MARKET INTELLIGENCE REPORT

COBRA

KEY TECHNICAL, POLICY AND MARKET DEVELOPMENTS INFLUENCING THE ELECTRIC VEHICLE BATTERY LANDSCAPE

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INTRODUCTION

New battery types are being developed at breakneck speed, competing on performance, cost and sustainability. Novel chemistries and technologies require thorough testing to understand properties of the battery – not only at its deployment but also during the use phase and after its decommissioning. This is why battery prognostics and health management (PHM) has been gaining much prominence in the last decade, signalling its value to industry and society. Accurate diagnosis and prognosis of battery performance lies at the heart of the field. With fast and accurate PHM, time-to-market and warranty risks of novel batteries are reduced, whilst battery lifetime and recyclability are increased.

However, so far, accurate prognosis and diagnosis of battery performance remains a time-consuming and complex task. This market intelligence report will give insight into the state-of-the-art of battery PHM, its main approaches, challenges, and trends.

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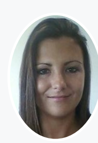

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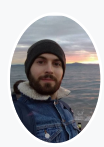

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OVERVIEW

The term **Prognostics and Health Management (PHM)** originates from the 1990s military aviation domain and has been picked up in the battery field during the last decade [1]. While **prognostics** aim to predict the future status of a system, **health management** (or diagnostics) uses generated information from the energy storage system to diagnose potential issues, and act upon them to keep the battery in a healthy state.

Prognostics and Health Management is used across all battery lifetime stages. Roughly speaking, at every lifetime stage, one begins by asking themself:

"What will this battery's state look like, in X years?"

Figure 1 shows the different battery lifetime stages and the respective parameters investigated in PHM.

Figure 1: Parameters investigated in PHM over a battery's lifetime

The similarities of PHM across battery lifetime stages lie in the topics addressed. In general, these include battery lifetime, safety, reliability, and performance (see table 1). The main differences between PHM across lifetime stages are the focal parameters applied. While R&D focuses on the optimisation of design parameters, the environmental condition parameters of batteries are used to support health management (see table 1). Also, logically, the testing environment across lifetime stages is different. Battery prognostics during R&D happens mostly in laboratory environments on battery test benches, whereas health management could be a virtual model within the EV Battery Management System (BMS).

Table 1: Focal PHM parameters investigated over battery lifetime phases

	FOCAL PARAMETERS	TOPICS ADDRESSED BY PHM
R&D	Chemistries, battery design and manufacturing features: electrode microstructure, pack design dimensions, coating thickness, drying temperature.	How can we design a battery that has a long lifetime, high level of safety, reliability, and performance?
USAGE	Real-time usage data: actual environmental conditions, user behaviour (charge-discharge cycles), accidents.	How can we increase battery lifetime, performance, safety, and reliability?
2ND LIFE	Historical usage data + additional characterisation outside vehicle for increased PHM accuracy	What is the battery's state of safety, and remaining useful life? When should we recycle/repurpose the battery?

DATA ACQUISITION AND HEALTH INDICATORS

In order to evaluate the state of health (SoH) of any battery with sufficient accuracy, it has to be tested. The most common test is performed by measuring a set of parameters during charge and discharge cycles. These parameters can be divided into:

- **Direct health indicators**: voltage, current, temperature and resistance,
- **Indirect health indicators**: features extracted by applying signal processing techniques, incremental capacity, and differential voltage analysis **[2]**.

As explained in the chapter above, this data can be acquired to analyse and prognose the battery state in different phases of its life. In the design and manufacturing phases, cycling tests are performed on the cell, module, and battery pack levels in **laboratories (testbeds)**, simulating various operational conditions, e.g., operational temperature range and vibrations.

During the use phase, the direct indicators are recorded through sensors connected to the **battery management system (BMS) in the vehicle**. A BMS based on this information actively balances the charging and discharging parameters of each cell, making sure they stay within safe operational regions (**more information on BMS and sensors can be found in this dedicated MIR here**). Apart from the active function of BMS, it can also store the cycling data, which can be extracted on-site by a battery expert or wirelessly uploaded online by the EV computer. The voltage, current and temperature curves resulting from cycling are then processed using a variety of techniques to obtain additional features allowing for a more precise estimation of SoH.

