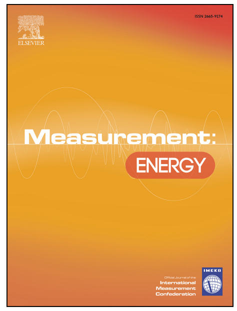

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Sensing-based Monitoring Systems for Electric Vehicle Battery – A Review

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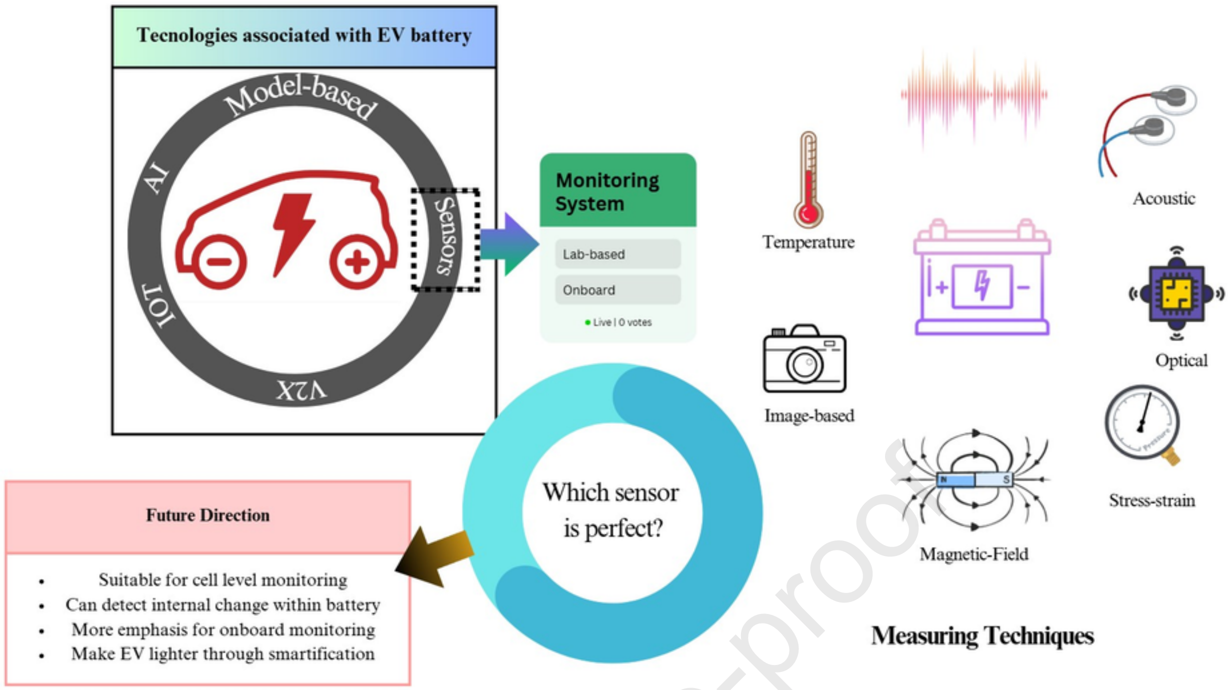
Abstract: The swift uptake of Electric Vehicles (EVs) has increased the demand for improved Battery Management Systems (BMS) to ensure the safety, efficiency, and durability of lithium-ion batteries. This review explores the current advancements in EV battery monitoring technologies, with a focus on sensing mechanisms that estimate critical parameters such as battery states and thermal conditions. Various sensor technologies, including image-based methods, acoustic sensing, force sensors, thermal sensors, magnetic probing and optical sensors, are reviewed and discussed, highlighting their advantages, limitations, and suitability for practical applications. Additionally, gaps and challenges within the field are identified, including cell-level sensing, onboard monitoring, data acquisition mechanism, fault diagnostics and the application of sensors for internal analysis. These challenges underscore the necessity of developing scalable, non-invasive, and cost-effective solutions.

Keywords: Electric Vehicle, sensors, battery management system, onboard monitoring, battery states.



Tecnologies associated with EV battery
Model-based
AI
Sensors
IOT
V2X
Monitoring System
Lab-based
Onboard
Live | 0 votes
Temperature
Acoustic
Optical
Image-based
Stress-strain
Magnetic-Field
Measuring Techniques
Which sensor is perfect?
Future Direction
Suitable for cell level monitoring
Can detect internal change within battery
More emphasis for onboard monitoring
Make EV lighter through smartification

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Nomenclature

AE	Acoustic Emission
AGM	Absorbent Glass Mat
AI	Artificial Intelligence
AMR	Anisotropic Magneto Resistance
BMS	Battery Management System
CAN	Controllable Area Network
DIC	Digital Image Correlation
DL	Deep Learning
DOD	Depth Of Discharge
ECD	Electrochemical Dilatometry
EMI	Electromagnetic Interference
EV	Electric Vehicle
FBG	Fibre Bragg Grating
FEWS	Fibre Evanescent Wave Sensor
FIS	Fibre Interferometer Sensor
FPI	Fabry-Perot Interferometer
I2C	Inter-Integrated Circuit
IC	Integrated Circuit
IR	Infrared
LBIP	Lithium Battery Intelligent Perception
LFP	Lithium Iron Phosphate
LMO	Lithium Manganese Oxide
LPM	Linear Prediction Model
MF	Magnetic Field
MSAB	Multi-Sensor Array Board
MZI	Mach-Zehnder Interferometer
NTC	Negative Temperature Coefficient
PCB	Printed Circuit Board
PTC	Positive Temperature Coefficient
R-CNN	Region-Based Convolutional Neural Network
RH	Relative Humidity
RTD	Resistance Temperature Detectors
RUL	Remaining Useful Life
SEI	Solid Electrolyte Interphase
SEM	Scanning Electron Microscopy
SLA	Sealed Lead-Acid
SOC	State Of Charge
SOH	State Of Health
SPI	Serial Peripheral Interphase
TFTC	Thin Film Thermocouples
V2X	Vehicle To Everything
XRPS	X-Ray Photoelectron Spectroscopy

1. Introduction

Due to the recent innovations and environmentally friendly policies contributed by the Electric Vehicle (EV), there has been a boost in EV usage worldwide in recent years. The heart of the EV is its battery, which controls its driving cycle. To monitor the EV battery effectively, a battery management system (BMS) must be employed. This system typically consists of sensors, communication and network protocol, a thermal management system, data storage and processing units, electrical management systems, and a control unit. The BMS performs various operations, including cell balancing, overcharge and discharge protection, finding the state of charge (SOC) and state of health (SOH), and switching. These operations are performed based on sensed factors such as battery voltage, power consumption, charging cycle, current, and temperature [1]. Although significant development has been made to enhance the robustness of the BMS, the adoption of EVs remains hindered by several factors. These include concerns regarding battery safety and reliability [2], charging time [3], range anxiety [4], and cost [5]. Most of these issues are directly linked to accurate battery health monitoring. A BMS that provides accurate and reliable monitoring and prediction of the SOC and SOH will undoubtedly contribute to resolving these challenges in the long run.

Various methods have been developed to monitor the SOC and SOH of EV batteries. They mainly include conventional sensing techniques, data-driven modeling, mathematical modeling, Internet of Things (IoT) and vehicle-to-everything (V2X), as shown in Figure 1. Through mathematical modelling, battery parameters such as thermal components, ionic movement, behavioral and equivalent circuits can be simulated to reveal the battery's state (SOC and SOH). Behavioral models are frequently employed to forecast battery performance by simulating diverse operational scenarios, including varying charging velocities, fluctuating load levels, and temperature fluctuations.

Data-driven modeling works by using large datasets collected by sensors and can predict key parameters of EV batteries, thus improving the performance of EV batteries. IoT transmits battery data to and from a cloud platform, which can be very useful for real-time monitoring of EV batteries. V2X monitors the current SOC of an EV battery, and if there is excess charge or the vehicle is idle, power is discharged back to the grid. There is no doubt that sensors play a crucial role in EV battery monitoring, as they not only provide reliable, accurate, and direct/indirect measurements of characteristic parameters of the batteries but also generate vast datasets for constructing data-driven and mathematical models. It is also clear that sensors are an essential part of V2X and IoT-based battery management systems.

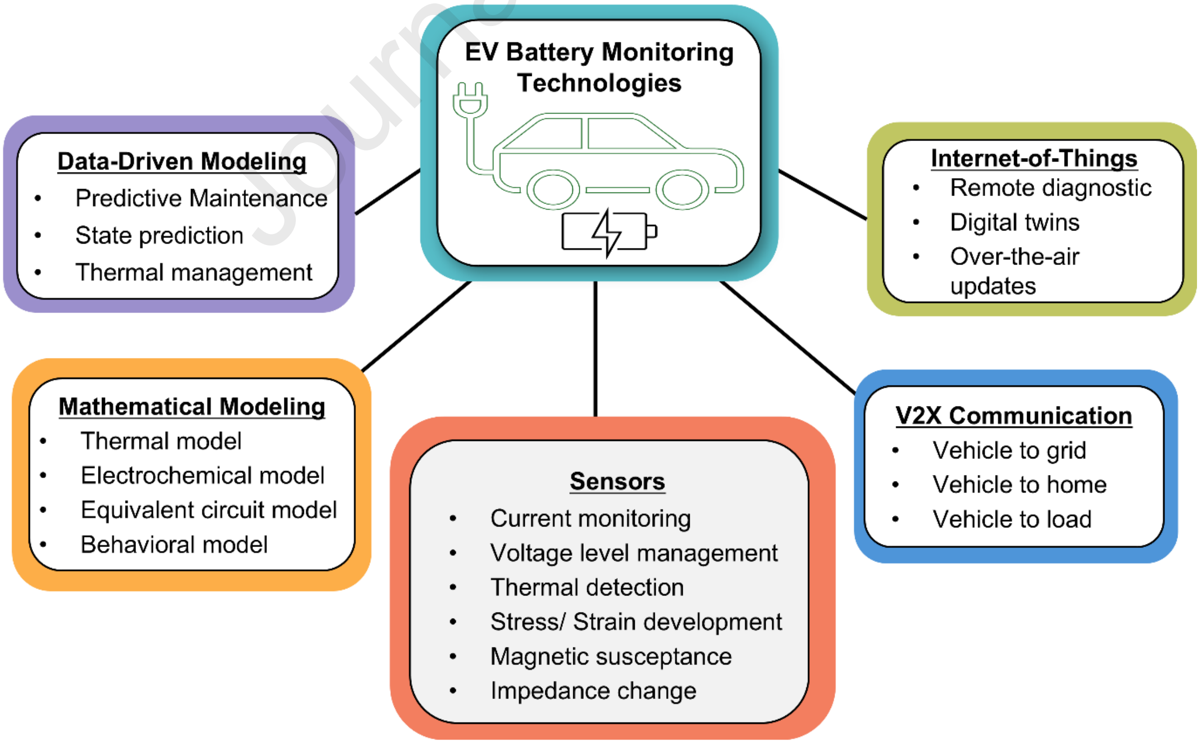


Figure 1. Overview of EV battery monitoring technologies.

Reviews have been carried out on the modeling-based techniques for EV battery monitoring. For instance, Zheng et al. conducted a detailed review of equivalent circuit models and battery degradation of Li-ion batteries [6]. The behavioral model is used to monitor the SOC and SOH of a battery. It also utilized approaches such as Kalman filtering [7] and Genetic Programming [8] by observing battery parameters, including voltage, current, and temperature. In the context of data-driven models and IoT, Ren et al. [9] and Poh et al. [10] provided an in-depth discussion of machine learning (ML) techniques used in the SOC and SOH estimation of Li-ion batteries. Li et al. investigated the IoT approach for EV batteries and detailed the challenges and scopes in terms of cloud computing for battery optimization [11]. Recently, the V2X has also been used in EV developments and integrated into the grid, home, and other DC loads (e.g., mobile phones, lights, motors, etc.). Rehman et al. [12] overviewed the V2X for sustainable EV adoption, including current architectures, standards, and gaps. As the aforementioned topics have been thoroughly reviewed, they are not included in this review manuscript. It is observed that past reviews on sensors for battery monitoring have not been particularly focused on their practical application in EVs. For instance, Xie et al. reviewed techniques for monitoring/assessing the thermal safety of batteries [13]. An et al. discussed the sensing technology for Li-ion batteries, highlighting stress, temperature, and gas sensors, but not from the EV perspective [14]. The sensing techniques employed in EV batteries differ from those utilized in conventional batteries. This disparity arises from the inherent space and complex constraints in EV designs, which necessitate the selection of sensing mechanisms that are both functional and compatible within the confined environment of an EV. Therefore, a comprehensive review of current sensing techniques for EV battery monitoring is necessary to define the state-of-the-art technologies and ascertain their suitability for laboratory and onboard monitoring of EV batteries.

This paper presents a comprehensive review of the recent developments in sensing technologies specifically designed for monitoring EV battery performance. The objectives are to gain insights into the sensing principle and the parameters measured by some notable EV battery monitoring sensors (e.g., image-based methods, acoustic sensing, force sensors, thermal sensors, magnetic probing, and optical sensors) and understand their application for EVs based on onboard or lab-based monitoring; to reflect on the metrological characteristics of the employed sensors in terms of accuracy, resolution and measurement range; and to present the gaps and discuss the future development of sensing technologies. The review is conducted through a comprehensive literature survey of sensing techniques developed or used for EV battery monitoring from laboratory research to practical uses in the last decade, focusing on the sensors for EV battery monitoring, battery state estimation, battery management system, and sensor-based battery monitoring. In the review, the sensing techniques are categorized by types of sensors. The working principle of each type of sensor, including their measurement accuracy, is briefly described, followed by a thorough review and discussion of its applications in both laboratory and practical conditions. The comparison, limitations, challenges, and future trends of the sensing technologies in EV battery monitoring, including their market size, are also included. However, technologies related to data-driven and mathematical models, IoT, and V2X for EV battery condition monitoring and diagnosis are not included in this review, as those topics have largely been reviewed. This is also to avoid losing focus in this review. The rest of the paper is organized as follows: Section 2 provides a brief discussion on BMS and their components; Section 3 describes recent sensing technologies for EV batteries; Section 4 gives a comparative study of the sensing technologies; Section 5 covers the limitations, challenges and future directions; and Section 6 remarks the review and findings.

