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Fault Bearing Recognition Based on MCSA Approach Using Principal Component Analysis and Power Spectrum Density

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Abstract
Early fault classification using the Motor Current Signature Analysis approach is extremely challenging for many reasons: prior knowledge of the descriptive parameters of the acquired stator current signal to be analyzed (harmonics number), analysis of this signal in the time domain does not offer satisfactory detection performance, and a low signal-to-noise ratio (SNR) has a dramatic effect on detection quality. This leads to considerable impairments in signal features. In this study, principal component analysis (PCA) combined with signal processing spectral methods (PSD and SPSD) is proposed as a new feature extraction technique for the efficient extraction of the power spectra and square spectrum features of the stator current signal in the presence of Gaussian noise to distinguish the healthy or faulty state of electromechanical machine. The use of PCA enables the extraction of principal components associated with different harmonic appearances, characterizing mechanical defects in these machines as the input vector of the classifier. This makes detection easier, even in poor SNR conditions, because PCA allows the removal of Gaussian noise. The simulation was performed using MATLAB software with various stator-current signals containing different harmonics describing these faults. The results obtained showed that such data from this combination would enable faults in electric induction machines to be distinguished and classified with a high degree of accuracy, irrespective of the number of harmonics and noise.
Keywords. Bearing fault, MCSA, Spectrum feature, Power spectrum density, Classification, Principal component analysis

Introduction

When we want to know the state (faulty or healthy) of a machine, the first step is to find the descriptive parameters of the system or the physical quantity on which to base it (A. Gheitasi, 2013; J. A. Pecina-Sánchez, D. U. Campos-Delgado and D. R. Espinoza-Trejo, 2011; S. Nandi and H. A. Toliyat, 1999; J. Chatelain, 1983). For this, if some use thermal methods to achieve this, others use methods based on the signals from these machines which can be either acoustic or electrical (García Marquez et al., 2020; Deepam Goyal et al., 2018; Manish Vishwakarma et al., 2017; Janssens et al., 2015). When we consider those based on signals, there are two analysis processes. One requires knowledge of the signal or system parameters beforehand and is much more accurate, whereas the other does not require knowledge of these parameters and provides acceptable results (Hangfang Zhao and Lin Gui1, 2019). As in real life, it is difficult for a given signal to know the parameters at first sight; the second is much more valued at the expense of the first. However, given the consequences and losses that can result from poor detection of defects in these machines, it is important to improve these processes to avoid any misinterpretation of the state of the system to be analysed. In this study, by applying Principal Component Analysis (PCA) to the Power Spectrum Density (PSD) and the Square Power Spectrum Density (SPSD), we show that it is possible, without knowing the parameters of the machine signal, to distinguish not only the healthy state from the faulty state, but also to distinguish between the most recurrent faults in electrical machines, without worrying about the number of harmonics that constitute them.

The remainder of this paper is organised as follows.

First, after providing a background to the present work, a brief presentation of the two methods, parametric and non-parametric, will be presented in Section 3. In Section 4, we present the four types of defects. We then discuss the method used to acquire the signal. Next, we explain how PSD, SPSD, and PCA work, and why this combination works. Finally, we end with the discussion in Section 9 and the perspectives in Section 10 after the simulation and results in Section 8.

Background

Monitoring electric induction machines is a resource-intensive task, especially when it comes to detecting the presence or absence of faults that may arise at any time. These faults, which are likely to cause more damage, must be intercepted in real-time. This implies a need for real-time detection systems. However, time is not sufficient, as the system must also be precise enough to avoid false positives or true negatives when it comes to capturing variations in the machine. For example, in the case of a nuclear power plant, it would be very unpleasant to be mistaken about the real state of the machine at any time because of the damage that could cause. Therefore, it is understandable that, from one system to another, detection tolerances are no longer the same, or that simply having an accurate real-time system would be the most desirable in general. Since then, researchers have been working on several cutting-edge solutions. The history of these solutions shows that there are two types of solution. The first is known as parametric, and the second is non-parametric (Hangfang Zhao and Lin Gui1, 2019). However, because of the precision offered by the former in terms of prior knowledge or determination of the parameters of the system under study, the latter is not widely used, especially for monitoring critical systems. However, the latter can be very useful because in the real world, most of these systems are unpredictable and sometimes poorly understood. Therefore, the idea of being able to comment on the state of these systems without prior knowledge can be of vital importance. Several studies mention their use in spectral estimation problems (Hangfang Zhao and Lin Gui1, 2019; Ahmadi, H., Khaksar, Z, 2011; P.Stoica and R.Moses, 2005). There is also work showing the effectiveness of combining them with Machine Learning algorithms and PCA to autonomously differentiate between types of modulation in marine environments (Wei-hua Jiang et al., 2018). As for PCA, works such as (Mikael J, 2022; Masayuki Tamura, Shinsuke Tsujita, 2007; Jiang WH, Cao XL, Tong F, 2015; Fan HB, Yang ZJ, Cao ZJ, 2004 ; Chan YT and Gadboi LG, 1989) demonstrate its use in various fields. However, the use of such combinations for fault detection in electromechanical induction machines has not been exploited. The aim of this work is to show that such an approach can be used to diagnose the most common faults in electromechanical induction machines, particularly wind turbines.

