

# Battery Diagnostics and Monitoring Methods

- A Comparative Analysis of Active versus Passive Approaches-

**Avedis Dadikozyan<sup>1)</sup>, Camiel Beckers<sup>1)</sup>, Tim Meulenbroeks<sup>1,2)</sup>,  
Erik van den Tillaart<sup>1)</sup>, Steven Wilkins<sup>1,2)</sup>**

*1) Powertrains Dept., TNO, Helmond, Netherlands, e-mail: [avedis.dadikozyan@tno.nl](mailto:avedis.dadikozyan@tno.nl)*

*2) Dept. of Electrical Engineering, Eindhoven University of Technology, Netherlands*

**ABSTRACT:** The rapid uptake of lithium-ion battery use across transport and energy storage applications increases the relevancy and the need for diagnostics and monitoring methods to ensure safety, reliability, and longevity. This paper presents a comparative study of passive and active battery diagnostic methodologies, focusing on their applications in real-world scenarios. Passive diagnostics utilize battery signals occurring during real-world use, offering a non-intrusive, cost-effective solution suitable for applications requiring minimal intervention, such as battery passports and large fleet monitoring. In contrast, active diagnostics employ controlled signals to gain deeper insights into the battery state, enabling precise tracking of degradation and early fault detection. Our study reviews implementations of these active system identification approaches, including Battery Management System (BMS)-integrated solutions and use of various cloud-based methods across European and Dutch projects. We examine the technical challenges of each diagnostic approach and provide a qualitative comparison between the two.

**KEY WORDS:** lithium battery, battery electric vehicles, passive battery diagnostics, active battery diagnostics, State-of-Health.

## 1. INTRODUCTION

The increasing deployment of lithium-ion batteries in mobility and stationary energy storage applications drives the need for diagnostics and monitoring systems to ensure reliable performance and safety. Modern battery systems contain many increasingly novel aspects of both software and hardware<sup>(1)</sup>. Alongside technology development, within Europe, legislation and regulations concerning the use of batteries are coming into force in the upcoming years. Within the Battery Regulation<sup>(2)</sup>, new requirements are set for comprehensive data reporting across a battery's lifecycle. Additionally, it is proposed that the measure of battery durability is included in the new regulation for Euro 7<sup>(3)</sup>. Both of these measures are placing increasing focus on the performance monitoring of battery systems. Therefore, accurate assessment of battery states and parameters is critical for the effective use of battery systems.

States are commonly defined as properties of the system which may rapidly change over time, whereas parameters are properties which either slowly change over time, or not at all. Diagnostics methods provide insights into the current state of batteries, enabling operators to make informed decisions that maximize battery performance and utilization. Within battery technology,

diagnostic methods represent a range of methodologies designed to assess State-of-Charge (SoC), State-of-Health (SoH), State-of-Function (SoF), State-of-Energy (SoE) and other vital performance indicators throughout a battery's operational life. Furthermore, where model-based approaches are used for the operation and control of the system, parameters useful for these models can be extracted online. An example is Digital Twinning, where it is vital that reliable data continuously flows from the physical battery system, towards its software representation, supported by the diagnostics of the battery.

Battery diagnostic approaches are broadly categorized into two main categories - passive and active. Passive diagnostic measures are where the states and parameters of the system are derived in-situ during normal operation of the battery system, providing that they can be observed from the operational data. Conversely, active diagnostic measures are where the system is deliberately perturbed in some form in order to observe states and parameters more clearly or which otherwise cannot be observed.

This paper presents a comparative review of active and passive battery diagnostic methods, based on real-world implementations. Section 2 outlines passive diagnostics while Section 3 focuses on active diagnostics. Section 4 offers a comparative analysis, while

Section 5 discusses regulatory relevance. Conclusions are summarized in Section 6.

