PREDICTION OF REMAINING USEFUL LIFETIME FOR LITHIUM-ION BATTERIES USING NEURAL NETWORKS

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ABSTRACT

Lithium-ion battery's remaining useful life (RUL) estimation with accuracy plays a critical role to improve operational safety and efficiency in different applications. The determination of exact RUL through precise methods enables various cell developments and fast-charging technology developments while decreasing cycle testing times. ANNs have demonstrated positive results in this field yet researchers face problems when selecting the optimal architecture as they optimize procedures with different datasets. Multiple ANN architectures such as LSTM, Bi-LSTM with attention mechanism, Transformer, CNN-LSTM, 1D-CNN, ResNet and TCN are introduced through this research work. An evaluation involving these ANN architectures is performed on 30 percent of training data from 124 LIBs across different charging protocols. A top-performing analytical model derived all its characteristics from individual charge–discharge cycles required only data from 40 cycles.

Keywords— Lithium-ion Battery; Remaining Useful Life; Artificial Neural Network; Battery Degradation; State of Health.

I. INTRODUCTION

The predicted amount of time or cycles a battery can continue to operate before it reaches its end-of-life is the Remaining Useful Lifetime (RUL) of a battery. Accurately predicting the RUL of lithium-ion batteries (LIBs) is crucial for advancing energy storage technology. This research presents a comprehensive machine learning framework to evaluate different artificial neural network (ANN) architectures for RUL estimation. The framework systematically optimizes seven ANN models across multiple charging conditions for a dataset used in [20] consists of 124 commercial lithium-ion batteries cycled to failure under fast-charging conditions, the lithium-ion phosphate cells were cycled in horizontal cylindrical fixtures on a 48-channel Arbin LBT potentiated in a forced convection temperature chamber set to 30°C., utilizing hyperparameter tuning to enhance predictive accuracy. Additionally, this research examines the impact of cycle window selection on prediction accuracy and computational efficiency. By establishing a structured methodology, [1] contributes to the integration of machine learning techniques into battery management systems, highlighting the potential of ANN-based models in enhancing the reliability and performance of LIBs. It has become a crucial technology powering portable electronics, renewable energy systems, electric vehicle storage, and various other applications. Their high energy efficiency and density make them a key component in the evolution of energy storage solutions. However, an essential aspect of battery management is the ability to accurately predict the remaining useful life (RUL) of a battery. RUL refers to the time a battery can continue functioning effectively before reaching the end of its lifespan.

As the demand for faster charging continues to rise, precise RUL estimation becomes even more crucial. It enables the identification of optimal conditions for battery performance enhancement while eliminating the need for extensive full cycle testing, thereby saving both time and resources. Predicting the remaining useful life of lithium-ion batteries remains a complex challenge, with many researchers utilizing machine learning techniques, particularly artificial neural networks, to improve accuracy. ANNs are well-suited for this task due to their ability to recognize patterns and structures within input data. The degradation of LIBs is influenced by various factors, including charge and discharge cycles, current levels, and temperature. Given their ability to detect these intricate relationships, ANNs serve as effective predictive models for estimating battery lifespan.

Despite the effectiveness of artificial neural networks in predicting the RUL of lithium-ion batteries, several challenges arise in their implementation. One major difficulty is the vast range of ANN architectures and configurations available, making it hard to establish a standardized baseline model for categorizing datasets and selecting the most suitable approach. Additionally, inconsistencies in training, validation, and testing methodologies across different studies hinder direct comparisons between models. Variability in evaluation metrics further complicates performance assessment, as different studies use distinct benchmarks and assessment techniques. The use of ANNs for predicting the remaining useful life of lithium-ion batteries presents several challenges. One of the main difficulties is the wide range of ANN architectures and configurations available, making it complex to establish a standardized baseline model for dataset categorization and model selection. Additionally, in-consistencies in training, validation, and testing procedures across studies limit the ability to compare models effectively.

However, there exist several challenges with the attempt to use ANNs for the prediction of RUL. This is because many ANN architectures and configurations are available in the literature and creating a baseline model to categorize the datasets and determine the appropriate model is challenging. Furthermore, variations in training, validation and testing procedures and time series across the studies have provided little possibility to compare the models. Fluctuations in assessment technology add to the challenges of evaluating performances of ANN, especially given variability in evaluation metrics. Moreover, many studies tend to highlight the performance of their primary models while giving scant information about hyperparameter tuning and training particulars. This allows further exploration and validation to ensure a fuller comparison in a unified machine learning framework. The rest of this manuscript highlights the related works, followed by research methodology, and the references that we came across during the research.

