An On-line SOH Prediction Model for Lithium-Ion batteries Using the Mahalanobis Taguchi Technology

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Abstract—**The lithium batteries are the most likely and demanding batteries on the market, due to advantages of no memory, small size, high power, long cycle life, and low cost. The global climate change and energy crisis, electric vehicles have been widely developed. Due to lithium batteries play an essential role in the energy storage system, and its reliability will affect driving tasks. Therefore, it is significant to evaluate the health status of lithium batteries in applications. If we can efficiently estimate the battery health prediction, will help it for providing users with timely battery replacement information, and maintain product reliability. In the past, most of the studies used spectroscopy and electrochemical techniques for battery SOH estimation. These estimation methods are sophisticated and have low accuracy. There is currently a lack of analytical methods that can effectively assess battery health. Therefore, in this paper proposes a novel approach for health status evaluation of lithium batteries based on Mahalanobis-Taguchi system. A set of real battery test data were used for simulation verification. Preliminary results show that this method can effectively and quickly predict the degree of battery health status. Moreover, the method can provide vital information to provide task scheduling on the use of electric vehicles.**

Keywords- Electric vehicle, SOH, Mahalanobis distance, reliability, data analysis

I. INTRODUCTION

As technology advances, a variety of batteries are used in different fields. Lithium batteries are the easiest and most demanding on the market due to their high power, small size, long cycle life, high energy density, no memory, and low cost. They can be used in portable electronic devices. Therefore, lithium-ion battery has become an integral part of daily life. Faced with declining air quality and climate targets, many governments around the world are looking to accelerate the development of the electric car market. The government uses various tools to promote electric cars (Yang, Slowik, Lutsey & Searle, 2016). Global climate change and energy crisis, electric vehicles have been widely developed. With the growth of the hybrid vehicle market, battery usage is expected to increase rapidly in coming decades. Lithium batteries play a crucial role in energy storage systems.

Therefore, reliability and maintenance related to the use of large batteries must be managed.

The battery management system helps maintain the program by evaluating the health of the battery (SOH). A battery's SOH is a measure of how much a battery degrades its health during its use, often by its internal resistance or its ability to provide a given amount of power. The battery management system must be able to predict when the battery wi ll approach the residual useful performance (RUP) threshold to provide enough battery replacement warnings for the user. Traditionally, SOH and RUP have been evaluated using data measured during emissions.

The discharge current over time is used to calculate the maximum capacity for each charge and discharge cycle, and the Bayesian Monte Carlo extrapolation model is used to predict the RUP measurements (He, 2011). Andre (2013) incorporated SOH into the framework using double kalman filtering and support vector machine methods, where the update of the capacitance and internal resistance of the voltage change during the pulse discharge was calculated by SOH. Eddahech(2012) used the equivalent series resistance in impedance spectrum to measure the degradation behavior predicted by SOH and circulatory neural network. Du (2010) and Schmidt (2010) have described a similar method of determining SOH using capacity and internal resistance as features. However, uncertainties such as temperature, vibration and unforeseen use can cause uncertainty, and these methods do not address these issues.

Therefore, in this paper proposes a novel approach for health status evaluation of lithium batteries based on Mahalanobis-Taguchi system. A set of real battery test data were used for simulation verification.

II. MAHALANOBIS TAGUCHI METHOD

Current trends in multivariate diagnostics and pattern recognition tend to favor data analysis programs. One such method is called the Mahalanobis-Taguchi System (MTS). In quality engineering, MTS is a method of developing multidimensional metrics such as Mahalanobis distance and Taguchi methods by integrating mathematical and statistical concepts. This article will discuss the Mahalanobis distance in MTS.

There are four stages of applying MTS as follow ：

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- Stage 1 ： Mahalanobis space (unit space) is used as a reference to construct the measurement scale.

1. Define variables for health status.
2. Collect data on all variables in the healthy group.
3. Calculate the standard value of the health group variable.
4. Calculate the Mahalanobis distance (MD) of all observations using the inverse of the correlation matrix. With these MDs and can define the zero point and the unit distance.
5. Use the zero point and the unit distance as the reference point or base for the measurement scale.

