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A Review on Data Driven Methods for Battery RUL Prediction Using Machine Learning Algorithms

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***Abstract*:**With the rapid development of new energy electric vehicles, the demand for batteries is increasing. The battery management system (BMS) plays a crucial role in the battery-powered energy storage system. Lithium-ion batteries are the primary power source in electric vehicles, and the prognosis of their Remaining Useful life is vital for ensuring the safety, stability, and long lifetime of electric vehicles. Remaining useful life (RUL) prognostics based on data-driven methods has become a focus of research. The development of a machine-learning method with high accuracy, high generalization, and strong robustness for evaluating battery health states is essential in the field of battery health management. Current research review on data-driven methodologies using Machine Learning Algorithm is summarized in this paper.

Index Terms: *Remaining useful life prediction, Machine learning Algorithms, lithium-ion batteries, Data-Driven methods*

I. INTRODUCTION

When it comes to both storing and producing energy, lithium-ion batteries are crucial. The usage of lithium-ion batteries in the transportation, communication, and aerospace industries is already widespread due to its better energy density, less weight, and longer charge and discharge cycle. The performance of the lithium-ion battery will degrade or perhaps fail as a result of the intricate physical and chemical changes that occur during the use process, which could pose a serious risk to public safety and cause significant financial losses. As a result, the question of how to effectively manage the prognosis and health of lithium-ion batteries has gained popularity and has been the subject of extensive research. The amount of time between the present and the end of a system's or asset's useful life is known as the RUL. Operational research has utilised the RUL concept extensively. The lithium-ion battery's RUL forecast is based on the number of cycles and battery capacity that will pass the failure threshold from the current cycle. By analysing the likelihood of battery failure and limiting safety concerns to achieve high efficiency and robustness, the RUL of a lithium-ion battery may be accurately assessed. The RUL of the battery is calculated using the remaining useable charges and discharge cycles before the threshold value is reached, or the value after which the battery is no longer regarded as safe to operate. Figure 1 Shows the principle of RUL Prediction. Remaining useful life (RUL) is an estimation of the length of time an item, component, or system is estimated to be able to function according to its intended purpose before requiring repair or replacement.

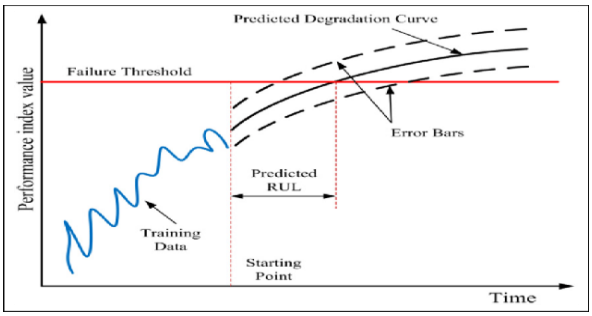

Fig 1: Principal of RUL Prediction

Remaining useful life prediction for lithium-ion battery storage system[1]Proposed the RUL prediction of lithium-ion batteries. Many techniques have been proposed and implemented to model the degradation of these complex systems, from which two approaches have arisen i.e, model-based approaches and data-driven approaches.

Various model-based and data-driven-based and hybrid-based methods for RUL prediction of lithium-ion batteries have been comprehensively evaluated. The analysis considers various aspects such as classifications, methods, characteristics, contributions, advantages, disadvantages, and research gaps.Generally, the main steps involved for RUL prediction is summarized in Figure. 2 including a three-stages procedure. In the first stage, various sensors are utilized to capture the characteristics of the battery such as the voltage, current, SOC, and temperature. Then, the battery capacity is estimated in Stage 2 by model-based method, data-driven method, or other approaches.

