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A Comprehensive Review on Advanced Fault Detection Techniques of Lithium-ion Battery Packs in Electric Vehicle Applications

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Abstract- Conventional engine-powered vehicles gradually decline in sales due to their emission effects as well as the unavailability of fuels in 2030. Alternatively, Electric Vehicles (EVs) which is substantially growing in the automobile sector due to their zero-emission and sustainable power. Electric Vehicles utilize lithium-ion batteries for their significant properties such as high specific power, long lifespan, high efficiency, moderate energy density, and minimum loading effect. A Battery Management System (BMS) is primarily used to monitor the battery operating conditions and its health in real time. Another primary role of a battery management system is to detect the fault that arises in the battery during its operation. This paper consolidates various internal and external battery faults and their detection techniques executed on the battery management system. The fault detection techniques are classified into model-based, Knowledge-based and data-driven methods programmed on BMS, which analyses the fault data acquired from the battery and stores the diagnostic trouble code (DTC) in the fault memory. Effective fault detection algorithms and appropriate sensors fixed around batteries help to detect battery faults in advance and alert the user to avoid catastrophic failure in EVs are discussed.

Keywords Li-ion rechargeable cell, Faults in batteries, Battery management system, Fault diagnosis techniques.

1. Introduction

Greenhouse gas emissions from road transportation are nearly 17% around the globe which can be reduced by switching to EVs worldwide. The sales of electric vehicles are growing due to their enhanced range, availability of various models, and efficiency. In 2022, the EV car sector sales have grown about 14% compared with the previous year and it is predicted zero emissions in 2050. At present, adopting electric vehicles is not widely popular globally due to selling costs and few charging infrastructure availability. The overall EV sales in November 2022 witnessed a marginal increase of 0.1% to reach 1,19,949 units. Besides, there was a leap of more than 185% as mentioned in Fig 1.

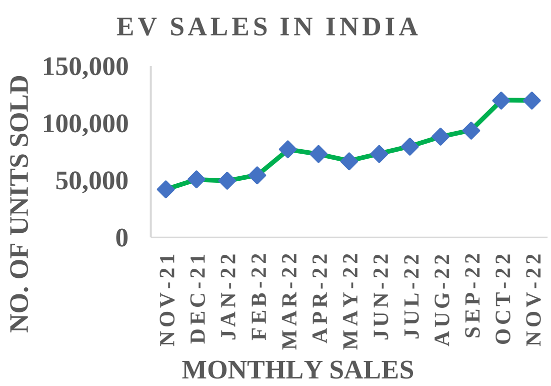

Fig. 1. Electric vehicle sales from Nov 2021- Nov 2022

Source: JMK Research

Li-ion batteries are widely used in consumer electronics compared to other energy storage based on greater power densities, extended lifespans, high energy density, and lower self-discharge characteristics at fluctuating temperatures [1]. A battery management system (BMS) is essential for monitoring the condition of lithium-ion batteries during their operation. A BMS is an embedded board connected to the battery bank to detect failures or faults and isolate the battery from potential issues caused during its operation [2]. The embedded software executes on BMS involves data collection, SOC estimation, cell balancing, SOH estimation, and thermal and charge management [3].

As depicted in Fig 2, In 2020, 124 battery-related fire accidents in electric vehicles were recorded, out of which 23% were due to long-term charging, 37.1% were idle explosions, and 39.9% were battery operating explosions. Battery faults are classified into Internal and External faults. Internal battery faults are the faults occurred in the battery internally caused by overcharging, overheating, internal short circuits, external short circuits, thermal runaway, and over-discharging. External battery faults are faults occurred in the battery externally caused by sensors connected to the battery, cell connection, and cooling system. Appropriate battery fault diagnostic techniques executed on battery management systems can detect internal and external faults that may significantly limit battery explosions and failures through effective monitoring and protection circuits. The fault-detection algorithms implemented on a BMS are classified into model and non-model techniques. Model-based techniques can be classified into Structural analysis, Parameter and State Estimation and Parity Space. Non-model-based techniques are classified into knowledge-based and signal-processing methods.

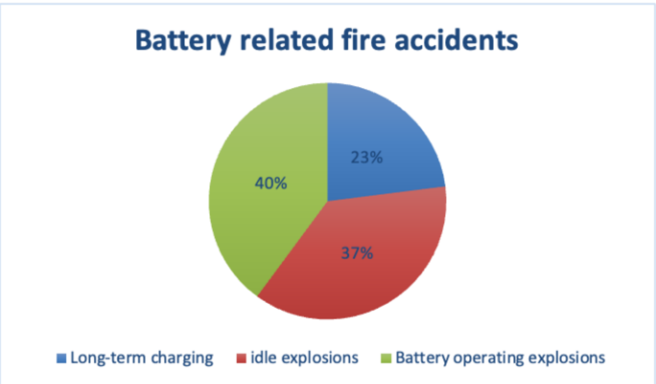

Fig. 2. Electric vehicle fire accident

Fault detection algorithms executed on the BMS are required to compute the present Cell Temperature, State of Charge (SOC), Cell voltage, Cell current, State of Health (SOH), Cycle Durability, and Discharging and Charging profiles of the battery are evaluated in real-time. The state of charge of a battery is computed using its initial charge and the maximum charge stored in the battery (1). The accuracy of the SOC can be improved by an effective technique called the Kalman Filter and Extended Kalman Filter. The SOH of a battery was calculated using the full battery charge and rated capacity. The SOC and SOH are useful to evaluate the battery's ageing and predict the valid or useful lifetime. Battery temperature is another important parameter for calculating battery ageing, which varies according to the charging and discharging profiles and atmospheric changes (2). The battery voltage and current were continuously monitored to find deviations from the expected values and any deviations. If any faults are calculated by the BMS, then the isolation circuit disconnects the battery banks from the chassis ground to avoid disastrous accidents. The novelty of the literature review comprises the various internal and external battery faults using knowledge-based, non-model based and data-driven methods integrating Machine Learning techniques used for fault diagnosis of battery packs in EVs. The flow of the study is structured as follows.

