Quest Journals
Journal of Electronics and Communication Engineering Research
Volume 10 ~ Issue 12 (2024) pp: 01-16
ISSN(Online) : 2321-5941
www.questjournals.org

Research Paper

Fault Diagnosis of the Electric Motor Drive and Battery System for Electric Vehicles

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ABSTRACT: *Fault detection and diagnosis (FDD) is very important for making sure that electric cars (EVs) are safe and reliable. The electric motor drive and battery system, which store energy, are important parts of the EV's power train that can go wrong in a number of ways. If you don't find and fix these problems right away, they could cause EVs to stop working and even very bad crashes. Permanent Magnet Synchronous Motors (PMSMs) and lithium-ion battery packs have gotten a lot of notice for their use in electric vehicles. Because of this, finding faults in PMSMs, their drives, and lithium-ion battery packs has become an important area of study. An accurate, quick, sensitive, and cost-effective FDD method is what it takes to be successful. Model-based and signal-based methods are two types of traditional FDD techniques. However, data-driven techniques, such as methods based on machine learning, have recently become popular because they seem to be good at finding faults. The goal of this paper is to give a full picture of all the possible problems that can happen in EV motor drives and battery systems. It will also look at the newest, most advanced study in finding EV faults. As a useful guide for future work in this area, the knowledge given here can be used.*

KEYWORDS: *Fault detection and diagnosis (FDD); electric cars; PMSM; lithium-ion battery pack; model-based; data-driven; machine learning; deep learning*

*Received 02 Dec., 2024; Revised 12 Dec., 2024; Accepted 14 Dec., 2024 © The author(s) 2024. Published with open access at **www.questjournas.org***

I. INTRODUCTION

The introduction of electric vehicle (EV) technology represents a groundbreaking advancement in the progression of transportation, providing a sustainable alternative to conventional internal combustion engine vehicles. Electric cars, characterized by their dependence on electric motors for propulsion, utilize energy stored in rechargeable batteries, which are essential to their functioning. The advancement of this technology has seen tremendous development in recent decades, resulting in enhancements in terms of range, performance, and affordability.

Electric motors are used in a lot of different fields, but they are most often found in electric vehicles. For the transportation sector, how safe and reliable EVs are is very important. However, because they work in harsh conditions, the motor and its drive system can develop different problems that affect how well they work and make EVs less reliable and safe. The IPMSM motor, which has a high power density and good economy, is the most common type used in EVs[1]. On the other hand, designers have to make their designs more complicated as the need for PMSMs grows and the cost of their materials stays high. This makes the PMSM more likely to have different kinds of faults. At the same time, the transportation business needs to keep running, even though EV motors work in different environments. Faults in an electrical motor drive system can happen in the motor itself or in the inverter. These faults can be broken down into three main groups: electrical faults, mechanical faults, and sensor faults [2]. There are different types of electrical faults, such as open or short phase faults, demagnetization faults, and open or short circuits of the switches in the inverter. These are technical faults that have to do with the rotor, like bearing faults, bent shafts, and airgap eccentricity. Sensor faults are problems with each of the different instruments. If these flaws are found quickly, the right steps can be taken to avoid expensive damage and catastrophic fails.

Due to its exceptional qualities, which include high power and energy density, extended lifespan, and environmental considerations, the lithium-ion battery system has emerged as the front-runner in EV applications for energy storage [3]. Hundreds of cells coupled in parallel and series often make up a battery pack. However, a variety of defects, including as battery misuse and actuator and sensor errors, can arise in battery systems, leading to rapid aging and degradation of the battery, EV failure, and hazardous accidents. Battery issues are said to be the cause of 30% of electric vehicle accidents [4].

Therefore, to provide safe and continuous EV operation, fault tolerant control and reliable online defect detection must be developed. However, early failure identification is difficult due to complicated procedures and other uncontrollable factors. An electric motor's operational state can be monitored and ascertained using the fault detection and diagnostic (FDD) technique, which enables early failure identification and prediction. Various defects can be found and diagnosed using FDD, and by taking the appropriate action, EV safety and dependability enhance [5].

In order to reduce the possibility of possible problems with battery systems and electric motor drives, numerous FDD techniques have previously been created. Model-based, signal-based, data-driven (knowledge-based), and hybrid approaches are the main categories into which FDD techniques can be divided. The model-based approaches rely on the discrepancy between the values that the system model and observers estimate and measure. Various model-based techniques exist, including but not limited to state observer, parameter estimation, finite element analysis (FEA), linear parameter varying, extended Kalman filter (EKF), and others[6]. Signal-based techniques do not require an accurate system model because the failure symptoms are retrieved from the output signals. The spectrum, phase, magnitude, deviations, and other aspects can be analyzed in order to extract the features using the time domain, frequency domain, or time-frequency domain [7]. Fast Fourier transform (FFT), Hilbert Huang transform (HHT), Wavelet transform (WT), and Winger Ville are a few feature extraction techniques[6]. Model-based and signal-based approaches are slow in fault identification, sensitive to load, and require prior motor expertise. The fundamental advantage of data-driven approaches is that, unlike model-based and signal-based methods, they may be applied without requiring prior knowledge of the model or signal pattern of traction systems. To implement the data-driven method efficiently, a significant amount of historical data under both healthy and problematic situations is needed; this is not regarded as an impossible obstacle. This method can also be applied to multiphase motors with more complex models and uncertainties; furthermore, it does not require the system model. The hypothesis test and test statistics, Principal Component Analysis (PCA), Independent Component Analysis (ICA), Canonical Correlation Analysis (CCA), Neural Networks (NN), Support Vector Machine (SVM), Bayesian Network (BN), Deep learning, and other machine learning techniques are some of the main and most popular approaches in data-driven methods.

