

Article

Advanced Artificial Intelligence for Fault Detection of Electric Motors

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Abstract

The growing need to assess the health of components has made fault detection an increasingly important research topic in recent years. While traditional techniques remain widely used, the expansion of artificial intelligence (AI) has introduced innovative approaches. Among these, autoencoders have demonstrated significant potential for detecting anomalies in electric motors. The aim of this paper is to identify which signals are most suitable for AI-based fault detection in permanent magnet synchronous motors (PMSMs). To achieve this, in addition to analyzing acceleration signals, which are commonly studied in the literature, this work broadens the investigation by including current, voltage, and temperature signals acquired from different positions. The proposed method is tested during endurance tests, where motors operate under highly variable and demanding operating conditions. The collected signals are then analyzed using a 1D convolutional neural network autoencoder (1D CNN AE) to detect possible faults. The results highlight the importance of considering not only acceleration but also alternative monitoring signals. In particular, temperature measurements proved to be crucial for identifying and localizing specific faults, while current and voltage provided valuable insights into motor behavior, such as changes in control strategy, even when they are not directly correlated with fault occurrence.

Keywords: fault detection; autoencoder; machine learning; electric motors; anomaly detection; neural networks; 1D CNN; preventive maintenance

1. Introduction

Fault detection is the process of identifying and diagnosing faults in machines and systems to ensure reliable operation. Initially, diagnostic methods relied on mathematical models and signal-based techniques to detect mechanical failures [1]. By analyzing monitoring signals, fault detection methods detect abnormal behavior and apply corrective actions before failures lead to severe damage. Effective fault detection minimizes downtime, reduces maintenance costs, and improves overall system efficiency [2]. Over time, these approaches have evolved towards more advanced predictive strategies, such as predictive maintenance and prognostics, which aim not only to identify faults but also to estimate system health and forecast potential failures [3,4]. The recent integration of big data and artificial intelligence (AI) has further advanced this field, enabling real-time processing of large datasets and the development of highly accurate predictive models [5,6]. Among AI-based methods, autoencoders (AEs) are especially well suited for fault detection tasks, as they enable unsupervised learning and anomaly detection without requiring labeled fault data [7]. Moreover, AEs have a flexible and modular structure that can be composed



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of different types of neural networks (such as convolutional neural networks (CNNs) or long short-term memory (LSTMs)) [2].

The diversity of employed methods highlights that, in the field of rotating machines, fault detection is highly flexible, as it can be implemented using a wide range of methods. Furthermore, there is also flexibility regarding the choice of monitoring signal. Different signals provide complementary information: electrical, mechanical, and hydraulic faults influence the system in different ways. The most common signals used for detecting anomalies are acceleration, current, temperature, and voltage, each with specific advantages and limitations [8–10]. Accelerometers are one of the oldest and most widely adopted sensors. They are particularly effective in detecting mechanical faults such as rotor imbalance, misalignment, bearing degradation, and eccentricity. These faults produce distinctive frequency components that can be detected through signal processing methods such as the fast Fourier transform (FFT) or short-time Fourier transform (STFT) [1]. For example, bearing damage typically generates harmonics related to the bearing geometry, while rotor eccentricity produces sideband frequencies around the fundamental component [8]. An example of the usage of accelerometers in electric motor fault detection is given by Chaudhari et al. [11]. They compare the fast Fourier transform to the discrete wavelet transform in the context of vibration signal analysis for fault detection of electric motor bearings. Both methods proved to be effective, but the discrete wavelet transform looks more suitable for this application due to the higher amplitudes of the frequencies used for fault detection. In another publication, Espinoza et al. [12] employed a machine learning model for rotor fault diagnosis. This fault detection algorithm reached very high levels of accuracy when monitoring the vibration of all bearings from a machine. Despite its effectiveness, vibration analysis is not always the optimal solution due to its high costs and installation challenges, especially in confined spaces and acoustically complex environments [13]. In such cases, vibrations from other components may overlap with those generated by the motor, reducing diagnostic reliability [9].

In recent years, current signal analysis has also gained significant attention in PMSM condition monitoring, since it provides a cost-effective and robust solution suitable for real-time applications. Current signals can often be measured without additional hardware, since current transducers (e.g., Hall sensors) are frequently integrated in the inverter [9,14]. Current analysis is sensitive not only to electrical faults, such as interturn short circuits, but also to mechanical and magnetic problems, including eccentricity [10,15] and partial demagnetization [16]. Faults typically appear as variations in the harmonic content of the measured current, which can be tracked in the frequency domain. For instance, Georgakopoulos et al. [17] examined the generation of harmonic components in inverter input current due to induction motor faults. These sidebands can be effectively identified using the discrete wavelet transform and can therefore be used for fault detection. Similarly, Chen et al. [13] combined continuous wavelet transform and deep convolutional neural networks to analyze current signals. This model successfully classified the operating conditions of both induction motors and permanent magnet synchronous motors, distinguishing between normal operation, inner race faults, outer race faults, and misalignment. Another example of current-based fault detection is given by Xiao et al. [18], who introduced a modified deep autoencoder to detect interturn short-circuit faults. This method adopts a distribution metric based on the maximum mean discrepancy and on the maximum covariance discrepancy to detect the incipient fault state more accurately. The results demonstrate that the proposed method is accurate and robust but also reduces the false alarm rate.

Temperature signals also play a critical role in condition monitoring, as excessive heating is one of the main causes of degradation in winding insulation and permanent magnets. Prolonged exposure to high temperatures can accelerate insulation breakdown, leading to

interturn short circuits, while overheating of the rotor may induce partial demagnetization. Monitoring the temperatures of the stator, rotor, and inverter enables early detection of abnormal operating conditions [9]. For example, Filho et al. [19] combined accelerometer and thermocouple measurements using a Park transform-based sensor fusion approach and a shallow artificial neural network. Tests on single-phase induction motors reached an accuracy exceeding 99.5%. A similar approach has been adopted by Owusu et al. [20], who utilized current and bearing-housing temperature signals in combination with autoencoders. In another publication, Mohammed et al. [21] proposed an innovative approach for the early detection of stator winding interturn short-circuit faults using fiber-Bragg grating (FBG) sensors to monitor winding thermal signature. Their experimental tests demonstrated that even a single shorted turn generates a localized thermal hotspot that can be clearly identified, with the measured temperature rise scaling proportionally with fault severity. This makes it possible not only to detect faults but also to track their progression and localization. The study further showed that thermal signature monitoring is particularly valuable under operating conditions where conventional electrical methods may struggle to identify early-stage faults. Alternative thermal monitoring can be carried out by means of thermal images. For instance, Dos Santos et al. [22] tested four convolutional neural network architectures in combination with infrared thermal images to distinguish 11 fault conditions. The authors report that, among the tested algorithms, the most accurate one achieved an accuracy of 98.18%.

Voltage signals are less commonly used alone for diagnostic purposes, but they can still provide valuable information about the condition of the motor and the inverter. Abnormalities in voltage waveforms, such as unbalances or asymmetries between phases, may indicate inverter malfunctions, insulation problems, or irregularities in the stator windings. Voltage monitoring is often combined with current analysis to increase the robustness of diagnostic systems and to provide a more complete assessment of overall performance [9]. An example of voltage signal-based fault detection is given in [23]. In this article, the authors exploit the variations in the load angle to detect interturn short circuits and demagnetization. Unlike other fault detection methods, this approach neither requires additional hardware nor modifications to the main control algorithm of the motor. The voltage signal has also been used by Haddad et al. [24], who employed a combination of fast Fourier transform and linear discriminant analysis to detect static eccentricity, interturn short circuits, and demagnetization faults. In another article, Choi and Joe [25] combined a convolutional autoencoder (CAE) with a deep neural network (DNN) to detect faults from three-phase voltage and current data, treating the phases as structured inputs. Among the various indicators, voltage imbalance and phase-to-phase variations proved to be sensitive to fault conditions such as misalignment and shaft imbalance. In addition, the integration of voltage harmonics and total harmonic distortion allowed the model to capture anomalies in the electromagnetic behavior of the machine. Optimized for real-time processing, the proposed framework achieved very high diagnostic accuracy, confirming the relevance of voltage-based analysis in fault detection studies.