- Stage 2： Validation of the measurement scale

1. Identify the abnormal conditions.
2. Calculate MD corresponding to these abnormal conditions to verify the proportion. The variables in the abnormal condition were standardized using the mean and standard deviation (SD) of the corresponding variables in the healthy group. The correlation matrix corresponding to the healthy group was used to calculate MD for abnormal conditions.
3. If the scale is correct, MD corresponding to abnormal conditions should have a higher value. In this way, you can verify the scale.

- Stage 3：Identify useful variables

Use the orthogonal array (OA) and the S/N ratio to find a useful set of variables. The S/N ratio obtained from abnormal MD is used as the response for each OA combination. Obtain a useful set of variables by evaluating the gain of S/N ratio.

- Stage 4 ： Future diagnosis with useful variables

Use scale to monitor conditions. This was developed with the help of a useful set of variables. Take appropriate corrective action according to MD value. The decision to take the necessary action depends on the value of the threshold.

The Mahalanobis distance is a squared distance (also denoted as D^2) calculated for the jth observation in a sample of size n with k variables using the following formula

$$MD_j = D_j^2 = Z_j^T \Sigma^{-1} Z_j \tag{1}$$

where, $j = 1$ to n, $Zj = (Z_{1j}, Z_{2j}, \dots, Z_{kj})$, $Z_{ij} = (X_{ij} - m_i) / S_i$, Xij is the value of the i-th characteristic in the jth observation, m_i is the mean of the i-th characteristic, S_i is the standard deviation of the i-th characteristic, Σ is the variance-covariance matrix.

In MTS, the MD obtained from (1) is scaled by dividing with the number of variables k. Therefore, the equation for calculating scaled MD becomes

$$MD_j = \frac{1}{k} Z_j^T \mathrm{R}^{-1} Z_j \tag{2}$$

III. CASE STUDT AND ANALYSIS

Battery health diagnosis process (Figure 1). First, collect battery lifecycle test data, such as voltage, current, cycle. The test data is divided into healthy and unhealthy, and the health data as training data, and calculate the Mahalanobis distance. Build a complete measurement scale and confirm the overall measurement. Finally, the critical feature variables of attribute screening are established, and the critical value is determined by Mahalanobis distance. Use this mode for battery health diagnosis and prediction. This study was based on the Battery health diagnosis process using the R Programming Language program for simulation and verification.

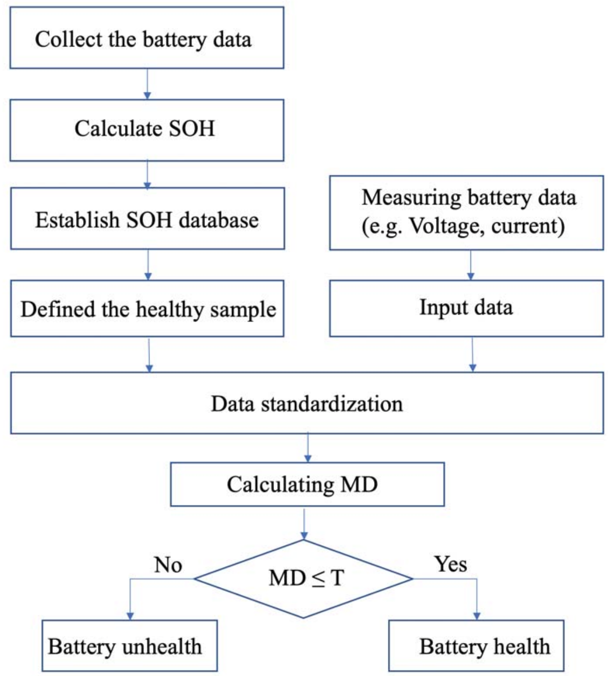
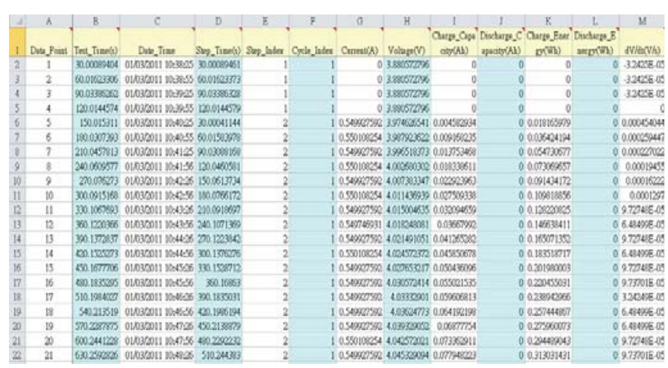


Figure 1. Battery health diagnosis process

The battery test data for this case is from the University of Maryland Advanced Life Cycle Engineering Center (CALCE) website, which uses the CS2_37 Lithium Battery ($LiCoO_2$) data set. Arbin Battery Tester tests this battery dataset. Each charge/discharge cycle of the battery is performed at full discharge depth until the battery fails. The output parameters include voltage, current, internal resistance and time. Recorded in an excel file.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Data_Point	Test_Time(s)	Date_Time	Step_Time(s)	Step_Index	Cycle_Index	Current(A)	Voltage(V)	Charge_Capacity(Ah)	Discharge_Capacity(Ah)	Charge_Energy(Wh)	Discharge_Energy(Wh)	dV/dt(V/s)
2	1	30.00089404	01/03/2011 10:38:25	30.00089461	1	1	0	3.880572796	0	0	0	0	-3.2425E-05
3	2	60.01623306	01/03/2011 10:38:55	60.01623373	1	1	0	3.880572796	0	0	0	0	-3.2425E-05
4	3	90.03386262	01/03/2011 10:39:25	90.03386328	1	1	0	3.880572796	0	0	0	0	-3.2425E-05
5	4	120.0144574	01/03/2011 10:39:55	120.0144579	1	1	0	3.880572796	0	0	0	0	0
6	5	150.015311	01/03/2011 10:40:25	30.00041144	2	1	0.549927592	3.974626541	0.004582934	0	0.018165979	0	0.000454044
7	6	180.0307393	01/03/2011 10:40:55	60.01583978	2	1	0.550108254	3.987923622	0.009169235	0	0.036424194	0	0.000259447
8	7	210.0457813	01/03/2011 10:41:25	90.03098169	2	1	0.549927592	3.996518373	0.013753469	0	0.054730677	0	0.000227022
9	8	240.0609577	01/03/2011 10:41:56	120.0460581	2	1	0.550108254	4.002600302	0.018338611	0	0.073069657	0	0.00019455
10	9	270.076273	01/03/2011 10:42:26	150.0613734	2	1	0.549927592	4.007303347	0.022923963	0	0.091434172	0	0.00016222
11	10	300.0915168	01/03/2011 10:42:56	180.0766172	2	1	0.550108254	4.011436939	0.027509338	0	0.109818856	0	0.0001297
12	11	330.1067693	01/03/2011 10:43:26	210.0918697	2	1	0.549927592	4.015004635	0.032094659	0	0.128220825	0	9.72748E-05
13	12	360.1220366	01/03/2011 10:43:56	240.1071369	2	1	0.549746931	4.018248081	0.03667992	0	0.146638411	0	6.48499E-05
14	13	390.1372837	01/03/2011 10:44:26	270.1223842	2	1	0.549927592	4.021491051	0.041265282	0	0.165071352	0	9.72748E-05
15	14	420.1525273	01/03/2011 10:44:56	300.1376276	2	1	0.550108254	4.024572372	0.045850678	0	0.183518717	0	6.48499E-05
16	15	450.1677706	01/03/2011 10:45:26	330.1528712	2	1	0.549927592	4.027653217	0.050436096	0	0.201980003	0	9.72748E-05
17	16	480.1835295	01/03/2011 10:45:56	360.16863	2	1	0.549927592	4.030572414	0.055021535	0	0.220455031	0	9.73701E-05
18	17	510.1984027	01/03/2011 10:46:26	390.1835031	2	1	0.549927592	4.03332901	0.059606813	0	0.238942966	0	3.24249E-05
19	18	540.213519	01/03/2011 10:46:56	420.1986194	2	1	0.549927592	4.03624773	0.064192199	0	0.257444867	0	6.48499E-05
20	19	570.2287875	01/03/2011 10:47:26	450.2138879	2	1	0.549927592	4.039329052	0.06877754	0	0.275960073	0	6.48499E-05
21	20	600.2441228	01/03/2011 10:47:56	480.2292232	2	1	0.550108254	4.042572021	0.073362911	0	0.294489043	0	9.72748E-05
22	21	630.2592626	01/03/2011 10:48:26	510.244383	2	1	0.549927592	4.045329094	0.077948223	0	0.313031431	0	9.73701E-05

