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Detection and prediction of motor faults through noise analysis

Wykrywanie i przewidywanie usterek silników poprzez analizę generowanego hałasu

Abstract. The noise generated by electric motors, with its great diversity, poses a complexity that facilitates fault detection with a certain amount of redundancy. Fault prediction becomes possible by combining digital signal processing and artificial intelligence. This paper focuses on fault detection using speech processing techniques, especially Linear Prediction Coding (LPC). The proposed technique extracts the parameters used to detect or predict faults based on Linear Predictive Coding (LPC). The obtained results demonstrate that the proposed technique is highly effective in detecting and identifying faults with unparalleled accuracy, particularly when the chosen p-order is greater than ten.

Streszczenie. *Hałas generowany przez silniki elektryczne, ze swoją wielką różnorodnością, stwarza złożoność, która ułatwia wykrywanie usterek z pewną ilością redundancji. Przewidywanie usterek staje się możliwe dzięki połączeniu cyfrowego przetwarzania sygnału i sztucznej inteligencji. Niniejszy artykuł koncentruje się na wykrywaniu usterek za pomocą technik przetwarzania mowy, w szczególności liniowego kodowania predykcyjnego (LPC). Proponowana technika wyodrębnia parametry używane do wykrywania lub przewidywania usterek w oparciu o LPC. Uzyskane wyniki dowodzą, że proponowana technika jest bardzo skuteczna w wykrywaniu i identyfikowaniu usterek z niezrównaną dokładnością, zwłaszcza jeśli wybrany p-rząd jest większy niż dziesięć.*

Keywords: Faults, Pattern recognition, Motor, Linear Prediction Coding (LPC)
Słowa kluczowe: Usterki, rozpoznawanie wzorców, silnik, kodowanie predykcyjne liniowe (LPC)

Introduction

In the recent years, researchers have been examining noise analysis as an effective method for diagnosing motor faults. Electrical systems are susceptible to various faults that can result in significant losses [1, 2]. To ensure the safety and proper functioning of electric motors, several studies have been conducted to better understand issues related to the detection of motor faults [3, 4]. In [5], the authors propose using infrared cameras to detect temperature variations in electrical components. An increase in temperature can indicate an electrical fault, such as an overload, phase imbalance, or a loose connection [6-7]. These techniques are limited to electrical faults only and are very dependent on the environment. In [8], the authors propose an acoustic listening method. This method uses listening devices to detect the sounds produced by partial discharges or electrical arcs in high-voltage equipment [9, 10]. The ultrasounds emitted by these phenomena can reveal the presence of electrical faults such as corona discharges [11, 12]. In [13], the authors examine vibration analysis. They demonstrate that electrical faults in motors and other equipment can cause abnormal vibrations. These vibrations are detected by sensors, and when analyzed, they enable the identification of potential problems, such as imbalances and mechanical deformations [14, 15]. In [16], the authors propose a method that evaluates the resistance of insulating materials in electrical systems. A megohmmeter is typically used to apply a continuous voltage between the conductor and the ground and measure insulation resistance. This enables the detection of insulation faults by measuring a material's ability to resist electric current without conducting electricity [17, 18]. Dielectric tests help prevent failures caused by faulty insulation [19, 20]. Finally, in [21], the authors present spectral analysis methods, essential for detecting electrical faults. This analysis examines the frequencies produced by electrical equipment to detect anomalies [22]. These methods help extend the lifespan of equipment, prevent sudden failures, and ensure the safety of electrical installations [23].

The sound noises emitted by a running motor contain crucial information about its health and performance. By closely examining the acoustic signals produced by the motors, it is possible to identify specific patterns related to various problems such as bearing wear, rotor imbalances, or electrical anomalies [24]. The frequency analysis of the sounds emitted by these motors thus plays a crucial role in detecting and localizing malfunctions [25].

By characterizing the failure processes based on signal analysis, it becomes possible to understand the frequency characteristics specific to the healthy or faulty operation of the monitored system, thereby enabling the definition of relevant symptoms related to the faults [26]. This approach has several advantages:

- Early detection of defects: By monitoring the noise, we can identify warning signs of failure, allowing for rapid intervention before the problem worsens.
- Precise location of problems: The specific acoustic characteristics help to identify the exact source of the defect, whether it is a defective bearing, a poorly adjusted belt, or a structural imbalance.
- Proactive maintenance: By utilizing this analysis, it is possible to plan preventive maintenance operations, thereby reducing unplanned downtime and associated costs.

