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Predicting the Remaining Useful Life of Lithium-Ion Batteries for Vehicle Using Machine Learning Algorithms

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ABSTRACT

The objective of this research to predicting the remaining useful life (RUL) of Lithium-Ion Batteries (LIB's) system by machine learning model for optimization of electrified vehicle battery storage system. Predicting RUL accurately can help extend the lifespan of batteries, reduce maintenance costs, and enhance overall system performance and safety Consequently, management system, battery state estimation, and estimation of the RUL. Various techniques are then used to predicted the model parameters, such as Linear Regression (LR), Support vector machines (SVM), Gradient Boosting (GB), AdaBoost (AB), Tree, and Random Forest (RF). The results showed that the best model is AdaBoost with a value of Mean Squared Error (MSE) is 9.816; Root Mean Squared Error (RMSE) with a value is 3.133; Mean Absolute Error (MAE) with a value 1.557; Mean Absolute Percentage Error (MAPE) with a value 0.007; and R-Squared (R2) with a value 1.000. Second model is Tree regression with a value of MSE is 32.734; RMSE with a value is 5.721; MAE with a value 2.914; MAPE with a value 0.011; and R-Squared (R2) with a value 1.000. According to a result, the suggested future research activity of battery efficiency AdaBoost models are useful for managing batteries. In this paper, quantitative evaluation is presented using two datasets with different batteries under different conditions. Quantitative evaluation of predictive models, particularly for estimating the RUL of lithium-ion batteries. This structured approach ensures a comprehensive and transparent presentation of the quantitative evaluation, allowing readers to understand the effectiveness of different predictive models under varying conditions. In addition, it is important to highlight that effective management and accurate prediction of battery usage can significantly contribute to improving the efficiency and sustainability of energy storage systems. This promotes the adoption of clean energy, reduces emissions, and encourages innovation and collaboration.

INTRODUCTION

An applications of battery powered devices and number has significant increased over the last decades. Car, motor cycle, laptops, mobile phones, electronic watches, drones, portable radios, remote controls, children's toys, and many others are a few examples of daily-life battery-operated appliances. Batteries are generally divided into two types, namely primary batteries and secondary batteries. Consequently, management system, battery state estimation, and estimation of the remaining useful life (RUL). This type of primary battery as disposable batteries are designed for one-time use and cannot be recharged, therefore it is thrown away immediately after use. This type of battery is usually applied to low power electronic equipment. While the secondary or rechargeable batteries, can be recharged multiple times, making them more cost-effective and environmentally friendly in the long run. Type of rechargeable battery can be recharged after being discharged this battery is also known as an energy storage battery. Frequency containment reserve is one of these applications of battery storage systems to power networks (Luque et al., 2023).

Valuation of efficiency and performance of lithium-ion batteries (LIBs) is crucial to their safe and reliable. However, the decrease in battery capacity, which is influenced by several factors, such as current rate, temperature, and battery aging path history, raises concerns about the safety of LIBs and their possible application in any devices (Luo et al., 2023). By reserving excess battery capacity, industrial consumers can ensure a more robust and reliable peak shaving strategy (Henni et la., 2022), which ultimately helps to optimize energy costs and enhance operational efficiency. Lithium-ion batteries are preferred over other battery technologies in various application due to long lifetime (Henni et la., 2022), (Kumar et al., 2023).

Smart energy systems leverage information and communications technology, artificial intelligence, and algorithms (Luque et al., 2023) to optimize energy production, distribution, and consumption. By integrating advanced technologies, these systems can enhance efficiency, reduce waste, and promote sustainability in energy management. They enable better monitoring, control, and coordination of various energy resources, leading to more reliable and resilient energy supply infrastructures (Asnada & Sulistyono, 2020). The voltage curves move leftward, and shape turns to be gentle, which shows that the charging capacity is decreasing, and internal resistance is increasing (Luo et al., 2023). Hence, the degradation characteristic can be identified from a slight shift in curve shape of constant current (CC) stage.

The phenomenon described is indicative of battery degradation. As a battery ages, its internal resistance typically increases, leading to a decrease in charging capacity and changes in voltage curves during the charging process. In the constant current stage of charging, (Luo et al., 2023) where the battery is charged with a steady current, the voltage curve initially rises sharply and then gradually becomes more gentle as the battery reaches its capacity. However, (Henni et la., 2022), (Kumar et al., 2023) as the battery degrades over time, this curve may shift leftward and the shape may become smoother, indicating reduced charging capacity and increased internal resistance. The battery degradation and continuous operation are almost significantly difficult to analyze correctly (Kumba et al., 2024).

Electric vehicles (EVs) are gaining popularity as an alternative to internal combustion engines (ICEs). However, the electrification of transport has not progressed equally throughout the world. Electric Vehicles are currently leading the paradigm shift in the automobile industry (Kumar et al., 2023), (Yun et la., 2023). EVs reliance on batteries, which currently have lower energy and power densities than liquid fuels and are prone to aging and performance degradation over time, restricts their mainstream adoption (Jafari & Byun, 2022).

