Deliverable D2.11

Health analysis results and 2nd life battery description

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Feasible Recovery of critical raw materials through a new circular Ecosystem for a Li-Ion Battery cross-value chain in Europe

WP2 - End-of-life LIBs Collection and Characterisation, Digital Tools and Battery Passports deployment

D2.11- Health analysis results and 2nd life battery description

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Contents

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List of Abbreviations

ACRONYMS	DESCRIPTION
SoH	State of Health
SoC	State of Charge
BESS	Battery Energy Storage System
BMS	Battery Management System
EV	Electric Vehicle
EoL	End of Life
DVA	Differential Voltage Analysis
DTV	Differential Thermal Analysis
ICA	Incremental Capacity Analysis
OEM	Original Equipment Manufacturer
IR	Internal Resistance
RUL	Remained Useful Life
RPT	Reference Performance Test (RPT)

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1. Introduction to this document

This deliverable includes the activities that have been carried out within task 2.5 “Advanced SoH assessment and 2nd life assembly” regarding 3 main different aspects:

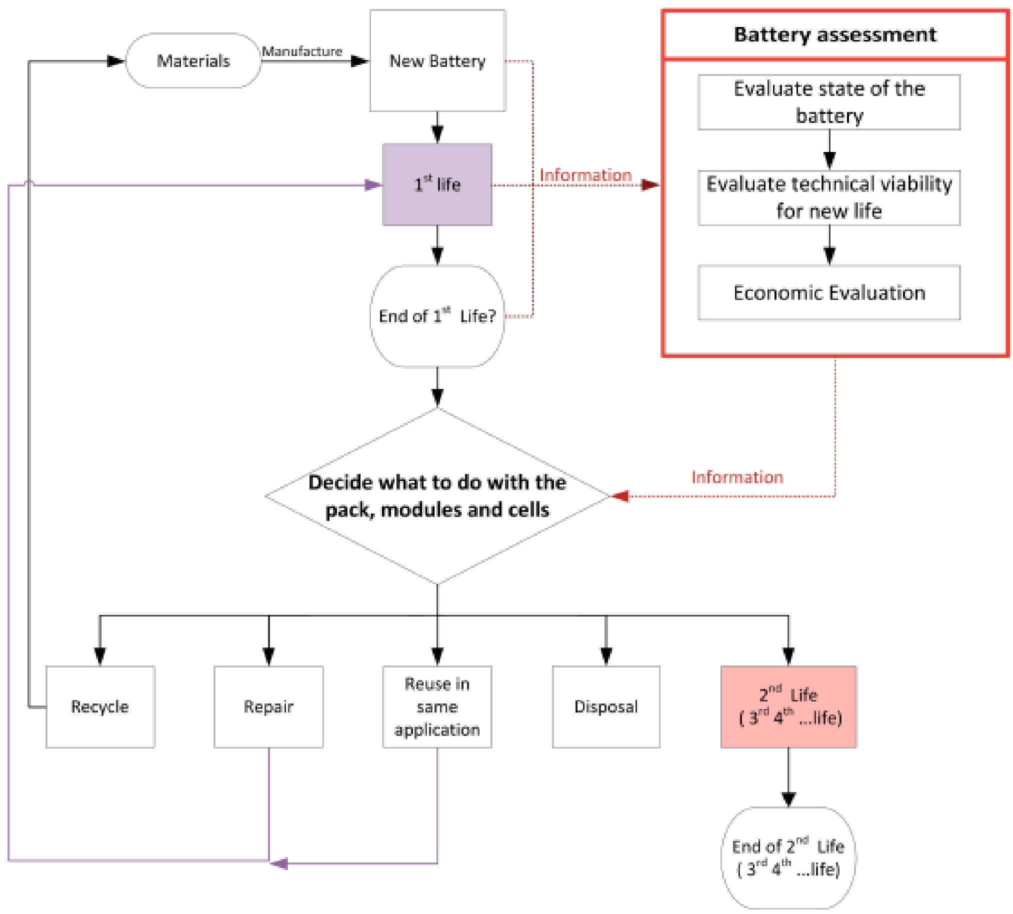
- Methodology identification and development of an assessment model to evaluate the State of Health (SoH) of batteries.
- Design and manufacturing of a second life battery storage system (BESS) for stationary applications using eco-design principles;
- Development of the Battery Management System for the 2nd life battery (BMS).

The work that has been done for these activities is reported in this deliverable that has been structured following the objectives of the task above reported.

2. Analysis of State of Health (SoH) assessment methodologies and implementation plan

2.1 Introduction

Electric vehicles are gradually replacing fuel vehicles to reach the target of energy conservation and emission reduction, which benefits from the policy support of the governments and the enhancement of the public environmental awareness in recent years. Lithium-ion battery has the characteristics of high cost performance, high energy and power density and long life, so one of its important application scenarios is electric vehicles. Upon End-of-Life lithium-ion battery pack dismantling from transportation and micro mobility vehicles to module level require extensive safety inspections and standard procedures to estimate the possibility for second life applications. The capacity of in-car batteries begins to decline with the use of electric vehicles. The End of life in the EV is reached when the battery capacity or power are not longer suitable for the user demand due to the battery ageing. Although the capacity of retired batteries has decreased, their remaining capacity can still play a great role in energy storage, such as reserve power supply of the park, renewable energy storage, stability of power grid, elimination of power supply and demand fluctuations . State of health (SOH) is an important index to evaluate the use value of batteries. The rapid SOH evaluation method for battery modules is a more popular topic in the secondary utilization of retired batteries. **Capacity test** is one of the most popular tests used to determine the remaining total capacity. While this test shows the remaining capacity, it misses to give insights on cell balance mechanisms and can't meet the requirements of large scale testing. SOH is a key parameter indicating the level of degradation and remaining performance, efficiency, and reliability levels of the battery module. In this document different SOH measurement techniques are compared to find a fitting solution for EV second-life battery module SOH observation. In general, methods of health factor analysis include the analysis of internal resistance and open circuit voltage range , incremental capacity analysis (ICA or dQ/dV analysis), differential voltage analysis (DVA), differential thermal analysis (DTV) , and sample entropy.



(Montes, T.; Etxandi-Santolaya, M.; Eichman, J.; Ferreira, V.J.; Trilla, L.; Corchero, C. Procedure for Assessing the Suitability of Battery Second Life Applications after EV First Life. Batteries 2022, 8, 122. https://doi.org/10.3390/batteries8090122)

- Factors
- Test Speed;
- Reliability/Accuracy;
- Cost and Cost of implementation and cost per module.

Explanation: We are thinking that some possible methods may need some training data with similar batteries which has an associated cost

- Development Time;

Amount of training data needed. Explanation: In case is needed some training data on similar batteries

- Safety;
- Ease of Implementation/Training time;
- Data outputs, (SOH, IR, RUL, electrical and thermal modeling, the safety of the cells/module)
- Ease of automatization and configuration;

Methodology suitability at different pack, module, or cell level.

- Need information on battery first life and specification sheet.

Explanation; We think that some information about the first life can ease a lot the process, for example, the number of cycles in 1st life, the years of the battery, or even the SOH indicator evolution.

- Degradation impact
    - Impact of the test on the RUL of the battery: it is worth mentioning if the SOH methodology degrades the battery.

Traditional assessment. We should be able to establish the traditional procedure (Complete charge and discharge) for the capacity analysis and maybe also some pulses or HPPC to characterize

- Fast assessment via some Health indicators (ICA, DV/DT, some EIS). With these, I see two options:

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- Obtain data with some cell tests but we would need to age them during long periods of time to see how the indicator that we select evolves with the degradation of the cell and train the model.
- Obtain data about health indicators while we perform the traditional assessment of second-life modules. Training a model with the data will be obtained. In the beginning, the SOH assessment will be slow but it would increment the speed with more tests performed.
- Hybrid solution. Age some cells, obtain health indicators, test modules at the beginning with the traditional assessment, check if the model works with the data trained, and use the data of the second life modules assessment to keep training the model for future modules.

The main issue with the training is that, as it says in the task, we are going to test 5 different modules. This complicates the training as we will need more data and If it is possible, from the same cells of the modules that we are going to assess. If not, at least the same chemistry and similar capacity. There are some other open sources of data that we can also explore if it is needed like https://www.batteryarchive.org/.

2.2 Methodologies

2.2.1 Incremental capacity analysis

There are multiple capacity testers available on the market with such capabilities. Based on a thorough market analysis, it has been found that the top suppliers of these devices are ARBIN Instruments (ARBIN, 2022) and CHROMA Systems Solutions (CHROMA, 2022). ARBIN Instruments is known for its high quality while CHROMA is known for being more affordable, but user-friendly. Despite being highly safe testing equipment requiring no development time for implementation, these devices are expensive and, apart from offering multi-channel testing capability, they do not increase testing speed. Researchers have developed ways to increase the testing speed of capacity testing through modelling (equivalent circuit models, or ECMs), incremental capacity analysis methods, and machine learning algorithms (Li et al., 2018; Yao et al., 2021). A developer (Mahdi) has built on this research to offer 1-hour

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partial-cycle capacity testing. However, this would involve purchasing third-party data and long development times of 6+ months for data filtering, model building, and algorithm training.

$$SOH(\%) = \frac{C}{C_N} \cdot 100$$

Table 1 ICA or dQ/dV analysis

Test Speed	Reliability/Accuracy	Cost equipment and per module	Development Time	Information on battery/cell first life and specification sheet.
5	8	5	3	6

2.2.2 Impedance testing

Alternative solutions involve moving away from capacity testing, entirely. One such solution is the rapid impedance tool using an impedance measurement device such as the Battery HiTester BT3562 supplied by HIOKI E.E. Corporation (HIOKI, 2021). This device would enable impedance measurements over a range of frequencies. As a result, impedance versus frequency curves, or Nyquist plots, for batteries with different State of Health levels can be obtained through a relatively short and straightforward data collection stage. These curves can be used to estimate the State of Health of batteries through a rapid impedance measurement using a few selected frequency points and data fitting with the existing Nyquist plots.

Table 2 Rapid Impedance tool measurements

Test Speed	Reliability/Accuracy	Cost equipment and per module	Development Time	Information on battery/cell first life and specification sheet.
10	8	3	8	8

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2.2.3 IR testing

Similarly, DC internal resistance (1 kHz impedance) and open circuit voltage tests can be done rapidly and at a very low cost using a standard voltmeter or digital multi-meter. During the development stage, DC resistance and open circuit voltages are measured at different points during the cycling of batteries with different known State of Health. As a result, DC resistance and open circuit voltage versus State of Charge curves for different State of Health levels are obtained. By measuring the DC resistance and open circuit voltage at a known State of Charge, the data can be fitted to the existing curves and State of Health can be estimated. However, the accuracy and reliability of this method would be very low. For example, the difference between the DC internal resistance for the 200-cycle curve and the 400-cycle curve is very small, as shown in Figure 1 below. Say the 200-cycle curve is equivalent to 90% State of Health and the 400-cycle curve to 80% State of Health, an error margin of 10% in State of Health estimation is unsatisfactory.

Table 3 IR testing

Test Speed	Reliability/Accuracy	Cost equipment and per module	Development Time	Information on battery/cell first life and specsheet
5	8	5	3	6

2.2.4 Machine Learning method

A major area of interest for battery management system, BMS, developers is battery modelling for real-time battery state (i.e., State of Health, State of Power, State of Charge) diagnostics and Remaining Useful Life (RUL) predictions. For Watt4Ever, knowing the State of Health already available would enable automatic characterisation of battery modules and eliminate the need for testing entirely. Multiple methodologies have been considered by researchers and BMS developers based on modelling and machine learning, or a combination of both (Noura et al., 2020; Yao et al., 2021).

However, the factors hindering its availability for users and the battery reuse/repurposing industry include:

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- Stochastic operation of the battery during use in a vehicle: resulting in non-linear degradation and making it difficult to create an appropriate model and machine learning algorithm that is comparable to real-life conditions.
- Lack of availability of historical datasets (such as the temperature profile, cycle history, and charge history) from the BMS.
- Lack of standardization concerning parameter monitoring by BMS among battery producers and BMS developers.
- Lack of standardization concerning the format and timestamps at which the parameters are monitored, and the data is stored, thus complicating data extraction and analysis.

Table 4 Machine Learning tools

Test Speed	Reliability/Accuracy	Cost equipment and per module	Development Time	Information on battery/cell first life and specification sheet.
8	7	3	10	10

2.3 Ultrasounds testing

The changes in guided wave signal features provide an indication of the physical processes during a charge-discharge cycle, which can be directly correlated with battery SoC. Guided wave ToF and SA reveal the progression of the electrode modulus and density distribution as a result of the intertwined electrochemical-mechanical coupling. Besides SoC, the guided wave measurements are also able to uncover the underlying electrochemical signature, e.g., intercalation staging and phase transitioning.

Alternative to BMS data analytics, the final method discussed in this article is a technique using ultrasound. Ultrasound at high frequencies (above 20 kHz) can measure the State of Health of batteries at the molecular level accurately, non-invasively, and very rapidly (TitanAES, 2021b). Ultrasound is highly effective at characterizing battery ageing by revealing material changes and detecting the growth of the secondary solid electrolyte interface, or SSEI

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(TitanAES, 2021b). Titan Advanced Energy Solutions offer the Scorpion as a rapid diagnostics tool for End-of-Life battery characterisation (TitanAES, 2021a). The Scorpion estimates State of Health in less than 10 seconds at 99% accuracy (TitanAES, 2021a). This high accuracy is maintained until the 35% SoH mark, when the battery is no longer usable anyway (TitanAES, 2021b). It is available through a leasing agreement of about 8 EUR/kWh (based on type of module to be tested using the device) so no capital expenditure and no installation costs (TitanAES, 2021a). The Scorpion device is designed for the modules to be tested with it, requiring client collaboration to identify the exact client's needs. Cylindrical battery types are not suitable for the Scorpion device.

Table 5 Ultrasounds testings

Test Speed	Reliability/Accuracy	Cost equipment and per module	Development Time	Information on battery/cell first life and specification sheet.
9	9	9	5	8

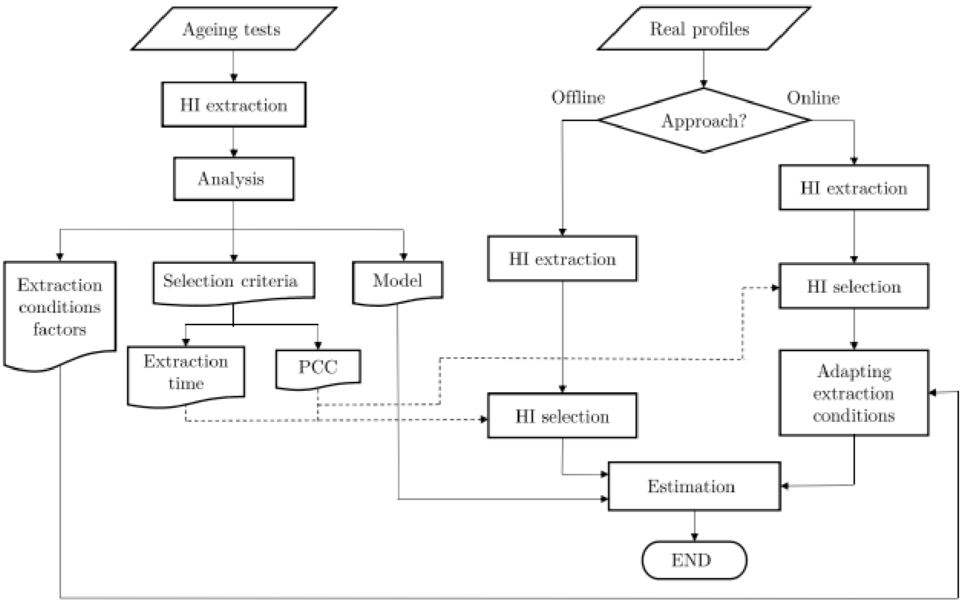

Fig. 2. Flowchart of the SOH estimation method for real profiles.

Figure 1 Flowchart of the SoH estimation for real profiles

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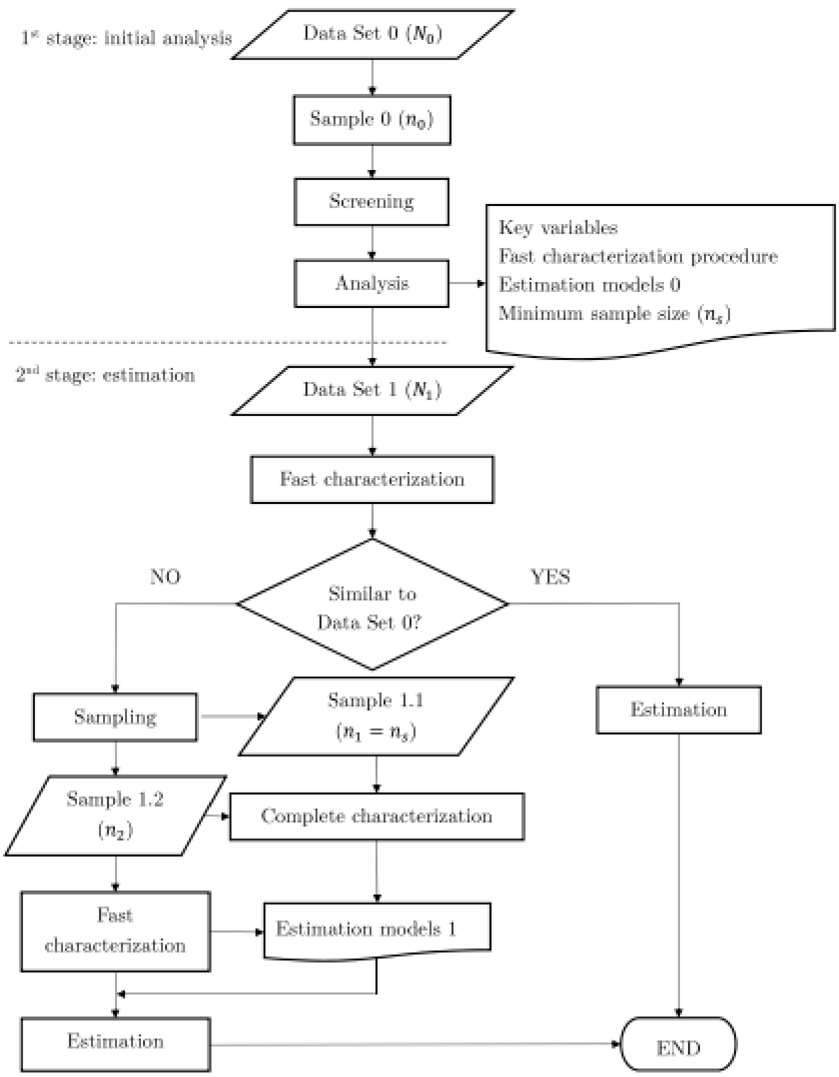

Figure 2 SoH analysis flowchart

(Fast capacity and internal resistance estimation method for second-life batteries from electric vehicles Elisa Braco, Idoia San Martín, Pablo Sanchis, Alfredo Ursúa ∗ Institute of Smart Cities (ISC), Department of Electrical, Electronic and Communications Engineering, Public University of Navarre (UPNA), Campus de Arrosadía, 31006, Pamplona, Spain)

$$SOH = \frac{Q_m}{Q_r} \times 100\%$$

SOH is one of the important parameters of lithium-ion batteries, which is calibrated according to the change of battery capacity, as follows: SOH = Qm Qr × 100% (1) where: Qr—rated capacity and Qm—current maximum available capacity of the battery, which is measured under rated conditions [26–28]. Due to the influence of temperature and measurement current multiplier, SOH

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values also vary significantly [29–31]. To ensure the performance requirements of lithium-ion batteries, IEEE standard 1188.1996 clearly states that when the battery SOH is less than 80%, it indicates that the end of life has been reached and the battery needs to be replaced [32–34].

