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Bayesian Optimisation in Deep Learning for Electric Vehicle SOC Prediction

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SOC, Lithium-Ion Battery, Bayesian Optimization, DL, CNN2D, BI-LSTM, RMSE, Max Error, Electric Vehicles, Hyperparameter Tuning, Feature Selection, Flask Application.

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ABSTRACT

SOC estimate is essential for electric car lithium-ion battery efficiency. Traditional deep learning models optimized using Grid Search often fail to achieve optimal hyperparameters, leading to reduced prediction accuracy. To address this, we employed Bayesian Optimization, which efficiently selects the best hyperparameters by leveraging past evaluations. Our study evaluated multiple DL models, including GRU, LSTM and BI-LSTM, optimized with 70 neurons, where BI-LSTM achieved the lowest RMSE and Max Error. As an extension, we implemented the CNN2D algorithm, known for its superior feature selection and optimization capabilities using convolutional layers and MaxPooling2D. CNN2D outperformed previous models with reduced RMSE and Max Error. Additionally, we developed a Flask-based application enabling users to predict SOC by uploading CSV data, enhancing accessibility and usability.

INTRODUCTION

EVs run on lithium-ion batteries, therefore precisely estimating the SOC is essential for battery management and vehicle performance. SOC estimation affects electric vehicle safety, battery life, and range. Traditional methods, including rule-based and model-based approaches, often suffer from inaccuracies due to complex battery dynamics and environmental variations. To overcome these challenges, deep learning techniques have been widely adopted to enhance SOC prediction accuracy. However, previous approaches primarily relied on Grid Search for hyperparameter tuning, which often led to suboptimal parameter selection, degrading the overall performance of SOC estimation models.

To improve hyperparameter selection, Bayesian Optimization has been employed as an alternative, offering a more efficient approach to finding optimal hyperparameters based on past evaluations. This work trained LSTM, GRU, and BI-LSTM deep learning models using Bayesian Optimisation. The lowest RMSE and Maximum Error were with BI-LSTM. Despite these improvements, feature extraction and selection remained a key challenge in enhancing model accuracy.

As an extension of our previous work, we implemented the CNN2D (Convolutional Neural Network 2D) algorithm, which is famous for automatically extracting and optimising important features using convolutional layers with MaxPooling2D. By leveraging CNN2D, our model achieved further reductions in RMSE and Maximum Error, improving SOC estimation accuracy. Additionally, we developed a Flask-based web application that allows users to interact with the model by uploading CSV files to predict battery SOC. This application enhances accessibility, enabling real-time SOC predictions and facilitating further testing across different datasets. Our findings demonstrate that CNN2D outperforms traditional deep learning models, EV lithium-ion battery SOC estimation with this technology appears promising.

LITERATURE SURVEY

a) Battery management solutions for li-ion batteries based on artificial intelligence:
https://www.sciencedirect.com/science/article/pii/S2090447923001028

The automobile industry, which has relied on petrol, diesel, and other engines, is being transformed by hybrid and electric cars. Automobile manufacturers have long been interested in lithium-ion batteries. Electric vehicles rely heavily on their battery management systems. The battery pack is the most expensive and crucial portion of an electric car, thus it must be regularly checked. The SOC of a Li-ion battery cannot be directly monitored, making precise measurement and computation difficult. AI has been used to predict Li-ion battery SOC and SOH in numerous ways. Li-ion battery condition estimate research uses six machine learning methods. This study found that random forest discharge prediction performed better with less accuracy loss than other models. The random forest regressor still only manages a mean absolute error of 0.0035, a median absolute error of 0.0013, and an RMSE of 0.0097, even when the maximum R2-score is 0.999. Our studies with a battery management system show that AI can properly estimate Li-ion battery state, improving electric car performance.

