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Intitulé

Development of an Intelligent Health Assessment Application for Bearing Machines .

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PREFACE

The prognostic is considered as one of the main PHM - Prognostics and Health Monitoring - layers. It aims to provide prior knowledge about the equipment with a risk of failure and to alert -offering a lead-time- the operator about the needed maintenance task, which leads to a lower maintenance cost with near to zero downtime and better spare parts organization. Therefore, prognostic is considered one of the most important research fields in the industry nowadays.

Since bearing exists in almost all rotating machines, improving the existing techniques for predicting failure at an earlier stage is necessary. The prognostic task remains challenging because the model applied in forecasting is different for each type of component, and it is also different according to the faulty part. Moreover, there is no universal predictive model for several kinds of bearing or a model that covers most types of failure. Thus, this research attempts to solve the bearing's generic prognostic model problem by building a forecasting algorithm based on fault feature detection.

My exploration in this field is continuous. However, I need to stop briefly to write this thesis. For that, I want to express my deep gratitude to my idle and my father (ربي يرحمه و يدخله جنته) for his belief and his continuous support, and my mother, whom she never stopped supporting and helping me reach the place I'm today. A special thanks go to my supervisor, Pr. BERRACHED Nasr-eddine for his guidance and especially his faith in me. I also appreciate and thank Mr. DENAI Mouloud for his availability and help. I am thankful to my mentors, Pr. BOUGHANMI, Pr. BENOUZZA, Pr. HAFFAF, Pr. KECHAR, and Dr. TLEMSANI for proofreading my manuscript. I might likewise want to express my deepest gratitude toward my wife, my three kids, and all my family for their love and uninterrupted support. Last and not least, I thank all LARESI members and my friends.

ملخص

يفرض التحدي الشديد في القطاع الصناعي في الوقت الحاضر على الشركة المصنعة تحسين عملية الإنتاج من أجل توفير الجودة خلال وقت تسليم تنافسي. يتطلب هذا التحسين أن تعمل المعدات في أفضل الظروف لأطول فترة ممكنة دون توقف. لذلك، فإن التوقف غير المخطط له وكذلك استبدال المعدات الجيدة قبل الوصول إلى دورة حياتها المقبولة يمثلان خسارة كبيرة، مما يؤثر بشكل مباشر على تكلفة المنتج النهائي. في مثل هذه الحالة ومع التطور التقني الهائل لأجهزة الاستشعار والمعدات في العقد الماضي، تم تطوير استراتيجيات صيانة جديدة تسمح بالانتقال من الصيانة التصحيحية إلى الصيانة التنبؤية.

تعد خطة التوقعات والرصد الصحي (PHM) أنسب خطة صيانة في هذه الحالة، والتي تتكون من اكتشاف الأعطاب قبل حدوث أي ضرر، من خلال مراقبة الحالات الصحية للمعدات وتوقع تعطلها. وبالإضافة إلى ذلك، ، توفر المعرفة المسبقة إمكانية شراء قطع الغيار في الوقت المناسب، فضلا عن تخطيط مهام الصيانة، وتجنب التعطل غير المخطط له.

في هذا البحث، نركز على تشخيص الآلات الدوارة وخاصة على عنصر المحمل. يعتمد النهج المقترح على استخراج الخصائص في مجالات متعددة من الاهتزازات. بعد ذلك، يتم تقليل الخصائص باستخدام مرشح الارتباط المتقاطع قبل إسقاطها في مساحة ثنائية الأبعاد باستخدام خريطة ذاتية التنظيم (SOM). لاختيار تقنية تخفيض الخصائص المناسبة، تتم مقارنة SOM بالقيم المتعددة المستخرجة من تحليل المكون الرئيسي (PCA). تعتبر النتيجة المؤشر الصحي (HI)، والذي سيتم استخدامه لاكتشاف العطب. ويمكن الكشف عن العمر النافع المتبقي (RUL)، الذي يتمثل في الوقت المستغرق من بداية العطب وينتهي بعطل الآلة. وبالتالي، ومن أجل التنبؤ بوقت عطب المكون الجديد، يتم إنشاء مؤشر الاتجاه (TI) من بقايا تحليل النموذج التجريبي (EMD) من أجل الحصول على إشارة رتيبة. أخيرًا، يتم استخدام تراجع عملية Gauss في هذه الدراسة كتراجع لمؤشر الاتجاه حيث توفر تنبؤًا دقيقًا للغاية لـ RUL. نظرًا لأن جودة تقدير RUL تعتمد بشكل مباشر على الخصائص المختارة، فإن هذا العمل يركز بشكل أساسي على استخراج الخصائص التي لها تأثير كبير في تحديد الحالة الصحية للآلة. من أجل التحقق من صحة عملنا، يتم اختبار الطريقة المقترحة على عدة مجموعات من بيانات المحمل المرجعية.

