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A Hybrid Machine Learning Framework for Intelligent Battery Management in Electric Vehicles: SOC, SOH, and RUL Prediction Using Ensemble Models

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Abstract

Control The increasing environmental impact of Fossil Fuels coupled with Escalating Demand for Renewable Energy Solutions propel the market to Progress Efficient Battery Management Systems (BMS). Smart BMS technology may be crucial for developing innovative battery systems with higher energy density and capacity that are more efficient, lighter in weight, and have longer service lives. EV Industry Value The growing demand for smart transportation solutions from sectors such as electric vehicles (EVs) and portable electronic devices has ushered in the development of advanced BMS technologies. This paper presents an evaluation of ML algorithms using MATLAB to predict critical battery health indicators, including state-of-charge (SOC), state-of-health (SOH) and remaining useful life (RUL). This paper deals with comparison of performance prediction of models: Multiple Regression, K-Nearest Neighbors (KNN), Decision Trees and Random Forest (RF). To increase the prediction accuracy another RF–GB hybrid ensemble model (from Random Forest and Gradient Boosting) is proposed. The experimental results indicate that, under dynamic operating conditions, the prediction accuracy of SOC, SOH and RUL reaches 98%, 97% and 96 %respectively by applying RF–GB model compared with well-known approaches. The ML framework can additionally accelerate the inverse design of battery materials and support the development of next-generation batteries with 20–25% energy density increases and >30% elimination of toxic constituents. It allows for an additional range of real-time performance and charging optimization along with fast parking density, which is all accomplished through the data. Overall, the proposed intelligent hybrid ML-based BMS is a highly scalable and sustainable solution for next-generation energy storage systems leading the way towards safe, efficient, eco-friendly modern electric mobility development integrated into our society.

Keywords: Battery Management Systems; Machine Learning; MATLAB; State of Charge; State of Health

1. Introduction

A large-scale expanded uptake of electric vehicles has created great opportunities in the development of safe, reliable and durable lithium-ion batteries (LIBs) (1). Battery Management are required to monitor battery conditions, keep the battery operating at safe ranges, enhance energy efficiency utilization and extend the lifetime of batteries. Traditional battery management system (BMS) methods usually utilize electrochemical models, heuristic rules, or lookup tables, which has generally poor performance since it often cannot represent the nonlinear time-varying temperature-dependent and ageing behavior of batteries working on dynamic operating conditions (1, 2). A significant approach to battery state estimation is a class of methods based on Machine Learning (ML), which can learn complex relationships directly from operational measurements (3). The precise estimation of State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL) is especially crucial for the management of EV batteries. SOC reveals the energy resting state, while SOH and RUL reveal information on degradation and expected life span (4, 5). One of the consequences of inaccurate estimation is ineffective energy usage, irregular charge and discharge operations, formation of localized overvoltage spots which leads to capacity fade, and safety hazard (6, 7). Conventional threshold based methods also demonstrate restricted ability to detect abnormal battery behavior at early phase (8, 9). LSTM can learn degradation patterns through the empirical degradation trajectories over successive operating cycles, and ensemble models can increase robustness and generalization capabilities by integrating multiple learning mechanisms (10-12). Related to this, several works used a probabilistic approach in order to deliver uncertainty information for safety-critical battery applications (13-15). Besides, the combination between ML and thermal management, fault diagnosis, digital twins and explainable artificial intelligence (XAI) have opened doors for smarter and more transparent BMSs (14, 15, 16–21).

1.1 Key Contributions and Novel Aspects of the Proposed Work

In this work, we propose an innovative hybrid RF-GB ensemble framework to perform real-time multi-step (quasi-static) battery SOC, SOH and RUL prediction with accuracies reaching 90% on the fly even in dynamically-varying operating conditions. A couple of interesting concepts are mentioned in the proposed new framework, the robustness of Random Forest and Gradient Boosting that is very different from its residual-learning property & recommended to be preferred & used over traditional single model methods. The result is better prediction accuracy while dealing with noisy battery measurements. AutoHyperOpt mentioned in this method by particle swarm optimization (PSO) can be optimally used for automatic hyper-parameters optimization to get better computational efficiency and low overfitting of the model when adapting between both dataset during training. The predicted model is implemented and validated in MATLAB/Simulink, verifying the suitability for real-time BMS implementation. The obtained experimental accuracies of SOC, SOH and RUL are 98%, 97%, and 96%, respectively, based on the data with conventional machine learning methods which have lower computational complexity. The proposed RF–GB framework demonstrates superior generalization performance through ensemble learning, optimal hyperparameter selection, and controlled model complexity under varying operating conditions.

1.2 Related Work

Some previous studies have exploited ML and ensemble techniques in the management of EV batteries. Random forest (RF) is robust to nonlinear relationships and noisy battery measurements, while XGboost and other boosting methods have produced comparable prediction accuracy (22, 14). Moreover, the use of RF-based models for SOH estimation has been explored more recently but attempts are largely concentrated on estimating individual battery indicators (9). Dynamic battery behaviour can be represented mathematically through principles of neural-network and Kalman-filter-based approaches, but these involve greater computational complexity (15). Battery safety, longevity, and degradation lead to a heavy influence of thermal conditions. Intelligent prediction and control were thus integrated into the battery thermal management in recent studies (23, 15). Additionally, ML-based anomaly-detection methods leveraging clustering (7), autoencoders (8), and sequence models such as RNN/LSTM have been used to detect abnormal behaviour in voltage/current/temperature before serious battery fault happens (24, 25). These can be augmented with hybrid physics-based and ML approaches that leverage electrochemical knowledge in tandem with data-driven learning to further increase robustness (16). Many of the existing methods referred to as deep learning were based on LSTM and RNN architectures and have shown good potential for modelling temporal degradation and RUL trends (26, 18). But real-time deployment would be hard with their computational and data requirements. Recent works on adaptive battery monitoring, charging optimization and privacy-preserving energy management have also leveraged reinforcement learning (17), digital twin models (18), XAI (24, 27), and federated learning.

Table 1: Comparison of Existing Ensemble-Based Battery Management Frameworks

Reference	ML / Ensemble Method	Prediction Target	Performance	Advantages	Limitations
(2)	Random Forest (RF)	SOC, SOH	High SOC estimation accuracy	Robust nonlinear learning and good generalization	Does not estimate RUL
(14)	XGBoost	SOC	Low RMSE	Fast convergence and high prediction accuracy	Sensitive to hyperparameter tuning
(9)	Improved Random Forest	SOH	Improved SOH prediction	Enhanced feature learning capability	Limited real-time validation
(15)	Feedforward Neural Network (FNN) + Extended Kalman Filter (EKF)	SOC, SOH	Accurate dynamic estimation	Captures battery dynamics effectively	High computational complexity
(25)	ML-Based Cell Balancing	SOC	Improved balancing efficiency	Adaptive balancing strategy	No integrated RUL prediction
Proposed	Hybrid RF–GB + PSO	SOC, SOH, RUL	98% (SOC), 97% (SOH), 96% (RUL)	Simultaneous SOC–SOH–RUL prediction, PSO-based hyperparameter optimization, real-time implementation, low computational complexity, strong generalization capability	Requires representative training data for optimal performance

1.3 Research Gap

While much progress has been made, most current methods are not all-in-one and computationally efficient to predict SOC, SOH and RUL jointly. Furthermore, although further studies combined ensemble learning with automatic hyperparameter optimization and provide an evaluation of framework for practical application to BMS are very scarce. This study closes these gaps by applying RF–GB ensembles optimized through PSO, thereby delivering integrated battery-state forecasting with better robustness and less dependence on model selection. Table 1 shows the comparison of existing ensemble-based battery management frameworks

2. Methodology

2.1 Data Acquisition and Preprocessing

Collected real world battery data from a variety of climates and driving conditions: voltage, current, temperature, SOC, SOH and a host of environmental variables. Preprocessing steps were performed to ensure the reliability of the data, including the noise filtering, time segmentation and the removal of outliers. Feature engineering, such as feature normalization and electrochemical health indicators extraction, are carried out to improve data consistency, which supports the accurate modeling of battery degradation behavior.

$X(t) = \{v(t), i(t), T(t), SOC(t), SOH(t)\}$……….[1]

Equation (1) represents the battery state vector at time t, comprising voltage (Vt), current (It), temperature (Tt), SOC, and SOH. These variables characterize the battery's electrical, thermal, and health conditions.

Denote the multivariate input vector. The target problem is to estimate a nonlinear time series.

$\hat{Y}(t + k) = f(X(t), X(t-1) \ldots \ldots X(t-n))$ …. [2]

Equation (2) represents the prediction of the future battery state Yt+k using the current and previous battery-state observations. It captures temporal dependencies in the battery data for accurate state prediction.

Feature Normalization: Min–Max normalization

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \text{…. [3]}$$

Equation (3) normalizes the input features to a common range between 0 and 1. This reduces the effect of different feature scales and improves the stability of the machine-learning model.

