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Lifetime Prediction of Lithium-Ion Battery Using Machine Learning For E-Vehicles

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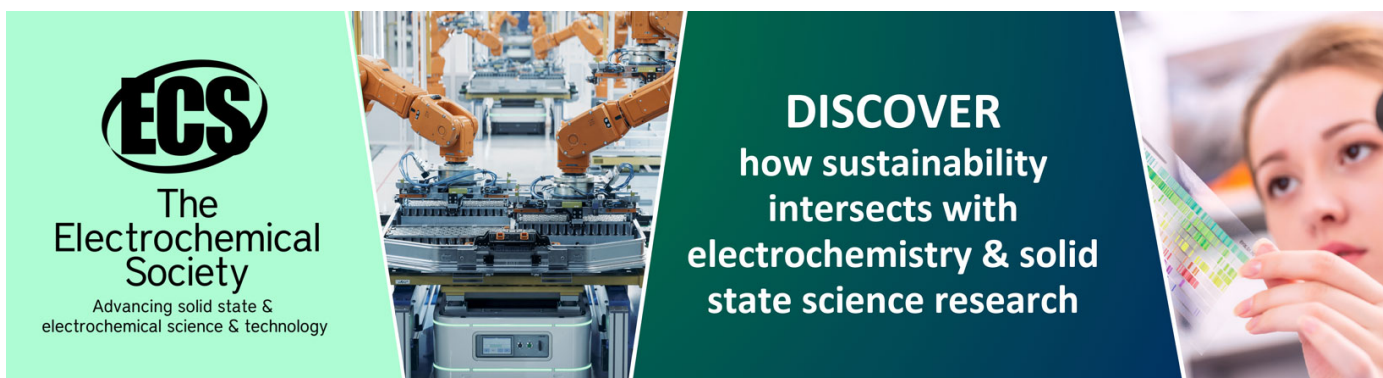
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Retraction

Retraction: Lifetime Prediction of Lithium-Ion Battery Using Machine Learning For E-Vehicles (*J. Phys.: Conf. Ser.* **1916** 012200)

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This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

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[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:[2107.06751v1](#)

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Lifetime Prediction of Lithium-Ion Battery Using Machine Learning For E-Vehicles

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Abstract. A life cycle of battery with long testing time and without contact measurement devices will be applicable for industrial applications. To this problem, the solution for potential will be provided by the combined technique of supervised learning and infrared thermography. The focus of the research will be on machine learning techniques. Artificial neural networks (ANNs) and support vector machines (SVMs) are used in conjunction with thermography to estimate the life cycle of lithium ion polymer batteries. The capturing of infrared images at 1 frame per minute and charging of 70 minutes followed by the discharging of 60 minutes for 410 cycles. For ANN and SVM models the input nodes of charging or discharging use the surface temperature profiles. The input will be in thermal profile for the result. Under 10 minutes of testing time, we can estimate the current life cycle of a studied cell with an error of less than 10%. In SVM the accuracy will be similar while comparing with ANN but the testing time will be longer.

Keywords: artificial neural networks, polymer batteries.

1. Introduction

Since the 1970s, Li-ion batteries are most promising and fast growing in the battery industry. Battery powered electric vehicles and small electronic devices use Li-ion batteries because of their long life span and high energy density. Even if the system is designed in a complex manner, the system will deteriorate overtime or usage. Li-ion battery failure causes high cost. To increase the reliability and protection of complex devices, prognostics methods and condition-based maintenance can be applied to battery management systems. The data obtained from the batteries' health information can be used to avoid catastrophic failures and malfunctions by the prognostic method. It's also used to plan ahead of time for repair. The only essential aspect needed for these applications is to determine battery health and estimate how long the battery will last. The remaining time or load cycles till the completion of the battery's life cycle is referred to as the battery's life cycle. For the development of a predictive model, knowledge of the battery's process of aging and advanced data processing techniques are needed.



The battery's RUL prediction methods can be classified as data-driven or model-based. Electrochemical behaviour of the battery under cyclic conditions are necessary requirements of model-based methods. Model-based methods approaches are widely used to estimate the battery's remaining life and to explain the power of battery cells. When a dynamic and complex system is in operation, it is hard to create an accurate analytical model in noisy or uncertain conditions. If the excessive temperature rises during the cycling phase, the battery may be undergoing thermal runaway or other severe ageing conditions, or it may already be experiencing thermal runaway. The use of thermography to probe the changes in external and internal thermal properties under battery cycling conditions is a better idea.