الكلمات الدلالية : استخراج ميزة الخطأ. تشخيص الفشل; التشخيص والرصد الصحي; مؤشر الصحة; مؤشر الاتجاه; تحمل. التكهنات العامة; مؤشر الصحة.

ABSTRACT

The intense challenge in the industrial sector nowadays imposes manufacturers to optimize the production process to offer competitive quality in short delivery time. These improvements request that the equipment should work in the best conditions as long as possible with near to zero downtime. For that, unplanned breakdown and replacement of good equipment before reaching their tolerable life cycle is a loss, directly influencing the cost of the final product. In such conditions and with the substantial technical evolution of sensors and computing resources in the last decade, new maintenance strategies were developed, allowing the move from corrective to predictive maintenance.

The prognostics & health monitoring (PHM) is in this case the most appropriate maintenance plan. It consists of detecting failures before any damage by monitoring the equipment's health and anticipating failure. In addition, prior knowledge offers the possibility of purchasing spare parts, planning maintenance tasks, avoiding unplanned breakdowns, and optimizing equipment durability and maintenance activities.

This research focuses on the rotating machines' prognostic, especially the bearing component. The proposed approach is based on extracting appropriate multiple domain features from the raw signals (mainly those related to vibration). Then, these features are reduced using a cross-correlation filter before being projected onto two dimensions space using a Self-Organizing Map (SOM). The SOM is compared with multiple values extracted from the Principal Component Analysis (PCA) to select the optimal ones by using some reduction techniques. Hereafter, the result is considered the Health Indicator (HI), used for fault detection. The fault detection allows for the Remaining Useful Lifetime (RUL) estimation where the fault represents the beginning of the RUL, and the Failure means its end. Thus, to predict the failure time for a new component, a Trend Indicator (TI) is built from the residual of the Empirical Model Decomposition (EMD) to get a monotonic signal. Finally, the Gaussian Process Regression (GPR) is used in this case study as a regression of the TI, where it provides a high-accuracy prediction of the RUL. Since the quality of the RUL estimation relies directly on the selected features, this work focuses mainly on relevant feature extraction and selection. The proposed method is tested on various real benchmarked bearing datasets to validate our work.

Keywords: *Fault feature extraction; Failure diagnostic; PHM; Prognostics and health monitoring; Feature fusion; Health indicator; Trend indicator; Bearing; Generic prognostics; Bearing health assessment.*

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Prognostics & Health Monitoring Background

Quote:

"Allah will raise those who have believed among you and those who were given knowledge, by degrees"

MUJADILA 58:11 - QURAN

I. Introduction to Prognostics & Health Monitoring

Companies nowadays are under pressure from their customers in the new industrial context. The challenge is to provide good quality products and services at lower cost, delivered quickly and at the right time. The manufacturing company must have reliable and well-maintained production tools to meet the demand for quality and quantity while respecting delivery times and costs. Thus, maintenance is applied to minimize downtime and fault occurrence (Boldt et al., 2013).

Maintenance can be divided into reactive and proactive. The first represents the response to work requests, usually identified by operators because a piece of equipment is broken or not functioning correctly, where it focuses on restoring the equipment to its normal operating condition. The second approach responds primarily to equipment assessment, root cause analysis, and preventive procedures.

