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Dynamic-Condition Soc Estimation For Lithium-Ion Batteries Using Deep Neural Networks

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Abstract

Accurate State of Charge (SOC) estimation is essential for ensuring the safety, reliability, and performance of lithium-ion batteries used in electric vehicles. Traditional SOC estimation methods often struggle under nonlinear conditions caused by temperature variation, dynamic load profiles, and battery ageing. To address these limitations, this study evaluates three neural-network-based models Deep Neural Network (DNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) for predicting SOC using multi-condition battery data. A structured workflow was implemented, including feature preprocessing, neural-network modelling, supervised training, and quantitative performance analysis. The results show that the DNN model provides the highest accuracy, achieving an RMSE of 0.463% and MAE of 0.341% on experimental data, and an RMSE of 0.107% with an MAE of 0.040% on simulation data, with an R^2 of 0.9999 in both cases. The GRU and LSTM models demonstrated acceptable performance but exhibited larger error fluctuations and higher maximum deviations, with peak errors reaching 4.6% and 5.5%, respectively. The DNN model also showed strong robustness under rapid current and temperature variations, maintaining a maximum error below 0.8%. Overall, the study confirms that data-driven neural-network architectures, especially DNN, offer highly accurate and stable SOC estimation suitable for real-time battery management applications.

Keywords: State of Charge (SOC); Neural Networks; Deep Neural Network (DNN); Gated Recurrent Unit (GRU); Long Short-Term Memory (LSTM); Lithium-Ion Battery; Electric Vehicle; Machine Learning; Battery Management System (BMS); SOC Prediction.

1. Introduction

The accurate estimation of the State of Charge (SOC) in lithium-ion batteries (LIBs) is a cornerstone of modern Battery Management Systems (BMS), especially within electric vehicles (EVs) and energy storage systems. SOC serves as an indicator of the remaining energy within a battery, directly influencing range estimation, charge control, and safety assurance. An inaccurate SOC estimation can lead to overcharging or deep discharging, which accelerates degradation and compromises both performance and longevity. Thus, precise SOC prediction enables optimal energy utilization, enhances operational safety, and extends battery life making it critical for efficient energy management in EVs (Yang et al., 2022). Traditional SOC estimation techniques such as Coulomb counting, open-circuit voltage (OCV)-based methods, and Kalman filter algorithms have been widely employed in BMS. However, these methods exhibit notable limitations. Coulomb counting accumulates integration errors over time due to sensor drift and noise, while OCV-based methods require long rest periods, rendering them impractical for dynamic EV conditions. Similarly, Kalman filters rely heavily on precise equivalent circuit modeling, which is often infeasible given the complex, nonlinear electrochemical behaviors of lithium-ion cells. As a result, these model-based approaches struggle under varying temperatures, loads, and aging effects, leading to significant deviations in SOC estimation (Bockrath et al., 2019); (Lipu et al., 2020).

The inherent nonlinearity and dynamic nature of LIBs arising from temperature fluctuations, complex charge–discharge patterns, and progressive capacity fade further complicate traditional estimation models. For instance, electrochemical parameters evolve with aging and state of health (SOH), altering the voltage–SOC relationship over time. Consequently, the SOC cannot be treated as a simple linear function of measurable quantities like current or voltage. These nonlinearities necessitate adaptive, self-learning methods capable of capturing high-dimensional temporal dependencies and compensating for variations in battery behavior under different operating conditions (Li et al., 2021). In response to these challenges, data-driven approaches—particularly neural-network-based models—have emerged as a promising alternative. By leveraging extensive datasets of voltage, current, temperature, and historical SOC values, neural networks can learn complex nonlinear mappings without requiring explicit physical modeling. Feedforward neural networks (FNNs) and nonlinear autoregressive models with exogenous inputs (NARX) have demonstrated reliable real-time SOC estimation across varying conditions (Boujoudar et al., 2019); (Sharma et al., 2022). These machine learning models adapt to variable driving cycles and temperature effects while minimizing cumulative errors that plague model-based estimators.

