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Advanced State of Health Prediction for Lithium-Ion Batteries Using Capacity Estimation and Feed-Forward Neural Networks: A Machine Learning Approach

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Abstract: - Accurate SOH estimation is a critical goal in pursuing the safe use of lithium-ion batteries. This article uses a novel Feed-Forward Neural Network approach based on a capacity estimation method for SOH prediction. In addition, the algorithm utilized was created using Matlab® 2023 software and proposes a Feed-Forward Neural Network method to predict the battery ageing process. This article employed experimental data from the NASA PCoE Research Center to determine and compare the Actual State of Health (SoHs) and Predicted State of Health (SoHs) during battery charge and discharge cycles. The validity of the algorithm was determined by the effects of cell degradation by comparing the Machine Learning methods and, by simulating and comparing the results of the Training, Validation, and Test curves, algorithm was tested. Finally, the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Percentage Error (RMSPE) errors demonstrated that the simulations conducted in this paper correctly represent the state of degradation of the batteries and confirm the results and the validity of the Feed-Forward Neural Networks suggested.

Keywords: Electric vehicles, FFN algorithm, lithium-ion systems, state of health, Machine Learning method.

I. INTRODUCTION

Wearable electronics have experienced rapid growth in recent years, where wearable devices such as smartwatches and fitness trackers have become widespread. As a result, the development of batteries used to power such devices has become increasingly urgent. Over the years, the development of more efficient and reliable batteries has become a very complex and expensive problem, but battery health monitoring can help to solve this problem. When used in electric vehicles, monitoring the health status of the traction batteries can increase the safety of the car and extend the life of the battery. The State of Health is an important indicator of the safety and availability of the traction battery pack. As the number of charge-discharge cycles increases for lithium-ion batteries, the State of Health decreases, decreasing the performance of the battery and increasing the temperature rise and voltage difference between the batteries, which reduces the lifetime of the whole pack. The State of Health is difficult to measure because the performance of the battery pack is affected by many tests, which also have high costs due to the large number of batteries and long time, and substantially limits the application of the battery system. Therefore, the detection and estimation of the State of Health under the condition of minimal cost and limited information has become important research. Existing State of Health estimation methods can be divided into two main categories: experiment-based methods and model-based methods. The model-based method can predict the battery properties according to the model of the battery and is crucial for various applications, including electric vehicles and energy storage systems. These methods primarily focus on accurately estimating the State of Charge (SOC) and predicting the Remaining Useful Life (RUL) of the batteries. Some model-based methods used for lithium-ion batteries are shown below. Leiva's 2020 paper summarizes the most popular theoretical and computational techniques used to model lithium-ion batteries and suggests some future challenges in the field. It discusses the use of methods such as Monte Carlo, multiscale models and phase field models, highlighting the importance of these tools in understanding the operation and ageing of batteries [1]. An overview of lithium-ion battery modelling methodologies was offered by Ji in 2024, divided into mechanism-based models and data-driven models. The author here explores the integration of mechanical information with data-driven methods to improve battery design and operational optimization [2]. Smith in his study in 2017 evaluated various models of lithium-ion batteries based on their accuracy, complexity, and physical interpretability. An initial classification into physical, empirical and abstract models is introduced, with a comparative analysis of their performance [3]. A comprehensive overview of lithium-ion battery ageing modelling methods is offered by Ali in his 2023 paper. The author took a multiscale approach, examining these methods at the particle, cell, and battery pack levels [4]. Finally, Tu, in his article in 2021, proposed two new frameworks to integrate physics-based models with machine learning, to achieve high-precision modelling of lithium-ion batteries. The author highlighted the importance of informing

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the machine learning model with the state information of the physical model [5]. These methods can estimate the State of Health of the battery using underpinning mechanisms in a simple, fast, and accurate model and do not require a large amount of expensive data. However, these have the problem of being based on design leakage, which cannot capture the true situation. The experiment-based method is based on a dataset collected by the capacity test, and compared with the actual health trend, the prediction results are more accurate. Promi in his article written in 2024 discusses the fundamental material chemistries used in lithium-ion batteries for electric vehicles, focusing on how material-level properties affect the electrochemical performance of the battery. The author explored in his study innovative material design strategies to improve energy density, safety, stability, and fast charging capabilities [6]. The use of electrochemical impedance spectroscopy (EIS) to understand charge storage mechanisms in lithium-ion batteries is explored in Gaberšček's paper in 2021. The author in his study emphasized the importance of improved experimental design and advanced data analysis using physics-based models [7]. Zhang in his paper in 2024 highlights promising experimental and simulation methods for understanding the interaction between the various components of lithium-ion batteries, to design knowledge-based training processes [8]. Finally, Smith in 2024 compared the single-sine method, currently the most widely used for lithium-ion battery diagnostics, with innovative methods using, for example, the fast Fourier transform or battery excitation via pseudo-random sequences [9]. However, in the experiment-based method compared with experiments in the accurate State of Health range, long cycle times are used, which increases the cost of the model, and the State of Health is limited over a wide range, which can only be used for a small range of State of Health. Experiment-based methods and model-based methods have been replaced by more innovative techniques including Machine Learning. Valizadeh in his 2024 paper explored the practical applications, challenges, and emerging trends of the use of machine learning in lithium-ion battery research [10]. The limitations of single-particle (SP) models using machine learning to improve predictive accuracy were expressed during the Olugbade study in 2024 [11]. Finally, Tu in his article in 2023 described integrating physics-based models with machine learning to improve accuracy and predictive efficiency [12]. Important Machine Learning techniques have been used for the calculation of the SOC and SOH of lithium-ion batteries. In particular, Marri in his paper compares different machine learning strategies, including multiple linear regression, polynomial regression, support vector regression (SVR), and random forest, for estimating the state of health (SOH) of lithium-ion batteries. The article highlights how SVR produced the best results, followed closely by multiple linear regression [13]. A comparative evaluation of various machine learning regression algorithms, including Support Vector Machine, Neural Network, Ensemble Method, and Gaussian Process Regression, to model the complex relationship between real-time driving data and battery state of charge (SOC) was carried out by Pranav in 2024. The author has shown that Gaussian process regression has demonstrated superior precision [14]. A new method of preprocessing using relative state of charge (SoC) was proposed by Zhang in 2023. The author described a hybrid learning model (HLM) combining ARIMA, GRU, and CNN for predicting the state of health (SOH) of lithium-ion batteries [15]. Finally, Li in his study proposes an improved firefly algorithm to optimize the particle filter algorithm, to improve the accuracy of state-of-charge (SOC) and state-of-health (SOH) estimation of lithium-ion batteries [16]. The primary goal of this article is to explore the importance of lithium-ion (Li-ion) batteries, which are extensively utilized in various applications such as electric vehicles (EVs)[19, 20, 21, 22, 23, 24], plug-in hybrid electric vehicles (PHEVs) [25, 26, 27, 28], grid power systems [29, 30, 31, 32], and unmanned aerial vehicle (UAV) technology [33, 34, 35, 36], owing to their impressive energy and power density. Notably, it addresses the critical issue of capacity deterioration that occurs after approximately 500 cycles of charge or discharge. To ensure the safe utilization of Li-ion batteries, accurate state of health (SOH) estimation is essential. This article emphasizes the necessity of real-time SOH prediction, as the estimation is crucial for battery management systems. To achieve this, the paper presents a methodology for determining SOH based on the cell's capacity through a feedforward neural network, a form of machine learning [37, 38, 39, 40, 41]. The findings illustrate that the proposed approach successfully estimates SOH with a Mean Absolute Percentage Error (MAPE) and a Root Mean Squared Percentage Error (RMSPE) below 1% for the total number of cycles, demonstrating its efficacy across all four battery varieties. As electric vehicles are widely used in the world, the lifetime of the battery used in electric vehicles is becoming increasingly important. The model of state-of-charge and state-of-health of the lithium-ion battery used in the electric vehicle was presented to estimate the accuracy of the ageing estimation with machine learning. The model of the state of charge reflects that the risk of abnormal cell events such as swelling and heat generation increases as the battery degrades. The prediction model uses the energy application dataset to verify the impact of ageing on the lithium-ion battery. The research verification is only verified through energy applications. Further, it can combine actual use data to adjust the parameters of the battery SOH prediction model, which can be more accurately applied to the battery. The lithium-ion battery in the electric vehicle predicts the remaining useful life. This study proposes a more accurate method of state-of-health of the battery life of the lithium-ion battery. This work aims to evaluate and optimize the performance of the Feedforward Neural Network machine learning algorithm using a dataset. In addition, classification and regression techniques were compared. In this research, the Performance Test dataset, which shows the conditions of the batteries, was used, and the 186 lithium-ion cells show three different states. The evaluation metric for all classification machine learning algorithms' success is calculated from accuracy and precision. Additionally, the performance of the regression machine learning algorithm was evaluated using R-squared, Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Percentage Error (RMSPE). According to the experimental results, the success of the machine learning algorithms with several different approaches indicates that the proposed algorithm is a required step for lithium-ion batteries. In particular, state-of-charge or state-of-health estimation for batteries must be calculated with a large data size, and it should be optimized as much as possible for real-life applications. Otherwise, many researchers need to preprocess and analyze features for battery experiments. Also, it will be hard to decide on a comparative algorithm choice from the machine learning algorithms. This work mainly focuses on evaluating and comparing the different Feedforward Neural Network machine learning algorithms used for portable backup lithium-ion batteries. Additionally, the resultant data provide comparisons of rechargeable batteries at different state-of-charge and ageing levels. This article is divided into the following chapters:

Chapter 2 will deal with the State of Health Estimation in Lithium-Ion Batteries;
Chapter 3 will address in detail the methodology of the FNN algorithm;
Chapter 4 will describe the results obtained;
Chapter 5 will describe SOH calculation results;
Chapter 6 will deal with the comparison with Existing Methods;
Finally, chapter 7 will report the conclusions.

II. STATE OF HEALTH ESTIMATION IN LITHIUM-ION BATTERIES

State of Health (SOH) and State of Charge (SOC) are crucial in the Battery Management System (BMS). In the infrastructure-less environment of battery management, the state of health is even more important, and the estimation accuracy is also directly related to the lifecycle and safety of the battery. With the rapid development of machine learning, the data-driven FNN method is one of the advanced methods to estimate the state of health. Considering the profound influence of electrode temperature on SOH estimation, an improved FNN state-of-health prediction method is proposed. Firstly, the relationships among electrode temperature, internal resistance, and state of health are investigated. Utilizing the influence of the electrode temperature, both the model prediction part and the SOH-related temperature recognition part are optimized. The experimental results show that the developed method can accurately analyze and estimate the state of health at any state of charge, using only voltage data without additional input. Accurate state of health (SOH) prediction is required for realizing long-term battery health in applications. State of charge (SOC) estimation accuracy and the simplicity of the model are some of the important aspects of accurate SOH prediction. Currently, most of the studies focus on predicting the SOH at the end of life and have a strong dependence on temperature and current data. These two sources of information are not always available in many applications where medium-term applications rely on consumer use. There is a strong need to develop models that can predict battery SOH based on the information available in consumer devices. Hybrid SOH models are a new category of models for the state of health that has attracted recent attention. However, they do require cell-specific information. The stage best suited to obtain this information occurs at the cell manufacturing level, before manufacturing products with the cells. Accurate and easy-to-implement models that do not rely on complex calculations or additional data are still required.

2.1 Machine Learning in Battery Health Monitoring

Lithium-ion batteries play a crucial role in electric vehicles, energy storage, and consumer electronics. Given their high cost and the importance of ensuring both safety and long lifespan, effective battery health monitoring is essential. Machine learning can greatly aid in predictive modelling and decision-making, helping to optimize performance and safety. Traditional methods often rely on physics-based models that treat batteries as uniform systems, which fail to capture their internal complexities or account for varied usage. Furthermore, battery degradation involves nonlinear processes and complex interactions, which remain poorly understood and difficult to model. This challenge is compounded by operational variability and the high costs of gathering detailed performance data. Monitoring and accurately assessing battery health also present difficulties, underlining the need for advanced analytical techniques. Machine learning can address these issues by improving our understanding of these complex systems, leading to better battery management. Feedforward neural networks (FNNs) are a pathway to the successful use of machine learning methods, especially in this example case of lithium-ion battery monitoring for a range of industries from electric vehicles and renewable energy storage to consumer electronics. Given the soaring cost of large-scale battery systems, as well as increasingly stringent requirements for safety and lifetime optimization, this has driven strong demand for accurate and effective battery health monitoring solutions. This means incorporating FNNs for predictive analysis as well as performance prediction and business decision support, thus boosting workplace productivity and functionality. Conventional approaches mostly use simple physics-based models, which consider batteries as homogeneous processes. But, these models ignore the reality of how users use those systems in widely varying ways. The underlying mechanisms of battery degradation are nonlinear and affected by a myriad of complex interactions, most of which are not well understood. The complexity of the battery system is compounded by a wide range of operational conditions and the whole variety of user protocols it encounters, not to mention the high cost of systematic data acquisition on full lithium-ion battery performance. Similarly, correctly detecting and measuring the physical state and health of Lithium-Ion batteries remains a considerable challenge with advanced analytics methods essential. By having improved models to better understand these complex systems, FNNs can play an essential role in enabling battery management strategies that are not only more efficient and accurate at mimicking the real behaviour of batteries but also durable enough, to extend the safe operation of battery technologies.

2.2 Dataset description

For the experiments, we adopt the NASA PCoE Research Center dataset [Alice Cervellieri, 2024 A] which is commonly used to evaluate SOH estimation methods. This dataset includes batteries' information collected at several values of temperature and cycle of charge and discharge conditions for each temperature. The input parameters are extracted from the NASA Dataset for Battery B0005. These are the capacity in the case of discharge, the cycle for integral current in the case of discharge, cycle for the capacity in the case of discharge. In this work, the author used experimental data from NASA PCoE Research Center to perform important simulations. The process consists of using the discharging phase to calculate the capacity and predict the SOH of lithium-ion battery B0005 of Dataset NASA Research Center.

2.3 Capacity Estimation Methods

The methods used to estimate the capacity are key to the operation of a Battery Management System (BMS) in infrastructure-less environments. The fact that the life cycle of the battery or even more is at stake makes accuracy in these estimation methods critical. In recent years, Advanced machine learning models like Feedforward neural network (FNN) and data-driven approaches have become the more advanced choices for predicting battery capacity as well due to development in predictive modelling techniques. Given the crucial effect of electrode temperature on capacity estimations, an improved FNN-enabled method is proposed to improve the prediction of capacity. The approach started with an investigation of the complex interplay between electrode temperature, internal resistance and battery capacity. The predictive model and the capacity temperature recognition components are tuned according to the effects of electrode temperature. Experimental results show that this technique provides a method for accurate SOH analysis and quantification under a variety of states of health using only the voltage measurements, without the need for additional inputs. Figure 1, Figure 2, and Figure 3 show the capacity of batteries B0005, B0006, and B0007 in function of cycles, under temperatures of 24°C. The reader can see that, for distinct cycles, capacity exhibits large differences. Moreover, for the same cycle, the values of the features also show substantial discrepancies.

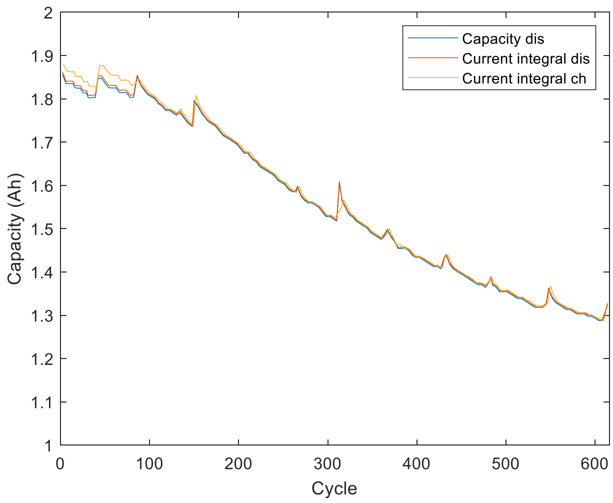

Figure 1. Trend of Capacity (Ah) as a function of Cycle for battery B0005.

