EUROPEAN COMMISSION

HORIZON EUROPE PROGRAMME – TOPIC: HORIZON-CL5-2022-D2-01

FASTEST

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

Deliverable D2.2: Definition of battery system testing for automotive, off-road and stationary use cases

Bruno Rodrigues

Organization: ABEE

Date: [29.08.2025]

Doc.Version: [1.1]

Co-funded by the European Union

UK Research and Innovation

Co-funded by the European Union under grant agreement N° 101103755 and by UKRI under grant agreement No. 10078013, respectively. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither the European Union nor CINEA can be held responsible for them.

Document Control Information	
Settings	**Value**
Work package:	WP2
Deliverable:	Definition of battery system testing for automotive, off-road and stationary use cases
Deliverable Type:	Report
Dissemination Level:	Public
Due Date:	30.04.2025
Actual Submission Date:	01.09.2025
Pages:	<25>
Doc. Version:	1.1
GA Number:	101103755
Project Coordinator:	Bruno Rodrigues | ABEE (bruno.rodrigues@avestaholding.com)

Formal Reviewers		
Name	**Organization**	**Date**
Daniela Fontana	COMAU	08.08.2025
Vijay Nagulapati	RSTER	18.08.2025

Document History			
Version	**Date**	**Description**	**Author**
0.1	07.07.2025	First draft version 0.1	Bruno Rodrigues (ABEE)
0.2	16.07.2025	Images and graphic added to the document	Bruno Rodrigues (ABEE)
1.0	22.07.2025	Add chapter about validation & metrics, information missing updated – List of abbreviations, figure titles.	Bruno Rodrigues (ABEE)
1.1	01.09.2025	Corrections made after the review from the formal reviewers	Bruno Rodrigues (ABEE)

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 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 characterisation 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
AGV	Automated Guided Vehicle
BMS	Battery Management System
CCD	Central Composite Design
DOD	Depth of Discharge
DOE	Design of Experiments
DT	Digital Twin
EIS	Electrochemical Impedance Spectroscopy
EOL	End of Life
FIM	Fisher Information Matrix
HPPC	Hybrid Pulse Power Characterisation
IEC	International Electrotechnical Commission
LGV	Laser-Guided Vehicle
LIMS	Laboratory Inventory Management System
OCV	Open Circuit Voltage
PINN	Physics-Informed Neural Network
RSM	Response Surface Methodology
SOC	State of Charge
TRL	Technology Readiness Level
UUT	Unit Under Test
WLTP	Worldwide Harmonised Light Vehicles Test Procedure
WP	Work Package

LIST OF TABLES

LIST OF FIGURES

Table of Contents

1. EXECUTIVE SUMMARY

Deliverable D2.2, "Definition of battery system testing for automotive, off-road, and stationary use cases", contains the thorough results of WP2 in the FASTEST project, which aimed to specify the best testing procedures for three primary applications. This document provides an in-depth analysis of how to apply advanced concepts from Deliverable D2.1 with a comprehensive review of use-case-specific boundary conditions and state-of-the-art DOE methodologies coupled with modern digital twin technologies.

Establishing intelligent, use-case-specific ageing test procedures is the primary objective of this deliverable, which will expedite the battery development lifecycle and produce the most valuable and statistically significant data. This document offers thorough testing protocols for each use case by incorporating recent advancements in battery testing standards [1,2] and utilising cutting-edge DOE methodologies like Fisher Information Matrix (FIM) analysis, Response Surface Methodology (RSM), and Physics-Informed Neural Networks (PINNs) [3]. The integration of these state-of-the-art techniques enables a paradigm shift from traditional empirical testing approaches to intelligent, predictive testing methodologies that can significantly reduce development time and costs.

For the automotive use case, a comprehensive weekly ageing cycle has been developed based on the WLTP standard [4]. Realistic yet accelerated test schedules that account for the state of the charging infrastructure and vehicle usage trends are included. The protocol addresses auxiliary load variations, thermal management considerations, and long-distance weekend travel scenarios as well as weekday commute patterns. The stationary storage approach uses normalised current profiles from grid service applications to meet the different operational requirements, including frequency control, peak shaving, and integration of renewable energy [5]. A protocol that uses high scenario predictability for off-road devices emphasises realistic cycling within predetermined operating windows, making it ideal for industrial applications like material handling equipment and AGVs [6].

This deliverable provides a comprehensive and transparent set of testing protocols and is a crucial component of the FASTEST hybrid testing platform. The vast virtualised testing capabilities enabled by these protocols, which aim to reduce testing time and costs by 20-30% while ensuring proper parameterisation and validation of virtual models, will support the project's ambitious goals. The framework represents a significant breakthrough in battery R&D procedures by seamlessly integrating virtual and physical testing methodologies through intelligent orchestration systems.

2. INTRODUCTION

2.1. Context of the FASTEST Project

Since Li-ion batteries are essential for reducing carbon emissions, testing their lifespan, performance, and safety requires a significant number of resources. Tests take a long time, equipment is expensive, and a general trial-and-error approach all make the R&D process slower. The FASTEST project directly tackles these problems by creating a fast-track hybrid testing platform that combines physical and virtual testing in a way that is comprehensive and integrated. The project intends to speed up battery research and development by using intelligent DOE methodologies, multi-physics virtual models, and a DT architecture. This will lead to battery systems that are more reliable, safer, and last longer.

2.2. Objectives of Deliverable

D2.2 is a key outcome of WP2, specifically "Design of Experiments, boundary conditions, and methodologies." The primary objective is to translate the theoretical DOE methods and use-case boundary conditions outlined in D2.1 into practical, enhanced approaches for evaluating battery systems [7].

The primary objectives of this document are to:

- Establish the most effective and intelligent ageing test processes for each of the three project use cases: automotive, stationary energy storage, and off-road mobile devices.
- Explain how sophisticated DOE methods will be used in these procedures to cut down on testing time and costs while getting the most information possible for model parameterisation and validation [8].
- Compare the suggested steps to the specific goals of each use case and the main goals of the FASTEST project as a whole.
- Explain how these described procedures will be used and managed as part of the larger FASTEST hybrid testing platform that is being built in WP6.

D2.2 provides us with the test frameworks we need to achieve these goals. These frameworks will be used, evaluated, and integrated throughout the rest of the project to help build the hybrid testing platform.

