FOBSS: Monitoring Data from a Modular Battery System

Georg Steinbuss†
georg.steinbuss@kit.edu

Benedikt Rzepka‡
benedikt.rzepka@student.kit.edu

Simon Bischof‡
simon.bischof2@kit.edu

Thomas Blank‡
thomas.blank@kit.edu

Klemens Böhm†
klemens.boehm@kit.edu

†Karlsruhe Institute of Technology (KIT), Germany
Institute for Program Structures and Data Organization (IPD)

‡Karlsruhe Institute of Technology (KIT), Germany
Institute for Data Processing and Electronics (IPE)

ABSTRACT

Efficient energy storage is crucial in future energy systems. The management of lithium-ion based batteries is a challenging topic of research in this area. To improve management systems, monitoring data is indispensable, be it for single battery cells, be it for systems of multiple cells — the topic of this article. However, regarding such modular systems, data that is openly available is rare. This article is a description of the FOBSS data set, which we have made publicly available. It consists of monitoring data of a battery system comprised of 44 battery cells. We record temperature and voltage with a high frequency down to the cell level. This renders our data unique and useful for future research. Additionally to descriptions of the setup of our battery system and of the data format, we provide an exemplary MATLAB file simplifying any further data usage.

CCS CONCEPTS

• **Hardware** → **Batteries**; • **General and reference** → *Measurement*.

KEYWORDS

Energy Data, Data set, Data descriptor, Lithium-ion Battery, Battery Management System

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1 INTRODUCTION

To reduce mankind's carbon footprint, energy storage must be efficient and reliable. In particular, storage is necessary to integrate renewable energy sources into future energy systems [8] and to meet our energy demand [5]. Various types of storage exist [8], like pumped hydro or thermal energy. Other common types of storage are electrochemical batteries based on lead-acid or lithium-ion. They come in many ranges, from small ones for mobile phones to bigger ones in electrical cars [7]. Lithium-ion based batteries have a very low self-discharge rate (loss of energy in non-use time) [8], and their costs of production are likely to drop. Berckmans et al. [1] estimate the limit of 100 $ per kWh to be reached in 2020-2025 for silicon based Lithium-ion batteries. They are indispensable regarding the development of future energy systems.

Because of their high energy density, lithium-ion batteries are sensitive to overcharging. So they must be monitored closely [10]. A battery management system (BMS) collects and estimates indicator values of the battery. Due to the importance of close monitoring, a lot of research on lithium-ion batteries focuses on their BMS [10]. Temperature, current and voltage are measured directly, indicators such as State of Charge (SoC) or State of Health (SoH) are derived from measured values. Clearly, SoC – the fuel gauge of the battery — is of upmost importance, be it to estimate the remaining range of an EV or to indicate the remaining charge in a mobile device to the user. However, estimating values such as SoC or SoH is far from trivial. Many methods exist [11]. When it comes to improve or compare existing methods, one must determine the accuracy of the estimates. To this end, monitoring data is used, i. e., measurements from batteries over time.

This article is a description of the FOBSS data set ("**F**requent **O**bservations from a **B**attery **S**ystem with **S**ubunits"), which we have made publicly available[1]. It comprises detailed measurements of a battery system consisting of multiple battery packs, each monitored by a subunit of the **B**attery **M**anagement **S**ystem (BMS). Each pack in turn is composed of several battery cells. Measurements are on the cell level, with a very high temporal resolution. A unique feature of our data set is that there are many cells connected in series. Such data is very useful for research on BMS integrating several batteries into one (see Section 2).

Paper outline: Section 2 describes possible applications for that data such as ours can be very useful for. Section 3 reviews existing battery data sets. Sections 4 and 5 describe our battery system and the format of the data we have recorded. Section 6 gives some details regarding the quality of our data set. Section 7 describes an exemplary usage file in MATLAB we provide together with the data set.

[1]G. Steinbuß, B. Rzepka, S. Bischof, T. Blank and K. Böhm, "Frequent Observations from a Battery System with Subunits", KITopen, 2019, https://www.doi.org/10.5445/IR/1000094469

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2 DATA USAGE

In this section we exemplarily describe three areas of research our data can be useful for. Clearly, there may be other areas as well, we do not claim completeness.

Development of battery models. Li-ion Batteries are extremely complex, nonlinear electro-chemical systems. A BMS must provide accurate estimations of the characteristics of each cell such as SoC and SoH. Such properties cannot be measured, but are derived from cell voltage, current and temperature. Respective algorithms run on embedded systems with limited memory and computational power. The FOBSS data can be used to develop models which yield an optimal trade-off between accuracy and computational complexity.