In the use of batteries, battery system degradation is an inevitable occurrence, requiring users to either provide a larger battery capacity to meet energy needs or be prepared for battery replacements. Battery degradation can be evaluated based on two parameters: state of charge (SoC) and state of health (SoH) (Hasib et la., 2021), with higher SoH such that all battery cells reach their end of discharge at the same time (Xia & Abu, 2021). SoC estimation is important for the efficient and reliable operation of battery application systems (Yun et la., 2023), (Hasib et la., 2021). With lower SoH and draws energy at a faster rate from the battery (Xi et al., 2019), (Huo et al., 2021). SoC refers to the level of charge and the power stored in the battery at a particular time, usually measured as a percentage of the battery's full capacity. Measuring SoC is crucial to understand how much the battery has been charged and how much power is still available for use (Xi et al., 2019). SoC measurement helps prevent excessive use that can lead to deep discharge, which can damage the battery and accelerate degradation (Huo et al., 2021). The SoC will be charged as electricity becomes more valuable, and the SoC will be discharged.

Performance state life prediction and estimation have become a vital issue in battery management and it's use (Gu et al., 2021), battery health state and remaining useful life prediction (Yang et al., 2017). Battery management, battery data sets, and RUL prediction feasibly helps to visualize the causes of battery aging and performance degradation. For better battery management and RUL prediction, it is important to select carefully the most appropriate datasets (Hasib et la., 2021), (Barre et al., 2021). Battery management is usually used to predict battery performance and quantify to maximize battery life in real-world situations (Chen et al., 2022).

By RUL prediction, is incredibly valuable for numerous industries, RUL prediction assists in timely predictive maintenance by delivering crucial information regarding fault occurrence (Che et al., 2021), (Ansari et al., 2021). By analyzing historical data, sensor readings, and other relevant information, predictive maintenance models can predict when equipment or machines are most likely to fail. During cyclic charging and discharging operations, the capacity of a battery can degrade over time due to various factors such as chemical reactions, electrode wear, and the formation of unwanted compounds within the battery cells (Shen et al., 2018). This degradation is often referred to as capacity fade (Zhang et al., 2018).

A probabilistic-based adaptive estimator is used cautiously for both state of energy (SoE) and state of charge (SoC) estimation using information-driven methodology. neural networks (NN) (Wang et al., 2016). Additionally, accurate battery models are examined. A comparison has been made between Linear Regression (LR) and Support Vector Machine (SVM). LR has been used, and it has been found that it exhibits stable and better competitive prediction performance than SVM in terms of the RUL of Li-ion batteries under constant discharge conditions (Xing et al., 2014). In this paper, an intelligent battery RUL prediction approach using the SVM model and the LR is proposed.

The objective of this research to estimate of battery RUL system by machine learning model for optimization of electrified vehicle battery storage system. Previous research has developed several models for assessing the readiness model to implementing RUL battery powered devices, but in the case of RUL, appropriate indicators and assessment dimensions are required. In addition, differences in perceptions of assessment dimensions and indicators are also a major problem that need to be addressed immediately. Based on the background and there is still a research gap found in the previous studies mentioned above, the formulation of the problem in this research is about the efficiency battery powered devices on performance in energy systems using machine learning.

The rest of the article is organized as follows: In section II, related work; describes the brief literature study of the offered design framework, battery selection, and lifetime factors influence of battery have been detailed, and the battery life prediction approaches. Then we explain the proposed method of ML Methods for RUL Prediction and estimation of Performance error indices in sections III. In Section IV, the major results are presented; Finally, in Section V, major conclusion and outlines for future research scope are delivered.

Lithium-ion (Li-ion) batteries have become ubiquitous in various aspects of our lives due to their numerous advantages. Some key areas where Li-ion batteries are widely used. Li-ion batteries are revolutionizing the transportation sector, particularly in EVs. Lithium-ion batteries are commonly used to provide power for electrical systems. In other words, they store and release electrical energy through internal electrochemical reactions. They offer high energy density, fast charging capabilities, and relatively long cycle life, making them the preferred choice for powering EVs, hybrid vehicles, electric bikes, and scooters. Additionally, Li-ion batteries are used in electric buses, trucks, and even airplanes, contributing to the electrification of transportation and reducing reliance on fossil fuels. The versatility, performance, and reliability of lithium-ion batteries have made them indispensable in modern society, powering essential technologies across multiple sectors and contributing to advancements in energy efficiency, sustainability, and convenience (Santoso & Kasih, 2024).

Lithium-Ion (Li-Ion) Batteries

Lithium-ion batteries typically consist of three main components: Cathode: The cathode is the positive electrode of the battery, where lithium ions are stored during charging. Predicting the RUL of lithium-ion batteries is crucial for ensuring reliability and safety in various applications (Nurdin et al., 2023). Several approaches have been developed over the years to improve the accuracy and robustness of these predictions (Lipu et al., 2018).

The cathode provides the source of lithium ions during discharge. Anode: The anode is the negative electrode of the battery, where lithium ions are released during charging and stored during discharge. During charging, lithium ions migrate from the cathode to the anode, and they move back to the cathode. Electrolyte: the electrolyte is the medium that allows lithium ions to move between the cathode and anode while blocking the flow of electrons. The electrolyte also provides a conductive path for ions to move within the battery. The primary reactions, explained in the general form of a carbon anode, are (1) for the charging process and (2) for the discharge process.

Charge Reactions:

At the anode: $Li_nC_6 \leftarrow Li_0C_6 + nLi^+ + ne^-$;
At the cathode: $Li_{m-n}MO_2 + nLi^+ + ne^- \leftarrow Li_mMO_2$; (1)
Global reaction: $Li_nC_6 + Li_{m-n}MO_2 \leftarrow Li_0C_6 + Li_mMO_2$.

where: MO_2 is the general form of the cathode chemistry, as an oxide of a metal (M), and n and m are the stoichiometric coefficients of lithium involved in the reaction. During the charge, lithium ions move from cathode to anode through the electrolyte, while the electrons move through the external circuit. During discharge, the process is reversed.

Discharge Reactions:

At the anode: $Li_nC_6 \rightarrow Li_0C_6 + nLi^+ + ne^-$;
At the cathode: $Li_{m-n}MO_2 + nLi^+ + ne^- \rightarrow Li_mMO_2$; (2)
Global reaction: $Li_nC_6 + Li_{m-n}MO_2 \rightarrow Li_0C_6 + Li_mMO_2$.

Usually these reactions are exothermic, as the transport of Li-ion is associated with heat generation. A comparison of different materials for Lithium-Ion batteries. As an example, for a cathode of $LiMn_2O_4$ and a carbon anode the equations following:

Discharge Reactions:

At the anode: $Li_nC_6 \leftrightarrow Li_0C_6 + nLi^+ + ne^-$;
At the cathode: $Li_{m-n}MO_2 + nLi^+ + ne^- \rightarrow Li_mMO_2$; (3)
Global reaction: $Li_nC_6 + Li_{m-n}MO_2 \rightarrow Li_0C_6 + Li_mMO_2$.

RUL Predicting

Predicting the expectation of RUL involves choosing the appropriate method based on the characteristics of the battery system, the available data, and the required prediction accuracy. Statistical methods provide a straightforward approach, while machine learning and hybrid models offer more advanced and accurate predictions for complex systems.

Predicting RUL accurately can help extend the lifespan of batteries, reduce maintenance costs, and enhance overall system performance and safety (Wu et al., 2019). The expectation of RUL can be estimated (Wu et al., 2019), (Florences et al., 2023). Mathematically, it can be expressed as:

$$\text{Mean RUL} = \frac{1}{n} \sum_{i=1}^{n} \text{RUL}_i \quad (4)$$

$$\text{Median RUL} = \text{Median}(\text{RUL}_1, \text{RUL}_2, \ldots \text{RUL}_n)$$

$$\text{RUL}_K = \sum_{i=1}^{N} \omega_k^i \ \text{RUL}_k^i \quad (5)$$

Indicators

The use of indicators that enable the evaluation and diagnosis of battery behavior through monitoring is highly desirable. Therefore, the following indicators have been established: Battery usage describes how a battery is used in a specific application by defining a set of characteristic parameters. State of Charge refers to the amount of stored electric charge in a battery, relative to its actual capacity (Utama et al., 2024). This performance indicator describes the amount of uncertainty explained by an independent variable.

State of Charge (SoC): The primary indicator in Lithium-Ion Batteries, providing information about the remaining energy inside the battery. SoC can be defined as in Equation (4), where Q is the actual capacity and Q_{max} is the maximum capacity of the cell. The equations following (Bobanac et al., 2021), (Rasul et al., 2021):

$$\text{SoC} = \frac{Q}{Q_{max}} \quad (5)$$

State of Health (SoH): The ratio between the maximum currently available capacity and the rated available capacity, indicating the aging condition of the battery. Mathematically the equation is as follows (Bobanac et al., 2021), (Rasul et al., 2021):

$$\mathrm{SoH} = \frac{Q_{max}}{Q_{N,max}} \tag{6}$$

where $Q_{N,max}$ represents the capacity before any reduction a decline.

To accomplish an obvious enhancement in SOH prediction of different LIBs, by develop SOH prediction approach based on diffusion model with transfer learning (Ahmad et al., 2022).

Linear Regression (LR):

Linear regression aims to model the relationship between a dependent variable (target) and one or more independent variables (features) by fitting a linear equation to observed data. Enhancing linear regression for better RUL prediction to improve the predictive performance of linear regression for RUL estimation. The basic form of a linear regression model is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \epsilon \tag{6}$$

where:
y is the dependent variable (RUL of the battery),
β_0 is the intercept,
$\beta_1, \beta_2 \ldots \beta_n,$ is the intercept,
ϵ is the error term.

By incorporating these enhancements, linear regression can become a more powerful tool for predicting the RUL of lithium-ion batteries, balancing simplicity and predictive performance.

Performance Evaluation Metrics

Performance evaluation metrics are essential for assessing the accuracy and effectiveness of predictive models, including those used for estimating the RUL of lithium-ion batteries (Sekhar et al., 2023). These metrics help determine how well the model's predictions match the actual outcomes (Wu et al., 2019). Here are some common performance evaluation metrics used in regression analysis, including RUL prediction (Wu et al., 2019), (Sekhar et al., 2023), (Khan et al., 2023):

Mean Absolute Error (MAE) is the difference between the original and predicted values, calculated by averaging the absolute difference over the dataset. It measures the average magnitude of the errors between predicted and actual values, without considering their direction. MAE is primarily a measure of accuracy for the developed model expressed on the same scale. If MAE is closer to zero, the model is more accurate. Lower values indicate better model performance.

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i) \tag{7}$$

Mean Squared Error (MSE) depicts the variance between the original and predicted values, as determined by taking the square root of the mean variance throughout the data set. It measures the average of the squares of the errors, giving more weight to larger errors. MSE is sensitive to outliers due to the squaring of errors. Lower values indicate better model performance.

$$\text{Mean Squared Error (MSE)} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{8}$$

Root Mean Squared Error (RMSE) is the square root of MSE, which provides an error metric in the same units as the original data. Lower values indicate better model performance. The RMSE is also sensitive to outliers. If RMSE is closer to zero, the model is more accurate.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{y_i} - \hat{y}_i)^2} \quad (9)$$

Mean Absolute Percentage Error (MAPE) measures the average absolute percentage error between predicted and actual values. Lower values indicate better model performance. MAPE can be problematic if the actual values are close to zero.

$$\mathrm{MAPE} = \frac{100\%}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} \left(\frac{\mathrm{y_i} - \hat{y}_i}{\mathrm{y_i}} \right) \quad (10)$$

R-Squared (Coefficient of determination) represents the proportion of the variance in the dependent variable that can be predicted from the independent variables. R-Squared shows how well the values fit the original values, with values ranging from 0 to 1. The higher the value, the better the model performs.

$$\mathrm{R - Squared} = 1 - \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{y_i} - \hat{y}_i)^2}{\sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{y_i} - \bar{y}_i)^2} \quad (11)$$

The battery lifecycle databases available to the general public do not provide ready-to-use data for the assignment (Wu et al., 2019), (Liu et al., 2016). In this research, The Hawaii Natural Energy Institute examined and the NASA Prognostic Center of Excellence dataset for batteries RUL is utilized, measured over 168 cycles under discharge temperature conditions of 240°C. From the source dataset, researchers created features that showcase the voltage and current behavior over each cycle. These features can be used to predict the RUL of the batteries. The variables used in research are: Cycle Index, Discharge Time (s), Decrement 3.6-3.4V (s), Maximum Voltage Discharge (V), Minimum Voltage Charge (V), Time at 4.15V (s), Time constant current (s), Charging time (s), and RUL. (Datasets Source available online from 2 websites: https://github.com/ignavinuales/Battery_RUL_Prediction and https://www.kaggle.com/datasets/ignaciovinuales/battery-remaining-useful-life-rul).

Several techniques have been suggested to recognize these RUL (Liu et al., 2016), (Attia et al., 2021); (Wu et al., 2019) utilized five ML methods such Random forest regression, decision tree regression, linear regression, Bayesian network, and gradient boosting regression. to construct RUL of Battery.

RESEARCH METHODS

Various techniques are then used to classify the model parameters (Santoso & Kasih, 2024), such as Linear Regression (LR), Support vector machines (SVM), Gradient Boosting (GB), AdaBoost (AB), Tree, and Random Forest (RF). To determine the number of predicting, various unsupervised ML predicted methods were used, such as k-means, hierarchical, and density-based spatial clustering of applications with noise clustering. In the proposed method, the entire SoC was divided into several sections considering the deviation of the parameter values according to the SOC (Hossain et al., 2022), to improve the accuracy of the SoC (Ciu et al., 2022). In another research (Sekhar et al., 2023) was used to reflect battery parameters dependent on the SoC.

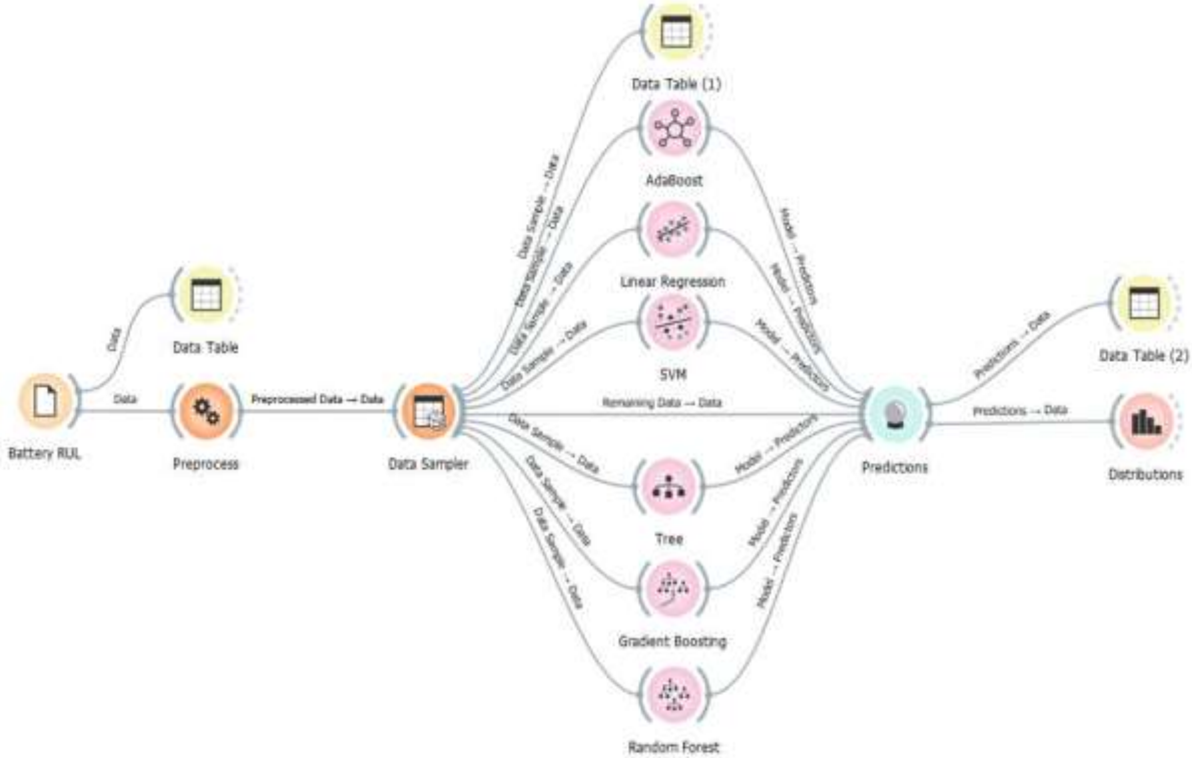


Figure 1. Classification Techniques Used to Predicting RUL Lithium-Ion Batteries Datasets

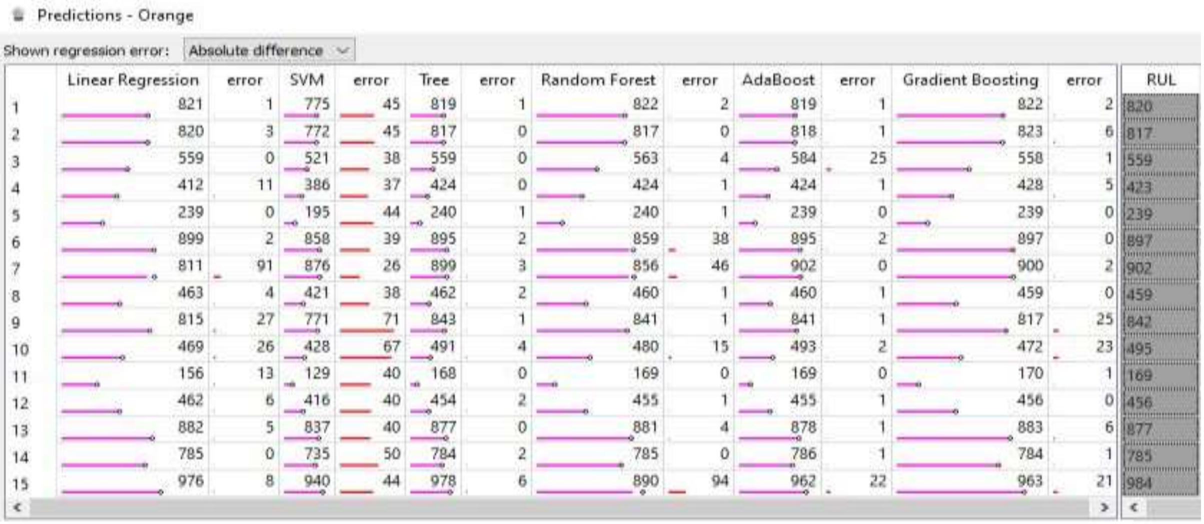
RESULTS AND DISCUSSION

Predictions - Orange

Shown regression error: Difference

	Linear Regression	error	SVM	error	Tree	error	Random Forest	error	AdaBoost	error	Gradient Boosting	error	RUL
1	821	1	775	-45	819	-1	822	2	819	-1	822	2	820
2	820	3	772	-45	817	0	817	0	818	1	823	6	817
3	559	-0	521	-38	559	0	563	4	584	25	558	-1	559
4	412	-11	386	-37	424	0	424	1	424	1	428	5	423
5	239	-0	195	-44	240	1	240	1	239	0	239	-0	239
6	899	2	858	-39	895	-2	859	-38	895	-2	897	-0	897
7	811	-91	876	-26	899	-3	856	-46	902	0	900	-2	902
8	463	4	421	-38	462	2	460	1	460	1	459	-0	459
9	815	-27	771	-71	843	1	841	-1	841	-1	817	-25	842
10	469	-26	428	-67	491	-4	480	-15	493	-2	472	-23	495
11	156	-13	129	-40	168	-0	169	-0	169	0	170	1	169
12	462	6	416	-40	454	-2	455	-1	455	-1	456	0	456
13	882	5	837	-40	877	0	881	4	878	1	883	6	877
14	785	0	735	-50	784	-2	785	-0	786	1	784	-1	785
15	976	-8	940	-44	978	-6	890	-94	962	-22	963	-21	984

Figure 2. SVM, Tree, RF, AB, and GB Methods Results



Predictions - Orange

Shown regression error: Absolute difference

	Linear Regression	error	SVM	error	Tree	error	Random Forest	error	AdaBoost	error	Gradient Boosting	error	RUL
1	821	1	775	45	819	1	822	2	819	1	822	2	820
2	820	3	772	45	817	0	817	0	818	1	823	6	817
3	559	0	521	38	559	0	563	4	584	25	558	1	559
4	412	11	386	37	424	0	424	1	424	1	428	5	423
5	239	0	195	44	240	1	240	1	239	0	239	0	239
6	899	2	858	39	895	2	859	38	895	2	897	0	897
7	811	91	876	26	899	3	856	46	902	0	900	2	902
8	463	4	421	38	462	2	460	1	460	1	459	0	459
9	815	27	771	71	843	1	841	1	841	1	817	25	842
10	469	26	428	67	491	4	480	15	493	2	472	23	495
11	156	13	129	40	168	0	169	0	169	0	170	1	169
12	462	6	416	40	454	2	455	1	455	1	456	0	456
13	882	5	837	40	877	0	881	4	878	1	883	6	877
14	785	0	735	50	784	2	785	0	786	1	784	1	785
15	976	8	940	44	978	6	890	94	962	22	963	21	984

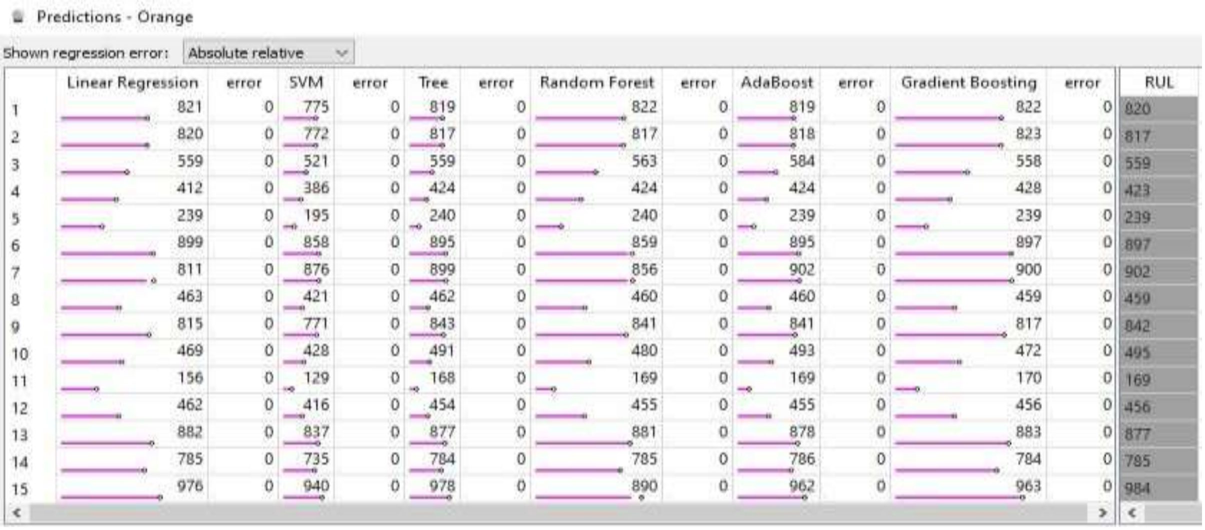
Figure 3. Absolute Difference LR, SVM, Tree, RF, AB, and GB Results

Predictions - Orange

Shown regression error: Relative

	Linear Regression	error	SVM	error	Tree	error	Random Forest	error	AdaBoost	error	Gradient Boosting	error	RUL
1	821	0	775	-0	819	-0	822	0	819	-0	822	0	820
2	820	0	772	-0	817	0	817	0	818	0	823	0	817
3	559	-0	521	-0	559	0	563	0	584	0	558	-0	559
4	412	-0	386	-0	424	0	424	0	424	0	428	0	423
5	239	-0	195	-0	240	0	240	0	239	0	239	-0	239
6	899	0	858	-0	895	-0	859	-0	895	-0	897	-0	897
7	811	-0	876	-0	899	-0	856	-0	902	0	900	-0	902
8	463	0	421	-0	462	0	460	0	460	0	459	-0	459
9	815	-0	771	-0	843	0	841	-0	841	-0	817	-0	842
10	469	-0	428	-0	491	-0	480	-0	493	-0	472	-0	495
11	156	-0	129	-0	168	-0	169	-0	169	0	170	0	169
12	462	0	416	-0	454	-0	455	-0	455	-0	456	0	456
13	882	0	837	-0	877	0	881	0	878	0	883	0	877
14	785	0	735	-0	784	-0	785	-0	786	0	784	-0	785
15	976	-0	940	-0	978	-0	890	-0	962	-0	963	-0	984

Figure 4. Relative LR, SVM, Tree, RF, AB, and GB Results



Predictions - Orange

Shown regression error: Absolute relative

	Linear Regression	error	SVM	error	Tree	error	Random Forest	error	AdaBoost	error	Gradient Boosting	error	RUL
1	821	0	775	0	819	0	822	0	819	0	822	0	820
2	820	0	772	0	817	0	817	0	818	0	823	0	817
3	559	0	521	0	559	0	563	0	584	0	558	0	559
4	412	0	386	0	424	0	424	0	424	0	428	0	423
5	239	0	195	0	240	0	240	0	239	0	239	0	239
6	899	0	858	0	895	0	859	0	895	0	897	0	897
7	811	0	876	0	899	0	856	0	902	0	900	0	902
8	463	0	421	0	462	0	460	0	460	0	459	0	459
9	815	0	771	0	843	0	841	0	841	0	817	0	842
10	469	0	428	0	491	0	480	0	493	0	472	0	495
11	156	0	129	0	168	0	169	0	169	0	170	0	169
12	462	0	416	0	454	0	455	0	455	0	456	0	456
13	882	0	837	0	877	0	881	0	878	0	883	0	877
14	785	0	735	0	784	0	785	0	786	0	784	0	785
15	976	0	940	0	978	0	890	0	962	0	963	0	984

Figure 5. Absolute Relative LR, SVM, Tree, RF, AB, and GB Results

Show perfomance scores

Model	MSE	RMSE	MAE	MAPE	R2
SVM	24667.878	157.060	156.716	330553288853016.312	0.763
AdaBoost	9.816	3.133	1.557	0.007	1.000
Linear Regression	1033.790	32.153	11.740	403892456073664.938	0.990
Random Forest	21.588	4.646	2.599	732535707024.589	1.000
Tree	32.734	5.721	2.914	0.011	1.000
Gradient Boosting	47.141	6.866	4.507	5232951781174.817	1.000

6025 | 6025 | 6×6025

Figure 6. Performance Score LR, SVM, Tree, RF, AB, and GB Methods Results

Based on Figure 2, 3, 4, 5, and 6 the selected models, namely LR, SVM, GB, AB, Tree, and RF overall showed that the best model is AdaBoost with a value of Mean Squared Error (MSE) is 9.816; Root Mean Squared Error (RMSE) with a value is 3.133; Mean Absolute Error (MAE) with a value 1.557; Mean Absolute Percentage Error (MAPE) with a value 0.007; and R-Squared (R2) with a value 1.000. Second model is Tree regression with a value of MSE is 32.734; RMSE with a value is 5.721; MAE with a value 2.914; MAPE with a value 0.011; and R-Squared (R2) with a value 1.000.

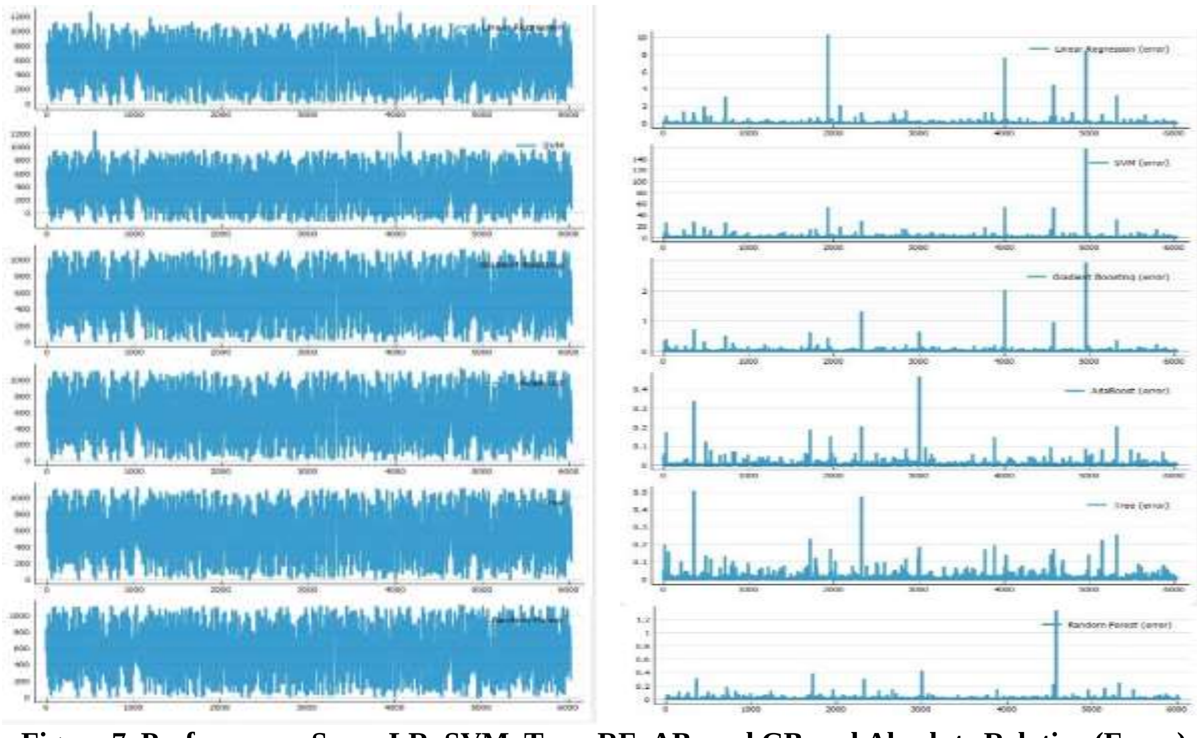


Figure 7. Performance Score LR, SVM, Tree, RF, AB, and GB and Absolute Relative (Error) LR, SVM, GB, AB, Tree, and RF Methods Results

Based on Figure 7 the selected models, to compare the results of LR, SVM, GB, AB, Tree, and RF methods in predicting the RUL of lithium-ion batteries, we can use difference absolute relative metrics. These metrics help us understand the performance gap between the two methods in a quantitative manner.

The selected models, namely Linear Regression, Support vector machines, Gradient Boosting, AdaBoost, Tree, and Random Forest. Based on the difference absolute relative (error) metrics, Random Forest emerges as the best model for predicting the RUL of lithium-ion batteries across both datasets. It consistently outperforms other models, including Linear Regression, SVM, Gradient Boosting, AdaBoost, and Decision Tree, in terms of MAE, MSE, RMSE, and MAPE. These findings underscore the importance of using advanced ensemble methods for accurate RUL prediction, which can significantly improve battery management and contribute to the efficiency and sustainability of energy storage systems (Khan et al., 2023).

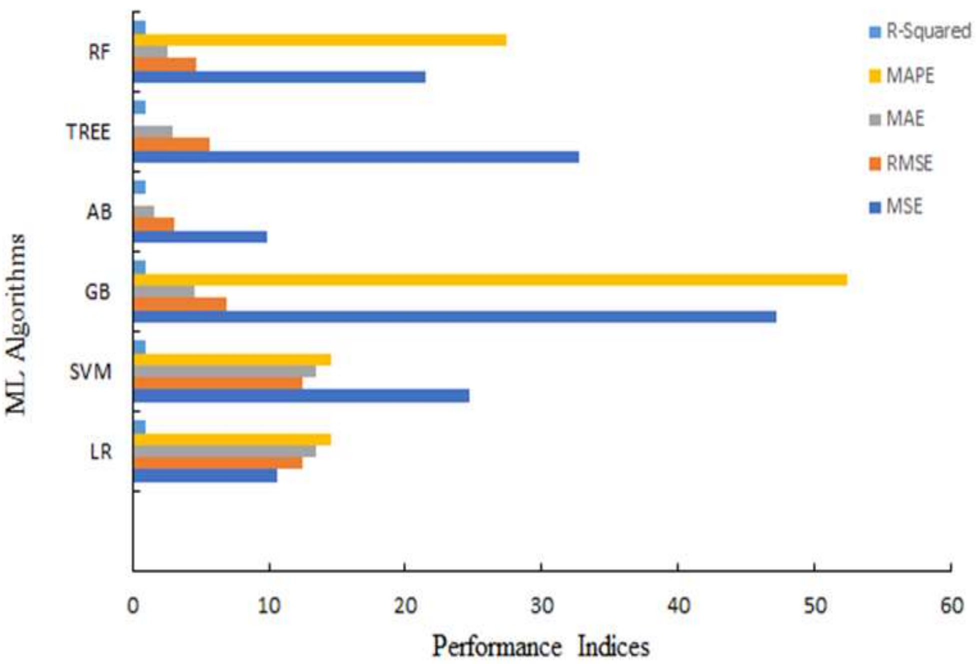


Figure 8. Performance Score LR, SVM, Tree, RF, AB, and GB Methods Results

Analyzing the distribution of prediction errors using histograms and boxplots provides a comprehensive understanding of the performance of different models. The comparison shows that ensemble methods like Gradient Boosting and Random Forest tend to have more favorable error distributions, highlighting their effectiveness in predicting the RUL of lithium-ion batteries with higher accuracy and consistency compared to simpler models like Linear Regression and Decision Tree. This detailed analysis further supports the recommendation to use advanced ensemble methods for battery life prediction in real-world applications. These findings underscore the importance of using advanced ensemble methods for accurate RUL prediction, which can significantly improve battery management and contribute to the efficiency and sustainability (Santoso & Kasih, 2024) of energy storage systems (Javaid et al., 2022). This comparison will provide a clear quantitative understanding of the performance gap between these methods.

CONCLUSION

The results showed that the best model is AdaBoost with a value of Mean Squared Error is 9.816; Root Mean Squared Error with a value is 3.133; Mean Absolute Error with a value 1.557; Mean Absolute Percentage Error with a value 0.007; and R-Squared with a value 1.000. Second model is Tree regression with a value of MSE is 32.734; RMSE with a value is 5.721; MAE with a value 2.914; MAPE with a value 0.011; and R-Squared (R^2) with a value 1.000. According to a result, the suggested future research activity of battery efficiency AdaBoost models are useful for managing batteries. Effective prediction and management of the RUL of lithium-ion batteries are critical not only for improving the performance and reliability of individual devices but also for broader societal benefits. This study has demonstrated through quantitative evaluation using two distinct datasets that advanced predictive models can accurately estimate the RUL of batteries under various conditions.

In this paper, quantitative evaluation is presented using two datasets with different batteries under different conditions. Quantitative evaluation of predictive models, particularly for estimating the RUL of lithium-ion batteries. This structured approach ensures a comprehensive and transparent presentation of the quantitative evaluation, allowing readers to understand the effectiveness of different predictive models under varying conditions. In addition, it is important to highlight that effective management and accurate prediction of battery usage can significantly contribute to improving the efficiency and sustainability of energy storage systems. This promotes the adoption of clean energy, reduces emissions, and encourages innovation and collaboration.

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