Estimation of essential battery state parameters for battery management systems (BMS) in Electric Vehicles using long short term memory (LSTM) and time series analysis combined with Extended Kalman Filter

Florence Gnana Poovathy[1*], Sradha N[2], Sruthi G[4],

[1*]florence.poovathy@vit.ac.in, [2]sradhanair125@gmail.com, [3]sruthicorneliawilfred@gmail.com

[1*]Electric Vehicle Incubation & Testing – Research Centre (eVIT-RC), Vellore Institute of Technology, Chennai

[1*,2,3] School of Electronics Engineering (SENSE), Vellore Institute of Technology, Chennai

Abstract

In a world actively moving towards sustainable growth, the efficient management of Battery Management Systems (BMS) in Electric Vehicles is critical. The precise estimation of essential parameters such as State of Charge (SoC), State of Health (SoH) and State of Power (SoP) play a pivotal role in the effective management of batteries through timely decision making by battery management systems (BMS). There are many machine learning (ML) base models to predict health, energy, power and other battery parameters. The proposed work combines predictive modeling and time series analysis with an extended Kalman filter to develop a framework for SoH, SoC and SoP prediction. This includes long short term memory (LSTM) based machine learning (ML) algorithms. In this article it is demonstrated that the suggested approach has better accuracy and resilience against modeling errors. The main finding of this study is that combining predictive modeling and time series analysis with extended Kalman filter can increase the accuracy of estimation of state variables and other essential parameters to more than 88% for various temperatures such as 0°C, 25°C, and 45°C that would suit most of the tropical countries.

Keywords

battery management system (BMS), predictive modeling, time series analysis, trend prediction, Long Short Term Memory (LSTM).

1. Introduction

The rise in the sustainable development movement amidst the exhaustion of fossil fuels has contributed to an increase in the prevalent usage of Electric Vehicles (EVs). The effective operation of BMS can only be achieved through efficient and precise estimation of State of Health (SoH), State of Charge (SoC), State of Energy (SoE), and State of Power (SoP). Usage of machine learning (ML) algorithms have not been much used in the literature to find the parameters needed for battery monitoring. The proposed system combines predictive modeling algorithms, time series analysis with extended Kalman filter (EKF) and implemented on a [1] Li-ion battery aging dataset. This is constructed from the Kalman filter (KF) theory which is a mathematical technique in which the state of a dynamic system is estimated and refined from noisy measurements. KF is utilized for linear systems and for a non-linear system like battery state estimation where the state dynamics are too complex, Extended Kalman filter is employed to perform prediction and correction steps. EKF is widely used in the autonomous vehicles industry for estimating cell parameters due to its effective performance in real-time estimation, refined control strategies etc. In the proposed system predictive modeling predicts the battery behavior based on historical data whereas time series analysis examines how battery related variables alternate in time based patterns.

Research by [2] Yu, Xiaoping, and Yufeng et al. reveals that lithium-ion batteries' capacity decreases with increased charge/discharge cycles, suggesting lower current levels. [3] ShuXiang Song et al. aimed to improve the BMS of electric vehicles by simplifying estimation of SoC and SoE. [4,5] Wang et al. (2021) found that while PTT(Pulse Transient Testing) and EIS(Electrochemical Impedance Spectroscopy) techniques are effective for offline SOH estimation of EV batteries, analyzing ultrasound transmission mechanisms and parameters can improve accuracy. [6,7] Zhang et al.'s study shows a Long Short Term Memory(LSTM) model with ReLU(Rectified Linear Unit) function for predicting lithium battery capacity and fading trend, but further validation with real-world data is needed. [8,9,10,11] Y. Ko et al.'s study developed a method combining AKF(Adaptive Kalman Filter) and ECC(Electrochemical Coulomb Counting) for lithium-ion battery capacity estimation, achieving a 1.7% RMSE in SOH estimation. [12] Zuolu Wang et al.'s paper evaluates rapid SOH estimation methods for Li-ion batteries in electric vehicles, highlighting non-destructive techniques like ultrasonic inspection for accurate estimation without operational disruption.

The research utilizes EKF and ML models to improve battery parameter estimation in electric vehicles (EVs). This comprehensive approach, combining predictive modeling and time series forecasting, results in significant accuracy improvements, especially in dynamic temperature environments. The Centre for Advanced Life Cycle Engineering's (CALCE) LiNiMnCo/Graphite-ion Battery datasets, specifically the INR 18650-20R Battery, were used to test our approach, which was evaluated against other prediction-based techniques and put to the test in a simulation. The battery data considered for evaluation included a capacity rating of 2000 mAh, a maximum voltage range of 2.5V to 4.2V, current rates up to 2C, and various C rates for charging and discharging cycles.

2. Methodology

2.1 Data set readiness

The dataset considered for the study has been created using the following procedure: A series of Li-ion batteries has been tested under three distinct operational profiles: charging, discharging, and impedance measurement, across varying temperatures of 0°C, 25°C, and 45°C. These temperatures were chosen because they would cover the temperatures of more than half of the world, 25°C is the nominal room temperature and the ideal temperature for countries like Jamaica, Guinea etc., 0°C for very cold countries such as Siberia, 45°C is for countries like India and other countries in Asia. During charging, a constant current (CC) of 1.5A was applied 4.2V of battery voltage is reached. A switch to constant voltage (CV) mode is made and waited until the current dropped to 20mA. During discharge, a fixed load current of 2A was set, with termination points at 2V, 2.2V, 2.5V, and 2.7V for different batteries. Electrochemical impedance spectroscopy (EIS) was employed for impedance measurements, encompassing a frequency sweep from 0.1Hz to 5kHz. The experiments were concluded once the battery capacity had diminished to 1.4Ahr (30% fade). Additionally, Beijing Dynamic Stress Test (BJDST) was conducted at both 50% and 80% battery levels.