2. Battery Management System

The battery management system (BMS) monitors and makes decisions about battery life and provides insights into the driving range and maintenance indication to the user. It is a combination of electronic components such as sensors, microcontrollers, diodes, actuators, switching devices, communication protocols, and relays [15]. The BMS takes input from sensors and carries out tasks associated with cell balancing, estimating SOC, SOH, and remaining useful life (RUL), maintaining battery temperature through cooling or heating, and detecting faults within the system [16]. Figure 2 showcases the block diagram of a typical BMS. The BMS functions like a brain, which makes decisions based on signals from the neurons. The sensors serve as the microcontroller's (or ICs') neurons, which make judgments to balance the cells, evaluate the battery's condition, and identify systemic issues. In the upcoming sections, a brief discussion on the functionalities of BMS and its components is provided.

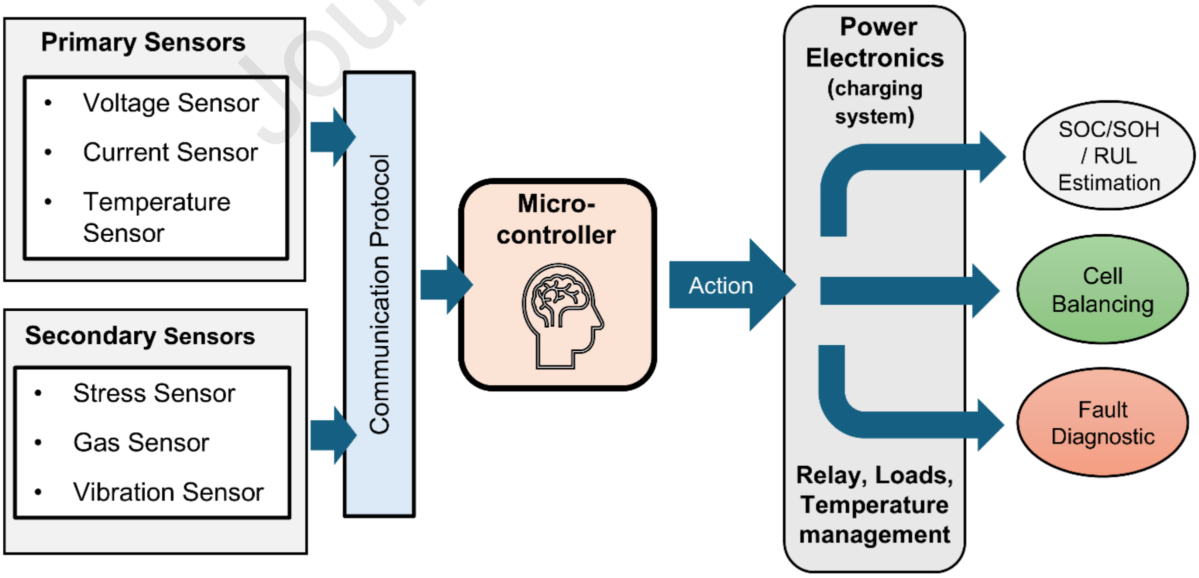


Figure 2. Block diagram of a typical BMS.

2.1 BMS Functionalities

Estimating the EV's various states, such as SOC, SOH, and RUL, is the main function of BMS. The SOC of the battery is an estimate of how much of its total capacity is left. It may be calculated as the rated to the remaining capacity ratio [17]. The BMS handles predicting this as accurately as possible. The simplest way to do it is by using a traditional voltmeter or coulomb counting technique [18]. There exist other methods that use a mixture of temperature, voltage, and current sensing to analyze SOC [19].

The SOH and RUL of the EV are also inspected by the BMS. It is an overall estimation of the battery's lifespan. It may be computed using the battery's internal resistance and capability [20]. Various factors are involved in diminishing the SOH, like temperature, charging cycles, vibration, stress/strain, battery age, overcharging/ undercharging, etc. [21]. Other than that, BMS handles cell balancing, fault analysis, and reliability estimation [22].

In the BMS, the role of power electronics is critical for both the control and protection of the battery. To facilitate bidirectional supply across vehicle-to-grid and grid-to-vehicle scenarios, EV charging ports incorporate single-stage or two-stage converters [23]. Their primary function is to convert the AC to DC during battery charging and vice versa when the EV is efficiently supplied to the grid.

For the protection of the battery and associated circuits, power electronic circuits are instrumental in implementing switching and isolation measures. Additionally, DC-DC conversion holds significant importance as various sensors, microcontrollers, and low-voltage components rely on the supply generated by the EV battery. Notably, the voltage output of the EV battery exceeds the ratings of the sub-components. As the EV battery comprises multiple cells connected in parallel, the BMS's responsibility is to monitor the voltage across each unit and implement active or passive balance techniques to ensure optimal charge distribution.

2.2 BMS Components

The actions of the BMS in terms of reliability are mainly dependent on components such as sensors [24]. Generally, multi-sensing is used to gather information on voltage, current, and temperature. Temperature measurement ensures the battery is operating at an optimum temperature and protects the battery from thermal runaway [25]. It is also possible to indicate SOC [26] and SOH [27] through temperature measurement. Voltage measurement is generally used for cell balancing [28] and for over- or under-voltage protection [29]. Current sensing enables the estimation of SOC through coulomb counting phenomena [30]. Its main function lies in determining SOH and RUL through charging and discharging cycle calculation [31]. Alternatively, gas [32], stress [33], and vibration sensors [34] are utilized to measure different parameters such as pressure and stress development of the battery. These measurements are essential as the gas built-up inside the battery could cause the expansion of the battery, resulting in excessive stress, vibration, and ultimately, permanent damage to the cells.

The communication protocol inside the BMS is an important aspect of its design. The controller receives signals from the sensors and dispatches the required output to the actuators for action to take place. In general, the established system is wired, but a wireless communication system is required to minimize battery size, reduce risks and simplify design.

In a wired system, the communication protocol involves a Controllable Area Network (CAN), a Printed Circuit Board (PCB), an Inter-Integrated Circuit (I2C), and a Serial Peripheral Interface (SPI) [35]. The wired systems are more prone to accidents, costly, and occupy more space [36]. In contrast, wireless systems reduce space and maintenance but are often attenuated by interference. For example, Seok et al. [37] designed a wireless system using Bluetooth connectivity for faster communication (0.072s) compared to the traditional wired CAN (0.264s). This system is validated for the EV scenario, albeit not considering thermal conditions. ZigBee protocol is utilized to establish intra-cell communications [38]. However, both Bluetooth and ZigBee can suffer from interference because of short-range and noise. Near-field communication is also used to read sensor data remotely [39] and tested by embedding it within individual battery cells (cell sensors). However, it lacks the range and security under EV applications. Wi-Fi is used to establish communication and tested in a small-scale prototype [40]. The above technologies so far are implants and are only used for cell sensors or are yet to be tested for onboard BMS. On the other hand, ultra-wideband is used for BMS communications due to its precise signal measurement by antennas and its ability to distinguish interference. It is expected to be used commercially in EVs [41].

Upon receiving sensor signals, the BMS sends signals to the relays and electronic circuits for necessary actions. For cell balancing, different components are used, such as inductors in a buck-boost configuration, MOSFET-based balancers, and flyback converters. Passive cell balancing dissipates excess power as heat through resistors, whereas active cell balancing, more prevalent in EVs, facilitates the energy transfer between cells. Zhang et al. [42] proposed the buck-boost configuration, where the mean and standard deviation of all cells are considered to balance the cells through charging or discharging. A similar procedure is also used with a MOSFET by controlling its gate current [43]. Alternatively, flyback converters can be used for voltage equalization [44], which provides a faster response. To protect the battery from short circuits, over-/under voltage and high-temperature conditions, relays are activated for disconnection purposes. It is important to emphasize that accurate and rapid voltage measurement is fundamental for cell balancing and protection. Furthermore, current sensor data is crucial during the active balancing process. Consequently, the selection of the voltage and current sensors, along with their respective power electronic circuits, must consider the response time and accuracy of measurement. The states (SOC, SOH, RUL) of the battery are mainly calculated or modelled by the microcontroller from the sensor data.

2.3 BMS selection based on EV type

Various forms of EVs exist, with the most popular being 2-wheelers, 4-wheelers and heavy vehicles. BMS components and their functionality vary based on the EV type. 2-wheelers generally have smaller and low-voltage batteries, while 4-wheelers and heavy vehicles generally have larger, high-voltage and robust batteries. Among all EVs, each vehicle type uses distinct battery types. Lithium-ion batteries are the most popular, while heavy vehicles often use fuel cells. This is because fuel cells provide a longer driving range and quicker refueling times. However, traditional batteries are more energy-efficient due to their energy conversion capabilities [45].

The 2-wheelers, such as bikes or scooters, occasionally employ lead-acid or maintenance-free lead-acid batteries. The basic difference lies in the fact that the former requires periodic maintenance and electrolyte replenishment, whereas the latter is sealed. Gel cell batteries are another candidate and offer a safer option as they use gel as a substitute for liquid electrolyte. For high-end bikes, absorbent glass mat (AGM) and lithium-ion batteries are more popular. In the context of 4-wheelers and heavy vehicles, lithium-ion is most dominant due to its lightweight, longevity, high energy and power density [46].

Nickel-Metal Hydrite batteries are used in certain hybrid EVs and older all-EVs. Nickel-Cadmium batteries are used in older EV models but are often avoided due to environmental safety issues. Solid-state batteries are emerging technologies and are considered the future of EVs due to their long-lasting performance capabilities [47]. They are ideal for heavy vehicles due to their higher energy density.

BMS architecture for 2-wheelers mainly comprises lightweight and cost-effective components. Its primary functions include monitoring basic cell voltage, current and temperature. Additionally, SOC estimation and cell balancing are integrated alongside overcharge/discharge and short-circuit protection mechanisms. The number of sensors dedicated to these tasks is relatively limited compared to 4-wheelers or heavy EVs. On the other hand, 4-wheelers or heavy vehicles employ a broader range of sensors, including those mentioned for 2-wheelers, along with multipoint temperature monitoring, SOH monitoring, thermal management control and fault detection. These additional tasks require higher precision and an advanced setup. Therefore, precise sensors are necessary to mitigate range anxiety and establish sustainable BMS systems.

3. Sensing Techniques for EV Battery Monitoring

For effective BMS operations, sensors play a key role by aiding with accurate, reliable, multi-point and real-time data to the system. By using different sensing devices, it is possible to measure battery characteristic parameters such as current, voltage, internal/external temperature, stress, etc. [48]. Figure 3 represents the overall monitoring cycle of EV battery systems. During the charge-discharge process, various sensors (e.g., Hall sensors, RTD, etc.) are responsible for measuring respective battery parameters. These parameters can then be fitted in traditional filter-based or data-driven models to estimate the battery's state and to perform fault analysis. Studies have also shown that it is possible to measure parameters such as gas [32], stress/strain [33], impedance [49], vibration [34] and internal temperature [50]. The following sections discuss various sensing technologies, ranging from lab-based to onboard-based sensing for EV battery measurement and diagnosis.

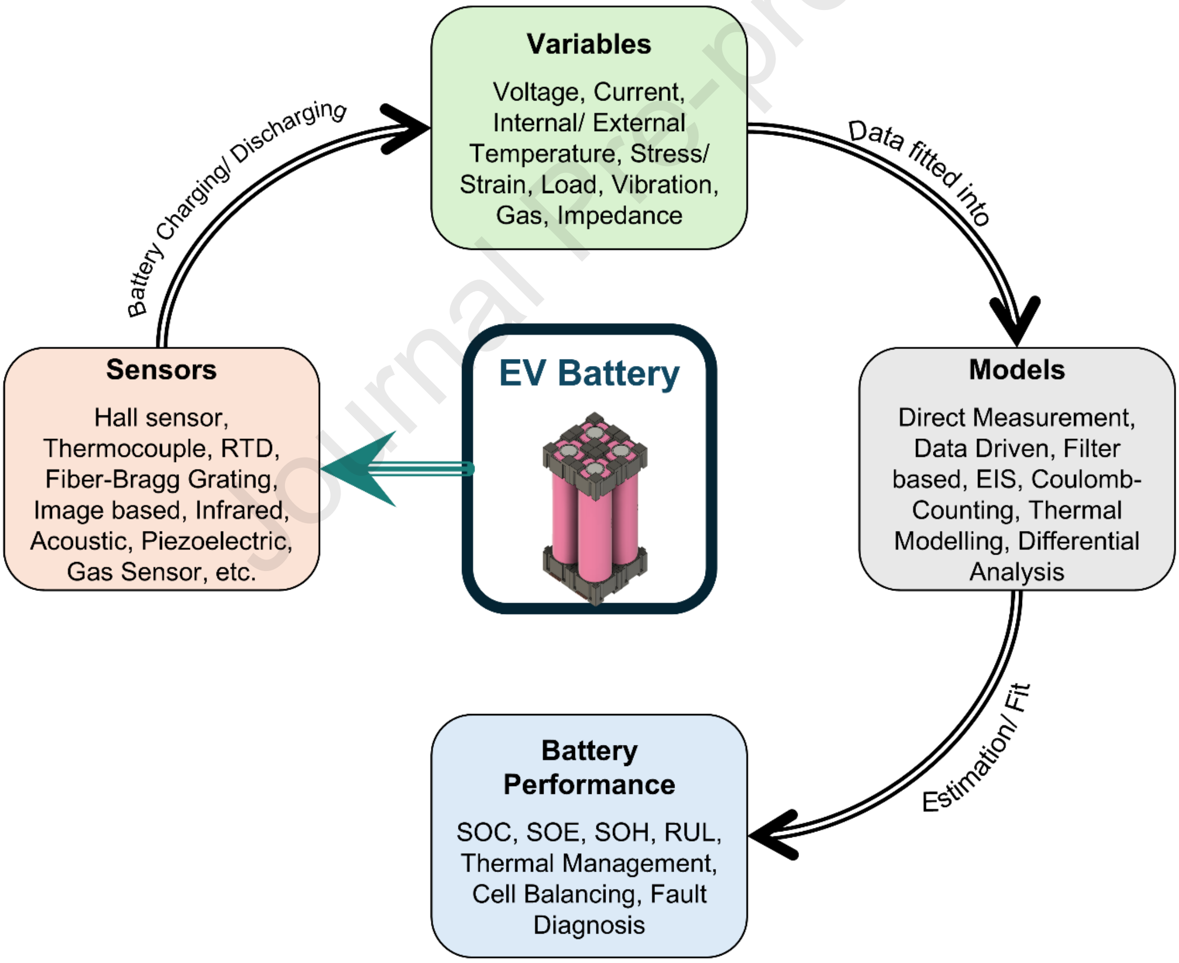


Figure 3. Monitoring cycle of the EV Battery performance.