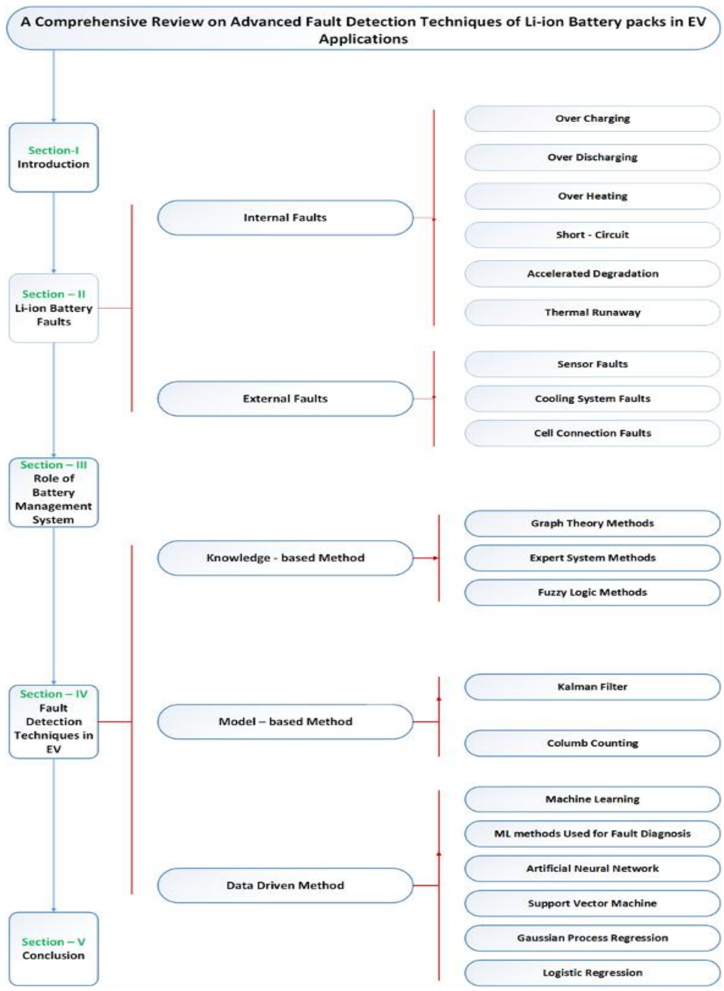

Fig. 3. Flowchart of the present study

Acronyms:

SEI	Solid electrolyte interface	SVR	Support vector regression
Li-ion	Lithium-ion battery	ISOMAP	Isometric feature mapping
ML	Machine learning	GPR	Gaussian process regression
KF	Kalman filter	LSTM	The long short-term memory
OCV	Open circuit voltage	SC	Short-circuit
RF	Random Forest	SVM	Support vector machine
RLS	Recursive least square	KNN	K-Nearest neighboring
UKF	Unscented Kalman filter	LR	Logistic regression
PWM	Pulse width modulation	ANN	Artificial Neural Network
FDI	Fault Detection Isolation	KSVM	Kernel space vector machine
EMF	Electromotive force	GNB	Gaussian naive Bayes
EKF	Extended Kalman filter	NI-MH	Nickel metal hydrate
BNN	Biological Neural Network	ECM	Equivalent circuit model
RL	Reinforcement learning	TR	Thermal runaway
XGBoost	Extreme Gradient Boosting	EIS	Electro-chemical impedance spectra
RVM	Relevance vector machine		

2. Lithium-Ion Battery Faults in EV

Fault diagnostics algorithms executed on the BMS are highly important and equal to application code. The lifetime of Li-ion batteries is shortened because of various conditions, such as high atmospheric temperatures and overcharging/discharging. Therefore, faults in Li-ion batteries are shown in Fig 4.

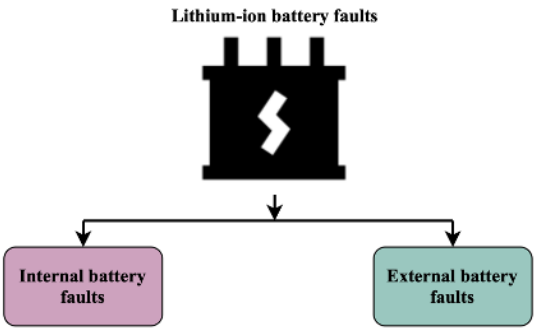

Fig. 4. Classification of Lithium-ion battery faults

2.1. Internal Faults in Lithium- Ion battery

Li-ion cell operation remains unclear (3), and it may be difficult to detect internal battery faults. The most hazardous characteristics of Li-ion batteries are sensitivity to rapid degradation and thermal runaway, which may reduce their utility and potentially threaten their owners' lives (4). Generally, abnormal operational responses of the battery, such as a decrease in voltage or state of charge, an increase in temperature or internal resistance, or a physical change, or swelling, are indicative of internal battery problems. Internal faults occurring in a Li-ion battery are shown in Fig 5.

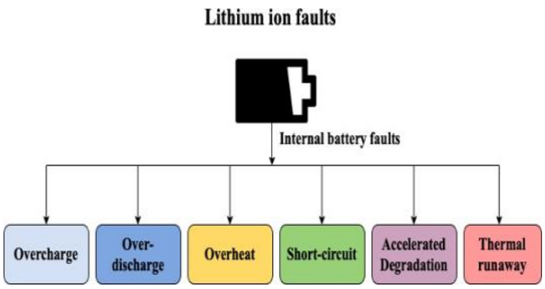

Fig. 5. Classification of Internal faults in Lithium-ion battery faults

2.1.1. Over-charge

Overcharging is the process of providing (or) delivering excess current to charge the battery. The inherent unpredictability of Li-ion cell capacity, inadequate voltage, current monitoring, and an inaccurate SOC forecast from the BMS all contribute to the potential of this occurrence (5). They acquire additional issues when overcharging batteries, such as rapid degeneration and thermal runaway. Furthermore, a standard battery pack can be overcharged if the charger charges continuously without disconnection while the battery is fully charged. In addition, when Li-ion batteries are overcharged, the electrochemical interactions cause the active materials to deplete. Moreover, gas buildup in enclosed batteries can lead to explosions during their operation (6). In addition to generating a short circuit inside the battery, the results show an excessively thick SEI layer. Finally, overcharging the cathode results in issues such as electrolyte breakdown, metal dissolution, and phase shift, which results in a fire explosion (7).

2.1.2. Over-discharge

Over-discharge of Li-ion batteries can cause due to variable capacity of the cell, low voltage and current monitoring, and inaccurate SOC estimation (5). Over-discharge may harm Li-ion batteries by initiating an undesired electrochemical reaction which results in thermal runaway and accelerated deterioration. Therefore, over-discharge reduces the battery life and increases the cell temperature variation. Consequently, Li-ion batteries are expected to develop internal short circuits (6). Gan et al. (8) used machine learning (ML) to design a two-layer defective detection system for Li-ion batteries to identify an over-discharge in electric vehicle batteries. If the battery voltage is compared to the cut-off voltage, the first layer can detect over-discharge. The second layer is a deterioration mechanism using the extreme Gradient Boosting (XGBoost) algorithm, activated whenever the battery voltage exceeds a certain threshold.

2.1.3. Over-heating

Overheating in the Li-ion battery occurs when the voltage regulator fails, it causes the battery to overheat by returning an excessive amount of power from the generator. In addition, internal and external short circuits, or both lead to overheating (9). Moreover, if a Li-ion battery is overheated, its components may degrade and release gas bubbles, causing it to enlarge or even explode (10). Overheating also results in thermal runaway which occurs, when a thermal reaction begins at a critical temperature because heat cannot escape as quickly as it is produced. Battery thermal defects were identified and classified using the Luenberger observer by Statista et al. [9]. These include convection cooling resistance faults, heat explosion faults, and internal heat resistance faults.

2.1.4. Accelerated-Degradation

The deterioration process is increased during storage at high temperatures due to interactions between the electrode and the electrolyte, changes in electrode material and corrosion of current collectors are also some other mechanisms of accelerated degradation. In some applications like EVs, the battery's lifespan decreases due to accelerated degradation. Moreover, it also causes contact deterioration surface layer deformation that results in material disintegration and loss of lithium [13].