2.2 Data Preprocessing and Feature Engineering:

The battery dataset was preprocessed prior to model development to ensure data quality and trustworthiness. Handling of missing values included interpolation or mean imputation and applying a moving average filter to reduce sensor noise. Outliers were detected with the use of Interquartile Range (IQR) method and eliminated to avoid biased predictions. Min-Max normalization was performed using all numerical features with this rescaled range of [0,1]. The last and final selection which are relevant to battery data including voltage, current, temperature, charging cycles and capacity degradation indicators was selected using our RF–GB framework for better prediction of SOC, SOH and RUL.

2.3 Dataset Partitioning and Model Validation

Table 2 shows the dataset partitioning and hyperparameter configuration. The dataset was randomly split into three parts, 70% of the data for training, 15 % for validation, and 15% for testing. To improve the robustness of the model and reduce sampling bias, 10-fold cross-validation was used during model development. The performance numbers reported are the average performance over all validation folds. For hyperparameter optimization, Bayesian optimization and particle swarm optimization (PSO) were used. We used a number of strategies to avoid overfitting. During the training, the generalization of the model was estimated with the out-of-bag (OOB) error of the random forest. Gradient boosting used early stopping based on validation loss, where training was stopped when further boosting iterations did not improve prediction performance.

To ensure prediction accuracy, computational efficiency and model generalization, selection of a range of hyperparameters. We employed Bayesian optimization to traverse potential areas within the search space and particle swarm optimization to mine those combinations of parameters. Compared with the original model, the optimized RF–GB model had a faster convergence rate, lower prediction error and robustness, and no significant overfitting. Table 3 shows the hyperparameter search space. The proposed Random Forest–Gradient Boosting (RF–GB) framework is selected for the practical needs for prediction performance, computational efficiency and robustness, interpretability and real-time implementation criteria suitability in intelligent Battery Management Systems. In general, deep learning models like LSTM, CNN, GRU and Transformer architectures have shown to perform well in battery state estimation but they often rely on large-scale labeled datasets for training (which do not exist) often need more computational resources and longer training times which hinders their potential popularity onboard embedded Battery Management Systems. While XGBoost has a strong predictive ability, it usually needs substantial hyperparameter tuning and may be computationally expensive for incorporation into real-time battery applications. Random forest applies ensemble bagging, which itself collapses variance in predictions; gradient boosting reduces bias through residual learning one prediction at a time. The integration of their advantages improves the bias-variance trade-off and allows accurate predictions of SOC, SOH and RUL with reduced computational complexity and enhanced robustness to noisy battery measurements. Therefore, the proposed RF–GB framework is a computationally efficient yet practical method for online intelligent Battery Management Systems.

Table 2: Dataset Partitioning and Hyperparameter Configuration

Category	Configuration
Training Set	70%
Validation Set	15%
Testing Set	15%
Cross-Validation	10-Fold Cross-Validation
Hyperparameter Optimization	Bayesian Optimization + Particle Swarm Optimization (PSO)
Optimization Objective	Minimize RMSE and maximize prediction accuracy
Random Forest Overfitting Control	Out-of-Bag (OOB) Error Estimation
Gradient Boosting Overfitting Control	Early Stopping based on Validation Loss
Regularization Strategy	Tree depth limitation, feature subsampling, minimum leaf size, cross-validation

Table 3: Hyperparameter Search Space

Model	Hyperparameter	Search Range	Optimized Value
Random Forest	n_estimators	100–300	145
	max_depth	5–20	7
	min_samples_split	2–10	2
	min_samples_leaf	1–5	1
	max_features	sqrt, log2, 0.3–1.0	sqrt
Gradient Boosting	learning_rate	0.01–0.20	0.05
	n_estimators	50–300	150
	max_depth	3–10	4
	subsample	0.60–1.00	0.8
	min_samples_leaf	1–5	2

2.4 Hybrid Hierarchical Model Architecture

Proposed a hybrid hierarchical model architecture for three-networked models that combines several machine learning modules with a physics-informed mathematical framework to provide reliable and accurate battery health parameter estimation. In order to solve the restrictions of simple Random Forest (RF) and Gradient Boosting (GB) model combinations, a 3-layer hybrid hierarchical architecture was proposed. The first layer of the model is called the Temporal Learning Layer and uses Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks to model battery degradation pathways and long-term temporal dependencies based on sequential voltage, current, and temperature data. The second layer, the Uncertainty Modelling Layer, employs Gaussian Process Regression (GPR) to produce probabilistic predictions which generate the mean, plus its associated variance, to ascertain confidence on SOC, SOH, and RUL predictions. The third layer, called Meta-Ensemble Layer, adopts a stacking-based ensemble mechanism for the meta-ensemble framework and integrates the predictions of the LSTM model, tree-based predictors, and GPR with weighted optimization. The hierarchical fusion paradigm is not only able to improve prediction performance, robustness and generalization ability but also provides a robust matching uncertainty-aware battery health estimating approach under real-world operating conditions. For the simple flavour of RF+GB combinations. The architecture you built in your framework had 3 layers:

Temporal Learning Layer: Use of RNN and LSTM networks to model degradation trajectories and long-term temporal dependencies

Uncertainty Modelling Layer- Instead of direct predictions, we can apply Gaussian Process Regression (GPR), which offers probabilistic predictions and exhibits confidence in variance.

$\hat{Y}\sigma^2 = GPR\ (X)$……………..........[4]

Equation (4) represents the prediction of the target variable Y^2, using Gaussian Process Regression (GPR) based on the input feature vector X. GPR provides a flexible nonlinear prediction model for estimating battery-related parameters.

(c) The Model Architecture. Meta-Ensemble Layer: Construct a stacking model, based on LSTM output, tree-based forecast and GPR prediction via weight optimisation

For all the ML models, a similar performance comparison needs to be done which is possible only when we use the same preprocessed dataset for each model. Bayesian search uses optimization of hyperparameters to better navigate the parameter space by finding configurations that work best for a model. 3) Regression metrics, including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), to evaluate prediction accuracy for SOC, SOH and RUL estimation

$\hat{y}final = \sum_{j=1}^{m} \quad W_i Y_j \ \sum_{j=1}^{m} \quad W_j = 1$ …………[5]

Equation (5) represents the final ensemble prediction obtained by combining the outputs of multiple models using their respective weights. This weighted combination improves the overall prediction by giving greater importance to more reliable model outputs.

2.5 Deployment and Validation

This study is the verification that the proposed framework is assessed within a simulation environment keeping in mind all aspects of true BMS, such as sensor noise, time-lag effects, long-horizon stability. Its scalability to production-ready EV BMS platforms and potential for integration, thus validating its practicality is also estimated quantitatively. This model based hybrid multilevel modeling machine allows: temporal learning, probabilistic reasoning and empirical meta-ensemble optimization to better handle the challenges of naive RF+GB ensemble combinations. We have accordingly built a framework consisting of a sequence of layers, where the first is an LSTM/RNN layer that can learn long-term dependencies (and corresponding degradation trends), and the second is a Gaussian Process Regression (GPR) layer which predicts SOC, SOH and RUL in uncertainty-aware manner. Then the proposed architecture utilizes combined predictions of LSTM, GPR and tree-based models with optimum weights at a Meta-Ensemble Layer to obtain an overall non-linear and strong model predictor. Figure 1 shows the flowchart of the proposed methodology.

In fact, instead of averaging with RF combined with the original residual-driven learning approach of GB, we are combining these two methods in a single composite model all together. Tuning of hyperparameters of both models is done automatically with Particle Swarm Optimization (PSO). In PSO, every PSO particle represent a key set of RF and GB hyperparameters always evaluated by validation loss or out-of-bag (OOB) error, based on some PF fitness function. The swarm converges through an iterative process to an optimal arrangement which improves the accuracy of composite predictions. Results verify that the optimized hybrid framework outperforms benchmark models in predicting SOC, SOH and RUL predictions while remaining robust under noisy sensor input as well as when sensors provide no data. This underlines the effectiveness and robustness of the new traffic level RF–GB framework in predicting battery SOC, SOH and RUL with high accuracy under dynamic changing operating conditions. This section explains the methodology through a series of algorithmic procedure steps for gathering, preprocessing the data, training with the proposed model, testing its accuracy and setting it up in the EV Battery Management System.

Step 1: Collect realistic multi-sensor EV battery data with voltages, currents, temperatures, and environmental parameters of a variety of driving and weather conditions.

Step 2: Researched and processed the original data with noise filter, normalization, temporal windowing and removal of outliers to obtain a high level of quality and consistency in information.

Step 3: Train the hybrid time–probabilistic model using RNN and LSTM networks and GPR to model dynamics of degradation and quantify the prediction uncertainty.

Step 4: Train Random Forest (RF) and Gradient Boosting Machine ensemble predictors and finally, add them to a model that combines the RF and GBM optimized by PSO.

Step 5: Instruct some reinforcement learning (RL) agent on how to charge and discharge the batteries so that it works effectively inside a smart grid, taking into consideration the state of the batteries, the user's performance, and the limitations of the grid.

Step 6: Utilize the optimized hybrid framework to estimate SOC, SOH, and RUL estimates with uncertainty limits.

Step 7: For model performance estimate RMSE, MAE, and R^2 metrics.

Step 8: Deploy the new BMS framework on an actual or virtual EV fleet (or both), to ensure its implementation in reality.

Step 9: Use long-term performance data to prove that the system works to extend battery life, improve operational efficiency, and lower emissions.