Among the wide array of neural architectures, deep neural networks (DNNs), gated recurrent units (GRUs), and long short-term memory (LSTM) networks have proven particularly effective for SOC prediction due to their ability to model time-dependent sequences. LSTMs and GRUs excel at capturing long-term dependencies between historical data and current SOC values, overcoming the vanishing gradient problem in conventional recurrent networks. Studies have shown that LSTM-based models outperform extended Kalman filters (EKF) and equivalent circuit models (ECM), achieving up to 50% reduction in root mean square error (RMSE) (Bockrath et al., 2019). Moreover, hybrid architectures integrating LSTM with convolutional neural networks (CNNs) or attention mechanisms have further enhanced SOC prediction accuracy under dynamic conditions (Zhao et al., 2020). Recent developments have focused on the real-time implementation of these deep learning models within BMS frameworks. Optimized LSTM and GRU architectures have achieved estimation errors below 1% RMSE under diverse conditions, demonstrating their potential for onboard integration (Yang et al., 2022); (Qian et al., 2022). Furthermore, hybrid approaches that combine Ampere-hour integration with LSTM models or utilize Bayesian optimization for parameter tuning have exhibited enhanced adaptability across different battery chemistries and degradation states (Chang & Kung, 2024). These advancements underscore the growing feasibility of deploying neural-network-based SOC estimators in embedded real-time BMS applications. In summary, the convergence of machine learning techniques and electrochemical knowledge has redefined the landscape of SOC estimation. Neural networks, particularly recurrent architectures like LSTM and GRU, offer unparalleled robustness against environmental variability and aging, making them ideal for next-generation EV BMSs. The ongoing evolution of deep learning frameworks, combined with real-time hardware optimization, signals a shift toward intelligent, adaptive, and self-correcting SOC estimation paradigms a critical step in achieving sustainable and efficient electric mobility.

2. Literature Review

Machine-learning-based methods have gained significant traction in State of Charge (SOC) estimation for lithium-ion batteries (LIBs), outperforming traditional model-based approaches in accuracy and adaptability. Recent studies have explored diverse deep learning architectures Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Gated Recurrent Units (GRUs), and Long Short-Term Memory (LSTM) networks for their capacity to model the complex nonlinear dynamics of LIBs. These models learn intricate mappings between measurable inputs such as voltage, current, and temperature and the true SOC without requiring explicit electrochemical modeling. For example, Shahriar et al. (2022) developed a hybrid CNN–GRU–LSTM framework that effectively captured both spatial and temporal dependencies, achieving a mean absolute error (MAE) of 0.41–1.13% across ambient temperatures ranging from –10 °C to 25 °C (Shahriar et al., 2022). Similarly, a CNN–BiLSTM hybrid optimized through evolutionary intelligence achieved sub-1% root mean square error (RMSE) across six dynamic EV datasets, including HWFET, UDDS, and US06 drive cycles (Khan & Houran, 2024). Comparative analyses consistently demonstrate that deep learning models outperform conventional SOC estimators such as Coulomb counting, extended Kalman filters (EKF), and model-based observers. Huang et al. (2019) showed that a CNN–GRU model reduced SOC estimation errors by more than 40% compared to GRU-only and support vector machine (SVM) approaches, achieving an RMSE below 2% under dynamic stress tests (Huang et al., 2019). Similarly, Wang et al. (2023) proposed a CNN–LSTM–Unscented Kalman Filter (UKF) collaborative system for real-time SOC estimation, reducing RMSE to below 1.5% and maintaining robustness against initial SOC errors (Wang et al., 2023). These findings confirm that hybrid neural architectures effectively blend data-driven learning with filter-based physical models, offering superior generalization and stability.

