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# ELECTRIC VEHICLE SYSTEMS FAULT DETECTION AND DIAGNOSIS FOR MOTOR AND BATTERY

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## Abstract

Electric vehicles (EVs) are essential for sustainable transportation, but their motors and batteries are prone to a variety of defects that may jeopardise safety, dependability, and performance. Effective fault detection and diagnosis (FDD) systems are critical to guaranteeing the continuing functioning and safety of EV systems. This study examines the most recent advances in FDD methodologies for electric motors and battery systems in EVs, with an emphasis on both model-based and data-driven approaches. For motor defects, classic signal-based techniques such as vibration and current signature analysis are presented alongside more modern machine learning and AI-driven systems like as neural networks and support vector machines (SVM). These AI-based solutions provide benefits such as early defect identification, resilience under changing circumstances, and fewer false alarms. FDD techniques in battery systems are divided into three categories: battery abuse, connection faults, and sensor faults. Additionally, this study investigates hybrid FDD techniques that include both motor and battery fault diagnostics, providing thorough monitoring of the EV's critical components.

***Keywords: Electric vehicles (EVs), fault detection and diagnosis (FDD), motor faults, battery faults, data-driven methods, battery management systems (BMS).***

## 1 INTRODUCTION

The worldwide transportation industry is shifting to electric vehicles (EVs) in order to minimize the environmental impact of conventional internal combustion engines (ICEs) and address the critical challenges of energy security and climate change[1]. Battery electric cars (BEVs), hybrid electric vehicles (HEVs), and fuel cell electric vehicles (FCEVs) are among the electric vehicles (EVs) that bring significant advantages in terms of decreased greenhouse gas emissions, increased energy efficiency, and lower operating costs[2]. Nonetheless, the widespread acceptance of electric vehicles (EVs) depends on the resolution of major issues about their reliability, security, and overall performance[3].

Electric vehicles are complex systems that rely heavily on their electrical components[4], particularly the motor drive and battery systems, which are subject to various faults and degradation mechanisms. Faults in these critical subsystems can lead to unforeseen failures, jeopardizing the vehicle's performance, efficiency, and, most critically, the safety of passengers and other motorists[3]. As a result, creating enhanced defect detection algorithms designed particularly for EV electrical systems has arisen as an important topic of research and development[5]. The growth of electric cars (EVs) is revolutionizing the automotive sector, providing answers to environmental challenges[6], Energy sustainability and reliance on fossil fuels [7]. However, the dependability and safety of EV systems are key considerations, particularly as they become increasingly common in daily commuting[8]. Fault detection and diagnostic (FDD) systems are critical in ensuring that important EV components, including as the motor and battery, perform effectively and safely[9]. In an electric car, the motor is responsible for translating electrical energy into mechanical motion, while the battery acts as the main energy source[10]. Faults in these systems can lead to performance degradation, reduced energy efficiency, safety risks, and even catastrophic failure[11]. For instance, motor faults like winding short circuits or bearing failures can result in motor inefficiency or breakdowns, while battery-related issues such as thermal runaway or capacity degradation can compromise the vehicle’s range and safety[12].

Thus, early and accurate fault detection is essential for maintaining the overall reliability and performance of EVs[13].Traditional fault detection techniques have evolved from model-based and signal-based methods, such as frequency analysis and thermal monitoring, to more advanced data-driven approaches that leverage machine learning (ML) and artificial intelligence (AI)[14]. These technologies have the potential to discover trends and abnormalities in vast information acquired from sensors, increasing the speed and accuracy of diagnostics[15]. As the energy storage part of EVs, the The lithium-ion battery system has grabbed the lead in EV applications because of its remarkable properties, such as high power and energy density, extended lifetime, and environmental concerns[16]. A battery pack typically consists of hundreds of cells coupled in series and parallel arrangements. [17]. However, different types of faults, Battery abuse, as well as actuator and sensor errors, may occur in battery systems, causing battery deterioration and accelerated ageing, EV failure, and deadly accidents[9]. According to reports, battery issues cause 30% of EV accidents[18]. Thus, implementing effective online problem detection and fault tolerant management is necessary to provide safe and continued EV operation. [19]. However, complicated procedures and other unforeseen circumstances make early defect identification difficult [20]. failure detection and diagnosis (FDD) is a method used to monitor and assess the operational status of an electric motor, allowing for early failure identification and prediction[10]. Various defects may be discovered and diagnosed using FDD, and implementing correct remedies increases the safety and dependability of EVs[9]. Several FDD strategies have already been established to lessen the potential of problems with batteries and electric motor drives in systems. FDD methodologies come into four basic categories: model-based, signal-based, data-driven (knowledge-based), and hybrid approaches[21]. This study is on the concerns and techniques presently utilised to detect and diagnose faults with electric vehicle batteries and motors [22]. In order for electric cars to run safely and efficiently, it looks at a range of concerns, including detection techniques, growing diagnostic trends, and the future of real-time, AI-driven monitoring systems[23].

