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FASTEST

**Fast-track hybrid testing platform for the development of
battery systems**

Deliverable D5.1:

Twin Ontology Definition and Data Asset Mapping

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Project Abstract

Current methods to evaluate Li-ion batteries safety, performance, reliability and lifetime represent a remarkable resource consumption for the overall battery R&D process. The time or number of tests required, the expensive equipment and a generalised trial-error approach are determining factors, together with a lack of understanding of the complex multiscale and multi-physics phenomena in the battery system. Besides, testing facilities are operated locally, meaning that data management is handled directly in the facility, and that experimentation is done on one test bench.

The FASTEST project aims to develop and validate a fast-track testing platform able to deliver a strategy based on Design of Experiments (DoE) and robust testing results, combining multi-scale and multi-physics virtual and physical testing. This will enable an accelerated battery system R&D and more reliable, safer and long-lasting battery system designs. The project's prototype of a fast-track hybrid testing platform aims for a new holistic and interconnected approach. From a global test facility perspective, additional services like smart DoE algorithms, virtualised benches, and DT data are incorporated into the daily facility operation to reach a new level of efficiency.

During the project, FASTEST consortium aims to develop up to TRL 6 the platform and its components: the optimal DoE strategies according to three different use cases (automotive, stationary, and off-road); two different cell chemistries, 3b and 4 solid-state (oxide polymer electrolyte); the development of a complete set of physic-based and data driven models able to substitute physical characterization experiments; and the overarching Digital Twin architecture managing the information flows, and the TRL6 proven and integrated prototype of the hybrid testing platform.

LIST OF ABBREVIATIONS, ACRONYMS AND DEFINITIONS

Acronym	Name
API	Application Programming Interface
BESS	Battery Energy Storage System
DoE	Design of Experiments
DT	Digital Twin
ETL	Extract, Transform, Load
FMI	Functional Mock-up Interfaces
FMU	Functional Mock-up Units
FTPS	File Transfer Protocol Secure
HTTPS	Hyper Text Transfer Protocol Secure
LIMS	Laboratory Inventory Management System
MQTT	Message Queuing Telemetry Transport
NaN	Not a Number
NoSQL	Not-Only Structured Query Language
R&D	Research and Development
SSB	Solid State Batteries
SQL	Structure Query Language
URL	Uniform Resource Locator
UUT	Unit Under Test
WP	Work Package

LIST OF TABLES

Table 1 Cell Level Data	18
Table 2 Module Level Data.....	18
Table 3 Cell Level Data	18
Table 4 Cell and Module Level Data.....	19

Table 5 Cell Level Data	20
Table 6 Module Level Data.....	20
Table 7 Visual Representation of Python Library Layers for Digital Twin Applications	27

LIST OF FIGURES

Figure 1 Task 5.1 Integration in FASTEST WorkFlow	11
Figure 2 Layered Structure Workflow for Python Library Data Mapping and Navigation.....	21
Figure 3 - Properties of each class.....	23
Figure 4 - Instance of a Cell class.....	24
Figure 5 - Graphical Representation of the Ontology: An Instance of the 'Module' Class Named 'Module 1'	25
Figure 6 - Graphical Representation of the Ontology: An Instance of the 'Test' Class with 'Preconditioning Test 1' and Its Associated Procedures, Bench, and Components.	25
Figure 7 Highlighting Task 5.1 within the Existing FASTEST Workflow	26
Figure. A Tests (1-7) Cell Level Testing Signal Specifications	31
Figure. B Tests (8-13) Cell Level Testing Signal Specifications	32
Figure. C Tests (14-17) Cell Level Testing Signal Specifications	33
Figure. D Tests (1-7) Module Level Testing Signal Specifications	34
Figure. E Tests (8-13) Cell Level Testing Signal Specifications	35

Table of Contents

1. Executive summary	9
2. Objective	9
3. Introduction	10
4. Background	12
4.1 Purpose of the Ontology.....	12
4.2 Incorporation of Functional and Testing of data	12
4.2.1 List of the IN/OP of the Module	12
4.2.2 Direction	12
4.2.3 Type	13
4.2.4 Data Type	13
4.2.5 Resolution	13
4.2.6 Scaling.....	13
4.2.7 Frequency.....	13
4.3 Ontologies in Digital Twin Development	14
4.3.1 Overview	14
4.3.2 Literature	14
4.4 Incorporation with LIMS and potential integration challenges	15
4.4.1 Digital twin data exchange	15
4.4.2 Potential integration challenges with physical test branches	16
5. Ontology Development.....	17
5.1 Overview	17
5.2 Characterization	17
5.2.1 Offroad and Industrial devices.....	17
5.2.2 Automotive Devices.....	19
5.2.3 Stationary	20
5.3 Library functionality	21
6. Results	22
6.1 Agnostic Ontology.....	22
6.1.1 Class	22
6.1.2 Properties.....	22
6.1.3 Relationships.....	23
6.1.4 Individuals.....	24
6.2 Development of a Python Library for User Interface with Data Mapping and Navigation in Digital Twin Application	26

6.2.1	Overview:.....	26
6.2.2	Library Structure:	26
6.2.3	Example Navigation Flow:	27
7.	Conclusion	28
8.	References.....	29
9.	Appendix	31
9.1	Detailed Signal Specification matrix	31

1. Executive summary

In the FASTEST project, to facilitate communication among all models and support the WP3 and WP4 for time and cost reduction in battery testing for different scales and applications, the ontology definition and data asset mapping need to be taken into consideration. D5.1 will tackle this problem and serve as an input for Tasks T5.2 through T5.4. Section 2 of this deliverable will carry out the study's objective, while Section 3 will consider the introduction of D5.1. The background of the purpose of the ontology and how the ontology of the Digital Twins (DT) will be different and the role of this in the DT will be addressed in section 4. In Section 5, we will work on developing the FASTEST strategy in terms of the characterization and data mapping library. This will give us a full picture of how the data mapping library will be built to be integrated into the DT as part of WP5, which will make it easier for the DT to connect to the physical test bench during the virtual test deployment. Section 6 of the D5.1 will describe the final result, which aims to demonstrate the functionality of the data mapping library. Section 7 will take the consultation into account.

2. Objective

The primary goal of the D5.1 project is to develop an ontology and data mapping library, which will enable data communication between all testing models across various scales and applications within the DT. This agreement will support and facilitate the communication between the DT and the physical test during the testing deployment in the DT and be considered as input for the physical test bench in the FASTEST. One of the objectives of FASTEST Deliverable 5.1 is to create a dedicated Python library that allows test specifications to be mapped appropriately in detail: in battery system level at cell and module level tests. And this will be a library for bringing raw sensor data from Excel files obtained during physical testing into a Digital Twin (DT). The system should also allow users to select tests and explore the data, to enable users to perform other DT activities. Finally, the Python model will comply with FMU/FMI standards in order to serve as a plug and play component of a co-simulation software, enabling the model to serve as a Digital Twin originated model to the broadest extent possible.

