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RESEARCH ARTICLE

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

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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.

INDEX TERMS Battery management system (BMS), predictive modeling, time series analysis, trend prediction, long short term memory (LSTM), state of health (SOH), state of power (SOP).

I. 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 and prediction of parameters such as State of Health (SoH), State of Charge (SoC), State of Energy (SoE) and State of Power (SoP). Though there are several methods of estimating these parameters, it is crucial to predict these values in order to 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] ata 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

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examines how battery related variables alternate in time based patterns.

Research by [2] Yu et al. revealed that the capacity of Lithium ion batteries decreases with increasing charge/discharge cycles, suggesting lower current levels. Reference [3] Song et al. aimed to improve the BMS of electric vehicles by simplifying the estimation of SoC and SoE. References [4] and [5] Wang et al. found that while pulse transient testing (PTT) and electrochemical impedance spectroscopy (EIS) techniques are effective for offline SOH estimation of EV batteries, analyzing ultrasound transmission mechanisms and parameters can improve accuracy. References [6] and [7] Zhang et al.'s study shows a long short term memory (LSTM) model with rectified linear unit (ReLU) function for predicting lithium battery capacity and fading trend, but further validation with real-world data is needed. References [8], [9], [10], Ko et al.'s study developed a method combining Adaptive Kalman Filter (AKF) and electrochemical coulomb counting (ECC) for lithium-ion battery capacity estimation, achieving a 1.7% RMSE in SOH estimation. Reference [11] 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 machine learning (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 data, was used to test this 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.

II. METHODOLOGY

A. DATA SET READINESS

The dataset available in NASA website was considered for applying the proposed prediction algorithm. Since SoH must be estimated, the Li batteries considered should have almost lost their capacity. Hence the data considered for this study was that of batteries whose capacity had diminished to 1.4Ahr (30% fade), which means the batteries have gone through several thousand cycles.

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. The experimental cycles continued until the batteries reached their end-of-life (EOL), defined by a 30% reduction in nominal capacity (from 2 Ah to 1.4 Ah). Since SoH must be estimated near EOL, we have utilized data from cells with 30% capacity fade. Each cycle contains time-stamped data including voltage, current, temperature, and capacity measurements, as well as detailed impedance profiles such as battery impedance, current ratios, and estimated electrolyte resistance. Electrochemical impedance spectroscopy (EIS) was employed for impedance measurements, encompassing a frequency sweep from 0.1Hz to 5kHz. Additionally, Beijing Dynamic Stress Test (BJDST) has been conducted at both 50% and 80% battery levels. This enables testing non-linear load and current profiles. High-resolution impedance profiles allow for deeper insights into power capability, further validating the model under dynamic and resistive fluctuation conditions. The data available in the NASA website have been obtained from Arbin instrument. The method of acquiring the data has been given in Fig. 1.

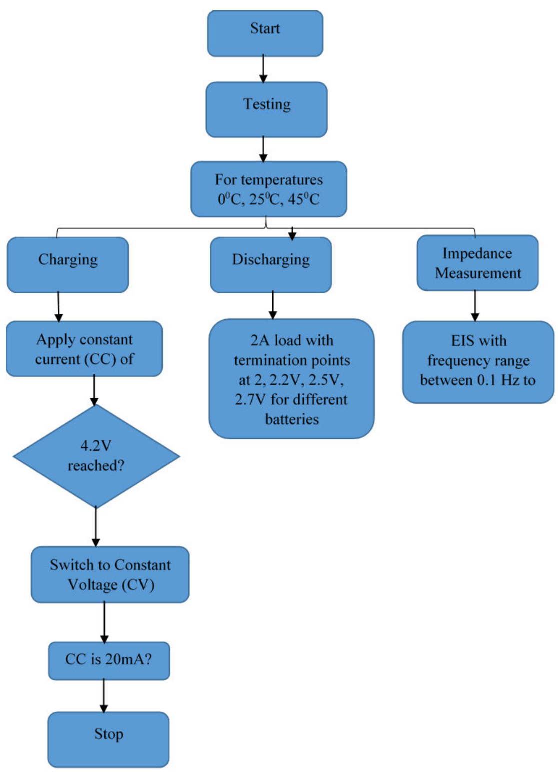

FIGURE 1. Procedure employed to obtain the data set for SoH prediction.

