School of Electrical & Electronics Engineering

VII Semester, Research Experiences for Undergraduates

Report on

SoC Estimation of Li-ion Battery using deep learning frame work for EV Applications

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School of Electrical & Electronics Engineering

Certificate

*This is to certify that the Senior Design Project entitled "**SoC Estimation of Li-ion Battery using deep learning frame work for EV Applications**" is a work carried out by, **Malhar Kulkarni (01FE21BEE016)** bonafide student of **School of Electrical & Electronics Engineering, KLE Technological University, Hubballi** for the partial fulfillment of the Research Experiences for Undergraduates 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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Lastly with unquantifiable affection we wish to express our sincere feelings to our parents and family members in the form of words which are restrictive in expression and quantum.

Malhar Kulkarni

Abstract

Accurate estimation of the State of Charge (SoC) is critical for efficient battery management in lithium-ion batteries, particularly for electric vehicles (EVs). This project evaluates advanced deep learning models, including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Temporal Convolutional Networks (TCN), and their hybrid combinations, under varying temperature conditions (0°C, 10°C, 25°C, and 40°C). The study employs key battery parameters such as voltage, current, and temperature to train these models using optimization algorithms like Adam and Stochastic Gradient Descent (SGD). Results indicate that hybrid TCN-based architectures, especially TCN-Bi-LSTM, outperform other models, achieving the lowest Root Mean Square Error (RMSE) values and demonstrating robustness under extreme thermal conditions. These findings highlight the transformative potential of deep learning in enhancing SoC prediction accuracy, paving the way for safer, more reliable battery management systems and fostering the global transition toward sustainable EV technology.

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1. Introduction

1.1 General Introduction

With the global emphasis on sustainable energy and the rapid adoption of electric vehicles (EVs), effective management of lithium-ion batteries has emerged as a critical focus area. Among the core parameters for managing battery health and efficiency is the State of Charge (SoC), which represents the available energy in a battery compared to its full capacity. Accurate SoC estimation is essential to ensure safety, enhance battery life, and address challenges like range anxiety, making it a cornerstone for widespread EV adoption.

Traditional methods for SoC estimation, such as Coulomb counting and open-circuit voltage measurement, have limitations under dynamic conditions. These methods often suffer from errors due to self-discharge, measurement noise, and temperature sensitivity, making them less effective for real-time applications. Inaccuracies in SoC predictions can result in overcharging or undercharging of batteries, reducing their lifespan, and posing safety risks like thermal runaway.

To overcome these limitations, advancements in machine learning and deep learning have provided a more robust and adaptive framework for SoC estimation. Modern deep learning architectures, such as Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Temporal Convolutional Networks (TCN), excel in capturing the complex, nonlinear, and time-dependent behaviors of battery systems. These methods leverage data from various sources, including current, voltage, and temperature, to deliver more precise SoC predictions.

The integration of these models into Battery Management Systems (BMS) can significantly improve real-time monitoring and operational safety. This project investigates these state-of-the-art deep learning techniques and their hybrid combinations to provide accurate SoC estimation under varying temperature conditions, highlighting their potential to advance battery technologies and foster the transition toward eco-friendly transportation solutions.

1.2 Importance of State of Charge Estimation

State of Charge (SoC) estimation is a critical parameter in the effective management of lithium-ion batteries, particularly in electric vehicles (EVs). It measures the remaining energy in a battery as a percentage of its full capacity and plays a crucial role in ensuring safety, optimizing performance, and prolonging battery life. Accurate SoC estimation prevents overcharging and deep discharging, which can lead to battery degradation and operational failures. It also enhances safety by minimizing risks such as thermal runaway, a significant concern in lithium-ion batteries. Moreover, precise SoC predictions enable energy optimization and improve the overall efficiency of EVs by allowing intelligent distribution of power across system components.