In summary, each monitoring signal provides partial but valuable diagnostic information. Vibration analysis is very effective for mechanical issues but requires additional sensors and careful installation; current analysis is cost-effective and versatile but may be less sensitive to mechanical faults; temperature monitoring is crucial for detecting overheating and preventing insulation or magnet degradation, while voltage analysis complements other techniques by highlighting inverter-related problems. For this reason, many modern approaches combine multiple monitoring signals to achieve more reliable and robust fault detection in PMSMs [9].

This research aims to determine which signals are most effective for AI-based fault detection in PMSMs. In addition to the acceleration signals commonly studied in the literature, this work extends the analysis to current, voltage, and temperature signals acquired in different positions. Since each of the analyzed signals exhibits greater sensitivity to specific types of fault, their combination could lead to a more robust fault detection method capable of identifying a wider range of failures. Furthermore, because certain faults can be detected through multiple signal types, the proposed approach provides a degree of redundancy: in the event of the failure or unavailability of a monitoring signal, other signals may still enable the detection of the same fault. The proposed method relies on data collected during endurance tests, in which motors are subjected to highly variable operating conditions, including fluctuations in torque, speed, and temperature. The monitoring signals are analyzed using a one-dimensional convolutional neural network autoencoder (1D CNN AE). The final objective is to implement the multi-signal approach into a quasi-real-time fault detection algorithm for test bench applications, capable of integrating and comparing information from multiple signals to improve diagnostic accuracy and reliability.

2. One-Dimensional Convolutional Neural Network Autoencoder

In this study, a 1D convolutional neural network autoencoder (1D CNN AE) was selected. As demonstrated by several publications [2,26], it is among the most accurate and reliable algorithms for AI-based fault detection.

CNNs were initially designed to process images (2D data), as traditional artificial neural networks (ANNs) showed limitations with this type of input, requiring too many parameters and performing poorly in training [5]. Unlike traditional neural networks, CNNs introduce two simplifications. First, neurons in a given layer are connected only to small, local receptive fields of the previous layer, instead of being fully connected. This allows the network to detect local phenomena. Second, the weights are the same across the entire input. These innovations made CNNs faster to train and less affected by overfitting or gradient vanishing [7].

The fundamental structure of CNNs is shown in Figure 1. First, the convolutional layers extract relevant features from the input by applying a set of learnable filters in the convolutional layer. The results of this operation are called feature maps. These feature maps are used as inputs for non-linear activation functions and subsequently downsampled by pooling layers. The goal of this step is to reduce dimensionality while preserving the relevant features. The sequence of convolution, activation function and pooling can be repeated multiple times to further reduce the dimension of the output and to learn more complex features. In the end, the output of the last pooling layer is flattened and fed into a fully connected neural network for the final classification or regression task.

After achieving significant success in the field of image analysis, CNNs have also been adapted to time-series data. Many studies have applied preprocessing methods, such as the discrete Fourier transform (DFT), to reshape acceleration signals into 2D matrices suitable for CNN input [27]. However, this approach is computationally expensive and requires very large datasets, which are often unavailable in common applications [28]. To overcome the limitations of conventional CNNs, one-dimensional CNNs (1DCNNs) were introduced. In this architecture, the filters are applied along the temporal axis rather than across two dimensions, enabling the extraction of frequency and time-localized features directly from raw signals [28]. The main advantages of 1D CNN AE are the improved feature extraction and a reduced number of parameters compared to fully connected AEs. This design allows the network to achieve superior accuracy, faster processing and lower computational cost while reducing data requirements [28]. For these reasons, 1D-CNNs are particularly suited

for real-time fault detection in electric motors, as they can handle current or vibration signals under variable operating conditions with minimal preprocessing and high efficiency [2].

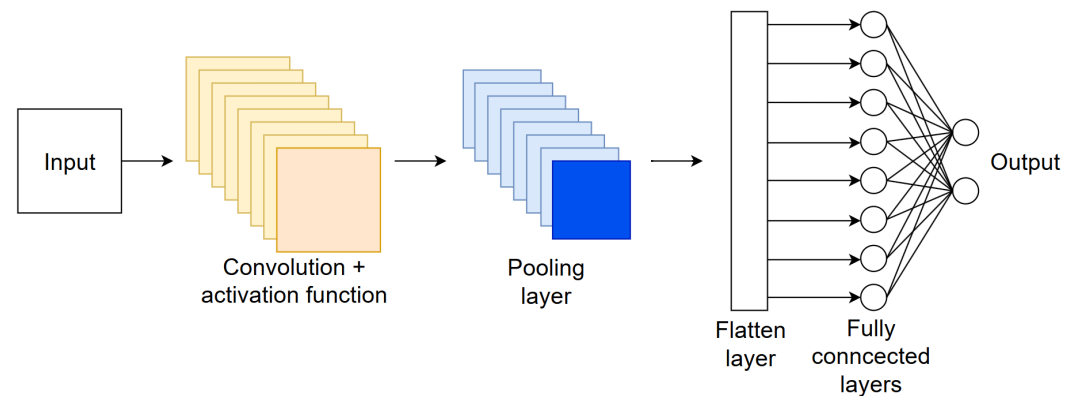


Figure 1. Fundamental structure of a CNN.

As discussed in the previous section, one of the emerging AI-based methods for fault detection is the autoencoder (AE). The typical structure of an AE is shown in Figure 2. It is an unsupervised neural network designed to learn compressed representations of data by reconstructing the input through an encoder–decoder structure. The encoder maps the input into a lower-dimensional latent space, while the decoder attempts to reconstruct the original data from this representation [29]. Dimensionality reduction is achieved by progressively reducing the number of neurons in each layer of the encoder until the bottleneck, constituted by the latent layer, is reached. The dimensions of the input and output layers are not fixed but depend on the variables present in the dataset, ensuring that the model can adapt to different signal types and application contexts. Subsequently, the dimensionality is gradually restored in the decoder until the reconstructed output is obtained. The training process aims to minimize the difference between the input and the reconstructed output. This property makes autoencoders effective for learning compact feature representations and for detecting deviations that may indicate faults [29,30].

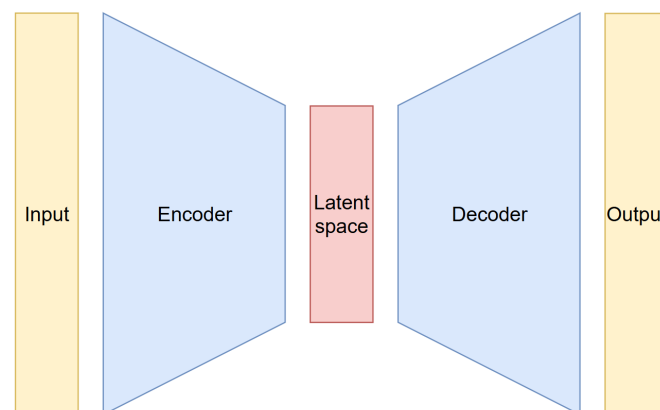


Figure 2. Structure of an autoencoder.

The 1D CNN autoencoder employs convolutional filters as the fundamental units of its layers. These filters slide along the input series, capturing local patterns and inter-variable relationships within the data. In this way, the network can extract complex dependencies that a standard fully connected AE might overlook [31]. Instead of pooling layers, the model relies on the stride to downsample the data in the encoder and to perform symmetric upsampling in the decoder, ensuring a lightweight and consistent computational flow [31]. The latent space, or “bottleneck,” is implemented as a convolutional layer. This design

improves reconstruction accuracy and computational efficiency, offering advantages over fully connected layers. Finally, padding is applied uniformly across all convolutional layers to maintain spatial dimensions. This ensures that input and output lengths remain aligned during both encoding and decoding, avoiding the loss of critical information through dimensionality reduction.

3. Autoencoder-Based Fault Detection

Once the structure of the 1D CNN AE is defined, a set of metrics is required to classify the state of the motor according to the reconstructed signal. This is achieved by comparing the reconstruction error with predefined thresholds, which are computed using the training and validation sets.