3. Introduction

The incorporation of digital twins in sophisticated battery technologies offers a revolutionary method for testing and optimizing battery performance in the ever-changing landscape of battery technology, [1]. A digital twin is a computer-generated model that accurately depicts a physical system, allowing for continuous monitoring, simulation, and predictive analysis. When it comes to battery testing, a digital twin can greatly expand our comprehension of battery performance in different situations, thereby enhancing efficiency, reliability, and lifespan [2].

The development of a digital twin for battery testing involves several critical components, among which ontology definition and data asset mapping are paramount. Ontology definition establishes a structured framework for organizing and interpreting the diverse data sets associated with battery testing. It provides a comprehensive vocabulary and set of relationships that describe the characteristics, behaviors, and interactions of the various elements within the battery system. This standardized framework ensures consistency and interoperability across different data sources and analytical tools, [3].

Data asset mapping, on the other hand, involves the systematic identification and cataloging of all relevant data assets required for the digital twin. This includes raw data from sensors, metadata, simulation models, historical performance data, and other pertinent information. By mapping these data assets, we create a detailed blueprint that outlines how data flows between different components of the digital twin, facilitating seamless integration and efficient data management, [4]. Together, ontology definition and data asset mapping lay the foundation for an effective digital twin of the battery testing model. They enable precise data alignment, robust analytical capabilities, and enhanced decision-making processes. This introduction sets the stage for a deeper exploration of these concepts, highlighting their importance in creating a digital twin that not only mirrors the physical battery system but also provides actionable insights for optimizing battery performance and extending its lifespan.

Figure 1 illustrates how task 5.1 integrates into the workflow of the FASTEST project. To facilitate the data mapping and communication of the DT with the physical testing bench, task 5.4 will integrate the data mapping and communication developed in D5.1 into the library's framework. After finishing the development and integration of the digital twin, it will play its role in the bigger loop by being responsible for choosing the appropriate simulation model and test procedure according to the unit under test, then forwarding the result to DoE (design of experiment) block where the parameters of the test procedure are calculated and sent to LIMS that in turn recommends when and which test branch (virtual/physical) should be used to launch the chosen battery test.

Task 5.1
User Interface with Data Mapping and Navigation in Digital Twin

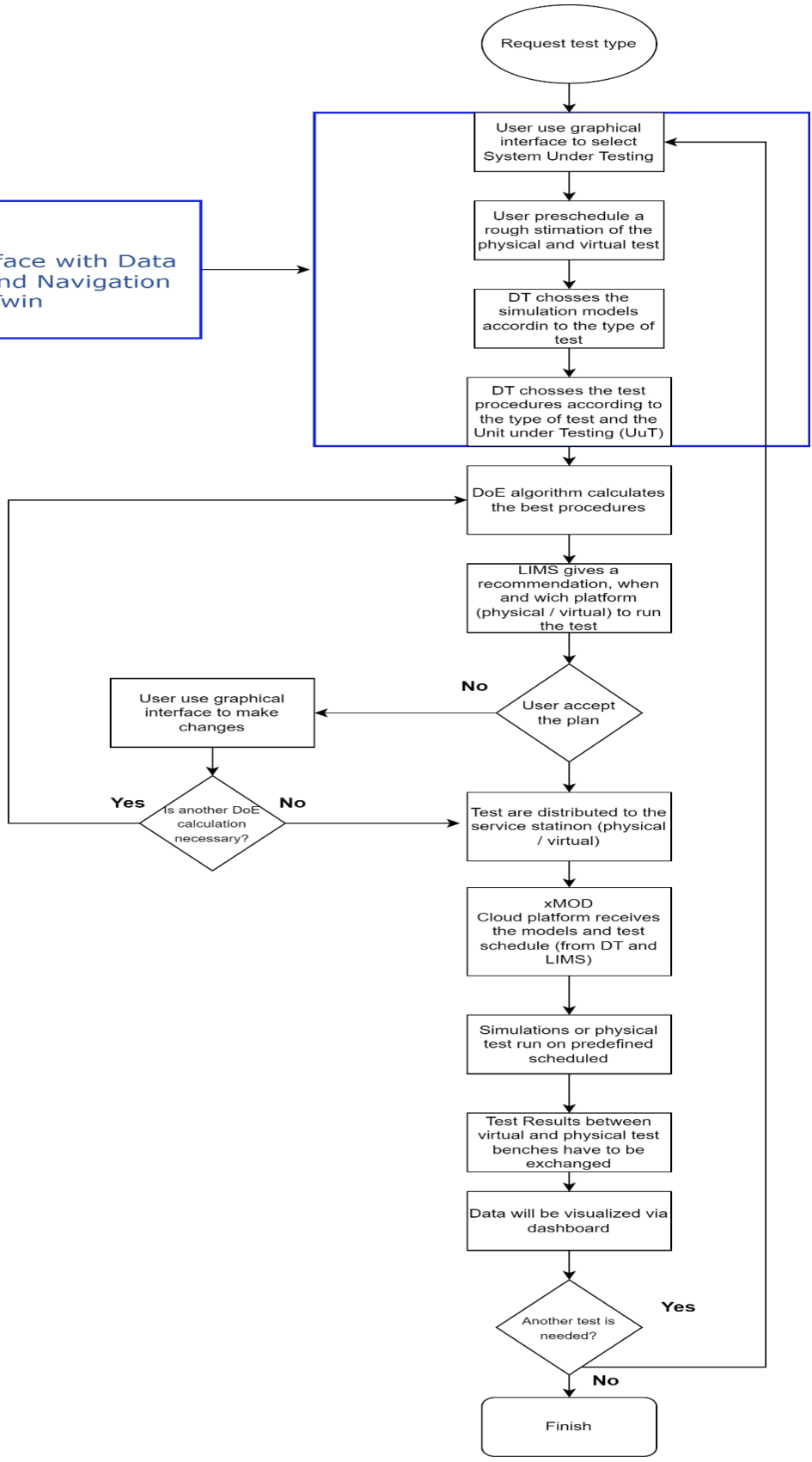


Figure 1 Detailed FASTEST Project Workflow Highlighting Task 5.1

4. Background

4.1 Purpose of the Ontology

The purpose of the ontology is to provide a structured knowledge representation framework that supports the objectives and requirements of the project. Ontology captures and organizes relevant concepts, relationships, and entities, and facilitates efficient communication, collaboration, and decision-making within the project. FASTEST project focuses on developing a fast-track testing platform for evaluating Li-ion batteries. By capturing the key aspects of battery testing methodologies, including safety, performance, reliability, and lifetime, the ontology facilitates a deeper understanding of the complex multi-scale and multi-physics phenomena in battery systems. Additionally, it supports the integration of Design of Experiments (DoE) strategies, virtual and physical testing approaches, and data-driven models within the testing platform. Ultimately, the ontology serves to streamline battery system R&D, accelerate innovation, and enhance the reliability, safety, and longevity of battery designs.