3.1 Stress-Strain/Pressure Sensing Techniques

When the battery gets charged and discharged, lithiation and de-lithiation occur at a regular interval. At every cycle, one of the electrodes loses some of its material while the other gains it. This produces pressure and can be monitored through various sensors, as discussed below.

3.1.1 Electrochemical Dilatometry

The thickness variation of the electrode or cell, albeit battery charge-discharge, is measured using Electrochemical Dilatometry (ECD). It provides information about expansion-contraction and reversible-irreversible dilation for various processes such as electrode reactions, solid electrolyte interphase (SEI) formation and side reactions. It can track minimal deviations in thickness ranging from millimeters to nanometers [51]. Since Solid Electrolyte Interphase (SEI) formation occurs on a nanometer scale (10-100 nm), the ECD measurement enables users to identify the amount of irreversible dilation [52]. As for monitoring electrode reactions and side reactions, both reversible and irreversible thickness changes are considered. Prado et al. [53] recorded a 300% expansion of silicon-based anodes using ECD measurement, which leads to cracking and permanent damage to the cells. ECD offers useful data on how electrodes expand and contract during the cell cycle, making it a critical tool for understanding electrode degradation and improving device performance [54]. It can also measure dimensional changes of both individual electrodes and complete cells, but these measurements provide different information.

Figure 4 demonstrates two different types of ECD measurement, such as Type 1 [Figure 4(a)] and Type 2 [Figure 4(b)], used for analyzing electrodes and entire cells, respectively. Type 1 [53] measures the thickness change in a single electrode, typically using a rigid glass to isolate the working electrode's expansion. The resolution of the capacitive displacement sensor used in this setup is 5 nm with a measurement range of 0-250µm, making it suitable for measuring the electrode level changes (due to SEI and side reactions). The application for Type 1 is mainly for the internal analysis of single electrodes and is thus applicable for scientific studies requiring in-depth analysis of electrode changes. In contrast, Type 2 [55] quantifies the change in thickness of electrochemical cell electrodes, separators and other constituents. This Type 2 setup used the sensor (version AT2-51) that has a resolution of 0.2 µm with a measurement range of ±0.5 mm. Thus, it is more appropriate for EV battery applications involving laboratory inspection. For onboard EVs, the battery module is made of thousands of cells. Therefore, the ECD setup would be expensive and require more space. The measurement would also be affected by mechanical vibrations, temperature fluctuations and non-uniform cell expansion.

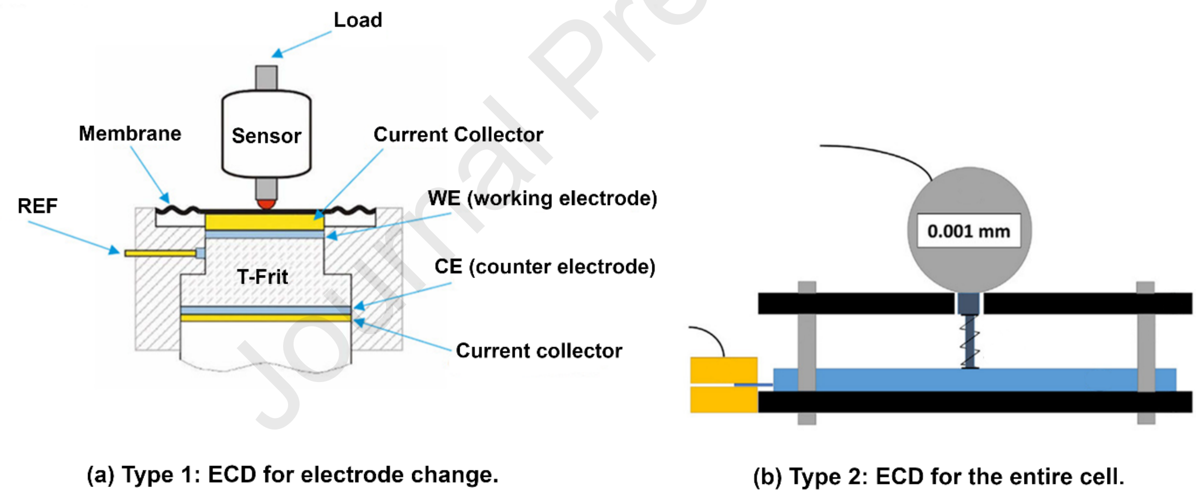


Figure 4. Two types of ECD-based measurement setups [51].

3.1.2 Strain Gauge

A strain gauge can measure deformation or stress by measuring the changes in its resistance under an applied force. It usually converts mechanical stress into an electrical signal, which can then be measured through a simple voltage divider circuit or by directly measuring the ohmic value. Strain gauges are used in various studies to track the health and condition of batteries. For example, Louli et al. [56] describe the operando pressure methodology on Li-ion pouch cells. Figure 5(a) shows a measurement setup where cells are uniaxially constrained in aluminum enclosures, with the jelly roll attached to a gas bag [Figure 5(b)]. This setup forces gas generated during cycling into the bag, allowing uniaxial swelling measurement. Force is recorded using sub-miniature load cells and converted to pressure (PSI) based on cell area, with a force-distributing plate ensuring uniform load application [Figure 5(c)]. Pressure changes of approximately 100 PSI correspond to thickness variations of tens of micrometers and are measured concurrently with electrochemical cycling. Figure 5(d) presents results for two electrode types, showing pressure variation during cycling and SEI formation timing.

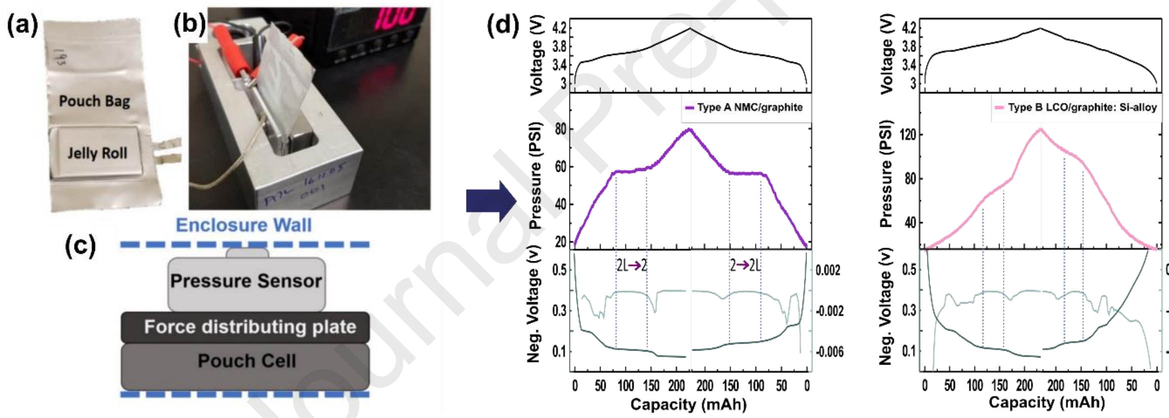


Figure 5. Experimental setup for operando pressure measurement of pouch cells and its results [56].

Hickey et al. [57] investigated battery SOC using strain gauges to detect dimensional changes in individual battery cells. Strain gauges were directly mounted on battery surfaces and compared their output to traditional voltage-based SOC estimation methods. It has been observed that during charge-discharge cycles, output voltages from strain gauges on individual cells corresponded with SOC patterns. The location of strain gauge placement significantly affected the measurement quality, with the thinned vent area providing the best results, and there was less polarization compared to open-circuit voltage measurements. A strain gauge is also used to detect thermal runaway in batteries and issue a warning when a certain temperature threshold is reached [58]. Surface-mounted thin film strain gauges are used to monitor SOC and volume expansion [59]. A neural network along the output of strain gauges is used to ascertain Li-ion batteries' depth of discharge (DOD) [60]. Although these methods are used in lab-based studies, the use of thin film strain gauges shows a promising candidate for monitoring the EV battery state [57,58]. For the measurement of EV battery volume expansion, strain gauges have demonstrated high accuracy, with metal strain gauges achieving a precision of ±0.5 μm and graphene-based gauges providing a precision of ±1 μm. Furthermore, strain gauges possess the capability to monitor cell deformation within a measurement range of 50 μm to 100 μm with a resolution of 0.01 μm. A range of commercially available strain gauges has been used in the experiments, including Vishay Precision Group (5.8 x 3.0 mm), LORD Microstrain (40 x 40 mm), MFL Strain Gauges (4.4 × 2.4 mm), PiexoMetrics, Hottinger Brüel & Kjær (2.0 × 1.2 mm) and Techni Measure (8.8 × 3.5 mm) [59].

3.1.3 Displacement Sensor

Displacement sensors are used to track the movement of an object by measuring the time required for a light or sound wave to travel between the sensor and the target object. These sensors are used to measure stress development in a battery during cycling. For instance, Makki et al. [61] measured the battery cell's expansion during charging and draining cycles using a precise displacement sensor [e.g., Keyence LK-G10]. As illustrated in Figure 6, the sensor is positioned 10mm above the fixture's top plate, which contains the battery. It records the displacement over time, capturing the rapid increase in displacement during charging, the gradual changes during the holding period, and the subsequent decrease during discharging.

The displacement sensor [e.g., Keyence LK-G10] has a measurement accuracy of ±0.60µm with a resolution of 0.01µm, and it could record a measuring range of ±1mm.

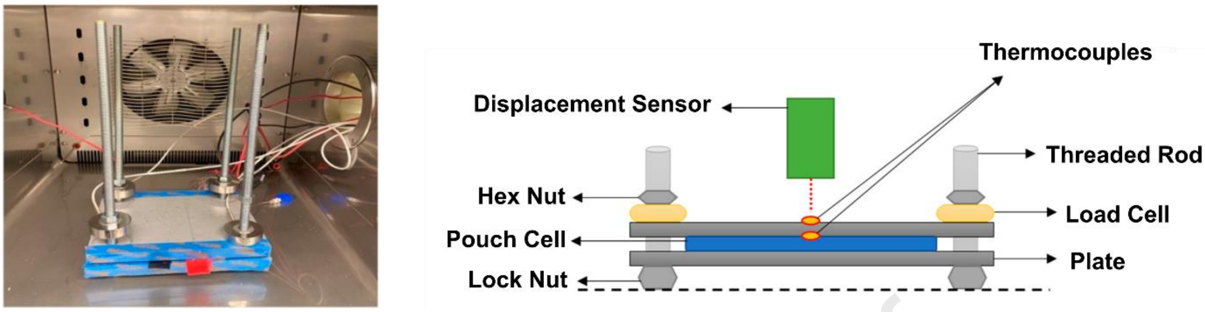


Figure 6. Displacement sensor-based measurement of battery stress [61].

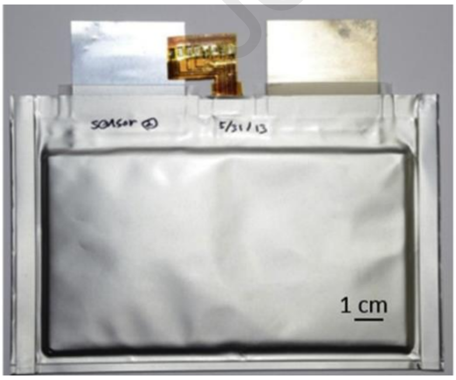
Deformation can also be measured using other high-precision displacement sensors [e.g., 404R10KL1.0]. Szurke et al. positioned the sensor [404R10KL1.0] at the top, bottom and center parts of the battery cells to measure the displacement [62]. This measurement can further be correlated with stress development. It is proposed that the SOC and discharge rates of batteries are related to stress and deformation. An eddy current sensor is mounted on the casing of the cells to detect changes in distance caused by cell expansion and compression [63]. The sensor has a sensitivity of around 10 mV/µm and is calibrated to react to displacements between 0.2 mm and 1.2 mm. It records the entire displacement signal resulting from the expansion of neighboring cells and the actual motion of the cell case. The collected data enhances multi-physics models of battery behavior, improving state estimation accuracy and providing deeper insights into intercalation effects. Though displacement sensors help monitor the battery stress, the battery's outer shell and small deviation of thickness make it challenging for onboard EV analysis. Among the models, the Keyence LK-G10 model provides high precision, which is essential to avoid accidents. The eddy current displacement sensor is particularly useful as it provides SOC estimation in addition to displacement measurements.

3.2 Temperature Sensing Techniques

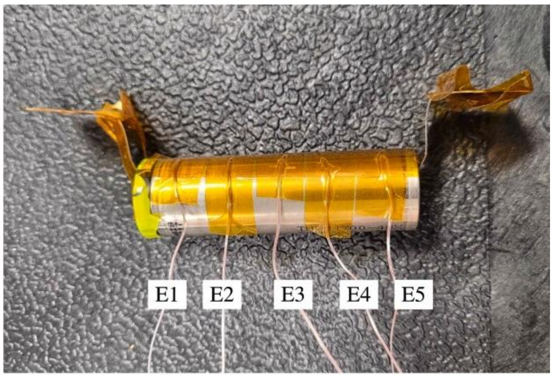
Lithium-ion batteries are temperature sensitive, and using them outside of their ideal range can hasten deterioration, lower capacity, and jeopardize safety [64]. Temperature monitoring of EV batteries is crucial for operating safely and efficiently. Generally, a working temperature ranging from 20°C to 50°C is considered optimal for lithium-ion batteries [65]. Research indicates that operating temperatures that deviate from the ideal range can have a substantial effect on battery longevity and performance. Wittman et al. reported that the capacity fading and material degradation of Nickel Manganese Cobalt cells increased as the room temperature dropped from 35°C to 15°C. [66]. In contrast, high temperature poses significant challenges for EV batteries, particularly in terms of thermal runaway and battery degradation. Various sensing techniques have been used for the EV battery's temperature monitoring, which are discussed in the following sections.