b) Application of electrochemical impedance spectroscopy in battery management system: State of charge estimation for aging batteries:

https://www.sciencedirect.com/science/article/abs/pii/S2352152X22022642

Long-standing research has focused on precisely calculating the state of charge (SoC) for electric and hybrid vehicles. Most current methods for evaluating systems on chips use an exact equivalent circuit model. Ageing batteries' impedance and capacity variations will influence estimate accuracy. This study proposes a new model update technique for the system-on-chip (SoC) algorithm that combines impedance spectrum detection into the battery management system. To begin, an accelerated ageing test is employed to assess battery age-related impedance spectrum change. The evaluated Li-ion batteries' ohmic resistance rises with age. Thus, the model's parameters and capacity depend on the ohmic impedance change rate. Test the proposed technique while charging and discharging. MaxAE is 29.9% at 1000 cycles. EIS modification keeps MaxAE around 5.4%, improving estimate accuracy.

c) DL Framework for Lithium-ion Battery SOC Estimation: Recent Advances and Future Perspectives: https://www.sciencedirect.com/science/article/abs/pii/S2405829723002623

An correct state of charge underpins lithium-ion battery reliability. It estimates end-to-end SOC for different battery chemistries under different operating conditions using raw battery operational data. After delving into SOC estimation challenges, a comprehensive technique based on deep learning is introduced. Next, we take a look at the most recent research on the topic and the latest deep learning applications for SOC estimation, with an emphasis on model structure. Three of the most frequent deep neural networks (DNNs) are completely connected, recurrent, and convolutional. We also discuss advanced uses like transfer learning and deep learning integration. Finally, methodology is used to examine data collection, model creation, and practical implementation issues and solutions. This work may enhance battery management efforts beyond SOC estimations.

d) Lithium-ion battery State-of-Charge estimation based on an improved Coulomb-Counting algorithm and uncertainty evaluation: https://www.sciencedirect.com/science/article/abs/pii/S2352152X22000986

Precision State-of-Charge predictions are essential for a good Battery Management System (BMS). Because there's no direct SoC access. Parametric errors, battery system nonlinearity, capacity loss from charge/discharge cycles, and time- and temperature-dependent battery attributes make SoC estimation problematic. Our mathematical model for predicting the performance of Lithium-ion battery systems on a chip (SoC) using an enhanced approach over a 10-year period is based on a 12V100Ah Lithium-ion battery.With a maximum error rate of 0.3 percent, the recommended technique estimates SoC more accurately than earlier analytical and heuristic methods.

e) Modified dual extended Kalman filters for SOC estimation and online parameter identification of lithium-ion battery via modified gray wolf optimizer: https://journals.sagepub.com/doi/10.1177/09544070211046693

For accurate lithium-ion battery SOC evaluation, Dual Extended Kalman filters (DEKF) should be optimised using a PSO-based Grey Wolf optimiser (MGWO). The specifications are determined by a battery test, and the circuit is of second order with two resistor-capacitor branches. The two most common types of dual extended Kalman filters are the parameter and state filters. The parameter filter lets you alter battery settings online, and the status filter estimates charge. MGWO improves the noise covariance matrix, improving SOC state estimation and reducing EKF linearisation error. Optimising the noise covariance matrix and adding online parameter identification improve algorithm accuracy, and the recommended method responds well to initial imperfection.

METHODOLOGY

A) Proposed System

In the proposed system, we enhance the accuracy of State of Charge (SOC) estimation for lithium-ion batteries by integrating CNN2D (Convolutional Neural Network 2D) with Bayesian Optimization. However, to further improve performance, we extended our work by implementing CNN2D, which effectively extracts and selects relevant features using convolutional layers and MaxPooling2D. CNN2D demonstrated lower RMSE and Maximum Error compared to previously used models, making it more reliable for SOC estimation.

Additionally, we developed a Flask-based web application that enables users to predict SOC by uploading CSV data. The application provides an interactive interface, allowing users to input real-time battery parameters and obtain accurate SOC predictions efficiently. This extension enhances model accessibility and usability, making it a practical solution for real-world battery management in electric vehicles.

B) System Architecture

As a first step in the Bayesian Optimised DL system design for accurate lithium-ion battery SOC estimate, a dataset of battery parameters including voltage, current, temperature, and capacity is obtained.These raw data values undergo normalization, a preprocessing step that ensures consistency and improves model efficiency by scaling values within a fixed range.

Following normalisation, data is split into a training dataset and a testing dataset. The proposed approach optimises traditional deep learning models such as LSTM, GRU, and BI-LSTM using Bayesian Optimisation during training and evaluation.As an extension, CNN2D is introduced to enhance feature selection and prediction accuracy using convolutional layers and MaxPooling2D.

The trained models are evaluated based on performance metrics, specifically RMSE and Max Error, to assess their predictive accuracy. CNN2D's improved SOC estimation performance was a result of its lower RMSE and Max Error compared to other models. The final predictions are then made available through a Flask-based application, allowing users to upload CSV data and predict battery SOC in real time. This interactive approach improves usability and accessibility for practical applications in electric vehicle battery management.

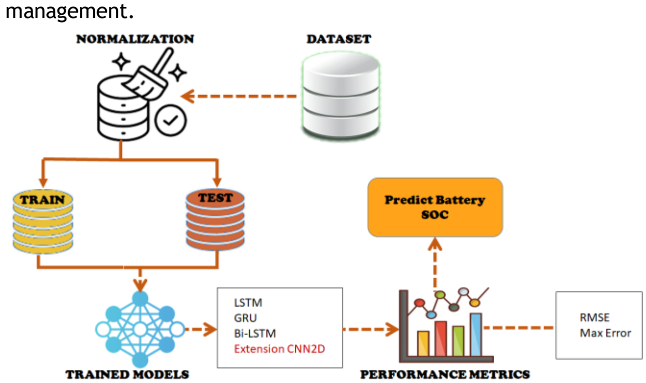

Fig.1. Proposed Architecture

C) MODULES

a) Data Preprocessing and Normalization
- Collects battery data, including voltage, current, temperature, and capacity.
- Performs data cleaning and normalization to standardize input values for accurate model training.

b) Dataset Splitting (Train-Test Separation)
- Divides the dataset into training and testing sets.
- Ensures effective model validation by keeping unseen data for testing.

c) Model Training with Bayesian Optimization
- Implements LSTM, GRU, and BI-LSTM models optimized using Bayesian Optimization.
- Identifies the best hyperparameters for improved prediction accuracy.

d) Extension with CNN2D
- Introduces CNN2D for enhanced feature extraction and optimization.
- Uses convolutional layers and MaxPooling2D to improve SOC estimation accuracy.

e) Performance Evaluation
- Compares models based on RMSE and Max Error metrics.
- Determines the most efficient model for SOC prediction.

f) Flask-Based SOC Prediction System

- Develops a user-friendly web interface for real-time SOC prediction.
- Allows users to upload CSV files and obtain SOC predictions interactively.

D) Algorithms

f) CNN2D:

CNN2D is employed in the extended system to enhance feature selection and improve SOC estimation accuracy. Unlike traditional sequential deep learning models, CNN2D uses 2D convolutional layers to extract spatial dependencies from battery parameters like voltage, current, and temperature. The MaxPooling2D layer further refines the feature maps by reducing dimensionality while retaining essential information, leading to more precise SOC predictions. When it comes to RMSE and Max Error optimisation utilising these layers, CNN2D outperforms LSTM, GRU, and BI-LSTM.

g) LSTM :

(RNNs like LSTM are appropriate for sequential data with long-term dependencies. Memory cells with input, forget, and output gates let the model recall valuable data and reject unnecessary data. Here, we apply LSTM to estimate lithium-ion battery SOC using prior voltage, current, and temperature data.

h) GRU (Gated Recurrent Unit)

By merging the input and forget gates into a single update gate, GRU simplifies LSTM. This reduces the number of parameters and speeds up training while maintaining performance. GRU is well-suited for SOC estimation as it efficiently captures time-dependent patterns in battery data, making it a computationally efficient alternative to LSTM.

i) Bi-LSTM (Bidirectional LSTM)

Reverse-engineering is an integral part of Bi-LSTM processing. This allows the model to improve its prediction accuracy by learning dependencies from both past and future time steps. For SOC estimation, Bi-LSTM helps in capturing both historical and upcoming trends in battery performance, resulting in a more accurate and stable prediction model.

