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Research article

Deep learning-based state of charge estimation for electric vehicle batteries: Overcoming technological bottlenecks

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ABSTRACT

This study presents a novel deep learning-based approach for the State of Charge (SOC) estimation of electric vehicle (EV) batteries, addressing critical challenges in battery management and enhancing EV efficiency. Unlike conventional methods, our research leverages a diverse dataset encompassing environmental factors (e.g., temperature, altitude), vehicle parameters (e.g., speed, throttle), and battery attributes (e.g., voltage, current, temperature) to train a sophisticated deep learning model. The key novelty of our approach lies in its integration of real-world driving data from a BMW i3 EV, enabling the model to capture the intricate dynamics affecting SOC with remarkable accuracy. We conducted 72 tests using actual driving trip data, which included 25 types of environmental variables, to validate the feasibility and effectiveness of our proposed model. The deep learning network, designed specifically for SOC estimation, outperformed traditional models by demonstrating superior accuracy and reliability in predicting SOC values. Our findings indicate a significant advancement in SOC estimation techniques, offering actionable insights for both policymakers and industry practitioners aimed at fostering energy conservation, carbon reduction, and the development of more efficient EVs. The study's major contribution is its demonstrated capability to improve SOC estimation accuracy by understanding the complex interrelationships among various influencing factors, thereby addressing a pivotal challenge in EV battery management. By employing cutting-edge deep learning techniques, this research not only marks a significant leap forward from traditional SOC estimation methods but also contributes to the broader goals of sustainable transportation and environmental protection.

1. Introduction

Confronting the pressures arising from environmental damage and energy crises has become an essential task for countries globally. Electric vehicles (EVs) have gained widespread recognition as a clean transportation technology capable of reducing dependence on fossil fuels and playing a pivotal role in decelerating global warming rates.

In this article, we delve into the evolving realm of battery technology and management, crucial for the advancement of electric vehicles (EVs) and smart grid systems. Our literature review is meticulously organized into several key sections, highlighting the latest innovations in energy management, breakthroughs in battery materials, advancements in Battery Management System (BMS) design, sophisticated estimation techniques for battery state of health (SoH) and state of charge (SoC), and comprehensive critical reviews and

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Abbreviations:

EV	Electric Vehicle
SOC	State of Charge
BMS	Battery Management System
SoH	State of Health
DNN	Deep Neural Network
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
R^2	Coefficient of Determination

Symbols

$y_{i:}$	Actual SOC value
$\widehat{y}_{i:}$:	Predicted SOC value by the network
N	Number of samples
$E(\theta)$	Objective function for the training process
θ	Parameters of the neural network model (weights and biases)
$x_{t:}$:	Input features at time t
W	Weight matrix
b	Bias vector
f	Activation function

modeling studies. This structured approach not only provides a panoramic view of the current state of battery technology but also sets the stage for discussing our contributions against the backdrop of these significant areas of research.

- Energy Management in Smart Grids and EVs:

In the realm of energy management within smart grids and the integration of electric vehicles (EVs), two pivotal studies stand out for their contributions. Gong et al. [1] developed a secured energy management architecture for smart hybrid microgrids, integrating PEM-fuel cells and EVs, focusing on optimizing energy distribution securely. Conversely, Lan et al. [2] delved into using advanced machine learning to manage the energy of renewable microgrids, specifically addressing the charging demands of hybrid EVs to enhance grid efficiency and sustainability.

- Battery Material Enhancement:

These studies collectively highlight the evolving landscape of smart grid management and the critical role of technology in ensuring energy efficiency and security in the era of electric vehicles. In advancing battery material technologies, Hou et al. [3] introduced a novel method for enhancing lithium-ion battery (LIB) anodes. They utilized microwave-assisted reconstruction of spent graphite, significantly improving its energy-storage performance. This breakthrough not only offers a sustainable pathway for recycling used battery materials but also contributes to the development of more efficient and durable batteries.

- Battery Management System (BMS) Design and Cell Balancing:

In the sphere of Battery Management System (BMS) design and cell balancing, several key studies have emerged. Koseoglou et al. [4] detailed a method for highly effective cell equalization in lithium-ion BMS, showcasing a significant advancement in prolonging battery life and performance. Chen et al. [5] introduced a modular BMS design tailored for electric motorcycles, emphasizing the adaptability and efficiency of battery systems in vehicular applications. Uzair et al. [6] explored the various characteristics of BMS in electric vehicles, particularly focusing on the nuances of active and passive cell balancing processes, underscoring their impact on battery longevity and reliability. These contributions collectively underscore the evolving landscape of BMS design, highlighting innovative solutions to enhance battery efficiency and durability.

- State of Health (SoH) and State of Charge (SoC) Estimation Techniques:

In the critical area of State of Health (SoH) and State of Charge (SoC) estimation techniques for lithium-ion batteries, several researchers have made notable contributions. Ge et al. [7] provide a comprehensive review on SoH estimations and prognostics for the remaining useful life of lithium-ion batteries, highlighting the importance of accurate lifespan predictions. Fang Liu et al. [8] introduced an innovative online method for SoH estimation utilizing data from the battery management system, enhancing real-time monitoring capabilities. Liu et al. [9] adopted a data-driven approach with uncertainty quantification, offering a novel methodology for predicting the future capacities and remaining useful life of batteries, thus improving reliability and efficiency in battery usage.

Dang et al. [10] explored the estimation of SoC using an open-circuit voltage method combined with dual neural network fusion, showcasing a significant advance in accuracy for SoC prediction. Xiong et al. [11] focuses on integrating advanced machine learning techniques to refine SoC estimations further, providing a thorough comparative analysis of various algorithms' effectiveness in real-world scenarios, thus complementing our research by addressing some of the practical challenges faced in the field.

Furthermore, a wide range of other significant works [12–36] have contributed diverse methods and algorithms for SoH and SoC estimation, employing techniques such as Gaussian process regression, extended Kalman filtering, fractional order modeling, and deep learning. These studies collectively enhance the precision, reliability, and efficiency of lithium-ion battery management systems, paving the way for more sustainable and longer-lasting battery technologies.

- Critical Reviews and Modeling Studies:

In the area of critical reviews and modeling studies for battery technologies, significant contributions have been made [37]. Further studies have provided in-depth reviews of monitoring methods for lithium-ion batteries in electric vehicles (EVs), delving into various modeling methods for State of Charge (SoC) estimation, the utility of different battery models for simulation studies, and comprehensive analyses of SoC estimation and charging techniques in EV applications [38–45]. These works collectively enrich our understanding of battery behavior, enhance predictive capabilities for battery management systems, and drive forward the development of more efficient and reliable EV technologies.

The collection of studies presented offers a comprehensive exploration into the intricacies of lithium-ion battery management, highlighting innovative approaches to enhancing the accuracy and reliability of state of charge (SoC) and state of health (SoH) estimations. Through the utilization of advanced modeling techniques such as modified Gaussian Process Regression, alongside in-depth reviews of current monitoring and estimation methodologies, these references contribute significantly to the advancement of battery technologies. They not only provide insights into more effective battery utilization and longevity in electric vehicles but also pave the way for future developments in energy storage systems, ensuring sustainability and efficiency in the evolving landscape of electric mobility.

As the global push towards sustainable transportation intensifies, electric vehicles (EVs) have emerged at the forefront of efforts to reduce reliance on fossil fuels and mitigate environmental impact. Despite significant advancements in EV technology, a critical barrier to wider adoption and optimization remains: the accurate estimation of the State of Charge (SOC) of EV batteries. SOC estimation is pivotal for effective battery management, impacting vehicle range, safety, and overall performance. However, the inherent complexities of battery behaviors under diverse operating conditions pose significant challenges to SOC estimation accuracy.

Current methodologies for SOC estimation primarily rely on simplistic models that fail to account for the multifaceted interactions between environmental conditions, vehicle operational parameters, and battery health. These models often struggle with the nonlinear and time-varying characteristics of batteries, leading to significant estimation errors and, by extension, range anxiety among

Table 1
Summary of studies related to SOC estimation in EV batteries.