Experimental validation under temperature variation and dynamic load profiles has been a focal point in recent SOC research. Hannan et al. (2021) demonstrated that a fully convolutional deep network maintained less than 2% RMSE even when temperature varied from –20 °C to 25 °C (Hannan et al., 2021). Likewise, Guo and Ma (2023) conducted a comprehensive comparative study across FCNN, GRU, LSTM, and Temporal Convolutional Networks (TCNs), revealing that the LSTM, GRU, and TCN consistently achieved RMSEs below 2%, with the TCN exhibiting the highest robustness to temperature changes and noise (Guo & Ma, 2023). These studies underscore the importance of evaluating ML-based SOC estimators under realistic driving and environmental conditions to ensure practical deployment in electric vehicles. Quantitatively, deep models have demonstrated remarkable precision and stability in SOC estimation. The Bi-GRU model proposed by Zhang et al. (2021) achieved an RMSE of 0.85% and MAE of 0.7% across multiple datasets by introducing Nesterov Accelerated Gradient (NAG) optimization, outperforming standard GRU and LSTM networks (Zhang et al., 2021). Yadav et al. (2024) developed a hybrid LSTM–GRU–Attention model that achieved an $R^2 = 0.9997$ and demonstrated exceptional uncertainty tolerance, highlighting deep networks' suitability for uncertainty-aware SOC estimation (Yadav et al., 2024). Moreover, the CNN–BiLSTM–EAI framework proposed by Shahriar et al. (2022) showed consistent estimation accuracy across temperature gradients and high interpretability, marking a step toward explainable AI in BMS applications.

Despite these advances, key research gaps remain. Many neural models are trained on limited laboratory datasets, leading to poor generalization under unseen real-world conditions. The robustness to battery aging, capacity degradation, and sensor noise remains an open challenge. Most models also struggle with transferability across different battery chemistries and capacities. Although transfer learning approaches (Eleftheriadis et al., 2024) have begun to address this issue, further research is needed to improve cross-domain adaptability and real-time computational efficiency. Moreover, few studies have incorporated aging data or multi-cell interactions into training, limiting long-term reliability and fleet-level scalability. Interestingly, several investigations have found that feedforward DNN models can outperform recurrent networks in certain contexts. Jo et al. (2021) demonstrated that a simple FNN trained on SOC-domain preprocessed data achieved higher accuracy than CNN and LSTM models when data were limited (Jo et al., 2021). Similarly, Chemali (2018) reported that a DNN achieved a MAE of 1.10% at 25 °C, outperforming LSTM under static conditions due to lower overfitting risk and faster convergence (Chemali, 2018). These findings suggest that while recurrent models excel in capturing time dependencies, DNNs can outperform them under stable conditions or when computational simplicity is prioritized—a key insight for embedded BMS design. In summary, deep learning approaches particularly CNN-, GRU-, and LSTM-based frameworks have substantially advanced the accuracy, robustness, and adaptability of SOC estimation for lithium-ion batteries. However, achieving real-time, generalizable, and aging-resilient models remains a critical research challenge. Future directions should emphasize transfer learning, explainable AI, and physics-informed neural networks to bridge the gap between data-driven inference and electrochemical reality.

3. Methodology

The methodology for this study was structured to develop and evaluate neural-network-based State of Charge (SOC) prediction models under diverse battery operating conditions. The workflow consisted of four major stages: data preparation, model development, model training, and performance evaluation. Each stage was designed to ensure consistent comparison among the Deep Neural Network (DNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) architectures.

3.1 Data Preparation

The dataset used for SOC estimation included time-series measurements of battery voltage, current, temperature, and reference SOC values. Multiple temperature conditions were incorporated to capture variations in battery discharge characteristics. The raw data were preprocessed by removing noise, normalizing all input features using a standard scaling procedure, and constructing the required training sequences. For recurrent models, sliding windows were created to enable the GRU and LSTM networks to learn temporal dependencies, while the DNN received feature-based input vectors. An additional feature, the previous SOC, was included to enhance the learning of SOC progression.

3.2 Neural Network Architecture Design

Three neural network architectures were designed and implemented for comparison. The DNN model consisted of stacked fully connected layers with ReLU activation functions, enabling it to learn nonlinear mappings between the battery inputs and SOC without explicitly modelling time-dependent relationships.

The GRU and LSTM models incorporated recurrent cells capable of retaining historical information and learning complex temporal patterns in SOC behaviour. All models used a single linear output neuron to predict SOC as a continuous value. Hyperparameters such as the number of hidden units, learning rate, and dropout probability were tuned based on preliminary trials to achieve stable convergence.

