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Department of Electrical & Electronics Engineering

VII Semester

RESEARCH EXPERIENCE FOR

UNDERGRADUATES (17EEEE305)

Under the Guidance of

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Vidyanagar, Hubballi.

Department of Electrical and Electronics Engineering

VII Semester

2024 - 2025

This is to certify that the Research Project entitled Estimation of the State of Health of the Li-ion Battery for EV Applications is a work carried out by, **Anusha Arun Yaligar (01fe21bee112)**, bonafide student of VII Semester, Department of EEE, KLE Technological University, Hubballi for the partial fulfilment of the Research Experience for Undergraduates (REU) Project assigned for VII semester, BE in Electrical Electronics Engineering. The project report has been approved as it satisfies the academic requirements specified by the University.

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Signature of Guide (Anoop Kumar Patil)	Signature of HOD (Dr. Saroja V Siddamal)	Signature of Registrar (Dr. B S Anami)

Name of Examiner Signature with Date

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Project associates

ABSTRACT

This study introduces a new method for estimating the State of Health (SoH) of Li-ion batteries by accounting for various factors that contribute to battery degradation. Using readily available datasets, essential parameters like temperature, voltage, and current are extracted to develop an optimized Backpropagation Neural Network model. This model efficiently evaluates and predicts the SoH of Li-ion batteries with improved accuracy. The approach broadens the scope of health estimation by incorporating a comprehensive set of features, resulting in enhanced prediction performance. A comparison with existing methods highlights the effectiveness of this approach. Additionally, potential future research avenues are explored, focusing on the role of artificial intelligence in advancing battery health prediction.

CONTENTS

INTRODUCTION

Lithium-ion (Li-ion) batteries are widely used in electric vehicles (EVs), renewable energy storage systems, and portable electronic devices due to their high energy density, long cycle life, and low maintenance requirements. However, the performance, safety, and longevity of these batteries depend heavily on their State of Health (SoH), which reflects the battery's capacity to store and deliver energy efficiently as it ages. Accurate SoH estimation is crucial for optimizing battery usage, ensuring safety, and predicting the remaining useful life, which directly influences the performance and reliability of battery-powered systems. Traditional SoH estimation methods, such as Coulomb counting, Open Circuit Voltage (OCV), and impedance spectroscopy, are often limited by complex calculations, high computational costs, and sensitivity to measurement noise. Additionally, these methods require extensive testing and are not suitable for real-time applications due to their reliance on physical models and empirical data. To overcome these limitations, data-driven approaches using machine learning techniques have gained popularity for their ability to model complex non-linear battery behaviours without the need for detailed physical models.

Recent advancements in artificial intelligence (AI) and machine learning have enabled the development of robust data-driven models for battery SoH estimation. Various models, including Support Vector Regression (SVR), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Feedforward Neural Networks (FNNs), and Multiple Linear Regression (MLR) models, have been effectively applied to capture complex dependencies in battery parameters and predict SoH with high accuracy. For instance, SVR has shown strong generalization capabilities in non-linear and high-dimensional problems, even with limited data, making it ideal for real-time battery health diagnostics. LSTM models, on the other hand, are particularly effective for sequence learning tasks, such as capturing temporal dependencies in battery aging data.

In addition to machine learning methods, model-based techniques like the Single Particle (SP) model and its improved variants have also been used for accurate SoH estimation by capturing the internal dynamics of Li-ion batteries. These models offer detailed insights into the electrochemical behaviour of batteries, enabling more accurate estimation of internal resistance and capacity degradation. Improved SP models, for example, incorporate electrolyte-phase potential differences and unmodeled dynamics, which enhance the accuracy of SoH estimation under diverse operating conditions.

Furthermore, advanced feature extraction methods, such as Principal Component Analysis (PCA), have been employed to optimize input features for machine learning models, improving prediction performance and reducing computational complexity. Techniques like Incremental Capacity Analysis (ICA) and Differential Voltage Analysis (DVA) have also been widely used to extract health indicators from charging and discharging curves, providing valuable insights into battery degradation.

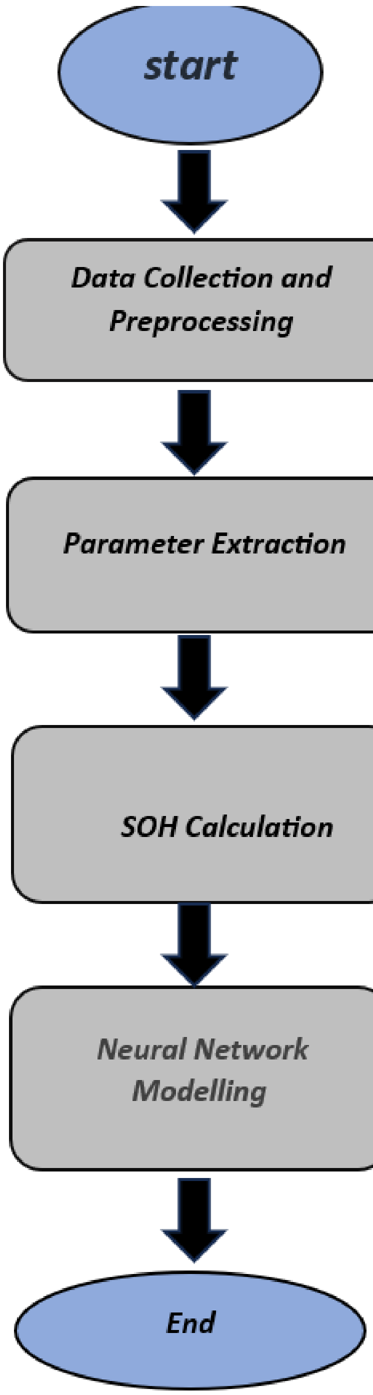
Despite these advancements, challenges persist in achieving high accuracy and generalizability under varying operational conditions. Transfer learning techniques have been introduced to mitigate this issue by pre-training models on accelerated aging data and fine-tuning them with limited normal-speed aging data, reducing the dependence on extensive cycling experiments. Additionally, advanced signal processing techniques, such as event-driven and level-crossing sampling, have been proposed to enhance data acquisition and processing, leading to reduced computational complexity and improved real-time performance.

This paper proposes a novel approach for Li-ion battery SoH estimation using an optimized Backpropagation Neural Network. The model leverages readily available datasets to extract key parameters, including temperature, voltage, and current, which significantly impact battery degradation. By incorporating a comprehensive set of features, the proposed methodology effectively captures the complex nonlinear relationships associated with battery aging, improving prediction accuracy and robustness.

A detailed comparative analysis is conducted with existing techniques, demonstrating the superiority of the proposed approach in terms of accuracy, reliability, and computational efficiency. Additionally, the study explores the limitations of the current model and provides insights into potential future research directions, including the integration of additional parameters, advanced neural network architectures, and cross-platform adaptability. This work contributes to developing intelligent battery health prediction systems, paving the way for more efficient and reliable energy management solutions.

BLOCK DIAGRAM

The block diagram illustrates the workflow of the proposed methodology, including data collection and preprocessing, parameter estimation using an equivalent circuit model (ECM), SoH estimation using derived formulas, and neural network-based SoH prediction.



METHODOLOGY

1. Data Collection and Preprocessing

The dataset was compiled from multiple sources, including datasets from different companies, containing values for voltage, current, and time instances under varying current rates (1C, 2C, 4C, and 6C). From these datasets, the relevant parameters (time, current, and voltage) were extracted for further analysis.

Using MATLAB, the extracted data was processed by importing the excel files containing current, voltage, and time details. A custom MATLAB code was developed to calculate the battery parameters R0, R1, R2, C1 and C2 for different amp-hour rates. This calculation was achieved by analysing the voltage and current behaviours at various time instances.

The raw data was then preprocessed to eliminate noise and ensure consistency, followed by normalization using the **mapminmax** function to scale the inputs and targets within a suitable range for neural network training. This preprocessing step was essential to enhancing the neural network model's learning efficiency and accuracy.

2. Parameter Extraction

To analyze the internal dynamics of the battery, key parameters (R0, R1, R2, C1, and C2) were extracted using a custom MATLAB code, which utilizes voltage, current, and time data. Graphs were generated to observe the behaviour of these parameters across different current rates, aiding in understanding the battery's electrochemical processes. This extraction enabled the formulation of resistance and capacitance values essential for SOH estimation.

3. SOH Calculation

SOH was calculated using resistance-based formulas derived from battery-equivalent circuit models. The approach involved three levels of calculation:

1. **SOH using R0 only:**

$$SOH = \frac{(R0_{eol}) - (R0_{init})}{(R0_{eol}) - (R0_{act})} * 100$$

2. **SOH using R0+R1:**

$$SOH = \frac{(R0_{eol} + R1_{eol}) - (R0_{init} + R1_{init})}{(R0_{eol} + R1_{eol}) - (R0_{act} + R1_{act})} * 100$$

3. **SOH using R0+R1+R2:**

$$SOH = \frac{(R0_{eol} + R1_{eol} + R2_{eol}) - (R0_{init} + R1_{init} + R2_{init})}{(R0_{eol} + R1_{eol} + R2_{eol}) - (R0_{act} + R1_{act} + R2_{act})} * 100$$

Where:

- R_{eol} = End-of-Life resistance, calculated as 1.3 * R_{act}
- R_{init}: Initial resistance, calculated as 0.95 × R_{act}
- R_{act}: Actual resistance obtained from experimental data

This hierarchical approach provided a comparative analysis of the SOH prediction accuracy at varying levels of circuit complexity.

4. Neural Network Modelling

A neural network model was developed using MATLAB to predict SOH values. Three models were proposed, differing in input complexity:

1. **Model 1:** Inputs: $R0_{init}, R0_{eol}, R0_{act}$
2. **Model 2:** Inputs: $R0_{init}, R0_{eol}, R0_{act}, R1_{init}, R1_{eol}, R1_{act}$
3. **Model 3:** Inputs: $R0_{init}, R0_{eol}, R0_{act}, R1_{init}, R1_{eol}, R1_{act}, R2_{init}, R2_{eol}, R2_{act}$

Each model was designed using a **Feedforward Neural Network** with 10 hidden layers. The **Backpropagation** algorithm was employed for training with the following parameters:

- **Learning rate:** 0.1
- **Epochs:** 500
- **Performance metric:** Mean Squared Error (MSE)

The data was normalized before training to enhance learning efficiency and accuracy. The network was trained using the **train** function in MATLAB with no data division, utilizing the entire dataset for training.

Upon completion, the model's performance was evaluated by comparing predicted SOH values with actual values using Mean Squared Error (MSE) as the performance metric. Graphical analysis was conducted to visualize the accuracy of predictions.

5. Implementation Tools

The entire methodology was implemented in MATLAB, utilizing its **Neural Network Toolbox** for model creation, training, and evaluation. Custom scripts were written for data preprocessing, parameter extraction, and SOH calculations.

This structured methodology provided a comprehensive approach to estimating SOH using resistance parameters and neural network modeling, contributing to improved accuracy in battery health prediction.

EXPERIMENTAL RESULT

4.1: Model 1: Inputs: $R0_{init}, R0_{eol}, R0_{act}$

4.1.1 Model Performance

The Feed-Forward Neural Network (FNN) was implemented using the Backpropagation algorithm to estimate the battery's State of Health (SOH). The model used R0_EOL, R1_EOL, R0_INIT, R1_INIT, R0_ACT, and R1_ACT as inputs and SOH (%) as the output. It consisted of 10 hidden layers with 10 neurons each and was trained using Gradient Descent (traingd). The model effectively predicted SOH by minimising the error between actual and predicted values.

4.1.2 Training and Convergence

The model was trained using the Gradient Descent algorithm (TRAINGD) with Mean Squared Error (MSE) as the performance metric. The training process was conducted for 500 epochs, and the network demonstrated good convergence behaviour, as shown in

Figure 4.1.1

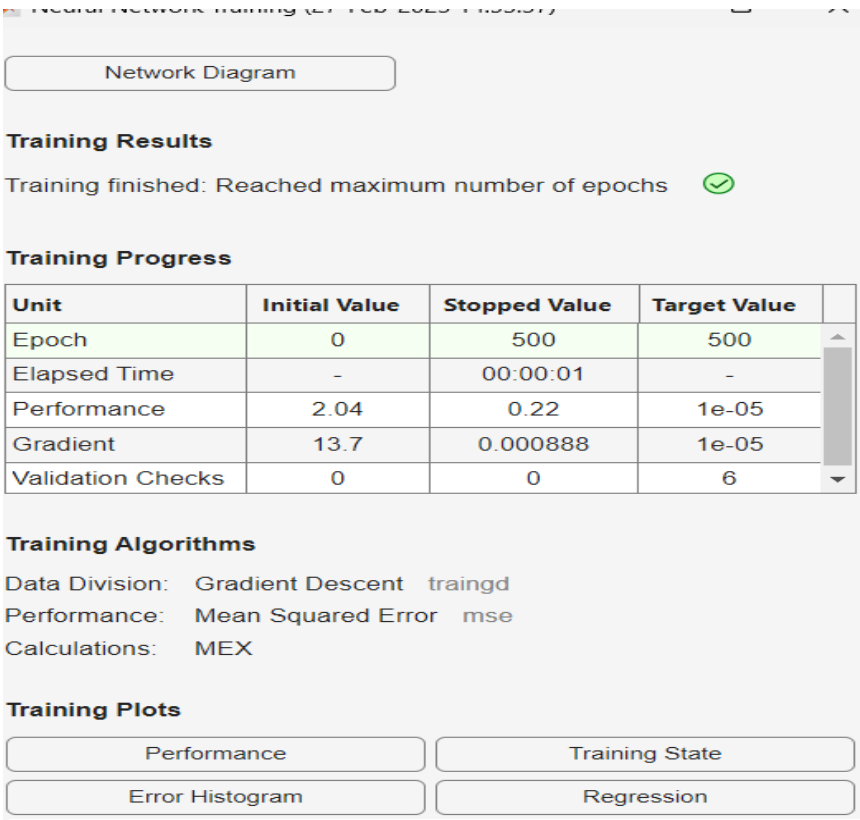


Figure 4.1: This figure illustrates the decreasing trend of the MSE throughout the training process, indicating effective learning and optimization.

4.1.3 Comparison of Predicted and Actual Values

To validate the accuracy of the model, the predicted values were compared with the actual measured values.

Figure 4.1.2

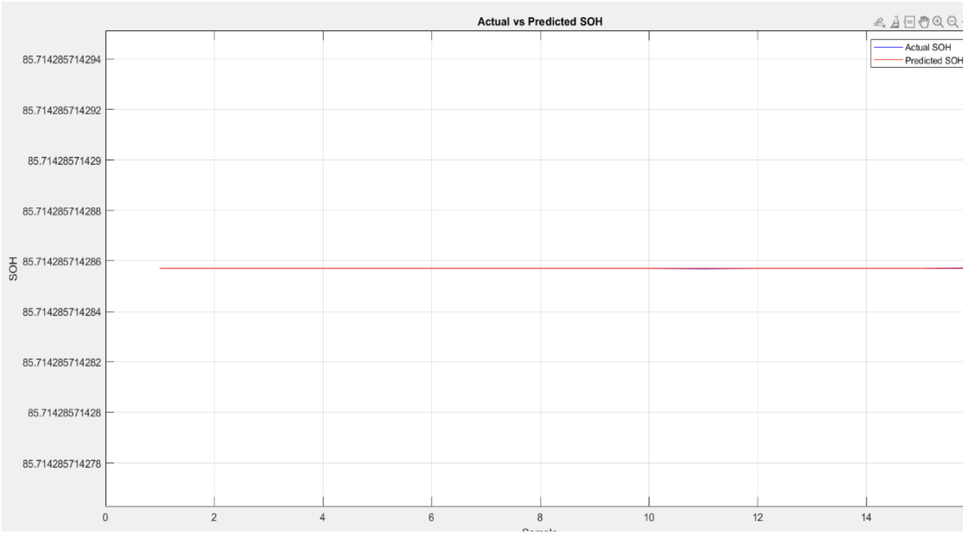


Figure 4.2:The graph shows a close alignment between the predicted and actual values, confirming the model's effectiveness. The minimal deviation between the two curves indicates high prediction accuracy

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4.1.4 Impact of Network Architecture

The performance of the network was also analyzed based on the hidden layer configuration. **Figure 4.4** shows the architecture used for this model.

Figure 4.1.3

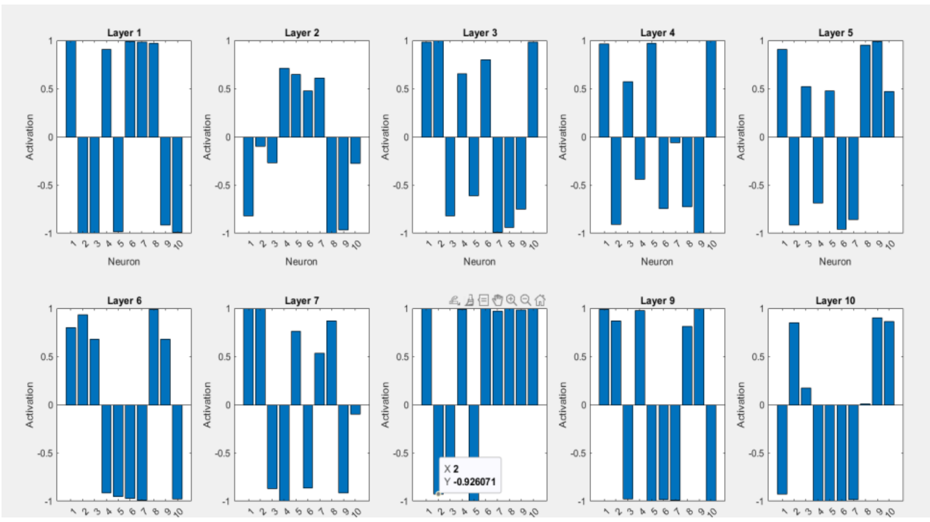


Figure 3.4:This architecture was found to be optimal for the R0 parameter prediction, ensuring a balance between model complexity and performance.

4.2: Model 2: Inputs: $R0_{init}, R0_{eol}, R0_{act}, R1_{init}, R1_{eol}, R1_{act}$

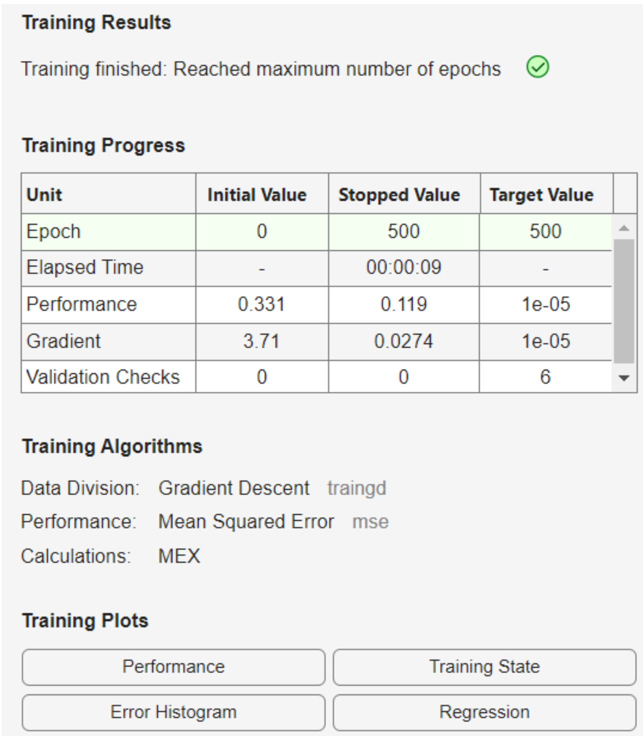
4.2.1 Model Performance

The **Feed-Forward Neural Network (FNN)** was implemented using the **Backpropagation algorithm** to estimate the battery's **State of Health (SOH)**. The model used **R0_EOL, R1_EOL, R0_INIT, R1_INIT, R0_ACT, and R1_ACT** as inputs and **SOH (%)** as the output. It consisted of **10 hidden layers** with **10 neurons each** and was trained using **Gradient Descent (traingd)**. The model effectively predicted **SOH** by minimizing the error between actual and predicted values.

4.2.2 Training and Convergence

The image shows the **Training Results** of the **Feed-Forward Neural Network (FNN)** used to predict the **State of Health (SOH)** of the battery. The model was trained using the **Gradient Descent (traingd)** algorithm with **Mean Squared Error (MSE)** as the performance metric. It ran for **500 epochs**, reducing the mean squared error (MSE) from **0.331** to **0.119**, indicating improved accuracy. The **gradient** decreased from **3.71** to **0.0274**, showing convergence. The training process took around **9 seconds**, demonstrating efficient learning.

Figure 4.2.1



Training Results

Training finished: Reached maximum number of epochs

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	500	500
Elapsed Time	-	00:00:09	-
Performance	0.331	0.119	1e-05
Gradient	3.71	0.0274	1e-05
Validation Checks	0	0	6

Training Algorithms

Data Division: Gradient Descent traingd
Performance: Mean Squared Error mse
Calculations: MEX

Training Plots

Performance | Training State
Error Histogram | Regression

Figure 4:"Training Progress Graph for R0 and R1 Model: Demonstrating the Neural Network's Convergence with Reduced Mean Squared Error (MSE) Over 500 Epochs."

4.2.3 Comparison of Predicted and Actual Values

The graph illustrates the actual vs. predicted SOH using a neural network trained with combined R_0 and R_1 resistance parameters. The predicted curve closely follows the actual SOH trend, indicating good model accuracy. This demonstrates that using both R_0 and R_1 enhances the network's ability to accurately estimate battery health.

Figure 4.2.2

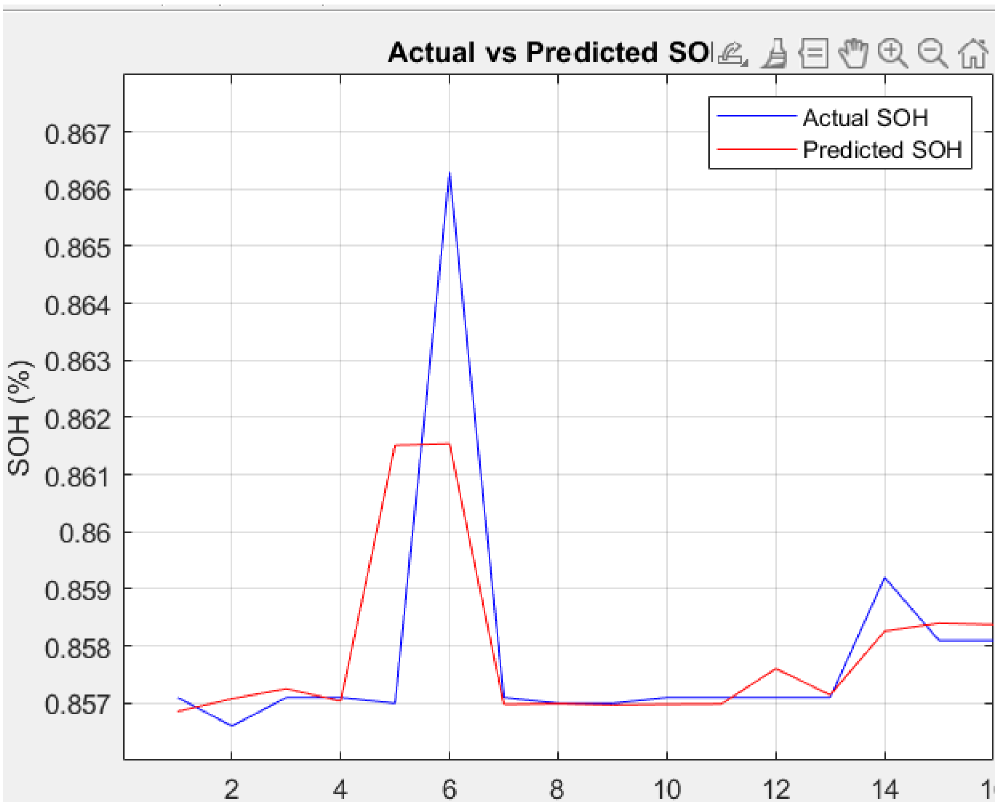


Figure 5:Comparison between Actual and Predicted State of Health (SOH) using a feedforward neural network trained on R_0 and R_1 parameters (initial, end-of-life, and actual values). The plot demonstrates the model's ability to approximate battery SOH.

4.2.4 Impact of Network Architecture

This figure illustrates the neuron activation levels across the 10 hidden layers of the Feed-Forward Neural Network used for predicting the State of Health (SOH) of the battery. The presence of varying activation values across neurons indicates that each layer is effectively learning and transforming the input data. The absence of constant zero or saturated values suggests that all neurons are actively contributing to the model's learning process. This diversity in activations is essential for capturing complex patterns in the dataset and improving prediction accuracy.

Figure 4.2.3

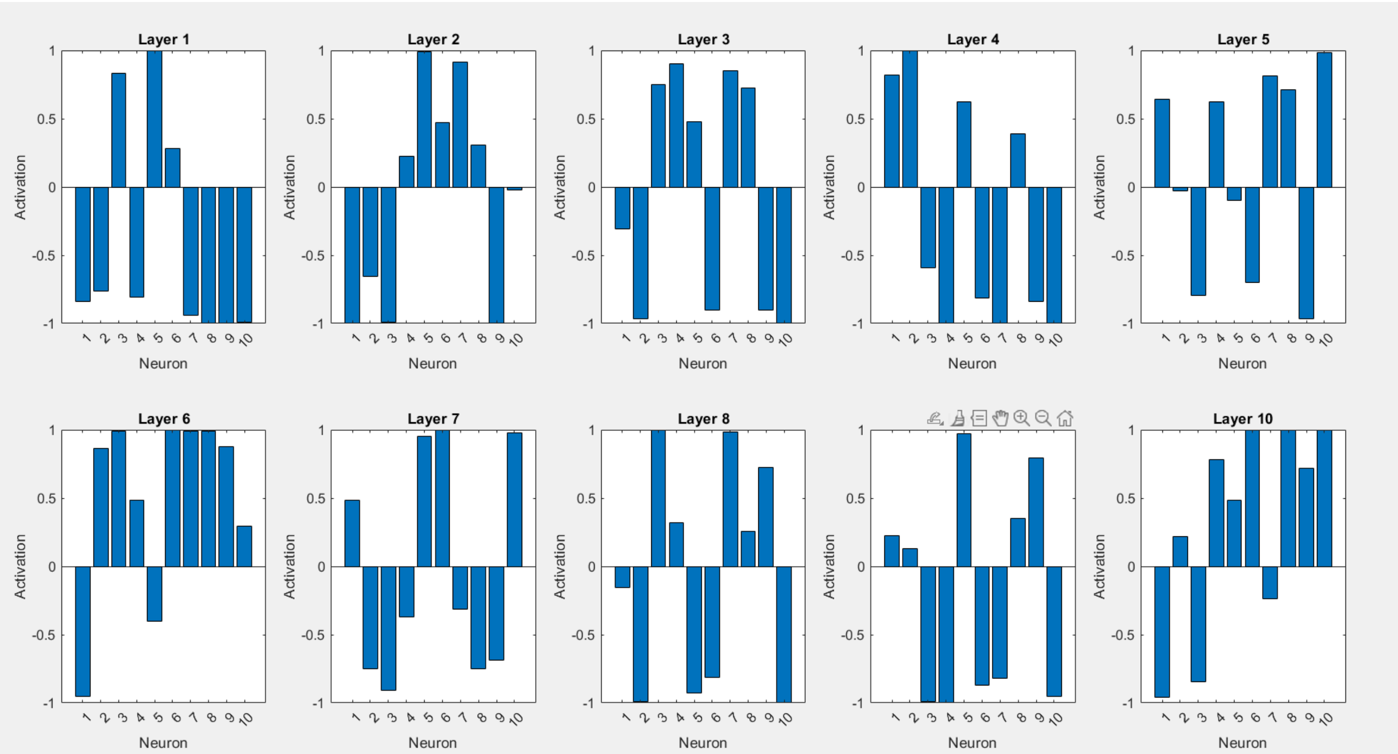


Figure 6: Neuron activations across the 10-layer Feed-Forward Neural Network used for SOH prediction. The diversity in activation values across neurons and layers indicates effective learning and proper signal propagation throughout the network.

CONCLUSION AND FUTURE STUDY

The research successfully demonstrates a robust and data-driven approach for estimating the State of Health (Soh) of lithium-ion batteries using an optimised Backpropagation Neural Network. By extracting critical battery parameters—R_0, R_1, R_2, C_1, and C_2—from experimental data under varying load conditions, and integrating them into a neural network model, the study achieved accurate Soh predictions with minimal deviation from actual values. The three-tier model architecture allowed for evaluating the impact of parameter complexity on prediction accuracy, with each level showing consistent convergence and performance improvement across training epochs.

The use of MATLAB as an implementation platform enabled seamless data preprocessing, network training, and visualisation. Comparative results affirmed that incorporating a broader set of internal battery characteristics enhances the model's ability to generalise and perform well under real-world operating conditions. This project highlights the immense potential of AI-based techniques in revolutionising battery management systems, especially in electric vehicles, where reliable Soh estimation is crucial for safety, longevity, and performance optimisation.

FUTURE STUDY:

To enhance the accuracy and applicability of the proposed model, several future directions are suggested:

1. Incorporation of Real-time Environmental Data: Integration of dynamic parameters such as wind speed, temperature variations, and traffic conditions can make the model more robust for real-world applications.
2. Vehicle Diversity and Parameter Adaptability: Expanding the model to include a broader range of vehicle types with varying mass, aerodynamic profiles, and rolling resistances will improve generalizability.
3. Energy Recovery Modelling: Inclusion of regenerative braking systems and their impact on energy efficiency will provide a more comprehensive estimate of SOF.
4. Advanced Machine Learning Techniques: Implementation of AI/ANN-based approaches such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) models can capture non-linear dependencies and improve predictive accuracy.
5. Battery Aging Effects: Future versions of the model should incorporate aging characteristics and degradation patterns of Li-ion batteries to enable SOF prediction over the entire battery lifecycle.

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