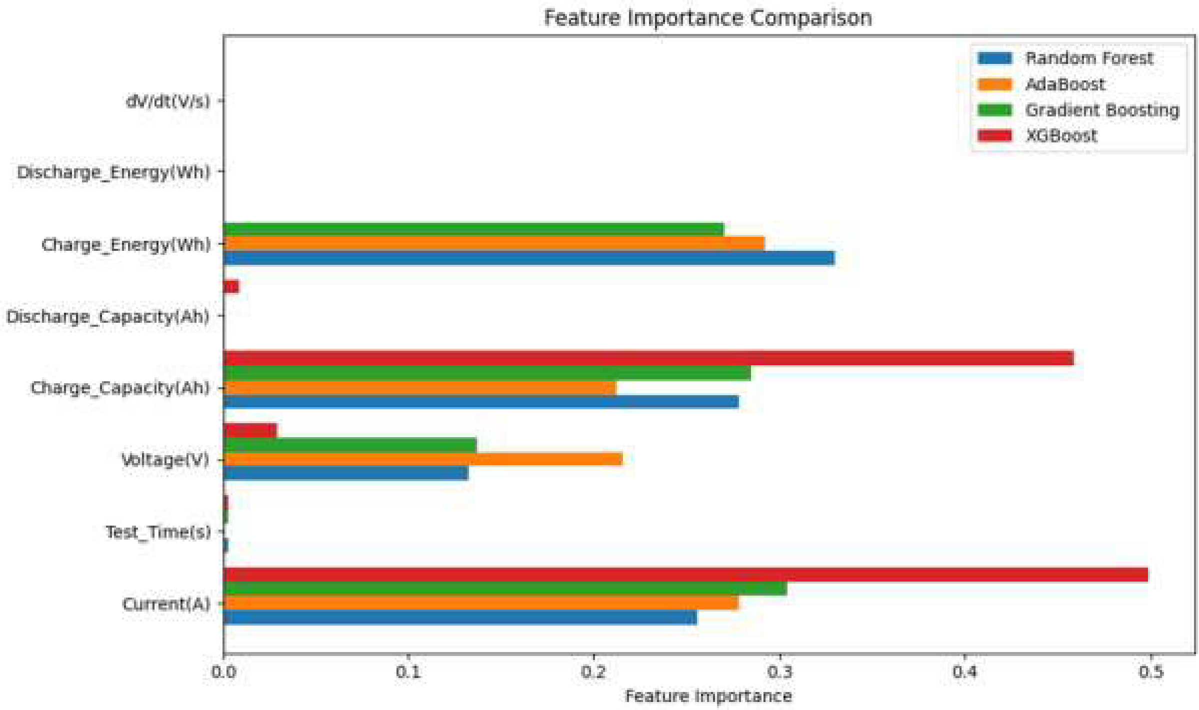

FIGURE 2. Feature importance graph for various parameters of the Li-ion battery: x axis explains the feature importance score and y axis represents the features for which the scores were obtained.

B. 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.

The feature-importance-score has been used for tree based models to ensure that each model received the best features and 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 observed from Fig. 2 that the feature importance graph shows varying priorities across models. Current has the lowest importance while Random Forest algorithm is used for parameter estimation, but it is the highest for XGBoost.

When XGBoost algorithm is to be preferred, voltage is least important but the same is most important 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. Hence, while using different algorithms for SoC, SoH and other parameter estimation, the most important features to be considered are current and charge capacity. Once the features have been finalized they are taken as inputs by machine learning (ML) algorithms to estimate various parameters.

The Extended Kalman Filter (EKF) was incorporated to refine parameter estimation by iteratively correcting model predictions using observed voltage measurements. The filter was initialized with an a priori state estimate and associated error covariance. The prediction step follows a simplified electrochemical discharge model represented by the relation:

$$x_t = x_{t-1} - I.\Delta t/C \tag{1}$$

where x_t denotes the predicted state at time t, I is the applied current, Δt is the sampling interval, and C is the nominal battery capacity, set to 2.1 Ah in this study. The error covariance matrix was updated at each iteration to incorporate process uncertainty, modelled as a small additive noise term.

The Kalman gain was computed to optimally weigh the discrepancy between predicted and observed states, enabling the correction of the a priori estimate. This recursive Bayesian framework enhances estimation robustness under sensor noise and temporal variability.

