SoC Estimation of Li-ion Battery using deep learning frame work for EV Applications

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ABSTRACT **— Accurately determining the State of Charge (SOC) is a cornerstone of efficient battery management for lithium-ion batteries in electric vehicles (EVs). This study evaluates the performance of advanced deep learning models, including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Temporal Convolutional Networks (TCN), as well as hybrid combinations of these architectures, under various temperature scenarios: 0°C, 10°C, 25°C, and 40°C. Optimization techniques such as Adam and Stochastic Gradient Descent (SGD) were employed to train these models. Results reveal that TCN-based frameworks demonstrated superior accuracy with minimal Root Mean Square Error (RMSE) values, highlighting their potential for enhancing SOC predictions. Furthermore, the findings underscore the significant impact of temperature on SOC estimation, pointing to TCN as a transformative tool for advancing battery management systems. These advancements are instrumental in fostering safer EV technology and supporting the global shift towards sustainable transportation.**

Index Terms — State of Charge (SOC), Lithium-ion Batteries, Electric Vehicles (EVs), Deep Learning Models, Temporal Convolutional Networks (TCN), Long Short-Term Memory (LSTM), Battery Management Solutions, Root Mean Square Error (RMSE) Analysis, Thermal Impacts, Performance Enhancement, Eco-Friendly.

I. INTRODUCTION

The State of Charge (SOC) is a critical metric for understanding the remaining energy in a lithium-ion battery, particularly in electric vehicles (EVs). Its accurate estimation not only ensures safety and prolonged battery life but also enhances operational efficiency. SOC data supports crucial decisions related to charging, discharging, and energy optimization, helping to reduce user concerns like range anxiety and build trust in EV technology.

Conventional SOC estimation methods, such as Coulomb counting and open-circuit voltage techniques, face limitations that hinder their effectiveness. These methods are often affected by factors such as self-discharge, temperature sensitivity, and measurement noise. Additionally, they may require extended observation periods, making them impractical for real-time applications. Such inaccuracies increase the risks of overcharging or undercharging, which can compromise battery health, reduce lifespan, and even pose safety hazards like thermal runaway.

To overcome these challenges, this research delves into advanced machine learning techniques, specifically deep learning models such as LSTM, Bi-LSTM, and TCN. The study also introduces hybrid configurations, such as TCN with LSTM or Bi-LSTM, and evaluates their performance under varying temperature conditions (0°C, 10°C, 25°C, and 40°C). Training of these models was performed using optimization algorithms, with Adam and SGD compared based on their effectiveness in minimizing prediction errors, measured by RMSE.

Results indicate that deep learning approaches, particularly those involving TCN, are highly effective in capturing the intricate dynamics and temporal patterns of battery systems. These methods surpass traditional techniques, enabling greater accuracy and reliability. Integrating these models into battery management systems has the potential to extend battery life, ensure operational safety, and support the global transition to cleaner automotive technologies.

Emerging deep learning models have transformed SOC estimation by providing precise predictions based on extensive data. Unlike traditional methods, which are prone to errors under complex conditions, advanced architectures like LSTM, Bi-LSTM, and TCN excel at handling the nonlinear behavior of battery systems and identifying temporal dependencies.

The study highlights RMSE as the primary performance indicator and assesses models at varying temperatures to account for thermal effects on SOC estimation accuracy. Among the architectures tested, the hybrid TCN-Bi-LSTM model consistently performed well, particularly in low-temperature environments. Moreover, the Adam optimizer outperformed SGD in minimizing errors, proving to be the more efficient optimization algorithm.

This research emphasizes the critical role of integrating optimized model architectures and temperature considerations into SOC estimation systems. The strong performance of TCN-based hybrid models demonstrates their potential for real-world implementation. By enabling more accurate and reliable battery management, this study supports efforts to enhance EV adoption, improve energy efficiency, and promote environmentally friendly transportation solutions.

TABLE 1. Parameter comparison of the proposed method with existing literature.

Ref. No.	Methodology	Battery Type	Input Parameters	Output	Performance Indices
[32]	DNN	CALCE dataset	Current, Voltage, Temperature	SOC	MAE, RMSE
[33]	DNN	Panasonic NCR 18650PF dataset	Current, Voltage, Temperature	SOC	MAE, RMSE
[34]	DNN	CALCE dataset	Current, Voltage, Temperature	SOC	MAE, RMSE
[35]	LSTM	CALCE dataset	Current, Voltage, Temperature	SOC	MAE, RMSE
[36]	LSTM	Panasonic NCR 18650PF dataset	Current, Voltage, Temperature	SOC	MAE, RMSE
[36]	BiLSTM	Panasonic NCR 18650PF dataset	Current, Voltage, Temperature	SOC	MAE, RMSE
[26]	GRU	Panasonic NCR 18650PF dataset and CALCE dataset	Current, Voltage, Temperature	SOC	MAE, RMSE
Proposed	LSTM, TCN, BiLSTM, TCN-BiLSTM, TCN-LSTM	LG 18650HG2 Li-ion Battery dataset	Current, Voltage, Temperature	SOC	MSE, RMSE

The comparison investigates diverse techniques for estimating the State of Charge (SOC), an essential parameter within battery management systems (BMS) utilized in electric vehicles (EVs) and renewable energy storage systems. These techniques encompass traditional deep neural networks (DNN) and cutting-edge methods like Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Temporal Convolutional Networks (TCN), and hybrid architectures such as TCN combined with Bi-LSTM. Advanced models excel in identifying complex, nonlinear relationships within battery operations, enabling more accurate SOC predictions across diverse conditions.

This research employs datasets, including CALCE and Panasonic NCR 18650PF, while proposing the use of the LG 18650HG2 dataset to achieve superior performance. Key input variables like current, voltage, and temperature are utilized for SOC prediction, represented as a percentage. Performance metrics include mean absolute error (MAE), root mean square error (RMSE), and mean square error (MSE), with MSE offering additional insights into significant prediction deviations. Results reveal that hybrid TCN-based models surpass others in SOC estimation accuracy, particularly under challenging conditions.

The analysis underscores the necessity of selecting optimal deep learning models for SOC estimation, as each approach has distinct strengths. For instance, Temporal Convolutional Networks (TCN) are adept at managing diverse time horizons and long-term dependencies, making them particularly effective in handling variable thermal conditions compared to standard convolutional or recurrent models.

This integrated methodology significantly enhances SOC prediction, laying the groundwork for developing reliable and versatile battery management systems. By addressing the challenges posed by fluctuating operating temperatures through advanced deep learning strategies, this study bolsters the adoption of EVs and renewable energy systems, contributing to a sustainable technological future.

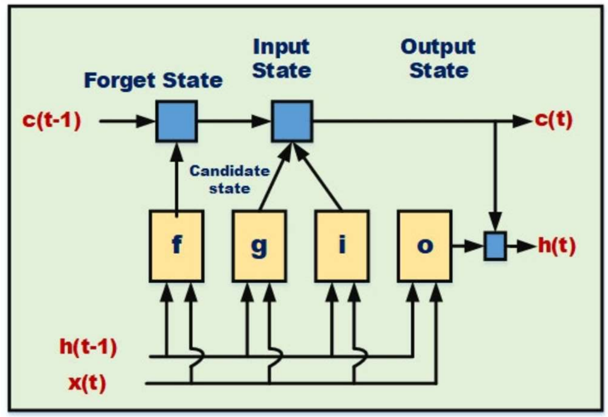

FIGURE 1. LSTM Structure [17], [36].

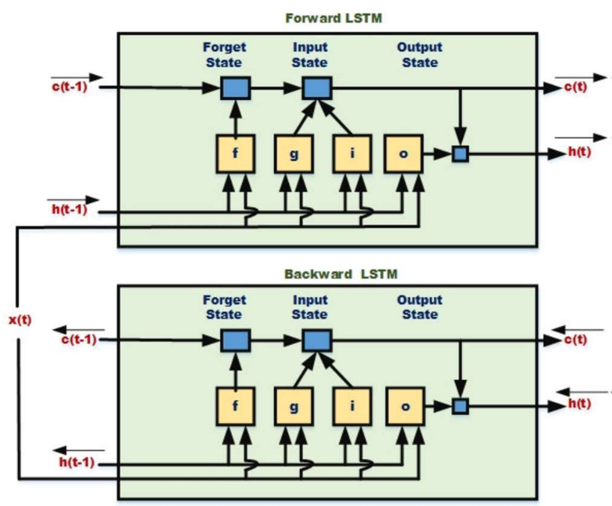

FIGURE 2. BiLSTM architecture [36].

II. LITERATURE REVIEW

Over the past few decades, a variety of methods for estimating the state of charge (SOC) have emerged, evolving from traditional approaches like Coulomb counting and lookup tables to more advanced techniques that incorporate model-based filters, such as the Kalman filter [12]. While traditional methods have limitations in dynamic environments, the Kalman filter can effectively capture non-linear battery behavior, though it is computationally demanding due to its dependence on precise battery modeling [13]. Recently, data-driven techniques, particularly LSTM, GRU, and DNN models, have gained popularity for their ability to directly map battery signals (current and voltage) to SOC, bypassing the need for complex modeling and feature engineering. Research has shown promising results, especially when combining models like LSTM-UKF, which enhance SOC estimation accuracy [17].

Advanced methods for estimating state of charge (SOC) include CNN-GRU, Bi-LSTM, and cascaded LSTM models, which are optimized for better generalization through algorithms like Ensemble Method, Particle Swarm Optimization, and Bayesian Optimization. Accurate SOC estimation depends on the relationship between key input parameters—mainly current, voltage, and temperature [20]. However, incorporating additional factors like load conditions, road conditions, and ambient temperature can further enhance accuracy [4]. Expanding the range of input features, such as historical data and current pressure readings, could significantly improve SOC predictions, opening new avenues for future research focused on integrating environmental factors to boost performance [7] [5].

III. OVERVIEW OF DEEP LEARNING ALGORITHM

Estimating the state of charge (SOC) of lithium-ion batteries is crucial for the dependable operation of electric vehicles (EVs), as it optimizes the battery management system (BMS), extends battery lifespan, and ensures safety [1] [36]. Traditional deep learning algorithms often face challenges in capturing non-linear behaviors; however, architectures like Bidirectional Long Short-Term Memory (Bi-LSTM) have emerged as strong alternatives due to their ability to learn complex patterns from extensive datasets. This development greatly improves the accuracy of SOC estimation [19].

This study explores advanced deep learning techniques, including Temporal Convolutional Networks (TCN), LSTM, and Bi-LSTM, for estimating the state of charge (SOC) of lithium-ion batteries. The dataset includes essential battery parameters such as voltage, current, and temperature, which are preprocessed for model training [10] [5]. The preprocessing simulates real-world conditions, and the model's performance is assessed using root mean square error (RMSE) across various temperatures, with a special focus on low temperatures where accuracy is critical. Post-validation processing further ensures the reliability of SOC predictions for real-time battery management system (BMS) applications [24]. This approach combines deep learning with optimization strategies to improve SOC estimation, leading to a more efficient and reliable BMS for electric vehicles. Additionally, the incorporation of advanced algorithms facilitates hyperparameter testing under different conditions, enhancing the performance and adaptability of SOC estimation across various energy storage applications in electric vehicles [33] [35].

A. LONG SHORT-TERM MEMORY

This section details the methodology for predicting the State of Charge (SOC) of lithium-ion batteries using Long Short-Term Memory (LSTM) networks. Renowned for their ability to manage time-dependent data, LSTMs are uniquely equipped to handle SOC estimation under a range of environmental and operational conditions.

The process begins with the acquisition of core battery metrics, including voltage, current, temperature, and SOC readings. These raw data undergo preprocessing steps such as filtering to eliminate noise and normalizing to align input features. The dataset is then split into separate subsets for training, validation, and testing to ensure robust performance evaluation.

Critical hyperparameters, such as the number of LSTM units and the learning rate, are carefully adjusted to maximize model performance. Model training utilizes the Adam optimization algorithm, chosen for its efficiency in navigating complex learning landscapes. To evaluate its suitability, the model's performance with Adam is benchmarked against the Stochastic Gradient Descent (SGD) optimizer. The primary metric, Root Mean Square Error (RMSE), is employed to gauge predictive accuracy, with lower RMSE values signifying improved results.

The model is further tested across a range of temperature settings (0°C, 10°C, 25°C, and 40°C) to ensure its robustness in real-world battery systems. This systematic approach enhances the accuracy and reliability of SOC predictions, reinforcing the practical utility of LSTMs in applications such as electric vehicles and energy systems.

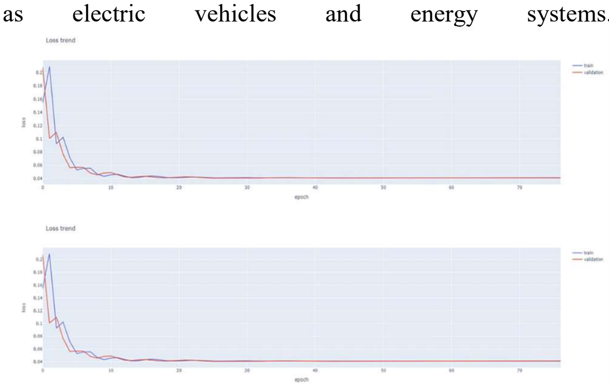

FIGURE 3. Loss function trajectories for the LSTM model trained using Adam and SGD

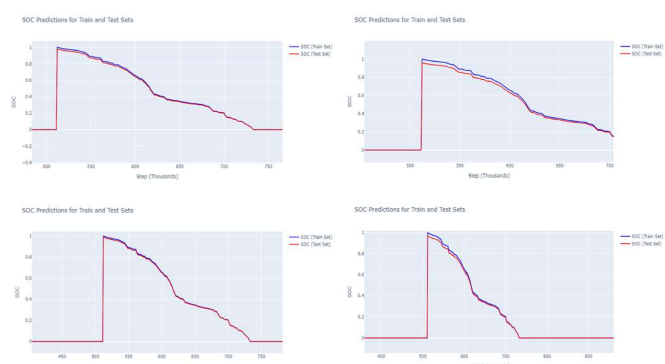

FIGURE 4 SOC predictions generated by the LSTM model across various thermal conditions (0°C, 10°C, 25°C, 40°C) over 200 epochs using both Adam and SGD optimization strategies.

B. TEMPORAL CONVOLUTIONAL NETWORKS (TCN)

Temporal Convolutional Networks (TCN) provide a highly effective solution for SOC estimation in lithium-ion batteries by processing time-series data in a computationally efficient manner. Unlike recurrent models such as LSTM and Bi-LSTM, TCN operates by parallelizing the data flow, leading to significantly reduced training times without sacrificing accuracy. The strength of TCN lies in its innovative use of dilated convolutions, which enable the network to capture dependencies over extended time horizons while keeping the number of network layers manageable. Additionally, the incorporation of residual connections into its architecture mitigates issues such as vanishing gradients, ensuring effective learning of complex, non-linear relationships between input factors like voltage, current, temperature, and SOC. This capability makes TCN models particularly well-suited for real-time battery management applications, such as SOC monitoring in electric vehicles. By seamlessly balancing computational speed with precise modelling, TCN ensures effective handling of intricate temporal patterns. This unique advantage supports the development of advanced battery management systems aimed at enhancing operational efficiency and promoting the adoption of sustainable energy technologies.

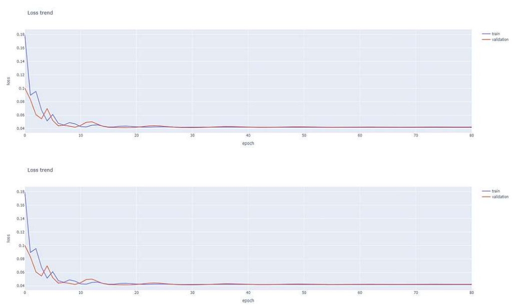

FIGURE 5. Loss function of TCN-based network trained with Adam and SGD Optimizer

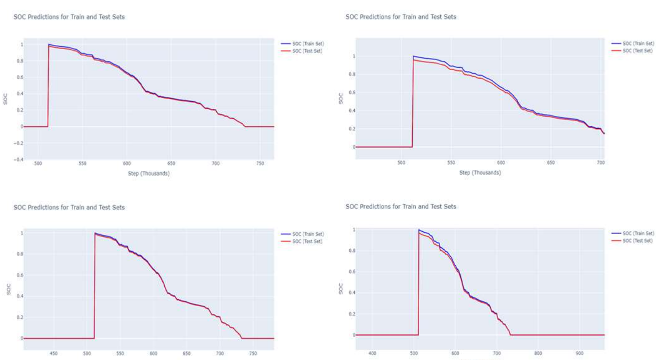

FIGURE 6. Soc Estimation with TCN network for 0°C, 10°C, 25°C, 40°C with Adam and SGD Optimizer with 200 epochs

C. BILAYERED LONG SHORT-TERM MEMORY

Bi-Directional Long Short-Term Memory (Bi-LSTM) networks provide an innovative approach to estimating the State of Charge (SOC) of lithium-ion batteries by processing data sequences in both directions—forward and backward. Unlike conventional LSTM networks, which depend only on previous data points, Bi-LSTM integrates both historical and future data, offering a holistic perspective on time-series battery behavior. This dual-directional capability makes it particularly effective for dynamic applications such as electric vehicles (EVs).

Bi-LSTM models analyze essential battery parameters voltage, current, and temperature to detect intricate relationships and temperature-agnostic characteristics within battery dynamics. By leveraging this comprehensive data processing capability, Bi-LSTM achieves exceptional SOC prediction accuracy, even in challenging scenarios such as extreme temperatures (0°C, 10°C, 25°C, and 40°C) or datasets with missing or noisy information. This robustness ensures stable and precise SOC estimations, making Bi-LSTM a reliable tool for real-time battery management. Additionally, this methodology contributes to extending battery lifespan, improving system safety, and optimizing EV performance.

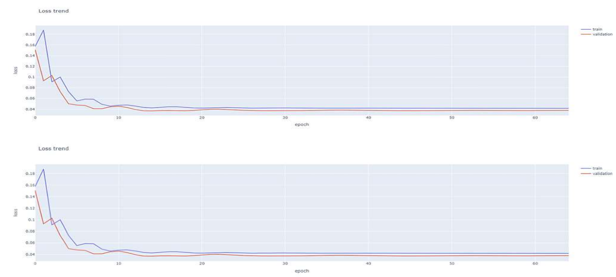

FIGURE 7. Loss function of Bi-LSTM-based network trained with Adam and SGD

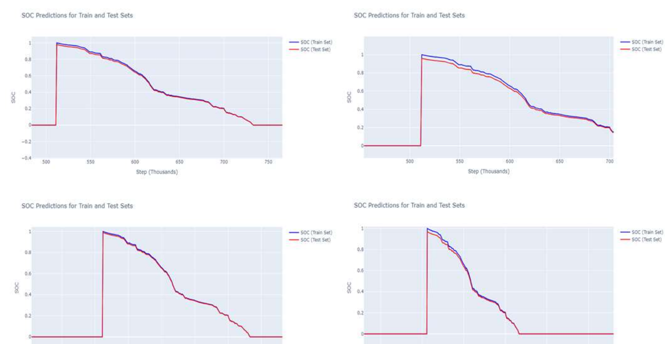

FIGURE 8. Predicted SOC across temperatures (0°C, 10°C, 25°C, 40°C) for Bi-LSTM over 200 training epochs using the SGD optimizer.

D. TCN WITH BI-LSTM

Integrating Temporal Convolutional Networks (TCN) with Bi-Directional Long Short-Term Memory (Bi-LSTM) networks results in a highly robust and accurate framework for SOC estimation. TCN, known for its ability to model extended dependencies in sequential data, complements Bi-LSTM's capability to leverage bidirectional temporal relationships. Together, these models create a powerful hybrid architecture capable of processing complex, non-linear patterns within battery datasets.

TCN's use of dilated convolutions extends its receptive field, enabling the network to effectively capture long-term dependencies without increasing complexity. Meanwhile, Bi-LSTM adds depth by interpreting battery behaviors through both historical and future insights. The resulting TCN-Bi-LSTM framework excels under diverse conditions, such as fluctuating temperatures (e.g., 0°C, 10°C, 25°C, and

40°C), ensuring accurate SOC predictions even in real-world, noisy environments. This hybrid approach delivers substantial improvements in computational efficiency and prediction accuracy, making it ideal for real-time battery monitoring applications. By optimizing SOC estimation processes, the TCN-Bi-LSTM model enhances battery reliability, improves safety standards, and supports the development of sustainable energy technologies for electric vehicles and renewable energy systems.

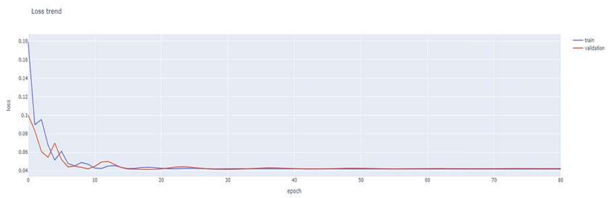

FIGURE 9. Loss function of TCN-Bi-LSTM-based network trained with Adam and SGD Optimizer

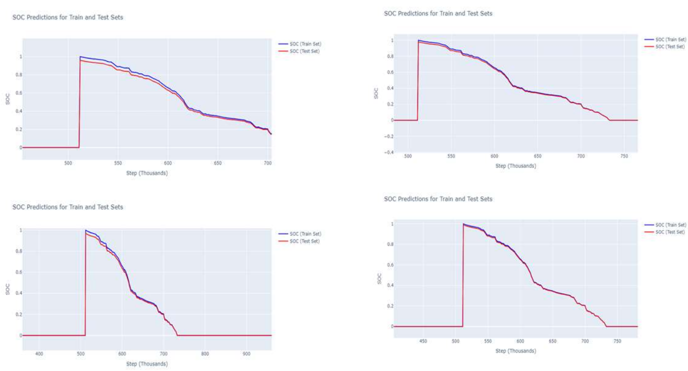

FIGURE 10. Soc Estimation with Bi-LSTM network for 0ºC, 10ºC, 25ºC, 40ºC with SGD Optimizer with 200 epochs

E. TCN WITH LSTM

The integration of Temporal Convolutional Networks (TCN) and Long Short-Term Memory (LSTM) networks presents an innovative solution for estimating the state of charge (SOC) in lithium-ion batteries. This hybrid approach harnesses the complementary strengths of both architectures: TCN's capacity to model long-term dependencies through dilated convolutions and LSTM's effectiveness in capturing temporal sequences. Together, these capabilities enable the model to address challenges like non-linear relationships among battery parameters and mitigate the vanishing gradient issue common in deep learning frameworks [40].

By offering rich temporal context, the TCN-LSTM model ensures precise and reliable SOC predictions across diverse operational conditions, including varying temperatures (0°C, 10°C, 25°C, and 40°C). Its efficient data processing capabilities and adaptability to sequential learning outperform traditional methods, making it ideal for time-sensitive battery management in electric vehicles. This framework enhances battery longevity, improves performance, and promotes operational safety [27].

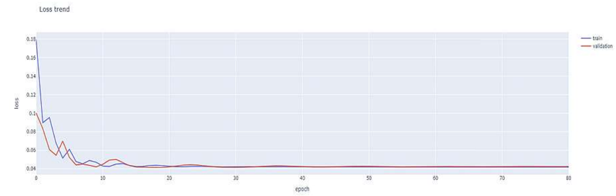

FIGURE 11. Loss function of TCN-LSTM-based network trained with Adam and SGD Optimizer

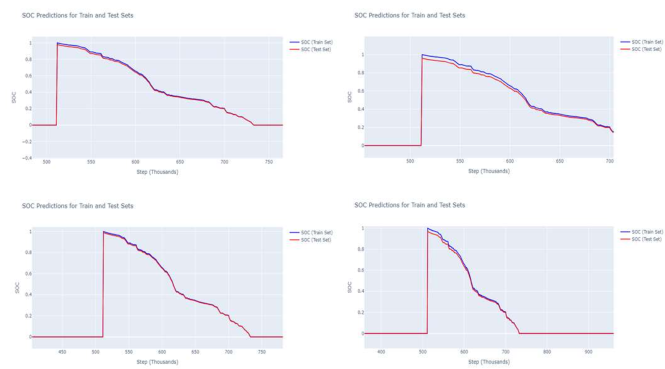

FIGURE 12. Soc Estimation with TCN-LSTM network for 0ºC, 10ºC, 25ºC, 40ºC with SGD Optimizer with 200 epochs

IV. EXPERIMENTAL RESULT AND DISCUSSION

This section presents a comparative evaluation of five deep learning models LSTM, Bi-LSTM, TCN, TCN-Bi-LSTM, and TCN-LSTM for predicting the state of charge (SOC) in lithium-ion batteries. The models were assessed under different temperature settings (0°C, 10°C, 25°C, and 40°C) using evaluation metrics such as mean square error (MSE) and root mean square error (RMSE). Both the ADAM optimizer and Stochastic Gradient Descent (SGD) were applied during training to analyze their impact on convergence rates and overall prediction accuracy. This rigorous evaluation provides insights into each model's performance under various operating conditions.

TABLE 2. Training configurations for SOC estimation of lithium-ion batteries using deep learning models.

Training Parameter	LSTM	BiLSTM	TCN	TCN-BiLSTM	TCN-LSTM
Optimizer	Adam/SGD	Adam/SGD	Adam/SGD	Adam/SGD	Adam/SGD
Epochs	200	200	200	200	200
Batch Size	32	32	32	32	32
Loss Function	MSE	MSE	MSE	MSE	MSE
Metrics	MSE, RMSE	MSE, RMSE	MSE, RMSE	MSE, RMSE	MSE, RMSE
Main Layer Type	LSTM	BiLSTM	TCN Blocks	TCN + BiLSTM	TCN + LSTM
Number of Layers	3	2	4	4	4
Units/Filters per Layer	512	128	64, 128, 256, 512	64, 128, 256, 512	64, 128, 256, 512
Activation Function	ReLU (Dense)	ReLU (Dense)	ReLU	ReLU	ReLU
Input Shape	(time_steps, features)	(time_steps, features)	(time_steps, features)	(time_steps, features)	(time_steps, features)
Output Shape	1	1	1	1	1

The training process for each deep learning model—LSTM, Bi-LSTM, TCN, TCN-BiLSTM, and TCN-LSTM—was meticulously designed to ensure consistency and optimized learning. These configurations aimed to capture both short- and long-term dependencies within the dataset while effectively modeling the complex temporal and non-linear interactions inherent to battery dynamics.

To enhance generalization and prevent overfitting, techniques such as dropout and L2 regularization were employed. Hybrid models, particularly those combining TCN with Bi-LSTM or LSTM, demonstrated superior capacity for capturing multi-resolution temporal features. This allowed them to deliver accurate and robust SOC predictions, even under varying temperature conditions. Among the evaluated architectures, TCN and its hybrid configurations excelled in extracting high-quality temporal patterns, solidifying their role as state-of-the-art methods for SOC estimation.

A. LSTM-BASED SOC ESTIMATION

The LSTM model showed notable accuracy improvements during training, with a consistent reduction in both training and validation loss (MSE), reflecting effective learning. After fine-tuning hyperparameters such as the learning rate, dropout rate, and batch size, the model's performance across test data at various temperatures is presented in **Table 3**. However, LSTM exhibited some overfitting, especially at low temperatures (0°C), where battery behavior becomes more unpredictable. While the model performed well in stable conditions, discrepancies between experimental SOC values and predictions were observed under extreme conditions. Although LSTM remains competitive with Bi-LSTM and TCN, it lags TCN when handling low-temperature scenarios, as shown in **Table 3**.

B. TCN-BASED SOC ESTIMATION

The Temporal Convolutional Network (TCN) demonstrates excellent accuracy and stability during training across various conditions, including low-temperature environments. The training and validation loss, measured by Mean Squared Error (MSE), steadily decreased, indicating effective learning and adaptation. After optimizing hyperparameters such as learning rate, expansion rate, and dropout rate, the TCN achieved strong performance across all test conditions, as shown in **Table 3**. It outperformed both the LSTM and Bi-LSTM models, showing lower prediction errors, particularly under extreme temperatures where battery behavior is highly variable. TCN's parallel processing significantly enhances training efficiency, completing the process faster than LSTM and Bi-LSTM, making it ideal for real-time SOC estimation in electric and hybrid vehicles. The TCN-LSTM hybrid combines the strengths of TCN with the sequential processing abilities of LSTM, further improving accuracy and ensuring reliable performance across varying temperature conditions. This makes TCN and its hybrid models highly suitable for deployment in real-world applications that require both computational accuracy and efficiency.

C. Bi-LSTM-BASED SOC ESTIMATION

The bidirectional long short-term memory (Bi-LSTM) model demonstrates strong performance in capturing complex time dependencies in battery data. By leveraging both past and future context with carefully tuned hyperparameters such as learning rate, batch size, and dropout rate, Bi-LSTM achieves strong performance across all test temperatures, as shown in **Table 3**. Its strength lies in handling bi-directional dependencies, improving predictability over standard LSTM, particularly in dynamic operations. However, the model faces challenges under ultra-low temperature conditions (0°C), where battery behavior becomes more unpredictable. Despite this limitation and its lower performance in such extreme conditions, Bi-LSTM remains competitive for SOC evaluation, providing reliable forecasts while balancing computational complexity and accuracy across a wide range of temperature scenarios, as indicated in **Table 3**.

TABLE 3. Performance Comparison of Deep Learning Models for SoC Estimation of Li-Ion Batteries Across Varying Temperature Conditions

Algorithm	Hidden Layers	Epochs	Training RMSE (%)	Testing RMSE @ 0°C	Max Error @ 0°C	Testing RMSE @ 10°C	Max Error @ 10°C	Testing RMSE @ 25°C	Max Error @ 25°C	Testing RMSE @ 40°C	Max Error @ 40°C
TCN-BiLSTM	5	200	0.0145 (1.45%)	0.0110	0.7000	0.0095	0.6500	0.0085	0.5000	0.0070	0.4000
TCN-LSTM	4	200	0.0150 (1.50%)	0.0130	0.8500	0.0080	0.6000	0.0090	0.5000	0.0090	0.5000
TCN	4	200	0.0198 (1.98%)	0.0185	1.4522	0.0170	1.3280	0.0155	1.2560	0.0150	1.2030
LSTM	3	200	0.0150 (1.50%)	0.0138	1.3204	0.0106	0.7120	0.0099	0.5100	0.0095	0.6030
Bi-LSTM	2	200	0.0170 (1.70%)	0.0160	1.5190	0.0119	1.1280	0.0126	1.1560	0.0128	0.9330

The proposed deep learning algorithms—LSTM, Bi-LSTM, TCN, TCN-LSTM, and TCN-BiLSTM—were evaluated for their state of charge (SOC) estimation performance across varying temperature conditions (0°C, 10°C, 25°C, and 40°C) over 200 training epochs. As shown in the table, the results indicate that TCN-based models outperform the other architectures in capturing complex temporal patterns in battery data. While LSTM and Bi-LSTM yield competitive results, TCN and its hybrid variants, such as TCN-LSTM and TCN-BiLSTM, demonstrate superior accuracy thanks to their advanced feature extraction and sequence learning capabilities. Among them, the TCN-BiLSTM model provides the best performance by combining TCN's strength in capturing temporal dependencies with Bi-LSTM's bidirectional learning approach. These results highlight the significant improvement of deep learning models over traditional methods, confirming their effectiveness for SOC estimation across different temperature conditions when trained for 200 epochs.

V. CONCLUSION

This study compares LSTM, Bi-LSTM, TCN, TCN-LSTM, and TCN-BiLSTM and evaluates deep learning models for state of charge (SOC) estimation in lithium-ion batteries under various temperature conditions. As shown in Table 3, the LSTM model performs well with an RMSE at 0°C after 200 epochs but demonstrates a better fit at 25°C. Bi-LSTM performs better overall, achieving an RMSE at 0°C and 40°C, respectively. The bidirectional learning of Bi-LSTM gives it an edge over LSTM. The TCN model also outperforms both, showing improved RMSE values, especially at 0°C and 40°C, which suggests better handling of physical feature separation. The TCN-LSTM model further improves time efficiency, achieving better performance across temperatures, particularly at 0°C and 40°C. However, the TCN-BiLSTM model outperforms all others in every respect, achieving the lowest RMSE values at 0°C and 40°C in Table 3. By combining TCN's feature extraction capabilities with Bi-LSTM's bidirectional learning approach, TCN-BiLSTM demonstrates the most accurate and robust SOC estimation across diverse conditions, making it the most effective framework for real-time applications, such as in electric vehicles.

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