In addition to improving battery performance, SoC estimation directly impacts user experience by providing reliable driving range predictions, thus addressing range anxiety a primary concern for EV users. It supports intelligent decision-making within Battery Management Systems (BMS), enabling real-time adjustments to charging and discharging strategies based on operating conditions. By integrating advanced techniques such as deep learning, SoC estimation can adapt to complex and nonlinear battery behaviors, providing more accurate and robust predictions under diverse environmental conditions. This advancement is essential for fostering widespread EV adoption and supporting the global transition to sustainable energy solutions.

1.3 Scope of the Project

The scope of this project focuses on advancing the accuracy and reliability of State of Charge (SoC) estimation for lithium-ion batteries, particularly in electric vehicle (EV) applications. By leveraging modern deep learning techniques, this study aims to address the limitations of traditional estimation methods, such as Coulomb counting and open-circuit voltage measurement, which are prone to errors under dynamic and real-world conditions.

The project involves the implementation and evaluation of advanced deep learning models, including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Temporal Convolutional Networks (TCN), and their hybrid configurations. These models will be trained and tested under varying temperature conditions (0°C, 10°C, 25°C, and 40°C) using datasets incorporating key battery parameters like voltage, current, and temperature. The scope also encompasses optimizing model performance with different training strategies and assessing their robustness in handling nonlinear battery behavior and thermal variations.

The outcomes of this project have far-reaching implications, such as enhancing Battery Management Systems (BMS) for safer and more efficient EV operations, addressing range anxiety with accurate driving range predictions, and contributing to the broader adoption of sustainable transportation technologies. Additionally, the project sets the foundation for integrating machine learning into real-time battery management, paving the way for further advancements in battery health monitoring and energy storage systems.

2. Literature Survey and Objectives

2.1 Overview of Existing SoC Estimation Techniques

State of Charge (SoC) estimation techniques have evolved over the years from traditional methods to advanced machine learning approaches. Traditional methods, such as Coulomb counting and open-circuit voltage (OCV) measurement, rely on simple physical principles but are limited by their sensitivity to measurement errors, temperature variations, and inaccuracies caused by battery aging. Coulomb counting estimates SoC based on the integration of current over time, but it suffers from cumulative errors due to sensor inaccuracies and self-discharge. Similarly, OCV methods require the battery to be in a steady state, making them unsuitable for real-time applications.

To overcome these challenges, researchers have explored model-based techniques such as the Extended Kalman Filter (EKF) and Particle Filter (PF). These approaches use mathematical models of battery behaviour to estimate SoC more accurately, considering nonlinear dynamics. However, their reliance on precise battery models and high computational demands limit their scalability and adaptability. Recent advancements in machine learning and deep learning have provided robust alternatives by directly mapping input signals (e.g., current, voltage, and temperature) to SoC, bypassing the need for explicit modelling. Architectures such as Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Temporal Convolutional Networks (TCN) excel in capturing the complex, nonlinear behaviour of batteries and handling temporal dependencies. Hybrid models, combining the strengths of different architectures, further enhance prediction accuracy and robustness under diverse operating conditions, such as extreme temperatures. These advancements represent a significant leap in the field of battery management systems, enabling real-time, reliable SoC estimation for modern applications like electric vehicles and renewable energy storage systems.

2.2 Role of Deep Learning in SoC Estimation

Deep learning has emerged as a transformative approach for estimating the State of Charge (SoC) in lithium-ion batteries, addressing the limitations of traditional and model-based methods. Unlike conventional approaches that require explicit modeling of battery dynamics, deep learning enables direct mapping from input signals such as current, voltage, and temperature to SoC. This capability eliminates the need for detailed physical models, making deep learning adaptable to complex, nonlinear, and time-dependent battery behaviors.