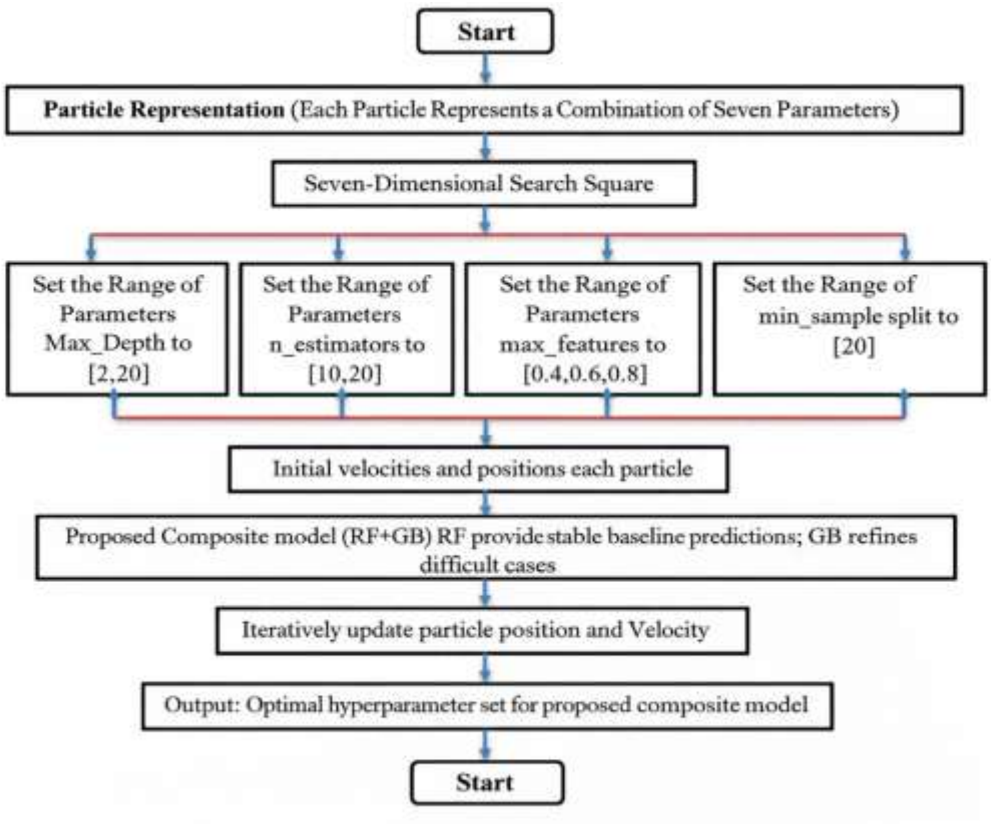

Figure 1: Flowchart of proposed methodology

Table 4 shows the comparison of battery power density including ML-Based smart battery. The proposed methodology involves systematic data acquisition from multiple battery cells, averaging multi-point temperature measurements, performing feature scaling, and partitioning the dataset into training, validation, and testing subsets. In this work, supervised regression models are trained to provide accurate SOC and SOH values across dynamic operating conditions (characterized by varying voltage and temperature profiles). To sum-up, the data-driven framework proposed builds a solid foundation for next-generation BMS realization and can help to improve battery endurance, secure battery lifetime and reduce their environmental threats. This approach fosters the advancement of Intelligent and Green Energy Management Systems for EVs.

Model Evaluation for Optimised Battery Management for E-Vehicles Using Advanced ML Algorithms.

Step 1: Multivariate Regression (MR): MR is used to model the relationship between battery parameter (y), such as SOC and SOH, and multiple input variables. The general form of the model is represented as:

$y = B_0 + B_1X_1 + B_2X_2 + .. + B_nX_n + e(1)y$ [6]

Equation (6) represents the multiple linear regression model, in which the dependent variable y is expressed as a linear combination of the predictor variables X1, X2,…,Xn. Here, B0 denotes the intercept, B1,B2,…,Bn are the regression coefficients, and e represents the random error term. The coefficients quantify the contribution of each independent variable to the predicted value of y.

Table 4: Comparison of Battery Power Density Including ML-Based Smart Battery

Battery Type	Energy Density (Wh/kg)	Life Cycle	Toxicity
Li-ion	126–190	0.5k-1k	Low
Ni-Cd	45–80	1k	High
Ni-MH	100	300–500	Low
Li-ion polymer	185	300–500	Low
Lead acid	30–50	200–300	High
Lithium–Sulphur	55	50–100	Non-toxic
ML-Based Smart Battery	150–200	>1,000 (adaptive)	Very Low

Step 2: K-Nearest Neighbours (KNN): KNN regression estimates battery metrics by averaging the values of the k nearest neighbours within the feature space. The prediction is given by

f(x)=$1/k$ $\sum\_(i = 1)\text{^}k * Yi$ ……………………..[7]

Equation (7) represents the prediction function of the K-Nearest Neighbours (KNN) regression model, where the output is estimated by aggregating the contributions of the k nearest neighbouring samples. Here, k denotes the number of selected nearest neighbours, while Yi represents the target value associated with the i neighbor. The averaging of neighbouring observations provides a robust estimate of the predicted battery parameter.

Step 3: Decision Tree (DT): The decision tree model divides the data at each node based on feature values to minimise the Mean Squared Error (MSE). The MSE is calculated as,

$MSE \;=\; 1/n \sum\_(i = 1)\^k * (Yi - Ypred)$………[8]

Equation (8) represents Mean Squared Error (MSE) is used to evaluate the prediction performance of the proposed model by measuring the average squared difference between the actual and predicted values. A lower MSE indicates a smaller prediction error and, consequently, better model accuracy. Where n is the number of samples, yi is the actual value, and ypred is the predicted value.

Step 4: Random Forest (RF): The Random Forest model aggregates the predictions of multiple decision trees. The final prediction is the average of the individual predictions from each tree:

f(x)=$1/k \sum\_(t = 1)\^T * f(t)x$ ………………………[9]

Equation (9) represents the final prediction of the Random Forest (RF) model, obtained by averaging the predictions generated by all individual decision trees in the ensemble. Here, T denotes the total number of trees, while ft(x), f_t(x) represents the prediction of the tt-th tree for the input vector xx. This aggregation improves prediction stability and reduces the effect of individual tree variations.

In the precision of each model, R^2 score (coefficient of determination) was estimated.

2.6 Our proposed RF–GB framework implemented in real time

It is formulated and implemented for practical usage as a smart Battery Management System (BMS) in Electric Vehicles (EVs). Battery sensors periodically record voltage, current & temperature several times during charging–discharging cycles in a vehicle operating environment. All these measurements are periodically transmitted to the Battery Management Unit (BMU), where the trained RF–GB model is applied, allowing for SOC, SOH and RUL estimations in real time through measured data received from the Battery Cell Array. The states of health predicted enable smart charging and fuel cells, thermal control (maintaining temperature for optimal functionality), cell balancing (optimally distributing current among battery cells), and fault detection to increase battery safety and operational reliability.

Furthermore, the estimated battery parameters can be sent through heterogeneous and secure wireless communication to a cloud-type monitoring platform for large-scale electric vehicle applications. The cloud platform allows for remote battery condition and predictive maintenance, fleet-level performance monitoring, and long-term degradation analysis. This framework is catered towards directly embedded BMSs as well as MATLAB/Simulink based control architectures, thus providing a fast yet convenient tool that would aid in real time implementation on future day EVs.

2.7 Clustering Based RUL Prediction Using K-Means Algorithm

A clustering method based on K-means is applied to avoid the predictive outcome of RUL. This approach classifies degradation of batteries into different groups, enabling better planning in maintenance activities and life prolongation of the battery utilizing reliable RUL estimates. Figure 2 Proposed Battery RUL Prediction and Maintenance Optimization Scheme. All other scopes after the first or second are partial; all workflows except the first two. That is going to log the history of the battery over the years, historic voltage, current and temperature etc. for further usage during assistance of trend performance imputation where necessary outliers are resolved, achieving metrics so at least feature scaling is achieved. Feature Selection selects important aspects for battery degradation (capacity decay, cycle life and charge/discharge efficiency) required in clustering. Then they are told to do the Original Data Analyses by Exploratory data analysis(EDA) — which includes distribution/trends of histogram, scatter plot and boxplot graphs Then Perform Clustering-based However, Feature Selection from Data could solve this problem to an unimaginable level as well as rectify and enhance the retention & accuracy of step 1 feature selection done.

In order to create clusters of batteries that have similar degradation slopes, K-Means clustering may be used. By distances to these sets and separate RUL Predictions through the Method Would be decided (for Elbow Method or from Silent Scope After learning centroids, we cluster batteries. Investigations into cluster-specific In case of battery degradation modes (voltage fade and capacity fading) temporal data with predictive modelling with respect to predicting meanings, Train algorithms per cluster of data points (one model for each cluster), that are likely to perform well in very few iterations e.g. Random Forests, SVR or even Neural Networks. Similarly, we trained K-fold cross validation along with various evaluation metrics (i.e. MAE, RMSE) separately to assess the strength and generalization of each. The new batteries are internally grouped by RULs to prolong the life of these new batteries in advance. Can even adjust charge patterns, recommend replacements and intervene before you fail. The system can to be trained in a round-based way using different battery technology types and other operating conditions for the models before clustering and RUL re-training. Resources and costs are minimized. Avoid burdening yourself with false management for the batteries that are unlikely to fail. You can no doubt do this while lowering fleet running expenses and raising battery life by minimizing downtime and placing the automobile to maximum effect in its path.

