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RESEARCH ARTICLE

Optimally Tuned Gated Recurrent Unit Neural Network-Based State of Health Estimation Scheme for Lithium Ion Batteries

K. DHANANJAY RAO[1], N. VIJAYA ANAND[2], T. KRISHNA SAI PANDRAJU[3], FAISAL ALSAIF[4], (Member, IEEE), AND TAHA SELIM USTUN[5], (Member, IEEE)

[1]Department of Electrical and Electronics Engineering, Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada 520007, India
[2]Department of Electrical Electronics Engineering, PVP Siddhartha Institute of Technology, Vijayawada 520007, India
[3]Department of Electrical Electronic Engineering, Dhanekula Institute of Engineering and Technology, Vijayawada 521139, India
[4]Department of Electrical Engineering, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia
[5]Fukushima Renewable Energy Institute, AIST (FREA), Koriyama 963-0298, Japan

Corresponding authors: K. Dhananjay Rao (kdhananjayrao@gmail.com) and Taha Selim Ustun (selim.ustun@aist.go.jp)

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ABSTRACT The rapid advancements in electric vehicle technology have elevated the lithium-ion battery to the forefront as the paramount energy storage solution. The battery's health tends to deteriorate gradually as it ages. Due to the inevitable physiochemical reactions that take place inside the battery, it undergoes degradation and at a certain point, it becomes unserviceable. The battery degradation can be estimated using state of health (SOH). This paper employs data-driven techniques to estimate the state of health (SOH) of a battery. To estimate health parameters, a vast quantity of data, such as voltage, current, and temperature, is gathered from the NASA Prognostics Center of Excellence. The data is resampled using the superior Fourier Resampling method and then fed to a machine-learning algorithm. In this study, SOH estimation is carried out using three different machine-learning techniques i.e. Long Short Term Memory (LSTM), Deep Neural Networks (DNN), and Gated Recurrent Unit (GRU). However, the performance and accuracy of SOH estimation using these algorithms are highly dependent on hyperparameter tuning. Therefore, the optimal hyperparameter tuning has been adopted in the present work to reduce the time and complexity of the estimation. Further, the performance of various proposed techniques has been compared against each other using different performance indices such as root mean square error (RMSE), mean absolute error (MAE), and R-square error. GRU technique proved to be excelling with RMSE of 0.003, MAE of 0.003, and R-square error of 0.004 while estimating the SOH of various samples of batteries. This detailed analysis will be helpful for users to evaluate the performance of a battery and plan for maintenance accurately and effectively with minimum downtime.

INDEX TERMS Gated recurrent unit, lithium-ion battery, state of health, battery management system.

I. INTRODUCTION

Lithium-ion batteries are considered the main energy storage systems (ESS) in Electric Vehicles (EVs). These batteries are mainly used because of their high performance, energy density, high thermal tolerance and capacity, etc. However, Lithium-ion batteries (LIBs) are prone to the phenomenon called aging. The battery's performance or health decreases due to the repeated usage of the battery. Eventually, at a certain point in time, the battery becomes unserviceable. This is due to the inevitable physiochemical reactions taking place inside the battery [1]. These LIBs are subjected to harsh working environments that decrease the battery capacity and increase the internal resistance due to which there is a need to measure the battery's lifetime [2]. To protect the LIB, a Battery Management System (BMS) is required. A BMS

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enables the real-time monitoring of LIBs and protects them from unsafe conditions. A BMS is mainly used to measure the State of Charge (SOC) and state of health (SOH) of LIBs.

Moreover, it also provides temperature control and performs cell balancing across the cells [3], [4]. Among these factors, the State of Health (SOH) is the primary parameter defining battery degradation and influencing its performance. Therefore, accurate SOH estimation is a necessary factor to keep EVs safe and reliable [5]. From the definition of SOH, it can be said that the SOH value of a fresh battery is assumed to be 100%. When the battery is completely drained in an EV during discharging, the SOH value drops to about [70 – 80]% and therefore the battery capacity is nullified, making the battery unserviceable. Upon the State of Health (SOH) of the battery declining to the range of 70-80%, the battery undergoes degradation and ultimately reaches the End of Life (EOL) phase. The [70-80] % threshold limit is set based on the battery capacity.

Therefore, the EVs will not be able to meet the required power demand and further vehicle propulsion is not possible. Thus, the battery operating conditions should be maintained between [80–100] % SOH [6]. SOH estimation techniques are broadly categorized into direct measuring, model-based methods, and data-driven techniques. Each of these methods has its drawbacks as compared with the others [7], [8]. The direct measurement techniques are easy to evaluate and implement but the obtained value is less accurate as it is in an open loop configuration and based on the precision of the sensors [9]. The model-based methods and filter-based methods are easier to implement and give relatively high accuracy estimation of SOH but the computational time and complexity of these methods are high [10], [11], [12]. Lastly, data-driven methods, also known as machine-learning methods are currently in the spotlight. These methods make use of large amounts of data obtained through continuous experimentation of LIBs. These methods provide high accuracy and efficacy [13], [14].

Although it is easy to implement, the training of data requires more time. It also varies based on the battery data given as input, which has been considered under different operating conditions. Estimation of battery SOH and RUL using SVM, a powerful machine learning technique has been investigated in [15], in which the pre-processing of data has been done using the Fisher ratio. Here, for optimal parameter determination, a linear SVR kernel was used. In [16], a comprehensive deep-learning approach was showcased, which illustrated its suitability in accurately estimating the remaining useful life (RUL) of a battery. To assess the aging characteristics of the battery, a model has been created that focuses on the degradation of battery capacity. This model employs the Support Vector Regression (SVR) technique to estimate the Remaining Useful Life (RUL) of the battery.