Compared with data sets containing only one cell [12][3] or only module and system level [4] measures, FOBSS facilitates testing algorithms on a real world system on cell, module and system layer.

Reduction of measurement accuracy. Accurate measurement systems are expensive. Nevertheless, our data consists of very frequent and accurate measures, as we will explain. Using our data set, one could implement algorithms which still provide good estimates of internal cell parameters, while being able to tolerate lower sample rates, higher noise levels and less accuracy. For example, unlike most battery systems, our system monitors the temperature of each cell. Data-driven algorithms could be developed to provide an accurate temperature estimation while reducing the number of temperature sensors per module.

Predictive maintenance. Since cells in our system are connected in series, they should behave similarly. Parameters such as impedance, SoH, SoC or measures like the current of each cell should not differ much. The reliable detection of cells whose behaviour changes in an unusual manner (e.g., inconsistent with the others) could indicate an upcoming system failure, before it is detected by state-of-the-art methods. Our data is particularly well suited to develop and assess respective tools for predictive maintenance.

3 RELATED WORK

There already exist public data sets on batteries [2–4, 6, 9, 12]. They facilitate SoC estimation or dealing with the battery's health. The specific aim for which the data sets were recorded usually differs. For example, regarding the battery's health, a data set might have been recorded to allow for estimations of the remaining useful life time (RUL) [12] or of the general SoH [14] or to analyze how partial charges and discharges affect the battery's health [13]. Regardless of the aim, almost all data sets provide measures of voltage, current and temperature. What differs is the type of battery, the environment it is in (e.g., a temperature-controlled chamber), its usage during the measurements and the frequency of the measurements.

The type of battery can differ by the exact battery cell used, e.g., its chemical composition, or whether it is only a single battery versus a composite system — like in our case. While data from single batteries is relatively common [2, 3, 6, 9, 12], data on a system of batteries is not. The only public data on a system of batteries we are aware of is the HIRF Battery Data Set [4]. The system consists of two battery packs with two batteries each, and measurements are taken on a battery and battery pack level every 0.3 seconds. Our system however has four battery packs with 11 battery cells in each pack, and measurements are taken on the cell and system level, i.e., at a significantly finer granularity.

When it comes to data sets for a single battery, the range is much broader. A good resource is a repository hosted by the CALCE Battery Group of the University of Maryland.[2] It currently contains six data sets with different battery types, different ambient temperatures and very different profiles of charges and discharges. The measurement frequency differs as well, from measurements taken every second to recordings only every 30 seconds. NASA also hosts a repository to provide data for prognostics purposes.[3] It does not only hold the HIRF data set [4], but also two other data sets on single batteries [3, 12]. These two data sets differ in the type of battery, the ambient temperature and the frequency of measurements. One data set contains records for every second [3], the other one has a frequency that varies and also depends on the operation [12]. For a charge operation, there is a measurement every 2-10 seconds, for discharges about every 10-20 seconds. Three other data sets on single batteries are available elsewhere [2, 6, 9]. While [6] does not reveal the frequency of measurements (there is no unit), [2, 9] both record measurements every 0.1 seconds. Our data is different from these ones because we have several cells in series. Additionally, the lowest frequency of measurements in our data (the temperature of cells) is about every 1.5 seconds. Every other parameter is measured every 0.25 seconds at least, which is comparably high. Hence, even when analyzing only a single cell, our data set can be a useful resource already for this reason.

4 OUR BATTERY SYSTEM

Our battery system consists of three main components: lithium-ion based batteries, an inverter and a BMS. See Figure 1. The inverter is used to charge and discharge the battery, providing electrical energy from the grid. The BMS monitors the voltage and current in the system as well as voltage, current and temperature in each battery cell. In our system, the BMS has several subunits. Each subunit as well as the overall voltage and current sensor is connected with a **C**ontroller **A**rea **N**etwork (CAN) bus (CAN 1 in Figure 1). A PC controls the inverter and collects its data (voltage and current). The PC and inverter are connected using **T**ransmission **C**ontrol **P**rotocol (TCP). The PC is connected to the BMS via the two CAN buses (CAN 1 and CAN 2 in Figure 1). The connection to the CAN 1 bus is for acquiring cell and battery data, CAN 2 is also used to send data to the BMS. The battery cells are grouped in several battery packs, each of which is monitored by a BMS-subunit. In Figure 1 these subunits are called slaves. The slaves gather temperature and voltage values for each battery cell and transmit these to the BMS master as well as to the PC. This guarantees detailed measurements of many similar battery cells working in the same environment.