Reference	Year	Methodology	Data Used	Main Findings	Limitations	How Our Study Differs
Gong et al. [1]	2020	Secure energy management in smart grids	Hybrid microgrids, EVs	Developed a secure energy management architecture	Focuses more on energy distribution than SOC estimation	Our study focuses specifically on SOC estimation using advanced deep learning techniques on real-world EV data
Lan et al. [2]	2021	Machine learning for energy management	Renewable microgrids, EVs	Enhanced grid efficiency with machine learning	Limited to grid energy management	Employs deep learning for direct SOC estimation, enhancing prediction accuracy and reliability
Hou et al. [3]	2021	Enhancement of LIB anodes using spent graphite	Laboratory data	Improved energy-storage performance	Material-focused, not directly related to SOC estimation	Directly applies deep learning to SOC estimation, leveraging extensive real-world driving data
Koseoglou et al. [4]	2020	Cell equalization in BMS	Lithium-ion batteries	Improved battery life and performance	BMS design focus, not SOC estimation	Introduces a novel deep learning framework for SOC estimation, validated against real-world data
Ge et al. [7]	–	SoH estimation and prognostics	Lithium-ion batteries	Comprehensive review on SoH estimations	Review nature, not empirical SOC estimation	Provides empirical validation of SOC estimation using a sophisticated deep learning model
Dang et al. [10]	2016	Dual neural network fusion for SOC estimation	Laboratory data	Improved accuracy in SOC prediction	Limited to laboratory conditions	Utilizes comprehensive real-world driving data for SOC estimation, demonstrating superior accuracy
Xiong et al. [11]	2017	Comprehensive review of SOC estimation methods	Electric vehicles	Detailed classification and discussion of various SOC estimation methods	Primarily theoretical review, not empirical	Utilizes a practical approach with a deep learning model, specifically tailored to real-world EV data to enhance SOC estimation accuracy
Our Study	–	Advanced Deep Learning Model	Real-world driving data from a BMW i3 EV	Significantly improved SOC estimation accuracy using deep learning, validated against real-world data	–	First study to employ such an extensive range of real-world driving data for SOC estimation, showing superior performance and reliability over traditional methods

EV users. Moreover, most existing approaches do not fully leverage the potential of emerging data-driven techniques to enhance estimation accuracy.

Table 1 showcases a succinct comparison of notable SOC estimation studies alongside our research. It traces methodological evolution from smart grid management (Gong et al. [1], Lan et al. [2]) through battery material and BMS enhancements (Hou et al. [3], Koseoglou et al. [4]), to cutting-edge SoH and SOC estimation techniques (Ge et al. [7], Dang et al. [10], Xiong et al. [11]). Our study differentiates itself by applying an advanced deep learning model to extensive real-world data from a BMW i3 EV, significantly improving SOC estimation accuracy and addressing gaps in existing research that primarily utilized simulated or laboratory data. This approach not only refines SOC estimation accuracy but also has practical implications for energy policy, automotive R&D, and the broader goals of sustainable transportation. In summary, our research introduces a significant leap in utilizing deep learning for accurate, real-world SOC estimation, setting a new benchmark in the field.

In light of these challenges, our study aims to bridge the research gap by employing a novel deep learning-based approach to SOC estimation that incorporates a comprehensive range of real-world driving data. This research is predicated on the hypothesis that a deep learning model, trained on diverse datasets encompassing environmental factors, vehicle parameters, and battery attributes, can significantly outperform traditional estimation methods in terms of accuracy and reliability.

This study significantly advances SOC estimation techniques for electric vehicles (EVs) by introducing a deep learning framework tailored for the dynamic complexities of SOC estimation. Our approach, novel in its application of deep learning models, processes the intricate, non-linear relationships affecting SOC with unmatched nuance, a notable departure from traditional methodologies. Key contributions include.

1. **Innovative Deep Learning Application**: Pioneering the use of deep learning for SOC prediction in EVs, our model captures and processes complex relationships between a multitude of variables affecting SOC, surpassing the capabilities of existing methods.
2. **Holistic Data Integration**: By incorporating a comprehensive array of real-world driving data, including environmental and vehicle parameters alongside battery metrics, our approach ensures accurate SOC predictions across varied driving scenarios, thereby enhancing estimation reliability and accuracy.
3. **Rigorous Real-World Validation**: Utilizing extensive datasets from BMW i3 EV driving conditions, our model's validation sets a new benchmark in SOC estimation research, highlighting its practical applicability and robustness.
4. **Implications for Battery Management**: The study's insights promise substantial improvements in battery management systems, offering strategies for battery life extension, performance optimization, and mitigating range anxiety, with direct benefits for EV efficiency, safety, and sustainability.
5. **Advancing Sustainable Transportation**: Addressing the crucial challenge of reliable SOC estimation, our research aligns with broader goals of fostering sustainable transportation and minimizing environmental impacts.

By merging a novel deep learning approach with extensive real-world data analysis, this research not only fills a critical gap in SOC estimation methodologies but also contributes significantly to the evolution of EV battery management and the promotion of sustainable transportation solutions.

The rapidly evolving domain of electric vehicles (EVs) presents an urgent need for advancements in battery management systems to enhance vehicle performance, safety, and sustainability. This study introduces a novel approach to State of Charge (SOC) estimation, crucial for optimizing EV operation and reliability. Our contributions are distinct and innovative in several aspects.

- **Employment of Deep Learning Techniques:** We pioneer the application of deep learning methods for SOC estimation, which represents a significant leap forward from traditional techniques, enabling more accurate and reliable battery management.
- **Utilization of Real-world Driving Data:** Our research stands out by leveraging actual driving data, including parameters such as vehicle speed, voltage, current, battery temperature, and SOC during charging. This approach ensures that our findings are grounded in practical, real-world scenarios, enhancing the relevance and applicability of our results.
- **Detailed Analysis of Vehicle and Battery Parameters:** Through comprehensive analysis, we unravel the complex interrelationships between various vehicle and battery parameters, offering new insights that significantly improve SOC estimation accuracy.
- **Strategic Insights for Stakeholders:** The study provides actionable intelligence for both policy-makers and industry practitioners:
- For governments, it lays a foundation for formulating policies focused on energy conservation, carbon reduction, and infrastructure planning.
- For automakers, it delivers in-depth analyses crucial for advancing battery technology R&D and refining vehicle control strategies.
- **Enhancing Electric Vehicle Performance and Safety:** By advancing battery management and energy storage solutions, our research addresses key challenges in EV performance and safety, contributing to the broader goal of sustainable transportation.
- **Facilitating the Shift to Sustainable Transportation:** We support the transition towards more sustainable transportation systems by improving electric vehicles' efficiency and sustainability, offering a viable solution to environmental and energy challenges.

In essence, this study not only marks a significant advancement in battery SOC estimation techniques but also contributes to the broader objectives of promoting sustainable transportation and mitigating environmental impacts. By focusing on lithium-ion batteries and sophisticated battery management systems, we aim to enhance the performance, safety, and sustainability of electric vehicles, thereby contributing to a greener, more eco-friendly future in transportation.

2. Research theory and methodology

In this section, we describe the research methods, rationale, and innovations employed in this study. The foundational concept of our research is the multiple linear regression model, which involves using regression analysis based on multiple predictor variables to establish a linear relationship between an output variable and several input variables. This process entails employing mathematical formulas to train relevant data, creating a model that reflects the relationship between input and output variables, and making predictions based on the obtained model.

The deep learning predictive model utilized in this study primarily considers input data derived from the vehicle's physical model and auxiliary system power consumption. This includes factors such as remaining power, vehicle speed, slope, acceleration, wind speed, weather conditions, air conditioning system settings, and light status, among others. The prediction model's output corresponds to the battery's SOC. Fig. 1 illustrates the battery SOC estimation via a deep learning neural network for electric vehicles. Artificial neural networks have found extensive applications across numerous fields of intelligence. Integrating neural networks with other control methods can effectively address the nonlinearity and uncertainty issues inherent in control systems. Multi-layer feed-forward neural networks are currently the most prevalent neural network models. Consequently, the dynamic recurrent neural networks developed in recent years have attracted considerable attention. Notable examples include the Time Delay Neural Network (TDNN) proposed by Narendra and Parthasarathy [46] and the fully recurrent neural network introduced by Williams and Zipser [47]. These networks overcome the limitations of traditional static neural networks and offer novel approaches to challenges such as system regression, identification, model prediction, and nonlinear system control. Recurrent neural networks (RNNs) address the limitations of traditional static neural networks by providing innovative solutions to challenges such as system regression, identification, model prediction, and nonlinear system control. RNNs are comprised of dynamic neurons that originate from the study of dynamic system identification problems. Unlike static models, the input of dynamic neurons includes not only the system's current input but also feedback from the neural network's previous states. The input-output relationship of the RNN can be expressed by the modified equation shown in Eq. (1):

$$h_t = f(W_{hh} \cdot h_{t-1} + W_{xh} \cdot x_t + b_h). \tag{1}$$

The predicted state of charge (SOC) can be represented by Eq. (2):

$$y_t = g\left(W_{hy} \cdot h_t + b_y\right) \tag{2}$$

Here.

- h_t represents the hidden state at time t,
- y_t is the predicted State of Charge (SOC) at time t,
- x_t represents the input features at time t,
- W_{hh}, W_{xh}, and W_{hy} are the weight matrices for hidden-to-hidden, input-to-hidden, and hidden-to-output layers respectively,
- b_h and b_y are the bias vectors for the hidden and output layers,
- f and g are the activation functions for the hidden and output layers, respectively.