3.2.1 Thermocouples

Thermocouples are used for temperature measurement based on the thermoelectric effect. They contain two different metals joined at a junction that generates emf when heated or cooled. Thermocouples are commonly used to monitor lithium-ion battery temperature and can provide accurate, real-time temperature measurements at specific points within the battery or on its surface. The interior temperature of lithium-ion batteries is tracked in situ using modified thermocouples and flexible thin film thermocouples (TFTCs) [67]. As seen in Figure 7(a), the TFTCs are made on opaque objects and subsequently moved over thin copper foils so that they may be integrated into the battery pouch cells during assembly. The embedded sensors capture temperature changes during high-rate charge and discharge cycles, providing reliable temperature measurements without causing adverse effects like electrolyte leakage or internal shorting. Experiments were carried out by cycling the battery between 2.7V and 4.3V at room temperature in a constant temperature sink with a charge/discharge rate of 3C(9A), 5C(15A) and 7C(21A). Results demonstrate that heat generation is most significant during high-rate discharge, with the temperature reaching 12℃ at 3C, 19℃ at 5C and 26℃ at 7C. Pre-buried T-type thermocouples were used in a similar method [68] precisely to get the interior temperature of a 280 Ah Li-ion battery. To evaluate the effect of the thermocouples on the internal resistance and overall electrical performance, an AC impedance meter is also used. Tests were carried out under a standard charge/discharge cycle with varying loads, and an overcharge test was also conducted at the end to evaluate thermal runaway risks. Results show that when the load is doubled, the temperature reaches 77˚C, exceeding the safety level, and a risk of thermal runaway occurs when the internal temperature reaches 110˚C under overload. Figure 7(b**)** shows how E-type thermocouples are connected to the surface of an EV battery. Gulsoy et al. examined the impact of embedded thermocouples on the surface ones [69] and showed that thermocouples embedded in the core had 4 °C higher temperatures than the surface.



(a) Thin Film thermocouples embedded inside Li pouch cells [67].



(b) E-type thermocouples are used for measuring the surface temperature of Li cylindrical cells [70].

Figure 7. Thermocouples for the internal thermal monitoring of lithium batteries.

Thermocouples can be embedded without affecting performance significantly during battery manufacturing [68], though they have minimal impact on electrical resistance and coulombic efficiency. It is also possible to insert the thermocouples during post-manufacturing, but this requires cell opening and resealing to ensure no leakage is present. The response time of thermocouples is important as EVs often experience drastic temperature changes. At a high cycling rate (2C discharge), thermocouples have a response time of ~2.72 seconds [70]. Thinner thermocouples [e.g., 20 AWG] exhibit the fastest response compared to the thicker thermocouples [e.g., 40 AWG], which usually take several minutes. The surface-mounted thermocouples can be affected by ambient temperature and cooling/heating systems that are active in EVs and may show inaccurate readings. In terms of accuracy, the T-type has a tolerance of ±0.5°C while the K-type has ±1.5°C. A trade-off between response time, durability, and measurement accuracy is thus required for EV battery monitoring.

3.2.2 Thermistors

Thermistors work on the principle of dependency of resistance to temperature and they can sense temperature changes. Thermally sensitive resistors have a good working temperature range and are used in different EV applications [71]. Positive temperature coefficient (PTC) and negative temperature coefficient (NTC) are the two most widely used thermistors that have been developed. Whereas NTC exhibits an inverse trend, PTC's resistance is proportional to temperature. Fleming et al. measured the Li cells' in-situ temperature using NTC thermistors [72]. Thermistors were bonded onto a flexible Kapton substrate, which was chosen for its physical and internal properties. The sensors were also coated with a conformal layer of Parylene to enhance their durability in harsh environments. A voltage divider circuit was created by connecting each thermistor in series with a precise resistor and a voltage source. This allowed for the measurement of the voltage between the resistive components. The

Steinhart-Hart method was then used to convert the recorded voltage to temperature. Figure 8 shows how the sensors were inserted inside pouch cells (Figure 8a) and cylindrical cells (Figure 8e) to monitor core temperature. (Figure 8b) and (Figure 8f) were the modifications of the cells for sensor placement, and (Figure 8c) and (Figure 8g) show their practical look after insertion. To display the ultimate internal structure, X-ray pictures of the cells were created (Figure 8d and Figure 8h, respectively).

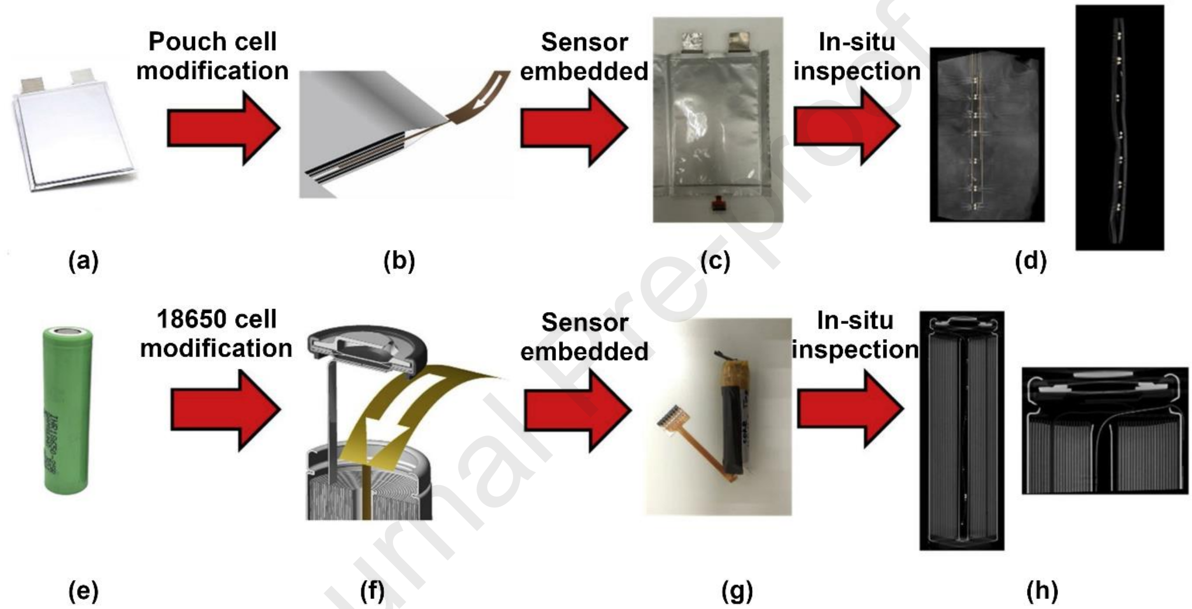


Figure 8. Thermistor arrangement for different measurement points [72].

In-situ temperature measurement was also done [73] where the thermistors were placed inside during the manufacture of Li cells. In [74], three NTC thermistors were placed inside three different locations of the battery to monitor the temperature.

Thermistors can be embedded within the electrode stack or mandrel core without affecting performance significantly. However, post-manufacturing insertion is challenging as thermistors need proper insulation and adhesion. Thin-film thermistors laminated onto Kapton substrates can respond within 1-2 seconds during 3.3C rapid discharge, while thicker thermistors may exhibit slight delays of 5-10 seconds [72,73]. Unlike surface-mounted thermistors, internally placed thermistors provide more accurate readings and minimize external interference. Thermistors offer higher accuracy than thermocouples with a tolerance of ±0.1°C, making them ideal for precise thermal monitoring. However, they may require proper calibration for self-heating effects (~0.5°C error). A balance between response time, placement and long-term stability is necessary for effective EV battery monitoring.

3.2.3 Resistance Temperature Detectors

Resistance Temperature Detectors (RTDs), unlike thermistors, are made of pure metals and establish a linear relationship between the resistance and temperature to monitor temperature changes. RTDs can be used to measure internal temperature and provide early warning for thermal failure of batteries [75]. Figure 9 demonstrates where the RTD is located inside the coin cell and how big it is compared to a real cell. It is suggested that, on average, the interior temperature was 5.8 ˚C warmer than the surface, and the sensor has a ten times faster response time.

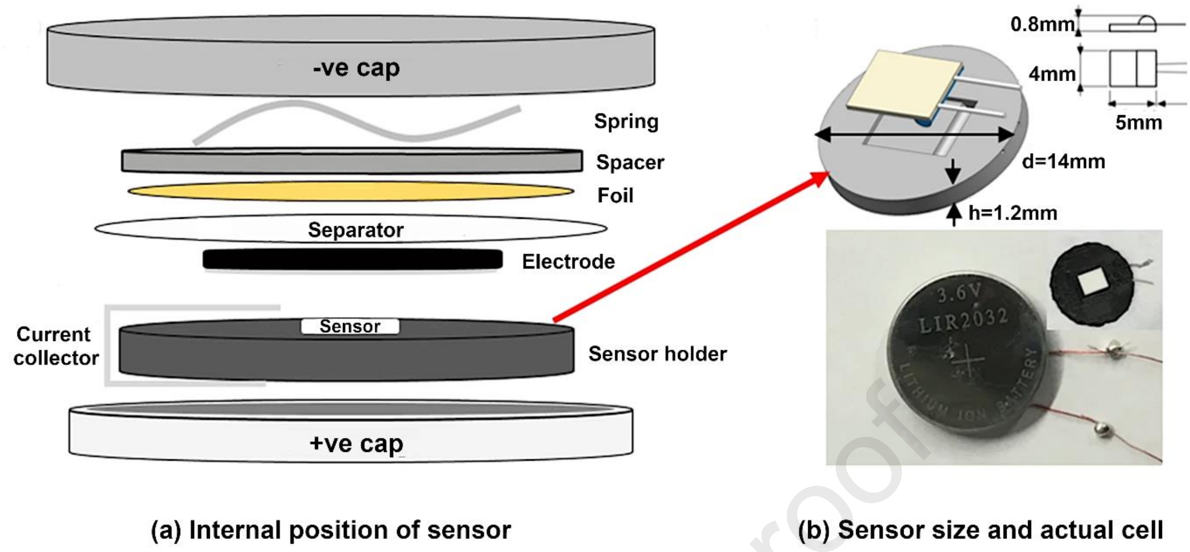


Figure 9. RTD's position inside a coin cell and its dimension [75].

The RTD monitors the surface temperature during battery charge/discharge cycles [76], with the data used to estimate SOC in the proposed thermal coupled model [77]. Flexible micro RTDs were developed and embedded inside Li batteries for faster monitoring of internal temperature [78].

RTDs can be embedded behind the cathode current collector or within polymeric spacers without affecting the electrochemical performance. Internally embedded RTDs can detect 90% of a temperature shift within 5 seconds, which is 7-10 times faster than external RTDs. This is because external RTDs suffer from thermal conduction delays [75]. Unlike surface-mounted RTDs, internally placed RTDs provide stable temperature readings, ensuring more accurate thermal monitoring. RTDs also offer superior efficiency, with a tolerance of ±0.1°C, making them highly reliable for EV battery safety. Additionally, RTDs exhibit long-term stability with minimal drift, but proper placement is necessary to avoid thermal conduction losses.

3.3 Imaging-based Sensing Techniques

Imaging-based sensing techniques are popular for the non-invasive monitoring of Li-ion batteries among the lab-based techniques. Digital Image Correlation (DIC), X-ray imaging, thermal imaging and multi-beam inspection are the most common methods. These techniques can be used to monitor stress/strain, temperature, SOC and SOH of the battery.

3.3.1 Digital Image Correlation

Digital Image Correlation (DIC) is a non-invasive image-based technique that captures images before and after deformation to determine the structural change. Figure 10 shows a typical DIC procedure [79]. The surface of the testing object is coated with black and white speckle patterns. The composition of the speckle pattern is high contrast features with varying grayscale intensities and an ideal diameter of 3-5 pixels. Based on the required resolution, which depends on the amount of deformation to be measured, the speckle size is varied from nanometers to millimeters. Images of the surface are captured using multiple cameras. Various images at different charging states are then processed, and a correlation function is applied to observe the shift in the speckle pattern. For 2D-DIC [Figure 10(a)], each frame is analyzed for the pixel shift, while for 3D-DIC [Figure 10(b)], frames from both cameras are merged for stereo matching. Szurke et al. demonstrated a DIC technique [Figure 10(c)] for Li-ion battery monitoring at different SOCs [80]. Leung et al. developed a method to inspect the stress/ strain evolution in a lithium battery using 3D-DIC [81]. A similar study is carried out to estimate the stress at the electrode level using 2D-DIC [82]. Internal temperature is also measured through thermal imaging under different battery states, and DIC is used to obtain temperature levels [83].

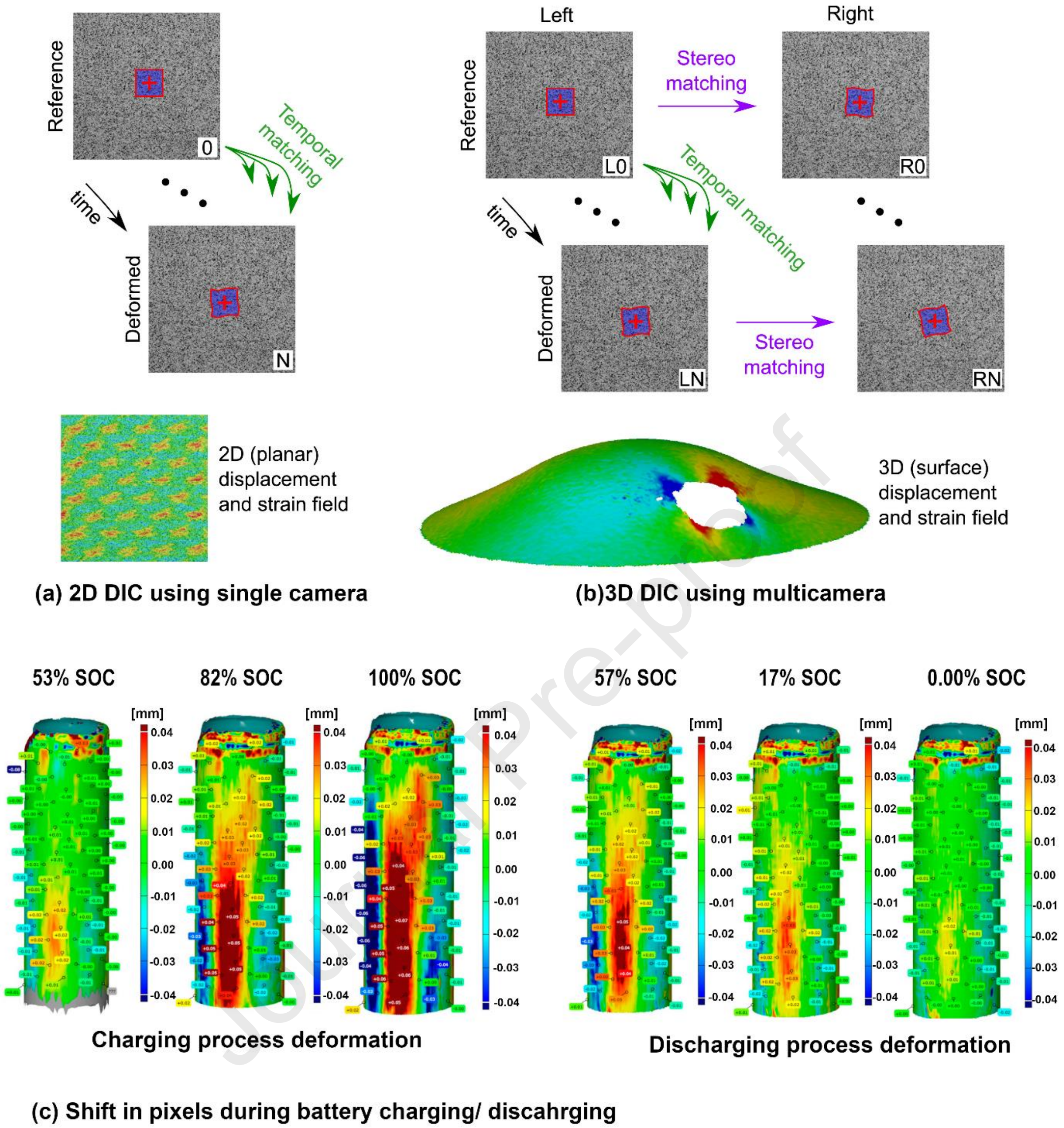


Figure 10. Correlation structure of DIC topology and its battery application [79, 80].