To optimize the parameters of the Support Vector Regression (SVR), the Artificial Bee Colony (ABC) algorithm is utilized. This particular approach has been proven to yield higher levels of accuracy when compared to the Particle Swarm Optimization (PSO) method, as stated in [17]. In [18], using maximum available capacity, a back propagation neural network technique is used to calculate battery health. A three-layer Backpropagation (BP) neural network is employed for the training and testing of data. Subsequently, dynamic and static current profile tests are conducted to assess the model's accuracy. Further, an online LIB capacity estimation using deep convolutional neural networks (DCNN) model has been discussed [19], which automates feature learning from extensive charge data. The datasets required for SOH prediction in this paper were obtained from the Centre for Advanced Life Cycle Engineering (CALCE) and the National Aeronautics and Space Administration (NASA) [20]. The estimation of the battery State of Health (SOH) is accomplished through a fusion of the Markov Chain and Prior Knowledge Neural Network (PKNN). A PKNN model, enhanced with a Markov correction algorithm, was developed for accurate estimation. PKNN exhibits effective fitting for complex nonlinear problems, and the Markov correction minimizes prediction errors [21].

In [22], an autoencoder model was introduced for multi-dimensional feature extraction. For the estimation of the battery's State of Health (SOH), a multi-input Long Short-Term Memory (LSTM) model was employed. Additionally, various sequence lengths of input data were scrutinized to identify the optimal sequence length through a feedback process. In [23], a new auto LSTM-based method was implemented. A new method for tuning the hyperparameters of a neural network which involves hyper parameter reduction algorithm (HRA) is discussed. LSTM neural network with attention mechanism (ALSTM) has been proposed in [24] which uses an attention mechanism to select the proper LSTM hidden layer output states to improve the training efficiency. In addition to traditional methods, recently hybrid methods have shown more accurate results [25], a hybrid method consisting of DNN, LSTM, and CNN is utilized to predict the battery's remaining useful life (RUL). This method showed improved accuracy within an acceptable execution time. A typical LSTM model was developed in [26], which simultaneously predicts the values of the state of energy (SOE) and state of charge (SOC) of the battery at the same time.

Recently, gated recurrent unit (GRU) networks have proved to give superior results over other methods, SOH estimation was performed using the GRU-RNN model which gave more accuracy when compared to RNN [27]. In [28], a different method consisting of GRU and CNN which is called convolution-gated recurrent unit (CNN–GRU) showed relatively accurate estimations of the SOH of the battery when compared to CNN and RNN alone. In the expansive duration, the assessment of the State of Health (SOH) and Remaining Useful Life (RUL) for Lithium-Ion Batteries (LIBs) was meticulously examined. This thorough evaluation encompassed the utilization of a Time Delay Neural Net-

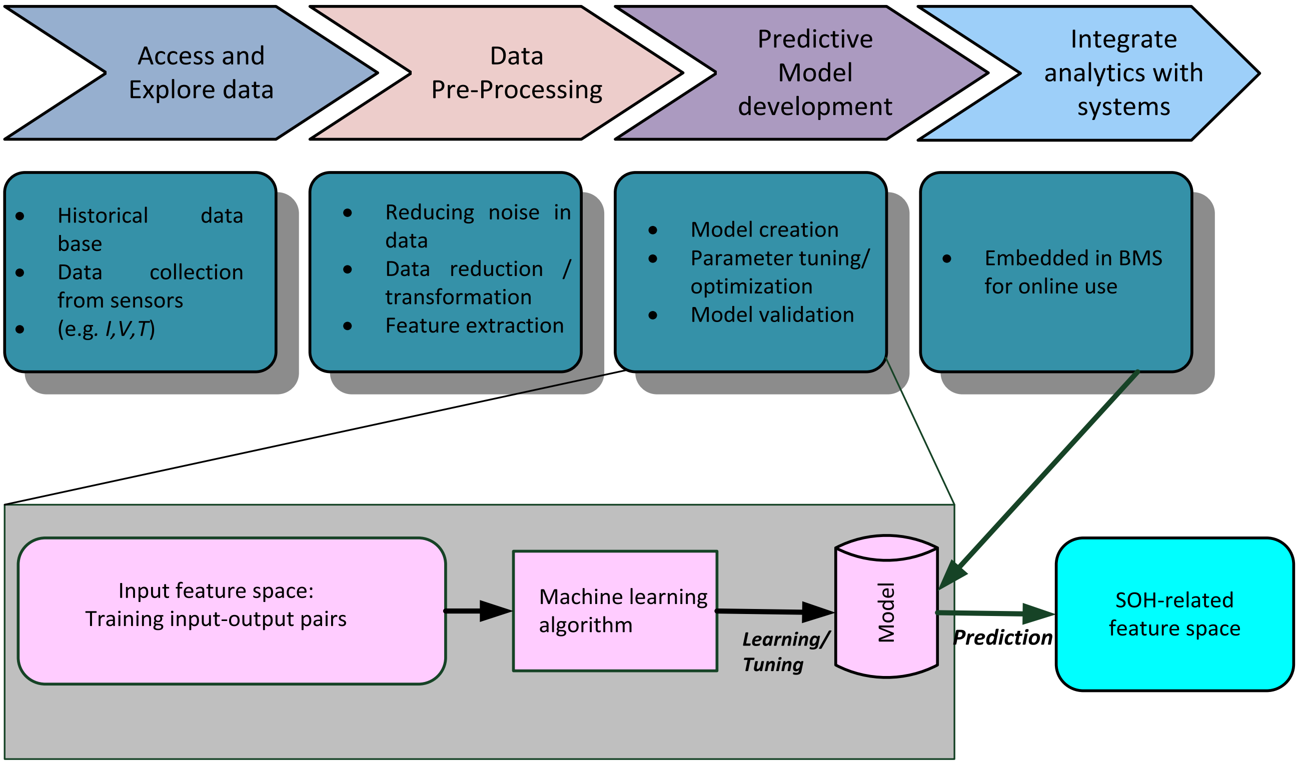

FIGURE 1. Machine learning-based SOH estimation steps for lithium-ion battery.

work (TDNN) and a Recurrent Neural Network (specifically, nonlinear autoregressive with external input, NARXRNN) to construct an advanced prognostic model that could accurately forecast the SOH for up to 30 cycles ahead. This model, as demonstrated in [29], demonstrated significant potential for improving the understanding and prediction of the health and longevity of LIBs. This method proved to be more accurate and yielded better results [30]. The SOH estimation approach which makes use of real-time driving patterns in a more practical environment has been done in [31], from a data-driven technique using sensible data about current, voltage, and temperature obtained from the Battery Management System (BMS). Offline learning on a server and real-time estimation of SOH on BMS is done.

