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Advancing battery state of charge estimation in electric vehicles through deep learning: A comprehensive study using real-world driving data

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ABSTRACT

Accurately estimating the State of Charge (SOC) in Electric Vehicles (EVs) is critical for battery management and operational efficiency. This paper presents a Deep Learning (DL) approach to address this challenge, utilizing Feed-Forward Neural Networks (FFNN) to estimate SOC in real-world EV scenarios. The research used data from 70 driving sessions with a BMW i3 EV. Each session recorded key factors like voltage, current, and temperature, providing inputs for the DL model. The recorded SOC values served as outputs. We divided the dataset into training, validation, and testing subsets to develop and evaluate the FFNN model. The results demonstrate that the FFNN model yields minimal errors and significantly improves SOC estimation accuracy. Our comparative analysis with other machine learning techniques shows that FFNN outperforms them, with an approximately 2.87 % lower root mean square error (RMSE) compared to the second-best method, Extreme Learning Machine (ELM). This work has significant implications for electric vehicle battery management, demonstrating that deep learning methods can enhance SOC estimation, thereby improving the efficiency and reliability of EV operations.

1. Introduction

The rising popularity of lithium-ion batteries is attributed to their increasing use in Electric Vehicles (EVs), driven by their high energy density and minimal self-discharge rate (Boulakhbar et al., 2022). Within these battery packs, accurately estimating the State of Charge (SOC) is pivotal for sustaining battery pack performance and ensuring the safe operation of EVs (Pan et al., 2023). This task is particularly challenging due to the inherent inconsistencies among cells within the battery pack (He et al., 2017). Due to its high energy density and minimal environmental impact, lithium batteries are rapidly being employed in EVs. EVs employ Battery Management Systems (BMS) for battery monitoring and safety protection in order to monitor battery state, anticipate remaining mileage, and optimize energy dispatch. One of the most important features in BMS is SOC of the batteries, where the estimation of the SOC is vital in determining the remaining range of EVs and the runtime of battery-power equipment (Vidal et al., 2022).

Recent research has introduced innovative approaches to improve battery management and SOC estimation. A hybrid modeling approach that combines physics-based reduced-order models with deep neural networks has been developed to forecast the Remaining Useful Life (RUL) of lithium-ion batteries, offering a promising method for long-term battery performance evaluation (Nascimento et al., 2021). This hybrid approach uses data-driven kernels to reduce the gap between predictions and observations, achieving improved accuracy with reduced-order modeling. Additionally, integrating domain knowledge into deep neural networks has shown significant advancements in predicting RUL, with a physics-based model extracting aging-correlated parameters from battery charging data to inform a deep neural network (Ma et al., 2024). This innovative approach demonstrates a high level of accuracy and efficiency compared to traditional data-driven methods. Moreover, early prediction of battery RUL has been enhanced with the use of Adaptive Dropout Long Short-term Memory (ADLSTM) combined with Monte Carlo (MC) simulation (Tong et al., 2021). This deep-learning-based algorithm offers precise early prediction with significantly less data, showcasing improved prediction accuracy and robustness.

Despite significant advances in SOC estimation, ongoing challenges exist due to the dynamic and complex nature of lithium-ion batteries. For instance, variations in temperature, current rates, and other environmental factors can affect the accuracy of SOC estimation models. Recent research has explored adaptive approaches to improve SOC

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prediction. An example is the improved Anti-Noise Adaptive-LSTM neural network, which offers robust feature extraction and optimal parameter characterization for more accurate SOC estimation (Wang et al., 2023a). An innovative approach to capacity estimation is the improved robust multi-time scale singular filtering-Gaussian process regression-long short-term memory (SF-GPR-LSTM) modeling method which has been proposed in (Wang et al., 2023b). This technique uses a multi-task training strategy to evaluate battery performance, enabling refined dynamic characterization of physical carrier transports.

Accurate SOC estimation is vital for the energy management system of vehicles, ensuring the reliability and affordability of EVs. However, SOC estimation poses challenges due to the intricate and nonlinear dependencies on temperature, battery health, and other factors in Li-ion batteries (Vidal et al., 2020). The data driven analysis have been discussed in (Hossain Lipu et al., 2020), where numerous algorithms, implementation factors, limitations and future trends of SOC estimation have been analyzed. Moreover, precise SOC estimation is essential for the battery balancing system, particularly considering the erratic dynamics batteries experience during the frequent acceleration and deceleration of electric vehicles (Chemali et al., 2018). In order to address the limitations of low precision, effectiveness, and relatively low robustness, the Internal Cascaded Neuromorphic Computing System (ICNCS) (Dong et al., 2024) and the Nesterov Accelerated Gradient (NAG) algorithm based Bidirectional Gated Recurrent Unit (Bi-GRU) network (Zhang et al., 2021) have been proposed literature. These approaches capitalize on the significant advancements in graphics processing units, which allow the networks to be trained at much higher speeds than in the past.

The effort of precisely estimating the SOC in batteries has been comprehensively studied in research, with an obvious focus on utilizing advanced approaches such as Deep Learning (DL) and Machine Learning (ML). Convolutional Neural Networks (CNNs), which are a subset of DL, have become a popular option in this area of study. For example, (Fan et al., 2022) utilized CNNs in the U-Net architecture to effectively tackle the issues of SOC estimation. In a similar manner, (Yang et al., 2022a) addressed the SOC by utilizing a temporal CNN that was trained on actual operational data from EVs. This study demonstrated the practical usefulness of the CNN in real-life situations. In addition, (Gu et al., 2023) presented a CNN-Transformer architecture, demonstrating its effectiveness in precisely evaluating the State of Health (SOH) of batteries. (Pradyumna et al., 2022) combined CNNs with electrochemical impedance spectroscopy (EIS) to accurately and reliably estimate battery capacity, while (Wang et al., 2023c) introduced a closed-loop CNN method to improve the accuracy of SOC estimation under various scenarios.

