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A Study on Remaining Useful Life Prediction for Prognostic Applications

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A Study on Remaining Useful Life Prediction for Prognostic Applications

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Abstract

We consider the prediction algorithm and performance evaluation for prognostics and health management (PHM) problems, especially the prediction of remaining useful life (RUL) for the milling machine cutter and lithium-ion battery. We modeled battery as a voltage source and internal resisters. By analyzing voltage change trend during discharge, we made the prediction of battery remain discharge time in one discharge cycle. By analyzing internal resistance change trend during multiple cycles, we were able to predict the battery remaining useful time during its life time. We showed that the battery rest profile is correlated with the RUL. Numerical results using the realistic battery aging data from NASA prognostics data repository yielded satisfactory performance for battery prognosis as measured by certain performance metrics. We built a battery test platform and simulated more usage pattern and verified the prediction algorithm. Prognostic performance metrics were used to compare different algorithms.

Prognostics and Health Management, Remaining Useful Life, Lithium-ion Battery, Linear Regression

1 Introduction

We study prognostic and health management problems related to remaining useful life prediction of mission critical components such as a lithium-ion battery state of charge and state of life and milling machine cutter usable cycles. We implemented linear regression methods and evaluated the prediction performance. A battery test platform is setup to enable further prognostic studies. We think neither purely data-driven nor purely model-based approaches would work well in reality. At most cases when no ground truth is available and lack of run-to-failure data, with the model knowledge and selectively process collected data, the hybrid approach works best, as far as the prediction accuracy and speed are concerned.

Chapter 1 introduces the motivation of the work, the background of prognostic research status and typical approaches, brief lithium-ion battery and milling machine cutter knowledge, previous researches and commercial value of the prognostic problems.

Chapter 2 formulates general prognostic problem and define the key application parameters. Lithium-ion battery external and internal key indices are described and milling machine cutter features are listed.

In Chapter 3, we modeled lithium-ion battery open circuit voltage (OCV) and evaluated the model fitting residues. Battery state of charge (SOC) and state of health (SOH) estimation and prediction are given. Linear regression is used to make prediction with confidence interval.

Chapter 4 describes the new battery test platform in University of New Orleans. It has the global diagram and key circuit designs.

Conclusions and future work are presented in chapter 5. It includes the findings of battery model and application lesson learn regarding linear regression method. The new test platform can be further developed and as a teaching resource for University of New Orleans.

1.1 Motivation

My research interest for prognostics starts from the daily use of battery. In many battery applications, how to detect good batteries from bad ones is always a hot topic. For example some AA batteries on a Walkman can last for tens of hours but some are less than half hour. Some batteries are good for remote controller but not for flash light. To evaluate AA battery remaining energy, some uses open circuit voltage while some uses short circuit current. People have experiences that laptop meter works better for new batteries. When battery getting old, or when using laptop in outdoor cold temperature, laptop may die long before the predicted time. All these experiences drove our curiosity higher and higher and so I choose to research on statistical fault prognostics.

Prognostic is very important to industrial usage nowadays. Growing demand for improving the reliability and survivability of safety-critical aerospace systems has led to the development of PHM. Instead of passively react to fault symptoms with limited fault-tolerant capability, a PHM system should predict failures actively and reconfigure control actions so that stability and acceptable performance of the entire system can be maintained. The emergence and successful applications of PHM technology over the last decade, especially the development of on-line prognosis techniques, gave rise to proactive fault tolerance control system, which is playing more and more important role in deep space exploring and military weapons. As all technology development would eventually serve public in civilian devices, so the prognostic research has great commercial value as well.

In Information and System Lab (ISL), Electrical Engineering department of University of New Orleans, we use statistical inference methods on target tracking and signal estimation. Statistical fault prognostic is naturally become our interest. In 2009, Louisiana Board of Regents setup the NASA EPSCoR DART-2 funding, for Louisiana universities to approach industrial groups. In 2010 program "LINK" links UNO with industry, research centers, and national labs. Also this field is different from traditional reliability field and it is under developing. The mathematical foundation is not yet solid. Hence it was a great opportunity we got into the prognostic research field.

The PHM society organizes a data challenge session annually, which provides an arena for all prognostic algorithms to compete in real applications. In year 2010 the data challenge focused on RUL estimation for cutters from a high-speed Computer Numerical Control (CNC) milling machine using dynamometer, accelerometer, and acoustic emission data. Both professional and student participants needed to submit estimated maximum safe cut cycles for given wear. I joined the data challenge competition and I won 1st prize in student category. It gave me great confidence that in University of New Orleans can do very well in the prognostic research field.

1.2 Prognostics and Health Management

There is no agreed definition of PHM yet. On Wikipedia, the definition is "Prognostics is an engineering discipline focused on predicting the time at which a component will no longer perform a particular function". The predicted time is defined as the remaining useful life (RUL). The science of prognostics is based on the analysis of failure modes, detection of early signs of wear and aging, and fault conditions. The discipline that links studies of failure mechanisms to system lifecycle management is often referred to as prognostics and health management (PHM). Technical approaches to building models in prognostics can be categorized into data-driven approaches, model-based approaches, and hybrid approaches.

