An Attention-Driven Sequential Learning and Rule-List Framework for Fuel Cell Efficiency Prediction in Hybrid Electric Vehicles

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ABSTRACT

The utilization of fuel cells (FC) in automotive technology has grown significantly, particularly in fuel cell hybrid electric vehicles (FCHEVs), which integrate fuel cells, batteries, and ultracapacitors (UCs). Through power electronic converters, these hybrid systems overcome the individual limitations of each energy source. However, the overall performance of FCHEVs depends heavily on converter control efficiency and the technical efficiency of the energy sources. Effective energy management systems (EMSs) are essential, as poor EMS design can result in reduced efficiency and accelerated degradation of fuel cells and batteries. This research proposes an intelligent machine learning (ML) framework to predict battery performance and charging behavior in hybrid electric vehicle systems using operational battery parameters. Key features analyzed include state of charge (SoC), voltage, current, battery temperature, ambient temperature, degradation rate, and charging cycles. The framework performs two classification tasks (2CA) and two regression tasks (2RT). Implemented models include Light Gradient Boosting Machine (LGBM), Extreme Gradient Boosting (XGB), Adaptive Boosting (AdaBoost), Bidirectional Long Short-Term Memory (Bi-LSTM) with attention mechanism, and rule-based models such as Optimal Decision Rule List Classifier (ODRLC) and Optimal Decision Rule List Regressor (ODRLR). These models are integrated into the proposed Attention Rule Framework (ARF) to enhance prediction accuracy and interpretability. Classification tasks predict battery type and optimal charging duration class, while regression tasks estimate efficiency and charging duration values. Experimental results, evaluated using accuracy, precision, recall, F1-score, MAE, RMSE, and R^2-score, demonstrate that ARF outperforms existing models. Visualization tools further validate its effectiveness, offering a reliable solution for intelligent energy management in electric vehicles.

Keywords: Fuel cell hybrid electric vehicle (FCHEV), fuel cells (FC), hybrid energy systems, energy management system (EMS), power electronic converters, battery performance, state of charge (SoC), battery degradation.

1. INTRODUCTION

The automotive industry operates within a complex landscape shaped by economic, technological, and environmental factors. Economic aspects, such as consumer demand and interest rates, influence sales, while technological advancements in safety and fuel efficiency drive innovation. Additionally, environmental concerns, including climate change and air pollution, play a crucial role in shaping regulations and consumer preferences. In response, FCHEVs emerge as a promising solution, offering zero emissions, a longer driving range compared to battery-electric vehicles, rapid refueling, a reduced dependence on fossil fuels, and greater energy efficiency than internal combustion engine vehicles. However, integrating fuel cell systems (FCSs) into electric vehicles presents several challenges, such as system control complexity, cost, and long-term durability. Fuel cells gradually lose performance over time due to material degradation, catalyst loss, mechanical wear, and variable operating conditions. This decline reduces efficiency, shortens lifespan, and raises maintenance and replacement costs. To address these challenges, an energy management strategy (EMS) can be implemented to optimize the performance of fuel cell systems, enhancing their competitiveness with other powertrain technologies.

EMS plays a crucial role in managing hydrogen storage, distribution, control, and optimization while also improving durability and reliability, resulting in increased efficiency, reduced energy waste, and lower operating costs for fuel cell vehicles. Various EMS frameworks have been developed, ranging from rule-based systems to global optimization algorithms such as Dynamic Programming and the Pontryagin Minimum Principle. Although such approaches provide theoretical optimality, their dependence on prior knowledge of driving cycles limits real-time applicability. Global sustainability represents one of the most relevant challenges that modern society has to face at present. The high dependence on fossil fuels has led humanity to an uncertain future due to the constant reduction in energy resources derived from gas and oil. A sustainable process involves adapting energy consumption to the availability of renewable energy, which represents a problem due to the variability and intermittency of renewable sources. A viable solution is to reduce energy consumption as shown in figure 1 so that imbalances do not occur between generation and consumption, thus enabling the use of renewable energy as a source and guaranteeing a sustainable future.