4.1 The Batteries

Our battery system has 4 battery packs, each one consisting of 11 battery cells. All cells are from the same manufacture. Their cathode consists of $LiNiMnCoO_2$, while their anode is from Graphite. The nominal voltage is 3.6 V and the rated capacity 40 Ah. The cells within each battery pack are connected in series. Thus, the nominal

[2] https://web.calce.umd.edu/batteries/data.htm
[3] https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/

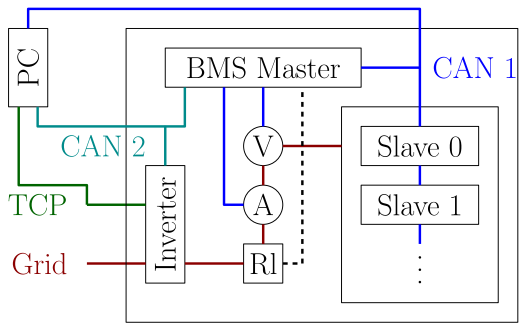


Figure 1: Schematics of our battery system (Rl = Relay stage)

voltage of a full pack is 39.6 V and the rated capacity of a whole pack remains 40 Ah. The packs are also connected in series, so the nominal voltage of our system amounts to 158.4 V.

4.2 The Inverter

The electricity grid is connected to the inverter by a three-phase alternating current connection capable of 400 V and 32 A. The inverter, a SM-500-C90 from Delta Electronika, is used to charge and discharge the battery. Positive current values indicate a battery charging process, negative values a discharging process. On the battery system side, the inverter outputs direct current. The voltage is in the range of [0 V, 500 V] and the current in [-90 A, 90 A], though the maximal power is limited to 15 kW. The inverter has an RJ-45 connection, which is used to connect it to a PC using TCP. This connection is used to set voltage, current and power with corresponding safety limits. Values currently set and measured are also read using this connection.

4.3 Battery Management System

Precise monitoring of batteries with BMS is crucial to ensure the correct working of the batteries. In modular systems like ours, the BMS is modular as well. Each battery pack is monitored by a subunit of the BMS — the BMS-Slave. Each BMS-slave transmits temperature and voltage of each cell within a battery pack to the BMS-Master using CAN 1. Connected to this BMS-Master are two sensors measuring the overall voltage and current. The values output by the current sensor are defined positive when the battery is discharged and negative when the battery is charged. This is contrary to the inverter, see Section 4.2.

Attached to the BMS-Master also is the relay stage displayed as 'Rl' in Figure 1. It is composed of three relays: the Precharge (PC), Highside (HS) and Lowside relay (LS). To connect inverter and battery, PC and LS relay are closed first. A resistor R (22 Ω) in the precharge line prevents high current peaks that could damage the system. Once the inverter's output capacitor and battery voltage are balanced, the HS relay is closed to bridge the resistance for usual system usage. The capacity of the inverter specified by its manufacturer is 560 μF. The BMS can open the relays when necessary and prevent the battery from damage caused by voltages or currents beyond the limits.

5 DATA RECORDS

We provide data on 19 different profiles we run on the battery system. Each profile consists of charge, discharge and rest steps. An example profile used in Section 6 is shown in Figure 2.