## 2. PASSIVE DIAGNOSTICS METHODS

### 2.1. Definition

Passive diagnostic methods monitor the battery through commonly available signals, such as voltage, current, and temperature, collected under normal operating conditions. Since these approaches require no external stimulation of the battery, they are non-intrusive and are often simpler to implement. This makes them well-suited for applications where minimal intervention and long-term monitoring are desirable, such as in the EU mandated Battery Passport<sup>(2)</sup> and large fleet monitoring. In such scenarios, passive methods provide insights into the battery's general condition without interrupting its normal operation. Also for low-level battery control, the BMS often contains passive diagnostics.

### 2.2. Battery Passport Use Case

#### 2.2.1. Approach

The goal of the battery passport concept is to provide transparency, traceability, and sustainability within the rapidly expanding battery supply chain. Dictated by the European Union's Battery Regulation<sup>(2)</sup>, this digital passport mandates comprehensive data reporting across a battery's lifecycle, from raw material sourcing to end-of-life management. In order to facilitate the data that flows into the battery passport, there is a renewed focus in the development of battery parameter and state estimation algorithms<sup>(4)(5)</sup>.

The Battery Management System (BMS) regulates the operation and safety of the battery and keeps track of the battery states such as SoC, SoH, and SoF. The EU regulation for battery passport would mandate future BMS to compute additional data, or expose existing data, that is required to be stored in the passport. Hence, the challenge for the design of regulation-compliant BMS is to define new algorithms to compute the additional data for battery passport. In the context of the current review, these algorithms essentially represent passive battery diagnostics.

TNO has developed one such algorithm to calculate round-trip efficiency<sup>(6)</sup>, which was implemented and tested on an embedded BMS, with operational battery passport demonstration<sup>(5,7)</sup>. Fig. 1 shows the results the algorithm, where the embedded software outputs several energy efficiency estimates, indicated in red. These are communicated via RestAPI to the cloud where, at set intervals, State-of-Health of the Round-Trip Efficiency (SoH\_RTE) efficiency is calculated and stored in the battery passport.

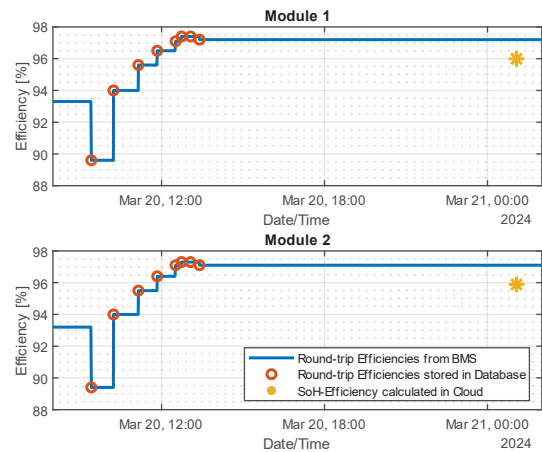


Fig. 1 Round-trip efficiency calculated on the BMS and the cloud for two battery modules, based on <sup>(5,7)</sup>.

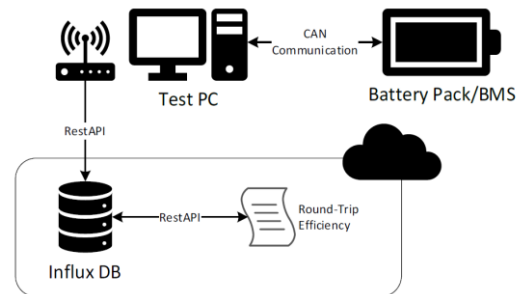


Fig. 2 Communication of the SoH\_eff algorithm, incl. communication via RestAPI<sup>(7)</sup>.

#### 2.2.2. Experience and Lessons learned

The work above describes a full development cycle of a State-of-X (SoX) algorithm with both an on-board embedded implementation on the BMS, and part of the calculation executed in the cloud. This edge/cloud implementation allows for the use of high-frequency data available on the BMS, yet also gives the possibility to offload the more computationally expensive tasks to cloud hardware. Simultaneously, there are challenges still to overcome in terms of cost of large data transfer and the security aspect to prevent manipulation of the battery passport values. Practical challenges exist in both the local and cloud area. The implementation of third-party software on an existing BMS, imposes strict requirements on memory use and computational load. Furthermore, an interface and reliable connection has to be established to the cloud to send all the information efficiently.

