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SOC - STATE OF CHARGE

1) Battery stacks based on lithium-ion (Li-ion) cells are used in many applications such as hybrid electric vehicles (HEV), electric vehicles (EV), storage of renewable energy for use at a later time, and energy storage on the grid for various purposes such as grid stability, peak shaving, and renewable energy time shifting.

2) The state of charge (SOC) of the cells, is defined as the available capacity (in Ah) and expressed as a percentage of its rated capacity.

3) SOC and SOH estimation algorithms, especially the enhanced coulomb counting algorithm, the universal SOC algorithm, and the extended Kalman filter algorithm.

4) SOC estimation of the battery can avoid unpredicted system interruption and prevent the batteries from being over charged and over discharged, which may cause permanent damage.

5) The general approach for measuring SOC is to measure very accurately both the coulombs and current flowing in and out of the cell stack under all operating conditions, and the individual cell voltages of each cell in the stack. This data is then employed with previously loaded cell pack data for the exact cells being monitored to develop an accurate SOC estimate.

6) The additional data required for such a calculation includes the cell temperature, whether the cell is charging or discharging when the measurements were made, the cell age, and other relevant cell data obtained from the cell manufacturer.

COULOMB-COUNTING-METHOD

1) The coulomb counting method, also known as ampere hour counting and current integration, is the most common technique for calculating the SOC. This method employs battery current readings mathematically integrated over the usage period to calculate SOC values

2) The coulomb counting method then calculates the remaining capacity simply by accumulating the charge transferred in or out of the battery.

3) the releasable charge is always less than the stored charge in the charging and discharging cycle. In other words, there are losses during charging and discharging. These losses, in addition with the self discharging, cause accumulating errors. For more precise SOC estimation, these factors should be taken into account.

VOLTAGE-METHOD

1) The voltage method converts a reading of the battery voltage to the equivalent SOC value using the known discharge curve (voltage vs. SOC) of the battery.

2) The voltage is more significantly affected by the battery current due to the battery's electrochemical kinetics and temperature. The need for a stable voltage range for the batteries makes the voltage method difficult to implement.

3) During testing the system function is interrupted (offline method) contrarily to coulomb counting (online method).

KALMAN-FILTER-METHOD

1) The Kalman filter is an algorithm to estimate the inner states of any dynamic system which can also be used to estimate the SOC of a battery.

2) Kalman filtering is an online and a dynamic method, it needs a suitable model for the battery and a precise identification of its parameters. It also needs a large computing capacity and an accurate initialization.

3) The Kalman filter automatically provides dynamic error bounds on its own state estimates.

4) It then becomes a model-based state estimation technique that employs an error correction mechanism to provide real-time predictions of the SOC.

Initial SOC Determination (charging and discharging state)

1) A battery can be operated at one of the three modes; charging, discharging, and open circuit.

2) With a constant charging current, the battery voltage increases gradually and reaches the threshold.

3) Once the battery has been charged by the constant voltage mode, the charging current drops first rapidly, and then slowly.

4) The initial SOC during charging can be deduced from these relationships.

5) At the discharging stage, the terminal voltage declines as the operating time elapses.

6) A higher current causes faster decline in the terminal voltage, leading to a shorter operation time.

7) The relationship between SOC and the discharging voltage at different currents can then be obtained, and the initial SOC during the discharging stage can be deduced.

Universal SOC Algorithm

1) Using linear system analysis in the frequency domain but without a circuit model, the OCV is calculated based on the sampled terminal voltage and discharge current of the battery.
2) Knowing OCV leads to SOC due to the well known mapping between OCV and SOC.

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How SOC values are evaluated?

The SOC values obtained by enhanced coulomb counting algorithm simulation are compared to the experimental SOC values deducted from the charging and discharging curves, which are given by battery data sheets.