The reconstruction error represents the difference between the input data and the output generated by the autoencoder. This metric is central to fault detection, since the network reconstructs normal data with low error, while anomalous data are poorly reproduced, resulting in higher reconstruction error values that indicate potential faults. In this work, the reconstruction error is measured using the mean absolute error (MAE), calculated as

$$MAE_i = \frac{1}{n} \sum_{j=1}^n |y_{true,ij} - y_{pred,ij}| \quad \text{for } i = 1, 2, \dots, m \quad (1)$$

$$\overline{MAE} = \frac{1}{m} \sum_{i=1}^m MAE_i \quad (2)$$

where n is the number of time points, m is the number of variables, $y_{true,ij}$ is the input value, and $y_{pred,ij}$ is the reconstructed output. MAE was preferred over mean squared error (MSE) because it showed lower variability on the test set, leading to a more stable and reliable evaluation. Once each motor testing cycle is processed by the autoencoder, the reconstruction error provides the basis for the analysis. However, a detection threshold must then be defined to decide whether the data correspond to a healthy or a faulty condition [2].

Selecting an appropriate detection threshold is critical since it directly influences the ability of the autoencoder to distinguish healthy and faulty behavior. Establishing a reliable threshold is often challenging, especially when it is not clear which part of the data is affected by a malfunction. Moreover, the available training set may be limited and fail to capture the full variability of the system. To address this issue, the approach used in this article, inspired by Lee et al. [32] and Givnan et al. [33], introduces two thresholds instead of one. This choice compensates for the limited data available during training. In fact, with small datasets, the reconstruction error is often higher than it would be with more extensive training. For this reason, the first threshold acts as an early warning indicator of abnormal behavior, while the second threshold provides a stronger indication of a potential fault. Both thresholds are derived from the distribution of the reconstruction error (MAE) across both training and validation sets. First, the lower and upper quartiles are computed as

$$Q_1 = \text{percentile}(\overline{MAE}_{[1:n_{training}+n_{validation}]}, 25) \quad (3)$$

$$Q_3 = \text{percentile}(\overline{MAE}_{[1:n_{training}+n_{validation}]}, 75) \quad (4)$$

where $n_{training}$ is the number of training cycles, $n_{validation}$ is the number of validation cycles, Q_1 corresponds to the value below which the lowest 25% of values fall, while Q_3 marks the value below which 75% of the data fall, thus separating the upper 25% from the rest. From these two quartiles, the interquartile range (IQR) can be calculated. It measures

the central dispersion of the data and provides an indication of variability as well as the presence of possible outliers. Its expression is given by

$$IQR = Q_3 - Q_1 \quad (5)$$

The two thresholds are then defined following Tukey's method:

$$threshold_{low} = Q_3 + 1.5 \cdot IQR \quad (6)$$

$$threshold_{high} = Q_3 + 3 \cdot IQR \quad (7)$$

The lower threshold indicates data points considered outliers, while the higher one highlights values that are outside the expected range. Although this method works well in many cases, it may be excessively restrictive when the training data do not fully reflect the variability of the motor. This limitation becomes evident, for example, during test cycles with strong fluctuations of speed and torque over very short periods. To improve flexibility, the final implementation of the algorithm also allows manual adjustment of the thresholds so that they can be tuned based on practical experience. However, this option was not used in the present study, and all results reported in this paper were obtained using the automatically calculated threshold values.

One advantage of this method is its ability to detect sensor failures. Since a sensor fault produces measurement cycles that differ significantly from those observed under normal operating conditions, such anomalies result in large reconstruction errors and can therefore be identified by the detection algorithm. On the other hand, since the method is based on the autoencoder's ability to reconstruct a cycle using data acquired from that same cycle, its effectiveness is limited to operating conditions similar to those seen during training. For this reason, changes in operating conditions, control strategies, or sensor configurations may degrade its performance and lead to reliability issues. This limitation is not critical, as the model can be retrained whenever significant changes occur. Moreover, the proposed algorithm is designed for endurance testing applications, where motors operate under controlled and relatively stable conditions. For this reason, changes in operating conditions, control strategies, or sensor configurations are expected to be rare.

4. Fault Detection Method

This section describes the application of 1D CNN AE-based fault detection in the context of electric motor endurance testing.

An overview of the experimental setup is given in Figure 3. The signals acquired from sensors mounted on the two motors are collected through a data acquisition system and used as input for the autoencoders. The reconstruction error is continuously visually monitored: when it exceeds the predefined thresholds, a failure may have occurred.

4.1. Test Bench

The experimental campaigns presented in this article were carried out on a dedicated bench located inside an isolated room, where both temperature and humidity could be controlled. This setup allowed the motors to operate under different environmental conditions, simulating realistic and harsh scenarios.

The test rig consists of two synchronous motors arranged in a back-to-back configuration. This means that one motor operated in traction mode, providing the required torque, while the other worked as a dynamic brake, absorbing the torque generated by the first motor.

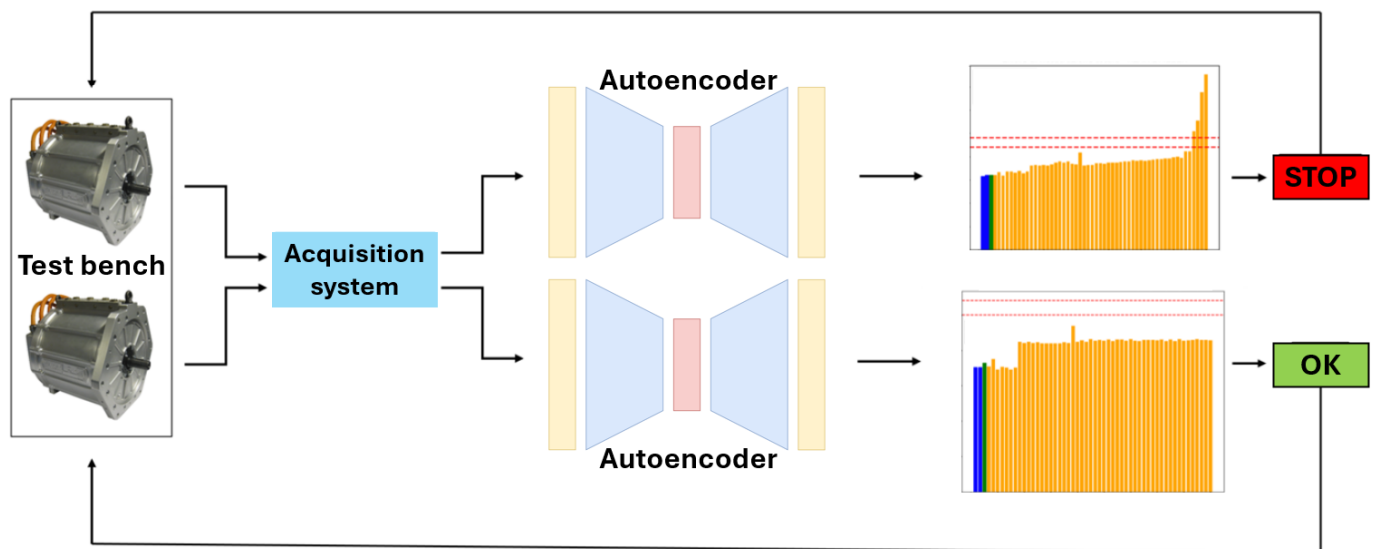


Figure 3. Overview of the electric motor endurance test bench.

Each motor is instrumented with several sensors to monitor its condition during the tests. A monoaxial accelerometer was installed to measure motor vibrations, while current transducers were used to record the phase currents. In addition, a voltage sensor measured the inverter output, thermocouples monitored the phase temperatures of the motor, and NTC sensors were used to measure the inverter temperatures. It should be noted that not all sensors were installed simultaneously in every test configuration. For this reason, all these signals are not analyzed in each case study.

4.2. Test Procedure

The endurance test consists of a series of cycles. Each cycle includes approximately 90 min of operation under load, followed by 90 min with the motor at rest. An example of the torque and rotational speed profiles used during the test is given in Figure 4. This 3 h cycle is repeated hundreds of times while maintaining the same speed and torque profile to reach the required minimum motor life. During these endurance tests, often conducted under extreme environmental conditions, fault detection becomes critical, as such conditions may cause premature anomalies.