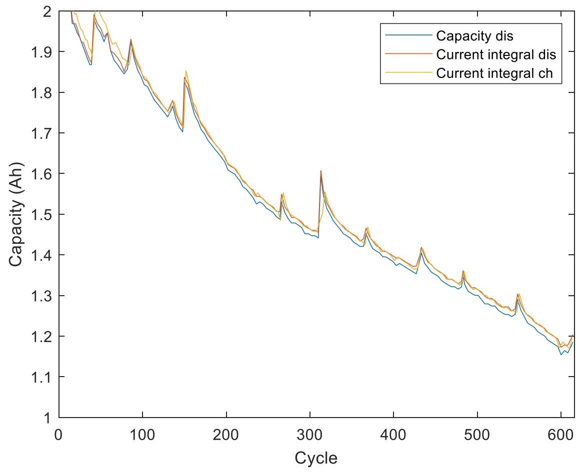

Figure 2. Trend of Capacity (Ah) as a function of Cycle for battery B0006.

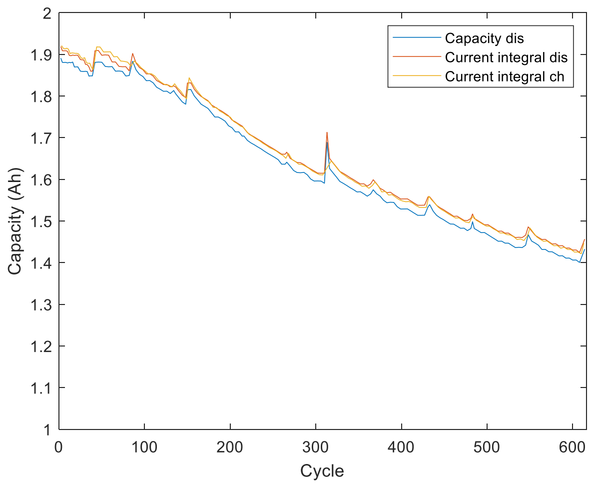

Figure 3. Trend of Capacity (Ah) as a function of Cycle for battery B0007.

III. METHODOLOGY

The network architecture comprises two hidden layers with 50 neurons and one output layer. The Trigger function is characterized by the ReLU function and Linear activation. Hidden layers use the Rectified Linear Unit (ReLU) function. The output layer has a linear activation function ('purelin'). When it comes to splitting data, the data is automatically split into. The splits of the data are done and provided as training (80%), validation (10%) and test (10%) set. The operation of the FFN algorithm is composed of several sequential phases. In the initial phase of the Forward Pass, the input data is transmitted through the network. The product of inputs and weights is calculated, bias is added, and the activation function is applied. The output of the final layer is associated with the target values (SOH). The second phase relates to the calculation of the Error, in which the difference between the expected output and the real one is determined. The third phase concerns the establishment of the Weights. The weights are revised using the BR optimization algorithm. The fourth phase is the process of iteration. The author repeated this phase for the number of epochs required or until a convergence criterion is established. The FFN model was developed by MATLAB® 2023. Figure 4 represents the proposed neural network architecture with an input layer composed of three parameters, that are the current_measured, the voltage_measured and the temperature_measure. In Figure 4 it is possible to see also 2 hidden layers with 50 neurons and one output layer. The author has created a multi-layer perceptron (MLP), which is integral to the Feedforward Neural Network (FNN) algorithm. Standard multi-layer perceptrons, with their multiple layers of interconnected nodes, possess the capability to approximate any measurable function with the desired level of accuracy and are here used for calculating the State of Health (SOH) of lithium-ion batteries. Their characteristics make them particularly effective in modelling the complex, nonlinear relationships inherent in battery health diagnostics. The author has used MLP structure to predict the SOH of lithium-ion batteries with high precision The accuracy of the approximation depends on the size and sufficient number of hidden layers. From considerations made mathematically, it is evident that the more complicated standard multilayer perceptrons can easily approximate any measurable function. The author used it for its ability to model the complex, nonlinear relationships inherent in battery state diagnostics. The prediction of the SOH of LIBs was carried out by the author by adopting the FNN algorithm with MLP structure for its accuracy so that an accurate study of the cell lifetime could be carried out.

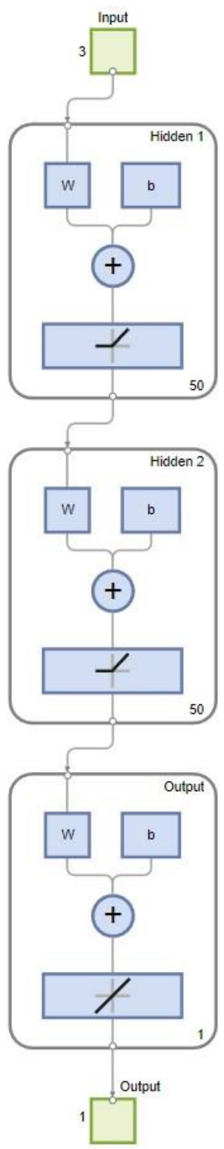

Figure 4. Diagram of the algorithm of Machine Learning

3.1 Characteristic of FNN

This paper investigates and studies the high-overall performance residences of Feed-forward Neural Networks (FNN) in estimating capability in addition to predicting the State of Health (SOH) of lithium-ion battery systems. This representation focuses on the key features of FNN like inputs, hidden layers, outputs, learning algorithms, transfer functions, training processes, architecture epochs, weights biases neurons activation functions and prediction ability using a graphical dataset as an exemplar for review. The primary aim of this paper is to reduce and simplify the numerous parameters and elements within feedforward neural networks applied for predicting SOH of lithium-ion battery systems. Dataset Representation allows a better understanding of the Network, and how data propagates along with information flow. In conclusion, the modular flow representation of FNN provides baseline explanatory groundwork to fellow researchers, scholars, scientists, and students in this domain that mislays the differentiation point for adopting machine learning through an FNN approach. A feedforward neural network is interpreted as a connected graph of a sequence of different layers as visible in Figure 4. It is a simple feed-forward neural network which consists of the connected single-layer perceptions. We review some of the characteristics of feedforward neural networks, like inputs, architecture, hidden layers, learning algorithms, transfer functions used in units in hidden and output layers and training process including epoch. In this research, the development environment, which facilitates the developer with various libraries, datasets, and algorithms, is exploited for implementing the various machine learning models and approaches. The various machine learning models are implemented using machine learning algorithms and trained with a suitable dataset of expected inputs and outputs. After that, the prediction task with new inputs is revealed, and the prediction capability and accuracy desired are attained with FNN. The mathematical equations for all the functions, output layer, hidden layers and Feedforward Neural Network (FFN) input layer are mentioned down in the code.

Input Layer:

Let x be the input vector: $x = [x_1, x_2, ..., x_n]^T$ where n is the number of input features.

1. **Hidden Layers:** For each hidden layer l (l = 1, 2 in our case):

a) Calculation of input to the layer:

$$z^{(l)} = W^{(l)}a^{(l-1)} + b^{(l)} \quad (1)$$

Where:

- $W^{(l)}$ is the matrix of weights for layer l
- $a^{(l-1)}$ is the output of the previous layer (for l=1, $a^{(0)} = x$)
- $b^{(l)}$ is the bias vector for layer l

b) Application of the ReLU activation function:

$$a^{(l)} = \text{ReLU}(z^{(l)})\text{ReLU}(z) = \max(0, z) \quad (2)$$

Mathematically, for each neuron i in layer l:

$$a^{(l)}{}_i = \max\left(0, \sum_j W_{ij}^l a_j^{l-1} + b_i^l\right) \quad (3)$$

2. **Output Layer: For the output layer (layer 3 in our case):**

a) Calculation of input to the layer:

$$z^3 = W^3 a^2 + b^3 \quad (4)$$

b) Application of the linear activation function:

$$y = \text{purelin}(z^{(3)}) = z^{(3)} \quad (5)$$

Where y is the final output of the network (the prediction of the SOH in our case).

3. **Leakage Function:**

The loss function used is typically the mean square error (MSE):

$$L = \left(\frac{1}{m}\right)\sum_i (y_i - \hat{y}_i)^2 \quad (6)$$

Where:

- m is the number of samples
- y_i is the actual value (SOH)
- $\hat{y}_i$ is the predicted value

4. **Bayesian regularization:**

The Bayesian Regularization (BR) training algorithm was used by the author in the algorithm of this paper to train the feedforward neural network. The objective of this choice was to predict the State of Health (SOH) of the lithium-ion battery cell. BR has several advantages including improving generalization and avoiding the phenomenon of overfitting in neural networks. In this way, BR can keep the net weights small.