Key architectures like Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) effectively capture temporal dependencies and sequential patterns in battery data. For example, LSTM networks leverage memory cells and gating mechanisms to understand long-term relationships, while Bi-LSTM models process data in both forward and backward directions, enhancing accuracy. Similarly, Temporal Convolutional Networks (TCN) utilize dilated convolutions to capture long-range dependencies in time-series data efficiently, enabling faster training compared to recurrent networks. Hybrid models, such as TCN-LSTM and TCN-BiLSTM, combine the strengths of these architectures to further improve SoC prediction under diverse conditions, including extreme temperatures.

Deep learning also facilitates the integration of data-driven optimizations, such as hyperparameter tuning, dropout, and advanced optimizers like Adam, to minimize prediction errors. These techniques enhance the reliability of Battery Management Systems (BMS) by delivering real-time, precise SoC estimates, ultimately extending battery lifespan, improving safety, and supporting the adoption of electric vehicles and renewable energy storage systems. Deep learning's adaptability ensures it can evolve with advancements in battery technology, making it a critical component in the future of battery management.

2.3 Objectives of the Study

- To improve the precision and reliability of SoC estimation in lithium-ion batteries, addressing the limitations of traditional methods.
- To implement and evaluate advanced deep learning architectures, including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Temporal Convolutional Networks (TCN), for their effectiveness in SoC prediction.
- To explore hybrid configurations like TCN-LSTM and TCN-BiLSTM, leveraging their combined strengths for enhanced accuracy and robustness.
- To assess the performance of these models under varying temperature conditions (0°C, 10°C,

25°C, 40°C) to ensure reliability across diverse environments.

- To investigate the impact of optimization techniques, such as Adam and Stochastic Gradient Descent (SGD), on model performance and error minimization.
- To demonstrate the feasibility of integrating these models into real-world BMS for real-time monitoring, operational safety, and energy optimization.
- To contribute to the advancement of EV technology by addressing range anxiety and promoting the adoption of safer, efficient, and environmentally friendly transportation systems.

3. Methodology

3.1 Overview of System and Workflow

The proposed system focuses on leveraging advanced deep learning models for accurately estimating the State of Charge (SoC) in lithium-ion batteries, especially under diverse environmental and operational conditions. The workflow is designed to systematically acquire, preprocess, and analyze data, implement deep learning models, and evaluate their performance for effective integration into Battery Management Systems (BMS).

I. System Overview

The system utilizes critical input parameters such as:

- Voltage: Captures the battery's electrical potential during charge and discharge cycles.
- Current: Reflects the instantaneous energy flow through the battery.
- Temperature: Addresses thermal variations that significantly affect battery performance and SoC estimation.

The raw data for these parameters is sourced from well-documented datasets, such as CALCE, Panasonic NCR 18650PF, and LG 18650HG2, covering a range of real-world operating conditions and thermal environments (0°C, 10°C, 25°C, and 40°C).

II. Workflow

1. Data Acquisition and Preprocessing:
   - Acquisition: Collect multi-parameter datasets with labeled SoC values.
   - Preprocessing: Normalize data to eliminate scale differences, filter noise, and ensure clean inputs for model training. Split the dataset into training, validation, and testing subsets to maintain consistency and enable unbiased model evaluation.

2. Deep Learning Model Development:
   - Model Selection: Begin with individual architectures such as Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Temporal Convolutional Networks (TCN) to analyze their standalone performance.
   - Hybrid Configurations: Develop advanced hybrid models like TCN-LSTM and TCN-Bi-LSTM to combine the time-series learning capabilities of LSTMs with TCN's strength in handling long-term dependencies.
3. Model Training:
   - Train the models using cutting-edge optimization techniques, including Adam and Stochastic Gradient Descent (SGD), focusing on minimizing key performance metrics like Root Mean Square Error (RMSE) and Mean Square Error (MSE).
   - Evaluate model performance under different thermal conditions (e.g., low temperatures like 0°C and high temperatures like 40°C) to account for thermal variability.

4. Performance Evaluation and Analysis:
   - Compare the models' predictive capabilities based on error metrics (e.g., RMSE).
   - Identify the architecture best suited for accurate and reliable SoC estimation under various real-world conditions.