PROGNOSTICS METHODS

The data gathered from tests not only enables the identification of the current SoH of the battery, but also help to **prognose its ageing**, i.e., the expected reduction of its capacity and available power in the future. The degradation of Li-ion batteries can be divided into two types: **charge-discharge cycling** (based on character and number of cycles, predominant in EVs) and **calendar ageing** (based on time of usage and operating conditions, most important in applications with shorter operation periods, e.g., uninterrupted power supply) **[3]**.

BATTERY TESTING VS VIRTUAL MODELLING

Prognostics during battery development is a **complex exercise** that requires **careful planning and time**: one must repeatedly test batteries over specific conditions until they're confident enough of the battery's performance and safety. As you can imagine, testing for multiple battery chemistries and designs adds up to the task at hand. Not only that – we cannot simulate all possible operational conditions and user behaviours (e.g., temperatures, charging and discharging speed), since every new variable would increase the number of tests.

Here, virtual models have the potential to reduce battery testing time. However, it is important to understand what virtual models can and cannot accurately estimate. Therefore, it remains complicated to accurately predict the battery's life while keeping a reasonable **time-to-market**. Especially safety testing is hard to replace since many safety tests are mandatory by law.

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The industry needs the most accurate prognoses (with an acceptable error of 2-5% [4]) to underpin warranties, schedule maintenance service and develop health-conscious battery management systems. There are three main approaches for battery prognostics: **physics-based**, **empirical**, and **data-driven**. The table below explains the characteristics, advantages, and disadvantages of these approaches **[4]**.

Table 2: Strengths and weaknesses of PHM approaches

APPROACH	STRENGTHS	WEAKNESSES
Physics-based (mechanistic): models simulating and analysing degradation behaviour, e.g., thermal behaviour, solid electrolyte interphase (SEI) growth, active material losses, and lithium plating.	• Very detailed information about the processes occurring inside the battery which can be used not only to predict degradation but also mitigate it through battery design and management. • High precision.	• Complexity of the models and relative paucity of available data makes it hard to verify the accuracy, both of the model itself and of its parametrisation. • Requires expert knowledge to develop physical models and are less flexible than data-driven
Empirical (phenomenological): a capacity fade curve parametrised by operating conditions, e.g., charge throughput, equivalent cycle number or time.	• Simplifies the prediction of degradation of Li-ion batteries by focusing on changes in the specific measures of degradation, such as internal resistance or cell capacity.	• They can fail to account for the complexity of Li-ion battery degradation, which usually depends on more than just time and cycle number. • Requires long historical data (at least 25% along the trajectory to end-of-life).
Data-driven (AI-based): uses measurements such as the current and voltage directly as inputs to a machine learning model in order to learn the remaining use life as the output.	• Enables predictions using only early-cycle data without the need for complex electrochemical models. • Can be used in real-time applications.	• Insufficient or biased training data can lead to inaccurate predictions or false results. • Comprehensive dataset with various ageing patterns is required to allow for generalisation of the method.

Recently a lot of attention has been drawn to **hybrid approaches** which combine strengths of the three methods presented above. Physics-based models are detailed and insightful, whereas data-driven approaches are less complex to build and have a high level of accuracy. Hybrid approaches make the link between both, by 'fine tuning' physics-based models with a data-driven approach **[5]**. One such example is to use field data to complement complex physics models and expensive testbed data with EV usage data, which is inexpensive and comprehensive due to availability in large numbers and coverage of all types of usage behaviours **[5]** Hybrid approaches can be divided into three categories according to the purposes: improving the performance of filtering methods, generating future observation data, and processing raw data **[4]**.

CHALLENGES FOR BATTERY PHM

As is the case with different topics in the battery field, the unprecedented interest in high-performance energy storage puts increased pressure on existing PHM methods, revealing their bottlenecks. Most of them lie in the lack of scalable and accurate prognostics techniques, limited tools and technologies used nowadays, as well as governance and cooperation in industry and research.