2.2 Data Cleaning

Data cleaning procedures involved the identification and treatment of missing data through data imputation, along with the removal of duplicates to prevent redundancy. Subsequently, Principal Component Analysis (PCA) was used for dimensional reduction, while Winsorization techniques were employed to address outliers. Feature importance scores were utilized to pinpoint the most influential features contributing to the target variables(SOC,SOH and SOP). To ensure equitable contributions during analysis, the data underwent Min-Max scaling and z-score normalization. Finally, the dataset was effectively partitioned into training, validation, and testing sets to assess model performance.

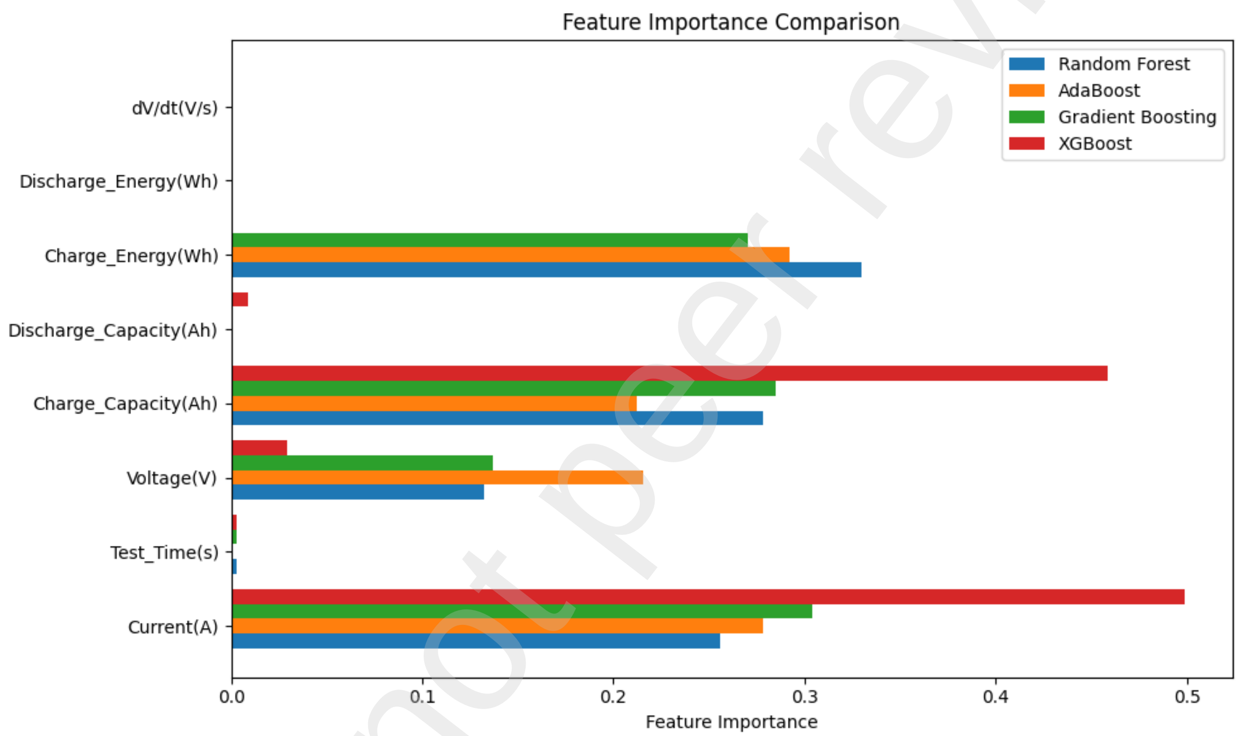

Fig 1: Feature importance graph for various parameters of the Li-ion battery: x axis explains the feature importance score and y axis represents the features for which the scores were obtained

The feature-importance-score has been used for tree based models to ensure that each model received the best features were utilized for training and testing the data, neural network models received layer-wise relevance propagation to understand the importance of input features.

It can be deduced from Fig. 1 that the feature importance graph shows varying priorities across models. Current has the lowest importance for Random Forest but the highest for XGBoost. Voltage is least important for XGBoost and most for AdaBoost. Charge Capacity is most important for XGBoost and least for AdaBoost. Charge Energy is most important for Random Forest and least for Gradient Boosting, highlighting the differing weight each model gives to the features. The highest feature importance score is 0.5 because this score represents the maximum relative influence any single feature has on the model's predictions, normalized across all features to maintain consistency and comparability within the given context.