1.2.1 Data-Driven Prognostics

Data-driven techniques utilize monitored operational data related to system health. Data-driven approaches are appropriate when the understanding of first principles of system operation is not comprehensive or when the system is sufficiently complex that developing an accurate model is prohibitively expensive. The method models cumulative damage and then extrapolating out to a damage threshold.

However, a principal bottleneck is the difficulty in obtaining run-to-failure data, in particular for new systems, expensive systems and human involved systems, since running systems to failure can be a lengthy, rather costly and danger process. These data sources may include temperature, pressure, oil debris, currents, voltages, power, vibration and acoustic signal, spectrometric data as well as calibration and calorimetric data. Features must be extracted high-dimensional data.

1.2.2 Model-based prognostics

Modeling physics can be accomplished at micro and macro levels. At the micro level, physical models are embodied by series of dynamic equations that define relationships, at a given time or load cycle, between damage of a system/component and environmental and operational conditions under which the system/component are operated. The micro-level models are often referred as damage propagation model. Macro-level models are the mathematical model at system level, which defines the relationship among system input variables, system state variables, and system measures variables/outputs where the model is often a somewhat simplified representation of the system. The resulting simplifications need to be accounted for by the uncertainty management.

1.2.3 Hybrid approaches

Hybrid approaches attempt to leverage the strength from both data-driven approaches as well as model-based approaches. A good example for the former would be where model parameters are tuned using field data. A bad example for the latter is when the set-point, bias, or normalization factor for a data-driven approach is given by models.

1.3 Application Fields

In this research, we implemented our prognostic algorithms on lithium-ion batteries and milling machine cutters. The Lithium-ion battery was chosen because it is so popular around the world. Whenever use laptop computer on battery, people understand the battery remaining useful life terms. Also the test setup is relatively easy and accurate. Run-to-failure data is inexpensive. In order to describe our research applications, it is necessary to introduce the basis of these two fields.

1.3.1 Lithium-ion Batteries

In 1912, G. N. Lewis began pioneering work on the lithium battery. The non-rechargeable version is commercially available at the early 1970s. However the lithium batteries have faced a big setback due to issues involving safety. Because of the instability of lithium metal during charging, research efforts shifted to a non-metallic lithium battery using lithium ions. Attempts to develop rechargeable lithium batteries followed in the 1980s but the endeavor failed because of instabilities in the metallic lithium used as anode material. In 1991, the Sony Corporation commercialized the first lithium-ion battery.

The instability of lithium metal shifted research to a non-metallic solution using lithium ions. Although lower in specific energy than lithium-metal, Lithium ion is safe. Battery packers usually put a protection chip inside battery cell to keep voltage and currents to secure levels. After Sony commercialized the first Li-ion battery, this chemistry has become the most promising and fastest growing on the market.

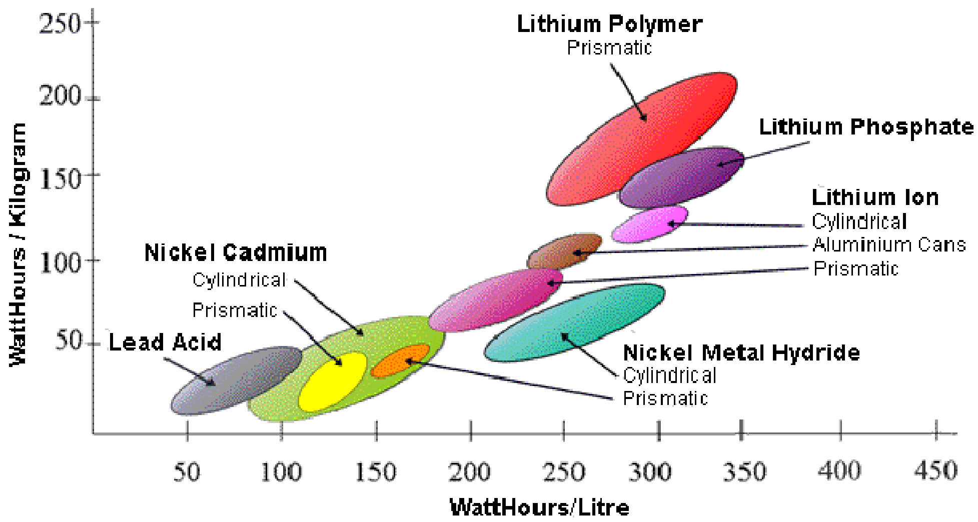

Figure 1 - Battery Energy Density Comparison

The specific energy of Li-ion is twice that of NiCd and the high nominal cell voltage of 3.6 V as compared to 1.2 V for nickel systems contributes to this gain. Improvements in the active materials of the electrode have the potential of further increases in energy density. The load characteristics are good, and the flat discharge curve offers effective utilization of the stored energy in a desirable voltage spectrum of 3.70 to 2.80V/cell. Nickel-based batteries also have a flat discharge curve that ranges from 1.25 to 1.0V/cell.