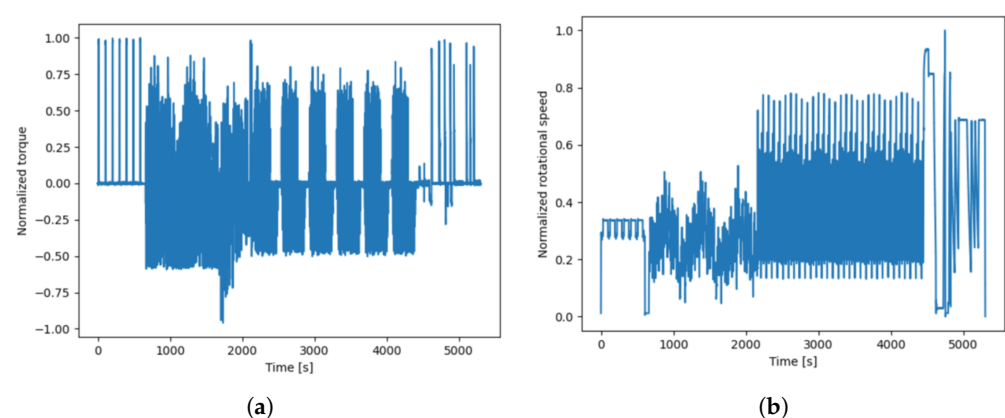


Figure 4. Example of the normalized torque (a) and rotational speed (b) profiles used during the underload phase.

4.3. Monitoring Signals

A number of different signals are used to monitor the state of the system in different positions. In particular, the signals analyzed during the case studies are local acceleration, D and Q-axis currents (i_d and i_q), D and Q-axis voltage, inverter driver temperature, inverter module temperature for phases U, V and W, inverter logic temperature, and motor phases U and V temperatures. The D- and Q-axis currents and voltages were selected because they represent the fundamental state variables of the PMSM in the synchronous reference frame and are directly involved in the field-oriented control algorithm [34]. As previously mentioned, not all sensors are simultaneously installed on the test bench in every configuration. The objective of analyzing the output of different sensors is to evaluate whether they can support fault detection and, when possible, provide information about the location of the fault.

The acceleration signal is processed to extract meaningful features for the AI-based fault detection method. In particular, order analysis is used to express the different frequency components of the signal in relation to the rotational speed of the motor, ensuring consistency and reliability, even under variable speed conditions. Input quantities derived from the acceleration signal include:

- The sum of all the frequency components at each sampling time. In particular, the 10–1500 Hz range was chosen for its relevance in bearing fault detection [35] while avoiding high-frequency electromagnetic noise [2].
- The value of the first and second mechanical orders. Even if previous studies have shown that the first four orders can highlight rotor anomalies [36], only the first two mechanical orders were retained to reduce redundancy and computational cost. Higher orders often provide information similar to that of the second order [37], making them less relevant for this study.
- The characteristic bearing orders, including FTF (fundamental train frequency), BSF (ball spin frequency), BPFO (ball passing frequency on the outer race), and BPFI (ball passing frequency on the inner race) [2]. Even if BPFI and BPFO have proven to be the most effective frequencies for bearing fault detection [36], all bearing-related components were retained to avoid the loss of potentially useful information.

4.4. Data Processing

The motor data are obtained from the sensors installed on the test bench, and the signals are recorded through the acquisition system integrated in the setup. Data are sampled every 0.25 s and stored for subsequent analysis. Once the signals are collected, the next step is to isolate the testing cycles and reduce the data size through time averaging. This process is applied to minimize the impact of noise and outliers and to improve the computational efficiency. The number of windows applied, which defines the points to which each testing cycle is downsampled, is derived according to the following formula:

$$N_{windows} = 2^{\text{int}(\log_2(\frac{\text{cycle length}}{40}))} \quad (8)$$

Each cycle is divided into windows with a 50% overlap, preserving temporal continuity. As a result, each cycle is downsampled to approximately 512 points, regardless of its original length. The data are then reshaped into a three-dimensional structure, with dimensions corresponding to number of cycles $\times$ cycle length $\times$ number of features. This structure serves as input to the autoencoder.

4.5. Features of the Employed Autoencoder

A 1D CNN AE is employed for data reconstruction. Its structure is shown in Figure 5. The final architecture and hyperparameter configuration were selected through a grid search aimed at minimizing the validation error at the end of the training phase. Several combinations of network depth, number of filters, kernel sizes and latent space dimensions were tested. As can be seen in Figure 5, the optimal setup is composed of two convolutional layers in both the encoder and decoder, with 256 and 128 filters, kernel sizes of 5, and a stride of 2. This depth is sufficient to capture relevant patterns in the data while preserving computational efficiency [38]. Unlike the encoder and the decoder, the latent space is based on a single layer structure with a dimension equal to 64. The same padding was adopted throughout the network to preserve feature alignment. This setup provided the best trade-off between reconstruction accuracy and model complexity on the validation set.

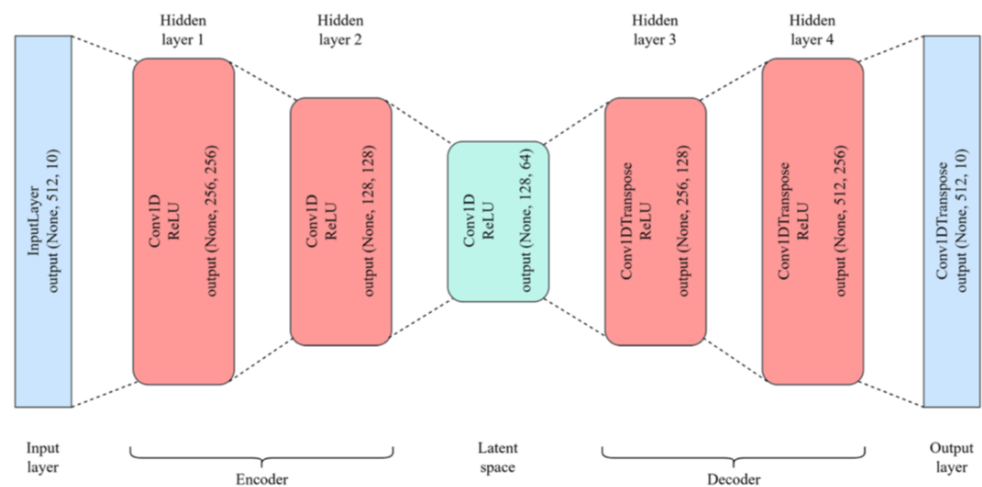


Figure 5. Structure of the employed 1D CNN AE.

The activation function is chosen as the rectified linear unit (ReLU), which is mostly used in deep learning because of its ability to manage non-linear relationships, allowing the network to capture complex patterns more effectively. At the same time, it promotes sparse activations, reducing the risk of overfitting and improving generalization. Another important advantage is that it avoids the vanishing gradient problem that often affects traditional activation functions. As a result, training converges faster and the optimization process becomes more stable [39,40]. Since the input data used in this study are always positive, ReLU is particularly suitable, discarding negative values while preserving positive ones.

To further increase robustness, L2-regularization is applied. This technique penalizes excessively large weights, encouraging the model to learn more general representations that remain valid also for unseen data [40,41]. In particular, a regularization factor of 10^{-5} is used.

The input data is normalized by means of min–max normalization, ensuring that all the input variables contribute equally to the learning process. This prevents features with larger magnitudes from dominating the training process. Moreover, it guarantees that the reconstructed signals remain bounded and nonnegative. In particular, the normalization is calculated only on the training set and then applied to the validation and test sets, avoiding data leakage and preserving the reliability of the evaluation procedure [41].

As far as training is concerned, in this study, the training dataset is obtained from the first 20 cycles acquired from each new tested motor, assuming healthy conditions at the beginning of its life cycle. These data are split into 16 initial training cycles (80%) and 4 final validation cycles (20%) for the autoencoder. This setup is chosen after sensitivity

analysis. This approach allows the network to learn from consistent, fault-free data, while the validation set serves as an independent benchmark to verify the quality of the training process. The employed batch size, which indicates the number of training samples used in each iteration of the training process within an epoch, is equal to 4. This value is kept low because the training set contains only 16 samples. This approach allows for more frequent updates to the model weights, which can help enhance learning given the limited data. As far as the learning rate is concerned, it is initially set to 0.001. A relatively high learning rate allows the model to learn efficiently in the early stages. From the first step, an adaptive strategy is then applied: whenever the validation loss does not decrease for 10 consecutive cycles, the learning rate is reduced by half, continuing until it reaches a minimum of 10^{-7} . This gradual reduction helps the network converge more precisely to the minimum of the loss function, avoiding oscillations around suboptimal values. The training process used the Adam optimizer, chosen for its fast convergence, robustness to noisy data, and relatively low memory requirements [39]. The loss function was the MSE between input and output. A maximum of 250 epochs was set, together with an early stopping criterion based on validation loss. Training is stopped when validation loss increases or remains steady within a tolerance of 10^{-6} . A minimum of 100 epochs is established to avoid underfitting.