3. General Battery Testing Procedures

The testing framework employs a systematic approach where system-level use case profiles are decomposed and adapted for lower-level component testing, ensuring consistency across all testing scales. For automotive applications, the complete WLTP-based weekly ageing cycle developed for pack-level testing provides the source material for cell and module-level test profiles. At the cell level, individual drive cycle segments are extracted from the complete weekly profile, with specific current and temperature conditions scaled to single-cell operation while maintaining the same stress characteristics. For instance, a highway driving segment from the pack-level profile that operates at an average current of 0.5C becomes a cell-level test segment at the same 0.5C rate, but with thermal conditions adjusted for single-cell heat generation and dissipation characteristics.

Module-level testing employs aggregated segments that represent the thermal and electrical interactions between multiple cells within a module assembly. The module-level profiles incorporate the same temporal patterns as the pack-level ageing cycle but account for current distribution effects, thermal gradients across cell arrays, and the influence of module-level thermal management systems. Temperature variations that occur naturally in pack-level operation due to cell positioning and cooling system design are replicated at the module level through controlled thermal cycling that matches the thermal stress patterns experienced in the complete system.

This hierarchical approach ensures that parameters extracted from cell-level performance and safety testing directly inform module-level test conditions, which in turn scale appropriately to pack-level validation. The critical insight is that while ageing protocols are optimised primarily for pack and system-level operation where real-world usage patterns are most accurately represented, the underlying stress mechanisms that drive degradation operate consistently across all scales.

It is essential first to establish a comprehensive set of generic characterisation tests that can be applied to battery cells regardless of their intended application, before developing use-case-specific ageing protocols. These standardised experiments, conducted at multiple temperatures (typically 15°C, 25°C, and 45°C), provide the fundamental data required to understand cellular behaviour and establish initial parameters for the models developed in WP3 and WP4. The performance and safety tests selected for the FASTEST project represent the most critical characterisation procedures necessary for comprehensive battery evaluation. The detailed experimental procedures for these tests are specified in WP3 documentation.

3.1. Tests of Performance

- **Preconditioning Test**: This test establishes a consistent starting point for all cells by charging them to their maximum specified voltage, then discharging them to a predefined State of Charge (SOC) and allowing them to stabilise.
- **Capacity Test**: This test measures the charge capacity of a cell by charging it to its maximum voltage and then discharging it at a steady current rate until it reaches the manufacturer's cut-off voltage.
- **OCV-SOC Test (Charge and Discharge)**: The Open Circuit Voltage (OCV) is mapped to the SOC by charging or discharging the cell in small steps and measuring the stabilised voltage at different SOC levels after letting it rest. Many battery models and BMS algorithms depend on this relationship.
- **Hybrid Pulse Power Characterisation (HPPC) Test**: This test checks the battery's power capability, such as its internal resistance and dynamic voltage response, by sending a series of short charge and discharge high-current pulses at varied SOC levels.

- **Thermal Test**: This test thoroughly describes how the cell behaves thermally by monitoring its temperature at various locations while subjecting it to different working conditions and controlled heating and cooling rates.

3.2. Safety Tests

Safety testing is crucial for ensuring that batteries can withstand abuse or faults and still meet the stringent safety standards of their intended use. These tests are done on both the cell and the module.

- **Tests at the Cell Level**:
  - **Overcharge Test:** Tests how the battery reacts when it is charged over its maximum rated voltage.
  - **Forced Discharge Test:** Checks the cell's integrity when it is discharged at rates higher than the allowed rate.
  - **Internal and External Short Circuit Tests:** These tests simulate short circuits to assess the effectiveness of the safety features.
  - **Thermal Abuse Tests (Extreme Heat, Thermal Cycling):** Subject the battery to extreme temperatures and rapid temperature changes to assess its thermal stability and management systems.
- **Module Level Tests:**
  - **Failure of Cooling System Test:** This test simulates a cooling system failure to see how well the module can stop thermal runaway.
  - **Test for Resistance to Moisture:** Checks how well the module seals and protects against water and humidity from entering.
  - **Internal Fire Test:** Checks to see if the module can keep an internal fire from spreading.
  - **High-Rate Charge Test:** Checks to see if it is safe to charge the module at currents higher than the regular rate.

4. Design of Experiments Methodology

4.1. Fundamentals of DOE in Battery Testing

Design of Experiments is a methodical approach to understanding the relationships between various factors that influence battery performance and lifespan. It enables efficient exploration of multidimensional parameter spaces while minimising experimental effort and maximising information extraction [40]. In the context of FASTEST, DOE methods enable intelligent experimental design that extends beyond the conventional one-factor-at-a-time approach, providing a comprehensive understanding of how factors interact and identifying the optimal conditions for running the experiment.

When you use DOE to test batteries, you can account for the fact that battery systems are naturally complex because many factors simultaneously affect performance, degradation, and safety. Traditional testing methods often fail to capture these interactions effectively, making it more difficult to understand how the system works and wasting testing resources. Classical DOE methods, such as factorial designs, enable you to systematically examine different combinations of factors to identify significant main effects and interactions. Fractional factorial experiments, on the other hand, let you quickly screen a lot of possible factors with less experimental effort.

Response Surface Methodology builds on basic factorial methods by providing mathematical models that illustrate the relationship between input factors and response variables in continuous design spaces. Central Composite Design (CCD) and Box-Behnken designs facilitate optimisation studies that identify the optimal operating conditions and provide a quantitative understanding of how sensitive factors interact with each other. These methods are beneficial for testing batteries because they allow you to continuously change operational parameters, such as temperature, current rate, and state of charge windows, instead of only at specific levels.

Statistical analysis frameworks, such as Analysis of Variance (ANOVA), provide rigorous methods for determining the significance of factor effects and the uncertainty associated with experimental results. Regression modelling lets you create mathematical relationships that can be used to make predictions within the experimental design space. Confidence interval estimation provides numerical measures of uncertainty that are crucial for making informed decisions and assessing risk. Residual analysis and cross-validation are two methods for verifying that the models we create yield reliable predictions and identifying any issues with the models or outliers in the data.

Multi-response optimisation techniques address the common problem in battery testing of having to consider more than one conflicting goal simultaneously. Desirability function approaches help identify operating conditions that meet acceptable performance standards across multiple criteria. Pareto frontier analysis, on the other hand, helps make decisions when perfect solutions aren't available by showing the trade-offs between competing goals. These methods are significant for batteries, where performance, lifetime, safety, and cost goals must be carefully balanced.