From the above-discussed literature, it has been observed that many data-driven has been techniques employed in SOH estimation but very few papers only focused on accuracy and computation burden simultaneously. To overcome the above issue, the fourier transform-based GRU machine learning technique has been proposed and compared with other widely used machine learning techniques (long short-term memory (LSTM), deep neural networks (DNN)). To obtain the best results in terms of computational complexity and also to enhance precision, the present work incorporates an optimally tuned hyperparameter-based GRU technique. Different GRU hyperparameters such as layers and units, learning rate, dropout rate, batch size, and activation function has been tuned using GridSearchCV from scikit-learn.

From the comparative analysis, it has been observed that the proposed optimally tuned GRU technique provides better results in terms of accuracy and computation burden. This proposed technique further enhances the suitability of the real-time estimation of the SOH of any battery chemistry. The paper's primary contributions can be succinctly summarized as follows:

- The Fourier transform-based GRU technique has been adopted to estimate the health of the battery.
- Incremental capacity-based input datasets have been considered as input to GRU which mimics the realistic battery internal degradation factor such as battery chemistry and working conditions.
- An optimal hyperparameter tuning-based GRU technique has been proposed for accurate SOH estimation of the battery.
- The proposed battery health estimation technique has been tested and validated under different charging and discharging profiles.

The subsequent sections of the paper are structured as outlined below: Sections II and III delve into the discussion of feature extraction and machine learning-based techniques for State of Health (SOH) estimation. Section IV discusses the analysis and discussion of the results. Final section V highlights the conclusion of the work.

II. FEATURE EXTRACTION AND ESTIMATION STEPS

Raw data cannot be given as input data to a neural network. This is because raw data usually consists of noises, duplicate or missing values, and is generally inconsistent. The data usually comes from unknown heterogeneous origins so it needs to be formatted. In this regard, the first step in creating a machine-learning model is the preprocessing of data. Preprocessing of data is essential for cleaning and filtering data before feeding it to a machine-learning model. If we do not apply to preprocess and feed the raw data directly, then the estimated result quality is poor. Therefore, to obtain good-quality results, a better preprocessing technique is required.

In this regard, a well-defined resampling using the Fourier Transforms (FT) technique is used. This technique works faster and more efficiently than traditional techniques. As we know, the input data is inconsistent and consists of different sampling lengths. The sampling size of the data may differ. Hence, to decrease the data sampling size, the FT method is employed. The FT resampling technique has certain merits, in which, flexibility is the main advantage. One more merit is that the neural network made with this method can be used to find the SOH of all kinds of batteries.

The Fourier transforms function $x(N)$ can be represented as

$$X^{(N)}(p) = \sum_{n=0}^{N-1} x_n e^{\frac{-j2\pi kn}{N}} \tag{1}$$

where $p = 0, 1, 2, \ldots, N$-1

Therefore, the input data consisting of voltage, current, and temperature values first undergo the FT preprocessing. This enables faster sampling of data given to the neural network.

The fundamental steps to estimate the SOH of the battery are elucidated in Fig. 1. The first phase is to gather information or dataset collection. However, sometimes the collected datasets may not be relevant to provide cell aging information. In this regard, the second phase demonstrates the feature extraction technique (Fourier transform) to monitor the aging mechanism of the battery exactly. In the third phase, the proposed machine learning models undergo training to extract features of LIB. After the training of the developed machine-learning model, in the final phase, it has been implemented for online BMS applications. Further, accurate and reliable feature extraction plays a pivotal role in SOH estimation. The provision of more meaningful and accurate input training data for training the developed machine learning models will yield more relevant predictions for the State of Health (SOH). Under the real-time setting, the voltage, current, and temperature data (depicted in Fig.2) have been recorded at NASA Ames Center during the charging and discharging of LIB and used as inputs for machine learning-based model training [20].

Initially, the battery cell was subjected to the process of charging in the mode of constant current (CC) at a rate of 1.5 A until the battery voltage had reached the threshold value of 4.2 V. Following this initial charging phase, the process transitioned smoothly into the mode of constant voltage (CV), where it continued until the charge current had gradually diminished to a significantly lower value of 20 mA. In order to provide a visual representation of the charging process, Fig. 2 was included, which showcases the curves depicting the changes in terminal voltage, temperature, and current throughout the entire charging process. Additionally, in order to provide further insight into the behavior of the battery during the discharging process, Fig. 3 was included, which illustrates the curves representing the variations in current, terminal voltage, and temperature at different levels of State of Health (SOH). It is important to note that the ICA technique, which stands for independent component analysis, proves to be an exceedingly effective tool for the purpose of analyzing the electrochemical dynamical behavior of LIB, otherwise known as Lithium-Ion Batteries [10]. Especially more focused on analyzing the lithium intercalation process and staging phenomena. In this regard, Capacity fade was observed by ICA curves. Further, the ICA curves have been obtained using (2). Differentiating the battery charging/discharging capacity by voltage leads to the ICA approach. Mathematically, ICA is denoted as

$$ICA = \frac{dQ}{dV}, \left[\frac{Ah}{V}\right] \tag{2}$$

To obtain the ICA curves to study the degradation process in battery, information about battery charging/discharging voltage, current, and time is required. The ICA curves during charging and discharging (Fig. 2(d) and Fig. 3(d)) have been used as one of the input features for training the proposed neural network technique. The value of the IC peaks will decrease with respect to the loss of active material (LAM). The occurrence of chemistry change (CC) may affect the intensity of the IC peaks and accordingly, new peaks may enter. When a battery is under-discharged (UD) or under-charged (UC), the IC peak will move to a broader range during battery degradation.

In the range of 3–3.2 V and 3.3–3.6 V (Fig. 2(d)), the intensity of IC peaks decreases as the degradation of SOH increases. This signifies that loss of active material (LAM) occurs during aging. The IC peaks between 3–3.2 V and 3.3–3.6 V move toward the right with the battery aging. The increase of polarization, or simply the increase of impedance, results in this phenomenon.

