

Review

Recent Advances of Artificial Intelligence Methods in PMSM Condition Monitoring and Fault Diagnosis in Elevator Systems

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Abstract

Permanent magnet synchronous motors are the dominant technology in industrial applications such as elevator systems. Their unique advantages over induction motors give them higher energy efficiency and significant reduction in energy consumption. Accordingly, the elevator is one of the basic means of comfortable and safe transportation. More generally, in elevator systems, electric motors are characterized by continuous use, increasing the risk of possible failure that may affect the operation of the system and the safety of passengers. The application of appropriate monitoring and artificial intelligence techniques contributes to the predictive maintenance of the motor and drive system. The main objective of this paper is a literature review on the application of modern monitoring methodologies using smart sensors and machine learning algorithms for early fault diagnosis and predictive maintenance generally. Thus, by exploiting the advantages and disadvantages of each method, a technique based on a multi-fault set is developed that can be integrated into an elevator control system offering desired results of immediate predictive maintenance.

Keywords: permanent magnet synchronous motor; fault diagnosis; smart sensors; condition monitoring; predictive maintenance; industrial applications; elevator systems



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1. Introduction

Permanent magnet synchronous motors (PMSMs) have become the primary electric motor technology for elevator systems because they offer compact size, high torque density and excellent low-speed controllability [1,2]. The PMSMs operate with rare-earth permanent magnets on the rotor eliminating rotor current needs and results in lower losses and higher efficiency and quieter operation that suits vertical transport applications [3]. The extensive use of PMSMs in elevators has generated an immediate need for reliable monitoring systems because these motors are often placed in inaccessible shafts or machine rooms where unexpected failures result in expensive downtime and dangerous safety hazards [4,5].

PMSMs demonstrate robustness yet they remain vulnerable to different types of faults which stem from mechanical wear and electrical stress and thermal degradation and manufacturing defects. The most common faults in PMSMs consist of bearing deterioration and stator winding inter-turn short circuits and rotor demagnetization and different types of eccentricity (static, dynamic or mixed) [6–8]. The faults generate torque problems and

produce audible noises and vibrations which can result in permanent rotor destruction and complete system failure [9]. The elevator industry requires immediate fault detection and isolation of such faults because ride comfort and positioning precision and operational continuity remain essential [10].

Traditional maintenance techniques operate through reactive methods depending on manual inspections and scheduled downtimes and threshold-triggered alarms from current and temperature sensors. The commonly used methods lack the ability to detect faults before they become major issues [11]. Predictive maintenance uses signal processing together with mathematical modeling and artificial intelligence (AI) to detect faults at an early stage that enables preventive action before performance degradation happens [12,13]. The transition supports Industry 4.0 goals because operational reliability depends on intelligent sensing and data-driven decision-making.

PMSM fault diagnosis heavily relies on signal-based condition monitoring methods. The time-series data from stator current and voltage and vibration can be used to extract fault signatures using fast Fourier transform (FFT), short-time Fourier transform (STFT), wavelet transform (WT), and Hilbert–Huang transform (HHT) [14–17]. The FFT analysis together with envelope analysis allows the detection of bearing faults through the identification of ball pass frequency inner (BPFI) and ball pass frequency outer (BPFO) harmonic components in the current spectrum [18,19]. The current signature distortions are used to detect the eccentricity faults through the analysis of predictable sideband frequencies, and the de-magnetization is observed through the symmetry and magnitude distortion of the rotor magnetic field [20–22]. Signal-based methods require handcrafted feature extraction as well as expert knowledge for results interpretation. Signal-based methods are affected by noise and may not perform well under non-stationary conditions that are frequent in elevators because of frequent start–stop cycles and variable loads [23]. Machine learning (ML) and deep learning (DL) techniques have recently emerged as solutions to overcome the limitations of the existing methods [24].

The supervised ML algorithms including support vector machines (SVM), random forests (RF), k-nearest neighbors (kNN), and Gaussian mixture models (GMM) have been successfully used for PMSM fault classification when statistical and spectral features are derived from wavelet or STFT analysis [25–27]. SVM classifiers trained with time–frequency domain features extracted from current signals have shown high accuracy in detecting bearing faults under different loads [28]. RFs have been used to detect stator winding faults by analyzing phase imbalance and thermal patterns [29–31].

Deep learning extends fault diagnosis by eliminating the requirement for manual feature engineering. The spatial hierarchies can be learned directly from raw sensor signals or spectrograms by convolutional neural networks (CNNs) and the temporal dynamics can be modeled by recurrent neural networks (RNNs) and long short-term memory (LSTM) networks [32–35]. These architectures can achieve superior performance in the case of elevators since they have an abundance of data from accelerometers or current sensors. The CNN-LSTM hybrid models achieve better performance compared to standalone ML methods through which they demonstrate fault classification accuracies exceeding 98% on PMSM benchmark datasets [36].

Current studies are investigating diagnostic systems that integrate signal processing with AI. Wavelet packet decomposition combined with a CNN classifier has shown increased robustness under noisy conditions [37]. The current signals are isolated through empirical mode decomposition (EMD) to get intrinsic mode functions that are then fed into deep models for classification [38,39]. The hybrid pipelines provide strong generalization and noise resilience that are essential for elevator deployments in real-world applications. Nevertheless, challenges persist. The data imbalance between healthy and faulty samples,

the scarcity of labeled fault data from elevators in the field, and the black-box nature of deep models cause trust and explainability issues [40–42]. These problems can be addressed through the implementation of transfer learning and domain adaptation as well as explainable AI (XAI). The use of pre-trained CNN models on industrial datasets followed by fine-tuning for elevator-specific PMSM profiles can minimize the requirement for large labeled datasets [43].

Real-time fault detection on embedded elevator controllers is made possible by the rising Internet of Things (IoT) and edge computing. Microcontrollers and edge devices are being used to deploy lightweight AI models for continuous PMSM health monitoring and wireless sensor network-based alert systems [44,45]. The decentralization process enables better scalability and faster maintenance decisions through reduced latency.

The integration of AI into the condition monitoring of PMSMs has significantly advanced fault-diagnosis capabilities in industrial contexts, yet research focused specifically on elevator systems remains scarce. Existing studies largely address general industrial environments, often overlooking the distinctive operational conditions of elevators, such as frequent start–stop cycles, low-speed operation, regenerative braking, confined installation spaces, and compatibility requirements with legacy infrastructure. Consequently, there is a lack of domain-specific datasets, methods, and benchmarks exclusively dedicated to elevators, which limits the effectiveness of current diagnostic frameworks. This review paper addresses this critical gap by systematically analyzing condition-monitoring and fault-diagnosis techniques for PMSM drives used in elevator traction systems, with comparative insights drawn from industrial PMSM studies. While research on induction motors (IMs) is considered when offering transferable retrofit insights, the core focus is on PMSMs due to their growing dominance in modern elevators.

The central research question guiding this work is how modern AI-, ML-, DL-, and IoT-based techniques can be designed, adapted, and integrated into condition-monitoring frameworks for PMSM drives in elevator systems to enable accurate, explainable, and real-time fault detection and predictive maintenance. This review paper synthesizes findings from the past five years—when the field has seen rapid progress—while referencing earlier foundational works where necessary. It highlights agreements, contradictions, and unique perspectives among existing approaches and exposes unresolved challenges, including limited domain-specific data, difficulties in real-time edge-AI deployment, lack of explainability in black-box models, and the absence of standardized protocols for elevator-focused condition monitoring. By consolidating and critically evaluating this fragmented body of knowledge, the paper contributes a domain-specific framework to guide the development of next-generation predictive maintenance systems for elevator PMSM drives, serving researchers, elevator engineers, IoT developers, and regulatory bodies concerned with safety and standardization. The paper is organized into seven sections starting with Section 2 explaining the role and typical faults of PMSMs in elevator systems. Section 3 describes smart sensor technologies and data processing techniques. Section 4 discusses ML and DL approaches for fault diagnosis. Section 5 depicts the literature studied, Section 6 outlines current challenges and future trends, and Section 7 concludes the paper.

2. PMSM in Elevator Systems and Fault Types

Modern elevator systems use PMSMs as their traction units' core because these motors deliver the exact control and rapid response that vertical transportation demands. The brushless motor design together with magnetic excitation produces less mechanical stress and thermal wear leading to extended system lifespan and improved passenger comfort. The ability to operate effectively at low and zero speeds makes PMSMs particularly suitable for gearless elevator drives, especially in high-rise and high-traffic installations. The

integration of PMSMs with compact gearless machines has revolutionized elevator design because it decreases shaft space requirements and energy needs while providing user-specific acceleration and deceleration curves [46,47].

A standard PMSM includes a rotor part that contains permanent magnets either placed on its surface or inside the rotor while the stator contains three-phase windings. The synchronous torque results from the magnetic interaction between the rotor's permanent magnets and the rotating magnetic field produced by stator currents. Surface-mounted permanent magnets exist as an alternative to interior permanent magnets based on the specific requirements for torque-speed performance and structural robustness. The design process of elevators using PMSMs needs specific optimization of stator slot count and winding design and rotor shape parameters because these parameters affect torque density and efficiency and harmonic distortion [48]. Elevator control systems use field-oriented control (FOC) and direct torque control (DTC) strategies to achieve precise torque and speed control under both low-speed and zero-speed conditions. Advanced control methods are fundamental for elevator operation because they enable the fulfillment of safety and comfort requirements through accurate floor-level and smooth acceleration. The regenerative braking function in PMSMs enables energy retrieval during downward motion and deceleration which boosts system operational efficiency. The regenerative braking function increases power flow complexity while requiring advanced stability monitoring systems especially when dealing with changing load demands [49,50].

Elevators function under specific operational and mechanical requirements including repeated starting and stopping and changing weights and restricted spaces with restricted ventilation. The operating conditions create excessive pressure on motor systems that lead to faster degradation of components throughout time [51]. Although PMSMs deliver superior performance under these limitations, they face multiple faults which remain unidentified and endanger safety while causing operational losses and increased maintenance expenses [52]. PMSMs experience four distinct types of faults including electrical and mechanical together with magnetic and thermal faults. The electrical faults in PMSMs consist of short circuits in the stator winding and open-phase conditions as well as inverter malfunctions. The main mechanical faults in PMSMs consist of bearing degradation alongside rotor eccentricities which exist as static or dynamic or mixed types and misalignment problems. Thermal faults in PMSMs originate from overloading or inadequate heat dissipation but magnetic faults manifest as partial demagnetization and flux weakening [53,54].

The main faults found in elevator PMSMs consist of bearing degradation together with stator winding inter-turn short circuits (ITSC) and rotor demagnetization and eccentricity faults affecting electromagnetic symmetry and torque generation and vibration characteristics through harmonic distortions in current and vibration signals [55–57]. The detection of overlapping fault signatures in elevator operating regimes relies on time–frequency analyses together with spectral kurtosis and ML techniques for fault signature distinction. The safety-critical elevator environment benefits from recent advances which combine sensor fusion with edge computing to improve fault detection robustness and real-time capabilities [58,59].

2.1. Bearing Faults

Bearing faults represent one of the most prevalent mechanical failure modes in PMSMs used in elevator applications, where the vertical shaft loads, rapid directional changes, and frequent start–stop cycles induce complex stress patterns. Bearings endure axial thrust, radial forces, and vibrations that can accelerate the onset of surface fatigue phenomena such as pitting, spalling, and cracking. These defects progressively exacerbate friction

and vibration levels and often lead to localized heating, further compromising bearing integrity [60,61].

The characteristic frequencies indicative of bearing faults, including the ball pass frequency inner (BPFI), ball pass frequency outer (BPFO), fundamental train frequency (FTF), and ball spin frequency (BSF), appear as distinct spectral peaks or modulate the stator current through torque ripple effects [62]. These frequencies are crucial diagnostic markers for early fault detection. Modern diagnostics employ advanced signal processing techniques such as envelope detection, spectral kurtosis, and continuous wavelet transforms to isolate these fault signatures even amid the noisy operating environment typical of elevators [63–65]. Moreover, cyclostationary analysis (CySA) is effective in capturing periodic fault-induced modulations caused by load variations. Additionally, sensor fusion strategies combining accelerometer vibration data and motor current signature analysis (MCSA) enhance the robustness and reliability of fault detection under variable speed and load conditions [66]. These methods allow cross-validation of fault indicators, reducing false alarms.

The advent of ML techniques applied to extracted time–frequency features has further improved automated bearing fault classification and prognosis, supporting predictive maintenance frameworks crucial to minimizing elevator downtime. Techniques such as CNNs and SVMs have shown superior accuracy in identifying bearing fault severity levels [67], particularly in applications involving multichannel and multiscale CNN architectures coupled with SVM classifiers [68,69].

Early fault detection, especially through high-frequency current analysis and CySA methods, enables intervention before significant damage occurs, extending the service life of bearings and the PMSM system overall. Furthermore, the use of advanced acoustic emission techniques, infrared thermography, and piezoelectric sensor arrays provides complementary data to improve diagnostic coverage and reliability in identifying lubrication deficiencies or early surface degradation under elevator-specific operating regimes. Cloud-connected monitoring platforms, incorporating digital twins of PMSM assemblies, further enhance early warning capabilities through continuous anomaly detection, allowing real-time condition-based maintenance [70]. The integration of these technologies supports the development of intelligent maintenance strategies that proactively reduce unexpected motor failures and optimize elevator availability.

2.2. Stator Winding Inter-Turn Short Circuits

Inter-turn short circuits in stator windings occur when insulation between adjacent turns deteriorates or fails, creating localized current loops that generate hotspots, distort magnetic fields, and increase thermal stress. Such faults are particularly hazardous as they tend to escalate rapidly, often leading to catastrophic winding damage if not promptly identified [71,72]. The operational environment of elevators, with humidity and thermal cycling from frequent operation, further stresses insulation materials.

Early symptoms of these faults include increased phase current imbalance, heightened total harmonic distortion, and detectable asymmetries in negative sequence current components [34]. These asymmetries are effective indicators of insulation degradation and can be monitored continuously. Diagnosis typically leverages analytical techniques such as Park vector analysis to monitor current asymmetries, while time–frequency transforms, notably wavelet packet decomposition and the fast S-transform, isolate transient and non-stationary fault components under the variable operating regimes of elevators [73,74]. These methods enable the separation of fault-related frequency components from load-induced variations. Model-based observers and residual generation methods have also been developed to estimate the location and severity of inter-turn faults by comparing measured currents

with healthy baseline models [75]. Such observers include Kalman filters and Luenberger observers, which help detect subtle fault signatures in real-time [76]. Although few studies target elevator applications directly, several PMSM ITSC diagnosis investigations using extended Kalman filter (EKF), tooth-flux analysis, or high-speed parameter estimation provide applicable paradigms for elevator drives [77–79].

The application of DL, particularly CNN trained on raw or pre-processed current signal data, reduces the dependence on handcrafted features and enhances the sensitivity and accuracy of fault detection and classification [80]. These AI models adapt well to changing load and speed conditions common in elevator operation. Furthermore, integration of thermal monitoring with electrical diagnostics provides additional prognostic capabilities, correlating the development of thermal hotspots with electrical signature changes, which is vital for scheduling maintenance and preventing sudden motor failures [81]. Thermal imaging and distributed temperature sensing technologies offer spatially resolved temperature profiles critical for this task [82].

Recent trends in reinforcement learning have also been applied to real-time model calibration, improving inter-turn fault detection in PMSMs exposed to variable elevator load patterns. Online adaptive impedance tracking methods offer enhanced resolution of small insulation degradations before they evolve into full-scale winding faults. Combined electromagnetic–thermal finite element modeling (FEM) supports virtual prototyping of winding fault progression, helping refine early detection thresholds and calibration strategies [83]. These advancements contribute to more reliable condition monitoring and adaptive maintenance scheduling, reducing unplanned outages in elevator systems.

2.3. Rotor Demagnetization

Rotor demagnetization arises from thermal overstress, excessive current, mechanical shocks, or aging phenomena, which are of particular concern in elevator applications due to regenerative braking events, overloads, and constrained cooling conditions inherent in compact elevator machinery [84]. The demagnetization reduces the rotor’s magnetic flux density and back electromotive force (EMF), impairing torque production, increasing torque ripple, and diminishing efficiency [9]. Demagnetization faults can be uniform, affecting all rotor poles evenly, or localized, impacting discrete magnet sections. Uniform demagnetization generally manifests as a global reduction in torque, whereas localized demagnetization induces spatial harmonics in the magnetic field, producing torque oscillations and acoustic noise [85].

Detection methods focus on analyzing current signature distortions, such as increased negative sequence current components and reductions in fundamental frequency amplitudes [86,87]. These current-based indicators are sensitive to flux weakening effects. Direct flux measurement through embedded Hall sensors, when available, complements indirect approaches that employ magnetic flux observers based on state estimators or extended Kalman filters (EKF) to infer magnet health from electrical measurements [88]. These observers model the machine’s magnetic circuit dynamics to detect anomalies.

Recent trends integrate ML models trained on fused sensor data encompassing temperature, current, and vibration signals, enabling early and reliable identification of magnet weakening, supporting timely preventive maintenance actions [89–91]. Multisensor fusion enhances robustness against noise and operational variability. These methods are essential to mitigate unexpected PMSM failures and maintain elevator reliability and safety. Additionally, magnetic equivalent circuit (MEC) models allow for real-time estimation of magnet flux degradation, while harmonic power analysis in stator back-EMF measurements reveals early deviations from baseline magnetic behavior. Industry-specific developments have introduced neural-enabled edge devices capable of real-time demagnetization detection

during elevator travel profiles [92]. Recent IEEE studies propose combining back-EMF monitoring with phase difference analysis between flux and current vectors for enhanced sensitivity in non-salient PMSM topologies [93]. Integration of these advanced diagnostic methods into elevator condition monitoring frameworks ensures timely detection and reduces costly downtime.

2.4. Static and Dynamic Eccentricity

Eccentricity faults reflect geometric inconsistencies in the air gap between the rotor and stator, often stemming from shaft misalignment, bearing degradation, or manufacturing tolerances. These faults are categorized as static eccentricity, where the rotor's axis is displaced but stationary relative to the stator, dynamic eccentricity, where the rotor wobbles during rotation, and mixed eccentricity, combining characteristics of both [94,95]. Such irregularities disrupt the electromagnetic field distribution, generating characteristic harmonic sidebands in the stator current spectrum at frequencies determined by the pole-pair number, slot count, and slip frequency [96]. The complexity of eccentricity fault signatures is compounded by overlaps with other fault-induced harmonics, complicating precise diagnosis.