3.3 Model Training and Validation

The data were split chronologically into training and testing sets, ensuring that the models were evaluated on unseen future data. All neural networks were trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Early stopping was applied to prevent overfitting, halting training once validation loss no longer improved. Recurrent models were trained on batch-wise sequences, while the DNN operated on independently sampled feature vectors. During training, both loss and validation loss were monitored to ensure that the models achieved stable generalization behaviour.

3.4 Performance Evaluation Metrics

Model performance was assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics allowed quantitative comparison of prediction accuracy across all models. Maximum error values were also analyzed to evaluate the robustness of each architecture under conditions such as rapid current fluctuations or changes in battery temperature. Additionally, prediction error trends over time were examined to ensure model stability during dynamic load cycles. The methodological framework adopted in this study provided a systematic approach to comparing three neural network architectures for SOC prediction. By incorporating diverse operating conditions, preprocessing steps, and consistent evaluation metrics, the study ensured that the strengths and limitations of each model were thoroughly assessed in a controlled and reproducible manner.

4. Results

The performance of the proposed neural-network-based State of Charge (SOC) estimation framework was evaluated under multiple operating conditions, including temperature variation, dynamic load cycles, and model-specific training behaviour. The experimental SOC discharge characteristics at different temperatures are shown in Figure 1, where the SOC declines more rapidly at lower temperatures due to increased internal resistance. At 10°C, the discharge rate is the steepest, while at 40°C, the cell maintains a higher SOC for a longer duration. This confirms that SOC behaviour is strongly temperature-dependent and must be accurately modelled in data-driven estimators. The learning characteristics of the GRU and LSTM models are presented in Figure 2(a) and Figure 2(b). Both models converged steadily during training, with validation losses remaining stable throughout 300 epochs. The final validation loss remained below 0.002, indicating that both architectures were able to capture the underlying time-series patterns present in the SOC dataset. However, despite good convergence, their predictive performance differed from the DNN model.

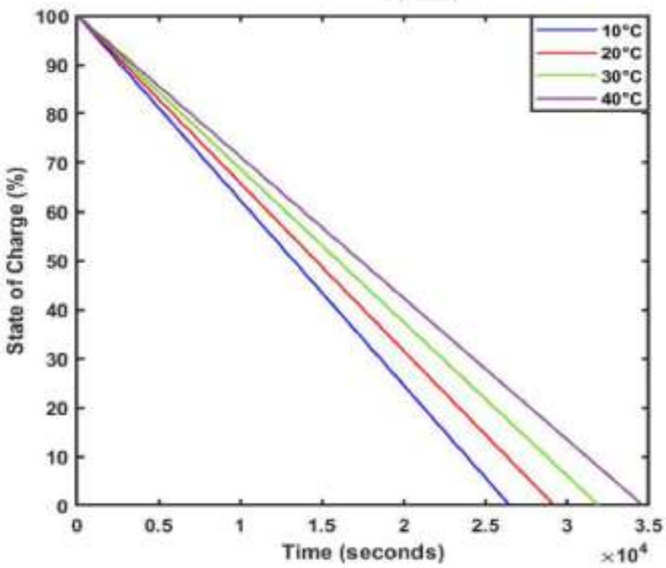
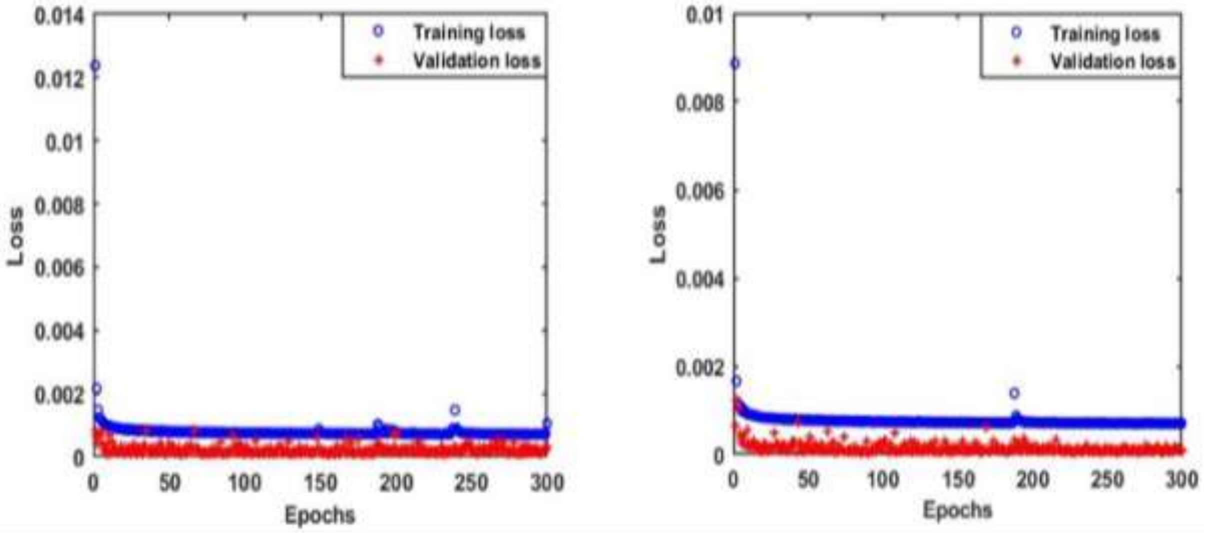