III. GATED RECURRENT UNIT MODEL FOR SOH ESTIMATION

In this section, the GRU technique has been formulated and discussed in detail.

A. GATED RECURRENT UNIT

Gated Recurrent Unit (GRU) networks are proposed to overcome the problem of long-term dependencies in RNNs. In terms of training, GRUs are rather faster to train. GRU is considered an improved version of RNN and LSTMs. GRU uses gates similar to an LSTM to control the stream or flow of information [32]. Unlike LSTM, a GRU typically consists of only two gates. The Gated Recurrent Unit (GRU) comprises an update gate, which governs the extent of information to be transmitted, and a reset gate, responsible for identifying information that can be omitted or forgotten. The eq. (3) and

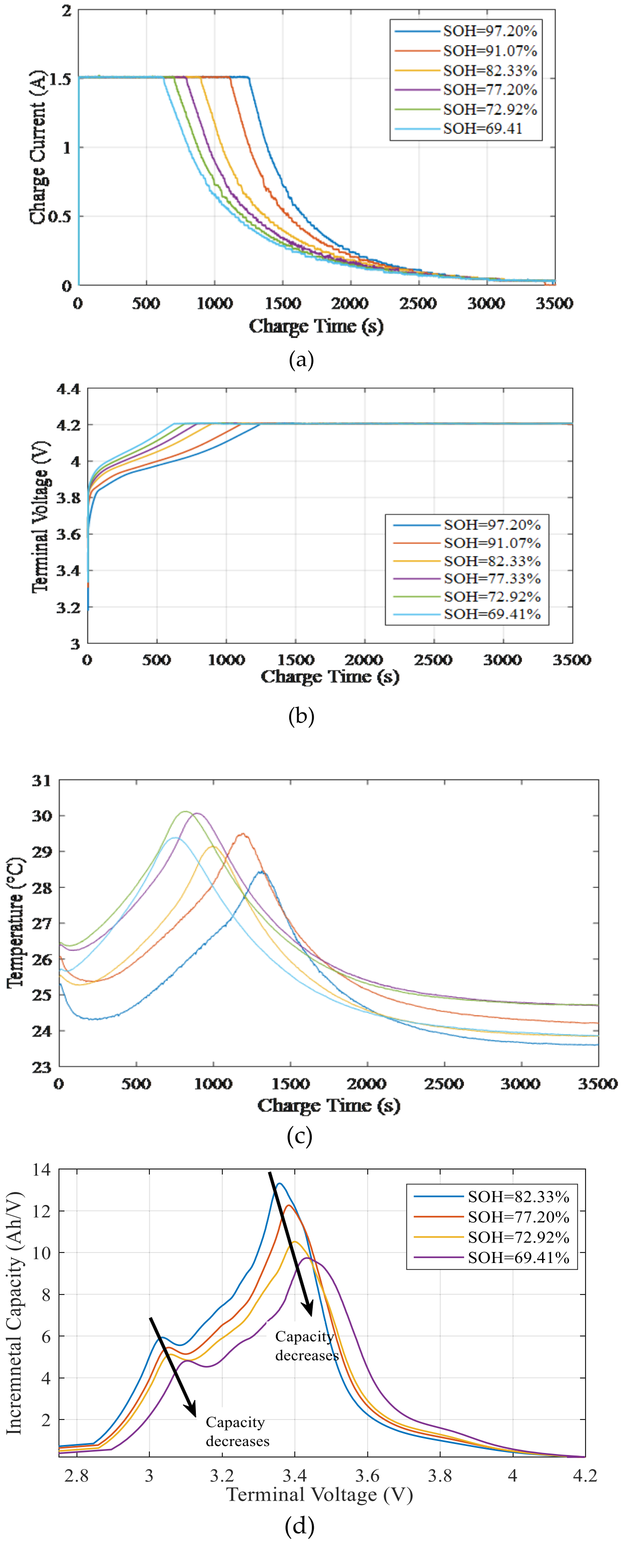

FIGURE 2. **Battery charging curves under different SOH (a) Current (b) Terminal voltage (c) Temperature and (d) ICA curve.**

eq. (4) represent the update gate and reset gate respectively.

$$r_t = \sigma(X_t * U_t + H_{t-1} * W_r) \tag{3}$$
$$u_t = \sigma(X_t * U_u + H_{t-1} * W_u) \tag{4}$$

