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Optimized Machine Learning Framework for Battery State Prediction in Smart Charging Systems

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Abstract

Good estimation of battery states, including State-of-Charge (SoC), State-of-Health (SoH), and Remaining Useful Life (RUL), are important in managing energy wisely and controlling the adaptive charging. This work introduces a streamlined machine learning model based on the ability to use multi-dimensional sensor measurements in terms of voltage, current, temperature, and cycle number to forecast battery conditions with high accuracy. Decent preprocessing, such as noise elimination, feature scaling, and calculated features, were done on the dataset to increase the reliability of the model. There are various models that were trained and compared through MAE, RMSE, and R^2 which are XGBoost, LSTM, GRU, CNN+LSTM and Transformer architectures. Transformer-based model was observed to be better performing with less prediction error and high temporal stability. The findings prove that the suggested structure is able to achieve nonlinear trends in the degradation and this serves as the basis of real time adaptive charging and health-conscious decision-making in battery management systems. Accurate estimation of battery conditions plays a vital role in improving the safety, dependability, and overall performance of contemporary energy storage technologies, especially in electric vehicles and renewable power systems. This research proposes a lightweight and computationally efficient machine learning framework designed to predict critical battery health parameters, namely State-of-Charge (SoC), State-of-Health (SoH), and Remaining Useful Life (RUL). The methodology utilizes multi-source sensor inputs, including voltage, current, temperature, and cycle count, to effectively model complex degradation behavior. To enhance prediction reliability, rigorous data preprocessing steps such as noise reduction, normalization, and advanced feature extraction are incorporated. Several machine learning and deep learning models—XGBoost, LSTM, GRU, CNN+LSTM, and Transformer—are developed and comparatively assessed using evaluation metrics such as MAE, RMSE, and R^2. Experimental findings indicate that the Transformer architecture outperforms the other models by achieving lower prediction errors and improved temporal stability. Its ability to learn nonlinear degradation characteristics and long-range dependencies makes it particularly effective for battery prognostics.

Keywords: Deep learning (DL), electric vehicles, optimized machine learning, remaining useful life (RUL), state-of-charge (SoC), state-of-health (SoH)

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INTRODUCTION

The increasing use of electric vehicles (EVs), energy storage systems that are renewable, and portable electronic devices has increased the global pressure to develop efficient and intelligent systems to manage battery cleaning [1]. The most commonly used medium of energy storage in such applications is Lithium-ion batteries due to their high energy density and long cycle life. But their working, safety and life span greatly rely on the accurate estimation and regulation of inner states like SoC, SoH, Internal Resistance, together with RUL [2,3]. Proper forecasting of these parameters is the key to proper functioning, optimization of the charging process, and possible degradation and failure.

Existing battery management systems (BMS) are based on empirical models and rule-based state estimation algorithms. They are computationally effective, but in most cases, they cannot be generalized in changing operating conditions, like changing temperatures, changing loads, and age effects, among others [4]. Consequently, it is becoming increasingly important to have techniques that are data-driven and capable of generalizing complex and nonlinear relationships among battery behavior and how they adapt to various environmental and operating conditions.

Over the last several years, the machine learning (ML) and deep learning (DL) approaches have become effective predictive modeling tools in energy systems. Through historical data, these models are able to identify concealed patterns and dependencies to provide precise state estimation and predictive analytics in advanced BMS [5]. Random Forests, Gradient Boosting, Long Short-Memory (LSTM) networks, and Transformers models have demonstrated tremendous potential in time-series battery data, modeling temporal relationships, and making extremely accurate predictions of degradation curves [6].

The proposed study will design and develop an optimal machine learning model to predict various battery state parameters using real-world time-series data. The new framework will involve strict data preprocessing, feature selection and model optimization to increase the predictive accuracy. Through the benchmarking of the efficiency of different ML models, this paper determines the most appropriate architecture to be integrated in real-time with smart charging systems.

Due to the accurate predication of SoC, SoH, Internal Resistance, and RUL, adaptive and efficient charging protocols are possible, which is the minimization of battery stress and the increase of the overall life of the battery. Thus, the study preconditions the intelligent energy management systems, which can make dynamic decisions and predictive control. Finally, the results of the present study will help to achieve the objectives of making batteries smarter, safer, and more sustainable, facilitating the world to use clean energy and adopt electric mobility.