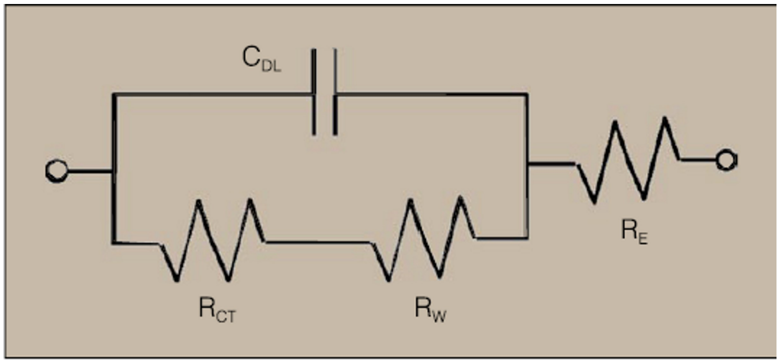
Case Study - NASA’s Mars Global Surveyor

1) An aerospace catastrophic battery failure occurred in NASA’s Mars Global Surveyor, which stopped operating in November 2006.
2) Preliminary investigations revealed that the spacecraft was commanded to go into a safe mode, which positioned the radiator for the batteries toward the sun.
3) Incorrect antenna pointing prevented the orbiter from telling controllers its status, and its programmed safety response did not include making sure the spacecraft orientation was thermally safe.
4) This increased the temperature of the batteries, and they lost their charge capacity

5) Headline :
" Mars Global Surveyor last communicated with Earth on Nov. 2, 2006. Within 11 hours, depleted batteries likely left the spacecraft unable to control its orientation. "

From <https://www.nasa.gov/mission_pages/mgs/mgs-20070413.html>

Lumped Parameter Model of Lithium Ion Cell



- Features extracted from sensor data of voltage, current, power, impedance, frequency, and temperature readings are used to estimate the internal parameters in the lumped-parameter battery model.
- double layer capacitance CDL
- charge transfer resistance RCT,
- Warburg impedance RW
- electrolyte resistance RE

Prognostics Algorithms to Predict Remaining Life of the Batteries

Statistics Based Baseline Model :-

- Battery health is directly tied to capacity.
- The battery is considered to be in a failed state when its capacity has faded by 30%.

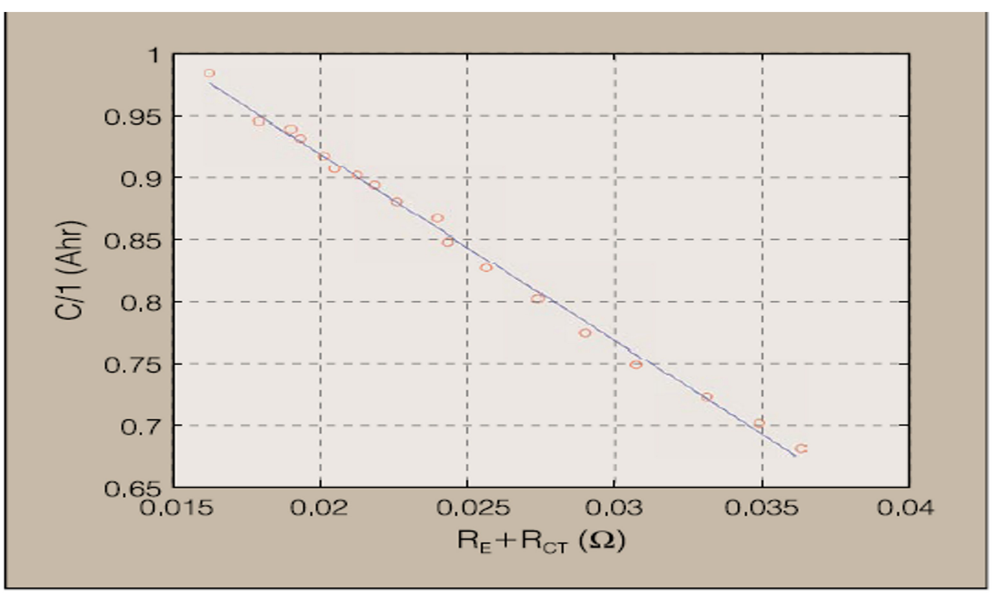
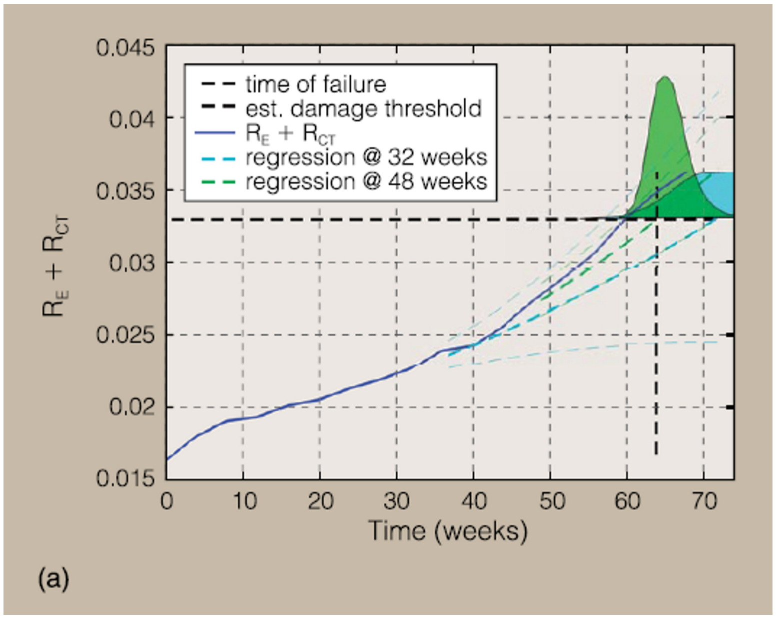


Fig. 5. Linear correlation between capacity, C/1, and impedance parameters, $R_E + R_{CT}$.

- There is a very high degree of linear correlation between the C/1 capacity (capacity at nominal rated current of 1A) and the internal impedance parameter RE+RCT.

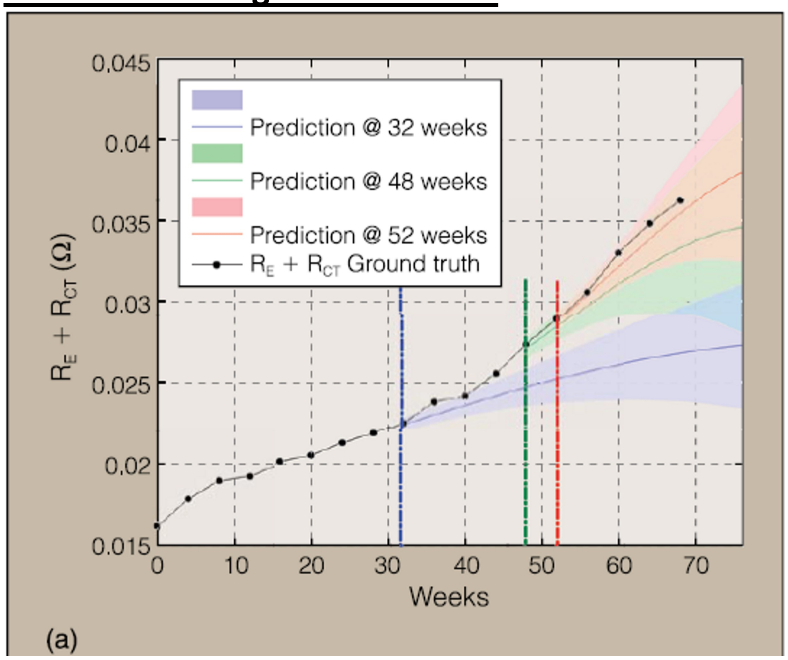
- This relationship can be exploited to estimate the current and future C/1 capacities.



- The prediction accuracy at prediction point t=32 weeks is rather poor. The prediction is late by 7.55 weeks.

- prediction accuracy performed at t=48 weeks is almost perfect, with an error of only 0.01 weeks.

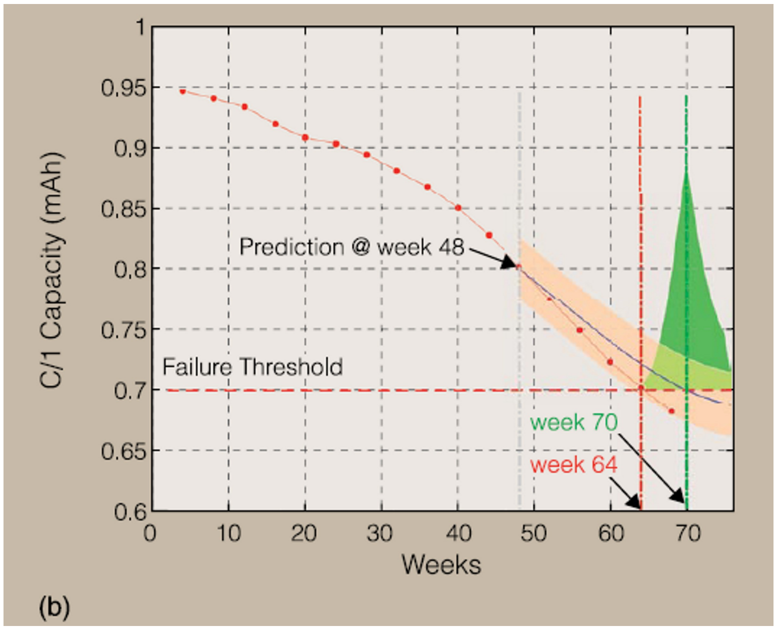
1) <u>Probabilistic Regression Model</u>



- We use GPR (Gaussian Process Regression) to regress the evolution of internal parameters (RE+RCT) of the battery with time at 45˚C.

- The prediction at t=32 weeks fails to follow the actual trend, it leads to extremely late end-of-life predictions.

- However, with some more learning data up to t=48 weeks it picks up the trend fairly well



- The end of- life prediction at t=48 weeks is 70 weeks with an error of +6 weeks of late prediction.

- These predictions got more accurate and precise by learning the non-linear dynamic details of the process, as more data were made available for learning.

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Particle Filter Model

- The behaviour of the previous methods indicates that the regression techniques fail to learn non-linear trends in the absence of full-range training data.

- Particles filters not only use the information available from the process measurements but also incorporate any models available for the process.

- In RVM regression, the task is to probabilistically learn the nonlinear patterns in data, which is multidimensional (say ndim), using an ndim-1 dimensional hyperplane in kernel-transformed hyperspace where the problem becomes linear.

- The overall process is broken down into an offline (learning) and an online (tracking and prediction) part.

- During offline analysis, relevance vector machine regression is performed to find representative aging curves. Exponential growth models, are then fitted on these curves to identify the relevant decay parameters like C and lambda:

$$\theta = C\exp(-\lambda t),$$

,where q is a internal battery model parameter like RCT or RE.

- SOC denotes the capacity of the battery in its current state compared to the capacity in its fully charged state.
- SOH describes the capacity of the battery in its fully charged state compared to the nominal capacity when brand new.
- By convention, SOC is 100% when the battery is fully charged and 0% when it is empty.
- SOH is 100% at the time of manufacture and reaches 80% at end of life (EOL).

- EOL is often defined as the point at which the actual capacity at full charge drops to 80% of its nominal value.
- The remaining number of charge/discharge cycles until the battery reaches EOL is the RUL of the battery.

The outputs can be classed into two main categories:

1) Short timescale over a single charge/discharge cycle to understand the SOC.
2) Long timescale over many charge/discharge cycles to understand the SOH.

DIFFERENT MACHINE LEARNING APPROACHES :

1) Linear Regression :
- A linear model that combined nine battery descriptors was used by Severson to predict the RUL of lithium iron phosphate/ graphite cells after 100 charge/discharge cycles.
- The model input the current cycle number, voltage, current flow, and capacity to predict the RUL with a typical error of 9.1%.

2) Random Forest Tree:
- An example of the successful application of a tree method to predict the RUL of a Li-ion battery is demonstrated by Mansouri and colleagues.
- Focusing on batteries in unmanned aerial vehicles, the authors aimed to extend the flying time window.
- The authors found that the random forest approach that inputs simply the variation of voltage with time delivered a typical prediction error in the RUL of 3.3%, outperforming linear models, a support-vector machine and a neural network.

3) Support Vector Machines:
- A support-vector machine is a generalization of the random forest where the functions trained are simultaneously classified in a multidimensional space rather than split along one input direction.
- Nuhic used a support-vector machine to predict both the SOH and RUL of Li-ion batteries.
- The support-vector machine took account of the voltage, capacity, cycle number and temperature to estimate SOH between successive cycles within 6.4%, and showed that the SOH and RUL was strongly influenced by environmental and load conditions.