BATTERY HEALTH IN A CIRCULAR ECONOMY: EMBEDDING AN AGEING MODEL IN THE SMART BATTERY SYSTEM

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Abstract: To enable continued use of used batteries and battery-powered devices through reuse, refurbishment, and remanufacturing, information on the state of health (SoH) of batteries is a crucial element. To date, various models for SoH prediction exist with varying degrees of certainty. A new empirical ageing modelling and monitoring for Li-ion batteries was developed, in which event counters for damaging events are integrated directly into the battery management system. The most relevant damaging events can be accounted for, such as cold charge, over-temperature, high currents, and particularly high or low average voltage. Reading out tracked data from a used battery may facilitate a quick and easy way to estimate the battery's health condition. As a result, a decision can be derived to determine whether a battery can still be used in a given application or whether it does no longer serve a useful purpose. Additionally, existing models may predict SoH more precisely using the tracked data.

1. INTRODUCTION

The European Commission has set the target for the EU to transition to a Circular Economy, in which linear production and consumption patterns of 'take, make, dispose' are replaced by an approach in which the value of products, components and resources is maintained for as long as possible and the generation of waste is minimized. On a product level, this requires aspects such as durability, reparability, upgradability, reusability, and recyclability to be designed into products from the outset.

Secondary (rechargeable) batteries are a critical component of mobile ICT (information and communication technology) devices such as smartphones, tablets, and wearables. Batteries support the functionality of such devices by providing energy when there is no connection to the power grid. Hence, they are a major factor in the development and global diffusion of mobile electronic devices. However, the capacity of secondary batteries of such devices, most commonly lithium-ion (Li-ion) batteries, inevitably decreases with usage and over time. As battery lifetime is a critical factor for users of mobile devices, significant research efforts are being made worldwide to understand and ultimately mitigate the degradation of Li-ion batteries.

After the first use phase of mobile devices such as smartphones and notebooks, the battery becomes a crucial factor in determining the probability of a continued use. Scenarios for continued use may include a second use phase by another user, refurbishment of the host device, or use of the battery as a spare part. In such cases, information on the state of health (SoH) of the battery is of critical interest. However, in practice, reliable data on battery SoH are commonly either not available or not easily accessible to the user. To date, not much research has focused on the potential of reusing batteries of mobile ICT devices after the first or second use phase of their host devices.

The work described in this paper aims to provide technical prerequisites to facilitate reuse by implementing advanced ageing modelling and monitoring directly into the battery. Ageing monitoring of batteries requires the development of battery data extraction methods, including hardware requirements, data compilation, data recording and methods for easy data readout.

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2. BACKGROUND AND APPROACH

The state of health is a parameter that reflects the condition of a battery (commonly capacity or power) as percentage relative to a fresh (unused) battery. For example, the SoH of a used smartphone battery with a nominal capacity of 3000 mAh and a current full charge capacity of 2700 mAh is 90 %. This means that the battery has already lost 10 % (300 mAh) of its initial capacity through use and calendar ageing. In this example, it may be assumed that the battery is still in a good condition and suitable for continued use.

Generally speaking, methods to predict the SoH of batteries can be categorized into two different approaches; experimental and adaptive methods [3]. Experimental methods may rely on the direct measurement of relevant parameters, such as battery voltage, current, impedance, resistance and/or temperature. When such measurements are not possible, models based on measured data may serve to predict SoH. One such method commonly deployed is Coulomb counting, in which the ampere hours (Ah) charged and discharged are counted to determine the full charge capacity. Other models include data maps, probabilistic methods and big data, among others [3]. Adaptive methods to determine the SoH include Kalman Filters, Fuzzy Logic and Least Squares, among other methods. However, adaptive methods result in a high computational load, which may in some cases be prohibitive for real-world applications [3]. Commonly, Li-ion batteries are equipped with one of the various methods to return a value on their current SoH. However, the accuracy of applied methods varies, and the user has no information on how the SoH was determined or how reliable the data is.

SoH estimations, along with other specific tasks, is commonly handled by a battery management system (BMS) integrated into the battery pack. A BMS is an electronic system that serves to monitor, control and protect rechargeable batteries. Among other tasks, BMS commonly monitor the state-of-charge (SoC), control cell balancing in battery packs, and prevent overcharge or deep discharge. A battery with a BMS is commonly referred to as a smart battery, as it collects and communicates data on itself to host devices and chargers. The System Management Bus (SMBus) allows the communication between smart batteries and the electronic device or external battery chargers. The Smart Batteries Data Specification [4] defines the data that flows across the SMBus between the Smart Battery, SMBus Host, Smart Battery Charger and other devices. A number of commands and parameters are stored in electronic components of the BMS. For instance, smart notebook battery packs commonly track and communicate data such as the nominal capacity of the battery, the remaining capacity at full charge, the SoH, the current state-of-charge (SoC), and the number of charge/discharge cycles. However, in some cases, a number of commands in the SBS are free for customization (Figure 1), which potentially allows the tracking and processing of additional data of interest.