DIC can accurately measure in-plane displacements with a high precision of ±0.01 pixels [84]. However, the precision obtained may vary depending on the algorithm used, the type of instrument used, the contrast of the image and other experimental factors. This precision can be enhanced to the micron level using a high-resolution camera. With proper calibration, DIC can provide an error below 0.1%. However, using the DIC for battery inspection is generally expensive and requires a complex setup. Thus, it is only suitable for lab-based monitoring [85,86]. For onboard monitoring, vibrations, varying light conditions and real-time processing limit its applicability. High-frequency vibration caused by the vehicle movement can also introduce noise in the measurement. Another cause of noise is the surface contamination that accumulates over time inside the vehicle, and this is difficult to avoid as the battery compartments are not readily cleanable.

3.3.2 X-Ray Imaging

X-ray imaging uses the radiation phenomenon of X-rays to capture images of the interior of objects and it is very popular in medical imaging. The EV battery's internal structure can be monitored using X-ray imaging. For example, X-ray tomography combined with deep learning [DL] has been utilized to inspect the structural health of EV batteries [87]. Figure 11 shows the steps involved, from collecting X-ray samples of the EV battery to training the transfer learning model to obtain the structural health status of the battery. The inside of the EV batteries was inspected by using an Ultra-Bright X-ray. As discussed by Dawkins, it is possible to define Li-ion characteristics in both solid and electrolyte phases as the EV accelerates [88]. Solid-state Li-ion batteries are also examined with X-ray tomography, and the output images are classified through DL [89]. This facilitates determining material distribution inside the battery.

X-ray absorption spectroscopy is also used to examine batteries, and a high penetration makes this method suitable for battery monitoring [90]. X-ray photoelectron spectroscopy (XRPS) is employed to collect data on surface chemistry and assess changes in the battery's core. This is done with the observation of a change in the material’s kinetic energy when the surface is bombarded with X-rays. It is also used during battery cycling to monitor the SEI and real-time electric potential change is visualized [91]. Despite all the progress, X-ray is mainly used to inspect EV batteries in the lab environment and is yet to be used in applications involving the EV in motion. Because it is not able to precisely track complex phase transformations in the battery's electrochemical performance [92], the large number of images is often difficult to process[93], and there are safety issues as well. So, this technique is only suitable for lab-based analysis of EV batteries.

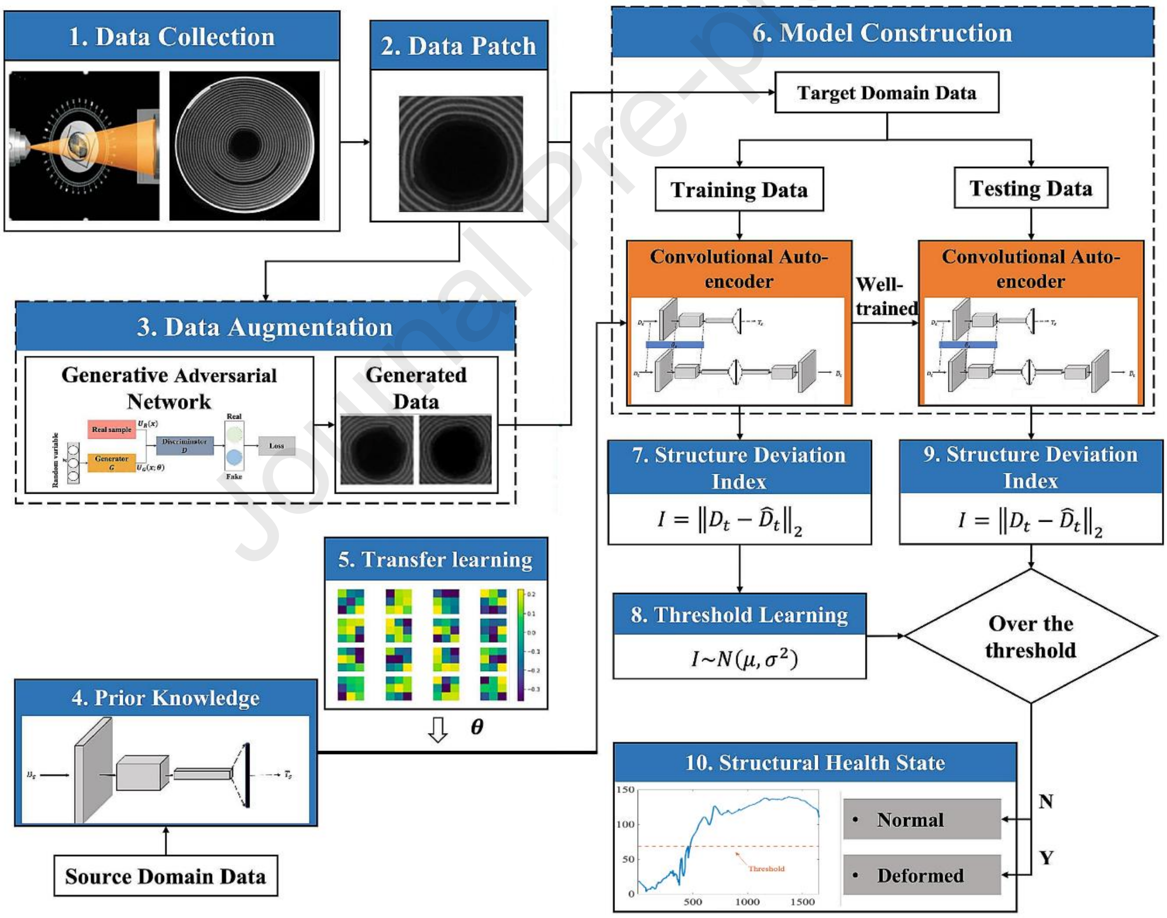


Figure 11. X-ray tomography and transfer learning for diagnosing the structural health of EV batteries [87].

Transmission X-ray microscopy can measure the 2D/3D structure of electrodes with a resolution of 10 nm and accuracy in the range of nanometers. The measurement range can be from tens of nanometers to micrometers [93]. In contrast, X-ray tomography has a slightly lower resolution (600 nm) with an accuracy of ±36 nm [89]. X-ray fluorescence microscopy has the lowest accuracy of ±1 μm and resolution in the micrometer range [92]. In terms of in-situ and ex-situ X-ray imaging, in-situ imaging is preferable for onsite EV battery monitoring because it can track changes in real-time from seconds to minutes, while ex-situ takes time as imaging is performed after complete cycling takes place. However, X-ray is suitable for lab-based monitoring, and ex-situ can be used for EV battery maintenance during post-manufacturing. In-situ can be used to study the formation of SEI in real-time.

3.3.3 Thermal Imaging

Thermal imaging is applied to EV batteries to inspect their temperature distribution and provide safety features (e.g., cooling, temperature distribution and circuit breaking) from thermal runaway. Tian et al. devised a methodology to observe thermal faults in Li-ion batteries by leveraging thermal graphics alongside a Region-based Convolutional Neural Network (R-CNN) [94]. As shown in Figure 12, images of the surface temperature were captured by the thermal camera, and after preprocessing, they were fed into the Lithium battery intelligent perception (LBIP) model that utilized Mask R-CNN to complete the thermal fault diagnosis. It can identify the temperature with 95% accuracy. The body temperature of cylindrical batteries was diagnosed using a thermal device such as FLIR E8 [95]. Infrared imaging was utilized to monitor batteries and automatically stop thermal runaways or other accidents. The obtained resolution was 320 x 240 pixels with an accuracy of ~ 98%. The system can work for a temperature range of -20°C to 550°C.

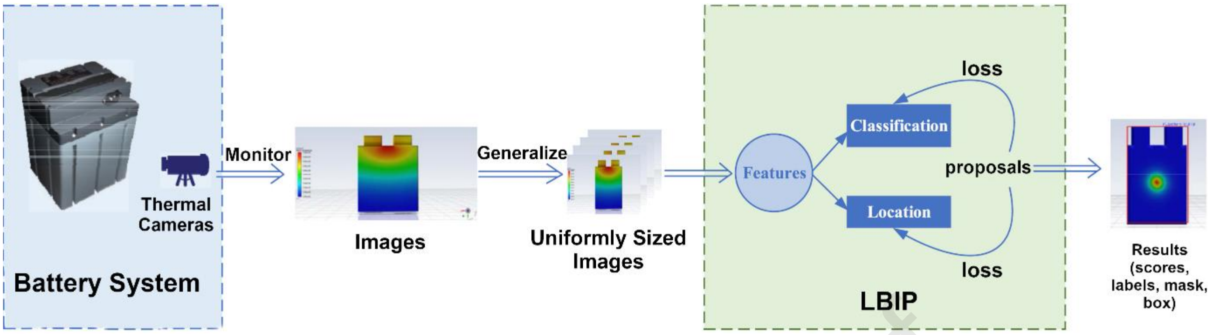


Figure 12. Thermal imaging technique to detect battery thermal state [94].

3.4 Acoustic Sensing Techniques

Acoustic sensing uses ultrasonic waves between kHz and MHz to observe the change in transmitted signal amplitude with cracks or changes in external parameters. Two ways acoustic sensing is used for battery monitoring: passive and active [96]. As shown in Figure 13(a), during passive acoustic emission (AE), one piezoelectric sensor is used along the battery, and it can sense any cracks, gas formation and SEI formation by sensing the signal emitted during such occurrences. Using passive acoustic, different stages of electrode lithiation were examined, and it was found that during the first cycle, most changes occurred [97]. By combining scanning electron microscopy (SEM) with AE sensing, it is feasible to identify alterations in the SEI layer and identify cracks [98].

Figure 13(b) depicts the working principle of active acoustic sensing. Two piezoelectric sensors are used, one to send the ultrasonic signal with a particular frequency inside the battery and the other to collect the signal and observe the changes. Lukas et al. developed such a technique to determine EV battery SOC using active AE sensing [99]. In addition to SOC, SOH estimation is also possible with AE sensors [100]. Thus, active AE sensing opens the door to battery state estimation, while passive is limited to the structural health of the battery.

The characteristics of a cell may be obtained using a pair of portable transducers and sensors, as shown in Figure 13(c). Deng et al. developed a method to scan the pouch cells to observe the changes at different cycles and ageing [101].

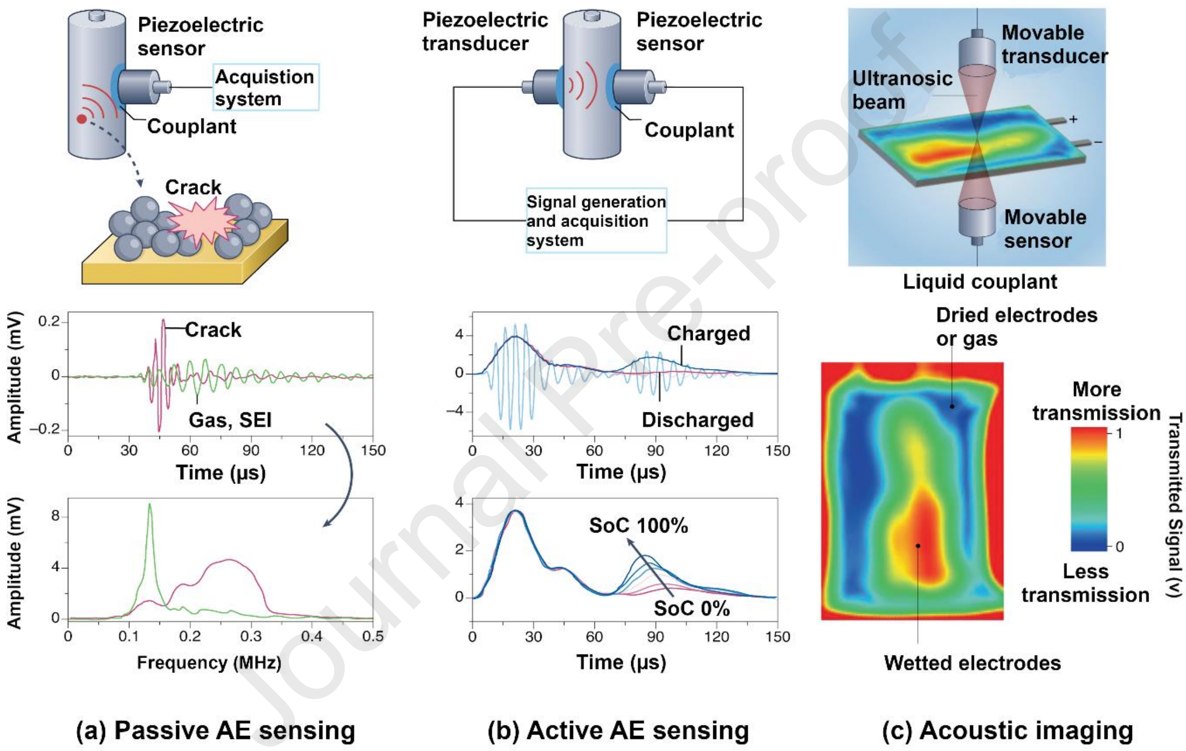


Figure 13. Different forms of AE sensing [96].

