State of Charge Estimation for Electric Vehicles Using LSTM and FNN: A Deep Learning Approach

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Abstract: Dependence on fossil fuel is one of the major contributing factors to climate change. While it does provide energy, it also presents significant problems. To mitigate this, the transportation industry is transitioning to battery-powered systems for a more sustainable future. This calls for a system that could manage the batteries for safe and efficient operation. This requires to accurately predict features such as State of Charge of a battery (SOC). Traditional estimation methods, such as Kalman filters and equivalent circuit models, often struggle with nonlinearities and uncertainties in battery behaviour. The aim of this study is to propose a hybrid model which utilises Feedforward Neural Network (FNN) and Long short-term memory (LSTM) FNN is employed as it possesses the ability to deal with complex nonlinear features that a battery management system would have to deal with while LSTM is used for modelling temporal dependencies., improving prediction accuracy over time. Experimental battery datasets are used to train and validate the model, and its results are compared to those of traditional techniques. The results show that even with different load and temperature circumstances, the suggested method delivers improved accuracy and robustness. This contributes to advancement in systems such as BMS by demonstrating the potential of deep learning models.

1 INTRODUCTION

The transport industry is a significant contributor to greenhouse gas emission and pollution. Electric vehicles (EVs) have emerged as a key solution for reducing carbon emission and dependence on fossil fuels. Lithium-ion batteries have been typically used as a single energy storage system in EVs due to their high energy density, low self-discharge and long life cycle M. Armand and J.-M. Tarascon, 2008.This has engendered the need for a Battery Management System(BMS) to enhance efficiency in key areas such as driving range optimization, fault diagnosis and mitigation, ensuring the reliable and safe operation of EVs (M.-K. Tran and M. Fowler, 2020). One of the key parameters of BMS is accurate estimation of State of Charge (SOC) of battery. The SOC of a LIB is defined as the residual charge of the battery and is given by the ratio of the residual capacity to the nominal, fully charged capacity of the battery (S. Bockrath 2019).

The importance of SOC estimation extends beyond just energy management. Inaccurate SOC prediction can lead to unexpected power losses and reduced battery lifespan affecting both vehicle performance and user experience. SOC also plays a crucial role in charging strategies, the absence of which can lead to safety hazards such as thermal runaways. SOC estimation is complex due to the nonlinear relationship between battery current, voltage and temperature (V. Chandran et al. 2021). Traditionally SOC estimation is done using electrochemical models such as Coulomb counting, Open circuit voltage and Kalman Filtering. However, these methods further contribute to estimation inaccuracy due to reasons such as error accumulation, need for a stationary state and reliance on accurate system modelling.

This research proposes a hybrid LSTM-FNN model for SOC estimation. The study aims to develop an efficient and accurate model by training it on real-world battery dataset. The proposed model is evaluated against standard metrics such as Root Mean Square (RMSE) and Mean Absolute Error (MAE) to demonstrate its effectiveness. The results of this

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research could contribute to advancing battery management systems in turn improving reliability.

The remainder of this paper is structured as follows: Section 2 presents a review of existing SOC estimation techniques and related research. Section 3 details the proposed methodology, including dataset selection, model architecture, and training process. Section 4 discusses the experimental results and performance evaluation. Finally, Section 5 concludes the study and outlines potential future improvements.

2 RELATED WORK

State of Charge (SOC) quantifies the remaining capacity available in a battery at a given time and in relation to a given state of agein (M. Hassini et al. 2023). Existing methods rely on complex electrochemical models which often suffer from inaccuracies due to the nonlinearity and environmental dependence. These limitations have driven towards the adoption of data-driven approaches, particularly machine-learning models. This literature review aims to examine the conventional SOC estimation methods and the development towards AI-powered approaches, highlighting advantages and challenges.

Ampere-hour counting is a fundamental method for State of Charge estimation, relying on the integration of current over time. It is one of the simplest SOC estimation techniques, offering a straightforward approach with low computational overhead. However, while computationally inexpensive, ampere-hour counting suffers from several limitations that hinder its accuracy and reliability, especially in real-world applications.The primary disadvantage being the accumulation of error over time since the method relies on continuous integration (K. C. Ndeche and S. O. Ezeonu, 2021). Furthermore, ampere-counting is highly sensitive to initial SOC as the accuracy of the entire process hinges on knowing the starting SOC with precision. Other methods include Open Circuit Voltage (OCV) based SOC estimation, which relies on the nonlinear relationship between OCV and SOC but is affected by temperature sensitivity which alters the OCV values for the same SOC leading to estimation errors. Additionally, OCV value differs for the same SOC depending upon whether the battery was previously charging or discharging making it less accurate in dynamic conditions (F. Elmahdi, et al. 2021). An alternate approach to SOC estimation is the Internal resistance method which leverages the correlation between a battery's SOC and its internal resistance. Despite being a fast and non-intrusive method, it is highly temperature sensitive. Furthermore, variation in battery chemistry requires careful calibration without which inaccuracies could be introduced.