In order to comprehend the causes and consequences of various electric motor drive types and battery system malfunctions, this study surveys them. Various FDD approaches are shown, and the benefits and drawbacks of current research as well as cutting-edge strategies are examined.

II. ELECTRIC MOTOR DRIVE FAULTS

Electricity, mechanics, and sensors are the three main types of problems that can happen in PMSM motor drives. These problems could happen in either the motor or the generator. A diagram of different electric motor drive problems can be seen in Figure 1.

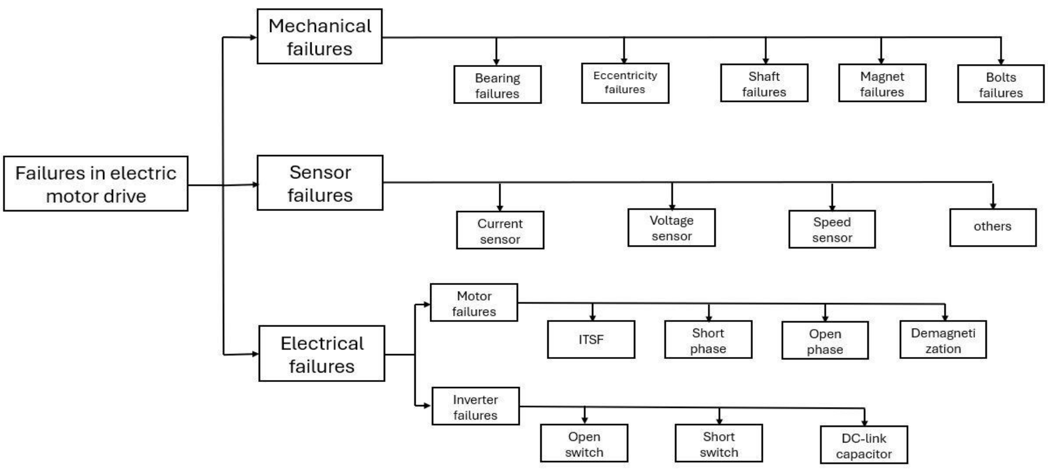

Figure 1: Various electric motor drive faults[38].

2.1 Electrical Faults

We already talked about the main electrical faults: open- or short-phase faults, demagnetization faults, winding interturn short-circuit faults (ITSF), and faults with the motor. There are also open or short circuits in switches and failures of DC-link capacitors that are linked to the inverter.

2.1.1 Interturn Short-Circuit Fault

A power surge, water, or mechanical, electrical, or thermal stresses can cause the stator turn-to-turn windings insulation to break down and degrade, which can lead to a short circuit in the windings [8]. It's called the fault (ITSF), and it fails more often than any other motor fault[9] .

Figure 2 shows that the shorted turns add another circuit loop that is linked to flux linkages made by the rotor magnet and other motor windings. Due to the low impedance and high coupled flux linkage voltage, the ITSF windings create a high-fault current. This causes the stator to overheat and carry too much current [10], [11].

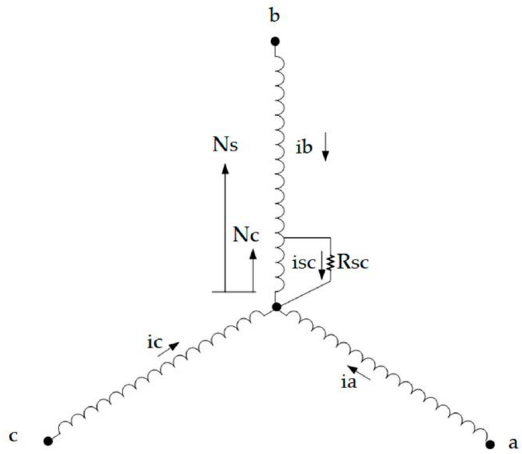

Figure 2: Interturn short-circuit fault in one phase winding of PMSM [8].

2.1.2 Demagnetization Fault

Demagnetization is the process of lowering the strength of the permanent magnet (PM) inside the IPMSM and can be brought on by physical damage, high-temperature operation, aging, or an inverse magnetic field. Additionally, an ITSF can cause partial demagnetization because of the induced reverse magnetitic field if it is not discovered and tolerated in a timely manner [12]. There are two types of demagnetization: reversible and irreversible. In the former, a field weakens control, while in the latter, demagnetization is permanent. One of the main causes of irreversible demagnetization is an improper operating point of the IPMSM due to the combined effects of temperature and a shift in the permeance curve[13]. Because there is less PM flux linkage when demagnetization occurs, the torque of the PMSM is decreased. As such, it adversely affects the efficiency and properties of the motor [14]. The current in demagnetized PMSMs must increase to compensate for the effect of a weakened PM and provide the same torque as a healthy state [15]; unfortunately, this entails increasing copper losses and temperature [16]. However, extreme heat can cause irreversible demagnetization that is significantly more severe [17]. As a result, the system's dependability and security would decline. It is essential to use defect detection and diagnosis technology in order to prevent such outcomes. Demagnetization fault can result in additional frequency components in stator current and the vibration and result in pulsation in torque and speed. Demagnetization fault detection can be accomplished with these signals [18], [19].