Although AE sensors show great potential for EV applications, their performance in onboard EV systems has yet to be tested. The resonant AE sensors [e.g., R15] have a frequency range of 50-200 kHz, while the wideband such as PAC WD, have 125-1000 kHz. Both sensors have been used in experiments to monitor the SOC and SOH of batteries. The maximum error of 3.07% was recorded for estimating SOC [102]. The use of AE sensors in EV applications is expensive [103] and easily distorted by background noise [104]. Additionally, complexity in signal processing and amplification is needed.

3.5 Magnetic-Field Sensing Techniques

Magnetic field techniques are non-invasive. Through proper establishment, its dynamic can be utilized to sense battery parameters such as current, SOC and SOH. These techniques involve establishing a field using coils and observing the change in the magnetism with battery cycling. This section provides an overview of magnetic field-based sensing technologies used for monitoring EV batteries.

3.5.1 Hall-Effect Sensor

Hall-effect sensors can detect magnetic fields by detecting the voltage produced when charge carriers in a current-carrying wire deflect under the influence of a perpendicular magnetic field. In parallel-connected battery strings, Hall-effect sensors [e.g., FDIB C16-5P4O5] track the current going through individual cells [105]. These sensors were placed around the cells to detect the magnetic field generated by the current, allowing for non-intrusive measurement without adding resistance to the circuit. The sensors provided bidirectional current measurement, capturing both charging and discharging currents. A multi-sensor array board (MSAB) integrates these sensors, supplying power and facilitating voltage measurement. Figure 14 shows the use of a micro Hall-effect sensor in an MSAB. Each of the sensors had a resolution of 20 mA, and it can measure current in the range of ±5 A. Additionally, the overall current flowing across a series battery pack during charge-discharge was measured using the Hall-effect sensor [ACS 712], which has a sensitivity of 66mV/A [106]. This method provides an accuracy of 98.5% after calibration in the measurement range 0-30 A.

Hall-effect sensors are ideal for monitoring EV battery's current due to their compact size, non-invasive measurement, and high accuracy. They can be used in both onboard vehicles and lab-based setups. The FDIB C16-5P4O5 sensor is suitable for studying individual EV cells due to its miniature structure and bidirectional feature, whereas ACS 712 can monitor an entire battery as it has a greater measurement range.

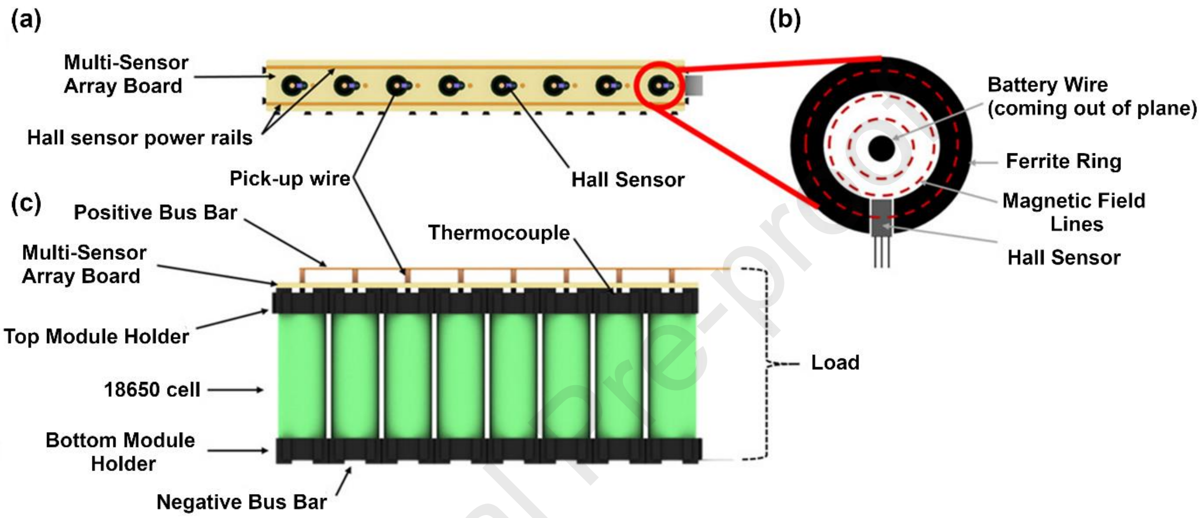


Figure 14. Multi Hall-Effect sensor measurement [105]; (a) MSAB from the top with Hall sensor position in each of the parallel cells, (b) detailed structure of the Sensor and (c) rear view of the setup.

3.5.2 Magnetic Field Probing

Magnetic field (MF) probing has been developed to monitor the battery SOH. When the MF is perpendicular to ion motion, the Lorentz force enhances electrochemical reactions by aiding mass transfer and uniform lithium-ion motion [107]. In contrast, a parallel MF aligns with ion paths, improving conductivity, diffusion, and overall performance [108]. Khare et al. determined SOH by creating a technique that uses MF probing on sealed lead-acid (SLA) batteries [109]. As shown in Figure 15(a), they used two identical coils around the battery, with external magnetic flux lines at ninety degrees to the internal field. Battery performance is evaluated during charge/discharge cycles by measuring changes in the induced electromotive force (emf) at the magnetic coil (secondary). By positioning the coils horizontally and vertically, the method provides insights into electrode structure, stratification, and current profiles, revealing changes in magnetic flux linkage during operation. The changes were ~ 12% due to stratification flux linkage. Although lead-acid batteries are not generally used in EVs, the concept may be utilized for EV lithium-ion batteries.

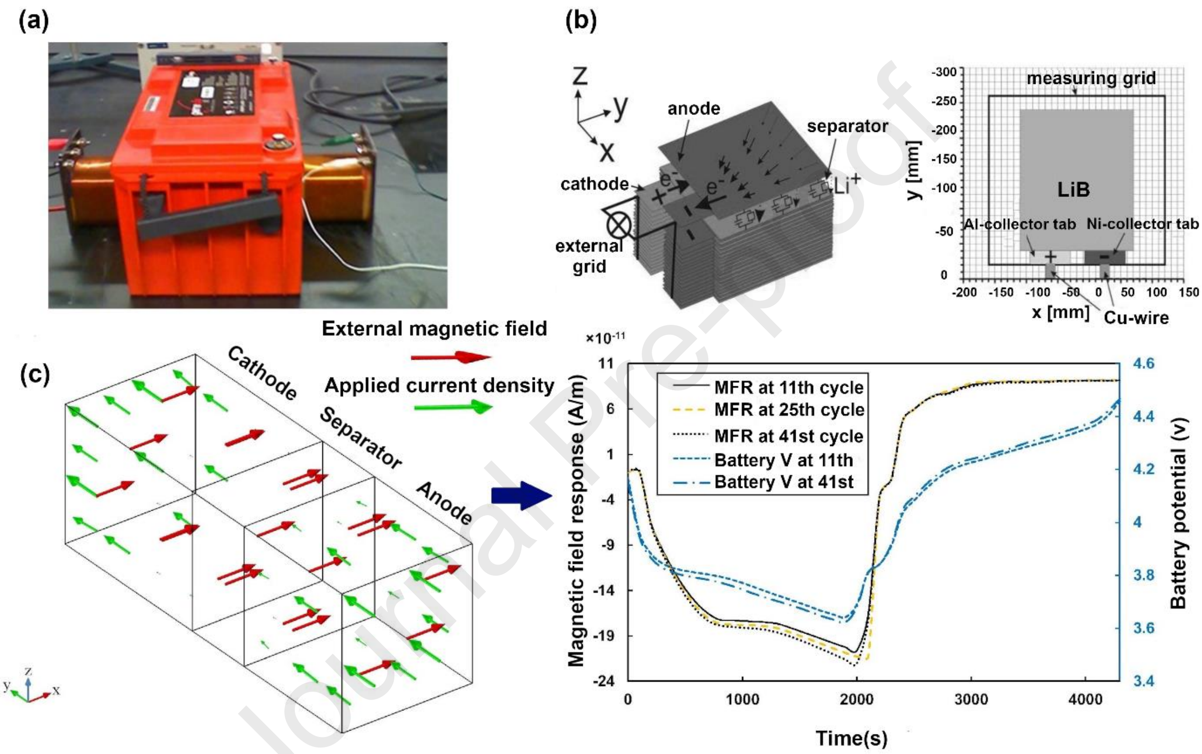


Figure 15. (a) Setup of MF coils around lead-acid batteries [109], (b) flow of the lithium ions and orientation of the AMR sensor in the x-y-z coordinate system [110], and (c) model of MF and lithium battery and the corresponding response [111].

Anisotropic Magneto Resistance (AMR), [e.g., Honeywell HMC 1053], sensors can detect three MF components (Bx, By, Bz) with high precision and are used for estimating the battery SOC [110]. On a modular grid with 10 mm steps, the sensors monitor MFs caused by current flow during charge and discharge pulses at a set distance from the battery [Figure 15(b)]. The measurements reveal changes in the battery's magnetic properties as the battery is charged or discharged, aiding SOC estimation for battery management systems. It shows promising results with a resolution of 5 nT and 0.1% reproducibility in a measurement range of ±600 μT.

Lithium batteries were investigated in a simulation environment such as COMSOL, where the magnetic field and lithium batteries were modelled and tested to observe the change in the SEI layer [111]. Figure 15(c) shows that the simulation model is made considering that the MF is perpendicular to the ion's movement. The bottom right figure [Figure 15(c)] shows how the MF response varies with the charge-discharge cycles. The MF response demonstrates that value decreases with cycle life, which is consistent with the SEI layer's expansion.

Although MF sensors can be a suitable candidate for EV monitoring, they require comprehensive analysis and investigation of potential side effects that may impact the battery's long-term exposure to MF.

3.6 Optical Sensing Techniques

Recently, optical sensing techniques have become very popular for battery monitoring, as they can be used to monitor battery temperature, stress/ strain, and SOC. Optical fibre sensors are considered ideal for their capability to measure various parameters of EV batteries.

3.6.1 Fibre Bragg Grating

Fibre Bragg Grating (FBG) sensors are a few millimeters in length and are made of optical fibres with repetitive gratings inside. As broadband optical signal transmits through the fibres, a signal with a particular wavelength is reflected [112]. Equation 1 presents the Bragg wavelength, λ_B under no influence, the effective refractive index is denoted by n_{eff}, and the grating period by Λ.

$$\lambda_B = 2n_{eff}\Lambda \quad (1)$$

Under the influence of temperature or stress/strain, there is a shift in wavelength, which can be expressed as,

$$\Delta\lambda_B = \lambda_B\left(\frac{1}{n_{eff}}\frac{\partial n_{eff}}{\partial T} + \frac{1}{\Lambda}\frac{\partial\Lambda}{\partial T}\right)\Delta T, \quad (2)$$

$$\Delta\lambda'_B = \lambda'_B\left(\frac{1}{n_{eff}}\frac{\partial n_{eff}}{\partial \varepsilon} + \frac{1}{\Lambda}\frac{\partial\lambda}{\partial \varepsilon}\right)\Delta\varepsilon, \quad (3)$$

where the wavelength shift $\Delta\lambda_B\ and\ \Delta\lambda'_B$ is dependent on temperature change or strain variation, respectively.

It is feasible to observe the battery's internal properties with the aid of FBG sensors. The FBG sensor is enclosed within the battery to track the difference between the internal and exterior temperatures, as seen in Figure 16 [113]. In the study, the sensor was positioned both within the battery and on its outside. It was suggested that internal temperature varies by around 4.7˚C compared to external temperature. The resolution of the sensor was 1 pm wavelength with sensitivities of 8.55 pm/°C and 10.24 pm/°C for external and internal sensors, respectively.

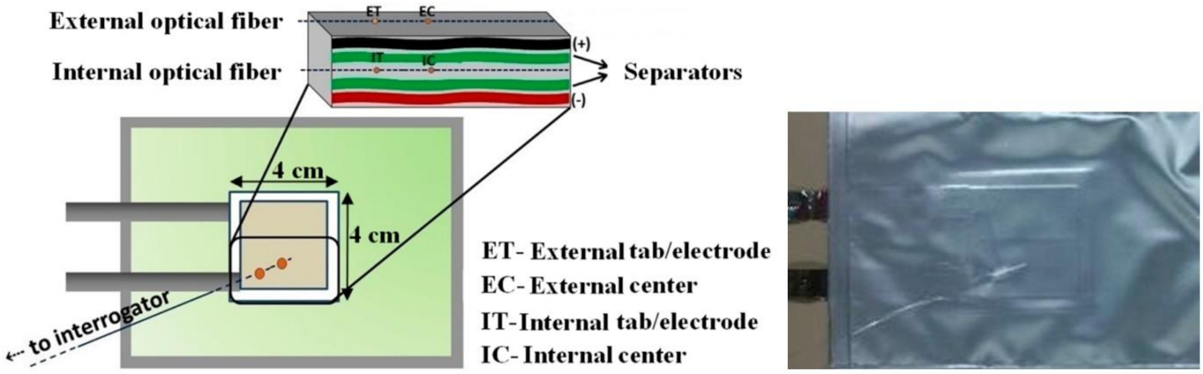


Figure 16. Schematic of internal and external position of FBG sensor along with actual pouch cell location [113].

In [114], stress inside a coin cell was monitored by embedding an FBG sensor inside the battery during charge cycles, and demonstrated that it could be both solid-state and liquid electrolytes. The system measured stress within 1.7 MPa to 62 MPa with a resolution of 1 pm. A tilted FBG was used to estimate the SOC of supercapacitors and produced independent of temperature crosstalk results [115]. Moreover, an advanced FBG sensor was constructed by Peng et al., which can monitor battery strain with more precision, having higher sensitivity compared to bare FBG [116]. With a resolution of 1 pm, it showed a sensitivity of 11.55 pm/με. The smaller size FBG sensors (about 5-7 mm in length and 0.2 mm in diameter) can be easily inserted into EV batteries. As they are capable of measuring both temperature and stress/strain inside a battery, they are expected to be a promising candidate in the EV market in the future.