### 1.1 Overview of Electric Vehicles

An electric vehicle (EV) is a vehicle that employs electric or traction motors for propulsion [24]. Electric motors are employed in a broad variety of vehicles; however, traction motors are more particular and utilised in systems such as locomotives. [25]. EV powering systems may be self-contained within the vehicle, such as with a battery, fuel cells, or an electric generator, or external, such as fuelled by energy from sources outside the vehicle via a collector system[26]. Electric vehicles can have only electric motors, but they can also have a combination of one or more electric motors with at least one other propulsion system. Such vehicles are a special category of EVs, called electric hybrid vehicles (EHV). Electric vehicles use electric motors for propulsion in place of conventional IC engines. Engine driven vehicles work on the principle of combustion get their energy from carbon based fossil fuels[24].

In contrast, EVs can use electricity generated through a wide range of resources such as fossil and non-fossil hydrocarbons, hydro/nuclear power and renewables[27]. Electricity is transmitted to the vehicles through overhead power lines, direct connection through cables or wireless energy transfer[28]. By using a storage system, the energy may then be stored onboard the vehicle[29]. Basic structure of an EV is shown in Fig. 1. Major components of an electric vehicle include storage battery, drive motor, motor controller, power electronics converters, charge controllers and battery management system (BMS)[30]. Depending upon the complexity of design, drive motor of the EV can be a single reversible motor/generator or individual motors and generator[31].

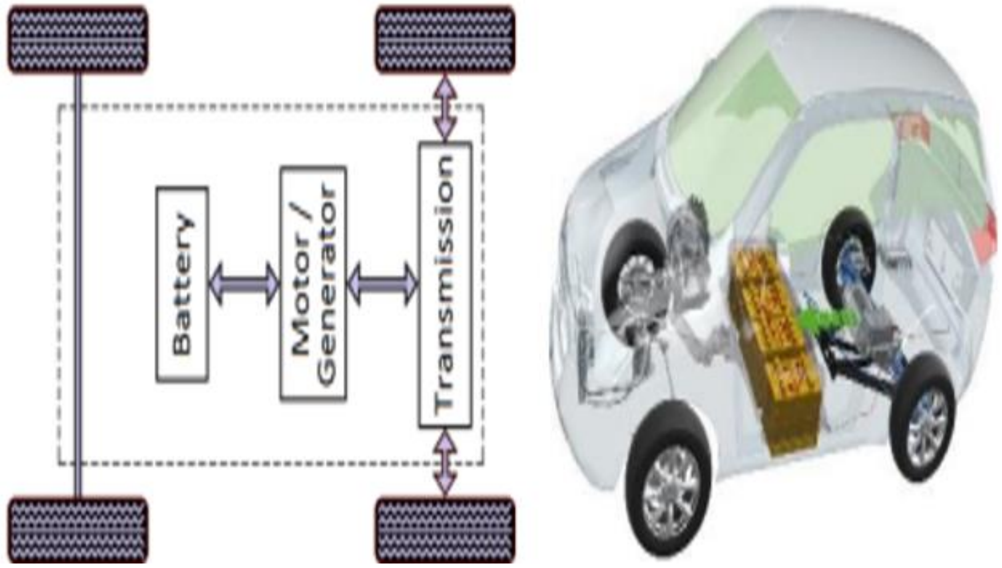

**Figure 1. Basic structure of an electric vehicle**[26].

### 1.2 Importance of Fault Detection in EV Systems

The reliability and safety of EVs heavily depend on the health of their motors and batteries[32]. Faults in these components can result in loss of efficiency, operational failures, and safety risks[33]. In the case of the motor, common issues such as stator winding faults, rotor eccentricity, or bearing failures can lead to inefficient performance or complete motor breakdown. Similarly, battery faults such as capacity degradation, thermal runaway, or short circuits can compromise the vehicle's range and safety. Thus, fault detection and diagnosis (FDD) systems play a pivotal role in ensuring the robustness of EV operations[34].

