

Research Paper

Accurate Battery State of Charge Prediction using Bayesian Optimized CNN2D Deep Learning Model with Flask-Based Application

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Abstract: Accurate estimation of the State of Charge (SOC) of lithium-ion batteries is essential for ensuring efficient battery management and reliable operation in Electric Vehicles (EVs). This work extends the SOC prediction framework by incorporating a CNN2D-based deep learning model optimized using Bayesian Optimization for improved hyperparameter tuning and feature extraction. The proposed model utilizes battery parameters such as voltage, current, temperature, and capacity from the Panasonic battery dataset to learn complex relationships influencing SOC behavior. Experimental results demonstrate that the CNN2D model achieves lower RMSE and maximum error compared to traditional deep learning models such as LSTM, GRU, and Bi-LSTM. Additionally, a Flask-based web application is developed to provide an interactive platform where users can upload CSV input data and obtain SOC predictions in real time. The proposed system improves prediction accuracy, reduces computational errors, and offers a practical tool for battery health monitoring and EV energy management.

Index terms - State of Charge (SOC), Lithium-Ion Batteries, Electric Vehicles (EVs), Deep Learning, Bayesian Optimization, CNN2D, Hyperparameter

Tuning, Battery Management System, Flask Web Application, SOC Prediction.

1. INTRODUCTION

The rapid growth of Electric Vehicles (EVs) has increased the demand for efficient energy storage systems and reliable battery management technologies. Lithium-ion batteries are widely used in EV applications due to their high energy density, long life cycle, low self-discharge rate, and high power capability. However, maintaining battery safety and performance requires accurate monitoring of internal battery parameters. One of the most important parameters is the State of Charge (SOC), which indicates the remaining capacity of the battery and helps in managing energy usage effectively. Accurate SOC estimation is essential for improving battery lifespan, preventing over-charging or deep discharging, and ensuring reliable vehicle operation.

Traditional SOC estimation techniques such as Coulomb counting, equivalent circuit models, and Kalman filter-based approaches often face challenges due to battery non-linearity, aging effects, and

varying operating conditions. In recent years, deep learning techniques have gained significant attention because of their ability to capture complex nonlinear relationships between battery parameters such as voltage, current, and temperature. Models such as LSTM, GRU, and Bi-LSTM have shown promising results in SOC prediction. However, the performance of these models strongly depends on the proper selection of hyperparameters, which can significantly influence prediction accuracy.

To address these challenges, this work proposes a Bayesian Optimization-based deep learning framework for SOC estimation of lithium-ion batteries used in electric vehicles. Bayesian Optimization efficiently selects optimal hyperparameters for deep learning models, improving prediction accuracy while reducing computational complexity. In addition to recurrent models such as LSTM, GRU, and Bi-LSTM, this work extends the framework by introducing a CNN2D model, which effectively captures spatial patterns and important features from battery data.

Furthermore, a Flask-based web application is developed to provide a user-friendly interface for SOC prediction. The system allows users to upload battery parameter data through a CSV file and obtain SOC predictions in real time. By integrating Bayesian optimization, CNN2D feature learning, and a web-based prediction system, the proposed approach enhances SOC estimation accuracy and provides a practical solution for intelligent battery management in electric vehicle applications.

The SOC values used for evaluation are directly obtained from the dataset and serve as ground truth for comparison with model predictions.

2. LITERATURE SURVEY

1. Battery management solutions for li-ion batteries based on artificial intelligence

Conventional, diesel, and gasoline-powered cars are now being replaced by second-generation hybrid and electric vehicles in the automotive industry. The automobile industry has long been interested in lithium-ion (Li-ion) batteries. The battery

management system (BMS) is one of the most important parts of an electric vehicle. The battery pack is the most important and costly part of an electric automobile, thus it needs to be closely watched over and managed. The several states of a Li-ion battery's cells, such as the State of Health (SOH) and State of Charge (SOC), are difficult to measure and calculate precisely since they cannot be immediately observed. This study looks at several approaches and techniques for applying artificial intelligence to estimate the SOC and SOH of Li-ion batteries. The estimate of the status of Li-ion batteries is thoroughly investigated using six machine learning techniques. Linear, random forest, gradient boost, light gradient boosting (light-GBM), extreme gradient boosting (XGB), and support vector machine (SVM) regressors are the techniques used. The discharge prediction utilizing random forest performs noticeably better at a modest loss of accuracy when compared to the other models used in this investigation. For example, the random forest regressor achieves only 0.0035, 0.0013, and 0.0097 for mean and median absolute error and root means squared error (RMSE), respectively, while having the greatest R2-score of 0.999. We demonstrated how AI techniques can accurately forecast the state estimate of Li-ion batteries, which can be used in conjunction with a battery management system to enhance the performance of electric vehicles.