Noise analysis is therefore an essential tool to guarantee the reliability of motors, improve their service life and optimize their performance, paving the way for smarter maintenance and better management of industrial assets.

The objective of this article is to explore state-of-the-art techniques for the detection and prediction of motor faults through the analysis of their sound noise. It will address the underlying principles, the signal processing methods and the machine learning approaches used to extract significant characteristics from the sound noises of the motors. Additionally, it will discuss case studies and practical applications, highlighting the benefits of early fault detection and the potential of predictive maintenance.

Acquisition and pre-processing of motor noise

The methodological approach involves the acquisition and analysis of data obtained using the test bench we built within our LABGET research laboratory.

A quality microphone is first used to pick up sounds from the motor. To achieve better results, it is essential to select the microphone's position and orientation relative to the motor. Additionally, it is crucial to avoid recording motor sounds when other motors or machines are operating nearby. A fourth-order anti-aliasing Butterworth filter with a cutoff frequency of 20 kHz is deployed to prevent spectral aliasing and ensure compliance with Shannon's theorem. Fig. 1 represents the test bench used for acquiring and analyzing data obtained from our LABGET research laboratory.

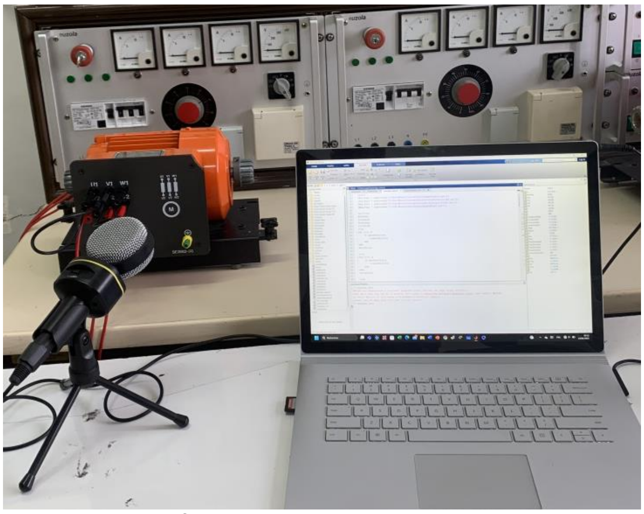

Fig. 1. Test bench for acquiring motor noise.

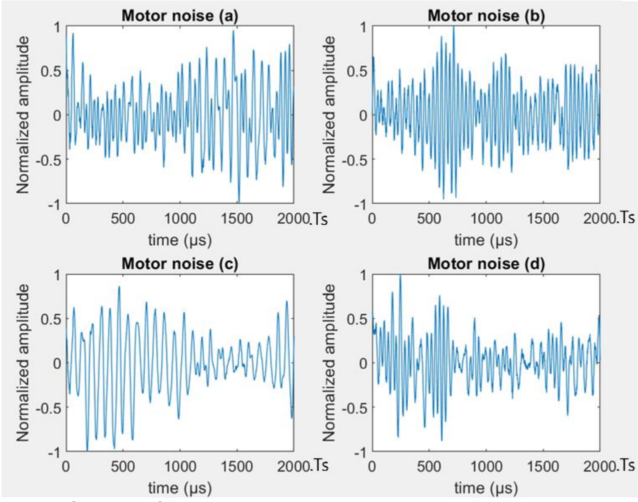

Fig. 3. Signals of motor states.

The experimental workbench is composed of a 0.6 kW asynchronous motor, supplied through a variable transformer to create overvoltage and under-voltage conditions. Additionally, all the motor phases' connections are accessible, making phase disconnection an easy task. A laptop is used for sound recording with a 16-bit resolution and a sampling frequency of Fs =44.1kHz (Ts = 22.6 μs). The sounds are also recorded in waveform format.

Once digitized, the signal undergoes a pre-emphasis operation, which consists of the 1st order high-pass filtering to raise the treble level and to naturalize the attenuation of the noise which is 12db / octave by an adequate filter [9].

