State of Health Estimation of Li-Ion batteries using Electrochemical Impedance Spectroscopy

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***Abstract*— Since, batteries have a limited lifetime, repeated charge and discharge cycles quickly deteriorate the electro-chemical properties of a battery. With the reduced capacity and several other changes in the state of health of a battery, the electronic device under operation might malfunction. The failure of electronic device during the operation can cause serious repercussions to the users in certain applications. This research was aimed to provide upgrade on Electrochemical Impedance Spectroscopy (EIS) technology to decipher the electrolytic properties and electrochemical health of the battery. The focus of this research was to design a test bet to gather experimental data of EIS scans of batteries with varying State of Health. Based on the footprints of scans, a state of health classification algorithm was proposed which categorized batteries according to the corresponding health of the battery. Tests were performed on hardware prototype to validate the designed algorithm that showed State of Health estimation accuracy of almost 90%. The main contribution of this project to existing EIS technology is the eradication of the requirement of battery modeling and parameter estimations from Nyquist plot to find the state of health of a battery (the remaining capacity of the battery). The proposed method simplifies the computational algorithm and reduces the processing time for rapid battery tester.**

I. Introduction

Li ion batteries have emerged as the backbone of rechargeable energy store. In 2013, the number of Li ion cell sold for electronic devices were reported to be around five billion [1] with exponential rise expected in the sales for coming years. The increased focus on Li ion batteries emerges from its ability to offer substantial power density and fast charge/discharge capability. and fast charge/discharge capability. coming years. The comparison of energy density of Li Ion technology is shown in figure 1 [1].

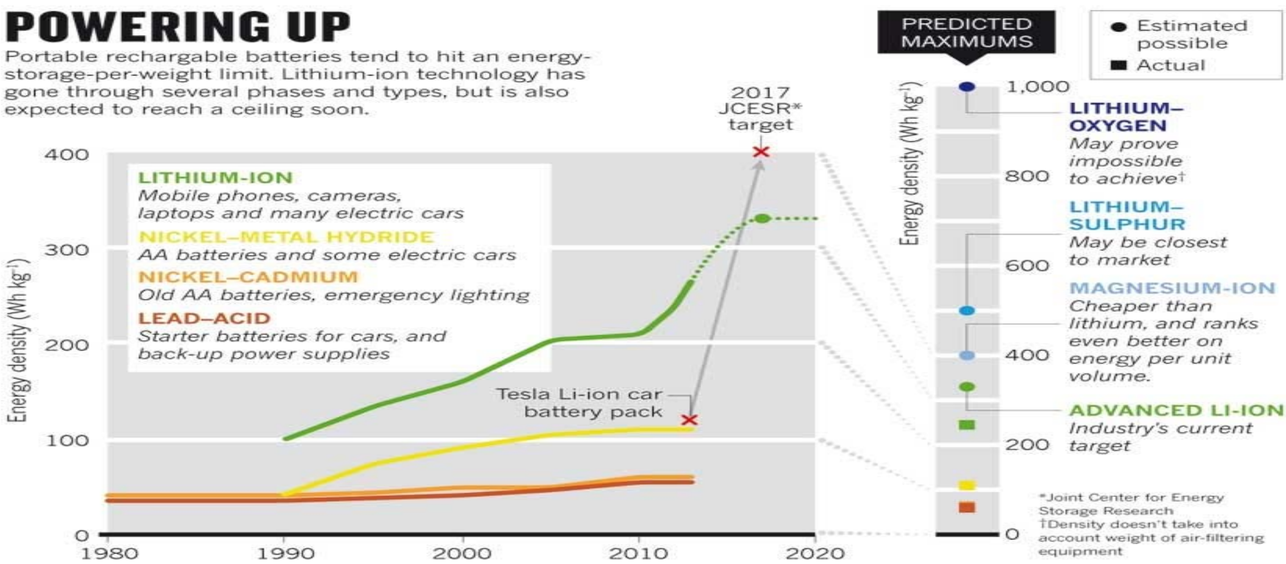

Fig. 1. Energy density comparison of Lithium ion technology with other battery technologies. The timeline shows significant increase in energy density for Lithium ion technology.

