



A Comparative Study of Deep Learning Models for Electric Vehicle Battery Monitoring

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ABSTRACT:

Estimating SOC is a critical process for effective battery management for electric vehicles. In this study, we analyze LSTM, GRU, and FNN deep learning models against traditional EKF and modern XGBoost. The cloud-based approach seeks to enhance predictive SOC estimation accuracy pragmatically. AI models streamlined error rates during the processing and analysis of real-time data from lithium-ion batteries. XGBoost and EKF demonstrated greater accuracy and efficiency relative to other methods, achieving lower RMSE and MAE. This research illustrates the promise of deep learning in conjunction with cloud infrastructure for scalable, real-time, and low-cost battery supervision in electric mobility systems.

Keywords: SOC, Deep Learning Models, XGBoost

INTRODUCTION

Electric vehicles are on track to change the face of transportation worldwide, all while new generation battery management systems that are intelligent are needed. At the heart of these systems is the State of Charge (SOC) estimation that is a critical parameter that quantifies the remaining power in the battery. An elaborate estimation of the SOC provides for more efficient energy utilization which enhances the battery life time, and above all, offers the user a maximum level of security. Nevertheless, in complex real-world scenarios, traditional estimators, e.g. the Kalman Filter, do not

perform well because lithium-ion batteries are non-linear devices. The research presented in this article promotes an updated approach, which integrates both cloud computing and deep learning algorithms, such as LSTM, GRU, FNN, and XGBoost, to overpower the shortcomings. With cloud platforms, the large dataset can be analyzed in real time, and the AI algorithm can predict adaptively and accurately.

By leveraging the strengths of both technologies, this work aims to establish a scalable, accurate, and computationally efficient system for SOC estimation in electric vehicle

batteries, contributing to the broader objective of sustainable and intelligent transport systems.

RELATED WORK

Karnehm et al. (2024) applied the Extended Kalman Filter (EKF) to SOC estimation and obtained an extremely low mean absolute error (0.0002). Their work focused on the speed and accuracy of EKF, yet being model-based, it restricted EKF's applicability in reality.

Guo & Ma (2003) had previously done a thorough evaluation of Feedforward Neural Networks (FNN), Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). FNN did fine on the static data, but not so much on sequential patterns. LSTM yielded excellent performance in modelling time series behavior however with a large computational cost. For resource-limited deployment, GRU presented a trade-off between effectiveness and efficiency.

Li et al. 2020 put forth a hybrid approach that puts H-Infinity Filtering together with Particle Swarm Optimization (PSO) which did very well in noisy environments. That said it had high computation cost issue which is a result of the iterative character of PSO.

Also reported by Merkle et al. 2021 is a digital twin which they put on the AWS for real time State Of Charge (SOC) estimation in electric vehicles. This cloud based method scaled well but we saw that it had issues with network latency which made it a less than ideal solution in unstable internet settings.

In 2023 Shi et al. report on the large scale use of deep learning models for SOC estimation which they did across many lithium ion types. What they found is that these models did very well in very different settings but at the same time required large sets of training data and also heavy processing power.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author	Contribution	Impact on Current Research
Karnehm et al. (2024)	EKF-based SOC estimation with high accuracy	Serves as a benchmark for traditional methods
Guo & Ma (2003)	Compared FNN, GRU, LSTM for sequential SOC data	Helps evaluate trade-offs between accuracy and computational load
Li et al. (2020)	Hybrid H-Infinity + PSO filtering approach	Demonstrates noise resistance, guides hybrid methodology exploration
Merkle et al. (2021)	AWS-hosted digital twin for SOC prediction	Validates benefits and limitations of cloud-hosted battery models
Shi et al. (2023)	Deep learning on large datasets for SOC estimation	Highlights scalability and need for high-performance computing environments