Spectral and time–frequency analysis methods, including Hilbert transforms and cyclo-stationary approaches, have been extensively employed to extract these components [97]. These techniques enhance fault component resolution under non-stationary operating conditions. Observer-based models such as extended Kalman filters and sliding mode observers effectively estimate eccentricity-induced flux perturbations and rotor position deviations, contributing to improved fault detection performance [98]. Complementary to these, zero-sequence voltage component analysis has also been shown effective in detecting various eccentricity types in PMSMs [99].

State-of-the-art signal processing tools, such as synchrosqueezing transforms and variational mode decomposition, provide higher resolution in time–frequency representations, enabling detection of subtle eccentricity features under the non-stationary and variable load conditions characteristic of elevators [100]. Complementing these, DL architectures trained on raw current, or vibration signals demonstrate superior ability to differentiate eccentricity faults from other defect types, enhancing classification accuracy and fault severity assessment crucial for condition-based maintenance [101].

Recent studies have also highlighted the value of quaternion signal representations in advanced signal processing. Miron et al. [102] provides a comprehensive theoretical overview of quaternion-based models and transformations, illustrating how such multidimensional representations can separate fault-related components in three-phase electrical machine systems. This forms a solid foundation for their potential adoption in eccentricity analysis of PMSMs. Furthermore, Li et al. [57] emphasize in their review that quaternion and other higher-dimensional signal processing techniques represent a promising research direction for future diagnostic frameworks, particularly for non-stationary and mixed-fault conditions in electric machines. As an additional practical perspective, Contreras-Hernandez et al. [103] demonstrate the effectiveness of quaternion signal analysis for broken-rotor fault detection in induction motors (IMs). Although the study focuses on IMs rather than PMSMs, it remains highly relevant since induction motors are still widely used in older elevator installations, which require continuous monitoring and frequent maintenance. This highlights that quaternion-based approaches are not only of theoretical interest but are already being applied to real industrial machines, reinforcing their suitability for future PMSM fault diagnosis in elevator applications.

In summary, the demanding operating conditions of elevator PMSMs necessitate advanced fault detection strategies to mitigate risks associated with bearing wear, inter-turn

winding faults, rotor demagnetization, and eccentricity. The continued evolution of signal processing techniques, combined with sensor fusion and AI, offers increasingly robust tools to identify faults at early stages and support predictive maintenance. Understanding the distinct manifestations and diagnostic signatures of each fault type is essential to developing comprehensive monitoring systems that ensure elevator safety, reliability, and operational efficiency.

Table 1 summarizes typical PMSM faults in elevator applications, presenting for each fault category the specific fault type, root causes, common symptoms, diagnostic approaches, and impact on elevator operation. This comprehensive overview highlights the relationships between electrical, magnetic, mechanical, thermal, and control-related degradations, enabling the systematic identification of diagnostic markers essential for condition monitoring and predictive maintenance strategies.

Table 1. Typical PMSM Faults in Elevator Applications.

Fault Category	Fault Type	Root Causes	Common Symptoms	Impact on Elevator Operation	Characteristic Diagnostic Method and Techniques
Electrical	Stator winding short circuit	Insulation degradation, thermal overload	Current imbalance, overheating	Sudden stop, increased energy loss	CSA, Thermal Imaging, Insulation Resistance Testing
Electrical	Open phase	Connector failure, wire breakage	Voltage drop, torque ripple	Reduced torque, Vibrations	Voltage and Current Monitoring, FSA, FFT
Electrical	Inverter fault	IGBT failure, gate driver malfunction	Irregular switching, noise	Motor stalling, control loss	PWM Signal Analysis, Oscilloscope Waveform Inspection, Harmonic Analysis
Mechanical	Bearing wear	Poor lubrication, contamination, fatigue	Vibration, noise, temperature rise	Vibration, potential motor seizure	Vibration Analysis (FFT, Time Waveform), Acoustic Emission Sensors, Thermography
Mechanical	Shaft misalignment	Improper installation, wear	Periodic vibration, load oscillations	Premature wear, loss of efficiency	Vibration Analysis, Shaft Position and Angular Displacement Sensors
Magnetic	Rotor demagnetization	Thermal stress, short-circuit Currents	Loss of torque, unsteady Operation	Reduced performance, control loss	CSA, Harmonic Analysis of Stator Currents, Magnetic Flux Sensors
Magnetic	Eccentricity (dynamic/static)	Manufacturing defects, bearing faults	Sideband frequencies in spectra	Vibration, rotor–stator contact	Spectral Analysis of Current and Voltage (FFT, Wavelet Transform), Observer-Based Models (EKF, SMO)
Thermal	Overheating	Overloading, cooling failure	Temperature rise, insulation degradation	Accelerated aging, risk of sudden motor shutdown	Infrared Thermography, Embedded Temperature Sensors, Thermal Cameras

Table 1. Cont.

Fault Category	Fault Type	Root Causes	Common Symptoms	Impact on Elevator Operation	Characteristic Diagnostic Method and Techniques
Sensor/Control	Encoder failure	Connector looseness, magnetic interference	Speed mismatch, erratic motion	Speed deviation, unsafe operation	Encoder Signal Monitoring, Redundant Sensor Cross-Checking, Signal Quality Analysis
Sensor/Control	Signal noise/interruption	EMC interference, cable degradation	Unstable speed or torque Readings	Control instability, fault triggering	DSP Filtering, Shielded Cable Inspection, Noise Analysis and Mitigation Techniques

The preceding analysis of stator, rotor, magnetic, and eccentricity faults demonstrates that each failure mode generates distinct yet sometimes overlapping signatures in stator currents, back-EMF waveforms, vibration spectra, or thermal profiles. At an incipient stage, these signatures are often weak and masked by load variations or environmental noise typical of elevator operation. Consequently, conventional diagnostic methods relying solely on steady state measurements frequently prove insufficient for reliable early detection. To overcome these limitations, modern condition-monitoring frameworks employ multiple sensors—current, voltage, vibration, flux, and temperature transducers—integrated with advanced signal-processing techniques. Methods such as spectral filtering, Hilbert–Huang and synchrosqueezing transforms, variational mode decomposition, and CySA provide high time–frequency resolution, enabling the isolation of fault-related components under non-stationary and variable load conditions. This pre-processing stage delivers clean and physically meaningful features that form the foundation for higher-level diagnostic tools, including ML classifiers and hybrid decision-making systems.

Table 2 provides an integrated mapping for elevator PMSM drives that links characteristic operating regimes to their most frequently observed fault modes, the corresponding signal-level signatures, preferred sensing modalities and input features, and the ML/DL families best suited for reliable detection. The mapping is intended as a practical decision aid for engineers and researchers: it shows which signals and features are most informative under each regime, and it indicates the ML/DL families that have demonstrated empirical suitability in the literature.

Recent research indicates that PMSM fault phenomena require strong sensing systems which operate with systematic signal conditioning. Multiple sensors consisting of high fidelity current and voltage sensors and thermal probes and vibration accelerometers and magnetic field sensors are needed to assess the health of PMSM. However, the analysis of noise and operational distortions and overlapping harmonics for accurate fault localization and severity estimation requires effective filtering and feature extraction methods for raw sensor outputs. Therefore, a solid framework for sensor deployment and signal conditioning must be established before studying data-driven and machine learning-based fault classification strategies. The following Section 3 explains sensing technologies and signal processing methodologies that enable precise fault feature identification to support intelligent diagnostic models. So, in Section 4 advanced ML Techniques for PMSM fault detection are examined with high-quality physically relevant data instead of unprocessed signals to produce reliable and actionable condition monitoring systems for elevator systems.

Table 2. Diagnostic Mapping for Elevator PMSM Operating Regimes.

Operating Regime	Typical Faults	Signal Signatures	Sensors/Input Features	Recommended ML/DL Techniques
Frequent start–stop cycles	Torque ripple, partial demagnetization	Torque oscillations, phase current distortion	Current, magnetic flux	CNN, LSTM, 1D-CNN+attention
Low-speed operation	Eccentricity, shaft misalignment	Air-gap flux harmonics, radial vibration peaks	Vibration, acoustic	SVM, RF, Decision Trees
Regenerative braking	Thermal stress, insulation degradation	Temperature rise, negative torque spikes	Thermal sensors, current	RNN, GRU, hybrid CNN-LSTM
High-load peak operation	Bearing defects, stator inter-turn faults	High-frequency AE, current envelope modulation	Acoustic emission, current	GAN, Autoencoders, Spectral clustering
Long idle periods	Moisture ingress, corrosion	Drift in impedance, insulation degradation patterns	Impedance, partial discharge	Bayesian networks, Anomaly detection (AE-based)

3. Smart Sensors and Signal Processing

The reliable condition monitoring of PMSMs in elevator applications requires an integrated framework combining high fidelity sensing hardware, standardized installation practices, and advanced signal processing. Low speeds combined with start–stop operations and variable load profiles and regenerative braking in elevator PMSMs create nonstationary dynamics that make fault detection more challenging than in steady state industrial drives. Modern monitoring systems use smart sensors that include current, voltage, vibration, temperature and magnetic field probes to capture robust data in situations with limited shaft access and compact machine dimensions.

Standards like ISO 10816-3/ISO 20816-1 [104,105] for vibration evaluation, ISO 13373-3 [106] for condition monitoring of rotating electrical machines and IEC 60034-1/IEC 60034-25 [107,108] for electrical machine thermal performance establish both installation and measurement protocols. Sensor selection combined with proper placement and calibration is essential for achieving diagnostic sensitivity towards stator inter-turn faults and bearing degradation and rotor demagnetization and eccentricity. The signals must first undergo pre-processing steps including filtering and normalization and synchronization and feature extraction to eliminate noise and operating point dependence for ML model usage described in Section 4.

3.1. Sensor Specifications, Placement and Integration

Accurate and reliable condition monitoring of PMSMs used in elevator systems requires precise deployment of various sensor technologies. The raw signals used for diagnosis stem from these sensors representing the essential components of the acquisition chain. The operational requirements of elevator motors require a specifically designed sensing approach because they operate at low to medium speeds with many start and stop cycles and need to produce high torque. This section provides an in-depth analysis of sensor types along with their operational principles and placement methods and integration challenges and trade-offs that occur in elevator systems.

- Current and Voltage Sensors.

The electrical performance of PMSMs provides essential information about their condition status. Multiple electrical faults including inter-turn short circuits and inverter-induced harmonics and demagnetization can be detected through continuous monitoring of three-phase stator currents and supply voltages. Hall-effect sensors and Rogowski coils and current transformers (CTs) and voltage dividers represent the common sensor technologies

used for these applications [109,110]. The IEC 61869 [111] standard for low-voltage AC and DC measurements defines Hall-effect or fluxgate current transducers that function at inverter outputs or motor terminals to deliver precise phase current waveforms [112]. The sensors provide both galvanic isolation and fast dynamic response along with compact dimensions but require proper management of saturation effects and thermal drift impacts.

The Rogowski coils serve best when applications need both wide bandwidth and high linearity to detect fast-switching anomalies from inverters [113]. The non-saturable core structure of these coils makes them suitable for retrofit installation in small motor control enclosures typical of elevator systems. The DC link stability and insulated gate bipolar transistor (IGBT) or SiC-based inverter switching performance can be monitored using capacitive or resistive voltage sensors. The voltage measurements help detect inter-turn short circuits through sequence component analysis and identify inverter switching faults by examining pulse shape distortions [114].

The signal quality of voltage dividers requires proper insulation and filtering to suppress high-frequency noise while preventing PWM switching transients from damaging the signal. The selection of measurement bandwidths must focus on the highest frequency component of interest which reaches into tens of kHz range to detect high-frequency inverter harmonics that could hide or simulate fault signals.

Sensor placement is also pivotal. The inverter output or motor terminals serve as common locations for installing current sensors to detect supply-side and motor-side anomalies. Placing sensors in positions that avoid both common-mode interference and magnetic coupling from power cables is essential. Elevator machine rooms require shielded enclosures and twisted-pair wiring to preserve signal integrity because of their high electromagnetic noise levels [115].

- **Vibration and Acoustic Sensors.**

PMSMs show mechanical degradation through bearing defects and rotor unbalance and shaft misalignment by producing distinct acoustic signatures and vibrations. The main tool for measuring mechanical oscillations is accelerometers. The two prevailing technologies in sensor manufacturing are micro-electro-mechanical systems (MEMS) and piezoelectric sensors. MEMS accelerometers are perfect for embedded condition monitoring modules because they offer small size, low power usage and multi-axis detection capabilities [116]. These devices have restricted bandwidth and reduced sensitivity which prevents their usage in detecting low-frequency faults.

The wide frequency response (0.5 Hz to several kHz) and high sensitivity of piezoelectric accelerometers allow users to detect high frequency bearing fault signatures including BPFO and BSF. The sensors need proper surface preparation before mounting them to bearing housing or motor end-shields using stud mounting or adhesive methods according to ISO 10816 and ISO 20816 guidelines for vibration measurement.

The space-constrained elevator environment makes MEMS-based wireless vibration sensors a suitable choice because they can be mounted within the shaft or placed above the cabin. The units come with built-in preprocessing functions and wireless communication capabilities but require proper management of battery duration and electromagnetic interference (EMI) sensitivity. The study by Hassan et al. [117] present an extensive evaluation of different vibration sensors that helps define their strengths and weaknesses in industrial operations to develop optimal predictive maintenance protocols for PMSMs used in elevator systems.

Acoustic sensors alongside vibration monitoring tools are becoming more popular for condition monitoring systems. Sensors use their ability to detect airborne sound waves that stem from mechanical interactions as well as friction and cavitation and fluid turbulence. PMSMs produce unusual acoustic emissions that stem from deteriorated

bearings and rubbing stator–rotor interfaces together with loose structural elements. The 20 kHz to 100 kHz frequency range of ultrasonic sensors makes them effective at detecting high-frequency stress waves indicating early-stage bearing defects and arcing in electrical contacts [118].

The combination of acoustic sensing allows fault detection without physical contact while supporting vibration data when sensor installation becomes difficult or physical contact becomes undesirable. The installation of acoustic sensors within elevator machine rooms and near shafts enables the detection of motor and auxiliary component anomalies including brake, pulley and guide shoe malfunctions. Vibration-acoustic channel fusion enhances fault detection precision and localization accuracy in nonstationary loading scenarios [119].

- Temperature Sensors.

The dual function of temperature monitoring in PMSMs includes identifying excessive heat because of overloading or insulation deterioration while offering necessary context for interpreting sensor data. Temperature sensors use three main types which include Resistance Temperature Detectors (RTDs) and negative temperature coefficient (NTC) thermistors and thermocouples. Pt100 and Pt1000 RTDs represent popular choices because they offer high precision along with excellent repeatability between $-50\text{ }^{\circ}\text{C}$ and $+250\text{ }^{\circ}\text{C}$ and are used to monitor winding temperature directly from the stator windings for early insulation aging and thermal overload detection. Thermocouples with types K or J operate at high temperatures better than other options and are commonly attached to motor housings or bearings. According to Mohammed and Djurović [120], the conventional RTD and thermocouple approaches fail to detect localized hot spots in the winding structure thus driving the development of advanced techniques including Fiber Bragg Grating (FBG) based sensing for complete in situ thermal monitoring. Direct measurement of rotor surface temperature presents practical challenges, so temperature estimation methods are commonly used to protect rotor magnets from demagnetization. A flux observer-based rotor temperature estimation model for PMSMs in EV applications was developed by Arjun and Binoj Kumar [121] which they integrated into a MATLAB simulation-validated demagnetization prevention control scheme.

The standard ISO 18436-7:2014 [122] provides guidelines for personnel qualification and interpretation of infrared thermal imaging within machine condition monitoring using thermography techniques.

Thermal sensors like RTDs and thermocouples and infrared thermopile sensors monitor winding hot spots and bearing temperatures but lack the ability to detect localized hotspots within the winding. The dynamic thermal behavior of motors operating under elevator duty cycles (short acceleration and deceleration and idle periods) needs high sampling rates and precise interpolation methods to detect swift temperature changes. The quick increase in winding temperature during upward acceleration indicates two possible problems: higher core losses or demagnetization in its initial stages. The diagnostic reliability improves through the combination of thermal measurements with vibration and current analysis. Distributed temperature sensing systems with fiber optic sensors track the entire stator winding continuously to detect insulation degradation issues before they become severe [123].

- Magnetic Field and Flux Sensors.

Partial demagnetization together with eccentricity and inter-turn shorts in PMSMs produces magnetic asymmetries affecting the flux distribution pattern. These anomalies become detectable by using hall-effect probes together with search coils and fluxgate sensors which function as magnetic field sensors. Hall-effect probes function as magnetic

field sensors when placed in air gaps or near stator teeth to detect spatial non-uniformities in magnetic flux density while providing localized magnetic field measurements. Search coils, typically wrapped around stator teeth or along the air-gap perimeter, are particularly useful for measuring time-varying flux linkages and dynamic magnetic phenomena under varying load conditions [124].

The combination of flux sensors with MCSA [125] enables advanced fault diagnosis techniques and the extraction of fault signatures from electromagnetic signals through sophisticated demodulation methods using phase current measurements [126,127]. The implementation of flux sensors into motor monitoring systems needs careful EMC design along with precise calibration procedures. The system uses this method to differentiate actual fault-related flux variations from inverter-generated electromagnetic interference as well as measurement system artifacts. The use of differential sensor arrangements together with digital compensation algorithms improves measurement fidelity by enhancing sensitivity while effectively eliminating common-mode noise and external disturbances [128].

Elevator PMSMs particularly benefit from distributed flux sensor arrays because these systems can detect spatially resolved magnetic flux anomalies. The high spatial resolution provides exceptional advantages in detecting faults caused by rotor or stator eccentricity because it allows for precise identification of uneven flux density patterns along the stator periphery thus enabling early fault detection and maintenance planning.

- Encoder: Position and Speed Sensors.

A PMSM requires rotor position and speed information for motor control operations while these signals serve as a basis for advanced analysis methods like order tracking and synchronous demodulation and phase-resolved analysis and time–frequency transformation precision. The precise measurement of rotor kinematic data improves diagnostic signal value through phase alignment and rotational referencing techniques for current and vibration and flux signals. The three primary types of rotor position and speed sensors deployed in PMSM-based elevator systems consist of encoders (optical and magnetic), resolvers and sensorless estimators. The performance characteristics together with environmental tolerances and integration requirements differ between each technology [129,130].