Fault detection in electric vehicle (EV) systems is crucial for ensuring safety, reliability, and performance[9]. As EVs rely on complex electrical and mechanical systems, particularly the motor and battery, any fault can lead to severe consequences such as reduced efficiency, safety hazards, or even total system failure[35]. Early fault detection helps prevent catastrophic breakdowns, reducing the risk of accidents and costly repairs. One of the primary reasons for fault detection in EVs is safety. EV batteries, especially lithium-ion batteries, are prone to thermal runaway, short circuits, and overcharging. If left undetected, these faults can cause fires or explosions[36]. Similarly, motor faults, such as winding failures or bearing issues, can lead to power loss or sudden vehicle stalling, endangering passengers[37]. Fault detection ensures that potential problems are identified before they escalate into safety risks[38]. Another key aspect is the optimization of vehicle performance. Faults in the motor or battery reduce energy efficiency, leading to higher energy consumption and decreased driving range[39]. Efficient fault detection systems help maintain the vehicle's performance by identifying issues such as battery degradation, ensuring timely intervention to preserve energy efficiency and extend the lifespan of key components[40].

### 1.3 Fault Detection Techniques for Batteries in EVs

Fault detection in batteries for electric vehicles (EVs) is crucial for ensuring safety, reliability, and efficiency. Batteries are the most critical components in EVs, and their proper functioning determines vehicle performance. Various fault detection techniques are employed to monitor battery health, prevent failures, and extend the battery's lifespan. One of the primary methods for detecting faults in batteries is voltage monitoring[9].

The voltage of individual cells within a battery pack is continuously measured to detect abnormalities, such as overvoltage or undervoltage conditions, which can indicate cell imbalance, degradation, or potential failure. This technique is essential for identifying discrepancies that could lead to thermal runaway or inefficient energy usage[41].

Current and temperature monitoring are also widely used in fault detection. Overheating is a significant concern for batteries, as it can accelerate degradation and lead to dangerous situations like fires. Sensors track the temperature of the battery cells, and if the readings exceed safe thresholds, alarms are triggered[42]. Similarly, abnormal current flow could indicate short circuits, aging, or internal damage within the battery. Combined voltage, current, and temperature data provide insights into battery conditions in real-time. Model-based fault detection is another advanced technique, where mathematical models of the battery's behavior are created and compared against actual performance. Discrepancies between predicted and actual data suggest potential faults. These models consider factors such as charge/discharge cycles, state of charge (SOC), and state of health (SOH). By using algorithms and simulations, engineers can predict the onset of faults before they become critical[43]. Another approach is state estimation techniques, which include Kalman filters and observers. These methods are designed to estimate internal states, such as the battery's SOC and SOH, from external measurements. Any deviation from expected values can be interpreted as a fault, such as capacity loss or internal resistance changes. Data-driven techniques, leveraging machine learning and artificial intelligence, are gaining traction[44]. These methods analyze large amounts of data collected from battery systems to detect patterns that indicate faults. By using historical data, these systems can predict potential failures, enhancing the accuracy and timeliness of fault detection[45].

## 2. EV Configurations

Since EVs lack the complex mechanical setups required to operate a traditional car, they are very adaptable. The motor is the sole moving component of an EV[46]. The motor may get its power supply from a variety of sources. If the motor and power source are linked by electrical lines, they may be installed in separate vehicle components. Additionally, as previously stated, EVs may either operate alone on electricity or in combination with an EM and an ICE[47]. Different configurations based on the kind of vehicle have been made possible by the flexibility in EC setup. Generally speaking, EVs are seen as systems that consist of three subsystems: an auxiliary subsystem, a propulsion subsystem, and an energy source. The energy supply, charging system, energy management system, and storage system are all components of the energy source[48]. The propulsion system is made up of drive wheels, gearboxes, controllers, power converters, and electromagnetic. Three parts comprise the auxiliary subsystem: a power steering unit, a temperature control system, and an auxiliary power source.