SOH is defined according to the internal resistance of the battery as follows: SOH = Re − R/ Re − Rn × 100% (2) where: R—internal resistance under the current state; Re—internal resistance of the battery when it reaches the end of life; and Rn—internal resistance of the new battery. Many scholars define battery SOH by internal resistance or estimate and predict SOH based on internal resistance of the battery [35–37]. The increase of internal resistance is also an important indicator of battery aging, and it is also one of the reasons for the further decline of battery SOH.

.2.3. The Definition of Capacity Contained in the Electrode With the use of lithium batteries, lithium ions will move along with the charge transfer. According to the electrochemical reaction mechanism of the electrode, the SOH of lithium batteries can be evaluated by the concentration of lithium ions in the electrode [38]. In the ideal state, SOH can be expressed as: SOH = Q Q0 × 100% (3) World Electr. Veh. J. 2021, 12, 113 5 of 23 where: Q—nominal capacity and Q0—smaller lithium concentration after multiple cycles.

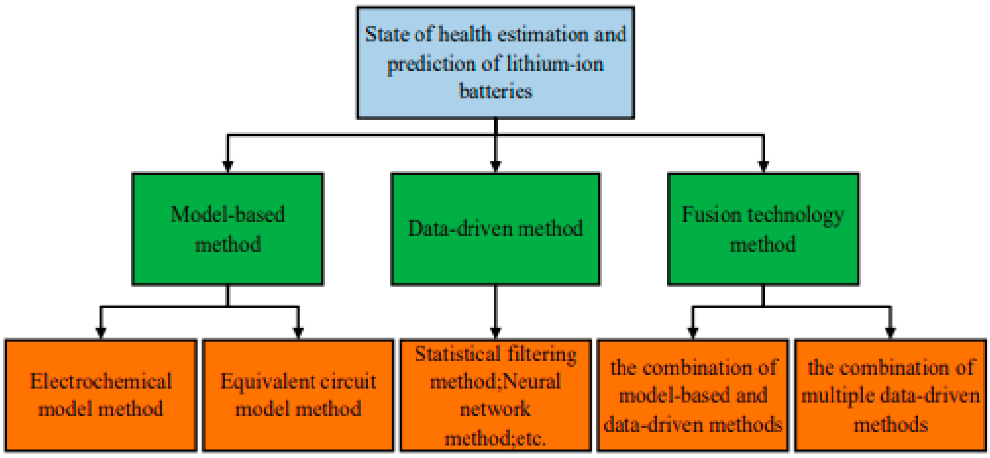

Figure 2. Algorithm classification structure.

3.1. Model-Based Method

Figure 3 Algorithm classification structure

Table 6 Algorlithm classification outputs

	Test Speed (H-L)	Reliability Accuracy (L-H)	Cost equipm ent and per module (H-L)	Development Time struggle (H-L)	Information on battery/ cell first life and specification sheet. (H-L)	AVG
ICA	2	4	2	3	3	14
IMP	4	3	2	2	2	13
IR	4	2	2	2	2	12
Batt Pass	4	3	1	3	1	12
Ultrasound	4	2	1	2	4	13

2.4 Conclusion

By comparing the assigned criterias, we find that ICA method shows the best results in multicritearia analysis. This is also one of the most popular methods used in testing the batteries by OEM and 2nd integrators. Also, most of the research work on rapid SOH testing has used some form of ICA as part of their thesis.

It has been very hard to find any research on module level rapid testing with cell monitoring. Cell SOH and balance is a important topic that has little to no research regarding the connection possibilities and monitoring, we that is an important topic that should be discovered.

Recomendation based on findings

We recommend to develop the SOH testing Methodology in a hybrid manner . First modules tested in slow manner with ICA tested 3 cycle CC attached to impedence meter that logs impedence values and cell values. Then move forward with fast just using the impedence meter and comparing the values.

identify a state of health testing methodology particularly suited for the ev battery module reuse business case and create an implementation plan and evaluation protocol

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3. SoH evaluation tool

After conducting a thorough review of existing literature, IREC has developed a procedural framework for the implementation of the Fast State of Health (SOH) assessment tool, as depicted in the **¡Error! No se encuentra el origen de la referencia.**. This procedure involves two SOH assessments: the traditional method, which includes a full charge and discharge to determine actual capacity, and the Fast SOH assessment, which entails a brief 10-second charge pulse, from which pertinent features are extracted and utilized as inputs for a pre-trained machine learning SOH model.

The Fast SOH assessment can be applied when there is sufficient training data available for a specific battery type. In instances where such data is lacking, only the traditional SOH assessment method can be employed. To gather the necessary training data, two primary approaches have been identified: either gathering data concurrently during the execution of traditional SOH assessments on modules or conducting targeted tests on cells or modules to accumulate training data.

In determining the most appropriate algorithm, IREC conducted tests utilizing four cells and a module sourced from a retired Hyundai Kona battery pack. Two predictive models, Feedforward Neural Networks and Extra Tree Regressor, are proposed and evaluated at both the cell and module levels. Both models demonstrate high accuracy in predicting State of Health, yielding Mean Absolute Percentage Errors lower than 1.75% at the cell level and 2.42% at the module level. Experimental measurements from retired batteries are utilized for the training and testing of these models and the models use three features: initial voltage, temperature, and internal resistance measured after a 10-second charge pulse

By employing the proposed method, the time required for testing and the cost of assessing batteries at their end of life are significantly reduced compared to traditional State of Health assessment methods, transitioning from hours to seconds. This streamlined approach eliminates the need for pre-processing tests or climate chambers, enhancing the efficiency and practicality of battery evaluation processes.

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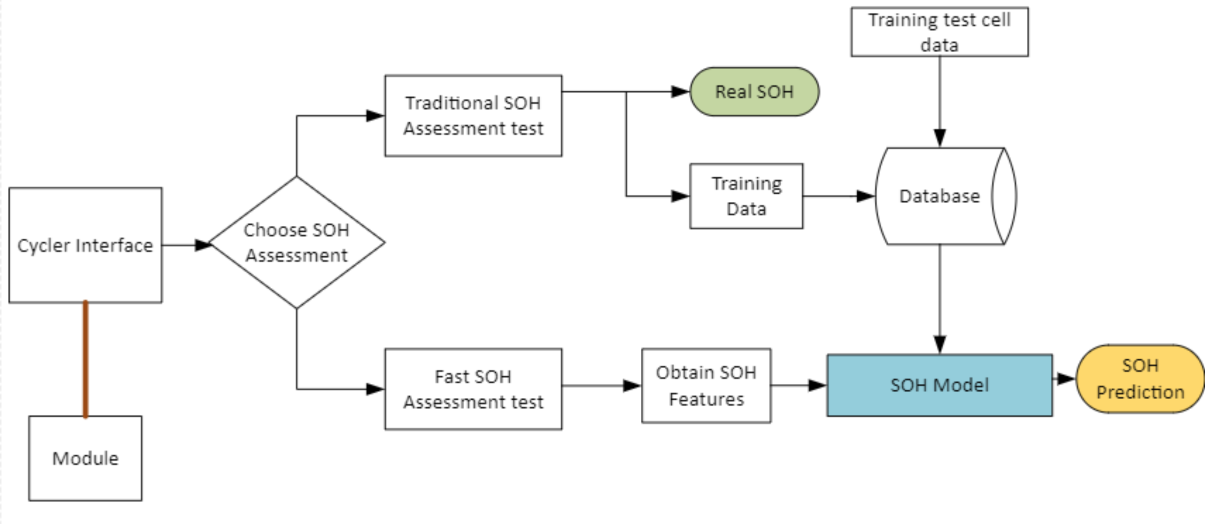

Figure 4:Procedural framework for the implementation of the Fast State of Health (SOH) assessment tool

3.1 Introduction

The number of Electric Vehicles (EVs) on the market has significantly increased in recent years [1]. With this growth, managing the increasing number of vehicle batteries reaching the end of their useful life (EOL) in the coming years presents a challenge due to low recycling rates [2]. On the other hand, EV batteries may retain enough capacity and power to be used in less demanding applications, offering an opportunity to reduce both the environmental impact and cost of EV batteries [3]. This is known as reuse or second life, and thanks to that opportunity, when EV batteries reach the EOL, an assessment should be conducted to determine if the battery may be suitable for a second life or if it will be directly sent to recycling. Battery assessment methodologies can be divided into 1) technical evaluation, 2) state of the battery evaluation, and 3) economic evaluation [4]. For the economic and state evaluation, it is critical to understand the battery's state of health (SOH), as the potential for reuse largely depends on it.

Batteries may end their first life with a wide range of SOH values, depending on the reason for reaching EOL and the duty cycle that the battery was subjected to during operation. However, a major challenge for the second-life industry lies in the lack of readily available information about the battery's SOH [5]. Consequently, tests to characterize the battery are often required. The traditional test defined in protocols, i.e., the UL 1974 or the IEC62619, to characterize a battery's SOH consists of performing a complete discharge and measuring the capacity discharged. This test requires significant time and energy because the battery must be charged before and after the test to ensure it is not left discharged at the end. This also translates to an economic cost for each characterization test performed.

To address these challenges, a fast battery health characterization test is explored in task 2.5.2. Various approaches have been studied to reduce the effort involved in evaluating SOH after the battery's first life [6]. These methods use indirect assessments [7], involving short tests to extract features and estimate SOH using pre-trained models. Features correlated with SOH are known as health indicators (HI). Depending on the nature of the test, the methods can be categorized as image-based [8], acoustic [9], force-based [10], thermal [11], or electrical [12].

- Image-Based Methods: These methods analyze the battery's internal structure, including pores, gaps, atom sizes, and chemical bulging. While effective in providing insights into degradation modes, they require dismantling the cell, which makes them unsuitable for direct application in fast SOH assessment. However, they can be valuable when combined with other methodologies [8].
- Acoustic Methods: These involve transmitting acoustic waveforms onto the battery surface and analyzing the reflected and transmitted waveforms. By comparing phase shifts during transmission and reception, SOH can be estimated [9].
- Force-Based Methods: These techniques measure the expansion and contraction forces inside the battery using force gauges. The magnitude of these forces can provide an estimate of SOH [10].
- Thermal Methods: These analyze temperature differentials during the charging and discharging phases. By examining temperature gradients and voltage ratios, SOH can be inferred [11].
- Electrochemical Impedance Spectroscopy (EIS): This involves applying an AC sinusoidal signal (voltage or current) at various frequencies to measure a battery's impedance [13]. Comparing current impedance values with historical data can allow SOH estimation, although this may be complicated in some chemistries or conditions [6], [16] .
- Electrical Tests: These tests can extract multiple features [12], such as the derivative of voltage with respect to time during charging or discharging [13],[17],[18], or the derivative of capacity charged/discharged with respect to voltage (Incremental Capacity Analysis)[19]. These analyses can better reflect battery aging modes [20]. Additionally, impedance values can be derived from short charge/discharge pulses [21]. Such pulses have proven effective for fast capacity estimation in second-life batteries across different Li-ion chemistries [22].

When certain HIs correlate with SOH, fast SOH assessments become feasible. Models linking HIs from fast tests to SOH can be developed using algorithms ranging from simple linear regression [19] to advanced data-driven approaches, such as Neural Networks [17]. Several studies employ Gaussian Process

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Regression, which provides confidence intervals for SOH estimation[23]. Another option, instead of assigning a value to the SOH, is to classify batteries based on their condition. For this task, algorithms such as k-means clustering are commonly used [24], [25].

However, HIs are sensitive to voltage, temperature, and current, limiting their reliability in fast-test scenarios. Current methods often require thermal chambers to stabilize ambient temperature and pre-test charging/discharging to set the battery to a specific initial voltage or state of charge [6]. Additionally, all data-driven models require training with battery testing data at various SOHs. Tests to obtain HIs require either long-term ageing test of a battery(s) or historical data from many batteries at different SOH levels, which is the case in the second-life battery industry. For example, in [19]The authors proposed a procedure to combine traditional tests with HI collection for model training by testing 40 retired EV batteries with varying SOHs.

Most fast SOH methodologies focus on individual cells, but second-life applications often prioritize reusing entire modules or packs to avoid costly disassembly [26]. In cases with high cell-to-cell variation inside the module/pack, disassembly and selecting the best cells may be beneficial. From the aforementioned methodologies, electrical tests are the most useful at the module level, as several HIs can be extracted.

¡Error! No se encuentra el origen de la referencia. compares studies proposing fast SOH assessment via electrical tests for used batteries. Despite achieving low Mean Absolute Percentage Error (MAPE), these methods have limitations:

1. **Dependency on Controlled Conditions**: Thermal chambers and pre-test voltage/SOC adjustments are required in all previous studies [16], [21], [23], increasing time and cost.
2. **Module-Level Challenges**: Existing module-level approaches [21] rely on module-specific training data, necessitating high-power equipment.

To solve these limitations in this deliverable 2.11, we propose the following solutions:

- A **multi-feature data-driven model** using internal resistance (IR) derived from a 10-second charge pulse, combined with initial temperature and voltage, is proposed. This eliminates pre-test charging/discharging (saving up to 3 hours) and thermal chambers by training models across diverse temperatures. Two machine learning models—a Feedforward Neural Network (FNN) and an Extra Tree Regressor (ETR)—are evaluated to capture non-linear relationships between features and SOH.
- **Reduced Training Costs**: Instead of training models on module-level data, cell-level data is applied to modules by accounting for internal pack configurations, minimizing equipment and training expenses.

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In summary, with the proposed model, the SOH assessment can be performed with 10-second tests while removing dependencies on controlled voltage, SOC, and temperature. The result is that by applying the proposed model, the viability of a second life can be evaluated rapidly, cheaply, and through a simple process.

Table 7: Comparative analysis of the proposed methods alongside other fast SOH assessment methodologies for used batteries.

Reference	Features	Test Time	Algorithm	MAPE at cell level	MAPE at module level
[21]	IR at 30% SOC and 23ºC	2 min	Polinomical Regression	2.1%	2.3%
[23]	dV/dt at 5% SOC at 25ºC	10s	Gaussian Process Regression	2%	-
[16]	EIS at 5% SOC at 23 ºC	25 min	Polinomical Regression	1.21%	-

3.2 Methodology

The proposed procedure for assessing the SOH in retired EV batteries is based on a fast electrical test. From this test, some HIs are derived, which, combined with the initial voltage and temperature, are used as features to train a model capable of predicting SOH. The methodology consists of the following steps:

- Testing Procedure and Data Collection
- Feature Selection (Health Indicators) and Data Preparation
- Model selection and training
- Model evaluation

<u>Testing Procedure and Data Collection</u>

Experimental data are obtained from testing EV Li-ion cells. Four LG Chem E63 cells were tested during three months, each with a nominal capacity of 63 Ah (Figure 5), extracted from a retired Hyundai Kona battery pack. The testing was conducted in the IREC Energy SmartLab using a BASYTEC cell cycler, with the cells placed inside an explosion-proof chamber. The testing procedure remained consistent across all cells, involving repetitive charge and discharge cycles following the standard C-rates specified in the cell datasheet. Every 50

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cycles, a Reference Performance Test (RPT) was conducted (Figure 6) from where the features to train the models are extracted. The RPT consists of:

Two full charge-discharge cycles to calculate the SOH, using the average discharge capacity divided by the nominal capacity, expressed by (1):

$$SOH = \frac{Q_{discharged1} + Q_{discharged2}}{2 \cdot Q_{nominal}} \quad (1)$$

Ten charge and ten discharge pulses, with a 30-minute rest period between pulses.

Figure 5: One LG Chem E63 cell tested.

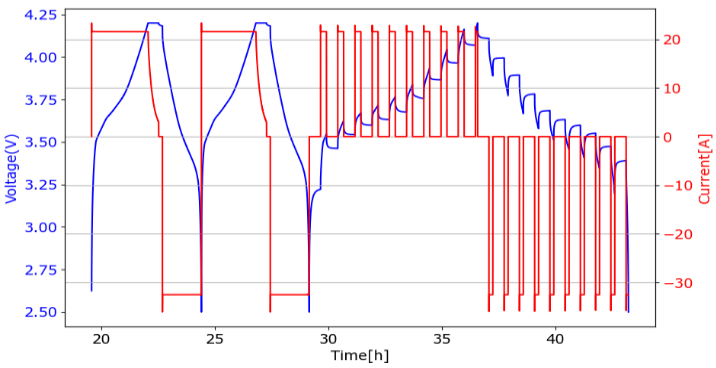

Figure 6: Voltage and current measurements in a cell during a Reference Performance Test

To analyze the possibility of reusing the models developed with cell data at module level, an RPT is conducted on a Hyundai Kona battery module, shown in Figure 7, with a 9s3p cell configuration. The module and cell characteristics are summarized in Table 8.

The module testing equipment utilized is a REGATRON battery cycler and a Hioki Data Logger to monitor each string's voltage and temperature from the module's single sensor.

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All tests are performed without controlling the temperature (ambient temperature ranges from 20°C to 28°C).

Figure 7: Hyundai Kona 9s3p module tested.

Table 8: Hyundai Kona Cell and Module battery characteristics.

	Cell	Module
Voltage Range	2.5-4.2V	22.5-37.8V
Configuration	-	9s3p
Capacity	63 Ah	189Ah
Energy Capacity	226.8 Wh	6.1 kWh
Standard ChargeCurrent	21.6A	64.8A
Standard Discharge Current	32.5A	97.5 A

Feature Selection and Data Preparation

After completing the tests, the data from each RPT is obtained and each pulse is intended to be used for extracting the HIs that can be related to the SOH. The IR is extracted from each pulse and used as a HI, following the method proposed in [23]. Due to the dependency of the IR on temperature and voltage, instead of limiting the model to a specific temperature or voltage, the three features: IR, voltage, and temperature are selected to train the model.

The charge pulses are processed obtaining a total of 303 pulses at different SOH values. From each pulse, the Internal Resistance after 10 seconds (IR_{10s})

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from the start is calculated with the equation (2). The choice of a 10-second period allows capturing two key contributions to the internal resistance: the ohmic resistance, which represents the immediate voltage drop due to the intrinsic resistance of the materials, and the polarization resistance, which accounts for slower electrochemical processes occurring within the battery during charge transfer [27]. Since we always use the same current for the pulses (I_{pulse}), this indicator is similar to what is proposed in [23] for fast SOH assessment of retired batteries, where they analyzed the voltage change rate after ten seconds (dv/dt).

$$IR_{10s} = \frac{V_{10s} - \mathrm{V_{ini}}}{I_{pulse}} \tag{2}$$

To extract the IR at the module level, it is necessary to deal with the 3p configuration. It is assumed that all three parallel cells share the same internal resistance. The equivalent internal resistance for a single cell is calculated using the relationship defined in the equation (3).

$$\begin{cases} \dfrac{1}{IR_{\mathrm{3p\ set}}} = \dfrac{1}{IR_{cell1}} + \dfrac{1}{IR_{cell2}} + \dfrac{1}{IR_{cell3}} \\ IR_{cell1} \approx IR_{cell2} \approx IR_{cell3} \end{cases} \rightarrow IR_{\,cell} \approx 3 \cdot IR_{\mathrm{3p\ set}} \tag{3}$$

where $IR_{\mathrm{3p\ set}}$ represents the measured internal resistance of the module, and 3 corresponds to the number of cells in parallel.

Finally, to finish the data preparation, the features are normalized to ensure consistent scaling, and the dataset coming from the cell testing is divided into training (80%) and validation (20%) subsets as in [28]. This stratification ensures that validation data from cycling conditions are unseen by the model, reflecting real-world applications where the battery usage history is often unknown. The dataset obtained from the 10 pulses test following the RPTs, is used for additional validation of the performance of the models trained exclusively with cell data for SOH prediction at the module level.