### 2.3. Heavy-Duty Fleet Monitoring

#### 2.3.1. Approach

Fleet monitoring plays a crucial role in optimizing transportation logistics and ensuring vehicle performance. The introduction of the first electric heavy-duty trucks to the market brings new considerations, particularly regarding range limitations

and the increasing importance of strategic charging planning compared to traditional refueling. In addition to operational concerns, detailed performance monitoring is essential for assessing battery health and long-term vehicle reliability.

By leveraging fleet monitoring in large EU projects such as MAGPIE<sup>(8)</sup>, TULIPS<sup>(9)</sup> and ZEFES<sup>(10)</sup> or Dutch national DKTI programs like ZEBRH<sup>(11)</sup> and CCBE<sup>(12)</sup>, real-world performance data from electric trucks can be systematically assessed, see Fig. 3 for approach. This monitoring enables the determination of key performance indicators (KPIs) related to energy consumption, SoC variations, and battery degradation trends. Such insights, when combined with technology outlooks, support scalability analyses for larger electric fleets. Beyond logistics optimization, this data is also crucial for predictive maintenance, fleet diagnostics, and infrastructure planning.



Fig. 3 Overview of E-truck monitoring approach.

An essential part of electric vehicle fleet monitoring is understanding the health of the vehicle's battery, and this is where passive diagnostics come into play. Through ongoing monitoring of parameters like SoC, voltage, current, and temperature, which are already part of a vehicle's Battery Management System (BMS), passive diagnostics can provide ongoing insights into the battery's general condition. This can help to identify early signs of degradation without the need for additional active tests or interventions. Passive diagnostics are particularly useful for long-term fleet management, as they allow fleet operators to track battery health over time with minimal disruption to the vehicle's operation.

A key challenge in electric truck fleet management is optimizing charging strategies due to limited range and shared infrastructure. Real-time monitoring of SoC and energy consumption trends are crucial for deciding which truck should charge first and how much charge is needed. In connection to the diagnostics and monitoring work, TNO has developed the Charge Planning Tool (CPT). This tool aims to streamline the charge management process by balancing charging load and reducing downtime. CPT makes use of monitoring and energy estimation techniques which ultimately results in a Digital Twin framework. This demonstrates how other technologies and tools can be supported from fleet monitoring activities.

### 2.3.2. Experience and Lessons learned

A well-established ecosystem of fleet monitoring services exists for conventional vehicles, with OEMs providing proprietary fleet management portals. Next to that, the FMS dataset is a standardized set of parameters describing heavy-duty vehicle operation, accessible through a common gateway. This FMS standard<sup>(13)</sup>, agreed upon and maintained by ACEA (the European Automobile Manufacturers' Association), aims to provide a uniform data interface across brands. Through this standardization, third-party fleet management units can often be integrated into vehicles, enabling centralized access to vehicle data from mixed-brand fleets. These portals typically support functions such as location tracking, fuel consumption analysis, and vehicle diagnostics. Fleet data is often analyzed in the background, and aggregated reports on vehicle and driver performance are provided. However, access to these services is frequently subscription-based, limiting the depth of available data.

Another limitation lies in the granularity of available vehicle data. While in-vehicle sensors collect detailed battery health indicators — such as voltage, current, and temperature at the pack or even cell level — this data is not always accessible to external monitoring systems. Allowing such data to be streamed to cloud-based fleet analytics platforms would unlock new opportunities for battery health diagnostics, charge management optimization, and fleet-wide predictive maintenance.

Ultimately, the integration of real-time diagnostics, digital twin modeling, and predictive analytics will be key to enhancing fleet efficiency, improving battery health, and ensuring reliable heavy-duty electric truck operations. The more detailed the available data, the greater the potential for optimizing both vehicle performance and large-scale fleet deployment.