Hence, conventional SOC estimation methods suffer from several limitations which makes it incompetent for real-world practice. These approaches are highly sensitive to external factors such as temperature variation and battery ageing. These shortcomings highlight the need for more adaptive techniques.AI-driven approaches, which rely on data-driven models, offer a promising way to improve the accuracy and reliability of SOC estimation.

AI-driven models like Long Short-Term Memory (LSTM) networks have been employed for accurate State of Charge (SOC) estimation in lithium-ion batteries (LIBs), effectively addressing the challenges posed by their highly non-linear behavior under varying environmental and operational conditions (S. Bockrath et al. 2019. This study demonstrates that LSTM outperforms traditional physics-based models like the Kalman Filter (KF), achieving a significantly lower root mean square error (RMSE). While this method provides a strong foundation, there is still room for further optimization in terms of computational efficiency and real-time applicability. In this study, we aim to build upon these advancements by refining the LSTM model, improving its adaptability to diverse operating conditions, and enhancing its real-world deployment capabilities.

3 METHODOLOGY

Conventional methods for SOC estimation struggle with various limitations as discussed above. This has paved the path for adoption of AI-techniques, specifically deep learning for SOC estimation (S. Guo and L. Ma, 2023). Deep learning models excel at capturing non-linear relationships and temporal dependencies in data, making them well suited for modelling battery behaviour (S. Nachimuthu et al. 2025). This section outlines the methodology employed for State of Charge estimation using a Long Short-Term Memory - Feedforward Neural Network system. The process includes data acquisition and pre-processing, model development, integration of the two networks, training, and performance evaluation. The overall goal is to develop a robust and accurate SOC estimation model capable of capturing the complex dynamics of battery behaviour.

3.1 Data Pre-Processing

3.1.1 Dataset Preparation

The dataset was sourced from the battery tests on an LG HG2 (3Ah) cell and a Panasonic cellusing a 75A, 5V Digatron Firing Circuits Universal Battery Tester with a voltage and current accuracy of 0.1% of full scale (P. Kollmeyer et al.). The dataset contained such parameters as Voltage, Current, Battery Temperature and Amp-Hours consumed or supplied by the battery.Columns like 'id' are superfluous, so these columns were dropped for redundancy.

3.1.2 Data Cleaning

No missing values were detected, eliminating the need to develop mitigation strategies. Data consistency was ensured when the dataset was analysed for anomalies revealing no notable outliers.

3.1.3 Data Transformation

To smooth out fluctuations a moving average filter was used which was applied to Voltage and Current values over a rolling window of previous timesteps in order to improve the accuracy.

3.1.4 Data Splitting

The dataset was divided into training and testing sets for model evaluation. Based on the dataset shapes:

Training set: 18 cycles
Testing set: 11 cycles
The split ratio is approximately 65% training and 35% testing.

3.2 Exploratory Data Analysis

This section presents the Exploratory Data Analysis (EDA) conducted on the battery performance dataset, which contains multiple sensor readings across different operating conditions.The dataset consists of multiple input features and a target variable:

- **Features:** Five input variables (Voltage (V(k)), Current (I(k)), Battery temperature (T(k)), average terminal voltage (V_avg(k)), and average current (I_avg(k))), representing various battery parameters.
- **Target Variable:** Represents an outcome metric related to battery performance.
- **Training Data:** 669,956 samples.
- **Test Data:** Comprises different test sets collected under varying conditions (0°C and 25°C).

3.2.1 Key Takeaways from EDA

- **Voltage range concentration**: Most data points are in the high voltage range, possibly affecting the model's ability to predict behaviors in lower voltage conditions.
- **Temperature variation**: The dataset covers a wide thermal range, which is crucial for battery performance modeling but may introduce high variability in results.
- **Current (C-rate) imbalance**: Most data is low-C-rate, meaning high discharge scenarios are underrepresented, which could impact model robustness in real-world conditions.