Optical encoders consist of a rotating disc with precisely etched patterns (e.g., lines or slots) and an array of photodetectors that transform mechanical rotation into high-resolution electrical pulses. The relative movement information from incremental optical encoders differs from absolute encoders which produce distinctive binary codes for each shaft position to prevent post-power-up homing. Elevator applications typically use high-resolution encoders (up to 10,000 pulses per revolution) for achieving precise cabin leveling and maintaining smooth speed profiles. A quadrature signal enables effective angular resolution below 0.01 degrees through resolution increase by a factor of four. The optical path of optical encoders becomes blocked by contaminants like dust and oil making their performance decrease when the mechanical alignment becomes misaligned. The sensors need rigid mechanical connection to the shaft along with environmental protection mainly for top-of-cabin and shaft-mounted installations found in elevator motors [131].

Magnetic encoders measure position data by employing a rotating magnet together with Hall-effect or magneto-resistive sensors. These devices prove superior against harsh and confined operating conditions and contaminants thus they work best for demanding elevator systems. The resolution of magnetic encoders measures between 256 and 1024 PPR yet modern interpolation techniques boost their effective precision level. The advantages of magnetic encoders become most evident in applications that involve gearless elevator motors and tight spaces with high vibration and temperature fluctuations [132].

Resolvers operate as rotary transformers to generate sinusoidal voltages representing shaft position data in an analog format. These devices demonstrate outstanding ruggedness

and immunity to electromagnetic interference and maintain reliable operation across temperatures ranging from $-55\text{ }^{\circ}\text{C}$ to $+155\text{ }^{\circ}\text{C}$. The native resolution of these devices remains average, but they deliver absolute position feedback with instant data delivery and no signal failures. RDCs process resolver signals to convert them into digital format. The motor drives often contain RDCs for resolver signal processing. Safety-critical elevator systems choose resolvers because they demonstrate high reliability. Recent improvements in resolver design now include optimized variable reluctance resolvers with three-phase symmetrical winding for better accuracy and reliability [133].

Back-EMF sensing along with sliding mode observers and Model Reference Adaptive Systems (MRAS) enable motor terminal quantity analysis to determine rotor position and speed without physical sensors. The combination of full-order sliding-mode observer (IFSMO) with phase-locked loop technology has been proposed to improve estimation accuracy [134]. Additionally, a sliding mode position observer for surface-mounted permanent magnet synchronous motors (SPMSMs) has been developed, employing a complex coefficient low pass filter (CCLPF) to extract the electromotive force (EMF) [135]. These methods eliminate the need for physical sensors, reducing hardware cost and complexity. However, they typically suffer from degraded accuracy at low speeds and during standstill—conditions frequently encountered in elevator start–stop cycles. Therefore, sensorless control is better suited to supplementary monitoring rather than as a primary diagnostic input in elevator applications.

The integration of position and speed data with other sensor channels including current and vibration and flux requires precise synchronization for advanced diagnostic algorithms to function correctly. The execution of order analysis together with time-synchronous averaging needs angular referencing for precision. BiSS-C and EnDat and SSI are serial encoder feedback protocols that offer high-speed real-time serial communication through built-in error correction and synchronization features.

IEC 60034-8 (Terminal markings and direction of rotation) [136] and IEC 61800-5-2 (Adjustable speed electrical power drive systems) [137] establish international standards for drive system integration of speed feedback by defining requirements for safety features and redundancy and environmental requirements. Position and speed sensors serve both to control stability and fault anticipation in predictive maintenance systems because they detect changes in deceleration profiles and torsional oscillations and load inertia signals that indicate mechanical deterioration.

- Installation and wiring considerations.

The success of condition monitoring sensors in PMSM elevator systems relies heavily on proper installation along with high-quality wiring infrastructure to maintain accurate and interference-free operation. The incorrect handling of cables leads to electrical noise generation which damages signal quality while hiding the faint signs of impending faults in bearings and demagnetization and inter-turn issues.

Sensor cabling requirements follow IEC 60204-1 [138] because it establishes safety guidelines for machine electrical equipment including wire safety rules and overcurrent protection and cable path directions and connector standards. The standards IEC 61000-6-2 [139] and IEC 61000-6-4 [140] define electromagnetic compatibility (EMC) immunity and emissions, respectively, for industrial environments. Sensor signals remain unaffected by external interference according to these standards while the monitoring system maintains immunity to EMI for nearby equipment.

The industrial standard for analog and digital signal transmission through current, vibration, temperature and flux sensors use shielded twisted pair (STP) cables. The twisted design of these cables minimizes differential-mode noise while shielding materials like foil or braid defend against external electromagnetic interference. Coaxial cables provide the

best solution when high-frequency operation or sensitive voltage measurements require better impedance matching along with superior shielding capabilities. The essential grounding step needs to follow either single-point or star-grounding methods to stop ground loops and common-mode noise from occurring. Diagnoses such as sideband modulations and transient spikes become undetectable due to poor grounding that causes voltage offsets or oscillations to mask these features [141].

The compact nature of elevator cabling routes requires sensors to be installed in challenging areas including machine rooms and shafts and the top of the cabin. The requirements for these applications need industrial-grade connectors that withstand mechanical vibrations and work across broad temperature ranges from -25°C to $+80^{\circ}\text{C}$ while achieving IP65 or higher ingress protection ratings. The connectors require locking systems such as M12 or bayonet connectors to stop vibration-induced connection loosening during repeated elevator movements. Wireless sensor implementations need local shielding together with RF coexistence planning to prevent interference from Wi-Fi as well as elevator control electronics and power electronics. Both wired and wireless systems need strain relief along with mechanical cable fixation to stop fatigue-related failures during extended operation.

The signal cables need to follow a separate path from power cables to minimize both capacitive and inductive coupling effects. Any unavoidable cable crossing must happen at a 90-degree angle. The cable trays must serve as protective devices against physical damage and should be made of non-conductive materials when installed near inverter heat sinks or EMI sources. Standard-compliant cabling combined with proper layout and environmental hardening approaches provide the essential requirements for maintaining long-term reliability and diagnostic sensitivity of condition monitoring systems in elevator PMSMs.

3.2. Signal Acquisition and Transmission

Properly installed sensors need to have their signals collected and synchronized before transmission and buffering for PMSM condition monitoring to work effectively. Elevator systems impose special operational demands because they have limited installation space and generate strong electromagnetic interference while requiring critical safety operation and fast data processing. Signal acquisition systems require a design that incorporates both high temporal resolution and noise immunity and flexible data communication functions.

- Synchronized Sampling and analog-to-digital conversion (ADC).

The foundation for signal fidelity depends on collecting high-quality samples. The complete set of sensor data including currents, voltages, vibrations, temperatures and magnetic fluxes needs to be sampled at frequencies that maintain fault-related information. The sampling frequency for data collection depends on the Nyquist criterion but engineers choose it based on expected harmonic or transient signatures. The sampling rate needed for bearing fault vibration signal detection reaches 10–20 kHz while current-based demagnetization detection requires sampling at 50–100 kHz. The sampling process requires both high sampling speeds and sufficient resolution from analog-to-digital converters (ADCs). The detection of low-amplitude fault signatures requires converters with at least 16-bit resolution for accurate measurement in noisy dynamic ranges [120].

The success of multi-sensor fusion depends on synchronized sampling. Multiple sensors need to capture their data at the same phase to perform valid correlation analysis. The time alignment between current signals and vibration signals becomes necessary to perform order analysis and time-synchronous averaging procedures. The phase mismatch becomes problematic during transient events (e.g., elevator start-stop or load reversal) because it hides fault indicators [142]. Advanced acquisition systems rely on simultaneous sampling ADCs together with time-interleaved conversion schemes and hardware-level

synchronization through shared clocks or triggers. IEEE 1588 [143] Precision Time Protocol (PTP) enables distributed sensors in elevator installations to achieve microsecond-level synchronization through systems that implement it.

- Edge Processing and Local Buffering.

Embedded microcontrollers or DSPs (Digital Signal Processors) serve as processing units that reside near sensors or inverter cabinet locations within elevator systems. The edge units perform first-level data processing which includes:

1. Analog filtering (anti-aliasing)
2. Signal scaling and normalization
3. Threshold-based event detection
4. Data compression using techniques like delta encoding or lossless Huffman

The nearby processing of data at the edge of the system decreases transmission bandwidth needs while enabling immediate fault detection to trigger warning systems before damage spreads. Local edge processing enables envelope detection or energy computation on vibration and flux signals according to [144,145]. Local buffering techniques using ring buffers and FIFO stacks maintain data integrity by preventing losses during network delays together with host system delays. Some edge devices extract features such as RMS and kurtosis and crest factor from data before sending summarized health indicators to the central controller according to [4].

- Communication Protocols and Data Transmission.

The reliable transfer of Condition monitoring data must reach a central processing unit which includes PLCs, PCs or cloud nodes for advanced analysis. The selection of communication protocol depends on the amount of data being transmitted and the need for real-time data transfer as well as the system architecture.

The industrial Ethernet protocols EtherCAT and PROFINET together with Modbus TCP provide high-speed deterministic communication that allows synchronized control of large sensor arrays. These protocols support real-time diagnostics and are widely adopted in elevator control systems. Modern systems implement Time Sensitive Networking (TSN) extensions to provide bounded latency and time-aware scheduling capabilities.

Fieldbus protocols including CANopen and RS-485 continue to be widely used in budget-friendly equipment replacements, but they operate at lower speeds (below 1 Mbps) with restricted network structures. The CAN-based systems demonstrate resistance to electromagnetic interference while supporting communication between multiple nodes through prioritized message processing [146].

Modern elevator monitoring systems adopt wireless communication for vibration and acoustic sensor applications that need placement in difficult-to-reach components (cabin, guide rails). The wireless technologies IEEE 802.15.4 (ZigBee), LoRa and BLE provide short-range communication while using low power consumption. The implementation of wireless communication systems demands thorough planning to eliminate interference while ensuring redundancy and power management systems [147].

Every transmission system needs to support error detection through CRC together with retry functions and secure authentication methods regardless of the communication medium. Higher-layer integration occurs through OPC UA MQTT or RESTful APIs that enable SCADA system and cloud service interoperability [148].

- Cloud Integration and Remote Monitoring.

The use of cloud platforms by elevator fleet management allows organizations to perform centralized health assessments and long-term trend analysis and AI-based diagnostics.

Multiple elevators spread across buildings or locations transmit their data through secure HTTPS over LTE/5G or wired backbones using gateways for aggregation.

Cloud-based systems enable the use of scalable computing power for detecting patterns and recognizing anomalies and performing predictive maintenance [149]. Edge-to-cloud data pipelines include:

1. Data preprocessing at edge;
2. Secure data encryption and transmission;
3. Temporary cloud buffering and storage;
4. Server-side analytics and visualization dashboards.

Cloud monitoring demands bandwidth-efficient methods which include sending events instead of waveforms and adaptive sampling or diagnostic feature uploads [144,150,151].

- Cybersecurity and Data Integrity

The rise in connected systems makes cybersecurity an absolute necessity. Operational schedules along with energy profiles and failure signatures present in sensor data make them vulnerable to exploitation attempts. IEC 62443 [152] (Industrial cybersecurity) standards enable compliance through:

1. Role-based access control;
2. Device authentication using certificates;
3. End-to-end encryption (e.g., TLS 1.2+);
4. Audit logging and firmware integrity checks.

Security breaches in elevator systems result in both operational risks and data theft incidents. Network monitoring systems need to operate independently from control logic while implementing intrusion detection systems (IDS) and fail-safe mechanisms [153].

3.3. Data Processing

To facilitate reliable ML and statistical modeling, signal processing must not only enhance relevant patterns but also compress and standardize diverse sensor inputs into interpretable forms. Once the sensor data has been successfully acquired and transmitted, the final critical stage in the condition monitoring pipeline is the transformation of raw signals into meaningful indicators of motor health. This transformation process—commonly referred to as signal processing or feature engineering—serves to isolate, enhance, and quantify the latent information embedded in noisy, multi-dimensional sensor outputs.

Elevator PMSMs present unique signal processing challenges due to their low operational speeds, frequent acceleration/deceleration events, and variable loading conditions. These factors render many classical signal analysis methods ineffective or unreliable. As such, advanced data processing pipelines must incorporate robust preprocessing, spectral and time–frequency analysis, feature extraction, and dimensionality reduction techniques tailored for nonstationary and transient operating regimes. Moreover, the ultimate goal of signal processing in this context is to generate compact, discriminative feature vectors that can feed into intelligent diagnostic and prognostic models. These models—often based on statistical learning or deep neural networks—depend on the quality and relevance of the extracted features. A well-designed signal processing architecture can significantly improve fault detectability, reduce false alarms, and enable early-stage anomaly detection under real-world elevator conditions.

The following subsections detail the core stages of the signal processing workflow.

3.3.1. Preprocessing

Preprocessing is the initial step in the transformation of raw sensor signals into analyzable data. The goal of preprocessing is to remove irrelevant information, correct distortions,

and standardize signals across varying operating conditions, thereby enhancing the reliability of subsequent analyses.

Step 1: Filtering

Real-world signals are invariably corrupted by noise, power-line interference, and irrelevant frequency components. Filtering is essential to suppress these unwanted elements while preserving the diagnostically relevant content of the signal. Depending on the nature of the fault and the sensor type, several filtering strategies are employed:

- **Bandpass Filters:** These isolate a narrow frequency range where fault-related signatures, such as bearing defect harmonics or rotor imbalance tones, are expected to occur. The filter's center frequency and bandwidth must be tuned according to motor speed and the specific mechanical resonance frequencies [154].
- **Notch Filters:** Used to eliminate dominant spectral components, especially the 50/60 Hz power supply fundamental and its harmonics. Removing these frequencies improves the visibility of low-energy fault modulations often buried beneath power line noise [155].
- **Butterworth Filters:** A widely used IIR filter known for its maximally flat frequency response in the passband. It is particularly suitable when signal fidelity and smooth transition between passband and stopband are important, such as in current signature analysis. Low-pass Butterworth filters are commonly used to isolate slow-varying trends, while high-pass versions help reveal impulsive fault transients [156].
- **Gaussian Filters:** These FIR filters are used for smoothing and noise reduction, especially when preserving the general shape of a signal is critical. Gaussian filters are highly effective in pre-filtering vibration or temperature signals prior to applying spectral or time–frequency transforms [157].
- **Kalman Filters:** Kalman filtering provides optimal recursive estimation of the true signal in the presence of Gaussian noise, based on a predictive model. It is particularly effective in real-time systems, such as when tracking slowly varying trends in temperature or shaft speed data during elevator duty cycles. Kalman filters can track changes even when direct measurements are incomplete or corrupted by noise [158,159].
- **Extended Kalman Filter (EKF):** A nonlinear extension of the Kalman filter, the EKF is often used for estimating system states such as rotor position or flux linkage in sensorless PMSM control. In condition monitoring, it can assist in reconstructing fault-relevant states that are not directly measurable, enabling advanced diagnostics under dynamic conditions [160,161].
- **Wavelet-based Filters:** DWT and wavelet packet transform (WPT) allow decomposition of signals into time–frequency bands. By thresholding or reconstructing selected components, wavelet filtering provides effective suppression of non-stationary noise while retaining transient fault features [162,163].
- **Median Filters:** Particularly useful for removing impulse-like noise from vibration signals, median filters replace each sample with the median of neighboring values, preserving edges while eliminating spikes.
- **Savitzky–Golay Filters:** Polynomial smoothing filters that preserve peak shape and width, ideal for preprocessing signals prior to envelope extraction or demodulation [164].
- **Adaptive Filters:** Implemented using LMS (Least Mean Squares) or RLS (Recursive Least Squares) algorithms, these filters dynamically adjust their coefficients to track and suppress time-varying noise patterns. They are valuable in elevator environments where inverter switching patterns or load profiles fluctuate unpredictably [165].
- **Hybrid Filtering Schemes:** In practical implementations, a combination of the above filters is often used. For example: A Gaussian low-pass filter followed by a wavelet-based denoiser can reduce high-frequency switching noise and retain transient impulses. A

Butterworth notch filter may be used in cascade with an adaptive RLS filter to eliminate both power-line interference and inverter harmonics. Kalman filters may run in parallel with static filters for trend estimation and real-time correction [4,25,166].

Filtering can be performed in either the time domain (e.g., convolution, recursive algorithms) or frequency domain (e.g., FFT-based spectral masking). Depending on system architecture, filtering may be applied: Directly in the analog domain (at sensor or signal conditioning level), Digitally within edge-processing units, or as part of centralized post-processing after acquisition. The choice and tuning of filtering approaches must consider the type of signal, the nature of the target fault, real-time constraints, and the computational capabilities of the embedded or cloud-based system.

A wide range of filtering techniques are available, each offering distinct advantages and limitations in addressing noise, interference, and fault signature preservation. Table 3 summarizes and compares the most used filters in PMSM condition monitoring, highlighting their typical application domains, key strengths, and practical challenges. This comparative overview supports the informed selection of appropriate filtering strategies based on the specific signal characteristics and elevator operating conditions.

Table 3. Comparative Overview of Common Filtering Techniques.

Filter Type	Application Area	Strengths	Limitations
Bandpass	Bearing faults, rotor Imbalance	Isolates fault-specific frequency bands	Requires precise tuning for motor speed and fault harmonics
Notch	50/60 Hz suppression, inverter noise	Removes dominant interference tones	May also suppress nearby fault-related content
Butterworth	Current signal smoothing, envelope analysis	Flat response, stable behavior in passband	Slower roll-off outside cutoff frequencies
Gaussian	Vibration and thermal signals	Smooths noise while preserving waveform shape	Not ideal for sharp transients or impulsive features
Kalman	Speed, temperature, flux trend estimation	Optimal estimation under Gaussian noise; real-time capable	Requires accurate system model, assumes noise statistics
Extended Kalman (EKF)	Rotor position, flux in sensorless PMSM	Handles nonlinear system dynamics	Computationally demanding; complex tuning
Wavelet	Transient and modulated signals	Excellent time–frequency localization; multiscale analysis	Requires selection of appropriate mother wavelet
Adaptive (LMS/RLS)	Inverter switching noise, variable loads	Adapts to dynamic noise environments	High computational demand, risk of misadaptation
Hybrid Filtering	Mixed or complex signal environments	Combines advantages of multiple methods	Increased design and parameter complexity

Step 2: Normalization and Denoising

Normalization ensures that the amplitude of sensor signals remains within a common scale, allowing for meaningful comparison across different operating points. For example, vibration amplitudes may be normalized with respect to the RMS level during steady-state operation, while current signals may be expressed in per-unit (p.u.) values relative to rated current [167].

Denoising techniques go beyond simple filtering by attempting to extract clean signal representations from noisy observations. Popular denoising methods include (a) Wavelet thresholding, where wavelet coefficients below a certain threshold are set to zero, and (b) EMD, which decomposes the signal into Intrinsic Mode Functions (IMFs) for subsequent filtering or reconstruction. Recent ML-based denoising methods, such as the

denoising universal domain adaptation network (DUDAN), have demonstrated effective removal of noisy samples while aligning fault-relevant features across domains, improving PMSM fault diagnosis under varying operating conditions [168]. These methods are particularly effective in retaining transient or impulsive components characteristic of early-stage mechanical or electrical faults.