## 3. ACTIVE DIAGNOSTICS METHOD

### 3.1. Definition

Active diagnostic methods involve applying controlled signals, such as current pulses or specialized charge-discharge patterns to the battery, to derive deeper insights into the battery's parameters. Broadly speaking, there are a relatively small set of methods once a battery is in situ in operation, to perturbate for diagnostic purposes, such as:

- Perturbation through off-board systems such as the charger or external charge controller, wherein unidirectional or bidirectional charging is used, to actuate the system.

- Perturbation from the onboard power electronics, such as inverter or DC-DC converter, wherein additional pulses are injected online to reveal parameters of the battery.
- Actuation from integrated power electronics within the battery pack; such as via the active balancing system, or in specialized cases via online methods such as EIS.

Active methods enable more precise tracking of parameters like internal impedance, capacity loss, and degradation trends, which are critical for accurate SoH estimation and early fault detection. These techniques offer a higher precision of diagnostic data, making them valuable for scenarios requiring advanced predictive maintenance or real-time fleet health assessments. Moreover in many cases observability of parameters is not possible in routine operation, and the fitting of more complex (higher parameter) models risks overfitting. While active methods are often applied in a lab environment for system identification, (typically to individual cells), in-field application on battery pack level is relatively uncommon still.

### 3.2. On-BMS Implementation

#### 3.2.1. Approach

In the European project iSTORMY<sup>(14)</sup> an active battery diagnostic system was designed, implemented and demonstrated on a stationary energy storage application. Distinctively, the diagnostic software runs on the BMS itself, granting unparalleled access to low level battery data. Additionally, as the energy storage system in iSTORMY uses battery packs of different chemistries connected through their own power electronics, power can be sunk and sourced from battery to battery, without power flowing to and from the grid. An overview of the setup is depicted in Fig. 4. By periodically performing autonomous active diagnostic cycles, diagnostic data based on an identical test protocol is gathered over time, whilst requiring minimal human time investment. Both battery pack capacity and impedance were measured.

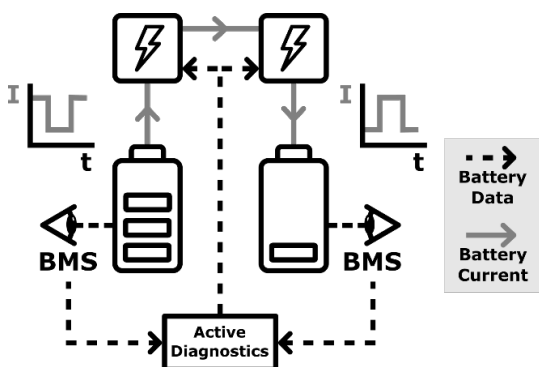


Fig. 4 Overview of iSTORMY battery diagnostic system setup.

#### 3.2.2. Experience and Lessons learned

The iSTORMY project demonstration highlighted the key advantage of active diagnostics over passive methods: the ability to conduct on-demand battery tests with controlled diagnostic protocols, leading to more consistent results over time. However, challenges such as communication interruptions between the BMS and power electronic converters affected protocol continuity, underscoring the need for robust fault-tolerant designs. Running the active diagnostic software on the BMS provided valuable access to low-level battery data, enhancing diagnostic accuracy but also introducing implementation constraints, including hardware limitations and the necessity for close integration with the BMS. Processing power and memory limitations within the BMS further restricted scalability, suggesting alternative implementations on separate controllers or cloud platforms.

### 3.3. Cloud-Based Implementation

#### 3.3.1. Approach

As electric buses become central to urban transportation, efficient battery management is essential for optimizing operational schedules and reducing costs. To address this, we introduce an active diagnostic system, termed the CheckUp Tool, which actively controls current and voltage using a bi-directional charger, enabling direct measurement of battery capacity and degradation. Application to a fleet of 48 electric buses in the VITALISE project<sup>(15)</sup> demonstrates the tool's ability to provide accurate and consistent battery health data, paving the way for optimized battery life. This scalable solution shows promise for broader electric vehicle deployments.

