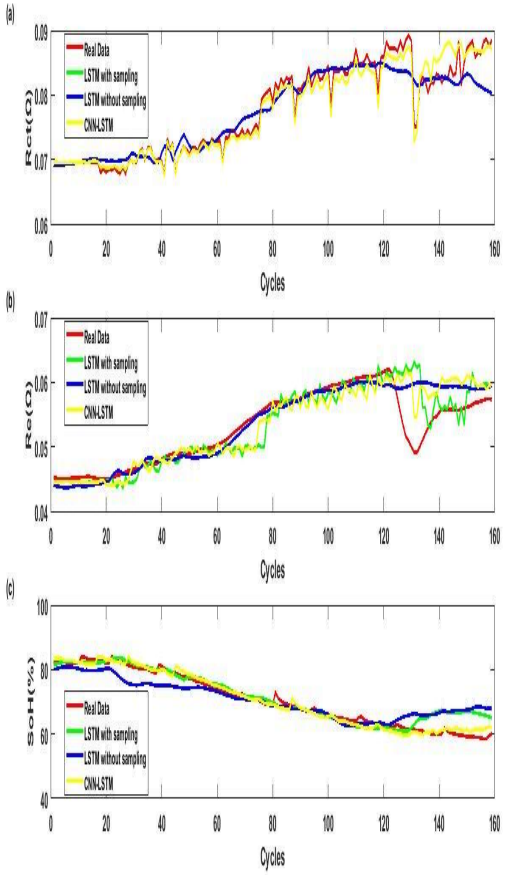


Fig.7. a) R_{ct} prediction, b) R_e prediction, c) SoH prediction using LSTM model with and without sampling and CNN-LSTM model

ACKNOWLEDGEMENTS

This work is funded by RUSA 2.0. Authors are thankful to the Anna University RUSA2.0/PO6 for giving the opportunity to work on the RUSA-funded project titled "Improved SoH by Soft Sensors and Controls for Battery Management Systems of Electric Vehicles".

REFERENCES

[1] https://www.fortunebusinessinsights.com/automotive - battery-management-system-market-105479.

[2] Van, C. N., & Quang, D. T. (2023). Estimation of SoH and internal resistances of Li-ion battery based on LSTM network. Int. Journal of Electrochemical Science, 18(6), 100166.

[3] Sadeghi, E., Gholami, M. & Saif, M. (2023). A systematic overview of power electronics interfaced electrochemical impedance spectroscopy for energy storage systems. Journal of Energy Storage, 62, 106850.

[4] Lin, M., Yan, C., Wang, W., Dong, G., Meng, J., & Wu, J. (2023). A data-driven approach for estimating state-of- health of lithium-ion batteries considering internal resistance. Energy, 277, 127675.

[5] Sun, Z., He, W., Wang, J., & He, X. (2024). State of Health Estimation for Lithium-Ion Batteries with Deep Learning Approach and Direct Current Internal Resistance. Energies, 17(11), 2487.

[6] Sun, H., Sun, J., Zhao, K., & Wang, K. (2022). Data-driven ICA-Bi-LSTM-combined lithium battery SOH estimation. Mathematical Problems in Engineering.

[7] Ouyang, T., Su, Y., Wang, C., & Jin, S. (2024). Combined Meta-Learning with CNN-LSTM Algorithms for State-of-Health Estimation of Lithium-ion Battery. IEEE Transactions on Power Electronics.

[8] Liu, Q., Kang, Y., Qu, S., Duan, B., Wen, F., & Zhang, C. (2020). An online SOH estimation method based on the fusion of improved ICA and LSTM. In 2020 IEEE/IAS Industrial and Commercial Power System Asia (pp. 1163-1167). IEEE.

[9] Xu, H., Wu, L., Xiong, S.,& Gao, L.(2023). An improved CNN-LSTM model-based state-of- health estimation approach for lithium-ion batteries. Energy, 276, 127585.

[10] Yanwen, D. A. I., & Aiqing, Y. U. (2022). Combined CNN-LSTM and GRU based health feature parameters for lithium-ion batteries SOH estimation. Energy Storage Science and Technology, 11(5), 1641.

[11] Qian, C., Xu, B., Xia, Q., Ren, Y., Sun, B., & Wang, Z. (2023). SOH prediction for Lithium-Ion batteries by using historical state and future load information with an AM- seq2seq model. Applied Energy, 336, 120793.

[12] Guo, Y., Yang, D., Zhang, Y., Wang, L., & Wang, K. (2022). Online estimation of SOH for lithium-ion battery based on SSA-Elman neural network. Protection and Control of Modern Power Systems, 7(3), 1-17.

[13] Zhang, M., Liu, Y., Li, D., Cui, X., Wang, L., Li, L., & Wang, K. (2023). Electrochemical impedance spectroscopy: A new chapter in the fast and accurate estimation of the state of health for lithium-ion batteries. Energies, 16(4), 1599

[14] Hosseininasab, S., Lin, C., Pischinger, S., Stapelbroek, M., & Vagnoni, G. (2022). State-of-health estimation of lithium-ion batteries for electrified vehicles using a reduced- order electrochemical model. Journal of Energy Storage, 52, 104684.

[15] Zhang, Q., Huang, C. G., Feng, G., & Peng, W. (2022). Electrochemical impedance spectroscopy-based state-of-health estimation for Li-ion battery considering temperature and state-of-charge effect. IEEE Transactions on Transportation Electrification, 8(4), 4633-4645.

[16] Zhang, C., Zhao, S., Yang, Z., & Chen, Y. (2022). A reliable data-driven state-of-health estimation model for lithium-ion batteries in electric vehicles. Frontiers in Energy Research, 10, 1013800.

[17] Chen, Z., Zhang, S., Shi, N., Li, F., Wang, Y., & Cui, J. (2022). Online state-of-health estimation of lithium-ion battery based on relevance vector machine with dynamic integration. Applied Soft Computing, 129, 109615.

[18] Zhao, S., Zhang, C., & Wang, Y. (2022). Lithium-ion battery capacity and RUL prediction using board learning system and long short-term memory neural network.