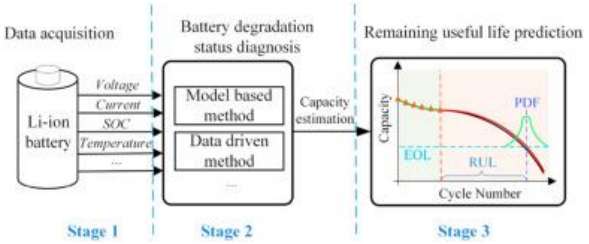

Fig 2: Procedure for RUL prediction

[2] The model assumes that solvent diffuses through the SEI (solid electrolyte interphase) and undergoes a two-electron reduction at the carbon SEI interface. The kinetics of the reduction reaction at the SEI–electrolyte interface and the solvent diffusivity are seen to be the most important parameters governing SEI formation. The capacity loss is seen to be a function of the thickness of the SEI layer and is seen to vary linearly over time. In [3], A Thevenin model with one RC branch is presented in which all the model parameters are constant. When this equivalent circuit models are used to estimate battery aging, model parameters include lots of internal battery parameters and resistance aging parameters. Moreover, model-based methods exhibit poor real-time performance characteristics.

It is of extreme importance to achieve accurate predictions of the remaining battery lifetime under various operating conditions. This is essential for the battery management system to ensure reliable operation and timely maintenance and is also critical for battery second-life applications. After introducing the degradation mechanisms, [4] provides a timely and comprehensive review of the battery lifetime prognostic technologies with a focus on recent advances in model-based, data-driven, and hybrid approaches. As neural networks and signal processing technology advance,[5] new data-driven approaches to lithium-ion battery RUL prediction and SOH monitoring are made possible. This study describes a neural network-based approach that combines extensive.For the purpose of predicting RUL and monitoring SOH in lithium-ion batteries, a short-term memory (LSTM) network with particle swarm optimisation and an attention mechanism is used.

In order to enhance the performance of online SOH prediction, the proposed semi-supervised learning framework has successfully made the best use of a large amount of unlabeled data.[6] Proposeda capacity of unlabeled data is subsequently estimated using an ILLR-based technique based on the four attributes. The ILLR-based method offers the distributions of the estimated capacity in addition to the estimated capacity itself.[7] Presents RUL-RVE, a Python tool for the assessment of Remaining Useful Life (RUL). Physical systems are normally subject to degradations that ultimately lead to failure, therefore prognostic technologies are crucial to estimate the lifetime of the system to be monitored.Since RUL is frequently random and unknowable, it must be inferred from information that is currently available, such as data from condition and health monitoring. The RUL has become more well-known recently as a result of the quick development of condition and health monitoring techniques.Nevertheless, because of its complex interactions with observable health data. As a result, current modelling advancements for RUL estimation. [8] review's main focus is on statistical data-driven methodologies that only use readily accessible historical observed data and statistical models. The methods are divided into two main categories of models: those that rely on knowledge about the asset's state that has been directly seen and those that do not.

Data-driven methods have been getting more and more attention towards the prediction of RUL as machine learning and artificial intelligence have developed so quickly. Also, a lot of performance information about lithium-ion batteries may be gleaned through real-world uses. This made the groundwork for using data-driven techniques to forecast the lithium-ion batteries' ageing life [9]. Compared with the other model-based methods, data-driven

methods are of nonparametric, and do not consider the electrochemical principles to some extent. Thus, degradation models of lithium-ion batteries are developed with various mapping and regression techniques and tools. The systems use merit measurements to control battery performance. The performance and condition of the battery are estimated using data like the state-of-health (SOH) and state-of-charge (SOC). In [10] suggested a clever way to look at the aforementioned factorsutilising a data-driven strategy. To estimate these values, we employ a machine learning technique that separates important features from the discharge curves.

RUL prediction based on Machine learning Algorithm modelling has made rise to numerous studies. Machine learning-based approaches have often provided a better performance than statistical approaches in terms of accuracy although more computational power is required.The proposed paper we have aimed to focus on A Naive Bayes (NB) and Gradient Boosting (GB) Machine Learning Algorithm for RUL prediction of batteries and the Error analysis of the model is carried out to optimize the battery's performance parameter.

The other sections of this paper are prepared as follows: Section II explains about the RUL Prediction Method Analysis. Section III Presents the Exposition of Machine Learning Algorithms. Section IV Presents Proposed work. Section V shows the experiment results of our proposed method. Section VI finally a conclusion is given.

II. RUL PREDICTION METHOD ANALYSIS

A review on prognostics approaches for remaining useful life of lithium-ion battery summarizes the approaches used in Li-ion battery RUL estimation. [11] Generally, the approaches for RUL estimation are divided into model-based and data driven.In this article a new data driven approach is proposed.