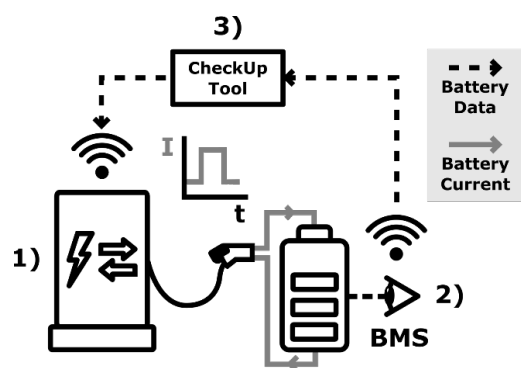


Fig. 5 Overview of the CheckUp Tool system. Battery health is measured by applying a diagnostic protocol, i.e. current/voltage setpoints, through a bi-directional charger.

The CheckUp Tool system consists of three main components: 1) a bi-directional charger, 2) a BMS data logging device and 3) the CheckUp Tool control software, see Fig. 5. All three components work together to form a control loop. A) The control software

sends a current/voltage setpoint to the charger, B) the charger applies the setpoint to the battery, and C) the battery measurements are sent to the control software. After completion the results are analyzed to calculate the battery capacity and the measurement conditions are recorded.

### 3.3.2. Experience and Lessons learned

The implementation of the CheckUp Tool within the VITALISE project provided valuable insights into the challenges and benefits of active battery diagnostics in an operational electric bus fleet. Experience in operating the CheckUp Tool revealed that applying the diagnostic protocol consistently is possible. At the same time, working in a real-world operational environment shows that maintaining consistency has its challenges, as can be observed in Fig 6.

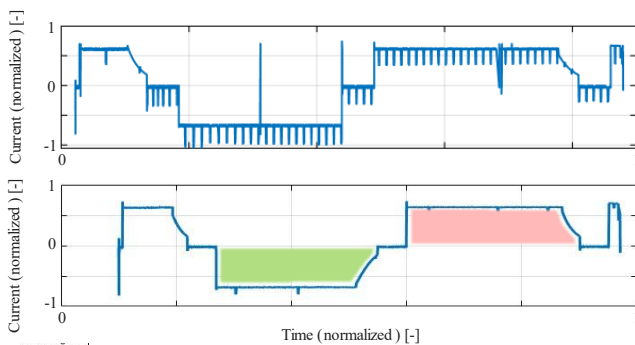


Fig. 6 Battery current from a bad (top) and a good (bottom) CheckUp Tool diagnostic sessions. Discharge (green) and charge (red) windows are highlighted for the successful session.

One key challenge is ensuring a stable high-frequency data communication between the vehicle, the cloud and the charger, as interruptions could disrupt diagnostics. To address this, significant effort is invested in communication stability strategies and safety procedures, improving overall reliability.

Another challenge is precise charger control, particularly during constant voltage phases, which required fine-tuning over time to achieve accurate results. On the operational side, integrating diagnostic sessions into the public operator's schedule generally works well, with efforts made to ensure that buses on the diagnostic charger are fully charged at the end of the check-up. Finally, automation of both the diagnostic sessions and the subsequent analysis proves to be highly beneficial, allowing for fully autonomous operation and consistently accurate results.

This experience underscores the importance of robust communication, careful charger calibration, seamless operational integration, and automation in scaling active battery diagnostics for larger electric vehicle fleets.

## 4. QUALITATIVE COMPARISON OF PASSIVE VERSUS ACTIVE DIAGNOSTIC METHODS

This section aims to draw a qualitative comparison between active and passive battery diagnostic methods, based on our experience in applying these techniques. Through the above examples, this paper presents an overview of implementations of both passive and active battery diagnostics in various European and Dutch projects. As such, this paper is not a comprehensive literature review, but rather a comparative snapshot of existing real-world implementations of this methods discussed.