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II. Literature Review

In order to characterize the batteries, several type of methods have been devised which can be segregated into destructible and non-destructible categories [2]. Although destructive methods give precise information about the chemical properties of battery, they are rarely employed because they are impractical, largely because when a battery is tested through this method, it can no longer be reused. Popular non-destructive methods used to determine the state of health of a battery are series impedance measurement, voltammetry and electrochemical impedance spectroscopy. The Ampere Hour (Ah) counting method is one of the most commonly used methods to determine the state of charge and capacity of the battery [3]. The drawbacks of this method are that the method is time consuming and involves complete charge and discharge of battery, which might not be pragmatic in certain applications. Another commonly used method for state of health determination of a battery is impedance measurement at single frequency or at a range of frequencies. However, this method provides limited information, as certain mechanisms show their effect in a specific frequency range i.e. at usually low frequencies [4].

Electrochemical Impedance spectroscopy has been verified on the laboratory scale as a promising method to determine a range of aging effects in batteries [5]. The method is quick and provides instant results. However, with the existing approach, the results are largely affected by variation in battery model used to calculate the parameters. The process of optimizing the parameters obtained from the Nyquist plot requires intensive processing and good initial estimate, which might not be possible sometimes. These restrictions limit the application of this technique. This research is aimed to find a reliable method through which EIS technology can be used to decipher the SoH of the battery without using Equivalent Circuit Modeling and parameter estimation. The proposed solution comprised of a strategy that employs the change in the shape of EIS scan to correlate to overall SoH.

III. Methodology & Experimental setup

For this study, 3.7 nominal voltage and 4.8Ah Li-ion batteries were chosen. A pool of 30 different samples of batteries was available from which every time, suitable numbers of batteries were chosen depending on the type of test. The batteries were accumulated after they served in the field to power up radio sets for a long period of time. The batteries comprised of a wide spectrum of SoH that made contrasts and comparisons in the results very prominent. The batteries were used with a serial adapter, which was used to ensure concrete connection of testing equipment to the battery terminals. Since all the batteries were of the same model and manufacturer, they had same electrical characteristics. The values are quoted from their datasheet in table 1:

TABLE I

Nominal Voltage	3.7 V
Capacity	4800 mAh
Maximum Charge Voltage	4.2 V
Minimum Discharge Voltage	3.0 V
Charge Cut off point	0.24 A
Safe operating temperature	0 – 40 degree Celsius

Table. 1 Characteristics of the batteries used in study

In order to find the impact of State of Charge (SoC) on the EIS method, a sample set of 14 batteries was selected. The batteries were completely charged initially and EIS scans were performed for each battery at an interval of discharge of 10% of the overall battery capacity using VMP2 biologic equipment. The discharge test was performed using Cadex c7400 battery analyzer and the battery was allowed to sufficient time such that a steady state condition was reached. The data of the EIS scan was logged in an excel file containing all the frequencies, real and imaginary impedance. The frequency range of 10 KHz to 50 mHz was selected to perform the EIS scans such that dielectric and electrochemical properties of the battery under observation could be investigated. All tests were performed at room temperature and pressure. Figure 2 shows an EIS scan of the battery. The points of interest chosen to design the SoH algorithm are labeled in figure 2 which correspond to different characteristics of the battery's electrochemical properties. The zero crossing point corresponds to series resistance. The maximum x and maximum y values correspond to double layer capacitance, charge transfer resistance and dielectric properties. The minimum x value corresponds to mass kinetic properties such as diffusion of ions and Warburg impedance.