In our case, we simply used an infinite impulse response filter (IIR) having the following transfer function:

(1) $$H(z) = \frac{1}{1-.09z}$$

Where H is the transfer function of the pre-emphasis filter.

We are led, subsequently, to process the data by working with consecutive frames of length L, with an interleave of 30% of the frame length. A weighting using the Hamming window in equation (3) is employed to minimize the impact of the GIBS phenomenon. The frame length L is chosen such that the frames have a duration about 100 ms. Fig.2 shows the stages of creating a database.

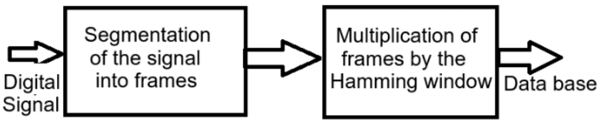

Fig. 2. Creation of the database.

Motor noise analysis

On one hand, the signal analysis constitutes, in any recognition system, a preliminary and essential step. On the other hand, analysis and synthesis are two dual activities. In Figure 3, we have plotted the amplitude, as a function of time, of four types of signals from the motor in four operating situations:

Fig.3(a) shows the amplitude of the noise coming from a fault-free (healthy) motor as a function of time. Fig.3(b) represents the amplitude as a function of time of the noise from a motor with an overvoltage supply fault. Fig.3(d) shows the amplitude as a function of time of the noise coming from the motor with a missing phase fault.

The primary objective of analyzing the noise signal generated by the motor is to extract specific relevant parameters. The signal processing methods have become increasingly refined, ranging from the simplest, such as autocorrelation and the zero-crossing rate, to the more complex, including short-term spectrum, wavelets, and linear predictive coding (LPC). We can roughly classify the analysis methods into two groups: temporal and spectral.

Temporal analyses

There are various temporal methods for analyzing and extracting parameters, such as estimating the rotor's rotation speed, including autocorrelation analysis, modified autocorrelation analysis, analysis based on the rate of zero crossing of the signal, and the SIFT (Simplified Inverse Filter Tracking) algorithm, as well as mixed analysis.

Autocorrelation analysis

This method is based on detecting the maxima of the autocorrelation function of a signal. The positions of these maxima give us the value of the speed of rotation of the rotor. The autocorrelation function is calculated on a slice of L samples, which covers several periods. The determination of the rotor's rotation speed by autocorrelation remains one of the robust detectors. The procedure to be followed for this method can be summarized as follows:

The acquisition signal is given by

(2) $$x(k) = x(k.Te)$$

where: *x(k.Te)* is the noise signal coming from the motor at the moment *kTe*, *x* is the digitized motor noise at the moment *k* and *Te* is the sampling period.

Normalization and segmentation of the signal in slices of duration varying from 50ms to 100ms.

Weighting of each segment by a Hamming window to reduce the GIBS phenomenon, whose expression is:

(3) $$w(k) = 0.54 - 0.46\cos(\frac{\pi k}{L})$$

Calculation of the autocorrelation function by the formula:

(4) $$r_{xx}(k) = \sum_{i=1}^{L} x(i).x(k+1)$$

where x is the noise signal coming from the motor and r_{xx} is the autocorrelation function of the signal x.

Autocorrelation measures the cross-correlation of a signal with itself. In other words, it examines how a signal resembles itself when it is shifted in time. It is a mathematical tool commonly used in signal processing. It enables the detection of regularities and recurring patterns in a signal, often used to calculate the frequency content of a signal (spectral density) or to analyze the signal without reference to its frequency content [13].

In Fig.4, we have plotted the autocorrelation function of four types of motor signals in four operating situations: Fig.4 (a) shows the autocorrelation function of the noise coming from a fault-free motor. It should show little regularity. Fig.4 (b) represents the function of autocorrelation of the noise from a motor with an overvoltage supply fault. It could reveal periodic patterns disturbed by noise. Fig.4 (c) shows the autocorrelation function of the noise from a motor with an under-voltage supply fault. It could also show regularities, but they differ from those of the previous case. Fig.4 (d) represents the autocorrelation function of the noise from a motor with a missing phase fault. Again, it should have distinct characteristics. The autocorrelation function enables us to examine these patterns and identify motor anomalies.