<u>Model Selection and Training</u>

Once the data is prepared, the next step is selecting a modeling approach. In this study, after comparing various options using the Python library Lazypredict—developed by MIT to evaluate a wide variety of ML models without tuning—two high-performing ML models are selected and compared.

- **Feedforward Neural Network (FNN):**

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The FNN is an artificial neural network characterized by its sequential architecture, consisting of densely connected layers where information flows from the input layer to the output layer [29]. For this study, the proposed model involves three consecutive layers with 32, 64, and 128 nodes, respectively. Each layer employs the Rectified Linear Unit (ReLU) activation function, to introduce non-linearity and enable the network to model complex relationships within the data. This design allows the model to effectively capture intricate patterns and relationships within the input features, making it well-suited for tasks like predicting the SOH.

The computations for each layer are described with the weight input calculation (equation (4)), the activation function (equation (5)), and the final Output (equation (6)).

$$z^{(l)} = W^{(l)} \cdot a^{(l-1)} + b^{(l)} \tag{4}$$

$$a^{(l)} = ReLU\left(z^{(l)}\right) = \max\left(0, z^{(l)}\right) \tag{5}$$

$$y = W^{(l)} \cdot a^{(l-1)} + b^{(l)} \tag{6}$$

where $z^{(l)}$ is the pe-activation vector for layer *l*, with a size corresponding to the number of nodes in layer *l* (n_l), $W^{(l)}$is the weight matrix connecting layer *l*-1 to *l*,$a^{(l-1)}$ is the activation vector from the previous layer and $b^{(l)}$ is the ias vector for layer *l*.

- **Extra Trees Regressor (ETR):**

In contrast to the FNN, the ETR [30] operates within the ensemble learning paradigm, specifically leveraging an ensemble of decision trees for regression tasks. During training, the model creates multiple decision trees (in this case, 100), and the final prediction is obtained by averaging the outputs of these individual trees. The 'extra' in Extra Trees highlights the increased randomness introduced during the tree-building process, setting it apart from traditional Random Forests. This ensemble approach proves to be particularly effective in capturing complex relationships in the input data, enhancing its ability to provide accurate predictions of continuous numerical values, such as those associated with SOH. This approach also leverages randomization and averaging to reduce overfitting making it effective on small structured datasets [30].

The basic working principle of the Extra Trees Regressor involves building multiple decision trees with high randomness and then averaging their predictions for regression tasks. Let's break this down further:

- Bootstrap Sampling: To train each tree, a random subset of the training data is selected (with replacement). This subset is typically the same size as the original dataset.
- Random Feature Selection: At each node of the tree, a subset of the features is randomly selected, and the best feature from this subset is chosen to split the data.
- Random Split Thresholds: For the selected feature, instead of searching for the best possible split (as is done in regular decision trees), Extra Trees randomly chooses the threshold (value) for the split.
- Tree Building: Trees are grown to their maximum depth without pruning (as opposed to Random Forests, where some pruning might occur).
- Prediction: Once the trees are built, predictions are made by averaging the predictions of all the individual trees. For regression tasks, the prediction is the mean of all tree predictions.

Both ML models are programmed in Python, using the TensorFlow and Scikit-learn libraries for the FNN and the ETR, respectively.

Model Evaluation

To evaluate the accuracy of the SOH prediction model, the Mean Absolute Percentage Error (MAPE) is computed, according to equation (7), and the Mean Absolute Error (MAE) is calculated using equation (8) . Here, n represents the number of observations in the dataset, y_i denotes the measured value for the ith sample and $\hat{y}_i$ is the predicted value.

$$\mathrm{MAPE}\ (\%) = \frac{1}{n}\sum_{i}\frac{|y_i - \hat{y}_i|}{y_i}\cdot 100 \tag{7}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i}|y_i - \hat{y}_i| \tag{8}$$

MAPE offers intuitive interpretability for comparing model performance across studies, as it normalizes errors relative to the true SOH values. However, its dependence on the actual SOH magnitude introduces a critical limitation: the same absolute error corresponds to a higher percentage error when the battery's SOH is lower. For instance, an absolute error of 2% SOH translates to a 2% MAPE for a battery at 100% SOH but rises to 2.5% MAPE for a battery at 80% SOH. Consequently, datasets dominated by batteries at lower SOH levels may misleadingly inflate MAPE values even if the absolute errors remain consistent. This sensitivity to SOH magnitude underscores the need for MAE, which directly reports the average absolute deviation (e.g., 2% SOH) without normalization.

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3.3 Results and discussion

From the testing, several RPTs are collated with pulses at different SOH. After cleaning and preparing the data, 303 samples are extracted from cell testing, and 90 samples are obtained from cells within the module (derived from module testing).

Figure 8 illustrates the relationship between the IR and SOH, with points representing data from cell tests and crosses representing data from module tests. The dataset spans a broad SOH spectrum, ranging from nearly 100% to 70%. Notably, the data reveals that IR_{10s} exhibits variability even at identical SOH values, influenced by factors such as temperature and voltage prior to the pulse. This underscores the importance of including temperature and voltage as features when using internal resistance for SOH prediction.

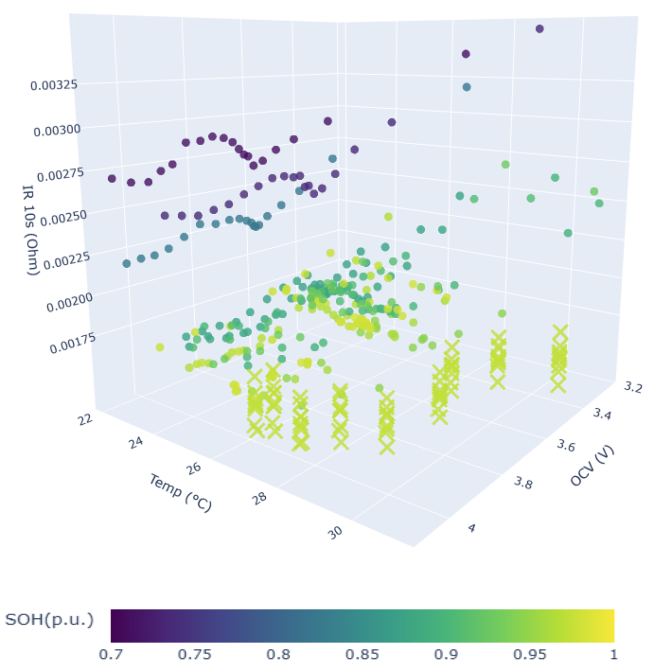

Figure 8: Relationship between cell IR, Temp, V and SOH obtained from the pulses applied to the cells (dots) and to the module (crosses).

The data from the cells is randomly divided into training (245 pulses) and validation (58 pulses) sets. After training the models, the predictions from both the FNN and ETR models for the randomly selected 58 pulses, along with the actual SOH values measured through testing, are shown in Figure 9. The accuracy of the models is evaluated with MAPE of 1.75% and 1.35% for the FNN and ETR models, respectively. These results show that the initial

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temperature, initial voltage, and IR can be used to accurately assess the SOH at the cell level.

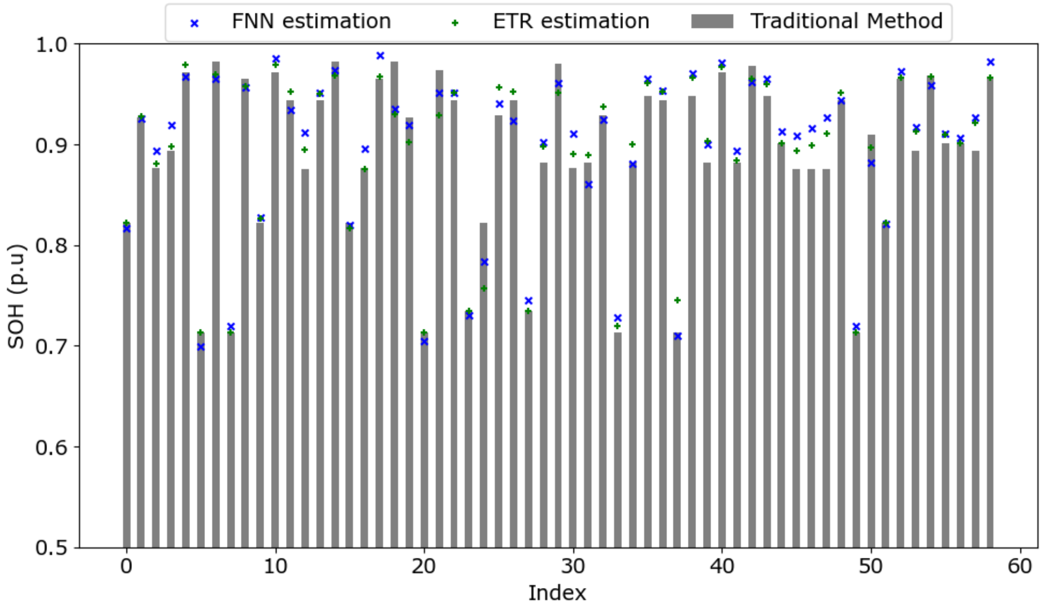

Figure 9: Comparison of the SOH measured with the traditional method with the predicted values obtained using the FNN and the ETR models for 58 samples.

Figure 10 shows the distribution of errors in the validation data, with vertical lines indicating the MAE for each model. The ETR model tends to overestimate the SOH at the cell level, while the FNN distributes errors more symmetrically.

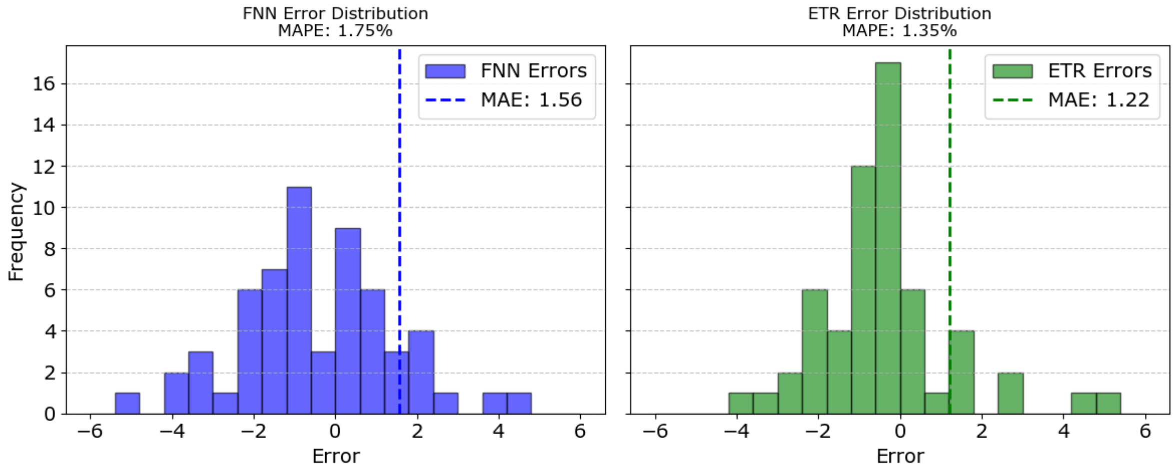

Figure 10: SOH (%) Error distribution with the predicted values obtained using the FNN and the ETR models for 58 samples.

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To evaluate the performance of models trained at cell level when applied at module level, the models are retrained using 100% of the data available at the cell level and evaluated against data recorded at the module level. Figure 11 shows the results for both models. The prediction for each cell in the module is made from the nine pulses conducted at the module level across different initial voltage levels. The blue X in the graphs represents the mean value of the SOH prediction for the module. The MAPE for the module predictions is 2.16% and 2.42% for the FNN and ETR models.

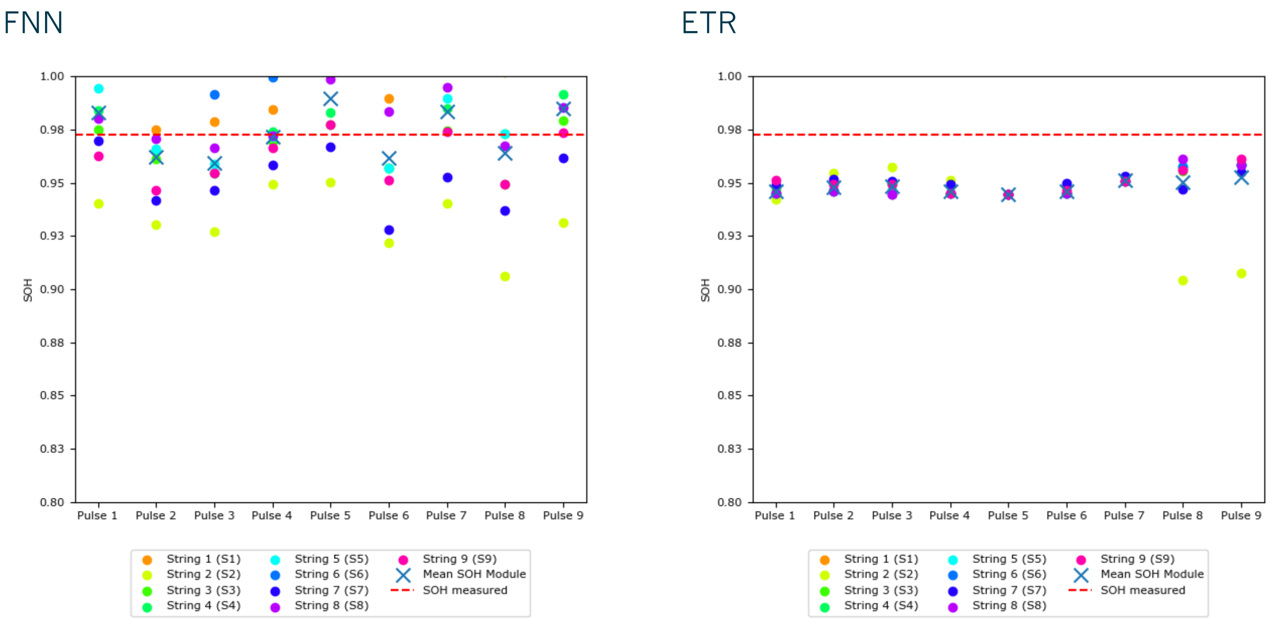

Figure 11: Comparison of the SOH measured at module level with the predicted values obtained using the FNN (a) and the ETR (b) models for each of the Strings in each pulse.

With both models, the error at the module level arises compared to cell level from several factors due to additional uncertainties introduced:

Temperature Measurement Limitations:

To use the model developed at the cell level, voltage and temperature measurements of each cell are required, as well as the temperature at the center of each cell surface (as in the original testing). However, the module under test has only one internal temperature sensor located in the corner of the module. This creates an error, as the measured temperature may not represent the actual conditions of all cells and is assumed to reflect the starting temperature for all cells at the beginning of the pulse.

Module Configuration (9s3p) and Calculation of IR:

The module's 9s3p configuration means that three cells are connected in parallel, and the measurements obtained correspond to this group of three cells rather than individual cells. Additionally, the model assumes that the IR of each cell within a 3p group is identical. In practice, IR varies due to manufacturing inconsistencies and cell aging, which introduces errors when applying cell-level models to module-level systems.

SOH Measurement at the Module Level:

Since the module cannot be disassembled, only one SOH measurement is available at the module level. When validating models, SOH predictions are made for individual cells, but errors are calculated using the module-level SOH measurement. This mismatch between the resolution of predictions and measurements introduces additional uncertainty.

Additional Error from Intermediate Connections:

The module uses two boards on each side to connect a series of string cell voltages to the DAQ. These intermediate connections can introduce noise, reducing the accuracy of measurements compared to cell-level testing.

Although both models have acceptable accuracy at cell and module level, the results show that ETR yields better accuracy at cell level and the FNN at the module level. The results also indicate that ETR is more precise, although it consistently underestimates the SOH at module level. On the other hand, FNN, despite having similar accuracy, is more imprecise, which may reduce user confidence in the model.

This performance dynamic could shift with the availability of more data. Neural networks typically excel with large datasets, as their ability to learn complex patterns and interactions becomes advantageous, often surpassing tree-based models like ETR in such scenarios. To evaluate this, we ran both models using different dataset sizes while keeping the validation dataset constant. **¡Error! No se encuentra el origen de la referencia.** shows how MAPE decreases as the amount of data increases, eventually stabilizing. This suggests that adding more data may not drastically reduce the error. The key appears to be incorporating data from more variable conditions to enhance data quality rather than merely increasing the quantity.

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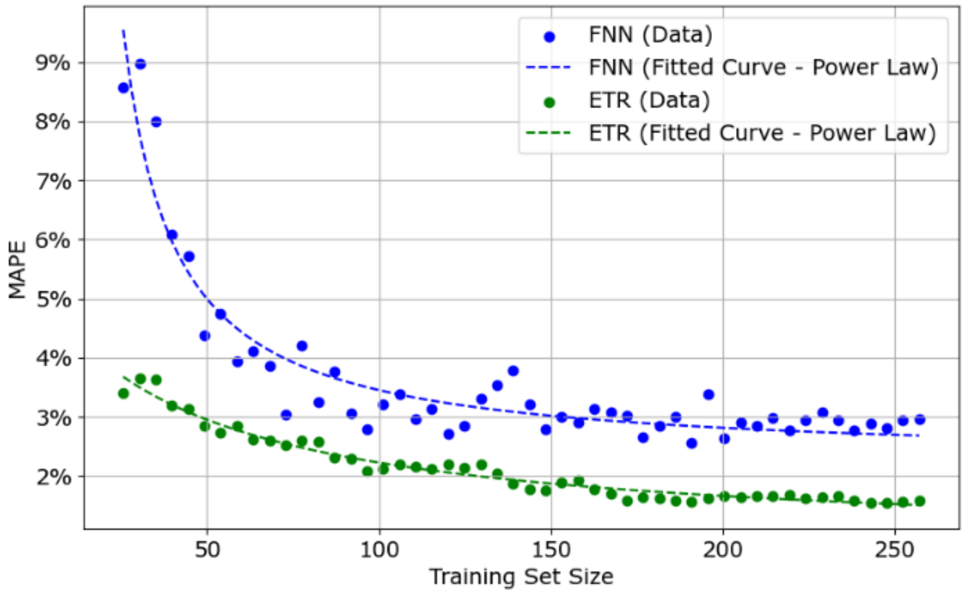

Figure 12: Impact of Training Data Size on FNN and ETR Model MAPE (Validation Set).

Furthermore, FNNs are well-suited for transfer learning and fine-tuning, allowing them to adapt pre-trained models to new, similar datasets with minimal additional training. This makes them particularly valuable when similar tasks or domains share underlying patterns, as the initial layers of the network can retain learned features while only the later layers are updated. While ETR lacks direct support for transfer learning, it can be retrained from scratch on new datasets with minimal computational overhead. However, this process does not leverage prior knowledge, making ETR less efficient in scenarios requiring adaptation to new but related data. Consequently, while ETR may be the better choice for small datasets in standalone tasks, FNNs offer greater versatility and scalability for applications where transfer learning or fine-tuning is feasible.

Comparing the developed models with the state of the art presented in **¡Error! No se encuentra el origen de la referencia.**, the proposed models achieve similar MAPE values at the cell level—1.75% and 1.35%—compared to the literature (2.1%) [21], (2%) [23], and (1.21%) [16].

Once the models are technically suitable, the first claim of the study is achieved: reduce the testing time. The traditional SOH assessment comprises at least one complete charge and discharge following C-rates recommended by the manufacturer. For the Hyundai Kona battery assessment, 5 hours of testing are required for each unit (module or cell). With the proposed methodology, after obtaining the training data, which took 3 months in the case of this study, each SOH assessment takes only 10 seconds of testing. Furthermore, since the models are trained with various initial temperatures, the need for a climate chamber is obviated, resulting in reduced initial investment costs and significant energy consumption savings.