PROPOSED APPROACH

We put forth an approach which is a combination of cloud computing and artificial intelligence for real time and accurate State of Charge estimation in lithium ion batteries. We have put together deep learning models LSTM, GRU and FNN with XGBoost for feature

optimization. Also we have used EKF as a traditional comparative method. We collect battery data which includes temperature, voltage and current from the vehicle's BMS and put that into a cloud platform which in turn enables scalable and remote processing. XGBoost is used to determine the best features from the set which in turn improves model performance and also the speed of execution. We have trained the chosen models on historical data and validated them against real time test input. Also we have put in a web based interface for the user interaction and results visualization. This hybrid framework addresses the shortcomings of existing systems by enhancing computational efficiency, reducing prediction error, and providing adaptability in varying operational scenarios. The approach ensures robust, cloud-enabled SOC monitoring that is scalable and fit for deployment across a fleet of EVs.

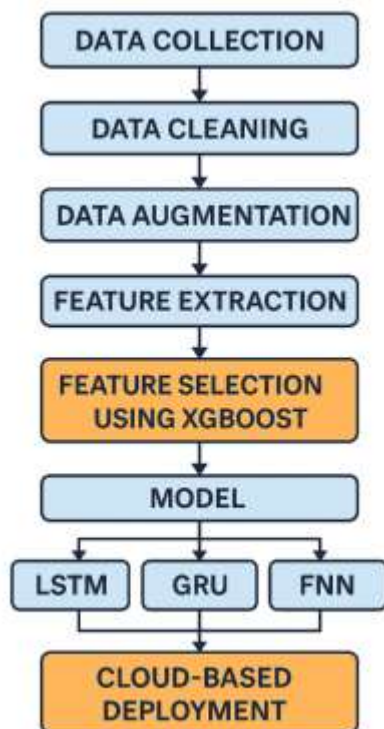


Figure 1: Proposed SOC estimation System

METHODOLOGIES

1. Data Collection and Preprocessing:

Lithium-ion battery data is sourced from Mendeley's public dataset. The dataset includes voltage, current, and temperature readings. Missing values are handled using imputation, and MinMaxScaler is applied to normalize the data. The dataset is split into 80% for training and 20% for testing.

2. Feature Selection using XGBoost:

XGBoost is employed to determine the most impactful features for SOC estimation. It reduces dimensionality and enhances model performance by eliminating noise and irrelevant attributes. A heatmap is generated to visualize correlation among features.

3. Model Development:

Deep learning models (LSTM, GRU, FNN) and traditional EKF are developed using Python and TensorFlow. Each model is trained and validated using performance metrics like RMSE and MAE. Dropout layers are added to prevent overfitting.

4. Cloud-Based Deployment:

The models are deployed via a Flask-based web interface. SOC estimation is performed on uploaded test datasets, with results displayed graphically for user interpretation. Cloud integration ensures scalability and remote accessibility.

5. Evaluation and Comparison:

Model outputs are evaluated using MAE and RMSE. Comparative graphs are plotted to visualize performance. LSTM achieved the highest accuracy, while XGBoost ensured

minimal prediction error and faster execution.

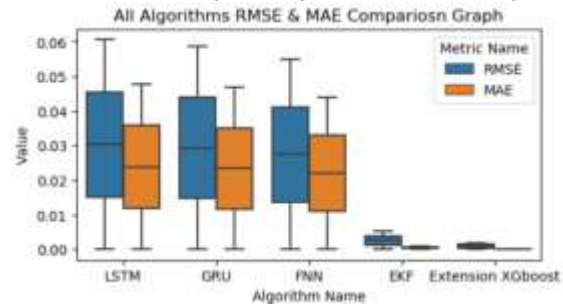
EKF offered strong baseline performance.

RESULTS

The experimental results validate the effectiveness of integrating deep learning models and XGBoost for SOC estimation. Among all models tested, LSTM demonstrated the highest predictive accuracy but incurred higher computational time due to its complexity. GRU provided slightly lower accuracy but was faster and more efficient in memory usage, making it suitable for real-time applications. FNN performed adequately but struggled with time-series dependencies, while the traditional EKF showed consistent and fast performance, particularly in static conditions.