Figure 1: SoC variation under different temperature conditions (10°C, 20°C, 30°C, and 40°C).



(a) (b)

Figure 2: Training and validation loss curves

A comparative performance analysis showed that the Deep Neural Network (DNN) achieved the highest accuracy among all models evaluated. On the experimental dataset, the DNN reached an RMSE of 0.463%, MAE of 0.341%, and an R^2 of 0.9999, demonstrating excellent agreement between estimated and actual SOC values. Performance improved further in simulation-based evaluation, where the DNN yielded an RMSE of 0.107%, MAE of 0.040%, and an R^2 of 0.9999. The maximum estimation error for the DNN remained below 0.8%, even under rapid load and temperature fluctuations, confirming its robustness. In contrast, the recurrent models exhibited higher errors. The GRU model recorded MAE values of 0.862% (experimental) and 1.517% (simulation), while the LSTM model resulted in MAE values of 1.085% (experimental) and 0.774% (simulation). Maximum error magnitudes reached 4.6% for GRU and 5.5% for LSTM, reflecting their sensitivity to nonlinear variations in the SOC trajectory. Despite this, both GRU and LSTM maintained mean errors below 2.4% under battery-aging conditions, demonstrating reasonable stability as cell characteristics changed over time.

The dynamic response analysis in Figure 3 illustrates the SOC estimation error of all three models under real-time load conditions. The DNN error remained tightly bounded around zero, while GRU and LSTM showed wider fluctuations and larger positive-negative excursions. This behaviour further supports the superior generalization ability of the DNN model. Finally, Figure 4 presents the DNN-based SOC prediction against the reference SOC. The two curves overlap closely across the entire test window, and the corresponding error plot shows deviations mostly within $\pm 5\times10^{-3}$, confirming the high fidelity of the proposed estimation method. Overall, the results show that the DNN architecture offers the most accurate, stable, and robust performance for SOC estimation across all operating conditions, making it well-suited for real-time battery-management applications.