DATA DRIVEN METHODS:

While the mechanisms and propagation rules of battery degradation are still unknown, data-driven techniques use past monitoring data directly to anticipate the degradation tendency of a battery. This approach develops a mathematical model or derives weight parameters based solely on training data, as opposed to adopting a particular physics-based model. This approach is more adaptable and useful because it does not need creating a complicated physics-based model, and it has garnered considerable interest from researchers all over the world. Based on whether they are based on data-driven methodologies, three categories of battery RUL prediction have been identified as shown in Figure 3 below

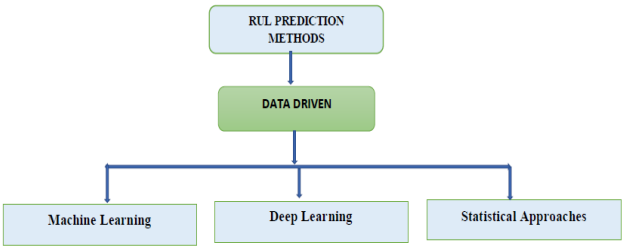

Fig 3: Data Driven RUL Method

Machine Learning Algorithms: Machine learning approaches can estimate battery RUL based on various measurements, such as current, voltage, and temperature, and, therefore, can be used at various operating conditions. The widespread use of data-driven residual life prediction in the field of equipment is encouraged by the continual improvement in the equipment's ability to continuously detect and monitor itself throughout its life cycle. Currently, the lithium-ion battery's data-driven prediction technique.RUL for batteries typically uses a solitary time-series forecasting model.[12]The prediction method's robustness and generalizability are insufficient. It needs more work to increase the prediction's robustness and accuracy. According to the predictions' outcomes, immediate preventive maintenance steps must be implemented to guarantee a reliable supply of electricity at all times. This study proposes

an integrated learning method based on monitoring data to suit the lithium battery degradation modelforecast their RUL. The relevance vector machine (RVM), the random forest (RF), the elastic net (EN), the autoregressive model (AR), and the long short-term memory (LSTM) Network are the five fundamental learners that make up the ensemble learning approach, which aims to improve prediction performance. In the ensemble learning approach, the final lithium battery prediction result is obtained by finding and determining the optimal weights of the basic learners using the genetic algorithm (GA).Battery cycle life study through relaxation and forecasting the lifetime via machine learning [13] GPR is a kernel-based probabilistic machine learning technique that has recently gained attention in battery lifetime prognosis. The Gaussian process is typically sensitive to inconsistent data. It is difficult to predict the state of charge (SoC) with battery management systems that are durable and reliable for electric vehicles. Predicting SoC estimation with significantly less degradation is exceedingly difficult because battery degradation is typically a non-linear process.[14] uses six machine learning algorithms to estimate the SoC of lithium-ion battery systems for use in electric car applications. The applied techniques are ensemble bagging (EBa), ensemble boosting, support vector machine (SVM), linear regression (LR), Gaussian process regression (GPR), and artificial neural network (ANN). To improve the battery's performance parameter, the model's error analysis is done.

Deep Learning Algorithms: One of the fields of machine learning known as "deep learning" developed from artificial neural networks and is characterised by several nonlinear processing layers (ANN).The deep network design of DL allows for the full collection of representative information from raw input data by stacking numerous layers on top of one another. In numerous domains, including image identification, audio recognition, and natural language processing, DL models have attracted significant attention and achieved notable successes.However, in the area of RUL prediction, it has not yet been completely utilised. Many studies using DL approaches for machine health monitoring have been conducted, but there are currently very few that concentrate on the use of DL for RUL prediction. Accurate RUL prediction can prevent fatal failures, lower maintenance costs, and dramatically increase the operational safety and reliability of industrial systems or components. In [15] research, RUL prediction is briefly introduced, and state-of-the-art DL techniques are reviewed in terms of four exemplary deep architectures: auto-encoder, deep belief network (DBN), convolutional neural network (CNN), and recurrent neural network. The deep learning approach increases remaining usable life forecast accuracy while decreasing the amount of time needed for characteristic testing, potentially increasing the power profitability of predictive energy management. In order to anticipate the remaining useful life, this article reviews, categorises, and compares various adaptive mathematical models on deep learning techniques. In [16] The modelling ability features are determined, and the adaptive prediction methods are categorised as a result. To evaluate various modelling accuracy in the deep learning calculation process, several criteria are provided. The most important characteristics of successful life prediction are employed to make pertinent deductions and recommendations, and the highly accurate deep convolutional neural network–extreme learning machine technique is chosen to be applied for the stable remaining life.[17] Although Multilayer Perceptron (MLP) has been used to forecast RUL, its network structure prevents it from automatically picking up salient features. This research proposes a unique deep convolutional neural network (CNN) based regression approach for estimating the RUL. Although CNN has been used for other tasks like speech recognition, computer vision, and natural language processing, this is the first attempt to use CNN for RUL estimate in prognostics.

