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Deep Hybrid Temporal Modeling with TCN-GRU-Transformer for Lithium-Polymer Battery State-of-Charge Estimation

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Abstract. Accurate state-of-charge (SOC) estimation is critical for safe and efficient battery operation in electric vehicles and stationary energy storage systems. This study proposes a hybrid deep learning model that combines a Temporal Convolutional Network (TCN) for local temporal feature extraction, a Gated Recurrent Unit (GRU) for sequential dynamics, and a Transformer block to capture longer-range dependencies in battery signals. The model is trained and validated using experimentally measured lithium-Polymer battery data and is benchmarked against standalone TCN, GRU, and Transformer baselines under the same data splits and evaluation protocol. On the test set, the proposed hybrid architecture achieves a mean absolute error (MAE) of 0.66%, a root mean square error (RMSE) of 0.88%, and a coefficient of determination (R^2) of 0.9992, consistently outperforming the individual models. The results indicate that integrating complementary temporal modeling mechanisms improves estimation accuracy and robustness, supporting real-time SOC prediction in practical battery management systems.

Introduction

The increasing use of electric vehicles and renewable energy storage solutions requires lithium-based batteries to function at their maximum operational abilities. The characteristics of lithium-polymer (Li-Po) cells make them suitable for various applications because they combine high energy density with pouch design options and their power capacity supports multiple uses from traction systems to unmanned aerial vehicles and portable electronics. Li-Po cells display complex electrochemical properties which create challenges for accurately monitoring their internal charge levels because their performance depends on temperature changes and their aging process and their response to different power demands [1,2].

The SOC indicates how much energy a battery still holds compared to its total capacity, which serves as a key measurement that battery management systems (BMS) use to monitor battery performance. The battery state of charge information helps to predict driving range and power derating and prevents unsafe conditions through its ability to identify overcharging and over-discharging dangers [3]. The continuous SOC miscalculations result in two major problems, which are wrong range predictions and premature device shutdowns and battery cells that suffer quicker degradation, which together decrease both operational efficiency and safety.

Conventional SOC estimation techniques, such as Coulomb counting, open-circuit-voltage (OCV) look-up tables, and observer-based approaches derived from equivalent-circuit or electrochemical models, can deliver strong accuracy when parameters are properly identified and

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operating conditions are relatively well controlled. In practical applications, however, their performance often degrades under aging effects, temperature variability, and complex real-world duty cycles. These limitations have motivated increased interest in data-driven SOC estimation methods that can better capture nonlinear dynamics and adapt to changing conditions [4].

Deep learning methods have therefore attracted considerable interest, as they can learn nonlinear mappings from measured signals to SOC without explicit physical models. Recent studies have explored recurrent neural networks (LSTM, GRU), Temporal Convolutional Networks (TCN), convolutional-recurrent hybrids, and Transformer-based architectures for SOC and state-of-health (SOH) estimation, with promising results on various lithium-ion chemistries[6]. TCNs leverage dilated causal convolutions to capture long temporal dependencies with high parallelism, while GRU/LSTM networks remain strong baselines for sequence regression, and Transformers with attention mechanisms can emphasize informative time steps and handle complex load profiles [6]. Nonetheless, most existing work focuses on cylindrical or pouch lithium-ion cells, and only limited attention has been given to lithium-polymer batteries within hybrid architectures that jointly exploit the complementary strengths of TCN, GRU, and Transformer. This gap motivates the present study, which investigates such a unified framework for SOC estimation in Li-Po cells [7].

This paper presents a hybrid deep learning model based on a TCN-GRU-Transformer architecture for SOC estimation in Lithium-Polymer batteries. The analysis compares architectural characteristics, computational demands, predictive accuracy, and practical implementation aspects. Furthermore, it investigates how integrating these three components within a single hybrid framework leverages their complementary strengths.

Methodology

A. Lithium Polymer Battery Dataset

High-quality data are a prerequisite for the development of reliable data-driven models. In practice, two main strategies are commonly adopted: (i) acquiring measurements through dedicated experiments on the target cell and (ii) exploiting datasets made available by trusted external sources. Although the former is generally preferred, since publicly available datasets rarely match the exact operating conditions of interest, the present study relies on a private dataset supplied by the author of reference [8]. All SOC estimation models are developed for a lithium-polymer cell, whose principal characteristics are reported in Table 1.

Table 1:Li-polymer cell: key specifications.

Attribute	Details
Manufacturer	Power-Xtra
Nominal capacity	350 mAh
Charging voltage	4.2V±0.05V
Nominal voltage	3.7V±0.05V
Discharge cut-off voltage	*3.0V*
Weight	*10.5 gr ±0.5 g*

The reference SOC is obtained off-line by combining high-precision Coulomb counting with periodic rest phases and OCV-based recalibration, following standard procedures adopted in experimental SOC studies. The available dataset covers a wide SOC range [0,100]% and different current rates, temperature conditions, and operating modes to ensure that the trained model generalizes beyond a single drive cycle.