Figure 2. Schematic diagram of battery data

At this stage, this study is based on the research of the Reliability Engineering Research Center of Ming Chi University of Technology (Huang et al., 2017) to develop an online SOC/SOH estimation model based on the capacity of the battery to define SOH. The battery is subjected to a cycle life test, and the discharge current (constant), instantaneous voltage, time and resistance are recorded every 30 seconds during the test, and a discharge curve is presented. The new variable: V' (the derivative of voltage versus time) develops a new model that simultaneously estimates battery SOC and SOH. In this study, the SOH was calculated for the battery in this case. Consolidate the case battery data and SOH calculation results and establish the SOH database by R language.

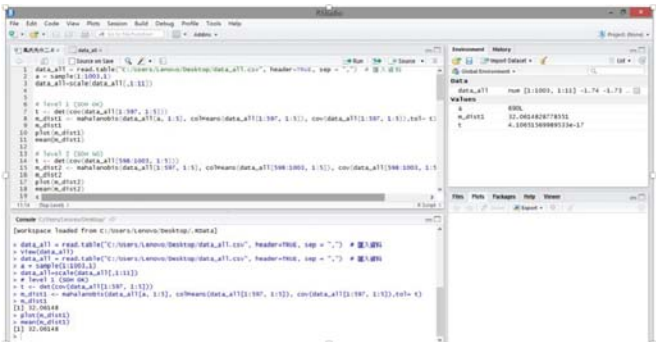


Figure 3. Schematic diagram of the SOH database

According to the ISO 12405-2 standard (Testing Specifications for Electric Road Vehicles - Lithium Ion Traction Battery Packs and Systems - Part 2: High Energy Applications) and IEEE Standard 1188.1996, when SOH < 80%, the battery will not function properly. It is defined as a battery failure. Therefore, this study used SOH≧80% as a healthy reference sample. At this stage, the battery-related variables (e.g., voltage, current, charge/discharge capacity) are measured for the battery to be tested as a test sample. Since the study is based on the battery data of the case, there is no original battery to be tested. Therefore, at this stage, the battery data in the data set will be selected as a test sample.

The random number is selected from the battery data in the data set as the input value of the test data. Data will be standardized by training data (health samples) and test data (test samples). Calculate the Mahalanobis distance between the test sample and the healthy sample. According to the Markov distance, it is determined whether the battery is close to a healthy sample, and if the Mahalanobis distance is less than a particular critical value, the test sample is determined to be healthy.

IV. CONCLUSION

In this paper, a real battery test data was used to model validation. Preliminary results show that this method can reduce unnecessary battery testing items, shorten data collection time, and efficiently predict the battery health status. Applying Mahalanobis distance to battery health, we can not only get a useful measurement scale to determine whether the battery is healthy. In this paper, we assume that the actual severity of all anomalies is known. However, we are not aware of the severity of the anomaly and will need to be studied in the future.

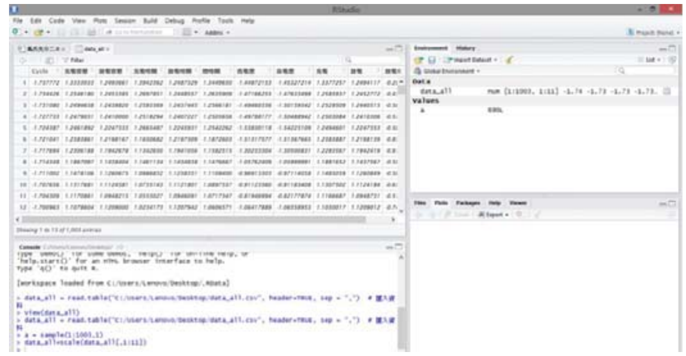


Figure 4. Schematic diagram of calculating Mahalanobis distance

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