II. RELATED WORKS

Various studies have explored the potential of different techniques in predicting the RUL of lithium-ion batteries. The deep-dive of the research is described here, explaining the identified research gap which can be addressed by understanding the pros and cons of the approaches. Junghwan et al. [1] demonstrated a machine learning prediction system for lithium-ion battery RUL through different ANN structure applications. Wei Xiong et al. [2] demonstrated an early cycle life prediction system based on WLS-SVM analysis of health indicators measured from voltage-capacity discharge curves. Danhua Zhou et al. [3] presented a temporal convolutional network design which requires fewer parameters while performing lithium-ion battery SOH and RUL prediction tasks. Donghui Li et al. [4] introduce their co-estimation method that uses CCCS data to simultaneously determine SOC, SOH and RUL of lithium-ion batteries. STRULF [5] developed which predicts lithium-ion battery RUL while handling capacity self-recovery and degradation.

Rui Wang et al. [6] developed a two-phase degradation mode equipped with dynamic change points to forecast lithium-ion battery RUL prediction. Yupeng Wei [7] introduced a dual attention GCN model to predict SOH and RUL values. The system employs two-stage optimization in combination with optimal graph entropy to analyze feature correlations and time-series patterns in the system. Guangzheng et al. [8] developed LS-PSF-LSTM which uses Lebesgue sampling and parallel state fusion for predicting RUL during early cycles. Daoquan Chen et al. [9] developed a Transformer neural network for Li-ion battery RUL prognostication which integrates DAE as a noise filtering tool for capacity measurement data.

Hector Beltran [10] demonstrated the use of CNNs for lithium-ion battery capacity prediction through partial charge/discharge data which exceeds competing models with 1.5 percent error. Li et al. developed a spatial-temporal network prediction system which integrates the capacity self-recovery effect for lithium-ion battery remaining useful life assessment [11]. Hong et al. [12] introduced a noise-resistant framework for lithium-ion battery RUL prediction utilizing the DAE combined with LSRCN structures. Wei and Wu developed a GCN-based model equipped with dual attention mechanisms for lithium- ion battery SOH and RUL estimation [13]. Hsu C-W [14] built a deep neural network system for lithium-ion battery remaining useful life (RUL) and voltage profile forecasting using information acquired from a single cycle. Fei et al. [15] developed an attention-assisted memory-augmented TCN model capable of quick RUL prediction from ten-cycle battery information.

Wang et al. [16] developed an anti-noise adaptive LSTM (ANA-LSTM) model which serves as a robust method to predict lithium-ion battery RUL. Ma et al. [17] developed an end-cloud collaboration framework to perform real-time lithium-ion battery SOH and RUL estimation. Liu et al. [18] developed a new method to forecast lithium-ion battery remaining useful life (RUL) through optimization of a long short-term memory (LSTM) network by utilizing an improved sparrow search algorithm (ISSA). The RUL prediction of lithium-ion batteries through Bi-LSTM with attention and variational mode decomposition uses a sequence-to-sequence model presented in [19]. Severson wt al. [20] and Mohammed [21] established a machine learning solution which utilized early-cycle data to estimate lithium-ion battery cycle lifetime. A neural network model [22] demonstrated potential for lithium-ion battery health evaluation and remaining useful life prediction. Shared feature extraction [23] together with specialized task-specific layers enables the model to obtain degradation pattern knowledge along with charge dynamic comprehension.

Jiang et al. [24] demonstrated a swift lithium-ion battery charging protocol through the use of deep Bayesian optimization connected to a recurrent neural network. Pang et al. [25] merge Gaussian process regression (GPR) with incremental capacity analysis (ICA) to develop a prediction system for lithium-ion battery remaining useful life (RUL). Zraibi et al [26] designed an online fault-tolerant machine learning system to predict RUL. A hybrid neural network framework [27] integrated convolutional neural networks with recurrent neural networks for lithium-ion battery state-of-health and remaining useful life predictions. Wang wt al. [28] and Kang et al. [29] presented an advanced transformer-based and transfer learning-based system which predicts lithium-ion battery RUL

III. PROPOSED WORK

The overall framework consists of several key steps: preprocessing, feature selection, data partitioning, data formatting, model implementation, and model evaluation and it is visually depicted in Figure 1.