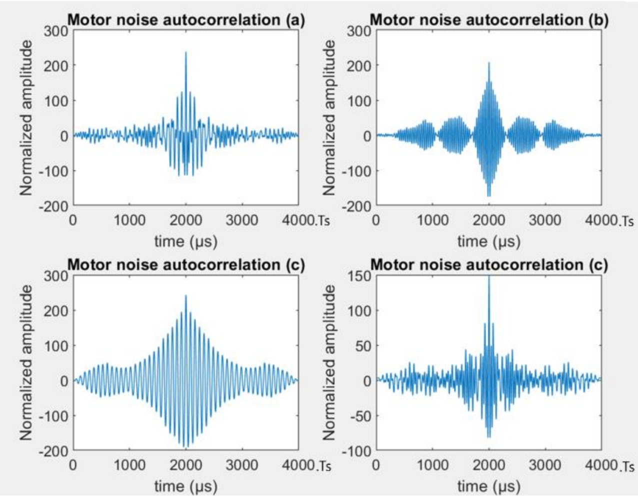

Fig. 4. Autocorrelation function of the noises coming from the motor.

Analysis by zero-crossing rate

The analysis of the zero-crossing rate ZCR is a tool commonly used to study the properties of signals, in particular in the field of signal processing [14].

The ZCR is calculated as follows:

$$ZCR = \frac{\text{Numbre of zero crossings}}{\text{Total duration of the signal}} \tag{5}$$

The ZCR analysis is very useful in signal processing. In our case, it is used to characterize the rhythmic regularity in motor noise.

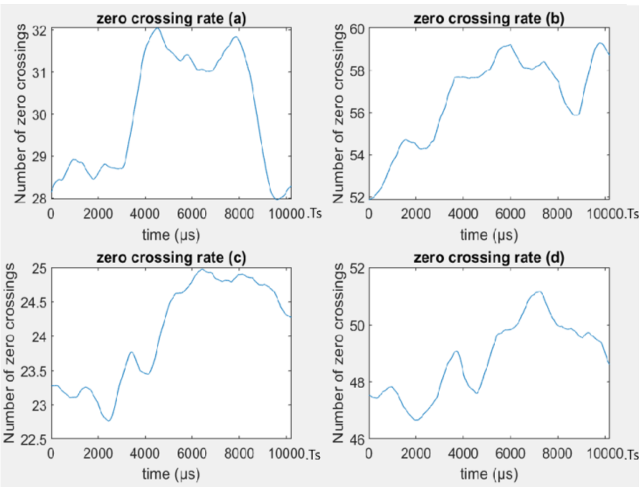

Fig. 5. Motor noise zero-crossing rate (ZCR).

In Fig.5, we plotted the zero-crossing rate of four types of motor signals in four operating situations: Fig.5 (a): the zero-crossing rate (ZCR) of the noise from a fault-free motor. It varies between 52 and 60. Fig.5 (b): the zero-crossing rate (ZCR) of the noise from a motor with an overvoltage supply fault. It varies between 28 and 32. Fig.5 (c): The zero-crossing rate (ZCR) of the noise from a motor with an under-voltage supply fault. It varies between 22 and 25. Fig.5 (d): the noise's zero-crossing rate (ZCR) from a motor with a missing phase fault. It varies between 46 and 50. This information is essential for diagnosing and identifying potential motor operation problems. The zero-crossing rate may vary depending on the nature of the defect and may serve as a basis for corrective measures.

Spectral analysis

Spectral analysis is a crucial technique for examining the frequency characteristics of a signal. It covers several techniques for describing signals in the frequency domain. In particular, it enables the determination of the response characteristics of a linear system using a transfer function, thereby facilitating an understanding of the frequency distribution in the signal.

Short-term Fourier transform analysis

The analysis of signals by the short-term Fourier transform (STFT) is a technique used to study the frequency properties of signals in the time-frequency domain. It is based on the discrete Fourier transform applied to shorter time segments. It uses a window that moves along the signal, making it possible to analyse different temporal sections, which allows detecting frequency variations over time. Thus, the Short-term Fourier Transform is a powerful tool for studying the frequency properties of a signal by taking into account its temporal variations. It finds applications in various fields, in particular, signal processing, speech analysis, and fault detection in mechanical systems.

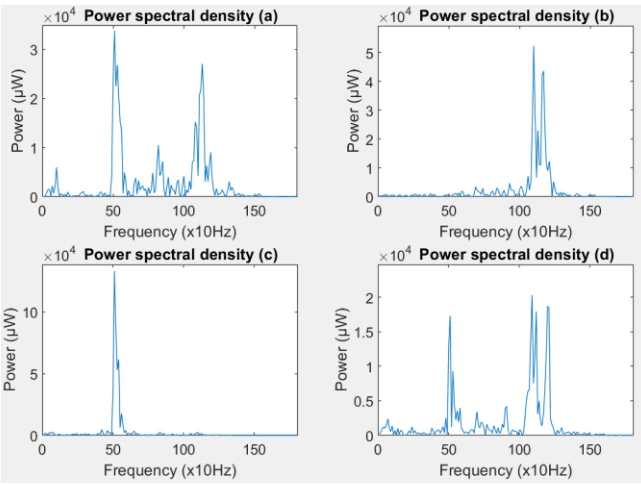

Fig. 6. STFT of motor noises.

In Fig.6, we have plotted the short-term Fourier transform of four signal segments, with a duration of 50ms, coming from the motor in four operating situations:

Fig.6 (a) presents the short-term Fourier transform of the data from a fault-free motor. In this power spectrum, four main lobes extending from *30 Hz* to *1500 Hz* are noticeable. These lobes represent the normal components of motor noise under regular operating conditions.

Fig.6 (b) shows the short-term Fourier transform of the noise from a motor with an overvoltage supply fault. Note the presence of two main lobes limited between *500Hz* and *1500Hz* on this power spectrum. This means that the fault introduces specific disturbances in this frequency range, which are caused by the voltage supply.

Fig.6 (c) presents the short-term Fourier transform of the noise from a motor with an under-voltage supply fault. Note the presence of a single main lobe centered between *400Hz* and *600Hz* on this power spectrum. This indicates specific disturbances introduced by the under-voltage supply fault, manifested in this frequency range.

Fig-6(d) shows the short-term Fourier transform of the noise from a motor with a phase defect. Note the presence of five main lobes located between *400Hz* and *1500Hz* on this power spectrum. Compared to the normal condition, these additional lobes could indicate irregularities in the motor's operation due to the missing phase.

This information can be used to diagnose potential problems in the motor's operation. The variation in the number and position of the main lobes in the power spectrum can provide valuable clues about the nature and severity of motor defects, thus helping to take appropriate corrective measures.

Analysis by LPC

Linear Predictive Coding (LPC) analysis is a signal processing technique used to model a signal *x(k)* and associate with it a linear filter that, subjected to a particular excitation, reproduces this signal as faithfully as possible. The essential objective of the modelling of a signal is to allow the description of its spectrum by a very limited set of parameters [14]. The classical modelling of a signal is based on a rational transmittance filter:

(6) $$H(z) = \frac{B(z)}{A(z)}$$

where, *B(z)* : polynomial in *Z* of degree *q.*

A(z) : polynomial in *Z* of degree *p.*

This model (H) is excited by a white noise *u(k)* of zero mean µ and unit variance σ in order to synthesize the signal *x'* (Fig. 7).

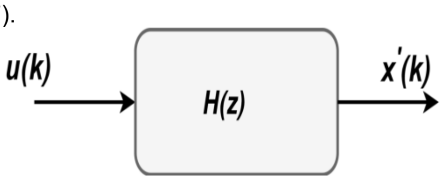

Fig. 7 Motor noise synthesis.

In the general case (p>0 and q>0), we refer to ARMA (Auto Regressive Moving Average) modelling. When B(z) =1 (p>0, q=0), this is an AR (Auto-Regressive) modelling: H(z) is an all-pole function. When A(z)=1 (p=0, q>0), the transfer function H(z) is that of a finite impulse response filter (FIR): it is a moving-average modelling, sometimes called adjusted average). The most used model is the AR model. Its modelling capabilities (ability to approximate the signal spectrum) are sufficient for many applications. Thus, the estimation of the AR model is based on linear prediction, and efficient algorithms are available for this purpose.

The ARMA model is obviously the one that has the greatest modelling capacity for a given degree, but its estimation is complex. As for the MA model, its modelling capabilities in our case are satisfactory. The linear prediction thus leads to an AR model, as shown in Fig 8.

A(z) is the inverse filter; it is used for the estimation of the linear prediction coefficients ai. This estimation is based on the assumption that each sample of the original signal x(k) can be approximated by a linear combination of the p samples that precede it:

(7) $$x'(k) = -\sum_{i=1}^{p} a(i).x(k-1) + e(k)$$

where, *x* is the noise signal generated by the motor, *x' is* the estimated signal, ***a*** is the AR filter coefficients and ***e*** is the prediction error,

In this expression, the coefficients $a(i)$ are called p-order prediction coefficients of the signal. The prediction error becomes:

(8) $$e(k) = \sum_{i=1}^{p} a(i).x(k-1)$$

Where $a(0)=1$

The prediction coefficients must be estimated according to a certain criterion. It is clear that the prediction in equation (7) is only possible if the signal x is autocorrelated; therefore, it should be expected that the autocorrelation matrix of the signal will play a crucial role in this estimation.

Energy of the prediction error

The estimation based on linear prediction is known as the LPC method. The excitation of the autoregressive model (AR) is a white noise process. Prediction error is a crucial concept in statistical modelling and machine learning. It measures the difference between the values predicted by a model and the actual values observed Fig. 8.

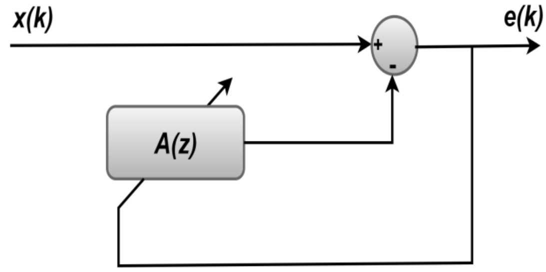

Fig. 8. Noise signal modelling

When evaluating a model, we aim to minimize this error. The bias-variance dilemma is a crucial aspect of constructing efficient prediction models. In this case, of modelling, the bias of our estimator is the difference between its prediction and the “true” value. The variance measures the dispersion of the values around their mean. In this context of modelling, the variance of the prediction error e(k) estimates the extent to which the model fluctuates around its mean to adjust to the data. The closer a model is to the data points, the lower its variance will be.

The expected error of our prediction model on the data not used for training can be broken down into the sum of the squared bias and the variance of this model. This decomposition enables us to understand how bias and variance affects the model's overall performance. Finding the right balance between bias and variance is crucial for obtaining a robust model.

Motor noise synthesis

The synthesis by linear prediction (LPC) based on the autoregressive modelling (AR) of the signal has as its objective the estimation of the parameters of a system (the LPC model) capable of generating the artificial signal x' and close to the original signal x. The analysis of the signal x makes it possible to estimate the coefficients of an inverse filter of transmittance A(z) (Fig. 9).

The excitation of the inverse filter, of transfer function *A(z),* by the original signal generates the prediction error e, the variance of which is minimized in order to obtain the coefficients *a(i)* of the *LPC* model. This model has the all-pole transfer function *H*:

$$H(z) = \frac{1}{1 + a(1).z^{-1} + ... + a(p).z^{-p}} \quad (9)$$

The all-pole transfer function H, excited by a white noise of unit variance generates a signal x' whose autocorrelation function coincides with that of the original signal x. the synthetic signal x' is used in our case to validate the accuracy of the modelling (Fig.10).

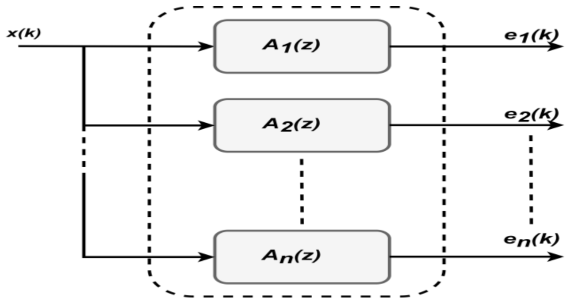

Fig. 9. Inverse filter of transmittance diagram.

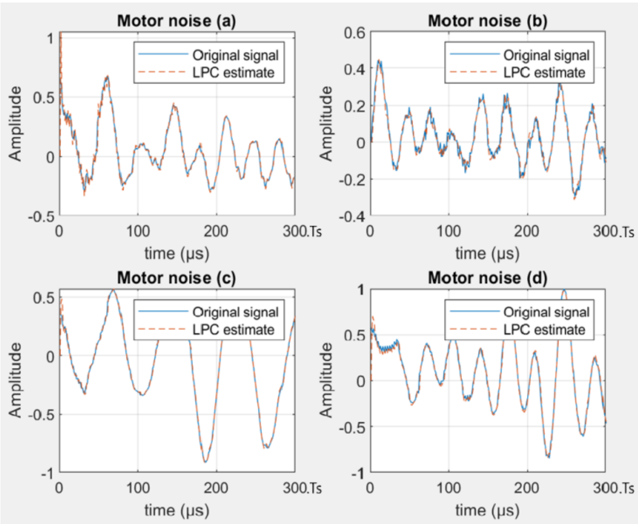

Fig. 10. Synthesis of noise from the motor

In Fig. 10, we have plotted four signal segments, each lasting 6 ms, originating from the motor in four different operating situations. Fig.10(a) presents the normalized amplitude of the original and synthetic signals as a function of time, illustrating the noise generated by a fault-free motor. Fig.10(b) shows the normalized amplitude of the original and synthetic signals as a function of the time of the noise coming from a motor having a power overvoltage fault. Fig.10(c) presents the normalized amplitude of the original and synthetic signals as a function of time of the noise coming from a motor having a fault of an under-voltage supply. Fig.10(d) shows the normalized amplitude of the original and synthetic signals as a function of time of the noise coming from a motor with a missing phase fault.

In Fig.11, we have plotted four signal segments, each lasting 6 ms, from the motor in four operating conditions, where Fig. 11(a) shows the normalized amplitude of the original and synthetic signals as a function of time for noise from a fault-free (healthy) motor. Fig.11(b) represents the normalized amplitude of the original and synthetic signals as a function of time for noise from a motor with a vibration fault due to a damaged bearing. Fig.11 (c) illustrates the normalized amplitude of the original and synthetic signals as a function of time for noise from a motor with a contamination fault (dust and humidity). At the same time, Fig.11(d) shows the normalised amplitude of the original and synthetic signals as a function of time for noise from a motor with a partial short-circuit fault in the stator.

From these results, it is noticed that the calculation model synthesizes the original signal with very high precision, especially when it exhibits slow variations (low frequencies). A slight difference between the original and synthetic signals is observed when the signal exhibits rapid fluctuations (high frequencies). This is due to the choice of the prediction order p. Thus, to synthesize the signal with very high accuracy under all conditions, it is necessary to choose a prediction order greater than 10. However, this leads to a longer calculation time to estimate the prediction coefficients, which affects the system's performance.

In general, the prediction order must be greater than twice the number of lobes present in the original signal's Fourier spectrum. Indeed, a resonator, that is, a filter *RII* of order two, models each lobe.

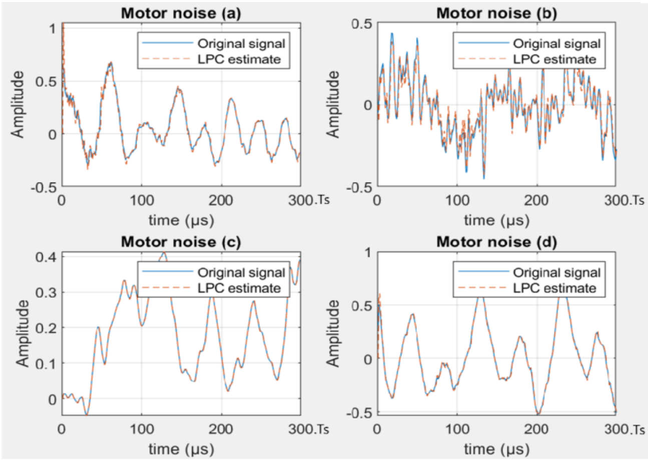

Fig 11. Synthesis of noise from the motor

Fault Detection and Classification

The acquired signal undergoes the same pre-processing (enhancement and normalization). For the autocorrelation method, we calculate the energy of the cross-correlation between the signal to be identified and the signals from our database, which was built during the analysis phase. The fault classification is based on the highest energy exceeding an empirical threshold. If the calculated energy is below this threshold, the signal is considered a new fault that must be classified in the database.