DATA GAPS

The two main ways to retrieve data on battery properties (testbeds and field data) are either incomplete or hard to come by. The **field data** from electric vehicles is considered by some researchers as difficult to work with, due to their high uncertainty and low quality caused by long periods of missing data, less accurate sensors in EVs, cell-to-cell variations within a pack or modules and extreme C-rates **[4]**.

Furthermore, **laboratory test data** is often generated for modelling projects but less often shared with others. This creates a cumbersome working environment for researchers who do not have access to a lab or the budget to acquire testing data. Namely, a wide variety and abundance of data is much needed to calibrate or train virtual models **[6]**. Because of that, many researchers use the few publicly available battery datasets to verify their prediction algorithms, e.g., dataset published by the Prognostics Center of Excellence at NASA Ames **[7]**.

SCATTERED KNOWLEDGE IN INDUSTRY AND RESEARCH

Battery testing data is not shared much between value chain partners because of commercial interests. Also, data sharing practices and standards are not in place as opposed to other industries (e.g., the semiconductor industry **[8]**). Furthermore, although the potential quantity of cycling data produced in electric vehicles is enormous, it is only accessible by the OEMs controlling the BMS. Most manufacturers do not share the data from any stage of battery lifetime, justifying it with security reasons. Of course, full ownership of cycling data also gives them a competitive advantage, allowing them to develop better battery design and vertically integrated end-of-life processes. Unfortunately, this also limits the number of stakeholders that can make use of the remaining battery life (e.g., recyclers, repurposers and remanufacturers). Moreover, due to the rapid development of battery chemistry types and designs, research knowledge on the prognostics models is scattered over different research and test centres. This further adds to the complexity and fuzziness of industry and research.

INSUFFICIENT SENSITIVITY OF HARDWARE

Battery cells and their packs are complex and dynamic systems. For example, cells can move, crack, and expand during usage which is difficult to accurately assess with current sensors used in prognostics. Both sensors used in physical testbeds and BMS systems cannot accurately account for several complex behaviours of cells. Dismantling the battery pack could provide insight but this is not desirable during testing and especially during usage. Besides, it is desirable to 1) know what the worst-performing cell in the battery is and 2) what is happening inside that cell. This is useful to develop better battery designs or health management strategies during the usage phase. Furthermore, while cell testing in laboratory environments allows the use of multiple more elaborate sensors per cell, this is not feasible in cars due to increased costs and space/weight constraints.

COSTLY AND TIME-CONSUMING TESTING

Ideally, OEMs would age the batteries over their whole lifetime before bringing them to market. However, this would dramatically increase their time-to-market, since the life expectancy of most batteries is between 14 and 18 years [8]. Continuous cycling is also extremely time-consuming. As a rule of thumb: one discharge-charge cycle at 1C takes 2 hours. Some of the newest batteries are estimated to sustain roughly 10,000 cycles [9]. In theory, this means testing a single battery over a continuous cycling program could take 830 days.

To compensate for this, battery ageing can be accelerated, which diverts further from actual use conditions. Extreme operating conditions, such as high C-rates or elevated temperatures, are often used to accelerate ageing. However, even with accelerated ageing, it can be slow to assess the degradation impact of individual manufacturing parameters such as materials and processing choices or design factors such as cell size, number of layers and electrode thicknesses, and formation protocol. Furthermore, rest periods between cycles have been shown to benefit the overall battery life, hence the batteries designed based on accelerated ageing results may have longer lifespans than predicted [10]. Using testbeds is also inflexible and expensive because of the signal acquisition systems needed [7]. It requires a lot of deep expertise and specialised equipment.