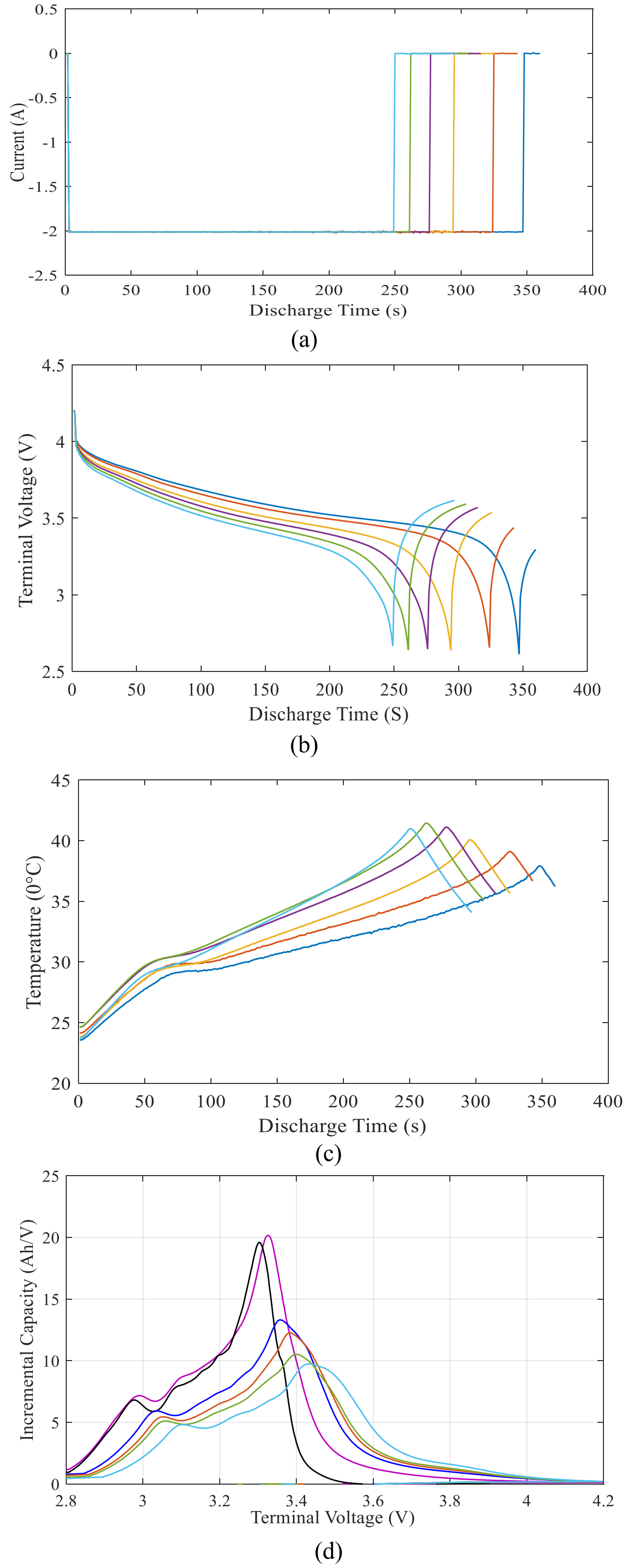

FIGURE 3. **Battery discharging curves under different SOH (a) Current (b) Terminal voltage (c) Temperature and d) ICA curve.**

The functioning of the Gated Recurrent Unit (GRU) comprises two steps, as illustrated in Figure 4. In the initial step,

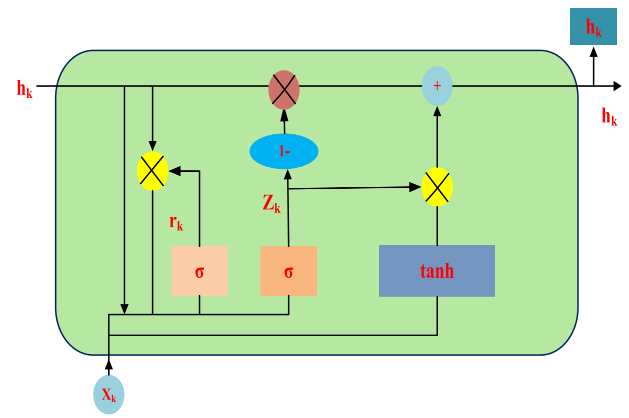

FIGURE 4. Architecture of a typical GRU.

a candidate hidden state $\hat{H}_t$ is generated. This is achieved by multiplying the input and the hidden state from the previous time instance with the output of the reset gate Rt. then, it is passed through the tanh layer. This can be observed from the equation (5).

$$\hat{H}_t = \tanh(X_t * U_p + (r_t \circ H_{t-1}) * W_p) \tag{5}$$
$$H_t = U_t \circ H_{t-1} + (1 - U_t) \circ \hat{H}_t \tag{6}$$

The candidate's hidden state, as derived from equation (5), is employed for computing the present hidden state Ht. The advantage of Gated Recurrent Unit (GRU) over Long Short-Term Memory (LSTM) lies in the utilization of a singular gate, specifically the update gate, which controls the information flow from both the previous hidden state and the candidate hidden state. This observation is reflected in the corresponding equation (6) [28].

IV. RESULT ANALYSIS AND DISCUSSION

A. DATA COLLECTION

The dataset required for the machine-learning model is obtained from the NASA Ames Prognostics Centre of Excellence. The battery used is 18,650 LIB's. In this process, a set of four lithium batteries 5, 6, 7, and 18 were taken. The data acquisition involved subjecting these batteries to two distinct operational profiles, encompassing discharge and charge cycles, under ambient temperature conditions. The charging of these batteries was carried under constant current (CC) mode at 1.5A until the voltage of the battery reached 4.2V. Subsequently, it proceeded in the constant voltage (CV) mode until the charge current descended to approximately 20 mA. The discharge test was conducted in Constant Current (CC) mode at a rate of 2A, persisting until the battery voltage reached 2.7V, 2.5V, 2.2V, and 2.5V for batteries 5, 6, 7, and 18, respectively. The experiments concluded upon reaching the End-of-Life (EOL) condition of the batteries. This is the condition when their capacities faded by 30% of the rated capacity (2 Ahr to 1.4 Ahr).

B. EVALUATION CRITERIA

The GRU-based technique (discussed in section III) is used to evaluate the SOH of the battery and compared with wisely used techniques. To quantify the performance of the proposed technique error analysis has been carried out. The performance indications are provided using the below techniques: Root Mean Square Error (RMSE): It is employed to provide insight into the error analysis of the SOH estimation. This can be obtained from the below formula

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{m}(SOH_{estimated} - SOH_{actual})^2} \tag{7}$$

Estimated SOH error value: The variance between the actual State of Health (SOH) value and the predicted SOH value can be calculated using the following formula (8)

$$SOH_{errors} = |SOH_{estimated} - SOH_{actual}| \tag{8}$$

Coefficient of determination (R^2) error: This is used to measure the extent to which the estimated value matches the actual value and is obtained using (9).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(SOH_{actual}(i) - SOH_{estimated}(i))^2}{\sum_{i=1}^{n}(SOH_{actual}(i) - SOH_{estimated}(i))^2} \tag{9}$$

C. RESULTS DISCUSSION

The raw data, which is distinguished by its unequal lengths, is not appropriate for being directly inputted into the neural network model. Consequently, to address this issue, the input data is subjected to resampling using the Fast Fourier resampling method (discussed in section II), which has been extensively described in the preceding section. To demonstrate the effectiveness of utilizing the Fourier resampling method, the eight battery datasets obtained from NASA are thoroughly examined. This evaluation aims to highlight the superiority of the Fourier resampling method when applied to the DNN, LSTM, and GRU models. Several hyperparameters have been tuned to enhance the model's performance, including the number of GRU layers and units, learning rate, dropout rate, batch size, and activation function. Hyperparameter tuning using GridSearchCV from scikit-learn.

GridSearchCV is a function that exhaustively searches over a given parameter space to find the optimal set of hyperparameters for a given estimator. A comparative analysis between these methods has been carried out and evaluated using different performance indices such as RMSE MAE and R square errors. Fig. 5(a) gives the analysis of different methods of DNN, LSTM, and GRU for battery 5. It can be seen that the results provide an accurate estimated value of SOH. The figure clearly illustrates the improved consistency of the estimated value when compared to the actual State of Health (SOH) value.

To study the robustness and efficacy of the proposed GRU technique, a comparative study among different machine

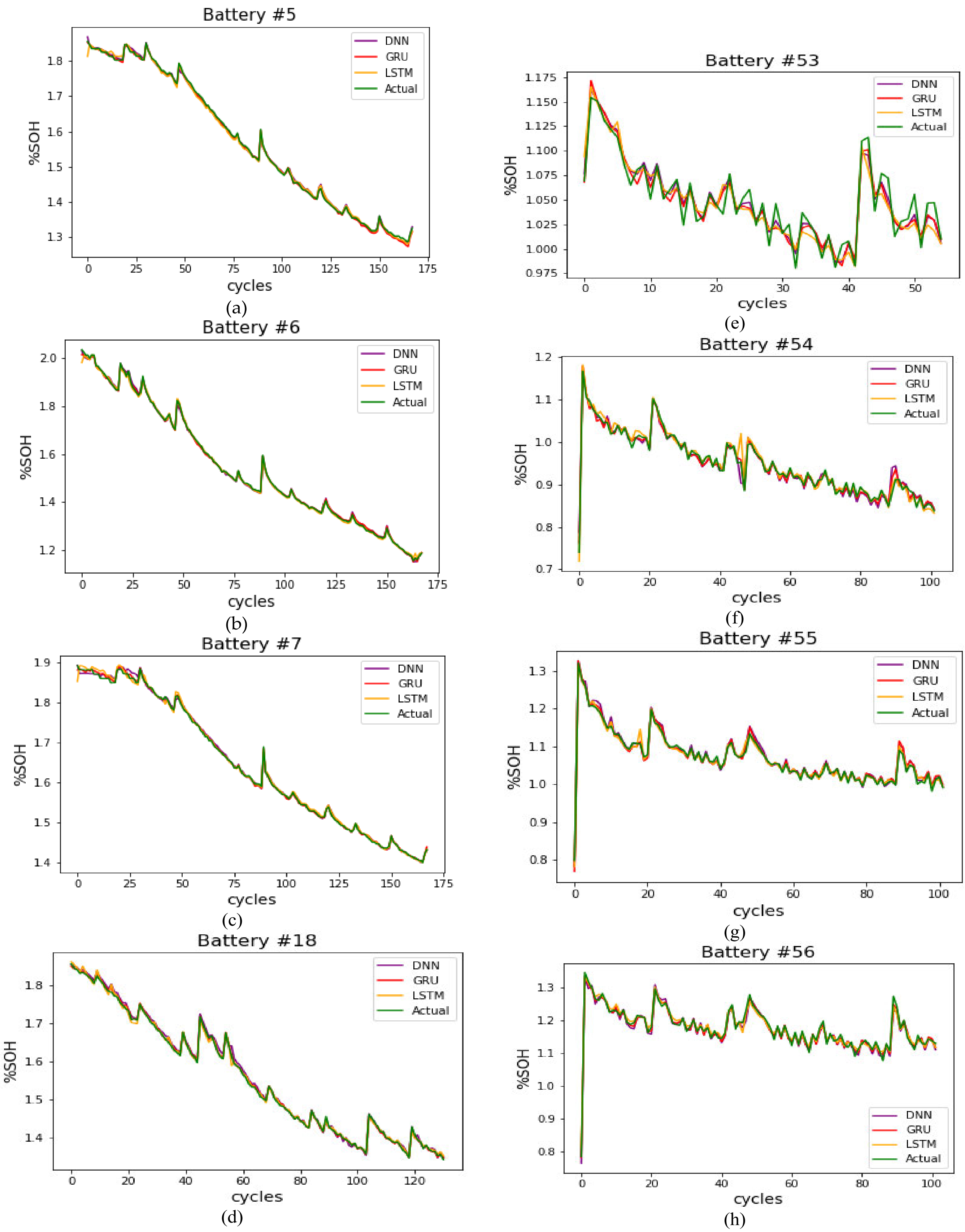

FIGURE 5. Comparative analysis of different Machine Learning Techniques (a) – (h).

TABLE 1. Various performance indices (DNN, LSTM, and GRU) in the case of batteries #5, #6, #7, #18.

	Battery #5			Battery #6			Battery #7			Battery #18		
Method	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
DNN	0.006	0.004	0.999	0.007	0.005	0.999	0.006	0.004	0.999	0.008	0.006	0.998
LSTM	0.007	0.005	0.999	0.007	0.005	0.999	0.006	0.004	0.998	0.006	0.004	0.998
GRU	0.004	0.004	0.999	0.005	0.004	1.000	0.004	0.003	0.999	0.003	0.003	1.000

TABLE 2. Various performance indices (DNN, LSTM, and GRU) in the case of batteries #53, #54, #55, #56.

	Battery #53			Battery #54			Battery #55			Battery #56		
Method	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
DNN	0.011	0.009	0.928	0.013	0.009	0.966	0.008	0.006	0.988	0.012	0.01	0.967
LSTM	0.015	0.013	0.859	0.011	0.008	0.978	0.008	0.006	0.987	0.012	0.01	0.961
GRU	0.013	0.010	0.902	0.010	0.007	0.982	0.008	0.006	0.988	0.009	0.008	0.98

learning techniques, namely the DNN, GRU, and LSTM models, in estimating the SOH for various batteries (B6, B7, B18 B53, B54, B55, and B56) has been carried out. Table 1 presents the findings that can be derived from the examination of various machine learning models. According to the results, the deep neural network (DNN) model yielded a root mean square error (RMSE) value of 0.006. On the other hand, the gated recurrent unit (GRU) model demonstrated a smaller RMSE value of 0.004. Lastly, the long short-term memory (LSTM) model produced an RMSE value of 0.007 for battery 5. For the same battery, the error analysis has been carried out using other error indices such as MAE and R^2 as depicted in Table 1. From error analysis, it has been observed that GRU provides the best results as compared to other widely used machine learning techniques.