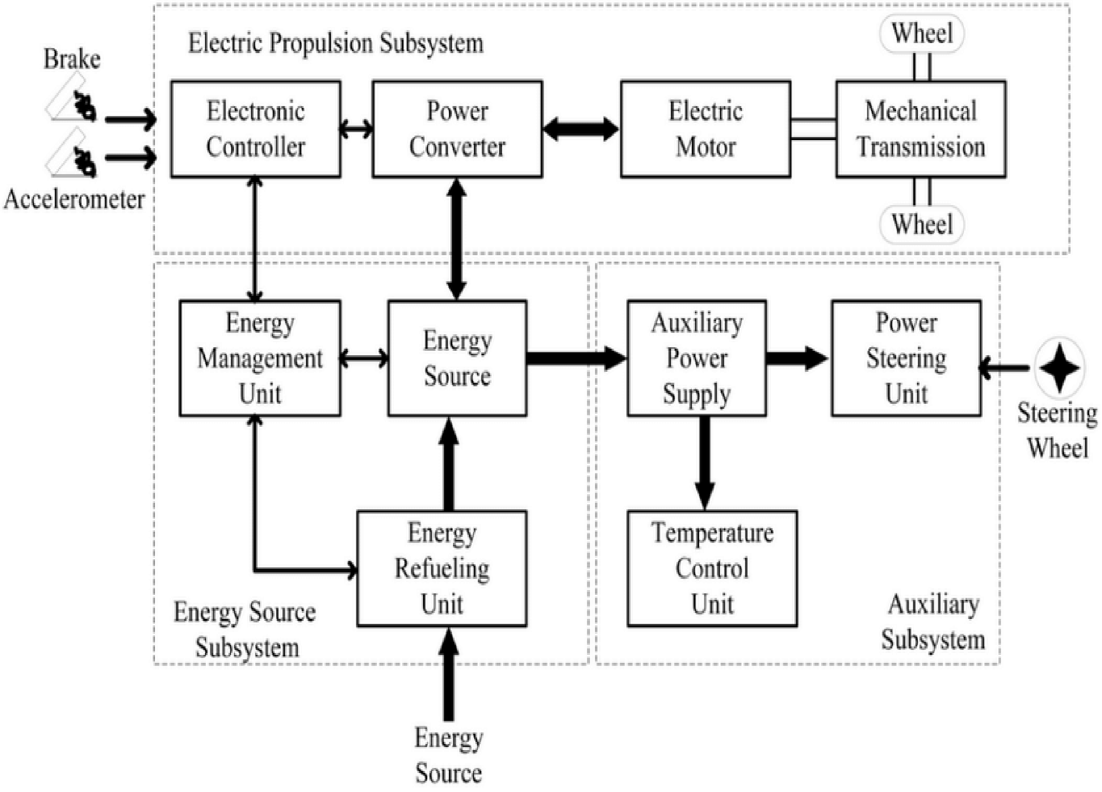

**Figure 2: EV subsystems**[49]

**3. Types Of EVS**

The most common type of EV can only move with electricity, using batteries as its power source[50]. They might collaborate with an ICE agent as well. They may, however, make use of other energy sources. We refer to them as hybrid electric vehicles, or HEVs. According to Technical Committee 69 on Electric Road Vehicles (ERV) of the International Electro technical Commission, a hybrid electric vehicle (HEV) is a vehicle that includes several energy sources, storage devices, or converters, with at least one of them being electrical energy[51]. This description lets HEVs come in many different forms. Therefore, both experts and regular people have names for each type of mixture. For example, cars that have both a battery and a capacitor are called ultra-capacitor (UC) supported EVs. What are they called? FCEVs. They have both a battery and a fuel cell. Because of these differences, EVs are put into four groups. Chargeable battery electric cars, hybrid electric cars, plug-in hybrid electric cars, and fuel cell electric cars[52].

Electric car with batteries BEVs get their power from batteries, which store energy and then use it to power the motor. Therefore, range depends on how much power the battery has. 100 to 250 kilometers is the normal range per charge[53]. In actuality, a number of factors have historically been linked, including driving habits, road conditions, temperature, car layouts, battery type, and vehicle age. Compared to refueling a typical ICE automobile, charging the battery may take up to 36 hours once the energy is depleted. Although there are other kinds that take a lot less time, none of them can match refueling a car. BEVs provide a number of benefits, including convenience, ease of use, and straightforward construction[49].

Electric-hybrid car An electrical power train (PT) and an internal combustion engine (ICE) work together to drive HEVs. This combination may take several forms, which will be covered in the next section. When the need for electricity is minimal, HEVs employ an electric propulsion system. This is very beneficial for situations like city transit, cutting down on idle fuel use (such in traffic jams), and lowering greenhouse gas emissions[54]. The vehicle turns to the ICE if a higher speed is necessary. Additionally, these two motor trains may work together to enhance performance. Turbocharged vehicles, such as the Acura NSX, to lessen turbo lag, often use hybrid power systems. This configuration improves acceleration and fills the gap between gearshifts, which leads to better performance. Electric car that is plug-in hybrid to increase the all-electric range of HEVs, the PHEV idea was developed. Since the electric motor serves as the primary drive in PHEVs, a bigger battery is required, even if the ICE and electrical PT are still used. PHEVs only utilize internal combustion engines (ICE) when their batteries are low. Although they are used for transportation, vehicles have an impact in many other sectors[55]. As a result, the change in the automotive industry brought about by EVs has a significant influence on the economy, the environment, and the electrical systems since they are electric. Because of the advantages, they provide in each of these areas, EVs are becoming more and more popular, but they also come with some drawbacks.