The performance of the model developed using cell data to predict at module level also shows similar performance to the method developed by [21], being the MAPE 2.16% and 2.42% for the FNN and ETR models respectively. Again, these values are similar to the 2.3% from the literature [21] with the model developed using module data. This shows that training the model exclusively with cell data is possible and can significantly reduce costs as testing cells requires cheaper testing equipment.

As a direction for future research, it is recommended to validate the model with other battery types. The use of transfer learning techniques is promising as a way to reduce training requirements. This extended validation will contribute to a comprehensive understanding of the model's applicability and performance on a large scale. Moreover, to industrialize this process, the models can be integrated into a workstation for SOH assessment following the procedural framework shown in **¡Error! No se encuentra el origen de la referencia.**. This procedure encompasses the initial phases of data collection through to the final phase of directly applying the fast SOH assessment to modules. The data required to train the models can be gathered directly during the execution of traditional SOH assessments on modules or by conducting targeted tests aimed at training cells, as done in the present study.

3.4 Conclusions

This study proposes a multi-feature data-driven model for the fast SOH assessment of batteries beyond their first life. The model successfully predicts the SOH of batteries with a testing period of only 10 seconds, for a characterized cell or module. This process eliminates the need for preconditioning the batteries to a specific voltage or temperature, resulting in a time and cost reduction compared to other fast SOH assessment methods.

The models are developed using data from tests conducted at the cell level in the IREC Energy SmartLab. The features utilized for model training included internal resistance obtained after a 10-second pulse, initial voltage, and temperature. Two machine learning models, namely a Feedforward Neural Network and Extra Tree Regressor, are employed. Both methods demonstrate high accuracy, with MAPE values of 1.75% and 1.35%, respectively.

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In addition, with the aim of reducing the cost of disassembling the module to evaluate cells, a battery module is tested to assess the suitability of the models developed at the cell level for predicting the SOH directly at the module level. The accuracy is lower compared to directly evaluating the cells, with MAPE values of 2.16% and 2.42% for the FNN and ETR models, respectively. This indicates that the chosen method and models are able to well capture the transition from cell to module with respect to the impact on SOH. This allows for training data to be generated by performing cell tests, which will significantly reduce the number of items that need to be tested (i.e., testing the most common cells on the market versus testing the most common modules on the market). As disassembly and assembly costs can be reduced when using a reused module, instead of breaking it down to cell level before remanufacturing a module, the proposed method can increase the potential that modules are used directly, by providing greater confidence in the module SOH estimate, which can accelerate the transition to second-life applications as well as reduce the cost to arrive to that decision.

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4. Design, assembly and testing of 2nd life batteries

4.1 Eco-design approach: introduction

This section provides a preliminary approach for establishing, implementing, and evaluating eco-design at product level in the scope of the development of Free4LIB innovations. According to the Directive 2009/125/EC [1]establishing a framework for the setting of eco-design requirements for energy-related products, eco-design consists of the integration of environmental aspects into product design with the aim of improving the environmental performance of the product throughout its whole life cycle.

To the aim of this project, eco-design is approached following the requirements and recommendations of ISO 14006:2020 [2]on Environmental management systems – Guidelines for incorporating eco-design, and the circular economy principles and aspects of design for circularity defined in the ISO/DIS 59004 [3]Circular Economy — Terminology, Principles and Guidance for Implementation.

Figure 13 shows an overview of the main steps for adopting eco-design strategies. It starts by understanding the product and defining its specifications into detailed product functions. Next, environmental aspects of the product are evaluated from the life cycle approach to determine which aspects have a significant environmental impact. Then, eco-design requirements are identified considering current and future legislation concerning product specifications, restrictions, or obligations, as well as other requirements established by international and national standards, and from interested parties related to the organization or development of the product. Eco-design objectives are then set by the organization and interested parties focused on improving the environmental performance of the product based on the results of the environmental evaluation, legal requirements and the strategy of the organization/project, e.g. increase energy efficiency by 20%, reduce disassembly time for easy repair, reduce the content of critical raw materials, etc. Lastly, these objectives are transformed into eco-design strategies that

[1] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32009L0125

[2] https://www.iso.org/obp/ui#iso:std:iso:14006:ed-2:v1:en
[3] https://www.iso.org/obp/ui/es/#iso:std:iso:59004:ed-1:v1:en

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result in the product concept development, which is evaluated to ensure compliance with the goals of environmental impact reduction and eco-design requirements.

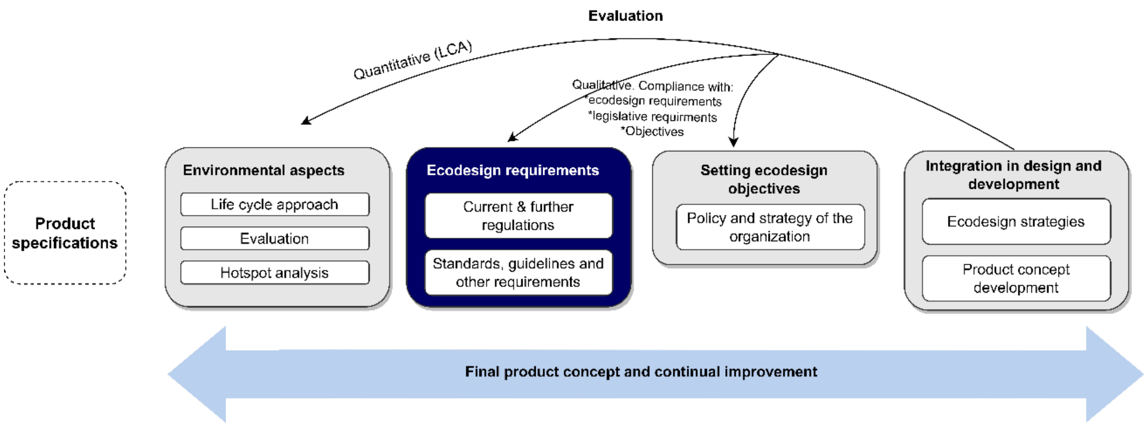

Figure 13. Steps for the implementation of the eco-design approach. Source: own elaboration based on ISO 14006:2020

In the scope of T2.5.3, this document is focused on the identification of the eco-design requirements of the project.

4.1.1 Regulatory requirements and obligations

New European Commission regulation on batteries and waste batteries.

This new regulation is part of The European Green Deal and it's built on the Strategic Action Plan on Batteries, the New Circular Economy Action Plan, the New Industrial Strategy for Europe and the Sustainable and Smart Mobility Strategy.

The new rules aim strengthening the functioning of the internal market (including products, processes, waste batteries and recyclates), promoting a circular economy and reducing environmental and social impacts throughout all stages of the battery life cycle.

The scope covers electric vehicle batteries and rechargeable industrial batteries with internal storage and a capacity above 2 kWh.

Eco-design and sustainability related obligations and requirements are listed as following:

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Restrictions of hazardous substances

Batteries shall not contain the following hazardous substances:

- Mercury. Batteries used in vehicles to which Directive 2000/53/EC [4]applies shall not contain more than 0,1% of mercury (expressed as mercury metal) by weight in homogeneous material.
- Cadmium. Batteries shall not contain more than 0,01% of cadmium (expressed as cadmium metal) by weight in homogeneous material, except those vehicles included in Annex II of the regulation.
- Substances listed in Annex XVII of REACH Regulation (EC) No 1907/2006 [5][6]– Registration, Evaluation, Authorisation and Restriction of Chemicals.

Exceptions on the use of risking substances are set for scientific research and development (of batteries) as defined in Article 3(23) of REACH: "scientific research and development: means any scientific experimentation, analysis or chemical research carried out under controlled conditions in a volume less than one ton per year".

Carbon footprint

- From 1st of July 2024, technical documentation shall be provided including a carbon footprint declaration of the battery per life cycle stage following the methodology established by the EC.
- From January 1st 2026, a label indicating the carbon footprint performance class of the battery must be included according to the performance classes set by the EC and labelling formats.
- From 1st of July 2024, technical documentation shall be provided demonstrating that the declared life cycle carbon footprint value is below the maximum threshold established by the EC.

Recycled content

- From January 1st 2027, technical documentation shall be provided containing information about the amount of **cobalt, lead, lithium or nickel recovered from waste** present in active materials in each battery model and batch per manufacturing plant.

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4 https://eur-lex.europa.eu/resource.html?uri=cellar:02fa83cf-bf28-4afc-8f9f-eb201bd61813.0005.02/DOC_1&format=PDF

5

6 https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:02006R1907-20241218

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Based on the methodology established by the EC for the calculation and verification of recycled content, technical documentation shall be provided demonstrating batteries contain the following minimum shares of materials recovered from waste present in active materials:

- From 1 January **2030**:
  a) 12% cobalt;
  b) 85% lead;
  c) 4% lithium;
  d) 4% nickel.
- From 1 January **2035**:
  a) 20% cobalt;
  b) 85 % lead;
  c) 10% lithium;
  d) 12% nickel.

Where justified and appropriate due to the availability of cobalt, lead, lithium or nickel recovered from waste, or the lack thereof, the EC shall be empowered to adopt, by 31 December 2027, a delegated act to amend the targets laid down for 2030 and 2035.

Responsible sourcing (due diligence policy)

Twelve months after entry into force of the Regulation, a set of the following responsible sourcing requirements shall be adopted:

- A company policy for the supply chain of raw materials shall be adopted. It includes:
  a) cobalt;
  b) natural graphite;
  c) lithium;
  d) nickel;
  e) chemical compounds based on the raw materials listed in previous points which are necessary for the manufacturing of the active materials of batteries.
- Establish and operate a system of controls and transparency over the supply chain, including:
  a) description of the raw material, including its trade name and type;
  b) name and address of the supplier that supplied the raw material present in the batteries to the economic operator that places on the market the batteries containing the raw material in question;
  c) country of origin of the raw material and the market transactions from the raw material's extraction to the immediate supplier to the economic operator;

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d) quantities of the raw material present in the battery placed on the market, expressed in percentage or weight.

- Identify and assess the adverse impacts associated to the risk categories:
    a) air;
    b) water;
    c) soil;
    d) biodiversity;
    e) human health;
    f) occupational health and safety;
    g) labour rights, including child labour;
    h) human rights;
    i) community life

Performance and durability requirements

Obligation to provide technical documentation containing values for the electrochemical performance and durability. In terms of eco-design, it considers information on indication of the **expected life-time** of the battery under the conditions for which it has been designed.

Labelling and information

- From 1 January 2027, batteries shall be marked with a label containing the **information on hazardous substances** contained in the battery other than mercury, cadmium or lead; critical raw materials contained in the battery.
- From 1 July 2023, batteries shall be labelled with the symbol indicating **'separate collection'**
- Batteries shall be marked with a QR code with access to the following information:
    - From 1 January 2026, the carbon footprint performance class
    - From 1 January 2027, the amount of cobalt, lead, lithium or nickel recovered from waste and present in active materials in the battery

Information accessible to accredited remanufacturers, second-life operators, and recyclers (as part of the digital battery passport)

- Detailed composition, including materials used in the cathode, anode and electrolyte;
- Part numbers for components and contact details of sources for replacement spares;
- Dismantling information, including at least:
    - Exploded diagrams of the battery system/pack showing the location of battery cells

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- Disassembly sequences,
- Type and number of fastening techniques to be unlocked,
- Tools required for disassembly,
- Warnings if risk of damaging parts exist,
- Amount of cells used and layout
- Safety measures

4.1.2 Eco-design strategies

¡Error! No se encuentra el origen de la referencia. presents the main s trategies to consider for the appropriate design of electric vehicle batteries from the eco-design and circularity perspective. These strategies have been identified from different reports and literature (Montes et al., 2022; Picatoste et al., 2022a, 2022b; Circular Economy Initiative Deutschland, 2020; Committee on Trade and Investment, 2005).

Table 9.Eco-design strategies for electric vehicle batteries by life cycle stage[7][8][9][10]

Life cycle stage	Eco-design strategies
Cell/ pack manufacturing	Concept/product related - Design for modularity and standardization of battery components for better maintenance, repairment, repurposing and recycling. - Design for long life - Simplicity of product architecture. - Lower the weight of the battery to achieve better performance during use (depending on the application). - Design for a minimum volume of battery components (depending on the application). - Design for easy dismantling to facilitate repair and recovery of battery components. Material selection - Avoid using toxic materials and substances as indicated in the New regulation on batteries and waste batteries and REACH regulation. - Avoid composite materials.

[7] Circular Economy Initiative Deutschland. (2020). *Resource-Efficient Battery Life Cycles*.

[8]Montes, T., Etxandi-Santolaya, M., Eichman, J., Ferreira, V. J., Trilla, L., & Corchero, C. (2022). Procedure for Assessing the Suitability of Battery Second Life Applications after EV First Life. *Batteries*, *8*(9).

[9] Committee on Trade and Investment. (2005). *ECODESIGN. Best Practice of ISO/TR 14062*.https://doi.org/10.3390/batteries8090122

[10] Picatoste, A., Justel, D., & Mendoza, J. M. F. (2022b). Exploring the applicability of circular design criteria for electric vehicle batteries. *Procedia CIRP*, *109*, 107–112. https://doi.org/10.1016/j.procir.2022.05.222

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	- Avoid/reduce the usage of critical-scarce materials. - Use recycled and recyclable materials, especially recycled cobalt, lead, lithium or nickel in compliance with the 2030 & 2035 content targets established in the new Batteries and waste batteries regulation. - Use light materials. - Use durable materials. Manufacturing - Avoid high energy-intensive production processes. - Prioritize the usage of renewable energies. - Recycle scrap (pre-consumer waste) Assembly - Simplicity of assembly process: reduce assembly/disassembly steps and energy processes. - Avoid the use of adhesives, glues or soldered in joints and connections, instead use detachable joints. - Minimize the number and type of fasteners (use same type), ensuring they do not require special tools and are easy to unlock. - Ensure joints are easily accessible and there is enough space to allow disassembly for repairment and at the end-of-life. Information access and communication - Provide sustainability information in compliance with the requirements of Digital Battery Passport and set in the new Batteries and waste batteries regulation (carbon footprint, recycled content, responsible sourcing, labelling, performance and durability, dismantling and safety)
Use	- Provide information on part numbers for components and contact details of sources for replacement spares. - Indicate dismantling instructions to facilitate repair and replacement of battery components. - Repair/recondition battery pack or individual modules to extend first life in the same or another vehicle.
End-of-life	Disassembly - Provide Dismantling information, including: i) Exploded diagrams of the battery system/pack showing the location of battery cells, ii) Disassembly sequences, iii) Type and number of fastening techniques to be unlocked, iv) Tools required for disassembly, v) Warnings if risk of damaging parts exist, vi) Amount of cells used and layout. - Provide information for the appropriate treatment of battery components and materials. - Automatize disassembly operations to reduce time and resources. - Reduce the type and number of tools for disassembly. - Use standard tools during disassembly processes. - Ensure traceability of separated battery components according to the information requirements of the Digital Battery Passport established in the new Batteries and waste batteries regulation. Reuse

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- Repair/recondition battery pack or individual modules to extend first life in the same or another vehicle.
- Repurpose battery pack or individual modules for 2nd life applications when the battery is sufficiently degraded to meet first life requirements in vehicles.

Recycling

- Ensure recyclates quality comparable to that of original materials.
- Recycle critical materials, particularly those specified in the new Batteries and waste batteries regulation (cobalt, lead, lithium, nickel).
- Guarantee traceability of recycled battery components and materials.

4.1.3 Eco-design applied to the development of the BESS

The eco-design principles above mentioned have been shared with W4E as the partner in charge of the design of the second life battery system with the purpose of checking which ones could be and have been implemented and which ones could not be included.

W4E was asked to fill the matrix below that contained an exhaustive list of possible eco-design actions (Figure 14).

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Definition of ecodesign strategies for 2nd life and recycled batteries

IREC FREE4LiB

Date:

Application:	*Describe the intended application of the battery under design.*	**Product specifications:**	*Describe relevant functions and technical-physical characteristics of the product to be designed/produced.*
Ecodesign objectives:	*Define specific objectives. E.g, material recovery, design for recycling, reducing disassembling time, reduce battery size*		

Note: Please select the actions according to the product application and objectives defined.

Stage	Ecodesign actions	Applicability	Ecodesign strategy (to be implemented)	Baseline (conventional action for comparison)	Comments
Cell/ pack manufacturing	**Concept/product related**				
	• Design for modularity and standardization of battery components for better maintenance, repairment, repurposing and recycling.	☑ ☐			
	• Design for long life				
	• Simplicity of product architecture.	☑			
	• Lower the weight of the battery to achieve better performance during use (depending on the application).	☐ ☑			
	• Design for a minimum volume of battery components (depending on the application).	☑			
	• Design for easy dismantling to facilitate repair and recovery of battery components.				
	Material selection				
	• Avoid using toxic materials and substances as indicated in the New regulation on batteries and waste batteries and REACH regulation.	☐			
	· Use of recycled content in the cells	☐			Specify the % of recycled content in anode, cathode,..
	• Avoid composite materials.	☐			
	• Avoid/reduce the usage of critical-scarce materials.	☐			
	• Use recycled and recyclable materials, especially recycled cobalt, lead, lithium or nickel in compliance with the 2030 & 2035 content targets established in the new Batteries and waste batteries regulation.	☐			
	• Use light materials.	☐			
	• Use durable materials.	☐			
	Manufacturing				
	• Avoid high energy-intensive production processes.	☑			
	• Prioritize the usage of renewable energies.	☐			
	• Recycle scrap (pre-consumer waste)	☐			
	Assembly				
	• Simplicity of assembly process: reduce assembly/disassembly steps and energy processes.	☑			
	• Avoid the use of adhesives, glues or soldered in joints and connections, instead use detachable joints.	☐			
	• Minimize the number and type of fasteners (use same type), ensuring they do not require special tools and are easy to unlock.	☑ ☑			
	• Ensure joints are easily accessible and there is enough space to allow disassembly for repairment and at the end-of-life.				
	Information access and communication				
	• Provide sustainability information in compliance with the requirements of Digital Battery Passport and set in the new Batteries and waste batteries regulation (carbon footprint, recycled content, responsible sourcing, labelling, performance and durability,	☐			
Use	• Provide information on part numbers for components and contact details of sources for replacement spares.	☑ ☑			
	• Indicate dismantling instructions to facilitate repair and replacement of battery components.	☐			
	• Repair/recondition battery pack or individual modules to extend first life in the same or another vehicle.				
End-of-life	**Disassembly**				
	• Provide Dismantling information, including: i) exploded diagrams of the battery system/pack showing the location of battery cells, ii) disassembly sequences, iii) type and number of fastening techniques to be unlocked, iv) tools required for disassembly, v) warnings if risk of damaging parts exist, vi) amount of cells used and layout.	☑ ☐			
	• Provide information for the appropriate treatment of battery components and materials.	☐			
	• Automatize disassembly operations to reduce time and resources.				
	• Reduce the type and number of tools for disassembly.	☐			
	• Use standard tools during disassembly processes.	☑			
	• Ensure traceability of separated battery components according to the information requirements of the Digital Battery Passport established in the new Batteries and waste batteries regulation.	☐			
	Reuse				
	• Repair/recondition battery pack or individual modules to extend first life in the same or another vehicle.	☐			
	• Repurpose battery pack or individual modules for 2nd life applications when the battery is sufficiently degraded to meet first life requirements in vehicles.	☑			
	Recycling				
	• Ensure recyclates quality comparable to that of original materials.	☐			
	• Recycle critical materials, particularly those specified in the new Batteries and waste batteries regulation (cobalt, lead, lithium, nickel).	☐			
	• Guarantee traceability of recycled battery components and materials.	☐			

Figure 14. Matrix to select eco-design actions undertaken in the design of the BESS

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4.2 BESS design, assembly and testing

4.2.1 Demonstrator description

Using the cells obtained after disassembly tasks, W4E designed the reassembled batteries and performed the assembly of the battery packs. The system will be based on 45 kWp power output based on reused batteries for which the battery storage capacity would be ~90 kWh. Installation and commissioning of the BESS will be performed by W4E. In this context, W4E will test all the battery modules before installation. Moreover, all the components of the BESS cabinet such as battery modules, BMS, PMS, protection devices, contactors, etc. will be mounted into the BESS cabinet by experts and engineers at W4E. The BESS will be commissioned and tested (Factory acceptance test – FAT) at W4E and then will be showcased for the project. The safety features of the BESS cabinet that will be installed at the school would be:

- Uniform temperature profile throughout the cabinet via combination of HVAC and ventilation fans distributed across the cabinet.
- Heat sensors to maintain SOA for the battery modules and derate once the temperature exceeds 35 ℃.
- Smoke sensors.
- Gas vent valve to eliminate buildup of gases and avoid thermal run away.
- Off-gas detection sensors to detect H2 N2 and prevent thermal run away before it could trigger.
- Double wall enclosure to improve thermal dissipation.

4.2.2 Methodology

The Strategyser methodology, widely recognized for its application in developing business models, serves as the foundation for the design and analysis of the Business Model Canvas in this project. This framework provides a systematic, visual approach to understanding, designing, and refining business models. It emphasizes a customer-centric approach by breaking down the complexities of a business into nine distinct building blocks, which are interconnected to create a cohesive and sustainable value proposition. For this project, the Strategyser methodology was instrumental in identifying and aligning the key components necessary to deliver a low-cost, decentralized energy system based on reused PV panels and EV batteries. By employing this methodology, the Business Model Canvas was developed to integrate critical aspects such as key partnerships, value propositions, and revenue streams with a clear focus on sustainability and affordability. The Strategyser approach facilitated collaboration between stakeholders, ensuring the alignment of technical, financial, and social objectives. For example, key partnerships with

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supply chain partners and local governments were mapped to support efficient sourcing and certification of second-life components. The methodology also helped prioritize value creation for underserved communities by focusing on energy independence, reduced environmental impact, and affordability as the core drivers of the business model. Additionally, the iterative nature of the Strategyser methodology allowed the project team to adapt and refine the business model based on evolving insights. For instance, community feedback and pilot testing results were used to evaluate assumptions, ensuring the replicability of the demonstrator across other low-income communities. This adaptability is a hallmark of the Strategyser framework, which emphasizes continuous learning and improvement. Ultimately, the methodology provided a structured yet flexible approach to designing a business model that balances technical feasibility, financial sustainability, and social impact, ensuring the success and scalability of the decentralized energy system.

Business model Canvas:

The Business Model Canvas for the BESS cabinet highlights a comprehensive approach to delivering sustainable and affordable energy solutions. This model focuses on integrating key partnerships, activities, and resources to create value for its target customer segments. By leveraging collaboration with building owners, supply chain partners, local governments, certification organizations, and energy grid operators, the business ensures access to critical components and expertise needed for the development and deployment of decentralized energy systems. These partnerships also foster innovation and continuous improvement in energy storage technologies. The key activities include the design, certification, and installation of the systems, as well as ongoing monitoring and maintenance. Training programs are also an integral part of the process to empower stakeholders and ensure efficient operation of the systems. The business model emphasizes the use of sustainable materials, such as 2nd-life PV panels and EV batteries, which align with its commitment to environmental responsibility and circular economy principles.

The value proposition centres on providing affordable and sustainable energy access, particularly for low-income communities, schools, and nonprofit organizations. These systems offer energy independence, reduce environmental impact by lowering greenhouse gas emissions, and minimize e-waste. They also contribute to local social development by enhancing energy resilience and promoting education on clean energy and sustainability principles. Furthermore, the modular design and replicability of the BESS cabinets enable broader scalability in various regions. Customer relationships are maintained through ongoing support from a dedicated team and regular updates on system performance. Workshops and training sessions play a key role in building trust and empowering users, particularly in low-income

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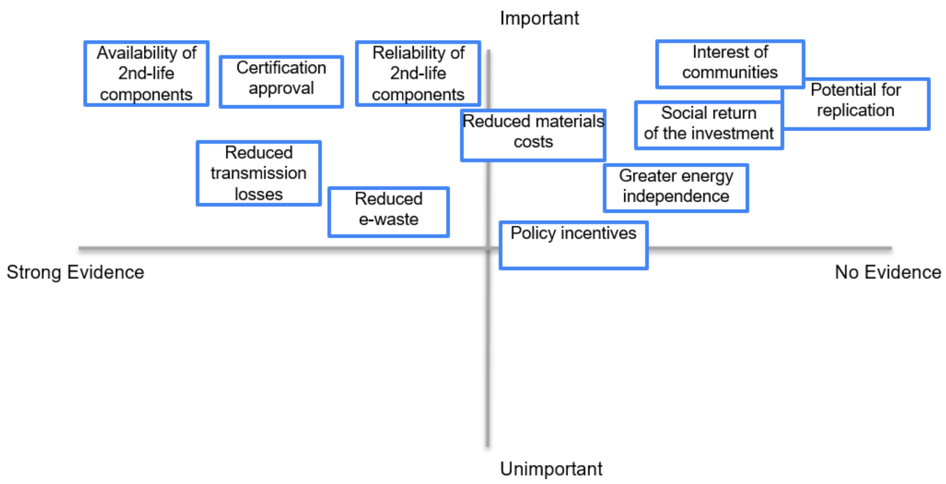
communities and schools. The business employs direct sales, community outreach programs, and online channels to reach its customers effectively. The cost structure includes R&D expenses, direct costs for labour and materials, and one-time installation and certification fees. Operational costs such as marketing and ongoing system maintenance are also factored in. Revenue streams are derived from grants and subsidies, maintenance contracts, savings on energy bills, and the sale of excess energy generated by the system back to the grid. This dual focus on cost efficiency and revenue generation ensures financial sustainability while delivering measurable social and environmental benefits.

<table>
<tr>
<td rowspan="2">Key Partners
– Building owners/manager
– Supply chain partners (PV, Batteries)
– Certification organisations
– Research institutions for innovation and continuous improvement.
– Energy grid operator</td>
<td>Key Activities
- Design the systems
- Obtain certifications
- Procurement materials
- Install, maintain, monitor
- Deliver training</td>
<td rowspan="2">Value Proposition
– Provide affordable and sustainable access to energy low-income communities
– Provide energy independence (greater control; increased resiliency, lower costs)
– Reduce environmental impact (less GHG emissions, less transmission losses, fewer e-waste)
– Local/social development
– Potential for replication</td>
<td>Customer Relation
– Ongoing support from dedicated team members
– Regular updates on the system's performance</td>
<td rowspan="2">Customer Segments
- Commercial and industrial
- Schools and Universities
- Organizations
- Local governments</td>
</tr>
<tr>
<td>Key Resources
– Engineers/technicians
– 2nd-life PV panels
– 2nd-life EV batteries</td>
<td>Communication Channels
- Direct sales
- Community outreach programs
- Online channels.</td>
</tr>
<tr>
<td colspan="2">Cost Structure
- R&D expenses
- Directs costs (labour costs, engineering, materials)
- One-time installation and certification fees
- Operational costs (R&D, marketing, sales)</td>
<td colspan="3">Revenue Stream
- Grants and subsidies
- Maintenance contracts
- Savings from reduced energy bills.
- Sales of excess energy generated by the system back to the grid</td>
</tr>
</table>

Hypothesis:

The hypothesis diagram for the BESS cabinet highlights key factors impacting the success of the business model, categorizing them based on their importance and the strength of supporting evidence. These factors range from technical aspects, such as the availability and reliability of 2nd-life components, to social and economic considerations, including community interest and policy incentives. The placement of each factor reflects its perceived significance and the confidence level in its impact on the business. At the top left quadrant, factors such as the availability and reliability of 2nd-life components, certification approval, reduced transmission losses, and reduced e-waste are both important and supported by strong evidence. These elements emphasize the technical feasibility of the BESS solution and its alignment with sustainability goals. The focus on 2nd-life components, such as used EV batteries, underlines the business's commitment to a circular economy while addressing environmental challenges. Reduced material costs occupy a central position in the "important" and "strong evidence" quadrant. This suggests that the economic viability of the BESS cabinets is closely tied to the ability to minimize material costs, a factor that directly influences the affordability and scalability of the solution. Strong evidence supporting reduced material costs highlights the practical feasibility of sourcing components cost-effectively.

In the "important" and "no evidence" quadrant, social and community-driven factors, such as the interest of communities, the social return on investment, and the potential for replication, are identified as crucial for long-term success. While evidence may be lacking, these factors point to the need for further research and pilot projects to validate their significance. Community involvement and the social impact of the project are particularly critical for addressing the needs of low-income communities and ensuring widespread adoption. Policy incentives appear in the "unimportant" and "strong evidence" quadrant, suggesting that while policy support exists, it may not be as critical to the business model's success as other factors. This could reflect the model's design to thrive independently of extensive policy interventions, relying instead on technical and community-driven elements. The overall hypothesis structure highlights a balanced approach, prioritizing technical reliability, cost efficiency, and sustainability, while recognizing the need to strengthen the evidence base for social and community-related impacts. By addressing these factors, the BESS cabinet business model aims to establish itself as a scalable, sustainable, and socially impactful solution for decentralized energy systems.



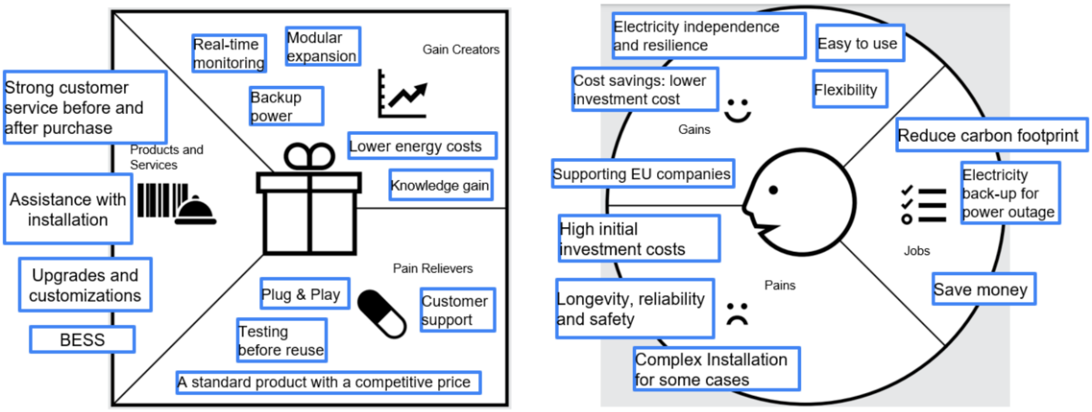
Desirability:

The list of customer segments would be B2C and B2B2C, that can be explained as follows:
B2C: Direct individual sales to Residential and C&I:

- EV charging stations to store and manage electricity to charge EVs.
- Residential sectors like social housing to store energy from solar panels or wind turbines for self-consumption.
- Rural or Off-grid Property Owners

B2B2C: Larger scale unit sales through partners:

- Solar Power Installers and Distributors to provide an energy solution to consumers.
- Telecom Providers to provide backup power to residential users for internet or phone services.
- Smart City Developers / Urban Planners to implement energy storage for distributed energy solutions across a wide number of buildings, transportation systems, and other urban infrastructures.
- Renewable Energy Service Providers to offer renewable energy solutions to residential or business clients and integrating battery storage for a more stable and reliable energy service.
- Government or Municipalities that wish to implement battery storage in public housing, schools, or public infrastructure to ensure resilient energy supply and lower energy costs for community members.



Also, the main considerations that characterizes our relationship to our customers can be:

- Long-term relationships: Focus on building ongoing relationships through continuous support, maintenance, and system upgrades to ensure customer loyalty and satisfaction over time.
- Personal assistance: Providing personalized consultations and tailored advice to help customers choose the right energy storage solutions, along with dedicated post-purchase support.
- Automated services: Offering automated tools like apps or dashboards for customers to monitor, manage, and optimize their energy usage in real-time, reducing the need for constant manual oversight.
- Transactional but reliable: Maintaining a straightforward transactional relationship while ensuring reliability, transparency, and consistency in product delivery and service quality.
- Proactive customer support: Anticipating customer needs and reaching out proactively with product updates, maintenance reminders, and energy-saving tips, ensuring smooth long-term operations.
- Loyalty programs: Implementing loyalty programs that reward repeat customers with discounts, upgrades, or exclusive offers, encouraging long-term commitment and referrals.

To evaluate the market, there are some consideration points such as market size, competition landscape, pricing potential, industry trends, industry challenges, that can be explained as:

- o The global battery energy storage market is expected to experience significant growth, driven by increasing demand for renewable energy, grid modernization, and electric vehicles (EVs). Market research projects a CAGR of around 25% from 2023-2030.
- o Both residential consumers (due to the rise of solar power installations) and commercial users (industries, utilities) are increasingly adopting BESS solutions to optimize energy consumption and reduce costs.
- o The market shows strong growth in regions like North America, Europe, and Asia-Pacific, driven by government policies, incentives for renewable energy, and the need for energy independence and reliability.
- o The market is competitive with established players like Tesla, Huawei, etc as well as other Chinese players and newer entrants focusing on innovations in energy storage technologies and smart management systems.

The channels to interfaces with the customer can be communication, distribution, sales channels. These channels can be direct contact or via partners. In this context, direct communication can be built such as website & online presence, social media & digital marketing, email campaigns & newsletters, webinars & educational content. There are also some indirect communications via Partners such as partner marketing & joint campaigns, industry events & trade shows. The direct sales and distribution will be direct-to-customer (D2C) or E-commerce platforms. Moreover, indirect distribution via partners are energy companies & utilities, installers & renewable energy companies, and retail distribution partners. The sales channels to this aim can be in-house sales team, online sales, showrooms or physical locations, while the indirect sales via partners will be channel partners & resellers, and OEM partnerships.

Moreover, there are main assumptions we are basing the desirability of the offer on and how are they changing over time, such as:

- o Growing demand for energy independence and sustainability
- o Rising concern over energy security and grid reliability
- o Cost savings and energy efficiency
- o Increased adoption of renewable energy systems
- o Technological integration and smart energy management
- o Flexibility and customization

Feasibility:

The most important key activities we must do to make the business model work will be Product development and innovation, Supply chain and battery sourcing, Manufacturing and assembly, and Sales and customer acquisition. These key activities can be sub-grouped as:

- o Product development and innovation:
  - o battery recycling & sustainability;
  - o technology integration;

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  - customizable solutions.
- Supply chain and battery sourcing:
  - battery collection and logistics;
  - refurbishment process.
- Manufacturing and assembly:
  - assembly of BESS;
  - quality control & safety standards;
  - FAT test after production.
- Sales and customer acquisition:
  - direct sales and partner channels;
  - partnership development.

Moreover, there are physical, human or financial resources that we require as key resources.

- Physical resources:
  - battery supply chain;
  - refurbishment and manufacturing facilities;
  - energy storage units and hardware;
  - logistics and distribution networks.
- Human resources:
  - technical expertise and engineers;
  - R&D team;
  - sales and marketing team;
  - customer support and after-sales service.
- Financial resources:
  - operating capital;
  - government grants and incentives.

The IP is also crucial for proprietary battery refurbishment processes, BMS software, energy optimization algorithms, and Norms for second-life batteries.

4.2.3 Design and Manufacturing of the BESS

The design and manufacturing of the BESS using the second life modules is detailed in this section. The BESS cabinet design has been drawn in SolidWorks and then, the CAD file has been sent to the metal construction company to manufacture the cabinet. The battery pack has been dismantled to modules to have a non-invasive module methodology in this regard. Therefore, the modules were not dismantled to cells to avoid safety risks. In this regard, the dismantled modules have been tested through different tests to check their level of safety, to check their state of health, and to check their insulation. The modules used in this BESS cabinet use lithium-ion pouch cells from LC company with 65Ah capacity for each cell. The nominal voltage of the module is 21.4V with the module capacity of 129.2 Ah and module energy of 2.77kWh. The weight of each module is around 13.4kg, with the dimensions of 152.0mm (L), 390.8mm (W), and 108.0mm (H). The final BESS cabinet specification is shown in the table below.

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Table 10. Specification of the BESS cabinet

WATT4EVER
BATTERIES FOR LIFE

BESS Specifications			
Battery Module			
General parameters	Config: 6s2p	V-nom: 21.4 V	No: of cells: 12
Dimension	450(mm) L	150(mm) W	110(mm) H
Nominal Rating	Capacity : 128Ah		Energy 2.56 kWh
Module Parameters	C-rate: 0.5	DoD: 80%	Cutoff Voltage: 16.5V – 25.2 V
Slider Dimension	700(mm) L	550(mm) W	165(mm) H
No: of Modules	Per Slider: 4		Per String: 36
PowerCab90	**90 kWh/ 45 kVA**		
Topology (DC side)	No: Series Modules: 36	Sliders: 10	Service Disconnector: 1
Energy	Nominal : 90 kWh		(@ 80% DoD): 72 kWh
Power converter System (PCS)	1 x KACO gridsave blueplanet 92.0 TL3-S XL (Grid connected)		
Electrical properties (AC)	Voltage: 400V (± 10%)	Frequency: 50 Hz	Power: 45 KVA
AC Current	Nominal: 66A	Peak: 193A	Continues Fault: 134 A
PCS installation	cabinet mounted with extended roof		
Cabinet Dimension	805(mm) L	910(mm) W	1938(mm) H
Heat load (@ 25℃ Ambient)	(@ 0.5C): 1.23 kW	HVAC: 1 x NOX40B0E1U00000 (door mounted)	
Cabinet Param	Cable Entry : Bottom (Plinth)	IP rating:	IP55 (No moisture ingress)

Regarding the design of the system, the single-line diagram (SLD) was sketched. In power engineering, a single-line diagram (SLD), also sometimes called a one-line diagram, is the simplest symbolic representation of an electric power system. A single line in the diagram typically corresponds to more than one physical conductor: in a direct current system the line includes the supply and return paths, in a three-phase system the line represents all three phases (the conductors are both supply and return due to the nature of the alternating current circuits). The one-line diagram has its largest application in power flow studies. Electrical elements such as circuit breakers, transformers, capacitors, bus bars, and conductors are shown by standardized schematic symbols. Instead of representing each of three phases with a separate line or terminal, only one conductor is represented. It is a form of block diagram graphically depicting the paths for power flow between entities of the system. Elements on the diagram do not represent the physical size or location of the electrical equipment, but it is a common convention to organize the diagram with the same left-to-right, top-to-bottom sequence as the switchgear or other apparatus represented. The single line diagram of the BESS that is going to be used in this project has been designed that can be seen below:

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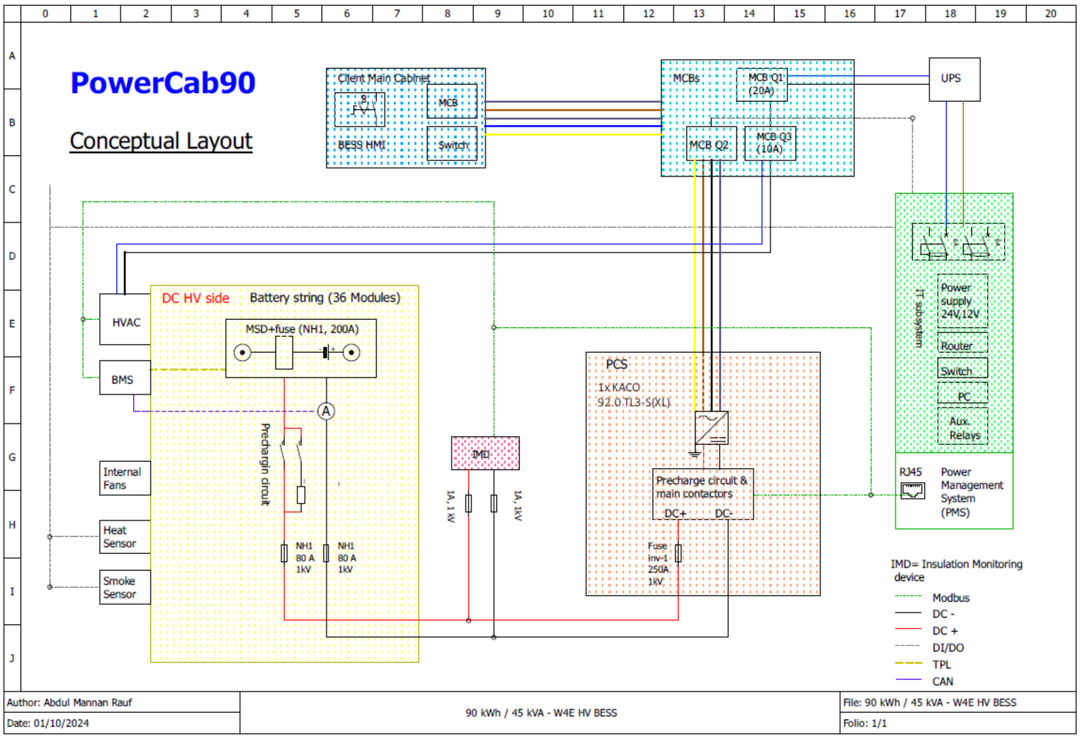

Figure 15. The single line diagram (SLD) of the BESS

Moreover, regarding the design of the battery cabinet and the modules, the CAD file has been designed to further integrate the battery modules inside the cabinet virtually before the real integration of the system. The mechanical design of each battery module together with the battery slider isometric view as well as the BESS cabinet can be seen in figure 16.

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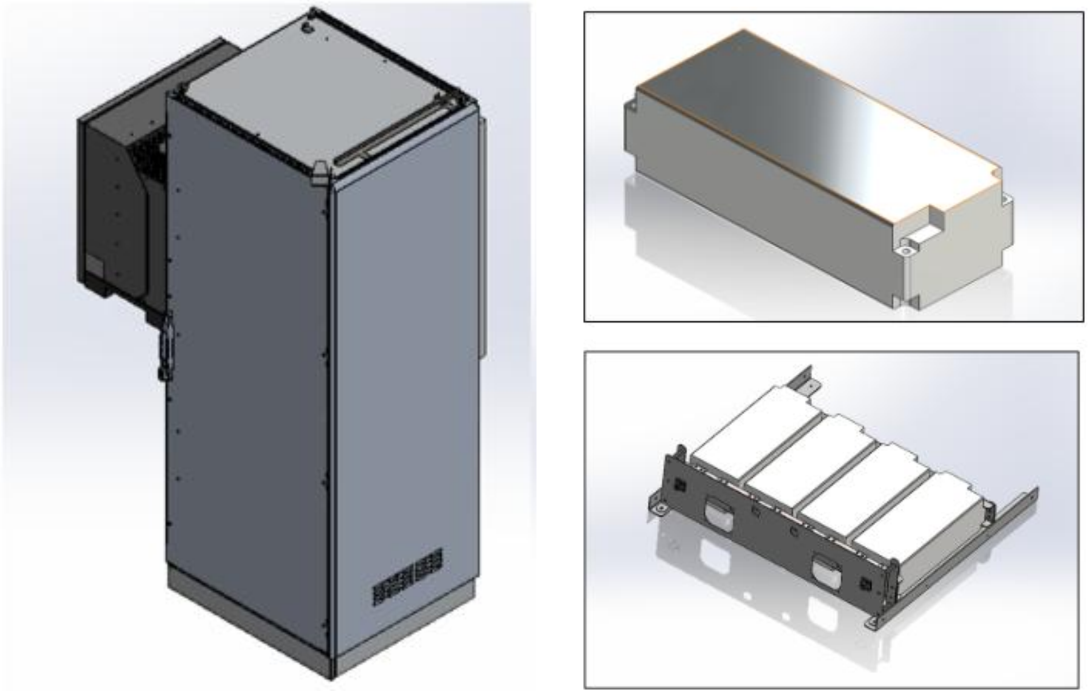

Figure 16. The CAD design of the BESS components: cabinet, module, sliders

The designed BESS represents an integrated outdoor battery Cabinets with high quality second life battery modules form leading EV OEMS. The energy and power rating of the cabinet is 100kWh – 50kVA, respectively. The cabinet is made up of double walled enclosure with the standard RAL9016 colour to ensure maximum solar reflection. The cabinet houses certified battery modules, power conversion system (PCS) and ancillary equipment including contactors, circuit breakers, fuses and service disconnect switches to correctly operate the batteries. An active forced air cooling/heating system (HVAC) is foreseen to ensure safe temperature of the battery modules between 5°C and 35°C.

On the DC side, the battery system is built form a string of 36 modules. Each module is 6s2p configuration with a nominal voltage of 21.4V. The voltage range of one battery string is 583V (fully discharged) to 918V (full charged). The estimated degradation is less than 30% of initial capacity over more than 4000 cycles at 80% DoD.

Mechanical integration:

The battery modules are placed on the battery racks. Each rack holds 4 battery modules and uses a three-bracket system to integrate the modules. The bracket slide on the 19” L-profile to ease in taking out and placing the rack.

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Table 11. Characteristics and values

Characteristics	Value
19 " L profile	Make: nVent
Number of 19'' L profile per single compartment	16
Number of Racks per single compartment	8
Bracket type	Custom make, (to be able to slide on the 19" L-profile
No of Module per base plate	4
Module connecting Bus bar length	12.6mm
Slider width	694mm
Vertical Module connection	Power connection (Amphenol connector)
Vertical rack spacing	175 mm
Slider Depth	515.4 mm
Slider Weight capacity	70 kg

Manufacturing and testing:

The manufactured sliders for each rack of the BESS cabinet is shown in figure 17. To support the battery modules within the BESS cabinet, custom slider assemblies were designed using CAD software, SolidWorks. The design phase focused on ensuring structural integrity, ease of installation, and the ability to securely support the weight of each battery module while allowing for maintenance access. Each slider was engineered with precise dimensions to match the internal layout of the cabinet racks and was reviewed for alignment with safety and functional standards. The design included cutouts and mounting features to facilitate seamless integration with the cabinet structure and battery enclosures.

Once the CAD models were finalized, the design files were sent to a specialized metal fabrication company for production. The manufacturing process involved laser cutting and bending sheet metal according to the CAD specifications, followed by welding and surface finishing to ensure durability. Key features, such as guide rails and fastening holes, were fabricated with high accuracy to maintain compatibility with the cabinet and battery units. The resulting sliders were then inspected to confirm adherence to the dimensional tolerances and design intent before being delivered for integration. As shown in Figure 17, the

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manufactured sliders were tested with dummy modules to validate the fit and structural performance. These tests verified that each slider could support the battery modules securely and allowed for straightforward installation and removal. The red markings seen on the modules and sliders served as visual guides for orientation and polarity during installation.

Figure 17. The manufacture sliders to be mounted in each rack of the BESS cabinet

As is mentioned, the slider system provides a modular, maintainable, and safe mounting solution for the BESS cabinet racks. The final assembly of the BESS cabinet incorporates the previously manufactured sliders, which were installed in each rack position to support the battery modules. These sliders allow for easy insertion and removal of the batteries, ensuring efficient maintenance and replacement procedures. The structural alignment of the sliders ensures that the modules remain securely in place during operation and transport. Each battery module connects seamlessly to the internal wiring harness and communication interfaces, maintaining a clean and organized layout within the cabinet.

The interior of the cabinet, as shown in figure 17, demonstrates the modular arrangement of the battery units, with consistent spacing enabled by the slider system. The cabinet also includes dedicated space for auxiliary components such as power distribution units and control electronics. The integration process was completed with a focus on accessibility and thermal management. All internal wiring was routed to ensure minimal interference with airflow and ease of troubleshooting, while the door panel was designed to house external access points and ventilation grills. To ensure optimal thermal regulation, the cabinet is equipped with an HVAC system mounted at the rear, as shown in the right figure. This system actively manages the internal temperature, preventing

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overheating and ensuring consistent performance of the battery modules under various environmental conditions. The HVAC unit is configured to operate autonomously, responding to internal temperature sensors to maintain a safe operating range. Its inclusion is crucial to the long-term reliability and safety of the BESS cabinet, especially in high-density energy applications.

Figure 18. The BESS cabinet ready to be tested

PCS specifications:

The employed power conversion system (PCS) introduces the technology of Silicon-Carbide (SiC) semiconductor on the inverter modules to increase the efficiency to 98.5% during charging and 98.7% during discharging. This high efficiency can also be seen in the partial load range. The PCS has high system flexibility meaning that AC and DC parallel operation is possible if needed. It is also capable of reactive power with easy control through open communication standard. The specification of the used PCS is illustrated in table .

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Table 12. Power conversion system specifications

KACO new energy.	Power Conversion System (PCS) gridsave 92.0 TL3-S-XL
DC input Data	
Voltage	668-1315 V
Max. DC voltage	1315 V
Max. input current	145 A
Max. short circuit current	300 A
Number of DC inputs	1
AC Output Data	
Rated output	92 000 VA
Max. power	92 000 VA
Line voltage	400 V
Voltage range (Ph-Ph)	300-580 V
Rated frequency (range)	50 Hz/60 Hz (45 Hz-65 Hz)
Rated current	3 x 132.3 A
Max.current	3 x 132.3 A
Reactive power/ cos phi	0-100% Smax/0.30 ind. -0.30 cap.
Max. total harmonic distorsion (THD)	<3%
Number of grid phases	3kWh
General Data	
Max. efficiency	Charge: 98.5%, Discharge: 98.7%
Operation mode	on-grid (charge/discharge)
DC parallel operation	` yes, 2
Communication	TCP/IP, Modbus TCP based on Sunspec
Standby consumption	<8 W without PCU,<14 W with PCU relay closed
Protective functions	overvoltage, overcurrent, overload, overheating, undervoltage
Circuitry topology	transformerless
Mechanical Data	
Display	LEDs
Control units	webserver
Interfaces	Ethernet, USB
Fault signalling relay	potential-free NOC max. 30V/1A
DC connection	Cable Lug
AC connection	screw terminal, max. 240 mm2 Cu or Al
Ambient temperature	-20°C - +60°C
Humidity	0-100%
Max. installation elevation (above MSL)	3000 m
Cooling	Temperature controlled fan
Protection class	IP66/NEMA 4X
Noise emission	<60 db (A)
HxWxD	719 x 699 x 450 mm
Weight	80 kg
Certifications	
Safety	IEC 62477-1:2012, IEC 62109-1/2
More Features	
Pre-charge	Yes
DC fuse	Yes
DC load relay +	Yes
DC load relay-	Yes

BESS test - Full charge and balancing:

To maintain an accurate SoC measurement, and ensure the SoH of the batteries in the system; the energy storage system has to be charged at least once per month to above 90% SoC (and lowest cell voltage above 3.9V) and kept above 90% SoC (and lowest cell voltage above 3.9V) until the unbalance between the highest and lowest cell voltage (displayed on the EMS under the 'Battery Detail' tab) is below 15mV (at least 12h).

In battery related applications, the derating profile validates the BESS safety protocols under high-temperature stress scenarios. The temperature derating curve illustrates the impact of module temperature on the output power capability of the BESS cabinet. As is shown in Figure 4, the system delivers near-maximum power in the moderate temperature range (approximately 10 °C to 35 °C). This range represents the optimal thermal operating window for the battery modules, where cell chemistry and internal resistance allow for efficient energy delivery without thermal stress. Below 10 °C, a slight reduction in power output is evident, attributed to the increased internal resistance of the battery cells at lower temperatures. This effect is typical in lithium-ion technology, where colder environments hinder ion mobility and reduce charge/discharge efficiency. The HVAC system integrated into the cabinet plays a key role in maintaining internal temperatures above this threshold during cold ambient conditions.

Conversely, as module temperature exceeds 35 °C, a sharp decline in output power occurs. This thermal derating is a critical protective feature to prevent overheating, degradation, or even thermal runaway. The power output drops steeply as the temperature approaches 50 °C, eventually nearing zero to safeguard the system. This behaviour confirms that the thermal protection algorithms are functioning as designed. The results of this test emphasize the importance of active thermal regulation. The cabinet's HVAC system ensures that the temperature remains within the optimal operating band, thereby maintaining maximum system performance and prolonging battery lifespan.

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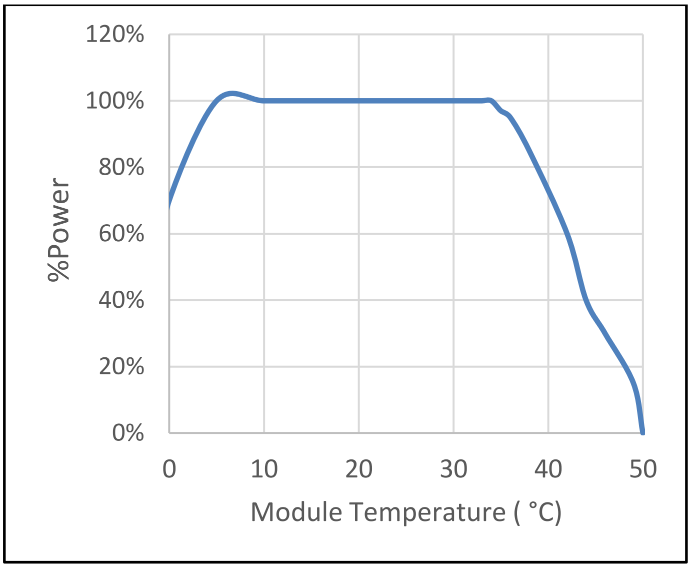

Figure 19. Temperature derating curve

Figure 19 presents the power derating curve as a function of the battery's state of charge (SoC). The graph shows the system's AC power output across a full charge cycle, from 0% to 100% SoC. It compares the theoretical maximum power output (green), actual power at a 0.5C discharge rate (red dashed line), and PCS (Power Conversion System) capability (black dashed line). The PCS maintains a flat output threshold well above the battery-limited values, confirming its oversizing relative to the BESS modules. The data reveal a modest increase in power output with rising SoC. At low SoC (0–20%), the battery output is slightly limited due to reduced cell voltage and internal constraints to preserve cycle life. This behaviour is expected, as most battery management systems enforce a conservative limit near the lower end of the SoC to prevent deep discharge, which can shorten the lifespan or damage the cells.

As the SoC increases beyond 20%, power delivery gradually improves and reaches a plateau between 60% and 100%. This reflects the region where the cells operate most efficiently, with stable voltage and reduced internal resistance. The curve for the 0.5C rate closely tracks the theoretical maximum, indicating that the cabinet can safely sustain higher power draw as the battery charges, aligning well with its design specifications. These test results confirm that the cabinet's energy management strategy is effectively aligned with battery characteristics. The PCS can handle higher power levels than the batteries can deliver, ensuring that system output is always governed by battery limits rather than power conversion constraints. This setup maximizes flexibility while maintaining safety and extending the operational life of the battery modules.

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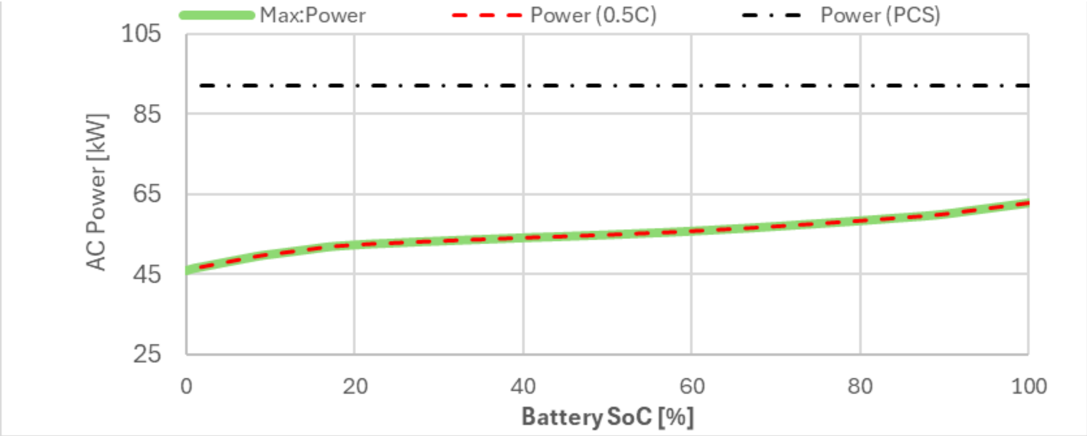

Figure 20. Power derating curve

List of harmonized standards

The present battery system, partly respect the following standards (for relevant aspects):

- NEN-EN-IEC 62619:2017: 'Secondary cells and batteries containing alkaline or other non-acid electrolytes-Safety requirements for secondary lithium cells and batteries, for use in industrial applications'
- NEN-EN-IEC 62485-2: Safety requirements for secondary batteries and battery installations. Part 2: stationary batteries
- NEN-EN-IEC 62620: Secondary cells and batteries containing alkaline or other non-acid electrolytes-Secondary lithium cells and batteries, for use in industrial applications

Conclusion of BESS manufacturing:

The successful manufacturing and assembly of the BESS cabinet demonstrate a well-executed integration of mechanical, electrical, and thermal systems. From the initial CAD design of the custom sliders to their precise fabrication and installation, each step was carefully planned to ensure structural stability, modularity, and ease of maintenance. The final cabinet design allows for efficient space utilization while ensuring safe and reliable battery installation using the tailored slider mechanism. The inclusion of the HVAC system has proven essential for maintaining optimal thermal conditions within the cabinet. Temperature and power derating tests have validated the system's ability to maintain performance across a wide range of operating conditions. The cabinet consistently operated within its safe temperature and power thresholds, showing effective thermal management and robust protection logic implemented at both the hardware and software levels. These test results confirm the BESS cabinet is compliant with design requirements and ready for field deployment.

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BMS was developed by IREC. The development and validation of the BMS are detailed in the next section 5.

5. Battery Management System

Specifically, in the definition of the 2nd life final BESS, one common and limiting element emerges when making decisions for suitability analysis: the BMS. This hardware component is responsible for estimating battery states and implementing optimal control strategies as needed.

Therefore, another key objective of this project is to define the specific hardware and software requirements for such a system in the current context. To validate its feasibility and potential for broader application, a prototype Battery Management System (BMS) will be developed and tested to validate basic BESS functionalities in a potential 2nd life stationary application.

Fundamentally, a BMS is the component responsible for managing and controlling batteries within a battery pack. These systems have evolved significantly, now incorporating advanced monitoring capabilities with precise sensors that measure pack/cell voltage, current, and temperature. Through the integration of accurate cell-characterized models in the BMS software, these measurements enable real-time computation of sophisticated algorithms. This provides critical real-time data on parameters like SoC.

BMS is essential for ensuring the safe and efficient operation of lithium-based battery packs. In the context of this project, the BMS must meet several functional requirements derived from both safety and performance goals. The primary roles of the BMS include:

<u>SoC Calculation:</u>
Accurately estimating the SOC using voltage, current, and time integration to inform system decisions and prevent deep discharge or overcharge.

<u>Safety and Protection:</u>
Monitoring critical parameters such as temperature, current, and voltage to detect fault conditions and take corrective action (e.g., opening contactors or triggering alarms).

<u>External Communication:</u>
Exchanging data with other systems, allowing real time monitoring and diagnostics.

<u>Remote Control Capability:</u>
Receiving commands from external interfaces to control BMS behaviour such as state transitions, resets, or data requests.

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These requirements guided the design, implementation, and validation phases of the BMS, ensuring it meets the demands of the project.

5.1 Hardware Development

The EV dismantled battery module used in this setup is a sealed unit with all internal components soldered. Due to this construction, accessing individual cells within the module would require physically cutting open the casing, which risks damaging the structural integrity and safety of the unit.

Figure 21. The EV dismantled battery module

To preserve the module's integrity and maintain safe operation, the entire module is treated as a single "cell" or unit in the context of this BMS. This approach is feasible since the EV dismantled battery module includes an integrated Cell Monitoring Controller (CMC) circuit developed by the car manufacturer. The CMC is responsible for internal cell balancing and monitoring, eliminating the need for external balancing mechanisms at the individual cell level.

This integration allows for easier deployment of the BMS, especially in scalable systems where multiple modules may be used. It also increases overall reliability, as monitoring is handled redundantly by the embedded CMC circuit within the module.

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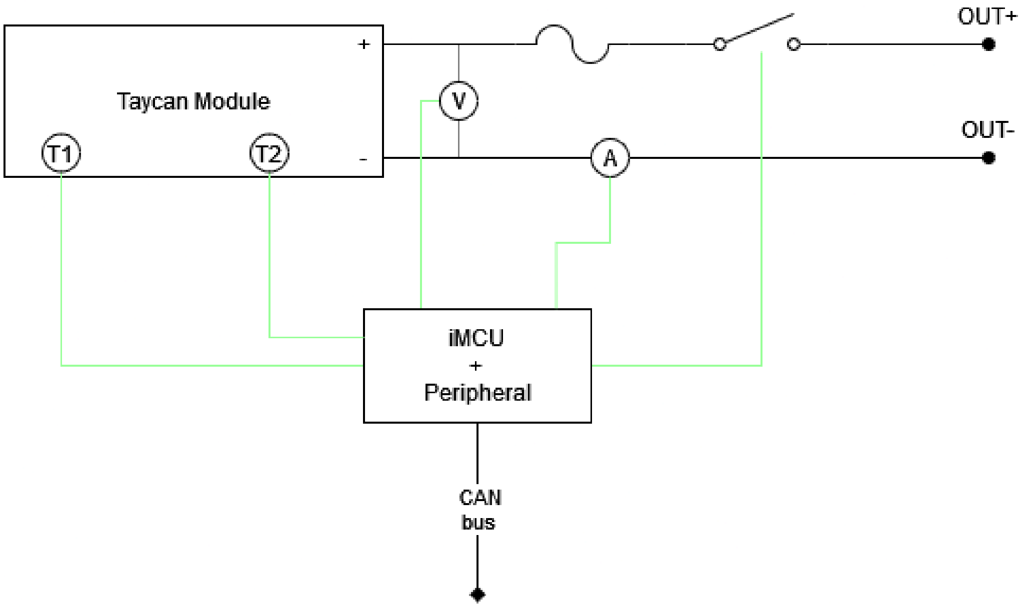

Figure 22. System schematic for the BMS

The final hardware setup can be seen in Figure 22, with each component described as follows:

- EV battery Module: The battery module itself.
- Temperature Sensors (T1, T2): Monitor to prevent overheating or unsafe temperature variations. The technology used is a precision CMOS temperature sensor.
- Voltage Sensor (V): Measures the output voltage of the battery module to ensure it remains within safe operating limits.
- Current Sensor (A): Measures the current flowing into or out of the module to monitor charge and discharge activity. The technology used is a Hall-effect current sensor.
- iMCU + Peripheral: The main control unit that collects sensor data, manages system behaviour, calculates SoC estimation, and handles communication via the CAN bus.
- Switch: A contactor that acts as a safety and control mechanism, allowing or interrupting power delivery to the output as needed.

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5.2 Battery Characterization & Model Development

The development of precise LIB models is fundamental to BMS performance, as these models form the core basis for all critical operational decisions. Accurate modelling enables reliable state estimation, health prognosis, and optimal control strategies, aspects essential for ensuring battery safety, longevity, and efficiency.

Nowadays, the Equivalent Circuit Model (ECM) is the most widely used technology in the BMS industry for developing LIB software, owing to its balance between simplicity and accuracy in capturing battery electrochemical dynamics. These models are employed both for characterization and real-time applications, such as estimating the SoC. ECMs represent a battery's electrochemical behaviour using passive electrical components (resistors, capacitors, voltage sources), which approximate dynamic voltage responses during charge/discharge cycles (*M. K. Tran, et. al, "Comparative study of equivalent circuit models performance in four common lithium-ion batteries: LFP, NMC, LMO, NCA," Batteries, vol. 7, no. 3, Sep. 2021*).

More specifically, the equivalent circuit model of a lithium-ion battery establishes mathematical relationships between battery components and their voltage-current (V-I) characteristics, SoC, and internal resistance. To capture the system's dynamic behaviour, the model typically incorporates:

1. A variable voltage source representing the open-circuit voltage (OCV) as a function of SoC
2. A series resistor accounting for the battery's internal resistance
3. Parallel resistor-capacitor (RC) pairs that model dynamic responses to current pulses, diffusion phenomena, and hysteresis effects.

Figure 23 illustrates a schematic representation of this typical ECM structure.

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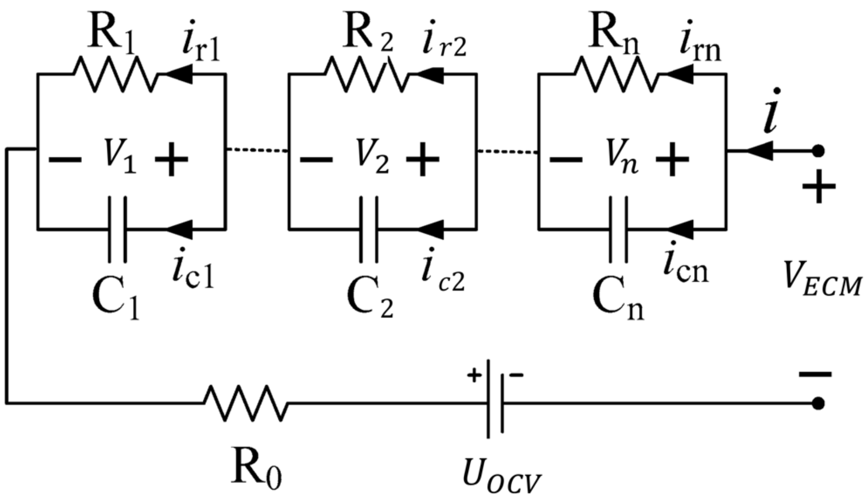

Figure 23. Concept & diagram of an ECM

For the scope of this project, ECM components conceptualization can be directly correlated with electrochemical parameters to represent cell dynamics:

- U_{OCV} represents the Open-Circuit Voltage (OCV) of a cell
- R_0 corresponds to the sum of resistive components related to the conductivity of both the cathode's solid material and the electrolyte,
- The RC pairs model the mass transfer dynamics and interfacial exchanges between the different layers comprising the battery's internal structure.

Within this system, the SoC is calculated linearly via coulomb counting, as shown in Equation (1), where:

- C_n is the battery's nominal capacity,
- η is the Coulombic efficiency,
- i is the battery current.

$$SoC = 1 - \frac{\int_{t_0}^{t} i \cdot \eta \cdot dt}{C_n} \quad (1)$$

From an ECM perspective, developing a model specifically tailored for subsequent observer design—used in SoC estimation—follows a well-established and widely adopted methodology for ECM integration.

The following equations illustrate how a 3RC ECM (as later implemented) calculates both the SoC and the voltages across individual circuit components in discrete time step k :

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$$SoC[k+1] = SoC(k) - (\eta \cdot \Delta t \cdot i[k])/C_n \tag{2}$$

$$V_{ECM}[k+1] = V_{OC}[k] - V_1[k] - V_2[k] \tag{3}$$

$$V_1[k+1] = \exp - \Delta t/R_1 \cdot C_1 - R_1 \cdot (1 - \exp - \Delta t/R_1 \cdot C_1) \cdot i[k] \tag{4}$$

$$V_2[k+1] = \exp - \Delta t/R_2 \cdot C_2 - R_2 \cdot (1 - \exp - \Delta t/R_2 \cdot C_2) \cdot i[k] \tag{5}$$

$$V_3[k+1] = \exp - \Delta t/R_3 \cdot C_3 - R_3 \cdot (1 - \exp - \Delta t/R_3 \cdot C_3) \cdot i[k] \tag{6}$$

These equations can therefore be directly incorporated into a state-space framework, structured according to the following formulations where x represents the state vector and z, from Equations (7) and (8), corresponds to the output vector containing the battery terminal voltage. A, B, C, D matrices are parameterized according to the empirically derived values of the RC pairs. The discrete-time state-space system is defined as:

$$x_{k+1} = A \cdot x_k + B \cdot u_k \tag{7}$$

$$z_k = C \cdot x_k + D \cdot u_k \tag{8}$$

This nonlinear state-space model serves as the foundation for state estimation algorithms, such as observer blocks embedded in BMS software. The specifications of the estimation algorithm implemented in the prototype BMS will be detailed in the following section.

First, the characterization specifications for the ECM to be integrated into the BMS prototype software must be established. This process involves parameterizing the OCV and RC components through standardized constant-current pulse testing of the entire battery module, which is modelled as a single cell (as presented in the previous section). Since testing is conducted using only module-level terminal voltage measurements (rather than individual cell monitoring), the experimental validation employs voltage cutoff limits corresponding to 20-80% SoC in the OCV profile to maintain safe operating conditions, in accordance with Nickel-Manganese-Cobalt (NMC) chemistry profile.

Regarding ECM configuration, the optimal number of RC pairs must be selected to accurately capture hysteresis dynamics. As shown in Figure 24, three RC pairs were chosen based on impulse response analysis of different ECM configurations in MATLAB, with validation against experimental measurements. As shown in Figure 24, adding more than three RC pairs does not significantly improve the model's ability to capture voltage dynamics for the present case. The 3RC model already captures both short-term and long-term dynamics accurately. Furthermore, MATLAB simulations show that, in terms of execution time, the 2RC model takes approximately 1.345 times the time of the 1RC model, while the 3RC model takes about 1.789 times the time of the 1RC. Since the BMS does not need to run multiple models in parallel, the 3RC model offers an optimal trade-off between accuracy and computational cost.

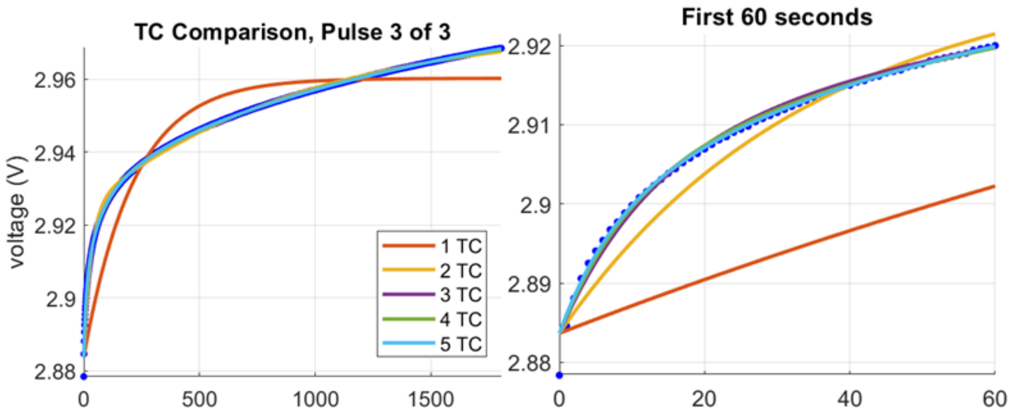

Figure 24. Optimal Calculation of necessary RC branches

With the ECM optimal architecture selected, OCV and R-C parameters can be characterized along SoC using battery experimental pulse test data shown in Figure 25. By applying an iterative parameter identification process (also implemented in MATLAB), the parameter values for the 3RC ECM can be determined.

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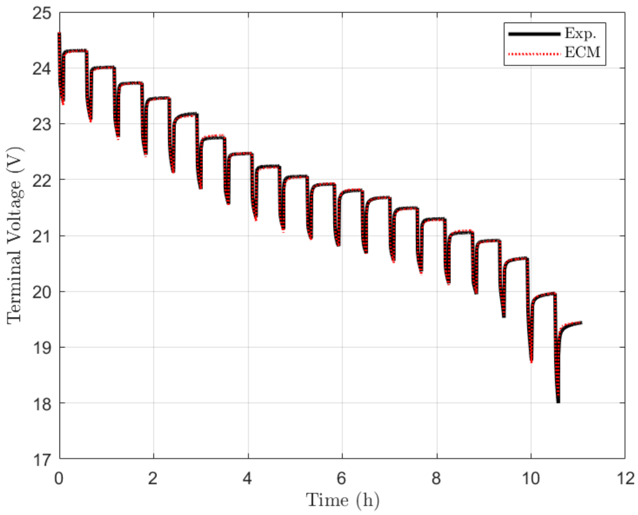

Figure 25. 3RC/ECM fit for module pulse test

The RC parameters obtained in the fit are used to populate the parameter look-up tables, enabling nonlinear characterization of the ECM component. With the ECM parameters fully defined, the system can then be expressed with parametric equations for ease the subsequent configuration in the SoC estimation algorithm. The resulting look-up tables and linearized values are represented in Figure 26.

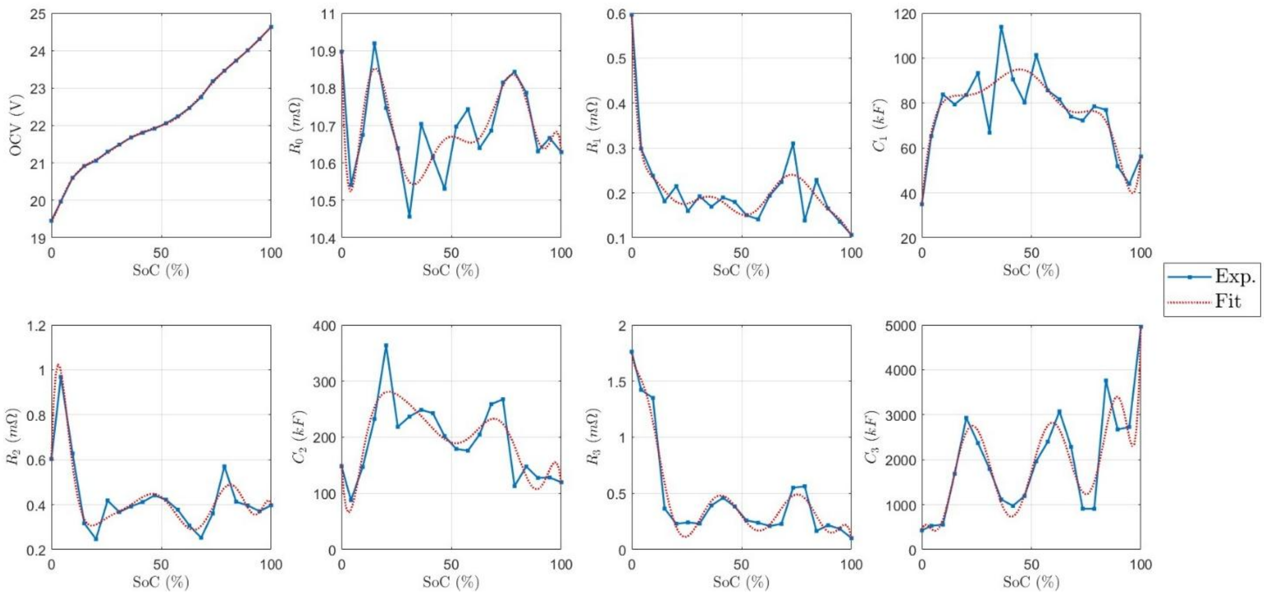

Figure 26. Parameter fitted values vs. SoC. Non-linear (blue), Parametric (red).

Figure 27 demonstrates the close agreement between the parametric model and experimental values (C/2 discharge test), achieving a sufficiently low Root Mean Square Error (RMSE) of 0.02607 for its later implementation in BMS prototype and validation purposes.

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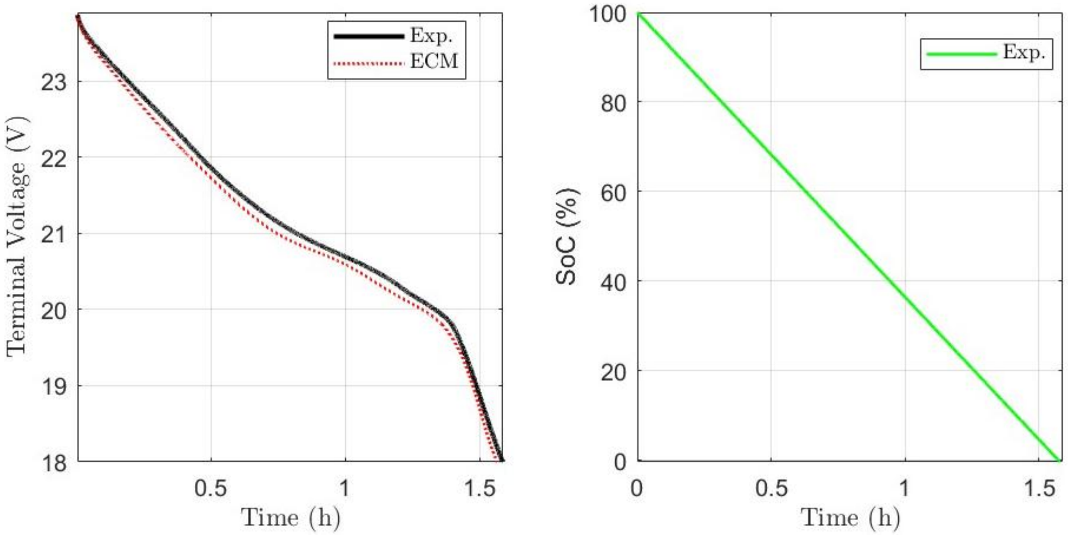

Figure 27. Linearized 3RC/ECM vs. C/20 discharge experimental data

The subset of ECM parametrized equations obtained from empirical characterization enables the implementation and configuration of the nonlinear state-space system (Equations 7 and 8), which captures the battery module dynamics to be embedded in the SoC estimation algorithm.

5.3 Embedded Software Development

The BMS software was developed to monitor and manage the battery module in real time. It includes routines for voltage, current, and temperature sensing, SoC estimation, and fault detection. A state machine controls the system behaviour across key states like Initialization, Idle, Normal Operation, Sleep, and Alarm. Control is done via terminal SPI, and communication is handled via CAN, for analyses purposes.

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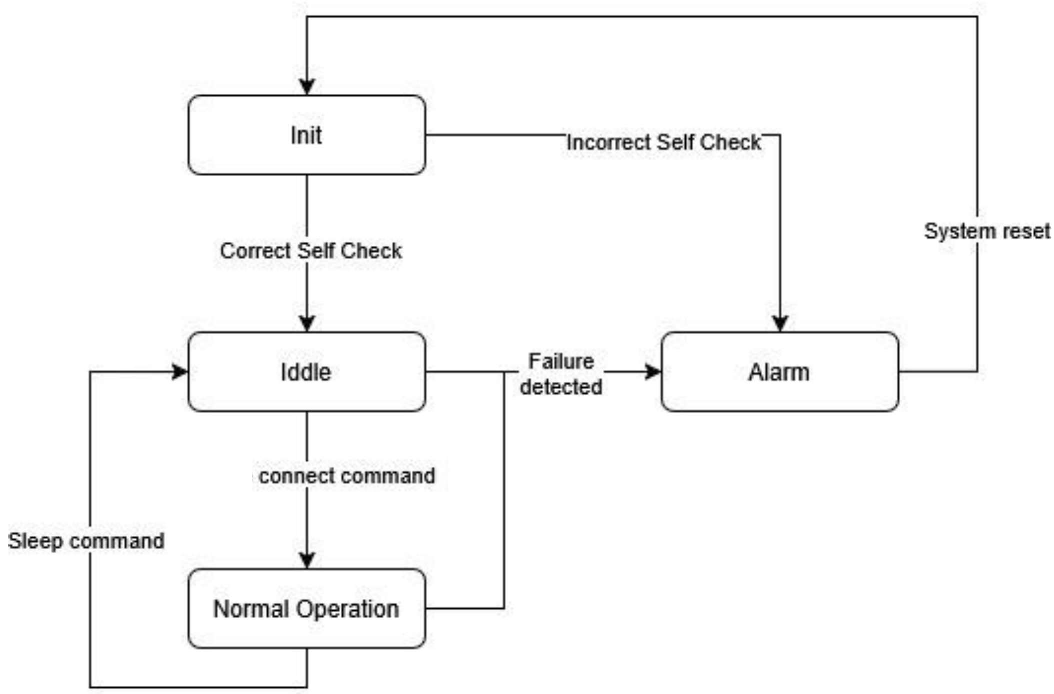

Figure 28. State Machine Diagram

The BMS software is organized into modular components that manage the safe and efficient operation of the battery module. Sensor data acquisition is handled through dedicated drivers. Real time responsiveness is achieved via interrupt routines, ensuring periodic data collection and system checks. Derived from the model development, an Extended Kalman filter (EKF) implementation is used to refine raw sensor data and calculate the SoC according to the insight provided by the non-linear state-space 3RC/ECM developed in previous section.

In addition, the system integrates CAN communication for transmitting diagnostics and system data. To control the states a terminal through SPI is implemented.

All these functionalities are implemented in the main loop, composed from the state machine mentioned above.

5.4 BMS Validation

To ensure the proper functioning, reliability, and safety of the BMS, a series of validation steps were performed. These tests were designed to verify both individual components and the complete integrated system under different operating conditions, including normal operation, fault scenarios, and real battery behaviour.

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1. Isolated Component Test (Without Battery)

Before integrating the full system, individual components were tested in isolation to verify their behaviour and do proper calibration. For example, the voltage sensing circuit was validated using a precision laboratory power supply to simulate different voltage levels and ensure accurate analogue to digital conversion. Similarly, the current and temperature sensors were tested using controlled inputs. This step ensured that the software correctly interpreted sensor data and that the CAN communication behaved as expected.

2. Entire System Test (Without Battery)

With all components connected but without a real battery, the system was powered and placed under controlled test conditions. Alarm scenarios—such as overvoltage, undervoltage, overtemperature, and overcurrent—were artificially triggered to confirm that the system responded correctly. This included verifying that the appropriate state transitions occurred and that the contactor was opened in fault conditions.

3. BMS and Battery Integration Test

After component level validation, the BMS was connected to an actual battery module. Basic charge and discharge cycles were performed to test functionality. The system's ability to monitor voltage, current, and temperature values was validated, and proper SOC calculation.

Figure 29. Test setup inside climate chamber, showing battery, sensors, and control interface.

4. Charge/Discharge Tests & SoC Validation

To evaluate the accuracy of the SoC estimation model, the battery was subjected to controlled current profile representative of a potential 2nd life use case. Measured SoC was compared against expected values based on SoC

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calculation in the BMS and model predictions. This test was crucial for validating the software's SoC algorithm under different load conditions.

First, to establish a potential usage profile for second-life battery applications, researchers at the National Renewable Energy Laboratory (NREL) utilize the REopt® techno-economic decision-support platform. This tool optimizes energy system design across multiple scales—from individual buildings to campuses, communities, and microgrids—by determining the optimal integration of renewable energy generation, conventional power sources, energy storage systems, and electrification technologies. The platform enables to simultaneously achieve cost reduction targets, resilience objectives, carbon emission mitigation, and enhanced energy performance metrics (*S. Mishra, et. al, Computational framework for behind-the-meter DER techno-economic modeling and optimization—REopt Lite, Energy Systems 2021*).

Building on the project framework, a strong use-case candidate for the BMS experimental validation process is the performance assessment of second-life battery energy storage systems (BESS) tailored for residential applications. In these scenarios, the BESS operates alongside photovoltaic systems and other renewable energy sources. The proposed system architecture is based on a REopt®-optimized smart grid model, which systematically incorporates three key parameters: (1) the available energy capacity of repurposed batteries—aligned with the FREE4LIB project's objective of deploying a 30 kWh second-life BESS, (2) the optimized renewable energy resources determined by REopt®, and (3) statistically validated residential energy demand profiles, exemplified by a building with six midrise apartments.

These annual demand profiles, officially sourced from Spain's Ministry for the Ecological Transition (MITECO), are presented in Table 1 (Source: "*Estadísticas de consumo energético Residencial," Ministerio para la Transición Ecológica y el Reto Demográfico*"). When scaled to six apartments, they determine the inputs for the techno-economic optimization process.

The REopt® platform's simulation methodology generates several operationally significant outputs, including a solar array configuration designed to meet the modeled building's peak demand. By analyzing various optimal photovoltaic system configurations and simulating their energy production, both the maximum and average energy throughput ratios are determined for the 30 kWh second-life BESS. These performance metrics are direct results of the optimization process and serve as critical indicators under representative real-world operating conditions.

Figures 30 and 31 present the simulated system's annual energy demand and energy dispatch over a one-year period. The results indicate that the batteries consistently reach similar depths of discharge (DoD), often approaching 100%, with minor variations depending on the specific demand profiles. Based on this behaviour, reference 100% DoD values per day-cycle are established, and the

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discharge timeframes associated to it are analysed to characterize the daily cycling pattern relative to average daily consumption. This analysis allows for the definition of discharge characteristics for each demand type. Corresponding representative discharge C-rates for cycling operation are included in a dedicated column of Table 13, categorized by demand profile.

Furthermore, relative BESS charge ratios can be determined based on available solar power and charge power outputs. The graphical data indicate that charging occurs within a relatively brief timeframe, as dictated by the solar generation curve and grid interaction patterns. This permits definition of an average charging period at a C/6 charge rate—a value consistent across all scenarios since REopt® adapts the solar capacity accordingly for each case.

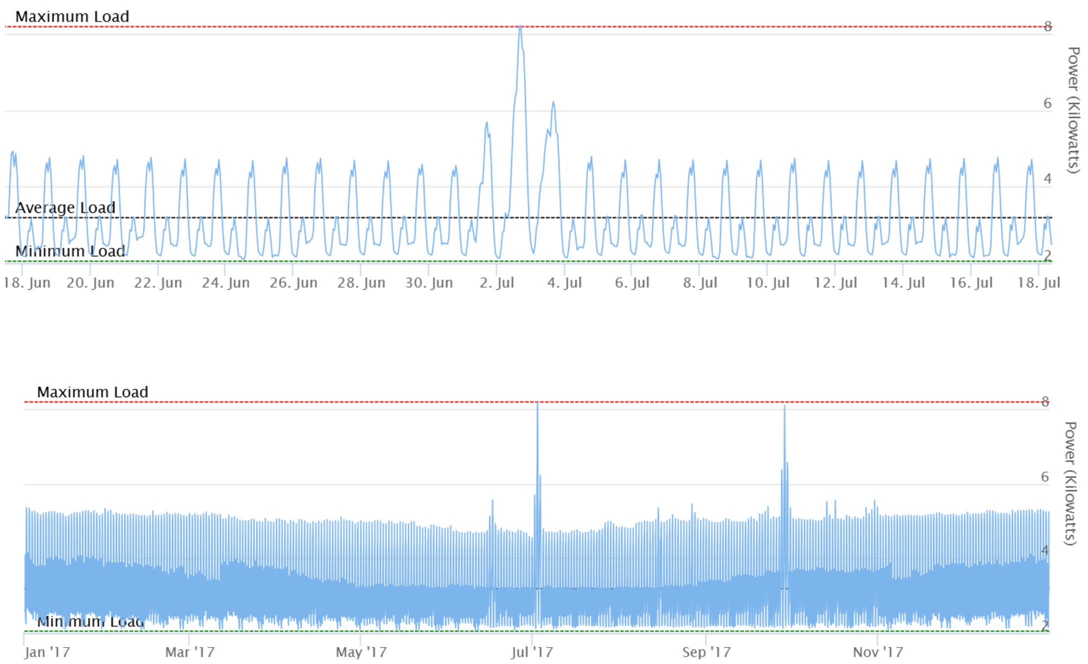

Figure 30. Average consumption energy demand for the residential building application: Detail for 18 June – 18 July (top); Annual profile (bottom). Source: REopt®

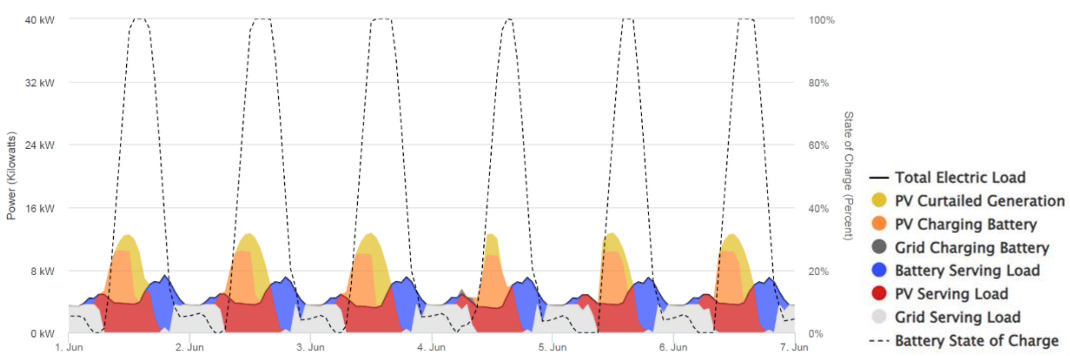

Figure 31. Detailed energy dispatch for the average demand profile within the smart grid in a specific timeframe. Source: REopt®.

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Table 13. Household calculated energy demand and battery usage (average DoD and C-rate) calculated in REopt®

Consumption type	Demand	Annual Energy [kWh/year]	Peak Power [kW]	C-rate Cycle
Low	Electrical	20.922	6,13	C/10
Average	Electrical	42.000	12,30	C/7
High	Electrical + Thermal	63.078	18,47	C/6

The REopt® simulation outputs support the development of a representative test protocol for the module in a battery cycler (*Regatron G5.BT.36.500.216*). The experimental methodology for BMS validation involves coupling the prototype BMS to the module to continuously monitor voltage, current, and temperature during a constant-current discharge, while the EKF estimates the SoC in real time during the representative test. The applied test profile replicates realistic operating conditions derived from the simulation-based load profile of the second-life residential application. To be conservative the maximum demand scenario ("Consumption type: High") from Table 13 and the previously define average charging period is used to define a constant current C/6 discharge-charge experiment as the input for the battery module cycler. This setup establishes a critical validation framework, where the SoC values measured by the cycler serve as ground truth—enabling a systematic comparison with the BMS's real-time measured and estimated outputs.

The following figures compare the BMS-measured values with the reference values recorded by the cycler.

The first plot, from Figure 32, shows the voltage measured by the BMS (blue curve) and the cycler (orange curve). At first glance, a drop of approximately 0.413 V can be observed between the two curves. This discrepancy is likely due to unaccounted impedances introduced by the measurement and protection circuit of the BMS prototype. Nevertheless, the BMS accurately captures the overall evolution of the voltage curve. Bridging this gap would require additional characterization of the impedance associated with the coupling of the measurement and protection circuit. However, since the BMS is a prototype rather than an industrialized product, it is difficult to precisely characterize the complex number for impedance associated with the circuit. Additionally, because the final impedance that the BMS should consider in a practical second-life BESS application has not been defined, this voltage measurement comparison test is considered sufficient for BMS validation purposes.

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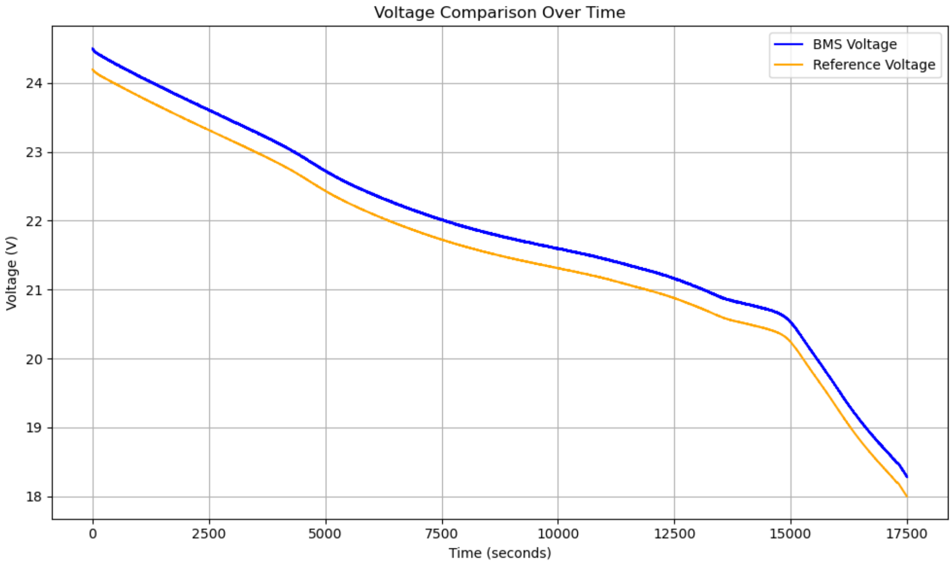

Figure 32. BMS vs. Cycler measurements: Module terminal voltage

Figure 33 presents the same comparison, but for current. It shows values that are close to the reference measurements, although some deviations around 0.521 A, are observed, likely due to the voltage drop introduced by BMS protection circuit.

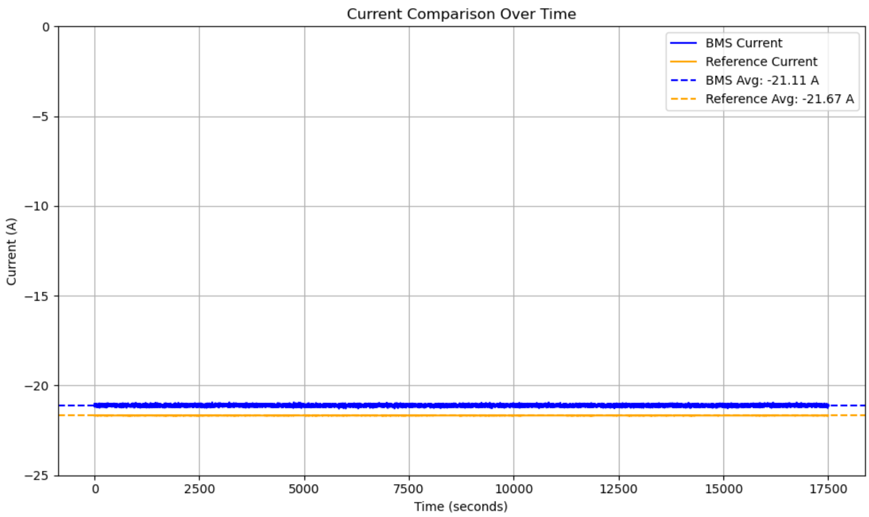

Figure 33: BMS vs. Cycler measurements: Current

Figure 34 shows the comparison between the SoC prediction provided by the BMS and the ground truth values obtained from the cycler. Since the BMS estimates SoC using voltage and current measurements based on the parameterized battery ECM and an EKF it is evident that the voltage and current

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drops introduced by the measurement and protection circuit will affect the accuracy of the SoC prediction. These deviations are observable in Figure 35, with a discrepancy of approximately 4% in SoC.

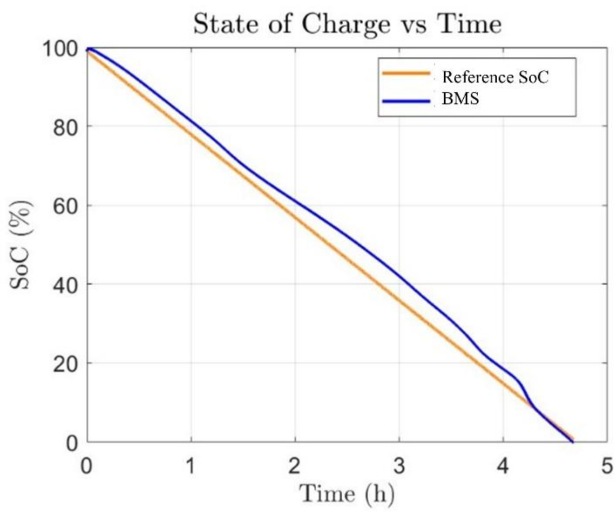

Figure 34: BMS vs. Cycler measurements: State-of-Charge prediction

Despite the observed deviations, it can be stated that the BMS provides meaningful real-time insight into the SoC, capturing a slope that closely resembles the expected behavior under a representative current profile. The curve, although shifted due to the offset in voltage and current measurements introduced by the additional circuitry of the BMS prototype. It can be reasonably assumed that, in a real application, if the added impedance introduced by the protection and measurement circuits is properly characterized and incorporated into the model using an industrialized version of the BMS prototype, the SoC estimation software accuracy would improve significantly. However, this level of refinement falls beyond the scope of the present BMS validation process.

Finally, Figure 35 shows the temperature readings from the sensors of the BMS prototype, which are located on the surface of the module enclosure. Since the discharge test was performed in a climatic chamber at 20 °C, the slight variations detected demonstrate that temperature can be tracked in real time, allowing the system to monitor and enforce safe operating limits.

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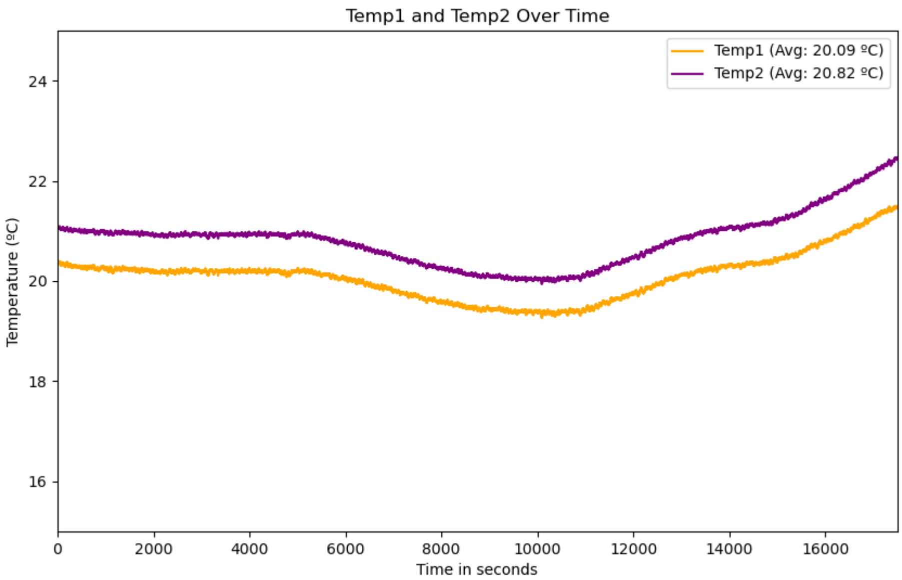

Figure 35: BMS temperature measurements

5.5 Conclusions

The BMS prototype effectively tracks voltage, current, and SoC trends, with minor offsets introduced by its measurement and protection circuitry. While small deviations are observed in voltage and current readings, the overall trends align closely with reference measurements, showing that the BMS captures the essential behaviour of the system only requiring to offset the measured data according to the calibration performed during these tests. The SoC estimation also reflects slight discrepancies, but the BMS provides valuable real-time insights, maintaining an accurate slope in accordance with expected behaviour under typical load profiles. These deviations could be further reduced in future applications if the impedance introduced by the protection and measurement circuits is properly characterized and integrated into the model. Additionally, the BMS successfully monitors temperature variations, which can be tracked in real time to ensure safe operation.

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