The AI fault detection algorithm runs on a Windows 11 system with an Intel Core i5-12500H CPU (12 cores, 16 threads, 2.5 GHz) and 16 GB of DDR4 RAM. Under these conditions, the autoencoder required approximately 0.2 s per training epoch, whereas the evaluation of a cycle was completed within a few tens of milliseconds.

The performance of the proposed algorithm, using only the acceleration signal, is compared with that of other AI-based techniques and traditional algorithms reported in [2].

4.6. Example of Fault Detection

Figure 6 gives an example of the usage of the proposed fault detection method. The trend of the reconstruction error is displayed by means of a bar chart. Each bar represents the value of reconstruction error obtained from each testing cycle. As new cycles are processed, the chart is dynamically updated, allowing quasi-real-time monitoring of motor conditions. The two thresholds are represented by means of dashed lines. It should be noted that the fault detection algorithm does not provide continuous feedback during endurance testing. Instead, the reconstruction error is evaluated at the end of each test cycle, and the diagnostic outcome is updated accordingly. Consequently, the proposed method should be regarded as a quasi-real-time monitoring approach. As shown in the image, when the reconstruction error remains below the thresholds, the input is very close to the reconstructed signal. On the other hand, when the reconstruction error exceeds both thresholds, the input signal becomes significantly different from the reconstructed one. This is due to the fact that the original signal has become significantly different from the ones belonging to the training set. This visualization provides an intuitive and effective way to track system health over time, offering immediate feedback on potential fault progression.

During testing, operators monitor multiple graphs of this type, each associated with one or more monitoring signals. An alarm is triggered whenever the reconstruction error exceeds either of the two predefined thresholds.

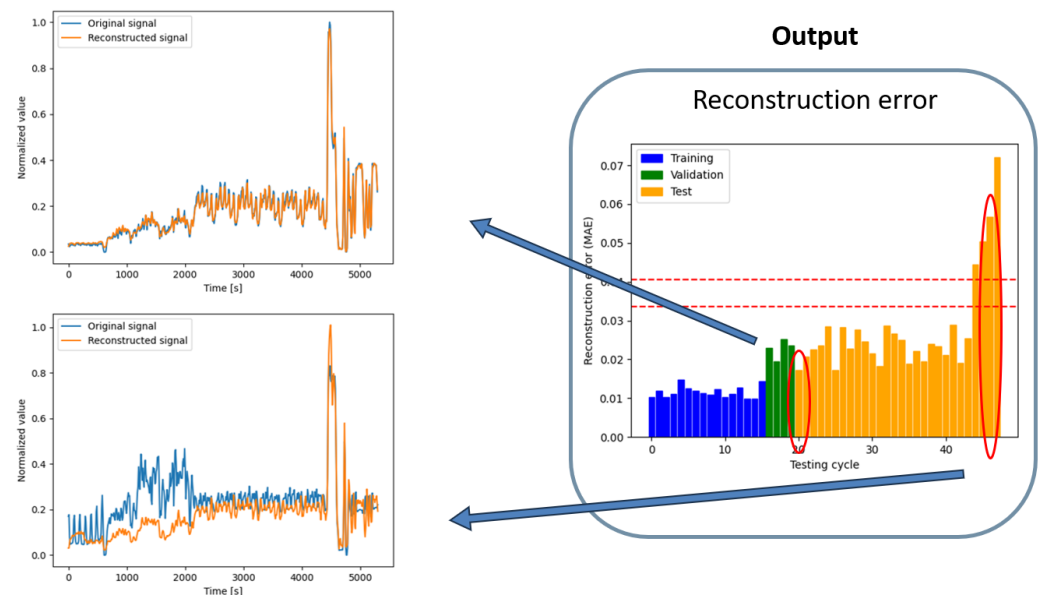


Figure 6. Example of fault detected by means of the reconstruction error estimated by the autoencoder. The two red dashed horizontal lines indicate the upper and lower thresholds. The circled cycle on the left represents a healthy cycle, whereas the circled cycle on the right shows an example of abnormal signal observed after a failure.

5. Case Studies

This section presents three case studies aimed at evaluating whether alternative monitoring signals, such as temperature, current and voltage, can support fault detection and, when possible, provide information about the location of the fault. In particular, Motors C and D differ in terms of design from Motors A and B, enabling an assessment of the robustness of the proposed methodology across different motor configurations.

5.1. Motor A

The endurance test of Motor A began on 5 February 2024. On 9 April 2024, the motor was transferred to another test bench, where testing continued until 24 April 2024, when a failure occurred. The change of test bench had a significant impact on several recorded signals. This aspect must be carefully considered when interpreting the results of the fault detection method.

In this experimental campaign, different acquisition systems were used for the accelerometers and for the other monitoring signals. Since these systems were not perfectly synchronized and since data from some cycles was lost, the number of recorded cycles differs slightly between the acceleration and the other signals.

As illustrated in Figure 7a, the reconstruction error on the mechanical orders of acceleration increases significantly after the relocation. Even minor variations in sensor placement can affect the measurements, making the data collected before and after relocation not directly comparable. Consequently, a consistent fault detection analysis across the two configurations cannot be performed. For this reason, the analysis was restricted to the signals recorded after the relocation, i.e., from 9 April until the occurrence of the failure. However, as illustrated in Figure 7b, even excluding the measurements collected before the relocation, no increase in the reconstruction error was observed. This means that the acceleration signal alone was not sufficient to detect the anomaly.

In a second stage, alternative monitoring signals were analyzed. First, the current and voltage signals were analyzed together. In this case, the current was considered in terms of its mean value rather than through order analysis. As shown in Figure 8, a clear increase in

reconstruction error appears immediately after relocation. This behavior can be explained by the different impedance of the cabling and connections between the inverter and the motor. Such variations affect the voltage drop along the lines and, consequently, produce slight differences in the measured voltage and current waveforms after the relocation. However, after this shift, no progressive increase in the reconstruction error was observed during the final cycles leading to failure. This indicates that these signals were not sensitive to the fault evolution.

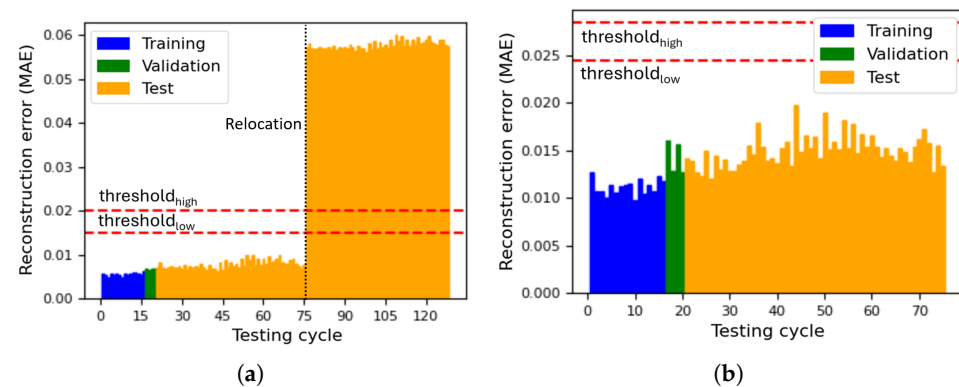


Figure 7. Reconstruction error trend of the mechanical orders during the whole endurance test of Motor A (a) and after relocation (b). A dotted vertical line is used to highlight the relocation.

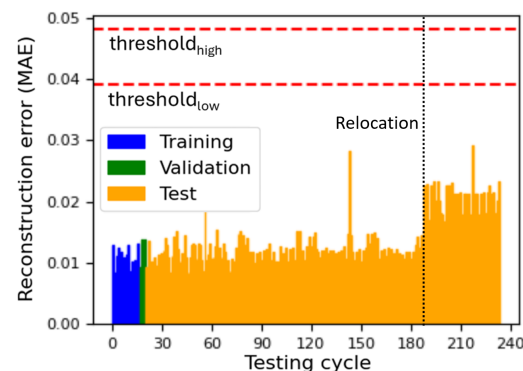


Figure 8. Reconstruction error trend of the voltage and current signals collected during the whole endurance test of Motor A. A dotted vertical line is used to highlight the relocation.