Statistical model: Statistical model predicts the damage initiation and progression according to the previous inspection results on similar machines. This method does not need knowledge on the ageing mechanism, while it requires a large number of effective data set. Among them, autoregressive (AR), autoregressive and moving average (ARMA), autoregressive integrated moving average (ARIMA) models are widely used for the modelling and prediction of the time series data. In [18] a novel hybrid Elman-LSTM method for battery remaining useful life prediction by combining the empirical model decomposition algorithm and long short-term memory and Elman neural networks. The empirical model decomposition algorithm is employed to decompose the recorded battery capacity verse cycle number data into several sub-layers. Comprehensive battery test datasets have been collected and used for model parameterization and performance evaluation.[19] SOC and SOH co-estimation scheme is proposed based on the fractional-order calculus. First, a fractional-order equivalent circuit model is established and parameterized using a Hybrid Genetic Algorithm/Particle Swarm Optimization method.

III. EXPOSITION OF MACHINE LEARNING ALGORITHMS

Machine Learning algorithms are the programs that can learn the hidden patterns from the data, predict the output, and improve the performance from experiences on their own. More complicated patterns of data can be learned and recognised by machine learning algorithms. Based on experience, various apps' system data. The most effective way for forecasting is machine learning, which gathers historical data throughout the life cycle. Additionally, by adaptively improving network parameters, they are appropriate for extremely nonlinear systems and approach the genuine state of the system. These techniques do, however, inevitably have their limitations. The main flow of machine learning is depicted in Figure 4.

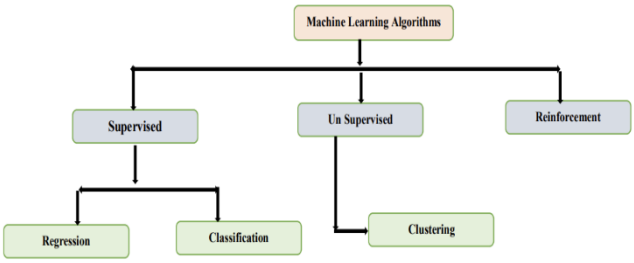

Fig 4: Flow of Machine Learning Algorithms

Machine Learning Algorithm can be broadly classified into three types:

1. Supervised Learning Algorithms
2. Unsupervised Learning Algorithms
3. Reinforcement Learning algorithm

Supervised Learning Algorithms:In supervised learning, the machine is expected to deliver known outcomes. The training data is already supplied with predefined labels or outcomes. The algorithm has to identify matching characteristics or common features among training data that reference predefined labels/outcomes. Post-training, the same features/attributes are compared to label unknown data. The two most common learning problems are usually solved by supervised learning are classification and regression. Classification deals with labelling input data with predefined labels. Regression deals with deriving outcomes of unknown input data based on learned correlations between training data and known outcomes. The derived outcome is a numerical value or result.

Some of the common machine learning algorithms that fall under supervised learning include K NearestNeighbor, Random Forest, Logistic Regression, Decision Trees, and Back Propagation Neural Network.

Unsupervised Learning: In unsupervised learning, the machine is expected to deliver unknown outcomes. The machine is exposed to unlabelled raw data samples and it must deduce structures present in the input data. This is usually done mathematically by either extracting similarities or removing redundancies. The outcome of machine learning is not a class/label or a numerical output; instead, the output is delivered by grouping similar data samples or identifying the odd ones.

