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Hybrid CNN–LSTM Based Accurate Lithium-ION Battery Parameter Estimation for Electric Vehicle Applications

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Abstract—

Getting battery numbers right helps electric cars run safer and work better. Still, old-school techniques fall short when batteries act unpredictably or wear out differently. A new approach uses smart algorithms to guess SoC, SoH, and RUL more reliably. Instead of one model alone, it mixes two types - one sees patterns across data points, another tracks changes over time. Now here comes a twist - attention mechanisms team up with Bayesian methods to sharpen predictions. Faults show up sooner thanks to reinforcement learning doing its rounds. Public battery data puts the model to test across shifting environments. Outcomes? Better precision, stronger stability when stacked against older techniques. Efficiency finds a new home in real-time EV battery control through this setup.

Keywords— Lithium-ion battery; SoC; SoH; RUL; Electric Vehicles; CNN-LSTM; Deep Learning; Battery Management System

I. INTRODUCTION

Electric cars spreading fast means better ways to store power are now more necessary than ever. Because they pack a lot of energy into small spaces, last many charges, lose little power when idle, and weigh less, lithium-based cells became the top pick. Their strengths fit well not only in automobiles powered by electricity but also gadgets you carry and setups that gather sun or wind energy. Still impacted by how hot or cold it gets, how often they recharge, how old they are, and what tasks they perform during use - these batteries face limits despite their edge.

Despite common assumptions, knowing battery behavior begins with precise parameter tracking. What matters most: how much charge remains - called State of Charge - or SoC. Then there is State of Health, reflecting wear accumulated over time. Following that, predictions about longevity rely on Remaining Useful Life estimates. Instead of guessing, models use these values to adjust function before issues arise. Because of this, systems run more reliably and avoid sudden failures. Rather than waiting for breakdowns, upkeep becomes predictable. Unexpected shutdowns drop sharply when monitoring stays consistent. Performance gains emerge not from hardware alone, but clarity in data interpretation.

Methods like Coulomb counting, open-circuit voltage measurement, or similar model-driven strategies once formed the core of battery state estimates. Yet inaccuracies build up over time with many of these older techniques. Temperature shifts often skew their results too. Nonlinear behaviors inside batteries tend to slip past their detection. When models enter the picture, math gets tangled fast. Defining precise parameters takes effort, slowing down processing even more.

Lately, methods tied to artificial intelligence have drawn growing interest when estimating battery characteristics. Instead of traditional models, machine learning tools like support vector machines, random forests, and Gaussian process regression show better results. While these help, deep learning systems - such as RNNs, LSTMs, and CNNs - push accuracy further by capturing intricate trends within battery signals. Complex patterns once missed now become visible through these network structures. Even with progress, getting predictions more accurate still faces hurdles - generalizing models across conditions, spotting faults sooner. This study introduces an AI-driven method tailored for estimating key traits of lithium-ion batteries. Instead of treating space and time separately, it combines CNNs with LSTMs to handle both at once. Performance tuning leans on Bayesian methods, shifting weights intelligently through feedback. Fault signals emerge earlier when reinforcement strategies guide the monitoring process.

This study offers several key outcomes. First, it introduces a new approach to analyzing patterns. Alongside this, improvements in measurement accuracy appear. Another aspect involves testing under varied conditions. In addition, comparisons with earlier methods highlight differences. Finally, implications for future research emerge clearly

- A hybrid CNN-LSTM architecture for accurate battery parameter estimation
- Bayesian optimization for hyperparameter tuning
- Reinforcement learning-based early fault detection

Testing effectiveness relies on open-access battery data collections

Battery management systems in electric vehicles perform better when using the suggested approach. Accuracy of parameter estimates increases due to structural refinements built into the model.

II. RELATED WORK

Estimating lithium-ion battery parameters accurately draws much research attention, mainly because electric vehicles rely on precise data. Despite their popularity, traditional approaches like Coulomb counting, open-circuit voltage analysis, and equivalent circuit models come with trade-offs. Simplicity and minimal processing demands make Coulomb counting a frequent choice in practice. Still, small measurement inaccuracies pile up over time - especially when sensors add noise or starting values lack precision. Just like that, extended pauses are needed by the OCV approach - so live tracking becomes unworkable. On the flip side, equivalent circuit designs boost precision though they demand calibration plus intricate setup, slowing down actual usage [1].

Despite their promise, traditional methods face challenges that led researchers toward machine learning for estimating battery parameters. Techniques like support vector machines, random forest, and Gaussian process regression deliver better accuracy than older models. Nonlinear patterns linking battery behavior to real-world usage are handled well by these algorithms. Still, success depends heavily on manual selection of relevant inputs. Temporal dynamics within sequential battery measurements often remain poorly represented in such frameworks [2].