HIGH COMPLEXITY OF VIRTUAL MODELLING

Due to a multitude of **factors influencing battery performance** (chemistries, composition, manufacturing processes, battery pack design, charge-discharge profile, etc.) and various **degradation mechanisms** (solid electrolyte interphase (SEI) growth, active material losses, and lithium plating), the prognostics models require complex and power-consuming calculations. Because of that, physical models are sometimes simplified to reduce cost – e.g., some physics-based models (falsely) assume homogenous degradation of cells throughout the pack, whereas others do not consider the change of usage conditions that one battery might endure throughout its lifetime [7]. Here, data-driven models are in general highly accurate for the testbed or field data on which they are trained, but they fail to provide much accuracy beyond similar usage conditions.

UNHARMONISED STANDARDS

Car and battery manufacturers must fulfil safety testing to certify their batteries and EVs, which prohibits faster prognostics. It takes expertise and time to figure out the necessary regulations per battery application and country of the corresponding market. Subsequently, even if one manages to develop a complex simulation of safety features, regulations (e.g., ECE R100) will require the physical demonstration of safety which diminishes the advantages of using elaborate models. On the side of battery performance, not much is standardised. In general, battery manufacturers do their own specific testing which leads to different battery qualities vary across industry. Figure 3 shows the differences in mandatory performance testing across the globe.

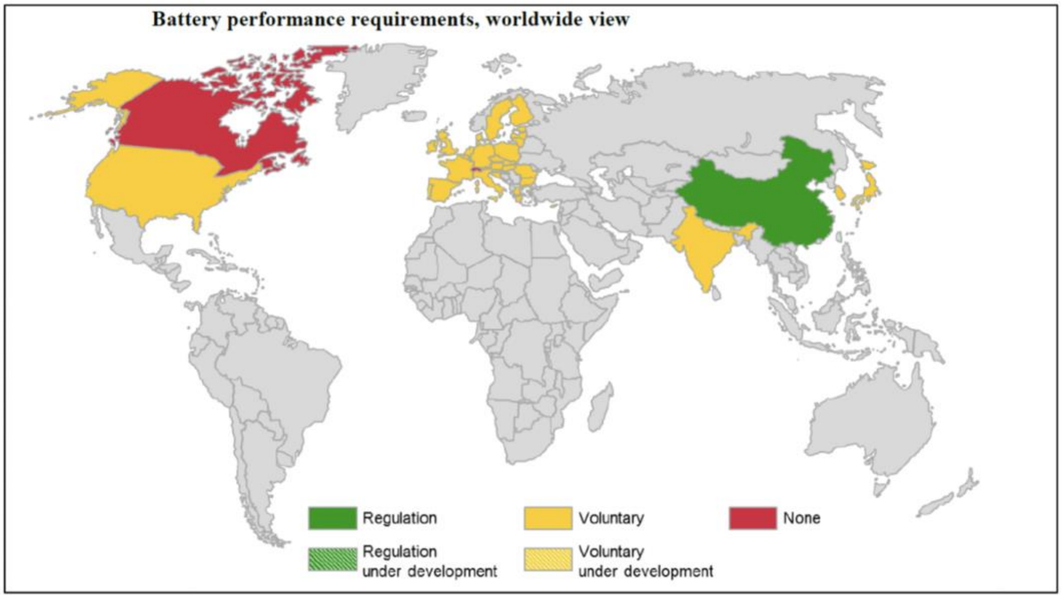

Figure 1: Mandatory battery performance testing ***[11]***

BATTERY PROGNOSTICS FOR 2ND LIFE APPLICATIONS

With the rise of e-mobility, our society is awaiting an **enormous return of used batteries** in the years to come. Eurecat works to make the most out of those batteries, by optimising the process from battery's first life to their next stage.

To get an idea of the battery's **remaining useful life (RUL)**, it is crucial to receive historical data on the battery's lifetime which is typically stored in the EV Battery Management System. This information not only gives us the cycling data but even more importantly the **log of errors and accidents** that occurred to the battery.

Further tests after battery extraction can supplement this data for more detailed and accurate results. The main challenge here is to develop a methodology to determine the state of a battery with the **minimum number of key parameters**, to reduce the time needed for classification and selection of their most suitable 2nd life application.