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

Research has traditionally focused on accurately estimating the state of charge (SoC) of electric cars (EVs) and hybrid electric vehicles (HEVs). The equivalent circuit model (ECM) is the foundation of the widely used SoC estimate techniques, which need a high level of model accuracy. As a battery ages, its capacity and impedance may alter, which will unavoidably impact the accuracy of the estimation. This study proposes a new model update technique for the SoC algorithm based on electrochemical impedance spectroscopy (EIS) and integrates the impedance spectrum detection method into the battery management system (BMS). First, an accelerated aging test is used to examine how the impedance spectrum changes as batteries age. For the

studied Li-ion battery, it is discovered that aging mostly results in an increase in ohmic resistance but has no discernible effect on the diffusion and charge transfer processes. Consequently, the capacity and model parameters are adjusted in accordance with the ohmic impedance change rate. Second, the suggested approach is tested in both charging and discharging scenarios. The SoC estimation value will be greater under charging conditions and lower under discharging conditions as the battery ages, according to the results. After 1000 cycles, the maximum absolute error (MaxAE) will be 29.9%. On the other hand, the estimation accuracy may be effectively improved by controlling the MaxAE within 5.4% based on EIS correction.

3. Deep Learning Framework for Lithium-ion Battery State of Charge Estimation: Recent Advances and Future Perspectives

Lithium-ion batteries depend on accurate state of charge (SOC) to function reliably. In the era of battery big data, which includes field and testing data, the deep learning technique—a game-changer in many fields—has lately surfaced as a viable answer to accurate SOC calculation. Using raw battery operating data as input for different battery chemistries under varied operating situations, it allows end-to-end SOC estimate. In order to evaluate the new applications of deep learning in SOC estimation with an emphasis on the model structure, this paper first outlines SOC estimation challenges and presents a general framework of deep learning-based SOC estimation. The fully connected neural network, recurrent neural network, and convolutional neural network—three common types of deep neural networks (DNNs)—are described. Additionally, sophisticated uses like transfer learning and combining deep learning with other techniques are covered. In order to provide insights into this field, difficulties and future prospects related to data gathering, model building, and practical applications are finally methodically evaluated. The current work has the potential to spur advancements in other battery management activities in addition to SOC estimates.

4. Lithium-ion battery State-of-Charge estimation based on an improved Coulomb-Counting algorithm and uncertainty evaluation

Designing an effective Battery Management System (BMS) requires an accurate assessment of a battery's State-of-Charge (SoC). This is because direct access to SoC is not possible. Battery model errors, parametric uncertainties, the nonlinearity of the battery system, battery capacity decline from charge/discharge cycles, and temperature- and time-dependent features are just a few of the numerous variables that contribute to poor SoC prediction. A mathematical model based on an enhanced Coulomb-Counting (iCC) technique and uncertainty assessment over a ten-year period is presented in this study to accurately estimate the SoC of a lithium-ion battery. The performance and efficacy of the suggested concept are assessed by experimental measurements utilizing a 12V100Ah lithium-ion battery. In comparison to other analytical and heuristic techniques, the findings show that the greatest estimation error utilizing the suggested method is 0.3%, confirming the high accuracy of SoC estimation.

5. Modified dual extended Kalman filters for SOC estimation and online parameter identification of lithium-ion battery via modified gray wolf optimizer:

A technique that uses dual Extended Kalman filters (DEKF) optimized by a PSO-based Gray Wolf optimizer (MGWO) is presented to accurately estimate the state of charge (SOC) of lithium-ion batteries. Two resistor-capacitor branches are used in a second-order equivalent circuit architecture. Battery testing determines the battery's specifications. State filters and parameter filters are the two categories of dual extended Kalman filters. State filters are used for SOC estimation, whereas parameter filters are used to modify battery parameters live. In the meanwhile, MGWO is used to optimize the noise covariance matrix, which lowers the linearization error from EKF and increases the accuracy of SOC's state estimate. The findings demonstrate that while the suggested approach can effectively adjust to the initial mistake, the algorithm's accuracy is increased

by using online parameter identification and noise covariance matrix optimization.

3. METHODOLOGY

This paper formulates the problem as a regression task in which the battery's State of Charge (SOC) is predicted by the model.

SOC, a continuous number with a range of 0 to 1 (or 0% to 100%), is the goal variable (output).

The model generates a projected SOC value based on input characteristics including voltage, current, temperature, and capacity. To assess the model's performance, these projected values are contrasted with the dataset's actual SOC values.

i) Proposed Work:

The proposed work focuses on improving the State of Charge (SOC) estimation of lithium-ion batteries used in Electric Vehicles by integrating Bayesian Optimization with deep learning models. Initially, the battery dataset containing parameters such as voltage, current, temperature, and capacity is preprocessed and normalized to ensure consistent input for model training. The dataset is then divided into training and testing sets to evaluate the performance of different deep learning architectures.

In the proposed framework, multiple models including LSTM, GRU, Bi-LSTM, and CNN2D are implemented for SOC prediction. Bayesian Optimization is applied to automatically determine optimal hyperparameters such as the number of neurons and learning parameters, improving model efficiency and prediction accuracy. As an extension to the existing approach, a CNN2D-based architecture with MaxPooling2D layers is introduced to enhance feature extraction and capture complex patterns in battery data. Experimental results demonstrate that the CNN2D model achieves lower RMSE and Maximum Error, indicating superior SOC prediction performance compared to other models. The dataset used in this work is a numerical time-series dataset (not an image dataset) consisting of battery parameters such as voltage, current, temperature, and capacity. For the CNN2D model, the input features

are reshaped into a 2D matrix format to enable convolution operations, rather than using actual image data.

To make the system practical and user-friendly, a Flask-based web application is developed. The application allows users to log in as an administrator and upload input battery data through a CSV file, after which the trained model predicts the battery SOC in real time. This integration of optimized deep learning models with a web-based interface enables efficient battery monitoring and supports intelligent battery management for electric vehicle applications.

Based on battery characteristics including voltage, current, and temperature, the regression model forecasts continuous SOC values.

ii) System Architecture:

The system architecture for the proposed Battery State of Charge (SOC) estimation framework consists of several stages including data preprocessing, model training, SOC prediction, and performance evaluation. Initially, the battery dataset containing parameters such as voltage, current, temperature, and capacity is collected and processed. A normalization process is applied to standardize the input data and improve model learning efficiency. After preprocessing, the dataset is divided into training and testing sets, where the training data is used to train deep learning models and the testing data is used to evaluate the model performance.

In the next stage, multiple deep learning models including LSTM, GRU, Bi-LSTM, and the extended CNN2D model are trained using the prepared dataset. Bayesian Optimization is applied to determine the optimal hyperparameters for each model to enhance prediction accuracy. The trained models are then used to predict the Battery State of Charge (SOC) based on the input battery parameters. Finally, the performance of the models is evaluated using metrics such as Root Mean Square Error (RMSE) and Maximum Error. The results are analyzed to determine the most accurate model, where the CNN2D extension provides improved SOC prediction performance compared to other deep learning approaches.

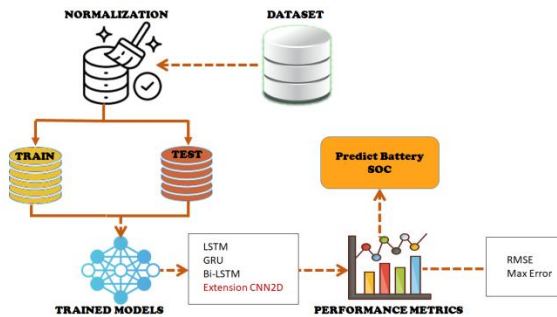


Fig.1. Proposed Architecture

iii) MODULES:

1. Dataset Collection Module

This module collects the lithium-ion battery dataset used for SOC estimation. The dataset contains important battery parameters such as voltage, current, temperature, and capacity obtained from the Panasonic battery dataset, which are used as input features for training the deep learning models.

2. Data Preprocessing and Normalization Module

In this module, the collected battery data is cleaned and normalized to improve the model performance. Normalization ensures that all input features are scaled to a consistent range, reducing data imbalance and helping the models learn patterns more effectively.

3. Training and Testing Module

After preprocessing, the dataset is divided into training and testing sets. The training data is used to train deep learning models, while the testing data is used to evaluate the prediction performance and validate the effectiveness of the trained models.

4. Deep Learning Model Module

This module implements different deep learning models such as LSTM, GRU, Bi-LSTM, and CNN2D for SOC prediction. Bayesian Optimization is applied to tune the hyperparameters of these models to achieve improved prediction accuracy and efficient learning.

5. SOC Prediction Module

The trained deep learning models analyze the battery parameters and predict the State of Charge (SOC) of the lithium-ion battery. This module generates the

SOC estimation results that indicate the remaining battery capacity for electric vehicle applications.

6. Performance Evaluation Module

This module evaluates the performance of the trained models using metrics such as Root Mean Square Error (RMSE) and Maximum Error. The evaluation helps in comparing the accuracy of different models and identifying the most effective algorithm for SOC estimation.

7. Web Application Interface Module (Flask)

A Flask-based web application is developed to provide a user-friendly interface for SOC prediction. Users can log in as admin, upload battery data through a CSV file, and obtain SOC prediction results quickly, making the system practical for real-time battery monitoring.

iv) ALGORITHMS:

a) 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.

b) 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.

c) 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.

d) 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.

v) Dataset Description

The Panasonic Lithium-ion Battery Dataset, which includes time-series battery operational data gathered under controlled settings, is the dataset used in this investigation. Key characteristics captured at various times throughout cycles of charging and discharging, including voltage (V), current (I), temperature (T), and capacity, are included in the dataset.

The matching State of Charge (SOC) values are supplied as ground truth labels, and these parameters are utilized as input features. The dataset is separated into training and testing sets for model assessment after being preprocessed using normalization methods.

4. EXPERIMENTAL RESULTS

The proposed system was evaluated using the Panasonic lithium-ion battery dataset, which includes important parameters such as voltage, current, temperature, and capacity. The dataset was preprocessed using normalization techniques and divided into training and testing sets for model evaluation. Multiple deep learning algorithms including LSTM, GRU, Bi-LSTM, and the extended CNN2D model were implemented to estimate the Battery State of Charge (SOC). Bayesian Optimization was used to select optimal hyperparameters for each model to improve prediction performance. The experimental comparison shows that traditional recurrent models such as LSTM and GRU achieved moderate prediction accuracy, while Bi-LSTM improved the

results by capturing bidirectional temporal dependencies in battery data.

The performance of all models was evaluated using Root Mean Square Error (RMSE) and Maximum Error metrics. From the RMSE comparison graph, the CNN2D extension achieved the lowest error value (around 0.0095) compared to LSTM, GRU, and Bi-LSTM, demonstrating superior prediction capability. The results also show that CNN2D effectively extracts relevant features from the battery data, leading to more accurate SOC estimation. Furthermore, a Flask-based web application was developed to demonstrate the practical implementation of the system, where users can input battery parameters and obtain SOC predictions in real time. The experimental outcomes confirm that the proposed CNN2D-based approach significantly improves SOC estimation accuracy and provides a reliable solution for battery management in electric vehicle applications.

The performance of the proposed models is evaluated using regression-based metrics, as SOC estimation is a continuous prediction problem. The primary evaluation metric used is Root Mean Square Error (RMSE), which measures the average deviation between predicted and actual SOC values. Additionally, Maximum Error is considered to analyze the worst-case prediction deviation. Lower RMSE and Maximum Error values indicate better model performance and higher prediction accuracy.

Since SOC is a continuous variable, classification metrics such as Accuracy, Precision, Recall, and F1-score are not applicable in this work.

Root Mean Square Error (RMSE), which calculates the discrepancy between the predicted and real SOC values from the dataset, is used to assess the performance of the suggested models.

RMSE is computed as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum (\text{Actual SOC} - \text{Predicted SOC})^2}$$

Where n is the total number of test samples.

A lower RMSE value indicates that the predicted SOC values are closer to the actual values, demonstrating better model accuracy.

Voltage	Current	Temperature	Power	Capacity	Voltage_A	Current_A	Power_Average
4.20007	2.10781	12.05326	8.85295	-0.14733	4.029908	-0.79806	-3.08994
4.1872	1.82851	12.05326	7.656337	-0.14685	4.029996	-0.7944	-3.07462
4.0828	-0.03756	12.05326	-0.15335	-0.14686	4.029763	-0.79563	-3.07978
4.09519	0.21887	12.05326	0.896314	-0.14681	4.029553	-0.79632	-3.08271
4.05835	-0.40586	12.05326	-1.64712	-0.14691	4.02927	-0.79823	-3.09065
3.95799	-2.11096	12.05326	-8.35516	-0.1475	4.028787	-0.80354	-3.11192
3.9033	-3.00679	12.05326	-11.7364	-0.1483	4.028195	-0.81063	-3.1399
3.88657	-3.20687	12.05326	-12.4637	-0.14918	4.027706	-0.81661	-3.16305
3.90523	-2.77161	12.05326	-10.8238	-0.14997	4.027234	-0.82201	-3.18408
3.96699	-1.61364	12.05326	-6.40129	-0.15042	4.026922	-0.8247	-3.19468
3.98243	-1.32864	12.04168	-5.29122	-0.15079	4.026644	-0.82682	-3.20306
4.03583	-0.40586	12.05326	-1.63798	-0.15093	4.026442	-0.82744	-3.20553
4.00945	-0.89012	12.04168	-3.56889	-0.15117	4.026157	-0.82935	-3.21322
4.00817	-0.90808	12.05326	-3.63974	-0.15142	4.025885	-0.83112	-3.22029
4.03583	-0.42301	11.8332	-1.7072	-0.15154	4.025676	-0.83183	-3.22315
4.01717	-0.76109	12.05326	-3.05743	-0.15174	4.02543	-0.83322	-3.22871
3.97793	-1.4397	12.05326	-5.72703	-0.15212	4.025106	-0.83596	-3.2396
4.00624	-0.9187	12.05326	-3.68053	-0.15239	4.02484	-0.83766	-3.24641

Fig 2:Dataset

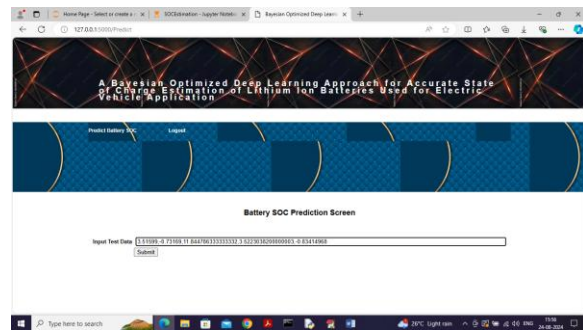


Fig 3: input screen



Fig 4: results

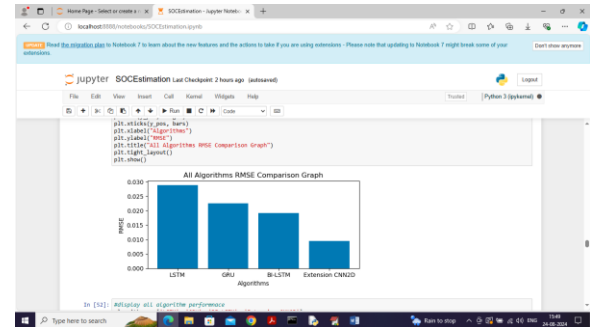


Fig 5: performance graph

5. CONCLUSION

This work presents a Bayesian optimized deep learning framework for accurate State of Charge (SOC) estimation of lithium-ion batteries used in electric vehicles. Multiple deep learning models including LSTM, GRU, and Bi-LSTM were implemented and optimized using Bayesian Optimization to improve prediction performance. As an extension, a CNN2D-based model was introduced to enhance feature extraction and capture complex relationships among battery parameters such as voltage, current, and temperature. Experimental results demonstrate that the CNN2D model achieves the lowest RMSE and maximum error, outperforming the other deep learning models and providing more reliable SOC estimation.

Additionally, a Flask-based web application was developed to make the system more practical and user-friendly by allowing users to input battery parameters and obtain SOC predictions in real time. The integration of optimized deep learning models with a web-based prediction system improves prediction accuracy, reduces computational errors, and supports efficient battery monitoring. Overall, the proposed extension using CNN2D with Bayesian Optimization provides an effective solution for intelligent battery management and reliable SOC prediction in electric vehicle applications.