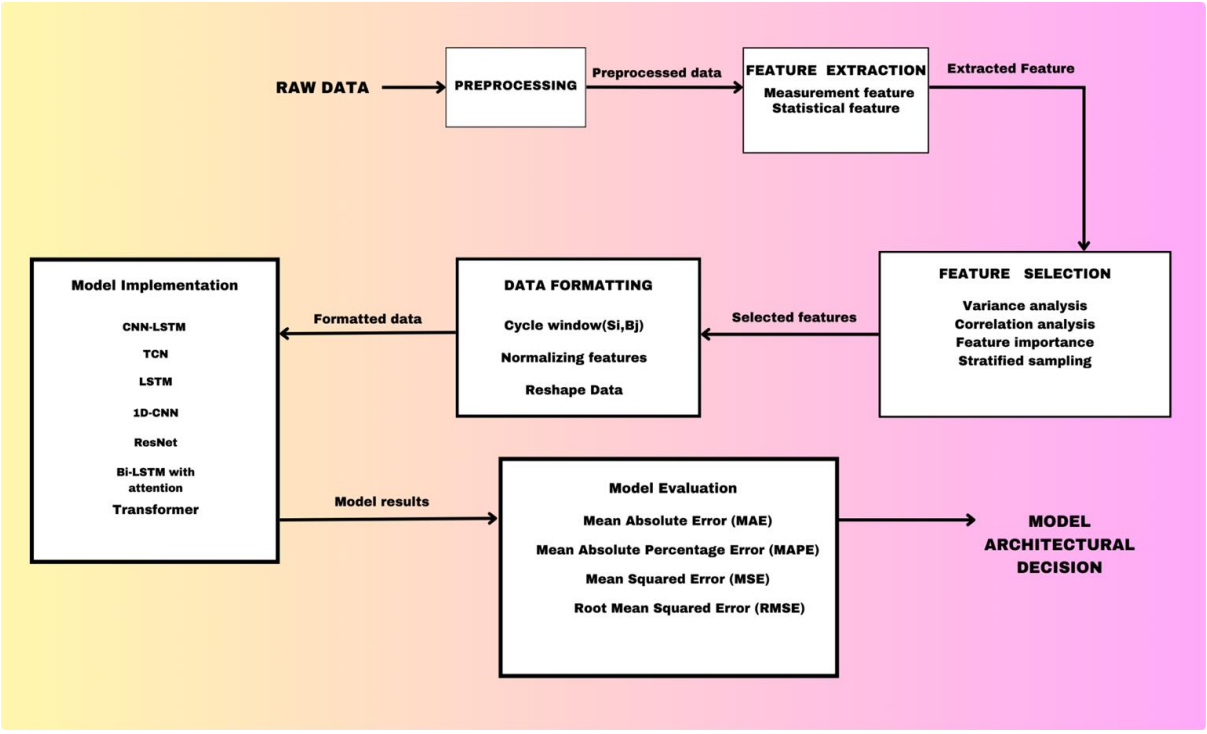

Figure 1: Proposed framework

I. Dataset Description

To support the development and evaluation of the proposed RUL prediction framework, we utilized a comprehensive and publicly available lithium-ion battery dataset. This dataset comprises 124 commercial cylindrical cells (A123 APR18650M1A), each tested under varying fast-charging protocols until they reached 80% of their nominal capacity, which served as the end-of-life criterion. The collected data spans roughly 96,700 complete charge-discharge cycles, with battery lifetimes ranging from 150 to over 2,300 cycles. All experiments were conducted at a stable ambient temperature of 30°C. Charging procedures varied across 72 distinct fast-charging regimes, while discharging followed a constant 4C rate down to 2.0 V. From these cycles, 14 key features were extracted, including internal resistance, charge/discharge capacity, temperature statistics, dQ/dV metrics, and charge/discharge current values. To ensure balanced training and evaluation, batteries were clustered using K-means and divided into training (41 batteries), validation (43 batteries), and test (40 batteries) sets. Feature selection was guided by variance and correlation analysis, and a fixed input window of (40, 40) was identified as optimal for effective early-cycle RUL prediction.

II. Pre-Processing

The data consisting of 124 batteries and all cells' properties are observed as various features based on the exposure with a one-step or two-step fast-charging policy. In these conditions, each battery will perform different degradation patterns till it's end of life. As each battery will have distinct battery life cycles, it is sufficient to observe the initial cycles to observe the common degradation of the batteries. The processed data contains the information of 100 charge-discharge cycles of the 124 batteries.

