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Estimation of Battery Remaining Life-time with Machine Learning Methods

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Abstract

The swift proliferation of renewable energy sources and electric grids causes discrepancies between energy supply and demand. This scenario causes variations in voltage and frequency levels due to discrepancies between energy generation and consumption, jeopardizing the stability of energy networks. The intrinsically fluctuating and unpredictable characteristics of renewable energy sources, such as the sun and wind, intensify these oscillations. In contrast to conventional have to have energy-producing systems, renewable energy systems have energy-producing systems and a restricted ability to adapt immediately to demand. In this environment, energy storage devices arise as a vital solution for the effective management of renewable energy generation and for sustaining grid stability. Research on Remaining Useful Life (RUL) and State of Charge (SoC) of batteries is essential for battery reliability, user satisfaction, and environmental sustainability. These studies provide benefits in energy efficiency, increased mobility, diminished battery replacement requirements, and superior waste management. Estimating battery longevity facilitates the efficient management of battery-operated equipment and the strategic planning of energy requirements. Deep learning techniques have made substantial progress in estimating battery capacity and longevity. Long-lasting batteries with substantial energy storage capacity, favored in industrial applications, are more efficiently assessed utilizing deep learning methodologies. This study analyzes the outcomes derived from the application of the Scaled Conjugate Gradient (SCG) technique for estimating battery capacity. It seeks to enhance the efficient management of battery systems and devise strategies that promote the sustainability of energy storage technology. This study's performance measures, comprising 1.098% MAPE, 0.9823 R^2, 0.0019 MSE, and 0.0302 MAE, enhance the effective management of energy storage systems, the optimal use of energy resources, and strategic planning to fulfill energy demands. This study's performance measures, 1.098% MAPE, 0.9823 R2, 0.0019 MSE and 0.0302 MAE obtained in this study on battery estimation, it supports the efficient management of energy storage systems, effective use of energy resources and strategic planning for energy demands.

Keywords: Battery, Battery management system, Deep learning, Predictive algorithm, Remaining useful life.

1. INTRODUCTION

The increase in energy demand, the increasing complexity of energy storage systems, the continuous development of energy storage systems, the increasing demand for electric vehicles and the incentives accompanying the development and changes; have made it necessary to make significant developments in battery management systems and battery technology. These developments have addressed predictive challenges, including remaining RUL and

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SoC. Estimating the remaining useful life of a battery is essential for informing people about its longevity. The capacity to forecast when a battery requires charging or replacement significantly influences planning and improves user experience.

Battery life prediction studies are very important for battery-based systems in terms of reliability, performance optimization and energy efficiency, especially with the expected increase in future electric vehicles and storage facilities. These studies reduce battery replacement; reduce waste management and mitigate environmental impact. They contribute to sustainable energy management with their environmental impact. In industrial products, extended service life and significant energy storage capacity are highly sought-after features, and machine learning techniques used for battery life prediction are expected to increase the accuracy of battery life projections.

Supervised learning algorithms are considered an important technique in data science and are frequently used in forecasting with input data such as energy, health, and population. Prediction algorithms, which focus on topics such as energy consumption and electrical grid stability, which require investment and where future projections are critical, have also been implemented in industrial processes together with diagnostic algorithms such as anomaly detection [1, 2, 3,4].

Prediction and diagnostic algorithms are widely preferred in industrial processes compared to traditional methods due to their fast-processing capacity, adaptability to real-time data, and ability to work simultaneously with alternative solutions [4, 5, 6]. With the rise of Industry 4.0, the importance of prognostic algorithms focusing on anomaly detection has increased. Machine learning methods, in particular, play a critical role in solving complex prediction problems such as estimating the operational life and remaining usage times of equipment in real-time systems. These methods increase prediction accuracy by dynamically modeling large and complex data sets and effectively use various variables to predict diagnostic or prognostic results. Predictive strategies provide approaches to estimate diagnostic and prognostic results through algorithms or models, thus increasing efficiency and preventing unexpected failures in industrial processes [6,7, 8].