4.2 Incorporation of Functional and Testing of data

This section focuses on explaining the structure of the resultant data from various tests. The purpose is to ensure that the data can be effectively implemented in the Digital Twin. In the Appendix 9.1, figures (A-E) presented in the image form of the signal specification excel document which provides a detailed view of the results of the physical tests at the cell and module levels. Specific information for each of the tests is explained in Deliverable 2.1, and all of them will be developed comprehensively in Deliverable 3.4. It is important to highlight that these inputs and outputs will be transmitted to the Digital Twin so that it can work with this data and be properly configured. The Digital Twin uses this data to create a precise and dynamic virtual representation of the real battery system, allowing for advanced simulations and analyses. This integration is crucial for optimizing the design and operation of batteries, enhancing their reliability, safety, and efficiency. Below, the columns of these tables are explained in detail for a better understanding.

4.2.1 List of the IN/OP of the Module

This column lists all the relevant inputs and outputs for the battery module, including temperature, voltage, current, time, and capacity. This list is essential as it clearly identifies what data is being introduced into the system and what data is being extracted. This distinction is fundamental for designing the system and ensuring its proper integration and functioning within the testing and simulation environment. Without a clear understanding of the inputs and outputs, it would be challenging to optimize and control the performance of the battery module.

4.2.2 Direction

The "Direction" column indicates the direction of the data flow, that is, whether the data is input (IN) or output (OP). This direction is crucial as it helps engineers understand how the data moves within the system. Knowing whether a datum is an input or an output allows for more effective management of information, ensuring that input data is processed appropriately and that outputs provide the

expected results. This is also vital for integration with other systems and for validating test results

4.2.3 Type

This column specifies the nature of the signal or data associated with the input or output, for instance, electrical, mechanical, or thermal. This type of categorization is important because different types of signals may require different methods of processing and analysis. For example, thermal data may need different analyses compared to electrical data, and each type may involve using different measuring instruments and calibration techniques.

4.2.4 Data Type

The "Data Type" column describes the format of the data, such as integer, float, string, etc. Knowing the data type is essential for the correct processing and storage of information. Different data types require different handling and analysis approaches. For example, integer data may be managed differently from floating-point data, and each can have different implications for the precision and accuracy of data analysis.

4.2.5 Resolution

The column "Resolution" indicates the precision of the data, expressed in terms of bits or specific units of measurement. Resolution directly affects the accuracy of measurements and the results of simulations. Higher resolution allows for more detailed and precise analysis of the module's conditions. For instance, in voltage measurements, higher resolution can reveal subtle fluctuations that could be critical for understanding the battery module's behavior under different operational conditions.

4.2.6 Scaling

Scaling provides information on how the data should be adjusted or transformed for use in analysis and simulations. This can include conversion factors or units of measurement. Scaling ensures that data is interpreted and used consistently throughout the system, facilitating comparisons and analyses across different datasets and tests. Without proper scaling, data could be misinterpreted, leading to incorrect conclusions and inefficient design decisions.

4.2.7 Frequency

The "Frequency" column details the frequency at which data is recorded or updated, for example, in Hz (Hertz) or cycles per second. The sampling frequency is crucial for capturing the dynamic behavior of the module and ensuring that the data is sufficiently detailed for simulations and analyses. High sampling frequency can capture rapid changes and provide a more accurate view of the module's performance, while low frequency could miss important details.

In summary, each column in these tables plays a crucial role in organizing and utilizing test data at the cell and module levels. Together, they provide a detailed and meticulous structure for documenting and analyzing these tests, which allows for a better understanding and optimization of battery systems through Digital

Twins. This information is essential when transmitting data from a virtual test environment to the digital twin where this data will be collected and interpreted.

4.3 Ontologies in Digital Twin Development

4.3.1 Overview

The concept of digital twins represents a significant advancement in the field of battery system development and optimization. By constructing a virtual replica, researchers have the capability to perform simulations across a range of scenarios, thereby forecasting results and enhancing battery technologies without the limitations associated with physical experiments. This chapter delves into the specific ontologies that underpin digital twin technologies within the context of battery systems. It discusses the current state of these ontologies and examines potential modifications or expansions that could facilitate more effective virtual testing of batteries. The adaptability and extension of these ontologies are pivotal for the accurate representation and analysis of battery behaviors under various conditions, thereby contributing to more precise and reliable battery technology developments.

Digital twin technologies for batteries necessitate the integration of complex data derived from multiple sources, including real-time sensor data from physical battery systems. The implementation of well-defined ontologies in these systems is paramount for achieving interoperability between different data types and sources. Such ontologies ensure that data across the digital twin network is consistent, facilitating effective analytics and decision-making. By standardizing the way data is described and interconnected, ontologies play a critical role in not only managing the data but also in enabling complex simulations that rely on data from diverse sources. This approach ensures that the digital twins accurately reflect their real-world counterparts and provide meaningful insights that are essential for optimizing battery performance and reliability.

4.3.2 Literature

Originally developed for sensor data integration and IoT applications, the SSN (Semantic Sensor Network) and SOSA (Sensor, Observation, Sample, and Actuator) ontologies provide frameworks that can be particularly beneficial for battery digital twins, [4][4][**Error! Reference source not found.**]. They enable detailed descriptions of sensors and measurements, crucial for monitoring battery conditions like temperature, voltage, and current utilized both the SSN and SOSA ontologies to enhance the functionality of their digital twin system, [7]. This integration allowed for a more detailed and structured representation of sensor data, observations, and actions within the system, facilitating improved interoperability and data analysis capabilities. This dual ontology approach leverages the strengths of both SSN and SOSA to provide a comprehensive framework that supports advanced monitoring and control functionalities within the digital twin environment.

The IoT ontologies, such as those proposed by on digital twins in cyber-physical systems, offer robust structures for integrating real-time data into digital twin environments, [8]. These ontologies are designed to handle dynamic and complex data streams, which are typical in battery operation and testing scenarios. Implementing these IoT ontologies in battery digital twins would facilitate the seamless integration of sensor data, enhancing the twin's ability to simulate and predict battery behavior under different conditions. The work by outlines an architecture for a digital twin specifically designed for battery systems, [9]. This architecture could guide the development of a specialized ontology that addresses the unique needs of battery testing, such as lifecycle management, degradation modeling, and performance optimization.