Afterwards, current and voltage signals were also singularly analyzed, considering only the test after the setup change, as illustrated in Figure 9a,b. As shown in the figures, in both cases, the reconstruction errors remained essentially constant throughout the test, providing no evidence of abnormal behavior.

The analysis was then extended to inverter phase temperatures. Figure 10 shows that the reconstruction errors remained stable throughout the entire endurance test, both during the test bench relocation and at the time of the final failure. This stability can be explained by the fact that the temperature sensors are integrated within the inverter and are less affected by external factors such as sensor placement or cabling. As a result, no discontinuities or anomalies were detected in these signals.

The inverter driver temperature was also analyzed. In this case, a slight increase in reconstruction error was detected immediately after relocation (Figure 11). This variation is attributed to the characteristics of the temperature sensor: the driver temperature is monitored using an external NTC mounted on the inverter heatsink. Such sensors have limited precision and are sensitive to the installation conditions, including the quality of thermal contact with the dissipator. Therefore, the detected variation is likely due to

measurement variability between the two configurations rather than an actual thermal change in the driver.

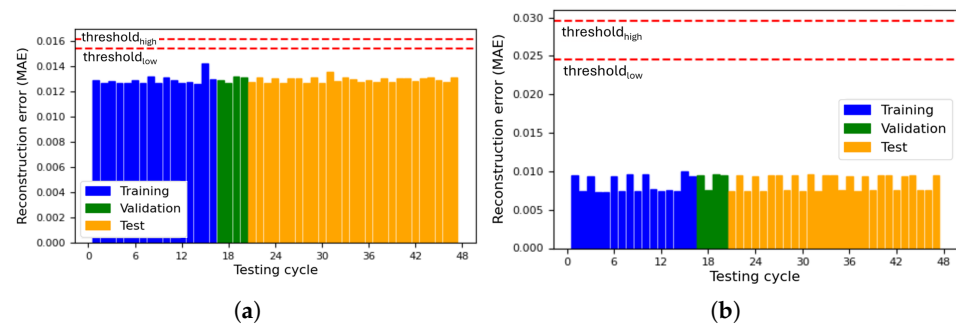


Figure 9. Reconstruction error trend of the current (a) and voltage (b) after relocation.

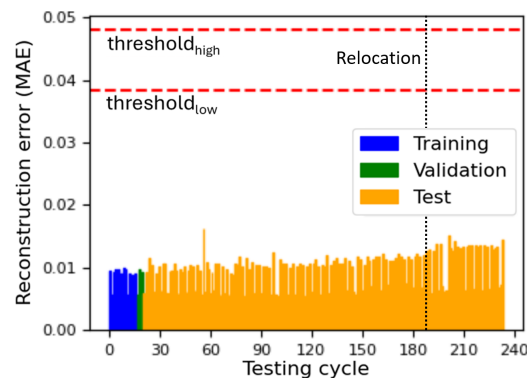


Figure 10. Reconstruction error trend of the inverter phase temperature signals collected during the whole endurance test of Motor A. A dotted vertical line is used to highlight the relocation.

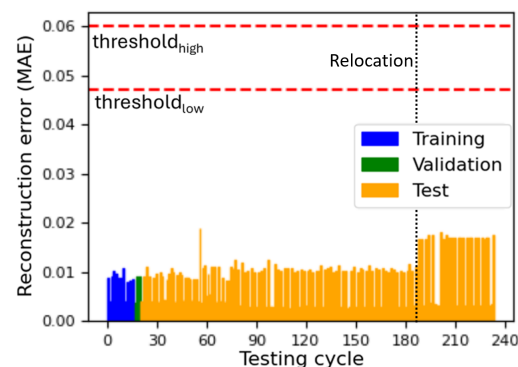


Figure 11. Reconstruction error trend of the inverter driver temperature signal collected during the whole endurance test of Motor A. A dotted vertical line is used to highlight the relocation.

Finally, the reconstruction error of the motor phase U temperature was analyzed. As shown in Figure 12, this signal clearly reveals the presence of a fault. The progressive increase in temperature suggests a localized anomaly in the corresponding stator winding, indicating overheating and progressive degradation of the insulation. This interpretation was later confirmed through discussions with test bench engineers, who identified overheating in phase U as the root cause of the failure.

The failure mechanism in this case was primarily thermal, developing as a progressive localized overheating in the phase U winding. This type of fault does not produce significant distortions in the overall current or voltage waveforms, as the overall power delivery remained stable and the fault did not develop into a short circuit. As a result, these signals did not provide useful diagnostic information in this specific case. Moreover, this

failure has a limited impact on the measured accelerations and can hardly be identified from accelerometers.

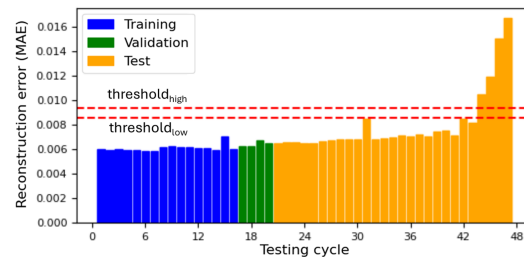


Figure 12. Reconstruction error trend of the phase U temperature after relocation.

Overall, the Motor A case study demonstrates the importance of adopting a multi-signal approach. While mechanical orders are effective for detecting mechanical faults, they are insufficient for capturing all failure modes. In this case, temperature signals were fundamental for identifying a thermally driven fault, demonstrating that the integration of multiple types of measurements is essential for achieving accurate and robust fault detection in PMSMs. Moreover, the fault was successfully identified even after the motor had been relocated and the experimental setup had changed, highlighting the robustness of the proposed monitoring approach against variations in installation and operating conditions.

5.2. Motor B

The motor analyzed in this case study was tested from 4 April 2024 until 29 May 2024, when an inverter failure occurred. Since the fault involved the inverter, an increase in the reconstruction error of the signals directly related to the inverter was expected in the final cycles of the test. For this reason, the first step of the analysis focused on these signals.

The first analysis was performed on the inverter phase temperatures and is shown in Figure 13a. Contrary to expectations, the error remained essentially constant throughout all testing cycles, without any noticeable deviation even in the final stages of the test. This outcome can be explained by considering the nature of these measurements. The temperature sensors mounted on the inverter phases mainly capture the average temperature evolution of the power modules. However, inverter faults are often caused by localized phenomena, such as sudden junction overheating or partial breakdown of a semiconductor component. These localized effects may not significantly influence the overall phase temperature measurement and therefore remain undetected in the measured signals. The same conclusion can be drawn for the driver temperature signals. As shown in Figure 13b, the reconstruction error remained stable throughout the entire test, with no increase associated with the failure. This behavior can be attributed to the operating condition of the drivers, which tend to remain relatively stable and are less exposed to the thermal stresses affecting power electronics during degradation. As a result, these signals did not provide relevant diagnostic information for fault detection.

In the next step, the motor current signals were analyzed (Figure 14a). Compared to temperature measurements, the currents exhibited a more dynamic behavior. However, their analysis was heavily influenced by the changes in control strategies implemented during the endurance test. These control variations introduced discontinuities and masked the presence of an anomaly linked to the inverter degradation. Moreover, the inverter failure did not manifest as a progressive distortion of the current waveforms. As a consequence, the reconstruction error remained stable, and no clear fault indication could be extracted from the current signals. The analysis was then extended to the motor voltage signals (Figure 14b). Their reconstruction error exhibited the same behavior as the currents. This similarity can be explained by the physical relationship between voltage and current

in the motor. The inverter defines the voltage waveforms through its switching strategy, which dictates the current behavior according to the motor impedance. Therefore, any modification in control strategy affects both quantities in a similar way, resulting in similar reconstruction error trends. Since the fault did not produce measurable distortions in the electrical supply, voltage signals failed to provide useful diagnostic information. It should also be noted that, in this case, no acceleration measurements were available and, therefore, vibration analysis could not be performed. However, since the fault originated in the inverter and did not produce detectable anomalies in any of the measured signals, it is reasonable to assume that acceleration data would likely not have contributed significantly to fault detection in this scenario. This case study yielded an unexpected result: none of the available monitoring signals were able to detect the inverter failure. This result can be explained by the fact that inverter faults are often associated with highly localized and rapid phenomena occurring at the semiconductor level. Such faults may develop within microseconds and may not significantly alter the cycle-averaged current, voltage, or temperature signals considered in this study. Furthermore, the available sensors monitored the overall motor-inverter system rather than the individual switching devices. Additional monitoring strategies, such as high-frequency phase voltage and current analysis, wavelet-based time-frequency methods, gate-driver signal monitoring, or model-based residual analysis, could improve the detection of inverter-related faults. However, it should be considered that the proposed algorithm was primarily developed to detect faults and progressive degradation in the motor. Therefore, inverter fault detection was not a primary design objective, and reliable identification of these failure modes would likely require dedicated high-frequency monitoring techniques specifically tailored to the inverter [42,43].