III. Feature Selection

From all the features, selecting limited features with best predictivity is essential. For more detailed overview selection, analysis of each feature's variance and skewness is observed which can be referred from Figure. 2. This observation helps in selection of 14 features based on the importance of the features. The features include internal resistance (IR), charge capacity (QC), discharge capacity (QD), average temperature (Tavg), minimum temperature (Tmin), maximum temperature (Tmax), charge time, average dQ/dV (dqdvavg), maximum dQ/dV (dqdvmax), minimum dQ/dV (dqdvmin), average discharge current (IDavg), maximum discharge current (IDmax), average charge current (ICavg), and maximum charge current (ICmax). The importance of these features can be referred from Figure. 3. Looking at variance, the variables like IR, QC, QD, dqdvavg, and dqdvmax have large variations within the first 40 batteries. This means that these parameters have lower stability across the cycles for these particular batteries compared to other batteries being studied.

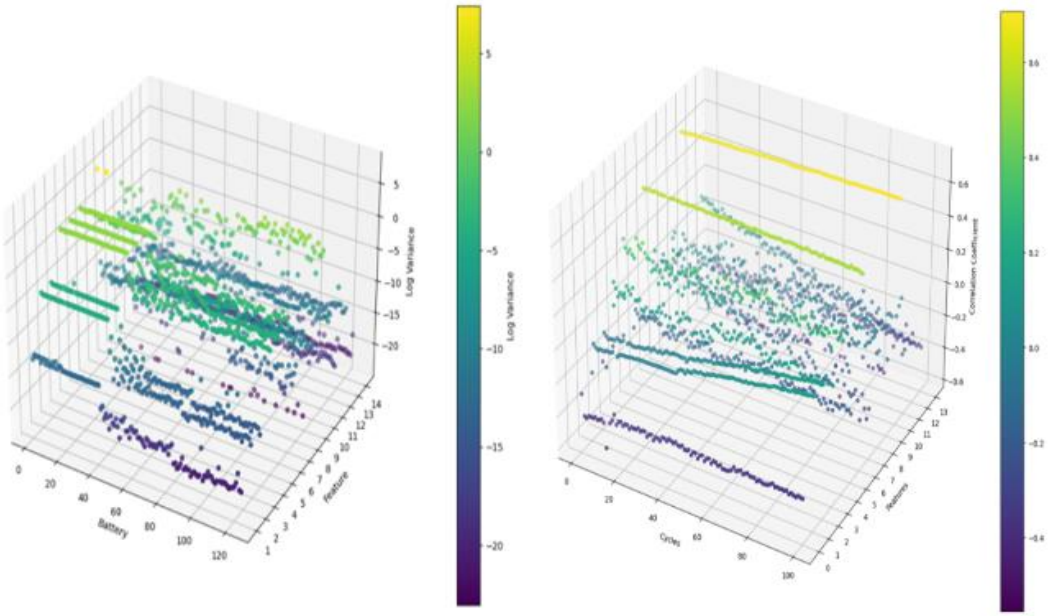

Figure 2: Variance and covariance of features

IV. Data Partitioning

To improve the accuracy of predictions, it is important to handle data without bias. To better understand the data and uncover hidden patterns, the batteries are grouped into four clusters using the K-means algorithm. This ensures that the clusters are more balanced. Visual representations of the data clearly show how the batteries are grouped based on the K-means results. Clustering analysis reveals significant differences among batteries, mainly due to variations in the cycling process. These findings are important for improving battery management and making more accurate RUL predictions. To ensure fairness in model training, the dataset is divided into training, validation, and testing sets, with each containing examples from all four clusters.