Step 3: Synchronization and Resampling

For accurate fault analysis, signals from multiple sensors must be temporally aligned. This is especially true for PMSMs, where rotor position and shaft speed can vary significantly during a single elevator run. Synchronization typically involves aligning signal windows based on encoder pulses, zero-crossing events, or shaft rotation indices [169].

Order tracking is a key resampling technique that transforms time-domain signals into the angular domain. By re-referencing signal samples to mechanical shaft angle rather than time, it eliminates smearing effects caused by speed fluctuations. This allows for clearer visualization of periodic fault features, such as those due to bearing defects, even during acceleration or deceleration events. In PMSMs, where speed variations and mechanical faults can significantly affect spectral analysis, order tracking is a critical tool for avoiding distortion of fault-related features [170]. Beyond conventional approaches that rely on tachometer or encoder signals, modern tacholess order tracking techniques enable temporal alignment and the extraction of periodic fault signatures without additional sensors [171].

Together, these preprocessing steps lay the foundation for accurate spectral, statistical, and ML-based fault detection workflows.

3.3.2. Frequency–Domain Analysis

Frequency–domain analysis stands as a fundamental tool for assessing the status of PMSMs. The analysis through frequency-domain helps engineers detect periodic patterns and harmonics together with minimal frequency components which normal time-domain signals conceal. The analysis of signals through spectral decomposition reveals initial indications of electrical and mechanical failures.

Elevator PMSMs pose challenges for frequency-domain analysis. The frequent start–stop operation together with variable speed profiles of these motors creates non-stationary signals that present analysis challenges. The operational effectiveness of classical techniques needs specific adaptation to handle these dynamic conditions.

The FFT represents the primary spectral method used for analysis. The process converts time-domain information into a frequency spectrum that shows both harmonic components and their intensity levels [172]. The application of FFT to motor current signals in elevator systems enables the detection of broken rotor bars by showing symmetrical sidebands surrounding the supply frequency. Vibration analysis of bearings produces frequency components which derive from rolling element geometry and shaft speed through BPFO and BPFI [173]. The common fault of static or dynamic eccentricity produces asymmetrical air gap conditions increasing energy at specific harmonic orders. The magnetic flux distribution changes in partial demagnetization of the rotor tend to decrease the amplitude of specific high-frequency harmonics.

The FFT method works under the assumption that all signal components stay stationary during the analysis period. The true condition of elevator operations stands in opposition to this assumption particularly during acceleration and re-generative braking phases. The process of spectral smearing occurs when fault components spread throughout the frequency domain because of which identification becomes more challenging [174].

The STFT serves as a solution for handling nonstationary signals. Each portion of the signal receives FFT processing after being split into small segments which overlap each other. The resulting output takes the form of a spectrogram which displays how the signal's

frequency components transform throughout time [175]. STFT enables elevator systems to detect brief inverter faults generating high-frequency bursts during speed ramp operations. The technique enables rotor unbalance detection through subharmonic energy surges and mechanical impacts resulting from door movements and platform misalignments. The main drawback of STFT lies in its constant time–frequency resolution. Time-localization improves with shorter windows, yet frequency precision suffers as a result. Time resolution improves while frequency resolution worsens with longer windows. The trade-off between time resolution and frequency resolution affects the instrument’s ability to detect specific fault types.

WT removes this problem through its flexible resolution system and gives excellent time precision for high-frequency data points and outstanding frequency precision for low-frequency data. Through the DWT a signal split into two distinct components including detail and approximation coefficients. The multi-resolution structure of this method allows it to detect brief high-frequency transients which arise from bearing damage. The wavelet method shows effectiveness in spotting stator winding inter-turn faults because these faults create sudden and localized current waveform variations. The detection of transient bursts that occur during motor startup or gear engagement proves effective through this approach. The continuous wavelet transform (CWT) provides advanced detail at the expense of requiring more computational power. The selection of an appropriate wavelet basis function determines how well wavelet methods perform in fault detection. Among the wavelet families used for fault detection Daubechies, Symlet and Morlet wavelets are most frequently applied because they excel at different fault patterns [176].

The speed variability of elevator motors makes frequency-based fault detection methods less effective. Order analysis solves this problem by resampling the signal based on the shaft’s angular position. Spectral components become assessable through rotational orders instead of fixed frequencies. Order tracking serves as a powerful tool to detect faults which rotate with the shaft including unbalance, misalignment and gear meshing problems. This detection method enables fault identification throughout speed variations because fixed-frequency methods become ineffective. The combination of accurate encoder feedback with high resolution allows signal resampling which preserves rotational resolution across all motor speed changes.

Cepstrum analysis proves to be another robust tool when dealing with modulated signals. The process begins with taking the logarithm of the magnitude spectrum followed by an inverse FFT application. The spectrum shows periodic structures through cepstrum analysis that normally remain invisible to observation. The periodic impulses produced by bearing faults cause signal modulation to appear. Regular peaks appear in the cepstrum because of modulation. The quefrency domain reveals patterns which help identify faults that result from inverter switching instability and eccentricity. Cepstrum analysis serves as a valuable additional technique to other methods because it helps detect fault information when spectral environments become complex and noisy [177].

The operational conditions of Elevator PMSMs require specific focus when implementing spectral analysis methods. The brief length of an ordinary trip restricts both data acquisition time and processing duration. Signals become more nonstationary due to the combination of regenerative braking with changing load profiles. The implementation of time–frequency or angular tracking methods becomes more practical under these conditions. The modern elevator systems incorporate edge-computing devices that enable real-time operation. The embedded digital signal processors and field-programmable gate arrays (FPGAs) in these systems run spectral analysis algorithms such as FFT and STFT and WT. The extracted spectral features including harmonic amplitudes alongside

energy distribution and fault-related sideband ratios serve as inputs to ML classifiers or condition-based maintenance systems.

The frequency-domain analysis tools serve as critical diagnostic tools for elevator PMSM fault detection. FFT serves as a fundamental tool for spectral evaluation yet STFT, WT, order tracking and cepstrum analysis provide better methods to analyze nonstationary signals and transient events. The monitoring system requires a specific choice of techniques depending on signal characteristics and fault types along with real-time processing limitations.

3.3.3. Time-Domain Analysis

Time-domain analysis serves as an immediate and efficient condition monitoring method for direct signal analysis. This approach operates directly on raw data or preprocessed signals before converting them to another domain making it suitable for systems with limited processing capabilities and requires real-time evaluation. Time-domain features deliver fast and easy-to-interpret signs of abnormal behavior in elevator applications because PMSMs function intermittently under dynamic load conditions [178].

The most basic signal attribute extracted from time-domain signals is the root mean square (RMS) value. The signal's total energy measurement is provided by this parameter which directly corresponds to vibration intensity and electrical power consumption. A gradual increase in the RMS of motor current or vibration can indicate bearing wear, increased friction, or imbalance. PMSM drives in elevator applications use repeated stator current RMS monitoring to detect load asymmetries which stem from misalignment or uneven passenger distribution.

The peak value together with the peak-to-peak amplitude represents typical features that monitoring systems utilize. The maximum signal excursions are measured by these metrics which show high sensitivity to brief impacts and fault-related transients. Mechanical looseness and gear tooth damage produce intermittent high-amplitude vibrations during elevator start-up operations. The peak-to-peak value grows earlier than spectral features become visible in these instances. Elevator operations require monitoring these metrics because faults tend to develop rapidly between service intervals.

The time-domain indicator known as crest factor reveals itself through its calculation of peak value to RMS ratio. This measure reveals the presence of sudden pulses within a signal. A normal motor maintains consistent crest factor measurements between operational cycles. The crest factor rapidly increases when defective rolling elements in bearings produce sudden impacts during operation. Crest factor tracking proves valuable for detecting local defects in elevator applications because it can detect defects during infrequent idle and low-speed phases when steady-state operations would otherwise hide them [179].

The kurtosis metric serves as a common measurement tool to assess the "tailedness" or peakedness of signal probability distributions. The detection of bearing pitting faults and debris-induced impacts becomes possible through kurtosis values indicating the presence of outliers or transient impulses in signals. The analysis of vibration signals by kurtosis methods during braking and deceleration phases of elevator PMSMs can detect abnormal shock-like events possibly related to shaft misalignment or loosened mountings or worn pulleys [180].

The amplitude distribution asymmetry of a signal can be analyzed through its skewness measurement to detect bias-related faults. Thermal deformation in stator windings and rotor magnetization irregularities produce asymmetrical current waveforms. The diagnostic framework becomes more comprehensive through the combination of this feature with others although skewness shows reduced sensitivity [181].

Time-domain features that use derivative calculations include signal slope and jerk as well as rate of change measurements. These features evaluate the signal's rate of

change which becomes essential during elevator acceleration and deceleration phases. The current derivative undergoes sudden changes because of control instability and mechanical backlash and inverter anomalies that produce abrupt torque variations.

The process of fault sensitivity improvement together with robust enhancement can be achieved by using statistical windowing methods combined with moving average analysis to extract time-domain features from defined signal intervals. The analysis of vibration signals through sliding window RMS and kurtosis calculations enables phase-dependent fault detection during elevator travel. Real installations benefit from this method because fault signatures appear intermittently and depend on specific context.

Multiple sensors including current and vibration and acoustic probes enable the extraction of time-domain features from each signal that can then be combined. The integration of multiple sensors enables the detection of intricate mechanical and electrical domain interactions [182]. A rise in vibration of RMS together with matching peak-to-peak current value indicates mechanical misalignment which leads to increased load torque. The combination of isolated bearing fault detection can be made through vibration kurtosis measurement when current signals remain constant.

The basic nature of time-domain features makes them susceptible to noise effects and operating point changes. The amplitude and variability of the signal changes when motor speed or load conditions alter which might result in incorrect alarms. Feature extraction requires the use of preprocessing techniques including normalization followed by trend removal and filtering methods. The short and regular elevator operating cycles allow operators to create baseline profiles for normal operation so they can monitor deviations from these established baselines over time.

The main benefit of time-domain features lies in their ability to work with embedded and edged computing systems. The computational demands and memory usage of time-domain features remain lower than those required by frequency or time–frequency methods. Real-time diagnostics benefit from these features because they operate efficiently within elevator control panels and smart sensors positioned near the drive. Cycle-by-cycle computation of these features enables simple rule-based algorithms and advanced classifiers such as support vector machines or decision trees [183].

Time-domain features serve as an efficient method to monitor PMSM elevator condition through their rapid and understandable approach. The effectiveness of time-domain features depends on accurate signal preprocessing along with window selection and statistical modeling. Time-domain metrics serve as fundamental components for condition monitoring systems because they offer fast operation alongside minimal computational demands while providing basic analysis.

3.3.4. Advanced Time–Frequency Decomposition

As signal complexity and nonstationarity increase in modern industrial systems, traditional spectral analysis techniques—such as FFT, STFT, or basic wavelet transforms—may become insufficient to fully capture transient events and nonlinear dynamics. This is particularly relevant in elevator PMSMs, where frequent load variations, regenerative braking, and short operational cycles produce highly nonstationary, mixed-source signals. To overcome these challenges, a family of advanced time–frequency decomposition techniques has been developed, focusing on adaptively breaking down signals into intrinsic, physically meaningful components. These methods aim to isolate fault-relevant features that are both localized in time and well-defined in frequency, while also being robust to operating condition variability.

A leading method in this domain is EMD. EMD is a data-driven algorithm that decomposes a signal into a finite number of intrinsic mode functions (IMFs), each representing a

simple oscillatory mode embedded in the original signal. The key advantage of EMD is that it does not require a predefined basis (unlike wavelets or Fourier methods), making it ideal for nonlinear and nonstationary signals [184]. In the context of elevator PMSMs, EMD can be applied to vibration signals to extract high-frequency modes associated with bearing faults or looseness, which appear during acceleration phases. Similarly, applying EMD to current waveforms during regenerative braking may help isolate asymmetries caused by inter-turn short circuits or inverter faults. However, EMD suffers from mode mixing and sensitivity to noise, that has led to the development of improved variants.

One such improvement is the ensemble empirical mode decomposition (EEMD), which mitigates mode mixing by averaging the decomposition over multiple noisy realizations of the signal [185]. Each realization involves adding white noise to the original signal, running the EMD process, and then aggregating the results. This ensemble approach helps ensure that closely spaced frequency components are separated into distinct IMFs. For elevator condition monitoring, EEMD enables the consistent extraction of weak bearing-related components even when masked by speed ramping noise or inverter harmonics. Moreover, the repeatability of the decomposition across elevator cycles makes EEMD a strong candidate for long-term degradation tracking [186].

An alternative and more mathematically grounded method is the variational mode decomposition (VMD) [187]. VMD addresses many limitations of EMD by formulating decomposition as a constrained optimization problem, where each mode is extracted by minimizing its bandwidth around a center frequency. Unlike EMD, VMD processes all modes simultaneously rather than iteratively, which results in better frequency separation and resistance to noise. VMD has been successfully applied to PMSM current signals to isolate fault-induced harmonics from control-related fluctuations [188]. In elevator systems, VMD can help detect rotor demagnetization or eccentricity through the separation of mid-frequency modes that would otherwise overlap. The parameters of VMD, such as the number of modes and the penalty factor, require careful tuning based on expected fault signatures and signal length, but the method's robustness often justifies the effort.

Another powerful tool is the WPT, which extends traditional wavelet decomposition by allowing both approximation and detail coefficients to be further decomposed. This creates a full binary tree of subbands, providing finer frequency resolution across the entire spectrum. In practical terms, WPT allows engineers to target narrowband fault signatures more precisely. For example, bearing inner race defects may produce energy in specific WPT nodes corresponding to their characteristic frequencies, even under fluctuating speeds [189]. In elevator PMSMs, WPT applied to stator current during door operations or car acceleration can isolate repetitive transient disturbances indicative of mechanical backlash or control instability. WPT's hierarchical structure also enables energy-based fault indicators, such as node energy ratios or entropy measures, to be extracted and tracked over time.

In addition to these decomposition techniques, HHT has gained popularity for its ability to produce instantaneous frequency representations. HHT combines EMD with the Hilbert transform, yielding time-varying amplitude and frequency curves for each IMF. This time–frequency mapping reveals how the energy distribution evolves with respect to time, making it especially suitable for capturing sudden changes due to impacts or electrical discontinuities [190]. In elevator motors, HHT can uncover torque disturbances caused by gear engagement or imbalance during movement between floors. The high temporal resolution of HHT also supports condition assessment during very short elevator trips, where other methods might fail to produce sufficient spectral resolution.

These advanced decomposition methods are computationally intensive, which traditionally limit their application to offline analysis. However, the emergence of embedded

DSPs, FPGAs, and edge-AI hardware has enabled real-time or near-real-time implementation in elevator controllers and smart sensor nodes. By performing decomposition locally, these systems can identify fault indicators early and reduce data transmission demands. For instance, VMD can be run onboard to extract two or three key modes from vibration signals, which are then passed through statistical classifiers or threshold-based decision logic for immediate fault alerts.

Despite their advantages, advanced decomposition methods require careful validation. Results can be influenced by signal length, noise levels, and tuning parameters. For practical deployment in elevators, it is essential to benchmark the decomposition output across multiple operation cycles and under varying loading conditions. Cross-referencing the extracted features with known fault signatures and employing ensemble diagnostics strategies—such as combining VMD outputs with time-domain RMS and crest factor—can greatly enhance diagnostic reliability.

In conclusion, advanced time–frequency decomposition techniques provide an adaptive, high-resolution framework for fault detection in PMSM elevator drives. They enable the extraction of transient, localized fault signatures that are often invisible to conventional spectral methods. As real-time processing capabilities expand, the integration of methods such as EMD, VMD, and WPT into smart elevator monitoring systems will play an increasingly central role in predictive maintenance and reliability optimization.

3.3.5. Feature Extraction

While individual signal processing domains—time, frequency, and time–frequency—offer distinct perspectives for analyzing condition-monitoring signals, their combined application can yield significantly more robust, accurate, and interpretable diagnostic models. This approach, referred to as combined or hybrid feature extraction, leverages complementary information from multiple analytical domains to overcome the limitations of each method in isolation [4,25,36,37,69,131,166]. For PMSMs operating in elevator systems, where fault manifestations are often subtle, transient, or masked by operational variability, multi-domain fusion provides a resilient framework for early fault detection and condition trend analysis.

In the time domain, features such as RMS, crest factor, and kurtosis provide rapid, computationally inexpensive indicators of signal energy, impulsiveness, and statistical deviation. However, they are inherently limited in frequency resolution and cannot localize fault-related spectral components. Frequency-domain features derived from FFT or envelope spectrum analysis, on the other hand, offer insight into harmonics, sidebands, and fault-related resonance patterns. Yet, they assume stationarity and often fail under time-varying operational loads—common in elevators. Time–frequency methods like WT, HHT, and VMD fill this gap by providing localized temporal and spectral information, enabling the tracking of evolving fault signatures such as those generated by demagnetization or inter-turn faults during startup or braking. Hybrid approaches leveraging DWT for signal-based detection and fuzzy logic for knowledge-based classification have demonstrated rapid and accurate diagnosis of inter-turn short-circuit faults in five-phase PMSMs—achieving fault detection within only two motor cycles [191]. Recent studies further enhance time–frequency-based analysis through hybrid DL models that leverage CWT for signal representation and attention-based spatiotemporal feature extraction, achieving superior fault classification performance in rotating machinery [25].

The combination of these domains begins at the feature extraction stage. For example, a vibration signal from the elevator motor may first be decomposed using VMD to isolate modes sensitive to bearing damage. From each mode, statistical features (e.g., kurtosis or energy) can be extracted in the time domain, while the dominant frequency component

can be identified via FFT. Concurrently, the raw signal can undergo WPT, from which node energy features can be calculated. This yields a multi-dimensional feature set that captures both the transient temporal profile and the steady-state spectral content, enhancing the discriminative power of the condition monitoring system.

In current signal analysis, hybrid feature extraction may involve extracting time-domain features such as mean, standard deviation, and slope during constant-speed travel, alongside frequency features such as sideband amplitude near the switching frequency, and instantaneous frequency obtained through HHT. This is particularly useful in detecting inverter-related faults or eccentricities that manifest differently depending on load or direction of movement. The fusion of time-domain and frequency-domain patterns allow the model to distinguish between benign operational variability and emerging defects.

Sensor fusion further amplifies the value of hybrid analysis. By synchronizing data from multiple sources—such as stator current, vibration, acoustic emissions, and even temperature—it becomes possible to correlate fault signatures across physical domains [192]. For example, a peak in vibration kurtosis aligned with a transient increase in current crest factor during upward motion may strongly indicate mechanical-electrical coupling issues such as misalignment or excessive friction. Similarly, when a shift in the dominant vibration mode frequency (from VMD) corresponds to a phase imbalance in current signals, it may signal partial demagnetization or stator eccentricity.

Implementing such multi-domain frameworks in elevator systems requires efficient signal handling pipelines. Preprocessing steps include signal synchronization, segmentation based on operating cycles, and normalization to compensate for variable speed and load conditions. Feature extraction modules run either sequentially or in parallel, depending on computational constraints. Advanced systems embed this functionality directly into edge computing platforms located near the motor drive or control cabinet. These embedded units perform real-time decomposition (e.g., using WPT or VMD), extract key features, and transmit only high-value indicators to supervisory platforms for long-term storage or advanced analytics.

Feature-level fusion is commonly followed by dimensionality reduction techniques such as principal component analysis (PCA), linear discriminant analysis (LDA), or autoencoders. These techniques reduce redundancy and enhance the generalization capability of ML models, especially when dealing with high-dimensional data from multiple domains. In elevator PMSM applications, combining reduced feature sets from current and vibration domains has shown to improve fault classification accuracy in detecting rotor faults under variable passenger load.

Another important consideration in multi-domain extraction is the adaptability of the system to evolving operating conditions. Techniques such as adaptive thresholding, domain-specific weighting of features, or reinforcement learning-based selection of the most informative features enable the system to maintain sensitivity without increasing false alarm rates. These methods ensure that the hybrid model remains robust as the elevator system ages or undergoes maintenance changes.

A complete end-to-end pipeline for data acquisition, signal processing, feature extraction, ML training, alarm generation, and database update in elevator PMSM drives is illustrated in our recent work [4]. Figure 3 in [4] provides a practical example of a functioning elevator installation where multi-sensor data are collected, pre-processed, and transmitted for real-time analysis. This real-world implementation highlights how the methodologies reviewed in this paper are applied in practice and demonstrates their feasibility in operational elevator systems.

In conclusion, combined multi-domain feature extraction is a powerful approach for enhancing fault diagnosis and condition monitoring in elevator PMSMs. It allows

the system to leverage the strengths of time, frequency, and time–frequency analyses while compensating for their individual shortcomings. The synergy of these methods, especially when coupled with multi-sensor fusion and embedded analytics, forms the foundation of intelligent, scalable, and resilient condition monitoring frameworks suitable for real-world elevator applications. A comprehensive comparison of the main signal processing techniques discussed above is presented in Table 4. This summary aims to provide a high-level yet technically informative overview of each method’s capabilities, limitations, and application focus within the context of condition monitoring for elevator PMSMs. The comparison spans methods from the time, frequency, time–frequency, and decomposition domains, as well as their combined use, evaluating them across criteria such as nonstationarity handling, resolution, computational cost, real-time suitability, and their most appropriate use cases. This unified view is intended to assist system designers and researchers in selecting the most appropriate techniques based on specific fault scenarios, operational conditions, and hardware constraints.

Table 4. Comparative Summary of Signal Analysis Techniques for Elevator PMSM Monitoring.

Method	Handles Nonstationarity	Time Resolution	Frequency Resolution	Computational Cost	Suitable for Real-Time	Best Use Case in Elevators
FFT	No	None	High	Low	Yes	Steady state harmonics
STFT	Yes	Fixed	Fixed	Medium	Yes	Transient fault Tracking
DWT/CWT	Yes	Adaptive	Adaptive	Medium–High	Sometimes	Impulsive event detection
Order Tracking	Yes	N/A	Very High (rotational)	Medium–High	Sometimes	Speed-dependent fault isolation
Cepstrum	Yes	Low	N/A	Medium	Sometimes	Modulation analysis
Time-Domain Features	Yes	High	Low	Very Low	Yes	Fast cycle monitoring
EMD	Yes	High	Medium	Medium	Limited	General fault mode isolation
Ensemble EMD	Yes	High	Medium	High	No	Robust IMF separation
VMD	Yes	High	High	High	Sometimes	Noise-robust decomposition
WPT	Yes	High	High	High	Sometimes	Subband energy tracking
HHT	Yes	High	Medium	High	Limited	Instantaneous frequency mapping
Combined Multi-Domain	Yes	Composite	Composite	High	Sometimes	Comprehensive fault characterization

The comparative table presented above uses a combination of qualitative descriptors and abbreviations to concisely convey the characteristics of each signal analysis method. The term “Yes” under handles nonstationarity indicates the method is inherently capable of processing signals with time-varying statistical properties, while “Partial” denotes limited capacity, and “No” means the method assumes stationary signals. “N/A” (Not Applicable) is used where a particular criterion, such as time or frequency resolution, does not meaningfully apply to the method—e.g., in order tracking, where resolution depends on rotational cycles rather than linear time or frequency scales. For Resolution columns, “Fixed” refers

to non-adaptive methods, “Adaptive” means resolution varies with signal content, and “Composite” in the case of combined techniques indicates that the method leverages both time and frequency resolutions depending on the fusion strategy. The computational cost row ranges from “Very Low” (e.g., simple time-domain statistics) to “High” (e.g., decomposition methods with iterative or optimization-based structures). Suitable for Real-Time is rated qualitatively, reflecting practical experience with embedded implementations or edge computing feasibility, using terms such as “Yes,” “Sometimes,” or “Limited”.

Based on the aggregate evaluation across dimensions, no single method emerges as universally optimal. However, for elevator PMSM monitoring, where nonstationary conditions, transient load changes, and constrained hardware resources are all present, a few methods stand out as particularly well-suited. WPT and VMD provide strong fault localization capability and resilience to noise, especially for mechanical faults such as bearing wear or misalignment. Time-domain features remain essential for their speed and reliability in rapid elevator cycles. For hybrid diagnostic systems, the combined multi-domain feature extraction approach offers the most comprehensive fault coverage, especially when implemented with modern edge-processing units. Thus, in practical terms, a layered architecture combining lightweight time-domain monitoring with VMD or WPT-based enhancement appears to be the most effective and scalable solution for real-world elevator applications.

4. Advanced Machine Learning Techniques for PMSM Fault Detection

The traditional signal processing methods provide useful results but encounter challenges when detecting PMSM faults under nonstationary elevator conditions that are either subtle or transient. ML techniques use multi-sensor data and advanced pattern recognition to detect faults at earlier stages with better reliability. This section delivers a complete analysis of current approaches by dividing them into supervised, unsupervised, and hybrid learning paradigms.

4.1. Supervised Learning

The foundation of PMSM fault diagnosis in elevator systems depends on supervised learning because it works best when labeled datasets containing fault types and normal operating conditions are available. Elevator operational reliability demands immediate detection of inter-turn short-circuits as well as rotor demagnetization and bearing degradation and mechanical misalignment and other subtle anomalies. The direct mapping capabilities of supervised algorithms produce high-confidence predictions which guide real-time maintenance decisions while ensuring passenger safety [193,194].

4.1.1. Classical ML Approaches

Supervised algorithms continue to show high importance for PMSM fault diagnosis when there are restrictions on computational resources or when datasets are limited to small to medium sizes. These methods require human-engineered features from multiple signal domains including time-domain metrics (RMS, kurtosis, skewness, peak-to-peak values), frequency-domain components (FFT amplitudes, harmonics, side-bands) and time-frequency representations (Wavelet Packet Transform coefficients, Hilbert–Huang Transform features) [195,196].

The binary and multiclass fault classification applications have widely adopted SVMs. SVMs build high-dimensional optimal hyperplanes which use kernel functions like radial basis function (RBF) or polynomial kernels to handle cases where classes are not linearly separable. The implementation of SVMs in elevator PMSM applications proves effective for identifying inter-turn short circuits and rotor demagnetization faults when training

data is minimal [197,198]. The system maintains accurate results because SVMs possess strong generalization abilities that help it resist variations in load and operational speed. The selection of kernel parameters together with feature scaling sensitivity requires SVMs to need careful preprocessing and cross-validation steps [199].

RF uses ensemble learning to build multiple decision trees that combine their predictions to reduce output variability and boost robustness. RF models show exceptional diagnostic capabilities when detecting mixed faults that involve mechanical and electrical problems in elevator PMSMs [200,201]. The RF model excels in noisy multi-sensor fusion applications because it can handle features from vibration and current and temperature signals. The lack of interpretability in RF models presents a challenge for elevator safety applications because they require explainable decisions [154].

The kNN algorithm uses non-parametric classification through proximity assessment within feature space dimensions. kNN works effectively for offline diagnostics and systems with low-dimensional feature sets because of its simple design and easy understanding [202]. The application of kNN to detect PMSM faults in elevators involves measuring distances between extracted time–frequency features to identify bearing wear and inter-turn faults. kNN faces scalability problems because both large dataset sizes and high-dimensional feature vectors lead to increased memory usage and delayed inference which limits its deployment in embedded elevator controllers [203].

Linear and quadratic discriminant analysis (LDA/QDA) construct linear or quadratic decision boundaries based on class-specific statistical assumptions. The LDA method requires equal covariance matrices across classes, yet QDA offers more flexible boundaries by relaxing this requirement [204,205]. The methods maintain both efficiency in computation and interpretability, making them suitable for implementation in low-power elevator systems. The linear nature of LDA and QDA restricts their ability to detect complex nonlinear fault patterns thus requiring additional feature transformation techniques [206].

GMMs provide a probabilistic framework for supervised classification that allows samples to be assigned to multiple classes through likelihood-based soft assignments. PMSM monitoring applications use GMMs to develop distribution models of multi-sensor features that detect rotor imbalance or bearing degradation [207,208]. GMMs demonstrate flexibility yet fail to represent fault signatures that are highly nonlinear or skewed because they work with Gaussian distribution assumptions [209].

AdaBoost together with XGBoost ensemble methods have gained popularity because they enhance predictive results through the combination of weak classifiers into a robust classifier. The decision tree-based gradient boosting process of XGBoost with added regularization capabilities helps reduce overfitting to deliver effective diagnostic results for complex fault systems with multiple interacting fault types [8,210,211]. The combination of high accuracy with efficiency demonstrated in elevator PMSM rotor and bearing fault detection through XGBoost demands proper hyperparameter tuning to prevent overfitting when working with limited datasets [212].

4.1.2. Deep Learning Models

DL architectures entered the field of PMSM fault diagnosis because classical ML methods require hand-crafted features and are sensitive to feature selection. The learning process of DL models creates hierarchical representations from raw or slightly modified signals which reveal sophisticated temporal and spatial patterns.

The ability of CNNs to identify spatial patterns makes them perfect for working with 1D signals from stator currents or vibration time-series and 2D representations like scalograms or spectrograms. Elevator PMSMs achieve high accuracy through CNNs when detecting rotor demagnetization and inter-turn faults and bearing defects during changing

operational loads [213,214]. Using rectified linear unit (ReLU) activations CNNs efficiently model nonlinearities while pooling layers create translation invariance that helps detect repeated fault patterns across cycles.

The ability of RNNs, especially LSTM and gated recurrent unit (GRU) networks to detect time-based relationships in sequential data makes them suitable for elevator fault monitoring during time evolution. Through LSTMs, the network solves vanishing gradient problems which enables it to maintain vital long-term dependencies needed for detecting both gradual wear and progressive insulation degradation. GRUs maintain comparable performance through their basic gating operations, decreasing computational demands. These architectural models demonstrate the ability to track fault signature changes during operational cycles which enable them to deliver predictive warnings about upcoming equipment breakdowns [215,216].

Transformers and attention mechanisms now serve PMSM fault diagnosis in scenarios that require handling complex temporal patterns and multiple correlated sensors during elevator operation. The network uses attention to concentrate on essential parts of the signal input that include motor acceleration or braking sections where faults typically appear. Transformer models present parallel computation capabilities that enable efficient processing of extended input sequences thus outperforming traditional RNNs in real-time elevator monitoring systems [217].

Unsupervised pre-training through autoencoders (AEs) and variational autoencoders (VAEs) allows supervised models to discover compact representations of normal motor operation [213,214]. The system can enhance its sensitivity to fault-indicative subtle deviations when these latent features are incorporated into supervised classifiers including fully connected DNNs or gradient-boosted trees. GANs have become instrumental in creating artificial fault data to enhance training datasets when actual fault occurrences remain scarce due to the low occurrence of catastrophic failures in elevators [218,219].

4.1.3. Hybrid Architectures

Recent research demonstrates how hybrid models using classical and DL approaches can benefit from their individual strengths when combined. The combination of WPT coefficients with CNNs or LSTMs enables hierarchical feature extraction before final fault categorization through interpretable classifiers like Fuzzy Logic or SVM. The combination provides both strong prediction abilities and explanation capabilities required by elevator maintenance engineers [220,221].

Different sensor modalities including stator currents, vibrations, temperature and acoustic emissions use feature-level fusion techniques. The combination of heterogeneous features becomes possible through hybrid models including CNN-LSTM networks with attention or transformer layers thus enabling the detection of multiple fault scenarios such as bearing misalignment with rotor demagnetization. Such architectures have demonstrated high robustness against noise and operational variability [222–224]. The combination of encoder–decoder networks with supervised classifiers within hybrid frameworks enables the improvement of latent representation sensitivity for identifying both minor and new faults. The implementation of attention mechanisms or transformer modules helps the model detect vital temporal or spectral signal segments specifically during elevator acceleration and deceleration and start–stop phases [225–227].

Deep and shallow models combined in ensemble hybrid architectures provide better resistance against overfitting and enhanced robustness. LSTM autoencoders and RF or SVM classifiers enable simultaneous fault pattern modeling of sequential faults alongside interpretable decision-making. The detection of progressive faults such as insulation

degradation and minor bearing misalignments has proven effective under real elevator operational conditions [228,229].

4.1.4. Advantages and Limitations

Elevators with their safety and reliability requirements need supervised learning methods that deliver both high accuracy and fast response times. The application of SVMs and RFs succeeds when representative labeled datasets exist because these methods deliver interpretable results at low computational cost. The implementation of CNNs together with LSTMs and GRUs and attention-based models enables automatic feature extraction of spatial, temporal and spectral patterns in current, vibration, temperature and acoustic signals [193–198].

Deep architectures deliver their primary advantage by modeling nonlinear relationships and temporal dependencies that enable early detection of faults like partial demagnetization, inter-turn shorts, and bearing wear during different load conditions [154,199–202]. The hybrid and attention-based models enhance both robustness and sensitivity through their ability to combine multiple domain features while focusing on essential signal segments like acceleration and deceleration and door operation phases in elevators [203–206]. Several challenges persist. Supervised learning requires extensive labeled data yet specific fault occurrences in elevators are rare making data collection challenging [207–210]. Deep models that handle high-dimensional data need substantial computing power but embedded or edge-deployed elevator controllers might not have enough resources. The black-box characteristic of deep networks makes it difficult to interpret their results, so maintenance engineers need to use hybrid methods or attention mechanisms or perform post hoc feature attribution for obtaining actionable information [8,211–214].

The training of supervised learning models with multi-domain features enables practical elevator applications to identify multiple fault types effectively. The initial models used hand-crafted features which included RMS, kurtosis and crest factor. Deep neural networks introduced a capability to automatically extract features from unprocessed or minimally transformed signals that enhanced their ability to handle variable operational loads [215–219]. The combination of attention mechanisms with transformer-based architecture enables better detection of faint or brief faults while avoiding additional false alarm occurrences. Hybrid pipelines which unite deep feature extraction with interpretable classifiers achieve a tradeoff between accurate predictions and clear model explanations [91,220–235].

The foundation of elevator PMSM fault diagnosis relies on supervised learning techniques that consist of classical, deep and hybrid models delivering both reliable results and prompt fault identification when there are enough labeled data and computational power available.

4.2. Unsupervised Learning

Unsupervised learning methods are critical in PMSM fault diagnosis for elevator systems, particularly when labeled fault data are scarce or new, previously unseen fault types emerge [193–195]. Unlike supervised approaches, unsupervised techniques rely on the intrinsic structure of normal operational data to detect anomalies, deviations, or clusters indicative of potential faults. This capability is especially valuable in elevator PMSMs, where operational variability, intermittent loads, and low-speed operation introduce non-stationary and subtle fault signatures that are difficult to capture with labeled datasets alone [196,197].

Early unsupervised strategies employed statistical and dimensionality reduction methods. PCA exploits correlations among multi-domain features—such as RMS, kurtosis, and

spectral components of current and vibration signals—to create a reduced representation of normal motor behavior. Anomalies are identified as deviations from this low-dimensional reconstruction [198,199]. While PCA is interpretable and straightforward, it assumes linear relationships and may not capture nonlinear fault patterns characteristic of elevator PMSMs. To address this, kernel-based extensions, such as Kernel PCA (KPCA), project data into higher-dimensional spaces, enhancing separability of anomalous patterns [200,201].

Clustering-based methods are another class of unsupervised approaches. GMMs model the probability distribution of normal operational signals and classify data points based on likelihood thresholds. In elevator PMSMs, GMMs can detect subtle shifts in current harmonics or vibration modes indicative of early-stage bearing degradation or rotor eccentricity [154,202]. However, GMMs assume Gaussian distributions, which may not hold under variable load and start–stop cycles. Alternative clustering algorithms, including k-means and hierarchical clustering, offer flexible grouping without strong distributional assumptions, enabling the detection of emerging fault classes. Nevertheless, these methods require careful tuning of cluster numbers and distance metrics and may struggle with high-dimensional features without prior dimensionality reduction [203,204].

The advent of DL has significantly enhanced unsupervised fault detection capabilities. Autoencoders (AEs), comprising encoder–decoder architectures, are trained to reconstruct input signals while compressing information into a latent representation. In elevator PMSMs, AEs are often trained exclusively on healthy operational cycles, learning the manifold of normal motor behavior across multi-domain features and multiple sensor channels. Faults are identified when reconstruction errors exceed predefined thresholds, signaling deviations from expected patterns [205–207].

VAEs extend this framework by introducing a probabilistic latent space, which enables the generation of synthetic healthy signals and provides a robust measure of anomaly likelihood. Encoder–decoder models effectively capture both temporal and spectral dependencies in current and vibration signals, facilitating detection of subtle faults such as inter-turn short circuits, partial demagnetization, and mechanical misalignments that may only appear during transient elevator movements [208–210].