The objective function with Bayesian regularization is:

$$F = \beta * ED + \alpha * EW \quad (7)$$

Where:

- ED is the mean square error on the data
- EW is the sum of the squares of the network weights
- α and β are regularization parameters determined automatically

5. **Specific Formulas for Each Layer:**

Input Layer:

$$a^0 = x \quad (8)$$

First Hidden Layer (l=1):

$$z^1 = W^{(1)x} + b^1 a^1 = ReLU(z^1) \quad (9)$$

Second Hidden Layer (l=2):

$$z^2 = W^{(2)a^1} + b^2 a^2 = ReLU(z^2) \quad (10)$$

Output Layer (l=3):

$$z^3 = W^{(3)a^2} + b^3 y = z^3 \quad (11)$$

6. **Size of Matrices**

- W^1: 50 x n (n is the number of input features)
- W^2 : 50 x 50
- W^3 : 1 x 50
- b^1, b^2 : vectors 50 x 1
- b^3 : scalar

7. **Final Prediction:**

$$y = W^3 * ReLU\left(W^2 * ReLU\left(W^{(1)x} + b^1\right) + b^2\right) + b^3 \quad (12)$$

The mathematical formulas described above completely developed the flow data through the neural network and concerned the input layer, the two hidden layers, and the output layer. Bayesian regularization is also used to add a layer of complexity to the optimization process, preventing overfitting and improving model generalization. The Bayesian regularization algorithm was applied by the author to train the feedforward neural network and predict the SOH of the battery. The training process consists of familiarizing with the discharge capacity, cycle numbers and other related data that constitute the inputs (X) for the SOH prediction (target data). The training goal would be to minimize a modified objective function that balances the network's ability to predict SOH with the simplicity of its topology. The author used Bayesian regularization to produce a robust model for predicting battery health with minimal tendency to overfit, which is essential for reliable estimation of battery health in various applications.

IV. Results

In this article, researchers have used an FFN neural network to predict the SOH of the cells. Input data taken from Dataset NASA has been considered for model development. The system was trained based on the Levenberg-Marquard backpropagation algorithm. The Levenberg-Marquard algorithm is used particularly for neural networks. It combines the advantages of the Gauss-Neuton algorithm and gradient descent. This algorithm has several advantages that make it preferable to backpropagation methods in several key ways. Firstly, LM blends the Gauss-Newton algorithm and gradient descent. This hybrid approach allows it to switch between the two methods depending on the situation optimizing both speed and accuracy. Secondly, LM is generally faster than standard gradient descent methods. It converges more quickly, especially for small to medium-sized networks. Thirdly, LM has higher memory requirements. It needs to store and manipulate large matrices. The algorithm adjusts the learning rate dynamically. When the solution is far from the optimal, it behaves like gradient descent and when it is close, it acts more like the Gauss-Network methods. In this article, this adaptability was used to efficiently find the optimal solution, in particular, LM minimizes the sum of square errors. NASA datasets for batteries #5,#6,#7, and #18 were simulated with the use of the FFN model. Figures 5, 6, 7, and 8 illustrate summary R2 plots in training, test and validation stages during training for NASA Prognostics Centre of Excellence PCoE batteries B0005, B0006, B0007, and B0018. Researchers have trained the neural network and confirmed it using the results of the simulations and the Scientific Literature with a dataset from NASA PCoE Research Center. The simulations carried out are satisfactory as they show values of R2 values close to 1.0.

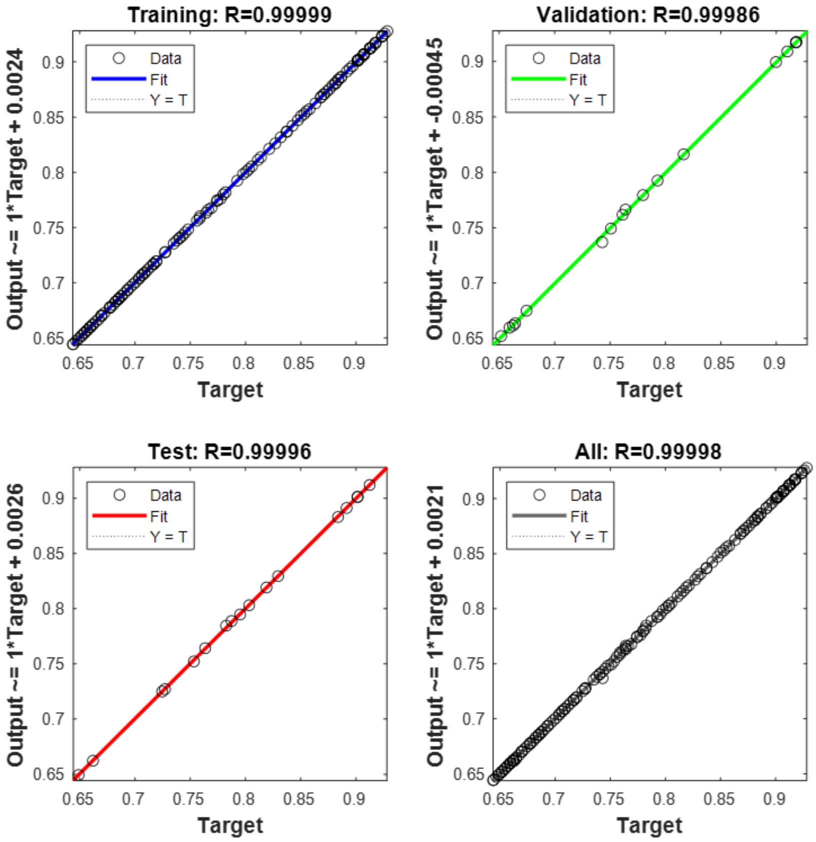

Figure 5. Trend of the phase of Training, Validation and Test for battery B0005.

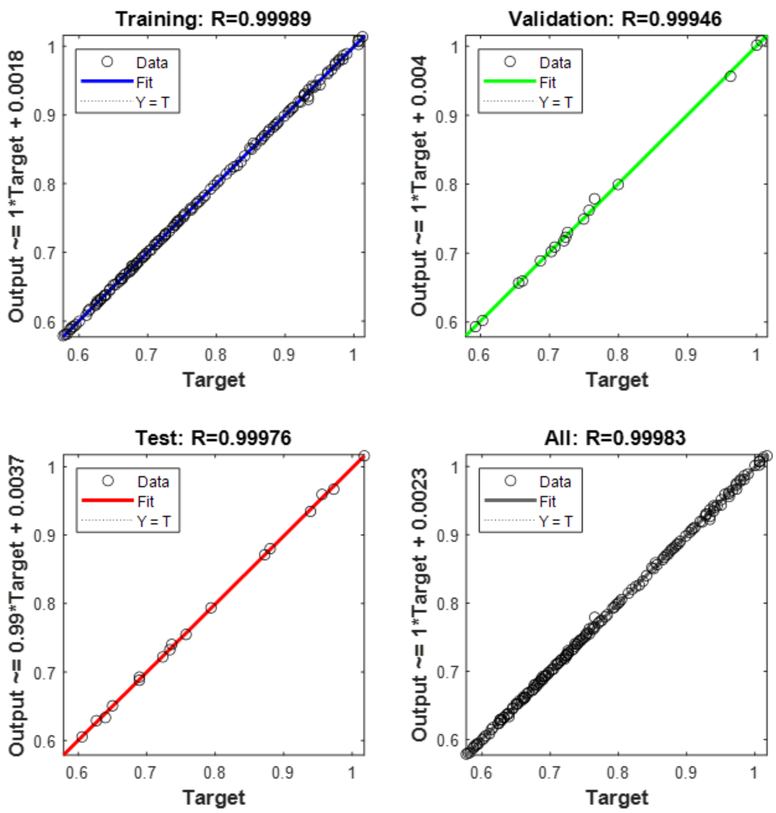

Figure 6. Trend of the phase of Training, Validation and Test for battery B0006.