6. FUTURE SCOPE

In the future, the proposed system can be further enhanced by integrating advanced deep learning architectures such as Transformer-based models and hybrid CNN-RNN frameworks to improve SOC

prediction accuracy under varying operating conditions. Additional battery parameters such as state of health (SOH), battery aging characteristics, and environmental factors can also be incorporated to build a more comprehensive battery management system.

Furthermore, the system can be extended for real-time deployment in Electric Vehicle Battery Management Systems (BMS) using IoT sensors and edge computing technologies. The current Flask-based web application can be upgraded into a full-scale cloud-based monitoring platform or mobile application, enabling continuous battery monitoring, predictive maintenance, and large-scale battery data analysis for improved EV energy management.

REFERENCES

- [1] Y. Khawaja, N. Shankar, I. Qiqieh, J. Alzubi, O. Alzubi, M. K. Nallakaruppan, and S. Padmanaban, "Battery management solutions for Li-ion batteries based on artificial intelligence," *Ain Shams Eng. J.*, vol. 14, no. 12, 2023, Art. no. 102213.
- [2] L. Wang, X. Zhao, Z. Deng, and L. Yang, "Application of electrochemical impedance spectroscopy in battery management system: State of charge estimation for aging batteries," *J. Energy Storage*, vol. 57, Jan. 2023, Art. no. 106275.
- [3] J. Tian, C. Chen, W. Shen, F. Sun, and R. Xiong, "Deep learning framework for lithium-ion battery state of charge estimation: Recent advances and future perspectives," *Energy Storage Mater.*, vol. 61, Aug. 2023, Art. no. 102883.
- [4] F. Mohammadi, "Lithium-ion battery state-of-charge estimation based on an improved Coulomb-counting algorithm and uncertainty evaluation," *J. Energy Storage*, vol. 48, Apr. 2022, Art. no. 104061.
- [5] K. Qian, X. Liu, Y. Wang, X. Yu, and B. Huang, "Modified dual extended Kalman filters for SOC estimation and online parameter identification of lithium-ion battery via modified gray wolf optimizer," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 236, no. 8, pp. 1761–1774, 2022.
- [6] P. U. Nzereogu, A. D. Omah, F. I. Ezema, E. I. Iwuoha, and A. C. Nwanya, "Anode materials for lithium-ion batteries: A review," *Appl. Surf. Sci. Adv.*, vol. 9, Jun. 2022, Art. no. 100233.
- [7] M. Lennan and E. Morgera, "The Glasgow climate conference (COP26)," *Int. J. Mar. Coastal Law*, vol. 37, no. 1, pp. 137–151, 2022.
- [8] J. P. Christophersen, "Battery test manual for electric vehicles, revision 3," Idaho Nat. Lab., Idaho Falls, ID, USA, Tech. Rep. INL/EXT-15-34184, 2015.
- [9] M. J. Lain and E. Kendrick, "Understanding the limitations of lithium ion batteries at high rates," *J. Power Sour.*, vol. 493, May 2021, Art. no. 229690. 43326
- [10] J. Liu and X. Liu, "An improved method of state of health prediction for lithium batteries considering different temperature," *J. Energy Storage*, vol. 63, Jul. 2023, Art. no. 107028.
- [11] S. Vedhanayaki and V. Indragandhi, "Certain investigation and implementation of Coulomb counting based unscented Kalman filter for state of charge estimation of lithium-ion batteries used in electric vehicle application," *Int. J. Thermofluids*, vol. 18, May 2023, Art. no. 100335.
- [12] K. Qian and X. Liu, "Hybrid optimization strategy for lithium-ion battery's state of charge/health using joint of dual Kalman filter and modified sinecosine algorithm," *J. Energy Storage*, vol. 44, Dec. 2021, Art. no. 103319.
- [13] H. Ben Sassi, F. Errahimi, N. Es-Sbai, and C. Alaoui, "Comparative study of ANN/KF for on-board SOC estimation for vehicular applications," *J. Energy Storage*, vol. 25, Oct. 2019, Art. no. 100822.
- [14] V. Selvaraj and I. Vairavasundaram, "A comprehensive review of state of charge estimation in lithium-ion batteries used in electric vehicles," *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108777.
- [15] R. Irle, "EV-volumes-The electric vehicle world sales database," *Glob. EV Sales*, 2021.

