PREDICTION FOR LITHIUM-ION BATTERIES BY MEANS OF A RANDOM FOREST ALGORITHM

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Abstract :

Lithium-ion batteries have a minimal environmental effect, a long cycle life, and a high energy density, making them ideal for storing power. However, it is subject to ageing, which means that after a specific amount of years, its capability can decline and it might fail more frequently. The reliability and safety of the device relies heavily on how close the estimate of remaining battery life really is. This research argues that machine learning may be used to develop a solution that can estimate how much longer a lithium-ion ones (li-ion) battery will last in service. The voltage generated by the output levels were monitored in the thingSpeak software, and the traditional substances connected by the discharge voltage information were considered to predict the battery's longevity after the li-ion battery was connected to a load. The dataset was evaluated and trained using random forest methods to predict the battery's lifetime.After factoring in everything discussed, the estimated number of remaining battery cycles is arrived at.In this study, ML and edge impulse are used to enhance the accuracy of Lithium ion battery life prediction algorithms. To better estimate the RUL of batteries made from lithium ion, this research has recently included the random forest approach.

Keywords—Lithium-ion,prediction,lifecycle,discharge voltage, thingspeak, data set, random forest, RUL

I. INTRODUCTION

The usage of rechargeable batteries is becoming more important as more and more people rely on electronic products like electric cars, mobile phones, etc medical equipment. Lithium ions are an essential element of the electrochemistry of a lithium-ion battery, making it ideal high-performance battery that can be recharged several times. Worries regarding the safety and reliability of lithium-ion batteries slow the development into practical applications. The dependability of electrical equipment and perhaps public safety are both at risk from age-related deterioration in battery performance. The number of times a battery can be charged and discharged before losing any of its capacity is known as its cycle life. A lithium-ion battery's cycle life varies greatly depending on how deeply it is discharged.

The "depth of discharge" describes the extent to which an electrical equipment is depleted. For example, an energy source with barely twenty percent of its total charge remaining has a far more prolonged cycle life then one had 80% half its capacity depleted [1]. Over time, a lithium-ion battery's safety and health (SOH) rating will decrease. Therefore, determining the battery's age is essential for security and peak performance. The lifespan of a lithium-ion battery may be estimated in a variety of ways. the equivalent of approximately one hour and 30 minutes over just a single 2500mAh battery powered by lithium-ion to do a life cycle estimate using discharge capacity techniques [2], [3], and [4]. It would take too much time to predict even a single battery. This study aims to speed up the process of predicting a lithium-ion battery's lifespan by combining integrated neural networks with Edge Impulse.

Li-ion Batteries (LiB) are one of the primary energy storage units used in many electronic and electrical appliances due to its extended life cycle, considerable capacity, excellent density of energy, and considerable specific energy. Lithium-i (Li-ion) cells or packs of varying capacity are used to power the vast majority of today's electronic devices. To guarantee the safe operation of a lithium-ion (Li-ion) battery, a more advanced monitoring system, offered by a system for managing batteries (BMS), is required. The variety of BMS activities that may be done is heavily influenced by the degree of complexity of an application. Learning how long batteries will last and analysing this data is vital to ensuring their effective operation. The ability to accurately predict how long a Li-Ion battery will last is essential for many electronic products today [1]. For example, mobile phones with single batteries use a simple technique that determines the battery's status by measuring its electrical voltage, fresh, and temperature. However, BMS requires complex algorithms to accurately forecast the aforementioned battery conditions and characteristics. In the case of complex applications, such as electric cars, this is particularly true. A battery's state of fitness (SOH) may be estimated from a number of factors, including the number of cycles it has been through, its voltage, current, temperature, ambient temperature, the current through the load, the voltage of the load, and its capacity. State-of-health (SOH) [2] allows you to estimate how many more charges and discharges you can get out of a battery, also known as the RUL. The pace at which the battery is drained varies with the demands of the various uses to which it is being put. Therefore, the implementation of the suggested intelligent technique for identifying the battery's present health state and remaining usable life may increase the overall efficacy of the system.