Contemporary electricity production/transmission/distribution system and infrastructure have been developed to meet the increasing energy demand with technological innovations such as smart grids (SG), artificial intelligence (AI) and Internet of Things (IoT). Electricity consumption is increasing worldwide and energy demand is getting worse with population growth. In response to the increasing energy demand, investments in power plants are emphasized, while distributed energy technologies have emerged as an alternative to traditional methods. Demand side management (DSM), which aims to reduce electricity consumption and carbon emissions by balancing supply and demand, has emerged as an alternative method. DSM aims to balance the load curve and protect energy supply security by distributing demand and restricting excessive energy consumption [9,10].

Turkey's 2017-2023 National Energy Efficiency Action Plan (NEEAP) emphasizes increasing demand side participation. As detailed in Action E10, the importance of establishing a market mechanism for demand side participation is emphasized [11].

The demand side participation mechanism, which includes adjusting the energy load produced by prosumers to provide the supply-demand balance of the electricity distribution grid and as a sustainable system, reduces the need for low-efficiency power plants and reduces the energy import costs spent to provide the supply-demand balance. DSM encourages adaptive energy use during periods of low demand to reduce technical losses and consumer costs and increase energy efficiency. In this way, a mechanism that works for the benefit of both sides of the network is ensured [10, 12]. With current technological developments, consumers will be able to react to real-time price signals from network operators. Energy service companies (ESCOs) are developing innovative business models using DSM. These developments, combined with daily, monthly and annual settlement opportunities and various rates, allow DSM to expand in the network, and the expected benefits are expected to increase even more in the future [12,13].

Energy consumption forecasting is very important for managing energy resources. Energy companies, distribution operators, policy makers, energy suppliers and institutions use these forecasting models that take into account seasonal changes, weather forecasts, economic factors, demographic data, past energy consumption data and consumption trends, industrial activities and market demands. Statistical methods, time series algorithms, regression analysis methods, neural networks and various data analytics methodologies are used for demand forecasting. Highly accurate and reliable future projections are critical for balancing energy supply, optimizing demand management, planning energy distribution infrastructure investments and planning the optimum use of energy resources. Demand projections enable electricity distribution and transmission system operators to make decisions with scientifically based methodologies regarding planning their investments and supply processes, managing inventory and warehouses, creating pricing strategies and balancing energy supply with projected demand. Consequently, energy demand forecasting is essential to ensure efficient and sustainable energy management, facilitate optimum use of energy resources, improve planning procedures and assist in making strategic decisions in the energy sector [14,15,16].

Estimating State of Health (SoH) and RUL is crucial for maintaining the reliability and efficiency of lithium-ion batteries in many areas such as electric vehicles, energy storage systems, and consumers. SoH measures the degradation of the battery by comparing the capacity of the battery at the moment of measurement with its nominal capacity and serves as an important indicator to evaluate the change in battery health over time. RUL estimation estimates the remaining life of the battery before its usable capacity is exhausted, thus providing input for a proactive maintenance plan that can minimize the impact of operational processes. SoH and RUL estimations are crucial for improving battery utilization processes and reducing operational downtime. Advanced machine learning methods, including hybrid models that integrate temporal data analysis methods with feature extraction from datasets, have demonstrated significant accuracy in explaining and predicting the complex, nonlinear degradation and capacity decay mechanisms of lithium-ion batteries. The described methodological approaches increase the probability of more accurate prediction of temporal attributes of battery performance compared to traditional physics-based linear models. They facilitate the use of battery management systems by providing accurate, close to scientific approaches [17,18].

The rapid expansion of renewable energy sources (RES) in the transmission and distribution grid has led to imbalances in energy supply and demand. Due to the fluctuations in voltage and frequency levels originating from RES production, the interest in energy storage facilities, which are alternatives that will ensure that the levels remain stable, has increased and research studies have increased. With the increasing demand for BMSs, the importance of the need for advances in Energy Management Systems (EMS) and battery technologies has been emphasized. Research on SoH and RUL estimation of batteries and the integration of BMSs into transmission/distribution grid topologies has accelerated [19,20,21,22].

This study aims to estimate the RUL of lithium-ion (Li-Ion) batteries. In the study, five different machine learning algorithms/models were implemented independently and the performances of the models were evaluated with the same performance metrics. The research results are expected to encourage the development of BMSs and future innovations with RUL estimation.