4.2. Model-Based Design of Experiments

Advanced model-based DOE methods use existing knowledge and models to improve experimental designs so that they get the most information possible. This is a big step forward from traditional empirical DOE methods [9]. The Fisher Information Matrix (FIM) provides a numerical measure of how easily parameters can be identified for a specific experimental design. This lets researchers improve test protocols to get the most accurate parameter estimates in physics-based battery models.

The relationship $FIM(\theta) = E\,[(\nabla\theta \log L(\theta))^{T}(\nabla\theta \log L(\theta))]$ is the mathematical basis for FIM-based design optimisation. Here, $L(\theta)$ is the likelihood function for the parameter vector θ. You can make the best designs by maximising the determinant of the FIM (D-optimality), minimising the trace of the inverse FIM (A-optimality), or minimising the maximum eigenvalue of the inverse FIM (E-optimality). Depending on the goals of the parameter estimation problem, each criterion has its own set of benefits.

Using FIM-based optimisation for battery testing enables the creation of current and temperature profiles that provide the most information about specific model parameters essential to us. This method makes sure that experimental work focusses on operating conditions that make parameters most sensitive, instead of areas where model response is less sensitive to changes in parameters. The result is testing that is more efficient, achieving the required level of parameter accuracy with less experimental work, or, on the other hand, obtaining higher parameter accuracy for the same amount of experimental effort.

Bayesian experimental design is another step forward that uses what we already know about parameter values and uncertainties to improve the optimisation process. Bayesian parameter estimation frameworks can use prior knowledge by changing the probability distributions of parameters based on experimental evidence. Sequential design optimisation lets you use adaptive testing strategies, where each new experiment is planned based on the results of all the previous ones. This method is beneficial for testing batteries because there is usually some information available from earlier tests or research about how batteries behave electrochemically.

Optimal control theory applications go beyond model-based design to include dynamic optimisation of test profiles for getting the most information. This makes it possible to create current and temperature profiles that change over time and are optimised to give the most information while staying within realistic limits on the rate of change, maximum values, and total energy throughput. Techniques for multi-objective optimisation can find the best solutions that are both informative and easy to put into practice by weighing the amount of information against practical factors like the length of the test and the limitations of the equipment.

4.3. Digital Twin Integration

Digital Twin technology enables you to continuously update models and run predictive tests on them throughout the battery's life. This represents a significant shift from static models to dynamic, evolving digital representations that improve with use [10]. Digital Twin ideas and DOE methods work well together to make both experimental design and model validation and improvement more effective.

Digital Twin systems can enhance the accuracy of their models and update parameter estimates by continuously incorporating new experimental data in real-time. Recursive algorithms, such as extended Kalman filtering, make it easy to update model parameters when new data become available. Model structure adaptation algorithms can also modify the complexity of a model based on how it has been observed to degrade or on new phenomena that have been discovered. Uncertainty propagation through model hierarchies ensures that uncertainties in parameters are accounted for at all levels of the system model, from the electrochemical models of individual cells to the predictions of how well the entire system will function.

One of the most effective applications of Digital Twin technology is virtual testing. With this technology, high-fidelity physics-based models can simulate experiments in virtual environments for significantly less money and time than they would in real life. For applications where speed is critical, reduced-order models enable the simulation and optimisation of systems in real time. Monte Carlo simulation, on the other hand, provides a comprehensive picture of uncertainty by considering both parameter and model structure uncertainties. Sensitivity analysis tools make it easy to find essential parameters and operating conditions quickly, which helps with both optimising experimental design and assessing risk.

Hybrid testing strategies adjust the workload between physical and virtual tests based on cost-benefit optimisation, considering model confidence, information value, and resource constraints. The Digital Twin framework enables real-time decision-making about whether specific experiments should be conducted in person or online, based on the accuracy of the current model and the expected information gain from each method. Risk-based testing prioritisation ensures that physical testing resources are focused on high-risk situations where model confidence is low or the potential outcomes are unfavourable. Virtual testing, on the other hand, addresses routine situations where model accuracy has already been established.

By continually verifying the accuracy of the virtual model, we can ensure that the transition from physical to virtual testing maintains the same level of accuracy throughout the testing program. Cross-validation with separate datasets allows you to assess how well the model predicts outcomes continually. Automated model performance monitoring identifies instances where the model's accuracy may have declined, indicating that additional physical testing may be necessary. This method ensures that the testing program remains as efficient as possible while also guaranteeing that accuracy standards are consistently met during the battery development process.

5. Optimal Battery System Testing Procedures

The central part of the FASTEST project is to run use-case-specific ageing tests that are meant to mimic real-world long-term use. These tests are in addition to the generic characterisation tests [11]. This section explains how to apply advanced DOE methods to combine the unique boundary conditions of each of the three use cases with the most effective testing processes [12]. The goal is to design test protocols that are not only accurate but also highly effective, allowing for the collection of data on degradation and longevity to occur more quickly.

5.1. Automotive Use Case

5.1.1. Objective

The primary objective of the automotive use case is to accurately assess and estimate the battery system's long-term durability, performance degradation, and lifetime under real-world driving and charging conditions. The process needs to be improved over the old, time-consuming ageing campaigns by employing an innovative, faster testing strategy that provides a wealth of data to validate the physics-based and data-driven models developed in WP3 and WP4.

5.1.2. Optimal Aging Test Procedure

The Worldwide Harmonised Light Vehicles Test Procedure (WLTP) is the basis for the ageing test. This ensures that it aligns with how vehicles are used in real life today. A comprehensive weekly itinerary that mimics a typical user's routine, including daily commutes and extended weekend trips, has been created to generate a complete and accelerated ageing profile. This routine will be followed until the battery reaches its End of Life (EOL), typically at 70–80% of its original capacity.

<u>The weekly ageing cycle has five working days (Monday to Friday) and an overnight charge that simulates charging at home.</u>

- **Morning Commute:** A 30-minute profile (To_work_profile) that includes city driving (based on WLTP) and highway travel (80–120 km).
- **Daytime Charge:** This feature makes it feel like you're charging at work.
- **Evening commute:** A 30-minute mirrored profile (From_work_profile) for the route back.
- **Evening Charge:** Makes you feel like you're charging at home again.