Electric car powered by fuel cells Fuel cell electric vehicles, or FCEVs, are powered by fuel cells that generate energy via chemical processes[56]. Since hydrogen is the most often utilised fuel in this sector, FCEVs are hydrogen fuel cell vehicles. They need special high-pressure tanks to transport the hydrogen. Oxygen, which comes from the surrounding air, is also needed for power production. The EM receives the energy from the fuel cells and uses it to power the wheels. A super capacitor or battery stores the excess energy[57].

**Table 1. Comparative analysis of several vehicle types**[46]

| **Type** | **Driving Component** | **Energy Source** | **Features** | **Drawbacks** |
|---|---|---|---|---|
| BEV | EM | Battery, UC | No emissions, reliant on battery, commercially available | Battery capacity, range, recharging time, charging station accessibility, elevated pricing |
| HEV | EM, ICE | Battery, UC, ICE | Low emissions, long range, commercially available | Controlling power sources, optimizing battery/engine size |
| FCEV | EM | Fuel cell (FC) | Little emissions, high efficiency, independence from electric power, commercially available | Affordability of fuel cell, fuel production method, fueling station availability |

## 4. Battery Management System Faults

Broken batteries, faulty connections, and malfunctioning sensors are the three primary categories of probable battery pack defects. Heat accumulation from any of these issues may hasten ageing or possibly result in thermal runaway and an explosion if they are not identified or addressed promptly. A battery system malfunction is seen in Figure 3

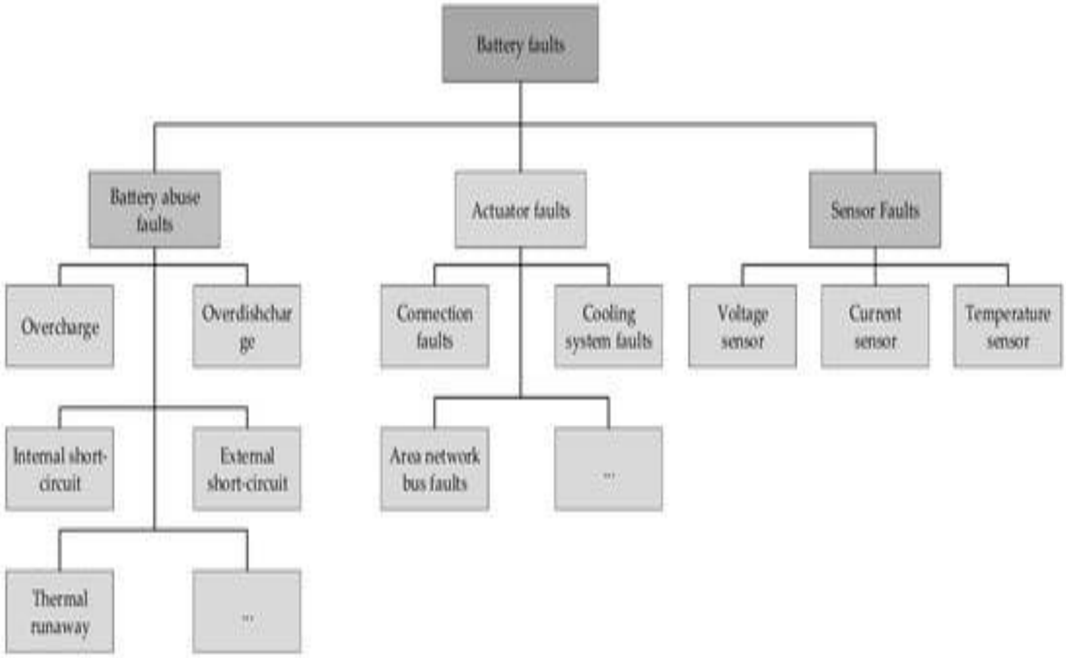

**Figure 3. Various battery faults**[58].

Battery system faults in electric vehicles (EVs) can be classified into three main groups: battery abuse, connection faults, and sensor faults. Battery abuse faults include issues like overcharge, over-discharge, internal and external short circuits, and thermal runaway. These faults, caused by errors in the battery management system (BMS) or cell degradation, can lead to chemical and physical damage, reducing battery performance and safety[58]. Internal short circuits are often undetectable early on but can escalate into severe faults. Connection faults involve issues like loose connections, cooling system failures, and controller area network (CAN) bus faults. These can cause overheating, reducing available power and increasing the risk of accidents or thermal runaway. Lastly, sensor faults affect the BMS, which relies on voltage, current, and temperature sensors to monitor the battery’s state of charge (SOC) and state of health (SOH). Faulty sensors can mislead the BMS, leading to undetected battery abuse and potential safety risks, further reducing the battery's lifespan and performance.