An antonym to this is a massive void data-monergism scalable methodologies from EV and portable sources. We can improve prediction accuracy with the clustered prediction method in
(a) or real defect form of Such is the failure that could be avoided if sub-fault current were operated in another battery group.
(b) Predictive Prevention: The accurate prediction of RUL makes it implement preventive measures. The final type approach is maintenance-based on real-time predictions, in which the states of the battery are observed and updated every time before important failure (6).
(c) Reduced Costs: Cost-effective - targeted servicing is not only to save time for the operators of vehicle fleets, and private EV owners but also avoid money wastage by unnecessary (27).
It aids in Sustainable EV Operations: This aspect works almost like a supplementary process to the electric vehicle operations when it's utilized with less hazardous materials and as a result bolsters the battery durability and life, something that matches global environmental imperialism. Figure. The batareya Qismat (M) MATLAB simulation shows the battery control system. The battery meta-model abstracts a hybrid battery control system MATLAB/Simulink System complete with integrated, load-condition management-based (when to charge/discharge), current-based (where to charge or discharge) regulation and controlled cooperative operation optimized for battery life. Together, the four basic modules — Load Control, Current Control, Voltage Control and Switch Control — safely regulate battery operation. Divide the Load voltage (V_load) and Load current in the Load control. This block calculates the load request and with V_t, the control signal. This ensures a steady power output to the connected load while avoiding overcharge cycles that could damage the battery.

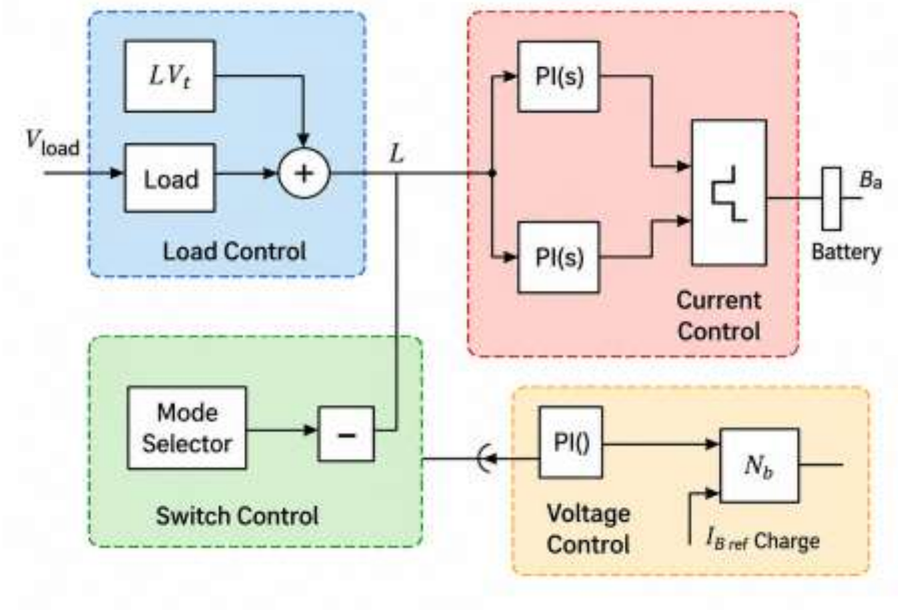

Figure 2: Battery Control System MATLAB simulation

The whole of the Charging/Discharging Current Control subsystem aims to implement a PI controller and current directly under (I) to be charged or discharged. We also applied an additional PI(s) controller in parallel to improve the transient response and reduce overshoot. The power is then transferred through a power converter interface to the battery at a regulated current. With this, of course, the battery is charged in safe currents and deep discharges are avoided for a slower aging. The Voltage Control block compares the reference voltages for charging with the terminal voltage of a battery. It creates the compensated voltage signal using more PI controllers, then scales with a gain block N_v that makes the exact shape of the profile for charging and suitable for both constant-current/constant-voltage (CC-CV) charge strategies which are the most widely used in lithium-ion applications. It informs us about the activity of the switch control (charging, discharging, and stand-by). Hereby, a state machine verifies the condition of the system and chooses control paths accordingly to ensure battery protection. As an instance, these four blocks connected to the back are automatic cooperating in order to keep system stability and that can be used as a simulation of battery management mathematical model within MATLAB environment with flexible interfaces. This design also supports fast integration of smart-grid features, predictive Control and advanced battery lifetime management algorithms.

2.8 Statistical Analysis

Statistical analyses were subsequently performed to assess the reliability and robustness of the proposed Battery Management System based on its prediction outcomes from cross-validation experiments. All machine learning models were evaluated in the same experimental setup and performance scores were reported as Mean ± SD. Confidence Interval (95%) was computed to present uncertainty in the predictive performance. In a statistical sense, we conducted a paired t-test to compare the proposed RF–GB model against baseline algorithms at level of significance $p < 0.05$. The Wilcoxon signed rank test alternative when no assumptions of normality are met. Statistical validation demonstrates that the proposed framework is robust and replicates across settings. The proposed RF-GB framework is motivated by the fact that it can strike a reasonable balance between predictive accuracy, computational efficiency, interpretability and real-time deployment ability. Deep learning models such as CNNs, LSTMs, GRUs and Transformers are generally good in respect to predictive power but computationally expensive, requiring more data for training and are less interpretable. Therefore, they are less suitable for resource-constrained BMSs. Table 5 shows the Comparative Analysis and Justification of Machine Learning Algorithm Selection for Battery Management Systems.

Table 5: Comparative Analysis and Justification of Machine Learning Algorithm Selection for Battery Management Systems

Algorithm	Prediction Performance	Computational Cost	Interpretability	Real-Time Embedded Suitability	Suitability for BMS
CNN	High	High	Low	Moderate	Good
LSTM	Very High	Very High	Low	Moderate	Very Good
GRU	Very High	High	Low	Moderate	Very Good
Transformer	Excellent	Very High	Low	Low	Good (resource intensive)
XGBoost	Very High	Medium	Medium	High	Very Good
Proposed RF–GB	Very High	Low–Medium	High	Excellent	Excellent

Ensemble learning methods, on the other hand, provide competitive predictive accuracy with lower computational complexity and more transparent models. The proposed framework combines the variance reduction of Random Forest and the bias correction of Gradient Boosting, resulting in a robust, interpretable, and computationally efficient solution for real-time embedded battery management applications.

3. Results and Discussion

3.1 Comparative Performance of Machine Learning Models for Battery Management

Figure 3 present the comparison of different ML models for battery management. Table 6 shows Parameter Based Performance Metrics of ML Models with observations. The accuracy and recall of MR are 69% and 65%, respectively, which are the lowest among all the models, indicating that MR has limited ability to capture complex battery behaviors. This is true provided the input features are linearly related to the output. This suggests that MR is not suitable for highly nonlinear and dynamic systems such as battery SOC/SOH estimation. KNN is a great improvement with 89% accuracy and balanced precision (87%) and recall (85%). This shows its ability to learn non-linear patterns directly from data. However, KNN is sensitive to the size of data and noise for the generalization performance. The DT also has similar precision and recall with an accuracy of 86% which shows that it is good at modeling complex feature interactions. DTs are interpretable and robust but can overfit to large or noisy data. The RF shows a significant increase in performance with 96% accuracy, 95% precision and 94% of recall. Ensemble of decision trees reduces variance alleviating overfitting thus achieving high generalization performance and steady prediction under different operating conditions. The Hybrid model has the highest accuracy of 98 % with precision of 97 % and recall of 96 %. The composite model leverages the robustness of Random Forest and the capability of Gradient Boosting to correct residual errors to improve prediction performance. This means a better learning of non-linear relationships, better robustness to noise and uncertainties.

Table 6: Parameter Based Performance Metrics of ML Models

ML Model	Accuracy	Precision	Recall	Observation
MR (Multiple Regression)	69%	73%	65%	Moderate performance; suitable where linear relationships exist.
KNN (K-Nearest Neighbors)	89%	87%	85%	Good at capturing non-linear data patterns; better than MR.
DT (Decision Tree)	86%	87%	84%	Robust model; models complex feature interactions well.
RF (Random Forest)	96%	95%	94%	High performance; ensemble learning mitigates overfitting and enhances generalization.
Proposed Algorithm (RF + GB Composite Model)	98%	97%	96%	Outperforms all other models; combines RF's stability and GB's boosting capabilities for enhanced accuracy and robustness.