In 1994, the cost to manufacture Li-ion in the 18650 cylindrical cell with a capacity of 1100 mAh was more than $10. In 2001, the price dropped to $2 and the capacity rose to 1900 mAh. Today, high energy-dense 18650 cells deliver over 3000 mAh and the costs have dropped further. Cost reduction, increase in specific energy and the absence of toxic material paved the road to make Li-ion the universally accepted battery for portable application, first in the consumer industry and now increasingly also in heavy industry, including hybrid electric vehicles.

In 2009, roughly 38 percent of all batteries by revenue were Li‑ion. Li-ion is a low-maintenance battery, an advantage that many other type batteries cannot claim. The battery has no memory and does not need exercising to keep in shape. Self-discharge is less than half that of nickel-based systems. This makes Li‑ion well suited for fuel gauge applications. The nominal cell voltage of 3.60V can directly power cell phones and digital cameras, offering simplifications and cost reductions over multi-cell designs. The drawbacks are the need for protection circuits to prevent abuse, as well as high price.

Aging is a concern for most Lithium-Ion batteries. Some capacity deterioration is noticeable after one year. The battery may frequently fail over two perhaps three years. The loss of charge acceptance of the Lithium-Ion batteries is due to cell oxidation, which is permanent. The estimation of how much charge acceptance capacity and the prediction of how long a battery can be used are interesting research topics and many researchers are working on. The prediction of this capacity is crucial in some mission critical applications, such as outer space vehicles, unmanned aerial vehicles (UAV) and portable military devices

1.3.2 Milling Machine Cutters

A reliable and intelligent monitoring system is very important for cutting process. A successful monitoring system can effectively estimate tool-wear progress. In a lot of applications, such as milling machines that cut one work piece without changing the cutter in the middle of the process, the monitoring system must predict the cutter remaining useful life.

1.4 Previous Researches

1.4.1 Early Battery Researches

In 1990, T. Matsushima et al. introduced and demonstrated rechargeable lead acid batteries remaining useful time calculation in ampere-hours method [1]. In 1994 an improved state-of-charge indicator was proposed by T. B. Atwater and it was patented in 1995 [12]. K. Kutluay published online estimation of Lead-Acid battery remaining useful life [3]. In [4] and [7], two noval battery model were discussed for battery prognostic.[6] and [11] are real prognostic application usage in Hybird Electrical Vehicle and Electro-Mechanical Actuators.

1.4.2 NASA Ames Research Center

Several prediction methods are available, of which the most common are based on battery internal resistance. However, the impedance measurement alone provides only a rough sketch of the battery’s performance. For example, a fully charged battery that has just been removed from the charger shows a higher impedance reading than one that has rested for a few hours after charge.

1.4.3 Researches for Milling Machine Cutter Prediction

Various methods have been studied in the area of tool wear estimation. Xiang Li et al. [2] presented the method of wavelet packet transform for online wearing prediction of a high speed milling cutter. High speed cutter wearing mechanisms in physics models were addressed. However, none of above paper predicted remaining useful life with respect to the asymmetric penalty function as in the 2010 PHM data challenge. This paper describes our algorithm in full and pays special attention to the connection between prognostic and diagnostic problems.

1.5 Prognostics application environment and setup

1.5.1 NASA Ames Research Center Battery Testbed

NASA PCoE published a dataset of 34 batteries as of this thesis is written. All batteries were charged in a constant current (CC) mode until the battery voltage reached 4.2 V and then continued in a constant voltage (CV) mode until the charge current dropped to 20 mA. Impedance measurement was carried out through an electrochemical impedance spectroscopy (EIS) frequency sweep from 0.1 Hz to 5 kHz. The data was collected during the period of spring 2009 to spring 2011.

These batteries were run through 3 different operational profiles (charge, discharge and impedance) at different ambient temperature (4, 24 and 43 degree C). Discharge was carried out at 1 Amp, 2 Amp or 4 Amp until the battery voltage fell to a certain value ranged from 2.0 V to 2.7 V.

The individual test diagram and battery test profile are described in appendix A1.

1.5.2 2010 PHM Data Challenge Competition

The 2010 PHM Data Challenge Competition provided milling machine data. The test bed is similar to the one used in paper [2]. Cutters are 6 mm ball nose tungsten carbide cutter. The end of these cutters is hemispherical, which is ideal for machines with 3-dimensional contoured shapes. Each cutter was used repeatedly to cut the same work piece little by little. The spindle speed of the cutter was about 10400 rotates per minute (RPM). The feed rate was 1555 mm per minute. Y depth of cut was 0.125 mm and Z depth of cut was 0.2 mm. Figure 2 shows the coordinates of X, Y and Z. Data were acquired at 50 kHz for all seven channels.