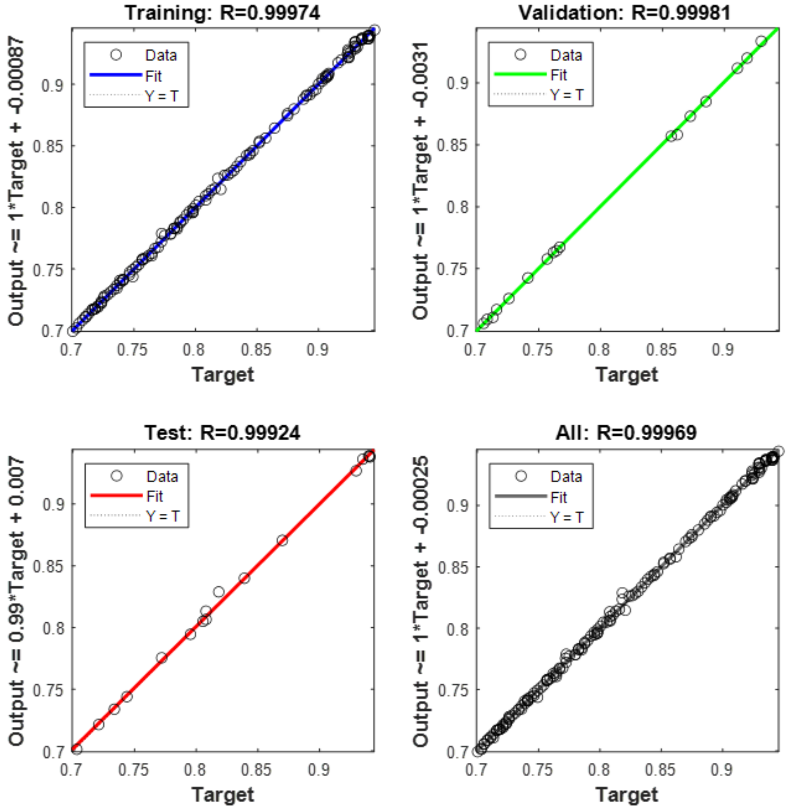

Figure 7. Trend of the phase of Training, Validation and Test for battery B0007.

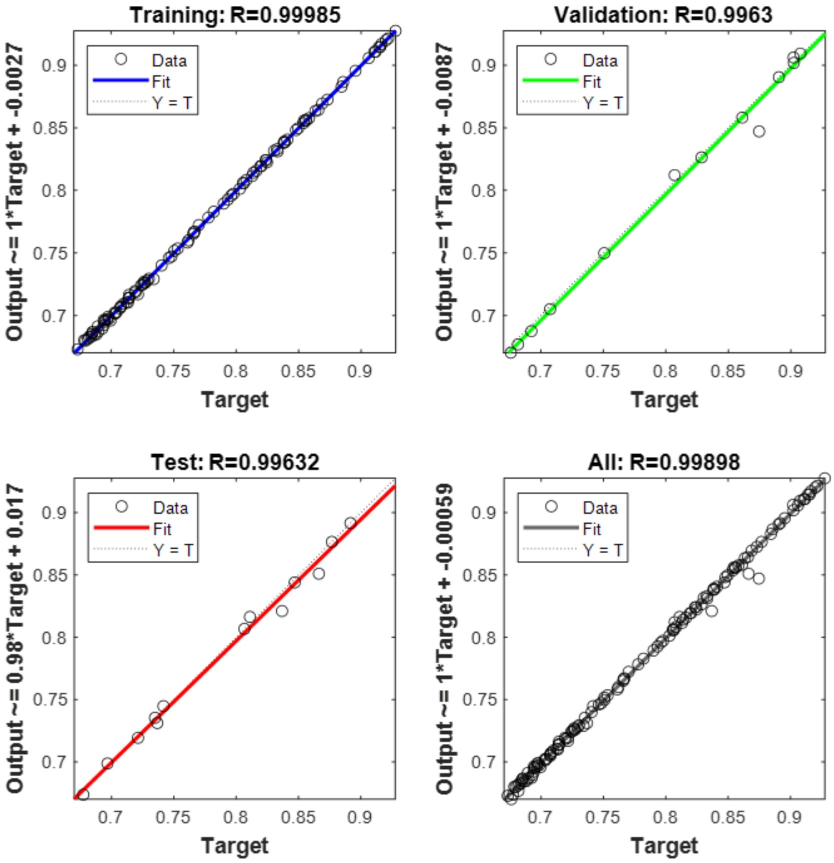

Figure 8. Trend of the phase of Training, Validation and Test for battery B00018.

4.1 Performance Evaluation Metrics

In this article, the author has calculated the Mean Square Error (MSE) for each of the phases of Training, Validation and Test using the corresponding equation [13]:

$$MSE=\frac{1}{2}\sum_{m=1}^{n}\left(O_a - O_p\right) \quad (13)$$

Where compares:

- MSE is the Mean of error squares;
- Oa is Actual output;
- Op is Predicted output.

The MSE is evaluated as the mean squared difference between the predicted values of the SOC and the actual values of the SOH. Lower values obtained indicate better performance of the algorithm.

The best validation performance trends between the Mean Squared Error (MSE) for the B0005 and B0006, B0007 and B0018 batteries from the NASA Prognostics Center of Excellence dataset are shown in Figures 9,10,11, and 12. Figures 9,10,11, and 12 show the trend of performance of Phases Train, Validation and Test in the function of the epochs of the dataset of B0005 and B0006, B0007 and B0018 batteries. For battery B0005, the Validation trend shows the best performance of 2.8097*10-6 at 7 epochs. For battery B0006, the validation trend shows the best performance of 1.7421*10-6 at 5 epochs. For battery B0007, the validation trend shows the best performance of 2.7298*10-6 at 5 epochs. For battery B0018, the validation trend shows the best performance of 6.9342*10^{-5} at 8 epochs.

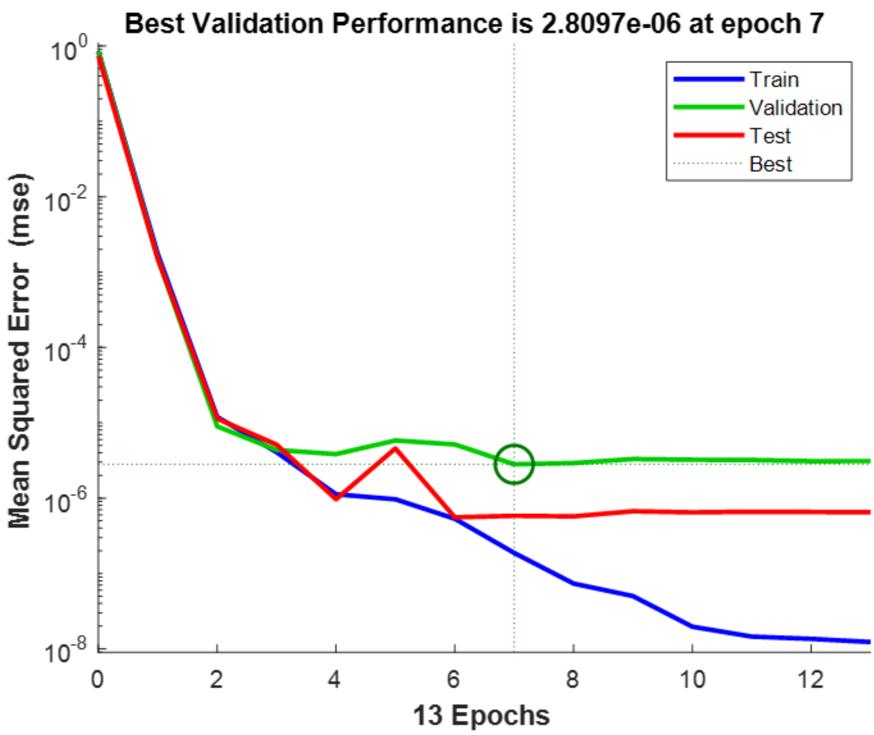

Figure 9. Best Validation Performance for battery B0005.