For that, many standards have been set; the NF X 60-010, X 60-011 standards and the French national organization for standardization AFNOR -EVS-EN 13306:2010 define maintenance “*as the set of actions for maintaining or restoring the property in a specified state or in a position to provide a specific service*.” At the same time, the NF X 60-300 and X 60-301 standards specify five types of maintainability criteria (Preventive maintenance, Corrective Maintenance, Organization of maintenance, technical documentation, and Manufacturer conditions). This chapter discusses this thesis's PHM background and objectives followed by our contributions.

I.1 Introduction

The value of the PHM is well illustrated when compared with classical maintenance strategies like corrective maintenance and preventive maintenance. The corrective maintenance is based on no fixes until the failure occurs, leading to unplanned breakdown, environmental risks, and subsequent damage to other parts. On the other hand, preventive maintenance is based on a preset schedule regardless of the machine's state between intervals. Replacing a component before its end of life leads to unnecessary downtime and parts costs. Therefore, the most appropriate maintenance plan, in this case, is the PHM –also known as case-based maintenance, CBM-which consists of scheduling maintenance activities only when a functional failure is detected. An effective predictive system is expected to provide early detection of the incipient fault, have the means to monitor the progression of the fault, and aid in making or autonomously triggering maintenance schedules.

By employing such a system, the health of a machine or a system can be known at any point in time, and the eventual occurrence of a failure can be predicted, enabling the achievement of near-zero downtime performance. Unnecessary and costly preventive maintenance can be eliminated, maintenance schedules can be optimized, and lead time for spare parts and resources can be reduced. Therefore, the PHM is considered one of the most important research fields in industry 4.0.

I.1.1 Predictive maintenance

Predictive maintenance is a proactive approach to maintenance that has become increasingly popular in recent years, particularly in industrial settings. It involves using advanced analytics, machine learning, and other technologies to predict when equipment is likely to fail, allowing maintenance to be scheduled before a breakdown occurs.

However, the implementation of predictive maintenance is not without its challenges. The success of predictive maintenance requires the availability of large amounts of high-quality data, which can be a significant obstacle for many organizations. Additionally, the deployment of predictive maintenance requires significant investment in terms of hardware and software, as well as the development of appropriate organizational and human resources capabilities.

I.1.2 Predictive maintenance in Industry 4.0

A key component of Industry 4.0, which has been called the fourth industrial revolution and is defined by the increasing integration of automation and data interchange in the manufacturing process, is predictive maintenance. Due to this paradigm change, numerous intelligent systems and cutting-edge technologies have been implemented to optimize industrial processes, boost production, and cut costs.

Predictive maintenance has had a big impact on Industry 4.0 since it has the ability to decrease downtime, boost productivity, and cut expenses associated with running the business. Manufacturers may ensure that their equipment runs more effectively, resulting in more output and lower operating costs, by optimizing maintenance activities.

I.1.3 Advantages and limitations of predictive maintenance

One of the main advantages of predictive maintenance (PdM) is that it increases equipment reliability and availability, which translates into higher productivity and lower downtime. By detecting potential issues in advance, maintenance teams can plan and schedule maintenance activities, avoiding unplanned downtime and production losses. predictive maintenance can also reduce maintenance costs, as it allows for more targeted and efficient maintenance activities. By focusing on the most critical equipment components, predictive maintenance can reduce unnecessary maintenance activities and spare parts inventory, resulting in cost savings.

It can also improve safety and reduce the risk of accidents. By detecting potential equipment failures in advance, PdM can prevent accidents and injuries caused by equipment failures. PdM can also improve environmental sustainability by reducing the amount of waste generated by unnecessary maintenance activities and by optimizing equipment performance.

However, PdM also has some limitations that should be considered. One of the main limitations is the need for high-quality data. PdM relies on historical equipment data, which must be accurate and representative of the equipment's operating conditions. If the data is incomplete or inaccurate, the PdM system may generate false alarms or miss critical failures, reducing its effectiveness. Another limitation of PdM is the need for specialized skills and expertise. PdM requires skilled data analysts and machine learning experts who can analyze the data, develop predictive models, and interpret the results.

I.2 Prognostics and Health Monitoring

Prognostics and health monitoring (PHM) is a rapidly evolving field that combines engineering, data analytics, and machine learning to monitor the health of equipment and predict when maintenance will be required. PHM can also incorporate historical data and contextual information to provide more accurate predictions of remaining useful life and maintenance needs.

I.2.1 PHM Architecture

In PHM, the layer responsible for evaluating the machine's health state is called diagnostic, while the prognostic stands for the future evaluation of the detected fault. The architecture can be described according to the seven functional layers (Provan, 2003) as depicted in Figure 1 (Medjaher, Camci, et al., 2012).

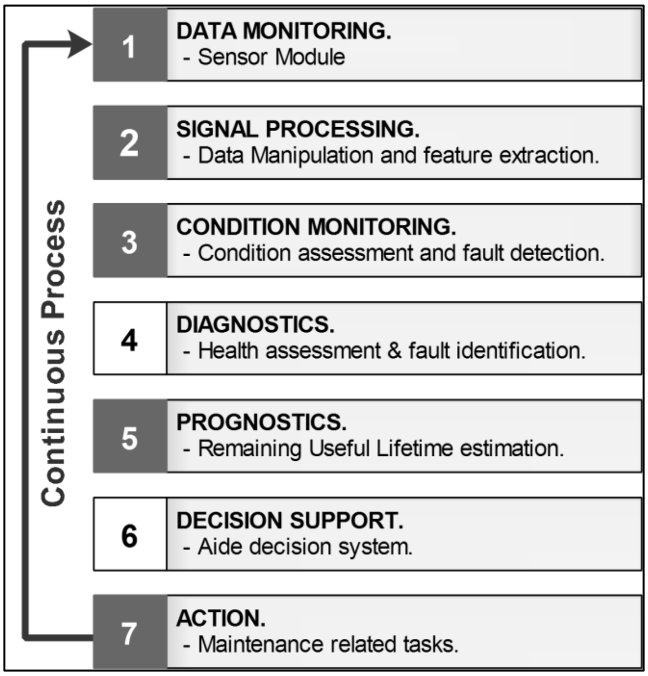


Figure 1: Open system architecture for prognostics and health monitoring layers

Continuous monitoring systems generally monitor potential failures by upgrading a machine with a fault prediction system. The machine can continue performing within tolerable parameters and be repaired at the most economically convenient time. The prediction capability of the monitoring system is the difference between simply saving the machine and saving the production schedule.

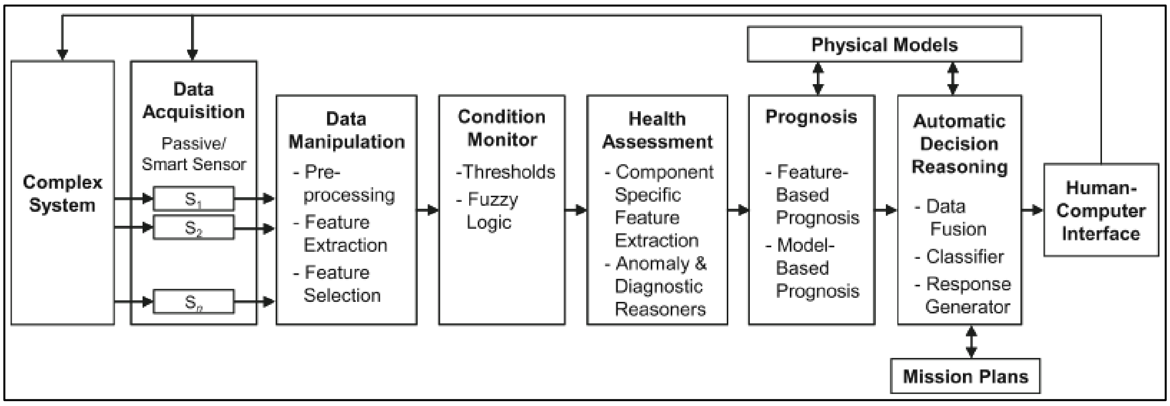


Figure 2: The seven modules in the OSA-CBM architecture

The structure connected to fault detection, fault diagnosis, fault prognosis, and control system is known as a Prognostics health management system. It employs several data analyses and decision-making techniques, including statistical analysis and data visualizations to perform feature extraction, fault detection, and prognostics.

Figure 2 represents the PHM architecture and the workflow between its seven layers (Lebold et al., 2003).

I.2.2 Prognostics models

There are various types of RUL estimator models, each with its own strengths and limitations. The choice of RUL estimator model depends on various factors, including the type of equipment, the available data, and the desired level of accuracy. Each model has its own strengths and limitations, and some models may be more suitable for certain types of equipment or operating conditions. However, all RUL estimator models share the goal of improving equipment reliability, reducing downtime, and optimizing maintenance activities.

I.2.2.1 Similarity model

One type of RUL estimator model is the similarity model, which is based on the assumption that the current condition of equipment is similar to its past conditions. The similarity model compares the current state of equipment to historical data to estimate its remaining useful life.

I.2.2.2 Survival model

Another type of RUL estimator model is the survival model, takes into account the probability of equipment failure over time and estimates the remaining useful life based on the probability of failure. This model requires a better knowledge about the failure signatures.

I.2.2.3 Degradation model

The degradation model calculates a component's RUL based on the historical deterioration of that component over time. It models the degradation process and forecasts when the component will approach a failure threshold using sensor data and other pertinent information. For parts like bearings or gears that deteriorate gradually over time, the degradation model might be especially helpful.

I.2.3 Critical components choice.

Deciding the monitoring level in an industrial system to acquire the data constitutes an essential step toward building a reliable PHM platform. The monitoring of industrial systems can be done on system or component levels (Gouriveau et al., 2016).

1. System-level: large-scale systems consisting of multiple components/subsystems.
2. Component level: components that show a high failure rate are considered critical.

However, performing PHM for a whole machine or system is challenging and still quite difficult in practice compared to the component-oriented PHM. A critical component is usually defined as a component whose failure leads to the unavailability of the whole system or has a high failure rate. In this scope, the current study focuses on bearing machines as a dominant type of asynchronous machine since they are one of the most used machines according to their multiple applications. Furthermore, most rotating machines consist of simple components assembled; any failure of these components may be detected from the sensor signals that monitor the parameters related to these components. The bearing faults are one of the foremost causes of breakdown in rotary machines, with over 40% of the motor faults. See Table 1 (Mosallam et al., 2015; Soualhi et al., 2015).

Table 1: Failure distribution of asynchronous motors (Gouriveau et al., 2016)

Failure percentage in %					
Component	O'Donnell 1985	Albrecht 1986	Bloch&Geitner 1999	IEEE-ERPI 2012	IEEE 2015
Bearings	41	50	41	55	51
Stator	37	40	36	36	16
Axle	10	10	09	/	28
Others	12	/	14	09	05

Different causes can induce bearings failures: most of these failures are related to poor lubrication, the presence of foreign objects, fatigue, and passages of residual electric currents. Therefore, it is not easy to accurately define the signatures of bearing degradation.

I.2.4 Bearing anatomy

There has been a clear motivation to develop reliable monitoring systems and prediction techniques due to the manufacturing industry's high cost associated with equipment downtime. Since rotating machinery exists in almost every industrial system, it is crucial to develop reliable techniques for predicting rotating element failure early enough to facilitate maintenance tasks. The failure of a rolling element bearing is one of the primary causes of breakdown in rotating machinery. Bearing failure can be catastrophic in certain situations, such as helicopter rotors, high-speed trains, and automatic processing machines. The bearings are mechanical organs. They represent a relatively simple, economical, and efficient junction type as it adapts pretty well at very low speeds (e.g., actuator bearings) and very high speeds (e.g., turbine).
To prevent disastrous consequences from bearing failures, the bearing life prediction is discussed in this thesis, starting by describing the bearing anatomy.

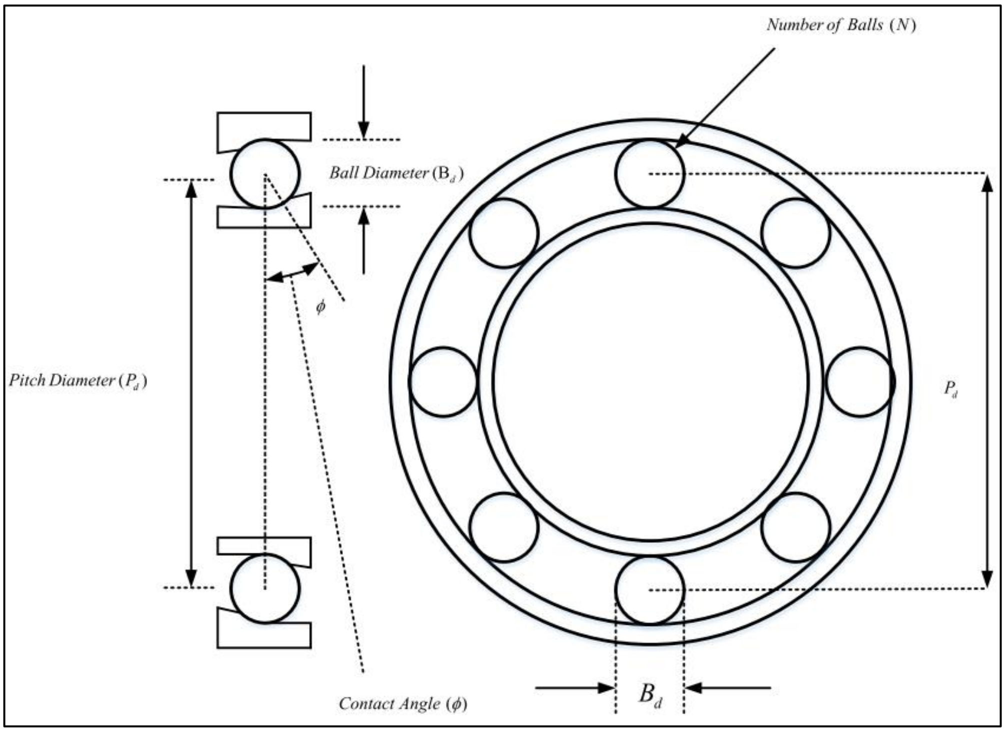


Figure 3: Bearing parameters

For a particular bearing geometry, inner raceway, outer raceway, and rolling element faults generate vibration spectra with unique frequency components. These individual frequency components and their magnitudes make it possible to determine the condition of the bearing (Fault Isolation). The bearing defect frequencies are linear functions of the running speed of the motor. Also, outer and inner race frequencies are linear functions of the number of balls in the bearing. Given the geometry of the bearing, the calculation of these frequencies is explained in (Dybała & Zimroz, 2014; Miao et al., 2011). For deep groove ball bearings with a stationary outer ring, the frequencies are given by the following equations:

$$FTF = \frac{F}{2}\left[1 - \frac{Bd}{Pd}\,.\cos\emptyset\right] \qquad \text{eq. (1)}$$

$$BS = \frac{Pd}{2Bd}.F\left[1 - \frac{Bd}{Pd}\,.\cos\emptyset\right] \qquad \text{eq. (2)}$$

$$OR = \frac{F}{2}.N\left[1 - \frac{Bd}{Pd}\,.\cos\emptyset\right] \qquad \text{eq. (3)}$$

$$IR = \frac{F}{2}.N\left[1 + \frac{Bd}{Pd}\,.\cos\emptyset\right] \qquad \text{eq. (4)}$$

Where:

FTF [Hz]: Fundamental Train Frequency / Cage Frequency.

BS [Hz]: Ball Spin / Ball Pass Frequency (BPF).

OR [Hz]: Outer Race frequency / Ball Pass Frequency Outer race (BPFO).

IR [Hz]: Inner Race frequency / Ball Pass Frequency Inner race (BPFI).

N: Number of balls.

F [Hz]: Shaft frequency (rotational frequency).

Bd [Inch]: Ball diameter.

Pd [Inch]: Pitch diameter.

$\emptyset$ [Radians]: Contact angle.

I.2.5 Bearing failures.

The failure of a machine is not as sudden as it seems. Science and new technologies proved that failure happened after certain degradation related to causes often unseen by humans.

The probabilistic failure mode of a given piece of engine hardware reflects its relative probability of failure versus its age. There are three categories of failure mode: wear-out, infant mortality, and random.

1. <u>Wear-out:</u> is the most common of the three since parts are increasingly likely to fail as they age.
2. <u>Infant mortality:</u> Conversely, it describes those situations where parts are more likely to fail early in life. Parts are usually considered safe from this mode once they pass a certain age.
3. <u>Random failure</u>: in this mode, parts or machines are equally likely to fail whatever their age. An unexpected failure situation allows for a simplified risk assessment using the mean time between failures (MTBF) analysis.

Metal deformities and cracks can cause faults in bearings, fragments on the surface raceway, improper installation, and incorrect handling of the bearing. Bearing failure can cause personal injury and unscheduled replacements or repairs, leading to high maintenance costs. To list and treat all the known types and causes of bearings damage is beyond the scope of this thesis. Therefore, only the most common bearing failure causes are mentioned. A specific defect frequency characterizes each defect or characteristic frequency, depending on which bearing component the fault occurs and the speeds at which the inner and outer races rotate. Different frequencies are generally obtained for defects on an outer race, inner race, and roller elements.

I.2.6 Fault diagnosis based on vibration analysis

Detection of progressive bearing deterioration during operation by vibration measurements has been in use for a long time, and this technique has become more economical and reliable in recent years. The overall vibration level indicates the bearing machine's global condition, including unbalance, misalignment, and bearing defects. Vibration diagnostic is usually concerned with the extraction of features from the sensor's signal and associating these features with healthy or faulty components of the bearing. Acquiring accurate vibration data is the key to effective machine monitoring, fault diagnosis, and prognostics. Quality data acquisition requires planning involving the machine, the nature of expected vibration data, available instrumentation, and the purpose of the testing (Niu, 2017).

Accelerometers are rugged, compact, lightweight transducers with a wide frequency response range. They have been used extensively in many machinery-monitoring applications. Generally, the machines have parts that generate high-frequency signals, such as gear sets or rolling element bearings like in our case study. Vibration sensors are used to measure vibration levels on the casing and bearing housings. They are inertial measurement devices that convert the mechanical motion to an electrical signal, and this signal is proportional to the vibration's acceleration based on the piezoelectric principle.

I.3 Problematic of this research.

The two traditional categories of maintenance (the corrective and the preventive) are considered wasteful against the PHM. In our case study, the problems in applying the PHM can be resumed in three main points:

1- **The Complexity of fault detection:**

The PHM application complexity remains in the diversity of symptoms that can be developed from the same fault, which makes the diagnostic hard and the prognostic even harder, mainly with the insufficiency of the amount of vibration data available.

2- **The Complexity of systems where the mathematical model cannot be extracted:**

Another problem of this research is the case of complex machines or systems where the model-based approach is not a possible solution. Thus, how to use only the available knowledge to predict future failures? For that, assuming that the available knowledge holds information about the future. Thus, the fact that the future is relatively predictable leads us to apply the data-driven approach, where the RUL is obtained when a health indicator (HI) exceeds a predefined threshold (Fault Threshold). However, the fault threshold is usually determined experimentally since the HI values of different bearings are generally different (Nabhan et al., 2015). In that context, and to build a generic bearing prognostic algorithm, different fault types, as well as other bearings types, are taken into consideration.

3- **Critical component choice:**

The factors of non-linearity (loads, clearance, friction, stiffness, and others) have a different influence on vibratory signals due to the complexity of construction and working conditions of rotating machines, which leads us to apply the prognostic on the critical component of the rotating machine rather than the entire system at once.

In this thesis, the data-driven approach is applied to study the bearings as the most critical component in rotating machinery.

I.4 Motivation and objectives

Maintenance is one of the main factors that lead the industry to the top or the bottom. It is crucial to improve product quality and on-time delivery as well as overall productivity. In 2003, the US Department of Commerce Statistics estimated that the industry wastes more than 180 billion dollars in excess maintenance annually (Niu, 2017). In this last decade, more research has focused on online fault diagnosis and prognosis by integrating complex machine learning algorithms. Still, for the bearing case, there is no study justifying the selected features' choice or their number; this is still an ongoing field of research (Sugumaran & Ramachandran, 2011). Therefore, researchers often overlook the study beyond selecting an adequate number of features, which includes the choice of inappropriate features. This is unsafe because the fault detection accuracy depends directly on the number and type of features used. In addition, false fault detection leads consecutively to a wrong prognostic.