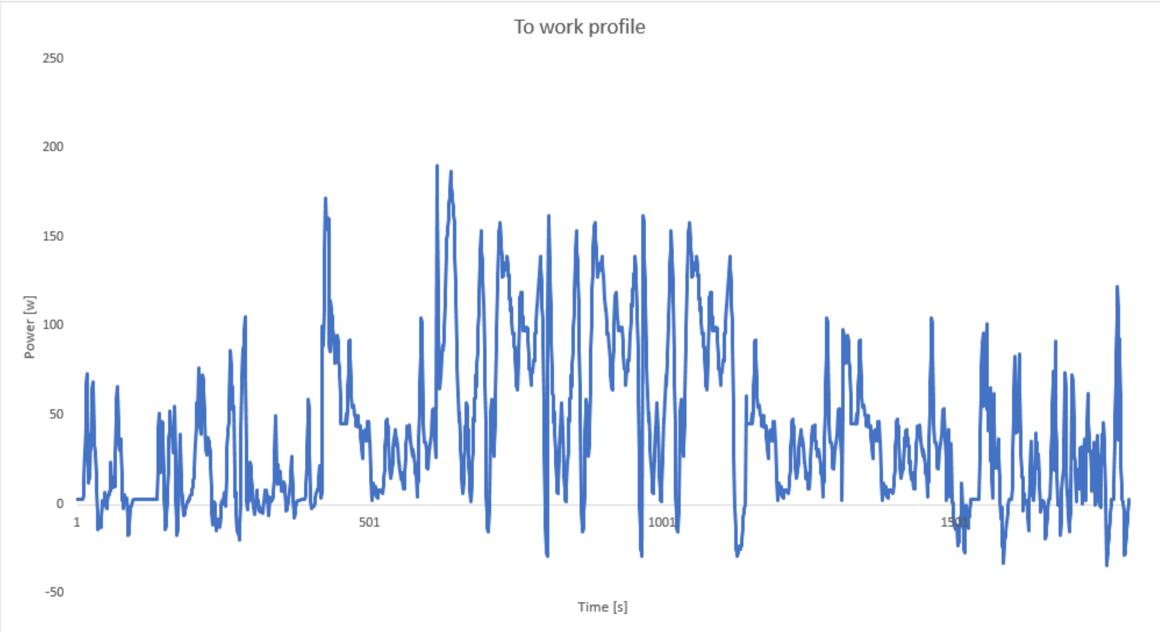

Figure 1 - Work profile cycle example

Weekend (Saturday and Sunday, once):

- **Long Trip with Fast Charge:** a multi-part trip that simulates a weekend break, including city and interstate driving phases and a fast-charging event in between.
- **A Brief Local Trip:** A 20-minute trip to the city is provided to demonstrate how people conduct errands in the area.
- **Return Trip with Quick Charge:** The return trip is the same as the outgoing trip, with a quick charge available before arriving home.
- **Final charge at home overnight**.

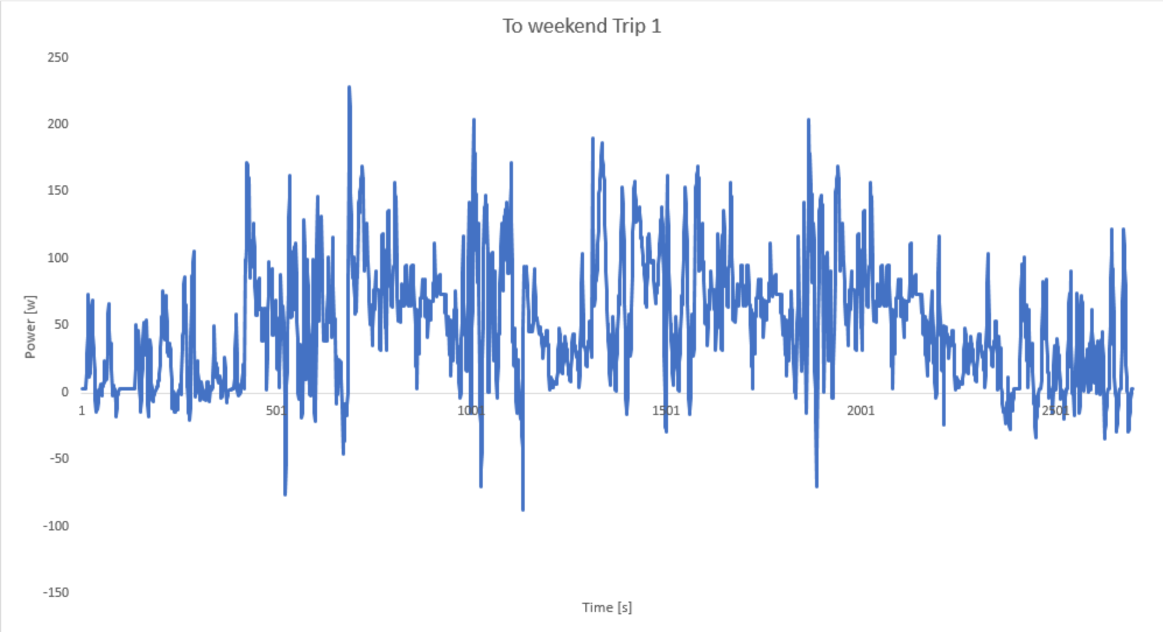

Figure 2 - Weekend cycle example

Tables 1 and 2 show a full schedule with start and end times.

Monday to Friday	Start time	End time
Charge at home	0:00	8:00
Going to work	8:00	8:30
Charge at work	8:30	17:30
Return from work	17:30	18:00
Charge at home	18:00	0:00

Table 1 - Working Days Schedule for Automotive Use Case Aging Test

Saturday	Start time	End time	Sunday	Start time	End time
Charge at home	0:00	8:00	Stay at Long Trip with Fast Charge	0:00	9:00

Long Trip with Fast Charge	8:00	12:00	A Brief Local Trip	9:00	9:20
Stay at Long Trip with Fast Charge	12:00	0:00	Stay A Brief Local Trip	9:20	15:20
			Return home	15:20	19:20
			Charge at home	19:20	0:00

Table 2 - Weekend Schedule for Automotive Use Case Aging Test

Periodic characterization tests (e.g., Capacity, HPPC) will be performed at set intervals (e.g., every 100 cycles) to track the degradation of key performance indicators.

5.1.3. Application of DOE for Optimization

We will use several DOE methods to make this testing process "smart" and "best":

1. **Model-Based DOE for Parameter Estimation:** The primary purpose of the ageing test is to obtain high-quality data for the parameterisation and validation of the advanced models from WP3 and WP4. A model-based DOE technique will be utilised instead of a fixed, pre-defined test matrix. We will use the Fisher Information Matrix (FIM) to assess the uniqueness of parameter identification for the test profiles we have. The FIM analysis helps identify the areas of the test cycle that provide the most information regarding specific deterioration parameters.

   $$FIM(U,\theta)=\frac{\partial f(U,\theta)}{\partial\theta}^{T}\frac{\partial f(U,\theta)}{\partial\theta}$$

   We ensure that the trials are set up to make the model parameters as straightforward as possible by optimising the test profile to achieve the highest determinant of the FIM (D-optimality). This lowers uncertainty and the need for repeated testing.