Electric vehicles (EVs) are predicted to make inroads towards the transportation market as pollution levels increase and oil prices rise. The ESS in an electric vehicle is a crucial component.

Lithium-ion (Li-ion) batteries have been the primary source of energy for EVs and consumer electronics until recently. They have the best combination of power/energy density and lifetime, making them the best choice for the ESS. However, ageing batteries become less effective over time, increasing the danger of mishaps (such as battery accidents in mobile phones and EVs). Therefore, in order to improve the overall dependability of the energy system, further research is required to precisely examine the health of the lithium-ion batteries and to predict its lifetime (for example, replacing the battery at the appropriate time and managing degradation precursors). A battery administration system (BMS) is necessary to ensure the safety of Li-ion batteries due to the fact that the state of charge of the batteries that can be recharged and their current condition are both variables in their safety. Standard components of such a system are the remaining usable life (RUL), position status (SOC), and health status (SOH). If battery RUL estimates were more accurate, maintenance might be scheduled less often. Data-driven RUL prediction for rechargeable lithium-ion batteries may be split down into the following categories: sequence prediction (neural network, relevance rector machine, greyish prediction), and filter observation (unscented particle filter, circular cubature powder filter, etc.). fitting (e.g., linearity model, single-exponential model, algebraic model). It is challenging to create an analytical model to track the loss in battery capacity.

A battery's RUL estimate is typically derived via a capacity test. Eliminating the need for complex physical or mathematical explanations of battery capacity reduction is only one of the numerous advantages of data-driven techniques. Data-driven methods include, but are not limited to, computational biology, Machine Learning, neural networks made up of computers, etc. This is why many analyses combine the results of many algorithms or utilise a single algorithm with data from a large number of models.

Since lithium-i (Li-ion) batteries have a relatively low self-discharge rate and a high energy density in comparison to other energy storage devices, they are being considered for a wide variety of uses. The short life cycle and high expense of upkeep of Li-ion batteries have hindered their widespread use.

Both time and use (calendar ageing and cycle retirement, respectively) contribute to a progressive deterioration in Li-ion batteries' performance, a process known as ageing. An old battery will increase the cost of repairs, reduce the equipment's lifespan, and reduce its dependability. In addition, no mechanism exists yet for reliably renewing Li-ion batteries, and early losses will result in a flood of spent batteries that are too dangerous to recycle. Dead batteries have a capacity that is less than 80% of their initial value. Using the residual useful lifetime (RUL), one may predict how long an item will last before breaking down. The clock starts ticking at the moment of observation and stops at the moment of death. The end-of-life (EOL) of a battery occurs when its age and number of cycles of charge-discharge reach a certain threshold.

The complex process of battery degeneration is regulated by electrochemical reactions. Temperature, fee, and discharge rate are only a few of the redox side reactions and operating circumstances that have a significant impact on battery life. This makes it harder to predict how long a battery will last. So, in a battery management method, accurately estimating the RUL under various operating conditions is a crucial and challenging job. According to RUL's projections, the system's return on investment (ROI) will decrease as its profitability increases.Automatic upkeep of the apparatus and battery life extending are both doable if the RUL can be expected with appropriate accuracy. Given the relevance of the subject matter, this article will give a comprehensive review of the current status of life span prediction technologies, focusing on the most recent developments using example-based, data-driven, and hybrid methods.

Approaches based on physical or electrochemical models, as well as driven by data methods, are also possible. There are several explanations proposed for why we age. If the electrochemical model is able to faithfully reflect the battery's internal variables, it can achieve high precision. A more precise mathematical definition, however, increases the complexity along with the cost.