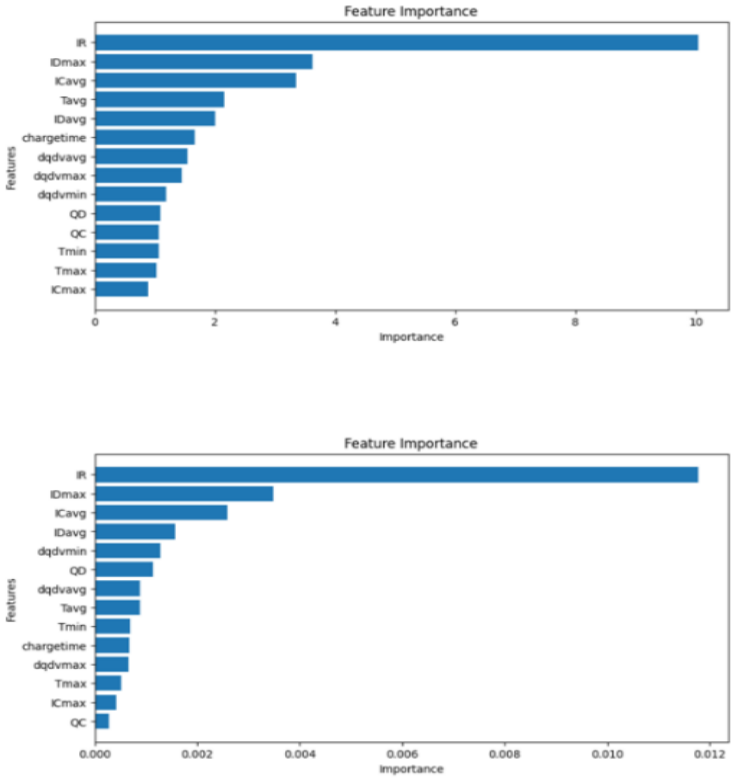

Figure 3: SHAP Methods for Feature Selection

V. Formatting the Data

As described in the introduction, a cycle window is a predefined segment of charge-discharge cycles used to extract data for predicting the Remaining Useful Life (RUL) of a battery. The proposed work expounds that the best cycle window is (40, 40) to achieve the highest accuracy of RUL predictions. This finding refutes the hypothesis in work done before that lengthy cycle windows would result in higher precision, possibly because the structure of the dataset may be weaker in long-term dependencies. The selection of cycle windows is a significant aspect of the ANN model for the RUL and the possibility of getting a high accuracy of the prediction with less information from cycles, depending on the definition and representativeness of cycle windows.

In order to improve the performance of the predictive models, the data are normalized and reshaped. Firstly, the data contains three dimensions: the batteries 124, the type of measured features 14 features for example voltage, current and temperature, and the cycles' number 100. For the better input for the ANNs, the data is transformed to the new form (124, 100, 14). This change serves to reorder the dimensions more or less clashing where the cycle count becomes the drive factor followed by the features. Such normalization and reshaping are essential because they make learning and training of the required patterns by neural networks easier, thus positively affecting the accuracy of the prediction of the remaining useful life (RUL) of the batteries.

VI. Model Implementation

Undergoing the concept of fixing the required cycle limit, a fixed cycle window $c_i = (s_i, B)$, where s_i and B represent the start and end of the window, respectively, the RUL for each cell *i* and *j* is computed as:

$$RUL_i = EOL_i - s_i \quad (1)$$

$$RUL_j = s_j + B - EOL_j \quad (2)$$

This flexibility based on second model of cycle windowing enables RUL prediction across multiple operational stages, with the RUL defined as:

$$RUL_{ij} = s_{ij} + B - EOL_{ij} \quad (3)$$

A. Dimensional Convolutional Neural Network

The 1D-CNN model applies several filters that are trainable, the process of convolution produces feature maps. The convolutions that are performed at each position *i* are represented as corresponding author *(a*a)(i),* where the symbol * indicates convolution and *a* stands for input data. This model performs well for sequential data since it can address local patterns proficiently.

$$y[n] = x[n-m]w[m] \quad (4)$$

where M is half the filter size.

B. Long Short-Term Memory

The advantages of the LSTM in processing sequential data, it is applied to predict the RUL of lithium-ion batteries. It includes several LSTM layers of such type that each layer is aimed at the revelation of temporal dependencies included in the battery cycle data. The model is trained and tested with batch size equals to 1, dropout equals to 0.0 because overfitting can occur and learning rate equals to 0.0001. In the case of LSTM settings, the number of LSTM units is set at 160 as it offered an optimal level of model complexity. Training process also becomes a backpropagation through time, which adapts maximum effectiveness of the model in subsequent cycles. In specific, the LSTM has an arrangement of memory cells which allows it to have long dependency on this sequence to improve its ability to predict RUL.