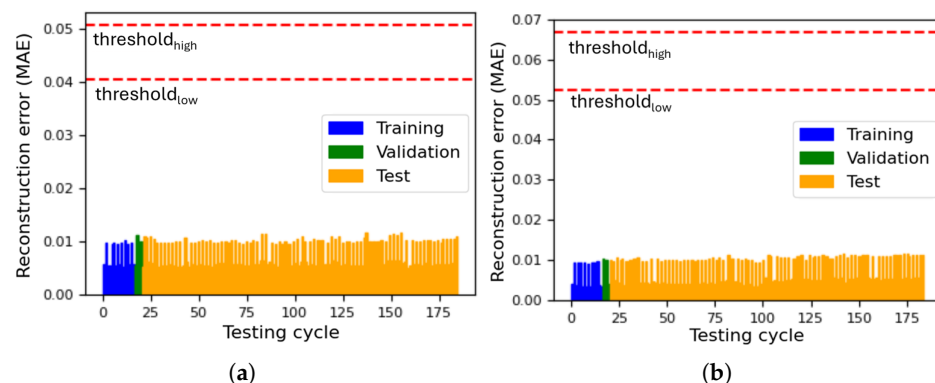


Figure 13. Reconstruction error trend of the phase (a) and driver (b) inverter temperature of Motor B during the whole endurance test.

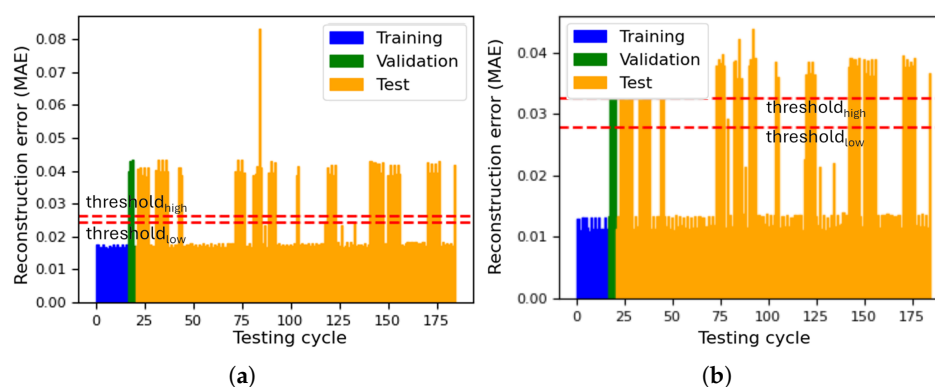


Figure 14. Reconstruction error trend of the current (a) and voltage (b) signals of Motor B during the whole endurance test.

5.3. Motors C and D

In this case study, two PMSMs that experienced bearing failures were analyzed. Both motors started in a healthy condition and were subjected to repeated testing cycles until the fault occurred. The proposed fault detection algorithm was then applied to evaluate its effectiveness. The objective of this analysis is not only to assess whether current signal analysis can detect bearing faults but also to evaluate whether electrical orders provide valuable information about the motor and its operating conditions.

The first analysis was performed by considering the mechanical orders, the bearing order and the band between 10 and 1500 Hz. As shown in Figure 15a,b, the autoencoder successfully identified the onset of the bearing fault. The reconstruction error increased significantly when the bearing defect developed, confirming the diagnostic effectiveness of mechanical orders for bearing faults.

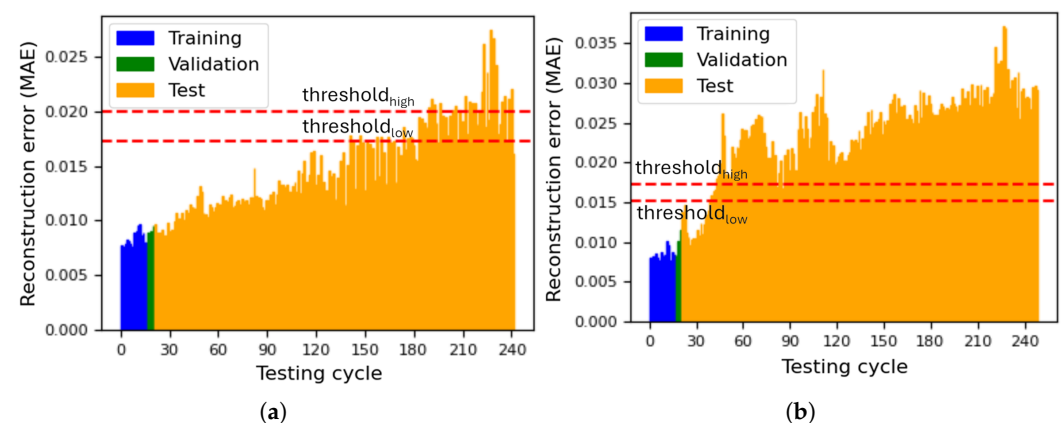


Figure 15. Reconstruction error trend of mechanical orders, bearing orders, and 10–1500 Hz band of the acceleration signal of Motor C (a) and Motor D (b) during the whole endurance test.

In the second phase, the aim was to evaluate whether the current-related electrical orders could provide additional information about motor behavior. Electrical orders are linked to anomalies in the stator current spectrum and in the magnetization process. According to the literature, specific harmonics in the stator current can provide valuable information about the health of the machine, including the presence of bearing faults. When the frequency spectrum is normalized with respect to electrical frequency, these harmonics appear as distinct orders, allowing a more consistent interpretation of the signal across varying operating conditions.

Kao et al. [44] reported that only a limited number of electrical orders concentrate most of the energy. Among these, orders 1, 2, 5, and 7 emerge as the most significant, thanks to their high amplitude. The 4th order also appears with a noticeable value, but being a multiple of the 2nd, it provides similar information. The remaining orders stay close to the noise level and provide only a marginal contribution. A few peaks can still be observed at higher frequencies, but a more detailed analysis shows that they correspond to sidebands.

To further validate the results obtained by Kao, Figure 16a,b show the temporal evolution of all the available orders obtained from the test bench during the analysis of motors C and D. In this case, the 1st order is not plotted in this graph, since its magnitude is much higher than the others and would mask their contribution. Its amplitude is known to be dominant compared to the remaining components, which makes it relevant in the analysis. Among the remaining orders, the 2nd and 5th orders consistently emerge with the highest values across the different cycles, followed by the 7th order, which maintains a smaller but stable contribution. The 4th order is not considered, since, being a multiple of

the 2nd, it offers essentially the same information, thus adding no further diagnostic value. The third and sixth orders remain at significantly lower levels.

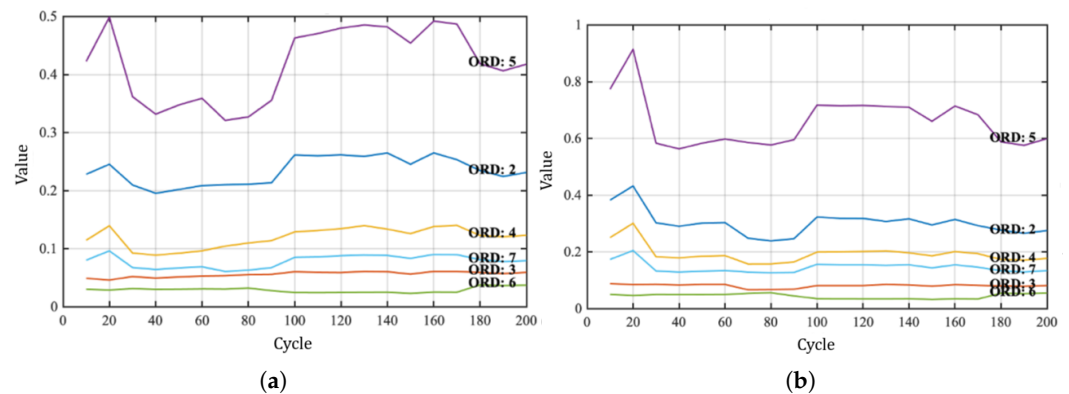


Figure 16. Electrical orders of the currents of Motor C (a) and Motor D (b) during the whole endurance test.