In (11,12) the researchers identified that rapid deterioration is a severe problem in Li-ion battery applications. When temperatures exceed their optimal range, the deterioration accelerates. In addition, several variables such as increasing impedance, increased cycle frequency, fluctuating state-of-charge levels, and higher voltage rates, promote deterioration of the exterior environment [15,16], Current collector corrosion, electrode composition fluctuations, and electrode-electrolyte interaction are three mechanisms leading to rapid degradation. Rapid battery ageing is a significant issue in several applications, including electric vehicles. In addition, it may accelerate the formation of surface layers and contact degradation, which results in electrode and material disintegration and Li-ion loss (3).

2.1.5. Short-circuit

Short circuits occur when the insulating layer between electrodes is unavailable or degraded. High temperatures, cell deformation, dendritic development, and compressive stress are associated with separator failure, as a result, temperatures may rapidly reach toxic levels, a phenomenon known as thermal runaway [17,18], because the electrolyte decomposes exothermically. An increase in the temperature from a short circuit causes thermal runaway. Large-capacity cells are more prone to undergo thermal runaway in the event of an internal short circuit than smaller-capacity cells (17). When tabs are coupled via a path with low resistance, an external short circuit is often the consequence. Moreover, gas generation from side reactions during overcharging may cause the cells to swell, resulting in electrolyte leakage (18). Alternatively, water immersion or collision might cause deformation. An electrical connection is established between the positive and negative electrodes when an external heat-conducting material contacts both terminals simultaneously (19). Li-ion diffusion limits current flow at the negative electrode when an external short circuit is present (18). But thermal runaway is caused by the heat released during electrolyte breakdown at the positive electrode. When a cell is subjected to a short circuit, the stored energy can release rapidly [19,20].

2.1.6. Thermal Runaway

A battery may experience thermal runaway owing to any of the above concerns. The extreme charging currents and high charging temperatures may also contribute to this issue. It is conceivable that a solid reaction occurs when the temperature is near the melting point of a Li-ion battery (20). As indicated in the preceding section, limited air circulation is an additional factor for the occurrence known as thermal runaway (21). Based on their observations, Galushkin et al. (22) determined that the likelihood of thermal runaway increased with each charge/discharge cycle. Researchers have also connected several exothermic battery activities to thermal runaway.

Table 1. Comparison of internal battery fault diagnosis

Author	Citations	Fault parameters	Faults in Battery	Technique	Achievements
Amardeep et al.	(23)	Battery model parameters	Detecting overcharge and over-discharge faults	Extended Kalman filter	This model efficiently detects the overcharge and over-discharge faults in real time.
Yang et al.	(24)	Fault parameters for abnormal voltages	Identifying the Li-ion battery faults	Artificial Neural Networks (ANN)	A complete battery fault diagnostics model for abnormal voltages is built based on extensive data regulation.
Jinget al.	(25)	Increasing temperature and decreasing voltage	Detecting overcharge faults	Ruled-based method	This model is efficient in detecting overcharge faults and alerts the users early
Vinay et al.	(26)	Fault parameters from Soc, temperature, and voltage	Li-ion battery overcharging and over-discharging	Fuzzy logic	This approach efficiently and precisely identifies overcharge and over-discharge issues in Li-ion batteries.

2.2. External Faults in Lithium-Ion battery

External battery failures can substantially impact the BMS's other operations and induce internal battery problems. External defects include various losses in temperature, voltage, current sensors, battery cell connections, and cooling units. The failure of the cooling unit is the most disastrous because it produces a thermal loss, especially thermal runaway, owing to the system's inability to create sufficient cooling (27). Therefore, External faults in a Li-ion battery are classified as illustrated in Fig 6.

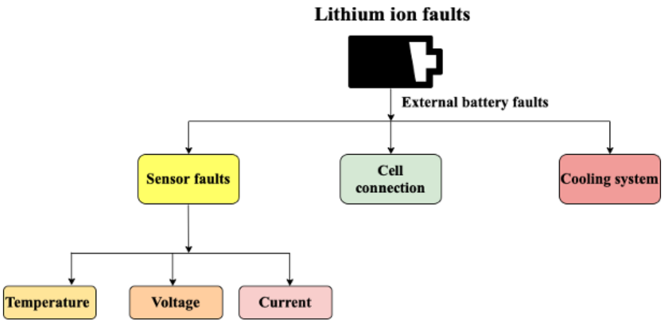

Fig. 6. Classification of External Faults in Lithium-ion Batteries

2.2.1. *Sensor Faults*

A dependable sensor-failure diagnosis system is necessary for safe and efficient battery operation. It also prevents internal defects, thermal runaway, overcharging, over-discharging, overheating, and both external and internal short circuits. Faulty sensors fail to monitor temperature, voltage, or current accurately. Numerous sensor failures can be attributed to physical causes, including vibration, impact, and electrolyte leakage. Corrosion around the battery sensor or faulty connections can also occur. A malfunctioning sensor may speed the deterioration of a battery, impede BMS operations owing to erroneous status evaluation, and cause other difficulties inside the battery itself. Providing accurate temperature data to the BMS is crucial to its ability to manage battery performance, making the temperature sensor an essential component of the Li-ion battery system. A defective temperature sensor might result in the BMS obtaining inaccurate data due to poor thermal management. Temperature sensor failure results in ageing at high temperatures, overheating, degradation due to high temperatures, short-circuiting, and thermal runaway. The battery lifespan may be dramatically reduced because of the extreme precision of the BMS temperature-control function. The voltage sensor checks the condition of each battery cell. A battery may fail internally because of overcharging and draining caused by a malfunctioning voltage sensor that results in inaccurate SOC and SOH calculations. The current sensor detects the amount of current entering and exiting the battery and provides this information to the battery management system. The urgent identification of the cause of a defective current sensor is required to avoid further issues. Current sensor problems might cause the cell to overcharge, over-discharge, or overheat, resulting in erroneous SOCs and other metric sizes that can affect the BMS's control operation.

2.2.2. *Cooling System*

The cooling system in a Li-ion battery helps to maintain a healthy temperature and eliminates the extra heat from the battery pack to maintain the ideal temperature. When the motor or fan of the cooling system stops working, it is often due to malfunctioning temperature sensors, fan wiring, or a blown fuse. The temperature sensor and cooling system faults have the same temperature dependence and cannot be distinguished from one another. Moreover, overheating of a battery may result in thermal runaway and failure, which can cause the cooling system to fail. Therefore, prompt diagnosis is essential.

2.2.3. *Cell Connection*

Vibrations induced by impurities may weaken the connections between cell terminals, leading to inadequate electrical connections and battery or cell connection issues. This problem may cause a substantial increase in cell resistance owing to insufficient current flow or overheating of the damaged cell. Voltage and temperature sensors facilitate the detection of this breakdown; however, if it is not resolved, more critical problems may occur, such as external short circuits or thermal runaway. Table 2 illustrates a comparison of different external faults in BMS.