Just like prognostics in the development phase, the estimation of remaining life can be helpful in determining the **right operational conditions and health management strategies** in the 2nd life application.

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SOLUTIONS AND TRENDS FOR BATTERY PHM

ACCELERATED TESTING AND TESTBED MANAGEMENT

Since battery testing in testbeds is time-consuming, it is important to make the best use of the battery test data collected. Here, a smart design of experiments is key. Approaches are underway in research to use fewer tests while increasing model accuracy. Several examples include deep-learning, Bayesian optimisation protocols and Gaussian process regression **[12]**–**[14]**. Deep learning methods are particularly powerful in finding battery ageing features **[5]** which can - colloquially speaking - be compared to *hidden tell-tales* of a battery's ageing trajectory. Whereas the first two approaches are used after testing, Bayesian optimisation can be applied to explore and exploit the next round of experiments performed in battery testbeds.

ADVANCED AND WIRELESS SENSORS

Advanced battery sensing technologies are being developed at a rapid pace to provide more detailed and insightful data on a battery's state. Some examples include high-precision contact-type displacement sensors or fibre optic sensors, both fitted to measure strains within the battery pack **[15]**. This sensor feature is particularly of interest in the unstable motion environment of an EV. Besides the research towards advanced sensors, market players are introducing wireless sensors and BMS to reduce the extent of wiring needed in a battery pack, as well as more robust signalling between BMS and sensors. The saved space from reduced wiring could allow for more sensors or more cells in the pack.

CLOUD-CONNECTED AND ADAPTIVE MODELS / DIGITAL TWINS

Within the domain of battery health management, cloud-connected and adaptive battery BMS models have surfaced in the last few years. These models can be updated and calibrated by the engineers remotely, and the data generated by the sensors in the vehicle can be accessed at any time. This creates flexibility for manufacturers to have live insights into a battery's health. Currently, most BMS can only export their data through physical connection with the receiver (e.g., workshops or private charging points), which reduces flexibility.

SUPPLEMENTARY DATA SOURCES

The untapped potential of recovered field data and the creation of synthetic data is under investigation **[16]**, **[17]**. Research has shown advantages of supplementing field data with a recovery process including **machine learning** and a small portion of testbed data. This recovery is needed since real-time data from field applications often does not represent the whole cycle as batteries are rarely charged and discharged completely **[16]**. Synthetic data, a nascent yet promising source of data, is created using existing test data. It scans the potential degradation of three key features (loss of lithium inventory, loss of active material in the negative electrode, and the positive electrode), and translates that back into a voltage response, through a mechanistic model. Thereby it creates a map of all possible degradation trajectories, caused by these three influential degradation mechanisms **[17]**.

POTENTIAL REGULATORY IMPROVEMENTS

In the 2020 Battery Directive proposal [18], the EC stated its intention to harmonise battery performance testing across the EU to remove internal trade barriers. Here, the focus of those tests lies on the product requirements put forth in the same proposal.

Moreover, as noted in our previous Market Intelligence Report on Reverse Logistics, the proposal states that purchasers of a battery should be able to get insight into its BMS and corresponding historical data. This is key to accurately diagnosing a battery's health at its end of life. To pinpoint the data in question, a set of parameters is included in the proposal's annex, covering both the state of health and the expected lifetime of batteries.

COMBINING A BOTTOM-UP AND TOP-DOWN APPROACH

Another solution to the bottlenecks of battery prognostics field is an approach undertaken by **the COBRA project**: developing a **physics-based model** that would not only accurately explain what is happening in a single cell layer, but also in the **full cell** and the **whole battery pack**. Creating a reliable cell degradation model is one thing but scaling it up to subsequent module and pack level is something else entirely. Each additional layer adds complexity due to the wide array of battery dynamics involved.

COBRA's approach is to validate the physics-based (**bottom-up**) model with a **top-down** model based on empirical tests of the complete battery. As a result, these two models should converge to one. Such a solution would increase the accuracy of prognosis and provide insightful information for the new battery designs.