### 4.1. Implementation Challenges

Passive diagnostics are generally easier and quicker to implement compared to their active counterparts. Since passive methods rely on existing sensors already present in the BMS, such as voltage, current, and temperature, no significant changes to the system are required. These methods are non-intrusive, meaning they can monitor battery health without interrupting regular operation. However, passive methods have limitations in capturing more granular insights into battery conditions, such as internal impedance or early-stage degradation. This makes them less suitable for applications where precise diagnostics are necessary.

On the other hand, active diagnostics involve applying controlled signals, such as current pulses or specific charge-discharge patterns, to the battery to gather deeper insights into its internal state. While these methods offer more precise data, their practical implementation is more complex. They require specialized hardware, like bi-directional chargers, and/or integration with the BMS, which can be challenging, especially in real-world fleet operations. In addition, active methods are dependent on stable communication between the vehicle, cloud, and charger, and interruptions in this communication may impact the continuity of the diagnostic processes.

### 4.2. Effort of Post-Analysis

The post-analysis effort required for passive and active diagnostics is generally comparable. In both cases, key parameters such as state of health (SoH), capacity, or internal resistance are derived from measured voltage, current, and temperature data using algorithms. While active diagnostics may offer higher-quality data due to controlled test conditions, the computational demands for interpreting this data are not significantly greater than those used in advanced passive SoH estimation.

A notable advantage of active diagnostics, however, is the ability to apply a consistent and repeatable measurement protocol. By using predefined current or voltage patterns, active methods

reduce variability in the diagnostic conditions, leading to more reliable and comparable results over time—an important benefit for long-term monitoring and trend analysis.

#### 4.3. Cost of Measurements

Passive diagnostics are generally considered more cost-effective, as they make use of sensors and data streams already available from the BMS. This makes them suitable for large-scale applications such as fleet monitoring, where continuous, low-intervention health tracking is needed. The computational tools required, such as filtering algorithms (e.g. Extended Kalman Filters) can be complex, but they are well-established in the field, with mature implementations and broad adoption.

Active diagnostics, while not inherently more complex in terms of post-processing, do require additional infrastructure such as bi-directional chargers and precise current or voltage control interfaces. The associated software is often less mature and more customized to specific applications, meaning integration and validation can still demand significant effort. However, these costs are primarily capital expenditures. A one-time investment in a dedicated diagnostic charger, for instance, can enable active testing across multiple vehicles or an entire fleet, making the approach scalable and cost-effective over time. Thus, while the complexity of the analysis is comparable between active and passive methods, the maturity and availability of tools differ significantly.

#### 4.4. Choosing Between Passive and Active Methods

The decision to use either passive or active diagnostics largely depends on the application's goals and the required level of diagnostic precision. Passive diagnostics are ideal for general monitoring where the goal is to track battery performance trends over time. They are best suited for large fleets or applications that require ongoing, cost-effective monitoring without the need for in-depth fault detection. Passive methods provide sufficient insights for applications like large fleet management, regulatory compliance (such as the EU's Battery Passport), and long-term operational monitoring.

Active diagnostics, on the other hand, are better suited for applications that demand higher precision and proactive maintenance. For example, in heavy-duty electric truck or bus fleets, where optimizing battery performance and preventing failures are critical, active diagnostics provide detailed insights into battery degradation, internal impedance, and capacity loss. These methods are invaluable for detecting early signs of battery failure, optimizing charging strategies, and improving long-term

fleet reliability. Additionally, the detailed insights from active diagnostics make them particularly useful for tasks such as warranty checks, where precise and controlled assessments of battery performance and degradation are essential.

#### 4.5. Combining Both Methods

A hybrid approach that combines both passive and active diagnostics may provide the most comprehensive solution for battery health management. Passive diagnostics can continuously monitor the battery's general health with minimal operational impact, ensuring that basic performance parameters are regularly tracked. Active diagnostics, when applied intermittently or during specific intervals, can provide detailed insights into the battery's condition, allowing for proactive maintenance and optimization of battery life.

### 5. RELEVANCE TO UPCOMING EUROPEAN REGULATIONS

Many of the upcoming European Regulations are potentially supported by diagnostic techniques. Often the combination between more traditional passive diagnostic algorithms and active diagnostic techniques will be required. There are two main items of legislation which will directly affect battery diagnostics in the next few years.