Figure 1: Smart batteries specification: optional command codes, reserved for additional manufacturer-defined functions [4].

Slave Functions	Code	Access	Data
ManufacturerName	0x20	r	string
DeviceName	0x21	r	string
DeviceChemistry	0x22	r	string
ManufacturerData	0x23	r	data
reserved	0x25-0x2e		
OptionalMfgFunction5	0x2f	r/w	data
reserved	0x30-0x3b		
OptionalMfgFunction4	0x3c	r/w	word
OptionalMfgFunction3-1	0x3d-0x3f	r/w	word

The approach of the work described in this paper is to use smart batteries' SBS free registers for monitoring of operation conditions and tracking of information about the nature and the number of critical harmful events experienced by the battery. Counting and weighing of battery-damaging events via this built-in ageing monitoring can then be used as input for model-based SoH calculation and prediction of failure, avoiding the need for elaborate electrical measurements on the battery in a reuse scenario.

2. LI-PO BATTERY AGEING MECHANISMS AND PARAMETERS

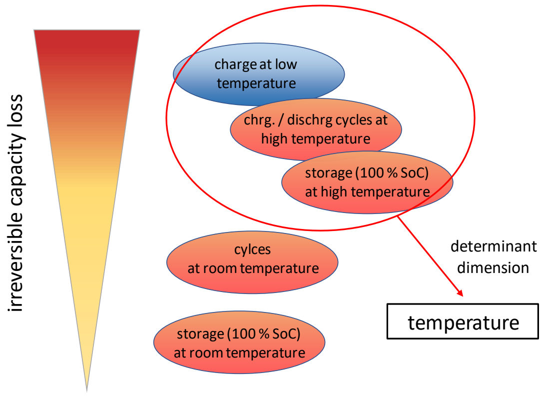
All secondary batteries degrade over time and with usage (charge/discharge cycling). This degradation is manifested as a loss of available capacity, energy and/or an increase in impedance, i.e. a reduction of power and efficiency. Due to the comparably high cost of Li-ion batteries, their degradation has been extensively studied by the research community over the past two decades. Ageing mechanisms are complex and strongly related to operating conditions, however, for the purpose of a simplified overview they can be divided into the following categories:

- Loss of active and accessible electrode material of anode and/or cathode
- Loss of active species (lithium)
- Loss of conductivity in electrodes or electrolyte
- Decomposition of electrolyte

As the different degradation mechanisms interact with each other, cross-correlated degradation effects may take place. A comprehensive overview of ageing mechanisms has been provided by [5] and [6].

The main factors influencing the state of health of lithium-ion batteries are temperature, the number of charge/discharge cycles, and the average state of charge while cycling. Furthermore, critical operating conditions, such as charging the battery at low temperatures, can lead to accelerated cell degradation. An overview on the operation modes defining degradation for lithium-ion batteries with organic electrolyte and graphite as negative electrode are shown in Figure 2.

Figure 2: Illustration of relevant operation modes of Li-ion batteries and their relative influence on the irreversible degradation. "100 % SoC" is used here to denote a state of high voltage.



Generally speaking, ambient temperature is the parameter affecting battery SoH the most. Low temperature charging, if not prevented by the BMS, will lead to low useable capacity and to accelerated capacity fading. Exposure of batteries to high ambient temperature leads to both high self-discharge and faster capacity fading while charge/discharge cycling. Besides temperature, high average cell voltage (SoC), and a high depth of discharge are prominent factors leading to accelerated capacity fading. High currents during charging (e.g. quick charging) or discharge are also known to accelerate irreversible capacity loss. A simplified overview of the main factors influencing the SoH of Li-ion batteries is shown in Table 1.