Other usages of ontologies are found to describe physical components, their physical attributes, states in a system and the relation in between them use an ontology to describe physical parts of a plant, such as root, stem or leaf, and the ontology is then used to extract rules for decision making, [10]. Another example in manufacturing is to represent industrial machines or machine parts, personnel, or environmental conditions such as temperature and humidity using an ontology developed a CNC machine tool ontology that includes concepts such as Material, Personnel, Device and Environment, [11]. The ontology is used to aggregate data from diverse sources.

For the specific needs of virtualizing battery testing, a hybrid ontology combining elements from both SSN/SOSA for sensor data handling and specific constructs from battery-focused digital twin architectures would be ideal. This ontology should include definitions of battery cells and modules, including their physical and chemical properties, standardized descriptors for test conditions, procedures, and expected outcomes, and descriptions of performance metrics such as energy capacity, charge/discharge rates, and efficiency. It should also include descriptions of common degradation pathways and failure modes specific to battery technologies.

4.4 Incorporation with LIMS and potential integration challenges

4.4.1 Digital twin data exchange

The communication of the data between the modules and the digital twin will take place. The users will be able to interact with the digital twin through a multi-purpose graphical user interface that shows:

- Information on models
- Simulation sequences
- Historical test data
- Performed model simulations.
- Outcomes of model simulations

To achieve the above functionalities, the digital model requires a communication hub where data is consistently exchanged between the digital twin components and outer components like LIMS and DoE. This is where the MQTT broker takes place. Additionally, the model management serves as an interaction point between the digital twin and LIMS for model exchange. It receives test requests from LIMS and determines which simulations, models and test procedures should run. After determining the test, another component called “Test Request Handler” acts as a connection point between LIMS/DoE and the model management module. All requested data including simulation and test procedure coming from LIMS are sent to the DoE component for the optimal procedure calculation. It then receives the results from DoE and forwards them to the co-simulation software to start the test execution. This way, the model management block, the test request handler and the MQTT broker facilitate a continuous data exchange loop between the digital twin, LIMS and DoE components for successful test runs on the co-simulation platform.

4.4.2 Potential integration challenges with physical test branches

To examine how the database model might look, we first look for the parts where the database is used in connection with the digital twin. The structure of the digital twin contains a model management block that is responsible for registering the aging, performance and safety models that are retrieved from WP3 and WP4 respectively. The database model should contain these registered models so that they can be retrieved quickly during the initial test phases. In addition to the models, data is also collected and analysed in connection with the digital twin.

As with any other process in this project, integrating the digital twin with the physical testing bench would potentially pose challenges in the data perspective. One of which is the rise of (NaN) values in the real time data being retrieved during the simulation/testing process on the physical bench. This potential loss could happen due to latency, packet loss or communication disconnection. This directly affects tasks like outlier detection and clustering in the data analysis services planned for the digital twin. To address this, data imputation methods could be studied and implemented in the data analysis service module in the digital twin accordingly.

Another potential challenge is latency in the real-time data between the digital twin deployed on the cloud (Azure VPC) and the physical test bench. Since Azure provides multiple regions for cloud deployments, the closest provided region shall be chosen, and the data streaming shall be tested to ensure minimum latency.

5. Ontology Development

5.1 Overview

The ontology development for batteries at both cell and module levels involves creating a structured framework to represent key concepts, relationships, and entities relevant to battery systems. At the cell level, the ontology includes concepts such as battery chemistry, performance metrics, and safety characteristics. It also encompasses various testing methodologies, including safety tests, performance tests, and durability tests. At the module level, the ontology expands to incorporate concepts related to battery pack architecture, thermal management, state-of-charge management, and module-level performance metrics. It also considers pack integration, including electrical connections, cooling systems, and mechanical mounting. Furthermore, the ontology includes concepts related to pack-level testing, such as module-level safety tests, thermal cycling tests, and performance validation tests under real-world operating conditions. Overall, the ontology development for batteries at cell and pack levels aims to provide a comprehensive knowledge representation framework that supports the design, testing, and optimization of battery systems.

5.2 Characterization

In the FASTEST project, three distinct use cases are considered,

1. Offroad and Industrial devices
2. Automotive devices
3. Stationary,

each having its distinct particularities and technical attributes. It is relevant for future data analysis to characterize the baseline for each use-case typical cell and module. This data is necessary when instantiating a cell or module in the Digital Twin, to ensure the correct configuration. Furthermore, each use case has unique requirements, which may result in different tests sequence or procedures. These specifics should allow to efficiently create instances of the Digital Twin for each use case, avoiding the storage of unnecessary simulation models and impacting the structure of the database.

Additionally, this characterization boosts traceability, helping in the identification of faults specific to each use case and in compiling useful statistics. Such detailed tracking enhances the capabilities of the Digital Twin, providing a more complete solution for FASTEST and opening doors for future analytics.

5.2.1 Offroad and Industrial devices

In this paragraph, we describe a typical off-road industrial application, specifically focusing on the technical specifications of a battery installed in an Automated Guided Vehicle (AGV). For this use case, we consider systems based on a nominal voltage of 51.2V and a capacity of 560Ah, composed of 6.4V modules connected in series and parallel.

D5.1: Ontology definition and Data Mapping of Virtual Assets

Below, we present the datasheet of the cell, the battery pack data and the cell testing data. The first table contains the manufacturer's data, while the second table summarizes the technical specifications and workload profile of system.

Typically, an AGV operates 24/7, moving heavy loads, and performs short, frequent charging cycles—up to 20 charges per day.

In Table 1, technical specifications are released by the manufacturer. We use this information to design the module and battery pack. Furthermore, this information helps us during the creation of testing procedures and validations of our items.

Table 1 Cell Level Data

Parameters	Description	Value
Capacity		280 Ah
Typical Voltage		3,2 V
AC Impedance Resistance(1KHz)		≤0.25 mΩ
Standard charge and discharge	Charge /discharge current	0.5 C/0.5 C
	Cut off voltage of charge / discharge	3.65 V/2.5 V
Maximum charge / discharge current	Continuous charge / discharge	1C/1C
	Pulse charge / discharge (30s)	2C/2C
Charging Temp.		0 °C~55 °C
Discharging Temp.		-20 °C~55 °C
Chemistry/ Cell Type	Prismatic cell LIFEP04	LFP

In Table 2, we summarize information related to a common use case for off-road and industrial devices. This table provides technical specifications for the module level as well as work cycle information.

Table 2 Module Level Data

Parameters	Value
Capacity	560 Ah
Voltage	6.4 V
Configuration	2S2P
SOC Range	[70-80]

In Table 3, we can find measurements related to the battery cell testing procedure carried out during the incoming quality control phase. This step is performed to verify the compliance of the item with the manufacturer's datasheet and to collect information needed for predictive maintenance models.