- [16] E. Chemali, P. J. Kollmeyer, M. Preindl, R. Ahmed, and A. Emadi, "Long short-term memory networks for accurate state-of-charge estimation of Li-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6730–6739, Aug. 2018.
- [17] D. Liu, L. Li, Y. Song, L. Wu, and Y. Peng, "Hybrid state of charge estimation for lithium-ion battery under dynamic operating conditions," *Int. J. Elect. Power Energy Syst.*, vol. 110, pp. 48–61, Sep. 2019.
- [18] B. Xiao, Y. Liu, and B. Xiao, "Accurate state-of-charge estimation approach for lithium-ion batteries by gated recurrent unit with ensemble optimizer," *IEEE Access*, vol. 7, pp. 54192–54202, 2019.
- [19] P. Eleftheriadis, A. Dolara, and S. Leva, "An overview of data-driven methods for the online state of charge estimation," in *Proc. IEEE Int. Conf. Environ. Electr. Eng. IEEE Ind. Commercial Power Syst. Eur. (EEEIC/I&CPS Europe)*, Jun. 2022, pp. 1–6.
- [20] Z. Huang, F. Yang, F. Xu, X. Song, and K.-L. Tsui, "Convolutional gated recurrent unit-recurrent neural network for state-of-charge estimation of lithium-ion batteries," *IEEE Access*, vol. 7, pp. 93139–93149, 2019.
- [21] Z. Yi and P. H. Bauer, "Effects of environmental factors on electric vehicle energy consumption: A sensitivity analysis," *IET Electr. Syst. Transp.*, vol. 7, no. 1, pp. 3–13, Mar. 2017.
- [22] F. Nadeem, S. M. S. Hussain, P. K. Tiwari, A. K. Goswami, and T. S. Ustun, "Comparative review of energy storage systems, their roles, and impacts on future power systems," *IEEE Access*, vol. 7, pp. 4555–4585, 2019.
- [23] J. Meng, M. Ricco, G. Luo, M. Swierczynski, D.-I. Stroe, A.-I. Stroe, and R. Teodorescu, "An overview and comparison of online implementable SOC estimation methods for lithium-ion battery," *IEEE Trans. Ind. Appl.*, vol. 54, no. 2, pp. 1583–1591, Mar. 2018.
- [24] V. Selvaraj and I. Vairavasundaram, "Flyback converter employed non-dissipative cell equalization in electric vehicle lithium-ion batteries," *e-Prime-Adv. Elect. Eng., Electron. Energy*, vol. 5, Sep. 2023, Art. no. 100278.
- [25] F. Yang, S. Zhang, W. Li, and Q. Miao, "State-of-charge estimation of lithium-ion batteries using LSTM and UKF," *Energy*, vol. 201, Jun. 2020, Art. no. 117664.
- [26] C. Li, F. Xiao, and Y. Fan, "An approach to state of charge estimation of lithium-ion batteries based on recurrent neural networks with gated recurrent unit," *Energies*, vol. 12, no. 9, p. 1592, Apr. 2019.
- [27] P. Eleftheriadis, S. Leva, and E. Ogliari, "Bayesian hyperparameter optimization of stacked bidirectional long short-term memory neural network for the state of charge estimation," *Sustain. Energy, Grids Netw.*, vol. 36, Dec. 2023, Art. no. 101160.
- [28] C. Menos-Aikateriniadis, I. Lamprinos, and P. S. Georgilakis, "Particle swarm optimization in residential demand-side management: A review on scheduling and control algorithms for demand response provision," *Energies*, vol. 15, no. 6, p. 2211, Mar. 2022.
- [29] L. Chen, Z. Wang, Z. Lü, J. Li, B. Ji, H. Wei, and H. Pan, "A novel state-of-charge estimation method of lithium-ion batteries combining the grey model and genetic algorithms," *IEEE Trans. Power Electron.*, vol. 33, no. 10, pp. 8797–8807, Oct. 2018.
- [30] M. Jiao, D. Wang, and J. Qiu, "A GRU-RNN based momentum optimized algorithm for SOC estimation," *J. Power Sour.*, vol. 459, May 2020, Art. no. 228051.