Further, to verify the efficacy of the proposed technique (GRU), the error analysis has been carried out for various battery sets and it has been observed that the proposed technique outperforms well. One important factor that contributed to the reduction of error values in the GRU model was the implementation of local normalization. This technique played a significant role in enhancing the accuracy of the estimated value. Figure 6(a-d) and Table 1, it can be observed that the low value of error indices indicates that the proposed Gated Recurrent Unit (GRU) technique performs significantly better when compared to other techniques such as Deep Neural Network (DNN) and Long Short-Term Memory (LSTM). To validate the effectiveness of the proposed techniques, they have been thoroughly tested and evaluated on additional batteries, namely batteries B6, B7, B18, B53, B54, B55, and B56.

The graphical representation in Fig. 5(b) to Fig. 5(h) demonstrates that GRU surpasses DNN and LSTM in terms of accuracy by closely tracking the actual State of Health (SOH). Furthermore, the insightful analysis provided by Table 1 and Table 2 clearly shows that the SOH error indices (RMSE and R2) are significantly lower in the case of GRU as compared to the widely used techniques, namely DNN and LSTM, when applied to different batteries (B5, B6, B7, B18, B53, B54, B55, and B56). Further, the Fig. 6(e to h), it becomes evident that the GRU exhibits the minimum error and is remarkably close to a value of zero. It can be noted that the training time for the GRU is the shortest, as mentioned earlier. This showcases that the overall computational burden of the proposed GRU is significantly low. Based on the aforementioned analysis, a keen observation can be made that the accuracy of State of Health (SOH) estimation is superior for each battery when compared to other widely utilized techniques. The amalgamation of the GRU method with the Fourier resampling technique has proven to be highly efficient and effective, surpassing the majority of existing hybrid models that require extensive training times. Upon further analysis, it has been observed that for real-time SOH estimation, the GRU model utilizing the Fourier resampling technique would be both cost-effective and impactful for Electric Vehicles (EVs) powered by lithium-ion batteries. Finally, consideration of hyperparameter tuning of the proposed technique reduces the time and complexity of the estimation as depicted in Table 3.

To assess computation cost and performance, two commonly employed metrics, namely floating-point operations per second (FLOPs) and run-time for all models, are employed. FLOPs, which gauge the number of operations executed per second for a trained model, serve as a reliable indicator that showcases the intricacy of a model. The lesser number of FLOPS in the proposed technique depicts that the proposed GRU technique is computationally efficient.

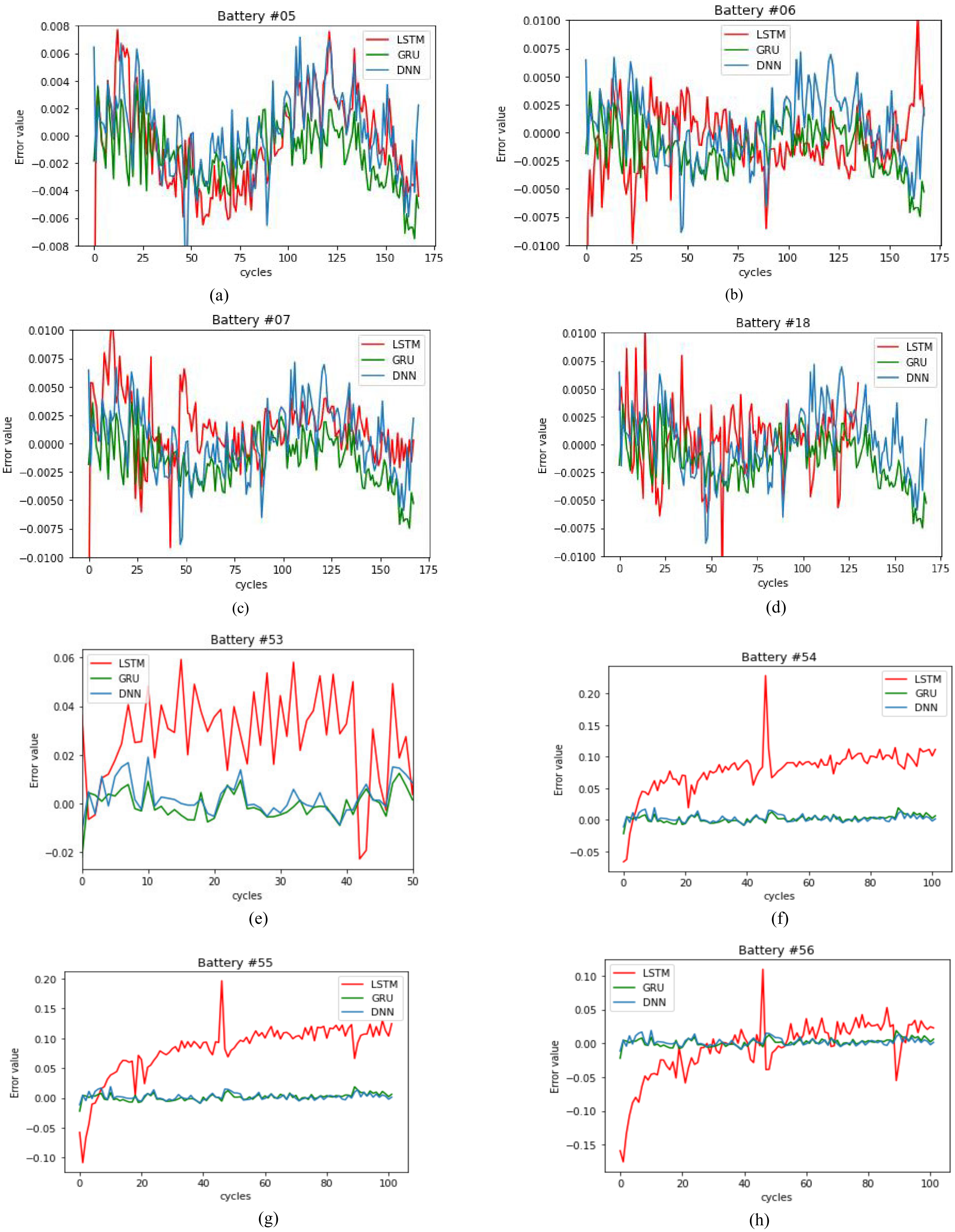

FIGURE 6. Error analysis of various batteries.