C. MACHINE LEARNING METHODS

In the proposed system machine learning models such as Random forest, MLP Regressor, AdaBoost, XGBoost and Deep learning models such as LSTM and Bi-directional LSTM have been chosen as mentioned in Fig. 2. [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] Let xn be one of the input data. The relationship between the data input xn at the time step n and the output On is represented by equation (2)

$$\begin{aligned} hnl &= gnl(Un \cdot xn + Wl \cdot hn - 1 + bx) \\ n &= gnK(VnK \cdot hnK + by) \end{aligned} \tag{2}$$

where gnK lth layer's function of activation at n, and l=1,2,. . . .,K. by and bx are the bias terms, VK, Wl and Un represent the metrics of weight, and hnl denotes lth layer with state vector. In order to minimize the loss function L(On, yn), (where yn 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 (EKF), 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. EKF is considered her along with machine learning methods because the former is very efficient in terms of parametric predictions and is being used as a part of algorithms in battery management systems (BMS) available in the market. Using ML models along with EKF would provide time-to-time prediction of battery parameters and early assessment of health of the battery. Hence, decisions w.r.t replacing, upscaling or second life usage of the batteries can be made earlier.

1) LSTM-EKF

Voltage, current and charge capacity are the battery system's fundamental dynamics and SoC and SoH are the state variable that 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. The LSTM network used in this study was designed as a single-layer sequence regression model to capture temporal dependencies in the input features, as depicted in Fig. 3. Prior to training, all input variables were standardized using a StandardScaler, and the data was reshaped into a three-dimensional format to match the input requirements of LSTM networks. The architecture consists of a single LSTM layer with 50 hidden units and no return sequences, followed by a dropout layer with a dropout rate of 0.2 to reduce overfitting. A final dense layer with one output unit was used to produce the continuous prediction of the target variable. The model was trained using the Adam optimizer with a learning rate of 0.001, the mean squared error (MSE) as the loss function, a batch size of 32, and a maximum of 100 epochs. Early stopping was applied to prevent overtraining and ensure generalization performance.

A fusion strategy combines the outputs of the EKF module (state estimates) with the LSTM model. 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) 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 Bidirectional Long Short-Term Memory (BiLSTM) 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.

The Bidirectional LSTM (BiLSTM) model in this study was structured to capture both forward and backward temporal dependencies in the input data. The architecture comprised two stacked Bidirectional LSTM layers: the first with 50 units to propagate temporal information across the sequence, and the second with 50 units to output a fixed-size vector. A dropout layer with a rate of 0.2 was placed between the two BiLSTM layers to mitigate overfitting. The final output layer was a single-unit dense layer to produce continuous predictions. The model was compiled using the Adam optimizer and mean squared error (MSE) as the loss function, and it was trained using the standardized, reshaped input data in a supervised regression setting.

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.

3) LSTM-CNN

The computational neural networks (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.

D. MATHEMATICAL MODEL OF LSTM+EKF

The mathematical model of the proposed LSTM+EKF can be given broadly as below. Let the variables considered be

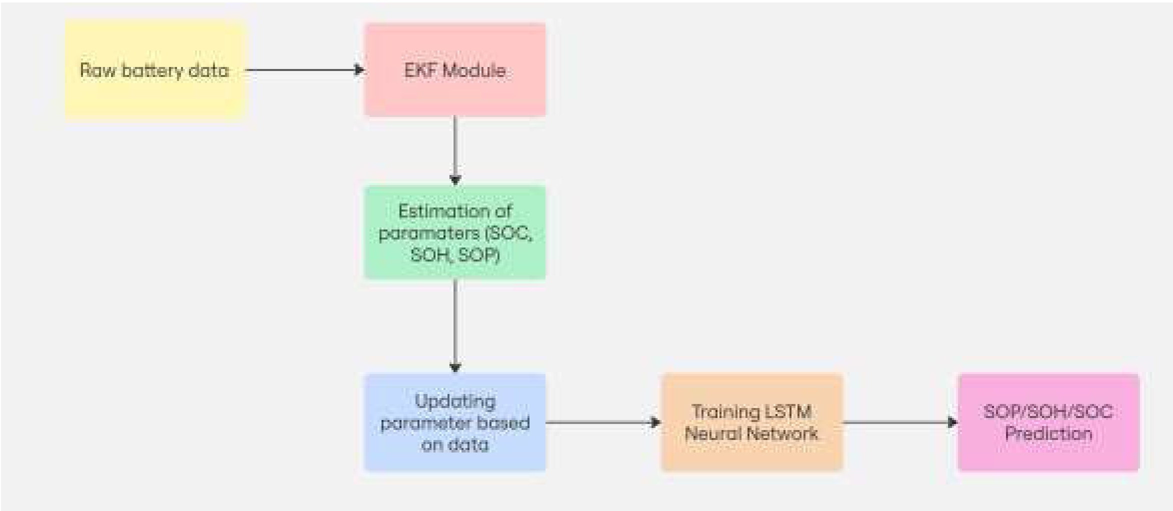

FIGURE 3. Flowchart of usage of data in LSTM+EKF model, for training and acquiring the battery parameters.