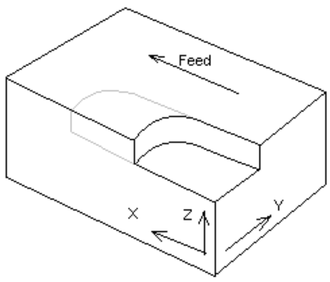

Figure 2 - Cutting Tool Coordinates

There are six individual cutter records, named c1, c2 ... c6. Records c1, c4 and c6 are training data, and records c2, c3, and c5 are test data. Each training record contains one "wear" file that lists wear after each cut in 10^{-3} mm, and 315 individual data acquisition files. In total 1890 cut files were provided to all participants.

2 Problem Definition

2.1 General Prognostic Problem Formulation

The prognostic problem is an optimization problem. When a system is running, prognostic algorithm should collect data in real time and give the best predicted remaining useful time, which should minimize the possible cost of underestimate and overestimate.

Minimize $f(t) = P_U(t) \cdot C_U + P_O(t) \cdot C_O$ (1)

where t is predicted remaining useful life; $f(t)$ is the total estimated cost. $P_U(t)$ is the probability of underestimate and $P_O(t)$ is the probability of overestimate. The C_U and C_O are underestimate cost and overestimate cost respectively

Different from other estimation problems, the cost function is usually unsymmetrical. C_O could be larger than C_O in many times. Take an example for aircraft battery remaining useful life estimation. Underestimate will result in just excessive wasted fuel but overestimate could result in crash or people in danger.

2.2 Lithium-Ion Battery Model

We found usually battery discharge profile is pretty constant. There is usually a filter circuit in between battery and load. It flats the discharge current. Hence the battery DC characteristic is more of a concern. In Figure 3 the simplest model is proposed.

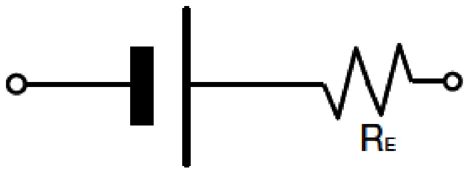

Figure 3 - Simplified Battery Model

A battery has an open circuit voltage. It is usually not measurable externally but it can be calculated when internal impedance R_E is known.

2.3 Lithium-Ion Battery Key Parameters

2.3.1 Open Circuit Voltage (OCV)

OCV is measured when no electric load applied to battery. OCV indicates the battery remaining useful life. Sometime the OCV is superficial and hard to estimate. We proposed a way to dynamically online estimate the internal resistance. During discharge phase, we introduce a small amount (+/-10%) load ripple. The corresponding voltage and current changes can be used to calculate battery internal impedance.

$$R_{\text{int}} = \frac{\Delta V}{\Delta I} \quad (2)$$

Knowing the impedance, OCV can be calculated as

$$U_{OCV} = U_{Term} + I \cdot R_{\text{int}} \quad (3)$$

2.3.2 Charge and Discharge Capacity

The battery real time State of Charge (SoC) is not measurable by tools directly. However SoC difference between two time points is calculable with current and time information.

$$C = \sum_{n=1}^{N} I_n \cdot \Delta t_n \tag{4}$$

2.4 Milling Machine Cutter Key Parameters

For the cutter wearing, we need to estimate the maximum number of cuts one could "safely" make for a given wear limit. By "safely", it means that the maximum wear of any flute does not exceed the wear limit. The penalty for over-prediction is smaller than that of under-prediction.

The estimation error is defined as Eq. (6)

$$d[n] = RUL_{Estimated}[n] - RUL_{Actual}[n] \tag{5}$$

where n is a wear limit. $d[n]$ is the estimation error at wear limit n. When overestimated, i.e. the estimated RUL is more than the actual RUL, $d[n]$ is positive. When underestimated, $d[n]$ is negative. The penalty functions are given asymmetrically as Eq. (2).

$$s[n] = \begin{cases} e^{-d[n]/10}, & d[n] < 0 \\ e^{d[n]/4.5}, & d[n] \geq 0 \end{cases} \tag{6}$$

The total score is calculated by summing up all penalties and least score wins.

$$S = \sum_{n=66}^{165} s[n] \tag{7}$$

There is no preset score benchmark for this competition. By testing the cutting cycle prediction scores of cutter 2, cutter 3 and cutter 5, the best algorithms are selected in professional team and student team.

3 Apply Linear Regression to Prognostic

3.1 Use Estimated Remaining Capacity as the Regressor

Linear regression allows us to estimate, and make inferences about population slope coefficients. Our aim is to estimate the causal effect on Y of a unit change in X. We start from fitting a straight line to data on two variables, Y and X.

Here we choose time as X, estimated capacity as the regressor Y.