2.1.3 Open or Short Switches in the Inverter

An essential part of electric motor drive systems is an inverter, as Figure 3 illustrates. Switching devices account for approximately 38% of driver faults [20] and are most likely to fail during operation due to high-frequency operation, high power stresses, aging, and other factors. These faults typically manifest as open-circuit or short-circuit failures. Open-circuit faults are typically caused by a disconnected wire or a failed gate signal. The drive system continues to function in spite of such a fault [21]. Phase-locking mode is used by the system when an open-circuit fault interrupts the defective phase winding stimulation in a switching device. Because of this, the drive system becomes unbalanced, the rotor experiences an uneven force, which lowers system performance significantly[2], causes audible vibrations, and may lead to secondary motor faults because there is no fault finding detector (FDD). The most common causes of short-circuit faults are overvoltage, overheating, malfunctioning protection components, or incorrect gate signals[21]. Moreover, instantaneous overcurrent results from a power switch short circuit, which continuously stimulates the faulty phase winding regardless of the rotor position. As a result, during the demagnetization phase, the defective phase produces a large amount of reversed braking torque, seriously impairing the stability of the drive system and ultimately leading to the system's failure [22]. The protective circuits activate in this instance because an overcurrent is generated right away, forcing the inverter to shut down and necessitating repairs before it can resume operation. Therefore, the safe operation of a PMSM drive depends on precisely and promptly locating power transistor faults and isolating them[23].

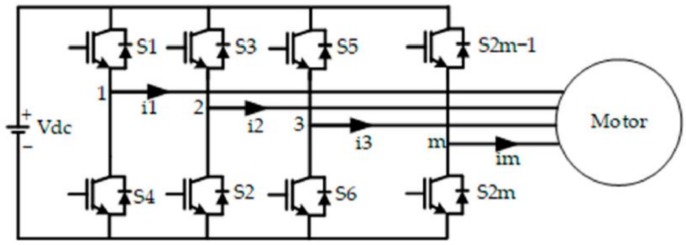

Figure 3: m-phase inverter of an electric motor [23].

2.2 Mechanical Faults

Just like electrical faults, mechanical faults also require prompt detection. Air-gap eccentricity and bearing defects are the two primary mechanical flaws. A bent shaft, a broken magnet, and loosening bolts are a few more mechanical issues [24].

2.2.1 Bearing Faults

Out of all potential motor faults, a bearing fault accounts for 40–50% of all faults and is the most common [25]. Inner raceways, outer raceways, cages, and ball bearings can all have bearing defects. Even in normal circumstances, inadequate lubrication, mechanical vibrations, misaligned shafts, overload, corrosion, and finally fatigue are the main causes of bearing faults. It is anticipated that additional faults, including air-gap eccentricity, ITSF, and even total motor failure, will arise if the bearing defect is not identified and fixed promptly [26]. In [27], Figure 1 shows the rolling bearing structure.

2.2.2 Air–Gap Eccentricity Faults

A rotor eccentricity fault within the motor is caused by a number of mechanical issues, including unbalanced loads, shaft misalignments, rotor imbalance, missing bolts, and bearing problems[24]. Static eccentricity (SE), dynamic eccentricity (DE), and mixed eccentricity (ME) are the three types of eccentricity, which is actually the uneven air gap between the stator and rotor. SE is the term used to describe the state in which the minimum air gap is fixed and rarely changes over time, primarily as a result of manufacturing. DE is caused by bent shafts, worn bearings, and rotor flaws where the minimum air gap location rotates with the rotor. The ME concurrently exhibits both SE and DE defects [28].

2.2.3 Sensor Faults

Various kinds of sensors, such as position, speed, voltage, or current sensors, are required to supply distinct feedback signals to a motor drive control system. Any flaw or malfunction in these sensors, which can result from vibration, temperature changes, moisture, etc., is referred to as a sensor fault [29]. Open circuits, gain deviation, and excessive noise are examples of sensor faults[30]. The motor's monitoring and controller system receives erroneous data if one of these sensors malfunctions, which can result in reduced performance or even total motor failure. Consequently, in order to prevent this kind of failure and decreased reliability, fault detection and diagnosis are crucial [31].

2.2.4 Current Sensor Faults

A three-phase PMSM's phase currents are measured using a minimum of two current sensors. Three types of current sensor faults exist: zero output, incorrect gain, and dc offset. While none of these require immediate attention, they can result in decreased efficiency and overheating [2].

2.2.5 Voltage Sensor Faults

System failure may occur quickly if the voltage sensor fault results in a sharp rise in the measured DC-link voltage. Quick fault identification and repair are essential in this case. Occasionally a malfunction may result in minute variations and aberrations in the recorded value, enabling the motor to run at a lower efficiency for a while. Any voltage sensor malfunction must eventually be found and accepted[2].

2.2.6 Speed or Position Sensor Faults

The position and speed sensors in the motor drive provide the control system with information about the rotor's position and speed. For this object, photoelectric incremental encoders are the most common type. Any issue with this sensor could impact the operation of the motor. The motor may stop, rotate in the wrong direction, decrease from the desired speed to zero, or—and this is the most dangerous—increase from the desired speed to the maximum speed at which the motor can operate. The final scenario leads to ongoing overload and potentially disastrous mishaps. FDD is therefore essential in averting these circumstances [2].

2.3 Battery System Faults

Three primary categories can be used to categorize the potential problems with the battery pack: sensor faults, connection problems, and battery abuse. Each of these faults has the potential to generate heat; if they are not identified or accepted in a timely manner, they may accelerate aging and even cause a thermal runaway or explosion [32]. A diagram of battery system malfunctions is shown in Figure 4.

