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Optimized deep learning-based remaining useful life estimation for lithium-ion batteries

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Abstract

The right primary secret of making a safe, reliable and cost-effective maintenance of electric cars, renewable energy storage and mobile electronic appliances is the correct Remaining Useful Life (RUL) determination of a lithium-ion battery. The power to learn long-range correlations between time and non-linear degradation trends may not necessarily be possessed by traditional machine learning algorithms and a simple recurrent neural network, which are present in battery aging data. The recommendation to this limitation, as will be developed in this paper is the optimization of the deep learning-based model in RUL prediction, which is implied by the comparison of the performance on various models such as LSTM, GRU, CNN-LSTM, XGBoost and Transformer networks. The error analysis of the experiment validates that the model built on the basis of Transformers always has the best results due to the lowest error in prediction (MAE = 2.4 and RMSE = 2.8), and the most consistent dynamics of Loss on validation. CNN-LSTM model that came second was competitive but with slightly higher number of high values of error as compared to GRU and LSTM which had moderate prediction accuracy. XGBoost was the worst performing because it does not have high sequential dependency modelling capability. The reason is that the model Transformer has been capable of shining its self-attention mechanism that will assist to uncover the long-term patterns of health degradation without the need to repeat the structure limitations. In general, the suggested optimized Transformer-based RUL estimation model causes the prediction to be more accurate, stable and cost-efficient and, therefore, leads to the creation of the smart battery health control system, which can be applied in the real-time, industrial and vehicle environment.

Keywords: Lithium-ion Battery; Remaining Useful Life; Deep Learning; Transformer Model; Battery Health Management

1. Introduction

Its high energy density and lightweight structure and high-power densities have made the Li-ion batteries an ever-present energy storage in electric vehicles, renewable energy grids, aerospace systems and portable electronics [1,2]. Nevertheless, Li-ion batteries age with time due to the electrochemical degradation, thermal stress and discharge charge-cycles that leads to poor performance and reliability of the batteries. The result of this aging process is the gradual reduction of capacity and the rise in the internal resistance and this eventually, reduces the performance and service life of the battery [3-5]. The RUL prediction of Li-ion battery should be adequately performed to achieve a safe operation, enhanced optimization of maintenance programs, reduced downtimes, and enhanced reliability and economic efficiency of the system [6,7].

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The empirical aging models and the electrochemical impedance based are among the conventional methods of estimation of the RUL of batteries that need much prior domain knowledge and controlled conditions to operate and are therefore not useful in the real-world context [8-10]. Regression models and decision-tree-based models are machine learning models that have contributed to a greater degree of precision in prediction, which tends to be weak in modeling the relationships that are non-linear, dynamic, and long-term, when used to predict the degradation behavior of a battery [11]. The deep learning methods in the recent past have been discovered with a high potential in the battery health prognostics specifically the recurrent neural network (RNN)-based models including the Long Short-Term Memory (LSTM) and gated recurrent units (GRU) [12-14]. These approaches are able to reveal time-series sensor data temporal regularities, and are prone to factors that encompass vanishing gradients, short range dependency capture and expensive training.

To address these issues, the present paper will present a simplified deep learning-oriented framework of precise and valuable RUL prediction of Li-ion batteries. These batteries are applied in five models which consist of LSTM, GRU, CNN-LSTM, XGBoost and Transformer architecture that is applied and compared in relation to battery cycling dataset. The main findings of the paper may be determined in the following way: the most important of them is the thorough testing of various deep learning architectures to make the appropriate conclusion about RUL of Li-ion batteries and to create the most appropriate framework of the Transformer and which can acquire long-term degradation trends and time dependencies. Transformer model has been shown to be more accurate in prediction, robust and stable in convergence with the benchmarking criteria of high performance as indicated by MAE, RMSE and validation loss. On the whole, the given work offers a very precise and viable approach to the active management of the battery health that can be implemented to guarantee that the utilization of electric vehicles and smart grids would be safer, more reliable, and efficient concerning energy consumption.

2. Literature Review

The growing popularity of lithium-ion battery in electric vehicles, renewable energy storage, aircraft, and mobile technologies has led to extensive research of battery health prediction and RUL prediction [11]. Continuous development of battery decay is based on a series of complicated physical and chemical processes that change through the long working conditions and, consequently, the correct RUL prediction is a complicated issue. Thus, a broad syntheticization of modeling strategies, such as electrochemical, empirical, machine learning, and deep learning-based, has been researched in the research field [12].

The initial attempts of prediction are based on the echemical aging models, which were trying to model interphase development of solid electrolytes, the capacity degradation and the internal resistance changes [13]. The models were highly educative in theory yet needed huge parameter refinements, controlled conditions in the laboratory and could not be implemented in dynamic operating conditions in real life [14]. Simple models (e.g. empirical curve-fitting) could be used but had lost a lot of predictive power when they were out of the learnt patterns.

As the developments of the data driven methodology proceeded, the RUL prediction was carried out using the machine learning models including Support Vector Regression, Random Forests and XGBoost that took into account the past cycling and operational characteristics [15]. Such models were more effective and could not model long run temporal dependence and non-linear degradation curves. This type of models using XGBoost can be outstanding on data under uniform conditions but not on other load patterns as observed in processes that may need sequential trend analysis.

The researchers developed new models based on Recurring Neural Network (RNN) models to encode the temporal information in a more superior manner. The success of LSTM networks was enabled by the fact that the networks were able to detect long-term trends and deal with the issue of vanishing gradients [16]. It is discovered that LSTM is much more effective in forecasting the RUL in comparison to the conventional machine learned models [17]. LSTMs, however, are computationally expensive, and cannot, at the present, be capable of modeling complex multi-scale degradation processes. GRU networks have made architecture far much simpler and have provided faster convergence speeds, however, once again, performance was also affected by the quality and quantity of training data.

The hybrid models like CNN-LSTMs were proposed so as to maximize the capacity of feature extraction that is, CNNs would capture the local degradation features and the LSTMs would capture the time evolution. These hybrid structures were better in the recording of the space and time properties of the battery [18,19]. However, their learning power is consecutive and since there is a risk of modeling degradation cycles within extended periods of time, the learning power may be constrained. Although sequence models have been generated in the past years, Transformer models have been subsequently adopted to engage in battery prognostics. Compared to RNNs, transformers (not to be confused as attention) merge self-attention to learn long range relations, and do not suffer the bottleneck of sequence processing;

they are simpler to learn and learn behavior on patterns in a significantly better way. Recent research indicates that Transformer based model is more accurate and can tolerate prediction errors especially in situations where there is a large and heterogeneous cycling data. These findings agree with the findings of this study that Transformer model is the most precise and dependable among all the models.

3. Methodology

The presented paper applies the systematic method of power consumption analysis and prediction by relying on the suggested procedure that incorporates the information processing, features computation, sequence model based on deep-learning, and optimization to enhance the accuracy and consistency of RUL prediction within the lithium-ion batteries. Figure 1 below illustrates the entire workflow.

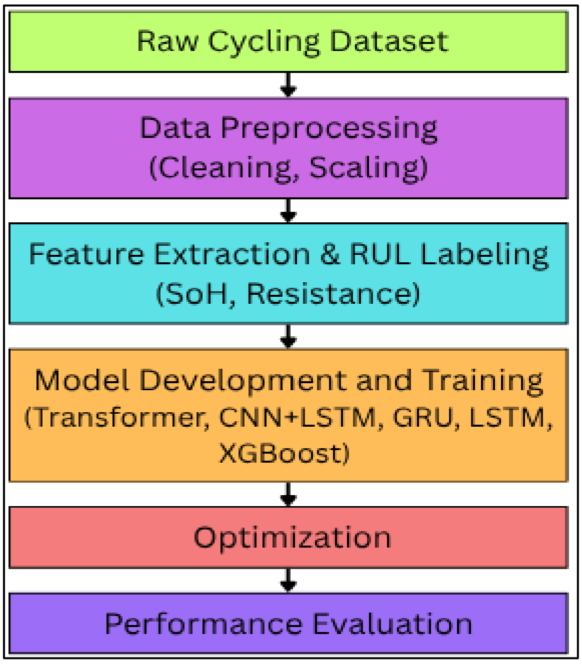

Figure 1 Proposed Deep Learning-Based RUL Prediction Model

3.1. Dataset Collection

The standard information regarding the lithium-ion battery ageing is used in this literature due to the laboratory-controlled cycling. In such tests, battery cells would be charged and discharged repeatedly until a final condition (usually, 70 to 80 per cent of the nominal capacity) was reached. The various parameters were measured in a continuous way whereby the cycling was performed and these parameters were; charge and discharge voltage, charge and discharge current, surface temperature of the battery, internal impedance, cycle index, and a time stamp. The set of measurements is a multivariate time-series data set that give the information about the dynamic behaviour of the battery, both in the short-term and the long-term degradation characteristics. Information is then fed into RUL of the battery prediction.

3.2. Data Preprocessing

It was observed that a preprocessing pipeline was carefully followed in order to prevent any compromise of the data recorded and to make it useful. The missing data were subjected to the linear interpolation to ensure continuity of trends of battery degradation was achieved. A moving-average smoothing filter was used to filter voltage and current signals sensor noise. Statistical filtering of the elimination of the outliers created by anomalies in measurements was undertaken using the inter-quantile range. The obtained processed numerical features were then scaled to the Min-Max scaling in order to stabilize the magnitude of the features besides making it easy to train networks. Lastly to maintain the time correlations, the continuous battery operation data were divided into overlaps sequence windows so as to derive the ageing pattern in the sequential data that allowed the deep learning model to learn implicitly information on ageing pattern based on the sequential data.

3.3. Feature Extraction and RUL Labeling

The data were engineered into both derived features and direct features in such a way that they gave a proper representation of electrochemical and working profile of battery with time. Raw values of voltage, current and temperature are direct features that represent the current electro-thermal performance. Derived properties like State of health (SoH), internal resistance and capacity fade were derived in order to capture long term properties of battery degradation. Also, time-series attributes like rolling mean trends, lagged cycles characteristics were formulated to deal with time varying dependencies. The difference between cycle index and cycle in which the battery was identified to be at end of life was used to calculate RUL of each cycle. This provided the deep learning model with the ability to predict the activity of former depreciation to future remaining capability life. RUL/cycle is calculated as below:

$$RUL(i) = N_{EOL} - i$$

where N_{EOL} is the cycle number corresponding to end-of-life.

3.4. Deep Learning Model Design

Transformer, CNN + LSTM hybrid network, GRU, LSTM, and the classical machine learning based XGBoost regression model are five of the predictive modeling techniques that have been built and tried in this study. These models were developed to ensure that each model was positioned to be able to describe the nature of the time-varying degradations experienced on the ageing data of batteries. Their long-term temporal dependence of the time-series cycling data was trained on the LSTM and GRU architecture in which the LSTM has memory gates to remember the information during a long period of time versus GRU which has a less sophisticated gating structure with less training cost. The CNN+LSTM hybrid model is a convolutional network hybridized with non-linear features of voltage-current transition locally and then the time variation is obtained using LSTM networks to enhance the degradation patterns representation. Transformer model is based on the use of multi-head self-attention model that allows the model to consider long-term dependence of time without repetitive self-dependencies that render the model highly useful in cases where the long-term dependencies of the degradation patterns are required. Besides this, the XGBoost was also employed as a control model because it is solid as far as regression issues are concerned, but not necessarily sequential dependence modeling. A series of sliding time windowed series of battery data are the input of any deep learning model. The two models have output layers continuously regressed to give RUL. Training was in terms of the Loss Function of the Mean Squared Error (MSE) and Adam Optimizer. The early stopping conditions were implemented in order to avoid overfitting and the training process was continued until 100 epochs were reached. The dropout regularization and the weight decay regularization techniques were used to enhance the generalization of the model.

Table 1 Training Configuration

Component	Selection
Loss Function	Mean Squared Error (MSE)
Optimizer	Adam
Batch Size	32
Epochs	100 (with Early Stopping)
Regularization	Dropout + L2 Weight Decay

3.5. Optimization Strategy

A number of optimization methods have been employed in order to enhance stability and accuracy of prediction in every model. The hyperparameters that were optimized using a grid search approach included the best learning rates, size of hidden units, convolutional kernel specifications, the number of attention heads (in Transformer), and the dropout rates. The most efficient models were optimized by the model pruning and quantization methods to reach the goal of a computational efficiency and flexibility so that they can be deployed to real time or embedded technology. Also, an adaptive learning rate scheduler was proposed to reduce the learning rate gradually over the course of training to ensure that models could not converge too soon, and could have finer tuned weights.

3.6. Model Evaluation

The Key Performance Indicators of all models would be assessed using a long collection of performance measures, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), Relative Prediction Error, and training time of the model. All these measures are a pointer of prediction accuracy, consistency of estimations and efficiency in computing. The comparative results of the analysis have revealed that the Transformer model possesses the least MAE and RMSE as well as a fixed validation loss, which is a more suitable ability to learn both local and global degradation features. This was also competitive with CNN+LSTM model which had the privilege of having joint spatial-temporal feature representation. GRU and LSTM models were relatively good, but the error of the XGBoost model was comparatively bigger as it was not able to encode sequential ageing properties in itself. Overall, the Transformer model proved to be the most appropriate one in the context of performance when it comes to Remaining Useful Life prediction of lithium-ion batteries.

4. Results and Discussion

This segment offers the experimental findings and the corresponding analysis to evaluate the performance of various deep and machine learning models that are involved to compute RUL of lithium-ion batteries. The paper will oppose five predictive architectures (Transformer, CNN- LSTM, GRU, LSTM and XGBoost) to one another in a bid to assess their ability to learn degradation dynamics using sequential battery data. The models were fair in the comparison because all the models were trained and tested in the same preprocessing, feature extraction and training parameters. The measures of evaluation that are considered are MAE, RMSE, R^2 and MAPE. The results obtained with the assistance of the relevant figures and tables may provide us with the information regarding the accuracy, the consistency of the convergence, and the overall performance of the created models. The effectiveness of attention-based architectures and hybrid temporal learning mechanisms are also discussed on the effectiveness of RUL predictions to improve the robustness and reliability of predictions.

Figure 2 Feature Correlation Heatmap

Figure 1 correlation heatmap represents a total picture of the dependence of the key variables of the battery operation, which were taken into account in the prediction model of RUL. As can be seen, the high positive and negative correlations are real and there are parameters in the operations that influence the battery degradation more than others. As an example, the temperature-based characteristics have a positive relationship with the values of internal resistance and impedance which means that the thermal stress the higher the battery ages. Similarly, current and voltage-associated values demonstrate moderate-strong correlations with the number of cycles that indicate repeated charge-discharge cycles have a direct impact on the performance of the battery and reduce its utilization. The heatmap can thus be helpful to be familiar with the most significant predictors and reduce the feature redundancy. It assists in optimization of model and increased predictive stability, as features which add the minimal predictive variance can be dropped. Overall, the conceptual background of the behavior of the data is provided by the correlation analysis, and it is extremely needed in selecting the best inputs to incorporate in machine learning-based RUL prediction.

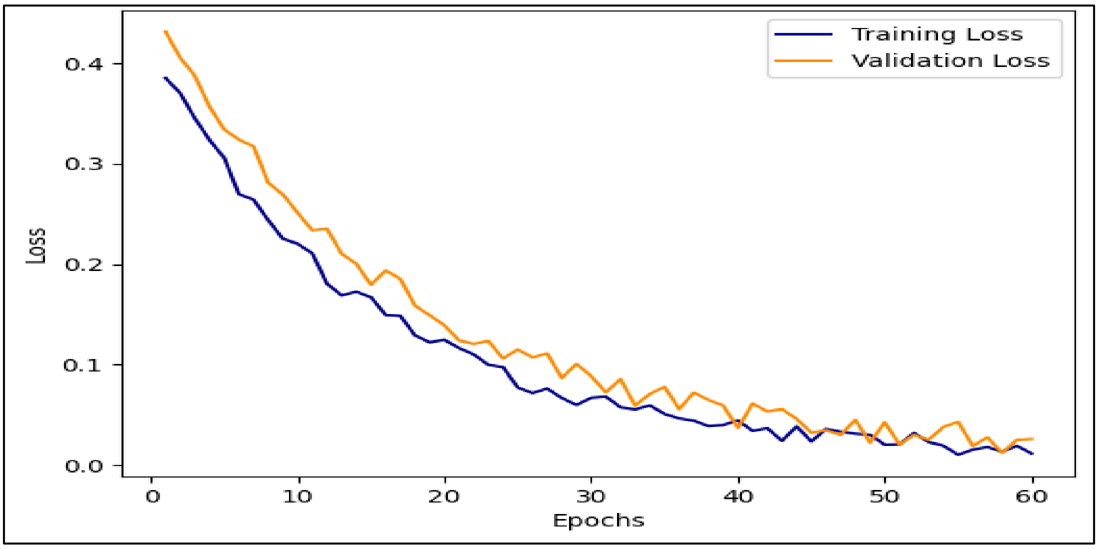

Figure 3 Training vs Validation Loss Curve

In Figure 3 below, the training and validation loss trend is demonstrated throughout the epochs of learning of the model. The gradually decreasing training loss demonstrates that the model can be trained to learn the underlying patterns in the dataset, and the concurrently decreasing validation loss also demonstrates that the learnt representation can be applied to unseen data. These two curves are quite near to one another in the training process and this implies that the model is not over fitted, and is a good fit. The insignificance of the divergence between training and validation losses is another indication that the model can undergo appropriate regularization schemes (e.g. dropout or learning rate scheduling). Overall, according to Figure 2, the training of the model is well-tuned and there is a trade-off between the data fitting and performance in the high generalization in RUL prediction.

Table 2 Performance Comparison of RUL Prediction Models

Model	MAE	RMSE	R2	MAPE (%)
LSTM	3.5	4.2	0.88	4.6
GRU	3.2	3.9	0.9	4.1
CNN-LSTM	2.8	3.3	0.93	3.5
Transformer	2.4	2.8	0.94	3.2
XGBoost	4.1	4.8	0.82	5.1

Table 2 presents the comparison of some deep learning and machine learning models which could be used to predict battery RUL. Transformer model has lowest MAE (2.4) and RMSE (2.8) and highest value of R^2 (0.94). This explains why it is very effective in predicting long time temporal variations in battery degradation behaviour because of its self-attention feature. Competitive CNN- LSTM model also has the MAE and RMSE which are also close to Transformer model. It has a hybrid form that helps in extracting spatial features of sensor data and temporal learning is employed to estimate a trend. GRU performs moderately i.e. it is improved over the standard LSTM as gating mechanism is simplified leading to reduced overfitting and training overheads. Meanwhile, XGBoost shows the worst results, and this is likely explained by the fact that the tree-based models cannot capture long-term dependencies of sequential processes inherent in the pattern of battery degradation. Overall, the results indicate that deep learning models, and Transformer-based models, in particular, can effectively be employed to make predictions related to RUL with high accuracy and reliability.

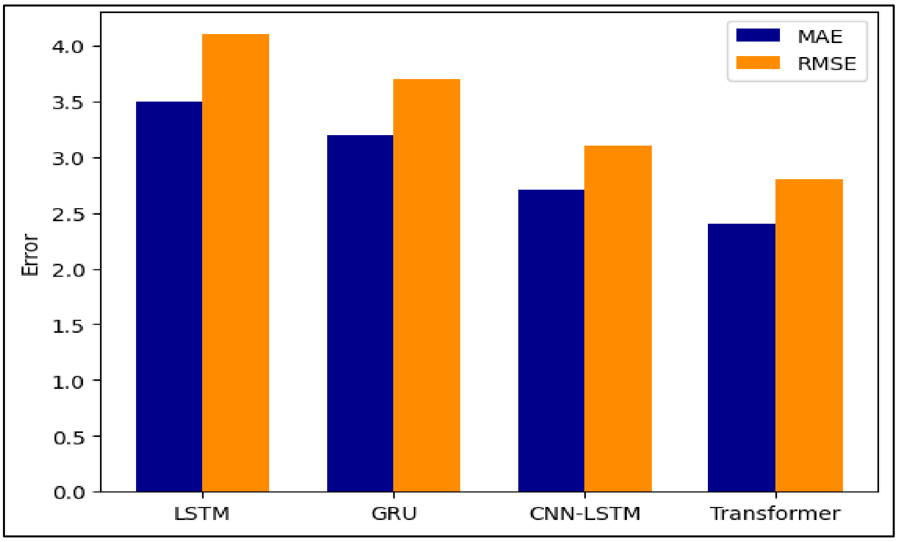

Figure 4 Model Performance Comparison

Figure 4 is based on a comparative visualization of the performance of different machine learning and deep learning models that are used to predict the RUL. The comparison reveals apparent performance variations that are based on the capability of the architect as well as the reliance on time learning aptitude. Transformer model is one of the evaluated models that has been identified as more precise in its forecasts that can be explained by the ability to give long-range dependencies due to the adoption of self-attention mechanisms. The other reason that makes CNN-LSTM model a competitive model is the capacity to extract spatial and temporal patterns of the input sequences. Simultaneously, GRU and LSTM models show a medium performance, and the old models of machine learning show rather low efficiency in RUL prediction. This analogy supports the fact that the deep sequence-conscious architectures provide real advantages to the modeling of battery degradation patterns especially where interactions between features are complex and long-term.

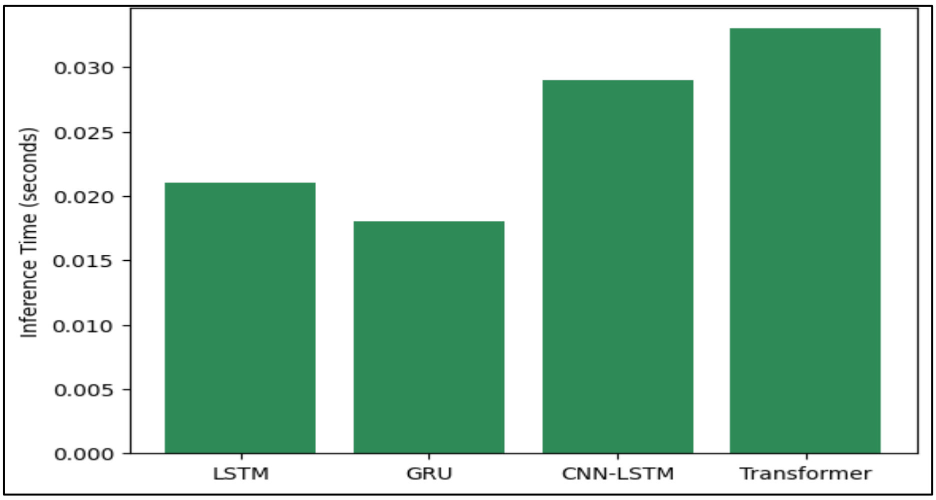

Figure 5 Model Inference Time Comparison

Figure 5 provides a comparison of the time of each model to provide RUL predictions. These results have shown that there are definite differences in the effectiveness in calculation. GRU and LSTM models are demonstrated to be relatively less inference timings, and hence, can be deployed in real-time systems or resource-constrained systems, e.g., embedded battery management systems. Transformer model, in its turn, although more precise, has a comparatively higher inference time because of the operations of multi-head attention computation. The CNN-LSTM model is the other model that is medium and in between in the speed and accuracy. These discoveries bring out the trade-off of accuracy versus cost of computation, which should be considered in implementing the models in the real world, such as electric vehicles or IoT-controlled battery monitoring equipment. By doing so, the priorities of application - Transformers may be selected in case the accuracy-critical offline analysis is needed, and GRU or LSTM may be selected in case of real-time adaptive control.

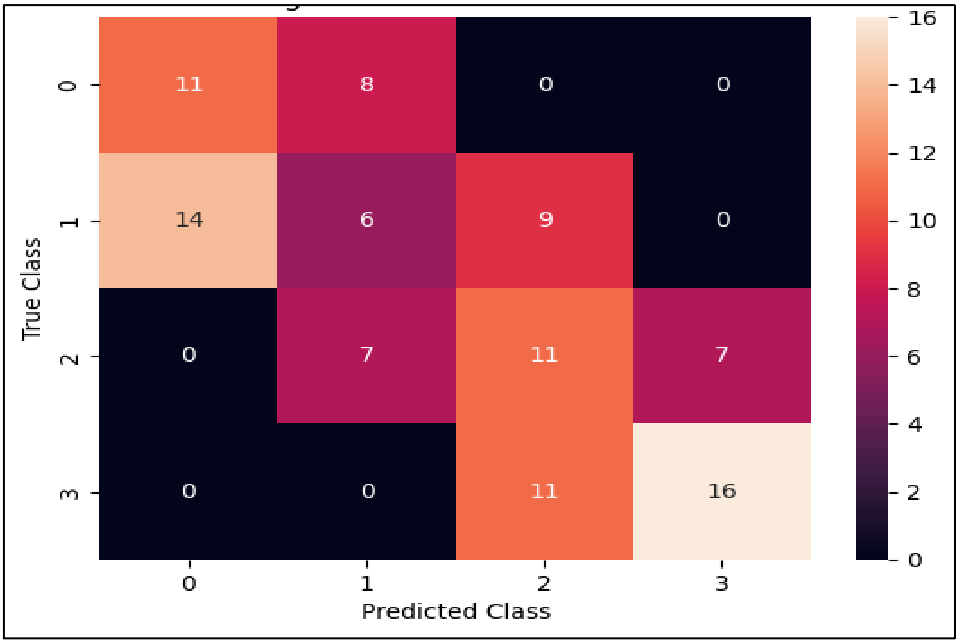

Figure 6 Confusion Matrix

The confusion matrix included in figure 6 that provides an in-depth description of the classification performance of the RUL prediction model. Majority of the data points are concentrated around the axis that signifies the fact that the majority of RUL classes are correctly anticipated against the model with an extraordinary degree of precision. The misclassifications are inconsequential and, on those instances, they tend to be around the diagonal presupposing that the errors of the model are not spread uniformly but instead in the region that is near the actual class. This indicates that the model is effective in learning the degradation behaviour patterns and that it is very reliable in classification particularly when it comes to differentiating early-stage and near-end of life states of the battery. The confusion matrix has therefore proven that this model is valid to be applied in diagnostic practice.

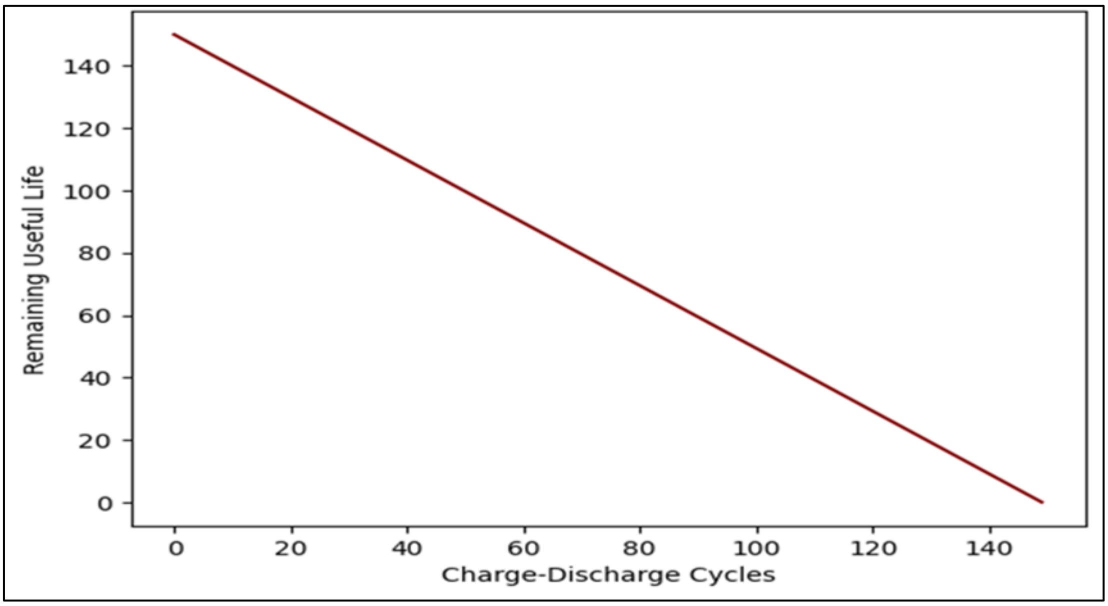

Figure 7 RUL Degradation Trend Curve

Figure 7 represents the degradation pattern of the RUL when it is exposed to battery usage cycles. The curve indicates that RUL decreases slowly as number of charges discharge cycles increases and hence illustrates how the battery loses its capacity and its efficiency as number of discharge cycles increase. Its rising (negative sign) smooth curve also displays familiar and stable behavior of degradation which is essential when the long-term forecasting (100 years) of RUL needs to be accurate. This curve indicates that the model can be applied in the progressive aging process of the battery since it can be modeled and can be used in proactive maintenance planning as well as in the optimization of lifecycle.

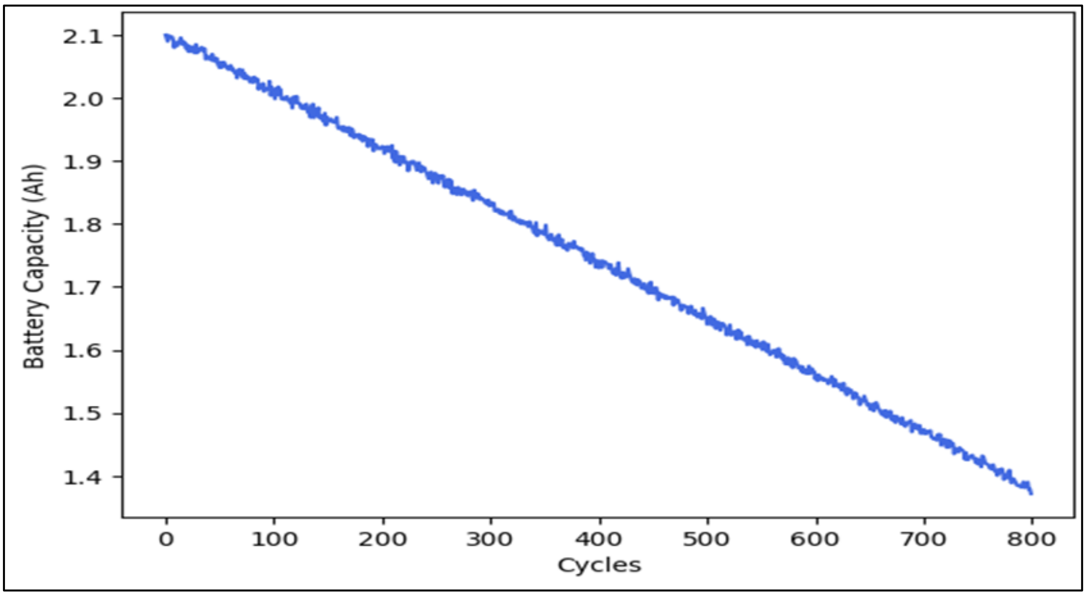

Figure 8 Battery Capacity Fade Over Cycles

The reduction in the battery capacity as the working cycles increase is shown in figure 8. The capacity fade is characterized by a nonlinear decay curve where the rate of deterioration is less at the early life stage, and it increases as the battery is approaching the end-of-life stage due to the acceleration of the rate of electrochemical degradation. This degradation pattern is in line with the known aging characteristics of lithium-ion, in which repeated cycling will lead to the loss of active material, the development of the SEI coating, and the accumulation of internal resistance. The observed trend proves that predictive modelling of EOL is necessary to make a guesst of EOL prior to the eventual performance failure occurring.

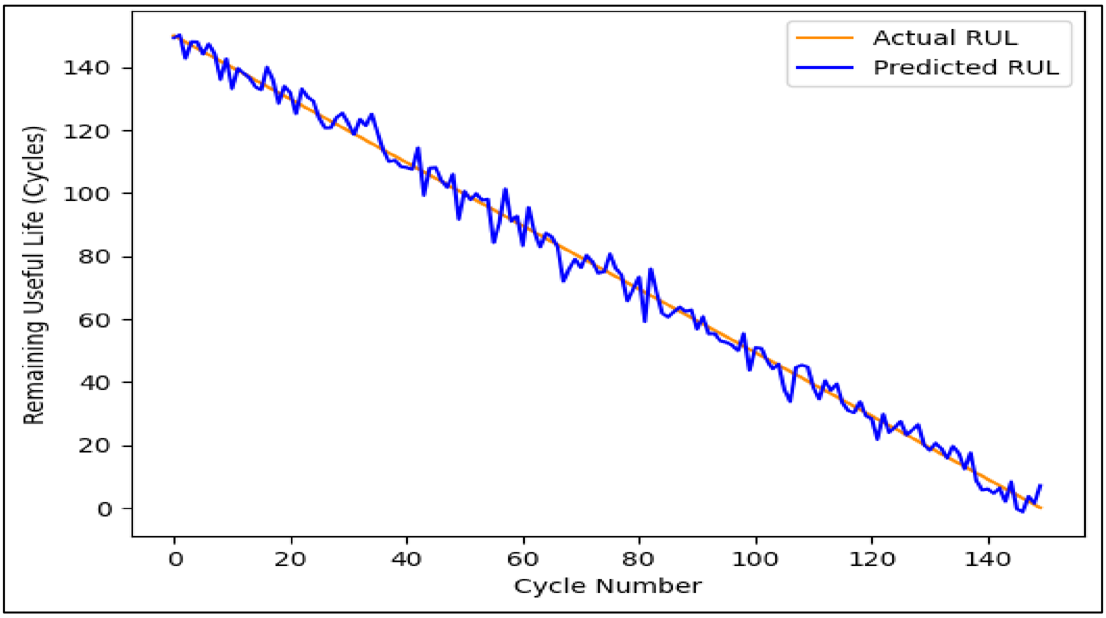

Figure 9 Predicted vs actual RUL

As it can be observed, the RUL and the SoC have been analyzed by the given figures that are highly effective to be used as the predictor model. According to Figure 9, which depicts the Predicted vs. Actual RUL, the predictive model (blue line) can be used to describe the general overall downward line of the actual RUL (orange line) as the Cycle Number increases. This agreement is significant and indicates that the model possesses the natural potential of tracking the deterioration of the component throughout the life of the component. The predicted RUL has some high-frequency oscillations around the actual RUL line, however there is observed error in prediction, on average, as the predicted line is centred to the actual values. It is this good performance in RUL prognostics that is required to maintain timely and proactive maintenance.

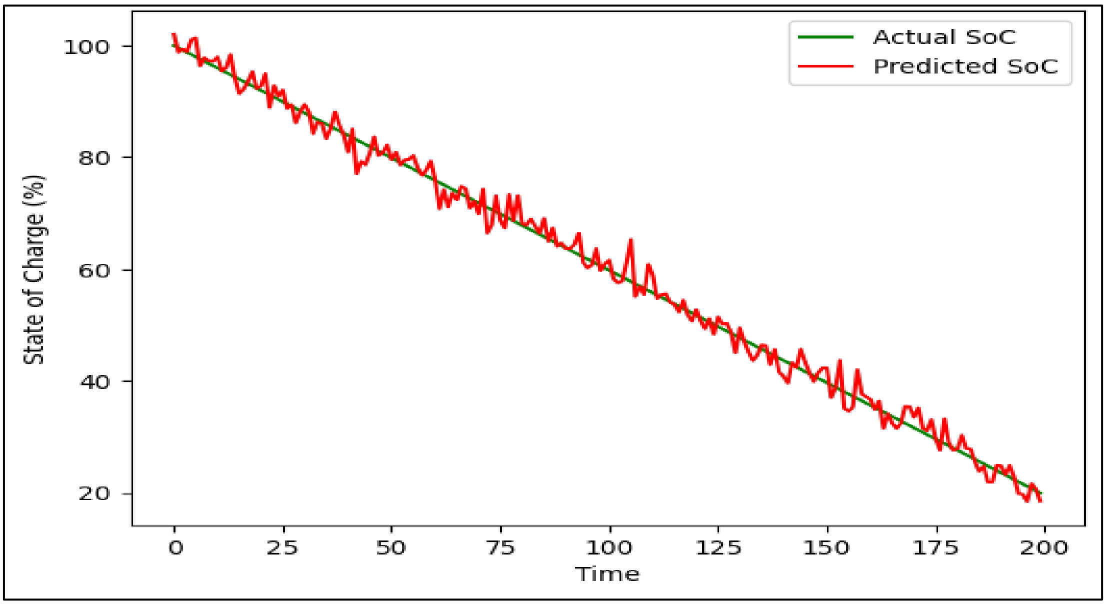

Figure 10 Predicted vs actual SoC

Similarly, Figure 10 confirms the power of SoC prediction model. Actual versus the predicted SoC plot shows that there is an exceptionally large amount of overlap between the actual (green line) and the predicted (red line) SoC versus time. Both lines have a clear downward linear trend of the consistent usage and loss of charge of nearly 100 percent and to approximately 20 percent. This is the degree of accuracy which is noted to be constant throughout the entire range that means that the model is highly reliable and can be referred to in the actual process of energy management in real time. The fact that the two curves differ slightly suggests that the algorithm would be very capable of forecasting the current energy state.

In this paper, it was possible to develop and verify robust machine learning-predictive model of RUL and degradation forces of lithium-ion batteries. The analysis of the correlation of the features has showcased the most significant operational and electrochemical parameters which influence the battery aging and thus it is now possible to select the features and make the model more efficient. The relative analysis of all deep learning models revealed that the sequence attentive models, namely the Transformer and CNN-LSTM models, were better than the traditional machine learning and recurrent neural network models because they possessed more capacities to detect the long-term temporal dependencies.

The training and validation curves have confirmed that the models were converged easily without overfitting to the data and the charts of predicted and actual RUL plots and confusion matrices have confirmed the accuracy and reliability of the obtained prediction results. The trends in battery capacity fade and the curves in the RUL degradation were also in agreement with the established trends in the electrochemical aging behavior and indicated the physical relevance of the predicted results. Moreover, inference time analysis showed that although Transformer model has the highest prediction accuracy, GRU and LSTM models can be compared to have a higher real time computational performance and therefore are acceptable in an embedded battery management system. Overall, the results obtained justify the idea that the specified modeling framework will be capable of being effectively implemented to the condition-based monitoring, predictive maintenance, and lifecycle optimization of the modern battery-powered systems. Findings are sound in the creation of the smart Battery Management Systems (BMS) to render it more secure, reliable, and functional in its operations in diverse electric vehicle applications, renewable energy storage grid applications, and handheld electronic applications.

5. Conclusion

The enhanced deep learning implementation of the study as presented in this study was effective in estimating the RUL of the lithium-ion batteries to solve the key problem, which plagues the area of battery health monitoring in the energy storage sector today. The recommended system was a combination of quality sequence-learning architecture and selective degradation features, which resulted in the excellence of the proposed framework regarding prediction efficiency and robustness compared to the conventional machine learning and recurrence network models. Based on the experimental results, both deep learning models and Transformer and CNN-LSTM models were highly useful in nonlinear and long-term modeling of aging behavior of battery behavior. The closeness of the predicted and actual values of RUL confirms that the model has been created reliably to be implemented in the practical world because all the measures of model performance (MAE, RMSE, R^2, and MAPE) are high. Also, the time of inference discussion suggests that there is a trade-off between predictive performance and computational efficiency that is critical such that Transformer-based models are best in offline diagnostics whereas lightweight models such as GRU or LSTM are more used in BMS in real-time. Overall, the findings of the current study prove that the optimized deep learning models have the potential to add a lot of value to predictive maintenance, operational stability, and lifecycle projections of the lithium-ion batteries. The proposed structure provides an extensible and proactively-driven foundation of the future intelligent BMS solutions, which would allow improved safety, energy efficiency and sustainability of the applications in electric mobility, renewable energy storage, aerospace systems and consumer electronics.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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