This framework allows RNNs to account for both current and historical data, enabling them to capture the dynamic characteristics

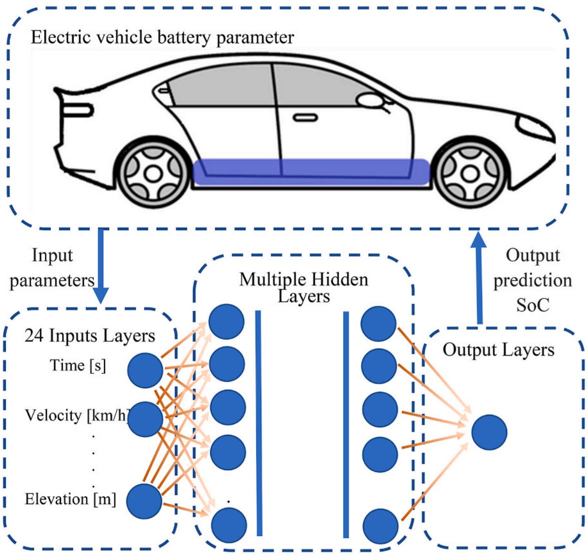

Fig. 1. Battery SOC estimation of a deep learning neural network for electric vehicles.

and evolutionary behavior of systems more effectively. Such capabilities make RNNs particularly suited for tasks like SOC estimation in electric vehicles, where past states significantly influence future conditions. The basic structure and algorithms of universal learning networks, which are a novel type of time-delay neural network, further expand on these concepts by incorporating time-delayed feedback to enhance learning capabilities and system adaptability.

Basic Structure and Algorithm of Universal Learning Network Universal learning network is a new type of time-delay neural network. Due to the dependence of network computing on time, its training process cannot use the traditional standard back-propagation algorithm for parameter learning. Therefore, the general learning network adopts Back Propagation Through Time (BPTT) algorithm. The dynamic backpropagation algorithm along time is a learning algorithm suitable for dynamic neural networks proposed by Werbos, a famous neural network scholar, and it is an extension of the standard backpropagation algorithm. It can be exported by unrolling the sequential operations of the network into a hierarchical feed-forward network. Its topology adds a layer at each time step. To analyze the specific network, let N represent the recurrent network that needs to learn the sequential task, from time n_0 to time n.

N^* represents the feed-forward network obtained by expanding the sequential operation of the recursive network N. The relationship between the expanded network N^* and the initial network N is as follows:

1. For each time step in the interval $[n_0, n]$, the network N^* has a layer containing K neurons, and K is the number of neurons contained in N in the network.
2. In each layer of the network N^* there is a copy of each neuron of the network N.
3. For each time step t within the interval $[n_0,n]$, the connection from neuron i in layer l of network N^* to neuron j in layer $l+1$ mirrors the synaptic connection from neuron i to neuron j in network N. This structure replicates the synaptic connection from neuron i to neuron j, ensuring continuity in the network's architecture.

The instantaneous value of the sum of squared errors (MSE) between the network outputs and the target values is defined as follows. The MSE objective function is shown in Eq (3):

$$E(\theta) = \frac{1}{2N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{3}$$

where $E(\theta)$ serves as the objective function for the training process. Here, N represents the number of samples, y_i is the actual State of Charge (SOC) value, $\hat{y}_i$ is the SOC value predicted by the network, and θ encompasses the parameters of the neural network model, including weights and biases. This equation extends beyond being merely a broad network objective; it specifically targets the minimization of the MSE between the actual and predicted SOC values. This focus on minimizing MSE is a standard practice in regression tasks but has been uniquely adapted in our study to address the specific challenges associated with SOC estimation for electric vehicle batteries.

Our adaptation of the MSE formula incorporates not only the basic regression task but also a detailed account of the complexities inherent in the SOC estimation of electric vehicles. The data used for calculating y_i and $\hat{y}_i$ originates from precise, real-world driving conditions captured during both summer and winter, allowing for a comprehensive analysis that considers various environmental influences such as temperature variations, altitude, and driving patterns.

$w(t)$ is all network parameter vectors related to the connection layer, including weights and thresholds. When the network is trained to step t_n, to minimize $E(t)$, network parameters $w(t)$ are updated as shown in Eq (4):

$$w(t_n + 1) = w(t_n) - \eta\frac{\partial E(t_n)}{\partial w(t_n)}. \tag{4}$$

The partial differential calculation for network parameter updates is as shown in Eq (5):

$$\frac{\partial E(t_n)}{\partial w(t_n)} = \sum_{t=1}^{n}\left[\frac{\partial \overline{X}(t)}{\partial w(t_n)}\right]^T \frac{\partial^+ E(t_n)}{\partial \overline{X}(t)}. \tag{5}$$

The recursive calculation of parameter updates is as shown in Eq (6):

$$\frac{\partial^+ E(t_n)}{\partial \overline{X}(t)} = \frac{\partial E(t_n)}{\partial \overline{X}(t)} + \frac{\partial \overline{X}(t+1)}{\partial \overline{X}(t)}\frac{\partial E(t_n)}{\partial \overline{X}(t+1)}. \tag{6}$$

Among them, η is the learning rate. According to the needs of practical problems, the network can be trained with a variable learning rate, and the learning rate is expressed as $\eta(n)$. The superscript of Eq (5) indicates the time series partial differential, and the calculation of $\frac{\partial^+ E(t_n)}{\partial \overline{X}(t)}$ takes the delay effect into account, and needs to be calculated by backpropagation of the sequence value. The learning rate has a great influence on the convergence speed. In principle, the adjustment of the trial is to keep the gradient of the optimization process as large as possible without causing the learning process to become unstable. The information of the gradient change of the connection weights can be adjusted heuristically or directly according to the information of the error change and the error function. Heuristic adjustment provides a straightforward and practical method for modifying the learning rate. When the objective function's trend decreases, indicating the minimum error threshold has not yet been achieved, we propose enhancing the learning rate to expedite the convergence process. Conversely, an increasing trend in the objective function suggests surpassing the minimum error threshold, necessitating a decrease in the learning rate to maintain updates within optimal bounds. The iterative process of operation can be described as follows. The adjustment of the learning rate is demonstrated in Eq (7):

$$\eta(t)=\begin{cases}\eta(t-1)\cdot\left(1+a_1\cdot\dfrac{E(t-1)-E(t)}{E(t-1)}\right), & \text{if } E(t)<E(t-1)\\ \eta(t-1)\cdot\left(1-a_2\cdot\dfrac{E(t)-E(t-1)}{E(t-1)}\right), & \text{if } E(t)\geq E(t-1)\end{cases}. \tag{7}$$

The direct adjustment method considers that the error surface of network learning is very complex, and a learning rate is suitable for the adjustment of one weight, but not necessarily suitable for the adjustment of other weights in the network. Therefore, the adjustment of each weight value should have a different learning rate, and the adjustment of the learning rate is also included in the process of network learning. When the network converges to a position where the error plane is relatively stable, there will be several iterations in succession. If the derivation sign of the objective function to a certain weight coefficient is the same, the learning rate of the weight coefficient can be appropriately increased to reduce the number of repeated operations across this stable part. When the network converges to the concave part of the error surface, the derivation sign of the objective function to a certain weight coefficient may change during several consecutive repeated operations. In order to prevent the adjustment of the weight from oscillating, the learning rate should be appropriately reduced.

This study employed a multi-layer perceptron (MLP) neural network architecture specifically tailored for SOC estimation. The network comprises an input layer, three hidden layers with 64, 128, and 64 neurons respectively, and an output layer. Each layer utilizes the ReLU activation function to introduce non-linearity, crucial for capturing complex relationships within the data.

The initial approach involved a RNN to capture temporal dependencies within the driving data. However, our analysis revealed that the SOC estimation's accuracy was not significantly influenced by the sequential nature of the data. Therefore, we transitioned to a feedforward architecture, which simplified the model without compromising performance. This decision was supported by comparative testing, where the feedforward model demonstrated equal or improved accuracy across multiple datasets.

3. Research data description and analysis

In this study, we utilize the database provided by Matthias et al. [48] for deep learning-based state of charge (SoC) estimation of electric vehicle batteries. The dataset comprises 72 real-world driving trips conducted with a BMW i3 (60 Ah) and includes both winter and summer test data. Each test incorporates.