2.3. Machine Learning Methods

In the proposed system machine learning models such as SVM, Random forest, MLP Regressor, AdaBoost, XGBoost and Deep learning models such as LSTM and Bi-directional LSTM have been chosen as mentioned in **Fig. 1**. [4] By using recursive processing of the inputs, predictive modeling algorithms have the capability to effectively recognize and [10] learn the correlations that are non-linear in the data. [6] The relationship between the data input x_n at the time step n and the output O_n is represented by equation (1)

$$h^n{}_l = g^n{}_l(U_n.x_n + W_l.h_{n-1} + b_x)$$
$$O_n = g^n{}_K(V^n{}_K.h^n{}_K + b_y) \tag{1}$$

Equation 1: Relationship between data input, time step, and output.

where $g^n{}_K$ l^{th} layer's function of activation at n , and l=1,2,….,K. b_y and b_x are the bias terms, V_K, W_l and U_n represent the metrics of weight, and $h^n{}_l$ denotes l^{th} layer with state vector. In order to to minimize the loss function $L(O_n, y_n)$, (where y_n indicates desired output), at every iteration RNN parameters are updated. Exponential smoothing models for time series forecasting such as Holt-Winters Method and Holt-Linear method are also employed to provide support for trend level and seasonality.

For the Extended Kalman Filter, the system dynamic and the measurement functions are linearized with first-order Taylor series expansions. This is done so as to make them compatible with the standard Kalman Filter framework.

2.3.1 LSTM-EKF

The battery system's fundamental dynamics are modeled and its state variables like SoC and SoH are estimated using the EKF. The LSTM network learns patterns of battery behavior and degradation over time by analyzing past data, including charge/discharge cycles and ambient variables such as temperature. A fusion strategy combines the outputs of the LSTM (predictions) with EKF (state estimates). The combination of LSTM and EKF enables more precise and reliable assessment of battery performance and health metrics. The combined technique can yield more accurate predictions of SoH, charge/discharge cycles, and discharge degradation in BMS for electric vehicles by utilizing the complementing capabilities of LSTM and EKF.

2.3.2 Bi-directionally stacked LSTM

Bidirectional LSTM, also known as BiLSTM, is a model that consists of two LSTM layers: one that processes input in forward direction and the other that processes input in the backward direction. Typically used in NLP tasks, the rationale behind BiLSTM (Bidirectional Long Short-Term Memory) is to enhance the model's comprehension of sequential relationships by analyzing time-series data such as battery SoH, SoC, and SoP in both forward and backward directions. This enables the model to better grasp the context of sequences, such as understanding the preceding and following words in a sentence. Compared to unidirectional LSTM, BiLSTM demonstrates good performance in tasks like sentiment analysis, machine translation, and text classification due to its enhanced ability to capture sequence dependencies from both directions.

2.3.3 LSTM - CNN

The CNN component preprocesses the input data, extracting features that highlight important patterns and trends. These features are input to the LSTM network, which learns the temporal dynamics and dependencies within the data. This hybrid approach enables the model to effectively capture both the spatial and temporal characteristics of the system, resulting in more accurate estimations of SoC, SoP, and SoH.

2.4 Proposed System

The proposed system consists of combined LSTM and EKF and the necessary libraries such as keras, statsmodels, sklearn etc are imported. The data is pre-processed through standard scaling, the missing values are imputed and the categorical values are encoded. The Extended Kalman Filter class is initialized with transition matrix, observation matrix, state mean, state covariance, observation covariance, transition covariance, then the filter is defined. The preprocessed data is split and made into features that were extracted and the target variable is predicted. The matrices from the EKF class are adjusted and the filtering is performed on the extracted features. The Min-Max scaler as mentioned in **Fig. 2**, is then applied to the filtered values from the extracted features, scaling the data to a specified range, typically between 0 and 1, by transforming the values based on the minimum and maximum values of the data.

Time Series Cross validation is performed to avoid data leakage through GridSearchCV with 5 subsets, the model is trained with 4 folds and evaluated on the rest one fold. Here each fold is used as a validation set only once with the process being repeated 5 times. This 4-fold training approach allows the model to be trained on a substantial portion of the data while reserving one fold for validation, thereby ensuring that each fold is used as a validation set only once and that the model is tested on diverse time periods. This method balances the need for robust model evaluation while accounting for temporal dependencies in the data.

Next, GridSearchCV is utilized for Hyperparameter tuning where it selects the best combination of hyperparameters based on the negative ROC (Receiver Operating Characteristic Area Under the Curve, which evaluates the ability of the model to distinguish between different classes by measuring the area under the ROC curve), MSE (Mean Squared Error), F1 (metric that balances precision and recall by calculating their harmonic mean, useful for evaluating performance on imbalanced classification problems) etc. L1 and L2 regularization techniques are implemented to increase the efficiency of the models.

Recurrent Neural Network (RNN) models such as LSTM, Bi-LSTM (Bidirectional Long Short Term Memory) and MLP (Multilayer Perceptron) Regressor models are initialized with MSE as its function. LSTM and Bi-LSTM are used for learning the long term dependencies. The gradient boosting models such as AdaBoost and XGBoost are optimized with Adam optimizer. The exponential smoothing models are fitted with the least squares criterion in which the Holt-Winters method uses level, trend and seasonality. The support vector machine (SVM) which is an ovreseen learning algorithm, is optimized with the Hinge loss function. SVM is needed for our method due to its effectiveness in high-dimensional spaces and its strong classification performance.

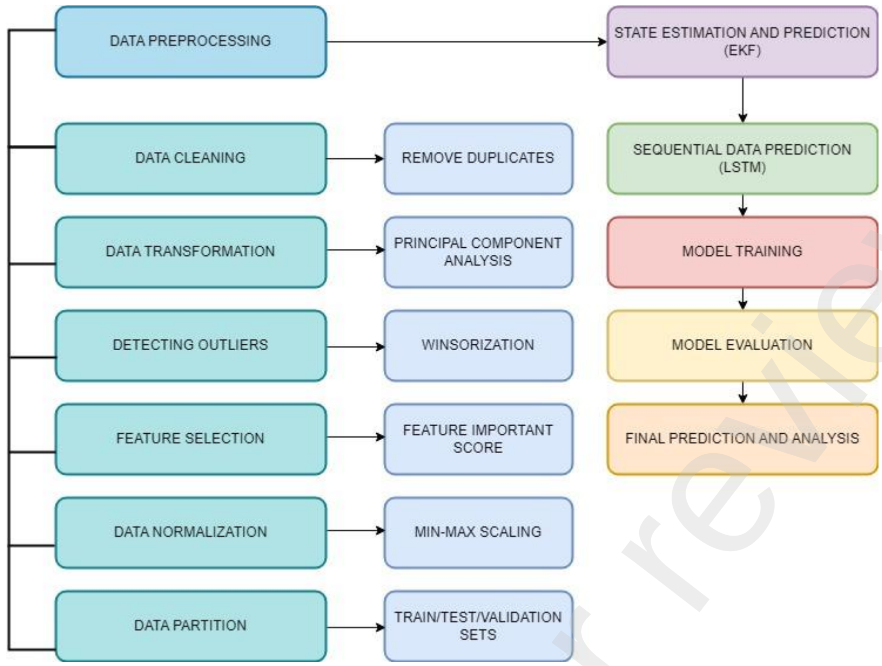

Fig. 2 highlights the processes involved in the proposed ML based technique.

Then both the machine learning models (LSTM, Bi-LSTM, MLP Regressor, AdaBoost, XGBoost, and SVM) and time series forecasting models (simple, double, triple exponential smoothing models using Holt-Winters method) are evaluated using performance metrics such as MSE, RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error). The results and the performance metrics are then visualized for further examination. The new system integrates an Extended Kalman Filter (EKF) with machine learning models like LSTM and CatBoost, combining traditional state estimation with advanced predictive analytics for enhanced accuracy and adaptability, unlike existing systems that rely solely on either EKF or machine learning models independently.

3. Result and Discussion

3.1. Evaluation Metrics considered for comparison

SoC, SoH, and SoP are the main parameters that have been derived from the raw data using the LSTM-EKF model developed in this work. These derived parameters are evaluated for MSE, RMSE and MAE error metrics using various algorithms such as LSTM (Long Short-Term Memory, RNN for capturing long-term dependencies), Bi-LSTM (Bidirectional LSTM, enhances learning by processing in both temporal directions), MLP Regressor (Multilayer Perceptron Regressor, a deep learning model for complex functions), AdaBoost (Adaptive Boosting, ensemble method that refines weak learners), XGBoost (Extreme Gradient Boosting, advanced gradient boosting for accurate modeling), SVM (Support Vector Machine, classification and regression algorithm optimized with Hinge loss), and Exponential Smoothing Models (Holt-Winters Method, time series forecasting technique using level, trend, and seasonality).

MSE, a standard metric for regression tasks, has mathematical properties that include a higher penalty for large errors, making it useful for highlighting significant deviations in terms of the squared differences between predicted and actual values and providing a clear baseline for comparison. Its mathematical properties include a higher penalty for larger errors, making it useful for identifying significant deviations from the true values in metrics like battery capacity, charge/discharge cycles, and performance efficiency. MSE provides a clear baseline for comparison by emphasizing larger errors. RMSE offers intuitive interpretation of prediction errors, sensitivity to large errors, and direct measurement of accuracy. Its units make it easier to understand the scale of errors and their impact on accuracy. Both MSE and RMSE have been chosen as evaluation metrics because MSE quantifies the overall error magnitude by finding the square of the difference between actual and predicted values, which emphasizes larger errors, while RMSE provides a measure of error in the same units as the target variable, offering a more interpretable scale of average prediction accuracy. Outliers can be addressed with MAE, a balanced measure of absolute error. MAE is cannot sense outliers and provides a straightforward understanding of the absolute magnitude of errors in the same units as the original data.

The combination of MSE, MAE and RMSE metrics offers a comprehensive view of battery management systems' performance, enabling a nuanced assessment of predictive capabilities.

3.2. State of Charge (SoC)

Table 1 compares Mean Squared Error (MSE) for different machine learning methods for estimating battery SoC at 45°C, 25°C, and 0°C, showing MSE values with and without the Extended Kalman Filter. The LSTM-EKF model is the proposed method in this comparison, featuring a combination of LSTM networks and EKF to improve estimation performance.The table shows that integrating EKF with various machine learning methods generally improves the accuracy of SOC estimation, as indicated by lower MSE values.

Table 1: Evaluation of estimation of State of Charge

S.No	ML Method	45 °C		25 °C		0 °C	
		MSE W/O EKF	MSE W EKF	MSE W/O EKF	MSE W EKF	MSE W/O EKF	MSE W EKF
1	**LSTM**	1.32E-01	2.74E-02	8.39E-07	1.13E-06	3.73E-07	1.76E-07
2	**LSTM+CNN**	1.11E-01	9.72E-03	2.10E-01	3.84E-02	1.99E-01	1.85E-02
3	**Gradient Boost**	2.19E-01	2.11E-02	4.15E-02	2.08E-02	9.10E-10	8.89E-10
4	**Bi-directional LSTM**	2.89E-02	9.72E-03	8.39E-07	2.10E-05	3.65E-07	2.30E-07
5	**Random Forest Regressor**	2.03E-02	1.54E-03	2.08E-02	1.41E-03	2.60E-10	2.51E-10
6	**MLP Regressor**	4.64E-02	2.81E-02	3.25E-02	1.73E-02	1.53E-07	1.18E-07
7	**AdaBoost**	6.89E-01	6.89E-01	9.07E-01	9.16E-01	3.46E-07	3.54E-07
8	**XGBoost**	7.73E-02	6.05E-02	6.76E-02	5.21E-02	5.75E-08	5.75E-08

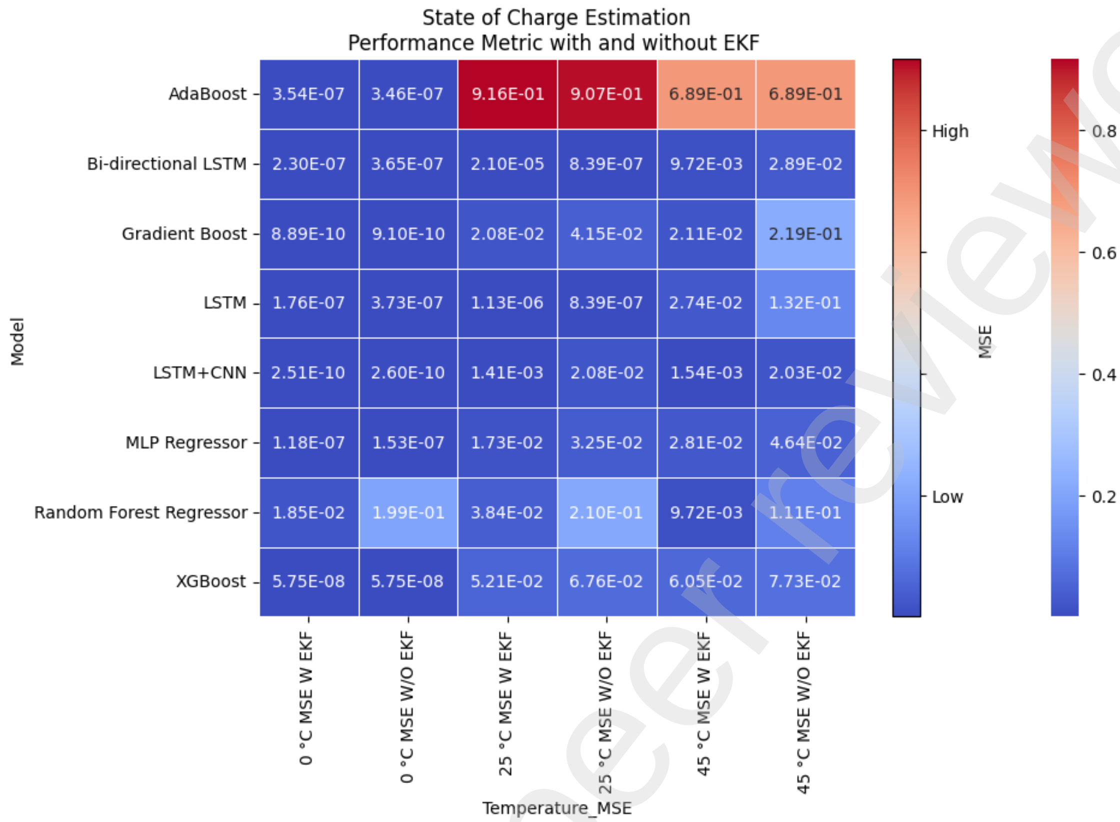

Fig 3: Heatmap of performance metrics for SoC estimation with and without EKF

Examining the SOC estimation as in Table 1 and MSE heatmap as in **Fig. 3**, the MSE has increased as the temperature rises. This trend is particularly pronounced in models such as AdaBoost, Bi-directional LSTM, and Gradient Boost, where the MSE shows a substantial increase from 0°C to 45°C. Comparing the SOC estimation with and without EKF, in Bi-directional LSTM and Gradient Boost models, the utilization of EKF results in a noticeable reduction in MSE across different temperatures. At 45°C, Bi-directional LSTM and Gradient Boost models show significant improvements with EKF, with reductions of 66.3% and 90.4%, respectively, highlighting EKF's effectiveness in reducing MSE. At 25°C, LSTM shows a substantial increase in MSE with EKF, while Gradient Boost shows a reduction of 49.9%. At 0°C, Bi-directional LSTM and LSTM models show notable reductions in MSE with EKF, with decreases of 37.0% and 52.8%, respectively.

This reduction suggests that EKF effectively mitigates estimation errors and enhances the accuracy of SOC estimation, particularly in dynamic and uncertain environments characterized by varying temperatures.

3.3. State of Health

The Mean Squared Error (MSE) for machine learning techniques used to estimate the State of Health (SOH) of batteries across three temperature settings is displayed in **Table 2**. The MSE values are compared with and without the Extended Kalman Filter (EKF), and the data is split into sub-columns for MSE without EKF and with EKF.

Table 2: Evaluation of estimation of State of Health

S.No	ML Method	45 °C		25 °C		0 °C	
		MSE W/O EKF	MSE W EKF	MSE W/O EKF	MSE W EKF	MSE W/O EKF	MSE W EKF
1	**LSTM**	1.43E-01	4.53E-07	1.00E-06	4.59E-07	8.55E-07	1.36E-07
2	**LSTM+CNN**	1.31E-01	4.20E-08	1.28E-01	4.37E-08	1.32E-01	2.43E-08
3	**Gradient Boost**	3.29E-09	2.49E-09	1.97E-09	1.98E-09	8.92E-10	9.50E-10
4	**Bi-directional LSTM**	1.43E-01	9.05E-07	2.54E-07	3.12E-07	5.56E-07	2.90E-06
5	**Random Forest Regressor**	3.13E-09	3.66E-09	5.54E-10	5.54E-10	2.68E-10	2.57E-10
6	**MLP Regressor**	1.91E-08	2.72E-06	2.09E-07	8.06E-07	9.38E-08	1.22E-07
7	**AdaBoost**	4.62E-07	4.89E-07	6.45E-07	6.82E-07	3.51E-07	3.53E-07
8	**XGBoost**	5.59E-08	5.59E-08	4.07E-08	4.07E-08	5.75E-08	5.75E-08

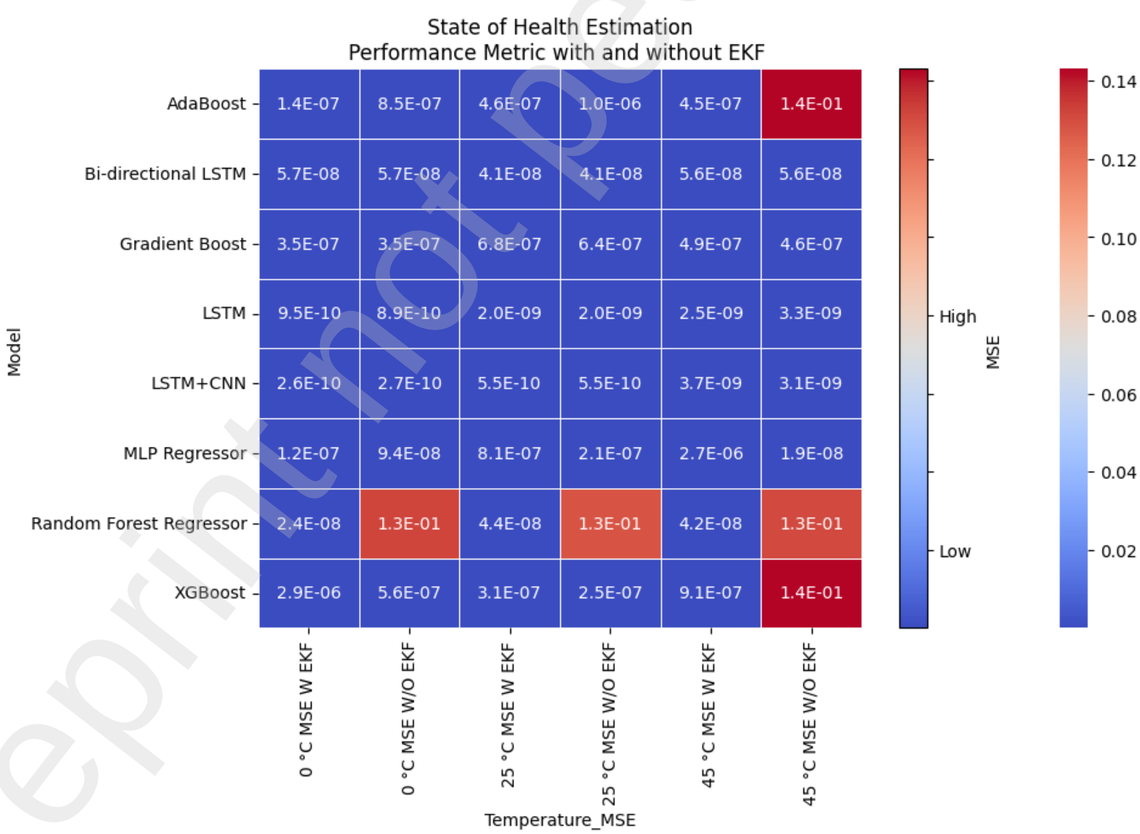

Fig 3 Heatmap of performance metrics for SoH estimation with and without EKF

In **Table 2** above, performance metrics such as MSE, MAE and RMSE are classified into with and without EKF which are exhibited with various models. At 45°C, LSTM+CNN shows a 99.99996%

reduction, and LSTM shows a 99.99968% reduction. At 25°C, LSTM+CNN shows a 99.99997% reduction, while at 0°C, LSTM shows an 84.1% reduction.A heatmap as in **Fig. 3** is used to visualize the performance metrics where darker shades indicate the best performance and the lighter shades represent the worst. Evaluating "with EKF " columns, LSTM, Bi-directional LSTM and XGBoost show consistent lower error rates. Random forest regressor and Support vector machine models exhibit mediocre performance all across the board.MLPRegressor along with the exponential smoothing models have higher error rates for both with and without EKF algorithm.

3.4. State of Power

The Mean Squared Error (MSE) values for different machine learning methods are displayed in **Table 3**, estimating the State of Power (SOP) of batteries at different temperatures. The values are displayed without and with the Extended Kalman Filter.

Table 3 Evaluation of estimation of State of Power

S.No	ML Method	45 °C		25 °C		0 °C	
		MSE W/O EKF	MSE W EKF	MSE W/O EKF	MSE W EKF	MSE W/O EKF	MSE W EKF
1	**LSTM**	2.28E-04	1.77E-04	2.10E-04	1.19E-08	5.19E-05	5.19E-05
2	**LSTM+CNN**	1.34E-01	2.23E-04	1.28E-01	6.78E-04	1.33E-01	2.48E-04
3	**Gradient Boost**	1.31E-04	1.28E-04	1.39E-04	1.30E-04	1.24E-05	1.68E-05
4	**Bi-directional LSTM**	1.47E-04	1.46E-04	1.48E-04	1.41E-04	2.46E-05	2.34E-05
5	**Random Forest Regressor**	1.86E-05	2.02E-05	2.09E-05	1.86E-05	8.53E-06	1.07E-05
6	**MLP Regressor**	3.88E-04	5.51E-04	6.07E-04	4.60E-04	1.69E-04	1.27E-04
7	**AdaBoost**	6.94E-02	6.59E-02	6.84E-02	6.33E-02	3.20E-02	3.16E-02
8	**XGBoost**	1.02E-03	9.85E-04	1.02E-03	9.85E-04	1.83E-03	1.82E-03

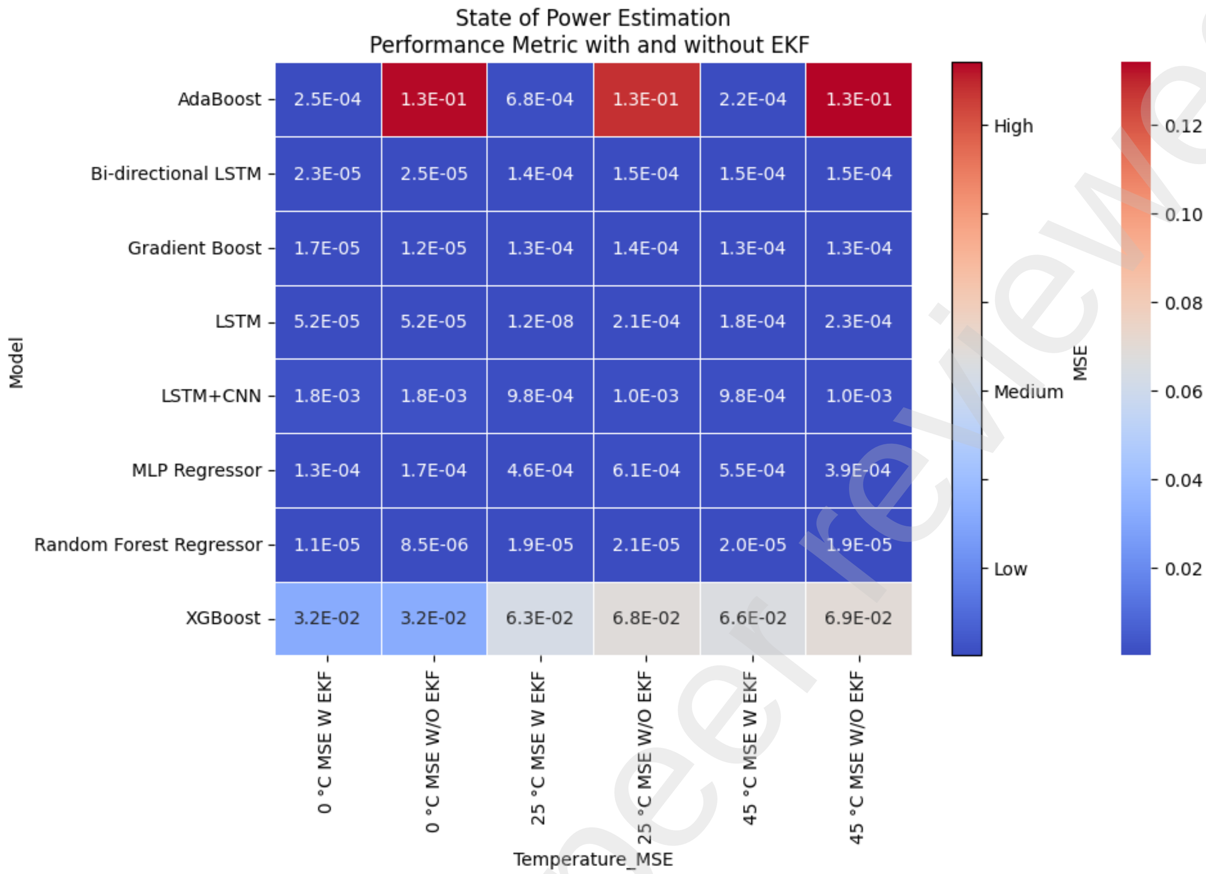

Fig 4 Heatmap of performance metrics for SoP estimation with and without EKF

LSTM along with EKF prevails as the superior model and shows consistent lower rates of error. From **Fig. 4**, Support Vector Machine and MLP Regressor exhibit higher error rates and thus are deemed less effective in discharge degradation estimation. Bi-directional LSTM performs better compared to XGBoost and AdaBoost with competent error rates. At 25°C, LSTM shows a 99.9999% reduction, and at 45°C, LSTM+CNN shows a 99.9998% reduction. Gradient Boost at 0°C shows a 98.6% reduction, while AdaBoost at 25°C shows a 7.5% reduction.