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TECHNICAL DEVELOPMENTS

PREDICTION USING DIGITAL TWIN – REDTOP RESEARCH PROGRAMME

50 electric taxis have collectively travelled 500,000km to provide data for REDTOP automotive research programme: Real-time Electrical Digital Twin Operating Platform. The cars were equipped with a data-collecting IoT device connected to cloud-based software provided by UK company Silver Power Systems. Researchers from the Imperial College used this data to develop a digital twin of the EV batteries showing real-time battery performance, SoH and enabling prediction of battery lifespan. The research was funded by the Advanced Propulsion Centre UK (APC).

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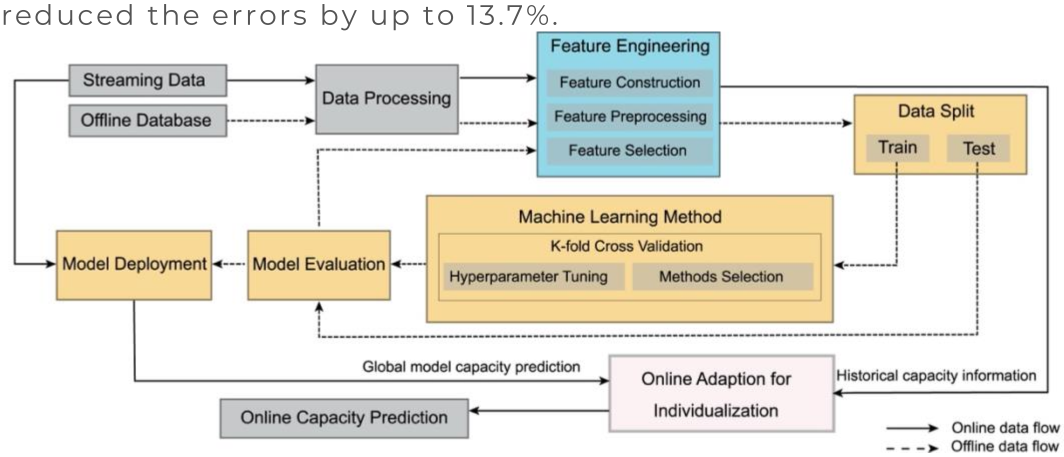
ML-BASED FRAMEWORK FOR ONLINE PREDICTION OF BATTERY AGEING

A recent paper published by Swedish and American researchers introduces a novel machine learning-based battery lifetime prediction framework. The framework uses features coming from histogram data instead of time series to develop offline global models. This saves computational power and memory in the predictions under generalised conditions. The time needed to predict the ageing trajectory of batteries in the corresponding datasets was less than 3.2 s. Secondly, the framework is equipped with an online model which feeds from the 7296 PHEVs fleet data and adapts the selected global model for cell individualised prediction. The online algorithm reduced the errors by up to 13.7%.



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SELF-HEALING BATTERIES UNDER DEVELOPMENT BY ISRAELI COMPANY

An Israeli company StoreDot has patented a method of battery reconditioning by temporarily deactivating individual cells or cell strings, slow and deep discharging, followed by slow charging to increase their capacity and safety. Currently, the cells can be deactivated by the BMS, but this change is usually permanent until the corresponding cell or module is replaced in the workshop.

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MARKET DEVELOPMENTS

WIRELESS BATTERY MANAGEMENT SYSTEM BY GENERAL MOTORS

General Motors has developed a wireless communication system between the BMS, and batteries installed in their EVs. The system gives access to multiple channels and broad bandwidth, allowing to run battery pack health checks in real-time. GM's solution reduces wiring within the batteries by up to 90% (lowering the vehicle's weight) and eliminates the need to redesign wiring configurations every time the company develops a new vehicle. The functionality of the new platform has been presented in the GMC Hummer EV Pickup and SUV available in 2023.