II. LITERATURE SURVEY

Battery management systems rely heavily on two parameters: [1] the battery's state regarding health (SOH) and its remaining usable life (RUL). Recent years have seen a proliferation of machine learning techniques offered for accurately estimating SOH and RUL in order to determine battery health. Through real-time simulations and a hardware approach, the proposed study develops a reliable mechanism for foreseeing the deterioration of batteries over time. In this study, we show how to successfully estimate the remaining useful life (RUL) and state of health (SOH) of a Li-Ion 18650 cell by considering many variables, such as the cell's state of charge, charge voltage transfer characteristics, internal resistance, and capacity. Different statistical models of batteries are built and deployed on a standalone hardware foundation in order to determine the best SOH and RUL algorithms based estimate technique. The experimental findings of this real-time application reveal that the SOH can be forecasted using a deep neural network technique, with an error rate of less than 5%; moreover, the RUL of a battery can be estimated using a long short time duration neural network model, with an accuracy of less than 10 cycles. This method showcases a variety of ML models running on a realistic hardware platform, resulting in longer battery life.

Since Lithium-ion batteries are increasingly employed as the primary power source in a wide range of electronic devices, it is crucial to be able to accurately anticipate their RUL in order to devise an appropriate maintenance plan and prevent catastrophic failure in the event of a power outage. Model-based approaches are often utilised for RUL prediction of lithium-ion batteries because to the ease with which Fifield measurements may be fi tted. Incomplete uncertainty quantification, however, renders these forecasts mostly inaccurate. In this research, we make use of the Gaussian simulator assessment theory to offer a model update strategy for RUL forecasting for lithium-ion batteries.

Uncertainties in the variables of the model, model form, and measurement error are quantified using an empirical deterioration model. Using a number of different uncertainties, it extrapolates the predicted reality to the point when the battery will die. The suggested method's key novelty is that it adjusts not only the model parameters but also the biassed function that takes into account the uncertainty in the model form. Additionally, a multi-parameter model update is implemented using a modular Markov cycle Monte Carlo technique. It can provide an accurate RUL forecast since uncertainties are taken into account routinely throughout the inference phase. We use a real-world NASA dataset detailing the life cycle of lithium-ion batteries to showcase the method's forecasting power.

To better anticipate the remaining useful life of batteries made from lithium-ion, [3] researchers are looking into a novel non-equidistant grey prediction model. When dealing with the actual, non-equidistant results of an accelerated degradation test for lithium-ion batteries, this method first eliminates any data that have intervals that are too large, then calculates the mean value of the residual data, and finally divides the data into segments based on the corrected mean interval and counts how many observations are in each group. Finally, the non-equidistance black forecasting algorithm is validated using data from an actual accelerated degradation test of lithium-ion batteries. The value of the posterior error ratio and the small error probability are then provided and compared to the threshold value, demonstrating that the non-equidistance grey prediction model is more accurate.

[4] The proper functioning of lithium-ion batteries (LIBs) is crucial to the continued operation of a broad range of electronic devices. For this reason, it is crucial to create techniques for estimating the RUL of LIBs, and are intended to sound an alarm before batteries die, so that electronic devices may continue functioning normally. In this research, we introduce the support raster regression-particle filter (SVR-PF) as a method for estimating LIBs' RUL. In order to examine the parameters of capacity fade, first a LIB power fade model is created. Then, the RUL prediction scheme for LIBs is established using these parameters to make predictions about the RUL and to revise the model's probability density via offline analysis. Instead of using a regular particle filter, which is the industry norm, SVR-PF is used to enhance the accuracy of predictions.

[5] An essential function of a battery management programme (BMS) is the evaluation of the battery's state of fitness (SOH) and forecast of its remaining usable lifespan (RUL). By using local voltage fluctuation and capacity variation during the charging or emptying process of battery as SOH indices, this research proposes a novel approach to SOH estimation and realises forecasting of RUL based on a particle filter. An NCM/LTO lithium-ion batteries pack is used to verify the system's efficacy. [6] In this research, we offer a method for determining when ESS (Energy holding systems) lithium-ion batteries will need to be replaced. As battery degradation continues, the batteries cannot be revived because of irreversible reactions. The battery gets EOL (End-of-life) when its capacity has dropped to 80% of its original capacity, at which point it must be replaced. The empirically based Unscented Kalman filter (UKF) may be used to the estimation of a battery's capacity. However, it is important to analyse the features since the pace at which capacity declines is influenced by the load profile of batteries. In this study, we anticipate the capacity of batteries by analysing their degrading features in relation to the present rate at which they are discharged.