To measure battery temperature, thermocouples adhered to the surfaces are currently used. This methodology enables for a smaller proportion of points on the surface to be sampled. Previous studies demonstrate that during charge and discharge cell temperature increases, this increment in temperature is being correlated to electrochemical and physical conditions of the cells. The thermal characteristics of the cells can be compared during charging and discharging of the RUL. In this review, the corresponding prediction errors and applications of the reviewed algorithms are focused. During battery testing increase in testing efficiency reduces the testing time. It's difficult to come up with a low-cost solution and predict the battery's life cycle in a limited amount of time.

2. Literature Survey

Predictive models of lithium ion battery efficiency in device environments should take into account electrochemicals, mechanical, and thermal degradation modes. Temperature history, charge/discharge rate and electrochemical operating window are the factors which controls rates of degradation. By overdesign and warranty costs lifetime uncertainty can be absorbed. With less test data, degradation models are helpful to predict lifetime more accurately. For next generation battery designs engineering feedback should be provided by the models. In this presentation, lumped surrogate battery models and multi-dimensional physical battery models are discussed. Commercial li ion chemistries models are compared to pack and cell-level ageing data using commercial lithium ion chemistries. To extend the lifetime of commercial battery systems more opportunities are explored today [1].

The rapid growth of renewable energy, as well as the continuous advancement of battery energy storage technology, has resulted in widespread use of renewable energy in power systems. In operation strategies optimization and system design, the battery degradation is an issue that is non negligible when battery energy storage systems participate. In many engineering areas, the remaining cycle life estimation of batteries and health assessment has gradually become a research hotspot and a challenge. This paper is focused on chemical reactions that take place within the battery because its power decreases and internal resistance value rises. From several aspects, the general life prediction models are analysed. In the survey, the characteristics of them based on application scenarios are discussed. In addition, a novel weighted ageing model with the implementation of the Ragone curve is suggested with the information given to better understand the ageing processes. The paper offers a detailed proof of the mathematical theory underlying the proposed model [2].

In automation the lithium ion batteries play a vital role; they experienced the multiplicity of degradation through power fade and also the capacity with predictive models. We can monitor the lack of accuracy by overdesign and excessive warranty costs, and the tests must now be absorbed, so in order to minimise the cost and also extend the life time, they create deterioration models that can predict life time with accuracy and with less input data. The feedback of engineering for cells can be provided by lifetime models. The life time prediction is mainly based on analysis and Bayesian approach with functional principal so the accuracy will be high [3].

Through aging mechanisms with Prior knowledge the lifetime of lithium ion batteries will be easily predicted by existing methods with the use of certain formulations of physical, chemical and also the

analytical method of battery but the dependence will be difficult in mode of practice, which will restrict these methods application. The lifetime prediction for lithium ion batteries is solely based on FPCA (functional principal component analysis) and a Bayesian approach in this research. The use of FPCA in this proposed method will create a non parametric model for lithium ion batteries based on residual lifetime and also evaluate the corresponding period by prediction using Bayes approach. This will allow the degradation model to be updated and the residual lifetime distribution to be determined. By using Bayesian updating we can achieve accurate prediction and also can obtain more precise confidence intervals. The Experiments will use data from NASA's Ames Prognostics Center of Excellence. In real-time prediction of batteries residual lifetime the final results confirmed that the prediction method performance is good with accurate output [4].

3. Proposed System

If there is a relationship between the input and output then regression is used. Our proposed system is linear regression for prediction of the battery. In supervised machine learning algorithms, the predicted output of linear regression has a constant slope and is continuous and hence it is helpful to predict the values continuously [5,6].

Data Preprocessing for Machine learning in Python. Preprocessing is the method of applying transformations to our data before feeding it to the algorithm. Data preprocessing is a method that is used to transform raw data into a clean data set [7].

In our proposed system the regression will be linear so the prediction will also be in linear regression. The subpart of the supervised machine learning algorithms where the output will be in continuous with a slope that will be in constant state is the linear regression.