The job of a battery management system (BMS) is to reduce the risks that come with Li-ion batteries so that they and the people who use them are safe. The most dangerous cases happen when there are faults, and the BMS should make them less common and less severe. Insulation, monitors, and workers are all safety features of batteries. Sensors that are attached to the cells also set the limits for voltage, current, and temperature. Despite this, these safety measures aren't always enough because battery issues can become more difficult with newer BMS hardware and software.

## 4.1 Battery Abuse Faults

These are the problems that can happen inside the battery, such as overcharge, over discharge, internal short circuit, external short circuit, temperature runaway, and more. Overcharge and over discharge faults can happen because of problems with the battery control systems or cells losing their ability to hold charge. These faults can lead to chemical and physical damage to the battery, degrading the battery’s performance and safe operation [59].The internal short circuit refers to the insulation failure between the layers inside the battery, while the external one notices the shorted positive and negative terminals [60] .An external short circuit is a more dangerous and noticeable fault than an internal short circuit, which is negligible in the early stages. However, the internal short circuit can turn into an intense fault after a while [44]Rapid voltage drop and thermal runaway are expected when a short circuit occurs.

Actuator Breakdowns this group of faults includes connection faults, cooling system faults, controller area network bus faults, and more. Due to the need for a lot of energy in EVs, the battery system is generally made up of many battery cells linked in a parallel–series pattern.[61] The link can break because of the way EVs work, which includes temperature changes, shaking, and wear and tear. When links aren't tight, power can be cut off, which could lead to an accident. Increasing the connection's resistance can make it heat up, which can hurt the battery's performance. Faults in Sensors An important part of an electric vehicle's safe, efficient, and useful performance is its battery management system (BMS)[13]. This unit is responsible for several tasks, including estimating the state of charge (SOC) and state of health (SOH) of the battery, thermal management, cell balancing, etc., by monitoring the voltage, current and temperature of the cells

**Table 2: Comparison of battery fault diagnosis**

| **Author** | **Fault parameters** | **Faults in Battery** | **Technique** | **Achievements** |
|---|---|---|---|---|
| Amardeep et al[58]. | Battery model parameters | Detecting overcharge and over-discharge faults | Extended Kalman filter | The overflow and overdischarge problems are found quickly and accurately by this type. |
| Yang et al[62]. | Fault parameters for abnormal voltages | Identifying the Li-ion battery faults | Artificial Neural Networks (ANN) | Based on a lot of data control, a full battery fault analysis model for odd voltages is created. |
| M brand et al[63]. | Increasing temperature and decreasing voltage | Detecting overcharge faults | Rule-based method | This model works well to find excess problems and lets users know about them early on. |
| Marian Tomasov et al[64]. | 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. |

## 5. Electric vehicle Drive Fault Detection and Diagnosis

Reliability and safety are of utmost importance in all applications, but they become even more critical in transportation systems, where continuity and safety are essential, regardless of the challenging operational, the state of EV motors. Electric motors and their drive systems can have problems, as we have already said. These problems will happen over time. If these problems aren't fixed, they can lead to worse performance, expensive fixes, or even major crashes[65]. To mitigate these risks, enhance reliability, prevent unexpected breakdowns, and reduce repair expenses, Fault Detection and Diagnosis (FDD) is widely implemented across different systems, including EVs[66]. FDD is a method designed to monitor motor performance, enabling the early detection, identification, and localization of faults. By detecting faults early, FDD allows for timely intervention, preventing the fault from escalating and ensuring fault tolerance[67]. An effective FDD system must meet several key criteria: (i) quick fault detection, (ii) robustness to fluctuating operating conditions, (iii) sensitivity without triggering false alarms, and (iv) minimal hardware requirements to avoid added complexity and cost[68]. The choice of appropriate fault indices is crucial for accurate detection, as faults can affect various motor parameters. By using multiple parameter fault indicators, the robustness and accuracy of the detection process can be significantly enhanced. An effective FDD system not only detects faults early but also supports fault-tolerant control (FTC). FTC enables the system to continue functioning, albeit in a degraded mode, after a fault is detected, thus avoiding immediate shutdowns and unexpected EV stops[10]. This is particularly important in transportation applications, where sudden failures can lead to safety hazards or costly disruptions. By implementing FDD in combination with FTC, EV systems can maintain a high level of reliability and safety while minimizing downtime[69].