2. **The Response Surface Methodology (RSM):** Key stressors, such as air temperature and the use of auxiliary systems like air conditioning, have a significant impact on how quickly batteries age. We will use RSM to examine how these aspects impact things efficiently. Instead of testing at multiple temperature points, a CCD or similar device will be used to create a response surface. This will let us simulate how things age across a wide range of situations with fewer experiments.
3. **Physics-Informed Neural Networks (PINNs)[1]:** PINNs and PI-DeepONets will be examined as surrogate models to accelerate the DOE

[1] Raissi, M., Perdikaris, P., & Karniadakis, G. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear

process significantly. You can quickly forecast how a battery will act in different situations by training these networks on a mix of outputs from physics-based models and sparse physical test data. This makes it possible to perform the DOE optimisation cycle (like FIM optimisation) in milliseconds instead of hours. This enables a testing strategy that is genuinely dynamic and adaptive, where the next test point is chosen in near real-time based on all prior results.

5.1.4. Evaluation

This optimised testing process directly works towards the goal of lowering time and expense. The data is accurate because a thorough, realistic weekly cycle is used. Model-based DOE eliminates unnecessary experiments and focuses experimental effort on the circumstances that yield the most helpful information. The project's goal of reducing development time and costs by 20–30% is achieved by utilising DOE to create an accelerated ageing profile and replacing some physical tests with validated virtual models. This reduces the overall time to reach EOL in the lab significantly compared to simple calendar or cycle ageing tests. The process gives us the high-quality data we need to create and test the TRL6 hybrid testing platform.

5.2. Stationary Energy Storage Use Case

5.2.1. Objective

The primary goal of the stationary energy storage use case is to evaluate the performance and longevity of batteries in scenarios similar to those encountered in real-world grid applications. Because client needs and uses can be quite different, the testing process needs to be flexible and able to demonstrate multiple ways of working, such as stabilising the grid, reducing peaks, or integrating with renewable energy sources.

5.2.2. Optimal Aging Test Procedure

There is no single standardised test process for stationary storage systems, such as the WLTP, which is used for cars. For this use case, the ageing tests will be based on a normalised current profile derived from trustworthy industry standards and data sources.

---

partial differential equations. *Journal of Computational Physics*, *378*, 686-707. https://doi.org/10.1016/j.jcp.2018.10.045

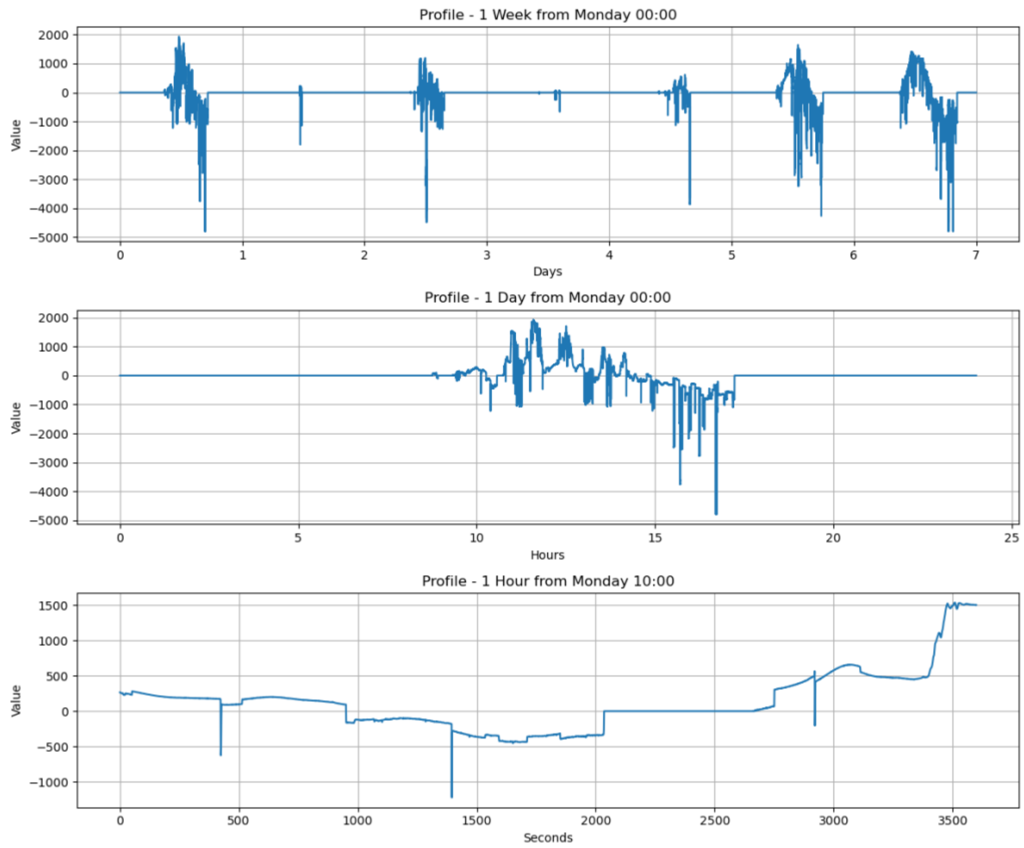

Figure 3 - Energy storage profile cycle example

The suggested method is as follows:

1. **Profile Design:** A 24-hour current profile will comprise several parts. This profile will have sections for critical stationary applications:
   - **Long-duration cycles:** This means storing renewable energy (such as solar) during the day and releasing it during the busiest hours of the evening.
   - **Intermittent, partial cycles:** These are similar to demand-response events or frequency regulation services, which involve quick, shallow charges and discharges.
   - **Moments when nothing happens (rest):** These are moments when nothing happens.

2. **Testing situations:**
   - **Temperature Variability:** Tests will be conducted at various temperatures to simulate how the storage system will be affected by different weather conditions.
   - **Cycling:** The 24-hour profile will keep repeating itself.
   - **EOL Criteria:** The EOL criterion isn't as strict as it is in the case of cars. A conventional benchmark is for capacity to drop to 70–80%; however, stationary applications may need various things. The test will keep going until there is a noticeable drop in performance. This lets you change things up based on the application being modelled.