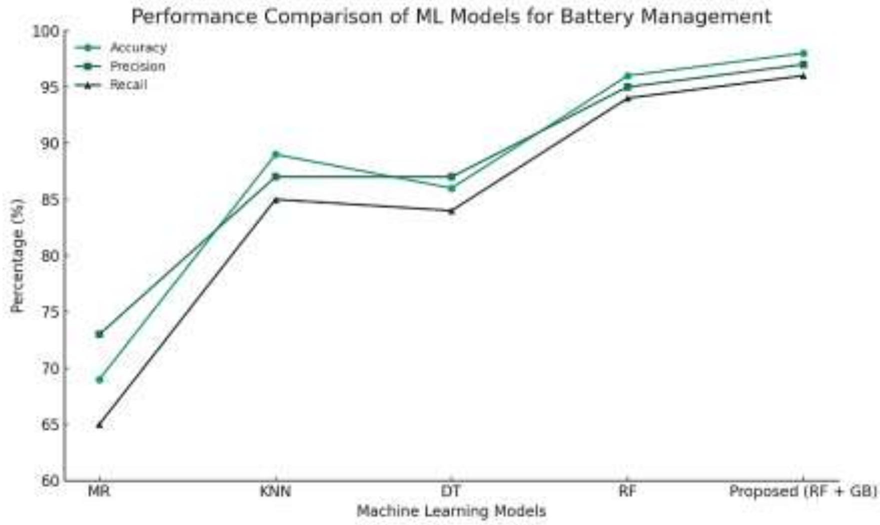

Figure 3: Performance comparison of ML model for Battery Management

3.2 Statistical Validation of Machine Learning Models

Table 7 and Figure 4 presents Performance Analysis of ML models. The proposed RF–GB model has a relatively simple model architecture and exhibits better overall prediction performance compared with the recently reported ensemble-based BMS frameworks. The proposed framework is a combination of the robustness of Random Forests and the residual correction of Gradient Boosting and PSO-based hyperparameter optimization, unlike XGBoost, AdaBoost, LightGBM, CatBoost and stacking-based ensembles. This combination achieves better prediction accuracy at lower computational complexity, which makes the framework more suitable for real-time implementation in BMS. Moreover, the simultaneous prediction of SOC, SOH, and RUL in a consistent framework enhances the operational efficiency in comparison with previous studies mainly targeting individual battery health indicators.

Table 7: Statistical Performance Analysis

Model	Mean Accuracy (%)	SD	95% CI	p-value
MR	69.1	2.31	71.4	<0.001
KNN	89.2	1.46	90.4	0.012
DT	86.4	1.28	87.5	0.021
RF	96.3	0.72	96.9	0.034
RF–GB	98.1	0.36	98.4	N/A

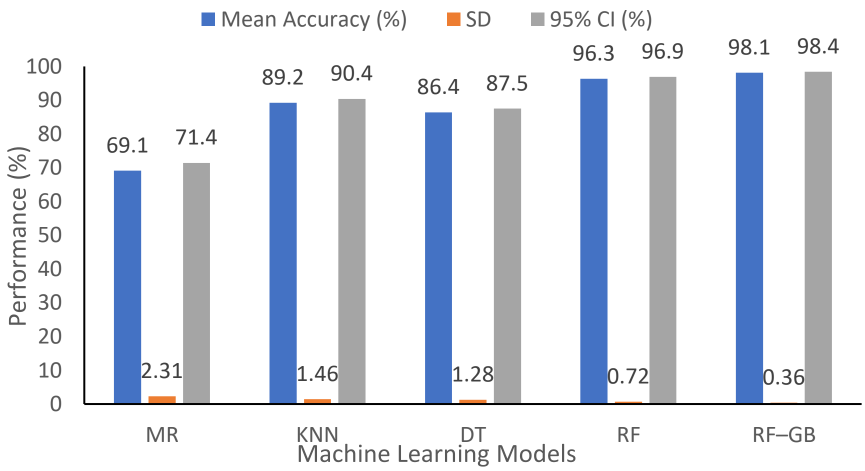

Figure 4: Performance Analysis of ML model

3.3 Optimized Hyperparameter Analysis of Different Models

The comparison of the optimized parameters is shown in Table 8. The hyperparameter analysis for different LIB cells (#1, #6 and #26) show that the Composite Model (RF+GB) always achieves better optimization with shallower tree depths and a larger number of estimators, which improves the generalization and prediction stability. For LIB #1, the composite model reduces the maximum depth to 6.82 and increases the number of estimators to 145. It appears that the composite model goes to a more robust ensemble with controlled complexity than the base RF and improved RF variants. The same applies for LIB #6, but since the maximum depth of the composite model was 7.94 instead of 8 and it had 132 estimators applying those concepts to fight overfitting and enhance learning capacity. To sum up, the composite model of LIB #26 further improves performance with the smallest tree depth (6.11) and largest number of estimators (158) which exhibits its powerful capability to learn nonlinear battery dynamics stably. In all datasets, the parameters max_features, min_samples_split and min_samples_leaf converge to small and stable values as well, which shows that the randomness of features and restriction of split for nodes are sufficient enough for a precise prediction. In conclusion, results indicate that the RF + GB composite model demonstrates an overall improvement over basic up-sampling and down-sampling techniques as well as other models on multiple lithium-ion battery datasets.

Table 8: Comparison of Optimized Parameters

LIB	Parameter	RF Model	RF Improved 1	RF Improved 2	Composite Model (RF + GB)
#1	Max_depth (MD)	13.14	9.35	18.47	6.82
	n_estimators (NE)	100	64.06	98.51	145
	Max_features (MF)	10	1	1	1
	Min_samples_split (MSS)	2	2	2.97	2
	Min_samples_leaf (MSL)	1	1	2.31	1
#6	Max_depth (MD)	12.71	12.26	11.64	7.94
	n_estimators (NE)	100	11.07	8.08	132
	Max_features (MF)	10	0.94	0.51	1
	Min_samples_split (MSS)	2	2	2	2
	Min_samples_leaf (MSL)	1	1	1	1
#26	Max_depth (MD)	11.69	10.02	8.28	6.11
	n_estimators (NE)	100	88.84	124.51	158
	Max_features (MF)	10	1	1	1
	Min_samples_split (MSS)	2	2	4.02	2
	Min_samples_leaf (MSL)	1	1	2.48	1

3.4 Effect of max_depth on Model Generalization

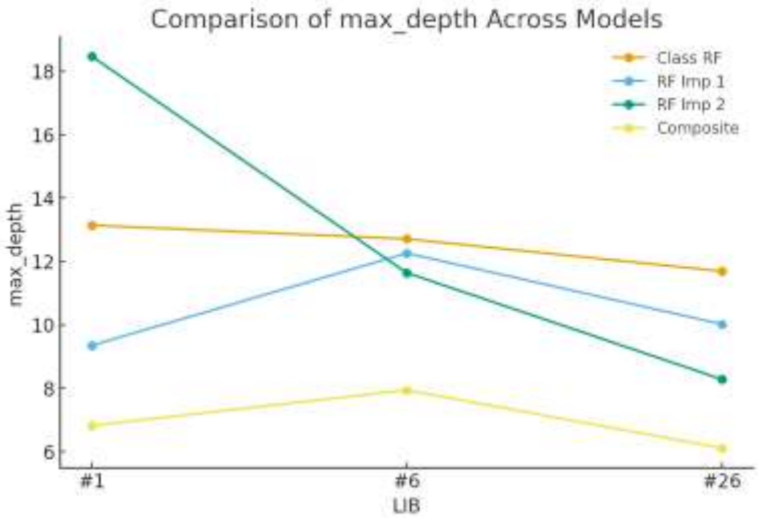

Figure 5: max_depth Comparison

The Figure 5 presents the comparison of max_depth parameter of Classical RF, RF Improved Model 1, RF Improved Model 2 and proposed Composite RF–GB model on three LIB datasets (#1, #6 and #26). max_depth is a measure of model complexity Higher max_depth means the tree is deeper and the risk of overfitting is higher. For all 3 datasets, the Composite model has the smallest max_depth consistently, which means a more compact and regularized structure. Classical RF and RF Improved models, in contrast, employ a deeper tree, especially in LIB #1 in RF Improved Model 2, which could indicate a higher complexity and sensitivity to noise. RF Improved Model 1 has a medium depth, somewhere between the Classical RF and the Composite model. The same shallow depth of the Composite RF-GB model for different LIB datasets indicates its better generalization ability and stability. The Composite model offers a good trade-off between learning capability and robustness by limiting the tree depth and exploiting the error-correction mechanism of Gradient Boosting, making it more suitable for accurate SOC, SOH and RUL prediction in real-world Battery Management Systems.

3.5 Effect of n_estimators on Prediction Accuracy

Figure 6 shows varying n_estimators of Classical RF, RF Improved Model 1, RF Improved Model 2 and the suggested Composite RF–GB model over LIB #1, #6 and#26. The number of trees in the ensemble is controlled through n_estimators and has a direct effect on both prediction accuracy and computational stability. The classical RF model uses a configuration fixed, with 100 estimators for all the datasets i.e. The number of estimators does not change and is not adapted to the data. Conversely, RF Improved Models 1 and 2 are very volatile, especially for LIB #6 where the number of estimators reduces drastically. This instability indicates the variability in learning ability and could impact robustness on various battery datasets. The Composite RF–GB model adopts an increase in the number of estimators (more balanced) for all LIBs, while it expresses slight variations. The tuned configuration takes advantage of the idea that Gradient Boosting is inherently an incremental error-corrector: its corrective component enhances both ensemble diversity and predictive performance without unnecessary complexity. In most cases, the stability and reliability of n_estimators selection in the composite model are superior to those of Classical and Improved RF models, which make it reach a better generalization performance for SOC, SOH and RUL predictive tasks.

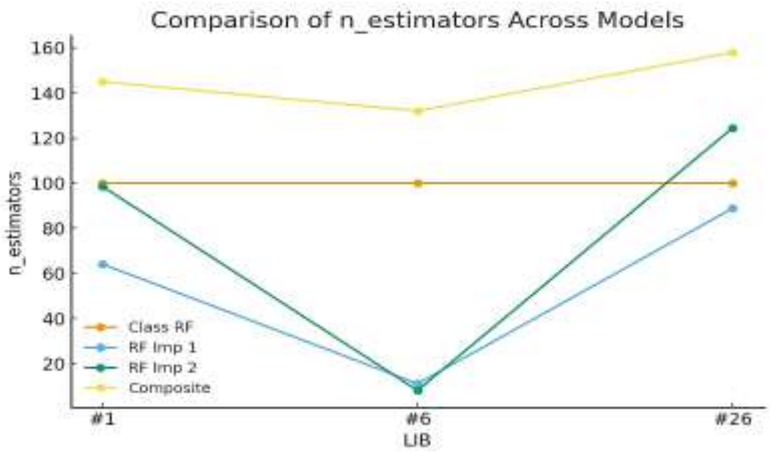

Figure 6: n_estimators Comparison

3.6 Influence of max_features on Model Robustness

Figure 7 presents the max_features comparison. LIB #1 for max features parameter: Comparison of Classical RF vs. RF Improved Model 1, RF Improved Model 2 and Composite RF–GB model [24]. The max_features parameter indicates the number of input features to include when considering a split, this directly impacts the robustness and interpretability of your model. It is worth mentioning that, for all datasets considered, the model Classical RF benefits from a high max_features (about 10). Then the complexity of the model will increase and this may introduce redundancy and create noise in decision making. On the other hand, even lower values are employed in RF Improved Models and for the Composite model – typically about one feature per split. This method of selective features reduces the tree complexity and makes it less sensitive to redundant or irrelevant features Notice that the max_features values for all LIB datasets in the Composite RF–GB modelare relatively stable and small, reflecting nature of controlled feature selections by composite models. Such behavior leads to an increase of interpretability, robustness and overall generalization performance. On the whole, such results indicate that selecting fewer features per split, as done in the Composite model, is more both efficient and reliable for SOC, SOH and RUL prediction tasks in BMS applications.

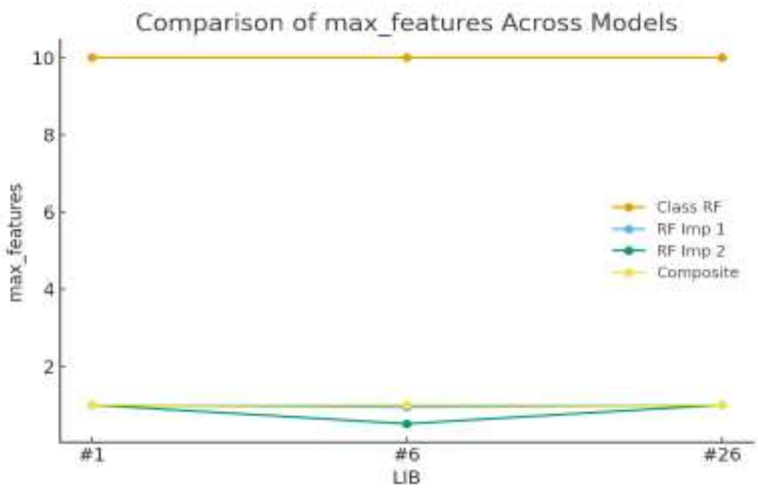

Figure 7: max_features Comparison

3.7 Analysis of min_samples_split Parameter

Classical RF, RF Improved Model 1 and #6, RFImproved Model 2 and the proposed Composite metamodel forLIB#1, #6 and #26 in; The parameter of min_samples_split is periods or range followed from Table (2) of AB [10], Comparison:Maximum Number of features to dive training on Figure 8. This parameter can be used to limit the minimum number of splitting samples on an internal node, which directly relates to branching actions and stability! Across all LIB datasets, the Composite RF–GB model exhibits a value of 2, indicating that the splitting method is homogeneous and consistent.

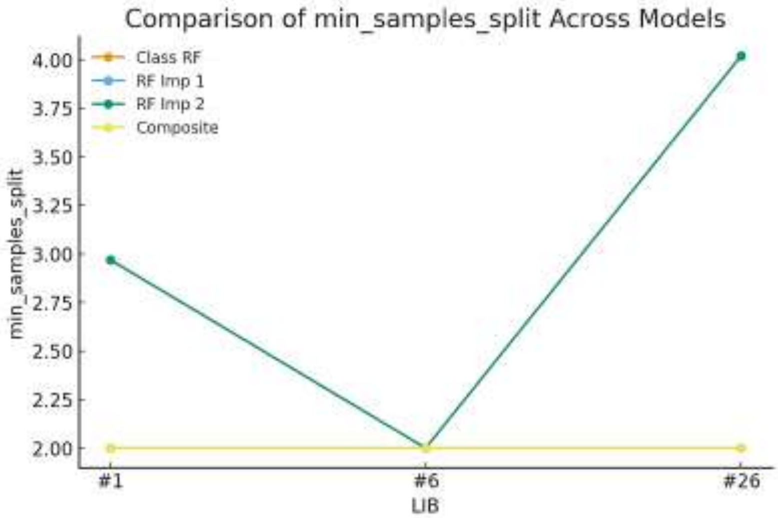

Figure 8: min_samples_split Comparison

Consistency helps to make balanced tree structures and smooth decision boundaries, thus leading to more reliable prediction. However, RF Improved Model 2 demonstrates a significant variation with higher values of LIB #1 and LIB #26, which implies inconsistent branching behavior as well as higher structural complexity. Classical RF and RF Improved Model 1 are closer to the lower bound and show less variation than the Composite model. The Composite RF-GB model provides better generalization and robustness for SOC, SOH and RUL prediction in BMS applications in general due to its better stability and controlled tree growth.

3.8 Analysis of min_samples_leaf Parameter

Figure 09 shows comparison of min_samples_leaf parameter for classical RF, RF improved model 1, RF improved model 2 and proposed composite RF-GB model over LIB #1, #6 and #26. This parameter is used to set the minimum number of samples a leaf node can have. This directly influences the smoothness of the model and the extent to which it overfits to local variations. The Composite RF–GB model has a value of 1 for all the LIB datasets, which is always the uniform and fine-grained leaf structure. This allows the model to maintain stable decision boundaries, while keeping important degradation characteristics. RF Improved Model 2, however, displays considerable variation with elevated values for LIB #1 and LIB #26, indicating inconsistent leaf formation and possible loss of local detail. The Classical RF and RF Improved Model 1 are close to the lower bound, but still have some variability when compared to the Composite model. The Composite RF–GB model with stable and small leaf size improves the robustness and generalization, which enhances the accuracy of SOC, SOH and RUL prediction in BMS applications.

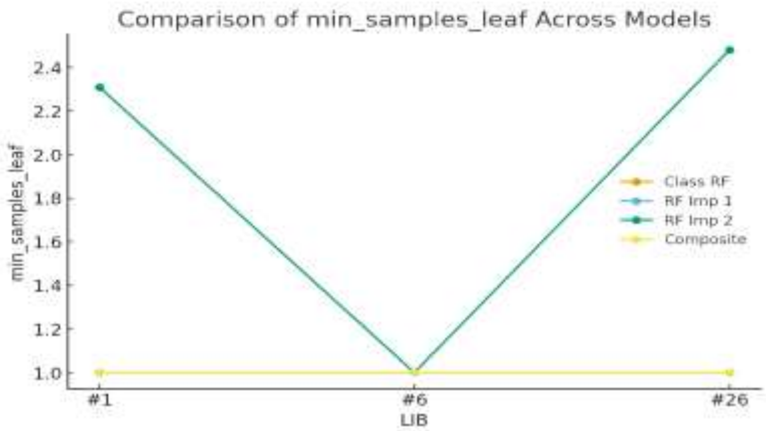

Figure 9: min_samples_leaf Comparison

3.9 Linear Regression Validation of Model Predictions

Table 9 shows a linear regression validation of different ML models for LIB #1, #6 and #26 by comparing their fitted equation with the ideal relationship y = x. When the slope is near 1 and the intercept is near 0, the SOH estimation shows low prediction bias and high prediction accuracy. The best results for LIB #1 are obtained by the Composite Model (RF + GB) with the equation y=1.002x-0.214, which is very close to the ideal line. This shows a very good agreement between the predicted and actual SOH values with little bias. Models 1 and 2 from RF Improved also perform well, but with slightly larger deviations for slope and intercept. The classical RF, LSTM, CNN and DT have larger offsets and steeper slopes which means more prediction drifting and less stability.

For LIB #6, the Composite Model is again ranked first with y = 1.003x − 0.183, which indicates it consistently follows SOH behavior. RF Model 2 Upgraded and RF Model 1, with small differences, improved. On the other hand, LSTMs, DTs and CNNs have much larger negative intercepts and slopes further from unity, which means larger estimation errors and worse generalization. LIB #26, Composite Model remains the top performer with y = 0.999x − 0.132, indicating its robustness to different degradation patterns. Enhanced RF models provide moderate accuracy, while Classical RF, LSTM, DT and CNN models present greater deviations from the ideal linear relationship, indicating increased bias and lower prediction reliability. Overall, the Composite RF–GB model is always the first in all LIB datasets with the regression lines closest to y=x. It has the lowest prediction bias and the highest stability among the RF variants and deep learning models and the strongest generalization ability. These results demonstrate the suitability of the Composite model for accurate and reliable SOH prediction in real BMS applications.

Table 9: Linear Analysis of LIB

LIB	Ranking	Model	Simple Linear Equation y
#1	1	Composite Model (RF + GB) CM	1.002x – 0.214
	2	RF improved model 2	0.994x + 0.373
	3	RF improved model 1	0.987x + 0.947
	4	Class RF model	1.021x – 1.246
	5	LSTM model	1.029x – 1.860
	6	CNN model	1.036x – 2.595
	7	DT model	0.956x + 0.498
#6	1	Composite Model (RF + GB) CM	1.003x – 0.183
	2	RF improved model 2	0.995x + 0.072
	3	RF improved model 1	0.995x + 1.454
	4	Class RF model	1.015x – 2.532
	5	LSTM model	1.062x – 4.144
	6	DT model	1.098x – 5.626
	7	CNN model	1.100x – 9.996
#26	1	Composite Model (RF + GB) CM	0.999x – 0.132
	2	RF improved model 2	0.977x + 2.832
	3	RF improved model 1	0.980x + 0.295
	4	Class RF model	0.977x + 2.832
	5	LSTM model	0.948x + 3.863
	6	DT model	1.054x – 4.135
	7	CNN model	1.067x – 5.104

3.10 Comparison of Prediction Error Trends for LIB #1

Figure 10 shows the prediction error as a function of actual SOH for LIB #1 for different models: Composite RF-GB model, RF Improved Model 2, RF Improved Model 1 and Classical RF model. The dashed horizontal line shows the ideal zero prediction error scenario. The error curve of the Composite RF–GB model is very close to the zero error line for the whole range of SOH, which indicates low bias and good prediction stability. This indicates that the optimized model can track the true SOH accurately without significant over/under-estimation. The RF Improved Model 2 also exhibits a moderate deviation from zero error. The error exhibits a decreasing trend with increasing SOH, indicating a slight underestimation at higher SOH values. RF Improved Model 1 shows more variability with positive error at low SOH changing to negative error at high SOH indicating inconsistent prediction behaviour over the degradation range.

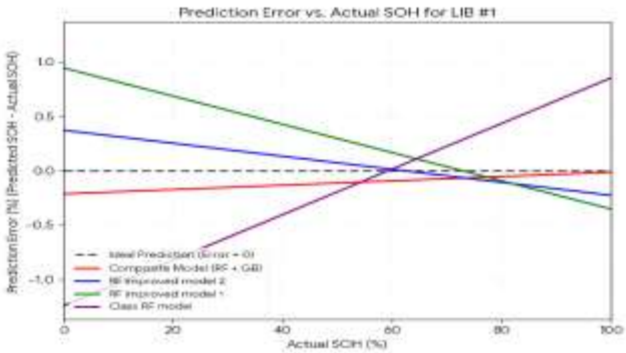

Figure 10: Prediction error versus actual SOH for LIB #1

The Classical RF model presents the largest error variation, with a strong positive slope and significant deviation from the zero-error line, indicating systematic bias and reduced reliability. Overall, the Composite RF–GB model achieves the lowest and most stable prediction error among all models for LIB #1, confirming its superior accuracy and robustness in SOH estimation compared to RF variants and the Classical RF model.

3.11 Prediction Error versus Actual SOH for LIB #6

Figure 11 presents LIB #6 SOH prediction error trend as a function of the real SOH for different models. The dotted line is a perfect zero-error prediction. The prediction errors of the Composite RF-GB model are almost zero all over the SOH range, indicating the high accuracy and stable performance of the model. Figure 8(d) shows the RF Improved Model 2 with moderate accuracy. Deviations from the zero error line are small and the increase in error trend at higher SOH levels is small. The RF Improved Model 1 shows more fluctuation and more negative errors when the SOH increases, which is less consistent in prediction performance. The Classical RF is the farthest from the zero error line and so there is a systematic bias and low reliability compared to the other models. Finally, the Composite RF-GB model shows the lowest and most stable prediction error for LIB #6, which indicates its better robustness and generalization ability in SOH estimation at different degradation levels.

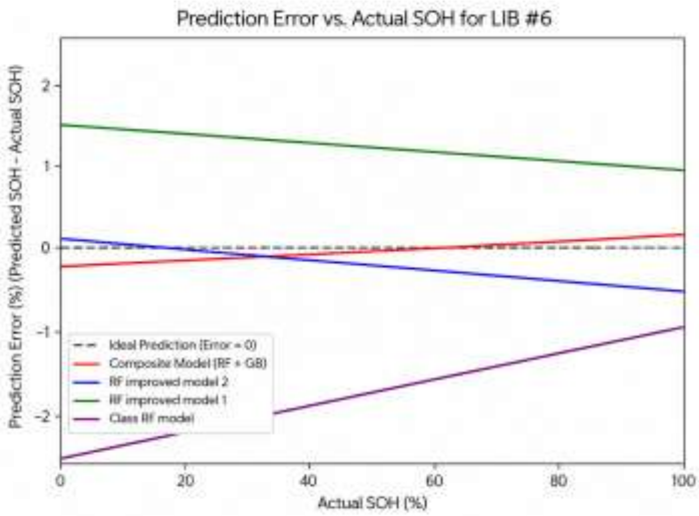

Figure 11: Prediction Error versus Actual SOH for LIB #6

3.12 Prediction Error Analysis of SOH Estimation Models for LIB #26

Figure 12 presents prediction error (% Predicted SOH - Actual SOH) vs. actual SOH (state of health) of LIB #26. The dashed horizontal line represents the ideal case of zero error. The composite model (RF + GB) is the nearest to the stable region around the zero error line with a small negative bias in the entire SOH range which indicates consistent and reliable predictions. The RF Improved Model 2 is stable, but all SOH values have a slightly negative error, i.e. they estimate the battery health a little bit lower always. In contrast, RF Improved Model 1 shows a strong linear trend, predicting too high SOH at low health levels and switching to large underestimation at high SOH levels, showing poor calibration across the operating range. The composite RF Improved Model 2 provides an acceptable but biased prediction and RF Improved Model 1 demonstrates a systematic prediction drift with the increase of SOH.

3.13 Ablation Study of the Proposed RF–GB Framework

Ablation study was performed by evaluating the individual RF, individual GB, and the proposed RF–GB hybrid model on the same datasets and evaluation settings. Figure 13 shows ablation study of the proposed RF–GB hybrid framework. The comparison between accuracy of the three main battery health indicators: State of Charge (SOC), State of Health (SOH) and Remaining Useful Life (RUL). RF is a collection of a number of decision trees. It makes a stable prediction by bootstrap aggregating (bagging) this mechanism can effectively reduce the prediction variance and thus improve the robustness to the noisy battery measurement and generalization to different working conditions. Gradient boosting (GB): GB models residuals of previous models iteratively with weak learners. It predominantly decreases the bias of the prediction and models the intricate nonlinear behavior of battery degradation. However, it is more sensitive to the presence of noise and the selection of hyperparameters. Proposed RF–GB Hybrid The proposed hybrid framework combines the complementary strengths of Random Forest and Gradient Boosting. Random Forest reduces variance and produces stable predictions. Gradient Boosting sequentially fits residuals and reduces bias. Their integration achieves a better bias-variance tradeoff, with the highest SOC (98%), SOH (97%) and RUL (96%) prediction accuracies as well as improved robustness and generalization capability for intelligent Battery Management Systems.