Regression analysis comes under predictive modelling technique. Regression technique is mainly used for forecasting and prediction. In modelling and also in analyzing data the usage of Regression will be higher than other tools. This process is primarily used for certain distinct purposes. The data points can be represented using regression analysis and this analysis will also help in analytical techniques for better decision making [8].

Data preprocessing will process the data by filtering and extracting the particular data which are necessary, it also includes cleansing and mining. The algorithm will be processed when the data will be feeded before processing, it also includes the Conversion of raw data set into clean data set [9-12] Figure 1 shows the graph. Figure 2 shows the block diagram.

A linear regression can be expressed mathematically as:

$$a_0 + a_1x + \epsilon = y$$

Where,

Y is the Target Variable or Dependent Variable

X is the Predictor Variable or Independent Variable

a_0 is the line's intercept.

a_1 is the Coefficient of linear regression

\(\epsilon\) is the unintentional mistake

The values of the x and y variables are training datasets in the Linear Regression model representation.

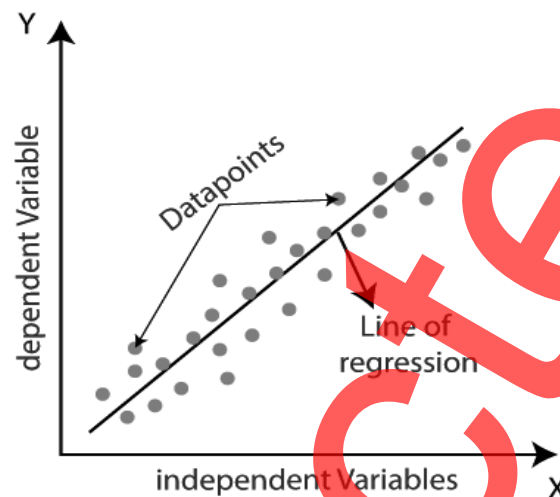


Figure 1. Graph

4. Block Diagram

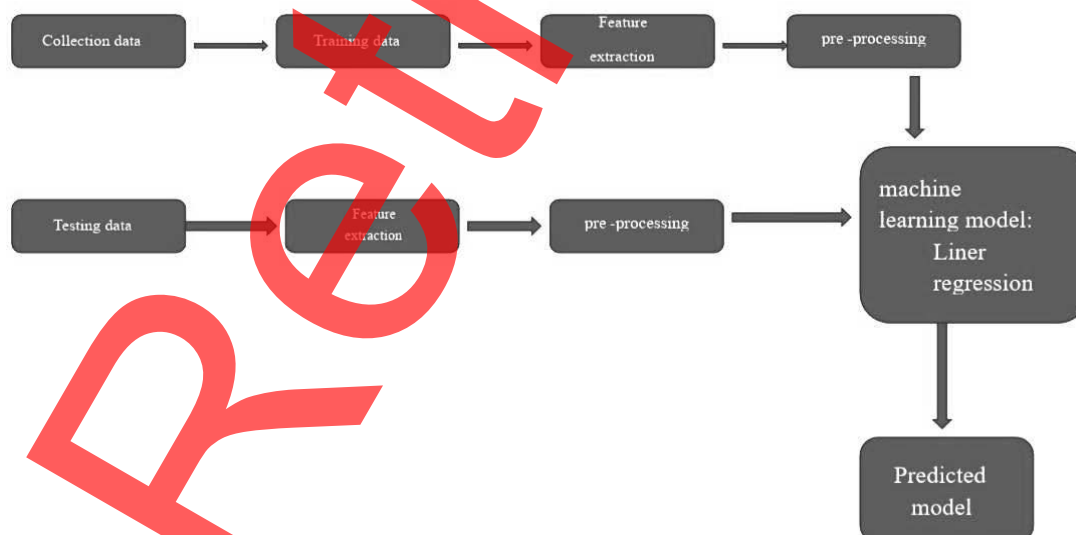


Figure 2. Block diagram

5. Result

After various tests with the model, it worked perfectly. The essential metrics of our paper was to predict the lifetime of lithium ion batteries precisely, We have tried to the best of our capacity to bring a system that predicts precisely. The result thus obtained from the model is precise and the system gives a clear status of when the battery in the Electric vehicle has to be replaced with a new one. Based on the battery which is given as the input, the model predicts the result on the basis of the datasets fed to the system.