Table 1: Simplified overview of the main influencing factors and their qualitative effect on calendar and cycle ageing of common Li-ion battery types. '+' denotes accelerated effect on ageing while '–' denotes a decelerating effect. [7]

Factors influencing the SoH of Li-ion batteries	**Calendar ageing**	**Cycle ageing**
High temperature	+	+
Low temperature	-	+
High voltage (SoC)	+	+
Low voltage (SoC)	-	+
High current (C-rate)		+
Low current (C-rate)		-

3. MODELLING OF LITHIUM-ION BATTERY AGEING

Numerous methods to model the degradation of Li-ion batteries can be found in literature, ranging from complex physical first-principles models to purely empirical models only valid for a specific set of operating conditions [5]. While first-principle physical models generally offer the highest accuracy and a direct insight into the interaction between the different chemical reactions and multi-domain dependence, empirical models are considerably easier to parameterize and less computationally demanding. Empirical models can be parameterized without detailed knowledge of the electrochemical cell design, albeit the accuracy may be improved by including some relations for the electrochemical reactions [5]. In the work described in this paper, the approach of an empirical model was followed. It was intended to use insights into existing empirical models, extended by additional experimental findings for predicting battery degradation caused by damaging operation conditions.

Since the model approach for predicting battery degradation behaviour is empirical, the scope of the model is limited strictly to the value range of tested parameters. The degradation characteristic is transferable for batteries within the same system. Nevertheless, specific parameters must be found for each cell type. The model focusses on the most dominant degradation mechanisms as described in the following subsections.

3.1. Capacity fading caused by charge / discharge cycles

The first cell degradation mechanism is the influence of charge / discharge cycles, measured in cycles normalized against the specific reference capacity (nominal capacity). The capacity decreases linearly with the number of charge / discharge cycles. Thus, the remaining capacity can be written as:

- $C(cyc) = C_0 \cdot k_n(T) \cdot cyc$,

where C_0 is the initial capacity, $k_n(T)$ is the degradation factor for the definition range n, and cyc are the equivalent cycle count. The capacity fade over the lifetime of the cell may not be linear, which may require differentiation of several ranges, such as degradation behaviour between cycles 0 and 500 (range 1), a different behaviour between cycles 501 and 800 (range 2), and so on, where different degradation factors may be applied as required.

3.2. Capacity fading caused by low temperature charge

Charging at low temperature will lead to loss of active species. Capacity fading due to low temperature charging events has been assumed to be linear with the number of low-temperature charging events experienced by the battery. Thus, a linear degradation modelling approach was applied. In this case, the remaining capacity can be written as:

- $C(cold\_event) = C_0 \cdot k_{cc} \cdot cold\_event$,

where C_0 is the initial capacity, k_{cc} is the degradation factor for cold charging, and cold_event is the event counter. However, it should be noted that experimental data carried out by the authors of this paper (unpublished data) showed that a polynomial approach may be more appropriate than the linear approach chosen here.

3.3. High ambient temperature capacity fading

Since the accelerated cell degradation at high ambient temperature is caused by activated processes, an Arrhenius approach is suitable for approximation the capacity fading factor. The fading factor can be approximated with:

- $k_n(T) = A \cdot \exp \{ -E_A / (R\ T) \}$,

where A is a pre-factor, E_A is the activation energy, R the universal gas constant, and T the temperature in Kelvin. Here, the only parameters to determine are the pre-factor and the activation energy.

4. TRACKING OF HEALTH-RELATED DATA IN SMART BATTERIES

Free registers of the SBS are used to track parameters relevant for the battery ageing model. In the sample notebook battery used for the work described here, the password-protected memory area of the SBS-compatible chip could be utilized for data tracking. 30 bytes of memory were available, corresponding to 15 event counters in a 16-bit data structure (2 bytes per counter). The tracked data is write-protected with a password but is readable from the standard SMBus.

Corresponding to the insights described in section 2 above, the following cell damaging categories were defined for tracking:

- Cold charge events
- Time span in over-temperature
- Time span with high currents

Overcharge and deep discharge events do not necessarily have to be counted as they can be expected to be prevented by the battery's protection circuit. Cold charge below a certain temperature may also be prevented by some BMS.

Several classes were defined for each damage category. As mentioned, in the example case at hand, a maximum of 15 classes could be defined, corresponding to the 15 available registers. Based on the findings of cell testing, specific criteria can be defined to be tracked by the SBS-compatible chip. Exemplary criteria for each category and class are provided in Table 2.