2. MATERIALS AND METHODS

2.1 Data Acquisition

The models used in this study were implemented using MATLAB version 2022b on a computer with an Intel Core i5 processor and an NVIDIA GeForce RTX 3050 Ti graphics card. The study used the "Battery Dataset" from the NASA Ames Prognostics Data Repository [23] and used data such as current, voltage, and temperature for RUL estimation with the dataset [24]. Table 1. provides the usage of this study dataset's detailed information and descriptions.

Table 1. Dataset Variables Descriptions

Variable Name	Description
cycle	Shows the number of charge-discharge cycles the battery has gone through in its history.
ambient_temperature	The ambient temperature during operation is measured in degrees Celsius.
datetime	Shows the date and time when battery data was measured.
capacity	Reflects the remaining capacity of the battery for its performance and shows the battery charge capacity, measured in ampere-hours (Ah).
voltage_measured	The actual output voltage of the battery measured at the relevant *datetime*, measured in volts (V).
current_measured	The actual output current value of the battery measured at the relevant *datetime*, measured in amperes (A).
temperature_measured	The internal temperature of the battery measured at the relevant datetime, measured in degrees Celsius (°C).
current_load	The current demand applied to the battery output load, measured in amperes (A).
voltage_load	The voltage demand applied to the battery by the output load, measured in volts (V).
time	The time elapsed since the beginning of the current cycle or measurement, measured in seconds or minutes.
flag	The indicator used to indicate the state of charge or discharge during data collection.

The NASA Ames Battery Dataset provides data for estimating RUL for lithium-ion batteries based on various parameters and conditions. It includes the number of charge-discharge cycles the battery has undergone since its first use and battery capacity data. Current, voltage and internal temperature data, which affect the internal functionality of the battery, are critical for battery capacity estimation, as are temperature data related to environmental factors. The dataset parameters provide the necessary data for accurate estimation of RUL, while also providing input to proactive maintenance plans related to operational requirements that will ensure safe and efficient operation of BMSs.