3. **Periodic Characterisation:** Standard performance tests (Capacity, HPPC) will be conducted regularly to monitor how degradation changes over time.

5.2.3. Application of DOE for Optimization

To generate a normalised profile that is both accurate and useful, DOE methods are necessary:

1. **Screening Designs:** Initially, a factorial or screening design will be utilised to identify the most significant stress elements for stationary applications. The depth of discharge (DOD) of the long cycles, the frequency and amplitude of the partial cycles, and the average temperature could all be factors.
2. **Best Mixture Design:** The 24-hour profile can be thought of as a "mixture" of various work approaches. You can utilise DOE methods for mixing experiments to find the ideal amount of each type of cycle (long-duration, partial, rest) to include in the normalised profile, thereby best representing a target application or creating an ageing test that is typically harsh but realistic.
3. **Model-Based Optimisation:** As in the car scenario, the test technique will be used in conjunction with the physics-based models from WP3. We will use the FIM-based method to ensure that the profile we generate has sufficient information to appropriately set the parameters for degradation models specific to stationary use, such as those that account for calendar ageing during prolonged periods of rest and cycle ageing during active use.

5.2.4. Evaluation

Even without a global standard, this method lets you consistently and reliably test the endurance of batteries for stationary use. Using DOE to create the normalised current profile ensures that the test is focused on the most critical stress elements and doesn't waste time evaluating situations that aren't harmful. This specialised technique provides a more accurate assessment of how long these specific applications will last and accelerates the ageing process compared to simple, repetitive cycling. This helps reduce development time and costs. The method can be applied in various ways to cater to the diverse needs of customers in the stationary storage sector.

5.3. Off-Road Mobile Devices Use Case

5.3.1. Objective

The primary objective of the off-road use case is to deliver a personalised ageing protocol that leverages the application's predictable usage patterns to accurately and efficiently predict the battery's lifespan. The primary focus is on industrial equipment, such as Laser-Guided Vehicles (LGVs) and Automated Guided Vehicles (AGVs), which often have regular and repetitive work cycles.

5.3.2. Optimal Aging Test Procedure

There is no one standard protocol for off-road devices, just like there isn't one for fixed storage. The main difference, though, is that the scenarios are very predictable, which makes the ageing test easier to understand and more accurate.

The suggested test method is based on usage statistics and has the following:

1. **Current Profile:** The profile features constant-current charge and discharge cycles that switch back and forth regularly, much like an AGV starts and stops, charges, and operates. Figure 1 shows an example of a load profile.

Figure 1 shows an example load profile for a big off-road mobile device.

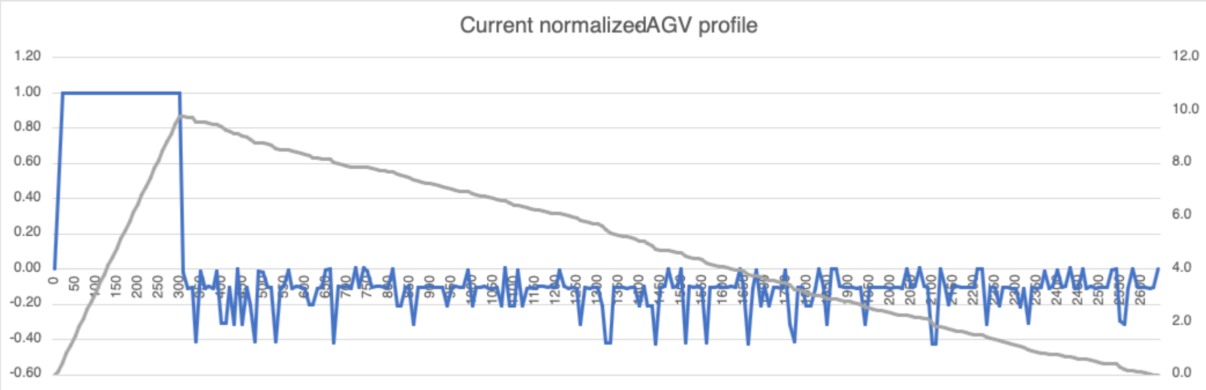

Figure 4 - AGV cycle profile example

2. **The conditions for testing:**
   - **Small SOC Window:** One crucial aspect of these AGVs is that they typically only work within a minimal SOC range, usually between 70% and 80% SOC, to maximise their cycle life.
   - **Temperature Variability:** The temperature changes are fewer than in cars, as the system operates in regulated indoor situations that are easy to forecast. The test will examine a range that is u. seful but not too wide, such as 25°C to 35°C.
3. **EOL Criteria:** The EOL criteria are based on the standard IEC 62620:2014, which stipulates that after 500 cycles, the battery should still retain 60% of its rated capacity and its internal resistance should be less than twice its initial value after 2000 cycles.

5.3.3. Application of DOE for Optimization

Even with a simple, repeating cycle, DOE is quite important for making the test as accurate and efficient as possible:

1. **Factorial Design:** A factorial design will be employed to investigate the impact of key parameters on lifetime in a controlled manner within a limited range of operations. The factors will be the exact SOC window (for example, 70–80% vs. 65–75%), the C-rate of charge and discharge, and the room temperature.
2. **RSM for Lifetime Modelling:** The results of the factorial experiment will be utilised to create a Response Surface Model (RSM) that shows how these factors affect battery life. This model will enable the quick forecasting of the lifetime of any set of conditions within the tested range. This will reduce the need for lengthy physical tests for each new variant of the usage profile.
3. **Model-Based Acceleration:** The experimental data will be utilised to set the parameters and check the ageing models from WP3. Once the models have been checked, they can be used to anticipate degradation far beyond the cycles

that were tested. This significantly speeds up the process of determining when the EOL criterion will be satisfied.

5.3.4. Evaluation

By leveraging the specific and predictable characteristics of the off-road use case, this method creates a highly effective and tailored testing regimen. The approach utilises DOE to accurately estimate how critical elements affect the specific operational window, thereby reducing the number of physical tests that need to be conducted. The FASTEST project's primary goals are fulfilled by using a combination of targeted physical testing and verified virtual models to quickly and cost-effectively certify battery lifetime against industry standards, such as IEC 62620:2014.

6. Integration into the FASTEST Hybrid Testing Platform

The best testing processes for this deliverable are not meant to be done alone. They are essential components of the entire hybrid testing platform being developed in WP6. For these procedures to be effective, they must integrate well with the other key technologies in the FASTEST project.