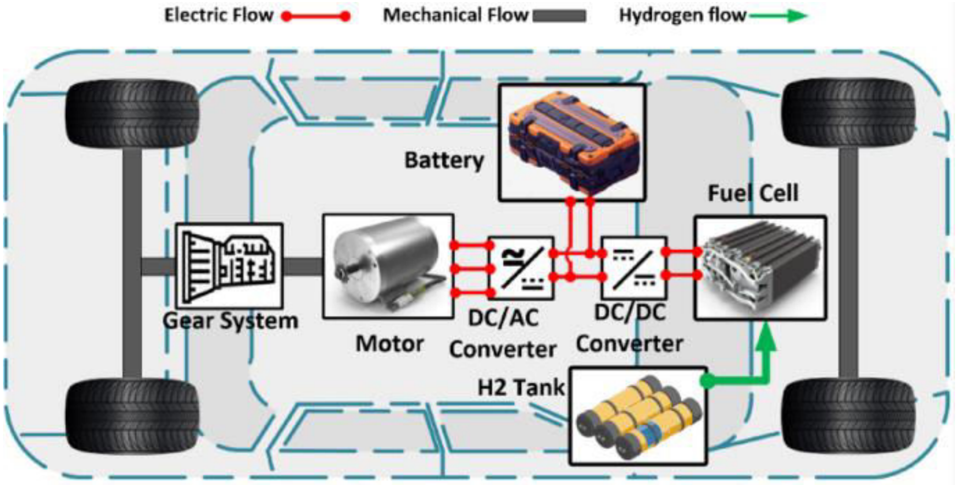


Figure 1: energy management in fuel cells

One of the main sectors where these measures can be most effective is the transport sector, urban and road, due to its high dependence on fossil fuels. The use of electric vehicles, especially in large cities with very congested areas, represents the ideal scenario in which to apply energy savings, since they can obtain energy for recharging batteries and fuel cells through sources that are entirely renewable, which would eliminate dependence on fossil fuels and lead to a completely sustainable process.

2. LITERATURE SURVEY

In Ref. [1], power management with the proportional integral (PI) technique was implemented by the authors to regulate the energy across photovoltaics (PV), fuel cells (FCs), batteries and supercapacitors (SCs). Multiple operational modes were operated for a hybrid device consisting of B/SC/FC in using a rule-based energy management technique. Jiang et al [2]. proposed a dynamic programming (DP) method for reducing hydrogen consumption in a hybrid power system with a fuel cell, battery and supercapacitor to provide energy to the power train. The author Li et al. [3] implemented a novel power management technique with rule-based fuzzy logic control with various multi-input sources, i.e., at first, the input sources consist of FC/B, and, later, the input sources consist of B/SC/FC for powering an electric vehicle. Ref. [4], the authors present an adaptive neuro-fuzzy inference system (ANFIS) to adequately manage the power between the FC and battery often used to provide power to electric vehicles (EV).

The author Chen et al., [5], proposed a power management technique divided into two sections, a wavelet-based and a radial-based solution, to refine the power output in an electric vehicle using neural networks. The authors designed a novel energy management mechanism focusing on wavelet transform approaches for controlling power among FC/B/SC to EVs. A Gray Wolf Optimizer (GWO) was designed by author Djerioui et al. [6] considering FC/B/UC as a hybrid power system for electric vehicle applications. In a parallel HEV, an FLC-based technique was designed to optimize the SoC, enhance fuel efficiency, minimize NO_x emissions and ensure greater drivability. For power split across accessible sources, an FLC-based intelligent energy management agent (IEMA) has been developed.

The author of Ref. [7] created an FLC to optimize system operation using the energy demands and the speed of the vehicle, as well as the SoC, as input variables. Marzougui et al [8]. designed a new power management technique incorporating three different aspects a rule-based algorithm, fuzzy-based control and flatness control for FC/B to supply electric vehicles (EV). Authors Fathy et al. suggested a novel energy management technique focusing on the slap swarm methodology (SSA) for maintaining energy in FC/BSC by assessing the consumption of hydrogen as the main objective function. Li et al [9]. adopted three methods to study the performance of energy management by combining the sources of FC/SC for sourcing an excavator: firstly, the dynamic programming method is applied; second, a model predictive control is designed, and third, Pontryagin’s Minimum Principle (PMP) with reduced consumption of hydrogen is applied. To reduce the cost of the overall system, the authors Yu et al. [10] introduced a novel hybrid FC/B/SC-fed EV architecture. In Ref. [11], to deliver power to a hybrid energy network, the authors developed a rule-based distribution method; in addition, to measure the strength of the batteries and ultracapacitors, a Bayes Monto Carlo methodology was also implemented.