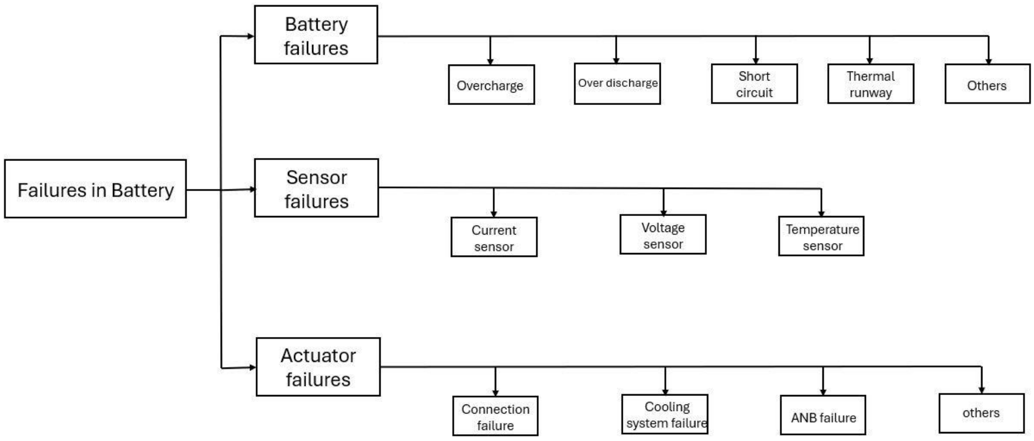

Figure 4: Battery system malfunctions

2.3.1 Battery Abuse Faults

This category of defects includes internal battery short circuits, external short circuits, thermal runaway, overcharge, and overdischarge. Faults related to overcharge and overdischarge can be caused by mistakes in the battery management systems and cell capacity degradation. These flaws may cause the battery to sustain physical or chemical damage, which would reduce its capacity and compromise its safety[33]. An external short circuit detects the shorted positive and negative terminals, whereas an internal short circuit is caused by a breakdown in the insulation between the battery's layers[34]. Compared to an internal short circuit, which is insignificant in the early stages, an external short circuit is a more dangerous and obvious defect. Nevertheless, after some time, the internal short circuit may develop into a severe fault [35]. When a short circuit happens, rapid voltage drop and thermal runaway are to be expected.

2.3.2 Actuator Faults

This category includes faults with connections, cooling systems, controller area network buses, etc. Owing to the high energy requirements of EV applications, the battery system typically consists of numerous battery cells connected in parallel or series. The connection may break down as a result of aging, temperature fluctuations, vibration, and the working environment of EVs. Unsecured connections have the potential to decrease power availability, which could lead to mishaps. The performance of the battery may be impacted and heat produced by increasing the connection's resistance [36]. One of the major battery faults is that if the cooling system fails, the battery temperature may rise above the permitted temperature range and possibly cause thermal runaway.

III. FAULT DETECTION AND DIAGNOSIS OF ELECTRIC MOTOR DRIVE

Safety and dependability are always top priorities in any application, but in transportation systems, they are even more important since, EV motors notwithstanding, transportation requires both continuity and safety. As was previously mentioned, various faults of various kinds are always possible with an electric motor and its drive system[38] [39]. Faults that go unnoticed can cause severe accidents, poor performance, and expensive repairs. In numerous systems with various applications, FDD is taken into consideration in order to reduce these risks, boost safety, prevent unplanned EV stops and expensive repairs, and increase reliability. FDD is a technique for monitoring motor performance in order to find, recognize, and locate errors as soon as feasible. FDD offers the chance to accept faults and take appropriate action as soon as they arise. To be deemed effective, an FDD technique must meet specific criteria, including: (i) quick detection times; (ii) resilience to changing operating environments; (iii) sufficient sensitivity without producing false alarms; and (iv) lack of need for extra hardware (because of its expense and complexity). The most important factor in fault detection is choosing the appropriate fault index. Using multiparameter fault indicators can increase the robustness and accuracy of the detection process because a fault can change a motor's parameters [40]. The overall schematic of the fault-tolerant control and FDD-equipped EV motor drive system is shown in Figure 5.

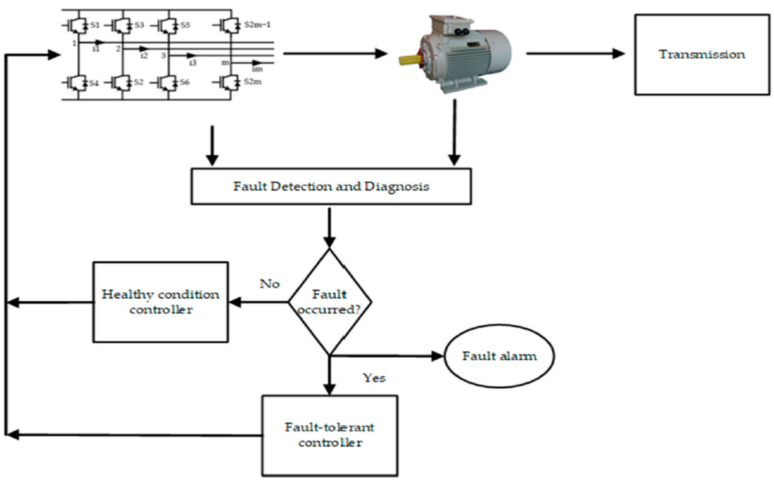

Figure 5: PMSM motor drive schematic with FDD and fault-tolerant contro[38].

The three primary classes of FDD methods used in PMSM motor drives are model-based, signal-based (also known as signal processing), and data-driven, as shown in Figure 6[41], [42]. . In certain applications, hybrid FDD methods—which combine multiple approaches to benefit from multiple approaches at once—are also employed. An overview of FDD categories can be found in Table 1.

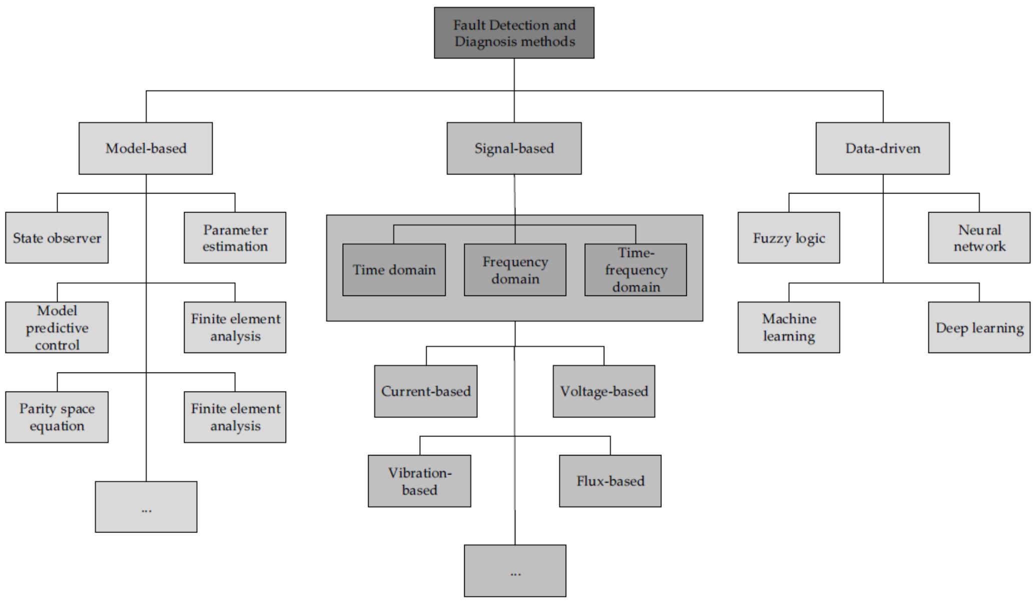

Figure 6: Different classes of FDD methods[38].

Table 1: Summary of FDD categories [38].

Type	Basis	Features
Model-based	Using the system model and the estimated parameters for fault detection	Immensely effective in simple systems with reliability and lower cost Sensitivity on occasion of varying parameters and load Prior model with knowledge needed
Signal-based	Using output signal and signal-processing methods for fault detection	Easy implimentation process Compatible for complex systems Usually slower detection speed, higher cost caused for faster detection
Data-driven	Using historical data for training the sysytem and fault detection	No prior knowledge needed No system model or signal pattern needed Compatible for complex systems Accuracy is high Quality and quantity are factors of affecting performance of FDD

3.1 Model-Based FDD Methods

By contrasting the measured values with the estimated values generated by the system model, model-based techniques are developed. The expected signal values in a healthy state are estimated in the first stage using the motor's mathematical model. The residual signals are then produced by comparing these estimated values with the actual measured signals. Depending on the intended fault type and fault detection methodology, different signals may be taken into consideration for fault detection. The residual signals indicate whether the motor is in good working order or has a fault in the second stage of model-based FDD[43], [44]. Model-based techniques are quick and efficient, but they require a precise system model, which has drawbacks and lowers the FDD method's effectiveness for complicated systems with lots of unknowns. Expert knowledge is also required [45]. Several model-based techniques exist[46], including linear parameter varying, finite element analysis (FEA), state observer[47] , parameter estimation[48], parity space equations[49], extended Kalman filter (EKF), and model predictive control (MPC), to mention a few. Numerous model-based FDD approaches have been presented; the following are some of the ones that have been examined. The general schematic of the model-based method is depicted in Figure 7[50], with the fault detection unit being the green cycle.

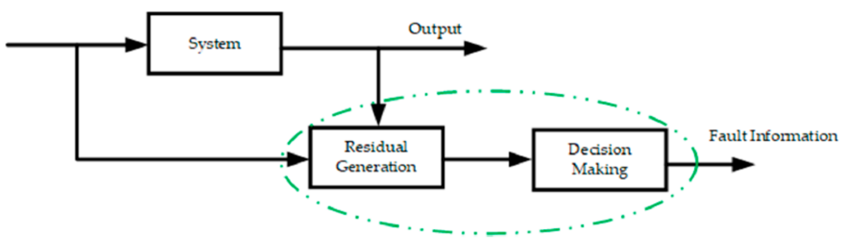

Figure 7: General diagram of model-based FDD workflow [50]

The state-observer method, as one of the most-used techniques with the general diagram shown in Figure 8[51], is usually divided into two main subgroups: voltage-based observer[52] and current-based observer[53]. The voltage-based methods are fast diagnosis techniques and can be used to increase the fault detection speed, but usually, extra voltage sensors are needed. Consequently, adding voltage sensors increases the system's cost, volume and complexity, which is regarded as a drawback for FDD techniques[54].

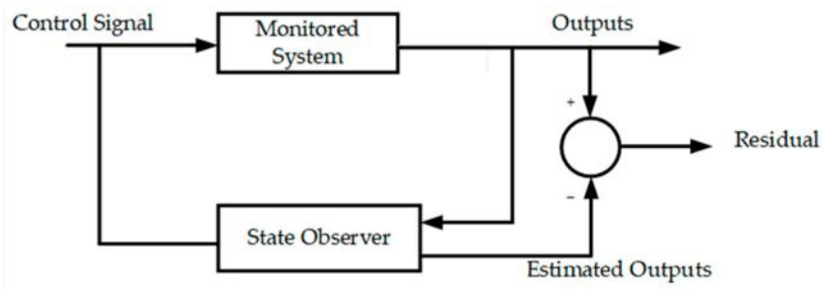

Figure 8: General diagram of state-observer FDD configuration[51]

The theory of interval observer has brought new ideas for fault detection and control integration. The interval observer scheme reduces computational load over the traditional observer-based fault detection scheme by doing away with the requirement to design a threshold selector and residual evaluator. In[55], an enhanced interval observer that makes use of the well-established mathematical model of the motor was employed. This observer exhibits greater resilience to electromagnetic disturbance and permits the detection of ITSF faults at an early stage.

Another useful residual observer that is gaining popularity and enhancing observer-based FDD methods is the Luenberger observer. The Luenberger observer is used for very low-to high-speed range encoder fault detection in[56]. The Luenberger observer's sensitivity to changes in motor parameters is a disadvantage, though. Sliding mode control systems are commonly used to address the nonlinearity of complex systems, and they exhibit greater robustness when compared to methods based on Luenberger observers.

The other model-based fault detection method is parameter estimation. Several motor and inverter parameters, including speed, resistance, back-EMF, voltage, and current, are estimated using system models in this technique and are regarded as the expected healthy values or references. These numbers are then contrasted with the actual parameter values that were obtained from the system online. The fault occurrence is revealed by deviations from the reference values. In order to identify and differentiate between single and multiple sensor as well as nonsensor faults, [57] uses the estimated DC-link current as the reference value and compares it with the actual measured value. In addition, the identified faults are isolated using the phase signal residual.

Another potent mathematical technique for estimating motor parameters in the event of a fault detection is the Extended Kalman filter (EKF), which is based on minimizing the variance of estimation error and applicable in nonlinear systems. They have a low false alarm rate, strong estimation against noise, and quick detection. To estimate the parameters for the next step, they require the measured signals and the most recent estimated values. The Kalman filter has a variety of uses; in[58], [59], it is employed for the purpose of estimating the state of autonomous driving vehicles and eliminating noise and anomalies. Because of its significance for state estimation, residual generation, and signal innovation, comprehensive information about the Kalman filter is supplied. The process for the Kalman filter is shown in Figure 9.

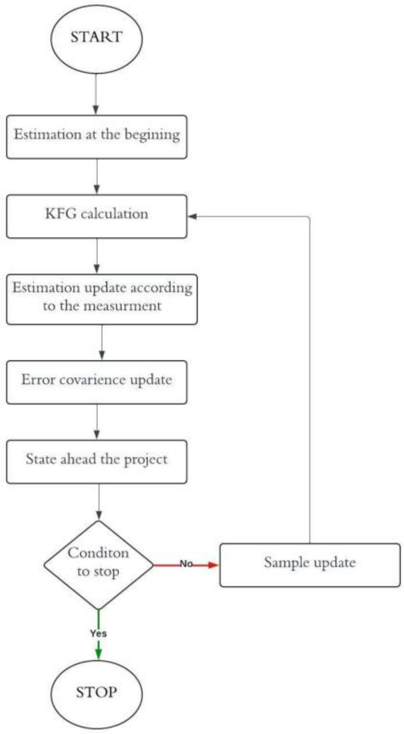

Figure 9: Kalman filter flowchart [59].

For computing parameters of electromagnetic devices, like motors, such as torque, flux density and linkage, and inductance, the Finite element method (FEM) is a very efficient method. It has been used for PMSM fault detection, particularly eccentricity, demagnetization, and ITSF faults, and yields accurate results by breaking down a large electromagnetic device into smaller elements and applying intricate mathematical equations[60].

Model predictive control is a motor drive control method that is becoming more and more popular because of its ease of use and excellent results. Recently, fault detection has made use of cost functions and MPC. Based on the control objective, MPC for PMSM motor drives can be split into two categories: model predictive torque control (MPTC) and model predictive current control (MPCC). MPCC takes precedence over MPTC because it requires less computational work and has a cost function that is simpler and more effective than MPTC[61]. Open-phase fault (OPF) in a PMSM motor drive with MPCC is identified in [62] using a cost function. Fault detection is carried out by the DC component and second harmonic component in the cost function intended for the current to track the references; the fault phase is located by using the phase angle difference of the stator current. This is a straightforward method whose performance is independent of parameter variations and operating conditions.

3.2 Signal-Based FDD Methods

A precise system model is not required for signal-based techniques, in contrast to model-based strategies. Consequently, signal-based FDD techniques perform better in complex systems with imprecise models and uncertainty in the parameters. These techniques work on the basis of extracting fault features, such as vibration, torque, current, voltage, and magnetic flux density[63], [64], from the motor output signals. Variations in output signals from the expected values under healthy conditions can be attributed to various types of faults. Based on the fault symptoms, one or more signals can be selected as fault indicators. After the fault features have been extracted from the measured values using signal feature extraction techniques, the fault occurrence and type can be determined by comparing the extracted features to a reference or threshold. The overall workflow for signal-based methods is summarized in Figure 10.

Figure 10: General signal-based FDD methods workflow[38].

Current signal-based fault detection is popular because current is cheap and easy to measure and available for motor drive control. MCSA-based diagnosis, dq-frame current analysis, negative- and zero-sequence current, and Park's vector approach are some methods. Phase current-based methods are easy to implement and require no extra hardware, but they have a slow detection rate (at least one fundamental period). In [65], MSCA-based partial demagnetization fault detection was proposed. The additional even harmonics in the stator current caused by partial demagnetization were used as fault indicators. In a dual inverter five-phase PMSM motor drive, the ZSC is analyzed for open-switch fault detection [66]. ZSC is zero when healthy, but it deviates from zero during open-switch faults and indicates fault. The open-switch fault indicator in[67] is the ratio of phase current positive sequence to negative sequence analyzed using Fourier series. Setting this fault indicator's threshold detects various open-switch faults. The DC current component shows the fault location. [68] proposes a simple normalized average current method for open circuit and current sensor fault detection and identification. This paper proposes a faster FDD fault detection method than current-based methods. In [69], the mean value of the secondary subspace harmonic and current magnitude were used to detect open-phase faults. This method is unaffected by motor parameters and operating conditions. Detecting the fault takes less than half the fundamental period.