GANs have emerged as another powerful unsupervised approach. GANs consist of a generator that synthesizes data resembling the training set and a discriminator that differentiates real from synthetic signals. When trained on healthy operational data, GANs can identify anomalies by analyzing the discriminator’s response. Variants such as AnoGAN and f-AnoGAN incorporate encoder modules to map real-time inputs into the latent space, enabling anomaly scoring in real-time. GAN-based methods can model highly complex distributions and detect subtle, nonlinear fault signatures often missed by traditional statistical or shallow methods, though their training demands high computational resources [8,211–213].

One-Class SVMs (OC-SVMs) represent another widely applied unsupervised technique. By learning a decision boundary around healthy operational data, OC-SVMs flag data points outside this boundary as anomalies. In elevator applications, OC-SVMs have been used to detect transient overloads, unusual vibration spikes, or changes in current harmonics indicative of rotor or bearing faults [214,215]. These methods are relatively interpretable and robust but sensitive to feature scaling, kernel choice, and hyperparameter tuning, especially under variable multi-domain elevator operational conditions.

Isolation Forests provide an alternative anomaly detection approach, relying on random partitioning of feature space to isolate abnormal points. Suitable for high-dimensional multi-sensor datasets, such as those in elevator PMSMs, Isolation Forests detect rare and early-stage faults without requiring labeled samples. Their independence from distributional assumptions makes them effective for complex, nonstationary elevator sig-

nals, although multiple runs or ensemble strategies may be needed for stable performance [216,217].

Recent advancements incorporate deep unsupervised learning into temporal–spatial modeling. LSTM autoencoders encode sequences of multi-sensor measurements, capturing temporal dependencies in current, vibration, and acoustic signals. The decoder reconstructs the original sequence, and elevated reconstruction errors indicate anomalies. LSTM-based models excel at capturing sequential characteristics of elevator operation, such as acceleration, deceleration, and door cycles, which can modulate fault signatures [218–220].

GRUs, offering similar temporal modeling with reduced computational cost, have also been applied for real-time monitoring in embedded elevator control systems. Sequence-based models effectively detect subtle degradation trends, including bearing wear or insulation deterioration, that accumulate over extended operational cycles [221,222].

Self-supervised learning has emerged as a complementary approach, creating surrogate tasks—e.g., predicting future current cycles, reconstructing missing vibration segments, or distinguishing shuffled versus sequential signal portions. These tasks enable the model to learn meaningful representations without explicit labels, which can then be used for downstream anomaly detection, improving sensitivity and robustness when elevator-specific fault data are limited [223,224].

Positive-Unlabeled (PU) learning bridges unsupervised and semi-supervised paradigms. Only a subset of positive fault instances is labeled, while the remaining data—including unlabeled anomalies and abundant normal operation samples—is leveraged to improve classification or anomaly detection. In elevator PMSMs, PU learning allows rare faults like partial demagnetization or inter-turn shorts to be detected effectively without extensive fault labeling [225,226].

Graph-based approaches, particularly GNNs, model relationships among multiple sensors as graph nodes and edges. Elevator PMSMs often deploy numerous sensors monitoring currents, vibrations, temperature, and acoustics. GNNs capture inter-sensor correlations, enabling detection of complex fault interactions such as combined mechanical–electrical issues, rotor eccentricity, or misalignment with bearing wear [227–229].

Finally, RL can be partially integrated with unsupervised or hybrid frameworks. RL agents adaptively adjust detection thresholds or feature weighting in response to changing operational states, learning optimal policies that maximize early fault detection while minimizing false alarms. Agents observe real-time signals and receive rewards based on accurate anomaly detection or early intervention, refining fault detection strategies over time. Though RL requires careful reward function design and significant computational resources, its adaptive nature complements unsupervised learning under dynamic elevator conditions [91,230,231].

In conclusion, unsupervised learning provides a comprehensive toolkit for PMSM fault diagnosis in elevator systems. From classical statistical and clustering methods to deep encoder–decoder architectures, self-supervised techniques, PU learning, GNNs, and RL-enhanced anomaly detection, these approaches enable robust, scalable, and interpretable monitoring even with limited labeled data, variable operational conditions, and multi-sensor configurations [232–235].

4.3. Semi-Supervised and Hybrid Learning

In practical elevator PMSM systems, operational constraints and safety-critical requirements often result in limited availability of labeled fault data. Specific fault types—such as partial demagnetization, inter-turn short circuits, or bearing looseness—may occur rarely or only under load conditions. At the same time, large volumes of unlabeled data reflecting normal operation are continuously generated by motor sensors, including stator current,

vibration, temperature, and acoustic emission channels. Semi-supervised and hybrid learning paradigms provide a strategic framework to exploit this data efficiently. They combine the advantages of supervised learning, leveraging labeled samples for targeted fault classification, with unsupervised learning, which captures the underlying structure of normal operating behavior to detect anomalies [193–197]. One prominent approach is self-training or pseudo-labeling, where a model initially trained on the limited labeled fault samples predicts labels for unlabeled operational data. These newly labeled samples are then incorporated into subsequent training iterations, effectively expanding the dataset and improving generalization. This methodology is particularly effective in detecting rare faults in elevators, such as early-stage rotor demagnetization or minor inter-turn faults, which might otherwise be missed by purely supervised models. Iterative self-training allows the model to progressively refine its decision boundaries while maintaining sensitivity to rare fault types critical in elevator applications [198–200].

PU learning represents a specialized semi-supervised technique particularly relevant for elevator PMSMs, where positive fault samples are scarce and negative samples (normal operation) dominate the dataset. PU algorithms train a classifier using only positive and unlabeled instances without explicitly labeling all negative data. In elevator diagnostics, PU learning enables robust identification of rare faults, such as transient insulation failures or rotor eccentricities, by focusing on the few confirmed fault events while still modeling the majority of normal operational patterns [151,201,202].

Co-training and multi-view learning extend semi-supervised approaches by exploiting distinct feature sets—such as time-domain statistical descriptors versus frequency-domain harmonics or wavelet coefficients—through parallel models. Each model predicts pseudo-labels for the unlabeled data, and predictions are shared iteratively to improve overall learning. This technique leverages complementary multi-domain features, enhancing robustness of fault detection under variable elevator loads, start–stop cycles, and regenerative braking [203–205].

Hybrid architectures integrate supervised, unsupervised, and reinforcement learning components within a single framework. RL has been applied for adaptive fault detection and predictive maintenance in PMSMs. An RL agent interacts with real-time motor data and learns optimal diagnostic or maintenance policies based on feedback, such as anomaly scores, operational efficiency, or fault detection success. RL allows dynamic adjustment of thresholds, selection of relevant features, and prioritization of sensor streams, ensuring sustained performance in evolving operational conditions, wear, and sensor drift. Semi-supervised models combined with RL leverage both labeled fault events and unlabeled normal operation, enabling adaptive thresholding and predictive maintenance strategies that optimize safety and reduce downtime in elevators [206–210].

DL-based semi-supervised strategies increasingly employ encoder–decoder architectures, where autoencoders reconstruct normal operation signals and deviations indicate potential faults. Variants such as VAEs and Denoising Autoencoders (DAEs) provide probabilistic modeling and robustness to noise, respectively. In hybrid semi-supervised frameworks, encoder–decoder networks can be combined with supervised classifiers (e.g., SVM or CNN) to refine latent space representations, ensuring that subtle deviations—such as minor bearing misalignments or shaft eccentricities—are detectable [8,211–213].

Contrastive learning is often incorporated into the latent space training of encoder–decoder models to improve separability between healthy and anomalous patterns, enhancing detection of novel or previously unseen fault types in elevator PMSMs [214–216]. Few-shot learning techniques, including Siamese Networks, Matching Networks, and Prototypical Networks, are employed to address the scarcity of labeled fault data. These models learn similarity metrics from minimal labeled samples and generalize to new fault

instances, effectively detecting rare conditions like inter-turn short circuits or partial bearing faults [217–219].

Graph Neural Networks (GNNs) extend semi-supervised learning to multi-sensor networks. Elevator PMSMs instrumented with arrays of current, vibration, temperature, and acoustic sensors benefit from GNNs that model sensors as graph nodes and learn relationships between them, capturing spatiotemporal correlations missed by single-sensor models. Hybrid semi-supervised GNNs integrate labeled fault nodes with large unlabeled sensor readings, detecting complex patterns such as combined electrical and mechanical degradation [220–223].

Ensemble methods, including XGBoost and hybrid Random Forest–autoencoder combinations, improve robustness and reduce overfitting. In elevator applications, these ensembles prioritize fault detection during high-risk operating intervals—such as rapid acceleration or emergency braking—enabling early intervention. Temporal models (LSTM/GRU) combined with ensemble classifiers capture both transient and persistent fault behaviors, allowing detection of subtle and progressive anomalies [224–226].

Activation functions such as ReLU play a crucial role in enhancing fault feature extraction within deep architectures. ReLU provides nonlinear transformations that maintain sparse, discriminative representations in hidden layers, which is essential for multi-domain elevator PMSM sensor data. In encoder–decoder networks, ReLU ensures fault-specific deviations are preserved in the latent space, improving anomaly sensitivity without introducing spurious artifacts. Complementary activations, such as Leaky ReLU or Parametric ReLU, further improve robustness against small fluctuations occurring during normal elevator operation [227–229].

In practical implementations, semi-supervised and hybrid learning models are deployed on edge AI platforms integrated with elevator controllers or motor drives. These deployments enable real-time inference, low-latency fault detection, and adaptive decision-making without reliance on cloud connectivity—critical for safety-critical systems. Computational optimizations, including quantization, pruning, and lightweight network design, ensure that even deep hybrid models, such as contrastive autoencoder ensembles or graph-based few-shot learners, operate efficiently within the limited memory and processing capabilities of embedded elevator hardware [89,230,231].

Despite these advancements, several challenges remain. Interpretability is essential for maintenance engineers who require actionable insights rather than opaque outputs. Hybrid systems increasingly integrate attention mechanisms, prototype-based explanations, or post hoc feature attribution to address this need. Data imbalance, where fault samples are orders of magnitude fewer than normal operation data, continues to challenge model calibration. Semi-supervised and PU learning approaches partially mitigate these issues, but rare-event detection remains an active research area. Continual learning and domain adaptation are also being explored to ensure that models trained on one elevator can generalize to new installations with minimal retraining, accounting for mechanical tolerances, sensor differences, and operational profiles [232–234].

In summary, semi-supervised and hybrid learning techniques provide a comprehensive, adaptive, and scalable framework for PMSM fault detection in elevator systems. By combining limited labeled data with abundant unlabeled signals, integrating PU learning, encoder–decoder architectures, contrastive learning, few-shot strategies, reinforcement learning, and multi-sensor graph representations, these approaches enable early, accurate, and interpretable fault detection. Edge deployment and real-time inference further position these methods as key enablers for next-generation smart elevators, ensuring operational safety, reliability, and efficiency under variable load and duty conditions [235].

4.4. Comparative Insights and Future Directions

Machine learning paradigms have revolutionized elevator system condition monitoring because they provide highly sensitive and adaptable predictive diagnostic tools for PMSM faults [193,194]. A thorough evaluation of supervised learning with SVMs, RF, kNN and LDA/QDA together with unsupervised methods and semi-supervised methods and hybrid approaches shows how each model has its advantages and disadvantages which determine their suitable use in elevator environments [198,199].

The supervised learning models including SVMs, RF, kNN, and discriminator analysis techniques (LDA/QDA) prove highly efficient with extensive labeled dataset availability [200]. The methods provide clear interpretability alongside low computational requirements and strong classification outcomes when dealing with established faults such as bearing defects and rotor imbalances [151]. The use of 1D CNNs, LSTM, GRU and attention-based architectures DL models improves fault detection capabilities through automated feature extraction and handling of complex temporal–spatial dependencies [8,195]. The integration of Transformer-based models allows the system to select essential signal segments during operational transients thus enhancing the detection of subtle faults including partial demagnetization and early insulation degradation [212]. Supervised learning methods face their main challenge because they need fault data labeling, yet such data is rarely available for elevator systems especially when dealing with infrequent or beginning-stage faults [208].

The approach of unsupervised learning solves the problem of limited available fault data labels by detecting anomalies through learning operational signal patterns [198]. The traditional methods OC-SVM, Isolation Forests and PCA provide easy implementation, but they struggle to detect complex and high-dimensional connections between data points [200]. Deep unsupervised models including Autoencoders, VAEs, and GANs break through these limitations by producing comprehensive latent representations which combine signal patterns and temporal characteristics of PMSM signals [208]. The ability to detect rare and novel faults has improved through Deep SVDD and self-supervised pretext tasks that enhance elevator systems' operational variability resistance [8]. PU learning improves detection performance using confirmed fault instances along with abundant unlabeled data to handle class imbalance issues [8]. The detection of anomalies through unsupervised methods may produce incorrect positive results because normal operational fluctuations could be mistaken for anomalies thus requiring precise calibration and domain knowledge integration [198].

The combination of supervised and unsupervised approaches through semi-supervised and hybrid models creates an adaptable system for detecting elevator PMSM faults [8]. The self-training, co-training and multi-view learning approaches allow models to use minimal labeled fault data while expanding their understanding through large unlabeled signal datasets to enhance decision boundary refinement and generalization capabilities [8,208]. Deep hybrid models use encoder–decoder architectures and contrastive learning and few-shot learning and reinforcement learning (RL) to address specific challenges such as early fault detection, rare-event classification, and adaptive thresholding [212]. Through reinforcement learning the system adjusts detection parameters and feature selection and maintenance scheduling while receiving operational feedback to optimize its performance [231]. GNNs enable multi-sensor data integration through spatial–temporal correlation analysis of current, vibration, temperature and acoustic emission signals to create a comprehensive motor health assessment [195]. The implementation of these hybrid approaches requires proper design to maintain a balance between complexity and interpretability and computational efficiency for edge deployment in embedded elevator controllers [218].

The different categories demonstrate opposite trade-offs in their deployment and computational operations. The combination of classical supervised models and shallow unsupervised methods provides both quick inference performance and low memory usage which makes them appropriate for embedded edge devices [151]. The accuracy along with temporal modeling and adaptability in DL models including CNNs, LSTMs, VAEs and Transformers comes at the expense of higher computational requirements [195,212]. The additional complexity of hybrid architecture from multi-stage pipelines and attention mechanisms and ensemble strategies results in the best fault coverage [8]. Model pruning and quantization alongside lightweight network design strategies are essential for real-time elevator performance while maintaining reliable detection [218].

Safety-critical elevator applications require interpretable and explainable features to remain vital. DL and hybrid systems function as black boxes because classical ML models offer straightforward decision criteria explanations. Recent advancements through attention visualization and prototype-based reasoning and post hoc feature attribution and hybrid interpretable classifiers help bridge this gap by enabling maintenance engineers to trust and use model outputs [8,198]. The safety of passengers together with elevator reliability demands special attention during operational decisions [193,194]. Model selection and performance depend on the data-related challenges that exist. Supervised models face limitations in generalization because of imbalanced datasets and insufficient fault samples and the differences between elevator installations [208]. The PU strategy alongside semi-supervised learning approaches solve these problems while transfer learning and domain adaptation help models apply to various elevator configurations [8]. The implementation of continual learning approaches helps maintain fault detection sensitivity through continuous operational profile changes and sensor deterioration and mechanical wear without requiring complete model retraining [213].

The future of ML-driven PMSM fault detection for elevator systems will advance through various directions. The direct integration of multiple sensor fusion into deep architecture systems has the potential to detect compound faults by analyzing electrical and mechanical as well as thermal interactions between components [195,197]. The development of edge AI will persist in decreasing latency together with energy usage and cloud infrastructure dependence to support real-time on-device diagnostic functions [218]. The expected future improvements in detection capabilities for new fault types and adaptive maintenance optimization stem from the integration of self-supervised learning with few-shot learning and reinforcement learning methods [8,231]. Self-explainable models under development will deliver actionable insights to maintenance staff while maintaining predictive accuracy thus building trust and improving safety alongside operational efficiency [198,224].

The research evaluation demonstrates how modern ML approaches can revolutionize the process of elevator PMSM fault diagnosis. Supervised models achieve excellent accuracy for fault classes that have sufficient labeling yet unsupervised models excel at detecting anomalies with limited data availability and semi-supervised and hybrid approaches learn from limited labels by incorporating unlabeled operational data [8,195,198]. The combination of multi-domain feature extraction with deep temporal-spatial modeling alongside reinforcement learning and encoder-decoder architectures and PU learning and few-shot learning and edge deployment creates an adaptive scalable framework [208,212,218]. The combination of these methodologies solves the multiple operational challenges and safety needs and data constraints which modern elevators face to develop predictive intelligent condition monitoring systems for future smart elevator applications [193,194,235].

Recent research has introduced several advanced methodologies that significantly extend the diagnostic and prognostic capabilities of PMSM condition monitoring, yet they

remain largely unexplored in elevator-specific applications. Signal-based approaches such as wavelet transformations combined with distance metrics [15] and magnetic flux analysis [124] have demonstrated improved sensitivity to early-stage faults, while CNN [67,220] and hybrid DL architectures leveraging multi-condition data [235] enhance classification accuracy across varying operational regimes. Advanced signal preprocessing methods [72,119] and multimodal sensor data fusion frameworks [116,117,119] further support robust feature extraction under noisy environments. MEMS-based wireless vibration transducers [116] and edge-computing-driven architectures [145] enable real-time deployment of such models, and robust sensorless anomaly detection strategies exploiting motor driver signals [225] are emerging as a promising avenue. Furthermore, cyclic spectral coherence-based techniques have shown potential for identifying nonstationary fault signatures in PMSMs [221]. Complementing these diagnostic advances, particle filter-based prognostics have been proposed as powerful tools for remaining useful life estimation in nonlinear and non-Gaussian degradation processes [236], and attention-guided graph isomorphism learning frameworks offer a new paradigm for joint fault diagnosis and RUL prediction [237]. These cutting-edge methods are comprehensively summarized and comparatively analyzed in the recent state-of-the-art review by Gherghina et al. [238], which highlights their potential to address current knowledge gaps in fault detection and prognostics of synchronous machines. Despite these advances, none of these methods have yet been systematically validated under the operational constraints of elevator PMSM drives, underscoring a critical opportunity for targeted research in this field.

Table 5 summarizes the most widely used ML techniques for fault diagnosis and prognostics in PMSM-based elevator systems, outlining their learning type, application domain, main advantages, and key limitations. As shown, supervised methods such as SVM and CNN achieve high accuracy when sufficient labeled data are available, while unsupervised and hybrid approaches are more effective for anomaly detection and rare fault recognition under limited data conditions.

Table 5. Machine Learning Techniques for PMSM Fault Diagnosis and Prognostics.