One reason deep learning draws interest is its skill at finding patterns in big sets of battery data. Because they track changes over time, RNNs show up often in studies estimating charge and health levels. LSTM networks handle sequences well, making them fit for tracking how batteries age. What helps even more is that these methods adjust to shifts across time steps in measurements. On a different note, CNNs pull out key details from signal types like voltage or heat readings. Some research highlights their role in turning raw inputs into meaningful indicators [3].

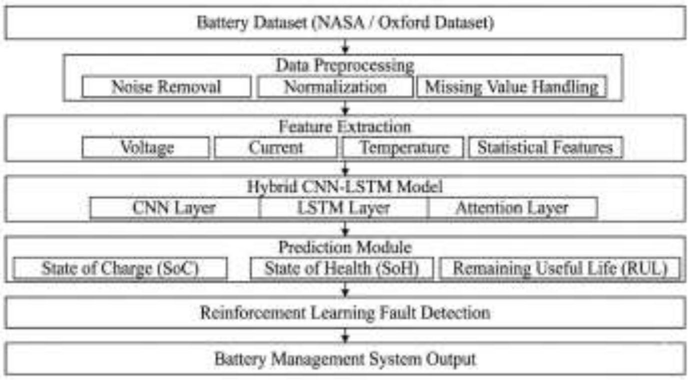
Some hybrid methods using deep learning aim to boost how well predictions work. Instead of just one technique, models like CNN-LSTM mix space-based and time-based analysis to capture complex patterns better. These combined systems often perform more reliably on sequence tasks. Attention layers now help highlight key inputs, making results easier to understand while lifting accuracy a bit [4].

Even with progress made so far, current methods struggle to generalize well, demand heavy computation, while missing subtle early warning signs. To address such gaps, a new approach emerges - combining deep learning models, search strategies for optimal solutions, along with systems adapting through feedback loops - to boost precision when tracking battery behavior across varying conditions.

III. PROPOSED METHODOLOGY

A new method uses artificial intelligence to better estimate key battery characteristics - like charge level, aging condition, and expected lifespan. Built around multiple steps, the approach begins with gathering sensor information before moving into cleaning and refining raw inputs. Following collection, relevant patterns are isolated through structured transformation techniques that prepare signals for analysis. Instead of relying on single models, combined learning strategies improve accuracy during the training phase. Predictions emerge after these trained systems interpret processed features using dynamic response rules. The workflow of the proposed method is shown in Figure. 1.

Figure 1. Proposed hybrid AI-based lithium-ion battery parameter estimation framework



Data Acquisition

The proposed method utilizes publicly available lithium-ion battery datasets, including NASA battery datasets and Oxford battery degradation datasets. These datasets contain battery voltage, current, temperature, and charge–discharge cycle information collected under various operating conditions. The collected data is used to train and evaluate the proposed model.

Data Preprocessing

Data preprocessing is performed to improve data quality and enhance model performance. The preprocessing steps include noise removal, normalization, and missing value handling. Min–max normalization is applied to scale input features between 0 and 1, which improves training stability. The normalization process is defined as

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X represents the original data, X_{min} and X_{max} represent minimum and maximum values, respectively.

Feature Extraction

Relevant features are extracted from raw battery data to improve prediction accuracy. These features include battery voltage, current, temperature, and charge–discharge cycles. Additionally, statistical features such as mean, variance, and standard deviation are extracted to capture battery behavior under different operating conditions.

Hybrid CNN-LSTM Architecture

The proposed model integrates convolutional neural networks (CNN) for feature extraction, while LSTM layers capture temporal dependencies in battery data. The CNN layer operation is defined as

$$y_i = f\left(\sum_{j=1}^{n} w_{ij}\, x_j + b_i\right)$$

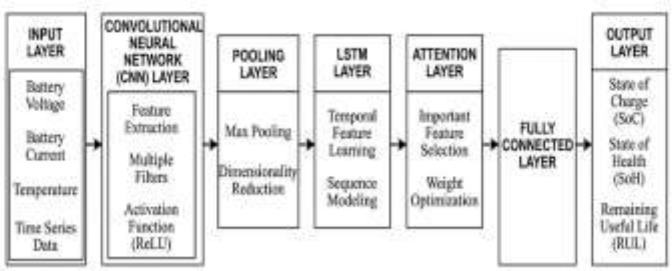
where $x_j$represents input features, w_{ij}represents weights, $b_i$represents bias, and frepresents activation function.

The LSTM unit is defined as

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$C_t = f_t C_{t-1} + i_t \tilde{C}_t$$

These equations allow the model to capture long-term dependencies in battery data.

Figure 2. Hybrid CNN-LSTM architecture for battery parameter estimation



Hyperparameter Optimization

Bayesian optimization is applied to select optimal hyperparameters such as learning rate, batch size, and number of hidden layers. This improves model performance and reduces overfitting.