The authors of [12] studied the effects of driving style, weather variables, infrastructure, and traffic intensity on energy consumption in BEVs via energy prediction models. For the BEVs in, the authors specifically addressed the effect of temperature on energy consumption performance for several EV commercial models on the basis of trip length, road grade, and driving habits via real-time data. In [13], energy consumption, cost savings, and emission calculations for ICEVs and EVs across different routes were carried out, neglecting any weather influences. Roumila et al. [14] divided the system into eight states according to battery SoC and load power and defined a reference power of the fuel cell in each state. Simulation results showed the effectiveness of this strategy but the definition of reference power of the fuel cell in each state was empirical. Nuesch et al. [15] included fuel consumption and the vehicle emission into one object function with different weights, and adopted a transient optimization method to minimize the target and managed the output power of the diesel engine and the battery in a hybrid vehicle.

3. PROPOSED SYSTEM

The proposed system introduces an intelligent prediction framework for analyzing battery efficiency and charging behavior in hybrid electric vehicles using advanced machine learning and deep learning techniques. The system integrates boosting algorithms, attention-based sequential learning, and rule-list learning models to improve prediction accuracy and interpretability. As shown in figure 2 by analyzing battery parameters such as state of charge, voltage, current, temperature, degradation rate, and charging cycles, the framework can predict battery type, charging duration class, efficiency, and charging duration. The proposed system also includes automated model selection, evaluation metrics, and visualization tools to support effective energy management and decision-making.

1. Data Collection: The system initially collects battery-related parameters from the dataset, including state of charge, voltage, current, battery temperature, ambient temperature, degradation rate, and charging cycles. These parameters represent the operational conditions of the hybrid electric vehicle battery system. The collected data forms the foundation for building predictive models.

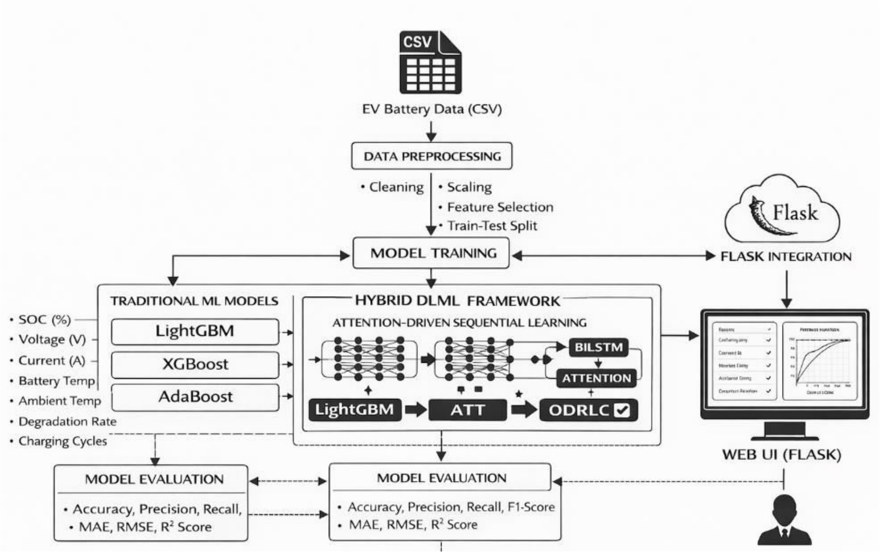


Figure 2: Proposed system architecture

2. Data Preprocessing: In this stage, the collected data is cleaned and prepared for model training. Missing values, inconsistent entries, and categorical features are handled using preprocessing techniques such as label encoding and normalization. The dataset is then separated into feature variables and target variables for classification and regression tasks.