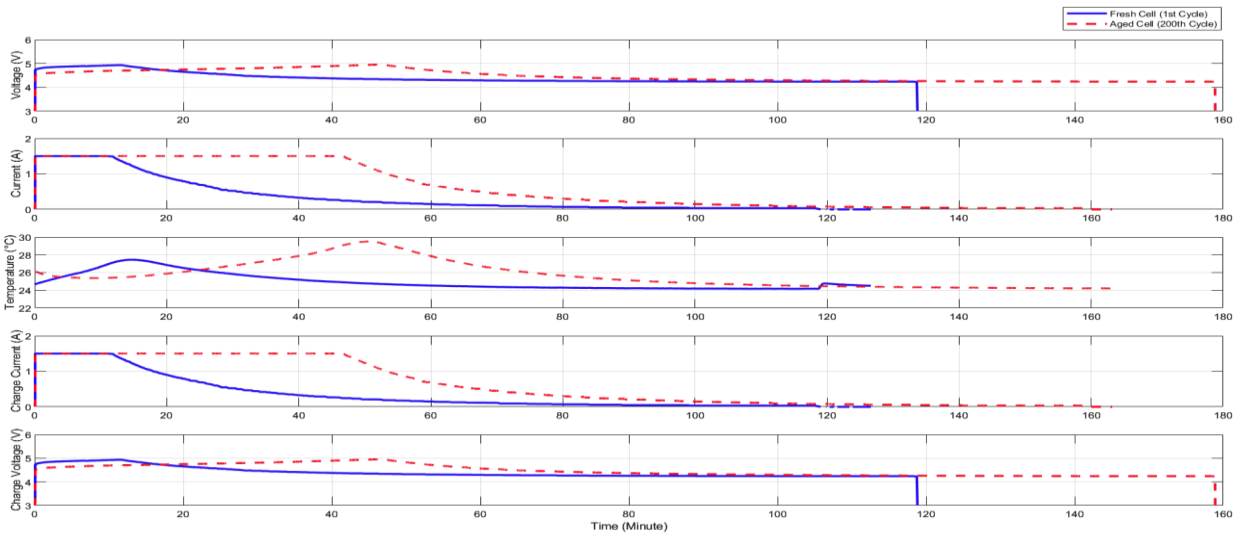

Figure 1. Data analysis chart

Figure 1 compares the voltage, current and temperature profiles of a new cell (cycle 1) with an old cell (cycle 2000), highlighting changes due to capacity deterioration and increased internal resistance with the number of cycles, i.e. usage. While the new cell performs consistently and as expected, the old cell operating at cycle 2000 shows inconsistent and erratic performance. Complementary variable data such as changing load characteristics and time in use enhance the dataset by reflecting the details of operational demands and evolving cycle-specific behaviors, while flag information indicates critical events in charge-discharge cycles for accurate analysis. This comprehensive dataset facilitates the creation of machine learning models that predict SoH and RUL as close as possible to the truth, and improves battery management systems for improved reliability, performance and proactive maintenance in battery application areas such as electric vehicles and energy storage systems [17,23].

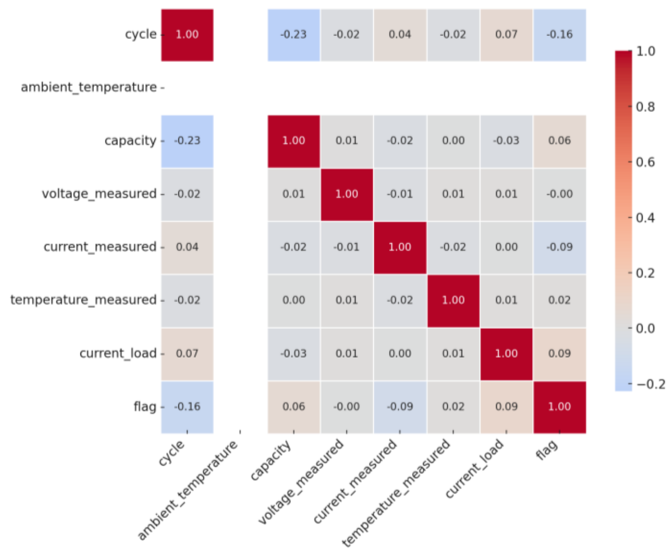

Figure 2. Correlation Matrix of Battery Dataset Variables

Figure 2. shows a correlation heat map analyzing the linear relationships between various variables used in industrial processes. Correlation coefficients range from -1 to +1, and are expressed in shades of red for positive correlation and blue for negative correlation. A correlation coefficient of +1 indicates a perfect positive relationship between two variables, while a correlation coefficient of -1 indicates a perfect negative relationship. However, the findings show that the correlations between the variables are largely low and there is no clear linear relationship. This indicates that the data considered may have more complex and non-linear relationships[10,24].

In particular, the negative correlation of -0.23 between cycle and capacity indicates that the capacity decreases with the increase in the number of cycles, and the positive correlation of 0.09 between flag and current_load suggests that under certain conditions, an increase in the load amount may affect the flag variable. However, the correlations between other variables are generally close to zero, indicating that there is no significant linear relationship between these variables. A detailed examination of the correlation matrix suggests that effective and reliable prediction can be achieved with the use of nonlinear models, especially advanced machine learning methods such as decision trees, support vector machines or neural networks.

2.2 Methods

The RUL estimation of lithium-ion batteries has emerged as a critical issue in energy storage and management systems, considering their safety, reliability, and sustainability implications. Lithium-ion batteries are widely used in electric vehicles, energy storage systems, and consumer electronics products [15,16]. Depending on usage, batteries experience capacity changes due to complex chemical and physical problems, including electrolyte decomposition, formation of electrode surface films, and structural degradation. The challenges brought by these degradation mechanisms are important parameters for prediction models that require advanced computational methodologies. While traditional physics-based models provide valuable information about fundamental electrochemical processes, they have difficulty in calculating the variability parameters present in real usage scenarios [24]. Machine learning algorithms and statistical approaches have gained importance in understanding nonlinear data and ensuring relationality. Random Forest (RF) and Gaussian Process (GP) algorithms are effective in quantitative measurement of uncertainty in nonlinear data sets. Optimization techniques such as Levenberg-Marquardt (LM) and Scaled Conjugate Gradient (SCG) combined with Bayesian Regularization (BR) technique minimize the risk of overfitting and are known to increase model accuracy. RUL estimation algorithms increase the possibility of BMS monitoring and enable the achievement of sustainable operational processes with safe, efficient and proactive maintenance plans.

The LM algorithm is an algorithm developed from the Gauss-Newton approach used for estimating parameters in nonlinear problems. The Gauss-Newton approximation efficiently determines the least squares problem with linear approximation. The LM algorithm, which is a version of the Gauss-Newton technique that stands out in the difficulties regarding the acceptable accuracy of the result; applies a correction factor during estimation. With this factor, the relativity of nonlinear problems is increased. When the factor is minimum; linearity decreases and the result accuracy moves away from reality. Thanks to this factor, the LM algorithm performs optimization by integrating linear and nonlinear parameters. The optimization approach and the minimization of the error are provided by the continuous change of the parameter, which is the correction factor. The LM algorithm is widely used in nonlinear data sets, regression analysis and optimization problems [25,26,27].

The SCG algorithm stands out as an optimization technique used to specify function parameters and is widely used with machine learning algorithms and artificial neural network models. SCG, which uses gradient-based techniques and is based on iteration of optimization, works with the approach of determining the minimum values of function parameters. SCG, produced from the Conjugate Gradient (CG) technique, increases the speed and accuracy of the optimization function with the factor called the scaling factor. The factor assigns values to determine the effect of the parameters on the function and is used for adjustments such as gradient calculations, parameter adjustments and parameter updates. The SCG technique offers fast convergence without critical computation or high memory demands and is useful for problems with large parameter details. In summary, the SCG algorithm, unlike the CG algorithm, has a scaling factor, thus; is a gradient-based optimization technique used to determine fast, stable and optimized function parameters [28,29,30].

The BR technique is a statistical methodology and a technique that reduces the overfitting problem encountered in regression models by applying the Bayesian framework. The overfitting problem is defined as the situation where a regression model fits the training data correctly but shows poor generalization ability and as a result leads to insufficient prediction accuracy in new data (test data). The BR approach reduces the overfitting problem by referencing the basic principles of Bayesian statistics. BR techniques provide more stable and reliable predictions by improving the generalization abilities of regression models [31,32].

The RF, a powerful ensemble learning technique, is extensively employed in regression and classification applications owing to its proficiency in generalization through the aggregation of predictions from numerous decision trees. Nonetheless, overfitting remains a significant concern to other machine learning models, especially when the model encounters noisy or insufficient input. Methods such as BR are essential in alleviating these problems. By implementing prior distributions on the model parameters and progressively refining these priors using the data, BR guarantees that RF models attain a balance between fitting the training data and preserving their capacity to generalize to unseen data. This adherence to Bayesian principles allows RF to deliver more consistent and dependable predictions in contexts such as battery RUL estimates, where consistency in predictions is essential [33].

The GP models are for RUL prediction problems because of their non-parametric characteristics and intrinsic ability to quantify uncertainty. Notwithstanding their adaptability, GP models may experience overfitting, especially in high-dimensional or sparse datasets. BR methods tackle this issue by integrating prior knowledge into the model training procedure. By establishing hyperparameters hyperparameter distributions and optimizing the marginal likelihood, Bayesian Regression facilitates the balance between model complexity and fit. This regularization enhances the GP model's generalization capacity, allowing it to deliver dependable forecasts and uncertainty bounds, which is particularly beneficial for essential applications like battery RUL forecasting [34,35]. The algorithm details of the models used in the study by correlating with different features are given in Table 2 and Table 3.

Table 2. LM – BR – SCG Model Details

Model Details			
Algorithm/Model	**Hidden Layer Size**	**Epoch**	**Division of Data for Training, Validation, Testing (Holdout validation)**
Levenberg-Marquardt	10	Automatically determined by Levenberg-Marquardt backpropagation algorithm (trainlm)	Train : %70 Validatin: %15 Test: %15
Bayesian-Regularization	10	1000	Train : %70 Validatin: %15 Test: %15
SCG	10	1000	Train : %70 Validatin: %15 Test: %15

Table 3. GP - RF Model Details

Model Details		
Algorithm/Model	**Functional Details**	**Division of Data for Training, Validation, Testing (Holdout validation)**
Gaussian Process	Kernel RBF Function	Train : %70 Validatin: %15 Test: %15
RF	n_estimators:100 (Number of Trees)	Train :%70 Validatin: %15 Test: %15

2.3 Performance Metrics

In this study, we employ regression metrics to evaluate the performance of our predictive model, focusing on the continuous nature of the output. The selected performance metrics R^2 (coefficient of determination), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) allow for a comprehensive assessment of the accuracy of the prediction algorithms and models. The selected performance metrics provide different quantitative assessments of the models

R^2 (Coefficient of Determination): R^2 quantifies the probability that the selected dependent variable variance can be predicted by the independent variables and represents the comprehensiveness of the model [37].

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \tag{1}$$ [37]

Mean Absolute Error (MAE): MAE is the average of model prediction errors and is a simple measure of model accuracy [36].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$ [36]

Mean Absolute Percentage Error (MAPE): MAPE is the percentage value of model prediction errors and allows comparison of model accuracy over different scales [36].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y_i}}{y_i}\right| x100 \qquad (3)[36]$$

Mean Squared Error (MSE): MSE is a measure that allows the evaluation of average errors by squaring the differences between model estimates and dataset values. Its weight increases according to model deviations [37].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2 \qquad (4)[37]$$

Performance metrics provide a balanced perspective in evaluating algorithms or models. R^2 shows how well the model captures the variance, MAE and MAPE provide insights into the average prediction error, and MSE evaluates more significant deviations. Using these performance metrics collectively allows the model to be evaluated from different aspects, allowing for selection and improving algorithms for improved accuracy.

A confusion matrix will be created for each method for the execution of the algorithms determined within the scope of the study and for the evaluation of performance metrics.

3. EXPERIMENTAL RESULTS

This study evaluates the results of LM algorithm, SCG technique, BR technique, RF algorithm and GP model used to estimate battery RUL. The aim of the study is to contribute to the efficient management of battery systems and to formulate strategies to increase the sustainability of energy storage system technologies. Input parameters from the "Battery Dataset" provided by NASA Ames Prognostics Data Repository are used to estimate the RUL of batteries. This study for RUL estimation independently runs multiple algorithms and models including LM algorithm, SCG technique, BR technique, RF algorithm and GP models and evaluates the accuracy of the models with the same performance metrics.

The SCG model performance metrics were obtained as 1.098% MAPE, 0.9823 R^2, 0.0019 MSE and 0.0302 MAE. These metrics used for RUL estimation have the potential to contribute to the effective management and reliability of energy storage systems. The performance metrics obtained from the models used in the study are detailed in Table 4. and Table 5. to evaluate the metrics of the training and test data sets.

In the next phases of this research, the performance metrics of the algorithms will be evaluated and improved for more accurate and reliable estimation of RUL. The models used in the research, which consist of optimization methods such as RF algorithm, GP model, LM algorithm and SCG technique, will be rigorously evaluated on the basis of estimation accuracy and computational efficiency. Comparative analyses will be performed to compare these algorithms with the methods frequently used in the literature, and the study will be advanced on solving the problems such as overfitting, uncertainty quantification, and adaptability to various operating environments. It is expected that these research findings will improve the methodological frameworks and significantly improve the RUL estimation with insights into the practical use of machine learning techniques in battery health monitoring systems.

Table 4. Train Dataset Obtained Results

Algorithm/Model	Performance Metric Results			
	MSE	MAE	MAPE (%)	R-Squared
Levenberg-Marquardt	0.0021	0.0348	1.215	0.9789
Bayesian-Regularization	0.0020	0.0315	1.140	0.9798
SCG	**0.0017**	**0.0295**	**1.100**	**0.9825**
Gaussian Process	0.0021	0.0332	1.1214	0.9789
RF	0.0016	0.0287	1.072	0.9854

Table 5. Test Dataset Obtained Results

Algorithm/Model	Performance Metric Results			
	MSE	MAE	MAPE (%)	R-Squared
Levenberg-Marquardt	0.0023	0.0356	1.243	0.9756
Bayesian-Regularization	0.0021	0.0321	1.150	0.9795
SCG	**0.0019**	**0.0302**	**1.098**	**0.9823**
Gaussian Process	0.0027	0.0365	1.324	0.9735
RF	0.0020	0.0311	1.115	0.9807

4. CONCLUSION

This study demonstrates that machine learning techniques have significant potential in accurately predicting battery life, providing remarkable advances in battery management systems and energy storage technologies. The findings, especially with the low performance metrics obtained in the training and testing stages of the SCG model, reveal that machine learning methods provide higher accuracy and precision compared to traditional mathematical methods. In this direction, the effective use of machine learning algorithms constitutes a reference for significant developments in areas such as electric vehicles and energy storage systems, where battery life extension, energy efficiency and safety are of critical importance.

The performance of the machine learning-based algorithms used in this study was evaluated by comparing them with similar studies previously conducted in the literature. The obtained results show that especially RF and SCG models are comparable to methods such as LSTM, RNN, and GPR, which are widely used in the literature for battery life prediction, and even superior in some metrics. The RF model achieved the lowest error rate with an MSE value of 0.0016 in training and 0.0020 in testing, while the SCG model outperformed many models reported in the literature with an MAE of 0.0295. The superior performance of the RF model can be attributed to its ability to capture complex nonlinear relationships and interactions between battery parameters, while SCG's efficiency is likely due to its second-order optimization strategy, which accelerates convergence in training. In addition, when evaluated in terms of R^2 value, the RF model achieved the highest determinism with an R^2 value of 0.9854 in training and 0.9807 in testing, indicating that it is a strong model for battery life estimation. On the other hand, LSTM-based models generally exhibit an MAE value of 0.0210 and above in the literature, while the SCG and RF models in this study achieved lower error rates. This could be due to the tendency of LSTMs to require extensive hyperparameter tuning and large datasets for optimal performance, whereas RF and SCG are more robust with limited data. However, deep learning models like LSTM and RNN might still be preferable in scenarios involving highly time-dependent degradation patterns, where sequential modeling plays a critical role. As a result, the MSE, MAE, MAPE, and R^2 values obtained in this study exhibit competitive performance compared to previous studies, indicating that the proposed methods support the potential for use in battery management systems and energy storage technologies.

However, some limitations, such as the fact that the dataset used is based on only a specific battery type and hyper-parameter optimization is limited, may have negative effects on the generalizability of the obtained results. Therefore, it is recommended that future research focus on conducting comparative analyses of different machine learning techniques to optimize RUL prediction, developing algorithms by dividing the dataset at different rates and with cross-validation, and including parameters representing various battery types. In addition, it is important to integrate different datasets and develop hybrid models on these datasets to overcome the limitations of estimations based on only one dataset. Hybrid models can provide higher accuracy and generalization capacity by combining machine learning algorithms with physical models and statistical approaches. When this approach is supported by hybrid datasets representing the characteristics and usage conditions of different battery types, it will contribute to obtaining more robust and reliable results in RUL estimations.

In addition, hyper-parameter optimization and direct comparisons with traditional mathematical models will ensure that the obtained results are based on more solid foundations. As the continuous developments in battery technologies and the demand for electric vehicles continue to accelerate, the development and use of machine learning methods in both industrial and academic contexts is of great importance. The positive impact of machine learning methods on battery management emphasizes the need for continuous research and improvement in RUL estimation aimed at meeting the changing demands in the framework of energy storage systems and sustainability. In this context, the implementation of the proposed improvements will not only provide higher accuracy and reliability in RUL estimation, but will also increase the acceptance of machine learning methods in industrial applications.

Authors' Contributions

Authors' Contributions			
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1	Kardelen Kamisli	0000-0002-5526-2767	1, 2, 3, 4
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*In the contribution section, indicate the number(s) that correspond to the relevant contribution type.			
1- Study design 2- Data collection 3- Data analysis and interpretation 4- Manuscript writing 5- Critical revision			

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