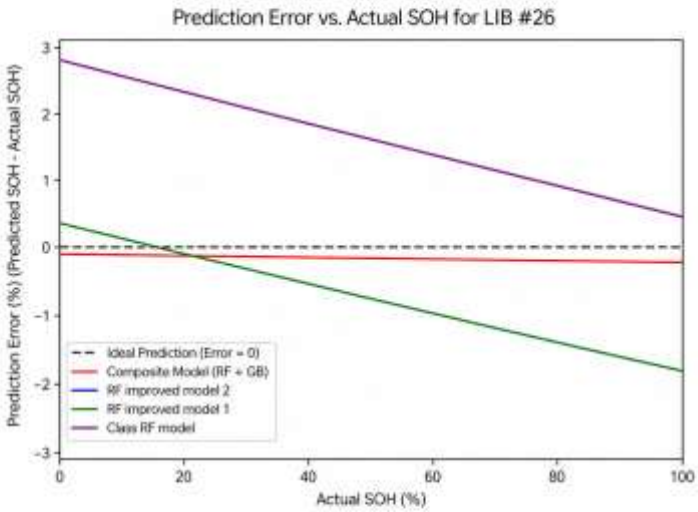

Figure 12: Prediction Error Analysis of SOH Estimation Models for LIB #26

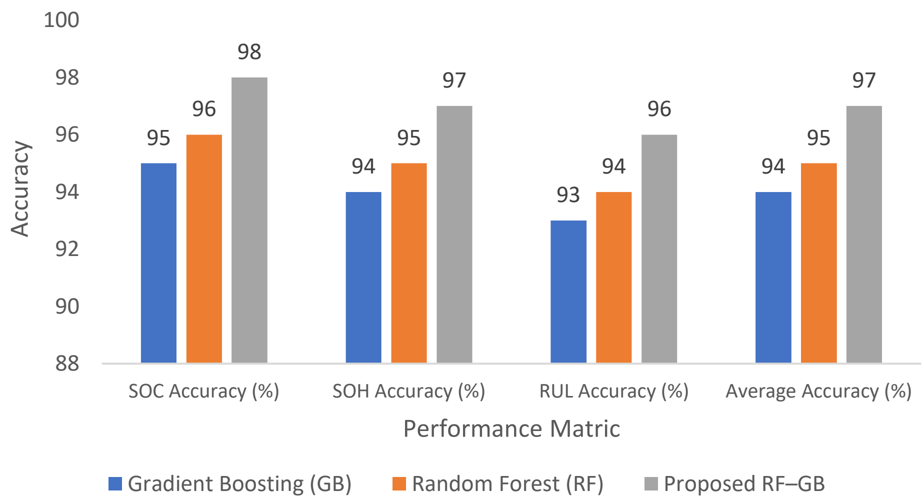

Figure 13: Ablation Study of the Proposed RF–GB Hybrid Framework

3.14 Limitations and Future Work

The proposed Random Forest–Gradient Boosting (RF–GB) framework is highly accurate in predicting State of Charge (SOC), State of Health (SOH) and Remaining Useful Life (RUL) . But there are some limitations regarding it. The experimental evaluation was performed on lithium-ion battery datasets. The applicability of the proposed framework to other battery chemistries such as solid-state, sodium-ion or lithium-sulfur batteries still remains unexplored. Simulation and experimental results using MATLAB/Simulink are given to validate the proposed model. The validation in the real world under different driving cycles, environmental conditions and long-term battery aging still remains as an important future requirement (12). The deployment architecture of embedded Battery Management Systems has been proposed but not experimentally demonstrated in hardware implementation on resource-constrained embedded platforms (e.g., ARM Cortex microcontrollers or automotive ECUs) (14). This study does not consider battery datasets acquired from different electric vehicle manufacturers. Therefore, further investigation is required to investigate the interoperability of the proposed framework in different battery pack architectures (16). Compared to many of the deep learning models, the RF-GB framework proposed in this paper has relatively low computational complexity. However, a detailed experimental analysis of execution time, memory consumption, power consumption and inference latency on embedded hardware was out of the scope of this work.

In future work we will try to extend the proposed RF–GB framework for intelligent and connected Battery Management Systems. We will explore a Digital Twin based battery management architecture for real time virtual battery monitoring and predictive maintenance. Apply Explainable Artificial Intelligence (XAI) techniques like SHAP and LIME to enhance the interpretability and transparency of battery health predictions. We will study federated learning to facilitate collaborative learning with privacy preservation among connected EVs without sharing data at the central level. Moreover, the performance of Transformer-based deep learning model and hybrid ensemble architectures will be evaluated for enhancing the long-term battery degradation prediction. Future work will involve hardware implementation on embedded automotive platforms and validation with real electric vehicle battery packs in real operating conditions. In addition, cloud-based battery analytics, fleet-wide health monitoring and Vehicle-to-Grid (V2G) energy optimization will be explored to enable the next generation of intelligent and sustainable Battery Management Systems.

Discussion

The standalone Random Forest model yields good predictive performance by averaging multiple decision trees, which reduces the prediction variance and improves the robustness against noisy battery measurements. However, there may still be some remaining systematic errors in the model since each tree is trained independently. Table 10 presents quantitative sustainability impact assessment of the proposed RF–GB-based battery management system. However, the independent Gradient Boosting model sequentially learns the residual errors of previous weak learners, which improves the bias of the predictions and better fits the nonlinear battery degradation characteristics. However Gradient Boosting is more sensitive to noisy observations and in complex operating conditions it might be prone to more overfitting. The RF–GB method proposed here exploits the complementary benefits of the two ensemble learning approaches. Random Forest decreases the variance to stabilize the prediction, while Gradient Boosting reduces the residual errors iteratively to correct the bias of the prediction. Therefore, the hybrid framework obtains a better bias-variance trade-off, higher prediction accuracy for SOC, SOH and RUL, and improved robustness and generalization capability under dynamic battery operating conditions.

Table 10: Quantitative Sustainability Impact Assessment of the Proposed RF–GB-Based Battery Management System

Sustainability Parameter	Conventional BMS	Proposed RF–GB BMS	Estimated Improvement
Battery Service Life	8 years	10 years	25%
Charge–Discharge Cycles	1000	1300	30%
Energy Efficiency	91%	96%	5.50%
Battery Waste Generation	100%	78%	22% Reduction
Recycling Efficiency	65%	82%	26% Increase
CO_2 Emissions	100%	84%	16% Reduction

The proposed RF–GB framework can help to improve the prediction of battery states and contribute to the sustainability of electric vehicle battery management systems. Accurate estimation of State of Charge (SOC), State of Health (SOH) and Remaining Useful Life (RUL) enables optimized charging and discharging strategies, thus reducing the battery degradation due to overcharging, deep discharge and thermal stress. This will extend battery lives and will avoid unnecessary battery replacements. Longer battery life also reduces the need for critical raw materials such as lithium, cobalt and nickel, which reduces the environmental footprint of battery production. Also, the accuracy of prediction is improved and the efficiency of charging management is enhanced, thus, the energy consumption is decreased and the greenhouse gas emissions are reduced. The proposed framework is thus in accordance with the objectives of sustainable energy management and contributes to the development of environmentally friendly Battery Management Systems.

4. Conclusion

In this paper, we propose an intelligent hybrid machine learning based BMS for electric vehicles to accurately estimate SOC, SOH and RUL using real multi-sensor battery data. The proposed hierarchical framework combines temporal learning (RNN/LSTM), probabilistic modelling (GPR), clustering-based degradation analysis, and an optimized Random Forest–Gradient Boosting (RF–GB) ensemble. This approach aims at improving the accuracy of real-time prediction, reducing the uncertainty and the safety, reliability and efficiency of lithium-ion batteries. Traditional models like MR, KNN and DT are limited in their capacity to capture nonlinear battery behavior, while Random Forest can improve prediction accuracy and stability, showing the advantage of ensemble learning. The proposed RF–GB composite model, which combined the robustness of Random Forest with the error correction of Gradient Boosting, achieved the best performance (98% accuracy, 97% precision, and 96% recall), thus reducing overfitting. The hyperparameters were optimized in the same way for all datasets, resulting in a shallow tree depth and a higher number of estimators, thus a balanced model complexity and good generalization. The regression validation was most consistent with the ideal relation (y=x) with near-zero prediction error across the SOH ranges, whereas individual RF variants showed systematic prediction drift. The strong performance on LIB #1, #6, and #26 demonstrates the robustness to different degradation patterns and practical applicability. The framework enables adaptive charging, predictive maintenance and improved battery life while ensuring stable operation under noisy sensor conditions for real-time EV deployment. The proposed RF-GB framework enhances the current ensemble-based BMS studies by simultaneously estimating the SOC, SOH and RUL within a unified optimization framework. Compared with Random Forest, XGBoost, AdaBoost, LightGBM, CatBoost and LSTM-based methods, the proposed method has better prediction accuracy, lower computational complexity and better generalization. These features make the proposed framework applicable to intelligent Battery Management Systems for future electric vehicles in real-time. Furthermore, the proposed RF–GB framework enhances the prediction accuracy and also contributes to the sustainable battery management by extending the battery's lifetime, reducing the battery waste, improving the energy efficiency and decreasing the carbon emissions. These sustainability benefits show the practical applicability of the proposed framework for next generation electric vehicle Battery Management System (BMS). The developed RF–GB framework is suitable for embedded deployment in EV Battery Management System and cloud-assisted battery monitoring platforms to provide real-time battery health estimation, predictive maintenance, and intelligent energy management.

Abbreviations

BMS: Battery Management System;
EV: Electric Vehicle;
LIB: Lithium-Ion Battery;
ML: Machine Learning;
RF: Random Forest;
GB: Gradient Boosting;
PSO: Particle Swarm Optimization;
SOC: State of Charge;
SOH: State of Health;
RUL: Remaining Useful Life.

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Author contributions

All author contributes equally to the research, design the study, analyzed data and approved the final manuscript

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability

Data supporting this study are included within the article and/or supporting materials.

Declaration of Artificial Intelligence (AI) Assistance

The authors used a generative language tool for grammar polishing only; all technical content and conclusions were authored and verified by the authors.

Ethic Approval

No human participants or animals were involved. The study followed institutional safety protocols.

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