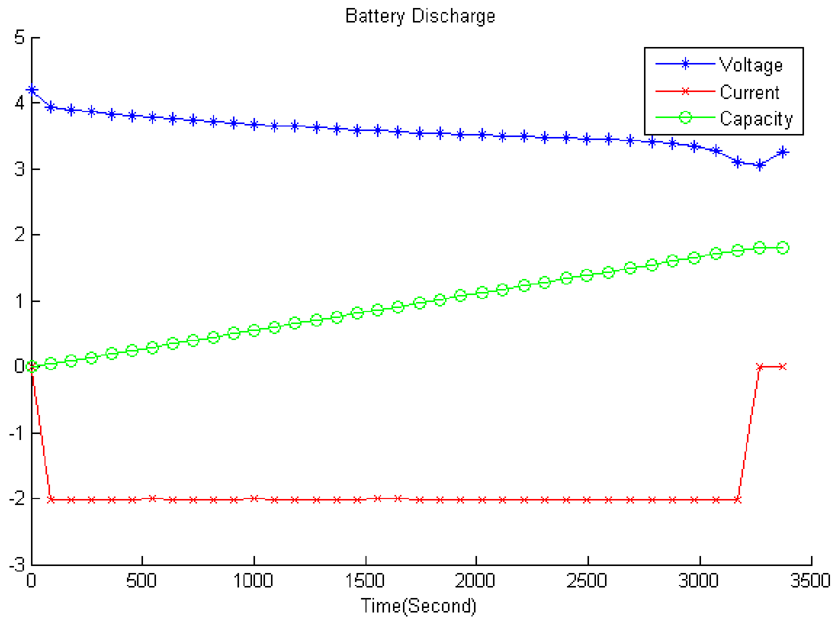

Figure 4 - Battery Discharge Plot

Figure 4 shows a typical battery discharge curve. The blue line (with star markers) indicates the voltage gradually goes down. The red line (with x markers) shows this is a constant current discharge at 2 Amp rate. The green line (with circle markers) is the cumulative used capacity.

3.2 Regression to Estimate End-of-Charge Time

For every new discharge cycle, we set the sample time as X. By comparing the current voltage with last cycle voltage, we estimated current discharge capacity as regressor Y. Then we use linear regression to predict at what time the estimated capacity reaches the limit, which is available from last discharge cycle.

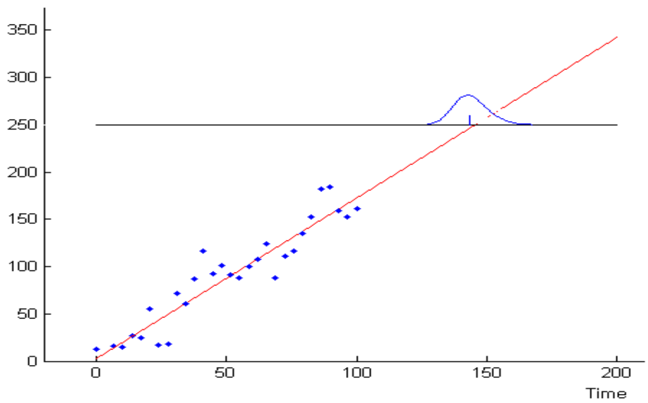

Figure 5 - Prediction on Synthetic Data

Figure 5 shows the linear regression progress. It shows at time t=100, a straight line is fit to existed data. By extrapolation it is predicted at time t=150, the key parameter reaches a preset level. For battery prediction, we predict at what time the capacity will reach last cycle value.

3.3 Regression Result on NASA battery data

Each set of NASA battery data has 200+ discharge cycles. Figure 6 shows the battery B0005 prediction results. The x axis is actual remaining useful time in seconds. The y axis is the predicted remaining useful time.

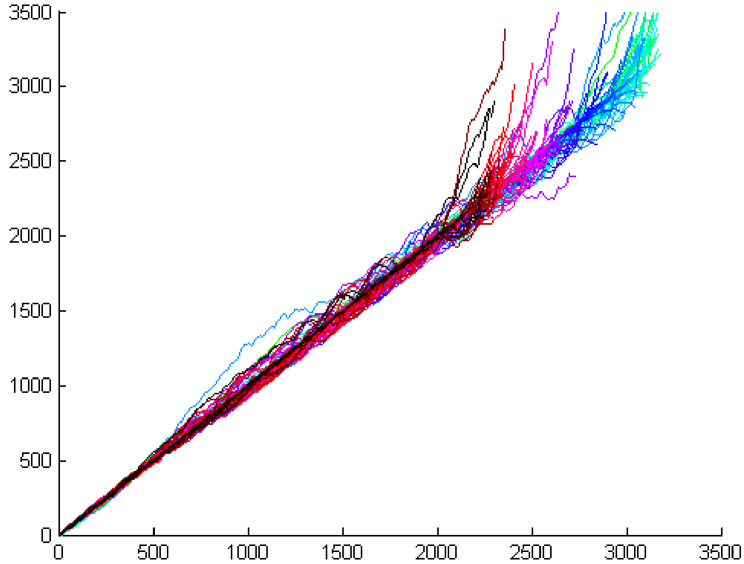

Figure 6 - Battery B0005 Prediction Result

We use histogram to demonstrate the predication result as in Figure 7, Figure 8 and Figure 9. The X axis is the prediction error. Less than zero is underestimating and above zero is overestimating.