Methods and Techniques

Parametric And Non-Parametric Methods

Parametric and non-parametric methods are used for the identification and description of system models. Both can be effective in monitoring the state of a given system [9]. If parametric methods require prior knowledge of the descriptive parameters of the signal before proceeding with its analysis, nonparametric methods do not. Indeed, for the latter, static estimators are used to help understand the system studied from the physical quantity describing it. In most cases, the signal is based on the PSD. Parametric methods use a number of procedures to reconstitute the model from the estimated parameters. We can then distinguish one that only focuses on describing the signal in a statistical way and using much simpler techniques and the other that tries to go back to the source of the signal by the prediction or the determination of these parameters (R. Kumar et al., 2021; Iqbal et al., 2019; E. Angola, 2017; El Houssin El Bouchikhi, Vincent Choqueuse, Mohamed Benbouzid, 2015). Among the methods used by the latter, the most used are high-resolution signal processing methods, of which ESPRIT-TLS is the most appreciated.

The PSD and SPSD Algorithms

PSD is a technique used to represent the signal acquired in the time domain in the spectral or frequency domain. Based on a periodogram, this technique explains how the signal power is associated with each frequency in the energy representation of the signal. This is the same principle used by the MCSA method to determine the characteristic frequencies of defects or defects that have occurred in the signal. Although it is impossible to determine the moment at which the defect occurred and to estimate the parameters, it offers the possibility of having an idea about the signal from the point of view of frequency harmonics (J. CusidÓCusido et al., 2008). Its mathematical formula is as follows:

$$PSD(X) = \frac{2 * dt}{n^2}((X_{real})^2 + (X_{img})^2) \quad (2)$$

where n is the number of samples and X is the signal. The square power spectrum density (SPSD) is the square of the PSD. It is more compact than the PSD and can be distinguished from it. It was used in the work of Jiang et al. (Wei-hua Jiang et al., 2018) for the recognition of modulation types in underwater environments as parameters for their neural network model.

The PCA Algortihm and Fusion with PSD and SPSD

One of the problems with PSD or SPSD is that, when the noise becomes too high, it is almost impossible to distinguish the harmonics of the signal. Thus, we obtain a signal composed of artifacts or subharmonics caused by noise. This is where Principal Component Analysis (PCA) comes in, as its name indicates, to extract or retain only the bare minimum of information needed to fully understand the PSD or SPSD. It not only has a noise-reducing effect but also a dimension-reducing effect on the data on which it is applied. However, it must be noted that the reduced data (new data) retains its originality.

It is used in many studies where the dimensions are large to reduce them to their main composition by eliminating any unnecessary superfluous that could, for example, models of Artificial Intelligence, cause either over-learning or under-learning. In other words, a model outside reality is modeled. PCA transforms interdependent data (too much variability) into meaningful data (less variability), and is independent. It is similar to eliminating the harmonics or the small variations of the same quantity in order not to consider them as quantities of different natures. With PCA, we can say that this data is only a combination or a modification of this plus this data or simply of this data. In other words, it allows the generalities of a set of data to be retained, allowing a clear expression of a phenomenon or phenomena. We discuss the creation of heterogeneity in apparently homogeneous data (Farzana Anowar, Samira Sadaoui, Bassant Selim, 2021; Wei-hua Jiang et al., 2018). The procedure used in this study is illustrated in Figure 1 below:

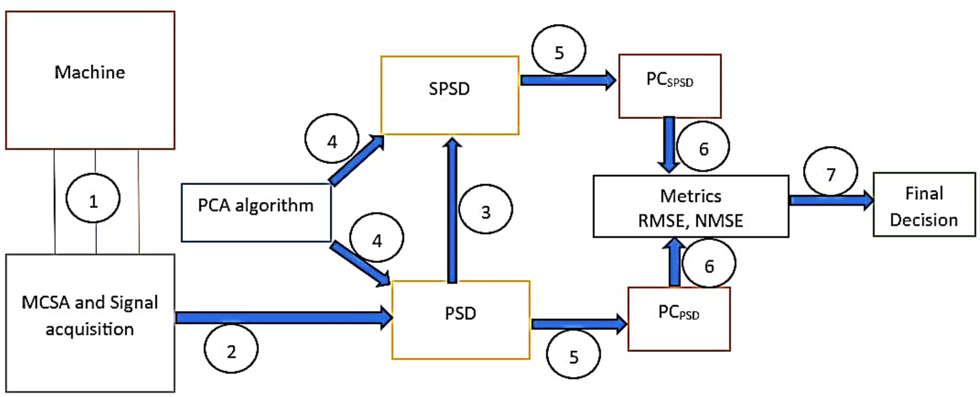

Fig. 1. Procedure flow chart. 1) signal acquisition from machine, 2) PSD computation, 3) SPSD computation, 4 and 5) Applying of PCA, 6) Metrics comparison, 7) Decision.

Materials and Area

Faults In Electromehanical Induction Machines

Like any other machine, electric induction machines are highly prone to defects owing to mechanical fatigue and abnormal internal variations. These defects can be caused by bearings, rotor bar problems, misalignment of the joint bars with loads, eccentricity problems, or problems with variable-speed drives. Thus, these defects can lead not only to a malfunction of the machine but also to its total loss by causing very serious accidents. This could lead to production stoppage or enormous costs for machine repair (Saad Chakkor, Baghouri Mostafa, Abderrahmane Hajraoui, 2014). The mechanical faults most likely to cause a machine to stop are numerous, but the most important ones, which are the subject of research in the scientific community, are listed in Table 1 (Saad Chakkor, Baghouri Mostafa, Abderrahmane Hajraoui, 2014).