5. System Integration and Deployment:
   - Integrate the optimal model into a Battery Management System (BMS) for real-time SoC monitoring, enabling enhanced battery safety, efficiency, and lifecycle management.

Significance of the Workflow

This workflow provides a structured approach for leveraging data-driven insights to address the limitations of traditional SoC estimation methods. By integrating advanced deep learning techniques, the system ensures reliable and accurate SoC predictions, supporting the operational demands of EVs and contributing to the global transition toward sustainable energy solutions.

3.2 Data Preparation and Preprocessing

Proper data preparation and preprocessing are critical steps in ensuring accurate State of Charge (SoC) estimation. These steps involve organizing, cleaning, and transforming raw battery data into a structured format that is compatible with deep learning models. The following outlines the key stages of this process:

1. Data Acquisition

The datasets used in this study include CALCE, Panasonic NCR 18650PF, and LG 18650HG2, which contain real-world battery parameters like:

- Voltage (V)
- Current (A)
- Temperature (°C)
- State of Charge (SoC) as the target variable.

These datasets provide rich temporal data under various operational and thermal conditions (0°C, 10°C, 25°C, and 40°C).

2**.** Data Cleaning

- Noise Removal**:** Filter out anomalies in battery signals caused by hardware inaccuracies or environmental interference.
- Outlier Detection**:** Identify and remove outliers using statistical methods, ensuring smoother input data for modelling.

3**.** Normalization

- To ensure uniformity across different parameters, all input variables (voltage, current, and temperature) are normalized to a range of [0, 1] using min-max scaling:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

- Normalization helps prevent bias and ensures faster convergence during model training.

4. Dataset Splitting

- The cleaned and normalized dataset is split into:
  - Training Set (70%): Used for model learning.
  - Validation Set (5%): Evaluates model performance during training to prevent overfitting.
  - Test Set (25%): Assesses the final performance on unseen data.

5. Feature Engineering

- Select key features such as voltage, current, and temperature, which are highly correlated with SoC.
- Derive secondary features like moving averages or time lags if needed to capture long-term dependencies in battery behavior.

6. Sequence Preparation

- For deep learning models like LSTM and TCN, the data is structured into time sequences to capture temporal dependencies. For instance, sliding window techniques are used to form input-output pairs.

7. Ensuring Dataset Quality

- Data is visually inspected using tools like matplotlib or seaborn to verify trends, patterns, and the absence of noise.
- Descriptive statistics are computed to validate that data distribution aligns with expected ranges.

3.3 Deep Learning Architectures Explored:

To enhance the accuracy and robustness of State of Charge (SoC) estimation, several advanced deep learning architectures were explored. These architectures leverage their unique strengths to model the complex, nonlinear, and sequential behaviour of lithium-ion batteries.

3.3.1 Long Short-Term Memory (LSTM)

LSTM networks are specialized recurrent neural networks (RNNs) designed to process sequential data while overcoming the vanishing gradient problem present in standard RNNs. They achieve this through memory cells and gating mechanisms that selectively retain relevant temporal information.

- Key Features:
  - Can handle long-term dependencies in time-series data effectively.
  - Incorporates input, forget, and output gates to control information flow.
- Role in SoC Estimation:
  - LSTMs process voltage, current, and temperature data over time to identify patterns and predict SoC.
  - Performs well under stable environmental conditions but may exhibit limitations with extreme variability.

3.3.2 Bidirectional Long Short-Term Memory (Bi-LSTM)

Bi-LSTM networks extend LSTMs by processing input sequences in both forward and backward directions. This bidirectional flow improves context awareness and prediction accuracy.

- Key Features:
  - Combines past and future context for better sequence understanding.
  - Suitable for complex time-series data with hidden dependencies.
- Role in SoC Estimation:
  - Particularly effective in detecting temporal patterns influenced by fluctuating environmental conditions, such as temperature changes.
  - Improves prediction accuracy for non-stationary time-series data, making it more resilient to noisy datasets.