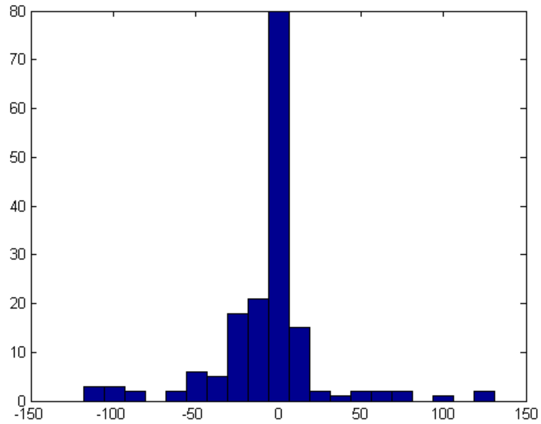

Figure 7 - RUL error at 2000 sec to end

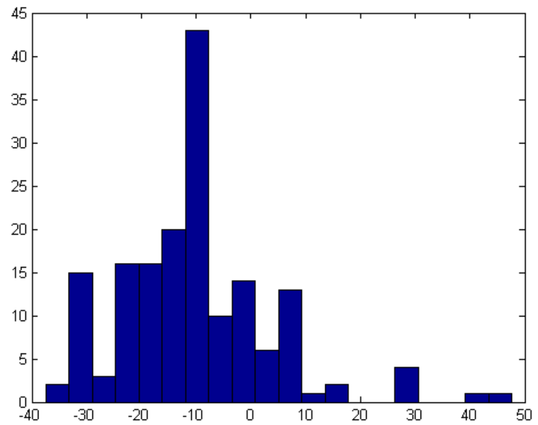

Figure 8 - RUL error at 500 sec to end

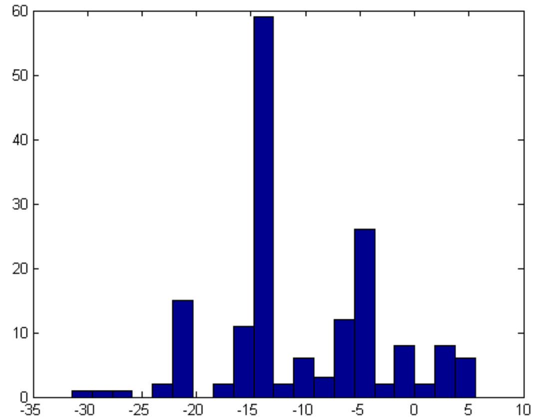

Figure 9 - RUL error at 100 seconds to end

4 UNO Battery Test Platform

4.1 Motivation of building the test platform

I believe the first hand data is critical to data-driven prognostic research. There are a few battery test beds were set in other research facilities. But a local battery test bed would enable our researchers to immediately verify the algorithms and to cultivate more thoughts. Building a battery test platform cost not much but it will be the first platform for prognostic purpose in University of New Orleans.

As the prognostic and health management science branch become stronger and stronger, I believe more researchers will join this field. And more students may choose it as their research interest. University of New Orleans has setup the Research Experience of Undergraduates problem to recruit a group of diverse, talented undergraduate students from around the nation, and to actively engage the recruited students into cutting-edge Integrated Sensing and Automated Scene Understanding (ISASU) research. This battery test platform will be a very good tool for some of them to practice prognostic researches.

4.2 Test capabilities

To conduct battery test and collect data for prognostic purpose, following objectives were set.

- Keep up to four batteries inside a controlled temperature environment
- Temperature can be set from 2 degree C to 60 degree C. Hysteresis is 1 degree C.
- Charger voltage from 1.2 V to 22.2 V, current less than 5 A, total power less than 50 W.

- Discharger works from 1.2 V to 22.2 V, discharge current less than 10 A. Total power less than 100 W
- 16 bit DAC to keep voltage and current sensing resolution 0.025%, accuracy 1%. Temperature accuracy 1 degree C.
- MATLAB and LabView Interface for control and monitoring.

4.3 Test Setup

The test setup is as following figure. A KWC-25 12V fridge is used as constant temperature chamber. A Computer power supply provides all power to relays and chargers. NI USB 6009 Data Acquisition device collects voltage, current and temperature readings and controls relays.

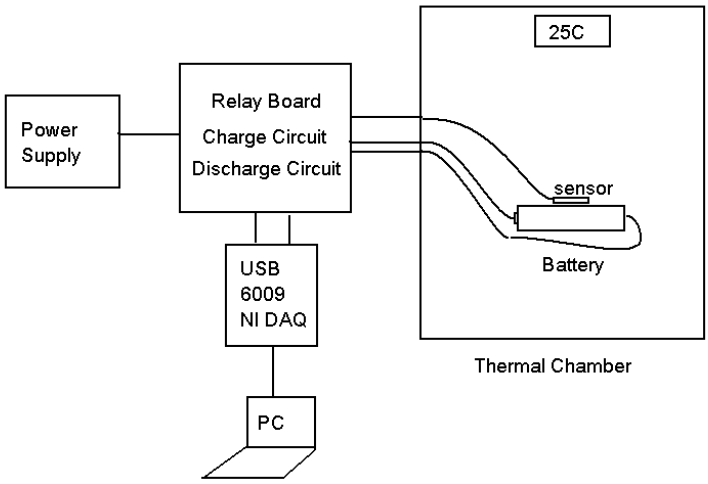

Figure 10 - UNO Battery Test Platform

4.3.1 Voltage Control Current Servo

To control the battery charge and discharge current, a voltage controlled current source is designed as following schematic. The control voltage is from USB 6009 analog output port. The circuit will keep the voltage on R3 equivalent to the input voltage, so that a controllable current is going through the target device.

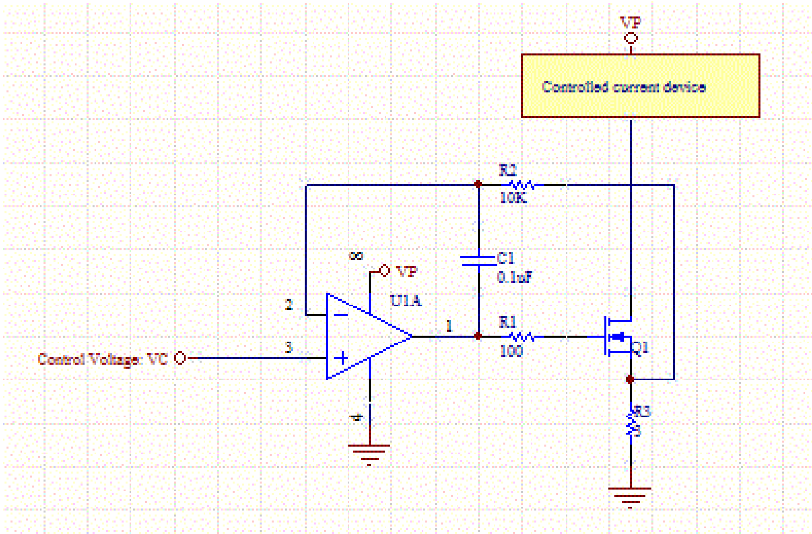

Figure 11 - Voltage Control Current Servo

4.3.2 Constant Current and Constant Voltage Charger Circuit

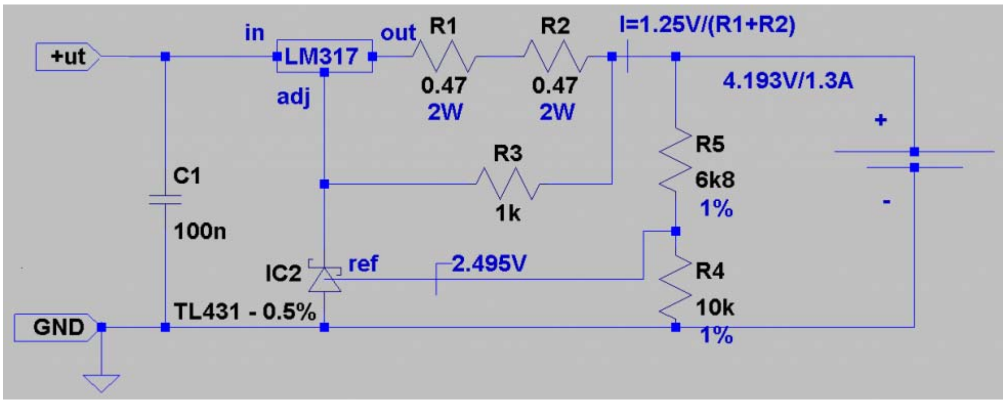

Figure 12 - Constant Current and Constant Voltage Charger Circuit

The CC-CV circuit is designed for lithium-ion battery charging. When battery voltage is less than 4.2V, IC2 will not function so that LM317 block is running in constant current mode. It keeps voltage across R1+R2 into 1.25V, which makes 1.25A charging current. When battery reaches 4.2V the IC2 will make LM317 into constant voltage mode. The voltage across R5 and R4 will not exceed 4.2V.

4.3.3 Impedance Measurement During Discharge Cycle

Every 5 minutes during discharge phase, a +10% and -10% ripple is applied to discharge current controller. The corresponding voltage changes are used to calculate battery internal impedance.

4.4 Test Procedures

A MATLAB code is written to control the USB 6009 DAQ actions and to collect all analog input values. Detailed algorithm is omitted in this thesis. In general the procedure is

- Initialize all relays and self-test
- Enable charger circuit and collect voltage, current and temperature
- After battery is fully charged, rest for at least 30 minutes and wait temperature back to constant
- Discharge the battery. Add impedance test waveforms every 5 minutes. Collect all data and protect battery from over-discharging.
- Rest 30 minutes and after temperature back to constant, start another test cycle

5 Conclusions and Future Work

5.1 Conclusions

By applying linear regression to battery and milling machine prognostics, we found that when last cycle discharge capacity is known, the prediction accuracy can be very accurate. At 1000 seconds before end of charge, the error is no more than 50 seconds. The linear regression performance is satisfactory.

A battery test platform was developed at ISL for prognostic data collection and algorithm development. We noticed that to estimate battery SOC is a key to End-of-Charge prediction. The existing battery prognostic data sets from NASA did not provide reliable battery impedance data, and it is hard to identify outliers. Using our own test platform, we can generate accurate battery usage data with real time measurements of temperature and internal impedance.

During the period of prognostic research, I joined the 2010 PHM Data Challenge Competition and I won first prize in the student category. I submitted a paper disclosing the winning strategy to Int. Journal of Prognostics and Health Management (ijPHM). I applied for Thesis Improvement Grant from graduate school of University of New Orleans and the proposal was awarded.

This thesis described the linear regression apply to lithium-ion battery and milling machine cutter wearing applications. Follow the same method many other prognostic problems can be solved in similar manner. I hope this thesis can be a bridge for readers solve more PHM challenges.

5.2 Future Work

I expect to expand the thesis work in the following avenues if time allows.

a) Apply weighted linear regression to improve the prediction accuracy. Currently the algorithm sets all points equal weights. Early time data keep impact the whole straight line fitting.

b) Analyze the relationship between battery temperature and internal impedance so as to estimate battery open circuit voltage more accurately. It will reduce the state of charge estimation error so that remaining useful life can be more accurate.

c) For the battery test platform, the long time running reliability need to be improved. The USB bus is still not reliable enough to sustain long time testing. A dedicated system bus, or embedded microcontroller will enable long term reliable cycle test.

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Appendices

A1. NASA Test Bed Circuit

In NASA Prognostic Center of Excellence website, there is not explicit schematic of the test bed. In order to better understand their online data, the following schematics are drew after on site visit and discussion to NASA researchers.

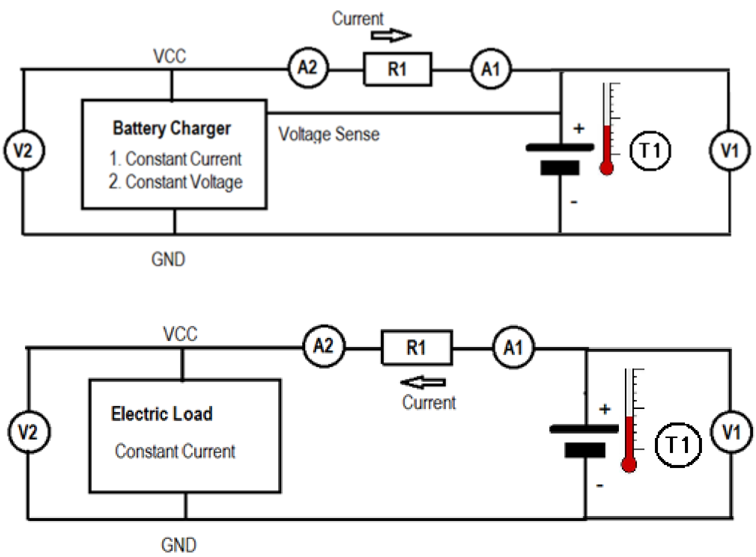

Figure 13 - NASA Ames PCoE Battery Testbed

A2. Test Battery Specification

We used 3.7V 2200mAh Tenergy Li-ion 18650 Cylindrical battery with tabs in our test runs. This appendix gives the battery specification for reference.

Illustration 1 - Tenergy 3.7V 2200mAH Li-ion 18650 Battery

Features

- Li-Ion 18650 cylindrical rechargeable battery with tabs;
- 3.7V 2200mAh high capacity
- High energy density and lower weight than other rechargeable batteries
- Manufactured under ISO9001-2000 to assure quality
- UL # MH48285
- Battery tested based on International Electrotechnical Commission (IEC) standard to ensure capacity, quality, and life time

Applications

- Building Laptop Battery
- Building portable power device needing high energy density and low weight

Product Specifications

- Capacity* Nominal 2200 mAh, Minimum 2150 mAh
- Dimensions:
- Diameter 18+/- 0.2 mm
- Height 65+/- 0.2mm
- Weight (Typical) Approx. 46 g yes
- Nominal Voltage: Average 3.7V
- Cut-off Voltage: 3.0V
- Internal Impedance: less or equal to 180 milliohm (with PTC)
- Cycle Performance: 90% of initial capacity at 400 cycles
- Cycle life: > 500 cycles
- Charge: Current = 0.5C mA Voltage = 4.2 V End Current = 0.01 mA
- Discharge: Current = 0.5C mA End Voltage = 3.0V
- Max. Charging current: 1.5C ma
- Max. Discharging current 1.5C ma (for continuous discharge)

VITA

The author was born in Ningxiang, Hunan, China. He obtained his College diploma in computer science from Hunan University in 1995 and Master's degree in computer science from Donghua University in 2004, respectively. He joined University of New Orleans electrical engineering program to pursue a Master's Degree, and become a member of Associate Professor Huimin Chen's research group in 2009. Before that he was with General Electrical as a team leader and program manager.