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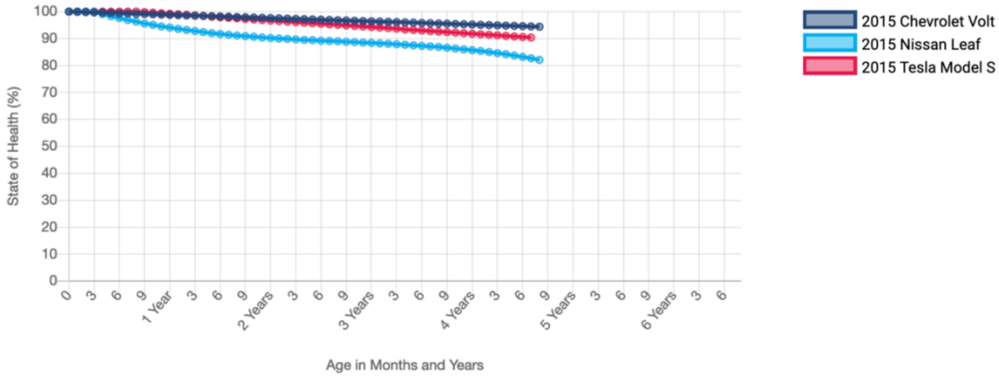
BATTERY DEGRADATION TOOL WITH DATA FROM 6300 VEHICLES

How do popular EVs compare when it comes to battery lifetime? A free to use tool provided by GEOTAB allows you to check the degradation speed of 24 EV models over the last 10 years, based on data collected from 6,300 corporate fleet and consumer vehicles. The company observes that good thermal management protects against degradation, e.g., the 2015 Tesla Model S with a liquid cooling system has an average degradation rate of 2.3% a year, while the 2015 Nissan Leaf with a passive air-cooling system degrades every year by 4.2%.



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PREDICTIVE ANALYTICS SOFTWARE HELPS TO MANAGE EV FLEETS

German battery analytics software company Twaice has secured a Series B funding of $26 million. The start-up is building a battery analytics platform which helps companies that operate a fleet of EV buses to monitor and forecast the state of the battery packs of each of their vehicles. Twaice also supports battery design engineers with the data they collect, in order to reduce testing effort, assess charging strategies, depth of discharge and different cell strategies.

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POLICY DEVELOPMENTS

NEGOTIATIONS OF THE NEW BATTERIES REGULATION BEGIN

The EU Council has adopted its negotiating position regarding the new battery regulation proposed by the EU Commission, which is expected to replace the Battery Directive from 2006. The Council strengthens the fundamentals of the document elaborated with the industry, focusing on battery passport, tight restrictions for hazardous substances and extended producer responsibility. Now the document will be negotiated with the Members States in the Parliament, aiming to agree on the final text in first reading.

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AN UPDATE OF THE EUROPEAN STRATEGIC ACTION PLAN ON BATTERIES

During the High Level Industrial meeting held in Brussels on the 23rd of March, the European Battery Alliance brought together key stakeholders of the battery value chain, summarised the achievements so far, and proposed an updated Strategic Action Plan for the year 2030. By 2021, the total level of investment in the EU battery value chain amounted to €127 billion, while a further €382 billion is needed to create a self-sufficient battery industry by 2030.

	Current Strategic Action Plan 2025	Updated action plan 2030
Annual demand in EU (mobility, ESS, last mile)	400 GWh	1.000 GWh
Annual GDP/added value created in EU	250 B€	625 B€
Domestic **cell manufacturing** coverage of EU needs	100% (committed)	90%
Domestic **raw materials/processing** coverage of EU needs	tbd	60%
Domestic **active materials** coverage of EU needs	tbd	40%
Domestic **recycling** coverage of EU ambitions	tbd	100%

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STRINGENT SAFETY STANDARD MAY SLOW DOWN EV GROWTH IN INDIA?

In 2021, India adopted a battery safety testing standard AIS 156, which appears to be the strictest in the world. For example, it includes a fire resistance test where the battery is subject to direct and indirect flame for over two minutes. This may cause delays in the development and roll-out of new electric vehicles in India but would also decrease the number of fire accidents that have recently occurred in India, as explained by the national Society of Manufacturers of Electric Vehicles (SMEV).

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