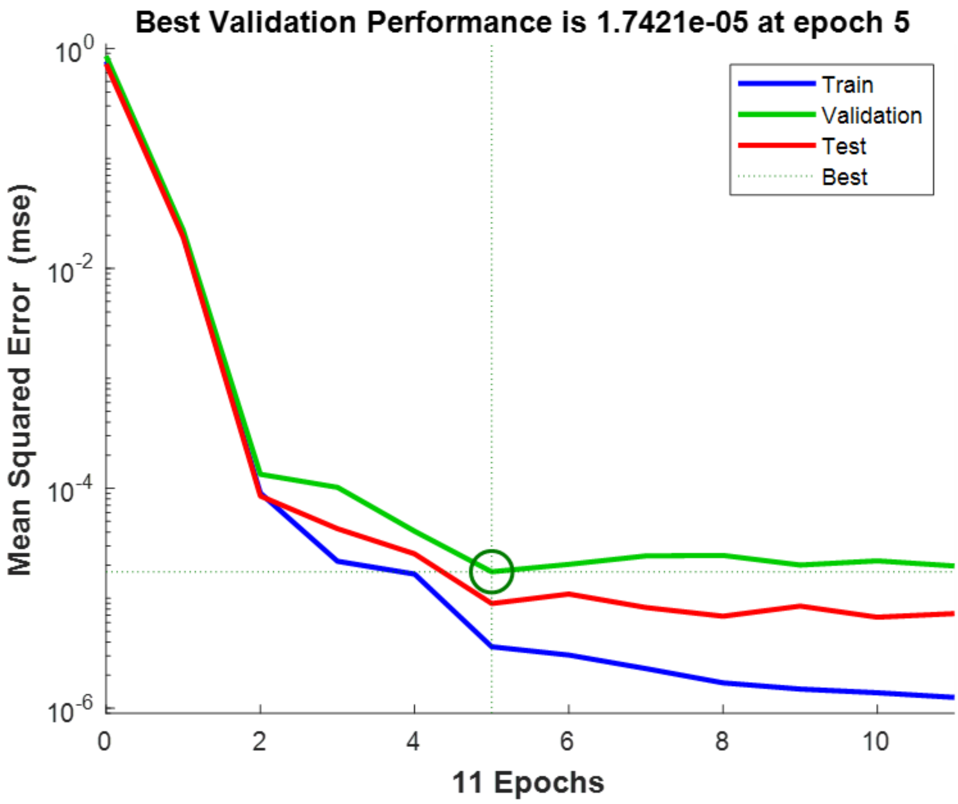

Figure 10. Best Validation Performance for battery B0006.

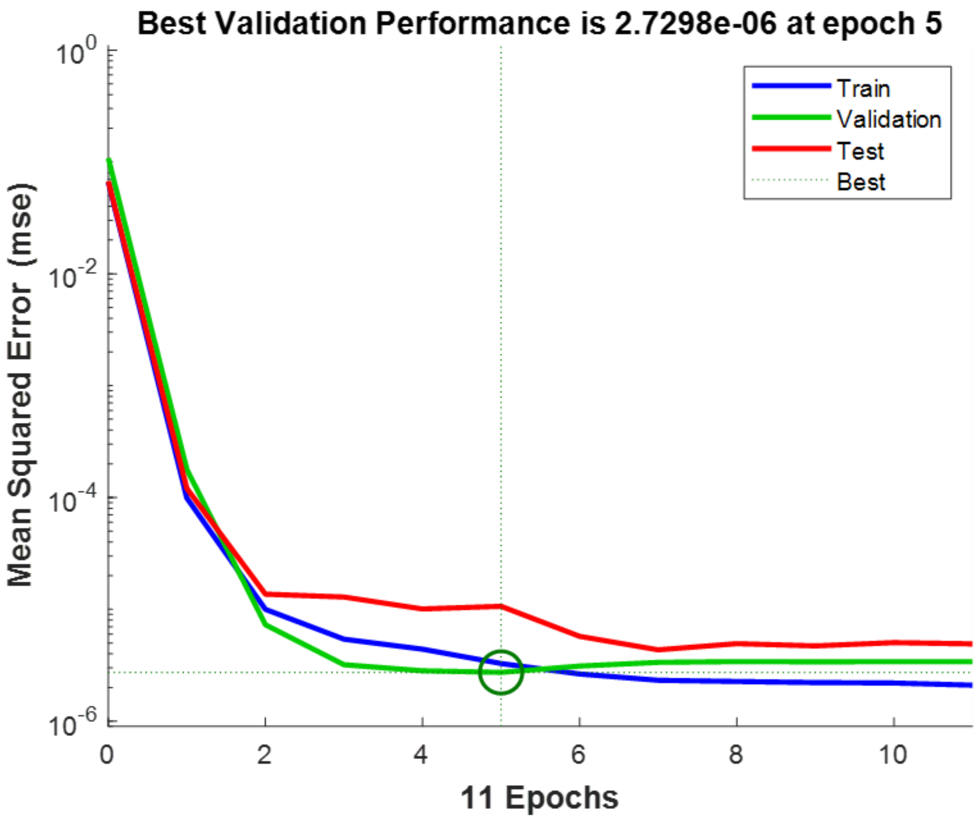

Figure 11. Best Validation Performance for battery B0007.

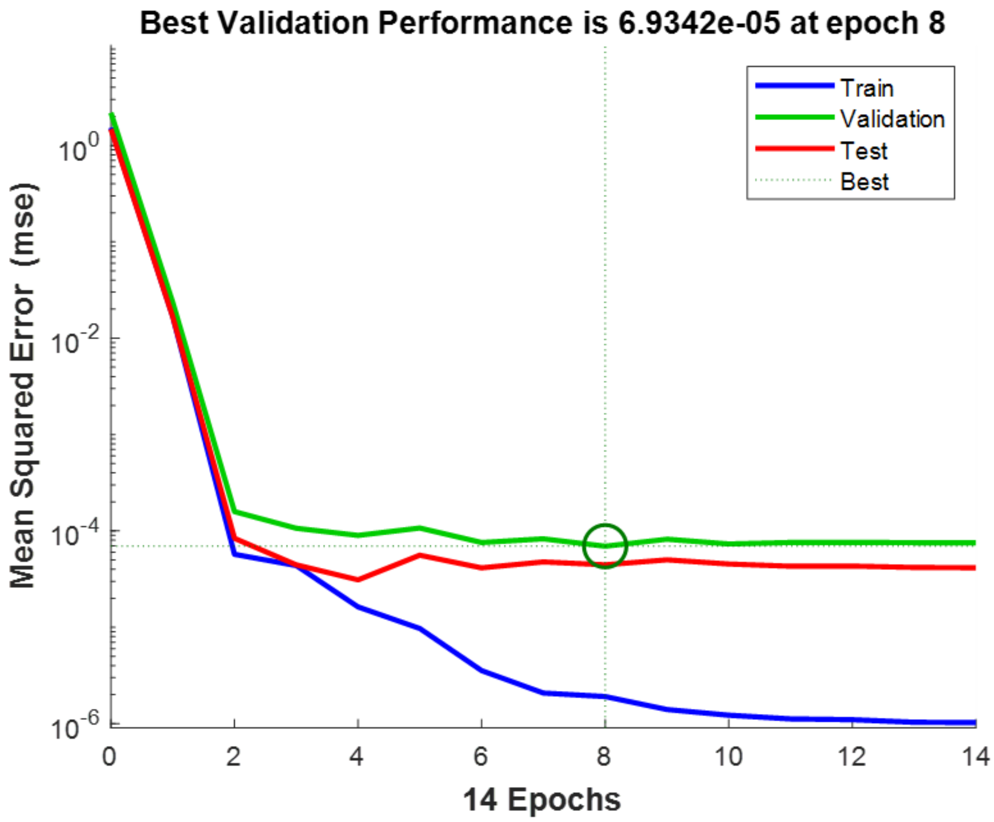

Figure 12. Best Validation Performance for battery B0018.

4.2 Evaluation Criteria – Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Percentage Error (RMSPE)

To assess the accuracy of the proposed approach, the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Percentage Error (RMSPE) were chosen as evaluation metrics. The aforementioned criteria are displayed in the following manner:

$$RMSPE = \sqrt{\frac{1}{N} * \sum_{i=1}^{N} \left(\frac{X_i - \hat{X}_i}{X_i}\right)^2} * 100\% \quad (14)$$

$$MAPE = \frac{1}{N} * \sum_{i=1}^{N} \left|\frac{X_i - \hat{X}_i}{X_i}\right| * 100\% \quad (15)$$

The location of the aforementioned item is as follows.

- Xi is a variable that represents the true State of Charge (SoC) values in a vectorial format;
- $\hat{X}$i is a variable that represents the predicted value of the SoC model;
- N is the number of samples.

The simulations were conducted using the Matlab® software, version 2023, and are visible in Table 1.

Table 1: Evaluation of RMSE Root Mean Squared Error of battery B0005, B0006, B0007, and B0018 of Dataset NASA PCoE Research Center.