Table 1. Frequency Signature of Rotating Machine Faults

Faults	Frequency	Parameters

Broken rotor bars	$f_{brb} = \left[k\left(\frac{1-s}{p}\right) \pm s\right]$	$k = 1, 2, \ldots$
Bearing damage	$f_{bng} = \lvert f_0 \pm k f_{i,o} \rvert$	$k = 1, 2, \ldots$ $f_{i,o} = \begin{cases} 0.4 n_b f_r \\ 0.6 n_b f_r \end{cases}$
Misalignment	$f_{mis} = \lvert f_0 \pm k f_r \rvert$	$k = 1, 2, \ldots$
Air gap eccentricity	$f_{ecc} = \left[1 \pm m\left(\frac{1-s}{p}\right)\right]$	$m = 1, 2, \ldots$

- f_0 is the power supply frequency,
- s is the slip (g) per unit,
- P is the number of poles,
- f_r is the rotor frequency,

$f_{i,o}$ is the frequency describing any wear on the inside or outside of the bearing ring, n_b is the bearing's ball number, and m and k are integers.

Signal Acquisition and Modling

As mentioned above, analysing a machine means first determining or choosing the size or characteristic of the machine that will allow us to understand it. Once this is defined, it is easier to proceed to the second step which is the actual analysis of the system or machine. Thus, we distinguish thermal methods from signal methods (acoustic or electrical). However, in the last few decades, it has been proven that methods based on the analysis of the stator signal from these machines allow for a better understanding of what happens inside these machines. This idea is simpler and makes it possible to dispense certain factors that can impinge on the monitoring of the latter. Thus, the advantages of this method are significant. For example, it eliminates the constraint of non-accessibility to these machines, eliminates the hypothesis that the sensors are poorly attached, avoids direct contact between the sensors and machine, and makes it possible to take measurements miles away from the machine without affecting the results of the analyses. This method, called machine current Signature Analysis (MCSA), is based on the principle that any fault occurring within the machine can be perceived as the cause of the disturbance of the normal signal of the machine, except for any fault (fundamental signal). By combining these with signal processing methods, it is possible to distinguish each defect uniquely based on their frequency characteristics in the acquired signal. This signal can be described as the sum of all frequencies of the defect, considering the surrounding noise. The mathematical expression (Equation 1) allows us to model the signal acquired from the machine (Saad Chakkor, Baghouri Mostafa, Abderrahmane Hajraoui, 2014).

$$x[n] = \sum_{k=-L}^{L} a_k \cos\left(2\pi f_k\big(w(n)\big) \times \frac{n}{F_k} + \phi_k\right) + b[n] \tag{1}$$

Results

Simulation And Results

The simulations were performed in MATLAB. The simulations were performed using the following parameters: values ranging from 0 to 50 in steps of 0.5. For the amplitudes, we worked with 2, four, and 6 amplitudes corresponding to the number of harmonics. As for the amplitude of the fundamental for each defect, we have denoted them as A0. PC1, PC2, and PC3 correspond to the principal components calculated using PCA. The amplitudes are in amperes (A), and the frequencies in Hertz (Hz) are presented in Tables 2 and 3. The frequencies used in this study were determined using the formulas listed in Table 1. By varying parameter k, we can obtain the desired number of harmonics for each type of fault, as shown in Table 3. Because the machine signal presented in Equation 1 is a summation of the fault harmonics, and because we wish to verify the impact of the number of harmonics on the robustness of the proposed method, the application of MOS algorithms such as MDL or AIC, as already applied in the following reference (F. Cong et al., 2012 ; A. Quinquis, 2008), may prove essential insofar as it is necessary to know it in advance, even if we assume it to be known for all fault types in the present work. Given that we have three

(3) Main Components, it was judicious to present the two corresponding NMSE and RMSE values, as shown in the figures below.

Table. 2. Faults amplitudes values**.**

<table>
<tr><th></th><th colspan="2">Bearing (Hz)</th><th colspan="2">Brokeen rotor bar (Hz)</th><th colspan="2">Misaligment (Hz)</th><th colspan="2">Eccentricity (Hz)</th><th>Fondamentale (A0)</th></tr>
<tr><td>2 harmoniques</td><td colspan="2">0.05
0.02</td><td colspan="2">0.06
0.03</td><td colspan="2">0.07
0.04</td><td colspan="2">0.08
0.05</td><td rowspan="3">1
2
3
4</td></tr>
<tr><td>4 harmoniques</td><td>0.09
0.06</td><td>0.05
0.8</td><td>0.1
0.07</td><td>0.06
0.09</td><td>0.11
0.08</td><td>0.07
0.1</td><td>0.12
0.09</td><td>0.08
0.11</td></tr>
<tr><td>6 harmoniques</td><td>0.13
0.1
0.09</td><td>0.12
0.11
0.08</td><td>0.14
0.11
0.1</td><td>0.13
0.12
0.09</td><td>0.15
0.12
0.11</td><td>0.14
0.13
0.1</td><td>0.16
0.13
0.12</td><td>0.15
0.14
0.11</td></tr>
</table>

Table. 3. Faults frequencies values.

<table>
<tr><th></th><th>Bearing (Hz)</th><th>Brokeen rotor bar (Hz)</th><th>Misaligment (Hz)</th><th>Eccentricity (Hz)</th><th>Fondamentale (Hz)</th></tr>
<tr><td>2 harmoniques</td><td>89.2480
189.2480</td><td>22.5250
25.8250</td><td>20.9900
79.0100</td><td>25.8250
74.1750</td><td rowspan="3">50</td></tr>
<tr><td>4 harmoniques</td><td>89.2480
189.2480
228.4960
328.4960</td><td>22.5250
25.8250
46.7000
50.0000</td><td>8.0200
20.9900
79.0100
108.0200</td><td>1.6500
25.8250
74.1750
98.3500</td></tr>
<tr><td>6 harmoniques</td><td>89.2480
189.2480
228.4960
328.4960
367.7440
467.7440</td><td>22.5250
25.8250
46.7000
50.0000
70.8750
74.1750</td><td>8.0200
20.9900
37.0300
79.0100
108.0200
137.0300</td><td>1.6500
22.5250
25.8250
74.1750
98.3500
122.5250</td></tr>
</table>

The results below are presented for 2, 4 and 6 fault harmonics. First, we present the PSD and the SPSD. Then we present the PSD-PCA combination. Next come the results of the SPSD-PCA fusion and finally we present the NMSE and RMSE on the principal components.