3.3.3 Temporal Convolutional Networks (TCN)

TCN models are convolutional neural networks designed for sequential data. They use dilated convolutions, residual connections, and causal padding to capture long-range dependencies efficiently without the sequential processing bottlenecks of RNNs.

- Key Features:

- Efficient training due to parallel processing.
    - Employs dilated convolutions for larger receptive fields with fewer layers.
    - Residual connections help prevent vanishing gradient issues.
- Role in SoC Estimation:
    - Captures both short-term fluctuations and long-term trends in battery parameters like voltage and current.
    - Demonstrates exceptional performance under diverse temperature scenarios due to its ability to model temporal dependencies effectively.

3.3.4 Hybrid Models (TCN-LSTM and TCN-Bi-LSTM)

Hybrid architectures combine the strengths of TCN for temporal feature extraction and LSTM/Bi-LSTM for sequential data processing. These models are designed to capitalize on their complementary capabilities for accurate and robust predictions.

- TCN-LSTM:
    - Combines TCN's ability to model long-term dependencies with LSTM's sequential learning capabilities.
    - Ideal for scenarios requiring extensive context understanding across large datasets.
- TCN-Bi-LSTM:
    - Enhances TCN-LSTM by adding bidirectional processing for improved temporal resolution.
    - Outperforms other models by capturing both past and future dynamics, making it particularly effective under extreme environmental conditions.
- Role in SoC Estimation:
    - Both hybrid models deliver superior performance by addressing weaknesses in standalone architectures.
    - They are resilient to noisy data, adaptable across varying operating conditions, and achieve the lowest RMSE values among all explored architectures.

3.4 Training and Optimization Techniques:

The training process for deep learning models plays a critical role in ensuring the accuracy and reliability of State of Charge (SoC) predictions. This section discusses the loss functions, optimizers, and hyperparameter tuning strategies employed to optimize the models.

3.4.1 Loss Functions and Optimizers (Adam, SGD)

1. Loss Functions:

The loss function evaluates the difference between the predicted and actual SoC values, guiding the model during training to minimize this error. The following loss functions are used:

- Mean Square Error (MSE):
  - MSE penalizes larger errors more heavily, encouraging precise predictions.
  - It is effective for regression tasks like SoC estimation.
- Root Mean Square Error (RMSE):
  - RMSE is used as a performance metric to interpret errors on the same scale as the target SoC values.

2. Optimizers:

Optimization algorithms are essential for updating model weights during training to minimize the loss function. This study explores:

I. Adam (Adaptive Moment Estimation):
  - Combines the benefits of momentum and RMSProp optimizers.
  - Adapts the learning rate for each parameter, leading to faster and more stable convergence.
  - Preferred for its efficiency in handling sparse gradients and noisy data.

II. Stochastic Gradient Descent (SGD):
  - A straightforward optimization algorithm that updates weights using the gradient of the loss function.
  - Requires manual tuning of the learning rate and benefits from momentum to accelerate convergence and avoid local minima.

Comparison:

- Adam outperforms SGD in terms of convergence speed and error minimization, making it the primary optimizer for this study. However, SGD remains useful for certain scenarios due to its simplicity and lower computational cost.

3.4.2 Hyperparameter Tuning

Hyperparameter tuning is essential for optimizing the performance of deep learning models. Key hyperparameters considered in this study include:

1. Learning Rate:

Controls the step size of weight updates during training.

Optimal range is determined experimentally (e.g., 0.001 for Adam, 0.01 for SGD).

2. Batch Size:

The number of samples processed before updating model weights.

Batch sizes (e.g., 32, 64) are tuned to balance between computational efficiency and model generalization.

3. Number of Layers and Units:

Adjusting the depth and width of models (e.g., number of LSTM units or TCN layers) ensures sufficient capacity to capture complex patterns without overfitting.

4. Dropout Rate:

Dropout (e.g., 0.2–0.5) is used to prevent overfitting by randomly deactivating a fraction of neurons during training.

5. Epochs:

The number of complete training passes over the dataset.

Experimentally tuned (e.g., 100–200 epochs) to ensure convergence without overtraining.

6. Expansion Rate (for TCN):

Determines how dilations expand in TCN models.

Optimal rates are chosen to ensure adequate temporal context coverage without excessive complexity.

7. Validation Frequency:

Periodically assesses performance on the validation set to monitor training and avoid overfitting.

3.5 Performance Evaluation Metrics

Evaluating the performance of deep learning models is critical to ensure the accuracy and reliability of State of Charge (SoC) estimation. The metrics used in this study assess the precision of predictions, the robustness of models under different conditions, and the overall effectiveness of the training process.

1. Root Mean Square Error (RMSE):

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

- Purpose: Measures the average magnitude of the prediction error. RMSE penalizes larger errors more heavily, making it a crucial metric for gauging prediction precision in SoC estimation.
- Interpretation: Lower RMSE values indicate higher accuracy and better model performance.

2. Mean Absolute Error (MAE):

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

- Purpose: Evaluates the average absolute difference between actual and predicted SoC values.
- Interpretation: MAE is less sensitive to outliers than RMSE, providing a balanced view of overall prediction errors.

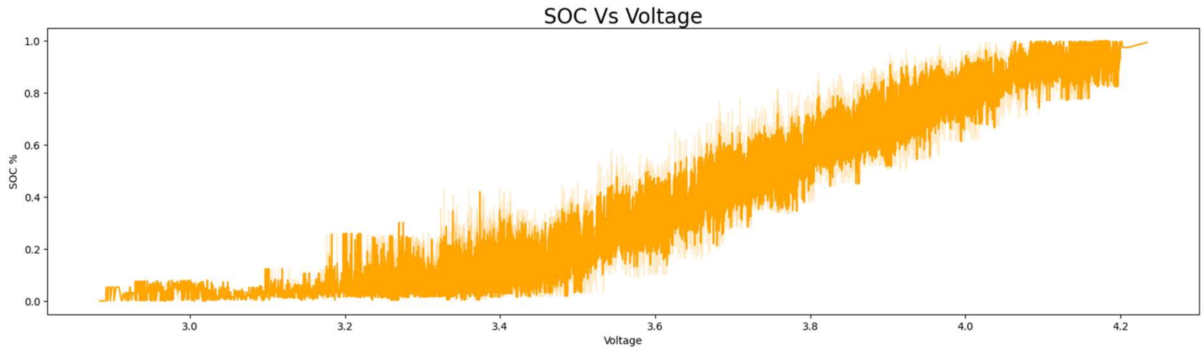
3. Mean Square Error (MSE):

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

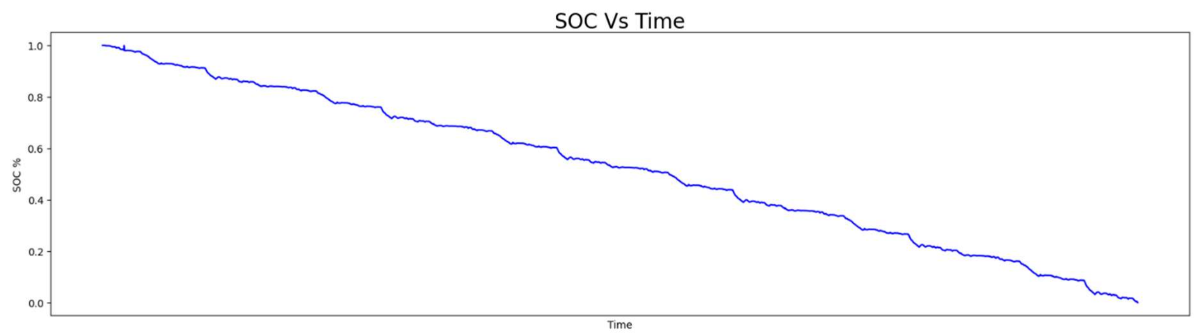
- Purpose: Used during model training to penalize larger deviations more heavily, encouraging the model to minimize significant errors.
- Interpretation: A complement to RMSE, indicating error distribution across predictions.

4. Results and Conclusions

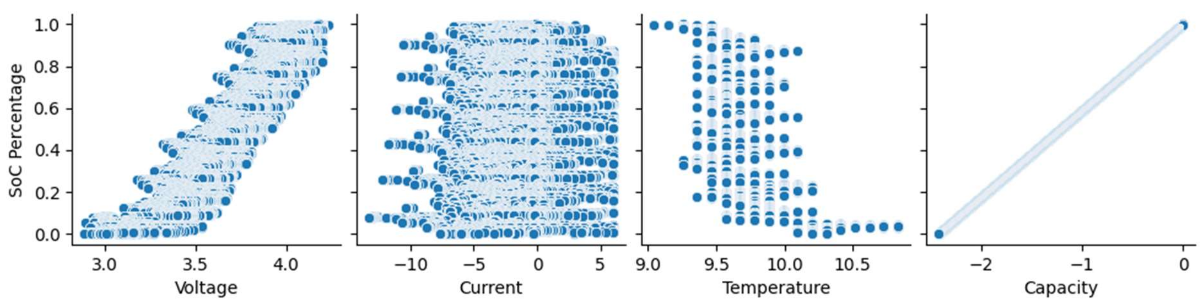
4.1 Results



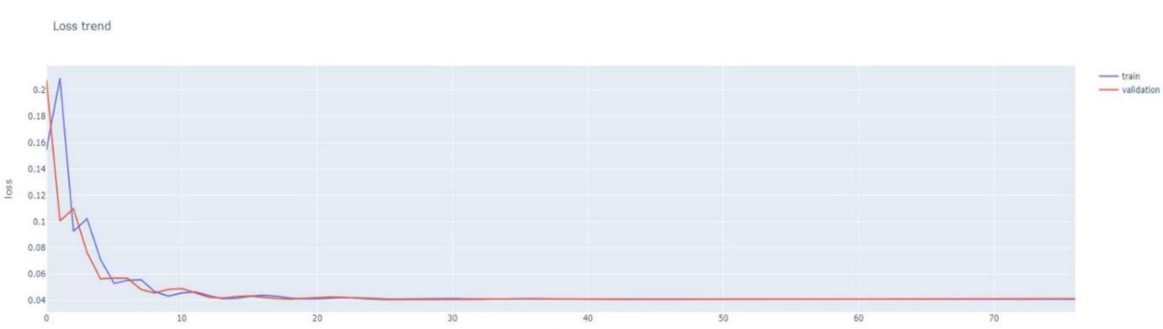
SOC Vs Voltage at 10^{o}C



SOC Vs Time at 10^{o}C



SOC Vs Voltage, Current, Temperature and Capacity at 10^{o}C



Loss function of LSTM-based network trained with Adam Optimizer

Algorithm	Hidden Layers	Epochs	Training RMSE (%)	Testing RMSE @ 0°C (%)	Max Error @ 0°C	Testing RMSE @ 10°C (%)	Max Error @ 10°C	Testing RMSE @ 25°C (%)	Max Error @ 25°C	Testing RMSE @ 40°C (%)	Max Error @ 40°C
TCN-BiLSTM	5	50	0.0190 (1.90%)	0.0170	1.4500	0.0155	1.2500	0.0148	1.2000	0.0140	1.0000
		100	0.0170 (1.70%)	0.0150	1.1000	0.0125	0.9000	0.0118	0.8500	0.0105	0.7000
		150	0.0160 (1.60%)	0.0125	0.8500	0.0100	0.7200	0.0098	0.7000	0.0090	0.5000
		200	0.0145 (1.45%)	0.0110	0.7000	0.0095	0.6500	0.0085	0.5000	0.0070	0.4000
TCN-LSTM	4	50	0.0198 (1.98%)	0.0185	1.4522	0.0170	1.3280	0.0155	1.2560	0.0150	1.2030
		100	0.0175 (1.75%)	0.0165	1.2000	0.0140	1.0000	0.0125	0.9500	0.0120	0.8000
		150	0.0165 (1.65%)	0.0145	1.0000	0.0110	0.8000	0.0105	0.7200	0.0100	0.6000
		200	0.0150 (1.50%)	0.0130	0.8500	0.0100	0.7200	0.0095	0.6000	0.0090	0.5000
TCN	4	50	0.0198 (1.98%)	0.0185	1.4522	0.0170	1.3280	0.0155	1.2560	0.0150	1.2030
		100	0.0172 (1.72%)	0.0165	1.4522	0.0125	0.9123	0.0119	0.6894	0.0110	0.7315
		150	0.0165 (1.65%)	0.0145	1.4070	0.0115	0.9150	0.0105	0.8220	0.0100	0.6500
		200	0.0150 (1.50%)	0.0138	1.3204	0.0106	0.7120	0.0099	0.5100	0.0095	0.6030
LSTM	3	50	0.0255 (2.55%)	0.0265	2.5610	0.0250	2.5020	0.0234	2.2840	0.0225	2.1234
		100	0.0221 (2.21%)	0.0236	2.4326	0.0214	2.3244	0.0195	1.8745	0.0188	1.6234
		150	0.0209 (2.09%)	0.0222	2.1000	0.0198	1.9510	0.0181	1.7850	0.0176	1.5050
		200	0.0201 (2.01%)	0.0222	2.3236	0.0153	1.8240	0.0176	1.5050	0.0182	1.6234
Bi-LSTM	2	50	0.0205 (2.05%)	0.0200	1.9010	0.0185	1.7000	0.0167	1.5510	0.0159	1.4890
		100	0.0185 (1.85%)	0.0198	1.8912	0.0152	1.6123	0.0125	1.5120	0.0120	1.3045
		150	0.0175 (1.75%)	0.0170	1.5210	0.0138	1.3710	0.0119	1.2150	0.0115	1.1670