Meanwhile, researchers have explored the use of Recurrent Neural Network (RNN) approaches, with a specific focus on LSTM. (Chemali et al., 2018) proved the effectiveness of LSTM-RNNs in capturing temporal relationships to accurately estimate SOC without the need for complex battery models or filters. (Chen et al., 2023) addressed the issue of unstable SOC estimation in lithium-ion batteries by utilizing LSTM-RNNs with enhanced input and restricted output. This approach effectively captured long-term dependencies and non-linear battery characteristics. (Chung et al., 2022) showed that LSTM-RNNs are effective at properly forecasting SOC in different environmental conditions, eliminating the necessity for complex lookup tables.

Moreover, the study of Extreme Learning Machine (ELM) has attracted interest in the field of SOC estimation research. In their study, (Dou et al., 2022) presented an improved version of the ELM model. They utilized the rapid learning abilities and generalization skills of the model, which were further strengthened by using the Salp Swarm Algorithm (SSA) for optimizing the model's parameters. (Zhang et al., 2023) tackled the issue of non-Gaussian disturbances in battery management systems by using an Outlier Robust Extreme Learning Machine (OR-ELM), taking use of ELM's strong capacity to adapt to different conditions. (Zhao et al., 2022) utilized a Multi-Input ELM (MI-ELM) method, together with online model parameter identification, to obtain excellent SOC estimation performance in various operational scenarios.

Devaraj and Kottoor (2024) proposed the ML and DL approaches to predict faults from battery features that considerably manage the energy in hybrid EV. It is also worth to mention that the hybrid models have also emerged one of the favorite approaches for solving the SOC estimation such as Adaptive Aquila Optimization Algorithm (AAqOA) and Deep Convolution Neural Network (DCNN) (Pisal and Vidyarthi, 2023), nonlinear auto-regressive models with exogenous input neural network (NARX) with LSTM (Wei et al., 2020), the Gaussian Process Regression hybrid with the CNN (Y. Y. Li et al., 2022), combination of multichannel convolutional and bidirectional recurrent neural networks (MCNN-BRNN) (Bian et al., 2022), CNN with Random Forest algorithm (Yang et al., 2022c), CNN-Bidirectional Weighted Gated Recurrent Unit (CNN-BWGRU) (Cui et al., 2022), Fuzzy Logic Controller (FLC) and Artificial Eco-system Algorithm (FLTAEO) for BMS (Justin Raj et al., 2022) and Multiscale Distribution Adaptation (MDA) combined with Deep Transfer Neural Network (DTNN) (Bian et al., 2021). These integrative models leverage various algorithms and techniques, contributing synergistically to bolster the accuracy and effectiveness of SOC estimation. The ongoing exploration and hybridization of different methodologies underscore the dynamic landscape of SOC estimation in EVs.

SOC estimation has also been addressed through widely recognized Kalman Filter (KF) methodologies, incorporating various adaptive and variant forms documented in the literature, such as the Adaptive Extended Kalman Filter (AEKF) (Jin et al., 2022), Improved Strong Tracking Unscented KF (Ananthi, 2022), unscented KF (UKF) and the H-infinity filter (HF) combination namely unscented H-infinity filter (UHF) (Liu et al., 2020), improved Cubature KF(CKF)(Li et al., 2021; Li et al., 2022), square root unscented KF (Liu and Yu, 2022), Modified Extended KF (MEKF) (Yang et al., 2022b), dual fractional order KF (Liu et al., 2022), joint algorithm of improved forgetting factor recursive least squares-extended KF (Ge et al., 2022), cubature Kalman filter and H-infinity (Ning et al., 2022) and Affine Iterative Adaptive Extended Kalman Filter (AIAEKF) (Wu et al., 2022). However, it is worth noting that distinctive advantages are offered by the FFNN approach employed in this research compared to these filter-based methods. Unlike KF and its variants, the FFNN excels in pattern recognition for estimation and prediction without relying on any particular model definition of a process and measurement model. One of the primary benefits of FFNN lies in its ability to perform pattern recognition and capture complex relationships within the data. By leveraging deep learning techniques and multiple hidden layers, the FFNN model autonomously learns intricate patterns and extracts relevant features from the input data. This adaptability enables FFNN to effectively handle different battery systems, driving conditions, and nonlinear behaviors, making it well-suited for SOC estimation in real-world scenarios.

In contrast, KF-based methods heavily depend on the formulation of a process and measurement model, which can be challenging to accurately define for complex battery systems. While these methods may be effective in certain applications, their performance can be limited by assumptions of linearity and the need for accurate model specifications. The FFNN approach, on the other hand, leverages its pattern recognition capabilities to learn directly from the data, bypassing the requirement of a specific model and enabling it to capture nonlinear and complex battery behavior more effectively. The mentioned methods highlight that DL, ML, and KF remain preferred options among researchers for SOC estimation and basically can be further explored. Data scarcity and confidentiality constraints imposed by manufacturers have hindered extensive investigations in this area.

Hence, this paper fills the research gap by introducing a novel SOC estimation approach derived from actual driving experiences with a BMW i3 EV, making use of the only accessible real-world data at hand (Trifonov, 2020). The main contribution of this research is the successful implementation of a DL FFNN model using this real-world driving data. The approach employed leverages voltage, current, and temperature—the established input features commonly used in SOC estimation—and applies a meticulous trial-and-error approach to select the most relevant features. By considering domain-specific information and understanding the significance of these input features, improved reliability and accuracy in SOC estimation have been achieved. However, it is important to note that according to the "No Free Lunch" theorem in artificial intelligence, each problem requires careful study because a particular AI approach might work well with one dataset but may not perform as effectively with another. This theorem underlines the importance of thorough comparative analyses and model validation to ensure the robustness of the approach (Moniz and Monteiro, 2021; Wolpert and Macready, 1997). Keeping this in mind, this research further explores the performance of different techniques through comprehensive comparative analyses with other deep learning approaches. The outcomes of this research make a significant contribution to the progression of SOC estimation techniques for electric vehicle batteries. The subsequent sections are structured as follows: Section 2 provides a concise overview of DL FFNN, and Section 3 delves into the application of DL FFNN for the SOC estimation model. Section 4 presents the results and subsequent discussion, and finally, Section 5 outlines the conclusion of the paper.