3.6.2 Fibre Interferometer Sensor

Fibre Interferometer Sensors (FIS) are often used to monitor temperature, strain, relative humidity (RH), potential of hydrogen (pH), and gas pressure. Unlike FBG, they have only two parallel reflectors separated by an air space. Under the influence of strain, this space will be deformed, and as a result, a shift in reflected wavelength is observed corresponding to equation 3.

To monitor the internal status of the battery, FIS was placed inside the core, like FBG. Figure 17 shows a type of interferometer technique, Fabry-Perot interferometer (FPI), where to detect the temperature and pressure during battery charging and discharging, a sensor was inserted within the battery [117]. The resolution of the sensor was 40 Pa/°C, and it produced a linear pressure response with 99.99% accuracy. The sensitivity was 26.6 nm/kPa for a pressure range of 10-280 kPa and 107 nm/°C for a temperature variation of 0-60°C, respectively.

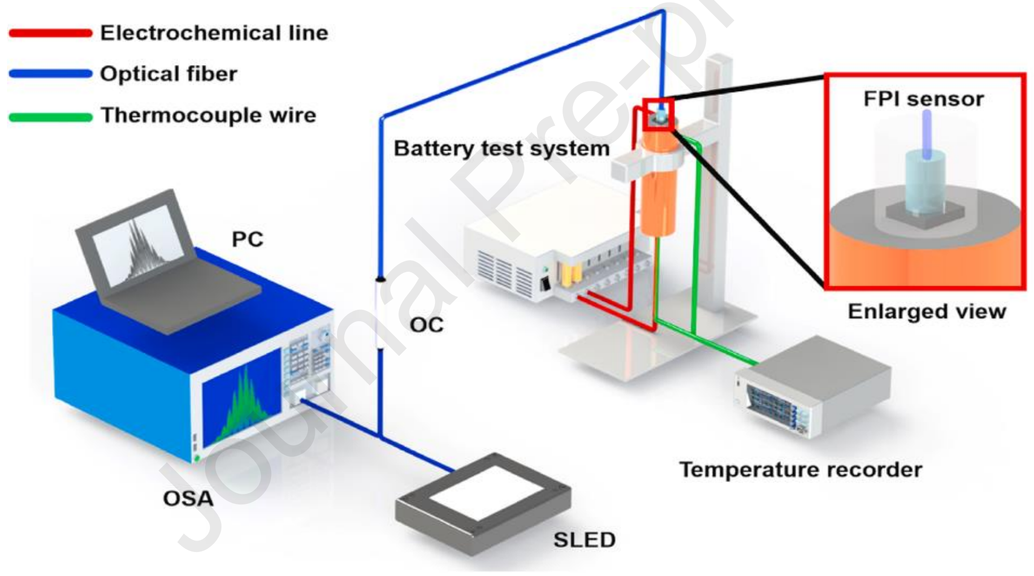


Figure 17. Fabry-Perot interferometer measurement for in-situ monitoring [117].

The Mach-Zehnder interferometer (MZI), a distinct kind of interferometry, may also be used to track various battery properties. Sun et al. examined a metal beam's temperature and curvature [118]. The sensor was fabricated and tested for curvature measurements by controlling the bend using a steel ruler, temperature measurements were also tested by observing the wavelength shift in a controlled temperature chamber over 20°C to 150°C. It shows a resolution of ±0.01 m^{-1} and ±2.23°C, for curvature and temperature, respectively. The same concept can be applied to batteries. FISs are a potential candidate for EVs as the temperature and pressure range closely align with the operation of batteries. The challenge lies in preventing battery capacity drop when inserting the sensor inside the battery, and this may be overcome by placing it in a position where there are no active elements present.

3.6.3 Fibre Evanescent Wave Sensor

A Fibre Evanescent Wave Sensor (FEWS) operates based on the interaction between the evanescent field, which is a field that extends into the cladding of the optical fibre, and the surrounding environment. Changes in the surrounding medium's refractive index can have an impact on the intensity and phase of light transmitted through the fibre when the evanescent field interacts with the analyte. This interaction results in changes to the transmitted spectrum, allowing the sensor to detect variations in the surrounding environment, such as chemical concentrations or physical changes.

For lithium-ion batteries with cathodes made of lithium iron phosphate (LFP) and lithium manganese oxide (LMO), a FEWS was employed [119]. Results demonstrated that during lithium extraction, the spectral response during LFP oxidation and reduction consistently increased in intensity, while LMO exhibited a distinct optical response with two peaks during lithium extraction and a reversed response during reduction. In another work, a FEWS sensor is inserted inside a sodium-ion battery, and the findings demonstrated the sensors' capacity to track sodium plating levels [120]. The experiments were conducted on a small scale where the wavelength was shifted between 500nm and 900 nm. Thus, an in-depth analysis is needed to establish its position in the EV battery market.

4. Comparative Overview

In the realm of EV battery monitoring, various sensing techniques offer distinct advantages and disadvantages, including their applicability in battery SOC and SOH monitoring. Table 1 provides a thorough summary of the various sensor-based technologies. The key points of each technology are briefly discussed below.

- Imaging-based methods (DIC, X-ray and thermal) offer a 2-D and non-invasive way to monitor the battery states. Although DICs are often costly and difficult to install into EVs, they can monitor both internal and exterior battery cell characteristics and have better accuracy and resolution compared to other techniques. X-rays can monitor internal parameters but are unable to track the phase changes within the battery accurately, causing safety issues. Thermal imaging offers a comprehensive view of thermal distribution with a good temperature range. However, it is not suitable for SOC or SOH monitoring and is often expensive and space-consuming. This makes it less applicable for integration into EV systems where real-time performance metrics are crucial.
- Both passive and active acoustic techniques offer in-depth insights into the structural integrity of battery systems. Passive acoustic methods can precisely detect structural changes, while active methods are more suitable for monitoring the SOC and SOH with a high accuracy (97%). However, both approaches are expensive and complex, making them more appropriate for lab-based monitoring rather than real-time applications. The need for complex signal processing and potential issues with sensor mobility further limit their practicality in dynamic environments. Acoustic imaging needs a complex buildup due to the movable sensors.
- Though ECD provides precise measurements with an accuracy of ±0.01% of battery internal changes, the system setup is complex and ideal for lab use. Type 2 is ideal for EV

battery inspection, but Type 1 may be used to understand battery behavior, as it involves battery shell opening. The strain gauges and displacement sensors can provide insights into the stress-strain relationships, SOC and SOH of battery cells and have a high measurement range. However, both methods are invasive and not the best for internal health monitoring. Their low sensitivity, accuracy and complexity in setup further restrict their applicability in practical EV scenarios, where non-invasive and real-time monitoring solutions are preferred.

- Thermocouples are widely used for EV battery temperature monitoring due to their wider temperature range (-200°C to 1300°C), fast response time and durability. They are relatively low-cost and have a simple design, making them accessible for various applications. However, their low sensitivity compared to thermistors and RTDs limits their effectiveness in detecting small temperature variations. Furthermore, thermocouples require cold junction compensation for accurate measurements and can be susceptible to electromagnetic interference (EMI) in high-power environments, which can pose challenges in EV applications. Thin film thermistors are ideal for EVs as the setup is easy and offers faster response time and sensitivity with a resolution of 0.01°C. RTDs can offer a long-term solution for onboard monitoring in EVs, as performance is stable in the long run, but a slower response time (~ 5 seconds) means a backup sensor may need to be present to detect critical moments such as thermal runaway.
- Hall-Effect sensor can monitor current with good sensitivity and high measurement range (0- 30A or ±1000 mT). However, it suffers from low resolution (milli Tesla) and limited speed, and external magnetic fields can adversely affect its measurements. While suitable for both onboard and lab-based monitoring, its performance may be compromised with fluctuating MFs, which are common in EV applications. The MF probing can measure

changes in battery internal parameters if it is used with proper care, but if it is applied too much, it might cause thermal runaway.

- FBG sensor is ideal for monitoring battery hotspots and deformation due to its high sensitivity (11.55 pm/με) to temperature and strain. It can also measure temperature from multiple points within a battery pack using a single fibre due to its distributed sensing capability. Additionally, FBG sensors are also resistant to EMI, ensuring stable operation in challenging environments. However, the cross-sensitivity between temperature and strain complicates data interpretation. Thus, specialized interrogation systems are needed, which can increase the costs, potentially limiting their widespread adoption. The FBG sensor excels over FIS and FEWS in terms of buildup and sensitivity but needs to be drilled inside the battery to monitor internal thermal conditions or strain.

Though each sensing technology has unique benefits and challenges, the ideal solution for monitoring the EV battery should be sensitive, non-invasive, cost-effective, and operate in the dynamic conditions of electric vehicles reliably. The needs of the battery technology and the operating environment will eventually determine which monitoring techniques are best.

Table 1. Comparison of different sensing techniques for EV battery monitoring.

Technology	Method	Advantage	Disadvantage	Comment
Imaging-based	DIC [80–83]	-Non-invasive, non-intrusive. -Monitors SOC, SOH, internal and external parameters. -Higher accuracy (±0.01 pixels).	-Speckle pattern can change the outer look. -Expensive, complex, takes space. -Measurement are affected by vibrations, varying light and surface contamination.	-Because of high accuracy it can be used in lab-based setup to examine battery or for maintenance. -High frequency vibration and required regular cleaning of surface, make it unsuitable for onboard EVs.
	X-Ray Imaging [87–91]	-Non-invasive, non-intrusive. -X-Ray Microscopy, Tomography and Fluorescent Microscopy have resolution of 10 nm, 600 nm and micrometer, respectively. -Highly accurate with ranges within ±36 nm to ±1 μm.	-Not precise tracking of phase changes. -Complex and safety issues	-Despite being highly precise and accurate, it is yet to be considered for onboard monitoring (for safety and cost issues)

		- Provide a clear picture of internal change.		
	Thermal Imaging [94,95]	-Non-invasive, non-intrusive. - Good temperature range (-40°C to 1000°C) -Monitors surface temperature of every location.	-Not suitable for SOC, and SOH monitoring. -Lacks accuracy (±2°C) and resolution (0.1°C) -Expensive and takes up space.	-It lacks accuracy and affected by dirt and lighting, thus suitable for lab setup.
Acoustic	Passive [97,98]	-Precisely detect structural changes (resolution in mm range).	-Not able to monitor SOC and SOH.	-Ideal for both onboard and lab-based monitoring. -Versatile as both narrowband (50-200 kHz) and wideband (125-1000 kHz) can be used based on requirement.
	Active [99,100]	-Ideal for monitoring SOC, SOH and internal changes. -Can monitor SOC with an accuracy of 97%.	-Expensive, complex signal processing and need for amplification.	
	Acoustic Imaging [101]	-Produces overall picture of battery state.	-Movable sensor needs complex buildup. Expensive.	-Ideal for lab-based monitoring.
Stress-Strain	ECD [51,53,55]	-Detects various electrochemical and structural phases of the battery providing an accuracy of ±0.01%	-Very complex setup and invasive. - Affected by mechanical vibrations, temperature fluctuations and non-uniform cell expansion.	-Type 1 ECD is suitable for lab-based experiments which involves battery opening

		-Able to detect minute changes with a resolution of 0.2 µm and measurement range of ±0.5 mm.		while Type 2 only for inspection of EV batteries in the lab
	Strain Gauge [56–60]	-Monitors SOC, SOH, stress and thermal state. -Measurement range is high, 50 µm to 100 µm with good resolution (0.01 µm).	-Invasive. - Less accuracy (±0.5% of full scale) compared to ECD	-To detect internal parameters, the techniques developed are either suitable only for lab experiments or are intrusive.
	Displacement Sensor [61–63]	-Monitors stress-strain, SOC, SOH. -Measurement range is up to 10 mm, suitable for lab-based setup. - Accuracy (±0.03% of full scale) is better compared to ECD and Strain Gauge.	-Invasive and not ideal for internal health monitoring. --Low sensitivity (micrometer range).	-Ideal for lab-based monitoring as it may fail to detect small deviations and affected by battery outer shell.
Temperature	Thermocouples [67–70]	-Wide temperature range (-200°C to 1300°C). -Fast response time for dynamic temperature changes. -Durable and robust. -Relatively low cost and simple design	-Low sensitivity, with a resolution of 0.1°C and accuracy (±1.5°C) compared to thermistors and RTDs. -Requires cold junction compensation for accurate readings.	-Ideal for both online and lab-based monitoring. -Thermocouple width can affect response time and external cooling/heating system.

			- Susceptible to electromagnetic interference (EMI) in high-power environments like EVs.	
	Thermistors [72–74]	- High sensitivity, with a resolution 0.01°C and good accuracy (±0.5°C), excellent for detecting small temperature variations. -Compact size allows for placement in tight spaces within the battery pack. -Cost-effective for large-scale deployments in battery modules. -Faster response time (1-2 seconds)	-Limited temperature range (-55°C to 125°C). -Post-manufacturing insertion to EV battery is challenging. -Non-linear response requires compensation or complex calibration for accurate temperature readings. -Less durable compared to thermocouples and RTDs, especially in harsh conditions.	-Ideal for both online and lab-based monitoring. -Thin-film thermistors can respond quickly to rapid discharge which makes it suitable for EV onboard applications.
	RTD [75–78]	-High accuracy (±0.1°C to ±0.5°C) and stability (resolution 0.1°C) over a broad temperature range (-200°C to 850°C). -Linear response simplifies signal processing and calibration. -Long-term reliability and low drift	-Larger and more expensive than thermocouples and thermistors. -Slower response time (~ 5 seconds) compared to thermocouples. -Requires external circuitry for current excitation.	-Ideal for both online and lab-based monitoring. -Can last for a long time without performance dip in EV.

Magnetic-Field	Hall-Effect [105,106]	-Non-invasive and non-intrusive -Monitors current with good sensitivity (accuracy of ±1%). -High measurement range (0-30A or ±1000 mT).	-External magnetic fields can affect reading. -Lower resolution (milli Tesla) and limited speed.	-The miniature models are suitable for lab-based setup and onboard. -The large ones are perfect for onboard monitoring.
	MF Probing [109–111]	-MF can help increase battery capacity and minimize the buildup of dendrite growth. -Resolution 5 nT and 0.1% reproducibility in a measurement range of ±600μT.	-High MF can adversely affect batteries by increasing temperature. -Flux linkage can vary around 12%.	-MF probing has been tested in lab-based setup, as it may positively affect battery, onboard monitoring of EVs needs to be introduced.
Optical	FBG [113–116]	-High sensitivity (11.55 pm/με) to temperature and strain, ideal for monitoring battery hotspots and deformation. -Can measure stress at range of 62 MPa with a resolution of 1pm. -Distributed sensing enables monitoring multiple points in a battery pack using a single fiber.	-Cross-sensitivity between temperature and strain can complicate data interpretation. -Requires specialized and costly interrogation systems for precise measurements. -Limited for very high-frequency or ultra-dynamic monitoring.	-The compact size and ability to measure both temperature and stress/strain makes it a promising candidate for onboard EV monitoring.