Table 3 Cell Level Data

Parameters	Value
------------	-------

Resistance pre charge	0.35 mΩ
Resistance post charge	0.15 mΩ
Capacity residual	218.01 Ah
Capacity Tot	621 Ah
Impedance	0.105 mΩ
OCV V	3.295

5.2.2 Automotive Devices

Focusing on automotive devices is of paramount importance due to the increasing demand for electric vehicles that require highly efficient and safe battery systems. Table 4 presented below details the essential technical requirements for batteries intended for use in the automotive sector. These specifications are crucial to ensure that the batteries not only meet performance and safety expectations but also facilitate effective integration with vehicle electrical systems.

The specific criteria listed include the operational voltage range, which significantly varies from 90V to 450V to accommodate different types of vehicles, from personal cars to light commercial vehicles. Additionally, a usable energy capacity ranging from 30 kWh to 100 kWh is specified, which is fundamental in determining the vehicle's range under various driving conditions.

Another key feature outlined in the table is the rapid charging performance, allowing the battery to reach 80% capacity in just 20 minutes—a critical characteristic for market acceptance of electric vehicles. Furthermore, the specifications detail the maximum discharge power and the operational temperature ranges for both charging and discharging, ensuring that the batteries operate optimally across a wide spectrum of environmental conditions.

These parameters not only reflect the direct technical needs of electric vehicles but also highlight the challenges associated with designing and testing battery systems that must be robust, efficient, and capable of handling the dynamic demands of modern electric mobility.

The following Table 4 encapsulates these critical technical details, providing clear guidance for the development and evaluation of batteries that meet the demands of the automotive market, aimed at enhancing the safety and efficiency of electric vehicles.

Table 4 Cell and Module Level Data

Parameter	Value
Chem. system	LFP
Nominal operation voltage range	90V - 450V
Usable Total Energy Capacity	30 kWh - 100 kWh
SOC of operation range	0% - 80%
Fast charging performance	0% to 80% in 20min / 1.7C
Peak discharge power	200kW
Temperature operating range	Charge: - 20°C~55°C Discharge: -30°C~55°C
Storage temperature range	-40°C ≤ 60°C

IP	P67 or higher (dust tight and Water-resistant)
Lifecycle of application	160.000 km 1100 full cycles(100% DoD)
Battery Pack Weight (1pack)	< 600kg
Energy Density - Pack	> 200Wh/kg
Energy Density - Module	>280Wh/kg
Power Density – Pack (1C)	>200W/kg
Power Density – Module (1C)	>280W/kg

5.2.3 Stationary

BMZ offers a range of battery energy storage system (BESS) products which include Hyperion, POWER4HOME, POWER2GO etc. The Hyperion range utilizes a modularization approach where multiple modules are interconnected to reach the desired energy requirements. Currently it uses a minimum of three modules which can deliver usable energy up to 7.5 kWh. It can be further extended output up to 15 kWh by connecting seven modules. The modules utilize cylindrical cells of 18650 format and can be operated in a wide range of temperature (-15~55°C). Once installed the BESS is in continuous operation. Table 5 and Table 6 shows the cell and module level data specifications, respectively.

Table 5 Cell Level Data

Parameters	Value
Cell model	TerraE 30E
Cell chemistry	Li-ion NMC
Format	18650 Cylindrical
Voltage range	3.2 ~ 4.08 V

Table 6 Module Level Data

Parameters	Value
Nominal voltage	51.4 V
Nominal energy	3.3 kWh
Usable energy	2.5 kWh
Charging current (max.)	29 A
Discharging current (cont.)	30 A
Discharging current peak (3s)	40 A
Depth of discharge (DoD)	<80 %
Charge operating temperature	0 ~ 45 °C
Discharge operating temperature	-15 ~ 55 °C
Internal protection of casing	IP20
Certification	IEC62619/VDE-AR-E2510-50/CE/UN38.3

5.3 Library functionality

In Figure 2 shows the layered structure workflow for Python library for data mapping and navigation for the DT. The library is structured into multiple layers, each serving a distinct purpose within the overall framework. At the topmost level, the Applications Layer encompasses the three proposed applications: off-road, automotive, and stationary systems. Beneath this, the battery system testing level, Second Layer is divided into cell-level and module-level testing. The Testing Methods Layer follows, detailing all the specific tests that are planned to be conducted. The third and fourth layer, to select the tests from cell level and/or module level, respectively. the Input/Output Layer, outlines the data inputs and outputs associated with each test. And it takes to the fifth layer where we have the selected test. Next and last is the sixth layer, the Signal specification layer provides detailed information on signals. This structured approach ensures a comprehensive and organized representation of the test selection procedure, facilitating efficient management and utilization of information across the project.

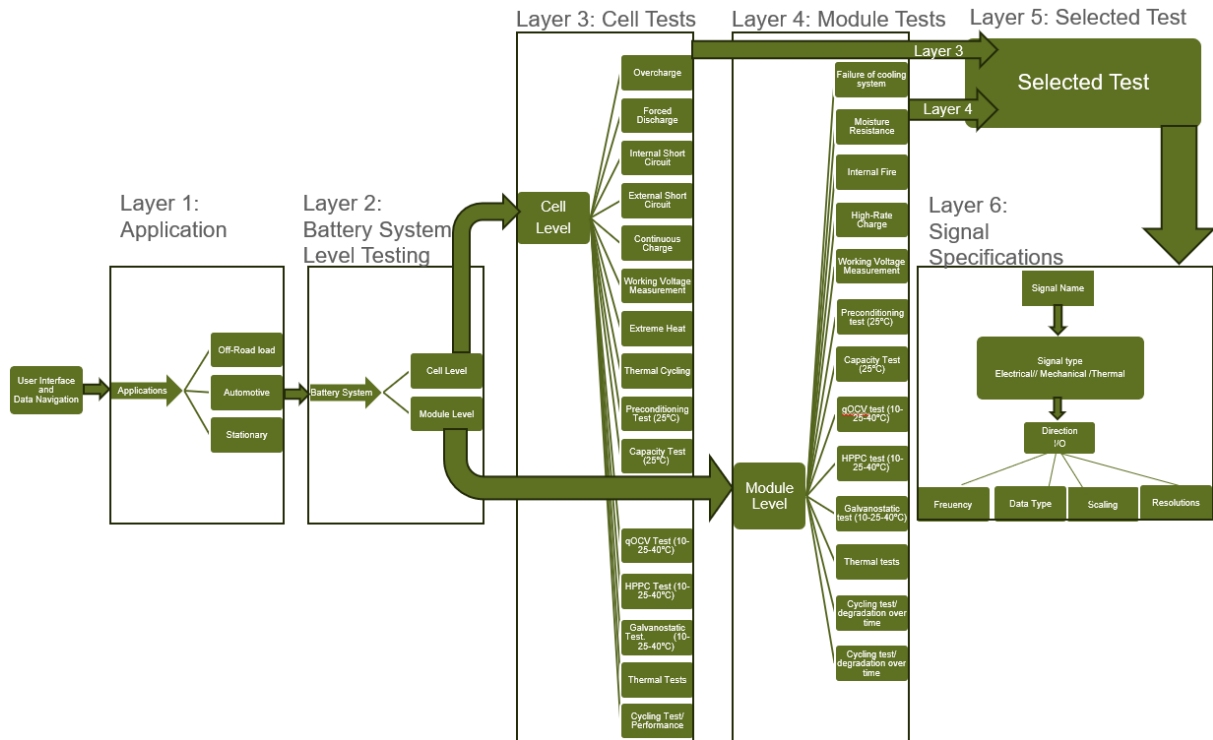


Figure 2 Layered Structure Workflow for Python Library Data Mapping and Navigation