as follows:

$$W = \begin{bmatrix} W_f \\ W_i \\ W_c \\ W_o \end{bmatrix}, \quad b = \begin{bmatrix} b_f \\ b_i \\ b_c \\ b_o \end{bmatrix}, \tag{3}$$

where, W indicates the weight, b indicates biases, f indicates forget gate, i indicates input gate, c indicates cell input, o indicates output gate. Computation of all the pre-activations can be expressed in vector form as:

$$X_k = \begin{bmatrix} f_t \\ i_t \\ \tilde{c}_t \\ o_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ tanh \\ \sigma \end{bmatrix} (Wz_t + b) \tag{4}$$

LSTM part ends here where the state vector has been obtained. Now, EKF will be applied to this state vector to estimate, predict and update the state, thereby increasing the efficiency of the algorithm. Application of EKF on the state vector can be expressed as follows:

$$\widehat{X}_{k|k-1} = f\left(\widehat{X}_{k-1|k-1}, u_{k-1}\right) \tag{5}$$

Once the state estimation has been completed, the update and covariance update is carried out as per the EKF procedure. These updates contribute to the precision in estimation and prediction of this hybridization strategy.

E. PROPOSED SYSTEM

The proposed system consists of combined LSTM and EKF and the necessary libraries such as keras, statsmodels, sklearn etc are imported. As explained in Fig. 4, the data is pre-processed through standard scaling, the missing values are imputed and the categorical values are encoded. The EKF class is initialized with transition matrix, observation matrix, state mean, state covariance, observation covariance, transition covariance, then the filter is defined.

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. 4, 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), Mean Squared Error (MSE), 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 and Multilayer Perceptron (MLP) 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

TABLE 1. Network specifications for different deep learning models used to estimate the battery parameters.

Model	Architecture	Parameters
LSTM	2stacked LSTM layers + Dropout + Dense	units=50, dropout=0.2, epochs=100, batch_size=32, optimizer=Adam(0.001)
Bi-LSTM	2 Bidirectional LSTM layers + Dropout + Dense	units=50, dropout=0.2, epochs=100, batch_size=32, optimizer=Adam(0.001)
LSTM+CNN	Conv1D → MaxPooling1D → LSTM → Dense	filters=64, kernel_size=2, LSTM units=50, dropout=0.2, optimizer=Adam(0.001)
MLP Regressor	Fully connected feedforward neural network (1 hidden layer)	hidden_layer_sizes=(100,),activation='relu', max_iter=500, solver='adam'

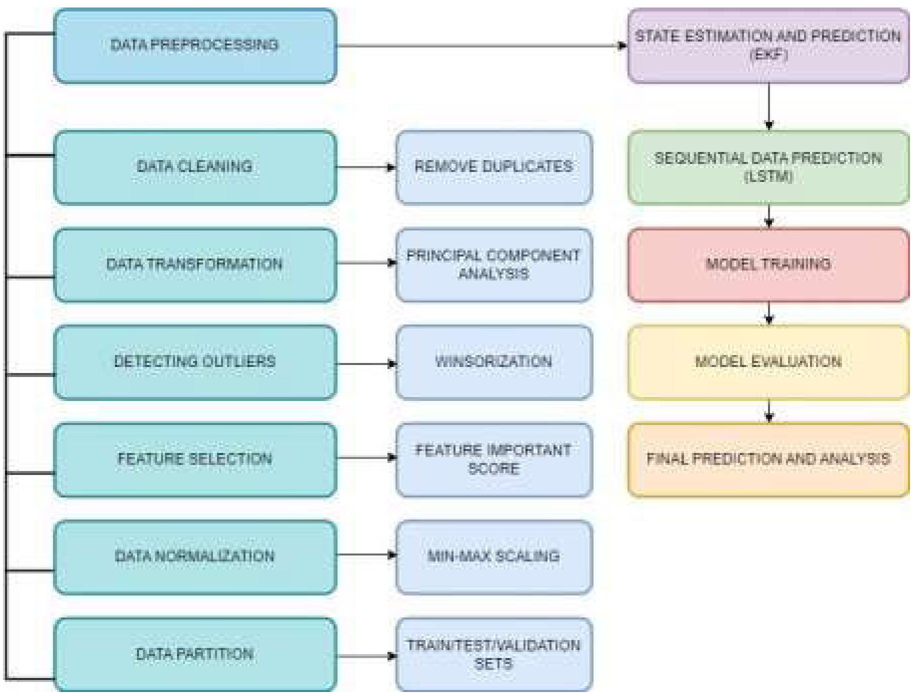

FIGURE 4. This flowchart highlights the various processes involved in the proposed ML based technique.

criterion in which the Holt-Winters method uses level, trend and seasonality.