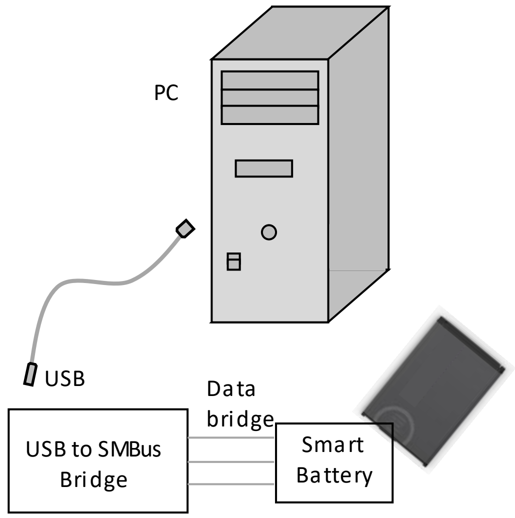
Table 2: Example for the definition of damaging classes to be tracked as event counters

Category	Class	Criteria 1	Criteria 2
cold charge	1.1	T < 5°C	t > 1 min
	1.2	T < -5°C	t > 1 min
over-temp.	2.1	T > 30°C	t > 1 min
	2.2	T > 45°C	t > 1 min
high currents	3.1	I > 5 C	t > 10 sec
	3.2	I > 15 C	t > 1 sec

5. DATA READ-OUT AND INTERPRETATION

The setup required to retrieve SoH data from the battery is illustrated in Figure 3. It consists of a PC running a program to read out and interpret data, and a USB to SMBus bridge, connecting the PC and the smart battery.

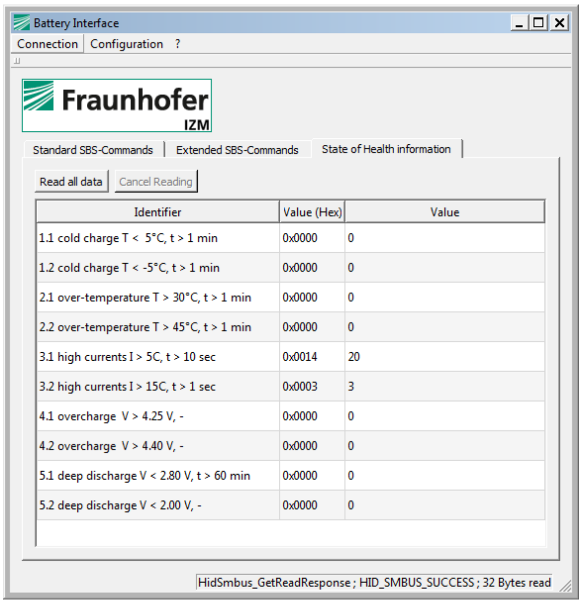
Figure 3: Illustration of the setup comprising a PC connected to the USB to SMBus bridge, which is connected to the smart battery.



The program consists of a front-end with several tabs to display data corresponding to standard SBS-commands, extended SBS commands, and SoH information, as shown in Figure 4. Standard SBS commands return the design capacity, full charge capacity, cycle count, manufacture date, and temperature, among others. Extended SBS commands require special privileges to interact with, e.g. via the input of a passcode, and include settings for safety alerts. The tab on SoH information displays values for the damaging classes tracked by the BMS (cp. Table 2). The data provides insights into the extent of harmful operation modes the used battery has experienced. Thereby, it facilitates a quick estimation of the condition the battery is likely in.

For example, the sample data included in Figure 4 imply the battery has experienced high currents beyond a C-rate of 5C lasting for more than 10 seconds on 20 occasions, as well as currents beyond 15C lasting for more than one second on three occasions. However, the battery has not experienced any cold charge, over-temperature, overcharge or deep discharge events. Hence, it can be deduced that the battery can be further used without restrictions. In a case where the data show that a battery has experienced a multitude of critical events, including cold charge, over-temperature, and deep discharge, it may be deduced that the battery is likely damaged and further use may not be appropriate or feasible.

Figure 4: Example of sample SoH data read-out via purpose-built interface.



6. SUMMARY AND OUTLOOK

Various models are currently used to estimate the SoH of Li-ion batteries in mobile ICT devices, however, their reliability varies and information on the prediction method applied are usually not communicated. In the evaluation of device batteries for their usefulness in a continued use scenario (e.g. reuse), readily available information of the approximate SoH of the battery can be an enabling factor. Electrical measurements to determine SoH can be time consuming and thus not economically viable in a reuse scenario. The work described in this paper aims to track data on battery SoH within the BMS of a smart battery. The tracked data can be used for advanced ageing modelling or can be read-out from a computer to gain insight into the likely condition of the battery. This may serve to enable the continued use of used batteries which may otherwise be disposed of due to high efforts required to gain insights into their SoH.

It should be stated that the SBS registers used in the work described in this paper are not always available for optional command codes, as the manufacturer may decide to utilize them for other purposes. A revision of the Smart Battery System Specifications may be required to allow for a standardized method on SoH data tracking as well as data read-out by relevant stakeholders, including actors involved in reuse, refurbishment and recycling activities.

7. REFERENCES

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