Dataset NASA PCoE Research Center	MAPE	RMSPE
B0005	9.0861e-05	1.5137e-04
B0006	2.0598e-04	3.0439e-04
B0007	2.6856e-04	3.8903e-04
B0018	6.9066e-04	0.0014

Lower values of RMSPE and MAPE indicate better performance compared to other algorithms. The results show the validity of the algorithm for simulations carried out on lithium-ion batteries.

V. State of Health Calculation Results

In this work, after having calculated the Actual SOH from the FFN model, the results obtained were used to predict the SOH value at the final time instant.

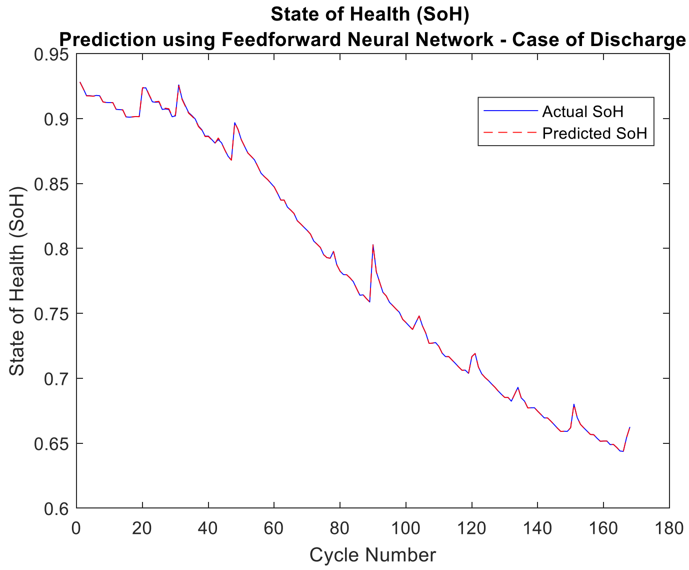

Figure 13. State of Health (SOH) Prediction using Feedforward Neural Network – Case of Discharge for battery B0005.

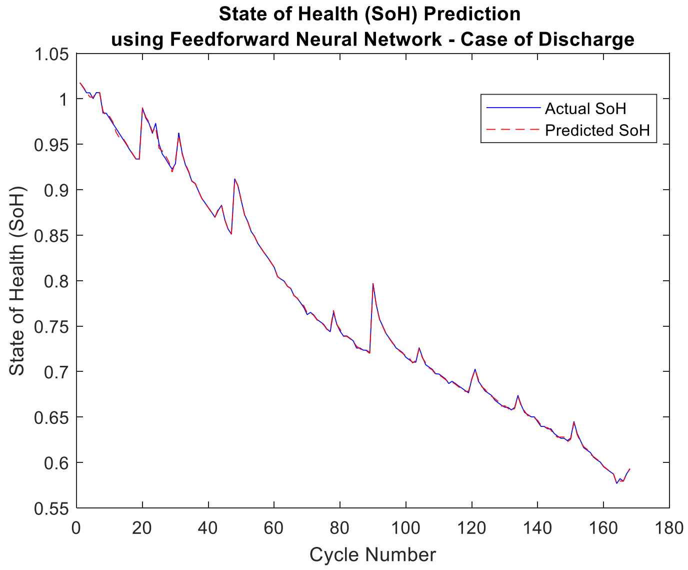

Figure 14. State of Health (SOH) Prediction using Feedforward Neural Network – Case of Discharge for battery B0006.

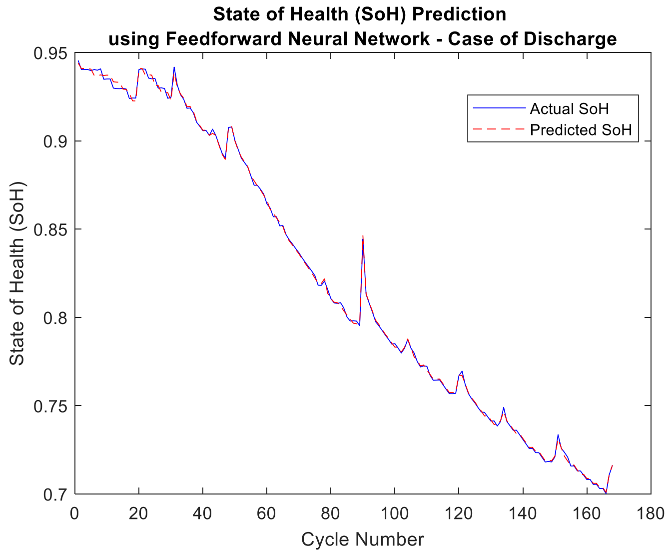

Figure 15. State of Health (SOH) Prediction using Feedforward Neural Network – Case of Discharge for battery B0007.

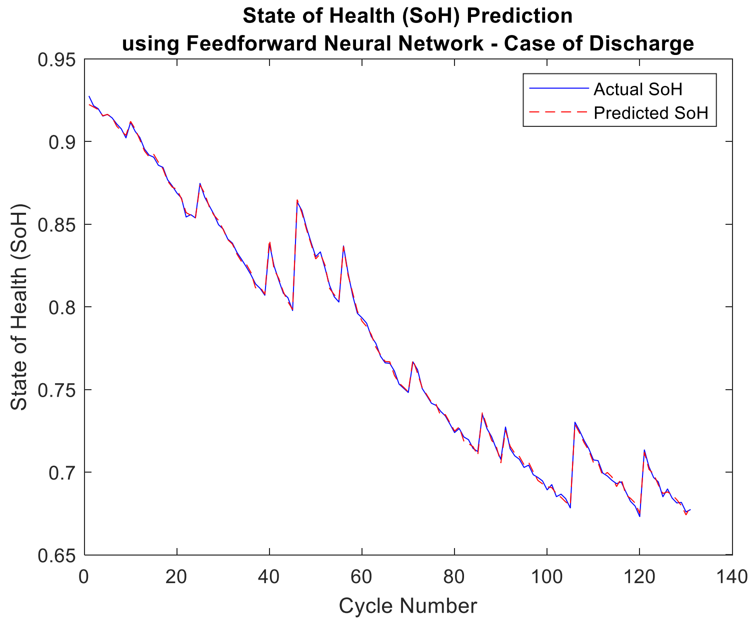

Figure 16. State of Health (SOH) Prediction using Feedforward Neural Network – Case of Discharge for battery B00018.

From the Figures 13, 14, 15 and 16 obtained it is possible to make a series of considerations, the proximity between the blue (real SOH) and red (Predicted SOH) lines indicates the accuracy of the model. Significant divergences could indicate areas where the model has difficulty predicting accurately. Patterns in the graph can reveal trends in battery degradation.

VI. COMPARISON WITH EXISTING METHODS

In the following Figures is it possible to see the error trend of the FFN algorithm for the phases Training, Validation and Test for the batteries B0005, B0006, B0007, and B0018 for NASA PCoE Research Center. For battery B0005 the maximum error is 0.005828. For the battery B0006, the biggest error is 0.01049. For the battery B0007, the biggest error is 0.005503. For the battery B0018, the biggest error is 0.0259. The results show the validity of the Feed Neural Network algorithm for all simulations carried out.

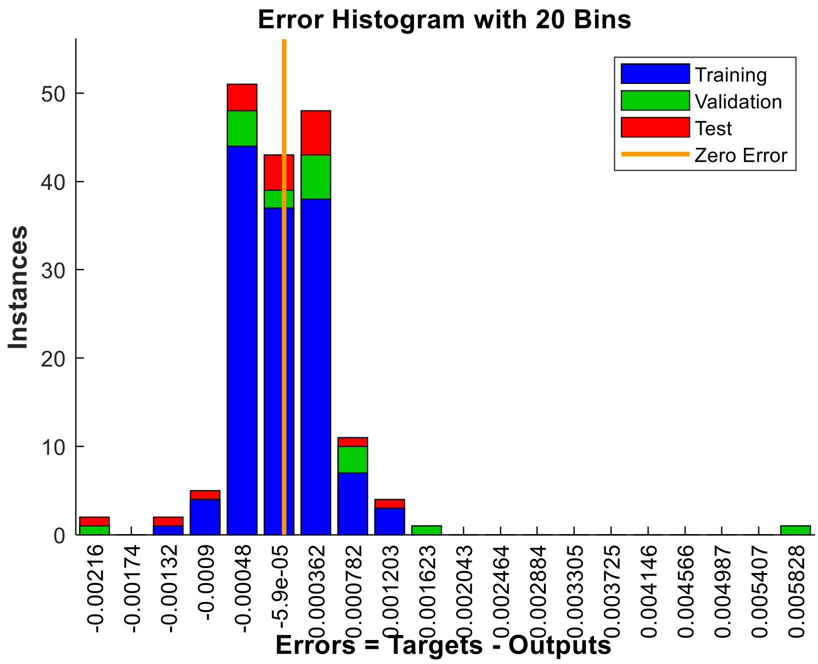

Figure 17. Error for Training, Validation and Test phase for battery B0005.