3. Feature Selection and Dataset Splitting: The selected battery parameters are organized as input features while target variables such as battery type, charging duration class, efficiency, and charging duration are defined as outputs. The dataset is then divided into training and testing sets using the train-test split technique. This step ensures that the models can be trained and evaluated effectively.

4. Machine Learning Model Training: Several machine learning algorithms such as LGBM, XGB, and AdaBoost are trained on the prepared dataset. These models learn the relationship between battery parameters and the target outputs. Their performance is evaluated to provide baseline comparisons with the proposed model.

5. Sequential Learning with Attention-Based BiLSTM: The system applies a Bidirectional Long Short-Term Memory network with an attention mechanism to capture sequential dependencies among battery parameters. The attention layer helps the model focus on important features that significantly influence efficiency prediction. This improves the learning capability of the deep learning model.

6. Rule-List Learning Model Integration: Rule-list learning algorithms such as ODRLC for classification and ODRLR for regression are used to generate interpretable prediction rules. These models analyze patterns in the dataset and produce rule-based predictions that improve model transparency. This step enhances the reliability and interpretability of the framework.

7. Model Evaluation and Best Model Selection: The trained models are evaluated using performance metrics such as accuracy, precision, recall, F1-score for classification and MAE, RMSE, and R^2 for regression. The system automatically compares the performance of deep learning and rule-list models. The best performing model is selected and saved for prediction tasks.

8. Prediction and Visualization: Finally, the selected model is used to generate predictions for battery efficiency and charging behavior. The system also produces visualization outputs such as confusion matrices, ROC curves, scatter plots, and correlation heatmaps. These visualizations help users understand model performance and battery parameter relationships effectively.

4. RESULTS ANALYSIS

The result analysis evaluates the performance of multiple machine learning and deep learning models trained on the fuel cell and battery dataset. The models including LGBM, XGB, AdaBoost, and proposed ARF are tested to perform 2CA and 2RT tasks using the processed dataset. Classification models predict battery type and charging duration class, while regression models estimate efficiency and charging duration values. The experimental results are analyzed using evaluation metrics such as accuracy, precision, recall, F1-score for classification tasks and MAE, RMSE, and R² for regression tasks. Visualization tools such as confusion matrices, ROC curves, and scatter plots are used to interpret the prediction performance and compare the effectiveness of different models.