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[7] In this research, a state-of-charge indicator and a moving-window-based approach for estimating the remaining battery life were created for lithium-ion batteries. The partial charging voltage curve of cells was used to derive the health indicator. A linear ageing model was built from the capacity data inside a moving window to anticipate the battery's remaining usable life, and Monte Carlo simulation was used to create prediction uncertainty. The electric car industry's actual battery management system served as the foundation for both the developed capacity estimate and remaining usable life forecast techniques. Cells were tested at several current densities (including 1 C and 2 C) and temperatures (including 25 and 40 °C) in the laboratory. The results of the deployment demonstrate that the margin of error for the capacity estimates was 1.5%. The root-mean-square error of remaining usable life projections was less than 20 cycles in the final 20% of the battery's lifespan, and the confidence intervals at 95% mostly cover approximately 20 cycles.

[8] This work proposes a methodology for simulating the functioning of a Lithium-ion battery. Because the internal impedance obtained by the method can represent its frequency characteristic, and that expresses the transient response and has a close relation to its life, it can be used for both numerical simulation of battery-powered equipment and lifetime estimation. Because the approach operates on data, neither a dedicated charging/discharging circuit nor physically removing the battery from the device is necessary. Laboratory testing and an evaluation of the suggested approach while riding an electric bike both show promising results.

[9] The battery capacity in EVs is an important metric that has to be evaluated precisely across the battery's life span. To better predict how much energy an electric vehicle's lithium-ion (Li-ion) battery can store, this research suggests a novel machine-learning model, called a Multi-output Convolved Gaussian-Process (MCGP) model. The suggested method may be used to improve the precision with which SOC estimates are made, and it can also serve as a reliable resource for estimating the RUL of a battery cell.

Two 3.6-V/16.5-Ah Li-ion battery packs are cycled experimentally to verify the suggested model's accuracy. [10] The RUL estimation of lithium-ion batteries is a critical problem in a smart battery management system. In order to conduct both the direct and indirect RUL estimate for lithium-ion batteries, this research provides an integrated prognostic strategy that unifies two kinds of health indicators (HIs): battery capacity and the duration interval of equal charging voltage variance series. The nonlinear patterns of battery deterioration are monitored using a data-driven tonic echo state networks (MONESNs) method to meet various practical needs. Two major contributions of this paper are 1) increasing the computing stability of the proposed approach by employing a set of MONESN submodels that that can also describe the indicators uncertainty, and 2) improving the predictive capability of each HI by implementing an HI correlation simulation and a cycle threshold transformation. This strategy amounts to a data-driven, prognostic framework that incorporates probabilistic analysis and has the capacity to deal with uncertainty. The effectiveness of the suggested method is shown using two collections of industrial lithium-ion battery data.

This method is likely to have wide applicability in other domains where data-driven prognostic techniques are required.

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[11] A novel non-equidistant grey prediction model is explored for its potential to improve lithium-ion battery residual life prediction. For the real-world lithium-ion battery accelerated degradation test results, which were not equidistant, we first removed outliers with excessively large intervals, then calculated the standard deviation of the residual data, and finally divided the data into segments based on the corrected average interval, counting how many observations were recorded for each segment.Once the accumulation process is complete, a (1, 1) model of the residual life of lithium-ion batteries can be developed, and a technique of precision inspection may be implemented. Finally, the non-equidistance grey forecasting framework is validated with real-world data from an accelerated degradation test of lithium-ion batteries; the posterior error ratio and small an error probability are calculated and compared to a threshold value; and the results show that the new model is significantly more accurate than the previous one.

