

Cellpy – an open-source library for processing and analysis of battery testing data

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Summary

Recent years have witnessed an exponential increase in battery research, driven by the need to develop efficient and sustainable energy storage systems. One of the main tools in battery research are battery cycling experiments, providing insights into performance, lifetime and quality of the battery. Due to the large variety of battery testing equipment and the resulting multitude of different and often proprietary data formats, combined with the large number of parameters involved, managing and processing battery testing data has often been a difficult and tedious task.

The Python library cellpy assists in solving these problems by

1. providing the tools to read different data formats,
2. converting those into one common data format that also includes relevant battery-specific meta-data, and
3. providing a data structure equipped with a set of methods that helps the user to easily perform simple and in-depth analyses of both single data sets and collections of data sets.

Statement of need

Typically, a battery-testing data set consists of simple time series data with voltage, current and capacity. Unfortunately, data from different equipment are measured and handled in different ways and stored in different, often proprietary, formats. Consequently, a direct and meaningful comparison of several cells tested under a variety of conditions can be challenging and requires more advanced data handling methodologies. Several open-source libraries focus on battery test-data extraction. However, most of them are dedicated to specific battery testing equipment: notably galvani ([Echemdata, 2022](#)) parses the proprietary BioLogic format, neware_reader ([Beyonder et al., n.d.](#)) parsing several versions of Neware data, and galv (formerly Galvanalyser) ([Battery-Intelligence-Lab, 2023](#)) supporting Maccor, Ivium and BioLogic formats. BEEP (Battery Evaluation and Early Prediction ([Herring et al., 2020](#))) provides a structured interphase for collecting and processing battery test data and exports to text format.

cellpy provides powerful and versatile tools for the simple and efficient handling of battery testing data originating from different battery cell testers, all the way from data collection to data analysis and visualisation, ensuring consistency, accuracy and comparability. cellpy can directly parse the data from most common commercial battery testers ([Arbin](#), Maccor, [PEC](#), Neware, BioLogic), in addition to offering full flexibility by allowing the user to provide other file format specifications (in YAML format). The data is converted into and saved in a common format, accommodating not only data from diverse testers, but also thoughtfully embedding battery-specific metadata (e.g., step-types, type of cell, type of chemistry, electrode properties, etc.). This makes subsequent data handling considerably easier and proves invaluable in

43 interpreting and comparing results across tests and conditions. In addition to translating data
44 to a common format, cellpy has a range of utilities for studying and analysing the data.
45 These include methods for the extraction of key characteristics from tests, cell comparison,
46 plotting and statistical analysis, as well as advanced tools such as incremental-capacity analysis
47 (ICA, dQ/dV), OCV relaxation analysis and batch processing of results from many battery test
48 (Andersen et al. (2019), Ulvestad et al. (2020), Huld et al. (2023), Spitthoff et al. (2023)).

49 The cellpy library provides a valuable toolset and has been in frequent use for both everyday
50 and advanced tasks in battery research. The ability to effortlessly import and process the data
51 through a simple but highly flexible API allows for quick and simple comparison of different cells.
52 At the same time, cellpy serves as an excellent starting point for researchers leaning towards
53 advanced analysis: cellpy can automatically convert data with different units, summarize and
54 perform statistical evaluations all the way down to the individual cycle and step level, while
55 giving the user fine-grained control of the behaviour through setting of parameters or directly
56 by using a more advanced, deeper API. This eases further use of the data, e.g., as features
57 for machine learning algorithm, and promotes reproducibility and traceability throughout the
58 entire process.

59 Implementation and architecture

60 cellpy is implemented in python and can be used as either a library within python scripts,
61 or as a stand-alone application for analysing battery cell test data. Internally, cellpy utilises
62 the rich ecosystem of scientific tools available for python. In particular, cellpy uses pandas
63 DataFrames as the “storage containers” for the collected data within the cellpy Data object.
64 This offers full flexibility and makes it easy for the user to apply advanced methods, analyses
65 of or transformations to the data in addition to the features implemented in cellpy.

66 The core of cellpy is the **CellpyCell** object (see Figure 1) that contains both the data (stored in
67 the **Data** object) as well as central methods required to read, process and store battery testing
68 data. The **CellpyCell** provides the appropriate interface and coordination of the resources
69 needed, such as loading configurations (e.g default reader, default raw-data location), selecting
70 readers for different data formats and exporters for saving the data.