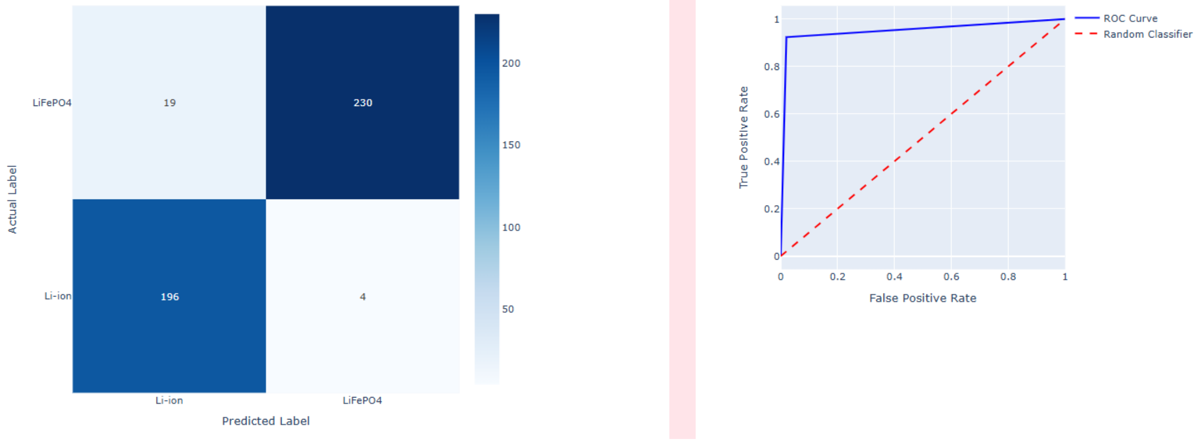


Figure 3: Illustration of confusion matrix and ROC using proposed ARF Model

Figure 3 illustrates the classification performance of the proposed ARF model for the battery type prediction task (2CA) using both a confusion matrix and ROC curve. The confusion matrix compares the actual and predicted battery classes, Li-ion and LiFePO4. According to the results, 230 LiFePO4 samples were correctly classified, while 19 were incorrectly predicted as Li-ion. Similarly, 196 Li-ion samples were correctly classified, whereas 4 samples were misclassified as LiFePO4. This indicates that the proposed ARF 2CA model achieves very high classification accuracy with minimal misclassification. The ROC curve on the right shows the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across different thresholds. The ROC curve is positioned very close to the top-left corner of the graph, clearly above the random classifier line, demonstrating excellent classification capability. The results indicate that the proposed ARF model significantly improves the performance of the 2CA battery type classification task compared to the baseline models.

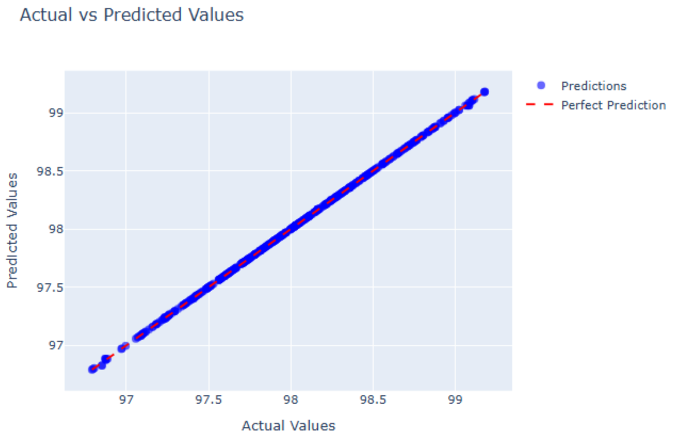
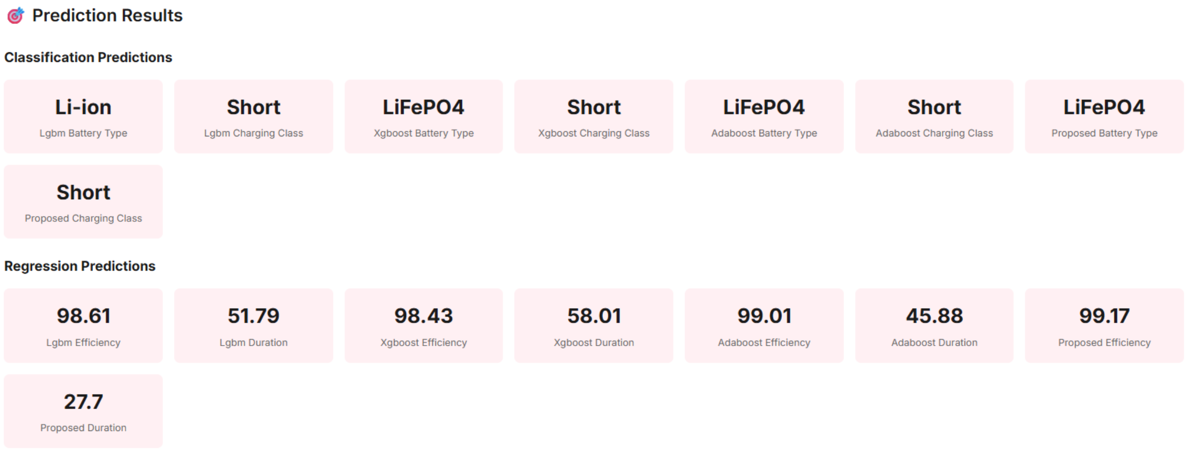


Figure 4: Confusion matrix obtained using proposed ARF for efficiency class

Figure 4 shows a scatter plot that illustrates the regression performance of the proposed ARF model for the efficiency prediction task (2RT) by comparing the actual efficiency values with the predicted values. Each blue point represents a predicted value generated by the model, while the red dashed diagonal line represents the ideal perfect prediction where the predicted value exactly matches the actual value. In this plot, the prediction points lie almost perfectly along the diagonal line, indicating a very strong correlation between actual and predicted efficiency values. This close alignment shows that the proposed ODRLR model produces highly accurate predictions with extremely minimal error. Overall, the visualization demonstrates that the proposed model significantly improves regression performance for the 2RT efficiency prediction task compared to the baseline models.