Voltage signal-based methods directly measure motor phase, line, and other voltages and detect faults by comparing them to reference voltages. FDDs are fast, reliable, and less prone to false alarms, but the voltage sensor adds cost and complexity. Common voltage base methods include symmetrical component analysis (zero and negative sequence) and dq-frame voltage analysis. Two-line voltages are analyzed and features extracted to detect one or two PMSM motor drive inverter open-switch faults[70]. It requires extra voltage sensors, but FDD is cheaper and simpler with fewer sensors. The detection time is 1/20 of the fundamental period, and it is fast. The fault indicator in [71] is the change in the d and q axis voltage angle due to demagnetization and the ITSF effect on magnetic flux. The demagnetization fault increases this angle, while the ITFS decreases it. Also, this paper analyzes dq-voltage to detect eccentricity faults. The zero-sequence voltage component (ZSVC) is used to detect and identify incipient ITSF in[72]. A high-frequency signal is injected to identify the type of fault detected by the ZSVC. The system costs more because the circuit to reach the neural point for symmetrical component analysis is needed.

The vibration signal spectrum from vibration sensors is analyzed to find fault symptoms. Most useful for mechanical fault detection. FDD cost and complexity increase when vibration sensors are mounted on the stator's exterior. External vibrations and environmental disturbances can also affect FDD performance and efficiency. Besides mechanical faults, demagnetization faults can be detected by analyzing electromagnetic vibration signals. Air gap demagnetization can cause low-frequency vibrations proportional to the motor's physical properties. This feature is the fault indicator extracted from the vibration signal by FFT in[73]. The demagnetization fault is found by comparing this index to Chebyshev's inequality thresholds. An orthogonal DWT was applied to vibration signals to obtain energy signals for rolling bearing fault detection, which is fast and accurate for early-stage faults[74].

Search coils are reliable for detecting motor faults, especially ITSF, demagnetization, and air–gap eccentricity. This method analyzes faults' electromagnetic signatures. Search coils wrapped around stator teeth are measured and analyzed for induced voltage to find the fault[75]. Faults are detected by adding harmonics to the air–gap magnetic field[76]. This method is reliable, but special installation during manufacturing increases FDD complexity and cost. A new ITSF detection structure using search coils is proposed in[77]. The cost is significantly reduced by reducing the number of search coils to twice the phases. ITSF is identified by analyzing the negative sequence of search coil voltages' second harmonic. This FDD method is transformed into a DC frame to improve its performance and allow stationary and non-stationary operations. Another flux variation-based eccentricity and demagnetization fault detection method is the hall-effect field sensor[28].

3.3 Data-Driven FDD Methods for Electric Motor Drive

Previous performance and features have made data-driven FDD methods popular in recent years. It trains the system to detect and classify faults using a lot of historical data in healthy and faulty conditions. Complex and ill-defined systems benefit from data-driven methods because they don't require mathematical model knowledge. They use historical data to evaluate the system or represent human expertise in rules as expert systems to analyze, learn, and solve complex problems. The model and trained system can extract hidden signal features and detect fault type and severity in early stages using historical data. The robustness and generalization ability of data-driven methods in different system operating conditions is due to their independence from system model, signal, and load [78]. This technique is statistical and AI-based. It uses probabilities, while the other uses classification[79]. Since artificial intelligence (AI) is the main component of data-driven methods, they are gaining popularity due to the rapid progress in AI and machine learning tools and the increasing complexity of systems. Three main machine learning methods are supervised, unsupervised, and semi-supervised[80]. To find the correlation between input and output, supervised learning requires labelled data for training and learning. In unsupervised learning algorithms, common data features are used to learn and classify large amounts of unlabeled data. The semi-supervised algorithm combines the two older algorithms. The system is trained to label unlabeled data using labelled data. For learning, all labelled data are used. Some data-driven and machine-learning methods for fault detection and diagnosis include artificial neural networks (ANN), fuzzy logic (FL), support vector machine (SVM), deep learning (DL), and others. Regardless of method, most data-driven FDDs follow these steps in Figure 11.

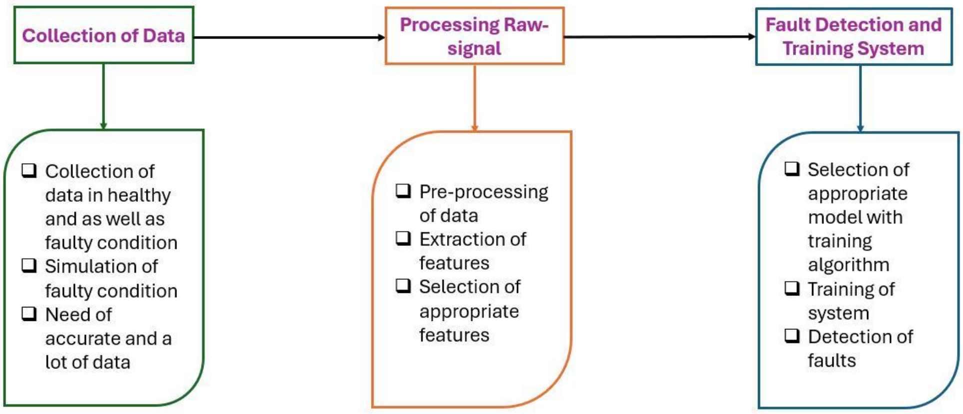

Figure 11: Data-driven FDD workflow[38].

3.4 EVs' Battery Fault Detection

As mentioned, EV safety and reliability are key factors in transportation electrification. One major part, the EV battery, can have many limitations. It always has faults, some of which can be fatal. Battery fault detection and diagnosis are as important as EV motor drive fault detection to solve these issues. Many types of research have been done in this field recently. Battery fault FDD methods are model-based, signal processing, and data-driven, following the same principles as electric motor drive FDD methods. Standard battery fault detection parameters are voltage, current, and temperature. Several FDD methods for battery faults are briefly introduced and reviewed in this section.

3.4.1 Model-Based FDD Methods for Battery Faults

Model-driven energy The foundation of FDD techniques is the generation of residuals using battery models, filters, and observers. An electrochemical, electrical, thermal, or a combination of these models can be used to model a battery[81]. Structural analysis, parity space equation, parameter estimation, and state estimation are the primary model-based FDD techniques for battery fault detection. The following is a brief introduction to some suggested model-based techniques.