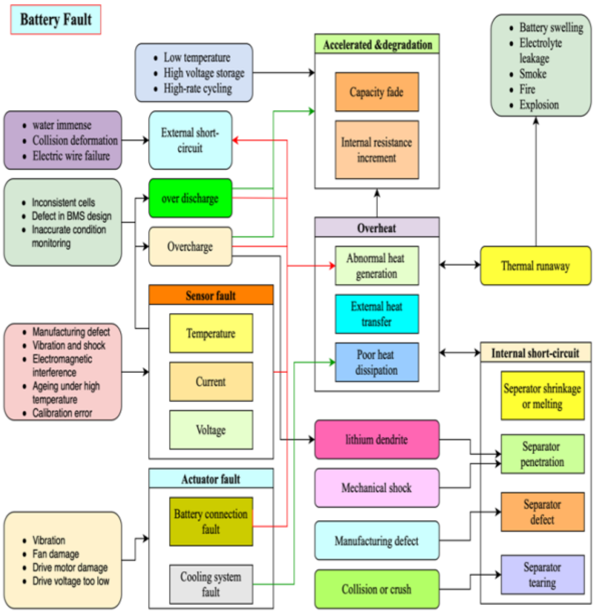

Fig. 7. Overview of Lithium-ion Battery Faults

Table 2. Comparison of external battery fault diagnosis

Author	Citations	Fault parameters	Faults in Battery	Techniques	Achievements
Xia et al.	(28,29)	Voltage measurement	Detecting sensor and cells faults	Fault-tolerant voltage monitoring technique for a series-connected battery pack	Sensor faults can be isolated without any hard ware setup
Lombard iet al.	(30)	Relationship between voltage sensor measurement and current sensor measurement	Identifying the sensor faults of Lithium-ion battery	Kirchhoff's law	Finished Lithium-ion Battery Fault Detection and Isolation of Current and Voltage Sensors
Liu et al.	(31,32)	Residues from the structural analysis theory generated based on the EKF method	Detecting the sensor faults	Structural analysis theory	Used for reducing the noise but also increased the computational cost
Liu et al.	(33)	Fault parameters from SOC, temperature, and voltage	Estimating the output voltage of faulty voltage	EKF	In accurate initial noise and robustness.

3. Role of Battery Management System (BMS) in Fault Diagnosis

A battery management system (BMS) is responsible for mitigating the hazards associated with Li-ion batteries to ensure the safety of the battery and its users. Faults cause the most dangerous situations, and the BMS should reduce their frequency and severity. Insulation, sensors, and contractors are battery safety precautions. In addition, sensors connected to the cells regulate voltage, current, and temperature working limits. Nonetheless, these safeguards are often insufficient since battery concerns may get more complicated with more modern hardware and software implementation of the BMS.

Consequently, BMS requires fault diagnostic techniques. These algorithms aim to identify defects early and conduct rapid repair actions for the battery and its users.

BMS includes the battery system's diagnostic subsystems and algorithms; it plays a crucial role in diagnosing issues. It employs sensors and estimated system status to monitor the battery system and then models or analyses the data to identify abnormal behaviour (34).

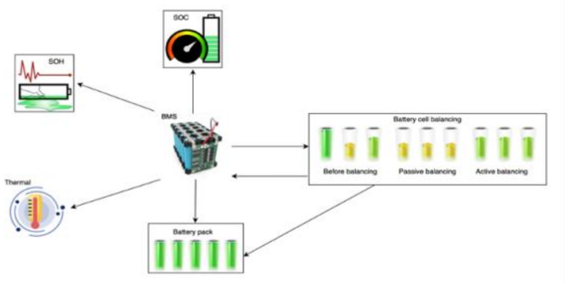

Fig. 8. BMS working

The fault diagnostic procedure of the BMS has depicted Several Internal and environmental factors that make it challenging to do this function without difficulty. Once a problem is identified, the appropriate action must be taken which involves the coordinated use of several defect detection methods. Insufficient data storage and processing capacity of the BMS's failure detection algorithms. Moreover, these defect detection methods must be precise and dependable while requiring little processing effort (31) due to the enormous number of cells in specific battery systems. Following is an overview of the most recent research and development efforts for Li-ion battery defect detection techniques.

4. Different Techniques for Fault Diagnosis

There have been various research performed on detecting techniques. As illustrated in Fig.9 defines the fault diagnostic techniques as knowledge-based, data-driven, and model-based.

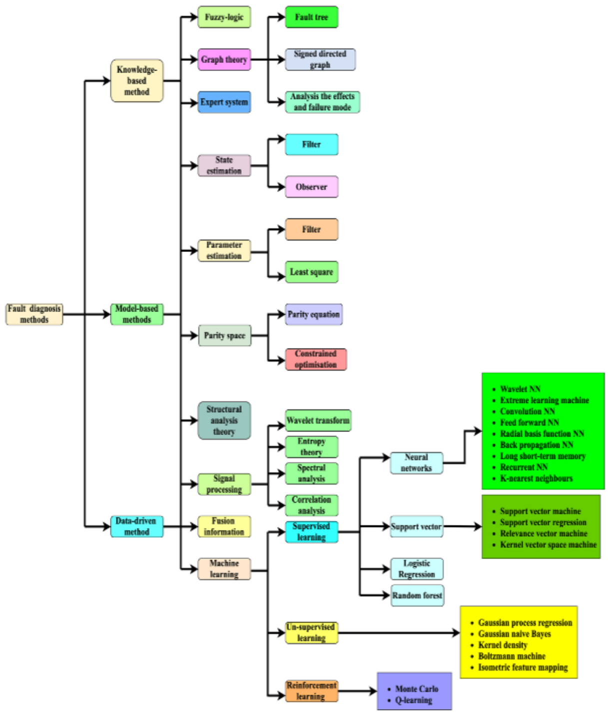

Fig. 9. Classification of fault diagnosis

4.1. *Knowledge-based Method*

Knowledge-based methods are suitable for complicated and nonlinear systems such as Li-ion batteries since they don't require mathematical modelling and can be applied to existing knowledge or observations. The working principles and diagnostic results of these systems are simple, but further studies of knowledge acquisition and representation, and Li-ion's fault mechanisms will be required when they are applied to Li-ion's fault diagnosis. There are several knowledge-based methods, but the most widely used are fuzzy logic-based, expert system-based, and graph theory-based. The basic block diagram of BMS with Fuzzy logic is shown in Fig 10. A battery series is connected with fuzzy logic control and SOC estimation unit, which is further connected to the PWM inverter and DC-DC converter via electronic switches. Each battery SOC is measured and transferred the data to the fuzzy logic controller, usually designed by using the Mamdani fuzzy interface system. This controller starts generating a suitable switching pattern to switch on the batteries for discharging and charging inputs operations. The fuzzy logic controller has the same number of outputs, and their operation is compared based on the batteries charging and discharging cycles.