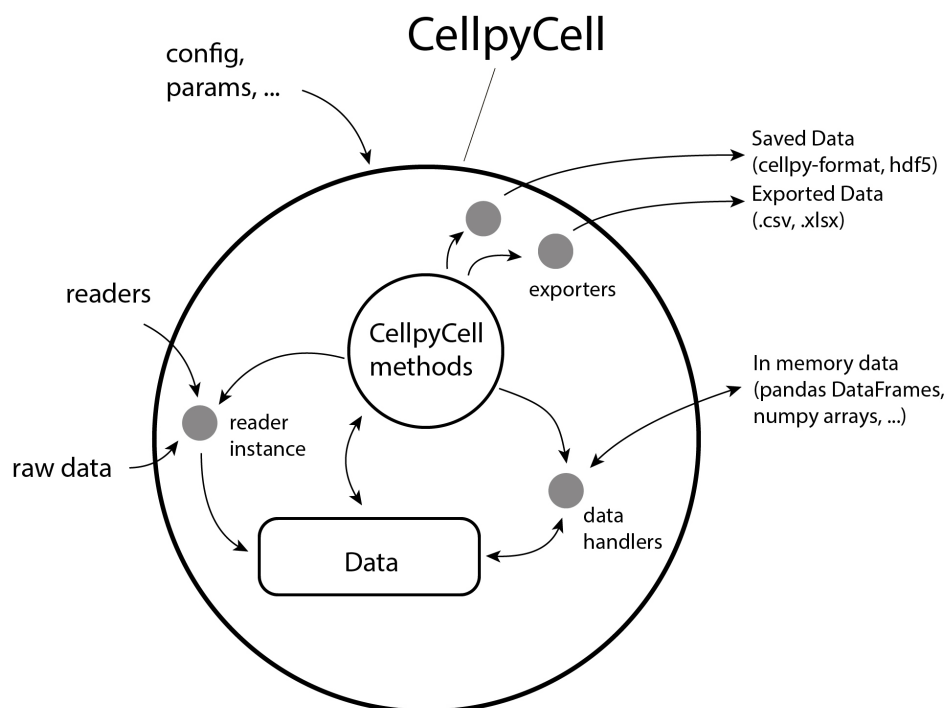


Figure 1: Illustration of the core object within cellpy, the **CellpyCell**.

71 The **CellpyCell Data** object stores both the battery test data as well as the corresponding
 72 meta data (see Figure 2). In addition to the central DataFrame containing the raw data (*raw*),
 73 the DataFrames *steps* and *summary* provide step- (e.g., maximum current, mean voltage,
 74 type-of-step vs. step number) and cycle-based (e.g., gravimetric charge capacity, coulombic
 75 efficiency, C-rates vs. cycle number) summaries and statistics respectively.

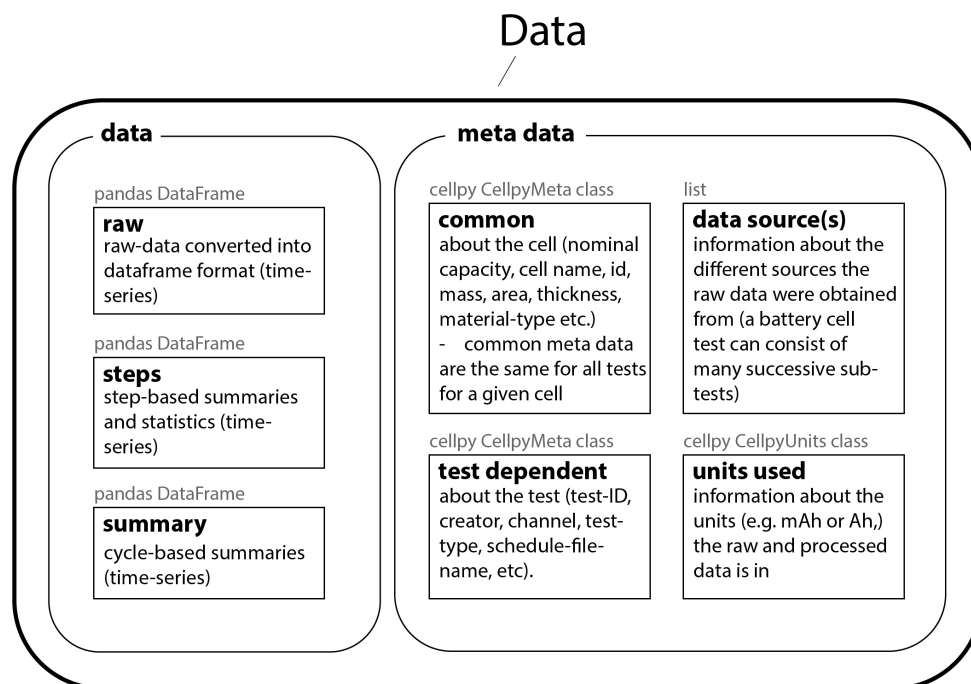


Figure 2: Summary of the types of contents in a **CellpyCell Data** object.

76 The most common data processing routines, such as extraction of charge/discharge voltage
 77 curves in different formats or selecting data for specified step-types, are implemented as
 78 methods on the CellpyCell object. In addition, the cellpy library also consists of a rich set
 79 of utilities (Figure 3) that can be used for further processing the data, both individually and
 80 within batch routines. Utility functions include e.g., ICA tools, assisting in creating dQ/dV
 81 graphs (employing different data-smoothing algorithms), or tools for OCV relaxation analysis.

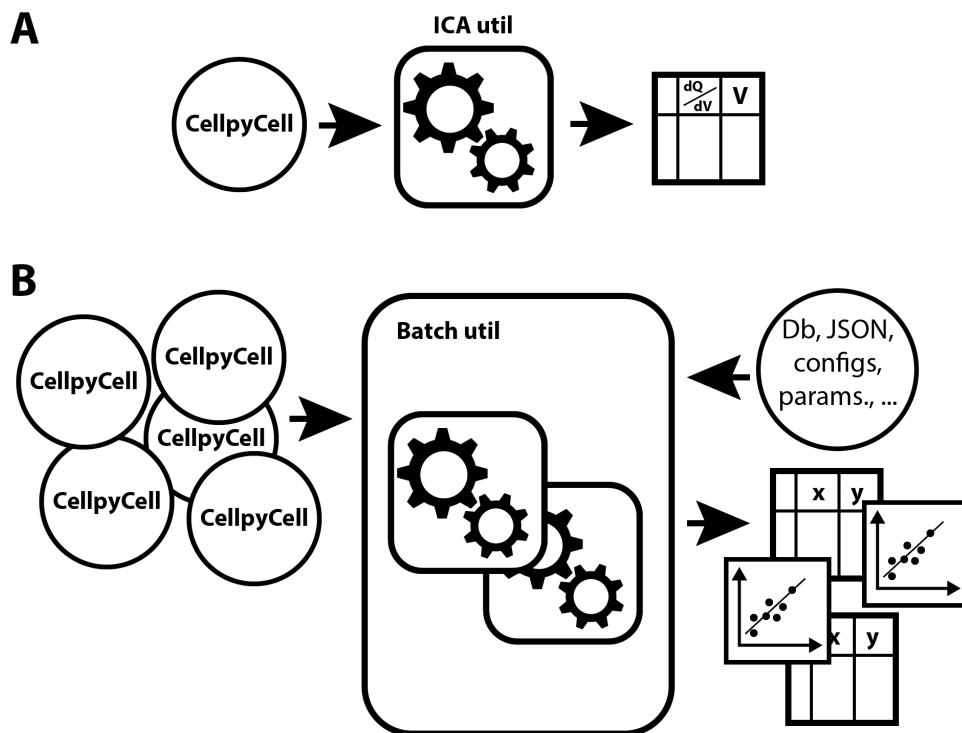


Figure 3: The cellpy library contains multiple utilities that assists in data analysis. A utility can work on (A) a single **CellpyCell** object, or (B) a set of CellpyCell objects such as the Batch utility that helps the user in automating and comparing results from many data sets.

82 The cellpy-file format (usually stored in hdf5 format) contains all the data contained in the
83 Data object together with additional relevant meta data, including information about the file
84 version.

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