		-Resistant to electromagnetic interference (EMI), ensuring stable operation in EV environments. -Compact, lightweight, and easy to integrate into battery systems.		
	FIS [117,118]	-Extremely high precision (±0.01m^{-1} and ±2.23°C), suitable for detecting micro-deformations or slight dimensional changes in battery cells during charge/discharge cycles. -Effective for localized, dynamic monitoring in structural health applications. -Capable of measuring small-scale vibrations or mechanical shifts as it can produce linear pressure response with 99.99% accuracy.	-Complex setup requiring precise alignment and isolation from external disturbances. -High cost due to the need for stable optical components and systems. -Susceptible to environmental instabilities like vibrations or temperature changes	-Temperature and pressure range closely align with EV battery applications. Applicable for onboard and lab monitoring.
	FEWS [119,120]	-Sensitive to chemical and refractive index changes, enabling the detection of gas emissions or electrolyte degradation.	-Limited sensing range (wavelength shifted between 500-900 nm), as the evanescent field only interacts near the fiber surface.	- Suitable for lab-based setup, onboard monitoring needs further analysis.

		-Compact and capable of in situ, real-time monitoring of chemical phenomena within batteries. -Useful for safety-critical tasks like thermal runaway or leakage detection	-Higher optical power loss, reducing efficiency over large monitoring areas. -Requires fiber modifications (e.g., tapering or etching), increasing fabrication complexity and cost.	

5. Challenges and Future Trends

The development of effective sensing techniques for EV battery monitoring continues and faces several challenges that must be addressed to enhance battery performance, lifespan and security. This section discusses the key challenges and future trends in the field of EV battery sensing, focusing on internal and external parameters, cell-level sensing, data acquisition and collection, fault diagnostics, onboard monitoring and market size.

5.1 Measurement of Internal Parameters

The performance and health of EV batteries are influenced by various internal and external parameters [121]. These are intrinsic to the battery's chemistry and internal operation. Measuring or estimating these parameters often requires specialized sensing techniques. The external parameters can be measured directly using external sensors. Based on the sensor properties such as size, range of measurement, resolution, etc., an appropriate selection is needed to ensure a suitable sensor is chosen for onboard or lab-based EV battery monitoring.

EVs' range is greatly enhanced with the introduction of lithium-ion batteries but these batteries have a complex buildup and pose complex electrochemical properties [122]. The complex internal structure of lithium-ion batteries makes it difficult to directly measure changes happening inside the cells [123]. Batteries are sealed systems, limiting access to sensors without compromising the cell integrity. Additionally, the dynamic nature of battery operation, with rapid changes in internal parameters during charging/discharging cycles, complicates accurate real-time measurements. When EVs accelerate, there is a large deviation between internal and external measurements, and studies reported a 15°C difference between core and surface [124]. The inside temperature may potentially grow up to 300°C - 400°C higher compared to the surface in the case of an accident, such as a thermal runaway [125]. In some cases, some sensors like thermocouples may provide a higher measurement range but lack sensitivity, which is an essential safety factor to avoid EV accidents. A proper guideline on EV battery sensors, based on all factors, needs to be developed.

The future scope of research in EV battery monitoring lies in developing non-invasive, robust, and scalable technologies to address the challenges associated with measuring internal parameters. Advancements in miniaturized sensors that can monitor internal features without compromising battery capacity are crucial. Optical sensors, though currently fragile, hold significant promise if their durability and integration can be improved. Advanced acoustic and magnetic field sensors with enhanced signal processing enable real-time internal monitoring. Furthermore, machine learning could be used to infer internal parameters indirectly from external measurements, reducing the need for invasive methods. Hybrid sensors combining multiple measurement techniques can give a complete view of battery health and performance while keeping safety and practicality in EV applications.

5.2 Cell-level Sensing

A key component of battery management is cell-level sensing, which enables accurate tracking of each cell's performance inside a battery pack. This granularity enables the detection of imbalances between cells. Current sensing methods in EVs are mostly stack-based, where the whole battery unit or many cells together are monitored using a single sensor [126]. If one of the cells gets damaged or blows off, within a very short time, the battery unit might face thermal runaway. Monitoring each cell is also important for cell balancing and performance enhancement [127]. Although a few parameters, such as voltage, current, and temperature are measured from the cell-to-cell level [128], others, including stress/strain, impedance, SEI growth, and gas formation, are not readily measured.

To allow accurate monitoring and control of individual cells inside a battery pack, future research must concentrate on developing cell-level sensing technologies. While parameters like voltage, current, and temperature are already being measured at the cell level in some instances, further exploration is needed to monitor more complex internal parameters, such as stress/strain, impedance, SEI growth, and gas formation. Innovations in small-scale, low-power, and cost-effective sensors that can measure these parameters without compromising cell capacity are essential.

5.3 Data Acquisition and Collection

Acquiring, storing, and analyzing the enormous volume of data produced by several battery sensors is quite difficult. For a thorough knowledge of battery performance and health, it is necessary to continually monitor and record battery metrics, including current, temperature, voltage, and state of charge/health. Current battery management systems in EVs are typically limited in their data acquisition and processing capabilities, often focusing on basic parameters (voltage, current, and temperature) [129]. More feasible techniques that can gather and analyze a wider range of data, including internal battery parameters, are needed to enable more accurate state estimation and health prediction. Reducing the number of wires and components to accommodate more space and make EVs more lightweight [130]. Moreover, different SOC and SOH models can have different data sets and sampling rates. While rapid acquisition is desirable, it is not always feasible due to the inherently slow nature of electrochemical reactions.

Various devices used for data acquisition range from microcontrollers to specific DAQs. In [131], a simple Arduino UNO can record voltage, current and temperature with a sampling range of milliseconds but is limited by operating voltage and current range. An ESP32-based DAQ [Xtensa 32-bit LX6 microprocessor] with a sampling rate of 0.5 Hz and storage rate of 130 kB/hour can withstand high voltages with a sacrifice of sampling rate [132]. A more expensive option, the National Instruments USB-6341 DAQ, offers voltage measurement precision down to approximately 8.4 μV (with a ±10 V range). Combined with external current sensing methods, such as shunt resistors, it enables precise measurements in the milliamps range (ranging from 3.05 mA for 0.1 Ω to higher values depending on the resistor value used) [62].

Investigating novel approaches to data collection and processing is necessary to manage the growing number and complexity of battery data. This includes the system's development, where each sensor is interfaced with wireless protocols that are sufficiently slow and energy-efficient, thereby forming a network of interconnected sensors. Additionally, advanced data processing algorithms can extract meaningful insights from the raw sensor data with minimal computational cost. By combining IoT technology with cloud-based development, remote data sensing may be made possible. This can assist minimize battery size while offering fleet-wide insights and predictive maintenance capabilities.

Additionally, the standardization of data formats and communication protocols across the EV ecosystem would ease seamless data exchange and collaboration among researchers, manufacturers, and service providers.

5.4 Onboard Monitoring

It is more challenging to inspect EV batteries in comparison to other system batteries because they are in continuous movement, have limited space and have a wide range of environmental changes. The main challenges include:

- Space constraints in EV design: Sensors designed for laboratory or industrial settings often lack the compactness needed for integration into EVs, where available space is limited due to the compact design of battery packs and surrounding components [133].
- Durability and reliability under real-world conditions: Sensors must withstand continuous vibrations, mechanical shocks, and rapid environmental changes, such as temperature and humidity fluctuations, which are common in EVs [134]. Many sensors developed in research lack real-world testing to validate their robustness under such conditions.
- Energy consumption of embedded sensors: Adding sensors increases the load on the EV battery, reducing its overall efficiency and driving range [135]. Minimizing energy consumption while maintaining accurate data collection is a persistent challenge.
- Interference with EV operation: Embedded sensors could disrupt battery functionality, introduce parasitic effects, or interfere with the performance of nearby electrical systems, including the motor and control units [136].
- Cost-effectiveness and scalability: The sensors developed for lab-scale testing often use advanced materials or technologies that are expensive and difficult to manufacture at scale for practical EV applications.
- Integration with BMS: Effective sensing requires seamless communication between the sensors and the BMS. Many existing sensors lack compatibility with current BMS frameworks, limiting their practical usability in EVs.

- Impact of multi-cell configurations: In multi-cell battery packs, monitoring individual cells is challenging due to the complex wiring, increased sensor count, and the risk of introducing additional points of failure [137].

Future research needs to focus on designing ultra-compact sensors that can fit into EV battery packs without occupying excessive space or interfering with other systems. Using materials like flexible electronics and nanoscale sensors could overcome these space constraints. Hybrid sensing like the integration of acoustic and optical sensing can detect multiple parameters. More field trials are necessary to test sensor technologies under conditions of vibration, mechanical stress, and environmental changes. Designing energy-efficient sensors with ultra-low power consumption will minimize their impact on battery efficiency and range. Research into energy harvesting technologies to power sensors from vibrations or heat within the EV could also be a promising direction. Developing robust signal processing techniques can ensure accurate measurements even under challenging conditions such as noise from vibrations or interference from external systems. AI-based noise reduction and fault-tolerant data handling could enhance sensor performance. Exploring wireless sensing technologies, such as RFID-based systems or optical fibre sensors, could reduce the need for additional wiring in multi-cell configurations and provide non-invasive monitoring options. Finally, developing hybrid sensors capable of monitoring multiple parameters (e.g., temperature, impedance, and stress/strain) simultaneously can reduce the total number of sensors needed, saving space and improving efficiency.

5.5 Control, Balancing and Fault Diagnosis

As advancements in EV battery technology progress, the significance of sophisticated control strategies, effective balancing methods, and robust fault diagnosis techniques becomes increasingly important. Advanced control algorithms, including model-based and data-driven approaches, have been developed to enhance battery performance and prolong its lifespan. For instance, the implementation of model predictive control allows real-time modifications predicated on anticipated future states, thereby improving efficiency and ensuring safety [138]. Despite these developments, the current control mechanisms used in the EV industry mainly rely on voltage or current threshold monitoring. Consequently, the future EV industry needs to shift its focus toward adopting model-based and data-driven control mechanisms.

In the current scenario, passive balancing is more dominant in 2-wheelers, while 4-wheelers mostly use active balancing with the help of high-precision voltage and current sensors. Active balancing techniques, which redistribute energy between cells, have shown promising results in extending battery life and improving overall system efficiency [139,140]. Consequently, cost-effective solutions are needed to enable the incorporation of active balancing into 2-wheelers as well. Moreover, the development of fast and precise sensors is essential for achieving improved balancing capabilities.

For fault diagnostics, the BMS industry generally uses rule-based (e.g., threshold checking), model-based (e.g., equivalent circuit model), or signal-based (e.g., impedance spectroscopy) methods. These effective fault diagnosis methods can detect anomalies early, thereby mitigating the risk of catastrophic failures. Recent advancements have witnessed the integration of signal decomposition, ML algorithms, and model-based approaches to identify faults such as overcharging, short circuits, and thermal runaway [138,141].

The future direction of control, balancing, and fault diagnosis in EV batteries will likely involve the incorporation of AI and ML techniques. These technologies can scrutinize extensive datasets derived from battery sensors to predict potential failures and the dynamic optimization of control strategies. Additionally, the advancement of smart battery systems capable of establishing communication channels with other vehicle systems and infrastructure will facilitate the buildup of more integrated and highly efficient energy management solutions [142].

5.6 Market size

With the rapid development of EVs as well as the EV battery industry, sensing technologies for EV battery monitoring continue to advance. Table 2 highlights a comparison of the market size of EV battery monitoring sensors and all other sensors used in EVs. The global EV sensor market size is estimated at 9.31 billion USD in 2024 and is growing at a rate of 12.7%, expected to reach 16.71 billion USD by 2030 [143,144].

Table 2. EV Battery sensor market size vs total EV sensor market size (USD billion)

Year	2024	2025	2030
EV sensor	9.31	10.49	16.71
EV battery monitoring sensor	5.7	6.4	10.7

In contrast, the market for sensors solely related to battery monitoring is capped at 5.7 billion USD in 2024 and is forecasted to reach 10.71 billion USD by 2030. These statistics demonstrate the dominance of EV battery sensors, occupying a market share of over 60% and highlighting the fact that EV users demand long-lasting battery life. This forecast showcases the importance of analyzing the current sensing technologies. Despite the growth and importance, several challenges need to be addressed for the sustainable development of future EV battery monitoring sensing technologies.

6. Conclusion

The growing popularity of electric vehicles has highlighted how important a strong BMS is to guarantee the batteries' longevity, efficiency, and safety. The present level of battery sensing technology for tracking important EV battery metrics, including charge level, health state, and temperature behavior, has been thoroughly examined in this study. While monitoring external variables like current, voltage and surface temperature is achievable using existing sensors, monitoring internal parameters such as impedance, stress/strain, SEI growth, and gas formation is challenging due to limitations in sensor technology and practical constraints within EV environments.

The review highlights significant advancements in image-based sensing, acoustic methods, stress-strain sensors, thermal monitoring, magnetic field probing and optical sensors for battery monitoring, each offering unique strengths but also facing limitations in scalability, durability, and integration into real-world EV applications.

Key challenges include space constraints, durability under dynamic operating conditions, energy efficiency of sensors, and integration with existing BMS frameworks. Real-world validation of lab-developed sensors and scaling innovative solutions for practical EV use is imperative.

Future research must prioritize the development of compact, non-invasive sensors capable of monitoring a broader range of internal parameters while maintaining cost-effectiveness and scalability. Hybrid sensing systems combining multiple techniques, coupled with advancements in AI for indirect parameter estimation, offer a promising direction for overcoming current limitations. Additionally, the integration of IoT-based monitoring systems and real-time data processing platforms can further enhance the capabilities of next-generation BMS.

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- Current technologies in electric vehicle battery monitoring are reviewed.
- Challenges of sensing-based techniques are discussed.
- Research gaps in the subject area and application of sensors are identified.
- Recommendations are provided for future research trends.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: