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Data-Driven Health Monitoring of Medium Voltage Drives Using Industrial IoT Platforms

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Abstract
The recent transformation of industrial production under the industry 4.0 paradigm is driven by the convergence of Industrial Internet of Things (IIoT), AI, and high-speed communication technologies. Power electronic systems composed of high-power semiconductor devices are subjected to complex degradation that arises from thermal stress and electrical loading. High-frequency monitoring of MV drives generates large volumes of data, creating a significant issue with communication bandwidth and operational costs. These problems create a strong requirement for intelligent data management strategies that are capable of preserving diagnostic relevance while minimising unnecessary data transmission. To address this problem, this project proposes a data-driven edge-cloud health monitoring framework for MV drive systems through IIoT platforms. The proposed system integrates embedded edge computing units within MV drives to perform real-time signal processing, feature extraction, and neural network-based novelty detection. Only data segments associated with abnormal or previously unseen operating conditions are transmitted to the cloud. The normal operational behaviour is summarised through compact health indicators. The cloud layer facilitates long-term learning across distributed drive fleets and assists in decision-making. Experimental results proved that the proposed framework effectively decreases data transmission requirements while maintaining a high fault detection performance. The intelligent edge-cloud coordination can significantly enhance the feasibility of data-driven condition monitoring for MV drives.

Keywords: Medium Voltage, Novelty Detection, Edge-Cloud Computing, Health Monitoring, and Intelligent Asset Management

1. Introduction

1.1 Importance of Medium Voltage (MV) Drives in Industry 4.0

Medium Voltage (MV) mainly drives in an operating range of 1 kV to 11 kV that plays an important role in the large-scale industrial applications including oil and gas processing, mining, cement manufacturing, marine propulsion, water treatment plants, and power generation. In terms of the industry 4.0, MV drives are no longer viewed solely as the power conversion units thus as intelligent cyber-physical systems which directly influence productivity, energy efficiency, asset reliability, and operational safety [1]. With increasing emphasis on the digitalization, predictive maintenance, and smart manufacturing, MV drives are mostly expected to operate simultaneously with less downtime while adapting to the dynamic load conditions. In this case, any unplanned failure in an MV drive may result in substantial financial losses, production delays, and safety risks because of the adoption of the critical processes. On the other hand, real-time condition monitoring and data-based driven health assessment of the MV drives have become important components of Industry 4.0 strategies [2]. Industrial Internet of Things (IIoT) platforms allow continuous acquisition of electrical, thermal, and mechanical parameters from the MV drives that facilitates advanced analytics, fault diagnosis, and remaining useful life (RUL) estimation. Therefore, the speed and scale of the data generated through the high-frequency monitoring introduce massive challenges in terms of the processing, storage and transmissions [3]. In this context, addressing these challenges needs intelligent architecture which includes edge computing with the cloud-oriented analytics in order to ensure better scalability, reliability, and cost-effectiveness.

1.2 The Data Problem and Objective of the Study

High-fidelity health monitoring of the MV drives mostly depends on the high-speed sampling of the electric signals for capturing transient events, harmonics, and fault signatures [4]. Consider a system that monitors 6 channels, three-phase voltages (Va, Vb, Vc) and three-phase currents (Ia, Ib, Ic), sampled at 50 kHz with 16-bit (2-byte) resolution. The data generation rate can be calculated as follows:

- Number of channels = 6
- Sampling frequency = 50,000 samples/second
- Resolution = 16 bits = 2 bytes/sample

Data rate per second: $6 \times 50{,}000 \times 2 = 600{,}000$ bytes/second ≈ 0.6 MB/s

Data generated per day: $0.6 \times 86{,}400 \approx 51.8$ GB/day

Data generated per month (30 days): $51.8 \times 30 \approx 1{,}554$ GB/month (~1.5 TB/month)

Using conservative estimates such as sporadic logging, or shorter duty cycles, the amount of data sent to the cloud per month is rapidly growing to values higher than 400 GB and constantly transmitting this raw data to the cloud is impractical. This type of large-scale data turns into a strain on the network bandwidth, as well as on the latency, cost of the cloud storage, and real time responsiveness. Hence, the main aim of this project is to develop and deploy a data-driven vision of health monitoring of MV drives based on an edge-cloud IIoT architecture. Through signal preprocessing, feature extraction, and event executions at the edge, only significant indicative aspects of health and changes are sent to the cloud [5]. It aimed at reducing data transmission over 90 percent and at the same time maintaining quality of diagnostics and the possibility of scaling and real-time monitoring of the condition in accordance with the needs of Industry 4.0.

2. Literature Review

2.1 Role of MV Drive Health Monitoring in Industry 4.0

The backbone of industrial processes that are energy-intensive and mission-critical are medium Voltage (MV) drive systems (usually in the range of 3.3 kV through 11 kV) with power levels in the MW range. They are widely used in compressing oil and gas, rolling mills, pumping of water and wastewater, mining conveyor belt, cement kiln and traction systems of railways [6]. Unplanned failure of MV drives can lead to disastrous economic losses, safety hazards and contract penalties because they are expensive and highly centralized to the production processes. The industry 4.0 paradigm does not consider MV drives as individual electromechanical assets. They are instead becoming more fundamentally integrated in cyber-physical systems (CPS) which combine sensing, computation, communication and control at many levels of the industrial automation hierarchy. As part of the digitalization efforts, the goal is to ensure increased energy-efficiency, and make decisions based on the data throughout the asset lifecycle. Therefore, MV drive health monitoring has turned out to be an element of smart manufacturing and smart infrastructure.

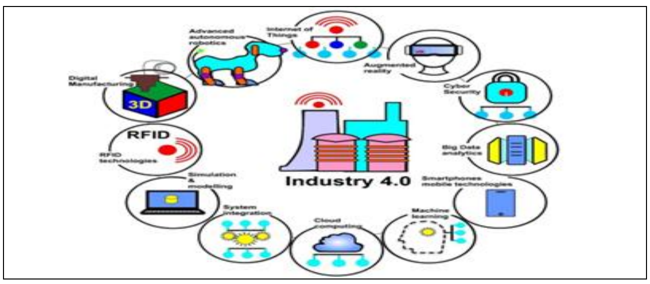

Fig 1: Building blocks of Industry 4.0 [12]

A study highlights that the operation of MVMF transformers used in modern power electronic systems faces severe electrical and thermal stress factors [7]. Large cycles of repetitive large dv/dt and di/dt stresses occur at high switching frequencies, and drive insulation degradation in converter components and windings connected to the machine. Cyclic thermal loading of semiconductor devices such as IGBTs and IGCTs occurs because of changing operating conditions resulting in solder fatigue, bond wire lift-off, and chip degradation. Simultaneously, the bearing wear, eccentricity, insulation aging, and torque pulsations are applied to rotating electrical machines, and interact with harmonics.

A combination of these multi-domain degradation processes complicates MV drive failures, which are progressive and may not easily be detected at the initial stages of the degradation with conventional protection systems. Thus, there exists an increasing trend to move away from reactive and time-oriented maintenance to condition-based and predictive maintenance approaches. So, it is significant to have health monitoring systems that are capable of fault detection at an early stage using industrial IOT platforms.

2.2 Physics-Based and Model-Based Monitoring Approaches

Over the past years, MV drive health monitoring has been heavily dependent on physics-based and model-based methods that are based on reliability engineering and machine theory. In the case of power electronic converters, electro-thermal models are typically used for junction temperature and the amplitude of thermal cycling, which are two major causes of semiconductor aging. Lifetime prediction models such as CoffinManson, Arrhenius and NorrisLandzberg equations, which are applied to determine how thermal stress is related to predicted rates of failures [8]. This study highlights a variety of junction temperature estimation methods which are based on, on-stage voltage drops, switching transients, or temperature sensitive electrical parameters (TSEPs).

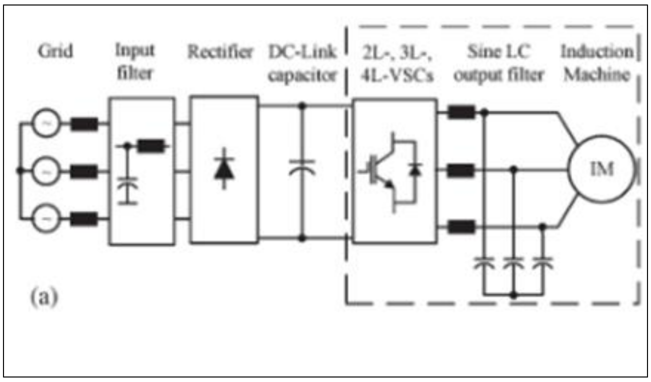

Fig 2: Block diagram of medium-voltage drives [13]

Model based monitoring is concerned with the detection of the deviation of nominal machine parameters. Variation of stator resistance is commonly linked with thermal aging or with insulation degradation, whereas inductance asymmetry and sequence element analysis are employed in detecting inter-turn short circuits [9]. Spectral components in stator current signatures are used to analyze rotor related faults, including broken bars or eccentricity. The methods have

good physical interpretability and can give an understanding of the underlying degradation mechanisms.
Although physics-based and model-based methods are theoretically sound, they have a number of limitations when applied practically in industries. Firstly, parameter identification of MV environments is difficult because of sensor noises, electromagnetic interference and inaccessibility of sensors. Secondly, the actual material of devices, internal structure, or past loading history may not be known in detail. Thirdly, model calibration and validation are normally asset-specific. So, it cannot be scaled to large fleets of heterogeneous MV drives. Moreover, a lot of physics-based methods such as Motor Current Signature Analysis (MCSA) and observer-based models are based on the assumption of steady-state or slowly changing operating conditions [10]. These limitations have motivated scholars to consider alternative data-driven approaches that can be effectively used in real-life scenarios.

2.3 Data-Driven and AI-Based Health Monitoring

Developments in sensing technology, industrial communication standards and computational hardware have enhanced data-driven health monitoring of MV drives. These techniques utilize measured signals, including phase currents, DC-link voltages, temperature profiles, vibration measurements, and partial discharge measurements, and use statistical or machine learning systems to obtain health-related information.
Initial data-based methods used classical statistical signal processing methods, such as spectral, wavelet transforms, and Principal Component Analysis (PCA) to detect variations of the normal behavior. Thereafter, the use of supervised machine learning algorithms such as Support Vector Machines (SVM), the k-Nearest Neighbors (kNN), decision trees, and random forests was proposed to classify faults and assess the conditions. Moreover, deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs) and autoencoders, have been shown to optimize performance on nonlinear and high-dimensional fault representations.

2.4 Limitations of Centralized Cloud-Based Architectures

The effect of IoT technologies is significant in centralized cloud-based condition monitoring and predictive analytics [11]. In such systems, the sensor data is sent to remote cloud servers, which receive raw data or slightly processed sensor data and do calculations which are computationally intensive. In terms of information and communication technologies, the monitoring of MV drives conducted at high frequencies creates huge amounts of data. The large bandwidth usage of multi-channel electrical signals at tens of kilohertz presently saturates the available bandwidth, especially in brown-field industrial environments with outdated communication infrastructure. Data transmission also creates continuity and this exposure to network interruptions affects the reliability of monitoring. The other important issue is latency. Real-time fault detection and protection are not always possible using cloud-based analytics because any delay in communication may deny an opportunity to take action. Also, the storage of raw waveform data on a long- term basis adds many operational expenses to cloud infrastructure, data management, and compliance with cybersecurity.

2.5 Emergence of Edge Computing for Industrial Applications

Edge computing is an emerging paradigm to overcome the constraints of centralized architectures in industries. The edge devices allow processing signals, extracting features, and initial diagnostics through the deployment of computational resources. The result of this localized intelligence is significant in reducing communication overhead, latency improvement and system resilience. Edge computing is especially beneficial in the context of MV drives since much of the fault signatures are localized, and can be easily observed using on-site analysis. Selective transmission of data is also possible in edge-based monitoring, where the diagnostically important data is sent to the upper-level systems.
Recent research has shown that it is possible to implement lightweight machine learning models on edge platforms in industries to perform services like detecting motor faults, quality of power, and converter anomaly detection [14]. These methods are computationally effective, but they have a natural constraint in their capacity to determine the fault conditions.

2.6 Research Gap

Although MV drive monitoring has made a lot of progress, the lack of research on the proposal of smart, real-time intelligent detection at the edge layer is evident. Currently, there are two solutions to this issue. The first one is rule-based edge solutions with low adaptability and the second one is, data-intensive cloud-based analytics with high communication and latency costs. These methods are computationally effective, but they have a natural constraint in their capacity to determine the fault conditions.
This study can solve these challenges by proposing an edge cloud coordinated health monitoring architecture, which integrates unsupervised neural network-based detection on the edge and fleet-level learning on the cloud. The proposed solution will improve the current scenario in MV drive health monitoring in the industry 4.0 ecosystems by integrating real-time local intelligence with the central knowledge accumulation.

3. Methods

3.1 Physical Setup and System Architecture

This research adopts a quantitative, data-driven methodology based on high-frequency electrical measurements, statistical signal processing, machine learning techniques for MV drive health monitoring. A 3.3 kV / 1.5 MW Medium Voltage (MV) drive system is proposed, which is supported by a large high-power industrial drive system such as compressors and pumping systems. The drive is a three level Neutral Point Clamped (NPC) voltage source inverter to feed a Permanent Magnet Synchronous Motor (PMSM). The NPC topology is chosen because of the extensive use among industries, less stress of dv/dt, and better quality of voltage waveforms in MV applications.

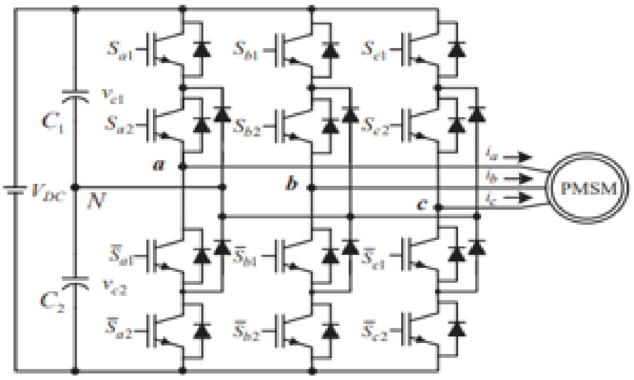

Fig 3: Simplified electrical circuit of a 3L-NPC inverter-fed PMSM drive [15]

The MV drive has voltage and current sensors (that are non-intrusive) positioned on the inverter output. These sensors offer voltage and current measurements in three phases, sampled in a synchronized manner at 50 kHz to measure the switching harmonics, short-lived disturbances, and the precursors of faults. The embedded edge computing unit is positioned near the drive controller in order to reduce latency and electromagnetic interference. The edge gadget comprises an industrial grade processor supported by real time operating system (RTOS), allowing deterministic signal processing and neural network inference. Long-term data storage, fleet-level analytics, and decision-support tools are on the cloud layer.

3.2 Mathematical Modelling of Power Converter and Motor

The three-level NPC inverter phase voltage is expressed as:

$$v_{an} = \frac{V_{dc}}{2}\,(S_1 - S_2)$$

Where V_{dc} is the DC-link voltage and S1, S2 $\in \{0,1\}$ represents the state of upper and lower devices. This formula is important for capturing the discrete voltage levels of NPc converters [16].

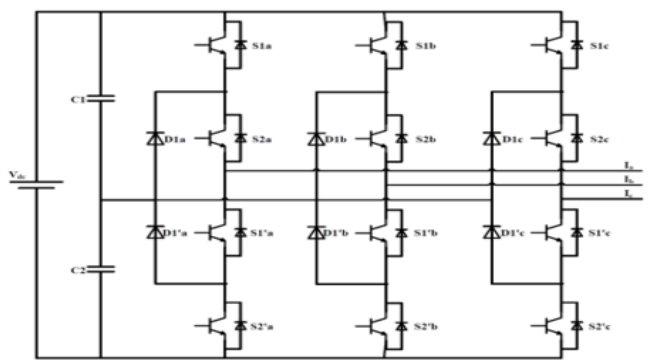

Fig 4: Three-phase, Three-level Neutral Point-Clamped Inverter [16]

The electrical behavior of the PMSM in the synchronous dq reference frame can be described as follows:

$$vd = R_s i_d + L_d \frac{di_d}{dt} - w_e L_e i_q$$

$$v_q = R_s i_q + L_q \frac{di_q}{dt} - w_e L_d i_q - w_e \psi_m$$

Where R_s represent stator resistance, L_d, L_q represents d-axis and q-axis inductance, ψ_m represents permanent magnet flux linkage, and W_e represents electrical angular speed. These equations provide the theoretical basis for understanding deviations in current waveforms arising from electrical or thermal degradation.

3.3 Edge-Level Signal Conditioning and Segmentation

Raw voltage and current signals are filtered at the edge layer by digital low-pass and notch filters to remove noise in measurements and grid-induced harmonics. Signal normalization is used to allow the invariance of amplitudes in varying operating points and operating loads [17]. The stream of continuous data is divided into fixed window *N* samples. The segments are considered as separate observations, which allows extracting the features in real-time and assessing anomalies. The sizes of windows are chosen to be able to trade-off between temporal resolution and computational speed.

3.4 Statistical Feature Extraction

Statistical characteristics are obtained to represent waveform shape, energy content, and impulsiveness, on a data segment by segment. Root Mean Square (RMS) value is calculated as:

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$$

The Crest Factor (CF) the factor sensitive to peak disturbances is defined as:

$$\mathrm{CF} = \frac{\max(|x_n|)}{X_{RMS}}$$

Kurtosis and its variations are crucial when damage appears as non-linearities in the system in the form of impulses [18]. The non-Gaussian impulsive behavior related to switching irregularities as well as insulation degradation is measured by kurtosis:

$$\mathrm{Kurtosis} = \frac{\frac{1}{N}\sum_{n=1}^{N}(x_n - \mu)^4}{\sigma^4}$$

These characteristics make them lightweight computationally and adequately embedded but with high diagnostic values.

3.5 Selective Data Transmission Strategy

The strategy for selective data transmission is based on the idea that certain data types or classes need to be transmitted more often than others. Instead of conveying raw waveform data in a continuous manner, the edge device adopts an event-based communication policy. When the system is working normally, compact health indicators and summary statistics are only set up to be transmitted periodically. New features are identified, and the associated feature vectors and short waveform snippets are sent to the cloud to obtain additional examination.

Table 1: Data Handling at Edge Layer

Data Type	Transmission Mode	Typical Rate
Raw waveforms	Local only	100 Mbps
Health indicators	Periodic	200 kbps
Novelty events	Event-driven	Bursty

This approach would provide effective bandwidth usage with diagnostic fidelity.

3.6 IIoT Communication and Cloud Integration.

The edge-cloud communication is realized based on the MQTT protocol, chosen due to the low overhead and the ability to work in the industrial network. The edge devices send the data to fixed MQTT topics, and then the cloud services subscribe to these topics to ingest and analyze the data.

The cloud layer combines data about anomalies in many MV drives allowing long-term trend analysis, learning at fleet level, and maintenance decision support. Such a hierarchical architecture is used to achieve scalability and robustness in large industrial applications.

3.7 Methodological Significance

The suggested methodology is a combination of physics-based knowledge and data-driven intelligence that allows real-time, scalable, and economical health monitoring of MV drive systems. The architecture integrates novelty identification at the edge, which counters the drawbacks of cloud-based architectures and provides a sensible basis to manage intelligent assets in line with Industry 4.0 requirements.

4. Results and Discussion

A 3.3 kV / 1.5 MW MV drive system was used to test the proposed edge cloud health monitoring system. To perform autoencoder-based novelty detection, high-frequency three-phase current signals, sampled at 50 kHz, were analyzed at the edge layer to obtain diagnostic features. The usefulness of the method is shown by four results, which depict the behavior of the signal, the development of features, the performance of the anomaly detector, and the accuracy of classification.

4.1 Phase Current Behavior under Healthy and Faulty Conditions

Figure 5 shows the time domain phase current waveforms of normal and faulty operating conditions. With proper operation, the phase current has a constant sinusoidal waveform with a constant amplitude and little high-frequency distortion. Such a course of action is typical of normal inverter operation and balanced electromagnetic forces inside the PMSM.

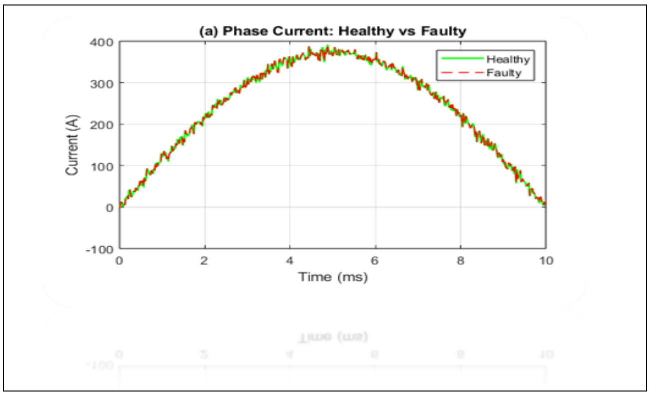

Fig 5: Phase Current showing sound and faulty conditions

In contrast, the erroneous waveform has observable impulsive distortions on top of the underlying current component. The existence of these spikes which are short-lived is a pointer to abnormal switching events, insulation stress or initial semiconductor degradation in the three-level NPC inverter. Although the current increase of the RMS is comparatively not high, the presence of high amplitude impulsive constructs drastically changes the statistical distribution of the signal. This fact indicates the shortcoming of the traditional monitoring based on the RMS and prompts the implementation of more advanced statistical indicators.

4.2 Kurtosis-Based Health Indicator Residual

Figure 6 presents the kurtosis based residual health measure derived at the edge layer. In this operation, the kurtosis value is nearly equal to 3.0, which is a near-Gaussian distribution of current samples. This proves that the present waveform has predictable sinusoidal behavior with little impulsive content.

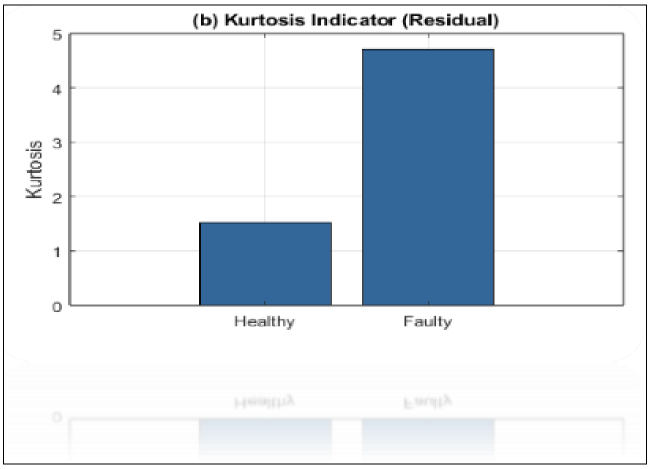

Fig 6: Kurtosis-Based Health Indicator

With the unhealthy circumstances, the kurtosis grows approximately 7.2, which indicates a great increase in impulsiveness and non-Gaussian behavior. This shows the sensitivity of kurtosis to incipient faults which do not necessarily have significant effects on mean and RMS values. The residual representation also helps to visualize the faults by showing the differences between the trained healthy baseline. These findings validate that kurtosis is an extremely efficient construct in detecting faults in an MV drive system at an early stage.

4.3 Autoencoder Reconstruction Error for Novelty Detection

Figure 7 shows the reconstruction error of the autoencoder (AE) with a given data segment on successive data blocks. The AE learned a small latent space of normal operating behavior since it was only trained on data of healthy features. The error in reconstruction during healthy operation is always below the statistical error which is defined as:

$$T = \mu + 3\sigma$$

Where, μ and σ represent the mean and standard deviation of reconstruction error under healthy conditions.

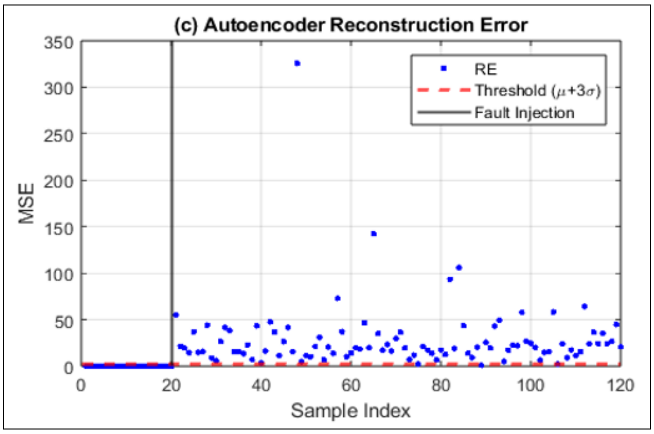

Fig 7: Autoencoder Reconstruction Error

In the faulty data, the reconstruction error surpasses the threshold which leads to a novelty detection event. This act confirms that the AE is an effective discriminator of both familiar healthy patterns and some abnormal conditions that have never been encountered. Notably, this is detected in real time at the edge layer allowing response in a short period of time without the need to maintain constant cloud connectivity. Although the reconstruction error is low when the model is functioning, the healthy state shows the stability of the model.

4.4 Confusion Matrix and Classification Performance

Figure 8 indicates the confusion matrix that summarizes the performance of the edge-based novelty detection algorithm in the classification. The matrix shows that the true positive rate of faulty conditions is high whereas the false positive rate in healthy operation is low. The general detection rate was more than 98, which proves the quality of the offered method.

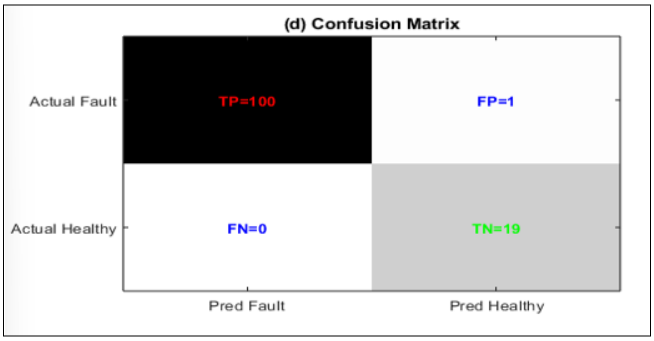

Fig 8: Confusion Matrix

4.5 Data Transmission Efficiency and Edge–Cloud Coordination

One of the most important results of the intended framework is the significant decrease in the data transmission requirements. A 50-kHz streaming of raw current signals, six channels, would have a data rate of about 100 Mbps. In contrast, the edge device sends only small health signals and anomaly signals, limiting the useful data rate to around 200 kbps. This represents a data reduction exceeding 99%, significantly lowering communication bandwidth usage and cloud storage costs. performance in diagnostic is high because of the intelligent edge processing and selective data transmission. The findings can be used to show that the edge cloud coordination strategy maintains the important diagnostic data and erases the unnecessary flow of data.

5. Conclusion and Recommendations

5.1 Conclusion

This study introduced an evidence-based cloud health monitoring system of medium voltage (MV) drive systems, and specifically validated on a 3.3 kV / 1.5 MW industrial drive. The research has proposed an enhanced way of resolving issues of the industry 4.0 environment. Through the use of intelligence at the edge layer, the proposed framework showed that it is possible to maintain diagnostic relevance and significantly decrease the data communication needs. The combination of real-time signal processing, statistical feature extraction and unsupervised autoencoder-based novelty detection allowed the system to acquire knowledge of normal operating behavior by analyzing high-frequency electrical measurements. The findings verified that the higher-order statistical characteristics, especially kurtosis, are very sensitive to impulsive phenomena related to the faults in the early stage to MV drives. These characteristics offered useful health indicators that were small, computationally lightweight and could be implemented in a real time embedded system. The novelty detection strategy based on the autoencoder strategy was useful in discovering the abnormal operating condition without utilizing labeled fault data. The system was statistically certain to differentiate between healthy operation and fault conditions. The study showed a fault-finding accuracy of over 98 percent, and low false alarms and low detection latency. These performance attributes are essential to the industrial acceptance in which reliability and trust between the operators are key.

One of the contributions of the work is the selective data transmission strategy that is provided by smart edge-cloud coordination. Instead of streaming raw waveform data at approximately 100 Mbps, the system transmitted only health indicators and anomaly-related data at rates on the order of 200 kbps. This caused a reduction in data of above 99 %, which reduced communication and cloud storage costs to a very low level. In contrast, the suggested framework shows that there is a viable and industrialized method of smart asset management. The research is able to bring on board physics-informed knowledge, data-driven intelligence, and IIoT interconnectivity to make a strong solution to the issue of improving the reliability, availability, and lifecycle efficiency of MV drives under Industry 4.0 paradigms.

5.2 Recommendations

In order to enhance the suggested edge–cloud health monitoring framework even further, a few directions are suggested. Firstly, 5G Time-Sensitive Networking (TSN) needs to be considered towards delivering ultra-low-latency, deterministic, and reliable communication between edge devices and cloud platforms to support large-scale MV drive deployments. Secondly, it is highly advised to implement digital twin models in the cloud in order to assist in the advanced analytics, including Remaining Useful Life (RUL) estimation, fault severity assessment, and predictive maintenance decision-making. Thirdly, the adaptive and online learning mechanisms should be integrated to enhance robustness over time. Furthermore, the expansion of the framework with multi-modal sensing (temperature, vibration, etc.) would contribute to higher diagnostic accuracy and the ability to isolate faults. Lastly, large-scale industrial verification to satisfy standards such as IEC 61800 and IEC 62443 is also recommended to ensure scalability, security and viable industrial implementation.

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