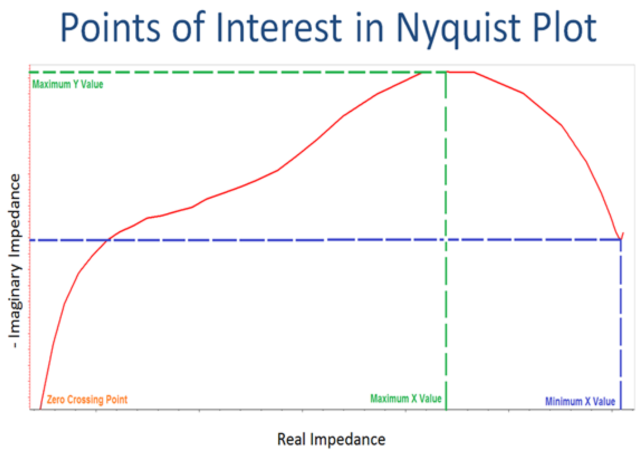

Fig. 2. Points of interest in Nyquist Plot

All these factors correspond to different electrochemical properties that relate to the ageing processes in a battery, as a result, EIS scan correlates to the health of battery. A program was written in Matlab that could record the points of interest in an EIS scans to study the correlations. The zero-crossing point, minimum x-value, maximum x-value, minimum y-value and maximum y-value were recorded for all EIS scans. However, before these points were directly calculated from the EIS scans, the raw data was processed to give a smooth EIS plot. In order to smooth the raw data obtained from the EIS scan, a moving point algorithm was implemented in Matlab.

Simple Moving Average (SMA) =

$$\frac{p_M + p_{M-1} + p_{M-2} + \cdots + p_{M-(n-1)}}{n}$$

$$= \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i}$$

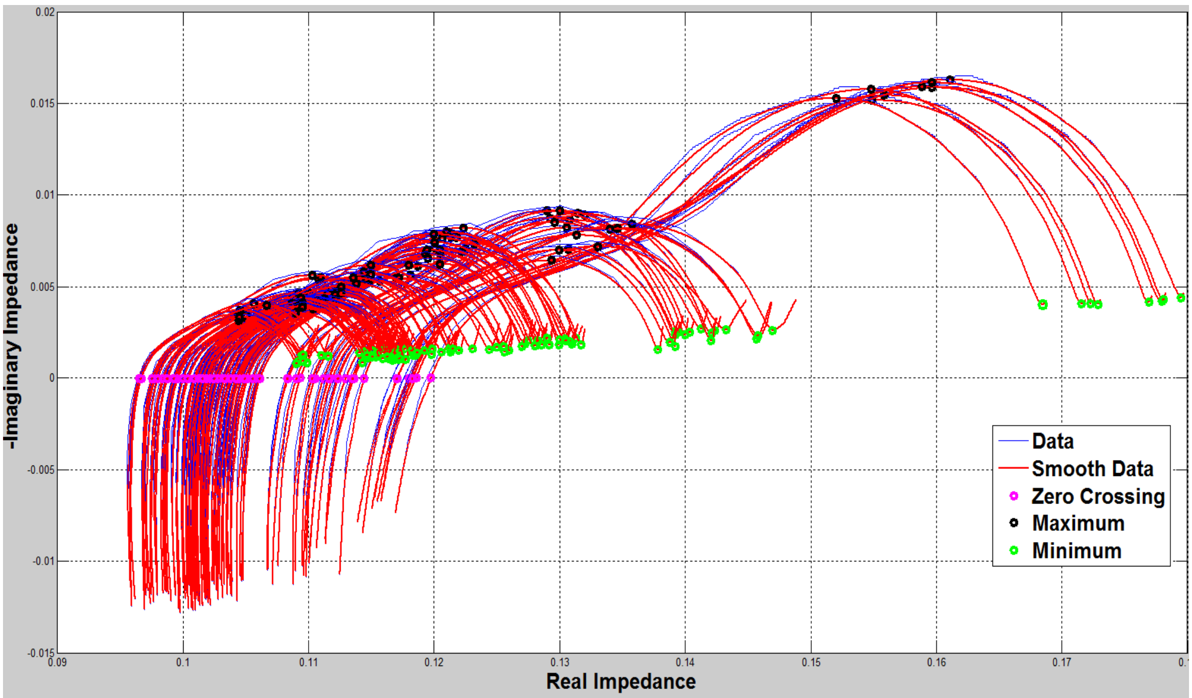

Fig. 3. All EIS scans with marked points of interests in Matlab. These points are used as potential markers from the EIS scan to correlate with the State of Health of a battery.

The points of interests were plotted individually on z-axis with different SoH on y-axis, SoC on x-axis as shown below:

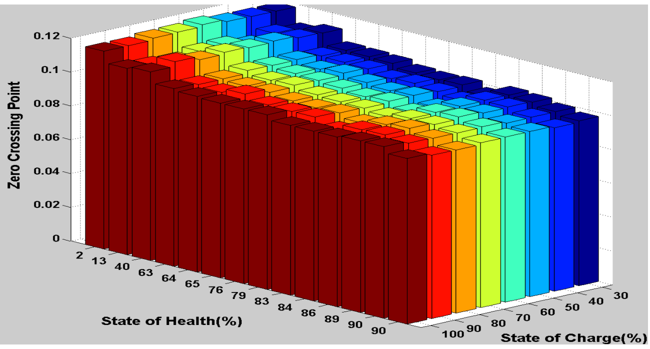

Fig. 4. Zero-crossing point as compared to batteries with State of Health and State of Charge.