II. EXPERIMENTAL RESULTS

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Find out how reliable a test is by comparing real positives and negatives. Following mathematical:

Accuracy = TP + TN / (TP + TN + FP + FN)

Accuracy=TP+TN/ TP+TN+FP+FN

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = TP/ (TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by percent of correctly anticipated positive observations relative to total positives.

$$\textit{Recall} = \frac{TP}{TP + FN}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

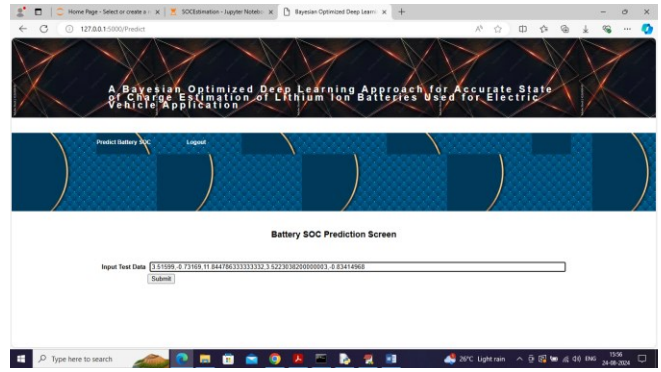

Fig.2. input value

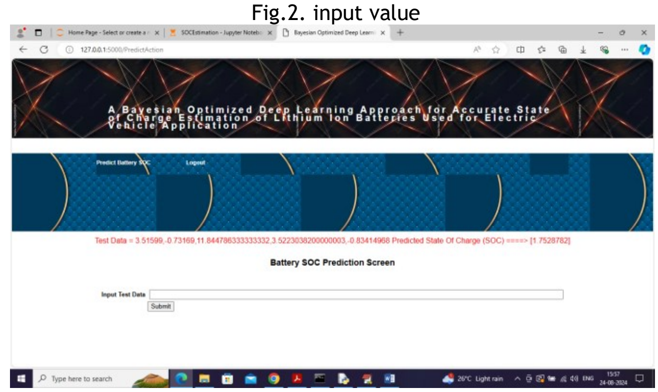

Fig.3. results

Sno	Algorithm Name	RMSE	Max Error
1	LSTM	0.028836	0.196723
2	GRU	0.022540	0.092101
3	BI-LSTM	0.019130	0.149095
4	Extension CNN2D	0.009464	0.045453

Fig.4. Accuracy table

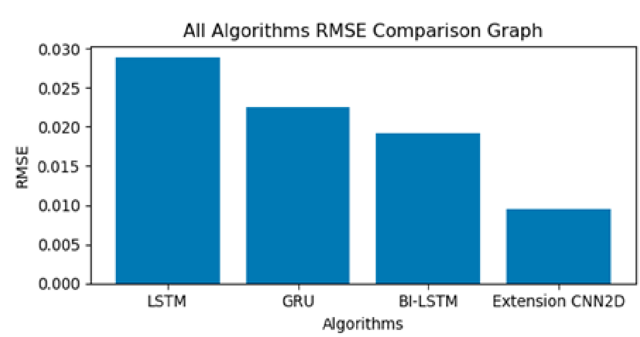

Fig.5. Accuracy graph

CONCLUSION

In this work, a Bayesian Optimized DL approach was implemented for accurate SOC estimation of lithium-ion batteries used in electric vehicles. Initially, LSTM, GRU, and Bi-LSTM models were optimized using Bayesian Optimization, with Bi-LSTM achieving the lowest

RMSE and Max Error. As an extension, CNN2D was introduced to enhance feature extraction, leading to further performance improvements. The results demonstrated that CNN2D outperforms traditional deep learning models by effectively identifying relevant battery parameters and reducing prediction errors. Additionally, a Flask-based application was developed to provide an interactive SOC prediction system.

FUTURE SCOPE

The proposed work can be extended further by developing hybrid models that combine CNN2D with LSTM or Bi-LSTM to leverage both spatial and sequential feature extraction, improving SOC estimation accuracy. Additionally, integrating the system with IoT-based battery management platforms will enable real-time SOC monitoring, enhancing electric vehicle performance. Expanding the dataset by including diverse battery types and varying temperature conditions can improve model generalization. Furthermore, deploying the SOC prediction model on edge computing devices will allow for efficient and low-latency battery management in real-world applications. Lastly, enhancing the Flask-based application with features like interactive visual analytics, historical trend analysis, and mobile compatibility will improve user experience and usability.

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