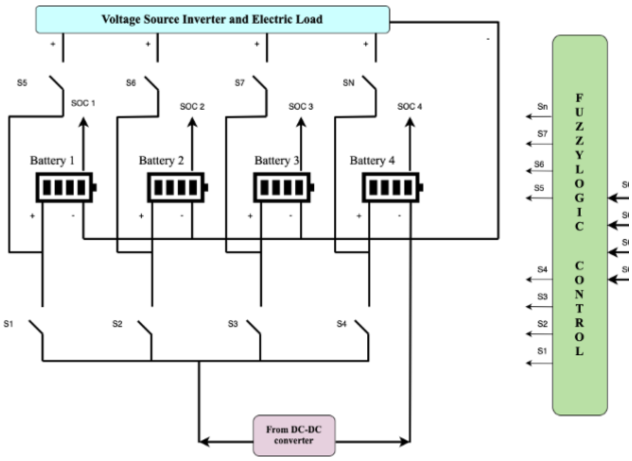

Fig. 10. BMS using fuzzy logic control

Specifically, a fault diagnostic network based on fault propagation relationships can be developed based on graph theory, including directed signed graphs, failure mode, effect analysis (25), and fault tree analysis (35) Subsequently, using an appropriate search strategy, a defect may be discovered. Expert systems are computer programs that model human thinking and decision-making (36). Information and norms were developed using a historical database and the vast knowledge of subject specialists. Fuzzy logic, which corresponds to human thinking processes and aids in processing qualitative information, can be used to diagnose faults by employing, fuzzy models, and fuzzy parameters. Table 3 illustrates the comparison of Knowledge-based methods.

Table 3 compares knowledge-based diagnostic procedures regarding their necessary technologies, merits, and demerits. The causal link in graph theory is clear and the diagnostic results are simple to interpret. However, complicated defect processes in battery systems make it hard to create diagnostic networks accurately. This method may experience several battery issues, such as sensor and actuator faults. An expert system technology doesn't use a physics-based model. Although, when used in battery systems, it also has various drawbacks, including difficulties in information acquisition and inaccurate knowledge representation. Anomalies detect that rapid SOC reduction, increased heat generation, and increased voltage variations can define battery failure states. The fuzzy-logic approach can be used to handle these fuzzy parameters. However, the implementation of effective regulations remains a significant challenge.

Table 3. A comparison of knowledge-based diagnosis method

Knowledge-based methods	**Technology**	**Advantages**	**Disadvantages**
Graph theory methods	Network for diagnostics; Relationship between fault propagation; Strategy Search	There is a clear connection; The outcomes of the diagnostic and analyzing qualitative are simple to understand.	A detailed knowledge of the fault mechanism is required and not appropriate for high-complexity systems.
Expert system methods	Acquisition and representation of knowledge base; The Rule Base	There is no requirement for a mathematical model, and the diagnostic results are straight forward.	Difficulty in acquiring and representing information; excessive reliance on the representativeness of knowledge and its integrity.
Fuzzy-logic methods	Fuzzy; The membership function	Perfect for controlling qualitative logic and understanding	Creating effective regulations is difficult due to the lack of self-learning potential.

4.2. Model-based Method

Model-based fault diagnostics acquire residual signals by comparing measured signals with model signals (37). A subsequent analysis will evaluate the residuals to determine the diagnostic results (38). The detection of model-based batteries involves developing a high-fidelity model (39), which includes electrical, thermal, and multi-physics models. In addition to the dynamic behaviour of batteries, these approaches can not only detect but also locate and evaluate the magnitude of defects. As a result, they have quickly become the standard method for Li-ions failure diagnosis. It should be emphasized that model uncertainty may affect these strategies. Noise- and interference-model-based approaches are classified into four types: parity space, structural analysis, state and parameter estimation.

Using an observer or filter makes it familiar for state estimation techniques to restore or estimate internal battery states, including SOC and internal temperature. When the predicted signals are compared with the sensor data, residuals, including defect information, can be calculated. For fault detection, model parameters need to be estimated based on the fact that failures affect the physical process of the system (40,41). Therefore, Li-ion batteries' electrical and thermal model parameters can be monitored to detect and isolate faults (FDI). Battery system dynamic models determine the correlation between the inputs and outputs of variables. The parity-space approach can validate this correlation by examining the inputs and outputs of a battery system [47], [48]. In structural evaluation theory, structural over-determination is discovered and employed followed by the analysis of fault detection and isolation [49–51].

These model-based approaches are compared in Table 4. Several methods have been employed, including Kalman filters, extended Kalman filters, unscented Kalman filters, particle filters, Lunberger observers, and adaptive observers to diagnose the faults in Li-ion batteries. With high real-time fault detection capabilities, state estimation may improve BMS status monitoring. Using parameter estimation techniques such as filtering will help discover specific Li-ion battery problems in combination with other methods [52–58]. Therefore, improved battery model accuracy and appropriate current excitation are needed (54). A simple method to isolate faults in sensors and actuators within Li-ion batteries can be accomplished by using different subsets of predicted no-faulty inputs and outputs. Structured analysis theory can conduct fault detection and isolate ability analysis regardless of Li-ion battery parameters, thereby reducing the time and effort associated with generating residuals for fault isolation.

4.2.1.1. Kalman Filtering

The approach involves measuring and evaluating the battery's input and output data, including current, internal resistance, voltage, and temperature. This information enables the creation of an electrical model of a battery, simulation of its behaviour under various operating conditions, and determination of the level of charging it requires with the help of this Kalman filtering.

This procedure involved two main steps: first, we entered the input data into a model and then used mathematical equations to illustrate how a battery works. As a result, theoretical calculations are made about the behaviour of the battery and its output data.

The algorithm then optimises or rectifies the model to minimise potential deviations by measuring the proper battery parameters, like voltage and current, and comparing the actual values to the predicted values. KFs can monitor a battery's complete discharge and charge cycles, indicating the state of charge (SOC) at every iteration while continuously reducing error margins.

The KF estimator is one of the most sophisticated and accurate estimators used by current battery management systems. It was sufficient to repeat the previous iteration of the battery management system to determine its current state. A system with linear ordinary differential equations will be consistent if the electrical model is accurate, including mathematical equations. A parameter set of Kalman filters can be used for these equations. Fig 11 shows different classifications of Kalman filters.

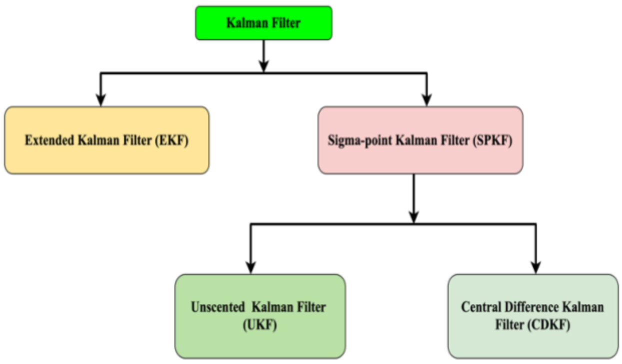

Fig. 11. Overview of Kalman filter

4.2.1.2. Alternative SOC Estimation Methods

SOC can be calculated using several alternative methods. While some are now in use, others are still in the research phase or are just concepts. The following techniques can be used when researching SOC determination options.

4.2.1.3. Thermal Voltage Method

This technique involves monitoring the battery's terminal voltage as it decreases during discharge. The SOC is determined based on the proportional relationships between a terminal voltage, the battery's electromotive force (EMF), and the state of charge. Due to a sudden reduction in terminal voltage towards the conclusion of discharge, there may be significant distortion in the estimations.