6. Results

6.1 Agnostic Ontology

To create the ontology, Protégé [12](Hardi, Horridge, Tu, & Musen, 2020) was used. Protégé is a comprehensive, free, open-source ontology editor and knowledge management system developed by the Stanford Center for Biomedical Informatics Research at the Stanford University School of Medicine.

Protégé supports various ontology languages, including the widely used Web Ontology Language (OWL), facilitating the creation, manipulation, and sharing of complex knowledge structures. It also features a user-friendly graphical interface that allows for intuitive design, visualization, and testing of ontologies. This makes it an ideal tool for modeling detailed ontological structures that define the relationships and properties of entities within specific domains.

In order to create an ontology, four components are essential: Classes, Relationships, Properties and Instances. In the following sub-chapters, these four components will be explained and detailed.

6.1.1 Class

A Class in the context of ontology design is a fundamental concept that represents a set of objects or individuals sharing common characteristics or attributes. Each Class defines a category or type of entity and can be thought of as a blueprint from which instances or individual members of that class are derived. In the FASTEST scope, the following Classes were identified:

1. Components;
 - a. Cell
 - b. Module
2. Test;
3. Test Bench;
4. Test Procedures;

Components are the entities that will be tested (except battery pack that is out of the scope of FASTEST), and cell, Module and Battery Pack are a subclass of Components. The class Test, as the name suggests, was created to characterize the test that will be made to a component. The same logic applies to the classes Test Bench and Test Procedures.

6.1.2 Properties

Properties, on a conceptual level, describe attributes or characteristics of the classes. They define the specific aspects of the class instances, such as measurements, conditions, or descriptive elements as well as their data types, enabling a more detailed and structured representation of the data within the ontology. Figure 3 displays all the properties relevant to each class.

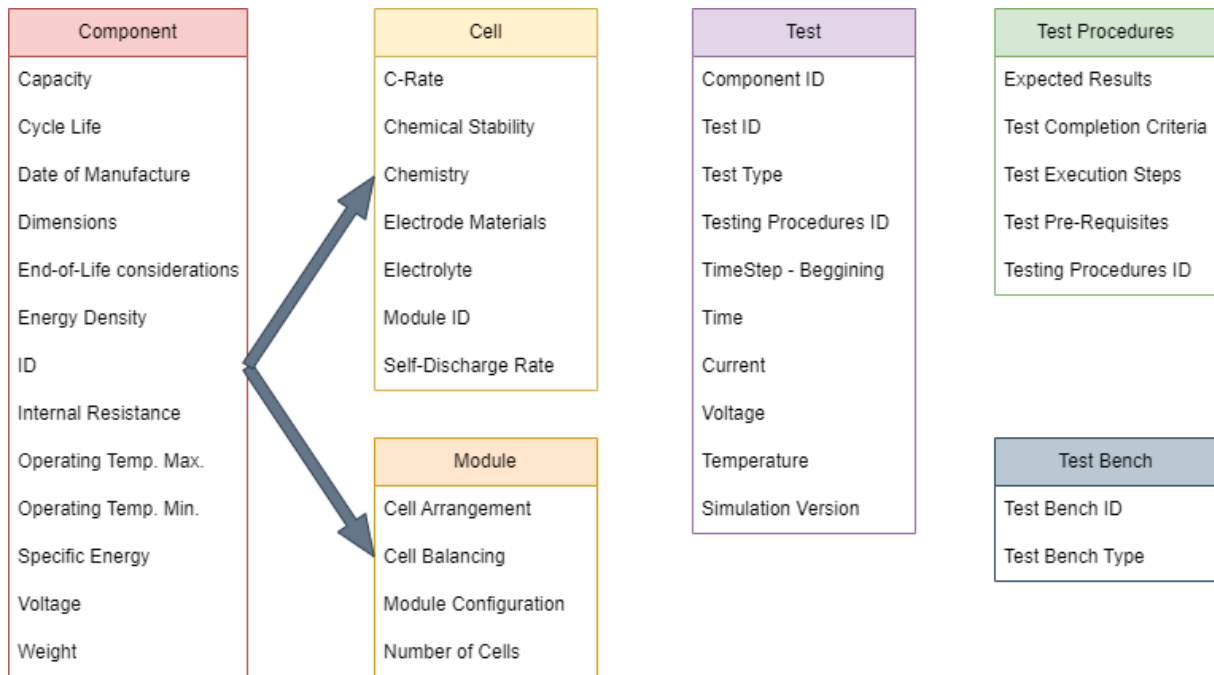


Figure 3 - Properties of each class.

Since it has been established that both Cell and Module are subclasses of the class Component, they share all data properties present in the Component class in addition to the properties specific to them. The Test class contains two main fields: test properties and test telemetry. Test properties are important for defining a test with parameters like Test Type and Test Procedure ID. Test telemetry, which includes parameters like Time and Current, is responsible for recording the outputs of each test. Telemetry data is the only dynamic data among the properties. Additionally, the Test Bench Type differentiates physical tests from digital ones. For instance, the xMOD Platform, which will be used in FASTEST as a tool to run virtual tests, is considered a virtual test bench.

6.1.3 Relationships

For the definition of the ontology itself, the last essential component is the Relationship. These, describe how different classes and instances are connected or interact with each other. They define the associations and dependencies between entities, helping to create a structured and meaningful representation of the data. Relationships are crucial for illustrating how different components of the ontology relate to one another, enabling a comprehensive understanding of the domain.

In the context of the FASTEST scope, the following relationships have been identified:

- **Belong:** This relationship indicates that one entity is a part of another. For example, a Test Belongs to Test Procedures.
- **Contains:** This relationship shows that one entity includes another. For example, a Module Contains Cells, and a Battery Pack Contains Modules.
- **Made in:** This relationship specifies the location or environment where an activity takes place. For example, a Test is Made in a Test Bench.

- **Made to:** This relationship defines the target or subject of an activity. For example, a Test is Made to a Cell and a Test is Made to a Module.