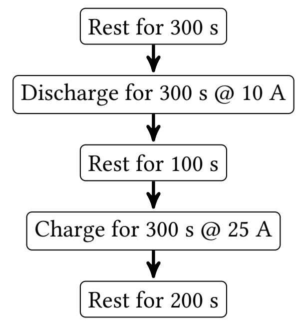


Figure 2: Exemplary profile

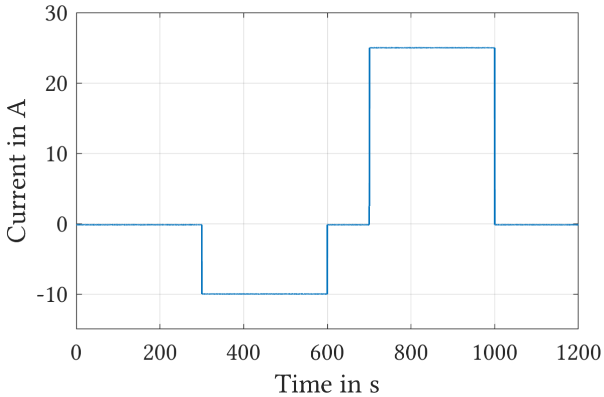
The file `profiles.xlsx` describes the profiles we run, how many times we do so, on which day, for how long and where the corresponding files are saved. Comments indicate whether anything about a specific run must be pointed out. Examples are when the battery did not rest before a run, or when the logging of measures does not stop after the described profile. The monitoring data provided is grouped by these profiles. For each profile we provide three folders with data: *battery*, *inverter* and *cells*. *battery* as well as *inverter* each contain two files giving the voltage and current of the respective entity. For the inverter, we measure voltage and current with its internal sensors, for the battery with the two sensors displayed in Figure 1. The inverter voltage and current are recorded every 0.1 seconds. The battery records them every 0.25 seconds. The folder *cells* contains 8 files. There are four files with the temperature of each battery pack and four with the voltage of each pack. Each such file contains the respective measurements for every cell in that battery pack. For example, the first column of File `Slave_0_Voltage.csv` contains the time in seconds, and the following 11 columns contain the voltage of each cell. The temperature of a single cell is measured every 1.5 seconds, and voltage is measured every 0.25 seconds. — Table 1 summarises the precision and the time resolution of the quantities mentioned.

Table 1: Precision and time resolution

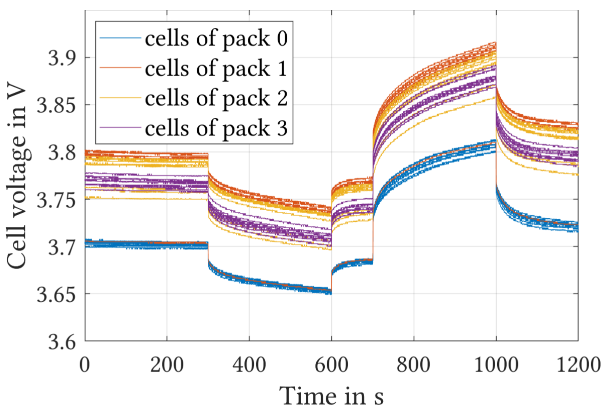
Quantity	Precision	Time resolution
Cell voltage	1 mV	250 ms
Cell temperature	1 °C	1.5 s
Battery current	10 mA	250 ms
Battery voltage	100 mV	250 ms
Inverter current	8 mA	100 ms
Inverter voltage	2 mV	100 ms

6 EXAMPLE PROFILE

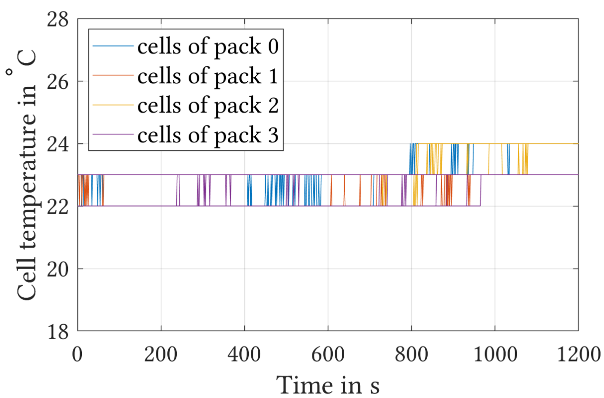
We describe our data sample for the profile from Figure 2. This allows for insights regarding the structure of the data. The current



(a) Current from inverter



(b) Voltage response of each battery cell



(c) Cell temperature of each battery cell

Figure 3: Example of monitoring data

measured by the inverter is plotted in Figure 3a. For the illustration we decided to have a rather short profile. The data itself features much longer periods of measurements.

Figure 3c graphs the cell temperatures during the run. For this short profile only a slight heat up is observable. Due to the resolution of the measurement, the temperature of many cells is equal, and the curves in Figure 3c are on top each other. This effect usually is not there with longer profiles. Temperature differences within a pack often are more significant in this case. Figure 3b shows the voltage response of each cell in the battery system. The cell voltages are spread in a range of about 100 mV.

Voltage and temperature differ from cell to cell and from pack to pack. This highlights the uniqueness of our data. No other data set provides insights on so many battery cells within a single system.

7 USAGE NOTES

Together with our data we provide a MATLAB script (`viewData.m`). The Figures 3a to 3c were produced by this script. To plot respective figures for other profiles in the FOBSSdata as well, the script needs to be modified only slightly. Hence, it reduces the effort necessary to analyse the data further. In the first half of the script the respective data from the `.csv` files is loaded into the MATLAB workspace using timeseries objects[4]. In the second half of the script the figures are created. To run the script, our data needs to be available in a folder called 'data', placed in the same directory as `viewData.m`.

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