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B. Data preprocessing

In the proposed framework, a deep learning model is trained and evaluated using a dataset with three input variables, cell temperature, terminal voltage, current and the corresponding SOC targets. Raw measurements are first filtered, synchronized, and reformatted into sequences compatible with the network input. The processed data are then split into two non-overlapping subsets for training and testing, respectively, each containing paired input–output samples obtained from laboratory measurements on the cell. Before training, the neural network architecture and its hyperparameters (such as the number of layers, hidden units, learning rate, batch size, and regularization terms) are defined. The model parameters are subsequently optimized on the training set by minimizing a loss function that penalizes the discrepancy between predicted and measured SOC. After convergence, the generalization capability of the model is assessed on the held-out test set using several error-based performance indicators to quantify the accuracy of SOC estimation. As summarized in Fig. 1, the overall workflow proceeds from data preprocessing through model training to final testing, after which the trained model can be deployed and its performance examined under real operating conditions.

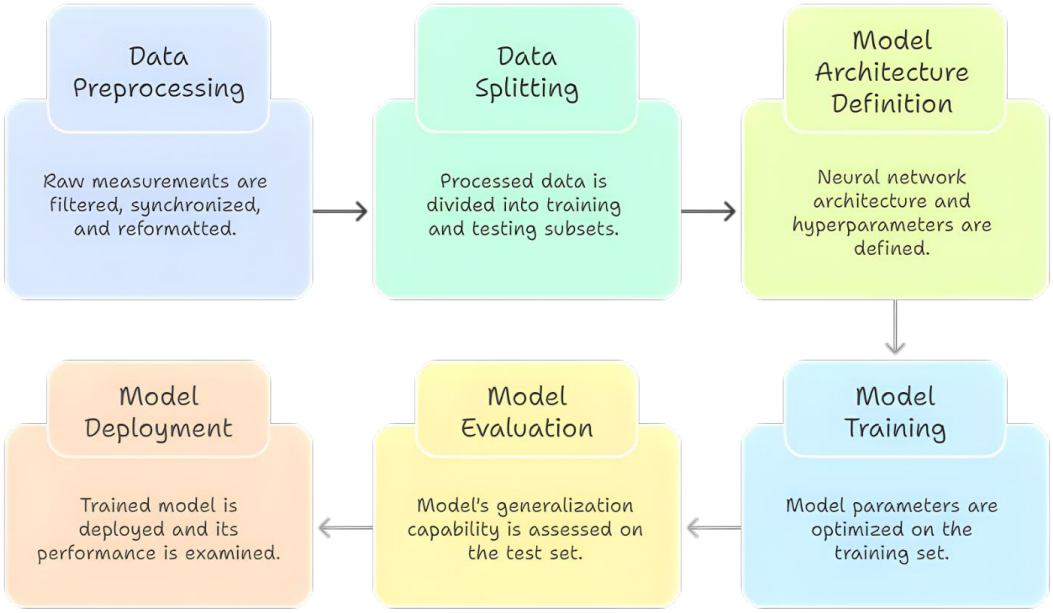


Figure 1:Deep Learning Model Training and Evaluation Workflow

C. Evaluation metrics

All models are trained using the mean squared error (MSE) between predicted and true SOC as the primary loss. The AdamW optimizer with a suitable learning rate and weight decay is used, together with mini-batch training and early stopping based on validation loss.

The metrics [9] are defined as follows:

$$MAE = \frac{1}{K}\sum_{k=1}^{k}|y_k - \widehat{y_k}| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_k - \widehat{y_k})^2} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

where y_k and $\widehat{y_k}$ denote the true and predicted SOC for sample k, $\bar{y}$ is the mean of the true value, and K is the number of samples.

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Base Model Architecture

In this section, we introduce the architecture of our hybrid model for SOC estimation. The approach combines three types of networks, a TCN, a GRU, and a Transformer encoder. Each one processes the same input sequence (such as voltage, current, and temperature) and outputs its own scalar SOC estimate. By bringing together these different ways of learning temporal patterns, the model aims to provide a more stable and accurate SOC prediction.