- **The LIMS (Laboratory Inventory Management System)** is the central part of the WP6 platform that will handle the running of various test processes. It will handle scheduling tests, assigning resources (both physical and virtual test benches), and maintaining a record of all test-related data and settings.
- **Digital Twin (WP5):** A digital twin will be created for each Unit Under Test (UUT), serving as the primary source of information. Before a test starts, the LIMS will retrieve all the necessary information from the DT, including the battery's history, its current state, and relevant virtual models. As the tests are run, all new data, whether it comes from real-life measurements or virtual simulations, will be given back to the DT. This will continue to add to the virtual model of the battery.
- **Virtual Benches (WP3 and WP4):** The methods depend on tests being virtualised. The strategy controlled by the DOE will dynamically choose whether a particular test point should be done on a physical bench or a virtual bench (by executing the verified models from WP3 and WP4). This sensible mix of real and virtual testing is the best way to save money and time.
- **Automatic Task Distribution (WP2 & WP6):** The DOE methods for each use case will be turned into a "smart algorithm service" that works with the LIMS. This service will assess the test requirements and the current state of the models (through the DT) to automatically create the optimal test plan, ensuring that tasks are distributed evenly across the available physical and virtual resources.

The platform's design enables you to utilise advanced resource optimisation strategies, helping you strike a balance between goals such as reducing costs, enhancing testing accuracy, using resources more efficiently, and maximising your time. Real-time decision algorithms consider the advantages and disadvantages of both physical and virtual testing at every stage of the experiment. They consider factors such as their level of certainty about the model, the amount of information they anticipate receiving, the resources available to them, and the cost of each choice. This dynamic optimisation ensures that physical testing resources are only used on experiments that are worth a significant amount of money when virtual models are uncertain. Virtual execution makes it easy and quick to do routine tests.

When you combine data from different parts of the platform, you obtain comprehensive datasets that can be utilised for both short-term testing decisions and long-term tasks, such as building and testing models. The platform keeps a record of all past data. This illustrates the process by which the data is transformed from raw sensor readings to processed and analysed data, and then to the final test results and model updates. Advanced data analytics tools identify patterns and trends that facilitate both short-term testing optimisation and long-term strategic decisions regarding how to prioritise model development and testing methods.

The platform consists of various components, making it easy to add or remove features at different testing sites and utilise the existing testing infrastructure. You can modify existing facilities or add new testing capabilities to them. If the software systems and testing tools from different companies have standardised interfaces, you can use them together. Cloud-based parts enable you to do more with features like testing and analysing data. You can change the platform to fit the needs of different organisations, but you can still use the same testing methods and data quality standards.

6. Validation and Performance Metrics

The validation framework for the FASTEST testing platform features multiple levels of testing to ensure that the methods created meet both technical performance standards and the requirements of real-world deployment. By verifying the accuracy of each model and the precision of parameter identification, component-level validation ensures that each part of the testing system functions correctly and reliably. It achieves this by employing statistical methods, such as cross-validation with separate datasets, parameter sensitivity analysis, uncertainty quantification, and significance testing for model parameters.

System-level validation checks how well the entire platform functions from start to finish. It achieves this by employing various methods, including comparison studies that demonstrate the effectiveness of hybrid testing methods, and real-world application case studies that compare laboratory predictions with field data. Long-term performance monitoring continually assesses the effectiveness of testing methods and seeks ways to enhance both the speed and accuracy of testing.

Key Performance Indicators (KPIs) are metrics that measure the effectiveness of a platform in various areas. Efficiency metrics aim to reduce testing time by 30–40% compared to traditional methods. They employ detailed measurement methods that separate physical test time from virtual simulation time, taking into account quality factors to ensure that accuracy is maintained or improved while reducing testing time. A comprehensive review of the costs of equipment, staff time, consumables, and infrastructure is necessary to achieve a 20% to 30% cost reduction. We accomplish this by examining the cost of creating a platform and the savings it generates when people utilise it more effectively.

Some of the goals for making better use of resources are to schedule and allocate resources so that physical test equipment is used more than 80% of the time, to have virtual test capacity that can support more than 1,000 parallel simulations, to use less than 50% of the energy that regular testing uses, and to automate more than 90% of the routine test execution tasks. These metrics ensure that the platform enables faster testing while maintaining high-quality standards and allowing more tests to run concurrently.

Quality metrics assess the accuracy and precision requirements that ensure the platform delivers results that can be trusted and used to inform business deployment decisions. In all cases, model prediction accuracy targets need to be at least 95% correlated with physical test results. On the other hand, the uncertainties for critical degradation parameters must be less than 5% for accurate parameter estimation. Repeatability standards state that tests performed again should not differ by more than 2%. Tests done in different labs using the same method should not vary by more than 5%, according to the rules for reproducibility.

Metrics for reliability and robustness ensure that the platform works consistently and reliably, making it suitable for business use. System uptime goals say that the system should be available more than 99% of the time during business hours. With fault tolerance, the system can fix itself for more than 95% of problems. Data integrity requirements ensure that all data is kept safe and that the testing process can be fully tracked. Robustness standards demonstrate that the system performs effectively with various types of tests and equipment.

Benchmarking studies confirm platform performance by comparing it to standard testing methods using the same battery samples, employing statistical analysis to measure the improvements made by hybrid testing methods, and conducting a comprehensive analysis of the time and cost required to obtain the same information. Industry benchmarking involves collaborating with top battery testing labs, participating in round-robin testing programs, and comparing performance to commercial testing solutions to identify further improvements and demonstrate competitive advantages.

Case study validation programs demonstrate the effectiveness of a platform in the real world by collaborating with automotive OEMs to compare fleet testing data, utility companies to conduct field demonstration projects with stationary storage, and industrial equipment manufacturers to assess the operational environment. These case studies demonstrate that predictions made in the lab are accurate when compared to real-world applications, that economic models are accurate when evaluated against operational cost data, and that processes for verifying compliance with regulations are effective for commercial deployment.

The whole validation framework ensures that the FASTEST platform makes testing faster and more effective in measurable ways, while still being accurate and dependable enough for use in commercial battery development. The methods we developed will help accelerate the development and application of batteries in various situations, as they have been tested in real-world scenarios and from both economic and technical perspectives.