C. Convolutional Neural Network with LSTM

To extract both spatial and temporal characteristics of the battery data, a hybrid CNN-LSTM model is employed. Process goes through a first layer of convolution that extracts important image features, and then LSTM layers to process these features over time. The model is initialized with a batch size of 2 with dropout of 0.15 and learning rate of 0.0001 is used. There are three LSTM layers embodied in the architecture which are important to strengthen the pattern capturing capability of the model. CNN component applies 64 filters with the kernels that have the size of 5 to extract the local features before passing the data for the LSTM layers. The integration of this hybrid approach is in an effort to develop the model's capacity to accurately estimate the remaining useful life of lithium-ion batteries.

$$y = W * x + b \quad (5)$$

where $*$ denotes the convolution operation, and y_t is the CNN output at time t

D. Bi-Directional LSTM With Attention Mechanism

To streamline the capabilities of the LSTM model, the Bi-LSTM-Attn model is initiated which includes the attention mechanisms and bidirectional processing. This architecture illustrates that a model has capability to believe previous and subsequent information during prediction which is advantageous in the case of time stamp data. The model has initialized with parameters such batch size of 2, dropout rate of 0.0 and learning rate of 2 × 10e-5. They reduced it to 4 layers and with 320 units in each layer to accommodate the complex dependencies of the data. This new proposed mechanism called the attention mechanism enhances the capability of focusing on time steps with higher significance to enhance the RUL estimation by the model. This work uses both bidirectional processing and attention to try to better capture the long complex process of a battery's life.

E. Residual Neural Network

The ResNet model is used to combat the inherent difficulties in training deep neural networks with concern to the degradation problem. This architecture also uses residual blocks which helps create shortcut connections which facilitate gradient flow during back propagation. To achieve high precision and to tune the model correctly, batch size is set as 1, learning rate=0.0001 and kernel size=5. There are several residual blocks arranged sequentially with 256 filters each block to capture more features of the input data. Among all these, the ResNet's structure can allow for training of deeper networks with no compromise on accuracy for RUL prediction. Based on the premise of residual connections, the ResNet model is designed to improve the accuracy and robustness of prediction results for lithium-ion battery lifetime.

$$y = F(x, \{w_i\}) + x \tag{6}$$

Where *F* is the residual function.

F. Transformers

For efficiency reasons and for the ability to make use of the parallel processing and the attention inferences Compute Transformers are used. The system has numerous encoder layers because each of them is built to encode distinct features of the input data. The model has an aim of a size 1 batch, dropout of 0.1 and a learning rate of 0.0001. It has 9 encoder layers and 14 attention heads – it can attend to different features over the battery cycles.

G. Temporal Convolutional Network

TCN is feasible replacement for normal RNNs because of the use of dilated convolutions. Such convolutions enable the model to pre-process advanced extra bits of the input sequence without the need to augment quantity parameters. compared to layer depth, the dilation factor, which determines the spacing between the filter values, rises in a step-up manner. That architectural choice helps to make sure that the network recognizes the patterns over the different time scales and increase the size of the receptive field with depth. Dilated convolutions and residual connections can also help the TCN to be more accurate in RUL prediction because the TCN is more effective than traditional CNN in predicting the remaining useful lifetime or even predicting the overall lifetime of the corresponding wearing equipment.

$$y[n] = \sum_{m=0}^{k-1} w[m]\, x[n - d\,.\,m] \tag{7}$$

where *d* is the dilation factor and *k* is the filter size.

IV. EXPERIMENTAL RESULTS

A. Model Evaluation

The models are evaluated by the Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) metrics.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Actual\ RUL - Predicted\ RUL)^2} \tag{7}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Actual\ RUL - Predicted\ RUL)^2 \tag{8}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |Actual\ RUL - Predicted\ RUL| \tag{9}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{Actual\ RUL - Predicted\ RUL}{Actual\ RUL}\right| \times 100 \tag{10}$$

The models were trained and tested and all metrics are analyzed and visualized in Figure 4a-e. Among all models, the proposed Transformer model showed strong performance, especially on the test set.