PSD and SPSD Simulation Results

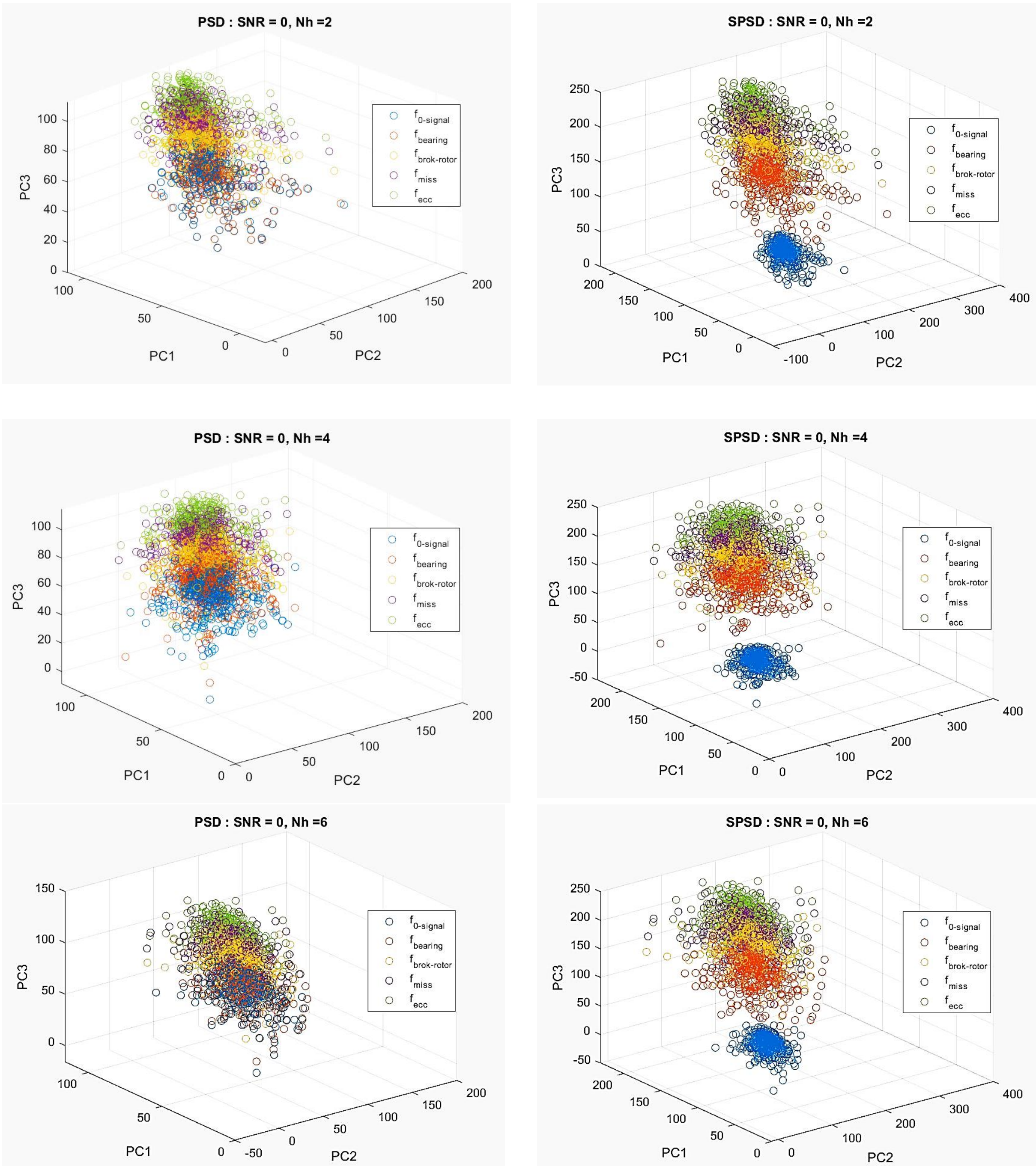

Fig. 2. PCA components using PSD and SPSD.

From these results, we can see that SPSD is much better than PSD. Unlike PSD, SPSD can separate the signal of a healthy machine from the signals of a faulty machine. However, owing to the noise of the two, there are difficulties in separating the defects very well. This is where the BCP is located. The results below show the changes that BCP makes to SDP and PDS.

PSD and SPSD with PCA Simulations Results

For displays, only the figures for SNR values of 0, 10, 25, and 50 dB are shown. This was done to determine the impact of PCA on the PSD and SPSD at different noise levels.

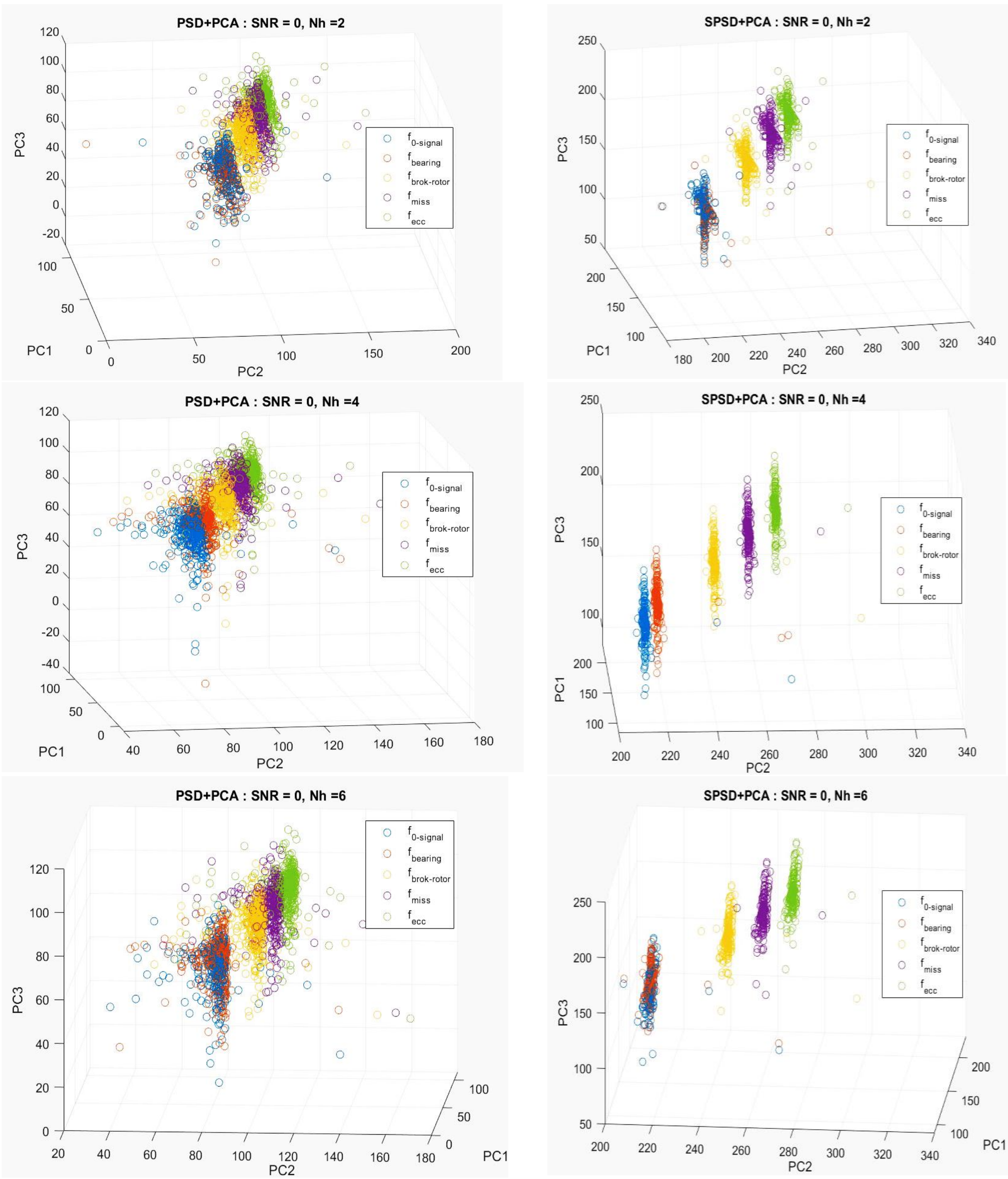

Fig. 3. PCA components using combination of PSD, SPSD and PCA.

For these results, we chose an SNR value equal to zero to observe the effect of the PCA, as mentioned above. It can be seen that PCA significantly modifies the PSD and SPSD. With its use, the signals can be better distinguished. Moreover, the PCA-SPSD fusion is better placed for a good distinction between the healthy signal and defect signals. The figure below provides an idea for an SNR value equal to 10 dB for the 2, 4, and 6 harmonics of the defects.

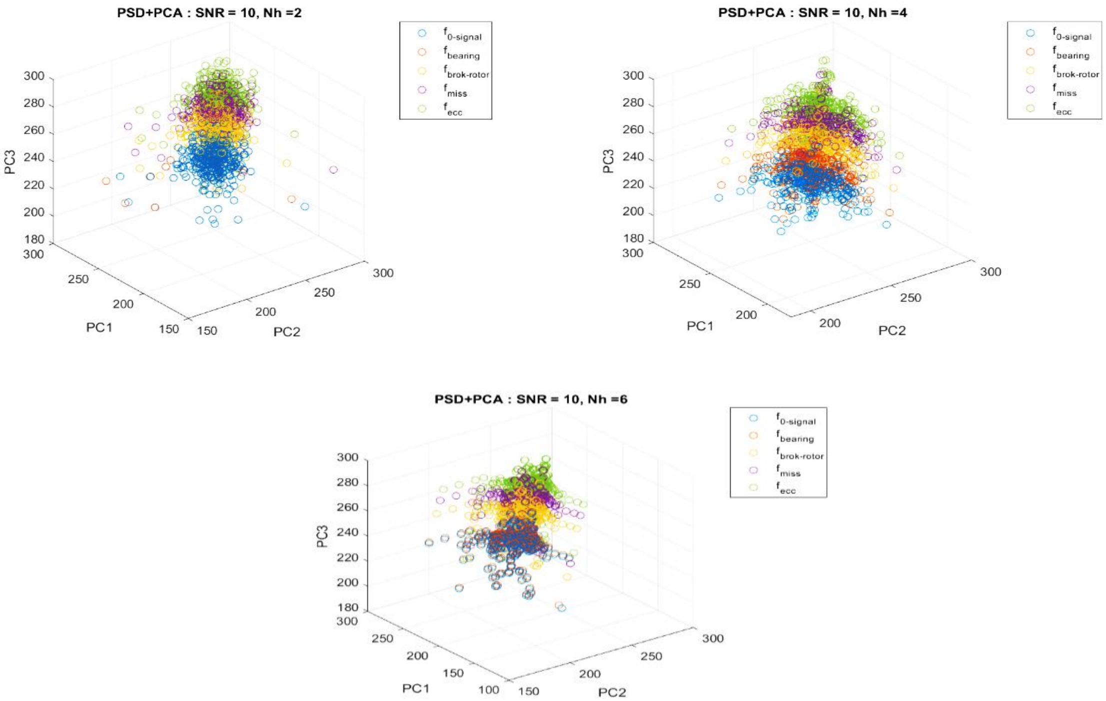

Fig. 4. PCA components using PSD and PCA combination for SNR =10 dB.

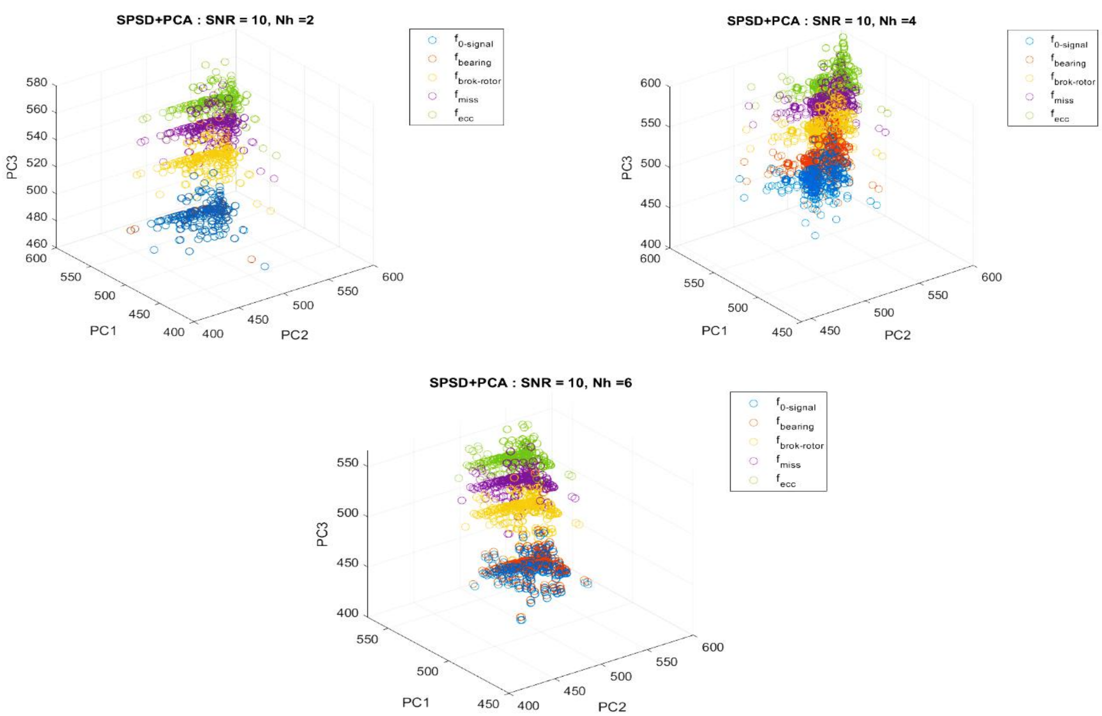

Fig. 5. PCA components using SPSD and PCA combination for SNR =10 dB.

To better understand this distinction to what extent, we present the NMSE and RMSE indicators of the principal components of these signals from the SPSD-SPSD+PCA point of view for two, four, and six harmonics of defects.

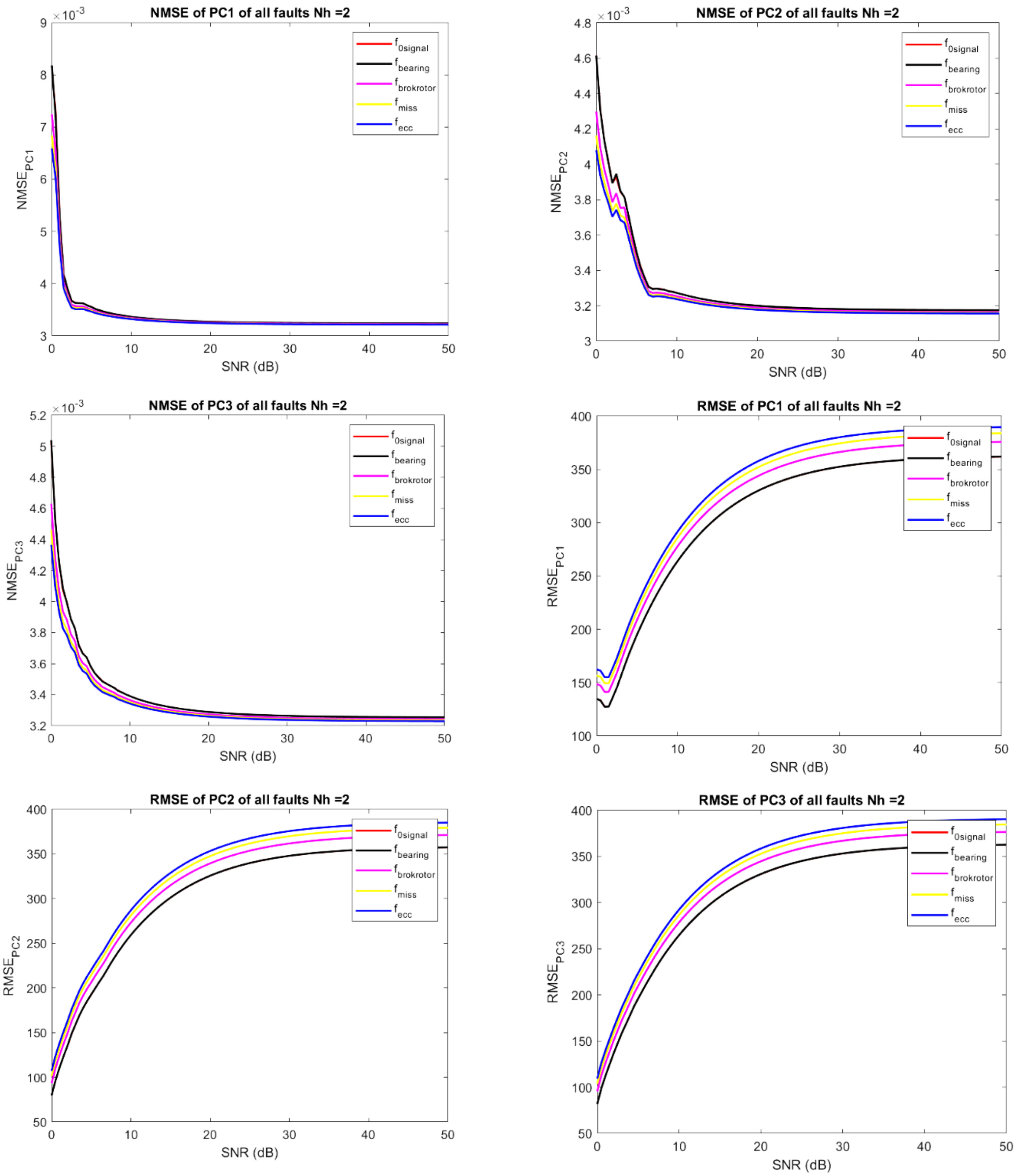

Fig. 6. NMSE and RMSE of PCA components for faults harmonics number equal 2.

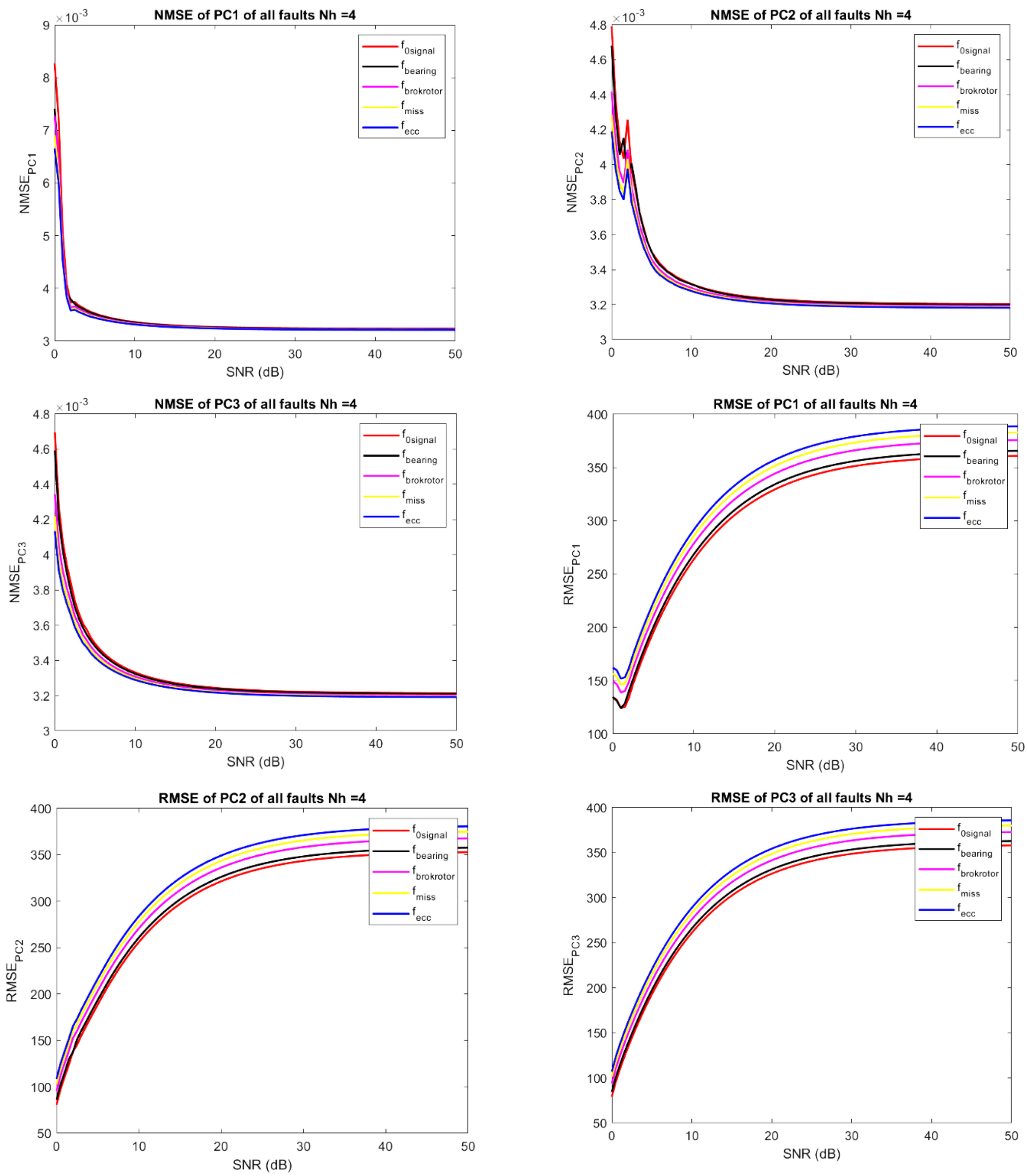

Fig. 7. NMSE and RMSE of PCA components for faults harmonics number equal 4.

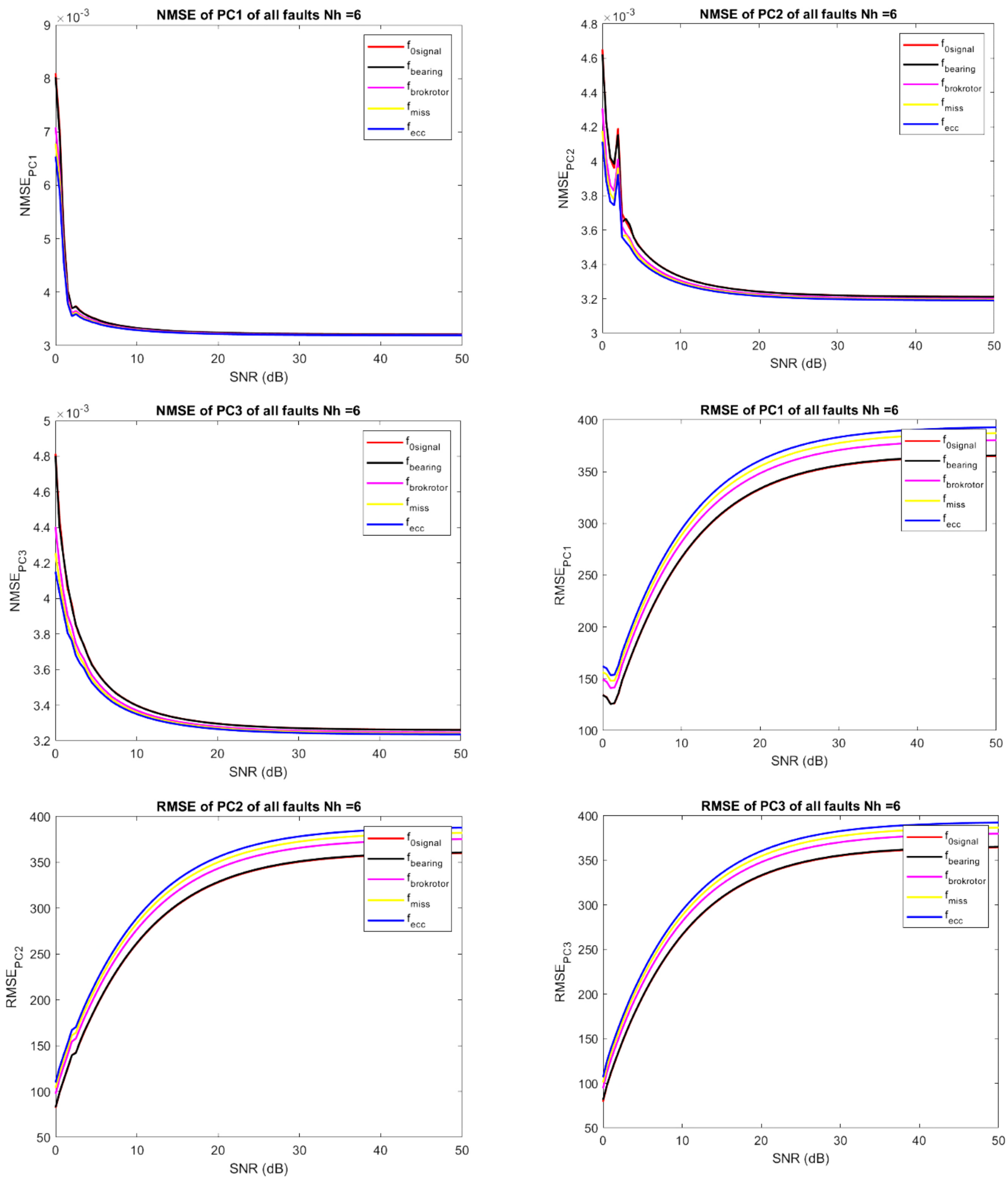

Fig. 8. NMSE and RMSE of PCA components for faults harmonics number equal 6.

Discussions

From the results presented in figures 2, 3, 4 and 5, it can be seen that the SPSD-PCA and PSD-PCA combination allows to distinguish the different signals much more clearly than the PSD-PCA combination. Moreover, in addition to seeing by the values of the NMSE on figures 6, 7, and 8, the evolution of the principal components according to the SNR, we can see there is convergence. And given the order of magnitude, we can say that when one of the 4 defects appears, it will be possible to differentiate it from the normal (signal of a machine without defect) to within 10-3. Which is good, on the one hand.

On the other hand, we can see that regardless of the number of harmonics, which can be previously determined by MOS algorithms such as MDL or AIC, that the NMSE and RMSE curves are almost the same. This leads us to say that the number of harmonics of the defects has no influence on the distinction of the healthy signal and the signals of the defects not only but of the defects between them. So even if we don't know le number of harmonics, it stays always possible to detect and separate a healthy and faulty state of the machine and this is great thing in life machine's monitoring.

Conclusions and Perspectives

The goal of this study was to demonstrate the possibility of distinguishing the healthy state signal of an electromechanical induction machine from any other fault state that may occur during its operation. After presenting the approach adopted to achieve this, we managed, using low amplitudes for four (4), to show that this combination could be adopted to monitor these types of machines because, who says monitor, says to be able to detect any change that may occur in it. However, it would be wise to associate it with automatic or intelligent processing algorithms to develop an intelligent identification and classification system. The simple reason is to be able to prevent or anticipate in time any damage by identifying in an automatic way one of these four (4) defects as of their appearance. Thus, in future work, we will attempt to combine this approach with Machine Learning or Deep Learning algorithms to build an intelligent system for the real-time monitoring of these machines. We also intend to apply this approach to a test bench by embedding the developed algorithms on a DSP board to validate the results obtained. The aim is to obtain an accurate, real-time system capable of autonomous monitoring of electromechanical induction machines and, more specifically, wind turbines.

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