6. Conclusion and Future Scope

A machine learning algorithm model is used to estimate the lithium-ion battery's lifetime in this analysis. Python v3 is used to code the model. To begin, various lithium ion battery datasets are collected from various sources, and the system is trained with the datasets using a machine learning algorithm. When a battery is given as input to the system, the hardware components collect the data of the input battery and store it in the cloud. The data of the battery is given as an input to the trained machine learning system, then the system analyses the data with the datasets trained and comes up with the result. The lithium ion battery's State of Charge (SoC) is the primary data used to estimate the battery's lifespan. The temperature, current, and voltage of the batteries are also factors in the prediction model. These are the data that is collected from the battery as mentioned in the earlier context. Thus finally after the analysis of the system, it displays the lifetime of the battery which then helps us know when to replace the current battery with a new one. The project was planned on the basis that, in the future E-Vehicles will play a major part in transportation and this project can be useful for that. And that this project will also help the industries in knowing about the demand of batteries for E-Vehicle from the data of when the customers change their battery. We hope that this model helps in providing some informational content regarding the lithium ion battery lifetime prediction models.

- ❖ Further scope of the project is to minimize the setup space and make it more compact.
- ❖ Developing a mobile application so that one can check their cars battery life from the comfort of their home.
- ❖ Maximise the precision of the model by feeding more datasets to the system and bring in more functionalities to the model.

References

- [1] D. Andre, M. Meiler, K. Steiner, H. Walz, T. Soczka-Guth, D.U. Sauer, *J. Power Sources* 196 (2011)
- [2] Yi L, Lou S, Wu Y and Yang T , *Optimal battery capacity based on lifetime prediction for improving the schedulability of the wind power Transactions of China Electrotechnical Society* 2015
- [3] Chai W, Li Z, Cai X and Wei X , *Variable step-size control method of large capacity battery energy storage system based on the life model Transactions of China Electrotechnical Society* 14 58-66 2016
- [4] Millner A , *Modeling lithium ion battery degradation in electric vehicles Innovative Technologies for an Efficient and Reliable Electricity Supply*, 349-356, 2010
- [5] Xiong R, Li L, Tian J., *Towards a smarter battery management system: a critical review on battery state of health monitoring methods. J Power Sources* 2018
- [6] Li F, Xie K, Zhang X, Zhao B and Chen J , *Optimization of coordinated control parameters for hybrid energy storage system based on life quantization Automation of Electric Power Systems* 01 1- 5, 2014

- [7] Qian K, Li Y, He Y-B, Liu D, Zheng Y, Luo D, Li B, Kang F. *Abuse tolerance behavior of layered oxide-based Li-ion battery during overcharge and over-discharge*. RSC Adv 2016;6:76897–904.
- [8] M. Suganya and H. Anandakumar, Handover based spectrum allocation in cognitive radio networks, 2013 International Conference on Green Computing, Communication and Conservation of Energy (ICGCE), Dec. 2013. doi:10.1109/icgce.2013.6823431. doi:10.4018/978-1-5225-5246-8.ch012
- [9] Haldorai and A. Ramu, An Intelligent-Based Wavelet Classifier for Accurate Prediction of Breast Cancer, Intelligent Multidimensional Data and Image Processing, pp. 306–319 Butler KT, Davies DW, Cartwright H, Isayev O, Walsh A. *Machine learning for molecular and materials science*. Nature 2018;559:547–55. Liu D, Zhou J, Pan D, Peng Y, Peng X. *Lithium-ion battery remaining useful life estimation with an optimized Relevance Vector Machine algorithm with incremental learning*. Measurement 2015;63:143–51.
- [10] Liu Jie, Saxena Abhinav, Goebel Kai, Saha Bhaskar, Wang Wilson, *An adaptive recurrent neural network for remaining useful life prediction of lithium-ion batteries: annual conference of the prognostics and health management society*. 2010.
- [11] Hannan MA, Lipu MSH, Hussain A, Mohamed A, *A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: challenges and recommendations*. Renew Sustain Energy Rev 2017;78, pp 834–54.