7. Conclusion

This deliverable has successfully created thorough best practices for testing battery systems in cars, stationary energy storage, and off-road settings. This represents a significant step forward in battery research and development, addressing some of the most pressing challenges currently faced by the battery industry. The work shown here takes theoretical DOE principles and use-case requirements from D2.1 and turns them into real-world testing protocols that are the basis for the FASTEST hybrid testing platform. This demonstrates how new digital technologies can be integrated with advanced experimental design to transform the way batteries are tested.

The testing protocols that were developed successfully combine advanced DOE methods, such as Fisher Information Matrix analysis, Response Surface Methodology, and Physics-Informed Neural Networks, to create innovative, flexible testing strategies that gather the most information while using the least amount of time and money. The full weekly ageing cycle, based on WLTP standards, provides realistic yet sped-up testing scenarios for cars that consider modern charging infrastructure capabilities, various usage patterns, and environmental changes, all while meeting regulatory requirements. The stationary energy storage method addresses the issues with grid service applications by utilising normalised current profiles to illustrate the unpredictability of grid demands and by regularly testing battery performance in various grid integration scenarios.

The off-road application protocol leverages the predictability of industrial use patterns to develop testing procedures that are highly effective for both equipment manufacturers and operators. This demonstrates how specific features of a use case can be leveraged to maximise testing coverage without compromising accuracy or reliability. Combining digital twin technology with model-based experimental design represents a significant step away from traditional empirical testing methods and toward intelligent, predictive testing methods that improve with experience, allowing testing resources to be utilised more efficiently in real-time.

The entire validation framework ensures that the results of virtual testing remain sufficient for applications where safety is crucial. It also meets the goal of reducing development time and costs by 20–30% compared to traditional testing methods. The hierarchical testing framework does a good job of linking characterising components at the component level with validating the whole system. It maintains accuracy and relevance at all levels of the system hierarchy while ensuring that parameters flow smoothly across testing scales.

The advanced DOE implementation enables you to efficiently explore multidimensional parameter spaces while reducing the work required for experiments by intelligently designing them to focus resources on operating conditions that yield the most information. When you combine machine learning with traditional electrochemical modelling, you can make better predictions and improve models over time with real-world data. This helps both in improving tests in the short term and in planning how to improve them in the long term.

The testing protocols were designed with clear goals in mind for industrial use, adhering to established rules, and allowing for growth in size for commercial applications. This means that the methods created can be effectively applied in various types of organisations without compromising the quality and consistency of the tests. The framework is compatible with multiple battery chemistries and applications, and it continues to meet current standards and certification processes. This means that it is possible to add new testing capabilities to existing testing facilities or build new ones.

The economic analysis shows that early adopters will benefit. It also demonstrates how technology transfer programs, standardisation activities, and collaborative development initiatives can contribute to the industry's overall transformation. The established testing protocols provide the FASTEST hybrid testing platform with a strong foundation for further development and validation in subsequent work packages. The platform has a modular design and standardised interfaces, which means that new battery technologies and applications can be added in the future.

Working with businesses and government agencies ensures that the methods created are helpful and can be applied more quickly. The thorough documentation and validation process also helps with both quick implementation and longer-term standardisation efforts. With these improved protocols, the FASTEST project is well-positioned to achieve its significant goals of transforming how batteries are tested. By taking a complete approach to creating, testing, and combining testing methods, it will do this. This will make battery systems that are more reliable, safer, and last longer.

D2.2 represents a significant advancement in the field of battery testing. It sets the stage for new research and development methods that will accelerate the creation of more efficient energy storage solutions for a carbon-neutral future. By utilising advanced experimental design, digital twin technology, and intelligent resource optimisation to their fullest extent, new avenues for accelerating battery development can be explored while maintaining the accuracy and reliability required for safety-critical commercial use.

REFERENCES

[1] International Organization for Standardization. (2020). Road vehicles — Safety requirements for traction batteries (ISO 6469-1:2019). ISO.
[2] Underwriters Laboratories. (2021). Standard for safety for batteries for use in electric vehicles (UL 2580). UL Standards.
[3] Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. Nature Reviews Physics, 3(6), 422-440. https://doi.org/10.1038/s42254-021-00314-5
[4] Tutuianu, M., Bonnel, P., Ciuffo, B., Haniu, T., Ichikawa, N., Marotta, A., ... & Steven, H. (2015). Development of the World-wide harmonized Light duty Test Cycle (WLTC) and a possible pathway for its introduction in the European legislation. Transportation Research Part D, 40, 61-75. https://doi.org/10.1016/j.trd.2015.07.011
[5] Mongird, K., Viswanathan, V., Balducci, P., Alam, J., Fotedar, V., Koritarov, V., & Hadjerioua, B. (2020). An evaluation of energy storage cost and performance characteristics. Pacific Northwest National Laboratory. https://doi.org/10.2172/1573487
[6] Hannan, M. A., Hoque, M. M., Hussain, A., Yusof, Y., & Ker, P. J. (2018). State-of-the-art and energy management system of lithium-ion batteries in electric vehicle applications: Issues and recommendations. IEEE Access, 6, 19362-19378. https://doi.org/10.1109/ACCESS.2018.2817655
[7] Román-Ramirez, L., & Marco, J. (2022). Design of experiments applied to lithium-ion batteries: A literature review. Applied Energy, 320, 119305. https://doi.org/10.1016/j.apenergy.2022.119305
[8] Prochazka, Wenzel & Pregartner, Gudrun & Cifrain, Martin. (2013). Design-of-Experiment and Statistical Modeling of a Large Scale Aging Experiment for Two Popular Lithium Ion Cell Chemistries. Journal of the Electrochemical Society. 160. A1039-A1051. 10.1149/2.003308jes.
[9] Montgomery, D. C. (2017). Design and analysis of experiments (9th ed.). John Wiley & Sons.
[10] Franceschini, G., & Macchietto, S. (2008). Model-based design of experiments for parameter precision: State of the art. Chemical Engineering Science, 63(19), 4846-4872. https://doi.org/10.1016/j.ces.2007.11.034
[11] Tao, F., Zhang, H., Liu, A., & Nee, A. Y. (2019). Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics, 15(4), 2405-2415. https://doi.org/10.1109/TII.2018.2873186
[12] Park, Saehong & Kato, Dylan & Gima, Zach & Klein, Reinhardt & Moura, Scott. (2018). Optimal Experimental Design for Parameterization of an Electrochemical Lithium-Ion Battery Model. Journal of The Electrochemical Society. 165. A1309-A1323. 10.1149/2.0421807jes.