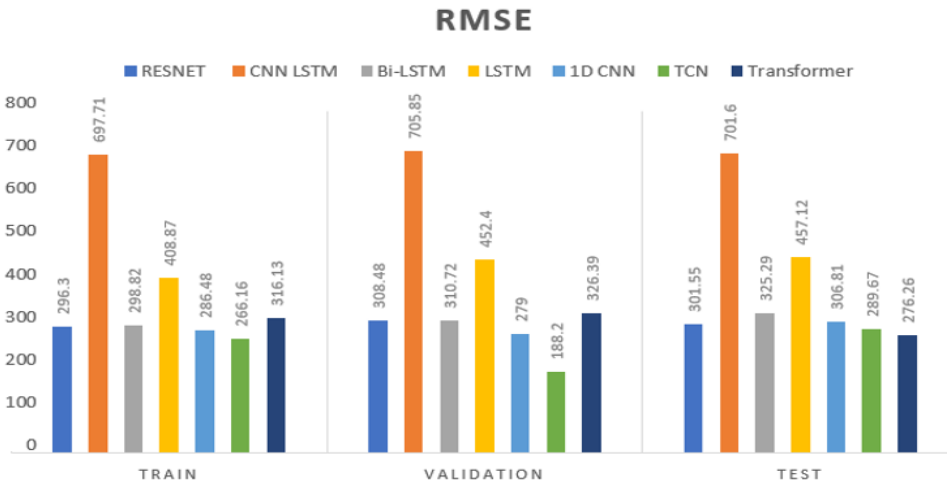

Figure 4a: Root Mean Square Error

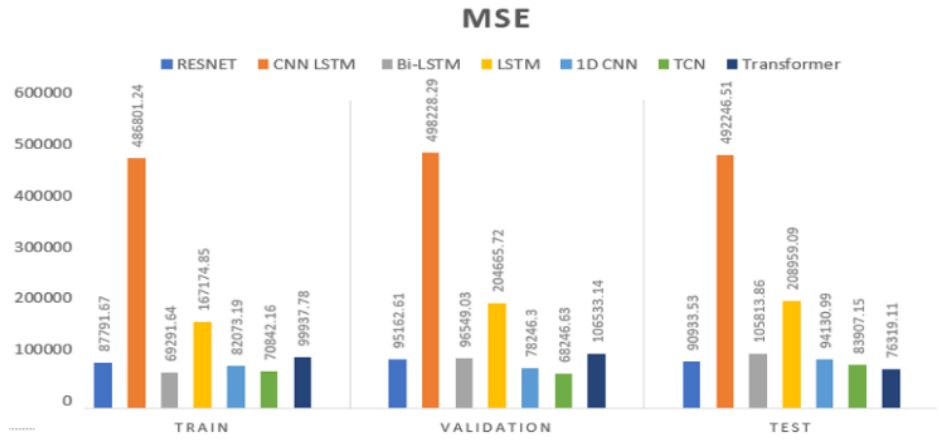

Figure 4b: Mean Square Error

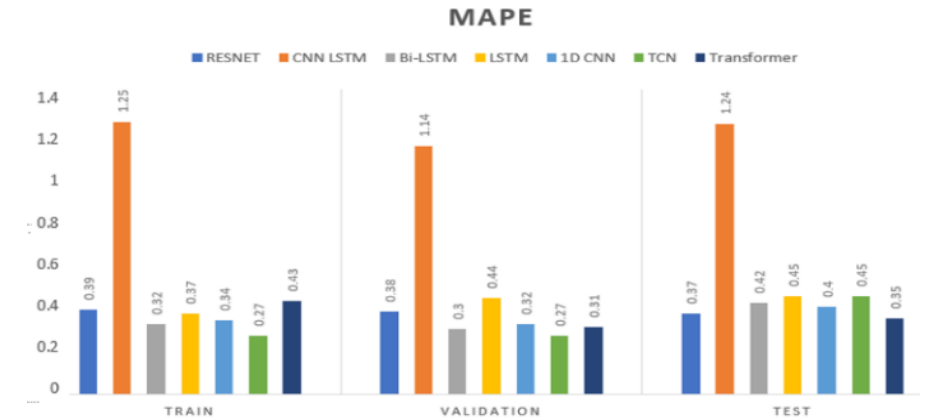

Figure 4c: Mean Absolute Percentage Error

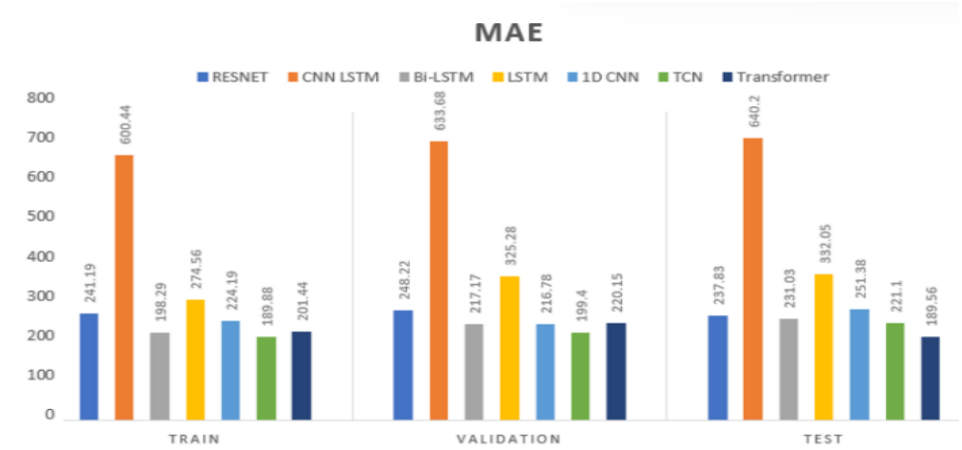

Figure 4d: Mean Absolute Error

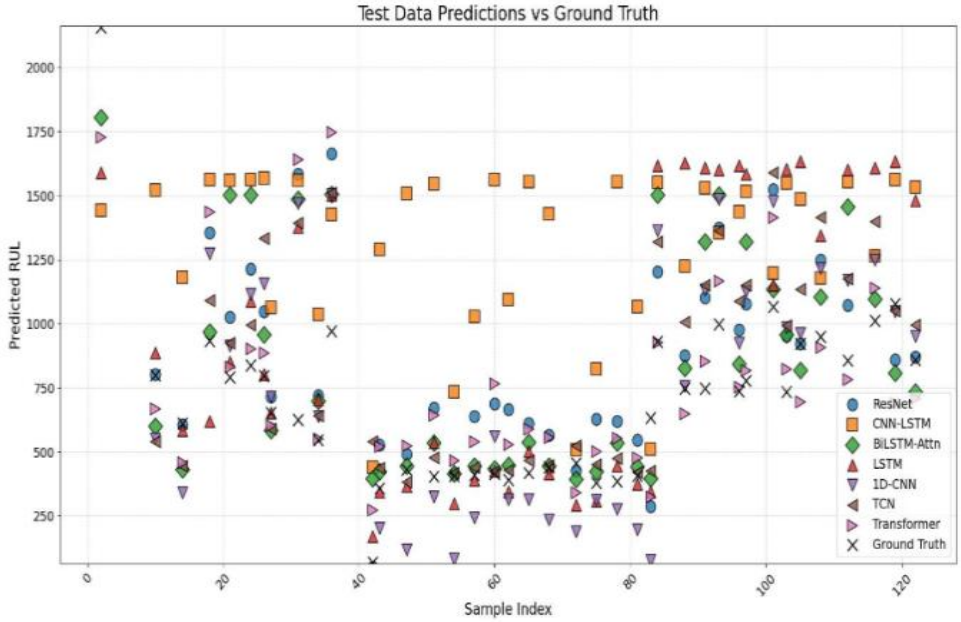

Figure 4e: Comparison of RUL Prediction Results

V. CONCLUSION

This research requires the creation of a single battery machine learning framework to perform extensive analysis for the comparison of different ANN structures. The scatter plot in fig. 5 provides additional insights into how each model's predictions compare to the ground truth across the training, validation, and test datasets. From the visualization, we observe that TCN and Transformer models consistently align well with the ground truth, supporting the RMSE results that identified these models as the most reliable.

Their predictions remain close to the actual values, with minimal spread or deviation. On the other hand, CNN-LSTM exhibits significant dispersion from the ground truth, confirming its high RMSE values. The model struggles to capture the underlying patterns, leading to poor performance. Architectures of the 1D-CNN and Transformer frameworks emerge from their respective structural level of complexity. Models with more than 4 layers in the 1D-CNN experience problems due to vanishing gradients even though adding additional layers can enhance performance. An increase in Transformer encoders leads to improved performance but goes beyond 9 encoders brings the risk of fitting the data too closely. The (40,40) cycle window configuration delivers the highest accuracy results among others. The new perspective arises from this finding about unestablished long-term data dependencies which challenges current ideas. The analysis resulted in a vital outcome where the exclusive utilization of cycle-by-cycle features produced a MAPE value of 10.7 percent. Within the established framework the model displays efficient performance which establishes the feasibility of accurate RUL prediction by using

minimal cycling data. The evaluation of seven neural network models for Train, Validation, and Test datasets appears in Fig. 4 through its four subfigures (MAE, MAPE, MSE, and RMSE comparisons). Each subfigure in Fig. 4 presents separate measures of model accuracy and generalization because TCN and Transformer yield better results than other models through their lower error metrics (e.g., Test RMSE measures at 289.6 and 276.2) but CNN-LSTM performs poorly (RMSE reaches 701.6). Visual comparison features critical value because the assessment provides definitive data-based guides for model selection alongside overfitting identification in CNN-LSTM systems and future development orientation.

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