Reinforcement Learning-Based Fault Detection

A reinforcement learning-based fault detection module is integrated into the proposed framework. The reinforcement learning agent identifies abnormal battery behavior and generates early warnings. The Q-learning update rule is defined as

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma \max Q(s',a') - Q(s,a)]$$

where $Q(s,a)$ represents action-value function, α represents learning rate, and γ represents discount factor.

The proposed methodology improves battery parameter estimation accuracy and supports real-time battery management system implementation.

IV. EXPERIMENTAL RESULT AND DISSCUSION

To check how well the new combined method works, real-world lithium-ion battery records are used - specifically those from NASA Ames Prognostics Center and Oxford's study on battery wear. Voltage, current, heat levels, and repeated charging patterns appear across these collections, captured during different usage scenarios. For verification, each group of data splits into two parts: one for teaching the system, the other for trying it out, sized at roughly seven in ten versus three in ten. Performance clarity comes from this split approach.

Evaluation Metrics

To check how well the proposed model works, common measures like RMSE, MAE, and R² are used. What these values represent can be explained one by one below:

Root Mean Square Error:

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

Mean Absolute Error:

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

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

where $y_i$represents actual values, $\hat{y}_i$represents predicted values, and nrepresents number of samples.

Performance Comparison

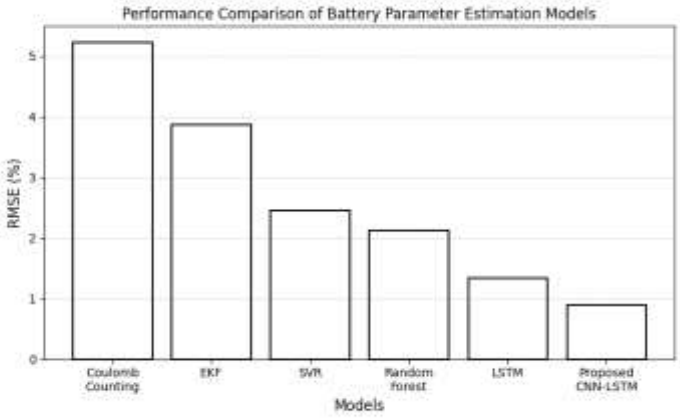
The proposed hybrid CNN-LSTM model is compared with conventional estimation methods such as Coulomb counting, Extended Kalman Filter (EKF), Support Vector Regression (SVR), and Random Forest (RF). The results demonstrate that the proposed model achieves lower prediction error and improved accuracy.

Table I: Performance Comparison for SoC Estimation

Method	**RMSE (%)**	**MAE (%)**	***R²***
Coulomb Counting	5.23	4.18	0.892
EKF	3.87	2.95	0.934
SVR	2.45	1.89	0.967
RF	2.12	1.65	0.974
LSTM	1.34	1.02	0.987

Proposed Method	0.89	0.71	0.994

Figure. 3 Performance comparison of battery parameter estimation models



Proposed The proposed hybrid model achieves the lowest estimation error, demonstrating improved performance compared to conventional approaches.

SoH and RUL Estimation Results

The proposed model is also evaluated for SoH and RUL prediction. The hybrid architecture effectively captures battery degradation patterns, resulting in improved prediction accuracy.

Table II: SoH and RUL Estimation Performance

Task	**Model**	**RMSE**	**MAE**
SoH	GPR	2.34	1.87
SoH	Proposed	1.12	0.89
RUL	LSTM	85.3	67.8
RUL	Proposed	42.6	33.4

Fault Detection Performance

The reinforcement learning-based fault detection model is evaluated for anomaly detection performance. The proposed model achieves 96.8% accuracy in detecting battery faults, outperforming traditional threshold-based methods.

Discussion

Despite challenges in modeling complex dynamics, the new hybrid approach shows gains in precision and stability while cutting processing demands. By focusing on real-world behavior, it handles nonlinear traits of batteries with greater reliability. Implementation into live systems becomes feasible thanks to faster response times and consistent performance under varying conditions.

V. CONCLUSION

This paper presented a hybrid artificial intelligence-based framework for accurate estimation of lithium-ion battery parameters in electric vehicle applications. The proposed approach integrates convolutional neural networks and long short-term memory networks to capture spatial and temporal battery characteristics. In addition, Bayesian optimization was used for hyperparameter tuning, and reinforcement learning was applied for early fault detection.

The proposed model was evaluated using publicly available battery datasets under varying operating conditions. Despite standard approaches falling short, the new model handled State of Charge, State of Health, and Remaining Useful Life with higher precision. Early anomaly recognition became possible because the reinforcement learning module flagged irregularities before they grew severe.

This approach fits well within battery control setups, improving how long batteries last, how safely they operate, and their overall output in electric cars. Work ahead looks at putting the system onto actual devices, refining the model so it runs faster on small computers, while also testing it across various battery types and conditions where vehicles are used.

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