A Feature-Turned XGBoost Model for Real Time SOC Prediction

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Abstract: **The evolution of cloud-based lithium-ion battery management systems has revolutionized state-of-charge (SOC) estimation. Traditional estimation methods, such as Extended Kalman Filter (EKF), struggle with accuracy and computational efficiency. This paper presents a comparative analysis of deep-learning-based SOC estimation algorithms, including Feedforward Neural Networks (FNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM). The extension introduces XGBoost for feature optimization, reducing RMSE and MAE errors. The integration of cloud computing enhances computational capabilities, allowing real-time estimation. Results indicate that EKF and XGBoost outperform conventional techniques, providing faster and more precise SOC predictions, ensuring efficient battery management and prolonging battery life for electric vehicles.**

INTRODUCTION

Electric vehicles (EVs) are key to achieving sustainable transportation, necessitating efficient battery management systems (BMS). Accurate SOC estimation enhances battery longevity and operational safety. Conventional estimation models, including equivalent circuit models and Kalman filters, are limited by low computational power. Cloud computing integration enables advanced deep learning approaches for SOC estimation. This study evaluates the performance of EKF, FNN, GRU, and LSTM on cloud platforms, optimizing estimation accuracy. Experimental results highlight EKF's superior precision, with XGBoost extension improving.

LITERATURE SURVEY

1. Extended Kalman Filter (EKF)

Karnehm et al. (2024) evaluated the Extended Kalman Filter (EKF) for SOC estimation, highlighting its high accuracy and speed when tested on the UDDS driving cycle dataset. The model demonstrated a mean absolute error (MAE) of 0.0002, making it one of the most precise estimation techniques. However, its reliance on model assumptions and lack of adaptability to highly non-linear systems pose challenges in real-world applications.

2. Feedforward Neural Network (FNN)

Guo C Ma (2023) examined the use of Feedforward Neural Networks (FNN) for SOC estimation. The model achieved good predictive accuracy but required significant computational resources. FNNs are advantageous in situations with static input-output relationships but struggle with sequential dependencies in dynamic battery environments.

3. Long Short-Term Memory (LSTM)

The same study by Guo C Ma (2023) explored Long Short-Term Memory (LSTM) networks, which excel at handling sequential dependencies and capturing long-term relationships in battery behavior. Despite achieving high accuracy, the approach demands extensive computational power, limiting its practical application in resource-constrained environments.

4. Gated Recurrent Unit (GRU)

Guo C Ma (2023) also evaluated the Gated Recurrent Unit (GRU) as a computationally efficient alternative to LSTMs. GRUs retain sequential learning capabilities while requiring fewer computational resources. However, they exhibited slightly lower accuracy than LSTMs, making them a trade-off option for cloud-based SOC estimation systems.

5. H-Infinity Filter G Particle Swarm Optimization

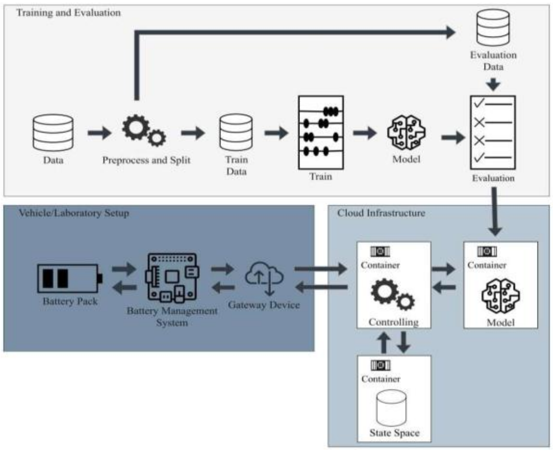
Li et al. (2020) introduced an SOC estimation method combining an H- Infinity filter with Particle Swarm Optimization (PSO). This hybrid approach effectively filters noise in battery measurements, making it suitable for real- world noisy conditions. However, the complexity of PSO-based optimization increases computational requirements.

PROBLEM STATEMENT

Current SOC estimation techniques exhibit high error rates and computational inefficiencies. Machine learning models lack real-time adaptability, impacting battery performance. A hybrid approach integrating deep learning, cloud computing, and XGBoost is required to enhance SOC prediction accuracy while minimizing computational overhead.

Proposed System:
The proposed system integrates deep learning with XGBoost for SOC estimation. EKF enhances real-time adaptability, while cloud deployment improves computational efficiency. XGBoost optimizes feature selection, reducing RMSE and MAE errors. This hybrid approach ensures accurate, scalable, and real-time SOC prediction for electric vehicles, enhancing battery performance and lifespan.

ARCHITECTURE:



METHODOLOGY

1. Data Collection and Preprocessing
Lithium-ion battery dataset sourced from Mendeley. Preprocessing includes missing value handling, normalization, and feature scaling. Data split into training (80%) and testing (20%).
2. Feature Extraction and Optimization
Feature correlation analysis using heatmaps. XGBoost applied for feature selection and optimization. MinMaxScaler normalization enhances model performance.
3. Model Training and Evaluation
Algorithms trained: EKF, FNN, GRU, LSTM, and XGBoost. Training conducted in Jupyter Notebook. Performance measured using RMSE and MAE metrics.
4. Comparative Analysis and Performance Metrics Comparison of deep learning models based on execution time and accuracy.EKF and XGBoost demonstrate superior performance. Cloud-based deployment ensures real-time processing.
5. Deployment and Real-World Testing
Flask-based web interface implemented for SOC prediction. User uploads test data, and the system predicts SOC values. Results displayed in graphical format for performance comparison

CONCLUSION

Deep-learning-based algorithms for State-of-Charge (SOC) estimation in cloud-based Lithium-Ion Battery Management Systems (BMS) offer significant advancements in accuracy and efficiency. Models like LSTMs, CNNs, and hybrid architectures excel in handling complex, time-dependent, and spatial data. Cloud integration enhances scalability, real-time monitoring, and computational power, making these systems ideal for large-scale applications. However, challenges such as data quality, model interpretability, and computational efficiency must be addressed. Future research should focus on improving data robustness, model generalization, and optimizing real-time performance for broader adoption

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