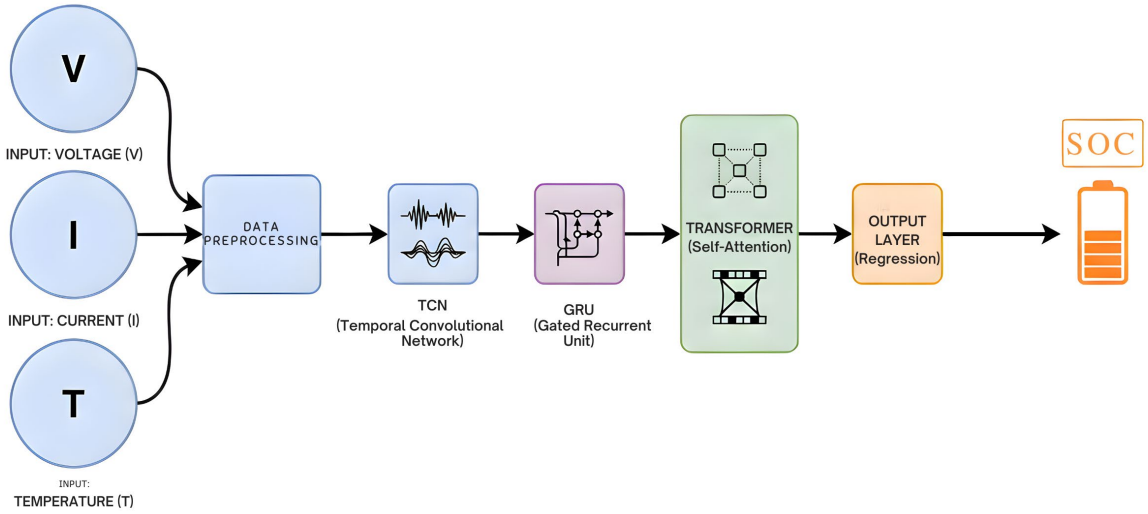


Figure 2: Architecture of the proposed model

A. Temporal Convolutional Network (TCN)

A TCN is a one-dimensional convolutional architecture designed for sequence modeling that enforces causality and preserves temporal order. Each layer applies a causal 1-D convolution along the time axis so that the output at time $t$depends only on inputs from times $\leq t$. Long-range dependencies are captured through dilated convolutions, where a kernel of size $k$with dilation factor $d$effectively covers $k * d$ past samples; stacking layers with increasing dilation yields a large receptive field with moderate depth and parameter count. Layers are organized in residual blocks composed of two dilated causal convolutions, non-linear activations, and dropout, with a skip connection that adds the block input to the block output to stabilize the training of deep stacks. The final temporal feature map is then reduced (by selecting the last time step or applying global pooling) and mapped by a fully connected layer to produce the SOC estimate [10].

B. Gated Recurrent Unit (GRU) Network

The GRU is a recurrent neural cell that maintains a hidden state $\mathbf{h}_t$ summarizing the battery's recent operating history and is particularly suitable for SOC prediction. At each time step, the GRU uses two gates, an update gate and a reset gate to control how much information from the previous hidden state and the new input (current, voltage, temperature) is incorporated into the candidate state, and then blends the old and candidate states to form $\mathbf{h}_t$. This gated mechanism allows the network to selectively retain or discard past information, mitigating vanishing-gradient effects and preserving long-range temporal dependencies without an excessive number of parameters. In the proposed SOC estimation framework, the final hidden state (or the sequence of hidden states) is passed through a dense output layer to map the learned temporal representation of the current-voltage trajectory to a scalar SOC value, enabling the GRU to capture the smooth, history-dependent evolution of SOC under realistic load profiles [11].

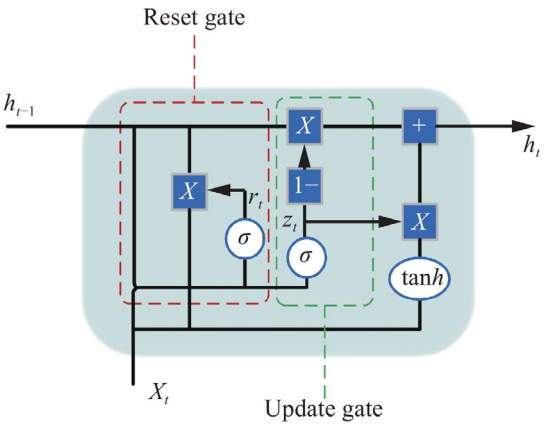


Figure 3: Architecture of the GRU model

C. Transformer Encoder

The Transformer encoder in our hybrid SOC estimation framework acts as a global context extractor that complements the local TCN features and the sequential memory of the GRU. After projecting the input battery time series (current, voltage, temperature–derived features) into a latent space and adding positional encodings, the encoder applies multi-head self-attention to let each time step attend to all others within the observation window. This mechanism enables the model to highlight informative segments such as current pulses or relaxation phases and to capture long-range dependencies that are difficult to model with convolutions or gated recurrent units alone. The resulting attention-based representation is then fused with the TCN and GRU outputs, providing a rich global-local description of battery dynamics that improves the robustness and accuracy of SOC prediction across varying load profiles [12].

Results and discussion

This section presents and analyzes the performance of the proposed hybrid architecture for SoC estimation in lithium-Polymer batteries, comparing a TCN, a GRU, and the hybrid TCN-GRU-Transformer model. All models are trained on 20 560 data samples and validated on 4 141 previously unseen samples. Figure 4 illustrates the predicted SoC trajectories versus the corresponding ground truth, where the brown curve denotes the reference SoC and the red curve indicates the model outputs. The qualitative assessment provided by these plots is complemented by quantitative performance indicators, namely the MAE, RMSE, and coefficient of determination (R^2), computed over the different operating conditions.

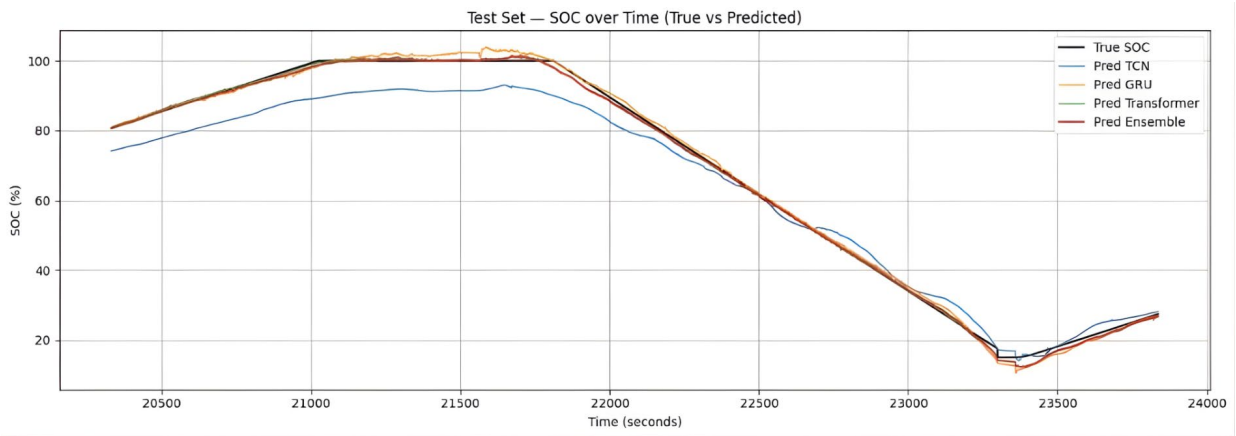


Figure 4: Results of SOC estimation in Lithium Polymer Battery

Table 2: SOC Prediction Performance Comparison

Model	MAE [%]	RMSE [%]	R^2
TCN	5.29	6.23	0.9584
GRU	1.09	1.37	0.9980
Transformer	0.69	0.90	0.9991
Hybrid (TCN-GRU-Transformer)	0.66	0.88	0.9992

According to the results presented in the table 2, TCN has the lowest predictive capability, indicating that temporal feature extraction by convolutional neural networks alone is insufficient to capture the nonlinear and history-dependent dynamics of Li-Po battery behavior. In contrast, both GRU and Transformer offer significantly higher accuracy, with Transformer proving to be the most effective standalone architecture, reflecting the advantage of attention mechanisms in learning longer-term dependencies in battery signals.

The proposed hybrid model provides the best results for all reported metrics, indicating that complementary temporal encoders increase the reliability of SOC predictions. This is also reflected in the SOC trajectories: the recurrent and attention-based models closely follow the reference SOC in dynamic operating profiles, while the TCN shows a more noticeable deviation during fast transients. Collectively, these finding support the conclusion that SOC estimation in Li-Po batteries benefits most from architectures that explicitly model sequential dependencies and global context, and that combining different types of approaches can further improve SOC prediction for practical BMS applications.

Conclusion

The aim of this work is to develop a hybrid deep-learning model for estimating the state of charge of lithium-polymer batteries using the combination of Temporal Convolutional Networks, Gated Recurrent Units, and Transformer encoders. The current, terminal voltage, and temperature are the primary inputs for the learning process, which is based on an experimentally acquired LiPo dataset.

A single models, such as GRU model and Transformer can deliver high predictive accuracy, achieving a test MAE value below 1% and R^2 values approximately 0.999. Basing on this baseline, the proposed approach improves performance further, achieving MAE = 0.6627%, RMSE = 0.8769%, and R^2 = 0.9992 on the test set. Moreover, the predicted SOC traces closely reproduce the ground truth evolution under multiple dynamic operating profiles, indicating stable tracking behavior.

Overall, combining complementary temporal feature extraction with attention-based sequence modeling produces an accurate SOC estimator for Li-Po cells. Future work will focus on: (i) adaptive ensemble combination via meta-learning; (ii) extending the framework to multi-task estimation of SOC and state of health (SOH); (iii) incorporating physics-based constraints and calibrated uncertainty estimates; and (iv) implementing refinements to meet real-time embedded BMS requirements.

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