The Leunberger observer and the battery's thermal model were used to find thermal flaws[82]. In [83], a method based on partial differential equations (PDEs) was presented for the detection of thermal failures in lithium-ion batteries. In order to make the fault detection robust to uncertainties, two PDE observers were used for both estimation and fault diagnostic.When it comes to fault detection, voltage signals are typically more precise and effective than temperature readings.

3.4.2 Signal-Based FDD Methods for Battery Faults

With this kind of FDD, signals are obtained straight from the sensors, processed, and examined to identify the flaws, typically by means of a threshold comparison. WT and FFT are the most often utilized signal-processing methods for examining the frequencies at which electrochemical reactions occur[84].

In [85], sample entropy analysis and the EMD of the voltage signal are used to identify different battery faults. Because sample entropy can identify unexpected voltage drops, this method can identify various fault types. This technique has a high accuracy because it makes use of EMD's noise cancellation.

Gas and force sensors were employed in [86]to identify the internal short-circuit problem. This technique is predicated on the detection of gas generated by chemical reactions resulting from internal short circuits and cell swelling. On the other hand, adding more sensors makes the system more expensive and complex.

3.4.3Data-Driven FDD Methods for Battery Faults

In the case of battery fault detection, data-driven methods and machine learning-based FDDs are growing rapidly recently 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. In the event of battery malfunctions, there is a significant gap in FDD techniques based on machine-learning tools.

Here are a few of the most recent data-driven techniques.

A general regression neural network (NN)-based approach for battery voltage fault detection was presented in[87]. The voltage was denoised using DWT, and the GRNN was trained using a number of parameters to achieve the maximum accuracy of more than 99%. This plan is able to identify, locate, and gauge the degree of the fault. Battery voltage faults were detected and their severity was estimated using SVM in[88]. Initially, the voltage data are denoised in order to improve precision and dependability. Afterwards, a modified covariance matrix—which was optimized via the grid search technique—was added as the SVM's condition indicator in an effort to shorten the detection time.

The long short-term memory CNN (LSTM-CNN) model and aberrant heat generation are the foundations for the battery thermal runaway detection proposed in[89]. In order to predict the temperature, LSTM-CNN is trained using actual EV data, and PCA is utilized to enhance the input feature. This approach is precise and capable of anticipating the thermal runaway fault.

An online hybrid FDD method based on the combination of LSTM-RNN and the equivalent circuit model (ECM) was proposed [90] in an effort to improve the accuracy and efficiency of FDD. The prejudgment module is used to lower the computational cost of the model, which is trained using real-world data.

There is a deficiency of thorough fault detection techniques, so some FDD schemes have been suggested. A battery pack was injected with various battery faults, such as voltage, discharge current, and temperature, in [152]. The data gathered from this process was used to train an enhanced radial basis function neural network (RBF-NN) to identify the faults. The suggested approach might achieve 100% accuracy in fault detection. In [91], a different multi-fault detection technique based on multi-classification SVM (MC-SVM) was presented. Undervoltage, overvoltage, overheating, and low-capacity faults were identified with this technique by employing MC-SVM, which achieved extremely high accuracy even with limited training data. The cost of producing inaccurate data is decreased by training using a small data set.

IV. CONCLUSION

EVs are the way of the future for transportation because of the increased focus in recent years on the necessity of electrifying transportation. In this sense, EV safety and dependability are crucial if EVs are to capture the largest possible market share. Two of an EV's primary components are the energy storage system and the electric motor drive. Lithium-ion batteries serve as the primary energy storage system in electric vehicles (EVs), and PMSM motor drives are becoming the preferred option for the power train due to their exceptional features. However, fault occurrence is unavoidable given the working environment and nature of EVs. As a result, fault diagnosis and detection have become essential tasks. A lot of research has been done in this area, but there is still room for improvement and filling in the gaps. The goal of this review paper is to provide an overview of various fault types that can occur in the PMSM motor drive and battery pack of electric vehicles (EVs), as well as FDD methods and recent developments in this field. This information will be useful for future research aimed at achieving fully safe and reliable electric transportation.

The motor side and inverter side faults are the two main areas of focus for the PMSM motor drive's FDD. As a result, this paper thoroughly examines several FDD techniques, such as model-based, signal-based, and data-driven approaches. The use of different machine-learning tools for PMSM motor drive fault detection has gained attention due to the complexity of the models involved, parameter uncertainties, and other limitations of model-based and signal-based methods, as well as the rapid advancement in machine-learning tools and their superior features. Up until now, numerous works utilizing deep learning tools—particularly CNN—have been presented, and notable advancements have been demonstrated.

The majority of FDD techniques that have been proposed thus far for battery fault detection are model-based in nature, with a particular emphasis on KF. But given the unknowns surrounding lithium-ion batteries and their nonlinear behavior, data-driven approaches may represent the way forward for battery FDD techniques. In the case of battery state estimation, numerous data-driven techniques, such as machine learning tools, have been applied thus far. However, only a few techniques based on neural networks, SVM, and deep learning are studied for fault detection.

The two main traditional approaches for EV fault detection are model-based and signal-based. The robustness and precision of the FDD are diminished due to the non-accuracy of the motor and battery models, particularly over time. Furthermore, signal-based techniques are slow and inappropriate for early fault detection due to measurement noise. Nonetheless, newer approaches—particularly the data-driven techniques discussed in this work—have the potential to overcome certain drawbacks and shape fault detection going forward. The methods presented have made significant progress in detecting early faults, handling uncertainty in parameters, taking lifespan into account, improving fault detection speed and accuracy, allowing for generalization, and detecting faults in non-stationary conditions.

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