🎯 Prediction Results

Classification Predictions

Li-ion	Short	LiFePO4	Short	LiFePO4	Short	LiFePO4	Short
Lgbm Battery Type	Lgbm Charging Class	Xgboost Battery Type	Xgboost Charging Class	Adaboost Battery Type	Adaboost Charging Class	Proposed Battery Type	Proposed Charging Class

Regression Predictions

98.61	51.79	98.43	58.01	99.01	45.88	99.17	27.7
Lgbm Efficiency	Lgbm Duration	Xgboost Efficiency	Xgboost Duration	Adaboost Efficiency	Adaboost Duration	Proposed Efficiency	Proposed Duration

Figure 5: Prediction obtained for all the 4 target classes

Figure 5 shows the Prediction Results page that displays the outputs generated by different machine learning models for both 2CA and 2RT tasks based on the input battery parameters. In the classification section, the models predict the battery type and charging duration class. The LGBM model predicts Li-ion battery type and Short charging class, while the XGB and AdaBoost models predict LiFePO4 battery type and Short charging class. The proposed model also predicts LiFePO4 battery type with Short charging duration class. In the regression section, the models estimate numerical values for efficiency and charging duration. The LGBM model predicts an efficiency of 98.61% and charging duration of 51.79 minutes, the XGB model predicts 98.43% efficiency and 58.01 minutes duration, and the AdaBoost model predicts 99.01% efficiency and 45.88 minutes duration. The proposed model produces the final predictions with 99.17% efficiency and 27.7 minutes charging duration, indicating highly optimized performance for the given battery conditions.

4.1 Comparative analysis

Table 1: Overall Performance Comparison of Classification models for battery type class

Model	Accuracy	Precision	Recall	F-Score
Existing LGBM	59.02%	61.71%	59.02%	58.60%
Existing XGB	57.91%	60.45%	57.91%	57.50%
Existing AdaBoost	48.55%	51.33%	48.55%	46.85%
Proposed ARF	94.88%	95.12%	94.88%	94.89%

Table 1 presents the comparative performance analysis of different classification models used for predicting the battery type in the 2CA task. The models evaluated include the existing algorithms LGBM, XGB, and AdaBoost, along with the proposed ARF model. From the results, the LGBM model achieved an accuracy of 59.02%, while the XGB model achieved 57.91% accuracy, showing similar moderate classification performance. The AdaBoost model produced the lowest performance with 48.55% accuracy, indicating weaker classification capability for distinguishing battery types. In contrast, the proposed ARF model significantly outperforms the existing models, achieving an accuracy of 94.88%, precision of 95.12%, recall of 94.88%, and F-score of 94.89%. These results clearly demonstrate that the proposed ARF model provides superior classification performance with improved prediction reliability for the battery type classification task (2CA).

Table 2: Overall Performance Comparison of Classification models for charging duration

Model	Accuracy	Precision	Recall	F-Score
Existing LGBM	95.77%	95.79%	95.77%	95.77%
Existing XGB	84.86%	86.34%	84.86%	84.59%
Existing AdaBoost	66.37%	68.24%	66.37%	65.23%
Proposed ARF	99.55%	99.56%	99.55%	99.55%

Table 2 presents the comparative performance analysis of different classification models used for predicting the charging duration class in the 2CA task. The evaluated models include the existing algorithms LGBM, XGB, and AdaBoost, along with the proposed ARF model. From the results, the LGBM model achieved a high accuracy of 95.77%, demonstrating strong performance in identifying charging duration classes. The XGB model achieved 84.86% accuracy, showing moderate classification performance compared to LGBM. The AdaBoost model recorded the lowest performance with 66.37% accuracy, indicating weaker classification capability for this task. In contrast, the proposed ARF model significantly outperforms all existing models, achieving an accuracy of 99.55%, precision of 99.56%, recall of 99.55%, and F-score of 99.55%. These results demonstrate that the proposed ARF model provides highly accurate and reliable predictions for the charging duration classification task (2CA) compared to the baseline models.