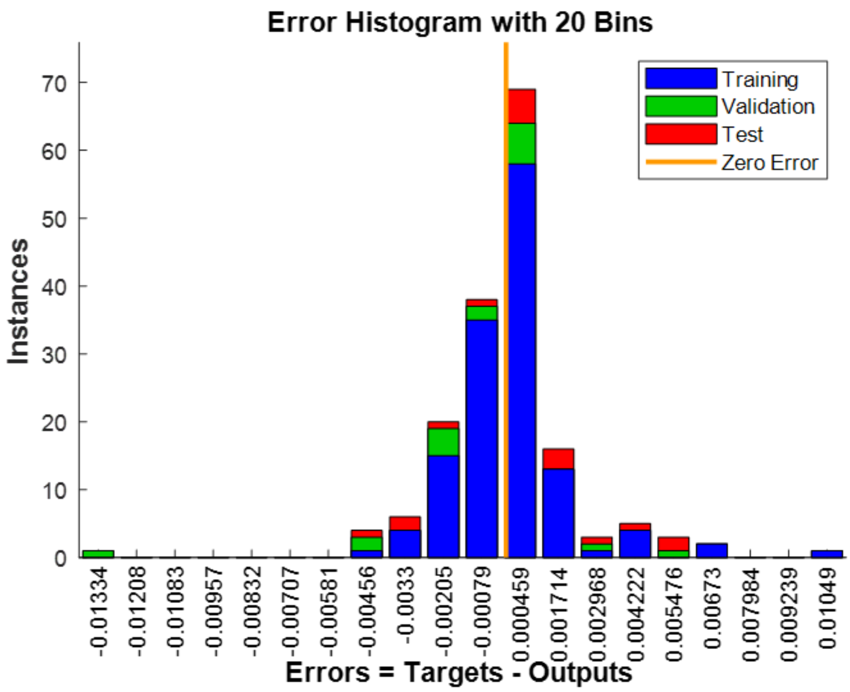

Figure 18. Error for Training, Validation and Test phase for battery B0006.

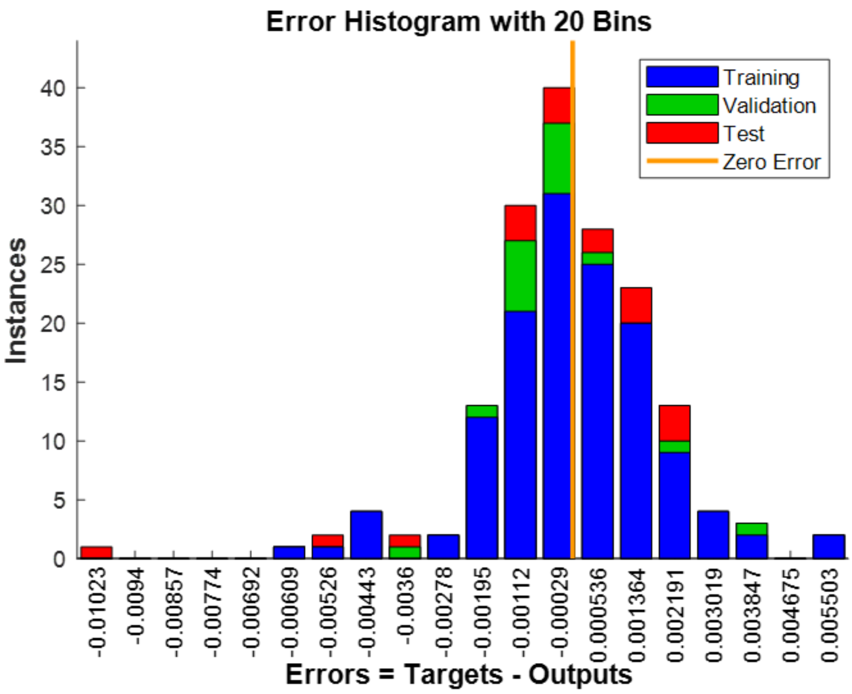

Figure 19. Error for Training, Validation and Test phase for battery B0007.

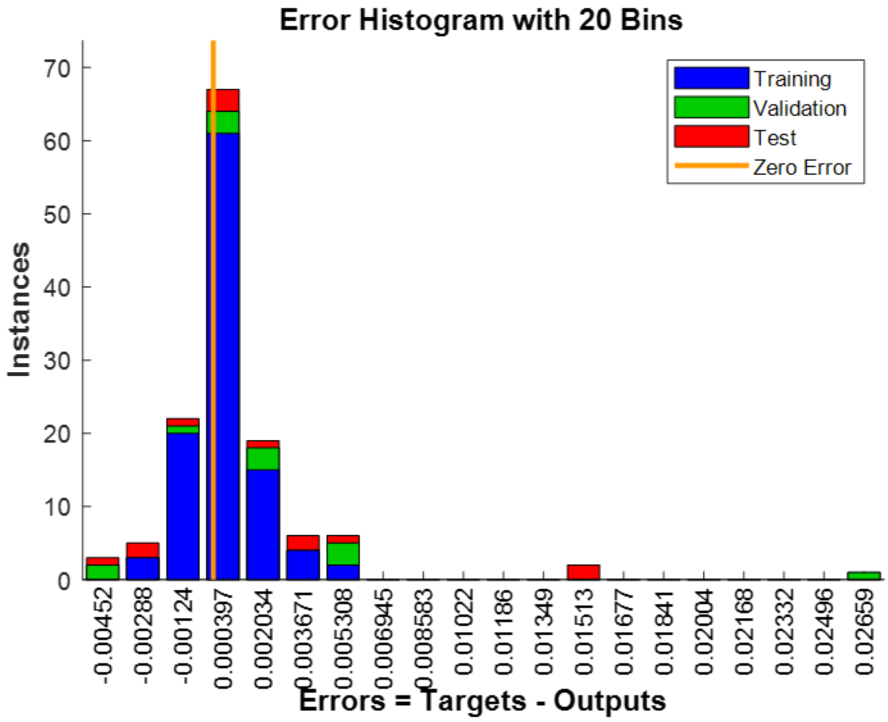

Figure 20. Error for Training, Validation and Test phase for battery B0018.

VII. Conclusions

The prediction of SOH takes place through different methods, such as model-based and data-driven methods to fully evaluate a predictive method that analyzes the state of degradation of the battery. However, evaluating internal resistance is often difficult due to numerous factors such as high complexity computational and measurement costs. In addition, evaluating the degradation process value of LIB during the tests in the charging and discharging phases leads to suboptimal results. For these reasons, in this article simulations have been conducted based on a new FFN algorithm. This article predicts the ageing phenomenon of lithium-ion batteries using a Bayesian Regularization training algorithm (BR). The goal was to compare Actual SOH with Predicted SOH curves and simulate the degradation of the battery. The robustness of the proposed algorithm against the phenomenon of battery ageing was evaluated for several cells in the dataset of NASA PCoE Research Center. The results were verified by comparison with the scientific literature, obtained lower values of MAPE and RMSPE, and higher values of R2. The proposed method of calculating the SoH State of Health using the FFN algorithm has numerous advantages. First of all, the most obvious we find is that it fully represents the relationship between the SOH values and the internal parameters of the battery. Excellent results were obtained from the study that provide accurate predictions of the degradation phenomenon of lithium-ion batteries and ensure the practical utility of the model for battery management and maintenance. In conclusion, the author with the use of this new predictive method provides SOH prediction for optimal battery management and ensures future researchers adequate information regarding balancing performance, cost and safety prediction. In the future, the author aims to create new applications of this Feed-Forward Neural Network method to address in greater detail an evaluation of the ageing phenomenon of lithium-ion batteries.

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