#### 5.1. EU Battery Regulation – Battery Passport

Concerning itself with the circular economy of batteries, the European Commission has defined the battery regulation, which comes into force in stages over the next few years. The idea is to be able to identify battery packs, their data for origin/manufacture, and a set of readable parameters from the BMS, to enable transfer between ownership, use, and ultimately to recycling. Fig. 7 illustrates the expected lifecycle for batteries originating from automotive, wherein the battery modules transfer use and ownership, supported by data and diagnostic functions.

The EU regulation 2023-1542 applies to all mobility and industrial batteries larger than 2kWh, requiring the accessibility of 10 BMS parameters and the maintenance of historical data. While the exact methodologies for these parameters are not defined, some level of transparency and standardization will be necessary. The regulation comes into effect by early 2027, leaving OEMs and suppliers with a short timeframe to negotiate compliance solutions.

Key parameters, such as remaining capacity, impedance, and residual lifetime, will require diagnostic measures. Potential solutions involve distributing data processing both onboard and in the cloud, with several approaches focused on privacy,

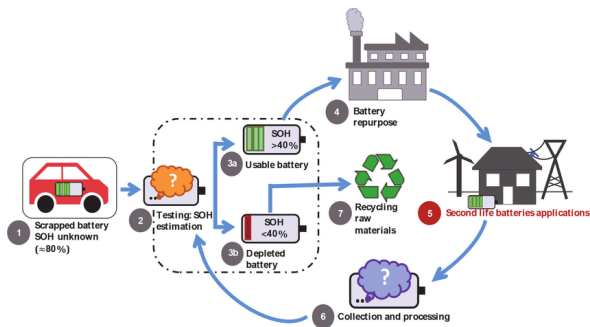


Fig. 7 Illustration of the circular economy of batteries (2).

cybersecurity, and anti-tampering, including Blockchain to preserve data sovereignty while enabling decentralized access.

Organizations like TNO are working on ‘Cloud BMS’ solutions that combine local BMS computation with high-resource cloud computing. As these technologies evolve, Battery Passport solutions are likely to become the most practical, as the algorithms and data are integrated at the cloud level. Additionally, during ownership transfers, BMS resets are often required to clear historic data, resetting algorithms while maintaining core safety functions, with diagnostic functions playing a crucial role in this process.

## 5.2. Battery Durability within Euro 7

Due to the importance of vehicle battery durability from an end-user viewpoint, the upcoming EURO 7 standard includes aspects relating to battery durability. Light duty concerns itself with energy capacity and range, whereas heavy duty only concerns itself with energy content. All categories establish a Minimum Performance Requirement (MPR), in terms of lifetime distance and calendar age (typically 5 years). Unlike the Battery Passport regulation, EURO 7 requires testing of the vehicles as part of In-Service Conformity (ISG). For light duty vehicles, both testing on a chassis dynamometer and testing through the charger, whereas the proposals for heavy duty vehicles are through the charger only. For heavy duty vehicles, three methods are proposed<sup>(17)</sup>:

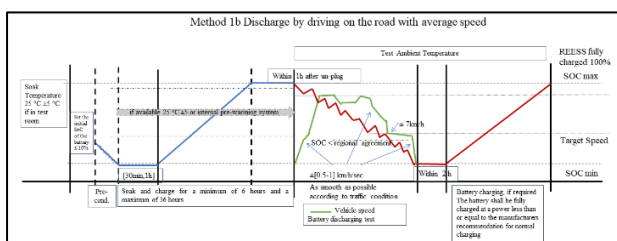


Fig. 8 Visualization of Method 1a.

- Method 1a: Wherein the vehicle is driven on a test track until the battery is empty, and then the capacity of the battery is determined through the charging process.