4.2.1.4. Impedance Method

The measurements of a battery's internal impedance, which varies overcharge and discharge cycles, are the base for this method. Here, measuring impedance while the battery is operating and obtaining accurate results while considering temperature provides the most problems.

4.2.1.5. Neural Networks

This network can calculate the SOC by learning from a lot of input data from a battery, including temperature, voltage and current and recreating the non-linear relations between these variables.

4.2.1.6. Fuzzy Logic

The maximum reliability of a microcontroller is a crucial requirement for both fuzzy logic and neural networks. To create a fuzzy logic model, any battery data can be used, which is imprecise. After evaluating the data, the model can identify battery attributes, such as the status of the charge.

4.2.1.7. Ultrasonic Detection

Wave signals can be used to assess a battery's capacity and sensitivity to help understand the internal structure of the battery. Wave signals can determine a battery's capacity and sensitivity to understand its internal structure. This technique involves calculating SOC using ultrasonography-guided wave technology. It will take a lot of time and work to implement this approach.

A single-SOC estimation approach has rarely been applied in modern battery management systems, combining several hybrid methods to enhance the results. For example, Coulomb counting can evaluate accuracy more accurately than the existing integration approach when paired with fuzzy logic or Kalman filtering.

4.2.1.8. Columb Counting

The battery current integration method is another term used in the coulomb counting technique. In this approach, the quantity of energy remaining in the battery is determined by measuring and integrating the discharging/charging current I(p). This approach measures the state of charge (SOC) at the previous time step SOC(p-1) and compares it with the amount of energy lost or added at the current time step to determine the energy in the battery

Table 4. Comparison of Model-based diagnosis

Model-based methods	Technology	Advantages	Disadvantages
State estimation methods	Restore the system state using Observers or filters	Excellent real-time performance; There is no requirement for a vast quantity of input signals	It is difficult to establish the fault's position and the damage's extent.
Parameter estimation methods	Evaluate a system parameter or Parameter for fault	Conductive isolation of faults.	High modelling precision and sufficient input excitations are required.
Parity space methods	The relationship that is equivalent to variables for input and output represent during the system model	Simple and quick; Ideal for isolating the faults.	The accuracy of the model and noise have an impact.
Structural analysis theory methods	System structural analysis the dynamic equations	It is simple to evaluate fault detection rate and isolability; the work load associated with selecting residual generators decreases.	The redundant is strongly dependent on System model information.

The SOC estimation in the coulomb counting method is done using the below equation,

$$\mathrm{SOC(p)} = \mathrm{SOC(p\text{-}1)} * \int_{p-1}^{p} \frac{I_p * \eta}{J_n} * dt \text{ -------- (1)}$$

SOC(p-1) = SOC at the previous time step

η = Efficiency

p = Current time step

p-1 = Previous time step

J = Charge capacity of the battery

This method is more accurate and reliable than the voltage translational method but does not consider the discharge rate, temperature, hysteresis, battery age, etc.

The method used by a BMS to estimate the SOC is described above in a generalized version. Various parameters are input to the BMS, depending on the technique utilized for SOC estimation. These parameters are then

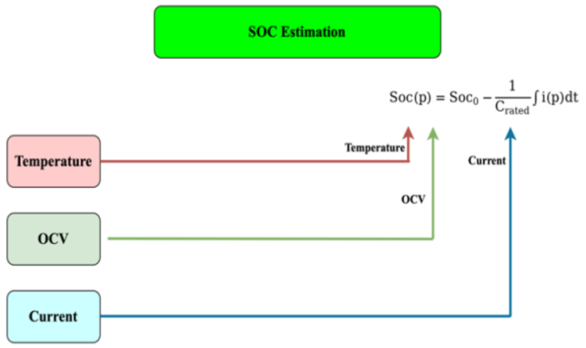

Fig. 12. SOC estimation

4.3. Data-driven Method

In contrast to relying on accurate analytical models and expert knowledge, data-driven methods evaluate and interpret running information directly. The fault diagnosis domain has been extensively characterized by processing the data signals, the use of machine learning, and the combination of information using fusion methods. Li-ion battery fault diagnosis is simplified by ignoring complex failure mechanisms of system structures, particularly for thermal runaway and battery degradation that is influenced by several unclear, coupled variables. It is challenging to evaluate and explain faults with these techniques in no-fault mechanisms exist. It is, however, necessary to preprocess raw data for Li-ion batteries when applying this approach. Moreover, many data-driven strategies have intrinsic constraints, such as the requirement for considerable historical information, which is associated with high computing costs and training complexity (55). Analyzing fault characteristics involving deviations, variances, entropies, and correlation coefficients, signal processing-based fault diagnosis often uses various signal processing techniques. Afterwards, the readings are compared to those under normal conditions to determine whether or not the situation is failing.

4.3.1. Machine Learning

Machine learning is a broad subject with many applications [61] presenting a detailed machine learning classification, explaining its various techniques. This article aims to provide a detailed type of machine learning approach used in BMS applications, as illustrated in Figure 12. There are three basic categories of machine learning methods: unsupervised learning, supervised learning, and reinforcement learning. Here is a concise overview of ML in BMS and a classification of each group:

4.3.1.1. Supervised Learning

Artificial Neural Networks are built based on biological neural networks (BNNs). These neural networks are divided into Classic NN and Modern NN. It uses several activation functions, including Sigmoid functions, to connect its nodes and sum their weights. A stochastic gradient descent approach is used to train neural networks using backpropagation (57). In data regression and classification analysis, support vector machines (SVM) are mainly used (58). In this paper, we present a kernel regression technique that has been applied to a wide range of linear and non-linear regression techniques, including relevance vectors (RVM) and support vectors (SVR)(59).

4.3.1.2. Unsupervised Learning

A key goal of this group is the clustering of data by similarity and dimensionality reduction (60), these methods are used in multi applications to compress data while maintaining its structure. The Gaussian process regression (GPR), kernel density, Boltzmann machine, and isometric feature mapping (ISOMAP) are among the methods in this category.

4.3.1.3. Reinforcement Learning

In Reinforcement learning, an agent performs actions and observes their effects to learn how to behave in an environment. RL serves primarily as a reward, policy, environmental model, and value function, which are essential for solving problems [66–68].

4.3.2. ML methods used for fault diagnosis

Some key challenges in the BMS include over-current and under/over protection, prevalent fault types in battery systems (64). The battery experiences irreversible chemical processes in charge/discharge mode, which might impact Li-plating and dendrite growth, especially at low temperatures. Furthermore, the production of dendrites as a result of anode-cathode interpolation might result in an internal short circuit, affecting battery safety and performance. Ignoring this essential issue may result in catastrophic failures due to thermal runaways. As a result, considerable investment has been made in fault detection and safety management for battery protection, utilizing model-based and ML methods (65).

Various efforts on diagnosis have been created in recent years using model-based methodologies. On the other hand, only a few research that leverages machine learning methodologies such as SVR [58], ANN [38], [57], and GPR (66) have been proposed. A data-driven technique for incorporating fault diagnostics of battery health using an SVM is proposed in (67). Hong et al. used RNN-LSTM to build a new deep-learning strategy for accurately predicting multi-forward-step voltage for battery systems. According to the investigation results, the proposed technique has a high predictive capability for battery voltage. Comparisons of different hyper-parameters [56] validate this technique's accuracy and stability.