TABLE 3. Computation costs for different techniques.

Model	Run Time (s)	FLOPs
GRU	0.0589	1297
LSTM	0.10680	1344
DNN	0.2087	1378

V. CONCLUSION

State of health estimation of battery is a challenging part and currently, there are no existing real-time meters for measuring SOH. This paper introduces a novel state-of-the-art technique employing a Gated Recurrent Unit (GRU) in conjunction with the Fourier resampling technique for the estimation of the State of Health (SOH) in lithium-ion batteries. Further, hyperparameters of the proposed GRU model have been tuned to enhance overall prediction accuracy. Three distinct methodologies (GRU, LSTM and DNN) were assessed for the estimation SOH of the battery. Based on the results, it is evident that among the three methods, the Gated Recurrent Unit (GRU) method exhibits superiority, delivering more accurate results. Due to insufficient data for batteries 53 and 54, the results gave more error values and showed less accuracy. Due to the usage of Fourier resampling and the addition of local normalization, the accuracy increased. Batteries B5, B6, B7, B18, B53, B54, B55, and B56 gave almost close to actual values with a minimum error of RMSE of 0.003, MAE of 0.003, and R-square error of 0.004. Thus, for practical purposes, optimally tuned GRU gives more efficacy than the LSTM and DNN methods. The real-time data captured from the Battery Management System (BMS) has been validated using the proposed technique due to its less computational time. The lesser computational time and higher accuracy depict that the proposed GRU-based technique is highly recommended for real-time health indication of battery. The limitation of the present work may include that the performance of GRU-based models can be sensitive to the choice of Hyperparameters. Suboptimal hyperparameter selection may lead to subpar model performance or increased vulnerability to overfitting. Also, the proposed model lacks the inclusion of physics-informed machine learning models to enhance the efficacy of health prediction. To overcome the above limitations, future work includes exploring the fusion of multiple modalities of data, including electrical, electrochemical, and physical data, to capture a more comprehensive understanding of battery behavior. This can involve combining data from multiple sensors and sources to improve the accuracy and robustness of SoH estimation. Also, one can focus on developing the techniques for online learning and adaptation that allow the model to continuously update and improve its predictions as new data becomes available. This would enable real-time monitoring and proactive maintenance.

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K. DHANANJAY RAO received the B.Tech. degree in electrical and electronics engineering from the Biju Patnaik University of Technology, India, the master's degree in electrical engineering from Jadavpur University, Kolkata, India, and the Ph.D. degree in electrical engineering from the National Institute of Technology (NIT), Raipur, India. He is currently an Assistant Professor with Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada, India. His research interests include modeling different energy storage systems (especially lithium-ion batteries and supercapacitors), state estimation, system identification, battery management systems, and electric vehicles.

N. VIJAYA ANAND received the M.E. degree in electrical and electronics engineering from Andhra University, Visakhapatnam, India, in 2002, and the Ph.D. degree in electrical and electronics engineering form JNTU Kakinada, Kakinada, in 2019. He is currently an Associate Professor with the Electrical Engineering Department, PVP Siddhartha Institute of Technology, Vijayawada, India. His research interests include high power converter design and control, EV chargers, and transportation electrification.

T. KRISHNA SAI PANDRAJU received the B.Tech. degree in electrical and electronics engineering from Jawaharlal Nehru Technological University Hyderabad, Hyderabad, in 2008, and the M.Tech. degree in power electronics and electric drives from the Vignan Engineering College (now known as Vignan University), Jawaharlal Nehru Technological University, Guntur, in 2011. He is currently an Research Scholar with the Department of Electrical and Electronics Engineering, Faculty of Engineering, CHRIST (Deemed to be University), Bangalore, Karnataka, India. He is currently an Assistant Professor with the Department of Electrical and Electronics Engineering, Dhanekula Institute of Engineering and Technology, Ganguru, Vijayawada, affiliated by JNTU Kakinada, Andhra Pradesh, India. His research interests include electric power distribution systems with Volt/VAr controls and power system optimization with heuristic algorithms, neural networks and fuzzy logic applications to power electronics, and electrical drive.

FAISAL ALSAIF (Member, IEEE) received the B.Sc. degree in electrical engineering from King Saud University, Riyadh, Saudi Arabia, in 2014, and the M.A.Sc. and Ph.D. degrees in electrical engineering from The Ohio State University, Columbus, OH, USA, in 2017 and 2022, respectively. He is currently an Assistant Professor with the Department of Electrical Engineering, College of Engineering, King Saud University, Riyadh, Saudi Arabia. His research interests include power and energy, power electronics, high voltage, smart grids, and power quality improvement.

TAHA SELIM USTUN (Member, IEEE) received the Ph.D. degree in electrical engineering from Victoria University, Melbourne, VIC, Australia. He is currently a Researcher with the Fukushima Renewable Energy Institute (FREA), National Institute of Advanced Industrial Science and Technology (AIST), where he leads the Smart Grid Cybersecurity Laboratory. Before that, he was a Faculty Member with the School of Electrical and Computer Engineering, Carnegie Mellon University, Pittsburgh, PA, USA. He has been invited to run specialist courses in Africa, India, and China. His research has attracted funding from prestigious programs in Japan, Australia, Europe, and North America. His current research interests include power systems protection, communication in power networks, distributed generation, microgrids, electric vehicle integration, and cybersecurity in smart grids. He is a member of the IEC Renewable Energy Management WG8 and IEC TC 57 WG17. He has delivered talks at Qatar Foundation, the World Energy Council, the Waterloo Global Science Initiative, and European Union Energy Initiative (EUEI). He also serves on the Editorial Board for IEEE ACCESS, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, *Energies*, *Electronics*, *The Electricity Journal*, *World Electric Vehicle Journal*, and *Information*.