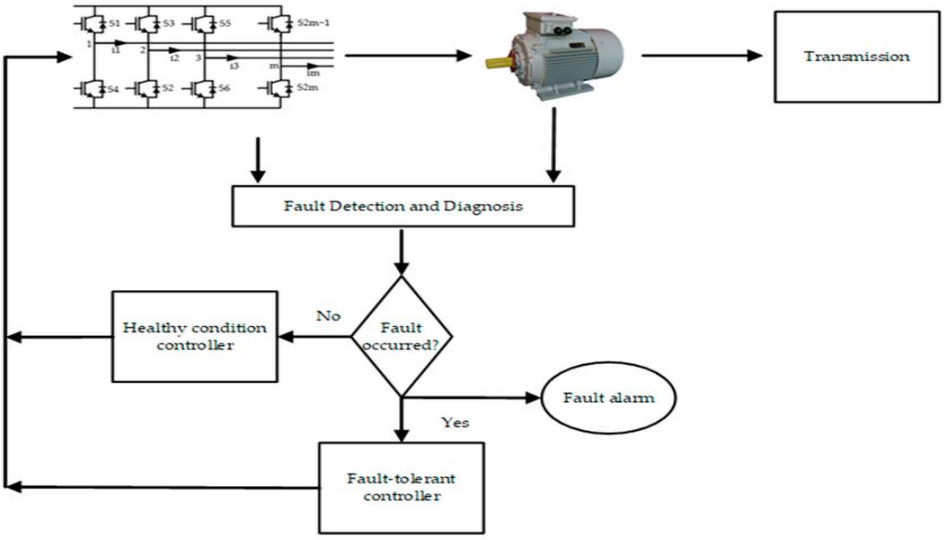

**Figure 4: PMSM motor drive schematic with FDD and fault-tolerant control**.[70]

### 5.1 Fault Grades of Drive Motor System

With the popularization of electric vehicles, there are internal faults in the drive motor and motor controller of electric vehicles, and the accidents caused by the lack of timely detection and treatment are gradually increasing[71]. According to the consequences and impacts of the drive motor system fault, the fault can be divided into four categories from light to heavy: slight fault, general fault, serious fault and fatal fault. Slight failure: When the electric vehicle has a slight failure, the vehicle generally can still run normally, or only need to deal with the electric vehicle to return to normal operation, such as the installation of bolts and wire fixture damage General failure: generally, refers to the failure. the performance of electric vehicles is affected to a certain extent, and it needs to run at reduced power. It should be opened to nearby maintenance sites for maintenance in time, such as temperature sensor burning, cooling pipeline leakage, etc. Serious failure: electric vehicle performance is obviously declining, the vehicle cannot run normally, should immediately choose roadside parking, waiting for rescue, such as speed, position sensor failure, motor bearing abnormal wear and tear[71]. The main components of the electric vehicle are damaged or the function fails, causing the vehicle to be uncontrollable, which is easy to pose a serious threat to itself and the surrounding pedestrians and the environment. Such as burning and breakdown of stator winding of driving motor, burning of power device IGBT of motor controller, etc.

### 5.2 FDD Methods for Battery Faults

Due to the same limitations of the model-based and signal-based methods, such as the inaccurate model and very nonlinear characteristic of the lithium-ion batteries, to reach higher accuracies and reliabilities, the data-driven methods and machine-learning-based FDDs are growing rapidly in the case of battery fault detection recently[72]. In [73] General regression neural network (NN) was used to come up with a way to find voltage faults in batteries. The voltage was smoothed out with DWT, and then a number of factors were used to teach the GRNN to get the best accuracy of more than 99%. This plan can find faults, figure out where they are, and guess how bad they are. In SVM was used to find problems with battery power and guess how bad they were[74]. First, the voltage data are denoised to improve dependability and accuracy. Then, to cut down on the time it took to find something, a changed covariance matrix was added as the SVM's condition indicator. This was made better using the grid search method[75]. In, battery thermal runaway detection is proposed based on LSTM-CNN, which stands for long-term memory CNN, and abnormal heat output. For better input, PCA is used, and real-world EV data is used to train LSTM-CNN to guess the temperature. This method works correctly and can warn you ahead of time about the thermal runaway fault. With the goal of making FDD more accurate and efficient, a mixed FDD method combining LSTM-RNN and the equivalent circuit model (ECM) was put forward[75]. The model is taught with data from the real world, and the processing cost has been cut by using the prejudgment module. Some FDD plans have been suggested to make up for the fact that there aren't many complete fault detection methods available. In different battery faults, voltage, discharge current, and temperature were all put into a battery pack. Data from these tests were then used to teach a better radial basis function neural network (RBF-NN) how to find the faults. The suggested way might be able to find faults 100% of the time. Multi-classification SVM (MC-SVM) was used to come up with another way to find multiple faults[76].