These relationships help to articulate the connections between different components within the ontology, ensuring a coherent and interconnected framework.

6.1.4 Individuals

To validate the ontology, instances or individuals were created. Instances represent concrete examples of the classes defined in the ontology. They are the actual data points that populate the ontology, giving real case scenarios to the abstract concepts and relationships. By creating instances, we can test the accuracy and consistency of the ontology, ensuring that the defined classes, properties, and relationships accurately model the real-world entities and their interactions. For example, an instance of the class Cell might be a specific type of cell used in a test, while an instance of the class Test could be a particular test conducted on that cell. By populating the ontology with these instances, it is possible to validate its structure and functionality, verifying that all necessary elements are correctly represented and interconnected. Figure 4 displays an instance of the class cell named cell 1.

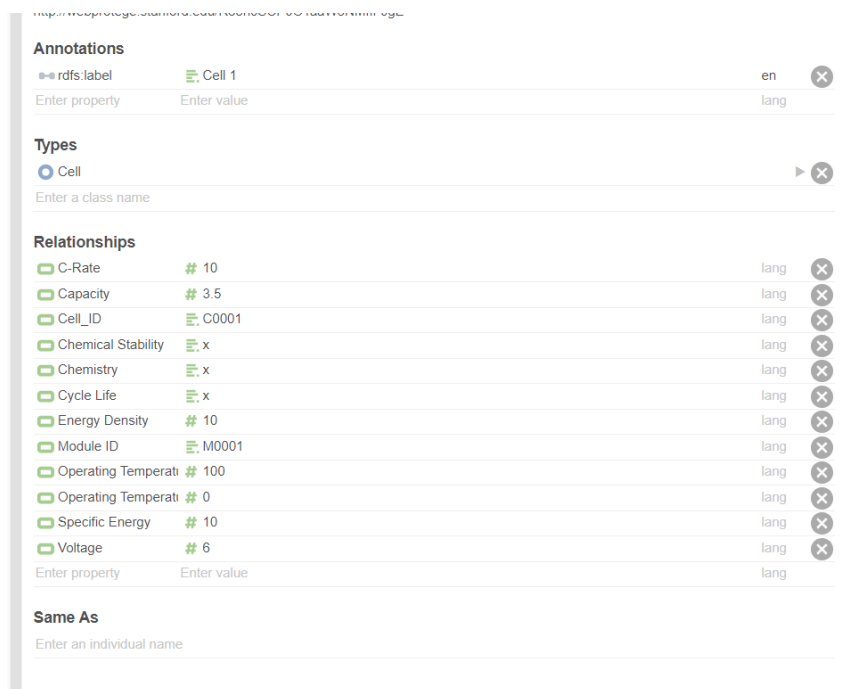


Figure 4 - Instance of a Cell class.

As it can be seen in the image, the properties attributed to the cell class have been populated with real values creating an instance of the class Cell.

It is also possible to create schemes as the one in Figure 5.

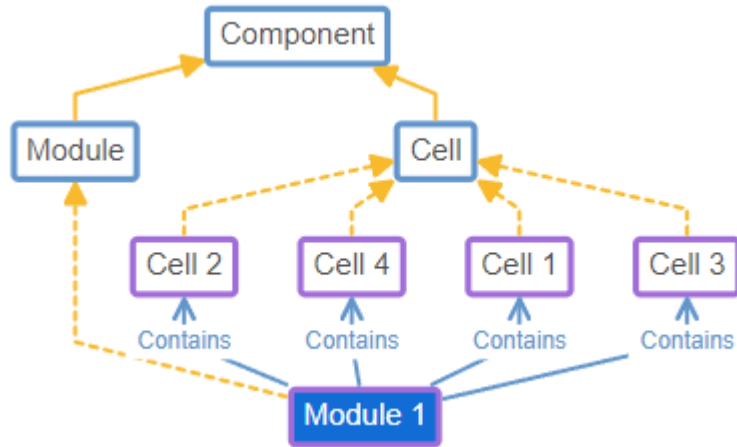
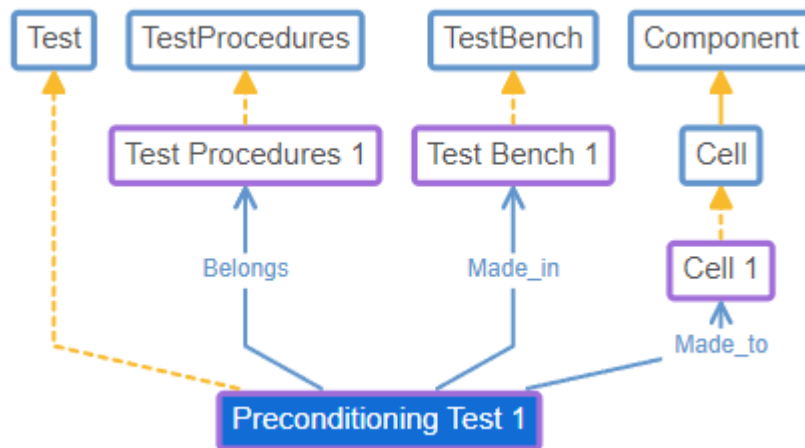


Figure 5 - Graphical Representation of the Ontology: An Instance of the 'Module' Class Named 'Module 1'.

As shown in this figure, Module 1, an instance of the class Module, contains cell 1 through 4 that are instances of the class Cell. Another example is seen in Figure



6

Figure 6 - Graphical Representation of the Ontology: An Instance of the 'Test' Class with 'Preconditioning Test 1' and Its Associated Procedures, Bench, and Components.

A Preconditioning Test, an instance of the class Test, that belongs to the Test Procedures 1, an instance of the class Test procedures, was made in the Test Bench 1, an instance of the Test bench class and was made to cell 1, an instance of the class cell.

With this, the ontology is defined, providing a structured and comprehensive framework for representing the entities, properties, and relationships within the FASTEST project. However, FASTEST is an ever-evolving project, and the ontology may undergo changes over time. As the project progresses and new requirements emerge, it might be necessary to introduce additional classes, relationships, or properties to capture the growing complexity and new insights. This flexibility ensures that the ontology remains relevant and continues to accurately model the dynamic and expanding scope of the project.

1. Descriptive Text

1. First Layer (Application Selection):

- Options: Stationary, Off-road Load, Automotive

2. Second Layer (Battery System Testing Level):

- Options: Cell Level Test, Module Level Test

3. Third Layer (Cell Level Tests):

- Options: 15 different test types (e.g., Test 1, Test 2, ..., Test 14)

4. Fourth Layer (Module Level Tests):

- Options: 13 different test types (e.g., Test 1, Test 2, ..., Test 14)

5. Fifth Layer (Selected Test):

- Selected Test name

6. Sixth Layer (Signal Specifications):

- Signal details relevant to the selected test and signal type.