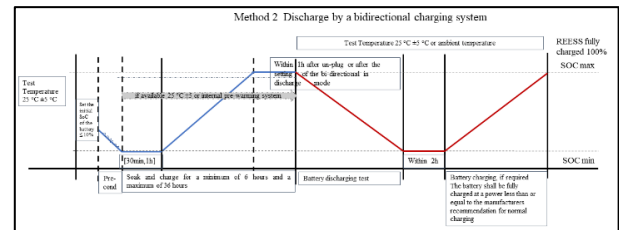


Fig. 9 Visualization of Method 1b.

- Method 1b: Wherein the vehicle is driven normally until the battery is empty, and the capacity of the battery is determined only through the charging process.

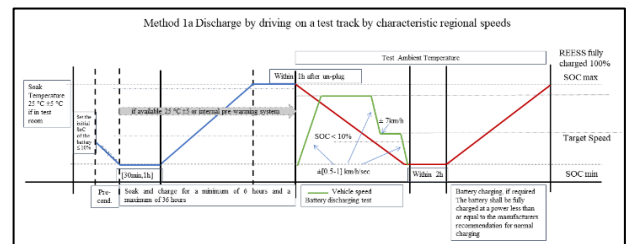


Fig. 10 Visualization of Method 2.

- Method 2: Wherein the vehicle is discharged through the charger, and then recharged, in order to determine the capacity.

At time of writing, it is also proposed that these methods are compared within a specified threshold, to those obtained via OBD (On Board Diagnostics). This proposal was discussed by the International Organization of Motor Vehicle Manufacturers (OICA) in the UNECE GTR22 group.

This proposal, would compare different diagnostic methods. Such an approach would strengthen trust in the OEM-specific OBDs, as well as a practically combine both active and passive diagnostic methods. It should be noted that this proposal is still in development, and ultimately may not be included – but illustrates potential challenges and opportunities in the field of battery diagnostics.

## 6. CONCLUSIONS

The rapid adoption of lithium-ion batteries in transportation and energy storage has made effective diagnostics and monitoring methods increasingly vital to ensure safety, reliability, and long-term performance. This need is further reinforced by evolving European regulations that emphasize the importance of accurate battery monitoring and diagnostics. In this context, the paper presents a comparative study of passive and active diagnostic methodologies, with a focus on their practical implementation in real-world applications.

Passive battery diagnostics is discussed in the context of battery passport and fleet monitoring. In the battery passport context,

these can be considered as part of the SoX algorithms. Typical challenges emerge when implementing these on embedded hardware, including requirements on memory usage. In addition, when combined with battery passport, reliable communication to a cloud environment becomes essential. In a Fleet monitoring context, passive diagnostics are demonstrated in an ‘offline’ settings where large datasets of real-world data are processed a posteriori. The main challenge here is the extraction of relevant diagnostic information from typically lower-quality, lower-resolution data.

In contrast, active diagnostics leverage controlled signals to extract detailed information on battery health, enabling precise tracking of degradation and early fault detection. Implementations such as on-BMS systems and cloud-based tools demonstrate that while these methods provide accurate and repeatable insights, they also introduce challenges related to hardware constraints, communication reliability, and operational integration. Nonetheless, both the iSTORMY and VITALISE projects highlight the potential of active diagnostics to support predictive maintenance and scalable fleet-wide health monitoring.

We draw a qualitative comparison of passive and active approaches, by discussing aspects such as the technical challenges and required implementation effort. Both methods have their place in battery health monitoring, with the choice depending on the specific needs of the application. Passive diagnostics are ideal for long-term, cost-effective monitoring of general battery health, while active diagnostics provide a higher level of detail for advanced predictive maintenance and fault detection. A combined approach that leverages the strengths of both methods can offer a robust solution for managing battery health in large-scale, complex systems like electric vehicle fleets.

As highlighted in the paper, emerging regulation and legislation act as a catalyst to develop new solutions, combining technology, methodology, and data-science towards a comprehensive tracking of the health of systems by both passive and active diagnostic means. In this paper the regulations around Battery Passport and Euro 7 were discussed as examples where combinations of passive and active diagnostics of battery systems will be required.

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