For the zero-crossing rate method, the mean value μ of the ZCR of the signal allows us to classify the fault (Fig. 5): (e.g., $52 < \mu < 60$: overfed motor). For the spectral method, the power spectral density (PSD) of each signal is calculated from the ten-recorded signals of the fault. The barycenter value of the ten PSDs is then calculated, and the metric distance, which is the most considerable Euclidean distance between the barycenter and the PSD of every signal, is determined. Classification is made by comparing the power spectral density (PSD) of the new signal with the barycenter of the reference signal. We calculate the power spectral density of the signal to be identified. The fault classification is performed using the nearest neighbour algorithm.

For the LPC method, we calculate the energy of the prediction error e(k) (8) using the inverse fault filters computed during the analysis phase, according to:

$$\sigma = \sum_{i=0}^{L} e^2(k) \quad (10)$$

The nearest neighbour algorithm is used to classify the fault. Finally, to test the effectiveness of the system, the rate of recognition (RR, accuracy) is calculated according to the following definition:

$$RR = \frac{\text{number of successful occurrences}}{\text{Total number of occurrences}} \quad (11)$$

Table 1: Rate of recognition and comparison.

METHOD	AUTOCORR	ZCR	STFT	LPC
Rate of recognition (RR)	60	96	80	100

Result and discussion

The first technique is based on analyzing the autocorrelation function of motor noise. This approach enables us to identify patterns within the noise, detect potential anomalies in the motor, and estimate the rotor's rotational speed. The second technique we have used is based on the zero-crossing rate of motor noise. Although this method is simple to implement and gives satisfactory results, it is sensitive to the background noise generated by the measuring instruments, particularly the microphone. It is more effective in detecting anomalies than in identifying them. The third method we have deployed is based on the spectral analysis of motor noise. This approach enables the diagnosis of potential problems in the motor's operation. The variation in the number and position of the main lobes in the power spectrum can provide valuable indications on the nature and severity of defects, which helps to take appropriate corrective measures. The fourth technique used is based on analysing motor noise by linear prediction coding. This technique is highly efficient for detecting and identifying defects with unparalleled precision, especially when the order p chosen is greater than ten. It is worth noting that for all the classification methods used here, an analysis window of 26 ms yields good results. Above this time, no enhancement is considered, and the processing time becomes larger.

Conclusion

Analysing the noise emitted by the motors is an effective method of diagnosing defects and monitoring the health of these complex electromechanical systems. By carefully examining the acoustic signals, characteristic patterns associated with various problems can be identified, thus enabling early detection of potential malfunctions. The advantages of this approach are multiple. First, it allows for the early detection of defects, thus facilitating rapid interventions to avoid more serious motor deterioration. In addition, it offers precise localization of problems, simplifying maintenance operations by directly targeting the source of the malfunction. Finally, it encourages a proactive approach to maintenance by planning interventions before problems disrupt operations, thus reducing unplanned downtime and associated costs. This noise analysis paves the way for smarter maintenance and more efficient management of industrial assets. Combining state-of-the-art techniques, signal processing methods, and machine learning approaches makes extracting significant information from motor noises possible, thus allowing a more accurate detection of defects and a more reliable prediction of their evolution.

The different motor noise analysis techniques presented here offer various approaches to detecting and diagnosing operating anomalies. Each method has its advantages and limitations, ranging from the simple analysis of the zero-crossing rate to the more complex use of spectral analysis and linear prediction coding. Combined wisely or adapted to the specific context, they can improve the reliability of the diagnosis of motor problems and guide the appropriate corrective measures, provided that the particularities of each method and the environmental and measurement conditions are considered to obtain accurate and reliable results.

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