4. Conclusion

The primary objective of the work was to provide a framework that combines predictive modeling and time series forecasting with extended Kalman filter to have a more accurate estimation of battery parameters for the effective management of batteries in Electric Vehicles. Through rigorous testing and evaluation of performance metrics, it is clear that LSTM based models such as LSTM and two-way stacked LSTM, when combined with EKF, demonstrate superior prediction accuracy and the ability to explain data variability compared to other techniques. At 45 degrees, the average improvement in performance was 39.98% when EKF was used with ML models. The bidirectional LSTM model paired with EKF showed the biggest increase in performance at 62.80% improvement in accuracy at 45 degrees. At 25 degrees, the average increase in accuracy was 41.22% when the models were combined with EKF, with the bidirectional LSTM model showing an increase in accuracy of 88.52%. At 0 degrees, the average improvement in performance was noted to be 40.09%, with the bidirectional LSTM model showing an increase of 60.36% with the extended Kalman filter. Additionally, the LSTM-CNN technique with extended Kalman filter (LSTM-CNN-EKF) promises to accurately estimate SOH, thereby providing valuable insights into battery degradation patterns. In the future, further research could focus on improving the interpretability and generalizability of prediction models, exploring real-time data aggregation and integration techniques to estimate SOH dynamic in BMS applications.

5. References

[1] B. Saha and K. Goebel (2007). “Battery Data Set”, NASA Prognostics Data Repository, NASA Ames Research Center, Moffett Field, CA.

[2] Z. Yu, C. Xiaoping and Z. Yufeng, "The influence of coupling of charge/discharge rate and short term cycle on the battery capacity of Li-ion batteries," 2019 3rd International Conference on Electronic Information Technology and Computer Engineering (EITCE), Xiamen, China, 2019, pp. 469-473, doi: 10.1109/EITCE47263.2019.9095137.

[3] ShuXiang Song, September 18, 2019, "NASA", IEEE Dataport, doi: https://dx.doi.org/10.21227/fhxc-ga72.

[4] Wang, Zuolu, et al. "A novel method of parameter identification and state of charge estimation for lithium-ion battery energy storage system." Journal of Energy Storage 49 (2022): 104124.

[5] Zuolu Wang, Guojin Feng, Dong Zhen, Fengshou Gu, Andrew Ball, "A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles", Energy Reports, Volume 7, 2021, Pages 5141-5161, ISSN 2352-4847, https://doi.org/10.1016/j.egyr.2021.08.113.

[6] M.-S. Ko, K. Lee, J.-K. Kim, C. W. Hong, Z. Y. Dong and K. Hur, "Deep concatenated residual network with bidirectional LSTM for one-hour-ahead wind power forecasting", IEEE Trans. Sustain. Energy, vol. 12, no. 2, pp. 1321-1335, Apr. 2021.

[7] M. Zhang, Z. S. Li and Z. Liu, "Lithium-ion Batteries Capacity Fading Prediction Based on Sample Entropy and LSTM," 2022 Global Reliability and Prognostics and Health Management (PHM-Yantai), Yantai, China, 2022, pp. 1-5, doi: 10.1109/PHM-Yantai55411.2022.9941844.

[8] L. Wan et al., "Joint Estimation of State of Charge and State of Health and Fault Early Warning for Energy Storage Power Station based on Double Unscented Kalman Filter Algorithm," 2022 Power System and Green Energy Conference (PSGEC), Shanghai, China, 2022, pp. 137-143, doi: 10.1109/PSGEC54663.2022.9881130.

[9] Iurilli, Pietro, Claudio Brivio, and Marco Merlo. "SoC management strategies in battery energy storage system providing primary control reserve." *Sustainable Energy, Grids and Networks* 19 (2019): 100230.

[10] M. Saad, N. Munir and C. -H. Kim, "Pattern Recognition Based Auto-Reclosing Scheme Using Bi-Directional Long Short-Term Memory Network," in IEEE Access, vol. 10, pp. 119734-119744, 2022, doi: 10.1109/ACCESS.2022.3221818.

[11] Muhammad Saad, Nauman Munir, Chul-Hwan Kim. "Pattern Recognition Based Auto-Reclosing Scheme Using Bi-Directional Long Short-Term Memory Network", IEEE Access, 2022.

[12] Zuolu Wang, Xiaoyu Zhao, Lei Fu, Dong Zhen, Fengshou Gu, Andrew D. Ball, "A review on rapid state of health estimation of lithium-ion batteries in electric vehicles", Sustainable Energy Technologies and Assessments", Volume 60, 2023, 103457, ISSN 2213-1388,https://doi.org/10.1016/j.seta.2023.103457.