[12] The capacity of a lithium-ion battery decreases with each new cycle and recovers after a rest interval. The term "relaxation effect" describes what happens in lithium-ion batteries. The relaxation effect has been shown to be an important factor in estimating the remaining service life. However, a plausible model is difficult to infer since there has been no linked mechanism study for the relaxation effect. In order to characterise the relaxing effect, this work makes an attempt to infer a diffusion polarisation model using a mechanism analysis. The test of simulation is then run to validate the model once its parameters have been calculated. The results are good in reflecting the dampened relaxing effect and quantifying regeneration potential.

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[14]In this research, we present an indirect RUL prediction approach based on its Genetic Ant Algorithm-Extreme Learning The machine (GAAA-ELM) model since it is challenging to estimate the RUL of a lithium-ion battery directly. The discharge time at equal voltage drop is chosen as the indirect characteristic measure of lithium-ion battery life. To confirm there is a connection between the two, the first-order incomplete correlation coefficient technique was used. The GAAA-ELM is used to construct both a prediction model for an equal-voltage drop discharge as well as a relationship model between the duration of the discharge and actual capacity. Weight and threshold of ELM are optimised with the help of GAAA. The suggested approach uses NASA data on batteries made with lithium ion to make predictions about their RUL. The suggested technique is proven to efficiently forecast lithium-ion battery RUL and get improved prediction accuracy when compared to the BP prediction method, the ELM prediction method, and the GA-ELM prediction method.

III. LI-ON BATTERY LIFE CYCLE PREDICTION

To gather data and generate sets for the test battery, the proposed system models hardware with sensors and controllers. Hardware with this system includes a voltage detection and a WiFi (ESP8266) module, in addition to the load and battery.

The suggested system's hardware implementation is shown in Figure 2. A voltage sensor should be connected such that its positive terminal points in the direction of the flow of electricity across the battery.

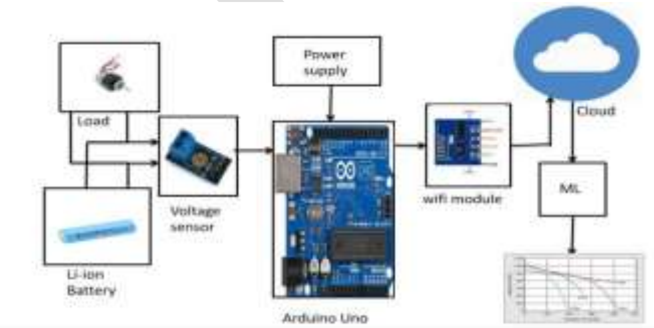


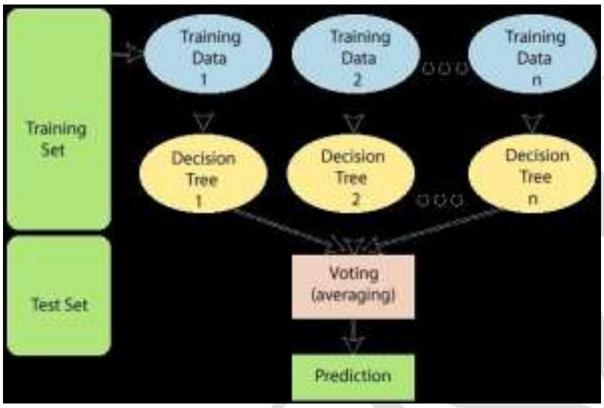
Fig.2.The prototype hardware of the proposed system

Both the A0 and A1 pins on the board that houses the Arduino Uno may be used to connect the voltage sensors. Using a scale model and a voltmeter that's calibrated with no load, the internal resistance of the battery may be determined. The voltage that can drop is zero when no current is flowing. Therefore, the voltage at the open circuit is identical to the theoretical maximum for this kind of battery. This fall, the internal insurgency is taking stock. The optimal battery voltage is calculated as the sum of the voltage drops across the resistors. The data is communicated to the server's computer through the wi-fi device after being downloaded to the Arduino Uno. After signing into the thingSpeak app, you'll have access to the gadget's acquired data. We'll use the default parameters to enter the discharge voltage data, and the result—the remaining total amount of cycles—will be shown in a graphical user interface on our computer's desktop. The lifespan of a lithium-ion battery depends on how often it is recharged.

STRANGE WOODS

Random Forest is a popular machine learning technique that belongs to the supervised learning family of methods. It may be used to solve classification and regression problems in machine learning. It uses ensemble learning, which combines several classifiers to solve a complex problem and improve the model's performance.Random Forest, in the authors' words, "is a classifier which incorporates a variety of trees of choice that represent different subsets about the data set being studied and takes the median to improve the reliability of the prediction of that set." The random forest predicts the output based on the average of all the individual trees' forecasts rather than the predictions of just one. With a larger forest, overfitting is prevented and accuracy is improved.

The below diagram explains the working of the Random Forest algorithm:



To begin, N individual decision trees are joined to produce the random forest, from which subsequent forecasts may be drawn.

The image and description below illustrate the processes involved:

We'll start by picking K random training data points.

Following the first step's specification of data points, in Step 2 you will build the subset-specific decision trees.

Third, set a goal for the whole amount of tree decisions you'll create, N.

Step Four: Continue as in Steps One and Two.

Determine which decision tree's predictions best fit the newly added data points, and assign them accordingly.

First, we must identify the variables we'll need to determine the discharged voltage levels. Voltage pin, starting voltage value, sec1, and tst1 all equal 0 since A0 is connected to the voltage source. A discharged battery's analogue value may be accessed through the Voltage pin.After being read, this information is sent to the cloud.Only if the Username and password for the wi-fi module match those for the device's internet connection.Using an API key, this wi-fi module can talk to the cloud.In order to process the discharged Voltage measurements, the user's credentials must be correct before the data can be delivered.If that happens, it will ask for a new key.

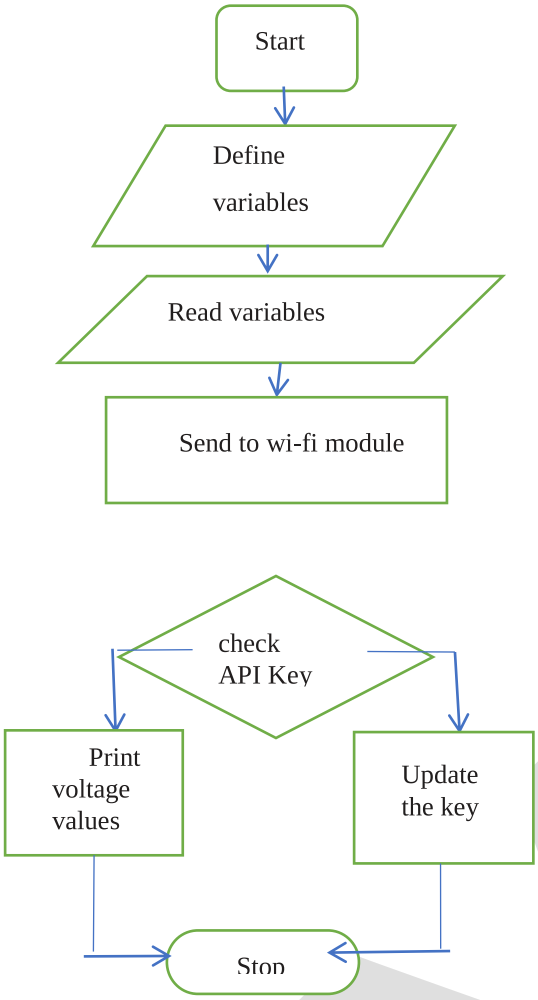


Fig. 5.Flow chart for the operation of the proposed system

IV. EXPERIMENT AND RESULTS

Step 1:A battery with dischared to the load and the voltage sensor senses discharged voltage across the battery .

Step2:The sensed data is sent to Arduino Uno.

Step3: Output from Arduino Uno is sent to Cloud with help of wifi module.

Step4: The collected data and the graph associated with that discharge voltage levels is now seen by logging into ThingSpeak software.

Step5: Based on the discharged voltage, the required values are provided as input to ML code.

Step6: The standard parameters that are associated with discharge voltage levels are considered .

Step 7:These standard parameters are given as the input to the desktop which is installed with libraries and ML code is also saved .

created_at	entry_id	field1
2023-03-08T06:21:23-05:00	1	143
2023-03-08T06:21:46-05:00	2	52
2023-03-08T06:22:09-05:00	3	32

2023-03-08T06:22:33-05:00	4	31
2023-03-08T06:22:56-05:00	5	67
2023-03-08T06:23:19-05:00	6	38
2023-03-08T06:23:43-05:00	7	25
2023-03-08T06:31:15-05:00	8	209
2023-03-08T06:31:38-05:00	9	185
2023-03-08T06:32:31-05:00	10	0
2023-03-08T06:32:54-05:00	11	384
2023-03-08T06:33:17-05:00	12	381
2023-03-08T06:33:40-05:00	13	0
2023-03-08T06:34:04-05:00	14	374

Cycle _Index	Discharge Time (s)	Decrement 3.6-3.4V (s)	Max. Voltage Dischar. (V)	Min. Voltage Charg. (V)	Time at 4.15V (s)	Time constant current (s)	Charging time (s)	RUL
1	2595.3	1151.489	3.67	3.211	5460.001	6755.01	10777.82	1112
2	7408.64	1172.513	4.246	3.22	5508.992	6762.02	10500.35	1111
3	7393.76	1112.992	4.249	3.224	5508.993	6762.02	10420.38	1110
4	7385.5	1080.321	4.25	3.225	5502.016	6762.02	10322.81	1109
6	65022.75	29813.49	4.29	3.398	5480.992	53213.54	56699.65	1107
7	3301.18	1194.235	3.674	3.504	5023.634	5977.38	5977.38	1106
8	5955.3	1220.135	4.013	3.501	5017.495	5967.55	5967.55	1105
9	5951.2	1220.135	4.014	3.501	5017.496	5962.21	5962.21	1104
10	5945.44	1216.921	4.014	3.501	5009.994	5954.91	5954.91	1103
11	435251.5	263086.1	4.267	3.086	269.984	443700	443700	1102
12	3228.58	1135.349	3.689	3.485	5033.076	5969.89	5969.89	1101
13	6019.9	1058.28	4.045	3.475	5053.843	5980.77	5980.77	1100

14	6026.59	1049.488	4.047	3.477	5046.43	5966.82	5966.82	1099
15	6008.07	1065.372	4.045	3.48	5033.076	5954.47	5954.47	1098
16	423271.4	168776.3	4.27	3.108	219924	430028.8	430028.8	1097
17	2261.34	883.2	4.038	3.901	1949.664	2922.69	6070.11	1096
18	2259.46	883.199	4.042	3.373	5181.377	6161.38	9310.98	1095
19	2256.61	878.4	4.042	3.374	5181.375	6154.37	9296.64	1094
20	2252.83	873.601	4.043	3.374	5174.334	6147.33	9243.58	1093

IV CONCLUSION:

We use a model built on a machine-learning-based method to estimate the lifetime of a lithium-ion battery in this study. At the outset, an algorithm using machine learning is trained with a multitude of open-source data about batteries that use lithium ion. When an input battery is added, the system's hardware automatically begins collecting data from the battery and uploading it to the cloud. A full, optimised neural network system is fed the battery data, and it analyses it in light of the facts it has been trained to identify. To best estimate the time a lithium-ion battery will survive, it is necessary to know its state of charge (SoC). The battery's internal conditions, such as its temperature, current, and voltage, are also included into the forecasting model. As said before, here are the results of the battery readings. When the analysis is complete, we can see how much longer the battery will last, letting us know when to replace it.

The project was designed with the hope that electronic automobiles would play a significant part in travel in the not-to-distant future, thus ensuring this effort will be useful in that respect. Businesses may also profit from this study since it will provide light on how often E-Vehicle batteries need to be changed by surveying customers. The goal of this model is to provide information useful for estimating the useful life of batteries with lithium ion.

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