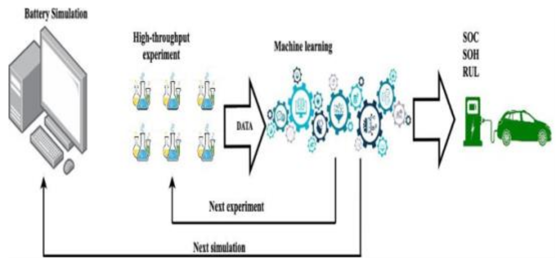

Fig. 13. Overview of ML in the Battery management system

Short-circuit (SC) battery abnormality can be diagnosed on-board using a robust and reliable algorithm presented [61]. Power management integrated circuits (PMICs) record voltages and currents from battery terminals for use by the likelihood algorithm.

In [62], supervised learning methods investigate the classification efficiency of ML approaches. The techniques considered for battery cell diagnosis are logistic regression (LR), k-nearest neighbours (k-NN), Gaussian naïve Bayes (GNB) and neural network (NN), and kernel space vector machine (KSVM). These non-linear and linear approaches have been shown to categorize unbalanced and damaged Ni-MH battery cells. LR algorithm is the simplest to set up and has excellent performance. Since the classification curve edge of the K-NN method is not smooth, it has a low classification efficiency when comparing KSVM with radial bias kernel. The classification performance is good in KSVM, where the functions of the radial bias kernel were better suited for properly functioning battery cells. In GNB, smooth curve classifiers are generated based on the probability of the occurrence of events, allowing for greater accuracy. It should be observed that NN provides a higher evaluation score with correctly identified data. However, some zones in their classification areas do not match the data pattern. As a result, to improve its efficiency, this technique needs a large amount of training data. In detail, a brief explanation of some of the machine learning algorithms in terms of fault diagnostic algorithms is given below.

4.3.3. Artificial Neural Networking

A highly nonlinear system's dynamics can be accurately captured by ANN. It is best suitable for Li-ion batteries due to all of these features as well as its very complicated and nonlinear stochastic properties. Its fundamental approach is to construct a nonlinear black box of an ANN-based fault diagnosis model by learning rules from recognized combinations of actual input and output data and then testing the actual input and output data that are undetermined to the model to validate the model. Usually, the training takes place offline. The ANN model is properly trained with enough data if it can successfully differentiate between the abnormal and normal situations of the battery system. There are numerous ANN variants, which can be broadly divided into two classes.

A combination of these techniques is frequently combined in Battery management system applications for long short-term memory networks (LSTM) and RNN-LSTM. In this instance, RNN and CNN are extended by LSTM, while RNN-LSTM is created by combining RNN and LSTM. Additional ANN variations exist, which S. Walczak [37] covered in detail. For fault diagnosis of Li-ion battery, however, only fundamental ANN, RNN, LSTM, RNN-LSTM, and a few other hybrid algorithms were used so far.

To assess the onset of battery faults and reduce the risk of fire, the long short-term memory recurrent neural network (LSTM-RNN) was used for multi-forward-step voltage prediction using the deep learning-enabled fault diagnostics technique [56]. To ensure model robustness and prediction accuracy, researchers used a sizable amount of actual operational data information from battery-powered cabs. Along with performance, consideration was given to how the environment as well as the driver's actions affected the Li-ion batteries. Cross-validation and comparison to actual operational data were used to evaluate the model's efficacy, dependability, and robustness. Because each LSTM model has a variety of structure parameters, parameter optimization, despite producing excellent accuracy, is a challenging and time-consuming process. It takes time to determine a battery's properties because of operational and environmental uncertainties, and training the LSTM model with a small sample size can affect how well it predicts.

As a result, building a model that can predict the status of a group of battery metrics in the face of battery ageing, changing road conditions, changing driver behaviour, and other environmental and operational variables is more difficult. S. Ortiz et al. [51] conducted a comparative analysis to determine the efficiency of five frequently employed algorithms: NN, Gaussian Naive Bayes (GNB), LR, KSVM, and k-nearest neighbours (k-NN). The objective was to classify the damaged and unbalanced Ni-MH battery cells. Even though LIB cells were not examined, this study showed that the NN-based diagnostic tool delivers a good evaluation score with accurate classified data.

4.3.4. Support Vector Machine (SVM)

Classification and regression-related problems are the main ones that SVM is used to solve. When used with regression, SVM is referred to as Support Vector Regression. In nonlinear systems like Li-ion batteries, this method has improved as a tool for regression analysis. For effective analysis, SVR turns into a linear model from the nonlinear model using a variety of kernel functions and regression techniques. The kernel space vector machine (KSVM) is an additional SVM variant, and [48] provides a more thorough explanation of SVM. It is not necessary to use an equivalent battery model for SVM-based fault diagnostic methods.

Yao et al. [59] utilized SVM in 2021 for determining the kind and severity of errors. The technique can only be used for situations requiring online fault diagnosis because the study indicates that 167 s is the least amount of time needed. The effects of battery ageing and temperature variation on cell parameters were not taken into account when recording the experimental results. Because LIB is subjected to a variety of environmental conditions and cell ageing is unavoidable, an incorrect forecast will result in real life. According to the study, the GS-fault SVM achieved a diagnostic accuracy rate of 95%. A machine learning parameter estimator (MLPE) that combines SVM and GPR was used to estimate the ECM parameters of LIB, the method of locating faults that closely resembles earlier ECM-based fault detection methods, such as residual generation and comparison with normal operating states, in a different study by Hashemi et al. [60]. In this study, SVM was not used specifically for defect diagnosis. The Li-ion battery overcharge (OC) and over-discharge (OD) fault scenarios were looked at in this multiple-model adaptive estimation (MMAE). Only the OC and UD faults of the Li-ion battery were examined in this work; however, various additional fault states may also be very severe in actual implementations.

Two additional support vector variants—KSVM and relevance vector machine (RVM)—have also been reported in the specialized domain. According to the author Ortiz et al. [51], who used it to classify defective and healthy battery cells, the KSVM method outperforms conventional SVM in data classification. This is particularly true given that the function and properties of the battery cell have been developed in an advanced manner thanks to the role played by the radial base kernel. More research is needed, as the effectiveness of the KSVM-based approach for Li-ion batteries was not assessed. Although Li-ion battery RUL is frequently predicted using RVM [61–63], LIB faults have not yet been identified using RVM.

4.3.5. Gaussian Process Regression

The Gaussian process regression aims to compress the data by reducing its dimensionality while preserving its structure and usage and clustering the data into groups. Furthermore, GPR uses kernel-based ML methods to identify diagnoses using the Bayesian model's historical data. The variance around the system's mean prediction is then used to calculate the behaviour's level of uncertainty.