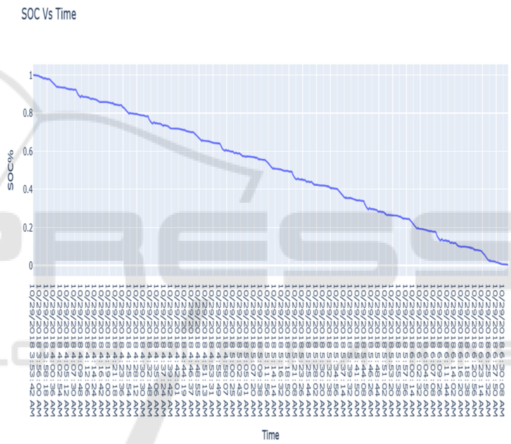

Figure 1: SOC vs time graph.

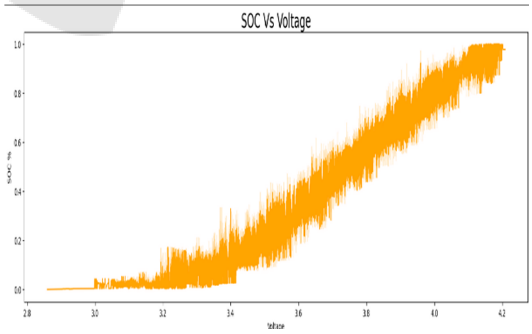

Figure 2: SOC vs voltage graph.

Figure 1 and illustrates the variation of SOC over time, capturing the charge/discharge behavior of the battery. Figure 2 depicts the relationship between SOC and voltage. This nonlinear dependency highlights the challenges of direct SOC estimation

3.3 Model Development

The integration of Long Short-Term Memory (LSTM) networks and Feedforward Neural Networks (FNN) was chosen for State of Charge (SOC) estimation due to the following reasons:

LSTM network has displayed the ability to capture long-term dependencies in sequential data, which is crucial for modelling battery behaviour over time (Y. Hua et al. 2018).

On the other hand, FNN is renowned for handling intricate interactions between non-linear features, improving feature extraction and ultimately raising system accuracy (P. Lara-Benítez 2021). Figure 3 illustrates a basic flow of the system.

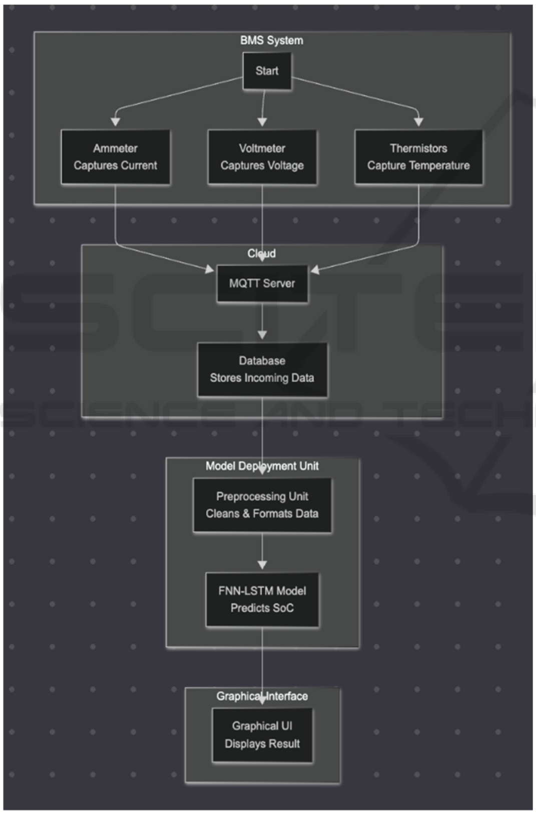

Figure 3: Schematic flow of theoretical structure.

3.3.1 Model Architecture

An LSTM network forms the initial stage of the SOC estimation system. The five input features Voltage (V(k)), Current (I(k)), Battery temperature (T(k)), average terminal voltage (V_ avg(k)), and average current (I_ avg(k)) are fed in the input layer. The LSTM network consists of three stacked LSTM layers, each containing 512 units with the “tanh” activation function. Dropout regularization with a rate of 0.2 is applied after each LSTM layer to mitigate overfitting. The Output Layer produces the LSTM network's output, which is then fed to the subsequent FNN which consists of the following:

- **Input Layer**: Receives the output from the LSTM network.
- **Hidden Layers**: The FNN consists of two fully connected layers, each with 55 neurons, using the SELU activation function to introduce non-linearity.
- **Output Layer**: The final output layer consists of one neuron, applying a linear activation function to generate a single SOC estimation value.

3.3.2 Model Training and Evaluation

The Adam optimizer with a learning rate of 0.00001 is used to train the FNN model.The Huber loss function is employed to balance robustness against outliers while maintaining sensitivity to small errors.The model is trained for 150 epochs with a batch size of 18, where early stopping is applied to avoid overfitting when validation loss does not improve any longer.This approach ensures the model generalizes well to unseen battery data while optimizing training efficiency.The model was evaluated using multiple error metrics such as Mean Absolute Error, Root Mean Squared Error, and Mean Absolute percentage error to assess the model's performance on the validation and testing sets.

4 RESULT AND DISCUSSION

This section presents the results obtained from the LSTM-FNN model for SOC estimation. The model's performance was evaluated using metrics such as Root Mean Squared Error and Mean Absolute Error. The model achieved a Root Mean Square Error (RMSE) of 0.0239 and Mean Absolute Error (MAE) of 0.0186 on the test dataset. Additionally, the Mean Absolute Percentage Error (MAPE) of 9.48% validates the model’s ability to generalize well across different SOC values. The hybrid model was proved effective in dealing with non-linear relationship within the data outperforming the traditional methods highlighting the suitability of deep-learning model for real time SOC estimation. As shown in Figure 4, 5 the predicted SoC closely follows the actual SoC over time during training and testing.

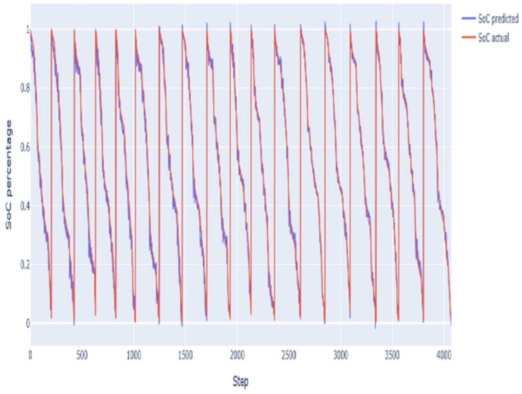

Figure 4: Result on training.

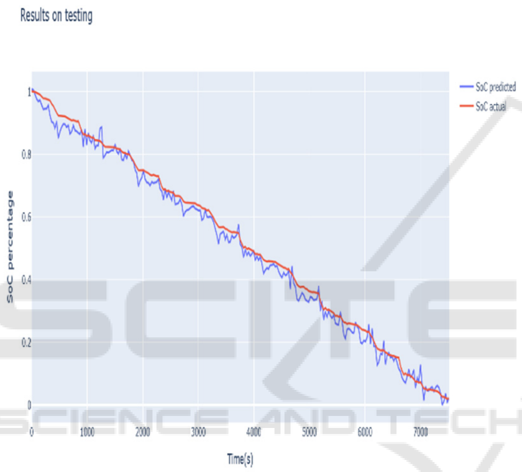

Figure 5: Result on testing.

5 CONCLUSIONS

This study was conducted to investigate the efficacy of a hybrid Long Short-Term Memory - Feedforward Neural Network model for State of Charge estimation in batteries. The research aimed to address the limitations of traditional SOC estimation methods by leveraging the strengths of deep learning techniques. The proposed LSTM-FNN model combines the ability of LSTMs to capture long-term temporal dependencies with the non-linear mapping capabilities of FNNs. Results demonstrate the superior performance of the LSTM-FNN model compared to standalone LSTM networks and other established methods, achieving a low RMSE and maximum error, as evidenced by the results presented in Section 4. The hybrid approach effectively captured the complex dynamics of battery behaviour, leading to improved accuracy and robustness in SOC estimation.

The success of the LSTM-FNN model highlights the potential of hybrid deep learning architectures for enhancing SOC estimation. The synergistic combination of LSTM and FNN enabled a more comprehensive representation of battery behaviour, resulting in improved estimations. While this research focused on a specific battery chemistry and operating conditions, the methodology can be adapted to other battery types and scenarios. Further investigation into incorporating additional factors like other various temperature conditions, and potentially exploring parallel architectures with convolutional layers (Manoharan et al. 2023), could yield even more robust and accurate estimations. This study contributes valuable insights into the field of battery management systems and paves the way for developing advanced SOC estimation techniques. The accurate and reliable SOC estimation provided by the LSTM-FNN model can lead to improved battery performance, extended lifespan, and enhanced safety in various applications.

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