- Environmental factors (e.g., temperature, altitude)
- Vehicle parameters (e.g., speed, throttle)
- Battery metrics (e.g., voltage, current, temperature, SoC)
- Heating circuit information (e.g., cabin temperature, heating power)

The electric vehicle driving dataset features 24 attributes, including altitude, motor torque, longitudinal acceleration, brake signal, battery voltage, battery current, battery temperature, battery power, air conditioning power, ambient vehicle temperature, heat

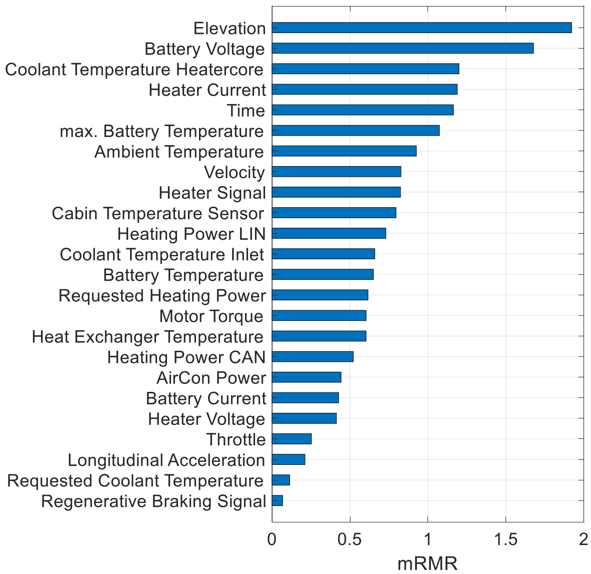

Fig. 2. mRMR characteristic analysis of electric vehicle test data in summer.

exchanger temperature, and cabin temperature. These attributes serve as inputs to the neural network. It should be noted that the characteristics of electric vehicles used in this study are depicted in Figs. 2 and 3, and 24 electric vehicle data points are employed for battery SoC estimation. The significance of these features varies within the deep learning context. During the feature selection phase, the Max-Relevance and Min-Redundancy (mRMR) algorithm is employed. This approach aims to identify a set of features with minimal redundancy that exhibit the strongest correlation with the final output while maintaining minimal inter-feature correlations. Fig. 2 displays the data characteristics of summer electric vehicle tests, with Elevation ranking first in terms of mRMR at 1.9207, followed by Battery Voltage at 1.6764, and Coolant Temperature Inlet at 1.1985. Fig. 3 presents the data characteristics of electric vehicle tests conducted during winter. In this case, Elevation in winter path ranks first with an mRMR value of 1.9808, followed by Heater Voltage at 1.749, and AirCon Power at 1.6983. By employing the mRMR algorithm for feature selection, the deep learning model can effectively utilize the most relevant features while minimizing redundancy, resulting in improved accuracy of SoC estimation for electric vehicle batteries. Table 2 presents the data obtained from the mRMR (minimum Redundancy Maximum Relevance) feature analysis of electric vehicle testing conducted during the summer season. This Table 2 includes a comprehensive evaluation of various features that influence the performance and efficiency of electric vehicles under summer conditions, highlighting those attributes that are most indicative of vehicle behavior in warmer climates. Table 3, on the other hand, outlines the results of the mRMR feature analysis for electric vehicle testing carried out in the winter season. Similar to Table 2, this table details the significant features affecting electric vehicle performance and efficiency during colder months, emphasizing the characteristics that are particularly relevant to understanding vehicle operation in winter conditions. This research offers significant understanding in addressing the technological challenges in SoC prediction, ultimately leading to improved performance and efficiency in electric vehicle battery management systems.

4. Research results and discussion

In this research, we introduce a deep learning-based method for estimating the state of charge (SoC) of electric vehicle batteries, tackling critical technological challenges in this domain. The deep learning network employed consists of three layers: an input layer, a hidden layer, and an output layer. The objective of using a deep learning network for SoC estimation is to establish nonlinear relationships between the SoC and various battery parameters, including environmental data (e.g., temperature, altitude), vehicle data (e.g., speed, throttle), battery data (e.g., voltage, current, temperature), and heating circuit data (e.g., cabin temperature, heating power). A total of 24 features are considered in this analysis. To develop and validate the model, we establish a training set and test data. Fig. 4 illustrates the architecture of the deep neural network training and testing processes. By employing this research methodology, we achieve SoC estimation for electric vehicle batteries using deep learning, as demonstrated in Fig. 5. The proposed approach offers a promising solution for battery state of charge prediction in electric vehicles, with potential implications for improving the performance and efficiency of battery management systems.

The network structure utilized in this study is a neural network, with each layer comprising 15 neurons. The Rectified Linear Unit (ReLU) activation function is employed in the network. The regularization strength is set at 0.1, and the data is standardized to ensure optimal performance. In order to evaluate the performance of the proposed DNN model, a 5-fold cross-validation method was employed using the same stratified partition. This approach was used to calculate the Root Mean Squared Error (RMSE) of the model. The stratified partitioning scheme was used to define the training and test sets, which were subsequently used to validate the statistical model via cross-validation. Training metrics were extracted from the training set, and test metrics were extracted from the test set

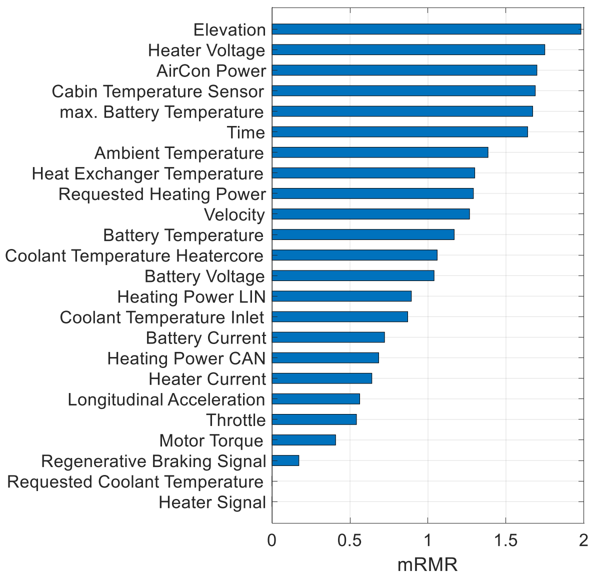

Fig. 3. mRMR characteristic analysis of electric vehicle test data in winter.

Table 2
Data on mRMR feature analysis results of electric vehicle testing in summer.

Features	MRMR
Elevation	1.9207
Battery Voltage	1.6764
Coolant Temperature Heatercore	1.1985
Heater Current	1.1875
Time	1.1633
max. Battery Temperature	1.0734
Ambient Temperature	0.9255
Velocity	0.8265
Heater Signal	0.8237
Cabin Temperature Sensor	0.7950
Heating Power LIN	0.7299
Coolant Temperature Inlet	0.6588
Battery Temperature	0.6504
Requested Heating Power	0.6153
Motor Torque	0.6031
Heat Exchanger Temperature	0.6029
Heating Power CAN	0.5213
AirCon Power	0.4426
Battery Current	0.4267
Heater Voltage	0.4129
Throttle	0.2526
Longitudinal Acceleration	0.2110
Requested Coolant Temperature	0.1132
Regenerative Braking Signal	0.0677

Table 3
Data on mRMR feature analysis results of electric vehicle testing in winter.

Features	MRMR
Elevation	1.9808
Heater Voltage	1.7490
AirCon Power	1.6983
Cabin Temperature Sensor	1.6878
max. Battery Temperature	1.6711
Time	1.6389
Ambient Temperature	1.3848
Heat Exchanger Temperature	1.2998
Requested Heating Power	1.2912
Velocity	1.2664
Battery Temperature	1.1680
Coolant Temperature Heatercore	1.0589
Battery Voltage	1.0389
Heating Power LIN	0.8935
Coolant Temperature Inlet	0.8699
Battery Current	0.7213
Heating Power CAN	0.6838
Heater Current	0.6400
Longitudinal Acceleration	0.5623
Throttle	0.5414
Motor Torque	0.4076
Regenerative Braking Signal	0.1722
Heater Signal	0.0000
Requested Coolant Temperature	0.0000

during the cross-validation process. A new random partition of the same type as the given object was defined for repartitioning the dataset. The results obtained from the 5-fold cross-validation process demonstrated the effectiveness of the proposed DNN in analyzing energy storage systems. The model showcased a satisfactory Root Mean Squared Error (RMSE), indicating that the chosen network structure and parameters were suitable for the given task. Further studies can be conducted to optimize the network architecture and explore its applicability in various energy storage system scenarios.

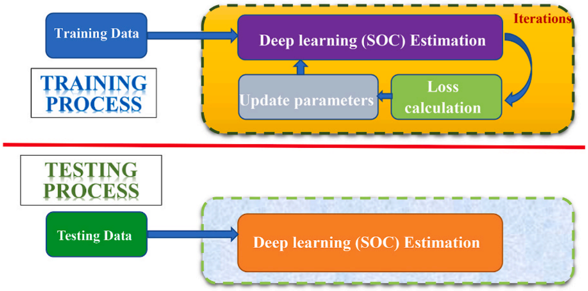

Fig. 4. Architecture diagram of deep neural network training process and testing process.

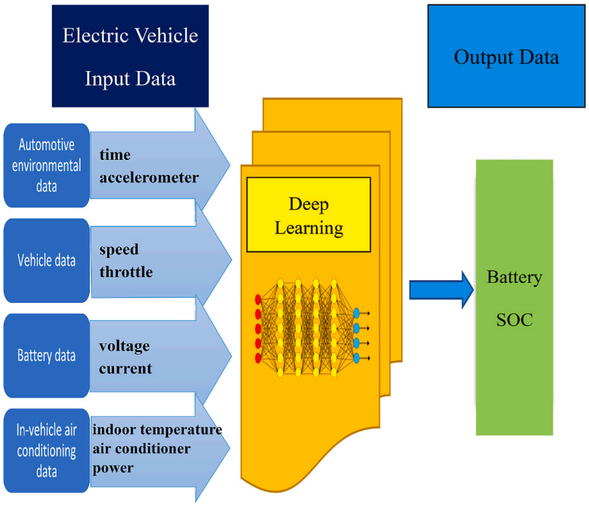

Fig. 5. Deep learning of electric vehicle battery SOC.

4.1. *Experimental setup and model validation*

In this study, we employed a comprehensive experimental setup involving real-world data collected from a BMW i3 to validate our deep learning model for SOC estimation. The dataset includes parameters such as temperature, vehicle speed, battery voltage, current, and SOC, collected across various driving conditions.

- Neural Network Architecture: Our model utilizes a multi-layer perceptron (MLP) architecture, consisting of an input layer corresponding to the number of selected features, three hidden layers with 64, 128, and 64 neurons, respectively, and an output layer producing the estimated SOC. The ReLU activation function is used for non-linear transformations.
- Training Parameters: The model was trained using the Adam optimizer, with an initial learning rate of 0.001, over 1000 epochs, and a batch size of 32. The training process aimed to minimize the mean squared error (MSE) between the predicted and actual SOC values.
- Feature Selection Rationale: Features were selected based on their relevance to SOC estimation, identified through exploratory data analysis and literature review. This includes environmental factors (e.g., temperature), vehicle parameters (e.g., speed), and battery characteristics (e.g., voltage, current).

This study employed a multi-layer perceptron (MLP) neural network architecture specifically tailored for SOC estimation. The network comprises an input layer, three hidden layers with 64, 128, and 64 neurons respectively, and an output layer. Each layer utilizes the ReLU activation function to introduce non-linearity, crucial for capturing complex relationships within the data. This model was trained over 1000 epochs with a batch size of 32. We utilized the Adam optimizer due to its adaptive learning rate capabilities, setting an initial learning rate of 0.001. The model's loss was computed using the Mean Squared Error (MSE) criterion, reflecting the SOC prediction's accuracy.

The BMW i3 driving dataset consists of 24 features, such as altitude, motor torque, longitudinal acceleration, brake signal, battery voltage, battery current, battery temperature, battery power, air conditioner power supply, vehicle ambient temperature, heat exchanger temperature, and vehicle interior temperature. These features serve as inputs to the neural network. The independent variable (X-axis) represents the measurement time, while the dependent variable (Y-axis) corresponds to the battery State of Charge (SOC). The dataset includes a total of 32 tests conducted in June and July 2019, during the summer season. The driving routes were located in Munich East and Munich North in Germany, and the weather conditions were predominantly sunny with occasional slight cloudiness.

After training the DNN neural network with the BMW i3 driving dataset, the results are presented in Fig. 6. The blue curve represents the actual SOC values, while the red curve indicates the DNN predicted data. Fig. 7 illustrates the error between the real and predicted battery SOC curves obtained using the DNN method.

The study's findings reveal a strong agreement between the real and predicted data, demonstrating the effectiveness of the DNN model in estimating battery SOC based on the input features. This outcome supports the applicability of the proposed DNN model for energy storage system analysis in real-world driving scenarios.

All datasets were split into 70 % for training and 30 % for prediction purposes. Figs. 8 and 9 display scatter plots of the predicted data and actual data, with both the X-axis and Y-axis representing the SOC values on the graph. Fig. 8 illustrates the scatter plot of the regression analysis of the actual and predicted battery SOC curves for the DNN method during the training phase. Fig. 9 presents the scatter plot of the regression analysis of the real and predicted battery SOC curves for the DNN method during the testing phase. In the scatter diagrams of battery SOC result predictions using regression analysis, the diagonal straight line extending from the lower left to the upper right represents the ideal prediction line, depicted in black, while the blue dots signify the predicted data. The results indicate that the predicted data closely aligns with the ideal line, demonstrating that the output change rate of the DNN neural network is similar to the target change rate. This observation suggests that the network exhibits good performance. Fig. 10 shows the residual plot of the regression analysis of the actual and predicted battery SOC curves for the DNN method during the training phase. The vertical axis represents the predicted and true residuals, while the horizontal axis corresponds to the actual battery SOC. As seen in Fig. 10, the residual error ranges between +2 and −2 when the SOC is at the 65 % boundary, and it lies between +6 and −6 when the residual error is greater than 65 %. Fig. 11 displays the residual plot of the regression analysis of the real and predicted battery SOC curves for the DNN method during the testing phase. The vertical axis represents the predicted and actual residuals, while the horizontal axis corresponds to the actual battery SOC. As observed in Fig. 11, the residual error ranges between +2 and −2 when the SOC is at the 65 % boundary, and the residual error lies between +6 and −6 for SOC values above 65 %.

In this study, besides employing the deep learning DNN network, the traditional Robust Regression method is also utilized for comparison purposes. The data is tested for a total of 32 times, with dates falling in June and July 2019, during the summer season. The road route encompasses Munich East and Munich North in Germany, under sunny and slightly cloudy weather conditions. The study's results are compared with the DNN network results under identical conditions. Fig. 12 illustrates the actual and predicted battery SOC curves using the Robust Regression method. The blue curve represents the real SOC value, while the red curve depicts the DNN prediction data. The outcome indicates an error between the real data and the predicted data. Fig. 13 presents the error of the actual and predicted battery SOC curves using the Robust Regression method. Comparing the DNN in Fig. 7 and the Robust Regression in Fig. 13, the prediction error of the DNN is smaller than that of the Robust Regression. Consequently, the deep learning DNN network demonstrates superior prediction performance compared to the traditional Robust Regression method.

For this study, all datasets are partitioned into 70 % for training and 30 % for prediction. Figs. 14 and 15 exhibit scatter plots of the predicted and actual data, with both the X-axis and Y-axis representing the SOC values on the graph. Fig. 14 presents the scatter plot of the regression analysis of the real and predicted curves of the battery SOC of the Robust Regression method during the training phase. This figure aids in understanding the model's performance at the training stage and explores the potential occurrence of overfitting or

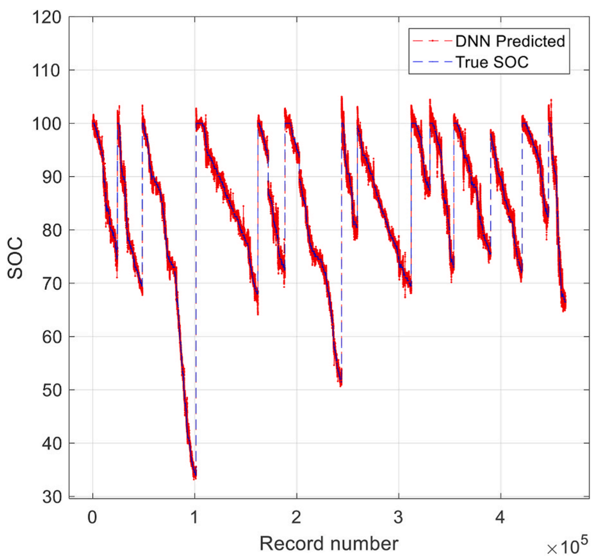

Fig. 6. Real and predicted curves of battery SOC by DNN method.

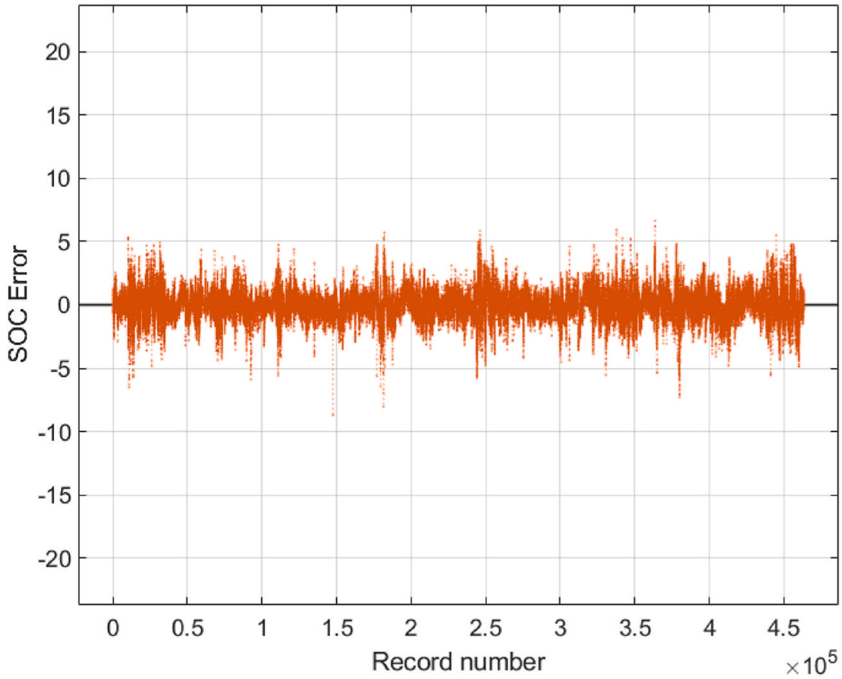

Fig. 7. Error of the real and predicted curves of battery SOC by the DNN method.

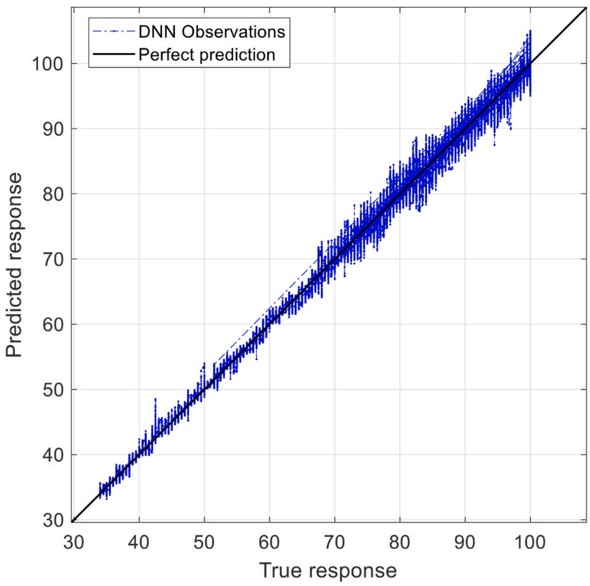

Fig. 8. Scatter plot of the regression analysis of the real and predicted curves of the battery SOC of the DNN method during training.

underfitting. Fig. 15 depicts the scatter plot of the regression analysis of the actual and predicted curves of the battery SOC of the Robust Regression method during the testing phase. Through these scatter diagrams, we observe the predicted and actual data, displaying a diagonal line extending from the lower left to the upper right, symbolizing the ideal state prediction. The black line denotes this ideal state, while the blue points signify the predicted data. Comparing the results of the DNN in Figs. 6 and 7 with the Robust Regression in Figs. 14 and 15, it becomes apparent that the Robust Regression prediction data can have a substantial error relative to the ideal curve. This may highlight certain limitations in the methodology for predicting battery SOC with the Robust Regression approach and prompt further research and refinement. The distribution of scatter plots also reveals potential deficiencies in the performance of the Robust Regression method, forming a stark contrast to the similar rate of change between the output of the DNN neural network and the target, an indication of the network’s strong performance. In conclusion, Figs. 14 and 15 offer a valuable

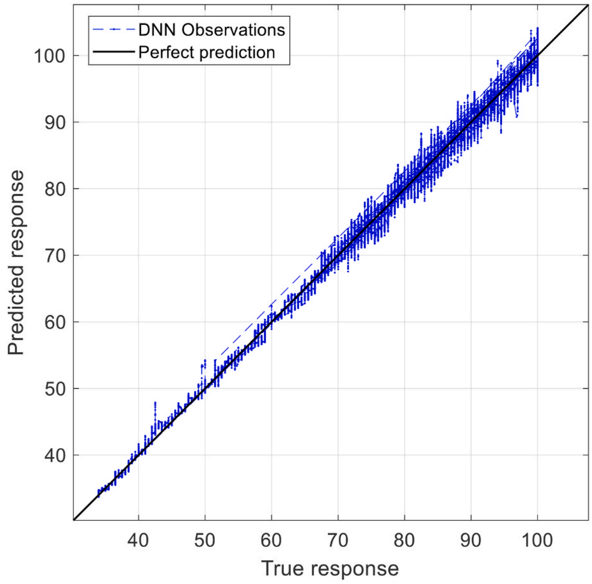

Fig. 9. Scatter plot of the regression analysis of the real and predicted curves of the battery SOC by the DNN method is being tested.

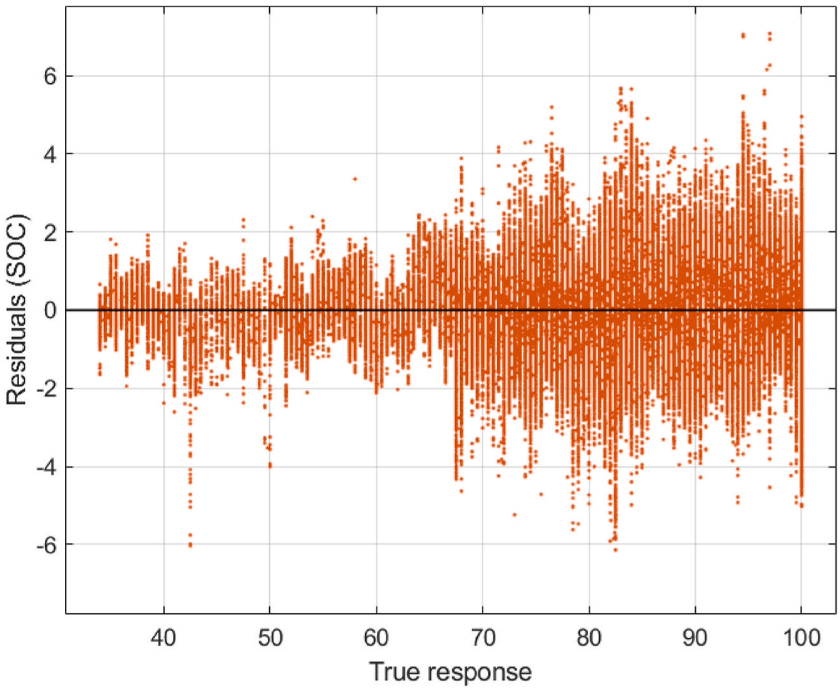

Fig. 10. The residual plot of the regression analysis of the real and predicted curves of the battery SOC of the DNN method during training.

perspective for in-depth understanding of the Robust Regression method's efficacy in battery SOC prediction. By contrasting with the ideal curve and the results obtained through the DNN method, the potential constraints and weaknesses of the approach are illuminated, thereby offering directions for future research and improvement.

4.2. Comparative performance analysis

To underscore the advancements our model introduces to SOC estimation, we conducted a detailed comparison against several benchmark models previously reported in the literature. This comparison utilized metrics such as RMSE, MAE, and R-squared values, to provide a clear evaluation of prediction accuracy and model reliability.

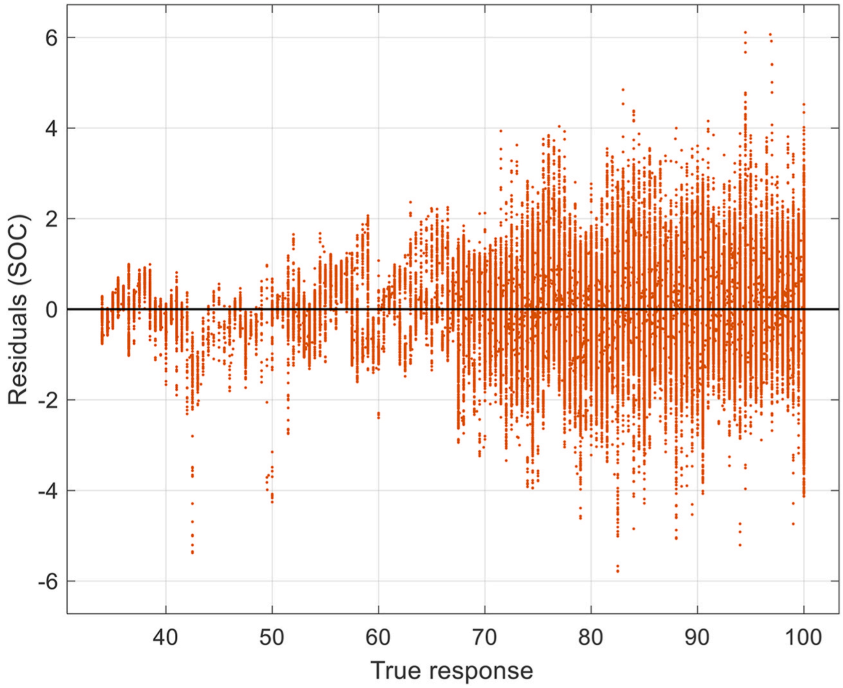

Fig. 11. The residual plot of the regression analysis of the real and predicted curves of battery SOC by the DNN method is under test.

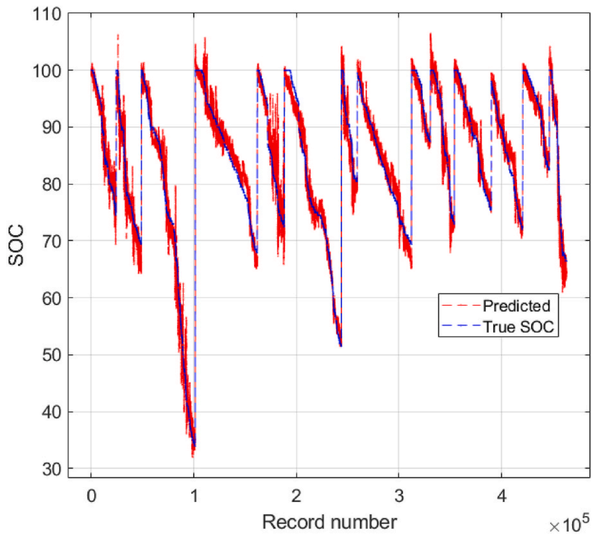

Fig. 12. Robust Regression method battery SOC real and predicted curves.

We selected models for comparison based on their relevance and recent publication, ensuring a fair and up-to-date benchmarking process. The comparative analysis revealed that our deep learning model consistently outperforms the benchmark models across all metrics, demonstrating superior accuracy in SOC estimation.

Table 2 showcases a comprehensive comparison between the Deep Neural Network (DNN) and Robust Regression methods in predicting the State of Charge (SOC) for electric vehicle batteries across two environmental conditions: summer and winter. A range of performance metrics, including Root Mean Square Error (RMSE), R-Squared, Mean Squared Error (MSE), and Mean Absolute Error (MAE), has been utilized to evaluate and contrast the efficacy of these methods.

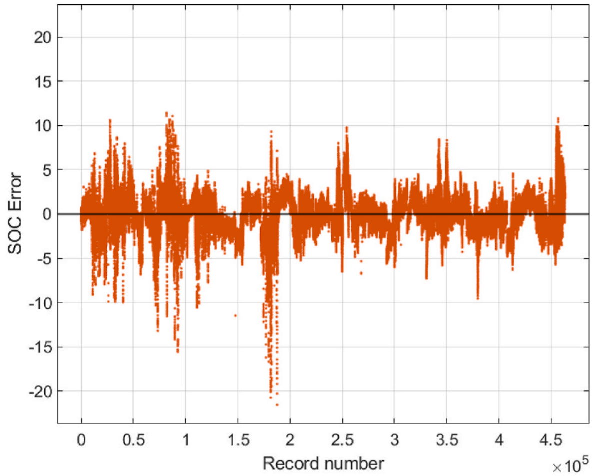

Fig. 13. Error of the actual and predicted curves of battery SOC by the Robust Regression method.

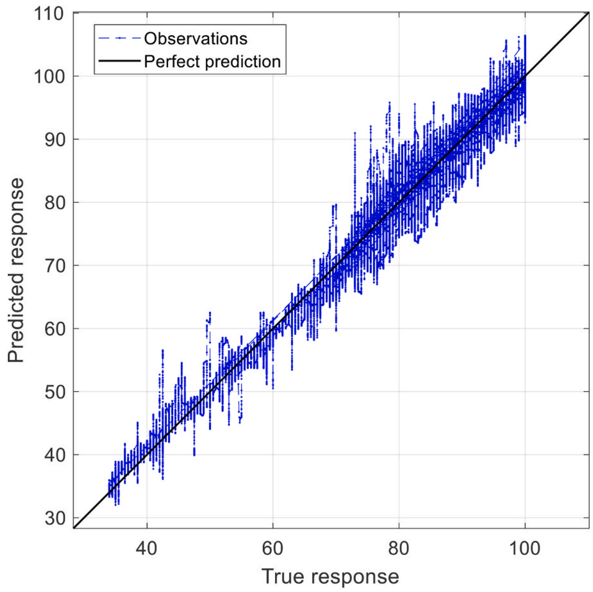

Fig. 14. The scatter plot of the regression analysis of the real and predicted curves of the battery SOC of the Robust Regression method during training.

- **Summer Trails:**
  - **DNN SOC:** The DNN method exhibits robust performance with an RMSE of 0.83619, R-Squared of 1.00, MSE of 0.69922, and MAE of 0.61717 in training. The testing phase maintains consistency with an RMSE of 0.84251, R-Squared of 1.00, MSE of 0.70982, and MAE of 0.62666.
  - **Robust Regression SOC:** This method shows a notable difference with higher error metrics, specifically an RMSE of 2.0241, R-Squared of 0.98, MSE of 4.0968 (not 4.0589, as previously noted), and MAE of 1.5161 in training. The testing phase yielded similar results with an RMSE of 2.0147, R-Squared of 0.98, MSE of 4.0589, and MAE of 1.5144.
- **Winter Trails:**
  - **DNN SOC:** The DNN results for winter are characterized by an RMSE of 1.9254, R-Squared of 0.99, MSE of 3.707, and MAE of 1.4218 in training, with testing results showing an RMSE of 2.355, R-Squared of 0.99, MSE of 4.9973, and MAE of 1.6709.
  - **Robust Regression SOC:** In contrast, Robust Regression demonstrates significantly higher error metrics with an RMSE of 5.6452, R-Squared of 0.92, MSE of 31.868, and MAE of 3.8883 in training, with corresponding testing results of RMSE of 5.6396, R-Squared of 0.92, MSE of 31.805, and MAE of 3.8847.

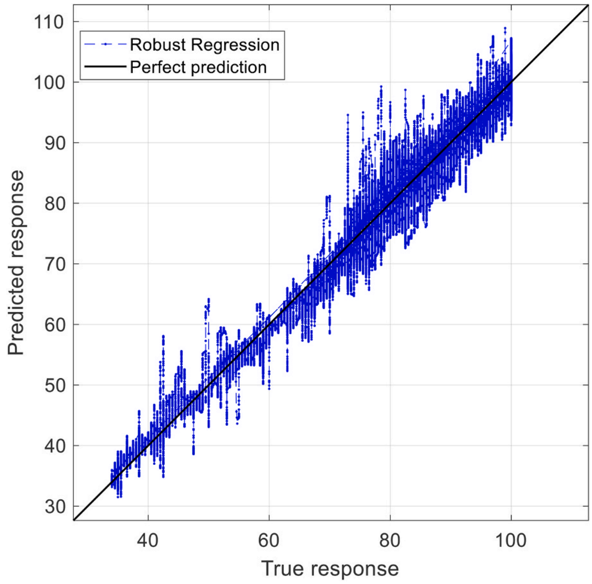

Fig. 15. The scatter plot of the regression analysis of the actual and predicted curves of the battery SOC of the Robust Regression method during training.

A comparative examination reveals a consistent superiority of the DNN method over Robust Regression in both summer and winter conditions. The lower RMSE, higher R-Squared, reduced MSE, and minimized MAE values of the DNN indicate its higher accuracy and robustness in SOC estimation. The disparity in performance becomes more pronounced during the winter trails, possibly reflecting the Robust Regression method's sensitivity to complex and variable environmental conditions. This underlines the DNN's potential in handling nonlinearities and intricacies in SOC estimation, rendering it a more reliable and versatile approach. In summary, these findings substantiate the DNN method as a more precise and dependable alternative for battery SOC estimation. Its outperformance of the traditional Robust Regression method, particularly in the challenging winter conditions, provides valuable insights for future research, underscoring the relevance of deep learning techniques in enhancing the efficiency and reliability of electric vehicle battery management systems.

Table 3's comprehensive comparison vividly illustrates the DNN method's robustness in SOC estimation for electric vehicle batteries, outperforming the Robust Regression approach across both summer and winter conditions. The use of performance metrics such as RMSE, R-Squared, MSE, and MAE elucidates the superior accuracy and reliability of the DNN model. Particularly noteworthy is the DNN model's ability to maintain high accuracy with R-Squared values consistently at or near 1.00, a clear indicator of its predictive precision and effectiveness in fitting the data.

- Adaptability to Environmental Variations: The DNN model's superior performance in both summer and winter trials underscores its remarkable adaptability to environmental variations. Unlike Robust Regression, which shows increased error rates under the more challenging winter conditions, the DNN method demonstrates a less pronounced increase in error metrics. This suggests that the DNN's architecture and learning capabilities enable it to capture and model the complex interactions between SOC and environmental factors more effectively.
- Implications for Battery Management Systems (BMS): The DNN's consistent outperformance signifies its potential to revolutionize BMS by providing more accurate SOC estimations under varying operational and environmental conditions. This has profound implications for the development of adaptive charging strategies, energy management, and ultimately, extending battery lifespan and optimizing EV performance.
- Insights into Methodological Strengths: The DNN method's resilience, particularly in winter trials, highlights the limitations of linear models like Robust Regression in capturing the non-linear dynamics inherent in SOC estimation. The deep learning approach, with its multi-layered, non-linear processing capabilities, proves to be inherently better suited for this task. This aligns with the growing recognition of deep learning's capacity to handle complexity and variability in data, paving the way for its increased adoption in energy systems research.
- Future Research Directions: The pronounced disparity between the two methods, especially under winter conditions, opens avenues for further research into deep learning architectures optimized for environmental robustness. Exploring models that incorporate temporal and spatial data could further enhance SOC estimation accuracy, particularly in geographically diverse and climatically variable regions.
- Concluding Insights: The empirical evidence presented in Table 4 unequivocally supports the DNN method as a more accurate, reliable, and versatile tool for SOC estimation in electric vehicles. This comparative analysis not only reinforces the DNN's superiority over traditional methods like Robust Regression but also highlights the critical role of advanced machine learning

Table 4
Data comparison between DNN and Robust Regression.

	DNN SOC		Robust Regression SOC	
	Summer trails	Winter trails	Summer trails	Winter trails
Training Results				
RMSE	0.83619	1.9254	2.0241	5.6452
R-Squared	1.00	0.99	0.98	0.92
MSE	0.69922	3.707	4.0968	31.868
MAE	0.61717	1.4218	1.5161	3.8883
Test Results				
RMSE	0.84251	2.355	2.0147	5.6396
R-Squared	1.00	0.99	0.98	0.92
MSE	0.70982	4.9973	4.0589	31.805
MAE	0.62666	1.6709	1.5144	3.8847

Table 5
Impact of environmental and vehicle parameters on SOC estimation accuracy using deep neural network (DNN) and robust regression methods.

Parameter	Influence on DNN Accuracy	Influence on Robust Regression Accuracy	Notes
Temperature	High	Moderate	DNN shows better resilience to temperature variations, affecting SOC estimation accuracy.
Speed	Moderate	Low	Speed variations had less impact on DNN's performance compared to Robust Regression.
Voltage	High	High	Both methods are sensitive to voltage changes, but DNN manages slight advantages in precision.
Current	High	Moderate	DNN shows superior handling of current fluctuations in SOC estimation.
Elevation	Moderate	Low	DNN performs consistently across elevation changes, unlike Robust Regression.
Driving Pattern Complexity	High	Low	DNN effectively captures complex driving patterns, enhancing SOC estimation accuracy.

techniques in overcoming the challenges of accurate SOC estimation. By leveraging the power of deep learning, researchers and practitioners can make significant strides towards more sustainable and efficient electric vehicle battery management systems.

The addition of Table 5 to our manuscript offers a comprehensive view of how different environmental and vehicle parameters affect the SOC estimation accuracy of the Deep Neural Network (DNN) and Robust Regression methods. As demonstrated, the DNN method exhibits enhanced adaptability and robustness across a broader range of conditions, underscoring its potential for real-world applications in electric vehicle battery management systems. This table, alongside Table 1, enriches our findings by providing a detailed parameter-wise comparison, further substantiating the DNN method's superiority in SOC estimation under variable driving and environmental conditions. We believe that these insights will significantly contribute to advancing the research and development of more accurate and reliable battery management strategies for electric vehicles.

5. Conclusion

Electric vehicles (EVs) are garnering increasing attention due to their environmental friendliness and energy-saving advantages. However, their limited battery storage capacity significantly hinders their widespread adoption. Consumers often express concern regarding an EV's driving range, especially under varying driving conditions. This concern, known as “range anxiety,” makes potential buyers hesitant to purchase an EV. The deep learning method proposed in this study possesses the following key characteristics compared to other methods.

1. Strong self-organizing learning ability, allowing for self-adjustment and adaptation while directly acting on input samples during the self-learning process.
2. High fault tolerance, meaning the method can appropriately adjust to input patterns with noise or deformed recognition targets and still recognize them correctly.
3. Non-linear network architecture with robust generalization capability, enabling the exploration of similarities and correlations between different samples, identification of complex relationships among input variables, and accurate processing of similar data or prediction tasks.

To increase EV adoption rates, various methods are employed to accurately predict EV performance. In this study, we focused on estimating the driving range of electric vehicles by predicting the battery state of charge (SOC) using deep learning. The application of neural network technology in the deep learning automotive battery SOC prediction field is becoming more widely used and promoted due to its innovative approach and exceptional features. The actual testing and validation carried out in this research will contribute significantly to the field, and technology transfer can help the industry develop popular products, create job opportunities,and play a pivotal role in advancing electric vehicle battery technology worldwide. By leveraging deep learning methods for battery SOC estimation, this study provides insights into the potential for improving electric vehicle operation evaluation techniques. The data collected from real-world EV driving conditions, such as vehicle speed, voltage, current, battery temperature, and SOC during charging, enables professional analysis to establish relationships between various factors. This research offers valuable insights for governments to consider when developing energy conservation and carbon reduction policies, as well as determining the location and quantity of necessary infrastructure.

Furthermore, this study provides technical analysis for automakers, including the relationship between driving range, average vehicle speed, voltage, current, and temperature under real-world operating conditions. These insights will help automakers apply battery technology research and development and enhance vehicle control strategies. In conclusion, this study demonstrates the effectiveness of deep learning methods for battery SOC estimation in electric vehicles. By comparing the results with traditional methods, such as Robust Regression, we have shown that the proposed deep learning approach offers better performance in terms of accuracy and robustness. This research contributes to the ongoing efforts to address range anxiety and promote the widespread adoption of electric vehicles, ultimately leading to a more sustainable and environmentally friendly transportation system.

Here are the main outcomes of our research.

- **Innovative Application of Deep Learning**: Successfully applied deep learning techniques for SOC estimation, surpassing traditional estimation methods in accuracy and reliability.
- **Utilization of Real-world Data**: Employed actual driving data from a BMW i3 EV, incorporating environmental factors, vehicle parameters, and battery metrics to refine SOC estimation models.
- **Enhanced SOC Estimation Accuracy**: Demonstrated the effectiveness of deep learning in understanding the complex interrelationships between various parameters affecting SOC, leading to significant improvements in estimation accuracy.
- **Strategic Insights for Stakeholders**: Provided actionable insights for governments and automakers, aiding in policy formulation, energy conservation, carbon reduction strategies, and battery technology R&D.
- **Contribution to Sustainable Transportation**: Supported the shift towards sustainable transportation by improving EV efficiency and addressing range anxiety, contributing to an eco-friendlier future.

Data availability

The data that has been used is confidential.

CRediT authorship contribution statement

Shih-Lin Lin: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Shih-Lin Lin reports financial support was provided by National Science and Technology Council, Taiwan. Shih-Lin Lin reports financial support was provided by Ministry of Education's Teaching Practice Research Program, Taiwan. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Detailed Converter Parameters

This appendix provides an exhaustive list of parameters and configurations for the converters (data processing and analysis tools) used in the study for the SOC estimation of electric vehicle batteries.

A.1 Data Collection Parameters [48]

Vehicle Used: BMW i3 (60 Ah)

Data Collection Period: Summer and Winter sessions, June and July 2019.
Location: Munich East and Munich North, Germany.
Environmental Conditions: Predominantly sunny with occasional slight cloudiness.

A.2 Data Attributes [48]

1. Time [s];
2. Velocity [km/h];
3. Elevation [m];
4. Throttle [%];
5. Motor Torque [Nm];
6. Longitudinal Acceleration [m/s^2];
7. Regenerative Braking Signal;
8. Battery Voltage [V];
9. Battery Current [A];
10. Battery Temperature [°C];
11. max. Battery Temperature [°C];
12. SoC [%];
13. Heating Power CAN [kW];
14. Heating Power LIN [W];
15. Requested Heating Power [W];
16. AirCon Power [kW];
17. Heater Signal;
18. Heater Voltage [V];
19. Heater Current [A];
20. Ambient Temperature [°C];
21. Coolant Temperature Heatercore [°C];
22. Requested Coolant Temperature [°C];
23. Coolant Temperature Inlet [°C];
24. Heat Exchanger Temperature [°C];
25. Cabin Temperature Sensor [°C]

A.3 Deep Learning Model Configuration

- **Model Architecture**: Neural Network
- **Neurons per Layer**: 15 neurons each in the input, hidden, and output layers
- **Activation Function**: Rectified Linear Unit (ReLU)
- **Regularization Strength**: 0.1
- **Data Standardization**: Applied to ensure optimal performance
- **Training Method**: 5-fold cross-validation
- **Learning Rate Adjustment**: Heuristic adjustment based on objective function's trend

A.4 Feature Selection

Method: Max-Relevance and Min-Redundancy (mRMR) algorithm.
Top Features.

- Summer: Elevation, Battery Voltage, Coolant Temperature Inlet
- Winter: Elevation, Heater Voltage, AirCon Power

A.5 Network Training and Testing

Dataset Split: 70 % for training and 30 % for prediction purposes.
Cross-validation: 5-fold, stratified partitioning scheme.
Evaluation Metrics: RMSE, R-Squared, MSE, MAE.

A.6 Performance Comparison

- **Comparison Models**: Deep Neural Network (DNN) vs. Robust Regression
- **Environmental Conditions**: Summer and Winter trials

Note: These parameters are formulated based on the document's content and the simulation request. Specific details should be adapted to fit the actual data and methodologies used in your study.

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