Tagade et al. [64] used GPR to determine the Li-ion battery degradation mode. Ortiz et al. [51] investigated the classification accuracy of five various supervised machine learning approaches using Gaussian nave Bayes (GNB) as one of the techniques for Li-ion battery defect identification. Each technique has advantages over the others, according to the research, with GNB demonstrating a remarkable degree of precision in identifying damaged and unbalanced battery cells. The GNB-based classifier's core idea is to create a non-linear smooth curve that classifies healthy and defective cells according to the likelihood that events will occur. Zhang et al. [65] demonstrated the efficacy of GPR in terms of diagnosis and prediction in Li-ion batteries. To precisely assess the capacity and estimate the RUL, which appear to be key markers of battery SOH, GPR was used. More than 20,000 electrochemical impedance spectra (EIS) were used to analyse degradation patterns. GPR is not used in this study to immediately identify or diagnose Li-ion battery system issues. Additionally, acquiring training data for ML models using EIS is a difficult procedure that takes a lot of time and the assistance of technical experts. In either case, a GPR-based fault detection model for the Li-ion battery system needs to be built first, which will take a lot more research.

4.3.6. Logistic Regression (LR)

This method uses predetermined criteria to categorise the observed data. This approach works well in both linear and nonlinear regression, as seen in the application of LR for Li-ion battery system fault identification and diagnosis [51], making it the most straightforward for two-class classification.

For the first time, logistic regression was applied to identify battery system flaws Ardeshiri et al. [34]. The authors demonstrated that the LR technique has the highest accuracy and is the simplest algorithm to set up when compared to the above ML-based fault detection strategies, including k-NN, KSVM, NN and GNB.

When acquiring model training and testing data for this work, consideration for the effects of various uncertainties in real-world applications was not made. Despite the researchers' claims of high accuracy and simplicity, much more study and improvement must be done before the proposed LR-based technique can be put to use in real-world applications.

There are several data-driven diagnostic approaches presented in Table 5. Detecting faults with signal processing is easy and efficient in Li-ion batteries dynamics are ignored; however, faults cannot be identified directly when there are multiple Li-ion batteries coupling. Machine learning algorithms can adapt the training set by adjusting their parameters and gaining knowledge from the present training samples. It is theoretically possible to improve the EM and ECM of batteries using a black-box model based on an ANN. However, insufficient Li-ion battery fault data may result in overfitting. An ANN that does not have a high generalization capacity may generate false warnings about the Li-ion batteries issue that is undesirable. In addition to having a greater generalization capacity than ANN, SVM can handle small samples [73-78], making it a handy tool for Li-ion batteries with limited fault data.

Table 5. Comparison of Data-driven diagnosis method

Data-driven based methods	Practical Applicability	Advantages	Disadvantages
Signal processing	Signal processing methods that are appropriate.	Implementable; Systematic and non-systematic applications are both possible.	Minor defects are challenging to detect and immediately identify; they are not suited for systems with a large number of interconnected components.
Artificial NN.	So far, the most common ML technique used to find LIB faults is. With enough fault data and further development, ANN-based methods could be used in real-world situations.	Sample-based self-learning; high flexibility, parallel processing	There is a need for a lengthy training phase and a significant amount of historical data; generalization ability is poor, and overfitting problems exist.
Support vector machine	With enough modelling skills and a good quality and quantity of training data, including data on errors, this method could be used in real life.	Excellent generalization abilities; Only applicable to limited sample sizes.	It is challenging to choose the best kernel function; large-scale training sets are inefficient.
Information fusion	Information fusion methods that are appropriate.	More precise diagnostic outcome.	It isn't easy to choose appropriate fusion algorithms.
GPR	Since only a small number of studies have been performed and GPR is not yet routinely employed in fault diagnosis, it is premature to draw any conclusions about its potential usefulness.	Accuracy, as well as flexibility, is good Covariance is provided to generate uncertainty levels.	Computational complexity is high Sensitive in selecting kernel functions which are complex
LR	It's too soon to say how well the model works in the real world because it hasn't been tested for adaptability, generalization, accuracy, and reliability.	Accuracy is good. Implementation is easy.	The challenging task is to accommodate a large number of the feature vector.

Detecting faults accurately in Li-ion batteries requires an effective fusion method to fully utilize Li-ion batteries' current multi-source information. Selection of the best kernel function is the most crucial step in SVM.

4.3.7. Future Challenges and Limitations of LI-ion battery fault diagnosis

Fault diagnostic algorithms have improved the safety of the Lithium-ion battery. Even though they have a few limitations as follows:

- Model-based approaches can quickly identify and isolate faults in real-time but require highly accurate prediction models. These models require high computation time to identify the faults.
- Fault diagnostic models depended on threshold and sensitivity needs to be considered.
- Signal processing methods have good dynamic performance but are sensitive to measurement errors and unable to identify faults as early.
- Knowledge-based approaches like expert systems need good rules to detect faults accurately.
- Complex knowledge-based methods like machine learning are accurate and compatible with nonlinear systems like the Li-ion battery, but data processing requires high computation time
- Even though model-based solutions are becoming widespread, battery model accuracy remains challenging, especially during the battery's lifespan.
- Data-driven, non-model-based strategies can help model developers to predict battery behaviour as it decreases.

The challenges of Lithium-ion battery fault diagnosis methods are as follows:

- Current methods assume that other system components are working normally to prevent isolating and identifying errors.
- After fault detection, the isolation of the faults from the main system is highly challenging.
- Due to a lack of understanding of the problem behaviour, fixing effective fault thresholds for early and accurate detection is difficult.
- Because physical faults are impractical and dangerous, fault simulation techniques require to capture battery failure behaviour.
- Thus, well-designed experiments are needed to study fault behaviour for modelling and simulation.
- Finally, more complicated methods that improve fault diagnostic accuracy require BMS computational capability enhancement.

5. *Conclusion*

EVs have gained popularity in the present scenario for several reasons to decrease the crisis of fossil fuels, eco-friendly etc., as well as a rapid rise of research in this area, especially on battery systems. In the overall structure of an EV, the main important component is the battery, where the BMS monitors the battery's complete operation. It is essential to enhance the performance of the battery, it is mandatory to go through several algorithms to study in detail for mitigating the faults. In this paper, we present an overall explanation of fault diagnosis techniques in Li-ion batteries and a detailed review of various classifications and comparisons of fault diagnostics techniques and their implementation in the battery management system.

It is possible to classify fault diagnostic approaches into knowledge-based, model-based, and data-driven approaches. The qualitative analysis in knowledge-based methods is quite simple, but these methods are unsuitable for high-complexity systems. Model-based methods are simple to evaluate fault detection, but the accuracy is less. Data-driven approaches are easy to implement in linear and non-linear systems. They have high flexibility and self-learning attributes. Even though there are several methods to detect and isolate the fault, there are various difficulties in Li-ion battery failure detection, including fault threshold selection, assumption-free fault isolation and BMS hardware constraints. Researchers will use the summary of the algorithms offered in this study to develop improved methods of fault diagnosis for Li-ion battery systems.

Credit author statement

Dasari Hethu Avinash: Writing–original draft, Writing–review & editing. Rammohan A: Conceptualizations, Investigation, Data curation, Project administration, Validation, Formal analysis, Writing– review & editing.

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Conflict of Interest

We know of no conflict of interest associated with this publication.

Data Availability Statement

The authors confirm that the data supporting this study are available within the article and supplementary materials.

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