Then both the machine learning models (LSTM, Bi-LSTM, MLP Regressor, AdaBoost, XGBoost) and time series forecasting models (simple, double, triple exponential smoothing models using Holt-Winters method) are evaluated using performance metrics such as MSE, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The results and the performance metrics are then visualized for further examination. The new systemintegrates an 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.

III. RESULT AND DISCUSSION

A. 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, Bi-LSTM, 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). Ensemble-based methods, such as Random Forest and Gradient Boosting, also demonstrated competitive estimation fidelity, particularly when augmented with EKF—although

TABLE 2. Comparison of various models with respect to runtime and memory requirement.

Model	Time (in seconds)	Peak Memory Usage (in MB)
LSTM	306.6	8.10
BiLSTM	456.2	12.41
LSTM-CNN	313.76	8.03
MLP Regressor	31.59	1.12
AdaBoost	0.97	2.02
RandomForest	4.54	1.27
Gradient Boosting	4.14	7.47
XGBoost	0.19	0.4

AdaBoost and XGBoost exhibited lower accuracy in select conditions, highlighting the necessity for algorithm-filter co-design.

- From a systems deployment perspective, XGBoost achieved the most favorable computational profile, requiring only 0.19 seconds of training time and consuming just 0.4 MB of memory, thus rendering it highly suitable for resource-constrained embedded Battery Management Systems (BMS).
- AdaBoost and Gradient Boosting also exhibited minimal computational overhead, making them viable candidates for real-time edge inference.

In contrast, while Bi-LSTM and LSTM+CNN architectures offer high predictive fidelity, their elevated training times (up to 456 s) and memory requirements (>8 MB) could present challenges for real-time deployment without further optimization through quantization, pruning, or hardware acceleration.

The experimental results demonstrate that Long Short-Term Memory (LSTM) and Bi-directional LSTM (Bi-LSTM) architectures exhibit superior predictive performance across a spectrum of thermal operating conditions. Specifically, the LSTM model integrated with an Extended Kalman Filter (EKF) attained a mean squared error (MSE) as low as $1.13 \times 10 6$ at 25 °C, while the Bi-LSTM–EKF hybrid consistently preserved low error bounds across extreme ambient temperatures.

The LSTM+CNN configuration further validated the efficacy of hybrid deep learning structures, maintaining robustness under high-variance thermal regimes (e.g., 0 °C and 45 °C). The hybrid EKF–LSTM framework demonstrates compelling potential for accurate, noise-resilient battery parameter estimation by effectively combining data-driven temporal learning with model-based recursive filtering.

The results motivate a dual-tier deployment architecture.

- For real-time, on-board BMS applications, lightweight tree-based models (e.g., Random Forest or Gradient Boosting) integrated with EKF offer an optimal balance between computational efficiency and estimation accuracy.
- Meanwhile, high-capacity architectures such as Bi-LSTM and LSTM+CNN are better suited for centralized, cloud-based analytics tasks including high-resolution SoH and SoP forecasting or fleet-wide diagnostics where real-time constraints are relaxed.

B. STATE OF CHARGE (SOC)

Table 3 compares 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. Examining the SOC estimation as in Table 3 and MSE heatmap as in Fig. 5, 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.

C. 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 4. 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.

In Table 4, 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 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. 6 is used to visualize the performance metrics where darker shades indicate the

TABLE 3. Estimation and evaluation of state of charge for various temperatures and errors.