Some of the common problems solved through unsupervised learning are clustering, association rule mining, and dimensionality reduction. Some of the common machine learning algorithms that fall under unsupervised learning include K-Means Clustering, Apriori Algorithm, KNN, Hierarchal Clustering, Singular Value Decomposition, Anomaly Detection, Principal Component Analysis, Neural Networks, and Independent Component Analysis.

Reinforcement learning algorithms: In reinforcement learning, a system called an agent is developed to interact in a specific environment so that its performance for executing certain tasks improves from the interactions. The agent starts from a predefined initial set of policies, rules, or strategies and then is exposed to a specific environment in

order to observe the environment and its current state. Based on its perception of the environment, it selects an optimal policy/strategy and performs actions. In response to every action, the agent gets feedback from the environment in the form of a reward or penalty. It uses the penalty/reward to update its policy/strategy and again interacts with the environment to repeat actions.Some of the common machine learning algorithms that fall under reinforcement learning include Q-Learning.

IV. RECOMMENDED ML ALGORITHMS

In the proposed work two supervised machine learning algorithms i.e, Gradient Boosting from Regression and Naïve Bayes from classification are compared for the RUL Prediction:

A. Gradient Boosting Regression:

In Machine Learning, we use gradient boosting to solve classification and regression problems. It is a sequential ensemble learning technique where the performance of the model improves over iterations. This method creates the model in a stage-wise fashion. It infers the model by enabling the optimization of an absolute differentiable loss function. As we add each weak learner, a new model is created that gives a more precise estimation of the response variable. The gradient boosting algorithm requires the below components to function as shown in Figure 5.

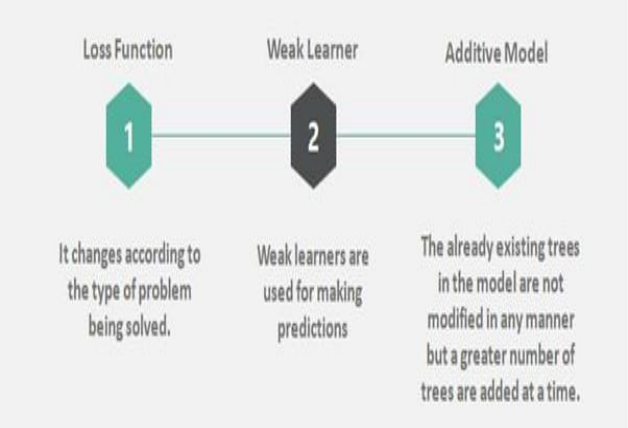

Fig 5: Gradient Boosting Functions

1. **Loss function**: To reduce errors in prediction, we need to optimize the loss function. Unlike in AdaBoost, the incorrect result is not given a higher weightage in gradient boosting. It tries to reduce the loss function by averaging the outputs from weak learners.

2. **Weak learner**: In gradient boosting, we require weak learners to make predictions. To get real values as output, we use regression trees. To get the most suitable split point, we create trees in a greedy manner, due to this the model overfits the dataset.

3. **Additive model**: In gradient boosting, we try to reduce the loss by adding decision trees. Also, we can minimize the error rate by cutting down the parameters. So, in this case, we design the model in such a way that the addition of a tree does not change the existing tree.

The state of charge estimation of lithium-ion battery systems by using an extreme gradient boosting algorithm for electric vehicles application, which acquires the nonlinear relationship model can with offline training. [20] The gradient boosting algorithm is the tree on based learning, which effectively performs and speeds. Voltage-time data used as an input of this system from the partial constant current phase; the proposed algorithm improves the accuracy of predicting the relevant. Additionally, no initial state of charge is required in our proposed method; thus, estimating the state of charge can consider each battery state. Gradient Boosting Tree is a type of ensemble where additional

trees are added at each stage to compensate the shortcoming of the existing model. These models are generally employed where features are too heterogeneous.[21] In this model of Gradient Boosting Regressor we have used Huber loss function in loss function parameter. X Consider a training set (x_i, y_i) (where i = 1, 2, 3.....N) and a differential loss function (i.e. 'deviance' in this case) L(y_i, z), where z is the predicted value. Initialize the model as

$$f_0(x) = argmin_z \sum_{i=1}^{i=n} L(y_i, z) \quad (1)$$

For each observation in each tree calculate the gradient which is given by

$$\theta_{jm} = argmin_z \sum L(y, z + f(x_i)) \quad (2)$$

Now, update the model of the succeeding tree with the gradient of the previous tree. This is given by

$$f_m(x) = f_{m-1}(x) + \sum_{j=1}^{j=Jm} l_{jm} * I \quad (3)$$

for each x which belongs to the region of that tree (i.e. R_{jm}) The overall output is given by $f_m(x)$.