2. Deep learning (DL) approach: feed-forward neural networks

In this work, the training of the datasets under consideration is conducted using a FFNN. The FFNN, characterized by its multi-layer perceptron structure, operates without employing recurrence; rather, it executes a forward pass of data to capture the non-linearities dictated by the dataset (Vidal et al., 2022). Fig. 1 depicts the FNN model comprising three layers: the input layer, hidden layers, and output layer. The selection of activation functions for each neuron is crucial. Based on the model developed by (Vidal et al., 2020), the activation functions for output, hidden and input are established in this paper. The expressions employed for each layer of the FFNN are derived from this model are:

$$\text{Clipped ReLU at output layer } y = \begin{cases} 0, & u < 0 \\ u, & 0 \le u \le 1 \\ 1, & u > 1 \end{cases} \tag{1}$$

$$\text{Hyperbolic tangent at hidden layer 1}: \; y = \frac{e^u - e^{-u}}{e^u + e^{-u}} \tag{2}$$

$$\text{Leaky ReLU at hidden layer 2}: \; y = max(0.3 * u, u) \tag{3}$$

$$\text{Linear function at input layer}: \; y = u \tag{4}$$

In this context, y signifies the output from each neuron, while u indicates the total input prior to entering the neurons. This input comprises the sum of the products of the respective weights and inputs, along with the bias, and is formulated as follows:

$$u = \sum_i w_{ij} x_i + b_j \tag{5}$$

In this configuration, x_i denotes the output emanating from the i th

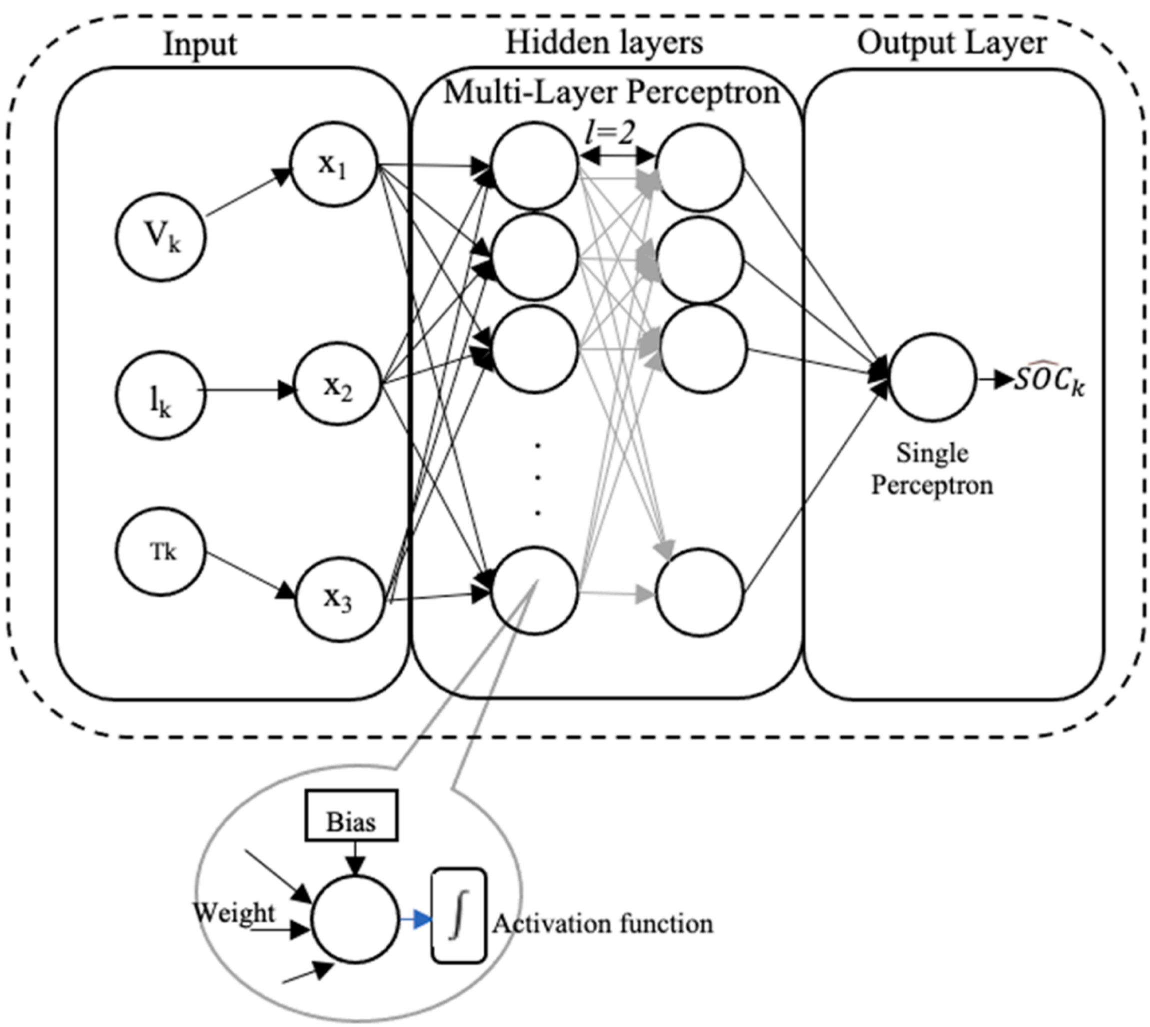

Fig. 1. The model of Feed-Forward Neural Networks.

neuron or node in the preceding layer, w_{ij} represents the weight interconnecting layers i and j, and b_j stands for the bias in the current layer. The optimization of weights at each layer is achieved using Adaptive Moment Estimation (Adam) (Kingma and Ba, 2015). This formulation involves the summation of the products of the respective weights and inputs, complemented by the bias. The interplay of these elements plays a crucial role in shaping the network's ability to capture and represent complex relationships within the data. The significance of these connections is underscored by the optimization process, where the weights at each layer are fine-tuned for enhanced predictive performance. The chosen optimization algorithm, Adam, ensures the efficient adjustment of weights, contributing to the overall efficacy of the FFNN in accurately estimating the SOC in electric vehicle batteries.