	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	RandomForest 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

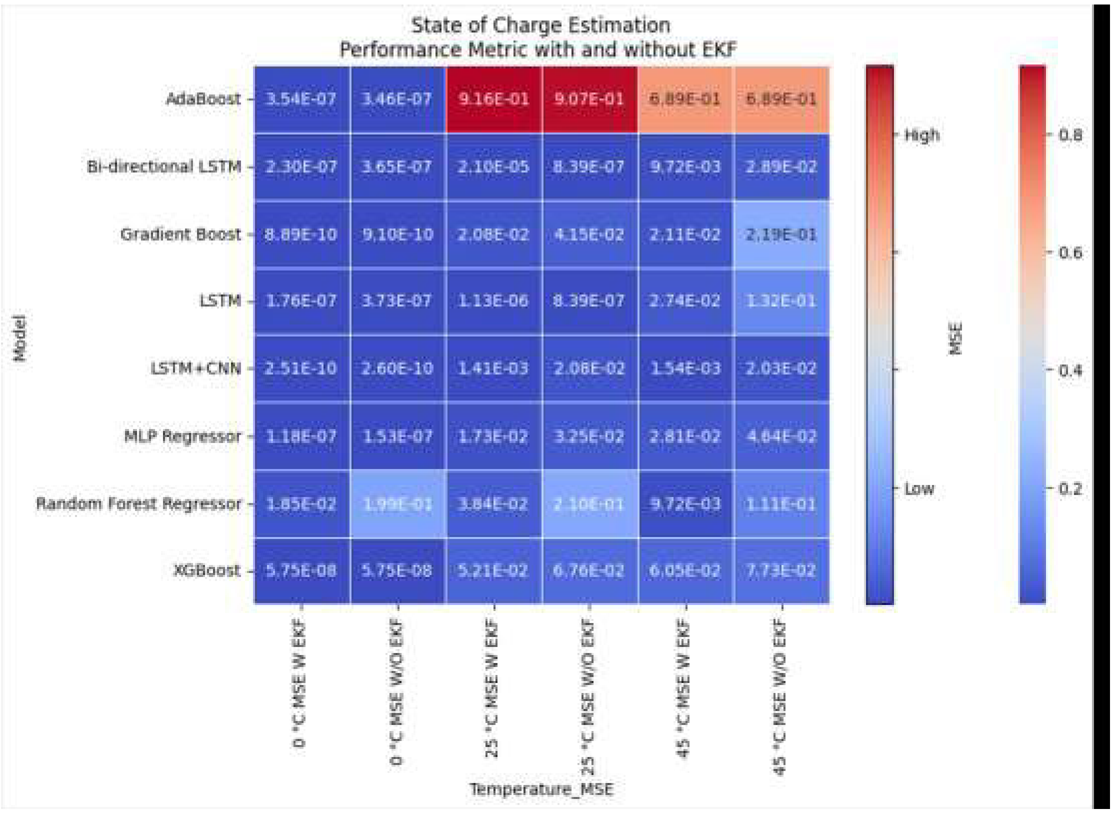

FIGURE 5. Heatmap of performance metrics for SoC estimation with and without EKF.

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.

D. STATE OF POWER

The Mean Squared Error (MSE) values for different machine learning methods are displayed in Table 5, estimating the State of Power (SOP) of batteries at different temperatures. The values are displayed without and with the Extended Kalman Filter.

- LSTM along with EKF prevails as the superior model and shows consistent lower rates of error. From Fig. 7, Support Vector Machine and MLP Regressor exhibit higher error rates and thus

TABLE 4. Estimation and evaluation of state of health for various temperatures and errors.

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

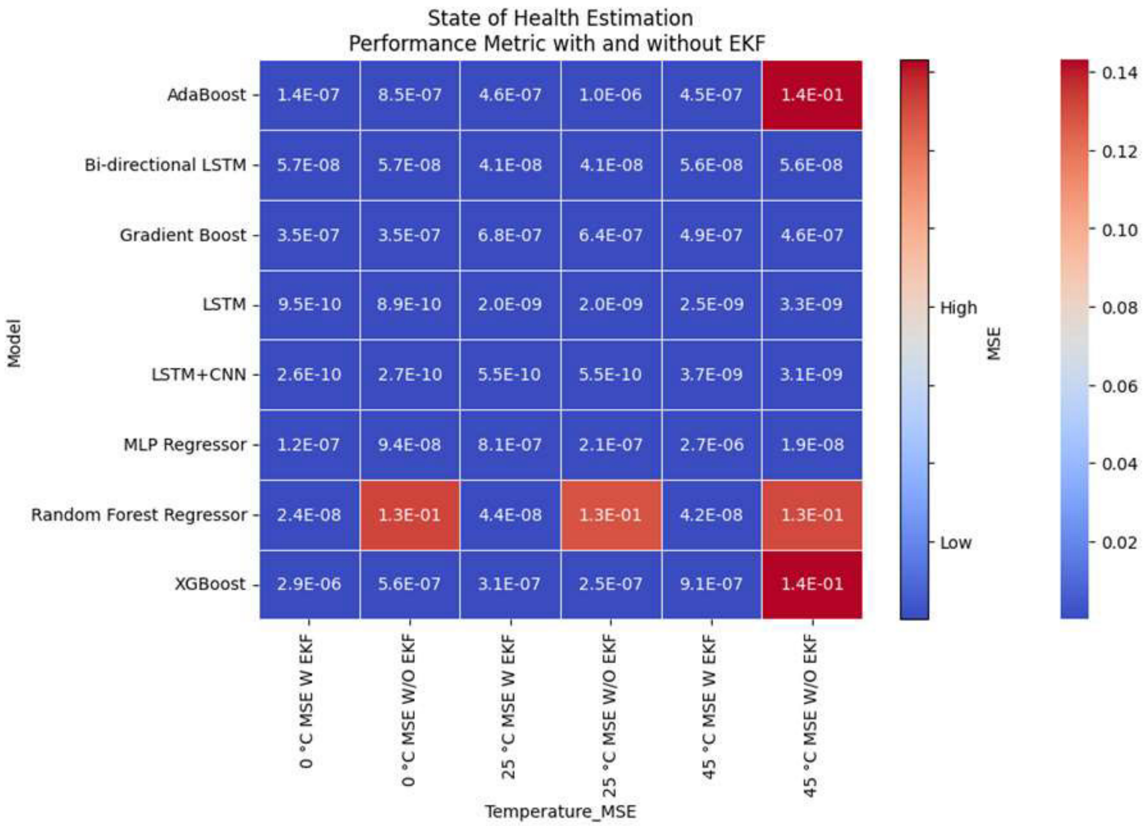

FIGURE 6. Heatmap of performance metrics for SoH estimation with and without EKF.

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.

E. EVALUATION IN TERMS OF RUNTIME COMPARISON WITH VARIOUS MEMORY UNITS

The proposed LSTM+EKF algorithm will be incorporated in a battery management system (BMS) for monitoring of realtime SoC, SoH and SoP values. These BMSs have micro-controller units (MCUs) that run the algorithm and save data for processing. Hence it is crucial to evaluate the performance of the proposed algorithm with respect to the memory capacity of various MCUs. Table 6 gives an insight on the different runtimes of the proposed and existing algorithms for different

TABLE 5. Estimation and evaluation of state of power for various temperatures and errors.

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

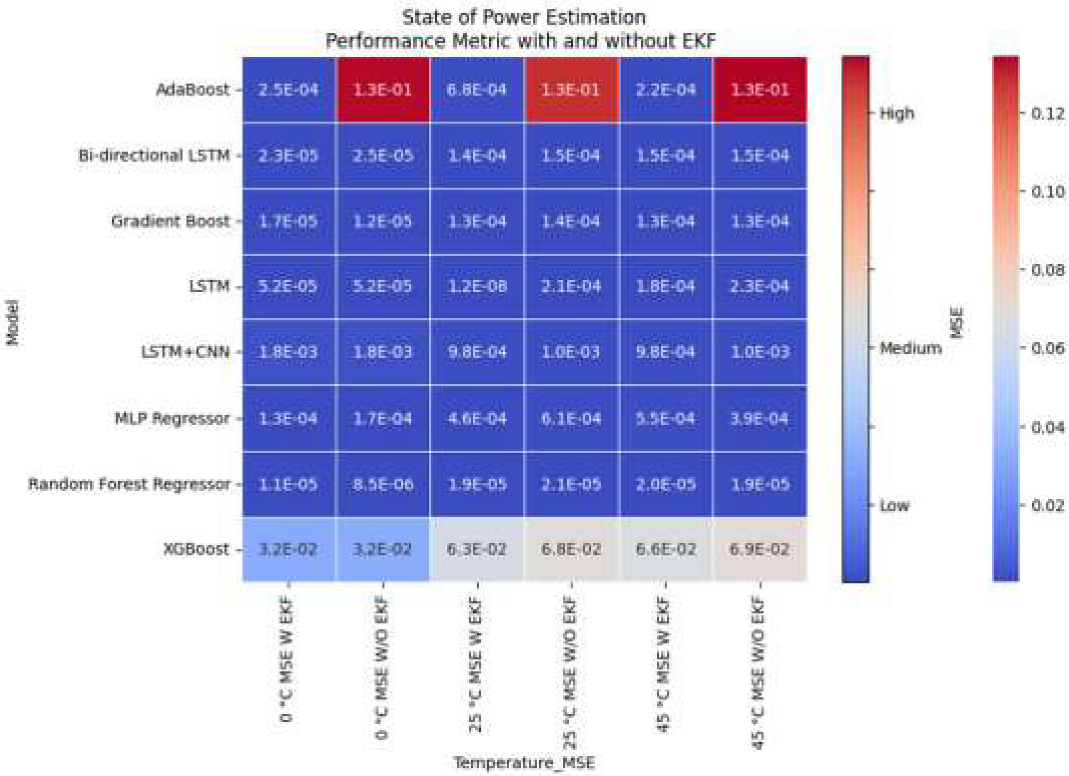

FIGURE 7. Heatmap of performance metrics for SoP estimation with and without EKF.

RAM capacities of MCUs from a minimum of 1GB to a maximum of 16GB.

- It can be observed that LSTM with EKF takes a maximum of 2.435 s with 1 GB and a minimum of 0.1517 s with 16 GB RAM.
- The least runtime has been exhibited by AdaBoost model with a maximum of 0.0302 s for 1GB RAM to a minimum of 1.89 ms for 16GB RAM.
- Compared to other algorithms in Table 6, LSTM+EKF shows higher runtime since occupies higher memory space as given by Table 2.
- But it can also be noted that though the run time is higher for LSTM+EKF, the time is in terms of seconds which can definitely be affordable as far as currently available BMSs in market are concerned.
- Also, it gives higher accuracy and efficiency with less errors. Hence, LSTM+EKF is one of the best models to estimate battery state parameters in real time in electric vehicles.

The Extended Kalman Filter (EKF) step involves low-dimensional matrix operations (state vector of size 2, covariance updates, and a scalar measurement update). In the

TABLE 6. Comparison of runtime for various algorithms with different memory availabilities.

S. No.	Models with EKF/RAM	Runtime in (s) 1GB	4GB	8GB	16GB
1	**LSTM**	2.435	0.606	0.3035	0.1517
2	**LSTM+CNN**	5.53	1.381	0.6906	0.3453
3	**Gradient Boost**	2.46	0.615	0.3077	0.1539
4	**Bi-directional LSTM**	0.035	8.64m	4.32m	2.16m
5	**Random Forest Regressor**	1.9m	0.4m	0.24m	0.119m
6	**MLP Regressor**	5.63m	1.41m	0.71m	0.35m
7	**AdaBoost**	0.0302	7.55m	3.78m	1.89m
8	**XGBoost**	1.62	0.40m	0.202m	0.101m

proposed implementation, each iteration required approximately 0.8–1.2 ms on a standard CPU (Intel i7, 16 GB RAM), with a peak memory footprint of <1 MB. This computational overhead is negligible compared to LSTM training and makes EKF highly suitable for real-time BMS deployment. The LSTM–EKF hybrid can therefore be implemented such that the LSTM provides predictive trends offline or on dedicated hardware, while EKF ensures lightweight real-time correction onboard.

For heavy vehicles and fleet of vehicles, the data obtained from every single cell, that is connected in series, in each module or the whole battery pack will be given as input to the LSTM+EKF algorithm. The runtime of all the mentioned algorithms would increase but since the LSTM and EKF combination has higher efficiency and lower error, the decision making process in BMS would not contain errors and hence many batteries-related accidents might be avoided in prior.

IV. FUTRE WORK AND DISCUSSION

The current framework of algorithm with LSTM and EKF was evaluated to find the battery parameters for a single cell. However, industrial deployment in electric vehicle fleets or stationary storage systems demands horizontal and vertical scalability. Since for a single cell the algorithm has been effective, the same can be extended to address modeling across battery packs, modularized learning for different battery types, and distributed processing across edge and cloud platforms. Noise and cyber security modules can calso be added as a part of the algorithm for higher integrity. For real-time integration, the trained LSTM model can be exported via ONNX or a similar platform for deployment on micro-controllers (MCUs). These MCUs can be connected with adaptive coding and modulation (ACM) and digital coding and modulation (DCM) modules for wireless communication of data. In future, plan is to implement the proposed hybrid model on low-cost embedded hardware and benchmark runtime performance and other metrics for real-world input stream conditions.

V. 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. Also, LSTM technique provides a runtime of 0.157 sec with 16 GB RAM which might be of great use when large real-time data is being communicated on-the-fly. 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 for different battery chemistries dynamically in BMS applications.

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