B. **Naïve Bayes**: The NB model assumes every predictor variable is independent. Thus, this means that it uses Bayes' Theorem in a naive way, which means it is a special case of a Bayesian Network. NB uses Bayesian statistics, which is based on Bayes' Theorem. It predicts the class of a test case with values T = a_1, a_2, a_3, . . . , a_n by choosing the class ci , which optimizes as shown in equation below by maximizing it . In Equation (4) P(c_i |T) denotes the conditional probability of class ci given test case T.

$$P(c_i|T) = \frac{P(T,c_i)}{P(T)} = \frac{P(c_i).P(T|c_i)}{P(T)} \quad (4)$$

In this model, the probability estimation of each class is provided by the training set. As the model tries to maximize Equation (4), the denominator is reduced as much as possible so it can be removed from the equation as it does not have a direct contribution to the prediction process.

In addition, NB classifier is able to calculate the joint probability P(T|c_i) by assuming that all the attributes are conditionally independent given the class c_i. Therefore, Equation (5) shows how the model calculates the joint probability. This shows that the predictions made by the model depend only on the values of P(c_i) and P(a_j |c_i).

$$P(T|c_i) = P(a_1, a_2, \ldots\ldots a_n, c_i)$$

$$\approx P(c_i)P(a_1|c_i)P(a_2|c_i)P(a_n|c_i) \quad (5)$$

$$= P(c_i).\prod_{j=1}^{n} P(a_j|c_i)$$

The main advantage of using NB is that it only needs small datasets for training. Moreover, training the model is fast and is not time-consuming. A naive Bayes (NB) model is proposed for RUL prediction of batteries under different operating conditions. [22] It is shown in this analysis that under constant discharge environments, the RUL of Li-ion batteries can be predicted with the NB method, irrespective of the exact values of the operating conditions. The case study shows that the NB generates stable and competitive prediction performance over that of the support vector machine (SVM). Robust Remaining Useful Life Prediction for Li-ion BatteriesaNaïve BayesianClassifier was shown in the figure 6 below. In [23] presents an empirical procedurefor predicting robust remaining useful life (RUL) using anaïve Bayesian classifier (NBC) with time as the response.

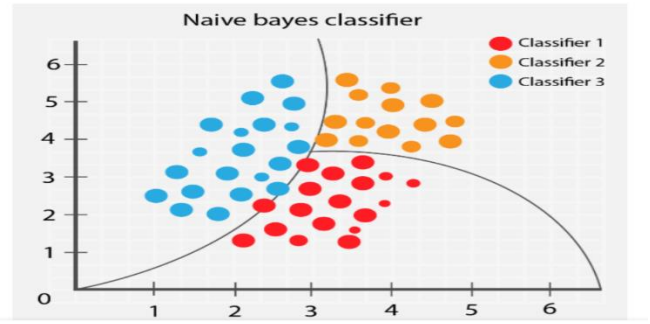

Fig 6: Naïve bayes classifier

The method is illustrated using public data for predicting Li-ionbatteryRULtoend-of-life(EOL).Abatterylifeprediction is obtained using the capacity values up to theprediction time. The root mean squared error (RMSE) isused for performance evaluation. Theprediction performance of the NBC is compared with that ofa support vector machine (SVM). Thus, Naive Modelassumes every predictor variable is independent. Thus, this means that it uses Bayes Theorem in a naive way, which means it is a special case of a Bayesian Network.

VI CONCLUSION

An empirical Procedure for Producing Robust and Practical RUL Predictions Using the Data Driven Machine Learning Algorithms. Using time as the Response, Stable and Accurate Predictions were obtained with a simple and efficient method and the Transformation to RUL is Straight forward. The method was illustrated using Hawaii Natural Energy Institute data set to predict RUL For Lithium-ion Battery. In this Paper we have reviewed data driven methods of Machine Learning Algorithms for Prediction of RUL.

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