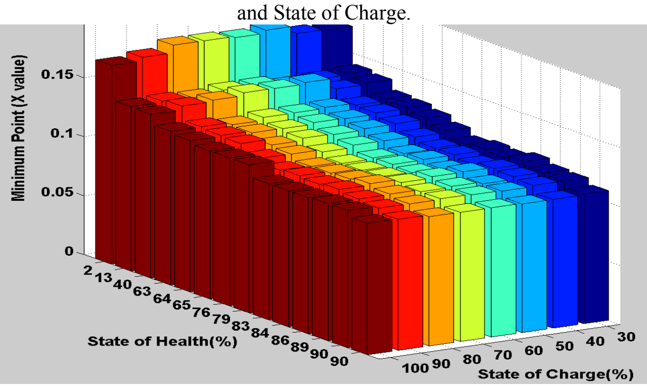

Fig. 5. Minimum point (X value) as compared to batteries with State of Health and State of Charge.

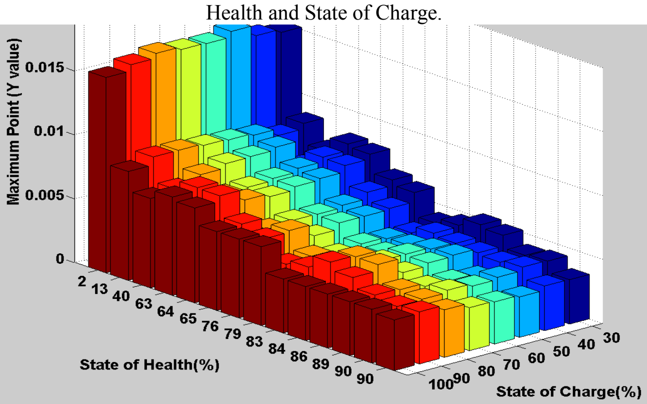

Fig. 6. Maximum point (Y value) as compared to batteries with State of Health and State of Charge.

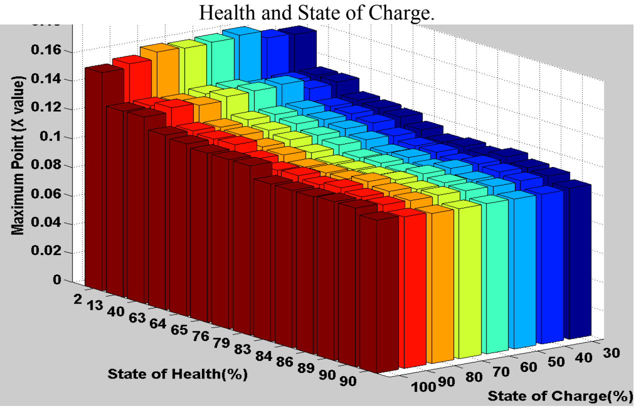

Fig. 7. Maximum point (X value) as compared to batteries with State of Health and State of Charge.

The data shows that the points of interest chosen for SoH algorithm had strong correlation with the electrochemical health of the battery. Based on the variation shown by the points of interest, the sensitivity factors were assigned to individual factors. More weight was assigned to the point of interest that showed larger correlation with the SoH. The overall function that relates all these point of interest to single function input value is shown below:

$$\textit{Function Input} = 30*Max_x + 20*Max_y + 40*Min_x + 10*Zero$$

The function input relation to the SoH (%) of the battery is shown in figure 8:

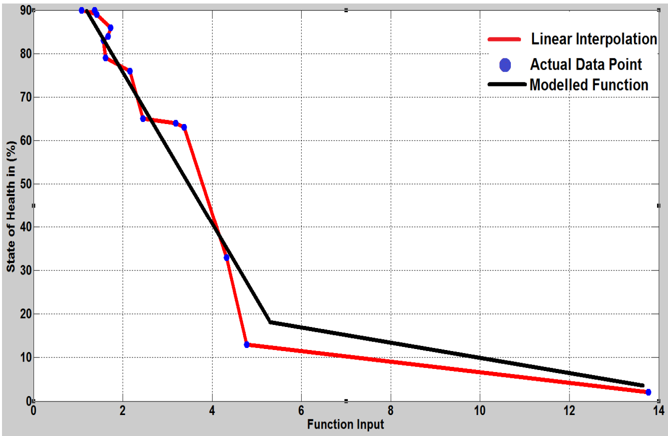

Fig. 8. Piece-wise linear model for SoH VS Function output

Since the function output cannot map directly to the SoH of the battery, another one to one function was required. A piece wise linear function was proposed such that the function input, x, maps to give SoH as a percentage as shown:

$$\text{State of Health}(x) = \begin{Bmatrix} -16.3 * x + 107.6, & 0 < x < 5.5 \\ -1.77 * x + 27.7 & 5.5 < x < 14.5 \end{Bmatrix}$$

IV. Results

After implementation of the SoH determination algorithm on the firmware of experimental hardware, tests were performed to verify the authenticity of the approach. For the evaluation of the proposed SoH determination algorithm, the batteries were fully charged and 5 consecutive tests were performed to verify if the results were coherent. The average error calculated from the tests that showed that for good batteries the error remained within 10% bracket, whereas, for poor batteries the variation was large (T13 and T14). The average time taken to complete the tests was also recorded as shown in figure 5.13. The SoH estimation is highly accurate when battery is fully charged.

The paper outlines a unique approach to find the remaining capacity (State of Health) of the battery using Electrochemical Impedance Spectroscopy (EIS). The proposed strategy eliminates the need of equivalent circuit modeling of the battery parameters and directly correlates the EIS scan footprint to electrochemical properties of the battery. However, the work is presented under assumption that battery was in steady state, fully charged and at room temperature. Variation in any of these factors can impact the performance of the proposed algorithm. Tests were performed to improve the efficiency and robustness of method by compensating the impact of the stated factors, however, that work is not covered as it is beyond the scope of this paper.

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Battery ID	State of Health in %	Test 1	Test 2	Test 3	Test 4	Test 5	Error Average(%)	Average Test Time(s)
Battery 1	63	61.1	62.55	63.16	62.6	63.02	-0.514	40.57
Battery 2	90	90.65	91.22	91.35	91.75	90.6	1.114	41.23
Battery 3	30	26.83	27.4	23.29	24.28	25.07	-4.626	40.94
Battery 4	65	68.28	69.45	69.73	69.21	70.4	4.414	40.56
Battery 5	2	0	0	0	0	0	-2	42.12
Battery 6	90	83.39	84.14	85.64	83.8	86.42	-5.322	40.68
Battery 7	89	81.64	81.73	83.19	82.42	82.65	-6.674	40.92
Battery 8	84	80.63	80.45	81.64	80.55	79.97	-3.352	40.77
Battery 9	79	80.41	80.27	79.85	79.81	80.7	1.208	41.25
Battery 10	76	75.73	74.01	75.38	74.95	73.31	-1.324	40.87
Battery 11	64	59.72	59.07	57.81	59.37	59.58	-4.89	41.39
Battery 12	13	20.96	23.07	20.48	21.52	23.1	8.826	42.51
Battery 13	86	77.12	77.68	79.27	77.06	77.98	-8.178	41.89
Battery 14	83	82.59	78.92	79.25	76.05	80.32	-3.574	41.05
Battery T1	55	55.59	55.84	55.08	56.83	55.5	0.768	40.74
Battery T3	81	83.22	83.34	82.63	82.5	81.23	1.584	41.28
Battery T2	71	73.74	75.96	75.24	75.7	74.52	4.032	40.84
Battery T9	22	8.79	9.14	13.33	16.75	16.5	-9.098	41.61
Battery T13	43	8.32	7.68	7.12	8.23	10.25	-34.68	41.53
Battery T14	42	23.7	22.65	23.16	23.63	22.49	-18.874	40.98

Fig. 9. SoH algorithm validation tests. This shows that the proposed strategy can be used to determine the State of Health of battery. The proposed technique works well for good batteries. However, the error in estimation is higher for low State of Health batteries. The reason being poor batteries are complex to model.