6.2.3 Example Navigation Flow:

- Layer 1:** The user selects **Application:** Off-road Load.
- Layer 2:** Proceeds to **Test Level:** Cell Level Test.
- Layer 3/4:** Chooses **Type of Test:** Example Test 10.
- Layer 5:** Register the test name
- Layer 6:** The co-simulation software, along with the Digital Twin (DT), navigated further to relevant details for next endeavors.
 - Signal Type:** Electrical/Mechanical/Thermal
 - Input/Output**
 - Scaling**
 - Frequency**
 - Resolution**

Table 7 Visual Representation of Python Library Layers for Digital Twin Applications

Layer	Options
Application	Stationary, Off-road Load, Automotive
Test Level	Cell Level Test, Module Level Test
Type of Test	Test 1, Test 2, ..., Test 14
Signal Type	Electrical, Mechanical, Thermal
Input/Output	Input, Output
Scaling	Various scaling options
Frequency	Various frequency options
Resolution	Various resolution opt

Key Features:

- **Data Mapping and Navigation:**
 - The library efficiently maps and navigates through multiple layers, providing users with detailed and structured information.
- **Excel File Interaction:**
 - Utilizes **openpyxl** and **pandas** libraries etc for reading, writing, and manipulating Excel files, ensuring smooth data storage and retrieval.
- **FMU/FMI Integration:**
 - Ensures compatibility with co-simulation software by supporting FMU and FMI standards, thereby enhancing system modeling and simulation capabilities.

7. Conclusion

In conclusion, the ontology definition and data asset mapping together establish a solid foundation for an effective digital twin of the battery testing model.

Deliverable 5.1 of the FASTEST project involves building a Python library with a six-layer system. This system includes data mapping from detailed test specifications on cell and module level of the battery system. Excel files containing raw sensor data from physical testing, the goal is to integrate this data into a Digital Twin where users can select tests and navigate data, leading the DT to perform further activities. Providing the Python model as one unit with FMU/FMI standards ensures seamless integration with co-simulation software.

In parallel, an ontology was developed. Ontologies are crucial as they provide a structured framework for organizing information, enabling a shared understanding and facilitating interoperability between different systems. The importance of the ontology being agnostic lies in its independence from specific use cases, allowing it to be universally applicable across various contexts. This independence ensures that the ontology can be adapted to different technological environments (e.g., SQL databases) without being tied to a particular implementation.

The ontology allows a solid understanding of the project before implementation. It lets us structure the database in an agnostic way regarding technology, ensuring flexibility and scalability. We defined classes, parameters, relationships, and instances within the ontology. These instances validated the ontology, ensuring that it accurately represents the real-world entities and their interactions within the battery testing model.

Data asset mapping systematically identifies and catalogs all relevant data assets needed for the digital twin, including raw sensor data from physical testing at the cell and module levels. By creating a detailed blueprint of data flow between user

choices and DT components, data asset mapping facilitates seamless integration and efficient data management in co-simulation software.

The user employs a graphical interface to select the System Under Testing and pre-schedule rough estimations of physical and virtual tests. The DT then selects simulation models based on test types. Task 5.4 integrates the data mapping and communication developed in D5.1 into the library's framework to facilitate DT communication with the physical testing bench.

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9. Appendix

9.1 Detailed Signal Specification matrix

Physical								
Fastest IN/OP Cell Test Models								
Test Name	Partners for physical validation of the model	Signal Name	DIRECTI ON (IN&OUT)	TYPE Elec, Mech, Them	DATA TYPE	RESOLUTION	SCALING	FREQUENCY
Overcharge (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Forced discharge (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Internal short circuit (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
External short circuit (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Continuous charge (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Working voltage measurement (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Extreme heat (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	N/A	N/A	N/A	x\
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms

Figure. A Tests (1-7) Cell Level Testing Signal Specifications

Physical								
Fastest IN/OP Cell Test Models								
Test Name	Partners for physical validation of the model	Signal Name	DIRECTION (IN&OUT)	TYPE Elec, Mech, Them	DATA TYPE	RESOLUTION	SCALING	FREQUENCY
Thermal Cycling (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Preconditioning test (25°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms
Capacity Test (25°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms
qOCV test (10-25-40°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms
HPPC test (10-25-40°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms
Galvanostatic test (10-25-40°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms

Figure. B Tests (8-13) Cell Level Testing Signal Specifications

Physical								
Fastest IN/OP Cell Test Models								
Test Name	Partners for physical validation of the model	Signal Name	DIRECTION (IN&OUT)	TYPE Elec, Mech, Them	DATA TYPE	RESOLUTION	SCALING	FREQUENCY
Thermal tests (WP3)	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms
	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Cycling test/ degradation over time (WP3)	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms
	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	1s
Cycling test/Performance (WP3)	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms
	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...6 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	1s
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-100...100 Ah	100ms

Figure. C Tests (14-17) Cell Level Testing Signal Specifications

Physical								
Fastest IN/OP Module Test models								
Test Name	Partners for validation of the model	List of the IN/OP of the model	DIRECTI ON (IN&OUT)	TYPE Elec, Mech, Them	DATA TYPE	RESOLUTION	SCALING	FREQUENCY
Failure of cooling system (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Moisture Resistance (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Internal Fire (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
High Rate Charge (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Working Voltage Measurement (WP4)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
Preconditioning test (25°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms
Capacity Test (25°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0...52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms

Figure. D Tests (1-7) Module Level Testing Signal Specifications

Physical								
Fastest IN/OP Module Test models								
Test Name	Partners for validation of the model	List of the IN/OP of the model	DIRECTION (IN&OUT)	TYPE Elec, Mech, Them	DATA TYPE	RESOLUTION	SCALING	FREQUENCY
qOCV test (10-25-40°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0..52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms
HPPC test (10-25-40°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0..52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms
Galvanostatic test (10-25-40°C) (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0..52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms
Thermal tests (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0..52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	100ms
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms
Cycling test/ degradation over time (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0..52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	1s
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms
Cycling test/Performance (WP3)	ABEE	Temperature	OUT	Thermal	FLOAT32	0.1 deg	-30...180 deg	100 ms
	ABEE	Voltage	IN	Electrical	FLOAT32	0.1 mV	0..52 V	100 ms
	ABEE	Current	IN	Electrical	FLOAT32	0.1 mA	-100...100 A	100 ms
	ABEE	Time	OUT	*	UINT32	10 ms	0...	1s
	ABEE	Capacity	OUT	Electrical	FLOAT32	0.1 Ah	-500...500 Ah	100ms

Figure. E Tests (8-13) Cell Level Testing Signal Specifications