Method	Learning Type	Elevator PMSM Application	Advantages	Limitations
SVM	Supervised	Rotor bar faults, demagnetization, inter-turn faults	High accuracy, works with small, labeled datasets	Feature sensitive scaling, low interpretability
RF	Supervised	Bearing faults, mixed faults, demagnetization	Noise robust, handles mixed features, variable conditions	Less interpretable, memory demanding
kNN	Supervised	Inter-turn faults, bearing classification	Simple implementation, works with small data	Slow on large sets, noise sensitive
LDA/QDA	Supervised	Embedded fault diagnosis, low-complexity systems	Fast, interpretable, low computational cost	Limited to linear/quadratic data
GMM	Unsupervised	Anomaly detection, fault clustering	Probabilistic clustering, handles unlabeled data	Assumes Gaussian distribution, less effective for nonlinearity
Autoencoder (AE)	Unsupervised Hybrid	Early fault detection	Learns nonlinear features, Unsupervised	Requires tuning, risk of underfitting
VAE	Unsupervised Hybrid	Anomaly detection under variable load	Models' data distribution, robust to noise	Complex training, latent sensitivity
GANs	Unsupervised	Novel fault detection, anomaly detection	Generates realistic signals, detects rare faults	Training instability, high computational cost

Table 5. Cont.

Method	Learning Type	Elevator PMSM Application	Advantages	Limitations
Deep SVDD	Unsupervised	Rare anomaly detection	Effective hypersphere mapping	Sensitive to hyperparameters
PU Learning	Semi-supervised Hybrid	Rare fault detection, partial labeling	Uses unlabeled datasets, improves detection	Risk of misclassification, needs careful initialization
CNN (1D, 2D)	Supervised	Automatic feature extraction current/vibration signals	High accuracy, no manual features	Requires large labeled datasets, high computational cost
RNN/LSTM/GRU	Supervised	Time-series monitoring, load-variation	Captures temporal dependencies, suitable for variable-speed drives	Long training time, gradient issues
Attention/Transformers	Supervised	Transient events detection (start–stop, acceleration)	Focuses on key signals, improves sensitivity	Complex architecture, High computational cost
Contrastive Learning	Semi-supervised Hybrid	Latent space separation, healthy vs. fault signals	Improves representation learning, enhances anomaly detection	Requires careful negative/positive pair selection
Few-Shot Learning	Semi-supervised Hybrid	Rare fault recognition, minimal labeled data	Effective for rare events, small data requirement	Sensitive to similarity metric, needs representative support set
GNNs	Hybrid	Multi-sensor interaction	Captures spatial relations	Complex, heavy computation
RL	Unsupervised Hybrid	Adaptive thresholding, maintenance policy	Learns dynamic optimization policies	Requires careful reward design, long training times
XGBoost/AdaBoost	Supervised Ensemble	Fault classification with tabular features	High performance, robust	Risk of overfitting, less interpretable
Encoder-Decoder	Unsupervised Hybrid	Reconstruction, temporal feature extraction	Suitable for multivariate data	Requires careful design, sensitive to input noise

To provide a structured and critical synthesis of the diverse diagnostic methodologies encountered in the reviewed literature, the studies were grouped into distinct technological categories according to their underlying working principles and data requirements. This categorization reflects fundamental differences in how the methods process condition-monitoring information, their level of model dependency, and their suitability for real-time deployment. To clarify the methodological synthesis and enable end-to-end comprehension, the two canonical diagnostic paths (Figure 1), are described below as stepwise processing pipelines. They represent the standard workflows for current signature analysis (CSA)-based and vibration/acoustic-based fault detection.

- Current/Voltage Signal Analysis (CSA Path).

Step 1—Signal Acquisition: Three-phase stator currents and phase-to-phase voltages are sampled via hall-effect or shunt sensors installed in the motor drive circuit. Typical sampling rate: 10–50 kHz (high resolution to capture transient harmonics).

Step 2—Preprocessing and Conditioning: Signals are synchronized and filtered (notch or bandpass) to remove switching noise and supply harmonics. Time-window segmentation is applied (e.g., 256–1024 samples per window).

Step 3—Feature Extraction: Frequency-domain features (FFT spectral lines, sideband components), time–frequency signatures (STFT, WPT), and model-based indicators (EKF

residuals, SMO estimates) are computed to capture incipient faults such as demagnetization or inter-turn short circuits.

Step 4—Classification/Prognostics: Extracted features are fed to ML/DL models (CNN, LSTM, 1D-CNN+attention, hybrid autoencoders) to classify fault types and estimate degradation trends. Training occurs offline, while inference can run on embedded controllers.

Step 5—Decision Integration: Outputs are integrated into the elevator controller to trigger alarms or predictive maintenance scheduling, with edge feasibility rated as high for most models once trained.

- Vibration/Acoustic Emission Path

Step 1—Signal Acquisition: Tri-axial accelerometers and AE sensors are mounted on the motor housing and bearing end-shields to capture mechanical dynamics. Typical sampling rate: 25–200 kHz (wideband to capture bearing and eccentricity signatures).

Step 2—Preprocessing and Conditioning: Signals are filtered (high-pass and whitening), synchronized, and windowed. Noise reduction techniques (wavelet denoising, empirical mode decomposition) are often applied due to structural resonances.

Step 3—Feature Extraction: Spectral kurtosis, envelope analysis, order-tracking, and CySA are used to detect repetitive impulsive faults from bearings, misalignments, or eccentricity.

Step 4—Classification/Prognostics: Features are used in ML/DL models (SVM, Random Forest, GRU, GANs, attention-guided GNNs) to identify fault progression and remaining useful life (RUL) trends.

Step 5—Decision Integration: Classifications are passed to the edge controller or gateway for maintenance scheduling and fleet-wide data fusion. Edge feasibility is moderate due to higher data volume and preprocessing demand.

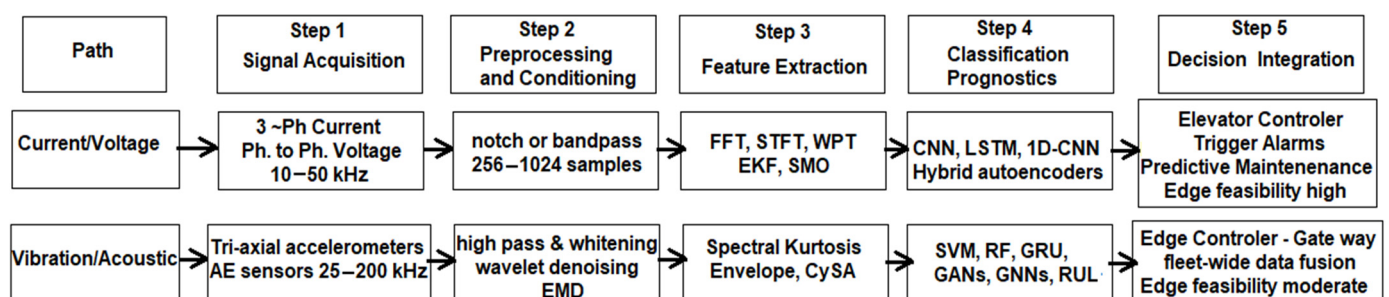


Figure 1. Block diagram of the two canonical diagnostic paths.

Table 6 presents a comparative overview of these categories, consolidating their typical input signals, dataset origin, operational contexts, reported performance metrics, sampling requirements, feasibility for edge or real-time execution, and their most common limitations.

To complement the glossary of performance metrics included in Table 6, detailed formulations and worked examples of classification and regression metrics (accuracy, precision, recall, F1, RMSE, etc.) are provided in [4]. In that study, the full set of equations is applied to experimental elevator PMSM datasets, thereby offering readers both theoretical definitions and practical application examples in a real case study.

Deep learning-based classification methods rely on data-driven feature extraction from raw current, vibration, or thermal signals, and achieve the highest reported accuracy (often exceeding 95%), but require extensive labeled datasets and high computational resources, which currently restrict their implementation on embedded controllers. Flux-based demagnetization detection techniques instead exploit physical signatures from magnetic flux and back-EMF waveforms, offering lightweight and fast deployment with lower computational demands, yet their performance is susceptible to noise and limited to specific fault types. Model-based parameter identification approaches use dynamic

electrical models and control loop signals to estimate system parameters in real time, achieving high precision under transient conditions but demanding extensive model tuning and providing no direct fault classification. Noise-robust ML classifiers extend conventional ML by incorporating noise-injection during training, showing strong performance in dynamic conditions while maintaining moderate computational cost, although they rely on well-designed noise models. Hybrid signal-based statistical methods combine handcrafted features from acoustic, vibration, and current signals, offering moderate accuracy with low computational requirements, but they depend on manual feature engineering and are less scalable to complex systems.

Table 6. Quantitative Comparative Summary of Representative PMSM Fault Diagnosis and Prognostic Techniques.

Method Technique Category	Signal Input Type	Dataset Type	Operating Conditions	Reported Metrics	Sampling Rate Window	Edge/Real Time Feasibility	Main Limitation
DL-based classification (CNN, hybrid DL)	Current, vibration, thermal	Laboratory (controlled)	Variable load and speed	Accuracy 95–98%, F1 $\approx$ 0.95	10–20 kHz/512–1024 Samples	Requires GPU; often offline inference	Needs large labeled dataset; limited interpretability
Flux-based demagnetization detection	Magnetic flux, back-EMF	Lab test bench	Nonstationary transients	Accuracy $\approx$ 90–93%	1–2 kHz/256 samples	Lightweight, real-time capable	Sensitive to noise; targets only specific faults
Model-based parameter identification (dynamic models)	Current, control loop signals	Industrial servo rigs	Transient and variable conditions	RMSE 2–4%, R ² 0.90–0.94	20 kHz/128-sample window	Real-time feasible on embedded MCUs	Complex tuning; not a direct classifier
Noise-robust ML classifiers	Current with noise augmentation	Laboratory (dynamic)	Dynamic with injected noise	Accuracy $\approx$ 94–96%	5–10 kHz/256–512 samples	Moderate compute (edge deployable)	Needs realistic noise modeling
Hybrid signal-based statistical feature methods	Acoustic, vibration, current	Lab and field (mixed)	Variable duty cycles and loads	Accuracy 88–93%, F1 $\approx$ 0.90	2–5 kHz/512 samples	Low compute (suitable for edge MCUs)	Requires manual feature engineering
Graph-based remaining useful life (RUL) prediction	Multisensor graph features	Public Benchmark + simulated	Progressive degradation cycles	MAE $\approx$ 3–5%, RUL accuracy 85–90%	10 kHz/Variable windows	High compute, suitable for server-side training	Needs large datasets, complex graph construction
Particle filter-based prognostics	Vibration, current degradation indicators	Simulated + lab	Nonlinear and non-Gaussian degradation	RMSE $\approx$ 5–7% (remaining life)	5–10 kHz/sliding window	Moderate (depends on particle count)	Computational cost; requires state space modeling
Comprehensive meta-analysis of methods (review synthesis)	Mixed signals (current, flux, acoustic)	Mixed (lab + field)	Stationary and dynamic operation	Accuracy range 82–99% (meta-summary)	1–50 kHz (reported range)	Mixed feasibility (method-dependent)	Provides generalized results, not directly implementable

In contrast, graph-based remaining useful life prediction frameworks represent multi-variate sensor data as graph structures and exploit attention mechanisms to infer degradation patterns, enabling simultaneous diagnosis and prognostics but at the cost of high data volume requirements and computational complexity. Particle filter-based prognostics operate on state-space models to estimate fault progression and remaining life through sequential Bayesian inference, showing robust behavior in nonlinear and non-Gaussian conditions, though they remain computationally heavy and sensitive to model parameterization. Finally, meta-analytical review syntheses compile results from multiple experimen-

tal studies to derive generalized accuracy ranges and performance benchmarks, providing valuable high-level insight but no directly deployable models.

This categorization clarifies the methodological landscape and highlights the fundamental trade-offs between accuracy, data requirements, interpretability, and real-time applicability. It also reveals that while several categories demonstrate strong performance in controlled laboratory environments, their adaptation and validation under the distinctive operating conditions of elevator PMSM drives—marked by low-speed start-stop cycles, regenerative braking events, and space-constrained installations—remain limited, underscoring a critical gap for future research.

5. Bibliometric Analysis of Recent References

To systematically identify the most relevant and high-quality literature on fault diagnosis and condition monitoring of elevator PMSMs, this review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. A structured search was conducted across six major scientific databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and MDPI. The search strategy combined Boolean keywords related to “elevator” or “lift”, “permanent magnet synchronous motor” or “PMSM”, and terms describing diagnostic and prognostic approaches such as “fault diagnosis,” “condition monitoring,” “predictive maintenance,” and “prognostics.” Only English-language publications from January 2015 to June 2025 were considered to ensure relevance to current technological developments.

The initial search identified 460 records. After automatic removal of 43 duplicates, 417 records remained for title and abstract screening. During this stage, publications that were unrelated to elevator systems (e.g., studies on wind turbines, electric vehicles, robotics), that focused exclusively on induction motors without relevance to elevator retrofit scenarios, or that addressed only control or design optimization without diagnostic content, were excluded. This resulted in the exclusion of 148 records based on abstract screening, leaving 269 full-text reports to be retrieved.

Of these, 8 reports could not be retrieved due to access limitations, and the remaining 261 full-text articles were assessed for eligibility. At this stage, studies were excluded if they were not focused on PMSM-based elevator drives ($n = 6$), did not present a relevant diagnostic or condition-monitoring methodology ($n = 12$), or lacked sufficient technical detail or measurable performance metrics such as accuracy, RMSE, or F1-score ($n = 25$). After applying these criteria, 218 studies were finally included in the qualitative synthesis. These selected works include experimental and simulation-based studies on condition monitoring, fault diagnosis, and predictive maintenance approaches, covering sensor-based and sensorless techniques, signal processing methods, ML and DL algorithms, and edge or IoT-based implementations specifically relevant to elevator PMSM traction systems.

In addition to the 218 core studies included through the PRISMA process, this review also incorporates a set of supplementary references. These include international standards and regulations (e.g., ISO, IEC), foundational theoretical works, general reviews on ML and signal processing, as well as a limited number of induction motor (IM)-related studies considered essential for providing historical background and ensuring methodological and conceptual continuity. With the inclusion of these supplementary references, the total number of references cited in this review amounts to 244.

The overall selection process is summarized in the PRISMA flow diagram shown in Figure 2, illustrating the numerical progression of records through each stage of the search, screening, and eligibility assessment process.

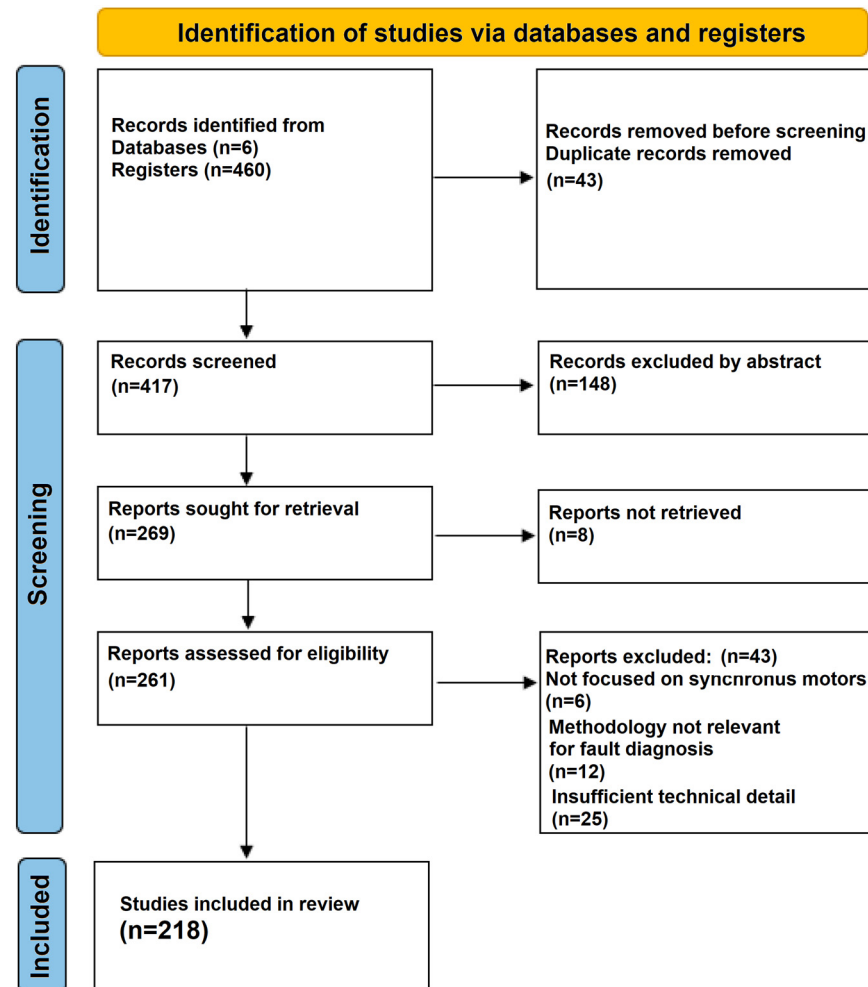


Figure 2. PRISMA Flow Diagram.

The publications per year presented in Figure 3 show an accelerated rise in publication numbers which achieved their highest ever total of 66 references during 2025. The increase in publications reflects global trends toward electrification along with predictive maintenance and digitalization and Industry 4.0 framework implementation in safety-critical systems.

The paper reveals that peer-reviewed journal articles (169 references, 69%) represent the most dominant type of publication (Figure 4a) followed by conference proceedings (14%) and review articles (7%). These and technical reports and standards make up the remaining 10%. Journal publications dominate the field because the field has shifted from exploration research to validated studies which demonstrate increasing scientific rigor and maturity. The thematic breakdown (Figure 4b) shows that PMSM condition monitoring receives the most attention with 40% (97 references) dedicated to general frameworks and holistic diagnostic approaches. Sensor-based methodologies comprise 19% (46 references), while ML-based methods form 13% (32 references). The remaining research deals with fault-specific studies about bearing faults and demagnetization and eccentricity and inter-turn short circuits even though these topics are critically important yet underrepresented compared to methodological advances.

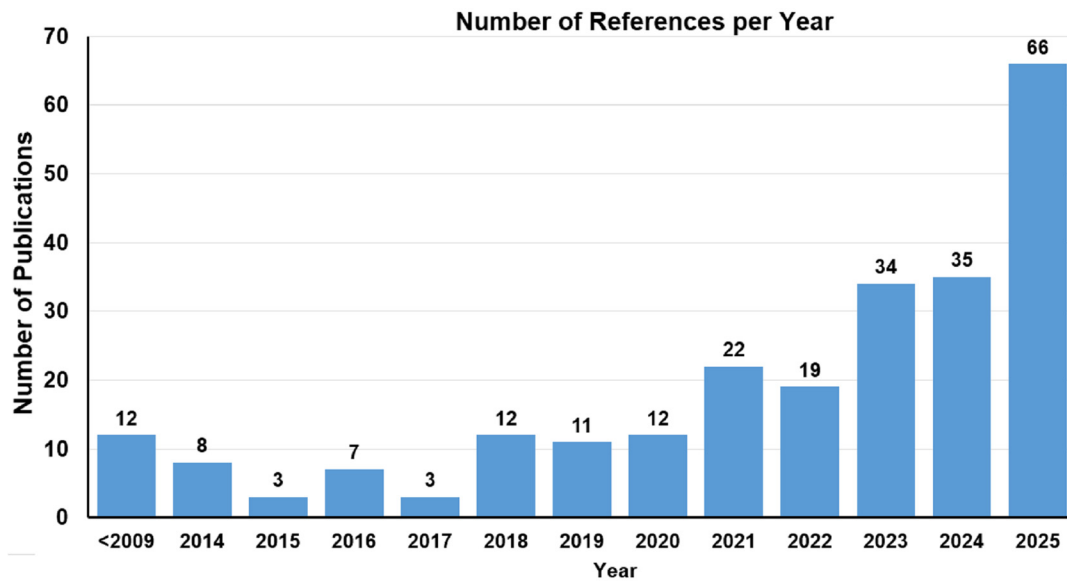


Figure 3. Publications per Year.

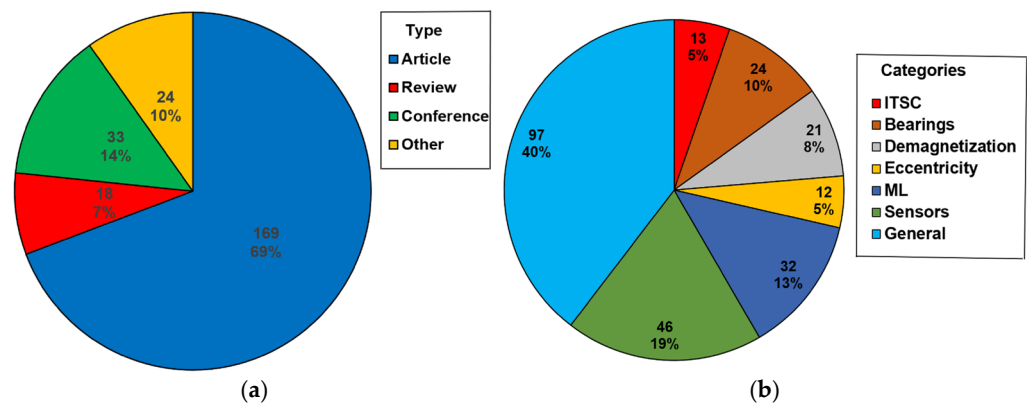


Figure 4. Categorization of the references studied: (a) type of references; (b) categories.

Current literature lacks studies that focus specifically on elevator systems and their operational requirements when it comes to fault diagnosis. This research gap is particularly noteworthy given that elevators represent one of the most widespread and safety-critical electromechanical infrastructures in modern urban life. Elevators are not merely transportation devices; they are indispensable components of the built environment, enabling accessibility, inclusivity, and efficiency in residential, commercial, and industrial buildings. Their uninterrupted operation directly affects millions of daily passengers, and any downtime or malfunction carries significant social, economic, and safety consequences.

From an industrial and market perspective, the elevator sector is widely recognized as a large and steadily growing domain, shaped both by the continuous expansion of new installations in rapidly urbanizing regions and by equally important modernization and retrofit activities in mature markets. These drivers reinforce the sector's position as a crucial area of investment, innovation, and regulatory attention. However, the existing body of academic and technical research does not yet reflect this importance with sufficient depth. Most investigations remain centered on PMSMs as individual machines, assessed under laboratory or general industrial conditions, while the elevator as a complete system—including traction and braking components, control strategies, safety interlocks, and human–machine interaction—is rarely addressed in a holistic manner.

At the same time, a substantial proportion of the worldwide installed base continues to rely on legacy systems that employ induction motors (IMs) and earlier generations of

drive technology. These installations often operate with limited or outdated maintenance practices, making them more vulnerable to unexpected faults and less equipped to benefit from emerging diagnostic tools. In this context, the adoption of artificial intelligence (AI), machine learning (ML), digital twins, and real-time multi-sensor monitoring is not merely a technical opportunity but an essential step toward aligning elevator maintenance with modern safety and efficiency expectations. Yet, systematic approaches for integrating these advanced techniques into legacy fleets remain largely unexplored in current research. This lack of domain-specific focus highlights the pressing need for future studies that do not only evaluate PMSMs in isolation but also consider elevators as complex, interconnected systems operating under distinctive regimes. Such research would fill a critical gap by linking technical fault diagnosis with the real-world operational demands, regulatory frameworks, and societal role of elevators in ensuring safe and reliable vertical mobility.

This gap represents a tremendous opportunity. A substantial improvement in operational reliability together with reduced downtime and enhanced safety can be achieved by installing intelligent condition-monitoring frameworks into IM-based elevator systems that utilize multi-sensor fusion and IoT-enabled remote data transmission and real-time analytics while supporting sustainability through extended asset lifetimes.

Recent industrial field observations and pilot deployments suggest that modernization combined with predictive monitoring could contribute to a measurable decline in elevator-related anomalies and service disruptions. For example, a large-scale analysis of maintenance records reported notable reductions in operational irregularities and fault occurrences following the integration of predictive diagnostic frameworks [239]. Similarly, a field experiment by Cui et al. [240] demonstrated that applying on-demand maintenance driven by fault prediction led to an 85.9% reduction in scheduled maintenance workload and a marked decrease in entrapment incidents across 762 elevators. While these studies do not directly report injury or fatality reductions, their outcomes indicate a likely positive safety impact. In parallel, U.S. national injury surveillance reports [241] record approximately 27 elevator-related fatalities and over 10 000 injuries annually, underscoring the critical importance of advancing predictive maintenance approaches to mitigate such risks.

Industrial initiatives involving proprietary maintenance platforms operated by leading elevator manufacturers demonstrate how remote and predictive monitoring can work. These isolated monitoring systems exist outside published scientific research in peer-reviewed journals. The lack of academic research that investigates elevator diagnostic problems creates a significant void. The current research aims to fill this essential knowledge gap. The research focuses on PMSM-driven and legacy IM elevator systems to develop diagnostic frameworks combining AI with real-time sensor data analysis and system-level safety protocols. Such innovations produce exceptional societal and scientific value because elevators operate at a global level with safety-sensitive systems.

The field has experienced rapid growth with substantial development, yet it shows little evidence of research focused on elevator systems which presents an essential opportunity for innovation. The large number of elevator installations combined with modernization requirements and data-driven diagnostic capabilities makes this research essential to link theoretical PMSM fault-diagnosis research to elevator system safety needs across the world.

6. Discussion

The review helps the field through its time-sensitive review of recent AI and condition monitoring advancements for PMSMs with attention to recent one-year publications. The paper addresses rotating machinery specifically in elevator systems that require analysis of unique operational challenges together with safety protocols. Modern society heavily relies on elevators because they serve as one of the leading electromechanical systems

supporting the movement of millions of daily passengers. Reliability and fault-tolerant operation represent essential matters because they affect public safety as well as the trust placed in these systems.

Elevator PMSMs have distinctive operational characteristics because they run through frequent start–stop operations while needing low-speed operation with high torque requirements and regenerative braking in restricted machine room or shaft environments. The distinctive operating characteristics produce fault patterns that differ substantially from industrial drive steady-state conditions. Most of the published research about PMSM fault diagnosis takes place in laboratory or industrial settings even though it fails to address the critical needs of elevator-specific studies. This work demonstrates the absence of relevant research while indicating that domain-specific models along with tailored monitoring approaches and datasets are necessary for elevator operations.

The paper integrates state-of-the-art AI/ML/DL approaches with IoT and edge-computing frameworks as a primary contribution. Recent work shows that combining DL models with transfer learning and explainable AI techniques and edge-enabled approaches enables predictive maintenance through real-time elevator controller implementations despite data limitations and imbalanced classes. The paper unites new developments to show the present state-of-the-art while identifying elevators as a vital domain for next-generation intelligent maintenance systems.

Elevator PMSM breakdowns result in essential risks for elevator passengers because they differ significantly from regular industrial system failures. Small issues in elevator systems can trigger problems with riding comfort together with floor leveling and braking reliability resulting in safety issues and public distrust. AI-powered predictive maintenance serves as an essential tool for creating safer vertical transportation systems that goes beyond cost optimization.

The analysis of the literature reveals both areas of convergence and points of divergence, along with perspectives specific to the elevator domain. Most studies agree that ML and DL methods can enhance classification accuracy, especially when supported by advanced signal preprocessing and multi-sensor data fusion. However, a large portion of existing research relies on laboratory datasets, raising concerns regarding their transferability to real elevator installations. Conflicting views also emerge on the use of sensor-based versus sensorless techniques, as sensorless approaches may be suitable for control tasks but tend to lose reliability under the low-speed operating conditions typical of elevators. Although DL models demonstrate high accuracy, their limited interpretability undermines trust, which is critical in safety-sensitive elevator environments. Moreover, the unique operational characteristics of elevators, such as frequent start–stop cycles, regenerative braking, confined space, and thermal constraints, produce distinctive fault signatures that require specialized diagnostic strategies. The widespread presence of legacy induction motor systems further demands methods that can generalize across motor types and enable effective diagnosis in mixed PMSM–IM fleets.

The bibliographic mapping also highlights several unresolved gaps that hinder the progress of the field. There is a lack of open datasets containing real operational data from elevator installations, and few system-level studies integrate traction, braking, control, and safety aspects within a unified diagnostic framework. Published field trials remain rare, leaving uncertainty about the performance of proposed methods under real-world conditions. There is also an urgent need for explainable AI models that can support certified maintenance decisions and ensure transparency in automated fault detection. In parallel, the growing connectivity of elevator fleets introduces emerging concerns regarding cybersecurity and data privacy, which are not yet adequately addressed in the current literature. In this context, the integration of IoT communication protocols, data security mechanisms,

and cloud-based decision-making has been examined in detail in [44], where encryption methods, authentication protocols, and secure communication channels for PMSM elevator applications were analyzed. The combined framework of [4,44] therefore demonstrates not only the diagnostic and monitoring pipeline but also secure data transmission and protection of elevator systems within IoT-enabled infrastructures. Advanced research in these directions is essential for enabling reliable predictive maintenance and ensuring the safe and efficient operation of the elevators of the future.

Modern elevator maintenance and commissioning practices are governed by a combination of statutory inspection regimes, European safety standards, and operational procedures; therefore, predictive diagnostics must translate signal-level fault indicators into actionable maintenance events and standardized acceptance checks. In this context, Table 7 consolidates the principal diagnostic parameters, inspection criteria, and regulatory compliance requirements that define the interface between condition monitoring systems and the operational decision-making framework in elevator PMSM installations. The table organizes the information into eight columns—Fault Indicator, Detection Method, Alarm Threshold/Limit, Required Action, Associated Maintenance Task, Relevant Standards/Regulations, Typical Sampling Rate and Window, and Edge/On-Site Feasibility—in order to provide a structured reference for integrating predictive analytics within routine and statutory procedures.

Each row corresponds to a representative class of fault modes (e.g., thermal overload, bearing degradation, insulation aging, misalignment, brake wear, sensor malfunction, control loop instability), summarizing how early signals detected by monitoring subsystems can be mapped to specific inspection steps, acceptance checks, or preventive actions. The inclusion of relevant standards explicitly references key regulatory frameworks such as EN 81-20 [242] and EN 81-50 [243], which define safety and testing requirements for elevator design and periodic inspection, as well as IEC 60034 and IEC 61508 [244] for electrical machine safety and functional safety. The Sampling Rate and Window column reflects typical acquisition settings observed in industrial deployments, ensuring that the data streams used for predictive algorithms are compatible with certification procedures. Finally, the Edge/On-Site Feasibility column indicates whether the required computation can be executed on embedded elevator controllers, facilitating compliance verification during field audits.

By combining these technical and regulatory dimensions, Table 7 bridges the gap between fault-level signal analytics and maintenance-level decision criteria, thereby enabling condition monitoring systems to support both predictive servicing and regulatory acceptance of elevator PMSM systems (Warn is in service soon and Crit is immediate safe-mode or shutdown).

Building on the fault taxonomy summarized in Table 1, the extended comparative analyses provided in Tables 2, 6 and 7 offer a more actionable perspective for practitioners by linking each fault type to its typical onset time, criticality level, signal and sensor requirements, recommended sampling windows, edge-deployment feasibility, and potential confounding factors, thereby translating fault signatures into concrete field-deployable monitoring strategies.

The future elevator challenges include supporting “elevator of tomorrow” systems that need to increase capacity and achieve faster operation with better energy efficiency while operating in denser urban environments. In this context, condition monitoring must evolve to:

- integrate digital twins capable of simulating real-time motor and drive behavior under varying passenger loads;

- leverage federated learning to enable knowledge transfer across fleets of elevators without compromising data privacy;
- address cybersecurity threats inherent in IoT-enabled predictive maintenance systems;
- ensure scalable and explainable AI models that can be trusted by manufacturers, service providers, and regulatory authorities alike.

Table 7. Standards and Operational Integration—Mapping of Fault Indicators to Maintenance Tasks and Acceptance Checks.

Fault Type	Key Indicators	Alarm (Warn/Crit)	Auto Action	Maintenance Task	Standards Tests	Sampling Latency	Edge Feasible *
Bearing defect	HF vib, sidebands, AE ↑, anomaly score	0.7–0.9/>0.9	Slow down reduce load	Vib and envelope analysis, grease, alignment	IEC 60034 vib, EN 81-20 insp.	2–5 kHz/min	✓
Stator short	Curr. imbalance, neg-seq, harm. ↑	Harm. ↑ > X dB/abrupt **	Safe mode inhibit start	IR, PD, winding check	IEC 60034, EN 81-50 elec.	10–20 kHz/s	△
Rotor demagnetization	Torque drop, DC flux offset, high I	5–15%/>15%	Degraded lockout	Magnetization, rotor polarity, replacement.	IEC 60034, EN 81-50 func.	1–5 kHz/s–min	△
Encoder fault	Miss pulses, jitter, pos. mismatch	>N lost/>ms latency	Safe stop	Replace encoder, wiring	IEC 61800-5-2; EN 81-20 level.	real-time/ms	✗
Thermal overload	Temp rise rate, thermal score ↑	80%/100%	Throttle, reduce load	Cooling, clean fan, insulation	IEC 60034, EN 81-20 thermal	1 Hz/min	✓
Inverter fault	DC-bus instab., sw. irregular, harm.	Trip limit	Trip, isolate drive	IGBT module checks	IEC 61800 fam., EN 81-50	10–20 kHz/ms	△
Guide wear	LF vib, acoustic, comfort ↓	RMS ↑/out of spec	Log & schedule	Guide roller inspection, lubrication, leveling test	EN 81-20 ride/leveling	1–5 kHz/h	✓
Brake anomaly	Brake torque var., temp ↑, ctrl instab.	<limit/interlock	Hold & block restart	Brake pad, piston insp., brake test	EN 81-20 brake; EN 81-50	1 Hz/ms–s	△

* ✓ = Feasible, △ = partially feasible and ✗ = not feasible. Arrows ‘↑’ and ‘↓’ indicate an increase and decrease, respectively, in the fault indicator or parameter ** Thresholds are indicative and depend on the motor model, the elevator operating load, the wear level and the accuracy of the sensors. Warn = service soon, Crit = immediate safe-mode or shutdown.

In summary, this paper connects modern diagnostic AI technologies to elevator PMSM requirements while emphasizing the need for domain-specific research in this safety-critical ubiquitous system that supports modern urban life.

7. Conclusions

The review presents the current developments in PMSMs condition monitoring and fault diagnosis for elevator applications through AI and ML and IoT predictive maintenance. The research focuses on specific elevator operational constraints and safety-critical requirements because general rotating machinery surveys do not address these domain-specific needs.

The research makes its primary contribution by uniting advanced AI diagnostic techniques from the past year with elevator PMSM practical needs because system efficiency and passenger safety and public trust depend on these failures. By synthesizing these advances and outlining future trends such as digital twins, federated learning, and explainable AI, the paper establishes a solid base for the development of intelligent, reliable, and scalable monitoring systems that will define the elevator of the future. This review paper therefore maintains a clear focus on PMSM-based elevator systems, with IM studies

referenced only when they offer methodological continuity or practical insights directly support PMSM condition monitoring, maintenance and retrofit strategies.

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Abbreviations

The following abbreviations are used in this manuscript:

AE	Autoencoder
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
CNN	Convolutional Neural Network
CBM	Condition-Based Maintenance
CRC	Cyclic Redundancy Check
CSA	Current Signature Analysis
CySA	Cyclostationary Analysis
DNN	Deep Neural Network
DL	Deep Learning
EKF	Extended Kalman Filter
EMI	Electromagnetic Interference
EMF	Electromotive Force
EN	European Norm
EV	Electric Vehicle
FGB	Fiber Bragg Grating
FFT	Fast Fourier Transform
FMEA	Failure Modes and Effects Analysis
FSA	Flux Signature Analysis
GAN	Generative Adversarial Network
HTTPS	Hypertext Transfer Protocol Secure
IEC	International Electrotechnical Commission
IGBT	Insulated Gate Bipolar Transistor
IM	Induction Motor
IoT	Internet of Things
ISO	International Organization for Standardization
KPI	Key Performance Indicator
LTE	Long Term Evolution
LSTM	Long Short-Term Memory
PWM	Pulse Width Modulation
ML	Machine Learning
MCSA	Motor Current Signature Analysis
MQTT	Message Queuing Telemetry Transport
NIOSH	National Institute for Occupational Safety and Health
OLE	Object Linking and Embedding
OPC	OLE for Process Control

PAC	Protection, Automation and Control
PCA	Principal Component Analysis
PLC	Programmable Logic Controller
PMSM	Permanent Magnet Synchronous Motor
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROFINET	Process Field Net
REST	Representational State Transfer
RMS	Root Mean Square
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
SMO	Sliding Mode Observer
SVM	Support Vector Machine
TCP	Transmission Control Protocol
TLS	Transport Layer Security
TSN	Time-Sensitive Networking
UA	Unified Architecture
VFD	Variable Frequency Drive
WPT	Wavelet Packet Transform

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