It is worth noting that, due to the nature of the available dataset, only integer electrical orders could be considered in this study. This represents a limitation, since many faults, such as demagnetization or eccentricity, often generate sidebands and non-integer orders, which are highly sensitive indicators of anomalies. Based on these observations, the most informative components are the 1st, 2nd, 5th, and 7th orders, and they were therefore selected for further analysis. The decision not to include all available orders was made to avoid handling an excessive amount of data and to focus only on those components that provide the clearest and most relevant information on the electromagnetic behavior of the motor.

The analysis of the selected electrical orders revealed additional insights into motor operation. As shown in Figure 17a,b, a sudden increase in reconstruction error occurs after cycle 85, corresponding to a change in the control strategy. After cycle 120, the control alternates at every cycle, meaning that one motor operates in traction while the other works in braking mode, with their roles switching at each cycle. This behavior confirms that electrical orders also provide important information about the behavior of the motor.

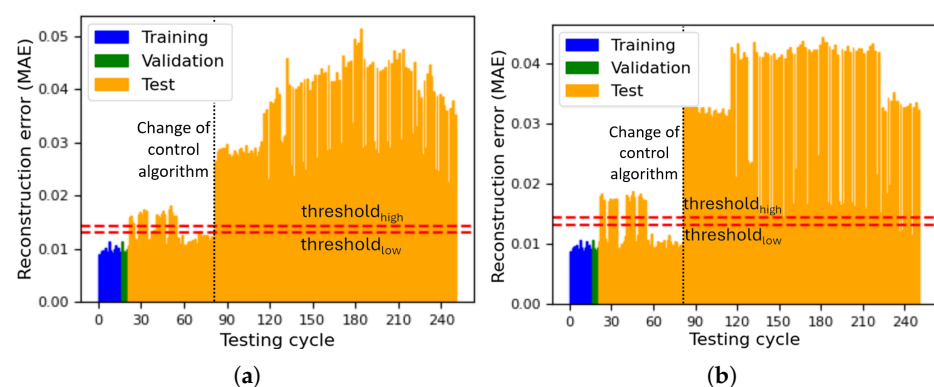


Figure 17. Reconstruction error trend of the electrical orders of the currents of Motor C (a) and Motor D (b) during the whole endurance test A dotted vertical line is used to highlight the change of control algorithm.

In this case, the failure was mechanical, and therefore, it could be detected using acceleration signals, whereas electrical orders did not detect it. However, the analysis showed that by combining both mechanical and electrical orders, it is possible to achieve a clearer view of motor behavior and to successfully detect the failure. This combination

not only ensures accurate fault detection but also improves the understanding of PMSM behavior under dynamic operating conditions. In particular, the analysis of the current orders revealed a change in the control strategy, which may be relevant for understanding the motor behavior prior to failure. In the end, the successful fault detection in the case studies of Motors C and D, whose design differs from that of Motor A, further suggests that the methodology is capable of detecting fault-related patterns across different PMSM configurations.

5.4. Performance of the Algorithm

Accuracy, precision, recall and F1-score classification metrics were employed to evaluate the performance of the proposed model [25]. Accuracy represents the proportion of correctly classified instances over the total number of observations. Precision quantifies the percentage of positive predictions that are actually correct, whereas recall measures the ability of the algorithm to correctly identify all positive instances. The F1-score is the harmonic mean of precision and recall and provides a balanced assessment of both metrics [25]. It is useful when datasets are particularly imbalanced and accuracy alone may lead to misleading conclusions. In general, high values indicate superior classification performance. These metrics are derived from four fundamental quantities: true positives (TPs), false positives (FPs), true negatives (TNs), and false negatives (FNs). As was done in [2], the corresponding values were determined by comparing the reconstruction error of each cycle in the test set against the higher threshold. For cycles occurring before the failure point, instances exceeding the threshold were classified as FP, while those remaining below the threshold were classified as TN. Conversely, for cycles occurring after the failure point, instances exceeding the threshold were classified as TP, whereas those below the threshold were classified as FN. All false negatives resulting from changes in the motor control strategy were disregarded, under the assumption that operators were aware that the observed fluctuations were attributable to the selected control mode rather than to anomalies in the algorithm. Furthermore, in the event of a relocation, only the outputs of the autoencoder trained on cycles collected after the relocation were considered. Finally, precision, recall, and F1-score values of zero were assigned to all cases in which no positives were present in order to penalize such situations appropriately.

Classification metrics were computed separately for each tested motor, and the final values presented in Table 1 correspond to the average across all motors.

Table 1. Model accuracy.

Accuracy	Precision	Recall	F1-Score
95.7%	83.2%	87.5%	85.1%

The results demonstrate a high level of accuracy while precision, recall and F1-score feature lower values than those obtained by similar AI fault detection algorithms [2]. The achieved performance remains satisfactory given the broader scope of the analysis, which detects a larger variety of fault types in multiple components.

6. Conclusions

The paper aimed to investigate the effectiveness of integrating multiple types of sensors to detect a wide range of fault conditions in PMSMs. In particular, the study focused on integrating vibration measurements with signals related to current, voltage, and temperature collected from different motor components, including the stator, rotor, and inverter. The aim was to evaluate whether these additional inputs could improve fault

detection capabilities while providing a deeper understanding of motor behavior under variable operating conditions.

Based on evidence from the literature and experimental validation, the 1D CNN AE proved to be a suitable architecture for unsupervised monitoring. Its ability to automatically extract meaningful features from raw data, combined with the requirement of limited training effort and computational resources, makes it an effective solution for fault detection in industrial environments. The results highlight the importance of adopting a multi-signal approach, combining acceleration, current, voltage, and temperature signals. Acceleration signals alone were not sufficient to detect all types of failures, particularly when the origin of the fault was not mechanical. In contrast, temperature measurements demonstrated strong diagnostic capabilities, enabling both detection and localization of failures. This was clearly observed in the case of Motor A, where an abnormal rise in phase U temperature was decisive in diagnosing the problem. On the other hand, current and voltage did not directly contribute to fault detection in the analyzed cases. However, they provided meaningful insights into motor behavior, such as variations in the control strategy. This additional information is important, as it helps prevent misinterpretation of reconstruction error variations and reduces the likelihood of false positives. The investigation of Motor B further revealed an important limitation: certain inverter faults may not produce detectable variations in the available signals. This finding highlights the need for complementary monitoring strategies. The proposed monitoring framework also demonstrated a high degree of robustness. In particular, the algorithm successfully identified the fault in Motor A even after its relocation, despite the changes in operating conditions and installation environment. Furthermore, the methodology proved effective across motors with different designs, as evidenced by its application to Motor A, whose architecture differs from that of Motors C and D. This indicates that the proposed 1D CNN AE is capable of detecting faults from patterns that are not strictly dependent on a specific machine design. Overall, these findings demonstrate that a multi-signal approach, based on the use of a 1D CNN AE, can significantly improve fault detection performance in PMSMs tested under realistic conditions. Integrating heterogeneous sensor data not only improves detection accuracy but also provides a more comprehensive understanding of system behavior, which is essential for reliable and robust condition monitoring.

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Abbreviations

The following abbreviations are used in this manuscript:

1D CNN	One-dimensional convolutional neural network
1D CNN AE	One-dimensional convolutional neural network autoencoder
2D	Two-dimensional
AE	Autoencoder
AI	Artificial intelligence

ANN	Artificial neural network
BPFI	Ball passing frequency on the inner race
BPFO	Ball passing frequency on the outer race
BSF	Ball spin frequency
CAE	Convolutional autoencoder
CNN	Convolutional neural network
DFT	Discrete Fourier transform
DNN	Deep neural network
FFT	Fast fourier transform
FTF	Fundamental train frequency
LSTM	Long short-term memory
MAE	Mean absolute error
MSE	Mean squared error
PMSM	Permanent magnet synchronous motor
STFT	Short-time fourier transform

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