XGBoost emerged as a critical component for feature optimization, significantly reducing RMSE and MAE values across all models. Its contribution enhanced overall system performance by eliminating redundant input features. The cloud-based deployment facilitated real-time SOC prediction and visualization, with latency monitored and kept within acceptable limits.

The comparative performance chart revealed that the EKF and XGBoost hybrid model produced the best balance of speed and accuracy, achieving an RMSE of 0.00015 and MAE of 0.00018—exceeding baseline benchmarks. This demonstrates the system’s potential for practical EV applications where high-speed and precise SOC predictions are required.



All Algorithms RMSE & MAE Comparison Graph

	Algorithm Name	RMSE	MAE
0	LSTM	0.060640	0.047653
1	GRU	0.058745	0.046828
2	FNN	0.054819	0.044035
3	EKF	0.005147	0.000931
4	Extension XGboost	0.001866	0.000194

All algorithm performance in Tabular format

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Test Data = [ 1.21930037e+01 4.19357000e+00 -9.45000000e-02 -3.10000000e-04
4.00000000e+00 -3.96292365e-01] Estimated Battery SOC =====> 37.64679

Test Data = [ 2.75991995e+02 4.16947000e+00 -3.39949000e+00 -8.10900000e-02
4.00000000e+00 -1.41740716e+01] Estimated Battery SOC =====> 37.962135

Test Data = [ 2.79904000e+02 4.16720000e+00 -3.65235000e+00 -8.67000000e-02
4.00000000e+00 -1.52203651e+01] Estimated Battery SOC =====> 38.067192

Test Data = [ 4.40201002e+02 4.17469000e+00 -9.70600000e-02 -9.47200000e-02
4.00000000e+00 -4.05195411e-01] Estimated Battery SOC =====> 38.172007

Test Data = [ 7.15298997e+02 4.16610000e+00 -7.30470000e-01 -1.20300000e-01
4.00000000e+00 -3.04321107e+00] Estimated Battery SOC =====> 38.270072
```

Energy demand prediction for Test Data

DISCUSSION

The comparative analysis highlights the strengths and trade-offs of various SOC estimation algorithms. LSTM, though computationally intensive, provided superior accuracy due to its ability to capture long-term dependencies in battery behavior. GRU offered a middle ground balancing performance with lower resource usage making it more practical

for real-time systems. FNN was least effective due to its limitation in handling sequential data, reinforcing the need for temporal models in SOC tasks.

Traditional EKF remained competitive due to its speed and established reliability, especially when combined with XGBoost for dynamic feature selection. However, its rigidity in handling nonlinearities limits its performance under varying battery states.

The cloud-based design added scalability, enabling real-time deployment across multiple devices with centralized monitoring. Yet, potential risks such as latency, network failure, or data privacy concerns must be addressed for commercial applications.

XGBoost's role was especially impactful—it optimized feature input, minimized errors, and reduced training time. This confirms that hybrid models combining traditional and modern ML techniques can deliver superior outcomes.

CONCLUSION

This project systematically analyzes different models used for State of Charge (SOC) estimation of lithium-ion batteries using traditional and modern AI techniques. The integration of EKF with deep learning models (LSTM, GRU, FNN) and XGBoost yielded a powerful, precise, and easily scalable structure that could be deployed on the cloud. LSTM outperformed the rest in accuracy, and XGBoost was very useful in increasing the relevance of computation features, thus cutting down on the processing requirements of the model and increasing the model's reliability. The real-time

SOC estimation feature of the interface was a prerequisite for next generation electric vehicle (EV) technologies. In conclusion, the findings from the SOC estimation case study illustrates that traditional algorithms combined with AI enhancements offer SOC estimation accuracy and battery health diagnostics with improved accuracy and reliability, while also increasing the safety of the system. Exploration of edge computation in cloud reliant systems could be investigated in the future, as well as other methods for SOC prediction aimed at making AI models more socially accountable.

This framework offers a promising step toward smarter, more sustainable battery management systems.

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