Table 3: Overall Performance Comparison of regression models for efficiency

Model	MAE	MSE	RMSE	R2-Score
Existing LGBM	0.16	0.043	0.20	0.85
Existing XGB	0.25	0.09%	0.31%	0.67
Existing AdaBoost	0.03	0.001	0.043	0.99
Proposed ARF	0.0007	0.00	0.002	1.000

Table 3 presents the comparative performance analysis of different regression models used for predicting efficiency in the 2RT task. The evaluated models include the existing algorithms LGBM, XGB, and AdaBoost, along with the proposed ARF model. The results show that the LGBM model achieved an MAE of 0.16, MSE of 0.043, RMSE of 0.20, and an R^2-score of 0.85, indicating reasonable regression performance. The XGB model produced slightly higher error values with an MAE of 0.25, MSE of 0.09, RMSE of 0.31, and an R^2-score of 0.67, suggesting comparatively lower prediction accuracy. The AdaBoost model demonstrated strong regression capability with a very low MAE of 0.03, MSE of 0.001, RMSE of 0.043, and an R^2-score of 0.99. However, the proposed ARF model significantly outperforms all existing models, achieving extremely low error values with an MAE of 0.0007, MSE close to 0.00, RMSE of 0.002, and an R^2-score of 1.000. These results clearly indicate that the proposed ARF model provides highly accurate and reliable predictions for the efficiency regression task (2RT) compared to the baseline models.

Table 4: Overall Performance Comparison of regression models for charging duration

Model	MAE	MSE	RMSE	R2-Score
Existing LGBM	11.39	190.84	13.81	0.77
Existing XGB	16.34	368.67	19.20	0.56
Existing AdaBoost	6.57	60.74	7.79	0.92
Proposed ARF	0.49	2.60	1.61	0.99

Table 4 presents the comparative performance analysis of different regression models used for predicting charging duration in the 2RT task. The evaluated models include the existing algorithms LGBM, XGB, and AdaBoost, along with the proposed ARF model. From the results, the LGBM model achieved an MAE of 11.39, MSE of 190.84, RMSE of 13.81, and an R^2-score of 0.77, indicating moderate prediction accuracy. The XGB model showed lower performance with higher error values, including an MAE of 16.34, MSE of 368.67, RMSE of 19.20, and an R^2-score of 0.56, suggesting greater deviation between actual and predicted charging duration values. The AdaBoost model improved the regression performance with an MAE of 6.57, MSE of 60.74, RMSE of 7.79, and an R^2-score of 0.92, demonstrating better prediction capability compared to LGBM and XGB. However, the proposed ARF model significantly outperforms all existing models, achieving very low error values with an MAE of 0.49, MSE of 2.60, RMSE of 1.61, and an R^2-score of 0.99. These results indicate that the proposed ARF model provides highly accurate and reliable predictions for the charging duration regression task (2RT) compared to the baseline models.

5. CONCLUSION

The research presents an intelligent machine learning framework for predicting battery performance and charging behavior in hybrid electric vehicle systems using operational battery parameters. The system integrates multiple machine learning and deep learning models including LGBM, XGB, AdaBoost and the proposed ARF framework to perform 2CA and 2RT predictive tasks. The classification models successfully predict battery type and charging duration class, while the regression models estimate efficiency and charging duration values based on real-time battery conditions. Experimental results demonstrate that the proposed ARF model significantly outperforms the existing models, achieving the highest accuracy and F-score for classification tasks and the lowest error values with the highest R^2-scores for regression tasks. Visualization results such as confusion matrices, ROC curves, and scatter plots further confirm the effectiveness of the proposed model in capturing complex relationships between battery parameters and performance outcomes. The proposed system provides a reliable and efficient approach for battery performance prediction and energy management, which can support intelligent charging strategies and improve operational efficiency in electric vehicle energy systems.

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