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Diagnosis and Prognosis of Faults in Electrical Drive Systems

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By:

Faleh Abdallah

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Abstract

Three-phase induction motors are the mainly used rotating machine in diverse sectors (industries, military, aerospace, aviation, human housing), due to their advantages such as robustness, and lower maintenance costs. However, in different environments of working, these machines expose to various internal stress such as electrical, mechanical, external high temperature, humidity or both. Prognostic and health management plays a crucial role in the safety, reliability and continuity of production of these machines. The research presented in this thesis aims to introduce new data-driven methods for fault diagnostic of three-phase induction motors fed by inverter and prognostic of roller element bearing degradation. These methods are based on analysing the electrical measurement from the sensors to define the health state of the system. Where, a new health indicator propose based on combined temporal features extracted from electrical signals (current and voltage), which use as input to the K-Nearest Neighbour to diagnose and classify different health states of three-phase induction motors including bearing wear and different broken rotor bars. In case of prognostic of remaining useful life of bearing degradation, first of all, a new proposed health monitoring extract from the few first historic vibration signal, that determine the point between the health state and degraded state in order to start the prediction phase. Secondly, after detecting this point, begin the phase of feature extraction and selection of the best monotone features depending on the monotonicity criteria, and reduce the selected features by Principal Component Analysis. Finally, the fused feature is used as input to Support Vector Regression to predict the remaining useful life. Where, the obtained results are attractive compared to the real remaining useful life.

ملخص

تعد المحركات الحثية ثلاثية الطور الآلة الدوارة الأكثر استخداما في قطاعات متنوعة (الصناعات ، والعسكرية ، والفضاء ، والطيران ، و الاستعمال المنزلي) ، نظرًا لمزاياها مثل المتانة ، وانخفاض تكاليف الصيانة. ومع ذلك، في بيئات العمل المختلفة، تتعرض هذه الآلات لمختلف الضغوط الداخلية سواء كانت كهربائية، ميكانيكية ، خارجية مثل ارتفاع درجة الحرارة، والرطوبة أو معا. تلعب الإدارة التنبؤ للصحة دورًا مهمًا في سلامة و موثوقية واستمرارية إنتاج هذه الآلات. يهدف البحث المقدم في هذه الأطروحة إلى إدخال طرق جديدة تعتمد على البيانات لتشخيص الخطأ للمحرك الحثي ثلاثي الطور الذي يتم تغذيته بواسطة العاكس والتنبؤ بالزمن المتبقي للحياة. تعتمد هذه الطرق على تحليل الإشارات الكهربائي من المستشعرات لتحديد الحالة الصحية للنظام. حيث ، تم اقتراح مؤشر صحي جديد يعتمد على دمج الميزات الزمنية المستخرجة من الإشارات الكهربائية (التيار و التوتر) ، والتي تستخدم كمدخل إلى ك أقرب الجار (k-Nearest Neighbor) لتشخيص و تصنيف الحالات الصحية المختلفة للمحرك الحثي ثلاثي الطور، بما في ذلك تآكل المحمل و انكسار قضبان في الجزء الدوار من المحرك. أما بالنسبة لتنبؤ من حالة الصحية لمحمل الدوار، أولاً وقبل كل شيء ، اقترحنا مؤشر مراقبة صحي جديد مستخرج من بعض إشارات الاهتزاز الأولي المقاسة ، والذي يحدد النقطة الخروج من حالة الصحية إلى حالة التآكل في المحمل من أجل بدء التنبؤ. ثانيًا، بعد تحديد هذه النقطة، تبدأ مرحلة استخراج عدد من الميزات من إشارة الاهتزاز في الجزء المتآكل من المحمل واختيار أفضل الميزات وفقًا لمعايير الرتابة، ثم تقليص هاته الميزات المحددة عن طريق تحليل المكون الرئيسي (Principal Component Analysis). أخيرًا، تُستخدم

Abstract

الميزة المدمجة كمدخل ل Support Vector Regression للتنبؤ بالزمن المتبقي للحياة. حيث أن النتائج المتحصل عليها نتيجة جد جذابة مقارنة بعمر الزمن المتبقي الحقيقي للحياة

Résumé

Les moteurs asynchrones triphasés sont les machines tournantes principalement utilisées dans divers secteurs (industries, militaire, aérospatial, aviation, maison humaine), en raison de leurs avantages tels que la robustesse et la réduction des coûts de maintenance. Cependant, dans un environnement de travail, ces machines s'exposent à diverses contraintes internes telles qu'électriques, mécaniques et externes telles que la température élevée et l'humidité. La gestion du pronostic et de la santé joue un rôle crucial dans la sécurité, la fiabilité et la continuité de production de ces machines. La recherche présentée dans cette thèse vise à introduire de nouvelles méthodes basées sur les données pour le diagnostic des défauts du moteur à induction triphasé alimenté par un onduleur et le pronostic un roulement à rouleaux. Ces méthodes reposent sur l'analyse de la mesure électrique des capteurs pour définir l'état de santé du système. Où, un nouvel indicateur de santé proposé basé sur des caractéristiques temporelles combinées extraites de signaux électriques, qui utilisent comme entrée le K-Plus Proche voisin pour classer différents états de santé d'un moteur à induction triphasé comprennent l'usure des roulements et différentes barres de rotor cassées. D'autre part, en cas de pronostique du roulement. Premièrement, une nouvelle proposition de suivi de santé extraite du signal vibratoire, qui détermine le point entre l'état de santé et l'état dégradé afin de lancer la prédiction. Deuxièmement, après avoir détecté ces points, commencez la phase d'extraction des caractéristiques et sélectionnez les meilleures caractéristiques monotones en fonction des critères de monotonie, réduisez les caractéristiques sélectionnées par Analyse en Composante Principale. Finalement, cette caractéristique fusionnée est utilisé comme entrée pour a la Machine à Vecteur de Régression afin de prédire la durée de vie utile restante. Où, les résultats obtenus sont un résultat attractif par rapport à la durée de vie réelle restante.

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Lists of Acronyms and Symbols

List of Acronyms

FDD	Fault Detection And Diagnostic
PHM	Prognostic And Health Management
T-F	Time-Frequency
CBM	Condition-Based Maintenance
CFRF	Characteristic Frequency Related To Fault
MCSA	Motor Current Signal Analysis
FFT	Fast Fourier Transform
STFT	Short Time Fourier Transform
WVD	Wigner-Ville Distribution
CWT	Wavelet Family Include Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
WPT	Wavelet Packet Transform
HHT	Hilbert Huang Transform
EMD	Empirical Mode Decomposition
RUL	Remaining Useful Life
AI	Artificial Intelligence.
TPIM	Three-Phase Induction Motor
CT	Concordia Transform

List of Symbols

β_0	is the maximum magnitude of the magnetic field
f_s	denotes the power frequency
n_s	is the number of turns per second of the rotating field
n_m	is the number of turns per second of the rotor (or output shaft)
s_p	represents the slip
τ	is the temperature coefficient of resistance;
f_{s1}	is the supply frequency
Δt	is temperature variation.

Problematic

Electrical rotating machines have an important role in different human life utilisations. Especially, these machines are used in industrial sectors. Among them, three-phase induction motors are substantial and widely used once compared to other motor types owing to their robustness, low cost, speed control, and easy maintenance [1, 2]. However, there exist some catastrophic events in critical sectors that lead to high maintenance costs and human injuries. These issues require putting these machines under continuous control to give actual information about health states using condition-based maintenance instead of systematic-based maintenance or corrective-based maintenance. Which, it decreases the maintenance cost and the number of undesired situations with the increase in reliability, safety and security [3, 4, and 5].

In this regard, condition-based maintenance (CBM) aims to continuous monitoring of a system. This can give useful information about the health states of the system and provide an alarm in case of detecting an anomaly in this system. And identifying the type of faulty component in the system at an earlier stage, as well as its severity level, can also be given with its remaining useful life. The implementation of this technique in the industrial sector required to pass or use usually three essential stages. Where, the first choose the type of signal analysis that analyse to extract features that provide information about the health status of machines; the signal processing technique can be time-domain analysis, frequency domain analysis or time-frequency analysis; and the last stage is fault detection, diagnostic [1] and/ or in some cases prognostic [6].

The first stage is to define which the proper signal or signals used to analyse the health state of the engine. This stage is discussed and mentioned the advantages and the inconveniences of each used signal analysis second chapter.

The second important stage in CBM of rotating machines is the technique of signal processing applied on a chosen measured signal in the first stage which can be the time domain, frequency domain, and time-frequency (T-F) domain. Where the convenient signal processing technique is extremely important, which depends on several conditions such as the state of the analysed signal that is measured during the steady-state regime, start-up regime, transient regime or mixed steady-state and transient regime. Also, depending on the type of analysed signal, e.g., vibration signal or acoustic signal has non-linear characteristics that require in major cases T-F techniques to analyse them.

In this context, the case of signal analysis measures at steady-state regime, which this case is often considered in the majority of published papers in literature [1-4] for electrical rotating machines analysis. Where the oldest signal processing technique is time-domain analysis, which is based on simple statistical features that are based on the mathematical formula to distinguish different health states of the engine applied directly to the analysed signal. The advantage of the time domain is having less computational burden among three existing types of signal processing techniques, the simplest technique, and proven high efficiency during its application for fault detection and diagnostic approaches without a priori knowledge of the fault in several papers [2, 7, and 8]. In addition to that, it is robust in the case of either load variation or speed [7]. Furthermore, it can apply either to linear or non-linear signals analysed in the steady-state regime as vibration signals [7, 9]. However, when a fault exists in its primary stage in the engine, this technique is considered ineffective or insensitive to detect them, either when a deficiency of a component existed in its deeply distributed stage [10]. Also, the most critical drawback of time-domain methods is an inability to properly diagnose the health states in the latest stages of the bearing degradation process to the failure [10, 11].

Therefore, the transformation of the row analysed signal from its temporal representation into frequency representation open the door to using characteristic frequency related to faulty (CFRF) component of each engine part [12]. Where, the existence of the fault appears directly on the spectral analysis [13] which defines as specific harmonics related to a fault, which has the precise mathematical formula [14, 15] (existing in detail in the next chapters). The famous analysed signal in this area is Motor Current Signal Analysis (MCSA) obtained by means of applying the Fast Fourier Transform (FFT) [14] on the stator current signals. Due to their simplicity of implementation, rapidity and more appropriate for electrical anomalies in electrical rotating machines [14, 16].

MCSA has been used in many works and still. Especially, the case of a three-phase induction motor supplied by the electrical network in stable loading mode and high loading modes [1, 14, 17, 18], where the stator current signal has less noise in its measured signal. That means it is an ineffective technique in contract cases, e.g., unstable loading mode, indirect supply using variable supply frequency in which the signal has a higher level of noise compared to the case of the electrical network signal. Besides that, the major issues related to the FFT technique are frequency resolution and spectral leakage [19, 20]. Moreover, it requires a long duration of the transformed analysed signal to show CFRF in the spectre. However, the long duration of a signal may include both regimes, steady-state and transient regimes in real operation of the engine [19], due to continuous load oscillations or variations; fluctuations in the waveform of the voltage; undesired harmonics that present in the stator current signal due to pollution in the electrical network; variation in speed. Which, under this circumstance, FFT is unsuited for the diagnosis of a fault in electrical rotating machines [21]. For the case of vibration analysis or acoustic analysis, FFT is considered ineffective due to the nature of these two types of analysed signals that have steady-state intervention by some transient regimes. In addition, some noise makes the extraction of frequency features at the early stage of degradation not an easier task via this traditional technique [12, 22, and 23]. Hence, the problem of noise can be eliminated by techniques called Cepstrum or Bispectrum, which belong to the Fourier family [24, 25]. However, these techniques require more time to execute. Where the characteristic frequencies related to faults are obviously visible. Moreover, the traditional FFT and Bispectrum spectre share the same limitation, that they fail to locate or give information about the time occurring of CFRF.

The second case of signal analysis can continue steady state with a high level of background noise as in the case of a frequency converter that is used to feed a three-phase induction motor (speed control); or both regimes, steady-state and transient regimes at the same time. To deal with such a signal analysis, advanced signal processing techniques and time-frequency domain can provide a better solution for fault detection and diagnostic of electrical rotating machines in this case [10, 21, 26, and 27]. Thereby, in the family of advanced signal processing techniques, for instance, the Multiple Signal Classifications (MUSIC) and Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT), noise subspace and signal subspace are two obtained signals after decomposing the analysed signal through these two techniques. That means they are robust against the high level of noise in the signal. Although this advantage, they need more time to process the analysed signal [28]. Moreover, these techniques have several drawbacks since they are difficult to interpret, and it is difficult to extract variations of features in the time domain for non-stationary signals. To overcome this problem of the non-stationary characteristics of the signal, procedures based on T-F representations come to overcome these limitations.

Therefore, the T-F analysis includes Short Time Fourier Transform (STFT), Wigner-Ville distribution (WVD), wavelet family including Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), Wavelet Packet Transform (WPT), etc. and Hilbert Huang Transform (HHT). STFT belong to the family of Fourier transform (FT), but presents information about time and its corresponding frequency component at the same time. Like FFT, STFT also has a limitation in the frequency resolution and fixed window [28-29]. Wigner-Ville distribution (WVD) belongs to Quadratic distributions. WVD does not require the window as in the case of STFT with the purpose to get an accurate localized energy density of T-F analysis. Hence, WVD resolution depends only on the length of the type of signal being analysed [30, 31]. An additional oscillatory will appear in applied WVD for each couple of the signals thanks to embedding noise in the analysed signal (cross-terms), which constitutes the main drawback of this technique [30, 31].

The wavelet transform family has become one of the widely used T-F analysis approaches [27], especially in the analysis field of induction motor fault diagnosis. Therefore, its application on the different analysed signals exhibits some advantages and some inconveniences. The advantage of this technique is the ability to deal with the analysed signal which has the characteristics of either stationary or non-stationary with a non-linear nature such as vibration and acoustic signals [12]. Although great and reliable results could be obtained about the health condition of electrical rotating machines in applied different techniques belong to this family. It has some drawbacks related essentially to the no-existed rule in choosing and selecting the convenient mother wavelet among different existing ones, and the determination of the exact value of scale [27, 32, and 33] for diagnosing various faults in different operation conditions. Furthermore, the computational complexity needs a large memory in a computer that requires more time for processing the analysed signal which seems unsuitable for processing a large analysed signal [12, 15] compared with frequency and temporal features techniques. The relation between window length and frequency resolution is opposite, which means that the resolution cannot be enhanced at the same time in both dimensions. Furthermore, it has some inherent deficiencies such as a distortion of border and leakage in energy which generate many small unwanted peaks across all frequency/ scales that make the obtained results confused and not easy to interpret in the case of the low-maintenance skilled engineering [12, 15, 30].

However, there are disadvantages in applying the wavelet family that can be overcome by dividing the analysed signal into mono-component signals. Which, each mono-component signal has its own fundamental frequency, which is done by applying empirical mode decomposition (EMD) on the signal. Then, T-F features can be extracted from the application of HHT on one selected mono-component signal that carries the characteristic related to the faulty component. Hence, this technique is a more appropriate technique with non-linear analysed signals (stationary and non-stationary signals) [10, 27]. And it can present effective satisfactory results for FDD. Nerveless, it is not recommended in their application to analyse a large signal [34] that also requires more time to process the analysed signal than time taking in using a technique based on the family of wavelet transform. The obvious distortion in the boundary and the mixed mode during the application of this technique (intrinsic mode function) has an effect on the exactness and result of the decomposition. Furthermore, this technology has powerful intrinsic adaptability, and hence, it is not possible to extract the mono-component signal within the limits of a previously specific frequency range [34].

In this thesis, we treat two essential phases in condition-based monitoring, which are based on a data-driven approach and machine learning algorithms using temporal features. The first phase includes a proposed methodology for fault detection and diagnostic (FDD) of a three-phase induction motor that has the following advantages:

1- Fault detection and diagnostics of electrical machines by non-intrusive monitoring technique.

2- Detection and isolation of both electrical and mechanical faults by using electrical signals.

3- High accuracy of pattern recognition by time-domain features extraction and machine learning.

4- High separability of system health states by the construction of new health indicator.

In the second phase, we were doing a primary work or brief introduction concerning a prognostic of the critical component called the rolling bearing element in a three-phase induction motor. Where it includes a prediction of the remaining useful life (RUL) of two bearings under the same working conditions of speed and load that also used a data-driven method based on temporal features and machine learning called support vector regression to predict the RUL of bearings after degradation occurs in this component.

Thesis organisation

The rest of this thesis organised as follow:

The first chapter includes general information related to the context of maintenance. Particularly, the maintenance strategy is called the condition-based method. Which, we give some definitions related to the Terminology dedicated to the diagnostic and prognostic that is widely used in literature; different maintenance strategies; a description of the three-phase induction motor, their faults and essential methods used to detect and diagnose this motor; and finally some information related to the prognosis of the rolling element bearing.

In the second chapter, we present an overview of fault detection and diagnostic of electrical relating machines based on the data-driven method, and also prognostic techniques based on the data-driven method or fusion method between the data-driven method and model-based method.

In the third chapter, we present our proposed fault detection and diagnostic method using combined temporal features and machine learning algorithms.

In the fourth chapter, we present our proposed prognostic method to predict the remaining useful life of bearing degradation.

In the last, we present general conclusions and future works about fault detection, diagnosis and prognostic.

Scientific Contributions

- International Publication

- F. Abdallah and M. Ammar, « Data-Driven Diagnostics Based on Non-invasive Monitoring Using Electrical Signals: Application to

Rotating Machines », *Iran. J. Sci. Technol. - Trans. Electr. Eng.*, vol. 0123456789, 2022. https://doi.org/10.1007/s40998-022-00562-w.

- F. Abdallah, M. Ammar, M. Noussaiba and S. Youcef, "Remaining useful life of bearings based on temporal features and support vector regression," 2022 19th International Multi-Conference on Systems, Signals & Devices (SSD), Sétif, Algeria, 2022, pp. 68-73, doi: 10.1109/SSD54932.2022.9955707.
- N. Mennai, Y. Soufi, A. Medoued and A. Faleh, "Grid Synchronization Techniques Analysis of DG Systems Under Grid Fault Conditions," *2022 19th International Multi-Conference on Systems, Signals & Devices (SSD)*, Sétif, Algeria, 2022, pp. 917-922, doi: 10.1109/SSD54932.2022.9955866.

- International Communications

- A. Faleh, A. Medoued, K.E. Hemsas and S. Bouaziz**,** “Energy production and harmonic compensation using photovoltaic generator” in Third International Conference on Technological Advances in Electrical Engineering ICTAEE18, December 10-11,2018, Skikda, Algeria.
- A. Faleh, and A. Medoued, “Fault detection and diagnosis of induction motor using support vector machine classifier”, First International Conference on Sustainable, Renewable Energy Systems and Applications (ICSRESA 2019), Tebessa, December 04-05,2019,Algeria.

Reference of Problematic

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Chapitre 01

General Information Related to the Maintenance Field

1.1. Introduction

Continuity of production, security, safety of operators, and machines in industrial sectors are essentials to get the best products with fewer unacceptable accidents and high economical revenue. In this regard, different maintenance strategies consider as one of the keys that can be set to give such properties in industries sectors.

At the beginning of this chapter; we provide some useful definitions related to maintenance that can help the reader to understand different terminologies related to maintenance with a description of different maintenance strategies that could be employed in industrial sectors. In the middle of this chapter, we will discuss the condition-based maintenance (CBM) strategy that is the topic of our research in this thesis, which include the detection and diagnostic of different anomalies in a three-phase induction motor using continuous monitoring. This motor is considered the principal component used in most industrial sectors. In this context; we include a brief description of this motor, different faults that can occur in it and fault generator, as well as the principal monitoring approach that existed in the literature used to monitor it health states. Also in this thesis, we describe principal methods that can be used in the prognostic area that help engineering to predict the remaining useful life (RUL) of a critical component such as bearing, this component has the high possibility of failure that can occur in this motor and other electrical motors.

1.2. Terminology dedicated to diagnosis and prognostic

It is important thing to define some essential words belong to maintenance terminology. Noted that, some definition are taken from book, thesis or research papers, which these definitions are useful for the reader or beginner researchers in this area of research for well understand the next subtitle of chapter and the whole thesis.

Tableau 1-1 Terminology dedicated to diagnosis and prognostic

Terminology	Definitions
Maintenance	Ensemble of activities intended to maintain or restore an asset in a specified state to perform a required function, or to ensure a specific service [1].
Health state	On say a system, is in a normal operating state, when the variables characterizing it (input variables, output variable, etc.), remain in the proximity of their nominal values. And the faulty

	system in the opposite case [1].
Fault (Defect)	A fault is any difference between the characteristic observed on the device and the theoretical characteristic. This difference is ideally zero in the absence of default [1].
Deficiency	A deficiency is the alteration or cessation of the altitude of an assembly to perform its required function (s) with the performance defined in the technical specifications. A deficiency is a malfunction of the system, then the process exhibits unacceptable performance from a performance point of view. It is clear that a deficiency implies the appearance of a defect since there is a difference between the measured and theoretical characteristic. On the other hand, a fault does not necessarily imply a deficiency since the device may very well continue to perform its main function [1].
Failure	Failure is the inability of a device to perform a required function. A failure always results from a deficiency and therefore from a fault. Fault→ deficiency (system under degradation) → failure [1].
Symptom	Change in an observable amount from normal behaviour [2].
Fault detection	The detection of a fault consists in deciding whether or not the system is in normal operating state [2].
Disturbance	Uncontrolled input signal whose presence is undesirable but considered normal [2].
Followed	Function permanently maintaining a history of the treatments carried out by the control / supervision system and a trace of the events that the system perceives [2].
Localization of faults	Determination of the type, location and date of a fault detected. It consists of tracing a set of symptoms to a set of faulty components [2].
Identification of faults	Determination of the size and temporal behaviour of a fault. It is a function that tracks the location [2].
Diagnostic	Determination of the type, size, location and time of occurrence of a fault. It is a function that tracks detection and includes location and identification functions [2].
Monitoring	A set of functions that run in real time with the aim of reconstructing the actual state of the process within the models used by the process control system. It consists of the recording of information as well as the recognition and indication of abnormal behaviour [2].
Supervision	Represents monitoring a physical system and making appropriate

	decisions to maintain its operation in the face of failures [2].
Features	Also called characteristics and signatures used to decide the health state of the system[3]
Prognosis	Prognosis in engineering systems is usually expressed with the estimation of the mean time to failure (MTTF), or the remaining useful life (RUL) [4].
Condition Based Maintenance (CBM)	The CBM is based on the exploitation of the data provided by the monitoring system which continuously tracks the health state of the system. The data gathered are processed and transformed to relevant knowledge in order to estimate the current state of the system and to predict its future one, and thus helping the maintainers to take adequate decisions at appropriate time [5].
Failure Prognostic	Failure prognostic corresponds to the "estimation of the time to failure and the risk for one or more existing and future failure modes"[5]
Remaining useful life (RUL)	Remaining useful life (RUL), which is known as prognostic distance or lead time in other applications, is an important metric for prognostics. Its definition can be described as the length between the current inspection time and the end of the plants allowed useful life [6].
Decision	This last step brings together all the actions necessary for operational safety. This is in fact the decision-making stage to apply the most appropriate actions to meet the requirements [7].

1.3. General information of Maintenance policies in industrial sectors

Figure 1-1 illustrates the diagram of two strategies of maintenance [8]. Generally, this diagram resumes the applied maintenance policies in the industrial sector to assure the proper functioning of different types of equipment in the company. In this context, to choose the convenient maintenance method, it is therefore necessary to be informed by the objectives of the management company, and the maintenance policy departments. But, it is necessary to know the operation and the characteristics of the equipment, the behaviour of the equipment in the operation, the conditions of application of each method, maintenance costs and production loss costs.

There are two main families of maintenance that can be identified in Figure 1-1: corrective maintenance and preventive maintenance.

1.3.1. Corrective maintenance

The purpose of corrective maintenance is to restore the equipment to the necessary lost qualities so that it is able to perform its functions again. It is generally adopted for equipment for which:

- The consequences of the failure are not critical,
- The repair is easy and does not require a lot of time,
- The investment costs are low.

Two forms of corrective maintenance can be distinguished such as curative maintenance and palliative maintenance [8].

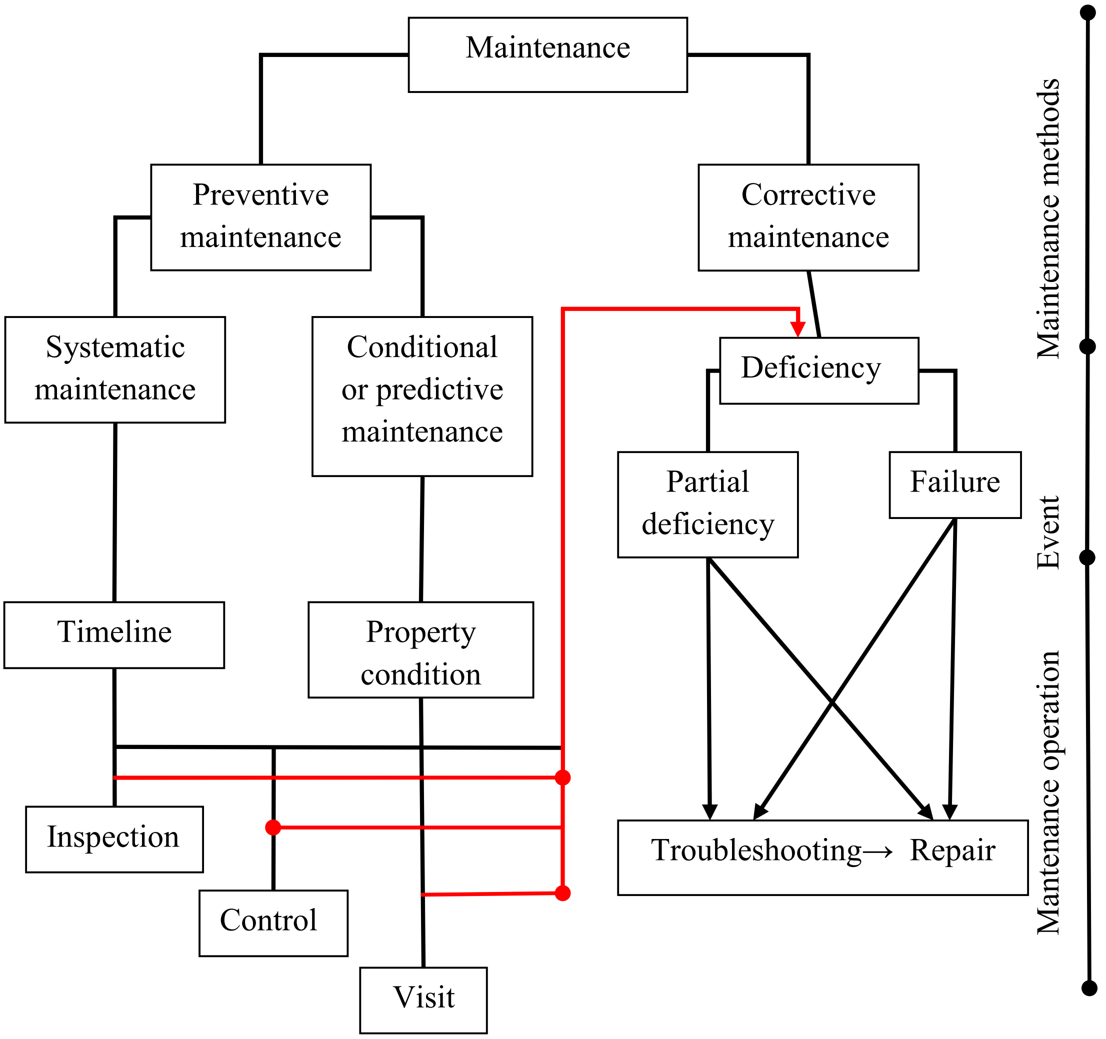

Figure 1-1Diagram of different methods of maintenance [8]

1.3.2. Curative maintenance

This type of maintenance allows the system to be permanently restored after the occurrence of a failure. It therefore causes unavailability of the system.

1.3.3. Palliative maintenance

Palliative maintenance is temporary maintenance, or in other term provisional [8].

1.3.4. Preventive Maintenance

Maintenance conducted at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or degradation of the system functioning [1, 8]. There are three specific forms of preventive maintenance: systematic preventive maintenance, conditional preventive maintenance and predictive preventive maintenance.

1.3.4.1. Systematic Preventive Maintenance:

Preventive maintenance carried out at pre-established time intervals or according to a defined number of units of use but without prior checking of the system condition. It uses, as an indicator, information from the operational context (usage time or the number of cycles) generally provided by usage management processes [1, 8]. During these interventions, the elements are replaced even if they are not deficiency [1].

1.3.4.2. Conditional preventive maintenance

In this case, maintenance activities are triggered based on information reflecting the state of degradation of the considered equipment. In the second case, the elements are replaced only if it is necessary [1].

It is subject to a predetermined type of event (diagnostic result, sensor data, wears measurement, etc.) that reveals the operating state of the system. This strategy is therefore based on the degradation of the equipment and not on its failure. It enables the maintenance operation to be triggered when a threshold (which represents the maximum tolerable degradation level) is crossed by an indicator [8].

1.3.4.3. Predictive preventive maintenance

Conditional maintenance carried out by following the extrapolated forecasts of the analysis and evaluation of significant parameters of the degradation of the property by considering all the influential parameters from future operational and environmental contexts as well as future maintenance actions [8].

This form of maintenance helps reduce the number of unplanned shutdown, and therefore system downtime. It allows maintenance operations to be planned in such a way as to use the equipment to the maximum of its possibilities. By monitoring equipment, it is possible to correct operating errors or anomalies that can lead to more serious failures later and improve safety by avoiding critical accidents. On the other hand, this form of maintenance requires the implementation of monitoring and measurement techniques which can be very expensive.

In this thesis, we interested by two last types, condition based maintenance and Predictive preventive maintenance. Therefore, from this two maintenance types we can define new term widely used in last decade by prognostic and health management [9 and 10].

1.4. Prognosis and health management (PHM)

Depending to references [9 and 10], the cycle of PHM illustrated in Figure 1-2 composed mainly by seven bloc to maintain the system safety and can done the timely proper action(s) before the system shutdown , named, data acquisition system, data processing (manipulation) condition assessment (health assessment), diagnostic, prognostics, decision support and finally, human machine interface (user interface).

- First bloc includes data acquisition, which it is ensemble information (digital data) measured through Sensors.
- Second bloc includes signal processing technique. In which, this bloc receives data from sensors or transducers or other signal processors and performs signal transformations and feature or descriptor extractions.
- Third bloc includes condition assessment (monitoring) that continuously compares the online data with certain expected or known values; it must also be able to generate alerts based on pre-set thresholds.
- Fourth bloc includes Diagnostic method, that determines whether the state of the monitored system, subsystem or component is degraded or not and suggests probable failures.
- Fifth bloc includes Prognosis method that can easily predict the future state of the monitored system, subsystem or component. The bloc builds on data from previous modules.
- Sixth bloc includes decision step. Its main function is to recommend maintenance actions or other alternatives to continue to operate the system until the accomplishment of its mission.
- Sixth bloc includes user interface. This bloc receives information from all previous modules. It can be built in the form of a Human Machine Interface HMI.

PHM aims to extend the life cycle of an engineering asset (machine) and its exploitation, while reducing maintenance costs, and system shutdown [9].

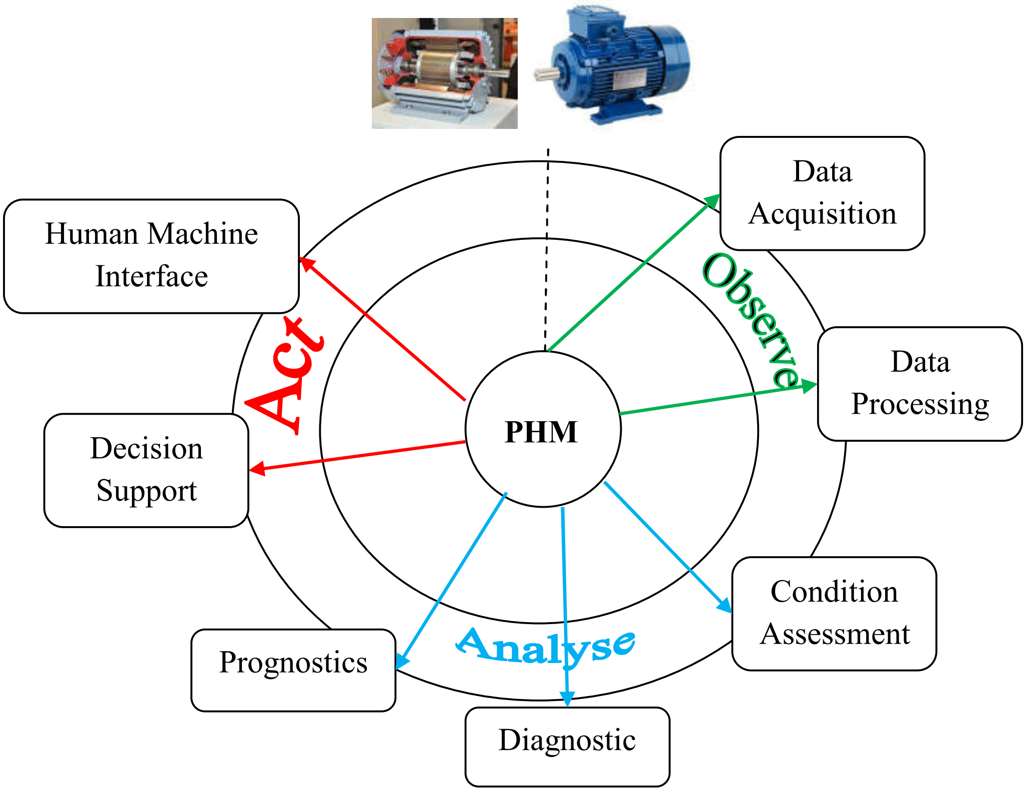

Figure 1-2Cycle of prognostic and health management

1.5. Induction motor and general information related to its conditional maintenance in industrial sectors

1.5.1. Induction motor description

The induction motor (IM), also called asynchronous motor, is an electrical rotating machine fed by mean of alternatives system of voltage and current signals using direct supply, such as electrical network, or indirect supply by converter (inverter). Firstly, Michael Faraday (1791-1867) in 1831, was discovered the induction phenomena. And then, Nikola Tesla in 1888 used this principle of induction (1856-1943) to realize and deposit the first patent on the induction machine, which it conceived in Strasbourg (France). Since that time, many improvements have been made to achieve the induction machine as we know today [11]. As reported in [12] that equal to 87% and 96.2% are the shipment percentages of three-phase induction motors and AC motors in Europe. Which make this machine is a particular motor used in industry, and for all kinds of systems or applications such as trains, lifting systems (elevators and cranes), ventilations, winding / unwinding systems, production chain drives, milling machines, robotics, and many other areas.

This machine is made up of several components that illustrated in Figure 1-3. It seems more appropriate to first define its main components. The induction motor is made up of: two electrical parts that are extremely important to its operation, such as the stator is the fixed part in this machine, and the rotor is the rotating part. And bearings are also very important mechanical parts in this machine and other kind of electrical rotating machines, which they used as medium between rotor and stator to assure the rotation of the rotor in the stator without friction between them.

1.5.1.1. stator

The stator of IM as shown in Figure 1-4, also called the inductor, is generally made up of three phases, in which each phase composed by windings. These phases are supplied by a system of three-phase voltage of frequency f_s.

1.5.1.2. Rotor

The rotor, also called the armature, can appear in two different ways. Indeed, there are squirrel cage rotors as shown in Figure 1-5 and wound rotors.

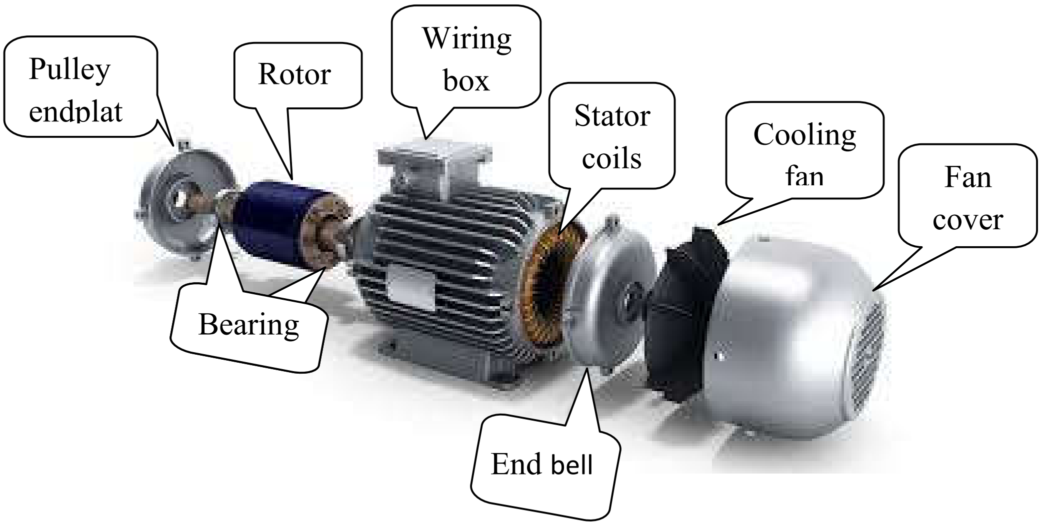

Figure 1-3 Composition and names of the different elements of the induction machine

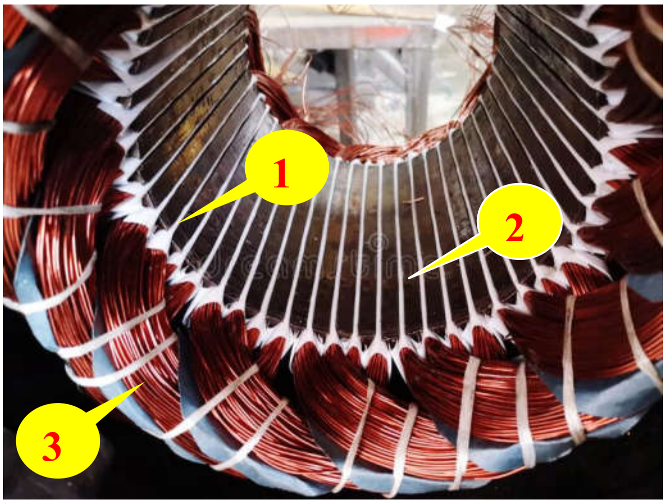

Figure 1-4 Stator construction of induction motor with, 1 slot, 2 magnetic circuit, and 3 end winding

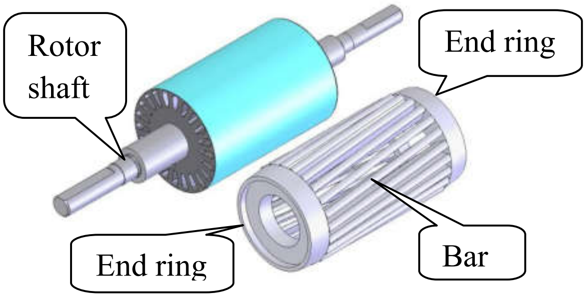

Figure 1-5 Squirrel cage rotor

Induction motors with squirrel cage rotors are the most commonly used in the industry. These consist of a cylindrical stack of ferromagnetic sheets notched with notches; these notches are used to inject the conductive materials (aluminium alloy) in them, in order to produce the rotor bars that are similar to the notch conductors in the stator. The extremities of these bars are related with two rings that are similar to the heads of winding in stator. The bars and the rings are thus connected to each other and constitute a closed circuit or a short circuit. In the case of high power motors, the bars are welded or brazed to the rings and are not injected, but placed. There are several construction kinds of squirrel cage rotor, such as double squirrel cages, double notches and deep notches.

As for the wound rotor also called the slip ring-rotor motor. It has a similar winding that the stator has. Indeed, it has coils connected to rings. An electrical connection was then possible with the rotor in order to allow a rotor starting, and make a possibility to control the speed of the motor. The rotor was short-circuited after start-up. However, the squirrel cage motors are much simpler to construct than the wound rotor motors, and therefore are lower in cost. Moreover, it has greater robustness. It constitutes the largest part of the induction motor in different services of life [12]. Furthermore, with the development of power electronics, the wound rotor motors are no longer used today [11].

1.5.1.3. Mechanical organs

In addition to these electrical parts, also this motor has mechanical parts such as the essential ones are the drive shaft and Bearings. In Which, the drive shaft is a transmission member that comprises a central portion, which it serves as a support for the rotor body and a shaft tip on which is fixed a half coupling. On the other hand, it is supported by one or more bearings. These bearings are placed on both ends of the rotor shaft which define its axis of rotation relative to the stator and provide free rotation. Other auxiliary organs that assure the protection of different induction motor elements against the exteriors constraints (environment) as the carcass that serves as a support and plays the role of envelope, Fan in order to evacuate the heat of the machine during the induction motor operation. The fan attached to the machine shaft rotates without any exterior powered.

1.5.2. Induction motor principle operation

As mentioned earlier, the induction machine consists mainly of electrical component, stator and rotor. These elements are constructed using special materials, and in such a way, that the induction motor can perform in the best possible manner. The stator, is a fixed part of the machine, is made up of 3P (where, P designates the number of pairs of poles) windings powered by an alternative system of three-phase voltage and current signals of frequency f_s. Which, it powered either by electrical network or converter.

The currents traverse through the stator coils creates a rotating magnetic field $\vec{\beta}$ in the air gap such that:

$$\vec{\beta} = \beta_0 \cos(2\pi f_s t) \quad (1.1)$$

Where, β_0 is the maximum magnitude of the magnetic field and f_s denotes the power frequency of the induction motor, and t represents the temporal function of the oscillation.

This rotating field has a so-called synchronous rotation speed equal to:

$$n_s = \frac{f_s}{p} [tr/s] \quad (1.2)$$

Where, n_s is the number of turns per second of the rotating field.

The magnetic field created by the stator revolves around the rotor (at a standstill during start-up) in order to create induced currents through its flow in the bars of the rotor. According to Lenz's Law, induced currents oppose the cause that gave rise to them by their effects. The circulation of currents in the rotor cage is possible, because the circuit is closed, and therefore, the forces of Laplace are resulted. This force is different at every point of the cage. This phenomenon makes it possible to create a torque and start the induction motor [11].

Fortunately, the mechanical rotational speed of the rotor never overtakes the synchronous speed of the rotating field. Thus, there remains a difference in force, and therefore in torque thanks to the condition:

$$n_s > n_m \quad (1.3)$$

Where, n_s is the number of revolutions per second of the rotating field, and n_m is the number of turns per second of the rotor (or output shaft).

This speed difference defines what we call the slip given by the equation:

$$s_p = \frac{n_s - n_m}{n_s} = \frac{\Omega_s - \Omega_m}{\Omega_s} \quad (1.4)$$

Where, s_p represents the slip ratio of the IM.

1.5.3. Brief presentation of anomalies, their generators and their observable effect during induction motor operation

1.5.3.1. Fault generators in induction motor

Although the great advantages that have this type of motors compared to synchronous motors and direct current motors. Naturally, they become aging during its operational life with less efficiency, due to degrade their different parts such as, electrical, mechanical or even magnetic component. Which, we can considered this case as low degraded motors during time. On the other hand, there are several fault generators that accelerate the degradation of the machine, among them [12]:

- Fault generators (fault initiators): motor overheating, electrical fault (short circuit), power supply overvoltage, electrical insulation problem, wear of mechanical elements (ball bearings), etc.
- Fault amplifiers as frequent overload, mechanical vibrations, humid environment, permanent heating, poor lubrication, etc.
- Manufacturing defects and human errors: manufacturing defects, defective components, inadequate implementation, and unsuitable protections, improper sizing of the machine, etc.

1.5.3.2. Description of principal induction motor faults

Therefore, According to the study carried out by EPRI (Electric Power Research Institute) published in 1986 [13] and by IEEE (Institute of Electrical and Electronics Engineers) published in 1985 [14, 15, 16], induction motor faults are mainly connected to two parts such as, electrical part is stator, and the mechanical part is bearing as illustrated in Figure 1-6 that shows the distributions of motor anomalies from these studies, and in Table 1-2 that describes the conditions under which these two studies were performed.

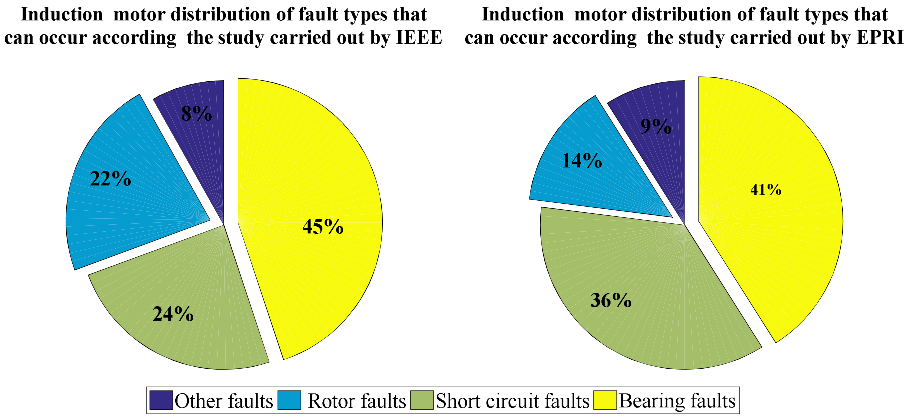

Figure 1-6 Distribution (in percentage) of induction motor faults according to studies carried out by EPRI [13] and IEEE [14-16]

Tableau 1-2 Data summary of which made it possible to determine the induction motor faults distribution [13-16]

Settings	IEEE	EPRI
Number of companies	33	46
Number of installations	75	132
Number of Engines	1141	4797
Number of faults	360	872

In resume, the principal faults related to different induction motor parts are as follow:

a. Faults related to rotor

The fault related to the rotor can be single or mixed faults as, broken rotor bars as illustrate in Figure 1-7.a which present a cumulative phenomena of crack develop from one to another that include the rotor magnetic circuit during induction motor operation that increase rapidly with the increase of number of broken bars until motor can't start [12], broken ring as show in Figure 1-7.b, broken rotor bars and ring commonly appears in larger motors that have more numbers of bars than smaller or medium motors [18]. Beside broken rotor bars and rings; Static and dynamic eccentricities also can appear as a fault that subjected by a rotor decentre in the stator (offset between the rotation centre of the shaft and the centre of the rotor). Usually, it caused by improper assemblage or installation of the motor, fault in bearings, charge fault, etc [12, 17], see Figure1-7.c and d.

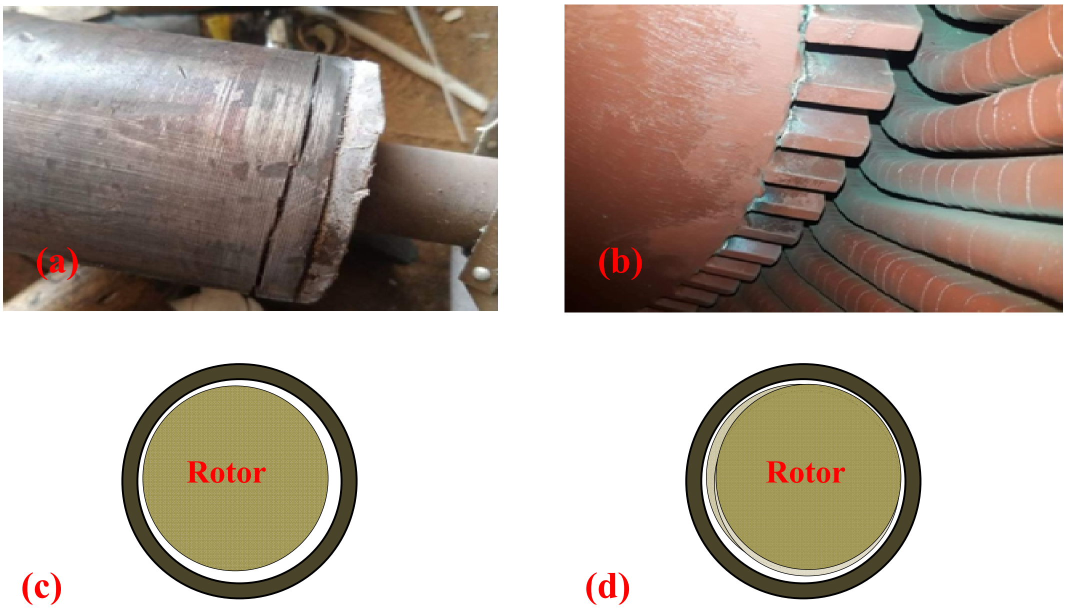

Figure 1-7 Fault related to rotor faults such as: (a) Broken a portion of ring, (b) Broken rotor bars, Schematic modelling of Static (c) and Dynamic (d) eccentricities

b. *The faults related to the stator*

The fault related to the stator can be single (or mixed) as: insulation fault, short circuit between turns, short circuit between phases, phase / frame short circuit, power supply imbalance, magnetic circuit fault. In general, the principal generators of stator faults or failures due to contaminants, vibration, abrasion, natural aging of insulation, voltage surge, blown fuse, a broken power line, bad connections, overload, locked rotor, an open contactor, etc. In this context, Figure 8 Shown some fault related to stator fault.

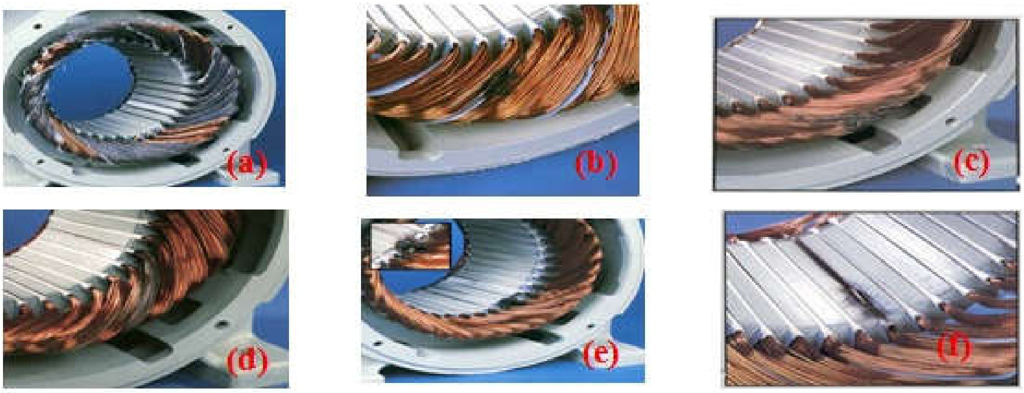

Figure 1-8 Fault related to stator such as: (a) Short-circuit in single-phased, (b) Short circuit phase-to-phase, (c) Short circuit turn-to-turn, (d) Short circuit in the coil, (e) Coil grounded at edge of slot, (f) Coil grounded in the slot [19]

c. *The fault related to bearing*

Generally, the major induction motor fault is related to bearing component, that can be single or multiple faults [20, 21, 22]; single fault is a localized fault or defect in one part of different bearing parts such as inner race bearing fault, outer race bearing fault, ball bearing fault, cage fault (See Figure 1-9 [23]). It consider as earlier sign of fault that develop into failure or Multiple fault (distributed fault), that affect the whole of bearing parts. This type of defect can be a failure in many cases, essentially caused by many generators that include contamination, misalignment, corrosion, improper lubrication and installation, undesired electrical, mechanical and environmental constraints, overloading [21-25]. Also, unbalance supply voltage condition or mode bearing current induced by inverter can damage the bearing component [21, 26].

Figure 1-9 Artificial fault related to bearing as: Inner race, Outer race, Ball, and Cage faults [23]

1.5.3.3. Observable effect of induction motor faults in different measurable signals

The observable effect or sign of induction motor faults used from the maintenance engineering through different measurable signals for all type of fault are observable on level of vibration signal that is a best analysing signal of mechanical faults which increase when the fault occurs, and current signal that is a best analysing signal of electrical faults [27]; most faults have an observable increase of temperature level up to normal working state [28 and 29]. Some electrical fault related to stator by analyse the voltage signals [12]. Certain faults can be detected by the change in sound (Acoustic emission) [30, 31], Electromagnetic torque (broken rotor bars) [32], torque (Eccentricity) [32], instantaneous power (misalignment faults) [33], and leakage current signal.

The operation under faults generates at least one of the following symptoms [34]:

- Unbalanced air-gap voltages and line currents;
- Increased torque pulsations;
- Decreased average torque;
- Increase in losses and decrease in efficiency;
- Excessive heating;
- Appearance of vibrations;

On general, there are sensible devices usually installed with electrical machines to protect them or protect the electrical installation and humans from catastrophic events as two types of faults related to stator, such as short circuit between phases and phase / frame short circuit through fuses, thermal relay and motor circuit breakers. These devices are effectives in protection but not to detect and identify the fault type as earliest initialization of the fault. however, the induction motor can work even with some faults, for instance with fewer numbers of turn to turn short circuit, that actually degrade the performance of induction motors by up the vibration level of the motor which lead to accelerate the bearing degradation. Also, this fault can be develop into short circuit of the whole windings, and therefore shutdown of the production system, which include in some cases a huge economic losses of the corresponding manufacturing. However, there are a group of methods used to detect and diagnose the occurrence of deferent faults as present in the next subtitle.

1.6. Principal monitoring approaches of induction motor in literature

In this phase, on resume the discussion on model-based and data-driven methods, that actually two out performing families in literatures for fault detection and diagnostic. Hence, there exists another named model knowledge based method which need a huge data that include the historical failure of induction motor in order to build such fault detection and diagnostic method that related to this family. For that reason on speak shortly only on two first methods such as model based and data driven methods.

1.6.1. Model-based method

This type of method is also known as a mathematical model [34-35] or an internal method, which relies mainly on prior knowledge of the monitoring system, which means knowledge about the various parameters that characterize this system in a state of health (in our case study, the system is an induction motor). Where, the physical phenomena that characterize their different parameters of the system during its health operation are described by mathematical model [34-36]. And then, the obtained model is compared continuously with the measured or calculated parameters during the operating life of a system. This includes the detection of the residual value between the evolution of the parameters measured or calculated in the event of faults with the initial parameters that characterize the system in health condition, as present in Figure 1-10, with the zero value or close to zero (close to zero is the value of internal perturbations or extern ones) mean healthy condition and otherwise is a defective system [34-37].

To build such model in case of induction motor, it should be passing through simplifying assumptions as [1, 35, and 11], we named some of them:

- Iron losses are neglected;

- The saturation of the magnetic circuit is neglected;

- The end effect of the coil heads is neglected;

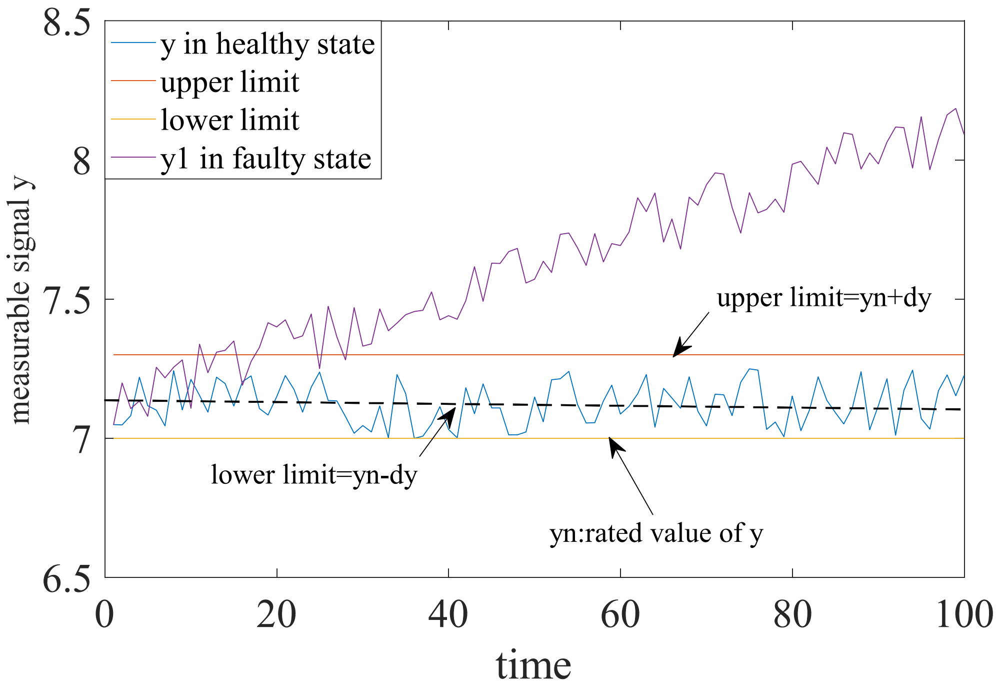

Figure 1-10 How to detect a fault in model based used the residual value

- The stator is considered to be smooth and the air gap constant (the effect of the notches is neglected);

- Harmonics of any origin, other than temporal, are neglected;

After that, the researchers in this model keep track of the parameter variations, for instance la value of stator resistance and stator inductance for stator faults and rotor resistance for rotor faults. However, the main disadvantages of this model that don't have the exact description of the system due to its dependence on simplifying assumptions that neglected several intern phenomena of the motor. Moreover, incapability of such model to follow anomalies of complex or non-linear components [36, 38], take in this case the mechanical fault as bearing fault that considers as the major contribution of failure in induction motor. Furthermore the resistance value change either in health state of induction motor with the change of its temperatures [12] by the following equation:

$$Rs = \mathrm{Rs}_0(1 + \tau.\Delta\mathrm{t}), \tag{1.5}$$

Where, Rs_0: the value of R at t_0=25°c;τ temperature coefficient of resistance; Δt temperature variation.

For these mentioned problems, datat-driven method are more attractive monitoring method, that can overcome such limitations.

1.6.2. Data-driven method

It would be interesting to give more information concerning the second method than the family of the model-based, that does not require any mathematecal model or simplifying assumptions, that is to say, without a priori knowledge of the process. therefore, we introduce the second family of monitoring methods. Which, it used in our contribution of this thesis, namely data-driven methods also know by external methods due to the main advantage, that depends only on the the direct monitoring (practical analysis) of observable quantities of the system that can be measured through different installed sensors such as current, vibration, voltages, flux, temprature, sound [36, 39, 40].

These methods the so-called «without model» are based on the analysis of acquisition signals and proposed algorithms. They have the advantage of the independence of the analysis from the internal fluctuations of the system. On the other hand, the information contained in the signals, not being filtered by the modelling, it remains intact [12]. This method is based generally on three essential steps as illustrate in Figure1-11 such as [8]:

- Data acquisition of the measured signal types (one or more that one signal);
- Signal processing technique of the monitoring signal, usually include features extraction, features selection and features reduction;
- Fault detection, fault diagnosis and classification;

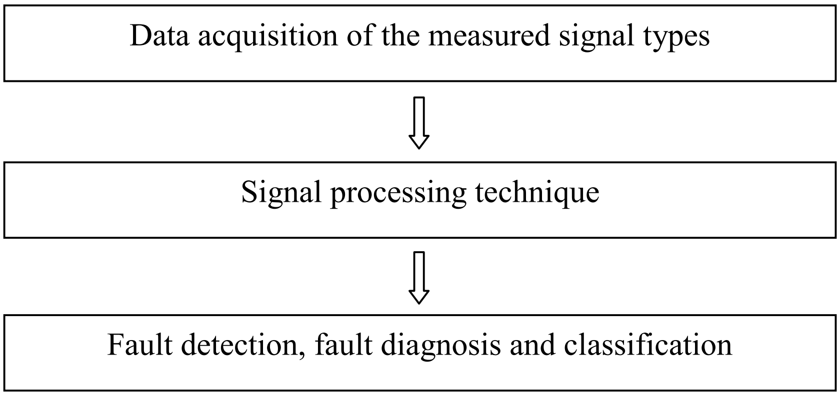

Figure 1-11 Principal steps usually used in data-driven method

In this method, we interested only on the description of different signal processing techniques and various features usually used in literature as indicator to define the health states of induction motor with some practical example to well understand. The main advantages and disadvantages of each measured signal type and signal processing techniques, will be introduced and well described in the next chapter, and mentioned some resumes of interesting works in our views of point of Fault detection, fault diagnosis and classification in the literature.

There are three main categories of signal processing techniques to analyse the acquisition signal, named:

1.6.2.1. Time domain analysis

Time domain analysis based on the idea of direct used of the waveform of the measured signals through an ensemble of extracted features to detect different induction motor states, which based en statistical features [39, 40] such as mean, root mean squire, variance, etc. each of them have its own precise mathematical equation as shown in Table 1-3 (see the equation from (6) to (21)). These features have different importance which some of them are sensible to detect precise fault and other to multiple faults. The physical meaning of some of them are [41]:

- Maximum refers to the biggest value of sample in all measured signal samples. Also called first moment;
- Median is the estimation of the centre of all samples by finding or calculating its median value;
- Minimum refers to the smallest value of sample in all measured signal samples;
- Mean is the average value of all samples in the measured signal;
- Variance is the squared difference between each sample of measured signal and the mean value of all the signal values;
- Standard deviation is the calculation of the power content or effective energy of a measured signal (the root value of the variance);

- RMS calculates the root mean square value of all samples in the measured signal.;
- Kurtosis is the measure of how steep the data distribution is about its mean value. Also called Forth moment;
- Skewnes is the measure of the asymmetry of the samples of all measured signal
  around its mean value. Also called third moment;
- Range (peak-to peak) refers to the difference between the maximum value of samples and their minimum value;

Tableau 1-3 List of some statistical features usually used in literature

Features	Equations	
Maximum	$S_1 = \mathbf{max}\{x(t)\}$	(1.6)
Medium	$S_2 = \mathbf{medium}\{x(t)\}$	(1.7)
Minimum	$S_3 = \mathbf{min}\,\{x(t)\}$	(1.8)
Mean absolute	$S_4 = \frac{1}{T}\sum_{t=1}^{T}\lvert x(t)\rvert$	(1.9)
Mean	$S_5 = \frac{1}{T}\sum_{t=1}^{T} x(t)$	(1.10)
Variance	$S_6 = \frac{1}{T-1}\sum_{t=1}^{T}\lvert x(t) - S_5\rvert^2$	(1.11)
Standard Deviation	$S_7 = \sqrt{S_6}$	(1.12)
RMS	$S_8 = \sqrt{\frac{1}{T}\sum_{t=1}^{T} x(t)^2}$	(1.13)
Peak-to peak	$S_9 = S_1 - S_3$	(1.14)
Square Mean Root	$S_{10} = \left[\frac{1}{T}\sum_{t=1}^{T}\sqrt{\lvert x(t)\rvert}\right]^2$	(1.15)
Kurtosis	$S_{11} = \frac{\sum_{t=1}^{T}\lvert x(t)-S_5\rvert^2}{T({S_7}^4)}$	(1.16)
Skewness	$S_{12} = \frac{1}{T{S_6}^3}\sum_{t=1}^{T}[x(t) - S_5]^3$	(1.17)
Average power	$S_{13} = \frac{1}{T}\sum_{t=1}^{T} x(t)^2$	(1.18)
Energy	$S_{14} = \sum_{t=1}^{T} x(t)^2$	(1.19)
Entropy	$S_{15} = -\sum_{t=1}^{T} E_p \ln E_p$	(1.20)
Energy Probability	$E_p = \frac{\lvert x(t)\rvert^2}{S_{14}}$	(1.21)

Note that: *T* is the total number of samples in the measured signal.

- Sum is the entirety of ensemble samples in the measured signal;

Also, there are further statistical features illustrated in Table 1-4, which are actually a combination of some statistical features illustrated above in Table 1-3.

The detection of different induction motor fault used statistical feature, essentially based on using pattern recognition technique. For instance, the Figure 1-12 illustrate two state of induction motor feed by electrical network in no-load level, the blue point is healthy motor state and red point for broken one rotor bar.

1.6.2.1. Frequency domain analysis

The time-domain curve shows or illustrates how an electrical current signal, for instance, changes over time. Whereas; the frequency domain project the measured signal from own temporal representation into its corresponding spectral frequencies. Moreover, the information of the phase shift that characterises the current signal can also include in its frequency-domain representation which over the possibility to return in time representation again after done a transformation. In this context; Fourier transform [17] is the famous transformation in this domain and the basic one of other techniques, the advantage of this technique reside in the analysis of induction motor anomalies (fault) based on the assumption that, when a fault occurs in this motor.

Tableau 1-4 List of combined standard statistical features used in literature

Features	Equations	
Waveform-Factor Shape Factor	$\boldsymbol{CS_1} = \frac{S_8}{S_4}$	(1.22)
Clearance-Factor	$\boldsymbol{CS_2} = \frac{S_9}{S_{10}}$	(1.23)
Crest-Factor	$\boldsymbol{CS_3} = \frac{S_9}{S_8}$	(1.24)
Marginal Factor	$\boldsymbol{CS_4} = \frac{S_1}{{S_4}^2}$	(1.25)
Impact Factor	$\boldsymbol{CS_5} = \frac{S_9}{S_4}$	(1.26)
Kurtosis Factor	$\boldsymbol{CS_6} = \frac{\frac{1}{T}\sum_{t=1}^{T} x(t)^4}{S_8}$	(1.27)
Peak- Factor	$\boldsymbol{CS_7} = \frac{S_1}{S_8}$	(1.28)
Impulse Factor	$\boldsymbol{CS_8} = \frac{S_1}{S_4}$	(1.29)
Upper Bound	$\boldsymbol{CS_9} = S_1 + \frac{1}{2}\frac{S_9}{T-1}$	(1.30)
Ratio of Energy to Entropy	$\boldsymbol{CS_{10}} = \frac{S_{14}}{S_{15}}$	(1.31)

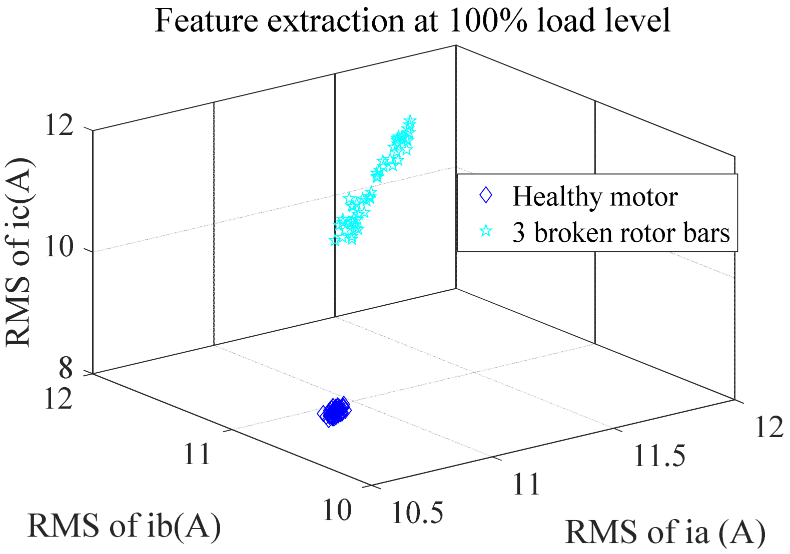

Figure 1-12 Root Mean Square (RMS) values compute from of three phase current signals in two health states of induction motor

The frequency spectrum change from its initial case (healthy motor). In which, the detection of special fault here can be easily detected based on special frequencies in the spectre. For more understanding how the special frequency related to fault can be detected, Take for instance, the example illustrated in Figure 1-13, which it present spectre frequency of current signal taken from induction motor with three broken rotor bar (red colour Figure 1-13.a), and healthy motor (blue one Figure 1-13.b) in full load condition used fast Fourier transform (FFT). In which, there are peaks close to the fundamental frequency exist in the faulty case and don't in healthy one. These peaks are used to detect this kind of induction motor fault that have the following equations:

In the left of the fundamental frequency, the frequencies related to fault $f_{brbleft}$ are:

$$f_{brbleft} = f_{s1}(1 + 2kS_p) \quad (1.32)$$

In the right of the fundamental frequency, the frequencies related to fault $f_{brbright}$ are:

$$f_{brbright} = f_{s1}(1 - 2kS_p) \quad (1.33)$$

Where, k=1,2,3,4. . . , S_p is the slip, f_{s1} is the supply frequency.

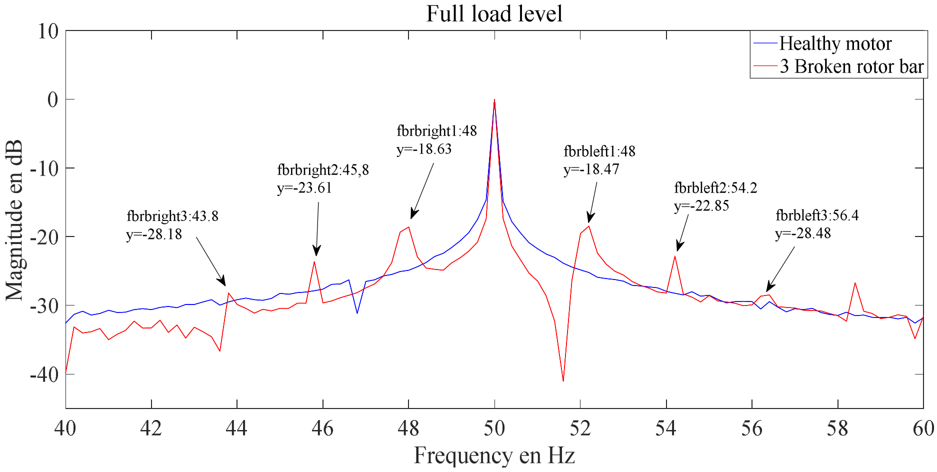

Figure 1-13 Frequencies spectrum in case of healthy motor (blue) and in case three broken rotor bar (red) used FFT applied on stator current

1.6.2.2. Time-frequency domain analysis

The frequency domain analysis present the spectral frequency that continent the information related to induction motor states, but it cannot give an information about the frequency related to fault how exactly appear in what instance of time. for that reason, there a third family of signal processing technique called time-frequency domain analysis that include several techniques such as short time Fourier transform (STFT) derived from theory of Fourier transform to used in time-frequency domain; Wigner Ville transform (WVT); wavelet family transform include continuous wavelet transform (CWT), discrete wavelet transform (DWT), wavelet packet transform (WPT)…; and Hilbert Huang transform (HHT). Usually, all these techniques are so effective in detecting and diagnosing induction motor fault in case of non-linear and non-stationary signal as vibration signal [36, 41].

1.7. Global overviews of Induction motor Prognostic stage

1.7.1. Relationship between diagnostic and Prognostic stage

In contrast to the task of fault detection and diagnostic, that only limited at identify the type of fault which can occur (or in other term localised it) in the monitoring system or detect the degree of fault severity of critical component such as detecting the numbers of broken rotor bars in induction motor [42], the degree of bearing damage [20], the numbers of short circuits between spires [43]; the task of prognostic aim at detecting the degradation severity stage before the failure occurs in the system that follows by a breakdown, this is down after detecting the first time to start prediction (FPT) on the system, that considers as a transfer point between the stage of normal operation and degradation as illustrated in Figure 1-14.

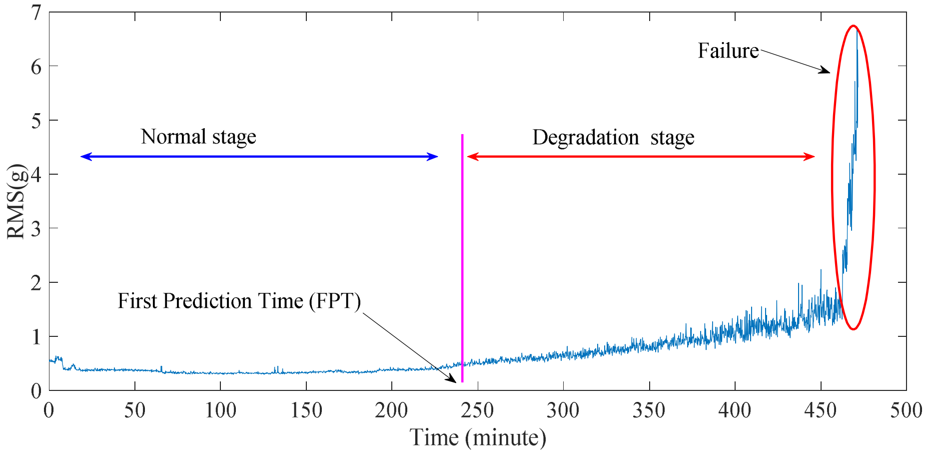

Figure 1-14 Bearing degradation trend used RMS indicator to predict RUL

And in the same time give the predicted remaining useful time (RUL) of system or critical component belong to the system. The relationship between diagnostic and prognostic as shown is a monitoring cycle of a critical system operation. Figure 1-15 shows this relationship in case of using historical knowledge of different health system stages during its past operation [44].

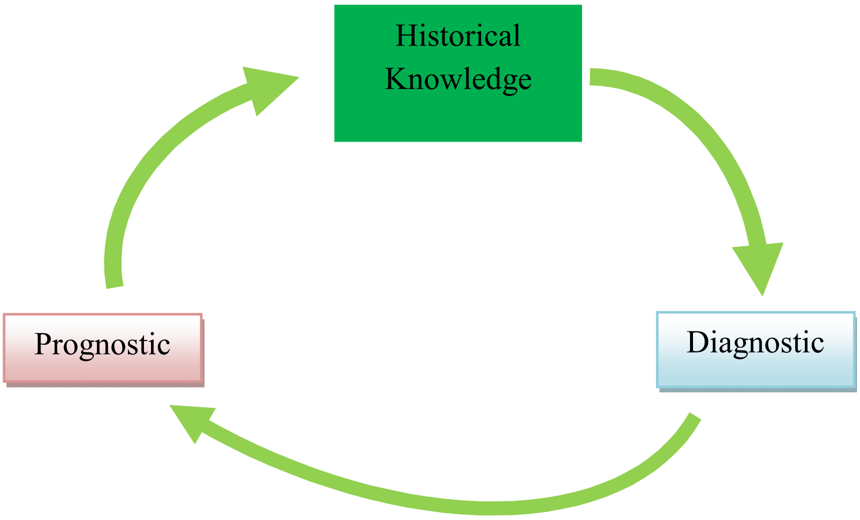

Figure 1-15 Closed loop between diagnostic and prognostic using historical knowledge [44]

1.7.2. Different prognostic methods in literature

According to reference [45], Figure 1-16 present the three main categories of prognostic methods, that is, model based method, data driven method, and reliability based method (experience based method). Further, three sub-categories that is the result of combination of different three main categories such as fusion of model and data driven methods, fusion of model and experience methods and fusion of data driven and experience methods. Also this figure menu by the assessment criteria related to their: applicaplity, cost, precision and complexity of each category and sub-category. The main methods are also motioned in the diagnostic methods they used the same principles and steps but differently used, that shown in new step called predicting the RUL of the monitoring system.

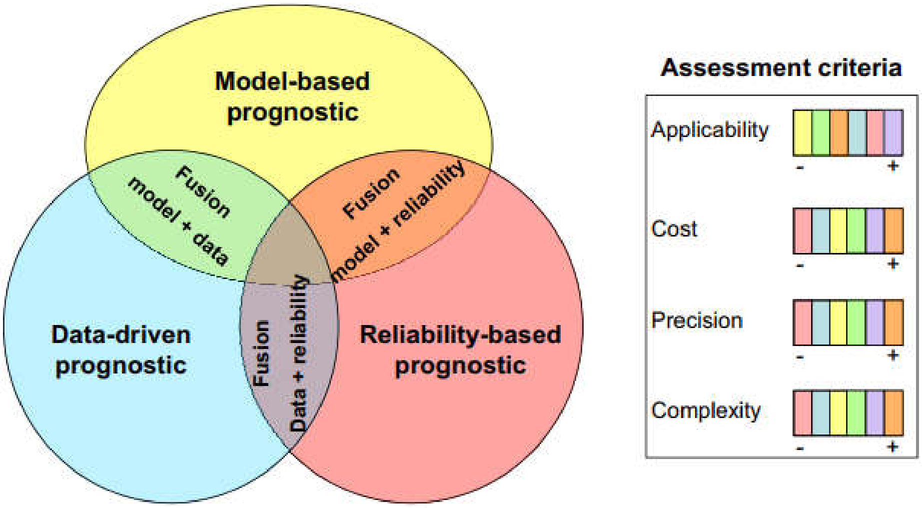

Figure 1-16 Different prognostic methods according to reference [45]

1.8. Conclusion

In this chapter, we presented some useful information that can help and clear some important information to the researchers, reader or student about the meaning of some widespread terminologies dedicated to the diagnostic and prognostic in the published papers or thesis that include:

- Maintenance strategies in industrial sectors;
- Light the spot-on diagnosis and prognostic (prognostic and health management) area with different methods especially those based on model-based method and data-driven method.

In the next chapter, we will present the state of the art or an overview of some interesting research papers, data-driven method with different applications of artificial intelligent classifiers for fault detection and diagnostic of electrical rotating machines (induction motor), data-driven method and fusion between data-driven and model methods for prognostic of bearing component.

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Chapitre 02

Overview on Fault Detection, Diagnostic and Prognostic

2.1. Introduction

In the context of condition-based maintenance, Prognostic and health management (PHM) have known interesting research. especially, with the use of different artificial intelligence algorithms to detect, identify, classify and predict the remaining useful life (RUL) of a critical system (the system used in production, security,...) or critical part in the system as the case of bearing component in different rotating machines for the main purpose to assure the continuity of production and service, decrease the cost of systematic maintenance strategy as well as reduce the number of catastrophic events in the industrial sector, military, etc.

This chapter includes the presentation of overview of two parts:

- The first part includes an overview of different proposed or improved diagnostic methods based on data-driven method, especially those based on used artificial intelligent algorithm in their research papers;
- In the second part, we interest to put the light on some interesting research that used data-driven or fusion between data-driven and model-based method to predict the RUL of bearing.

2.2. Part 1: Overview on Diagnostic Methods used Data-Driven model.

In the past four to five decades, there have been several researches provide new monitoring techniques used data-driven method for induction motors fault detection and diagnostic (FDD) based on:

2.2.1. Vibration signal analysis

The interesting advantage to analyse the row vibration signal for FDD purpose consist in their using. Which, it is independent of supply kind whose used to feed electrical rotating machines, best choice to analyse the health state of large electrical rotating machines (TPIM). Especially, those anomalies related to mechanical components [1-7] (bearing faults, gearbox faults, unbalance rotor, misaligned rotor, bowed…). Consequently, there are several proposed FDD approaches based on analyse this type of signal. In this context, we mentioned some interesting works are resumed as follow:

Spectral kurtosis technique was proposed by F. Immovilli et al in [8] that used statistical analysis to compute the energy of a specific spreading bandwidth of vibration signal to detect generalized fault in bearing. Also, this proposed method can be extending to apply on row stator current signal.

An investigation of the ability of features extraction in time domain analysis extracted from vibration signal by J.Zarei in [9] for fault diagnostic of bearing faults. Which, time domain features proved promising results through the high level of accuracy in detecting and diagnosis bearing faults using neural network (NN).

J. Seshadrinath et al diagnose the most frequent faults in induction motor feed by variable frequency drives under variable speed and loads in [10]. These faults are bearing fault and two severity of inter-turn short circuit. After applying the signal processing technique called dual tree complex wavelet transform, They found that the energy extracted in the level eight from each axis of the measured vibration (tri-axial vibration signals) can be give the best isolation of different considered fault, in which its efficiency was compared with discrete wavelet transform (DWT) by mean of two classifiers, SVM and k-nearest neighbor (*k*-NN) with higher results.

In [11], X. Jin et al used trace ratio linear discriminant analysis for fault diagnostic. In which, this feature reduction technique provide better accuracy in combined with 1NN in reduction of 9 time features and 6 time-frequency features from wavelet coefficients of vibration signal. in order to identifier various single point faults and generalized fault in bearing component than traditional techniques of feature reduction such as principal component analysis (PCA), local preserving projection, canonical correction analysis, maximum margin criterion, linear discriminant analysis (LDA), and marginal fisher analysis.

No-electrical contact fault detection method presented by Maruthi.G.S. and V. Hegde in [12]. This method based on measured vibration analysis using Microelectromechanical systems (MEMS) to detect single point fault and multiple faults in bearing component by mean of spectral analysis (FFT) under two conditions, load levels (no- load and full load conditions) and under unbalanced voltage conditions.

In [13], P.Konar et al used the capability of Genetic Algorithm (GA) and Rough Set Theory (RST) for the selection of relevant information from radial vibration signal. To do that, they combined feature extraction based on RMS value, that it extract from two powerful time-frequency technique, mono-component signals obtained after applying Hilbert Transform techniques (HT), and Continuous Wavelet Transform (CWT).

In [14], C. Wu et al used (CWT) , tree kernel construction for the phase of feature selection of relevant features from several statistical features. In which, they extracted from vibration signal, and finally diagnosis decision of various bearing faults via Support vector machine (SVM).

The impact of common mode current on bearing component was discussed by A. Prudhom et al in [15].this phenomena induced in case of using inverter supply (VDS) to feed three phase induction motor which accelerate the degradation of bearing, the authors simulate this phenomena on two bearing through test bench which found common mode current induce fault in two bearings through detecting the characteristic of faults in outer race bearing fault for the first bearing and inner race bearing for the second one via Short Time Fourier Transform (STFT) applied on row vibration signal.

Bearing fault diagnostic method was developed by J.Tian et al in [16]. Which, it is based on extracted different fault features that can represent various bearing faults using spectral kurtosis (SK) technique and cross correlation applied on vibration signal, in addition to used RMS value. Which their method has the ability to detect a faulty component without healthy reference.

A new method of feature extraction to identifier faulty signal from health signal for bearing component proposed by H. Zhao et al in [17]. This method based on calculates the approximate entropy of different wavelet packet transform levels of vibration signals to detect bearing fault.

Normalization of generalized angular deterministic signals was proposed by J. Urbanek et al in [18] for bearing fault detection based on vibration analysis that can deal in the same time with the problem of load and speed variations.

Nayana B R et al presented four new used features for bearing fault diagnosis in [19], called waveform length (WL), slope sign changes (SSC), simple sign integral (SSI) and Wilson amplitude (WAMP) extracted in time domain, in addition to use two other features ,mean absolute value (MAV) and zero crossing (ZC). These feature present a best discriminative of fault compared to six classical feature in time domain usually used in various papers.

In [20], J.Bulla et al Present a bearing fault diagnosis method based on extraction of statistical parameter from sub band of vibration signal obtained after applied filter banks in 2 different ways (uniform and uninformed sub bands). Then, they used these features as input to ANN with feed forward connections that give best classification accuracy for six faults.

H, Li et al present a new bearing fault diagnostic method in [21] based on adaptive symmetrized dot pattern (ASDP) combined with density-based spatial clustering of applications with noise (DBSCAN). Also they used Hill function (HF) and GA to increase the patterns separation between SDP states.

C. Abdelkrim et al propose a method of Geared motor fault diagnose that located in industrial sector in [7]. In which ,They diagnosis the outer race and inner faults, and both faults in the same time, through extracting and selecting feature between five statistical indicators computed from RMS value of the measured vibration signals , and used them as input to the Adaptive Neuro-Fuzzy Inference System (ANFIS) in order to identifier these faults.

A comparative study have been done by P.Agrawal and P.Jayaswal in [22], between SVM and ANN for rolling element bearings fault diagnosis using CWT applied on vibration signal and used energy entropy methods, which they found that SVM has better accuracy than ANN.

In [23], K.Bhakta et al proposed method for bearing fault diagnosis based on cepstrum analysis and ensemble algorithm called Gradient Boosting (GB).

D. S.Chandra and . Y. S. Rao I n [24] discussed fault diagnosis method of spherical roller bearing in frequency domain for case of large motor of 630-kW rated installed in industry sectors by mean of analyse vibration signal via FFT to analyse and extract dominant frequency features.

A. Guedidi et al in [25] proposed a fault diagnosis method of various rolling bearing faults (inner race and outer race faults, and ball) based on analyse the vibration signal using variational mode decomposition (VMD). Then, statistical features have been extracted after choosing the most sensitive IMFs of VMD that used as input to ANN for fault classification

Nayana B R and Geethanjali P Proposed in [26] to use of 6 new features that extracted from vibration signal for bearing fault diagnosis called time dependent spectral features (TDSF), which they found that 3 features of them among 4 selected features are selected by wheel based differential evolution (WBDE) and Particle swarm optimization (PSO) techniques.

The mentioned proposed works above that analysed the row vibration signal are interesting and effective. Hence, the majority of these works used time-frequency techniques to extract interesting features, that they have the ability to isolate and identifier different considered faults in those works. Moreover, due to non-linear nature of this signal, time-frequency techniques need in its processing phase on the signal computational time burden. Also, vibration sensors used to measured the analysed vibration signal are expensive, require specific positions on the engines that not available in some complex system whose continue these engines [2, 27]. therefore, in major industrial plants, vibration sensors installed only on large and critical motors in the system[6, 28, 29], in construct they do not use this signal analysis in the monitoring of medium and low power motors in industrial plants due to the expensive cost of vibration sensors [28, 29].These disadvantages open the door to use the second interesting and most used analysed signal for FDD called electrical signal analysis, in which it overcome the limitation mentioned that related to vibration analysis. Especially, those papers analysed the measured current signals in their proposed work of FDD.

2.2.2. Stator current analysis

The use of current signal analysis or current monitoring by researchers in different proposed approaches for FDD of electrical rotating machines divide according to analyse of single phase of stator current signal or more than one phase, and the type of signal processing technique applied on stator current signal. The first group used frequency domain via applied the most used, popular and easily application called FFT or its belonging derives on stator current signal in order to extract from the obtained spectral analysis, the frequency related to faulty component (FRTFC) or fault signatures (spectre lines related to faults) that known in the field of conduction monitoring by motor current signal analysis (MCSA). This technique is more convenient in identifying electrical faults [1, 4]. Also, time-frequency domain can be used to extract FRTFC. The second group based on using three phase current signal (vector pattern of Concordia or Park transforms, statistical features) with application of different signal processing techniques in their proposed methods. Consequently, we mentioned some interesting works done in bibliography that used these two mentioned groups to analyse current signal:

A modified bispectrum technique presented by F. Gu et al in [30], which they associate the technique with the statistical indicator called kurtosis value of the raw stator current signal for fault diagnostic of bearing and belt looseness.

V.N. Ghate and S.V. Dudul propose a fault detection method in [31] for interturn short circuit in stator winding, rotor eccentricity, and both faults simultaneously in induction motor based on statistic features extracted from stator current signals which used suitable selected feature by PCA as input to Cascade Neural-Network.

A hybrid model was proposed for fault detection and diagnostic by M. Seera et al in [28], they exploit the characteristic of fuzzy min–max (FMM), neural. (NN) in addition to that the classification and regression tree (CART). Based on these combinations and frequency features extract spectral analysis using power spectral density (PSD) applied on stator current know by MCSA in order to detect and identifier broken bars, short circuit faults in stator winding, eccentricity problems under unbalanced voltages with various load conditions. The hybrid model provides better results than separated use of FMM and CART for FDD.

An investigation of the ability of motor current envelope by J. Wang et al in [32] applied on stator current signal for fault diagnostic of various electrical and mechanical faults in three phase induction motor. Which they found that this technique have a higher rate precision using Naïve Bayes, k-nearest neighbor, and support vector machine classifiers than traditional technique used stator current signal (MCSA).

D. Z. Li proposed a method of Bearing Fault detection (outer race) in [33] based on using higher order spectral analysis (enhanced Bispectrum technique) with injection of auxiliary frequency (AF) in stator current signals in order to improve the extraction of frequency characteristics related to different faulty components.

Squared Envelope Spectrum (SES) technique proposed by Valéria C. M. N. Leite et al in [29]. Which it is applied on the stator current signals for fault detection of outer race in bearing. In addition to that, they use Spectral Kurtosis based algorithm, the wavelet Kurtogram and Fast Kurtogram in order to enhance the SES capability of outer race fault detection.

A fusion method for FDD was proposed in [34] by R.J. Romero-Troncoso et al. In which, they use two signal processing techniques such as Complete Ensemble Empirical Mode Decomposition (CEEMD) and the technique of advanced signal processing so-called Multiple Signal Classification (MUSIC) have been applied on stator current in case of inverter supply in order to detect and diagnose single broken rotor bar, mixed eccentricity and both faults in the same time. This proposed method has the main advantage that can be used either in steady state regime as well as in start up regime.

In [35], V. Fernandez-Cavero et al present the state of the art of fault detection using time-frequency techniques in transient state applied in case of inverter–fed three phase induction motor on the electrical measurement signals

In [36], R.H. Cunha Palácios et al present a comprehensive evaluation of six different machine learning (ML) algorithms for fault identification of various electrical and mechanical faults under variable load and unbalanced voltage conditions through analyse some amplitude of the half sinusoid of the stator current signals. In which, they prove their capability of various MLs in the identification of various faults. Which, the classification precision have been obtained differ from classifier to another. Also, each ML has own characteristic compared to other in diagnostic a fault.

Subspace techniques (high-resolution spectral analysis techniques) and Least Squares Estimator used by Y.Trachi et al for fault detection in [37] , which they combined together to reach the ability to separate different the frequency signatures related to broken rotor bars and bearing faults, and in the same time have the ability to give their severities levels.

By using two distinct extracted frequencies investigated by S. Esakimuthu et al for bearing FDD method in [2]. Where, they extracted from spectral analysis of stator current signals using Fast Fourier Transform. And the diagnosis phase was done by means of support vector machine with high level of precision. Also they used the same technique in other works to detect two artificial holes in the outer race of the same bearing in [38].

A comparative study presented by J. Burriel-Valencia et al in [39] between five different signal processing techniques, in frequency and time-frequency domain such as FFT, Modulus of the Analytic Signal (AS), Extended Park Vector Approach (EPVA), Cepstrum and Harmonic Order Tracking Analysis (HOTA). In which, they search which the technique is more optimized and give the best FD accuracy in combined with SVM to identifier broken rotor bars. Through this comparative study, authors found that the technique of harmonic order tracking analysis (HOTA) with Welch spectrum give the best classification accuracy in direct and indirect supply kinds.

C. P. Mbo'o and K.Hameyer Propose Bearing fault diagnosis method in permanent magnet synchronous machine (PMSM) in [40],. It is based on extract six statistical features from frequency domain of stator current and evaluates these features through linear discriminate analysis (LDA). Then, the Bayes classifier was used for bearing fault diagnosis.

Some selected amplitude from the half sinusoid of stator current in time domain analysis in [41], R. H. C.Palácios present a fault diagnosis method based on multi-agent system (MAS) with divers classifiers. This MAS technique used to identifier bearings, breakages in squirrel-cage rotor bars, and short-circuits in stator winding between the coils under mechanical load conditions and different sinusoidal power.

Online fault diagnosis method Presented by L. A. Garcia-Escudero et al in [42] of broken bar, a faulty bearing and mixed eccentricity in induction motor. it is based on using robust statistical techniques and applied the Quality Control applications, which it have the advantage that can be applied with different sources can feed induction motor.

After applied continuous wavelet transform, S. Singh, and N. Kumar in [43] proposed to use two features have been extracted from stator current named by maximum relative wavelet energy criterion (MRWEC) and the second is maximum energy to Shannon entropy to detect bearing defects(outer race defects with deferent severity levels) in case of variable speed drive.

M. Akar and H. S. Gercekcioglu present a fault detection method in [44], through the analyse of the harmonic of the instantaneous power factor of signal to detect angular misalignment, parallel misalignment and mixed misalignment faults.

Hilbert–Huang transform (HHT) was used by E. Elbouchikhi et al for rolling elements bearing fault detection proposed in [45]. This method needs only two essential steps, the first step is contain in decomposition of stator current signal into mono-component signals (IMFs) by applying EMD on its . Then, they analyse the obtained mono-component signals to identify the fault signatures in the second steps through the extraction of instantaneous amplitude (IA) and instantaneous frequency (IF) from them.

An analytical model to simulate induction motor with a single-point faults in bearing proposed by M.Ojaghi et al in [46] through using multiple coupled circuit modelling. And FFT to extract single-point fault characteristics.

Empirical Mode Decomposition (EMD) technique used by Y. Amirat et al in combined with statistical tool such as mean value and standard deviation in [47] for fault detection purpose. Which it is based on analyse the stator current signal of different bearing faults. In which, their method has advantage that doesn't need to define the order of the intrinsic mode function that contain the information about bearing faults.

A new health index extracted from three phase current signals was proposed by M. Soualhi el al in [48] was proposed for early FDD approach of bearing and gear faults. This health index used as input Adaptive neuro-fuzzy inference system (ANFIS) which allow them to diagnosis seven different faults in bearing and gear at variable load and speed conditions in the same time with high classification accuracy.

A fault diagnostic method presented by S. Zgarni et al in [49] that based on hyper-spheres decision boundary used Support Vector Data Description (SVDD) as an alternative intelligent classifier to Multiclass Support Vector Machine (MSVM). Which they can overcome the problem of accuracy reduction when a few outliers of features appear in space of representation using PR technique in case of using MSVM as a diagnostic decision, in which its application gives a high accuracy level.

X.F. St-Onge proposes an enhanced feature extraction approach in [50] based on temporal features (RMS). In which, they use PR technique to diagnose various electrical faults in induction motors via symmetrical components (SCs) of Clark transformation applied on three phase current signals.

Mutual information was proposed to used in FDD method of different bearing fault severities in induction motor by G. H. Bazan in [51]. mutual information was extracted from two phase of current signals in time domain to evaluate the faulty machine from healthy machine, that done under several operation condition of the machine by varying the coupled load, voltage unbalance, kind of the supply frequency.

Long Short-Term Memory networks proposed for detection of different Bearing defects via stator current analysis by F. Immovilli et al in [52].

A. H. BOUDINAR et al present a fault detection method of bearing fault progressive in [53] by using a specific sub band harmonics related to signature defects in bearing parts that help to in reduction of the large time usually taken when applied a processing technique called the Root-MUSIC on the analysis of the current signal. Which provide a high efficiency to detect these faults in bearing, either can give its severity levels compared with traditional technique named power spectral density (PSD).

A. Khlaief et al present a method of features engineering in [54] that can be used in both signal monitoring, current and vibration signals for different bearing fault detection and diagnostics (single and combined faults). In which, they used GA in order to select these features engineering among 17 features that extract from three domains of signal processing techniques.

Y-J Yoo propose an algorithm based on using principal component analysis (PCA) in order to find easily features from the transformation of current signals into frequency domain via FFT and identifier the abnormal motor through using fault detection index called Hotelling's $T2$ in [55].

The technique called Independent Component Analysis (ICA) was used in several works in field of FDD of three phase induction motors that can extract and select the relevant features among N features. Among these works, the work done by Z.Wang et al, T.W. Chua et al and T. Yang et al. In [56], T.W. Chua et al proposed a fault diagnosis method based on association of features from both domains, time and frequency technique. Where, they applied ICA to extract features and select for detection and identification of broken rotor bars and bearing faults. In contract, Z.Wang et al in [57] present fault diagnosis method that also used ICA but in combination with FFT to built new feature extracted from only one stator signal phase and in frequency domain to diagnose two broken rotor-bars and bearing fault under variable speed. However, the work done by T. Yang et al in [58], is an improved work compared to that done by Z.Wang et al and T.W. Chua et al used ICA. Which, they propose fault diagnosis method also two broken bars and bearing fault. This method based on two successive analyses, the first FFT of stator current signals and second ICA to extract relevant features from spectral analysis. In which, it has the advantage that it is not need to know the slip or load levels in case of inverter supply.

Each work from the mentioned works above that analyse the row current signal with different signal processing techniques to detect and identifier the fault which make these among the interesting and effective proposed approaches in the field of condition monitoring. However, although the wide use of MCSA in some of these works or other works exist in bibliography, it has some limitations consist in its applicability, in which the frequency related to faulty component (FRTFC) can be only isolate by this technique in case of high load level [59, 60], steady state regime [3, 34], and also convenient only in case of electrical network that used as direct source to supply THIM [59, 60, 61]. In contract, advanced signal processing techniques solve these problems. However, they require to get the results a computational time. In addition, its interpretation need expert person with high experience in condition monitoring of health state of rotation machine to interpret the obtained results after applied these techniques.

2.2.3. Concordia and park transforms

Among the second used of the current analysis by researchers, the projection of the three phase current into two currents of Concordia or Park transform(CT or PT), then, they plot the obtained currents into two dimensional representations. In which, in ideal case with health state engine, the Concordia currents illustrate by circular form and by elliptical form in Park currents. In other hand, deformed circular or elliptical form defines the faulty engine as the work done by: Fatiha Zidani el al proposed fault diagnosis method in [62]. This method uses pattern vector of two current signals of CT under different load conditions with fuzzy logic (FL) approach to detect and diagnose stator faults. The accuracy results indicate the ability of FL approach to detect a fault with its severity level. Other work used these forms presented by I. Y. Onel and M. El H. Benbouzid in [63]. Which, they were compared these two transformation techniques, PT with CT using FL approach in order to define which transformation is more convenient in identifying the faulty pattern of different bearing failures. Where, they conclude from the obtained results that the capabilities of fault diagnostic of different bearing failures using PT better than CT. H. Razik et al develop FD approach in [64]. Which it can be used as alarm to inform the operator about the induction motor states, specifically, the approach give information about the number of broken bar in motor (severity of fault), and eccentricity problem under load levels up to 50%. For that, a complex technique of Fourier transform was applied on extended Park’s vector approach, and then, they used GA to search the amplitude of line spectrum of faulty mode. And afterward, a FL approach have been utilised to detect the degree of severity and give in the same time to the operator the information needed about the engine. And in case of faulty mode present its severity level. I. Aydin et al applied PCA on park’s vector in [65] for fault diagnostic of two different severities of short circuit in induction motor. The features vector obtained by the reduction technique used as input to FL for stage of FD decision about the induction motor health states.

Recently, A. Faleh and A.Method in [65], have been proposed a new health indicator based on combined standard deviation and skewness extracted from Concordia current to diagnose bearing and broken rotor bars faults using K-Nearest Neighbor where the results were promising.

H-C.Chang et al propose an approach to detect and identifier broken bar and dynamic eccentricity faults in [66], this approach based on frequency component related to fault extracted (FCRF) from spectrum analysis via FFT. And they give its severity levels such as normal, caution, warning and dangerous of each fault by fuzzy inference system using two currents $I_{\alpha,\beta}$ of CT in order to obtain the severity index. I. Bandyopadhyay et al proposed time domain fault detection and diagnostic approaches in [67]. Which, the time domain features was extracted after made transformation of three phase currents into two current signals of CT. In which, they used these temporal features to detect and diagnose a switch degradation that contain in inverter whose used to feed induction motor. The diagnosis stage of different switch states was done by SVM classifier.

The above approaches based on current and vibration analysis are among the most widely preferable signal analysis owing to their non-intrusiveness, reliability and easily measurable. Therefore, their effectiveness of these signal analysis depends on the loading mode of three phase induction motor and signal-to-noise ratio of sensors. Therefore, there are other analysed signals used in literature as acoustic analysis [68], flux analysis, thermal analysis. Which, they are low effective, less used and less popular than vibration and current analysis

2.2.4. Other analysed signals

We mentioned some recent work that have been used acoustic analysis**,** flux analysis and thermal analysis to analyse the health state of electrical rotating machines, and they can also used as complement to vibration and current analysis to get more accuracy level. Acoustic or sound analysis have been used and still used in various domains such as medicine, military. Also, it can be used in condition monitoring of electrical rotating machines which has the advantages to been cheaper, no-invasive technique [27, 68]. In this context, A. Glowacz proposes two methods of feature extractions from acoustic signal, and used these features as input of to KNN, backpropagation NN classifier and modified classifiers to identifier broken rotor bars and broken ring of rotor in [67]. These feature extraction methods called by SMOFS-32-MULTIEXPANDED-1-GROUP and -2-GROUPS (Shortened Method of Frequencies Selection Multiexpanded-1-GROUP and 2 Groups). Other work of A.Glowacz and Z. Glowacz proposed fault diagnosis method in [40, 2016] of two types of shorted coils in auxiliary winding, and main winding in single phase induction motor. Which they extracted features by main of a technique called Method of Selection of Amplitudes of Frequency - Ratio 30% of maximum of amplitude Multiexpanded (MSAF-RATIO30-MULTIEXPANDED) applied on analyse acoustic signal. And they used the KNN the K-Means clustering and the Linear Perceptron NN for fault diagnostic and classification in proposed method. Another work done by D.H. Pandya et al was proposed fault diagnostic method of five different defects in bearing [70]. In this work others used asymmetric proximity function to select the optimal features from nine temporal features whose extracted from IMFs that obtained from acoustic emission after applied the technique of signal processing called EMD. And then, they used the selected features as input to KNN in order to diagnose and classifier these five fault classes. However, acoustic analysis has the main drawback consist in noisy environment where there exist several motors and machines behind the critical monitoring motor make its analysis difficult task due to mixed sounds in the measured signals to analyse[27, 68].

Flux analysis has been used by C.Dias and F.H. Pereira in [6]. In which, other propose fault diagnostic method to detect broken rotor bars. Their method based on use frequency features, time features and both type of features in the same time that extracted from measured flux signal via embedded sensors whose installed in the stator of three phase induction motor to overcome the drawback of MCSA in low load levels. Which, they used the obtained features as inputs to three following classifiers, MLP , KNN and SVM for fault diagnostic and classification stage. Y. Park et al proposed a method of fault detection of eccentricity, broken bar, load unbalance, and misalignment faults in induction motor based on analyse the flux in air gap in [6], through embedded sensor implemented in the coil of stator to measure the flux signal, and then, they applied STFT to extract the characteristic frequency of each mentioned faults. In [72], M. Skowron et al present a fault diagnosis method via axial flux signatures of short circuit between inter-turns and broken bar under various damage severities in induction motor supply by PWM inverter. This method based on using the advantage of combined self-organizing Kohonen network (SOM) and (ANN). Therefore, the main disadvantage of this kind of signal analysis continued in implementation of sensor, which requires installing it inside the machine with some role to get good fault detection.

Thermal images analysis got noticeable attention by some researchers in last recent years due to being no-invasive method for FDD, and it has the ability to identifier which component has a defect in the machine[27]. In this regard, Thermal images analysis was used by A.Glowacz and Z. Glowacz to analyse three states of induction motor, health, two broken rotor bar and ring fault in [3].which, they proposed tow Fault diagnosis methods. These methods based on extract features by a technique called Areas Selection of Image Differences (MoASoID), and they identifier a fault by KNN classifier, K-means, the back propagation NN. G.Singh et al propose two Fault detection methods for inter turn fault and its severities during state up and steady state in induction motor through infrared thermography analysis [72]. Therefore, the major difficulty faces this technique, natural overheating of the machine when work with variable load or overloading machine. In addition to that permanent fault as shorted coils between low numbers of spires cause permanent heating in the machine [3].

The all above works of data driven method based on various signal analysis have the own merits and demerits, which mean the accuracy differ from each signal analysis to another and depend to the kind of signal processing techniques applied on the signals. consequently, in recent literature, some researchers go towards fusing more than one signal analysis in order to benefits from each signal analysis merits to up the level of accuracy in identifying the kind of fault through technique called fusion of various measured signals.

2.2.5. Fusion analysis signals

The fusion approaches consist in mixed various features extracting from two or more types of measured signals. Also, these methods can be used one signal processing technique or more for the main reason to obtain high level of precision in identifying the faults. Firstly, We mentioned some quasi similar works for features extraction phase in [59, 60, 74, 75, 77, 79], authors have been share the similar way of features extraction from both voltage and current sensors , frequency features from current signals[59, 60, 74, 75] and time domain features after applied Concordia transformation (CT) on current and voltage signals [59, 60, 74, 75, 77, 79], except the reference [77], M. Frini et al used features from Concordia and parks transforms of current and voltage signal that done after filter the electrical signals via EMD. In addition to Concordia and Park transforms, they used features from Frenet–Serret formula and classical fault indicator (frequency features) To form a set of health indicators for gear fault diagnosis. However, they differ in their contributions in using the technique of feature selection or not and in the type of artificial intelligent, whether if it is supervised or unsupervised for features classification of various faults. In [79], R. Casimir et al used two classifiers kNN and linear discriminant functions determination to classifier three broken rotor bars and unbalanced stators faults. In [59], O, Ondel et al used the sequential backward selection algorithm (SBS) for feature selection and *KNN* for diagnostic decision of health induction motor and three broken rotor bar. Also in [60] and in [75], O, Ondel et al used the same classifier K-NN in [60]. But, they introduce the technique of Kalman algorithm for the main objective to prediction an intermediate state or unknown load level continent between two known load levels for faulty and normal mode such as three broken rotor bar and stator fault respect to [60] and [75]. In [74], A. Soualhi et al also used SBS algorithm for feature selection and unsupervised AI classifier named artificial ant clustering (AAC) inspired from real behaviour of ant in gathering food. Which they used this intelligent algorithm for bearing and different broken rotor bar faults. A. Widodo et al present a combination between ICA and SVM classifier in [78]. in which, they extract 78 feature from time and frequency domains from six measured signals (three signal of current and other for vibration signals), then the selection of relevant features done by ICA in order to enhance the accuracy of SVM to classifier bearing fault, bowed rotor, broken rotor bar, eccentricity, broken rotor bar, phase unbalance.

Recently, the work done by P. Gangsar and R.Tiwari in [1], that present a comparative study between stator current and vibration analysis, also they combined both signals, in order to check the capability of each analyzed signal in time domain through three temporal features; standard deviation, skewness and kurtosis to diagnosis electrical and mechanical faults. Nine states of different electrical and mechanical faults in induction motor with one health state were diagnosis using multiclass SVM (MSVM). They found that vibration analysis give best results, in case of mechanical faults and less with electrical faults and inverse in case for current analysis and a bite improvement when used both analyzed signals. Also, another interesting proposed method was presented by M.Z. Ali et al for fault detection and diagnostic in [79]. This method based on combined two different measured signals (current and vibration signals) that have been measured simultaneously. And they applied Matching Pursuit (MP) and Discrete Wavelet Transform (DWT) for feature extraction purpose. Two motors have been used in order to validate the proposed method of FDD. The first motor used for fault diagnosis of Different single- and multi-electrical faults and the second motor used for single- and multi-mechanical faults.

2.2.6. The deep learning family

The all mentioned approaches belong to data driven category have to pass through essential steps (**see Figure 1-11 in chapter 1**); first step, have to choose the convenient electrical measurement signal to analyse the state of electrical rotating machines used for the proposed FDD method; Second step define the symptoms of fault that can separate different classes (temporal features, frequency component related to fault) by mean of two phases, the phase of features extraction and features selection , in which, it have to use in this phase one domain of signal processing techniques or more named time domain appertain statistical features, frequency domain appertain frequency features or statistical features, time-frequency domain appertain frequency features or statistical features or combined features from more than one domain [48]. Last step is the decision phase which consists in applying different machine learning classifiers.

Therefore, these proposed methods or most existed methods are considered by some researchers as classical methods, in which they have several drawbacks. First, there are no specific features or optimal features can be used to identifier the same fault with different use of the engine in real life with or without direct supply. Second, the phase of applied various signal processing techniques on the electrical measurement need time to identifier the fault. Especially, those methods based on used advanced signal processing techniques in their works. Moreover, each signal processing technique has own advantages and disadvantages. Therefore, these researchers have been combined the two phases of feature extraction and selection in one phase in their proposed FDD methods. In which, these methods are free from using or selecting the convenient signal processing techniques depending to the nature of signal being analyzed due to the problems related to these techniques. In this context, the first applied of 1D Convolutional Neural Networks (1DCNNs) belong to the deep learning family by T. Ince et al for fault diagnostic of bearing faults in [80]. Which have the advantage to detect a fault in real time thinks to fuse two essential phases, feature extraction and selection in same time from stator current signal after the analysed signal pre-processed. Convolution deep belief network have been used by H. Shao et al in [81] for bearing fault diagnostic. In which, they have the advantage to use directly the row signal (vibration) from sensors after reduce its high dimensionality by auto-encoder. Where, it gives higher results in indentifying faults compared to traditional use of machine learning algorithms such as SVM and ANFIS with signal processing technique. Another work done by L. Eren et al that also used 1 DCNNs in [82], which in this time used pre-processing vibration data from two different and long datasets of vibration signal collected during experimental application of bearing from healthy to faulty state. Which, it provide high classification accuracy compared to classical supervised classifiers. Another recent work propose by the author T. Ince in [83] for FD, That use in the first time to diagnose broken rotor bars by deep learning based on 1DCNNs. Which, 1DCNNs has the advantage of directly monitor signal through used the stator current after its pre-processing step compared to other Machine learning algorithms. Which need a relevant features based on features extraction and selection.

2.3. Part 2: overview Prognostic methods

In this part, we present brief abstracts of some interesting prognostic works in literature based on data-driven methods and fusion between model method based and data-driven method as follow:

A. Soualhi et al present a great work for bearing degradation assessment approach, that it is based on associate a detection fault features related to each bearing part through extracting them from the spectre of HHT applied on choosing IMFs that continue the fault information, fault diagnostic stage via SVM, and final stage concern in the determination of RUL by Machine learning algorithm called support vector regression (SVR) [84].

S. Hong et al have been proposing a methodology to assess the level of bearing degradation. Hence, four severity levels are used for that, such as normal, slight degradation, severely degradation and final level bearing life is a failure. This method based on the use of combined techniques WPT-EMD for features extraction and self-organization mapping (SOM) for feature reduction [85].

D. Wang et al proposed an approach based on extract new feature to form health indicator. That, it is done by means of using STFT and non-negative matrix factorization (NMF) and construct it using a SOM network to assess the degradation performance of bearing [86].

Y. Wang presents an approach based on used two-stage for data-driven prognostic, Health and degradation stages. The degradation stage was detected by a remarkable deviation in the trend of the health indicator, which is a result of the fusion of fourteen statistical features into one. Then, estimate the RUL by mean of enhanced Kalman filter and an expectation-maximization algorithm through this fusion health indicator [87].

T.H.E. Lotus et al have been proposed to use for the first time a new feature called Wiener entropy with SVR machine learning to estimate the RUL of bearing degradation [88].

L. Ren et al investigate three powerful temporal features, RMS, CF and Kurtosis besides one feature extracted from frequency domain called by frequency spectrum partition summation used for the first time, as input to the deep neural network DNN model. That it is used to predict the RUL of rolling bearing [89].

D. A. Tobon-Mejia et have been Investigated WPD with a Mixture of Gaussians Hidden Markov Models (MoG-HMM) to estimate the RUL of bearings, which they used for that, the energy of all last levels of decomposed analysed signal through WPD [90].

K. Javed et al have been proposed an approach based essential on feature extraction, that they introduce the trigonometric functions on the analysed signal, and cumulative transformation to obtain the best bearing curve for prognosis purpose [91]. Also, another work of K. Javed et al, is based on the same step for an accurate prognostic approach. Which, it compared with the classical use of temporal features in prognostic. However, in this time, authors select the best features by evaluating their fitness in term of their characteristics such as monotonicity and trendability for the convenient curve that used later to predict the RUL. In which, this approach has been applied to two groups of mechanical components such as cutting-tool and bearings for RUL prediction with promising results [92].

Y. Liu et al proposed a new advanced fault features. Which, they are sensitive to the degradation of bearing through a technique called phase space reconstitution (PSR) and approximate diagonalization of Eigen-matrices (JADE). These features are used as input to the extreme learning machine (ELM) to train and predict the RUL of bearing [93].

Y. Lei et al proposed a mutual feature based on selecting one feature among each group of features that have similar characteristics in multiple extracted features and Fuses them by mean of SOM to build a health indicator called weighted minimum quantization error. Then, they used him as input to particle filtering-based algorithm and Paris–Erdogan mode to predict the RUL [94].

L. Saidi et al used the kurtosis value as a health indicator computed from the spectral kurtosis to detect the degradation of bearing in wind turbine high-speed, and SVR algorithm to predict the RUL of this critical component [95].

W. Ahmad et al proposed an approach for bearing RUL based on the alarm in the determination of the first time to failure by mean of RMS usually used as a health indicator (HI) in this field of research. Then, a dynamic regression model was applied to estimate the RUL of bearing [96].

J. Coble and J. W. Hines investigate the ability of GA in selecting optimal features that have good metrics such as monotonicity, prognosability, and trendability [97].

P. Tiwari and S.H.Upadhyay proposed a novel method of prognostic and health assessment (PHA) of bearing degradation. That, it based on extract singular and energy entropy values from each IMFs of EMMD that applied to vibration signal, and then, reduce them by curvilinear component analysis to one vector, in order to use her as input to SOM network [98].

L. Liao proposed a genetic programming (GP) approach as a solution to search for a discovered feature that has the higher monotonicity, in case of no clear feature trend of bearing degradation, that has a low level of monotonicity. Which, they choose 68 features extracted from six sensors (vibration sensor, current sensor and 4 temperature sensors). the discovered feature are selected after applied high order polynomial function to smooth the trend of features, then choice depends on higher monotonicity features [99].

E. Sutrisno et al present three different proposed methodologies of data-driven to estimate the RUL; the first one based on a technique called moving average of spectral kurtosis, which used as a health indicator and bayesian monte Carlo to update the parameter of exponential model for prediction purpose; the second method, authors extract 32 feature from radial and vertical vibration and used PCA to reduce them into three trends, in order to used them as input to least squares-support vector repressor to estimate the RUL of bearings; and the final method, vibration frequency signature anomaly detection and survival time ratio are used to estimate RUL of bearings[100].

J. Yu presents a health degradation assessment of the bearing method. In which this method is based on a combined hidden Markov model (HMM) and contribution-based method analysis to assess the actual state of bearing degradation. Also, on using dynamic principal component analysis (DPCA) in order to extract relevant features from 11choosing features and proposed hidden Markov model-based Mahalanobis distance as assessment indicator [101].

H-E Kim et al propose in their paper a technique for precise assessment of the remnant life of bearings of High Pressure-Liquefied Natural Gas (HP-LNG) pump based on prior knowledge of fault, and they used health state probability estimations for detecting the health degradation states through using SVM classifier to predict these states. And then, from the obtained prediction states, optimal remaining useful life based on historical knowledge of HP-LNG degradation and current state of bearing. [102].

N. Li et al propose an enhanced EM for Predicting RUL of Rolling Element Bearings. for that, the improved method to detect the first predicting time to start prediction based on alarm of 3σ interval, through calculated the standard deviation of kurtosis in health state that actually used as monitoring index to start the prediction of RUL using the health index RMS. And they used the particle filtering (PF) method to initialize the parameter of EM to predict the RUL prediction. The improved EM gives the best result compared with the original EM and Paris model [103].

A. Ginart et al proposed an alarm to start predicting RUL of pump shafts through vibration signal that used the 6 value of standard deviation that normalized by the mean value in health state. Then, they used Exponential Model (EM) as a medium to predict RUL [104]

R. Huang et al investigate the advantages of both self-organizing map (SOM) and backpropagation neural network (BPNN) for bearing health degradation assessment (BHDA), for the main purpose are, to estimate RUL of this component. In which, they used mutual features (frequency defective features and temporal features) as input to SOM to extract from it, the indicator called the minimum quantisation error (MQE), that is used as input to BPNN to estimate the RUL [105].

S.S.H. Zaidi et al present a prognostic method based on HMM to predict the RUL of gear in DC machine [106].

F. D. Maio et al have been investigate both categories data driven-approach via and model-based approach via exponential regression to estimate the RUL. Which, they used to benefit from their advantages and eliminate their disadvantages [107].

X-S. Si et al used Both Bayesian updating and expectation maximization (EM) algorithm for RUL estimation, which they combined to follow the path of the degradation model through using linear degradation model and an exponential-based degradation model proposed by Gebraeel et al to show the efficiency when they implement their proposed method on degradation historical data [108].

N. Z. GEBRAEEL et al proposed an improved method for the assessment of stochastic parameters in applying two different exponential models (EM) for RUL of bearing degradation via the Bayesian updating (BU) method [109]. For that, they use information from the monitoring component (bearing) to update these stochastic parameters, that they are necessaries for EM to estimate the residual life.

N. Gebraeel develops a bearing degradation model approach, which is based on compute and also continuously updates the RUL of EM. in this approach, he combines the reliability that concentrates on characteristics at the population level, and condition monitoring that treats the characteristics of specific component[110].S. A. Khan et al present an investigation of generative adversarial networks (GANs) to model the degradation bearing trajectory of health indicator to estimate the RUL [111].

X. Li et al propose an intelligent RUL prediction approach based on using deep learning such as CNN. Which, they investigate the information from applied the time-frequency technique called STFT for prognostics, and technique of the multi-scale feature extraction is performed using CNNs [112].

B. Wang et al proposed an enhanced fusion prognostics approach that used RVM regressions and EM of bearing degradation. They employed a metric based on the Fréchet distance to select the optimal cure used for RUL estimation [113].

X, Jin et al present an RUL approach that has two-step anomaly detection and prognosis. Which, they used the linear autoregressive model to filter two orthogonal vibration signals, and then extract their related energies after applied a wavelet packed transform on residual vibration signals. These energies are added together to build a health index that used to detect anomaly using Box-Cox transformation in order to determine the threshold and begin estimating RUL through using an extended Kalman filter [114]

C. R. Lim and D. Mba proposed a state-space based RUL approach for gearbox bearings in aircraft. In this approach, authors have been adopting the Switching Kalman Filter (SKF), instead of KF for gearbox bearings model estimations and RUL prediction [115].

A. Soualhi et al propose an interesting work that combines fault detection, diagnostic and also prognostic for a rolling bearing health condition. To do that, authors use temporal features extracted from vibration signal measurement as a health indicator, AAC that belongs to experience-based method to detect different degradation bearing classes during its life working, HMM to predict the next step, and ANFIS employed to estimate the RUL of bearings [116].

M. Rezamand et al employed an adaptive Bayesian algorithm to predict RULs of different selected statistical features that they extracted from vibration signal after applying DWT on it. Then, the obtained RULs are fusion into one RUL used an operator called ordered weighted averaging (OWA) to provide an accurate estimation RUL of wind bearings[117].

Lei Ren et al proposed a new deep learning network for bearing RUL, called Multi-scale Dense Gated Recurrent Unit Network (MDGRU). The MDGRU is constructing to overcome the weakness of two deep learning network, the RNN and CNN models. Which, it composed of, pre-trained Restricted Boltzmann Machine (RBM) network to initialize the feature layers, multi-scale layers, skip gate recurrent unit layers, and dense layers, that make him powerful network to predict the RUL compared to mentioned network models [118].

X. Li et al proposed deep convolution neural networks (DCNN) for RUL of bearing degradation [119].

Through the analysis of acoustic emission, M. Elforjani, and S. Shanbr have been used three machine learning algorithm (Multilayer Artificial Neural Network (ANN) model Support Vector Machine Regression (SVMR), and Gaussian Process Regression (GPR)). And, they use two features extraction, such as RMS and Signal Intensity Estimator (SIE) for the estimation of the RUL of slow speed bearing [120].

A.Faleh et al have been proposed prediction method of remaining useful life of bearings under two different conditions [121], the first bearing tested under constant load and speed and the second under variable speed (wind turbine bearing). The proposed method based on using temporal feature and support vector regression.

2.4. Conclusion

The most resumed paper in this chapter return to diagnostic methods than prognostic methods that help us to well understand different features can be used to identify the fault in three-phase induction motor. As well as they open the door to use them in the area of prognostic method as the case of predict the RUL of bearing degradation using temporal features. In which, there are variety of monitoring signals that can be used to identify the health state of a three-phase induction motor (electrical rotating machines). However, the most used signals in condition-based maintenance are current and vibration signals.

In this context, for the next two chapters, we will use:

- Current signal analysis to monitor the health states of three induction motor in the third chapter.
- Vibration signal to predict the RUL of bearing component in fourth chapter.

Reference of Chapter 02

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Chapitre 03

Fault Detection and Diagnostic of Three-Phase Induction Motor

3.1. Introduction

Data-driven method is based on monitoring different electrical signals that are measured via different sensors, as mentioned in the third chapter, the main disadvantage of monitoring a vibration signal is the costly vibration sensors, beside require an advanced signal processing technique to analyse it. Which, the analyse of the current signal (voltage signal) is the better choice in the case of three-phase induction motor fault detection and diagnostic (FDD) which requires cheaper current sensors (voltage sensor) with the simplest signal processing technique.

In this regard, our proposed method for FDD of three phase induction motor is based on investigating the advantage of temporal features that are extracted from current signals (voltage signals) to identify the different faults.

3.2. Proposed method for fault detection and diagnostic

The global overview of the proposed methodology is illustrated in Figure 3-1, which requires three essential stages to detect and diagnose a fault in a rotating machine (IM) [1]: acquisition system, signal processing, fault detection and diagnostics. This proposed method can be applied to two electrical signal types (three-phase current signals as well as three-phase voltage signals). Each stage will be described below.

3.2.1. Description of the process

3.2.1.1. Presentation of induction motor test bench

The data used in this chapter were collected from **Ampere Laboratory, University of Claude Bernard Lyon 1**, that used a test bench is composed of a three-phase squirrel-cage induction motor Leroy Somer LS132S, IP 55, class F, standardized T ° C = 40 ° C, rated speed S1. This engine is characterized through:

- The nominal voltage between phases: 400 V
- Power frequency: 50 Hz
- Rated speed: 1440 rpm
- Nominal useful power: 5.5 kW
- The power factor: cos $\phi = 0.84$
- Rated current: 11.4 A
- The number of pairs of poles: $p = 2$
- The stator resistance per phase: 1.315 Ω
- The number of notches on the rotor $Nr = 28$

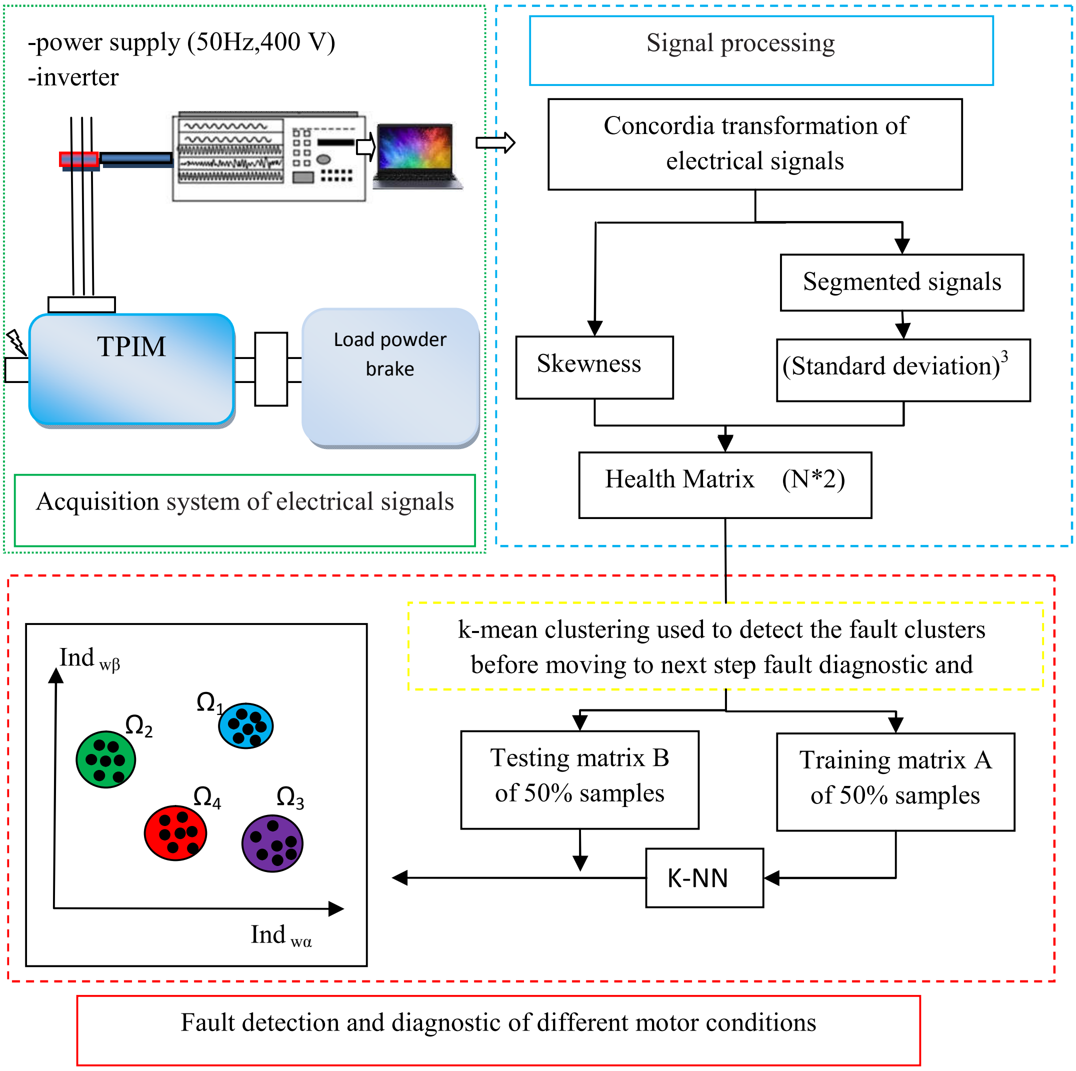


Figure 3-1 Global overview of the proposed methodology for fault detection and diagnostic

- The number of notches on the stator Ns = 48
- The windings in the stator of test bench are star-coupled.

The motor is loaded by a powder brake. The maximum torque (100 Nm) is reached at the nominal speed. This brake is sized to dissipate a maximum power of 5 kW. The Figure 3-2 shows this engine test bench.

3.2.1.2. Data acquisition

The signals recorded by the acquisition system as illustrated by the Figure 3-3 are:

- ✓ The three phase current signals
- ✓ The three phase voltage signals
- ✓ The speed of rotation
- ✓ Vibrations in the following directions:

- Vertical direction and perpendicular to the motor axis, with an accelerometer on the opposite side of the coupling
- Direction parallel to the motor axis, opposite side of the coupling
- Horizontal direction and perpendicular to the motor axis, opposite side of the coupling

The acquisition system used to measure these signals has:

- Eight differential inputs called fast channels which can be sampled up to 10 MHz on 14 bits. These inputs were used to measure voltages as well as currents.
- Eight common mode inputs called slow channels on which the sampling frequency can reach 1 MHz on 16 bits. One of these inputs was used to measure the speed of rotation.
- Four inputs are reserved for accelerometers measuring vibrations. The "accelerometer" inputs also offer the possibility of obtaining a sampling frequency of 100 kHz. Piezoelectric accelerometers are powered by constant current sources providing between 1 and 10 mA under 28 V.

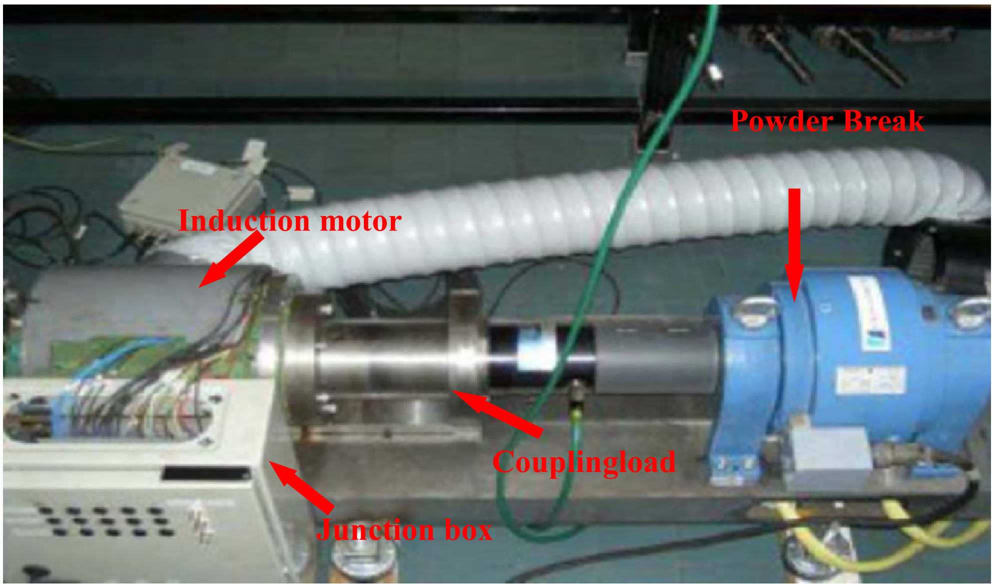


Figure 3-2 Squirrel-cage induction motor coupled to different loads

The Figure shows the device set up for the acquisition of signals: machine load and signal acquisition assembly.

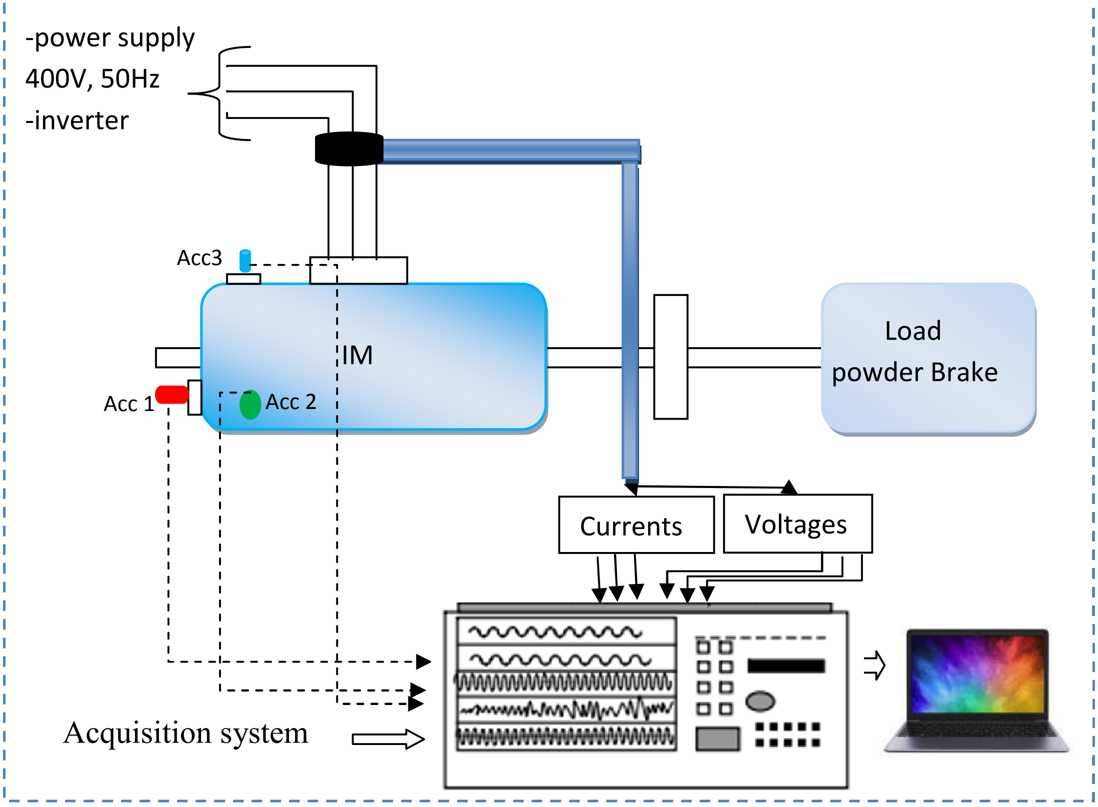


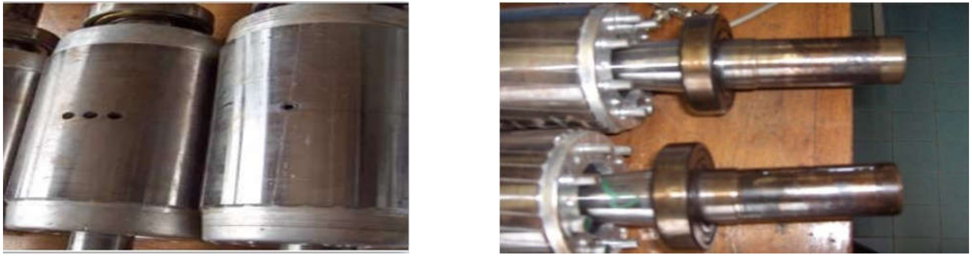
Figure 3-3 Signal acquisition system

3.2.1.3. Modes of operation studied

The operating modes used to validate the diagnostic procedure in several load levels are listed in Table 3-1. Each of them is represented by a class in the decision space. The faults were created in the rotor of the induction machine (1 and 3 broken rotor bars were broken by drilling the bar of the squirrel-cage Figure 3-4. (a)). And used a natural ageing bearing has been provided by SECCO after being used in a real application (Figure3-4 (b)).

Tableau 3-1 Operating modes used to constitute the learning set and the test sets

Operating mode	Types of defects	load rate (For Pu = 5.5 kW)	Supply type
healthy motor	Without fault	0%, 25%, 50%, 75%, 100%	- Network - Inverter
One broken rotor bar	Rotor fault	0%, 25%, 50%, 75%, 100%	- Network - Inverter
Three broken rotor bars			
Progressive wear (natural aging)	Bearing fault	0%, 25%, 50%, 75%, 100%	- Network - Inverter



(a) (b)

Figure 3-4 (a) 1 Broken bar and 3 Broken rotor bars, (b) Bearing wears

All these measures were used in order to validate the implementation of our diagnostic approach. Some of these measurements will be used to build the learning set as well as the test sets.

3.2.2. Signal analysis

The temporal analysis considers a signal processing technique among three existing ones. This technique has proved its efficiency and gives better results for FDD in several works [2-6]. In this regard, we employ it in this present work. In which, the statistical features are extracted from electrical signals after making a Concordia transform (CT).

In the next, the geometrical representation of CT, and the fast Fourier transform (FFT) technique usually used to detect a fault in TPIM will be presented in order to show some difficulties and limitations related to real applications for Fault detection. Especially, in the case of inverter supply compared to the power.

3.2.2.1. Concordia transformation (CT)

There are two transformations that can be used to project three electrical phases (current signals and voltage signals) into two electrical phases by applying Concordia transformation (CT) or Park transformation (PT). These transformations have been used in [1, 3, 7, 8, 9-12], with diverse use to build the pattern vector as temporal features [1, 13, 14, 3, 13], and a geometric representation [9-12] by taking the difference between the shapes in the health state system. It is a circle in the case of CT, and an ellipse in park transformation. On the other hand, a deformed circle or ellipse compared to the first state point out non-healthy states.

Figure 3-5 illustrates an overview of CT, as well as the illustration of geometrical representation in the case of a healthy and faulty motor. In this regard, these transformations help to reduce the number of electrical signals to make the observations of each healthy state easier in two-dimensional representations. At the same time, it can be describing a TPIM operating phenomenon [9].

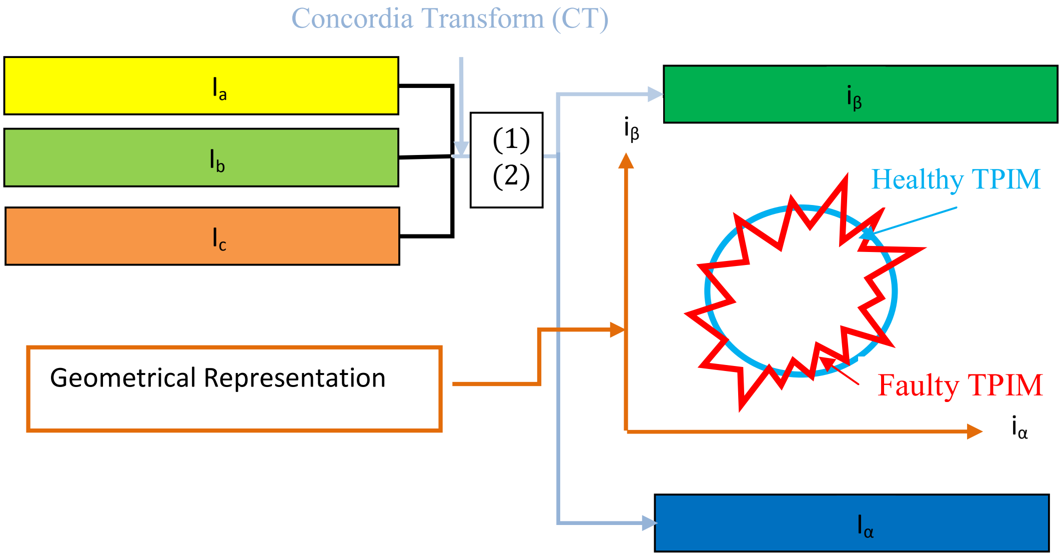


Figure 3-5 CT and its corresponding geometrical representation for healthy and faulty TPIM

Electrical signals in Concordia vector components ($i_{\alpha,\beta}$, $v_{\alpha,\beta}$) are a function of the main phase variables of currents ($i_{a,\,b,c}$) and voltages ($v_{a,\,b,c}$), respectively, given by:

$$w_\alpha = \sqrt{\frac{3}{2}}\mathrm{i,v_a} - \frac{1}{\sqrt{6}}\mathrm{i,v_b} - \frac{1}{\sqrt{6}}\mathrm{i,v_c} \qquad (1)$$

$$w_\beta = \frac{1}{\sqrt{2}}\mathrm{i,v_b} - \frac{1}{\sqrt{2}}\mathrm{i,v_c} \qquad (2)$$

Where, W stands for the current (i) or the voltage (v) in Concordia axis.

In the next, we will present the geometrical representation of CT of three-phase current signals in the case of the induction motor with bearing wears, one broken rotor bar, and three broken rotor bars compared with the healthy state of the induction motor for two different sources of supply such as network supply (power supply) and inverter supply, with two load levels (0% and 100 % of rated load).

d. In case of power supply

Figure 3-6 presents the current vector of CT in case of bearing wear. Which, there is a clear difference between the two health states, healthy motor and motor with fault. But, a big difference in no-load level (Figure3-6.a) compared to full load level (Figure 3-6.b).

Figure 3-7 presents the current vector of CT in case of one broken rotor bar. Which, there is a clear difference between the two health states, healthy motor and motor with a fault in no-load level (Figure 3-7.a) than full load level (Figure 3-7.b), which presents a low difference.

Figure 3-8 presents the current vector of CT in the case of three broken rotor bars. Which, there is a clear difference between the two health states, healthy motor and motor with a fault in no-load level (Figure 3-8.a), but lower than the case of one broken rotor bar in Figure 3-7.a and than full load level (Figure 3-7.b), which present a lower difference.

The main difference between the severity level of broken rotor bars presents in thickness, which is bigger in the case of three broken rotor bars than one broken bar.

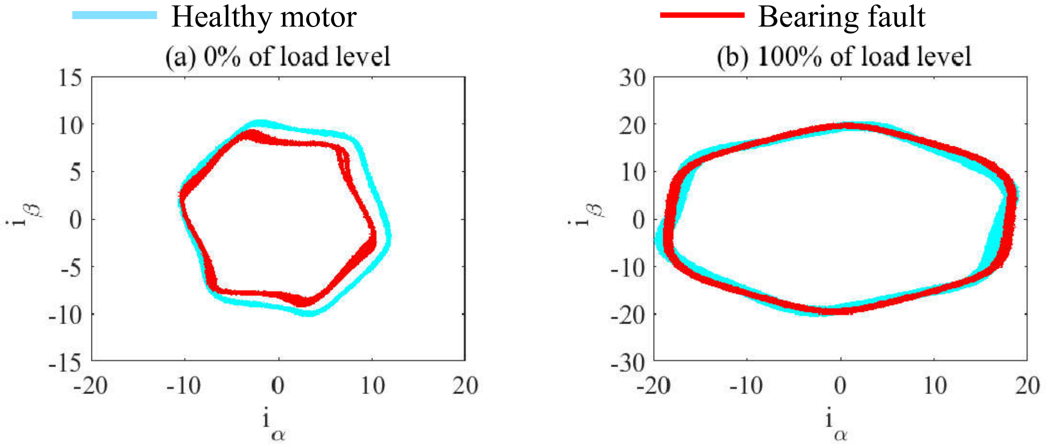


Figure 3-6 Current vector of CT presented in case of bearing fault

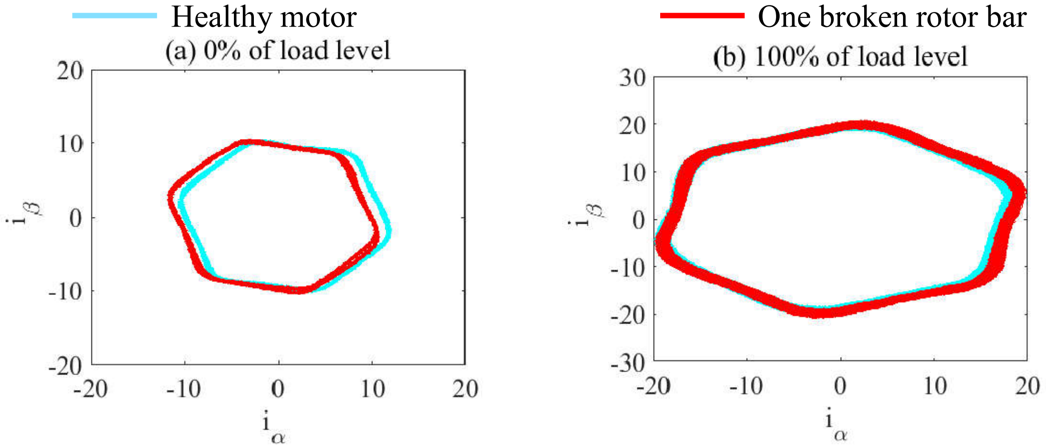


Figure 3-7 Current vector of CT presented in case of one broken bar

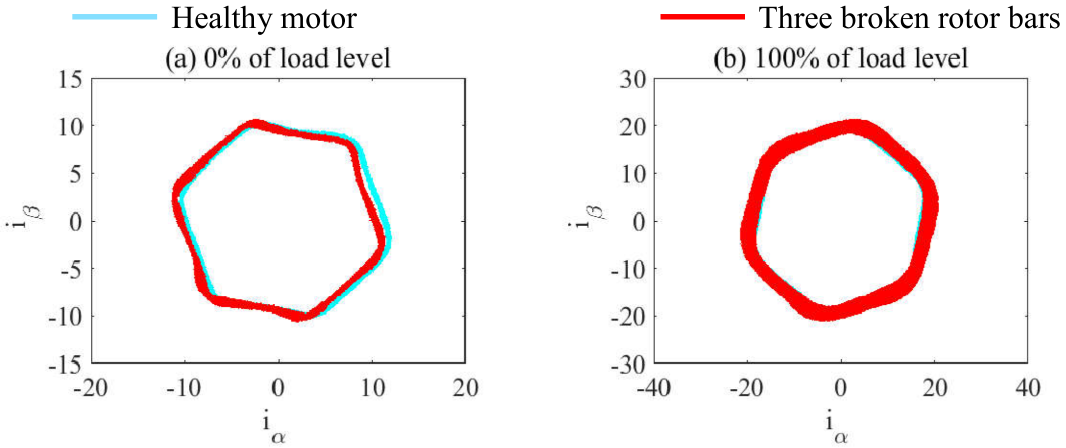


Figure 3-8 Current vector of CT presented in case of three broken bars

e. In case of inverter supply

Figure 3-9 presents the current vector of CT in case of bearing wear. In which, there are low difference between two health states, healthy motor and motor with fault in no-load level (Figure 3-9.a) with a notches in the two boards of sharps, and we could say, there is no-difference in case of full load level (Figure 3-9.b).

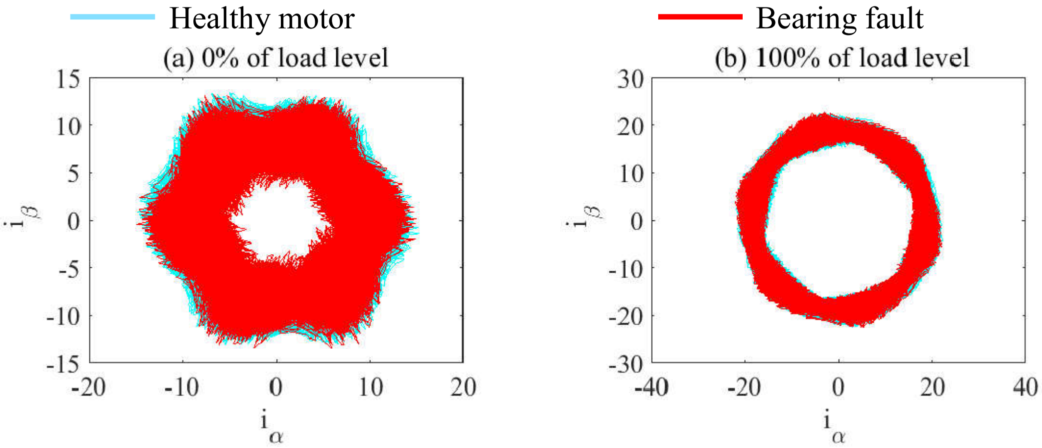


Figure 3-9 Current vector of CT presented in case of bearing fault

Figure 3-10 presents the current vector of CT in case of one broken rotor bar. In which, there is also as the case of bearing wear, a low difference between two health states, healthy motor and motor with fault in no-load level (Figure 3-10.a) with a notches in the two boards of sharps, and we could also say , there is no-difference in case of full load level (Figure 3-10.b).

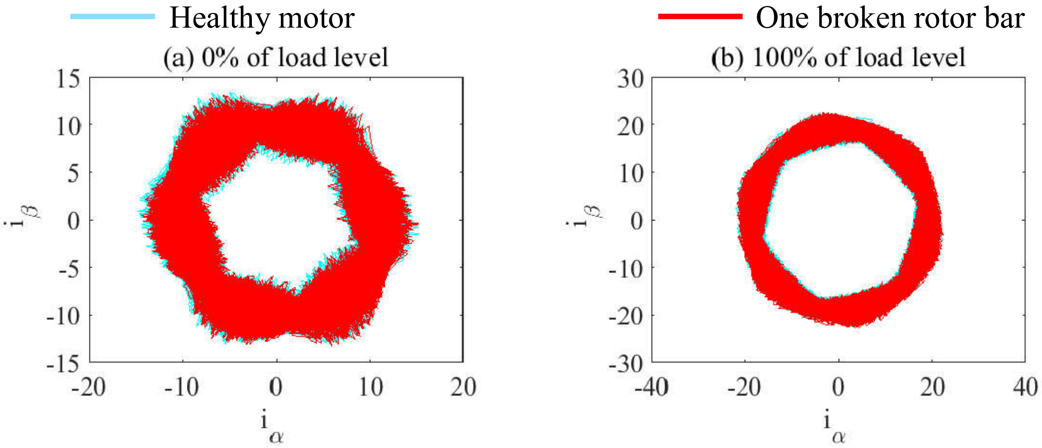


Figure 3-10 Current vector of CT presented in case of one broken bar

Figure 3-11 presents the current vector of CT in the case of three broken rotor bars. Which, there is also the case of bearing wear and one broken rotor bar, a low difference between two health states, healthy motor and motor with the fault in no-load level (Figure 3-11.a) with notches in the two boards of sharps, and we could also say, there is no difference in case of full load level (Figure 3-11.b).

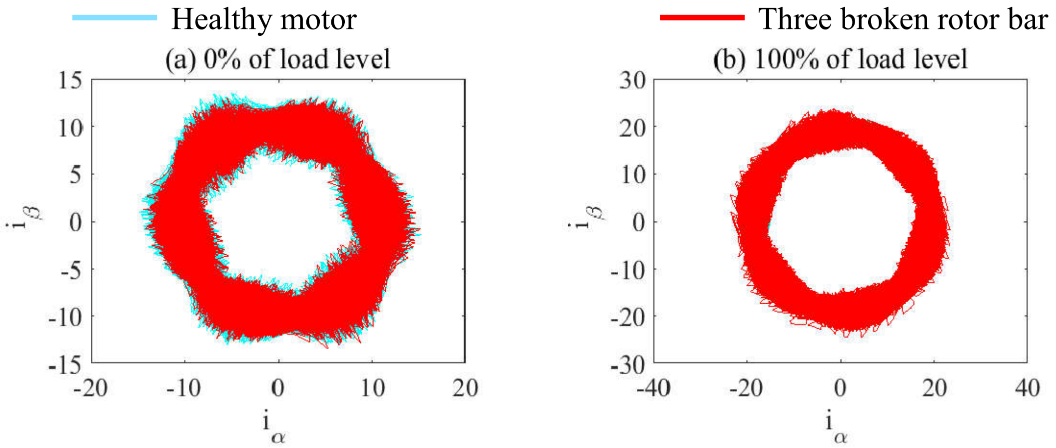


Figure 3-11 Current vector of CT presented in case of three broken bars

In comparison, to the results of the two supply cases, the CT is more convenient to apply and gives better results in the case of power supply than inverter supply. Owing to the high background level of noise that exists in the electrical signal provided by the inverter that returns to the switch mechanism in this device. As a result, Concordia transformation requires a good signal quality to provide better results [10] or using a filter to remove noise in the signal as in [11]. And, it is much more convenient to give better results for fault detection with low load levels. In literature, researchers use Fuzzy logic to make a decision about the state of the induction motor [9, 12].

3.2.2.2. Fast Fourier Transform (FFT)

This Technique is based on frequency analysis. And it is the classical and the most popular one in the area of fault detection and diagnostic of electrical rotating machines by the name of motor current signal analysis (MCSA). This is a transformation of a signal from its temporal domain into its corresponding frequency domain. In which, the diagnosticians used specific frequencies related to each fault that can occur in the machine. In our case induction motor with:

a. Broken rotor bar f_r have the following equation :

$$f_r = f_{s1}(1 \pm 2\mathrm{kS_p}) \tag{3.1}$$

b. Equation of bearing defect parts:

There are four localised part in the ball bearing that have the following name:

- inner race (f_{id});
- outer race (f_{od});
- cage (f_{cd});
- ball (f_{bd});

Their frequencies related to fault equation of each part is given by:

$$f_{id} = \frac{\mathrm{n}}{2} f_{\mathrm{rm}} \left(1 + \frac{\mathrm{bd}}{\mathrm{pd}} \cos(\gamma)\right) \tag{3.2}$$

$$f_{od} = \frac{\mathrm{n}}{2} f_{\mathrm{rm}} \left(1 - \frac{\mathrm{bd}}{\mathrm{pd}} \cos(\gamma)\right) \tag{3.3}$$

$$f_{bd} = \frac{\mathrm{bd}}{2\mathrm{pd}} f_{\mathrm{rm}} \left(1 - \left(\frac{\mathrm{bd}\ \cos(\gamma)}{\mathrm{pd}}\right)^2\right) \tag{3.4}$$

$$f_{cd} = \frac{1}{2} f_{\mathrm{rm}} \left(1 - \frac{\mathrm{bd}}{\mathrm{pd}} \cos(\gamma)\right) \tag{3.5}$$

Where, k=1,2,3,. . . , S_p is the slip, f_{s1} is the supply frequency, f_{rm} is the mechanical rotational frequency, n is the number of balls and γ is the angle of contact. These four defects depend on the geometrical characteristics of the bearing as shown in Figure 3-12.

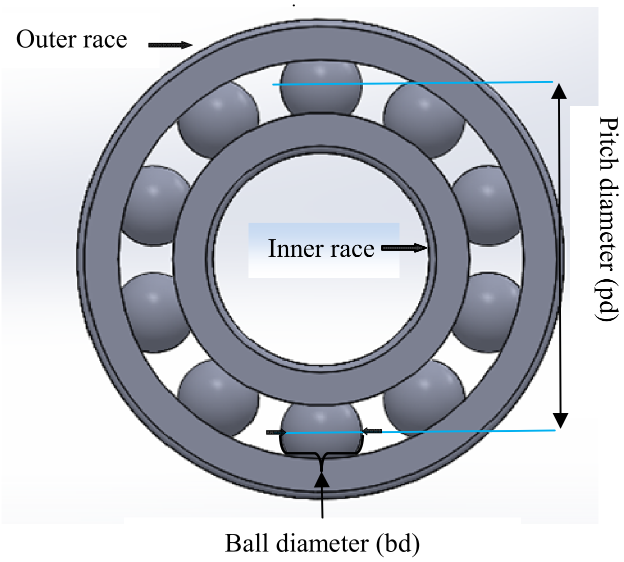


Figure 3-12 Geometrical parameters used to identify bearing faults

In the next of this phase, we illustrate the spectral analysis of the studied faults, as well as their signature if they exist on the spectre.

f. In case of power supply

Figure 3-13 presents a spectre analysis of the current signal i_a in the case of the healthy and faulty motor with bearing wear in no-load (Figure 3-13.a) and full load levels (Figure 3-13.b). the difference in the two states for the two load levels resides in the second, third, fifth and seventh order of harmonic to the fundamental. In addition to that, there are two inter harmonics, such as 25 and 75.

Noted that:

There is no-specific harmonic or frequency characteristic of generalized bearing fault (FCGBF) used to detect this type of fault. In our case, bearing wear [14-17].

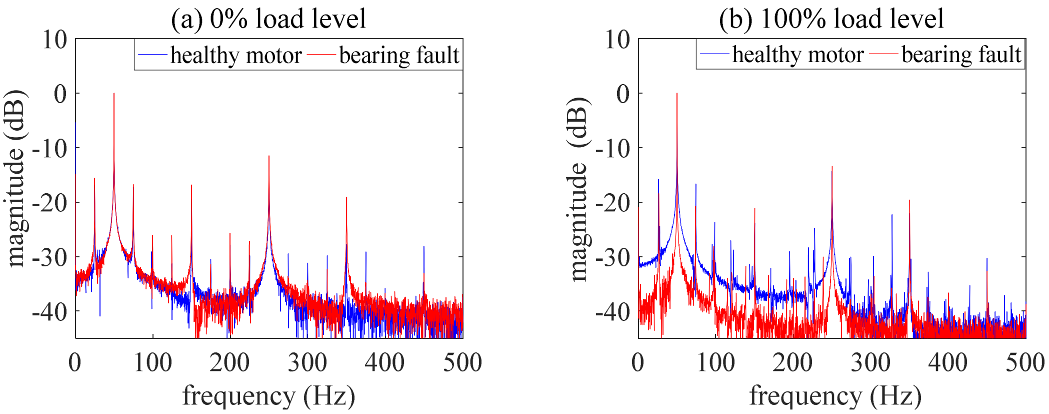


Figure 3-13 FFT applied on stator currant in case of bearing fault

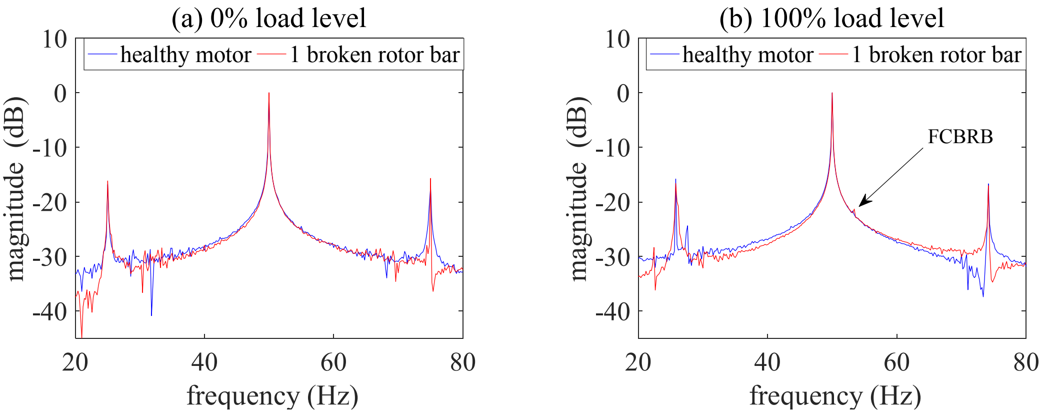


Figure 3-14 FFT applied on stator currant in case of one broken rotor

Figure 3-14 presents a spectre analysis of the current signal i_a in the case of the healthy and faulty motor with one broken rotor bar in no-load (Figure 3-14.a) and full load levels (Figure 3-14.b). There is only one peak on the left of the fundamental frequency with little amplitude related to the frequency characteristic of broken rotor bar (FCBRB) in full load level.

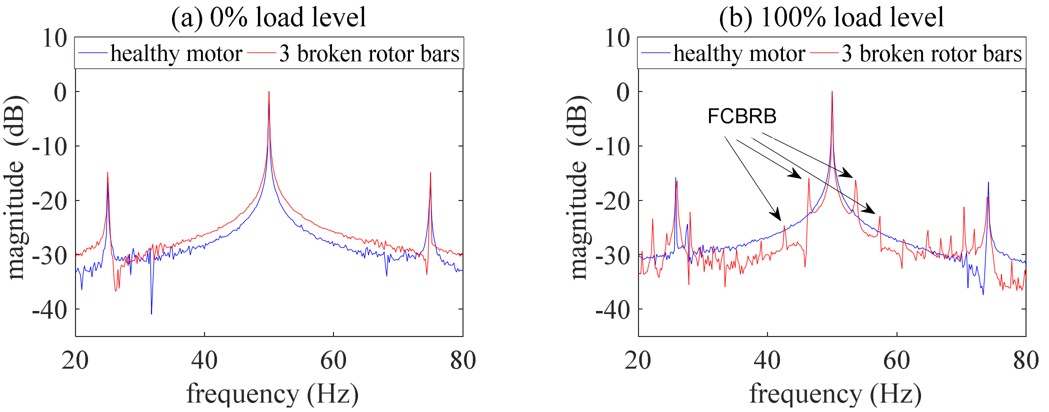


Figure 3-15 FFT applied on stator currant in case of three broken rotor bars

Figure 3-16 presents a spectre analysis of the current signal i_a in the case of the healthy and faulty motor with bearing wear in no-load (Figure 3-16.a) and full load levels (Figure 3-16.b). the difference in the two states for the two load levels resides in the third, fifth and seventh order of harmonic to the fundamental as the case in power supply (Figure 3-9). In addition to that, there is the same impact of inverter exists also on spectral analysis as in Concordia transform that is higher in no-load level compared to full load level.

g. *In case of inverter supply*

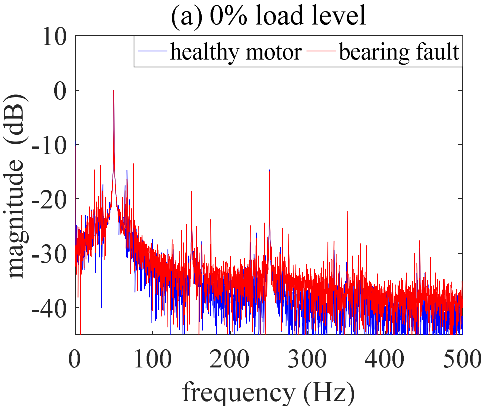


Figure 3-16 FFT applied on stator currant in case of bearing fault

Figure 3-16 presents a spectre analysis of the current signal i_a in the case of the healthy and faulty motor with bearing wear in no-load (Figure 3-16.a) and full load levels (Figure 3-16.b). The difference in the two states for the two load levels resides in the third, fifth and seventh order of harmonic to the fundamental as the case in power supply (Figure 3-9). In addition to that, there is the same impact of inverter exists also on spectral analysis as in Concordia transform that is higher in no-load level compared to full load level.

Figure 3-17 presents a spectre analysis of the current signal ia in the case of a healthy and faulty motor with one broken bar in no-load (Figure 3-17.a) and full load levels (Figure 3-17.b). There are no peaks related to a fault in this spectral analysis due to the high level of noise in the signal.

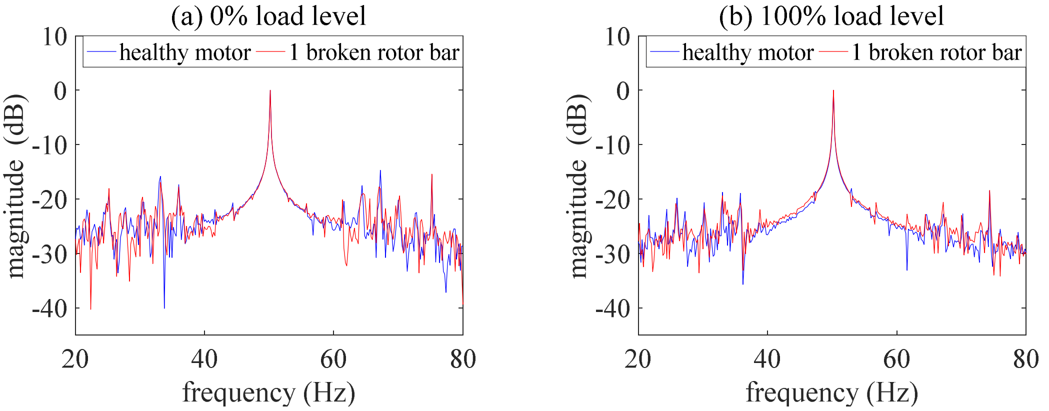


Figure 3-17 FFT applied on stator currant in case of one broken rotor

Figure 3-18 presents a spectre analysis of the current signal i_a in the case of a healthy and faulty motor with three broken bars in no-load (Figure 3-18.a) and full load levels (Figure 18.b). There are only two clear peaks related to FCBRB close to the fundamental harmonic in the spectral analysis of full. And the other peaks are seen before (see Figure 3-15.b) are hidden by the high level of noise in the signal. There is a clear difference in Figure 3-15 in the case of power supply compared to Figure 3-18 in the case of inverter supply.

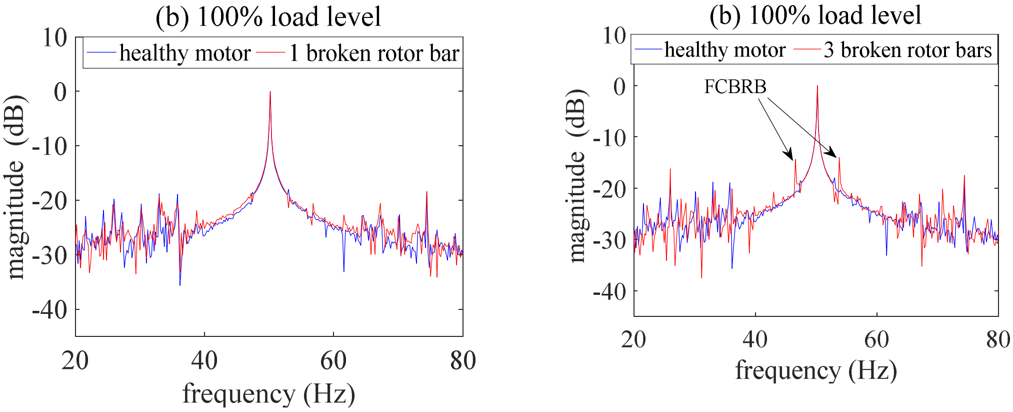


Figure 3-18 FFT applied on stator currant in case of three broken rotor bars

From the results presented about the spectral analysis using FFT. Where, it is more convenient to use in case of power supply than inverter supply, with high loading levels than low loading levels, and with broken rotor bar than bearing wear (generalized bearing fault).

In addition to that, the reference [18] has been mentioned same other limitations as:

- Leakage: the supply component is usually several orders of magnitude greater than the fault components. In case of the fault components appear close to the mains they can be buried by the leakage of the supply component.
- Oscillating loads: in some case, oscillating loads generate harmonic components that can be confused with fault components, leading a wrong diagnosis.
- Steady state regime: the main drawback is that this analysis is only suitable for IM working under steady state conditions.

Furthermore, the interesting reference [19] also has been a good discussion of the limitations and the alternative solutions given by researchers to pass these limitations related to FFT. The best solution to analyse and identify the frequency related to faults, in this case, is the use of the time-frequency technique [20].

The application of CT and FFT depended on the good quality of the signal to give better results, which this case not available when the inverter uses to supply the induction motor as shown in the above results. These limitations lead us to propose an alternative method that can be used to overcome these limitations. Which, it is based on the use of combined temporal features.

3.2.3. Proposed strategy for fault detection et diagnostic

The advantage of CT consists in their better performance in the case of power supply with low load levels using geometrical representation for fault detection and bad discrimination of fault in the case of inverter supply. However, our proposed strategy of FDD used in this thesis repose on combined statistical (temporal) features extracted from currents or voltages of CT instead of geometrical representation, and FFT transform which is not effective in identifier a generalized bearing fault as clarified above.

In this regard, to implement our proposed method, it needs firstly to divide a whole measured current (or voltage) Concordia signal into N number of segments as shown in Figure 3-19.

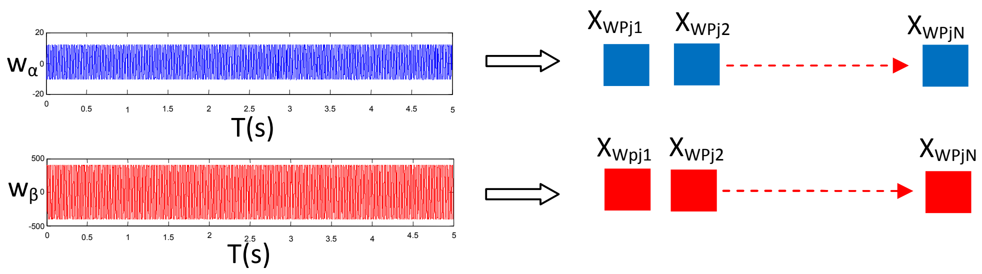


Figure 3-19 Divided the whole Concordia signals into N segments

- First temporal features is standard deviation (σ_p) to compute each segment from the segmented signal;
- Second skewness value (skew) of the whole signal;

Their mathematical equations are given below as:

$$\sigma_p\left(X_{wp_{jN}}\right) = \left[\frac{1}{q-1}\sum_{\tau=1}^{q}(x(\tau)-\bar{x})^2\right]^{\frac{1}{2}} \tag{3.6}$$

Where, q is the total number of samples in each segment of the signal W, and $\bar{x}$ is the mean value of all the samples $x(\tau)$ in the same segment $X_{wp_{jN}}$, defined as:

$$\bar{x} = \frac{1}{q}\sum_{\tau}^{q} x(\tau) \tag{3.7}$$

$$skew\,(W_j) = \frac{1}{(Q-1)\sigma_{W_j}{}^3}\sum_{\tau=1}^{Q}\left(x(\tau)-\overline{W_j}\right)^3 \tag{3.8}$$

Where, Q is the total number of samples in the signal, σ_{W_j} and $\overline{W_j}$ is standard deviation and mean of the whole signal, respectively.

Finally, the proposed health indicator (Hind) is a multiplication of standard deviation (3.6) with skewness (3.8), as illustrate in Equation (3.9):

$$Hind = \mathrm{skew}(w_j) * \left(\sigma_p\left(X_{wp_{jN}}\right)\right)^3 \tag{3.9}$$

This proposed method based essentially on classifying N observations denoted by ($ind_{w\alpha}$; $ind_{w\beta}$) into several classes Ω_C. Where, C is included in [1,..., N]. Each observation here is characterized by a vector including two health indicators corresponding to the two-current or voltage signals in Concordia axis. As a result, a health matrix (3.10) is built from these vectors in order to be used it in the next step of FDD.

$$health\ matrix = \begin{bmatrix} \mathrm{ind}_{w_{\alpha 1}} & \mathrm{ind}_{w_{\beta 1}} \\ \mathrm{ind}_{w_{\alpha 2}} & \mathrm{ind}_{w_{\beta 2}} \\ \vdots & \vdots \\ \mathrm{ind}_{w_{\alpha n}} & \mathrm{ind}_{w_{\beta n}} \end{bmatrix} \qquad (3.10)$$

3.2.3.1. Fault detection and diagnostic of different faults

In this phase, we use two artificial intelligent algorithms, k-mean clustering in order to detect different fault classes, and k-nearest neighbours (KNN) to identify and classify in the same time different health states.

h. Fault detection by mean of k-mean clustering

This step aims to check the ability of the proposed Hind to separate each existed health state in the space domain using k-mean clustering algorithm. Which, it is an unsupervised procedure that applied to generate clusters or groups from data set including different health states [21]. It is based on partitioning each feature vectors $x_i = \left(\mathrm{ind}_{w_{\alpha i}}, \mathrm{ind}_{w_{\beta i}}\right)$ from the health matrix (10) into a specific number k of clusters designating its affiliation as illustrated in Figure 3-21 in the case of no load health matrix.

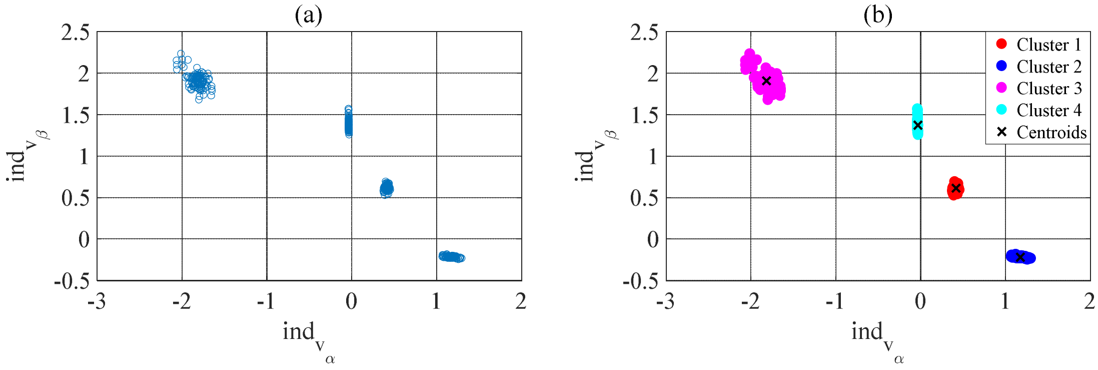


Figure 3-20 Principle of k-mean clustering: (a) health matrix in case of no-load and (b) clustering result of (a)

This can be done by decreasing the sum of squares within-cluster [22-25]; *that is*, it finds the centres cluster {μ_e, e=1,2,…, k}, that reduce (M) as follow [23] :

$$M = \sum_{e=1}^{k} T_e \tag{3.11}$$

Where, Te the within-cluster sum of squares for cluster e is reformulating:

$$T_e = \sum_{i=1}^{n} u_{ei} \left| x_i - \mu_e \right|^2 \tag{3.12}$$

In which $u_{ei}=1$ if x_i is in the cluster *e* (of size $n_i = \sum_{i=1}^{h} u_{ei}$) and zero otherwise,$\mu_e$ is the average of cluster *e* and h is the number of feature vectors of cluster *e*.

$$\mu_e = \frac{1}{ni} \sum_{i=1}^{n} u_{ei} x_i \tag{3.13}$$

i. Fault diagnostic and classification by mean of k-Nearest Neighbour classifier (K-NN)

Machine Learning (ML) classifiers (artificial intelligent clasifiers) have greatly enhanced the maintenance strategies for fault detection and diagnostics by automatic system health assessment. However, the efficiency of such models is evaluated by classifying the different health states of the system [26]. The presented work in [25] carries out a comparative study between different classifier models such as k-Nearest Neighbour, Naive Bayes (NB), Artificial Neural Network (ANN) and Support Vector Machine (SVM). According to their results, K-NN classifier presents the best classification accuracy with less computational execution time and fewer tunning parameters. In [27], a comprehensive review of fault diagnostics in rotating machinery using AI algorithms is presented, which mentioned that K-NN is one of the popular diagnostic tool widely applied in different applications due to its simplicity of implementation and less complexity, which has proven its efficiency for fault diagnosis of rotating machinery in several works[7, 22, 25, 27-30]. Due to these advantages, K-NN is a suitable classifier for the present work due to its performance and flexibility for our proposed methodology.

K-NN is a supervised Machine Learning which needs two essential phases to classify each state in its corresponding class, the first is the training dataset in which all states Ω_C are considered as known, and the testing unknown states for the second phase. To do that, we should divide the health matrix (3.10) randomly into two matrices of the same dimension (N, P), in our case, training matrix A and testing matrix B with:

$$B = \left\{ \left(\mathrm{ind}_{w_{\alpha 1}}, \mathrm{ind}_{w_{\beta 1}} \right), \left(\mathrm{ind}_{w_{\alpha 2}}, \mathrm{ind}_{w_{\beta 2}} \right), \ldots, \left(\mathrm{ind}_{w_{\alpha n}}, \mathrm{ind}_{w_{\beta n}} \right) \right\} \tag{3.14}$$

The classification of unknown xi feature vector from B using K-NN algorithm is based on the following rules: first, find the K nearest neighbours of x_i among all y_i vector features existing in the training matrix A. Second, compute the number of these features based on the class of K neighbours. The similarity of x_i and every neighbour feature is the result of the neighbour features in a specific class. The classification decision of each feature in matrix B depends on majority number of volt obtained from this result as illustrated in Figure 3-21, this is expressed as [28]:

$$f(B,\Omega_C) = \sum_{A\in KNN} \mathrm{sim}(B,A)\, \mathrm{Y}(A,\Omega_C) \tag{3.15}$$

where B is the testing data; $f(B,\Omega_C)$ is the result of the nominee class Ω_C with respect to B; sim(B,A) is the similarity of each feature in B and the feature of training data A; $\mathrm{Y}(A,\Omega_C) \in \{1,2,3,4\}$ is the class number of the training data A with respect to Ω_C.

The searching of K-nearest neighbours of x_i in B and other features in A depends on the measure of the distance between them. There are many metrics to measure this distance, such as Euclidean distance (3.16), Minkowski (3.17), etc [22, 25]. Further information about this algorithm is given in [28].

$$D(x,y) = \left(\sum_{i=1}^{m} |x_i - y_i|^2\right)^{\frac{1}{2}} \tag{3.16}$$

$$D(x,y) = \left(\sum_{i=1}^{m} |x_i - y_i|^r\right)^{\frac{1}{r}} \tag{3.17}$$

Where, x and y are the feature vectors obtained from the testing matrix B and the training matrix A, respectively, and m is the dimension of the feature vector.

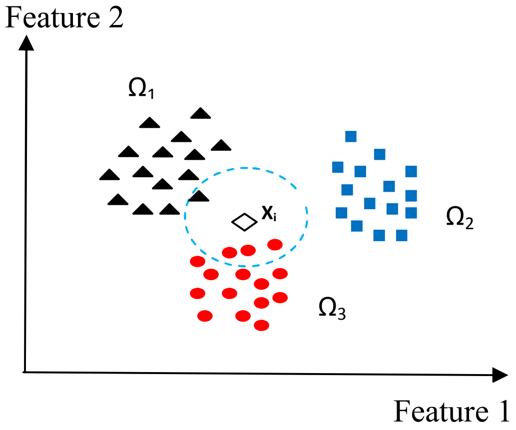


Figure 3-21 K-Nearest-Neighbour classification method

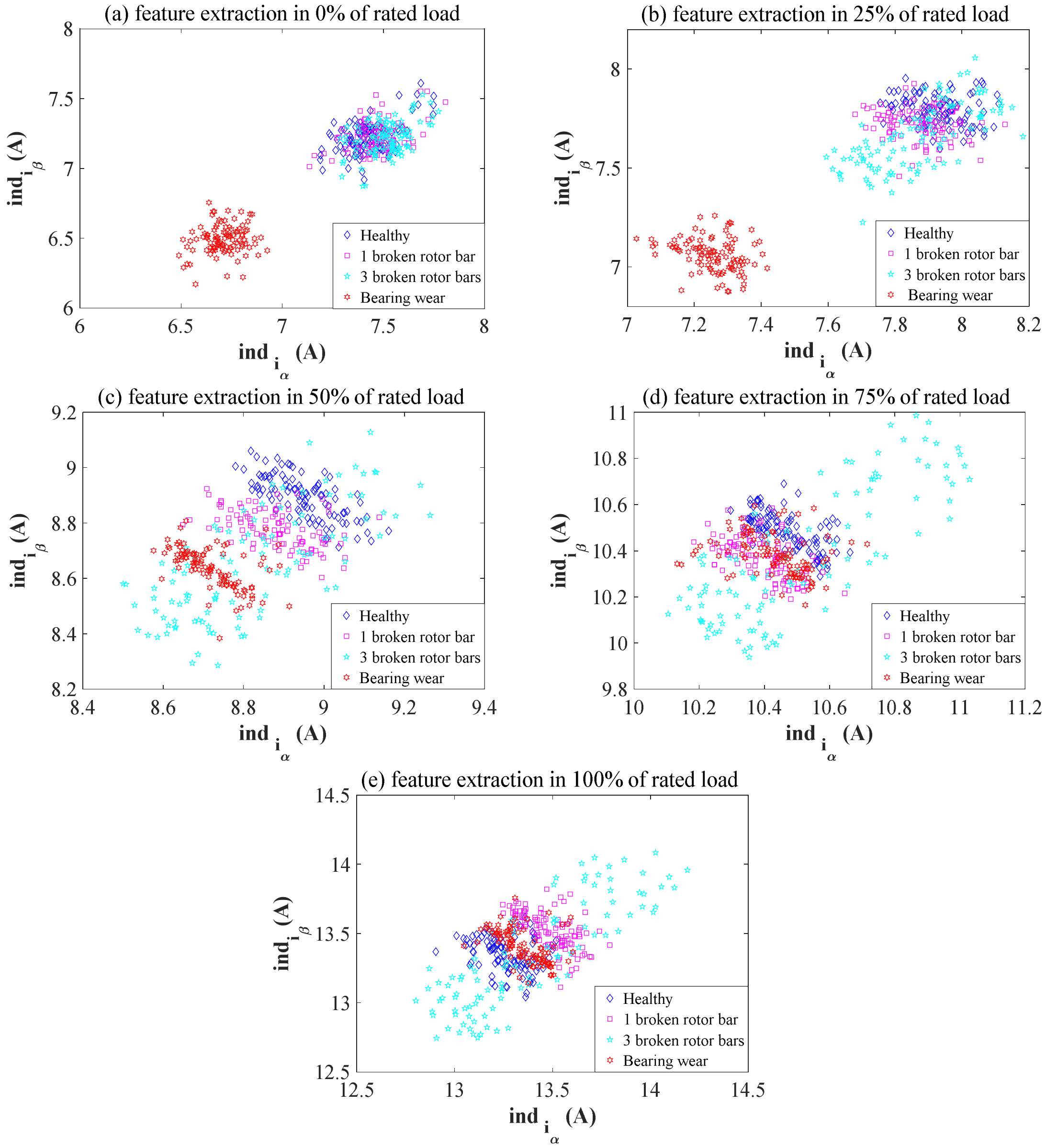
3.2.4. Result and discussion

3.2.4.1. Feature extraction

At this third stage, we present our obtained results in five load conditions, such as 0%, (25%), (50%), (75%) and (100 %) of rated load that include traditional feature called standard deviation, in addition to show its combination with skewness as explained above in case of:

a. Current signals of CT:

Figure 3-22 shows the results of extract the feature called standard deviation from two axes of Concordia current signals. Obviously, the plots show an overlap between the features of different motor's states. Specially, the case of electrical faults that have an overlap for all loading modes and in the load mode up to 50% of rated load for all health states. The case of mechanical fault (bearing wear) present a clear separation our their features in low load conditions (< 50% of rated load) using Concordia current signals, which means it can easily detect this type of fault under the low and no-load conditions without using complicated techniques as employed in [15, 16, 17]. Further information can be remarked that the scatter plot of different loading modes shows a clear severity level between one broken rotor bar and three broken rotor bars as geometrical representation in case of power supply, which appears in the dispersion factor between the features within the class of three broken rotor bars compared to one broken bar. In which, it increases when the loading mode increased.


(a) feature extraction in 0% of rated load

(b) feature extraction in 25% of rated load

(c) feature extraction in 50% of rated load

(d) feature extraction in 75% of rated load

(e) feature extraction in 100% of rated load

Figure 3-22 Standard deviation extracted from Concordia currents for five load conditions

The combination of this two temporal features in Figure 3-23 that illustrates the obtained results for all loading mode after applying the proposed method above. In this Figure, for each condition of five load levels, one can see the separation between features of different health states is high, and a low dispersion within the same health state of each classes of the three-phase induction motor health states compared to only use one temporal feature, as seen in Figure 3-22 . This combination of temporal features can reveal also the degree of severity that appears in the space occupied by one broken rotor which it is lower than that occupied by the three broken rotor bars (Figure3-23). This can be helpful in determining the severity level by using the proposed method.

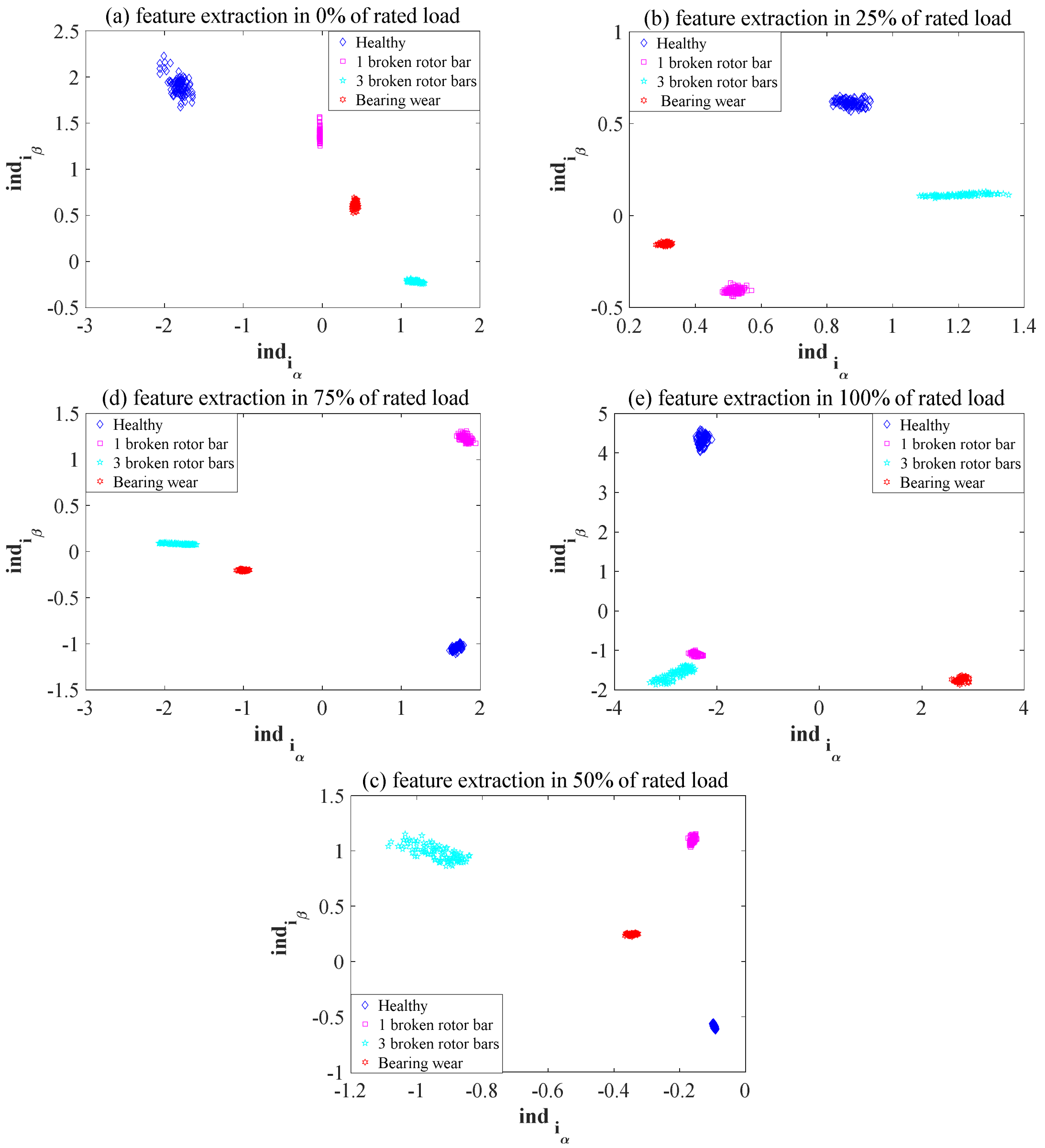


Figure 3-23 Combined statistical features extracted from Concordia currents for five load conditions

b. Voltage signals of Concordia Transform:

This method can also be applied to Concordia voltage signals. in this type of signal we limited our presentation in temporal feature for standard deviation with two loading mode 0% and 25% of rated load as illustrate in Figure 3-23 that return to give the same observation. In which, all features for each health state are mixed together. Furthermore, this Figure cannot show the degree of severity as the case of standard deviation extracted from Concordia courant signals in Figure 3-22**.**

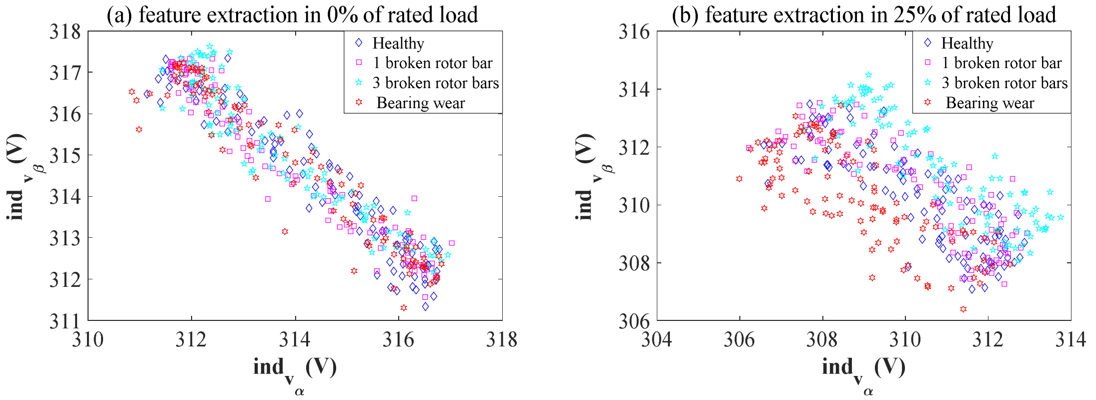
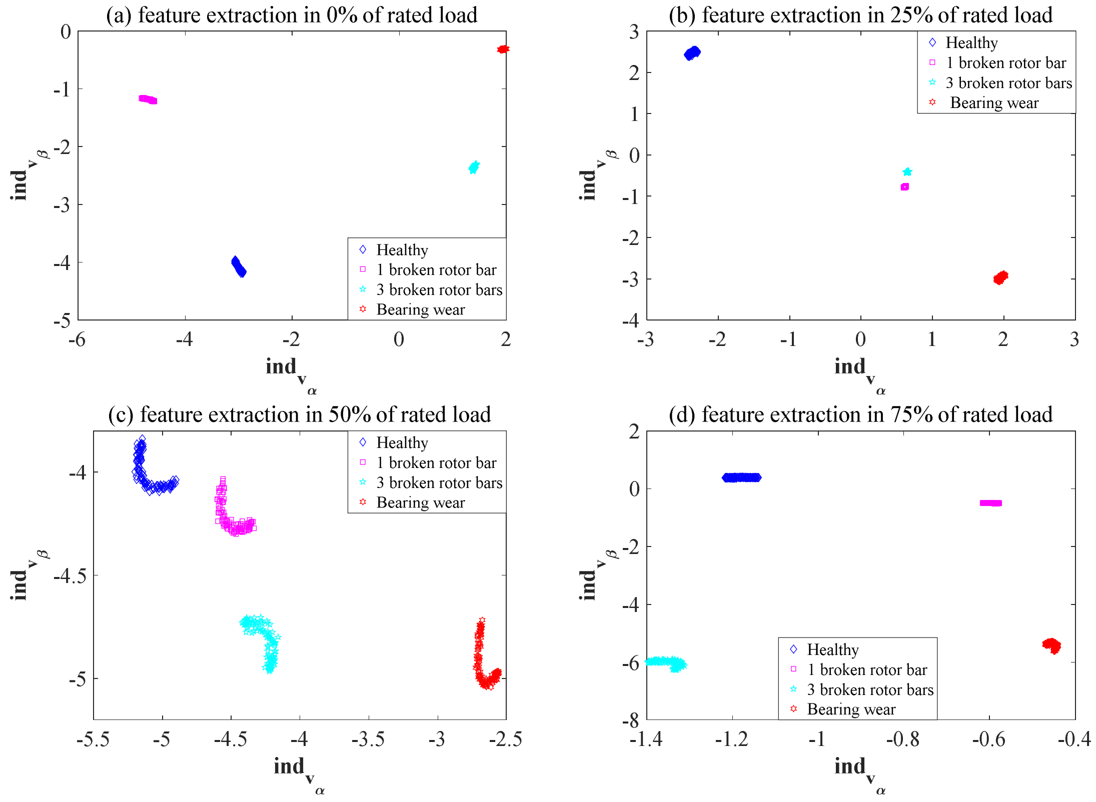


Figure 3-24 Standard deviation extracted from Concordia voltages for two load conditions

However, the proposed method can be also applied on this type of signal (Concordia voltage signals) as seen in Figure 3-25 with clear separation between different health states of induction motor.



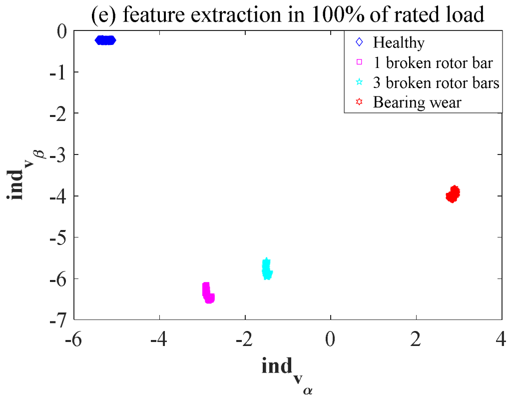
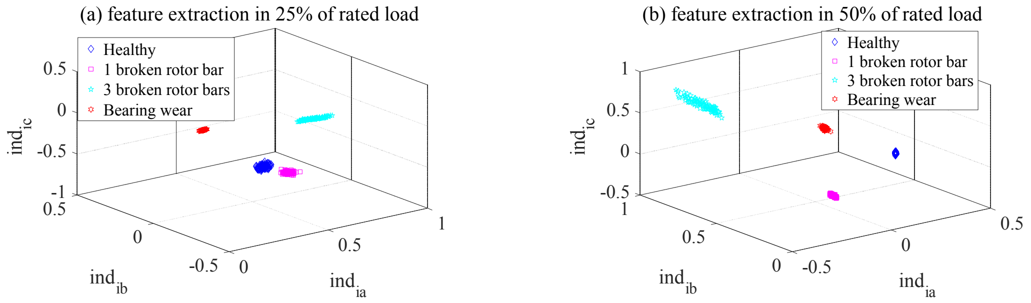

(e) feature extraction in 100% of rated load

Figure 3-25 Combined statistical features extracted from Concordia voltage signals for five load conditions

As a conclusion of the step of feature extraction, Concordia current signals show interesting results in case standard deviation for the analysis of the different conditions studied in this work. Especially, the mechanical fault (generalized bearing fault) compared to the one's extraction from Concordia voltage signals. This fact explains why the majority of published papers analyse stator current instead voltage signal.

The direct application of the methodology proposed in the third section on three-phase current signals without making a Concordia transform display in Figure 10, shows the scatter plots of the combined statistical features extracted from three-phase current signals under various load conditions. There is a high separation between the different classes for three loads: 25%, 50%, and 100% of the rated load. Nevertheless, there is an exception for 75% of the rated load (see Figure 10c), which has an overlap between the healthy state of the induction motor and the motor with one broken rotor bar. Based on this exception, the proposed health indicator extracted from three-phase currents is less efficient with various load conditions as in the case of two Concordia currents. This is the main aim of using Concordia transform for fault diagnosis. Moreover, Concordia transformation helps to reduce the number of electrical signals to make the observations of each healthy state easier in two-dimensional representations, as seen in Figure 23.


(a) feature extraction in 25% of rated load

(b) feature extraction in 50% of rated load

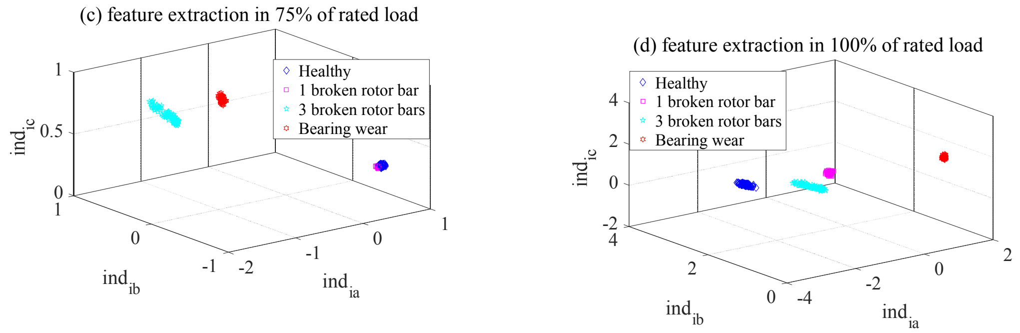


Figure 3-26 Combined statistical features extracted from three phase currents for four load conditions

3.2.4.2. Fault diagnostic and classification using KNN

From the results presented in two Figures 3-23 and 3-25, it is obviously clear that any ML classifiers can provide high results. This means they can be used to identify the studied motor's conditions with high classification accuracy as seen in Table 3-2, the accuracies have reached 100% for various loading conditions and electrical signal types by using each ML classifier in this Table, such as KNN, SVM, Discriminant analysis (DA), and decision tree (DT), which offer the same efficiency for the proposed method of FDD, but with the different time factor, the latter depends on the complexity of the algorithm used by each classifier. For this reason, the most convenient classifier for our case is the one that provided the less execution time to classify the four health states in a three-phase induction motor.

In this context, the Coarse K-NN is the fastest algorithm among all sub-groups of K-NN and different sub-groups of other ML classifiers as illustrated in Table 3-3, which justifies the use of this classifier in the present research paper. Therefore, the results presented in Figures 3-23 and 3-25, and the classification accuracy in Table 3-2 prove the robustness and the efficiency of our proposed method for fault detection and diagnostic of broken rotor bars and bearing wear.

Tableau 3-2 Classification accuracy used ML classifiers in different load conditions and electrical signals

ML classifiers	Accuracy (%) in \ Load condition	0%	25%	50%	75%	100%
KNN, SVM, DT, DA	Concordia currents	100	100	100	100	100
	Concordia voltages	100	100	100	100	100

Tableau 3-3 Computational time taking by different Machine Leanings in the data training phase

Classifier models		Execution time corresponding to each load level (s)					Mean execution time (s)
		0%	25%	50%	75%	100%	
SVM	Coarse gaussian	1.389	1.379	1.367	1.415	1.371	1.384s
	Cubic	2.957	1.437	1.468	1.442	1.436	1.74
	Fine gaussian	1.415	1.373	1.375	1.379	1.396	1.387
	Linear	1.468	1.477	1.437	1.435	1.433	1.45
	Quadratic	1.430	1.485	1.453	1.435	1.438	1.448
	Medium gaussian	1.376	1.387	1.405	1.377	1.370	1.383
k-NN	Coarse	**0.885**	**0.877**	**0.871**	**0.864**	**0.877**	**0.874**
	Cosine	0.906	0.876	0.877	0.871	0.880	0.882
	Cubic	0.877	0.886	0.874	0.883	0.870	0.878
	Fine	0.926	0.900	0.872	0.876	0.922	0.913
	Medium	0.910	0.865	0.881	0.878	0.881	0.883
	Weighted	0.882	0.889	0.891	0.885	0.878	0.885
Decision tree	Simple tree	0.934	0.889	0.895	0.869	0.876	0.892
	Medium tree	0.887	0.864	0.865	0.860	0.918	0.878
	Complextree	0.896	0.868	0.859	0.873	0.898	0.886
Discriminant analysis	Quadratic	1.093	0.927	0.909	0.886	0.897	0.942
	Linear	0.940	0.972	0.965	0.944	0.968	0.957

3.3. Conclusion

The proposed method in this chapter provides the best results compared with the results provided by Concordia representation and fast Fourier transform in the case of inverter supply. This method has the ability to solve the problem caused by a switch in the converter device (inverter) that converts direct currents to alternative currents with a high level of noise. The present method is based on proposed a combination of temporal features such as skewness and standard deviation. This combination provides the best separation between different health induction motor states. For that, any machine learning classifiers could be used to classify various health states. However, the KNN classifier provided less execution time among different machine learning classifiers, which makes it the suitable classifier for our proposed method.

In the next chapter, we will present a prognostic method based on vibration signal, time domain features and machine learning algorithm to predict the remaining useful life (RUL).

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Chapitre 04

Bearing Remaining Useful Life Prediction

4.1. Introduction

FDD of three-phase induction motor based on detecting the change in measurable signal and then identifying the fault. Also in some cases determine the severity level of this fault. In which, the faulty component replace immediately. On the other hand, the prognostic methods aim to detect incipient degradation in the system (a component in this system). Then, start the process of remaining useful life (RUL) prediction of this system (component) and continue this operation with the increased severity of the damage before the failure stage. This operation helps the maintenance engineer to reduce the cost of immediate replacement as well as for systematic maintenance.

Bearings are the major contributor to failures in medium and large three-phase induction motors, also in all types of electrical rotating machines. In this context, we predict the RUL of bearing degradation using also data-driven method. In which, we analyse the vibration signals instead of current signals and employ artificial intelligence named support vector regression (SVR) in order to predict the RUL.

4.2. Proposed flowchart of bearing remaining useful life (RUL) prediction

Figure 4-1 illustrates a different step in the proposed flowchart that has been used to predict the RUL of bearing. In, this flowchart is constituted of six following steps:

1- Data acquisition
2- first time to start prediction (FPT)
3- Signal processing
4- Feature smoothing
5- Feature reduction
6- RUL

4.2.1. Data acquisition

The datasets used here contain two types of different vibration analysis signals, the first one is an axial vibration signal taken from an accelerated ageing platform called PRONOSTIA [1], as seen in Figure 4-2.

PRONOSTIA “is an experimentation platform (see Figure4-2) dedicated to test and validates bearings fault detection, diagnostic and prognostic approaches. This platform has been designed and realized at AS2M1 department of FEMTO-ST2 institute. The main objective of PRONOSTIA is to provide real experimental data that characterize the degradation of ball bearings along their whole operational life (until their total failure). This experimental platform allows conducting bearings' degradations in only few hours, and thus it is possible to get significant number of experiments within a week. PRONOSTIA is composed of three main parts: a rotating part, a degradation generation part (with a radial force applied on the tested bearing) and a measurement part" [1].

From this platform, we take a dataset of two bearings under 4000 (N) of load level and 1800 rev/min of induction motor speed. These two bearings named bearing 1-1 and bearing 1-3.

Figure 4-3 show a defect of the bearing before and after raining this experimental setup (for more information about this platform for interested reader, see the reference [1], which show a fault of multiple kind (all bearing part have a defect).

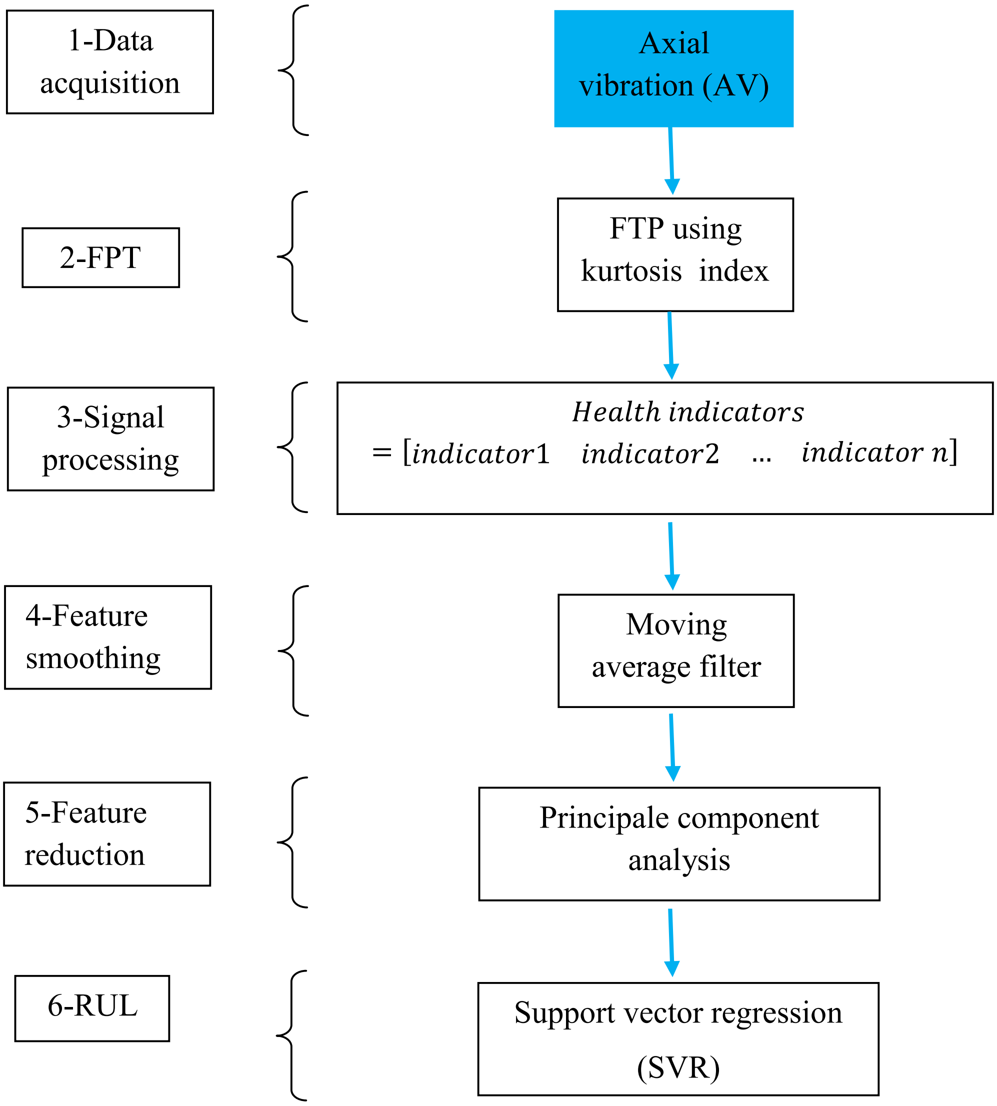


Figure 4-1 Flowchart of the proposed method used to predict the RUL of bearing

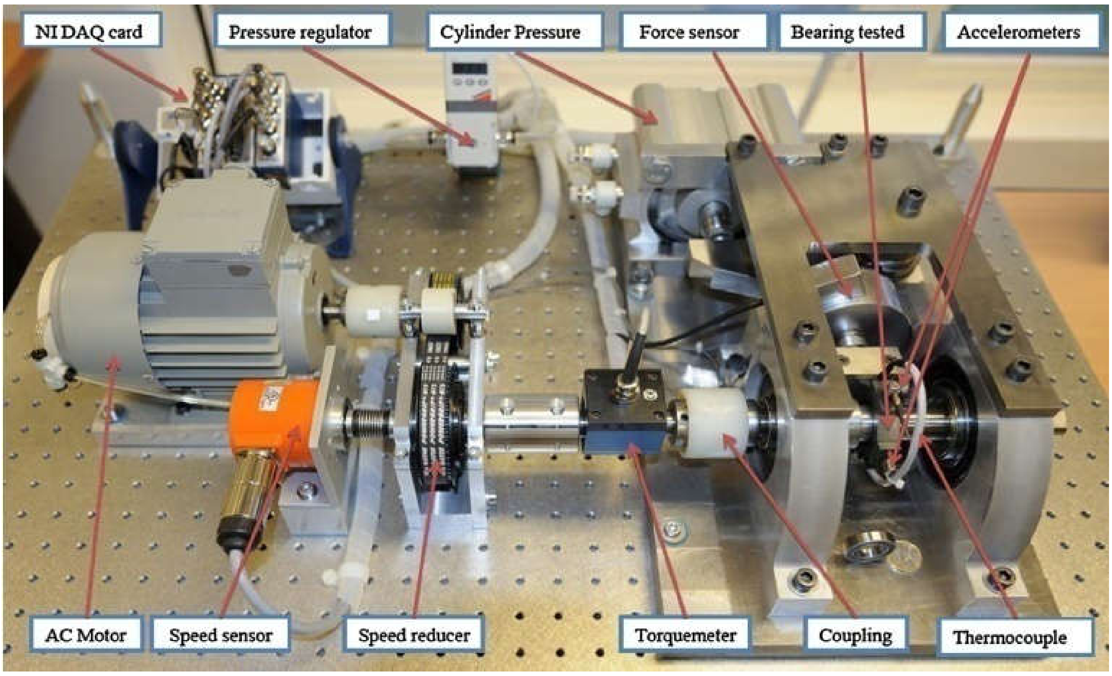


Figure 4-2 Experimental setup used in PRONOSTIA platform [1]

Figure 4-3 Healthy and damage bearings

4.2.2. First time to start prediction (FPT)

When we return to Chapter 01, Figure 1-14 and its explanation, which we represent again in this chapter as a Figure 4-4, we mentioned some information about the concept of first prediction time (FPT), which is the point that separate to the essential stage of bearing life operation [2], normal stage (healthy stage) and degradation stage [2-3]. The question comes to our minds how we can detect it?

The answer to this question is in the reference [2], where the authors detect this point by using the kurtosis indicator as health monitoring in a particular value to start prediction (alarm). Because, the kurtosis indicator is sensitive to an incipient fault, as reported in [2, 4, and 5].

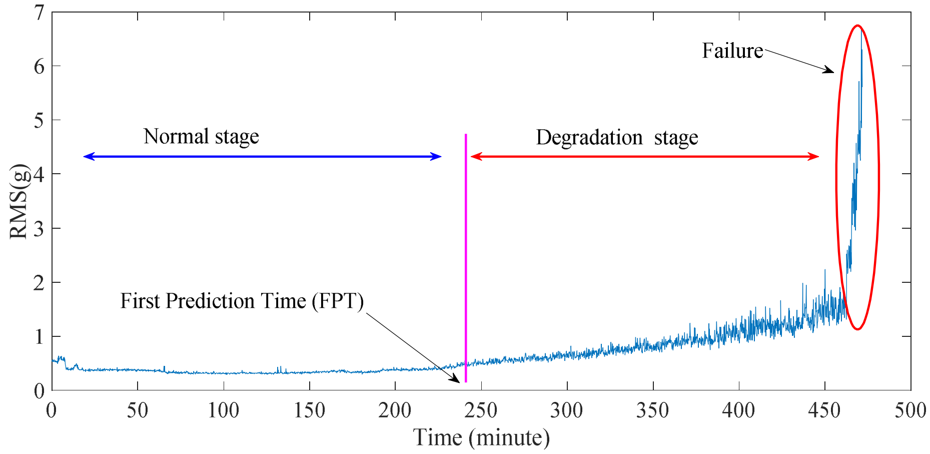


Figure 4-4 Bearing degradation trend used the RMS indicator to predict RUL

The way of used this indicator depending to N. Li et al in [2] as the following algorithm:

1- Calculate a number N_{S11} of kurtosis value S_{11} from the historic measurements of vibration signal in stage of health state of the bearing vibration (in the beginning of measure the vibration signal);

2- Calculate the mean S_5 and the standard deviation S_7 of the obtained N_{S11} of S_{11}.

3- Calculate new value of S_{11} from new vibration measurement, and done a comparison between:

$$|S_{11} - S_5| > 3 * S_7 \qquad (4.1)$$

If the condition (1) is:

- True pass to the following step.
- Faux return the same step until the condition is true;

4- Verify if the third step is true for new S_{11}, if it is not, then return to the third step until this condition is true;

5- If the fourth condition is true. It is an alarm to start prediction of RUL of bearing component;

For well understanding this algorithm, Figure 3-5 illustrate how can detect the FPT via kurtosis index;

Noted that we did some modifications on this algorithm exactly in the fourth step for three successive values of kurtosis to get the best FPT because the authors don’t specify the number of vibration sections used to compute the NS11 value of kurtosis, and for the best detecting of the position FPT.

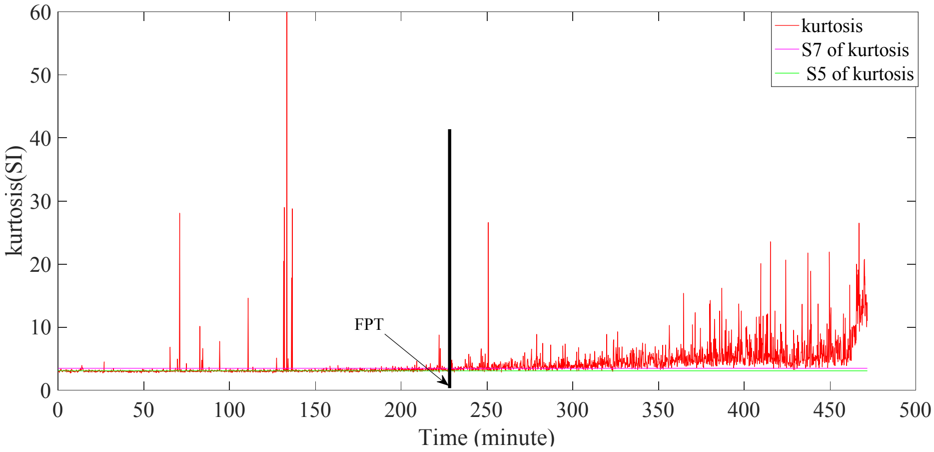


Figure 4-5 The way of detecting the FPT through the kurtosis index

4.2.3. signal processing

In these datasets, no information was given about the result of the final failure belonging to each bearing part, which means a challenging task to predict RUL based on used frequencies related to different bearing faults as a health indicator to detect and follow the growing deficiency in these bearings. Time domain analysis mentioned in the second chapter is considered the simplest solution in comparison with frequency analysis and time-frequency analysis [6] to predict the remaining useful life, which is used for that purpose. The use of multiple features belonging to temporal analysis in Tables 3 and 4 seems to be the best idea to use in our work, in which each feature is sensitive to local or global damage in bearing [4, 7, 8, and 9]. The use of several features offers the advantage to benefit from the advantage of each one of them to predict the RUL and assess the health state of a system [10-11]. This solution is used in either diagnostic approaches or prognostic approaches [4, 6]. Hence, there are other works that used statistical features and or frequency features, but a difference is localised in the feature number and /or the number of signal processing techniques used in their proposed algorithms [4, 6, 10, 12, 13, 14, and 15]. The time domain features selected for our algorithm are: mean (S_5), standard deviation (S_7), Kurtosis (S_{11}), Skewness (S_{12}), Peak to Peak (S_9), RMS (S_8), Energy (S_{14}), Entropy (S_{15}), Shape Factor (CS_1), Crest Factor (CS_3), Impulse Factor (CS_8), and marginal factor CS_4.

4.2.4. Feature smoothing

Due to the nature of the vibration signal, such as non-linear and non-stationary, and in some cases, the level of the noise signal up to the vibration generated by the fault itself as seen in Figure 4-6. For instance, the RMS in Figure 4-4 taken from bearing1-1 has a high level of fluctuation, making it used as a health indicator for RUL less effective. For that purpose, smoothing the obtained features is essential to make the prediction of RUL less complex with lower error entre the estimation RUL and the real one. The filter employed in the proposed method is a moving average filter (MAF) that has the following equation to smooth each selected feature:

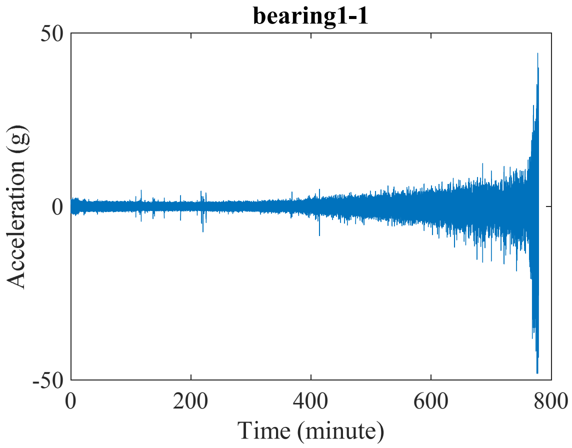


Figure 4-6 Profile of bearing1-1

$$y_n = \frac{x_{n-1}+x_n+x_{n+1}}{3} \tag{4-2}$$

Where, y_n is the smoothed feature and $x_{(n)}$ is the directly extracted feature from the vibration signal, which can be for instance RMS. Which; the smoothing RMS trend and without smoothing one is in Figure 4-7. From this Figure, it is more appropriate to use a smoothing trend than the no-smoothing trend for the RUL of bearing.

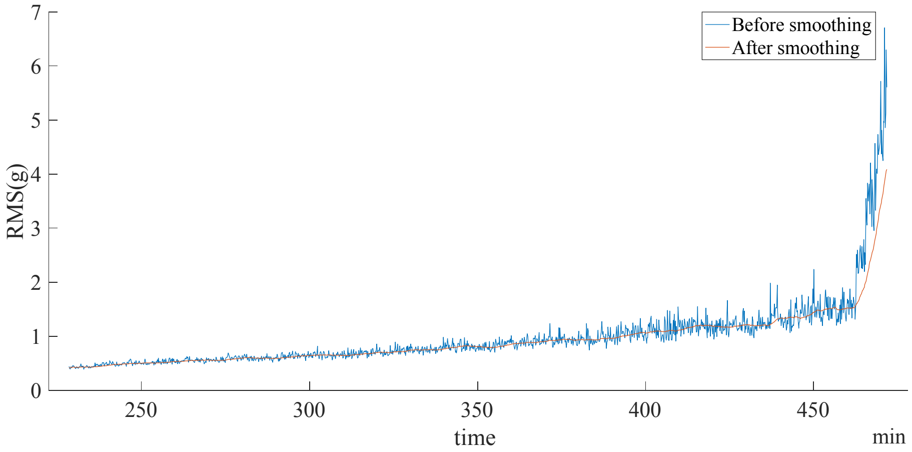


Figure 4-7 Trend pattern used RMS value before and after smoothing

4.2.5. Feature reduction

In our case, there are 12 temporal features, which mean the space of representation is R^{12}. However, in such a case, one needs to apply a technique that reduces the space of representation inferior or equal to R^3 , this technique is called features reduction that allows such transformation. Among these techniques, are principal component analysis (PCA) [16], linear component analysis (LCA), independent component analysis (ICA), etc [17]. In our proposed method, we choose PCA as a features reduction technique, due to its widely used in the area of diagnostic [18] as well as prognostic [19] for feature reduction.

4.2.6. Remaining useful life of bearing using SVR

As mentioned before, the actual research is based more and more on machine learning for classification purposes as presented in Chapter 02 or for regression purposes in order to track the RUL of the critical system (component). In our case, the bearing component, that considers a critical component in all types of rotating machines. Especially, in medium and large induction motors, which contribute up to 40% of failure in these motor.

We use of data-driven method also in this method for RUL based on SVR which is a version of SVM that is used to classify different existing classes in the system [5, 16? 20, 21, 22]. However, the main difference here is to predict the point $\hat{x}_{t+p}$ in the degradation trend from the previous point X_t (see Figure4-8), where:

$$X_t = \{x_t + x_{t-r} + x_{t-2r} + \cdots + x_{t-(n-1)r}\} \quad (4.3)$$

This process continues to predict the next point from the previous point until the failure occurrence as follows:

$$\hat{x}_{t+p} = f(x_t + x_{t-r} + x_{t-2r} + \cdots + x_{t-(n-1)r}) = f(X_t) \quad (4.4)$$

And use each gotten point in the predicted trend to predict the corresponding remaining useful time (RUL).

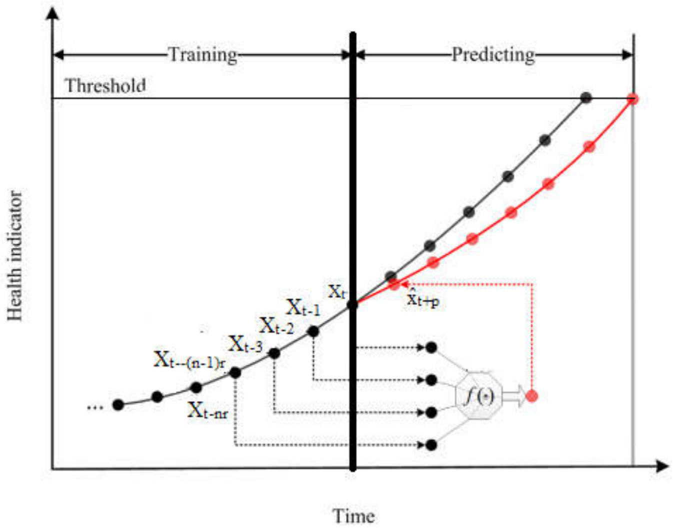
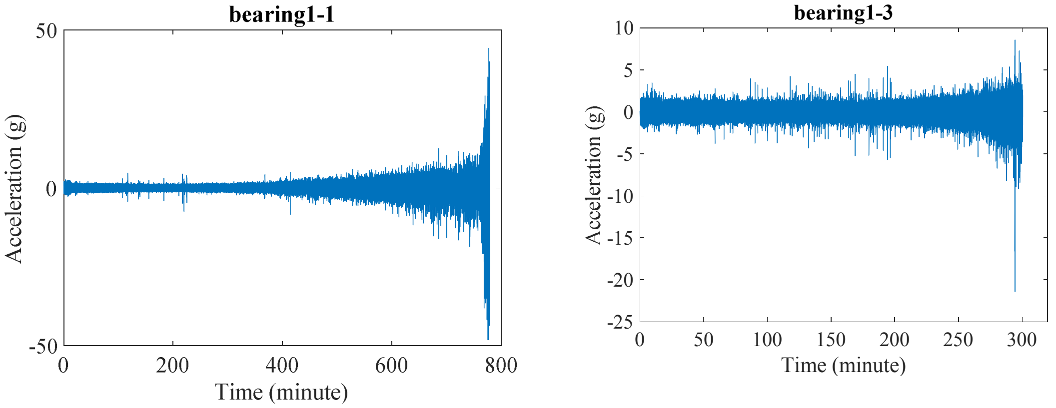


Figure 4-8 predicting process of data-driven method

4.3. Result and discussion

In this phase, we present the results of applying the proposed method to predict the RUL of bearings. In this regard, Figures 4-9.a and 4-9.b illustrated the measured vibration data during the degradation of two bearings named bearing1-1 and bearing1-3 in the axial direction. Which, every 10 seconds, they measured 2560 samples, by using the sampling frequency of 25.6 kHz. From these figures, the vibration signals show increasing values before the degradation occurs with some perturbations in these profiles during the test.



(a) Vibration signal of bearing 1-1 (b) Vibration signal of bearing 1-3

Figure 4-9 Profiles of two bearings during the test

4.3.1. Feature reduction

4.3.1.1. Feature reduction using PCA without feature selections

After applying feature reduction using the PCA technique to 12 features, such as mean (S_5), Standard Deviation (S_7), Kurtosis (S_{11}), Skewness (S_{12}), Peak to Peak (S_9), RMS (S_8), Energy (S_{14}), Entropy (S_{15}), Shape Factor (CS_1), Crest Factor (CS_3), Impulse Factor (CS_8), and Marginal Factor CS4. PCA1 has a better increasing value than PCA2 that has a decreasing and increasing trend at the same time during bearing degradations as seen in Figure4-10 and Figure4-11.

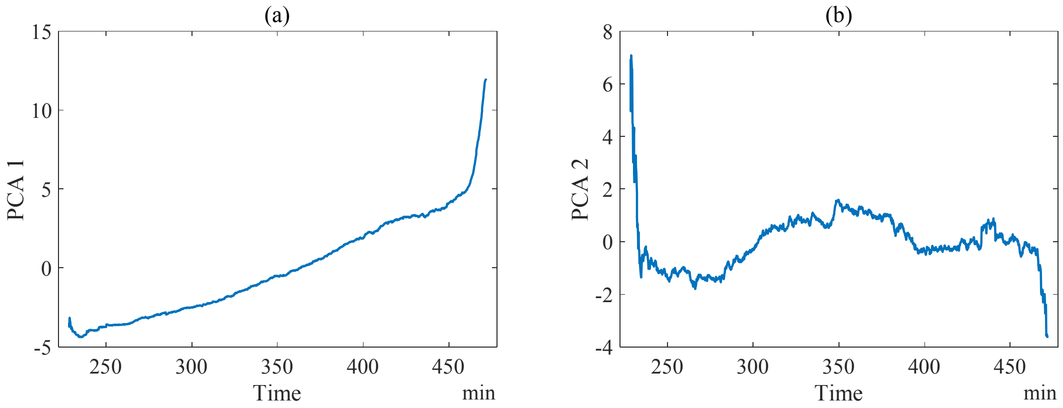


Figure 4-10 PCA1 (a) and PCA2 (b) in case of reduce all features for bearing 1-1

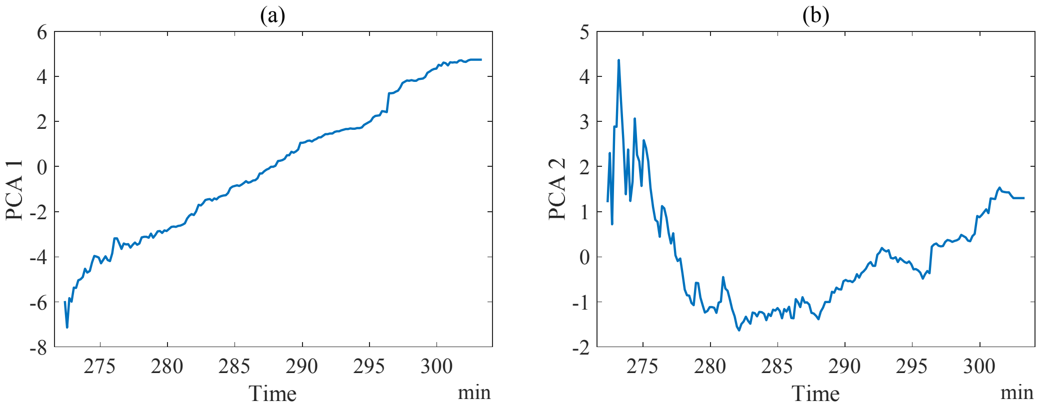


Figure 4-11 PCA1 (a) and PCA2 (b) in case of reduce all features for bearing 1-3

4.3.1.2. Feature reduction using PCA with feature selections

In this case, we choose the criteria of monotonicity to select the best feature trends among the 12 trends of temporal features. Each temporal trend has a level of monotonicity superior to 0.5 and is selected to be reduced by the PCA technique. As a result:

c. In case of bearing1-1

Standard Deviation (S_7), RMS (S_8), Peak to Peak (S_9), and Energy (S_{15}) are the four selected features that have a monotonicity level superior to 0.5 as seen in Figure 4-12. These features are reduced using PCA, which PCA1 has a better-increasing value than PCA2 that has a decreasing and increase during bearings degradation as seen in Figure 4-13, and also has a better-increasing trend compared to the case of reducing all features without selection (see Figure 4-10.a).

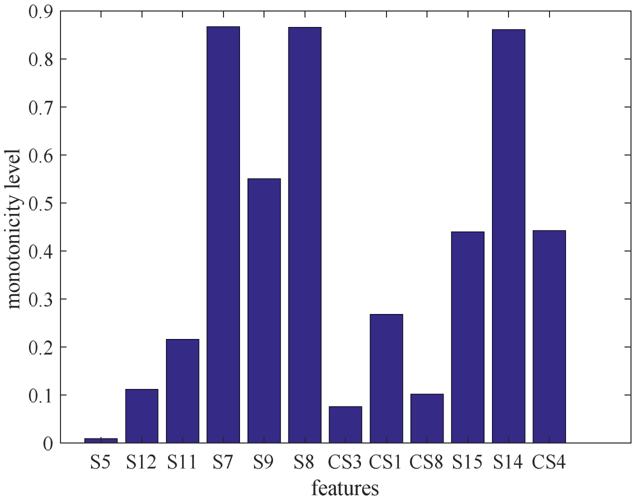


Figure 4-12 Monotonicity level of 12 features for bearing 1-1

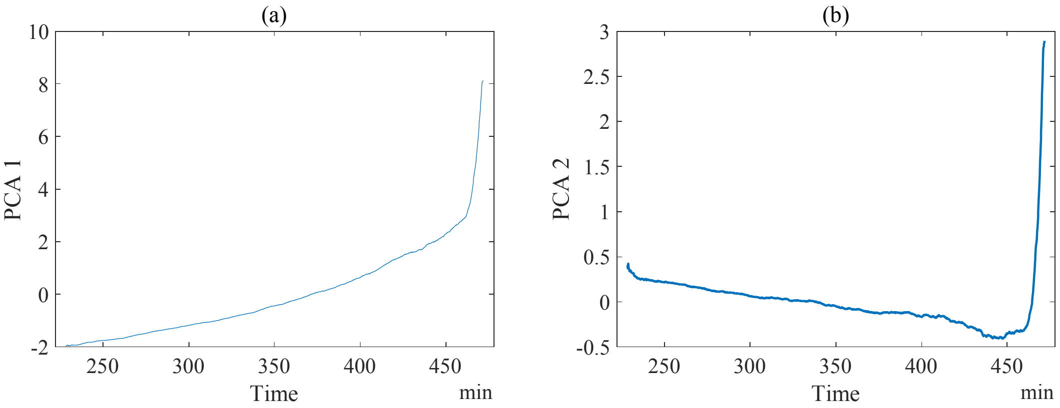


Figure 4-13 PCA1 (a) and PCA2 (b) in case of reduce selected features for bearing 1-1

d. In case of bearing1-3

As shown in Figure 4-14, only Standard Deviation S_7 and RMS S_8 are the two selected features when compared to bearing1-1, which has a monotonicity level of up to 0.5. These features are reduced using PCA, where PCA1 has a better-increasing value than PCA2, which has a decreasing and increasing trend during bearing degradations as seen in Figure 4-15 and also has a better-increasing trend compared to the case of reducing all features without selection (see Figure 4-11.a).

From these results, the technique of selecting the best monotonicity level of feature trends followed by feature reduction using the PCA technique gives the best results compared to the case of using only the feature reduction technique.

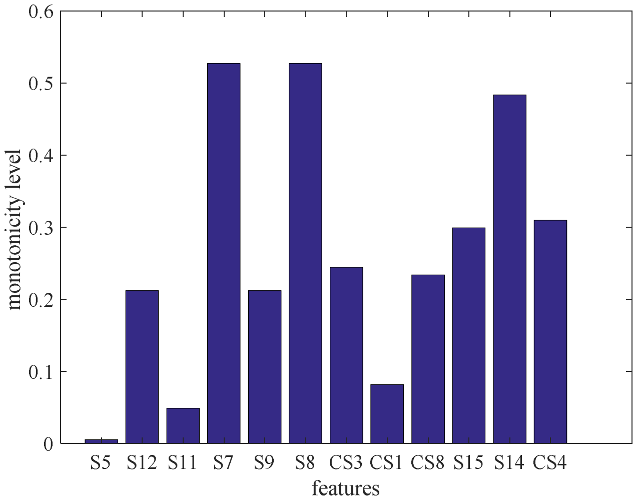


Figure 4-14 Monotonicity level of 12 features for bearing 1-3

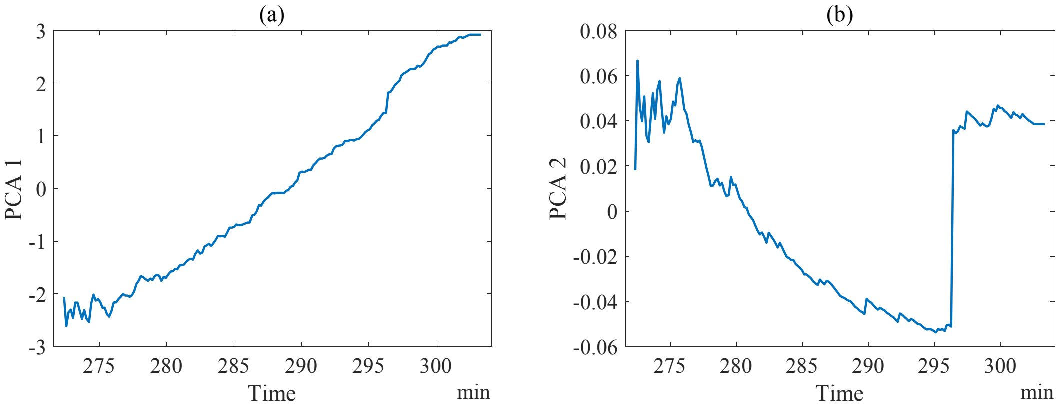


Figure 4-15 PCA1 (a) and PCA2 (b) in case of reduce selected features for bearing 1-3

4.3.1.1. Remaining useful life (RUL) of bearing1-1

Figure 4-15 shows two cases of remaining useful life (RUL) of bearing1-1: in feature reduction without selection using PCA1 as a health indicator to predict the RUL (see Figure 4-15a), and with feature selection and reduction using PCA1 (see Figure 4-15.b). Whereas, the predicted trend in Figure 4-15.b is closer to the real trend (real value) of the RUL of bearing than in the case of no selection, as confirmed by Table 4-1. This means that in this case, the selected features give the best accuracy of RUL compared to the case of reducing all temporal features.

4.3.2. Remaining useful life (RUL) of bearing using support vector regression (SVR)

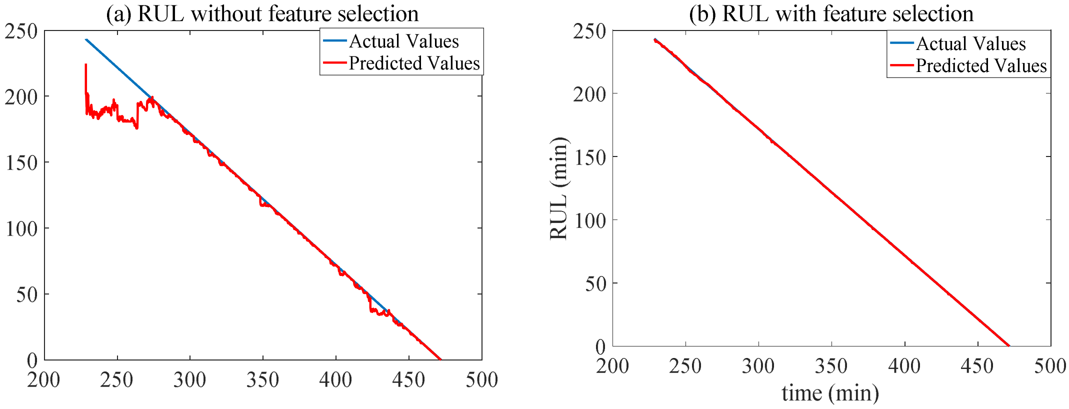


Figure 4-16 Remaining useful life of bearing 1-1in case of : (a) without feature selection and (b) with feature selection

4.3.2.1. Remaining useful life (RUL) of bearing1-3

Figure 4-16 show two cases of remaining useful life (RUL) of bearing1-3, feature reduction without selection using PCA1 as a health indicator to predict the RUL (see Figure 4-16.a), and with feature selection and reduction using PCA1 (see Figure 16.b). Where, in the beginner of prediction, the predicted trend without feature selection in Figure 16.a is closer to the real value of RUL of bearing than in the case of feature selection in Figure 16.a. after that, the two cases give closer values as confirmed by Table 4-2. This means in the case without a selected feature gives the best accuracy of RUL compared to the case of selected features.

Tableau 4-1 Some point of bearing1-1 RUL taking in case feature reduction without selection and with selection

RUL percentage	predicted value without selection (min)	Predicted value with selection (min)	Actual value of RUL (min)
5%	190.5623	232.0710	231.4583
15%	194.1005	207.8913	207.0500
25%	182.5827	183.2341	182.8100
35%	154.9352	158.6993	158.4017
50%	117.4194	121.8834	121.8733
65%	85.4161	85.4253	85.3450
75%	60.8574	60.9056	60.9367
85%	33.7124	35.0754	36.6967
95%	12.2418	12.3132	12.2883

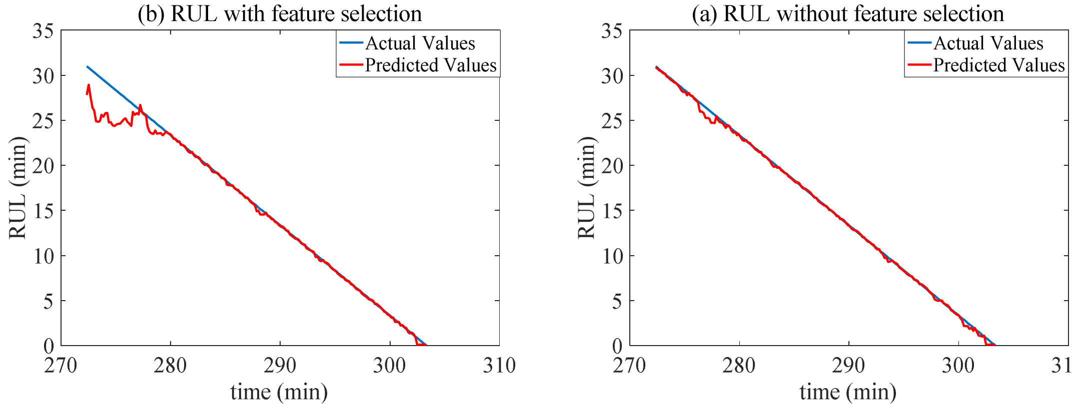


Figure 4-17 Remaining useful life of bearing 1-3 in case of: (a) without feature selection and (b) with feature selection

Tableau 4-2 Some point RUL of bearing1-3 taking in case feature reduction without selection and with selection

RUL percentage	predicted value without selection (min)	Predicted value with selection (min)	Actual value of RUL (min)
5%	29.4964	25.5972	29.6267
15%	25.7624	25.6096	26.5967
25%	23.4751	23.4798	23.3983
35%	20.0762	20.2036	20.3683
50%	15.5475	15.5666	15.6550
65%	10.8427	10.8292	10.9417
75%	7.8153	7.8153	7.9117
85%	4.7277	4.5969	4.7133
95%	1.5446	1.4982	1.6833

4.4. Conclusion

In this present chapter, we present a brief introduction to the prognostic method of bearing degradation in order to predict the RUL based on support vector regression. From the obtained results, the precision of predicted time depends mainly on the degree of monotonicity level of different temporal features. The reduction feature trend is considered as the health indicator to predict the RUL of bearings that give the best results. Especially in the interval near the end bearing life working that can be used as an alarm to change the bearing before failure happened.

Reference of Chapter 04

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General Conclusion and Future Works

The work presented in this thesis deals with the integration of fault diagnostic and prognostic in the operational safety of electrical drive systems. Diagnostic makes it possible to determine which components in the system (three-phase induction motor) are faulty and therefore need to be repaired or replaced. The prognostic makes it possible to anticipate faults or the level of degradation providing information on the future state of the systems (remaining useful life) from which maintenance actions can be considered.

To begin the study (chapter 1), we established general information related to the field of different maintenance policies used to ensure the reliability and operational safety of industrial systems. The purpose of this study was to set diagnostic and prognostic within conditional preventive maintenance. This preliminary work highlights two major approaches. The first approach uses a mathematical model that describes the physical phenomena of a system; it is based on residues, which is the difference between a real measure and the estimated one. It uses a residual-based mathematical model to detect faults and track system degradation. However, it uses a simplifying assumption to help construct a model. Furthermore, this approach can't describe a mechanical component as bearing and gear. The second considered approach in this thesis is a data-driven method. This approach consists in analyzing the measurement signals (current, voltage, vibration, etc) to construct a vector that indicates the health state of the system. This vector is then used in pattern recognition technique (PR) to detect changes in the measurement data via supervised classification methods such as KNN, SVM, ANN, etc. in the case of prognosis, this method is used to predict the remaining useful life of bearings or to predict the different degradation stages of bearings.

The second part (chapter 2) aims to present a review of the data-driven approaches with different use of electrical measurements (vibration, current, voltage, acoustic emission, flux magnetic and thermal image) and different use of machine learning to detect and diagnose various faults, as well as provide the merits and demerits of each type of measured signal. On the other hand, the prognostic part of rolling element bearing presents a review of data-driven approaches based on vibration analysis and mixed approaches between data-driven and model-based approaches in order to predict the next degradation stage and the remaining useful life of this critical component.

The third part (chapter 3) aims to present the proposed method for fault detection and diagnostic based on a data-driven approach via the analysis of electrical signals such as current and voltage. where, we present the disadvantage of applying fast Fourier transforms to detect the different frequencies related to various faults, especially in the case of a three-phase induction motor feed by an inverter, that return to the switch mechanism which introduces harmonics that hid the different frequencies component related to faults. As well as present a geometrical representation of Concordia transforms and its inability to show the faulty pattern in the deformed circle in the case of inverter supply. The proposed methodology deals with the mentioned problem in the case of inverter-fed induction motor by combining sensitive health indicators to the fault, skewness and standard deviation extracted from Concordia transform of electrical signals. These temporal features are the best alternative solution for fault detection of the frequency domain. The detection of different health states (health state, bearing wear, one and three broken rotor bars) is conducted using k-mean clustering which has the ability to regroup unknown data into separated clusters of the same fault type and the number of existing health states. Fault diagnostic and classification of various health states is performed using the k-Nearest Neighbour classifier. The proposed method gives high classification accuracy through K-NN in various operation conditions with less computational time compared to other Machine Learning classifiers. This ensures the effectiveness and robustness of the proposed methodology for fault detection and diagnostic.

The fourth part (chapter 4) aims to present the proposed prognostic method to predict the remaining useful life of tow bearings mounted under constant load level and speed, which is based mainly on feature reduction technique (principal component analysis) to reduce all features or only the selected features among different extracted temporal features from vibration signal depending on monotonicity level. The use of the fused features as a health indicator allows better prediction of the remaining time of bearing before the failure stage using support vector regression. The noticeable thing is that the efficiency of the predicted remaining useful life of bearings is related to the quality of the measured signal when a selection of features depends on the monotonicity level and reducing features by PCA. The obtained results are promising in terms of the effectiveness and accuracy of predicted time before the failure stage using the present method.

The work carried out within the framework of this thesis could give rise to additional studies of which we present some point that seems important to us, they are summarized as follows

1- Diagnostic and prognostic of another electrical drive systems, in particular wind turbine using other signal processing technique.
2- Diagnose the induction motor under transient state (variation of speed and load).
3- Fault diagnostic of renewable energy system.
4- Fault diagnostic of micro-grid.