**Table 3: Summary of reviewed EV battery faults detection**

| **Faults** | **Features** | **Ref** |
|---|---|---|
| Thermal faults | Robust and effective Simple | [77] |
| Short circuit | Detecting both internal and external short circuit | [78] |
| External short circuit | Online, fast and accurate detection Generalization capability | [79] |
| Sensor fault | Simple | [80] |
| Sensor fault | Simple and efficient | [42] |
| Internal short circuit | Online, fast and accurate detection | [81] |
| Sensor faults Short circuit Connection faults | Online, comprehensive fault detection | [82] |
| Detecting and locating various faults | High accuracy | [83] |
| Internal short circuit | Fast and simple | [72] |
| Voltage fault | High accuracy Severity estimation | [74] |
| Voltage fault | High accuracy Estimating fault severity and location | [73] |
| Battery failure Thermal runaway | Highly precise Online fault detection Fast Trained based on real-world data | [84] |
| Battery faults | 100% accuracy | [85] |
| Over/under-voltage Overheating Low capacity | A small training data set High accuracy | [76] |

### 5.3 Drive motor system fault diagnosis and maintenance process

The main parts of fault analysis for a drive motor system are finding the fault, figuring out what kind of fault it is, locating it, and fixing it. Finding faults, or checking different system factors to see if the system is not working right, is called fault detection. Fault type: Once the system failure has been found, it is necessary to further analyse and infer the data in order to figure out the fault type. The position of the fault is linked to the type of flaw and its healing [62]. It is important to get a better idea of the fault type, find the exact position and reason of the fault, and set up a good base for fault recovery. The most important part of fault diagnosis is fault recovery, which is also the point of fault diagnosis. After figuring out what caused the fault and where it is, the right steps are taken to fix it and finish the fault analysis. The process for finding faults in the drive motor system is the same as that used in vehicles[86].

After the owner hands over the faulty electric vehicle to the maintenance shop, the electric vehicle maintenance personnel should first ask the owner about the fault of the electric vehicle and make further inspections to check whether there is odor and leakage in the electric vehicle; using a dedicated fault decoder to read the vehicle ' s fault code, freeze data frames, data flow, etc.,

## 6. Data-Driven FDD Methods for Electric Motor Drive

Data-driven Fault Detection and Diagnosis methods have gained significant traction due to their effectiveness in handling complex systems without requiring detailed mathematical models. These techniques rely on large datasets from both healthy and faulty system conditions, enabling them to detect and classify faults by learning patterns and correlations within the data[87]. This is particularly beneficial for systems like electric vehicles (EVs), where traditional model-based methods struggle due to the complexity and variability of system dynamics. Data-driven methods, unlike traditional approaches, can uncover hidden features in the data, allowing for early fault detection, even at incipient stages, and offering insight into the severity of the fault[88]. Their robustness and ability to generalize across varying operating conditions make them ideal for dynamic environments like EVs. These methods are divided into two main categories: statistical-based methods, which rely on probability to detect faults, and artificial intelligence (AI)-based methods, which utilize machine learning (ML) algorithms for classification and prediction. [89]AI, particularly machine learning, plays a crucial role in data-driven FDD, with techniques being categorized into supervised, unsupervised, and semi-supervised learning. Supervised learning relies on labelled data to train models for fault classification, while unsupervised learning detects anomalies based on patterns in unlabelled data[90]. Semi-supervised learning combines both approaches, leveraging labelled data to label unlabelled data and improve system performance. Various machine learning tools are employed in FDD, including artificial neural networks, support vector machines , and fuzzy logic (FL), each of which excels at different aspects of fault detection, such as handling non-linear data, classifying faults, and managing uncertainty. With the rapid advancements in AI and machine learning, data-driven FDD methods are becoming increasingly important for enhancing the reliability and safety of EV systems by ensuring timely fault detection and diagnosis[91].

## CONCLUSION

In summary, the reliability, safety, and efficacy of electric vehicles (EVs) are contingent upon the implementation of defect detection and diagnosis (FDD) systems. Motors and batteries, which are essential components of electric vehicles are susceptible to a variety of malfunctions that may result in operational inefficiencies, elevated maintenance expenses, and potential safety hazards. The timely identification of these defects is facilitated by FDD methods, which enable preventive actions that improve the vehicle's performance and longevity. Modern techniques and conventional model-based methods have demonstrated efficacy in the identification of defects in battery and motor systems. Nevertheless, obstacles persist, including the necessity for more comprehensive solutions, the complexity of system integration, and real-time monitoring.

In the future, research and development should concentrate on enhancing the efficiency, accuracy, and robustness of FDD systems, while simultaneously addressing the practical challenges associated with their implementation. These developments will guarantee the safe and dependable operation of electric vehicles as they continue to be instrumental in the transition to sustainable transportation.

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