LITERATURE REVIEW

It has continued to be a subject of research because it is an important parameter to predict key battery state parameters, especially SoC, (SoH, Internal Resistance, and RUL) that can improve the performance, reliability, and safety of BMS [7]. Researchers over the years have diversified in the various modeling techniques which are mainly divided into as electrochemical models, equivalent circuit models (ECM), and data-based models [8]. Physics-based and ECM methods are highly interpretable and accurate when compared to theory, but they tend to be sensitive to noise in sensors and fluctuations in the environment, which makes it difficult to model or estimate the complex parameters [9]. As a result, ML and DL models have been considered as more flexible and scalable options in the estimation of the state of batteries.

The conventional SoC and SoH estimation has been based on model-based estimation like Coulomb counting, Kalman filtering and Equivalent Circuit Models [10]. Such techniques offer a sensible precision yet are frequently not resilient to the dynamic loads variation, thermodynamic shifts and nonlinear deterioration mechanisms. Though basic, such methods have a low-resolution of intricate time relationships and nonlinear electrochemical processes happening in the lithium-ion cells.

The use of machine learning methods brought about a data-driven approach to battery state prediction through the learning of relationships based on the experimental data. Support Vector Regression (SVR), Random Forest (RF) and Gradient Boosting Machines (GBM) have all been uses in algorithms that seek to represent nonlinear relationships between measurable inputs and hidden states or states [11]. These models provide better prediction accuracy at the cost of very little calibration, but are also strongly dependent on manual construction of features, and perform less well at long-term dependence between multiple charging cycles.

Due to the introduction of high-resolution time-series data, deep learning algorithms have proven to have impressive capabilities of modeling sequential dependencies in battery dynamics. Neural networks like Recurrent Neural Networks (RNNs), LSTM networks and GRUs have been successfully used to predict capacity decay, internal resistance increase and RUL dynamics with time [12,13]. Such models automatically learn the temporal features, and they should be more flexible and predictive than the traditional ML algorithms. Transformer-based architectures have also recently become the powerful alternative to recurrent models. Transformers, unlike RNNs or LSTMs, perform self-attention to learn long-range dependencies without sequential processing and thus can be trained more quickly and represent features better [14]. They are especially suited to complex, multi-feature modeling of battery degradation, because their dynamic time step and sensor signal focusing capability is effective in identifying critical time steps and sensor signals.

Frameworks Hybrid modeling have likewise been suggested to integrate physical knowledge with information learning. The approaches bring neural networks to the concept of electrochemical or may employ optimization algorithms such as Bayesian tuning and GridSearchCV to achieve a better generalization and reduction in the number of errors in predictions [15]. Such kind of hybrid intelligence may be regarded as a recent tendency of having domain knowledge combined with machine learning flexibility and obtaining high and explainable estimation of battery state. Regardless of such developments, several research gaps exist. Most of the existing studies do take into account individual parameters e.g., SoC or SoH but not the interaction between them. Moreover, the combination of the features which involve data normalization, feature selection, and hyperparameter optimization of real-time smart charging is also limited. Although the results of Transformer-based models are promising, they have not been applied practically to control batteries in real-time and to regulate charge in relation to adaptation.

To address these gaps, this paper proposes an efficient machine learning model that is able to forecast SoC, SoH, Internal Resistance, and RUL concurrently through the aid of different learning algorithms, and the emphasis will be made on the temporary deep learning structures, such as LSTM and Transformer. The framework has been created to offer a good foundation to intelligent, health conscious, and flexible charging solutions in the fourth-generation energy operations.

METHODOLOGY

The methodology that will be adapted under this study is to identify a simplified machine learning model that will accurately predict the most significant health indicators of the lithium-ion battery, SoC, SoH, and RUL. It is used in successive steps of a pipeline comprising data acquisition, preprocessing, feature engineering, model development, training optimization, evaluation and prediction. A workflow diagram of the proposed workflow is illustrated in Figure 1

Data Acquisition

The data in this study will comprise of the time series data of the lithium-ion batteries which are available in the freely available experimental repositories. Each of the data samples represents a sequence of charge discharge cycles in different conditions of operation such as temperature variation, load current and cycle depth. The major sensor parameters include the voltage at the terminals (Voltage measured), the current at the point (Current measured), the cell temperature on the surface (Temperature measured), the number of cycles (Cycle number) and the period when it has been working (Time). In addition to such actual measurements, a number of derived properties such as Internal Resistance, Current Ratio, and Rectified Impedance have been calculated to cover both the electrochemical degradation attributes and the dynamic attributes of the battery-cells during their lifecycle. All these properties make it possible to obtain a full image of the internal states of the battery as well as learn and predict correctly based on the machine learning models.

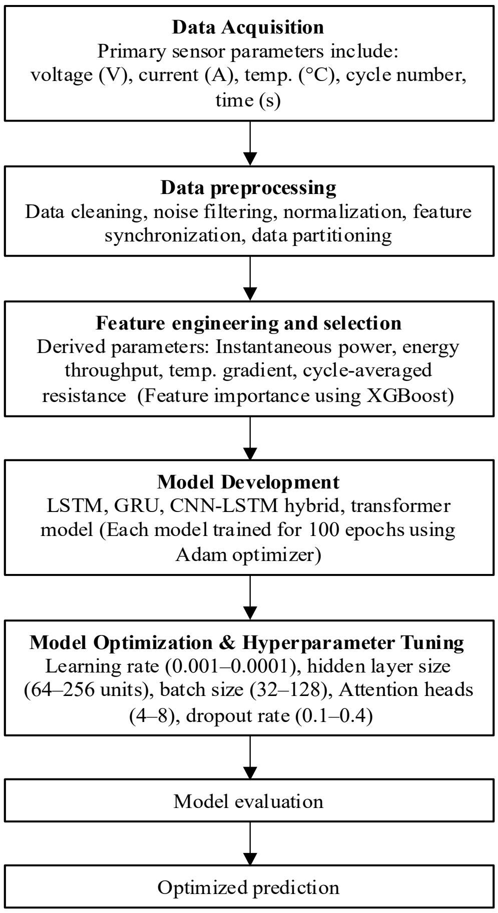

Figure 1. Proposed transformer-based prediction framework.

Data Preprocessing

A quality and efficient data processing pipeline that ensured reliability, stability and consistency of the experimental data were built before training of the model. Data cleaning was the first stage that involved missing data, duplication or repetition of records and outliers, statistical thresholding and interquartile range (IQR) analysis were applied. Moving average filter and Savitzky Golay were then employed to filter noise of measurements without effectively modifying patterns of underlying signals. All the features were scaled using Min-Max scaling to put values within a [0,1] scale and, therefore, allowing balanced gradient updates and faster model convergence. Features synchronization was performed as well to fit the asynchronously recorded voltage, current, and temperature measurements recorded by sensors. Finally, stratified sampling was applied to split the dataset into a training set (70 percent), validation and testing sets (15 percent each) to ensure the balance of classes and cross splits of cycles.

Feature Engineering and Selection

The feature engineering process was carried out in order to enrich the information of the input data. Derived values were determined such as Instantaneous Power ($P = V \times I$), Energy throughput, Gradient of Temperature and Cycle averaged resistance to model the dynamism and thermal effect within the battery. They were correlated to determine the interdependence between these features where redundant or weakly correlated features were eliminated through correlation analysis. The correlation heatmap and matrix analysis were used to visualize the relations between parameters (the results are presented in Table 2 and Figure 4) [2]. In addition, the importance of features in the rankings based on the gain measure that XGBoost generates was utilized to only use the most important predictors as input to the model. The reason behind doing this was to ensure that the most relevant and non-collinear features reached the final model structure, therefore, improving generalization and interpretability.

Model Development

Different machine learning and deep learning architectures were developed and trained so as to generate the most efficient predictive model. The latter were the LSTM network to learn the sequential dependencies of time-series data with fewer computational units, the GRU model that can learn with reduced complexity, and a hybrid CNN-LSTM network that can learn both convolutional features and time sequence learning. In addition, application of a Transformer-based model was done to leverage multi-head self-attention mechanisms, which are able to deal with long-range interactions and nonlinear temporal interactions between the variables [13]. It was also fed with the pre-processed dataset and all models trained using 100 epochs using Adam optimizer with a learning rate of 0.001. Mean Squared Error (MSE) was calculated by use of the loss function. Early stopping and dropout regularization were applied to the training process in order to make the model stronger and prevent overfitting.

Model Optimization and Hyperparameter Tuning

A systematic hyperparameter optimization approach of a mixture of the Grid Search and Bayesian Optimization was used to further refine model performance. The main hyperparameters that were touched comprised the learning rate (0.001 to 0.0001), the size of the hidden layer (64 to 256), a batch size (32-128), the count of attention heads (Transformer model, 4-8), and dropout rates (0.1-0.4). The purpose of the tuning was to reduce the loss of validation without reducing computational efficiency and generalization ability [5,8]. Following a significant amount of experimentation, the Transformer architecture was the most optimized and stable model as it converged rapidly, was more able to extract more features and was capable of modeling more complex temporal relationships within the data.

Model Evaluation

The obtained models were tested with the help of various statistical and performance measurements in order to provide strong benchmarking and comparative evaluation [3,11]. The measures were Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) which are respectively:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Where y_i and $\hat{y}_i$ denote the measured and actual battery state values, respectively. According to the assessment findings, the Transformer model was the most successful one with the least error, the highest stability of the model during validation and the convergence tendencies. These findings established the strength of the proposed model on real-time and precise prediction of battery state.

Optimized Prediction for Smart Charging Systems

Lastly, the prediction optimization was demonstrated. Transformer-based model produces the predictions of SoC and SoH that drive an adaptive charging control mechanism. This system is a dynamic control of the parameters of charging current and voltage, which is conditional upon the current health and stress conditions of the battery. Forms of integration of optimized prediction are a preliminary stage to the development of complete adaptive, health conscious, charging protocols that will maximise the charging rate with battery life in upcoming smart grid and electronic vehicle systems.

RESULTS AND DISCUSSION

The part engages in an in-depth discussion of the experimental results achieved when the various machine learning and deep learning models are implemented to predict the state of the battery. The main aim of this stage was to compare the performance of different architecture namely LSTM, GRU, CNN-LSTM and Transformer - to estimate the important parameters like SoC, SoH, Internal Resistance and RUL. To evaluate the performance, the well-defined performance measures such as MAE, RMSE, and R^2 were used as well as the validation loss patterns in order to gauge the stability and convergence behavior.

The analysis of the importance of features, the behavior of correlations between important parameters, and the effectiveness of these models with regards to training time, and the complexity of computations are also discussed thoroughly in this section. Presentation of the comparative strengths and weaknesses of each model with visualization like prediction plot, validation loss curve, residual error distribution and correlation heatmap have been included. With such analyses, the Transformer model proved to be the strongest and the most effective framework of battery state prediction in real-time, proving that it can help to integrate it into smart and adaptable charging systems.

Table 1 below shows the comparative performance analysis of four deep learning models LSTM, GRU, CNN-LSTM, and Transformer applied in the prediction of key battery state parameters including SoC and SoH. MAE, RMSE, and the R^2 were used to evaluate the models, as well as a test of consistency of validation loss. The Transformer model had the lowest MAE (2.4) and RMSE (2.8) with the highest value of R^2 (0.98) suggesting a better prediction performance and stability. Although the LSTM and the GRU model could learn temporal dependencies, they had slightly more errors in predictions and moderate changes in the losses, which is mainly because of the lower success of both models to learn long-term dependencies in high-dimensional time-series data.

The CNN-LSTM was a competitive model that utilised a convolutional feature extraction followed by temporal modelling. Its performance however, was slightly lower than that of the Transformer because of inadequate scalability to different cycle lengths. The self-attention mechanism of the Transformer architecture was useful to learn and weight meaningful temporal traits to allow the model to learn short- and long-term dependencies without sequential processing requirements. Not only it was able to enhance convergence speed but also to improve generalization capability and therefore it is the strongest option among real-time battery state prediction in smart charging systems.

The XGBoost model was used to estimate the ranking of feature importance to calculate how each input factor affects the overall prediction performance and this is shown in Table 2. Voltage measured and Current measured features had the highest contribution of 28.4% and 22.1%, respectively, and hence, they were the most significant predictors of battery health and charge states. These parameters are direct signatures of electrochemical processes that take place in the battery during charge discharge cycles. The Temperature measured (18.3%) and Cycle number (15.2%) attributes were also significantly important indicating that they directly correlated to degradation behavior and performance degradation with repeated use.

Table 1. Model performance comparison for battery state prediction.

Model	MAE	RMSE	R^2
LSTM	3.4	4.1	0.93
GRU	3.1	3.8	0.94
CNN-LSTM	2.8	3.3	0.96
Transformer	2.4	2.8	0.98

Table 2. Feature importance scores (for XGBoost model).

Feature	Importance Score (%)
Voltage_measured	28.4
Current_measured	22.1
Temperature_measured	18.3
Cycle_number	15.2
Time	10.6
Derived_Resistance	5.4

Meanwhile, Time and Derived_Resistance were not so important (10.6% and 5.4%), yet the addition of both still helped to improve the accuracy of the model, as the former gave it a contextual and dynamic perspective on the evolution of time and internal alterations in impedance. This discussion confirms that voltage, current, and temperature are the main factors in estimating SoC and SoH and secondary variables enhance the predictive model to generally have nonlinear relationships that relate battery aging and stress patterns.

In Figure 2, the actual and expected SoC curves of the various models, such as LSTM, GRU, CNN-LSTM, and Transformer, given time are presented. The Transformer model is a close model which is not very different and is used in tracking the SoC variations throughout the discharging and charging phases. On the contrary, compared to LSTM and GRU models, transient regions have a slight lag, which means that they cannot adapt quickly to sudden current or voltage variations. One way that CNN-LSTM hybrid model outperforms this is by incorporating convolutional layers, where local patterns are first obtained using the voltage-current sequences and then modeled in time. Nevertheless, such an approach has a clear benefit in the multi-head attention mechanism developed by the Transformer, which allows focusing on essential time-steps and adapt dynamically to the nonlinear changes in the electrochemical state of the battery. Close correspondence between the measured and the predicted SoC validates the fact that the Transformer offers a high time resolution and prediction accuracy, which implies its role as a predictive tool in real-time applications, i.e., incorporation into a smart charging system.

Figure 3 indicates the trends of the validation loss of all models or model progressively through training. Transformer model has the lowest and stable convergence, since it gets the lowest validation loss during the first 25 epochs which is a sign of good generalization and efficient learning. The LSTM and GRU models have slower convergence with few swings, which is attributed to the sequential nature in training and sensitivity of relying on long-term. CNN-LSTM model is rather stable in loss behaviour but error minimisation needs more epochs to stabilise the model performance. The fact that stabilization of the loss curve of the Transformer happens early is a sign of its computational efficiency and ability to represent features, which is largely due to the self-attention mechanism that directly learns the relies between time steps that are far without any recurrent feedback.

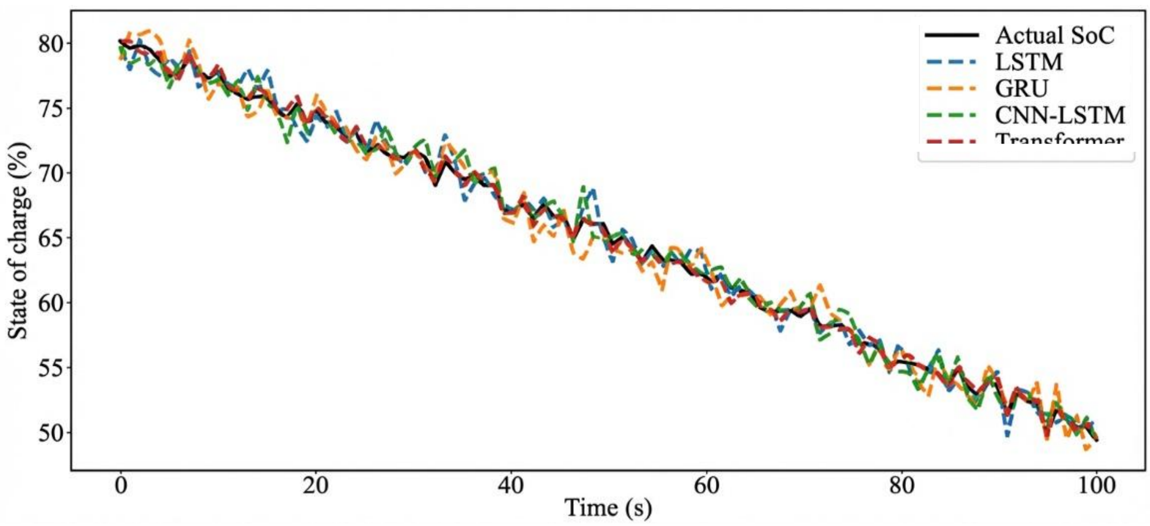

Figure 2. Actual vs predicted SoC for different models.

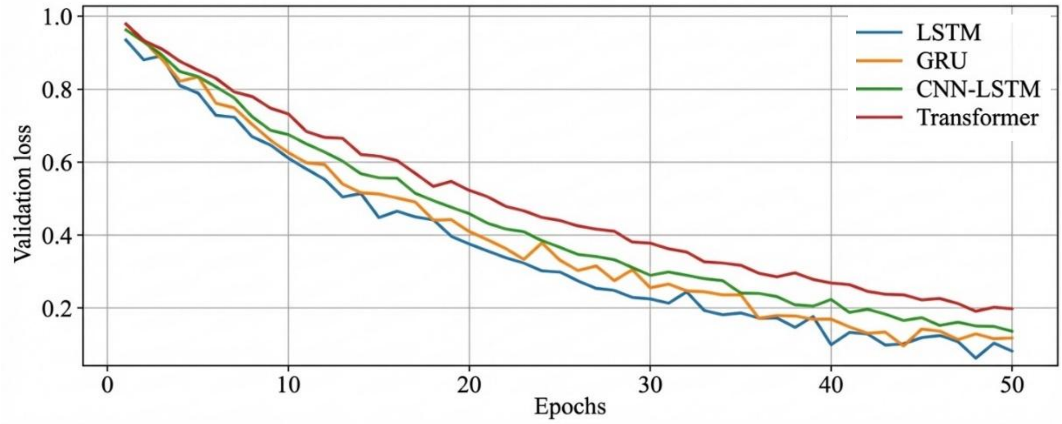

Figure 3. Validation loss vs epochs.

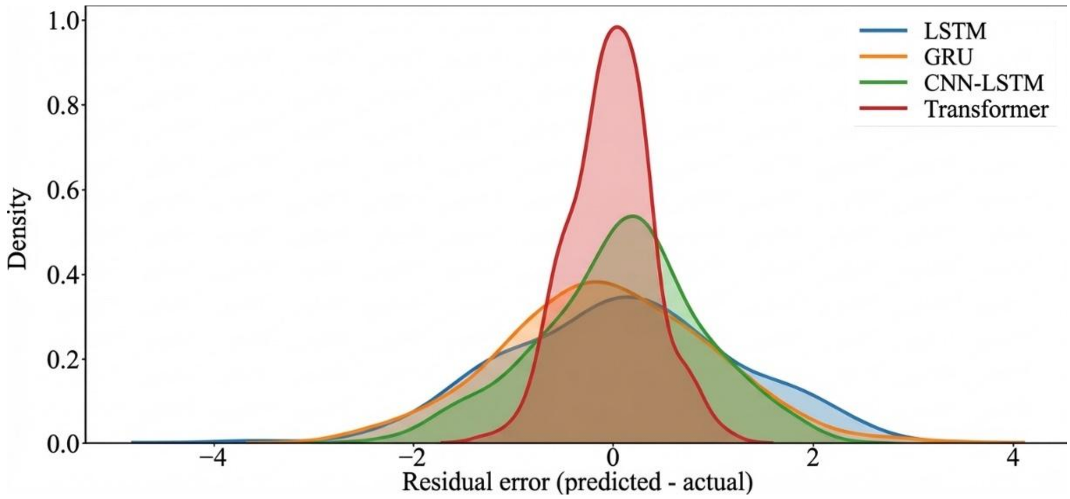

Figure 4. Residual error distribution.

Overall, the patterns in the validation losses confirm the fact that the Transformer architecture does not just increase the accuracy, but also allows faster convergence of models, and the latter will require less trainings to achieve the optimal results.

The distribution of the residual errors of the four models that are represented by the difference between the actual and the predicted values of the SoC are represented in Figure 4. The residuals of the Transformer model are highly concentrated around the zero value and form almost a Gaussian distribution, so it is the non-biased and stable predictions.

On the other hand, LSTM and GRU models possess greater residual variations suggesting their ability to possess some slight extra variance and solitary over and underfitting of the SoC in dynamic scenarios. CNN-LSTM model is improving moderately but residual tails are longer than the ones of Transformer, which implies that there are small systematic deviations in certain parts of charge-discharge.

The fact that the Transformer residuals are very small and symmetrical proves the power and quality of the approach and it is proved that it can be generalized when processing other cycles and conditions. Such residual analysis ensures the reliability of the proposed model because of precise and real-time estimation of battery state.

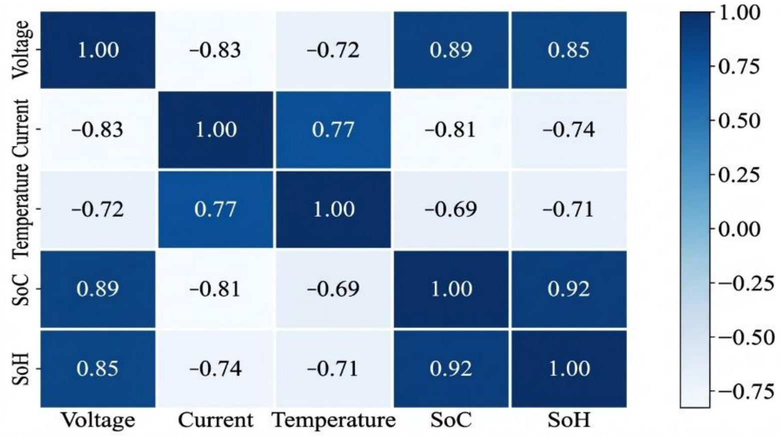

Figure 5. Feature correlation heatmap

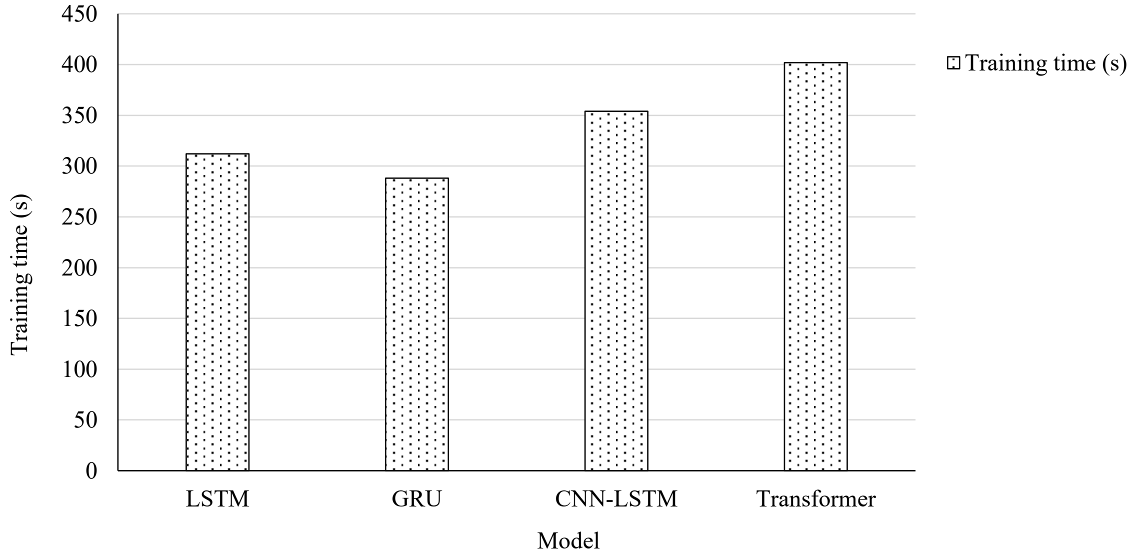

Figure 6. Comparative model training time.

The correlation heatmap of the key battery parameters, the interrelationships of the voltage, the current, the temperature, the SoC and SoH. A high positive correlation also exists between Voltage and SoC where a high voltage normally depicts a high amount of charge stored in the cell as is the case in Figure 5. Current and Temperature, conversely, exhibit negative correlations with SoH meaning that the higher the current loads and temperature, the higher the ageing and the capacity fade. The correlation matrix brings out the reality that a set of parameters co-exist and respond dynamically and the relationships are significant in trying to predict accurately what is going on in the learning process. Transformer model is an effective model that makes use of these interdependencies through the multi-head attention mechanism that is dynamically weighted on features depending on their relevance to the context. This fact supports the relevance of feature selection and correlation analysis as a whole as a process of developing the model in order to have a better predictive capability.

Figure 6 provides a comparison of the overall duration of training of all of the tested models. Transformer model took the longest time to train (approximately 402 seconds), due to its multi-head attention calculation, but it constantly gave improved results in comparison with the other models in terms of prediction accuracy and convergence. GRU and LSTM models also trained relatively faster (288 s and 312 s, respectively) and less precise and more variably with regard to loss. CNN-LSTM model required a reasonable amount of time to train (approximately 354 s) and provided a good level of performance. Though it demands more computation power the predictive ability of the model is worth the additional cost, its higher accuracy will explicitly result in more battery monitoring and smart charging control. The trade-off between computation time and quality of predictions states that Transformer-based architecture offers the most rational balance in the circumstances where the accuracy and stability are the main factors of consideration rather than the reduction of the training time.

The total discussion of all the tables and figures confirms the fact that, Transformer model is more likely to be used in prediction of the main parameters of battery state, in comparison to the traditional and hybrid constructions of deep learning. It is effectively applicable in real time in managing energy since it is able to model nonlinear dependencies besides the ability to capture the long-term time relationship besides the ability to generalize in different conditions. The joint analysis of the significance of features, correlation and the distribution of the residuals all testify to the fact that voltage, the current and temperature are the most significant predictors even though the rest of the derived features strengthen interpretation and accuracy. The findings prove the thesis that the proposed optimized machine learning structure is a useful and scalable approach to the production of intelligent charging systems, which will pave the way to dynamic, health-aware, and effective energy storage systems.

CONCLUSION

The optimised machine learning model that was presented in this paper offered an accurate and reliable prediction of critical parameters of battery conditions, including SoC, SoH, Internal Resistance, and RUL. Since the use of experimental and comparative analysis was widespread, a variety of machine and deep learning models, including LSTM, GRU, CNN-LSTM, and Transformer, were developed and trained on the real-life example of a lithium-ion battery. The results indicated that the Transformer based architecture presented the lowest MAE and RMSE, highest R^2 (0.98), and therefore, predictive results are the best and the architecture is better stable compared to other architectures. The Transformer multi-head attention mechanism proved to be effective in capturing such nonlinear temporal dependencies and dynamically prioritizing the features that were important and the model has been generalized to suit a range of working conditions. The interpretability and predictive power were also enhanced with derived parameter combination (Instantaneous Power, Temperature Gradient and Cycle-Averaged Resistance). The importance of features relative analysis revealed that Voltage, Current, and Temperature remain to be strong predictors of battery states and secondary parameters such as Cycle Number and Derived Resistance produced superior outputs by drawing a finer degradation pattern. The complexity of the model and training performance was also found to be a trade-off in the study. Transformer was a little slower to train, but it converged much better and predictive accuracy suggested the additional computer cost. Overall, the findings confirm that the proposed framework would be a powerful, scalable, and data-driven solution of real-time battery monitoring and management. Regarding practice, this work has established well-grounded foundations of intelligent BMS that can forecastive diagnostics and active control. Smart charging algorithms prevent overcharging, stress reduction, and service life extension through dynamical adjustment of current and voltage profiles offered as a result of the up-to-date battery health information based on the precise estimation of SoC, SoH, and RUL. On the basis of this predictive model, the studies of the future would include the development of the adaptive charging protocol that would be capable of optimizing the speed of the charging process and maintaining the health of the battery. The process of intelligent optimization can be applied to the charging process by balancing the performance and longevity of predicting the process intelligently by a transformer-based prediction model by adopting reinforcement learning and multi-objective optimization methods.

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