		200	0.0170 (1.70%)	0.0160	1.5190	0.0119	1.1280	0.0126	1.1560	0.0128	0.9330

Performance Comparison of Deep Learning Models for SoC Estimation of Li-Ion Batteries Across Varying Temperature Conditions

4.2 Conclusions

This study explored the application of advanced deep learning models for State of Charge (SoC) estimation in lithium-ion batteries, focusing on improving accuracy, robustness, and adaptability under varying temperature conditions. Traditional SoC estimation techniques, such as Coulomb counting and open-circuit voltage methods, face limitations due to noise, measurement inaccuracies, and temperature dependency. To address these challenges, deep learning architectures including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Temporal Convolutional Networks (TCN) were implemented, along with hybrid configurations like TCN-LSTM and TCN-Bi-LSTM.

The results demonstrated that deep learning approaches significantly outperform traditional methods by effectively capturing the nonlinear behavior and temporal dependencies of battery systems. Among all tested models, TCN-BiLSTM achieved the lowest RMSE values, indicating superior accuracy and robustness, particularly under extreme temperature variations. Additionally, the Adam optimizer consistently outperformed Stochastic Gradient Descent (SGD) in minimizing error and improving convergence speed. The integration of these models into Battery Management Systems (BMS) has the potential to enhance real-time SoC monitoring, battery longevity, and operational safety in electric vehicles and energy storage applications.

Future work can further optimize these models by incorporating additional environmental factors, expanding training datasets, and refining model architectures for improved real-world deployment. By advancing SoC estimation techniques, this research contributes to the development of safer, more reliable, and energy-efficient battery technologies, supporting the global transition toward sustainable electric mobility.

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