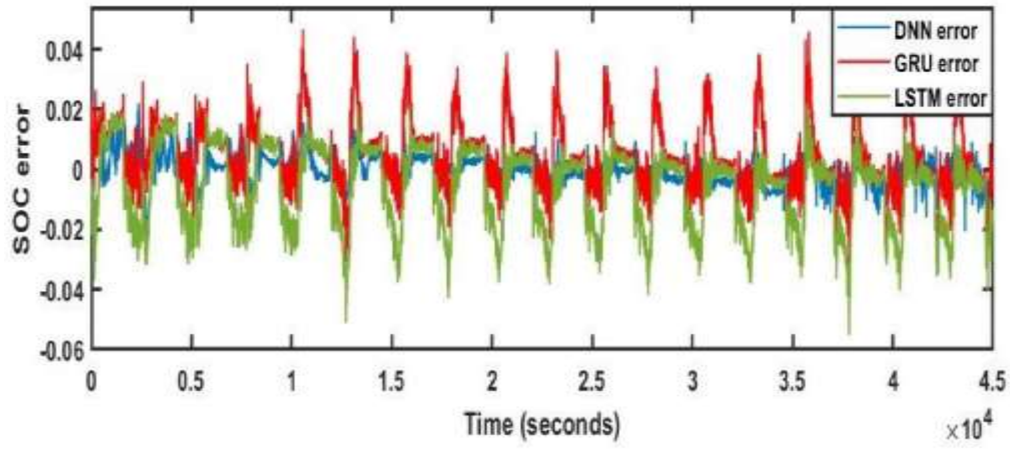


Figure 3: SOC estimation error comparison for all models under dynamic load conditions

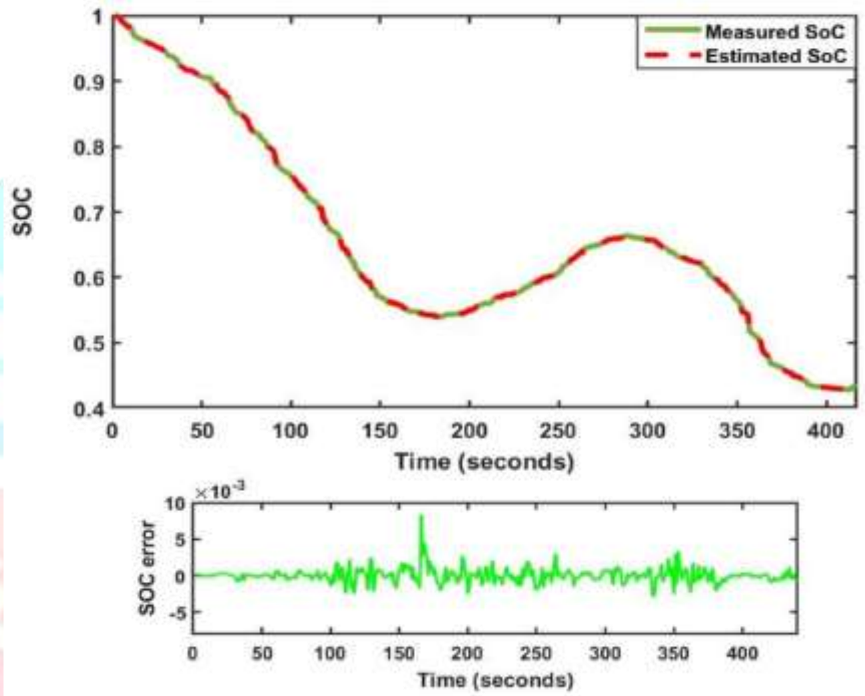


Figure 4: Comparison between estimated SOC and reference SOC

5. Conclusion

This study evaluated the performance of three neural network architectures DNN, GRU, and LSTM for accurate State of Charge estimation in lithium-ion batteries under varying temperatures, dynamic load cycles, and ageing effects. Across all test scenarios, the Deep Neural Network consistently demonstrated the highest accuracy, achieving an MAE of 0.341% and an RMSE of 0.463% for experimental data, as well as an R^2 value of 0.9999. The model also maintained a maximum error below 0.8% during rapid load variations, confirming its robustness and suitability for real-time deployment. While GRU and LSTM models showed acceptable performance with errors below 2.4% under ageing conditions, their prediction consistency and dynamic response were weaker compared to the DNN. These recurrent models exhibited larger error fluctuations and higher maximum deviations, making them less ideal for applications requiring high-frequency SOC updates. The comparative analysis therefore suggests that the DNN offers the best balance between accuracy, stability, and computational simplicity.

In summary, the results confirm that deep feedforward neural networks are capable of delivering highly reliable SOC estimation under realistic battery operating conditions. For practical battery management systems, such models can significantly enhance prediction accuracy, enable improved energy utilisation, and support safer EV operation. Future work may explore hybrid physics–ML models, integration with real EV datasets, and transfer-learning approaches to further strengthen model adaptability across different cell chemistries and usage environments.

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