3. Using the deep learning (FFNN) for SOC estimation problem

The data quality is assessed by examining the extent to which the desired domain information is present in the dataset used to train the FFNN, considering the presence of noise or irrelevant information. Given that FFNN is a data-driven technique, it is crucial to acknowledge that measurement noise and error, while undesirable, are often inherent and cannot be entirely eliminated. Hence, these factors must be considered when conducting the training and testing phases of a DL network. This study utilizes a genuine dataset obtained from the measurement of 70 journeys made by the BMW i3 EV (Trifonov, 2020), furnished with a 60 Ah battery pack, for the simulation experiments. Data is collected with mounted EV sensors, through the OBD port at 1 Hz sampling rate. It is important to note that the acquired dataset contains *Not a Numb*er (*NaN*) elements due to errors or missing values in the actual measurements. Therefore, a data cleaning process is necessary for the raw data obtained.

In this study, the dataset incorporates two critical SOC features: the SOC estimated by the EV manufacturer and the displayed SOC presented to the end user. This comprehensive dataset aims to capture the nuanced dynamics of the battery's charge status as perceived by the manufacturer and as communicated to the EV user. Consequently, the SOC measured by the EV manufacturer is meticulously selected as the output variable for the proposed model. This choice aligns with the industry's emphasis on leveraging the manufacturer's estimation for precision and reliability in SOC determination. Simultaneously, the input variables for the FFNN model encompass essential parameters such as measured voltage, current, and temperature of the battery pack. This multidimensional input approach ensures that the FFNN model accounts for key factors influencing SOC, offering a holistic perspective on the battery's state. To provide clarity on the SOC estimation process, Fig. 2 visually represents the FFNN-based SOC estimation, depicting the intricate interplay of input variables. Additionally, the detailed configuration of

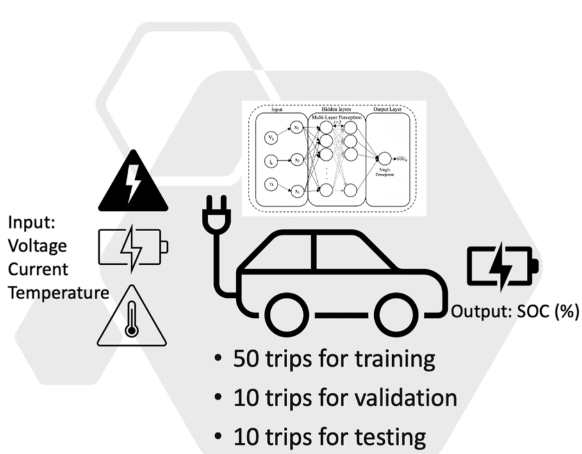

Fig. 2. SOC estimation using FFNN.

data for training, validation, and testing is meticulously outlined in Table 1, facilitating transparency in the experimental setup and aiding reproducibility in subsequent studies. This robust dataset and configuration lay the foundation for a comprehensive and insightful exploration of SOC estimation in electric vehicles.

Fig. 3 illustrates the FFNN inputs, encompassing voltage, current, and temperature data from 50 BMW i3 EV trips, with SOC as the output. The dataset, comprising over 800 thousand instances used for training (approximately 78 % of the total data), ensures robust learning. The allocation of about 11 % for validation and 12 % for testing processes contributes to a comprehensive evaluation of the FFNN model. It is noteworthy that the maximum SOC values intentionally fall below 100 %. According to (Lucchetta, 2021), this cautious approach, ensuring a driver-displayed SOC of 100 % at an estimated 86.9 % SOC, and vice versa, is implemented for battery safety and lifespan considerations within the optimal operational range.

To evaluate the efficacy of FFNN alongside other machine learning methods, we utilized several metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Maximum Error (MAX ERROR), and Standard Deviation (STD DEV). The explanations for these metrics are outlined below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}} \tag{7}$$

where

$\hat{y}_i$- predicted data

y_i- actual data

n-number of data points

RMSE quantifies the standard deviation of the residuals, providing insight into the dispersion of prediction errors. On the other hand, MAE gauges the average magnitude of errors in a set of predictions, irrespective of their direction. Additionally, STD DEV assesses the robustness of the proposed FFNN, while MAX ERROR identifies the peak error at a specific time.

Fig. 4 shows the process flow for our study on battery SOC estimation in EVs. The flowchart outlines the key steps from data collection to performance evaluation and results analysis, which have been discussed previously. The process begins with data collection, where real-world data from a BMW i3 EV is gathered. This data includes various parameters such as voltage, current and temperature, that serve as inputs for the model. The collected data is then used to establish the input-output configuration for the SOC estimation model. Next, the data is divided into training, validation, and testing sets to prepare for model development and evaluation, which has been discussed in Table 1. This division ensures that the model is properly trained and validated before final testing. Overall, the flowchart serves as a guide through the various stages of the study, illustrating the sequence of processes and their interconnections.

4. Results and discussion

All simulations in this work were conducted using MATLAB on a MacBook Pro Processor with a 2.40 GHz Quad-Core Intel Core i5 and 8 GB RAM. Evaluating the performance of FFNN in minimizing RMSE involves experimental determination of hidden layers. For the training-testing process, one hidden layer and two hidden layers were implemented, and the best results were documented for comparative analysis. Additionally, other machine learning techniques, including LSTM, GRU networks, and ELM, will be employed for performance comparison.

To ascertain the optimal configuration of hidden layers and neurons at each layer, the training and testing simulations were repeated ten

Table 1
Characteristics of Training, Validation, and Testing Sets.

Battery	Used Profiles	Training	Validation	Testing	Input	Hidden layer	Output
Battery pack of 60Ah lithium-ion	Real driving trips	Trips no. 1-no. 50 (830, 796 instances) based on 50 trips of driving	Trips no. 51- no. 60 (114, 230 instances) based on 10 trips of driving	Trips no. 61- no. 70 (118, 974 instances) based on 10 trips of driving	Input #1: Voltage, Input#2: Current; Input #3: Battery Temperature	2 : consists of 20 neurons for each hidden layer	Real measurement of SOC in%

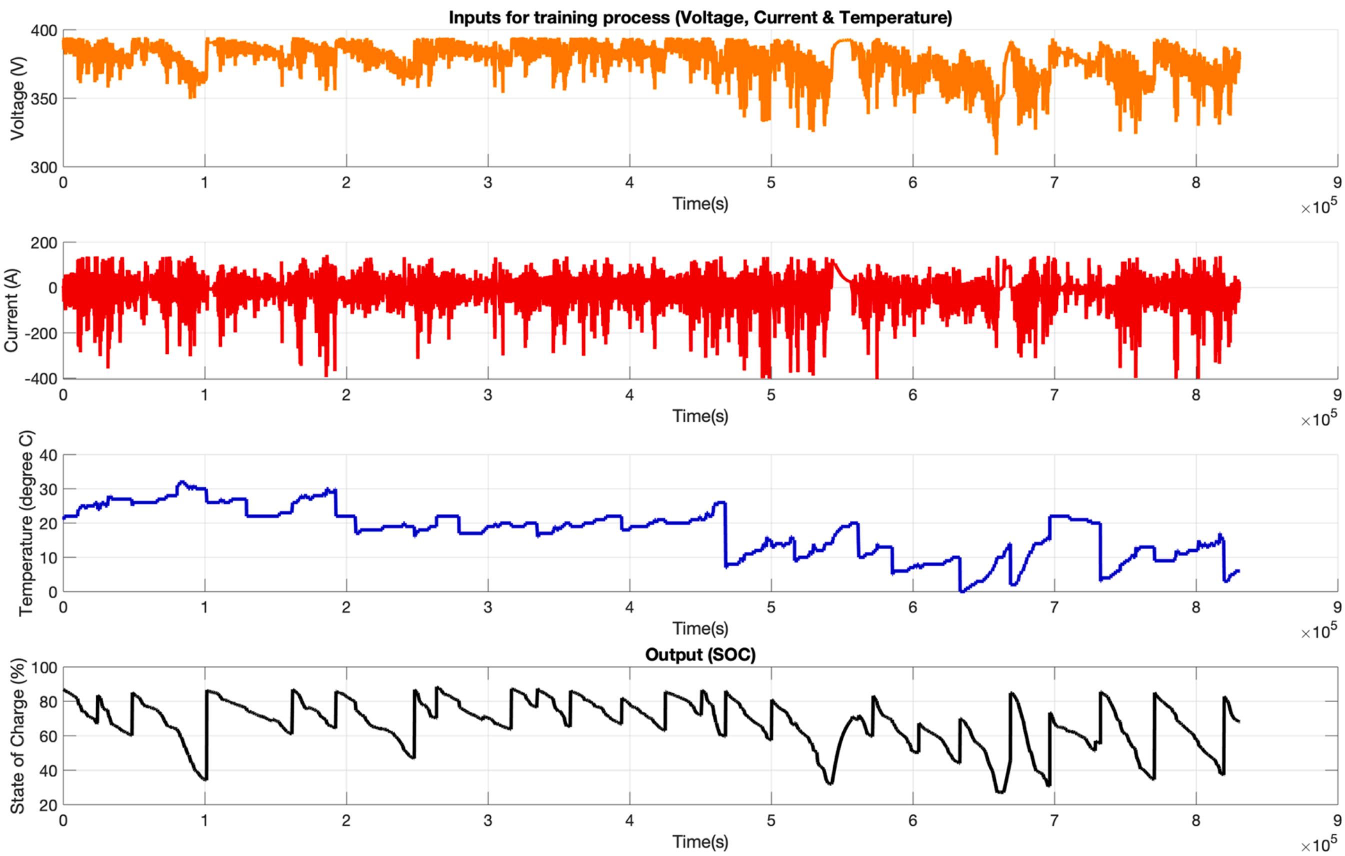

Fig. 3. Selected data for training the input-output of DL.

times. This approach accommodated the random initialization process of optimizing weights and biases and allowed for an evaluation of the developed FFNN model's consistency. This study specifically chose a single hidden layer and 2-hidden layers, with the number of neurons varied at each hidden layer (5, 10, 20, and 25). Fig. 5 illustrates the simulations, highlighting that the best results were achieved with a single and 2-hidden layers using 20 neurons. However, the results indicate that the FFNN model with 2-hidden layers consistently outperformed others across all metrics. Consequently, 20 hidden neurons at each hidden layer were selected for developing the FFNN model for the SOC estimation problem.

The evaluation of the machine learning models for state-of-charge (SOC) estimation involves key metrics, primarily RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). Among the models considered – FFNN (Feed-Forward Neural Network) with 2 hidden layers, FFNN with a single hidden layer, LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), and ELM (Extreme Learning Machines) – FFNN with 2 hidden layers consistently outperforms others. It attains the lowest RMSE (8.3460) and MAE (7.1662), indicating a superior ability to predict SOC accurately. The FFNN with a single hidden layer, although performing well, exhibits slightly higher error rates. LSTM and GRU, being recurrent neural networks, struggle to match the accuracy of FFNN, while ELM positions itself as a strong competitor, securing the second-best performance.

Beyond accuracy, the standard deviation (STD DEV) metric provides insights into the stability and consistency of predictions. Lower standard deviation values suggest more consistent results across different instances. FFNN with 2 hidden layers demonstrates not only accuracy but also consistency, yielding a lower STD DEV (8.1000). In contrast, FFNN with a single hidden layer, LSTM, and GRU show higher variability in predictions. ELM, while not reaching the level of consistency displayed by FFNN with 2 hidden layers, maintains a competitive standard deviation (6.37912), positioning itself as a stable alternative to more complex models.

In the comprehensive evaluation of machine learning models for state-of-charge (SOC) estimation, the simulation process was conducted rigorously, with FFNN and ELM undergoing ten iterations, while LSTM and GRU, due to their computational demands, were executed only once. The results, detailed in Table 2, encompass key metrics, including RMSE, MAE, MAX ERROR, and STD DEV. Notably, FFNN with 2 hidden layers, featuring 20 neurons, consistently outperformed all other models across these metrics, affirming its accuracy and reliability in predicting SOC. ELM secured the second-best performance, showcasing competitive results, especially considering its remarkable speed during the

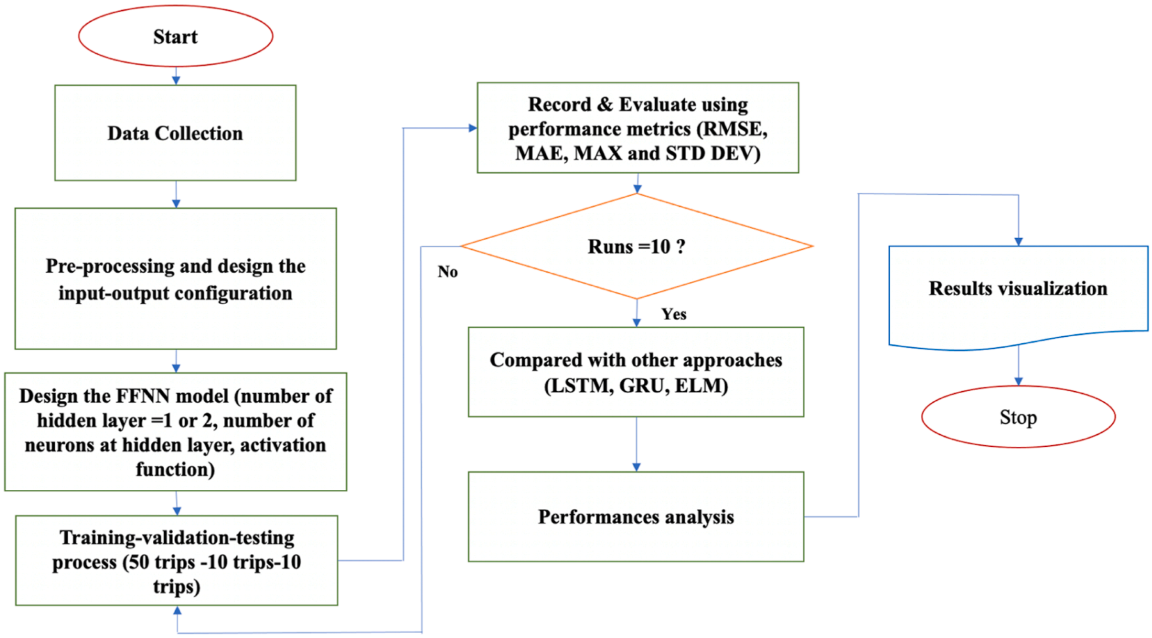

Fig. 4. Flowchart of SOC estimation using FFNN.

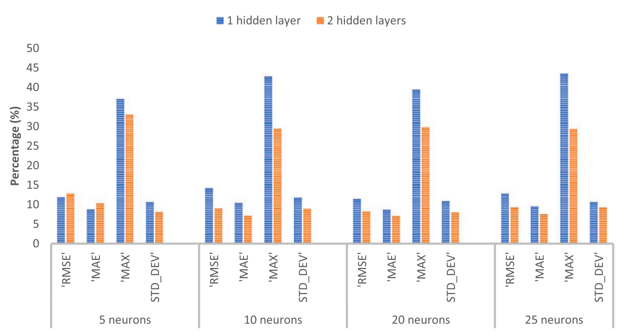

Fig. 5. Performance metrics for single and 2-hidden layers of FFNN models.

Table 2
Optimal outcomes achieved by various machine Learning approaches.

Performance Evaluation (%)	FFNN	FFNN single hidden layer	LSTM	GRU	ELM
RMSE	8.3460	11.5271	11.8127	18.5928	11.2176
MAE	7.1662	8.8024	10.8469	13.4434	10.3032
MAX	29.8497	39.5179	60.7218	53.4680	34.0408
STD. DEV.	8.1000	10.9645	6.82071	14.1475	6.37912

training process. This efficiency stems from ELM's unique approach, where input layer weights are randomly allocated, and output layer weights are calculated using the generalized inverse of the hidden layer output matrix (Bai et al., 2016). This distinctive feature accelerates ELM training significantly, making it a noteworthy model for those prioritizing computational efficiency without compromising on accuracy.

An exhaustive evaluation of the FFNN model's performance is presented in Fig. 6, encapsulating a comprehensive analysis across ten simulation runs. The figure provides a detailed visual representation of the variations in Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Maximum Error (MAX ERROR). This in-depth performance analysis offers a nuanced understanding of how the FFNN model responds to different simulation instances, shedding light on its robustness and reliability in diverse scenarios. Notably, the optimal outcomes were observed during simulation #3, aligning with the detailed results

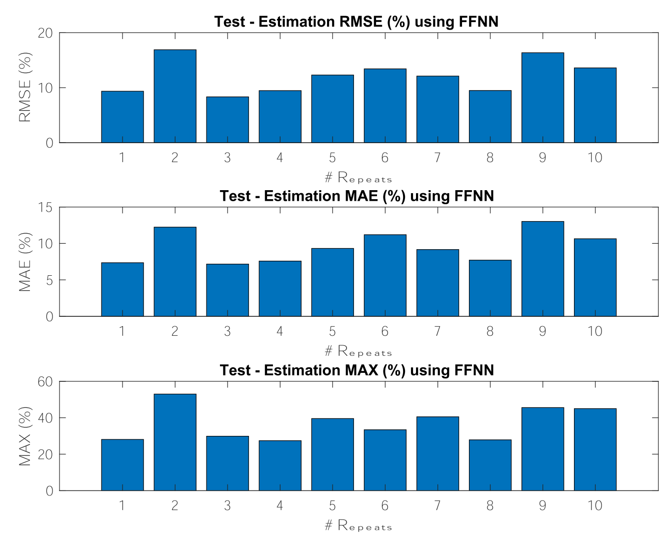

Fig. 6. Assessment of performance during the testing process across ten simulation runs.

outlined in Table 2.

The results of SOC estimation by FFNN, FFNN (1 hidden layer), LSTM, GRU, and ELM are presented in Figs. 7, 8, 9, 10, 11, respectively. It is evident from these figures that FFNN with 2-hidden layers exhibits the most accurate predictions, closely aligning with the testing data pattern. The maximum error recorded by FFNN is below 30 %, occurring at time 2303 s as illustrated in Fig. 7. Conversely, GRU demonstrates the least favorable performance, as depicted in Fig. 10. Despite its slightly lower maximum error compared to LSTM, the overall predictions by GRU deviate more substantially from the actual testing process. These nuanced observations contribute to a thorough understanding of how each model responds to the complexities of real-world SOC estimation scenarios.

From all the simulations conducted for all machine learning techniques, it can be noticed that even though FFNN able to track the pattern of the output of SOC from the real data testing, the performances are still can be improved. From the training data shown in Fig. 3, it can be noted

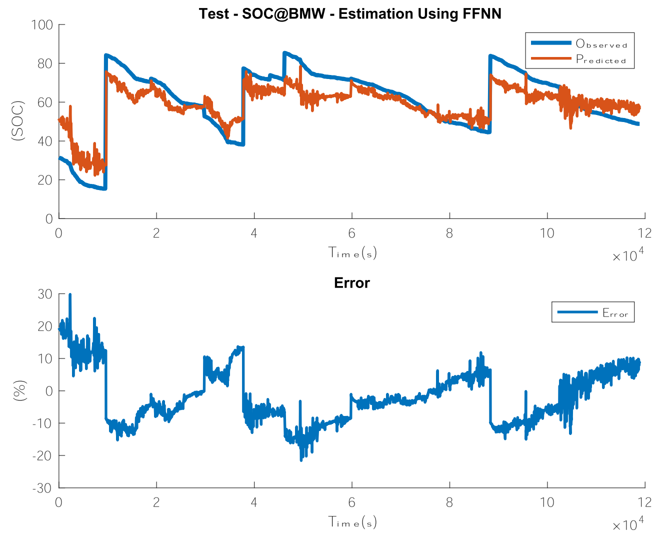

Fig. 7. SOC estimation obtained by FFNN from simulation #3 (the best).

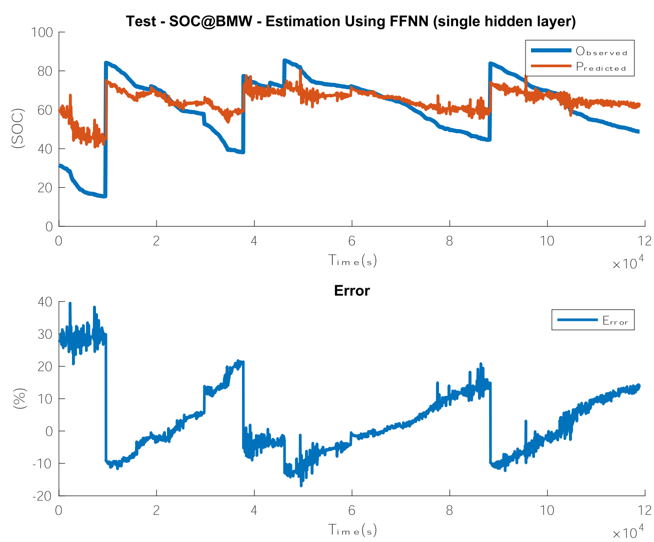

Fig. 8. SOC estimation obtained by FFNN for single hidden layer.

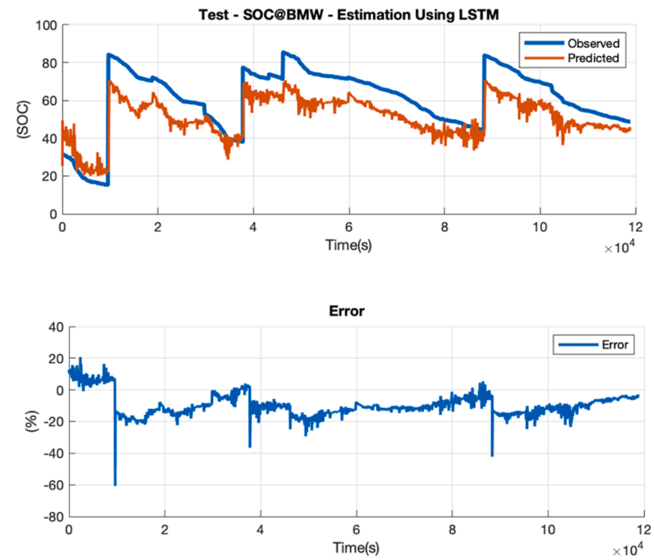

Fig. 9. SOC estimation obtained by LSTM.

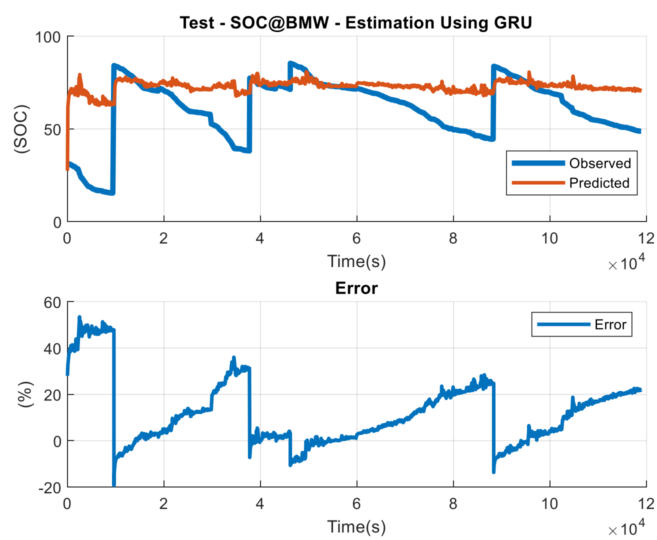

Fig. 10. SOC estimation obtained by GRU.

that the temperature distributions are ranging from 5 °C to 35 °C. Given that this temperature range may cover the requirements of numerous EV use cases, it would have been advantageous to record data from significantly higher or lower temperature ranges. This could enhance SOC estimation accuracy, particularly in more extreme operating conditions for EVs (Lucchetta, 2021). In addition, in this driven data of a BMW i3 EV, there are numerous parameters have been recorded such as elevation, regenerative breaking charge, speed throttle, ambient temperature, distance, duration and traffic conditions apart from the parameters used in this study. Thus, the impact of these parameters can be explored in the future that can give direct or indirect effects to the performances of SOC as well as State of Health (SOH) of the battery packed. This holistic exploration promises to provide a richer understanding and could lead to advancements in SOC estimation models and the overall optimization of electric vehicle battery management systems.

Moreover, the diversity in modeling approaches also could enhance the robustness and generalizability of SOC estimation models. Lastly, addressing real-world challenges related to EV usage, such as dynamic charging scenarios, varying driving patterns, and diverse geographic locations, could further enrich the scope of research. Conducting experiments under these specific conditions and incorporating their complexities into the SOC estimation models may yield more accurate and adaptable solutions for electric vehicle battery management.

For future endeavor, the focus on hardware-based solutions and innovative approaches to in-memory computing could significantly enhance SOC estimation and battery management systems. Recent research has presented interesting possibilities in these areas, with applications that may contribute to the advancement of SOC estimation technology. A promising approach is the brain-inspired hierarchical interactive In-Memory Computing (IMC) system (Ji et al., 2023), which addresses the 'von Neumann bottleneck' through cost-effective, eco-friendly carbon-based synapse arrays. This system facilitates high-speed analog multiply-accumulate operations and enables cross-modal interactions, pointing to new opportunities for efficient hardware implementation in battery management.

Another avenue for exploration is the multimodal neuromorphic sensory-processing system with memristor circuits designed for smart home applications (Dong et al., 2023). This approach utilizes low-cost, reliable materials to build an environmentally friendly sensory-processing system. Its emphasis on low-energy consumption and parallel processing could inspire similar innovations in battery

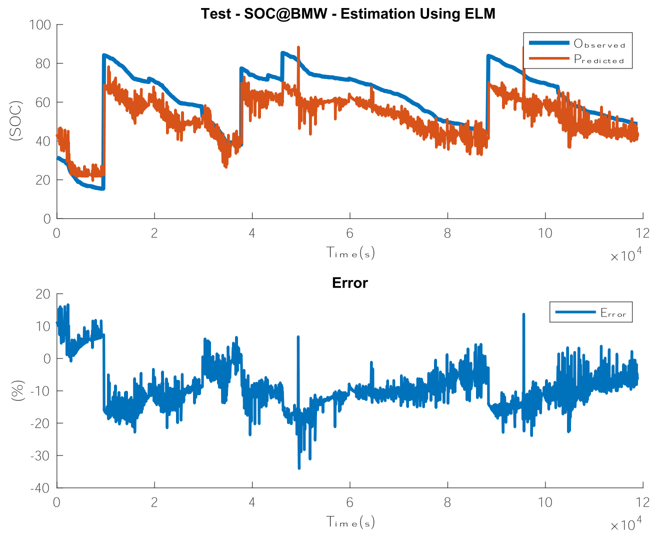

Fig. 11. SOC estimation obtained by ELM.

management systems, focusing on energy efficiency and streamlined hardware designs. The third potential area for future research involves a memristor-based Pavlov associative memory circuit (Zhou et al., 2022), demonstrating an evolution from battery-like capacitance to resistive switching memory. This novel approach, with its simple hardware implementation and biophysical mechanism exploration, offers a glimpse into how associative memory circuits could be adapted for SOC estimation, allowing for robust and adaptable solutions.

These directions, based on advanced hardware technologies, could offer improved accuracy and efficiency in SOC estimation, ultimately contributing to more reliable and robust battery management systems in electric vehicles and beyond. Further research in these areas could unlock new methods for handling the complex challenges of SOC estimation, with the goal of achieving enhanced performance and reliability in battery systems.

5. Conclusion

This study pioneered the application of a deep learning methodology, specifically the FFNN, to achieve precise estimation of the battery's SOC by leveraging real driving data obtained from a BMW i3 EV. The optimization process for FFNN involved critical design parameters, including the number of hidden layers, neurons, and input-output configurations. It was imperative to fine-tune these parameters, recognizing their substantial impact on the accuracy of SOC predictions. Through extensive comparative analyses with other machine learning techniques, such as LSTM, GRU, and ELM, utilizing identical input-output configurations, the simulations yielded compelling results. The findings affirm that FFNN consistently outperformed the selected techniques, showcasing superior SOC estimation capabilities. Importantly, the detailed discussions today provided deeper insights into the nuances of these results, elucidating the strengths of FFNN with 2 hidden layers, the comparative performance of ELM, and the challenges posed by GRU. In light of these discussions, it is evident that FFNN stands as the optimal choice for accurate SOC estimation, providing a solid foundation for future research endeavors. Recommendations for future studies involve exploring additional parameters or features to enhance the complexity of SOC modeling in real EV scenarios. Additionally, investigating various input-output configurations for driving trips will further enrich the evaluation of the developed deep learning approach as well as hardware-based solutions and innovative approaches to enhance SOC estimation and battery management systems.

CRediT authorship contribution statement

Mohd Herwan Sulaiman: Writing – original draft, Formal analysis, Conceptualization. **Zuriani Mustaffa:** Writing – review & editing, Validation. **Saifudin Razali:** Methodology, Data curation. **Mohd Razali Daud:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data sharing not applicable to this article as datasets can be obtained from the literature.

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