Thus, our motivation and objective are to extract in an automatic way the relevant features to be used in prognostics. The optimization of the RUL estimation process is also considered an objective of this thesis, as long as our main objective is building a generic bearing trend indicator.

A reliable prognosis relies on condition monitoring since the prediction of the future state of an asset implies that its current state is known. Therefore, condition monitoring is the key to implementing efficient maintenance management strategies. Hereafter, through the use of PHM, we aim to achieve the following objectives:

- Estimating the future machine’s health state (The machine in this case of study is represented by its critical component, which is the bearing).
- Improving maintenance techniques and equipment reliability through the effective prediction (and then avoidance) of equipment failures.
- Extend the literature review of the bearing prognostics by exploring new methods.

I.5 Research contributions

This research attempts to solve the bearings' generic predictive maintenance problem using a data-driven approach. Therefore, we propose a generic method for bearing prognosis. Our contributions are illustrated in:

1- Relevant fault feature identification:

A health indicator is built using the relevant fault features extracted from multiple domains of the raw vibration signal. The health indicator aims to be used in the condition assessment and RUL identification.

2- Generic bearing RUL estimation:

A trend indicator (TI) is built based on the health indicator for RUL estimation, where generic means that the condition assessment and the prognostic methods should provide acceptable results for multiple types of bearings under various working conditions.

The methodology of our contribution is inspired by the work of (Mosallam et al., 2014b), where the proposed method is based on extracting time and frequency features for bearings, followed by calculating the pairwise symmetrical uncertainty for the feature selection. Then, the features are compressed to a lower dimension using PCA before applying the empirical mode decomposition (EMD), where the residual is considered the trend indicator. The results of our proposed method are compared with the work of (Guo et al., 2017), where a recurrent neural network-based health indicator (RNN-HI) for RUL prediction of bearings is presented. In addition, the PHM 2012 database (Nectoux et al., 2012) is used in both references to validate the results.

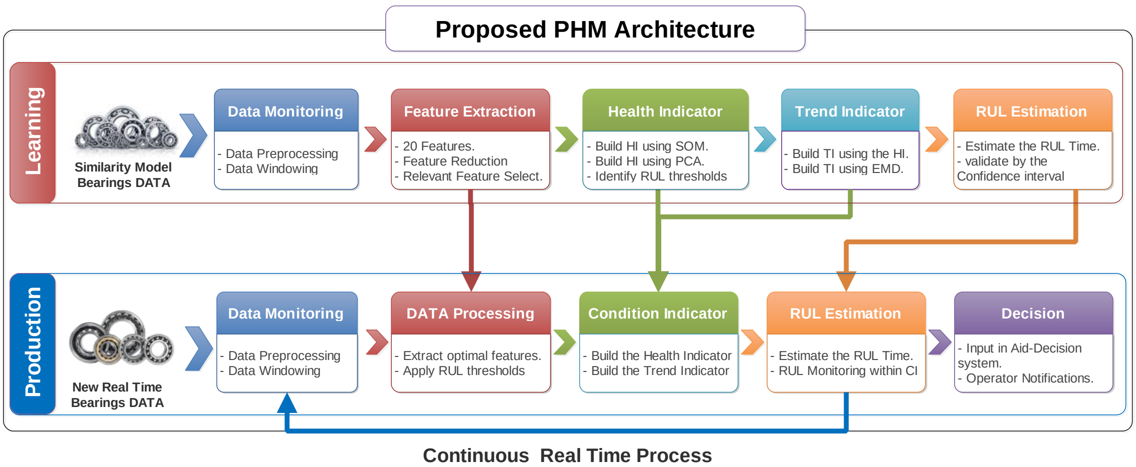


Figure 4: Our Proposed PHM Architecture

I.6 Assumptions

In terms of the proposed algorithm's application, some assumptions are applied, such as:

- The fault of the bearing machine is due only to the fault of the critical component, which is the bearing in this case study.
- The bearing starts from a healthy state and degrades gradually until the end of life (EOL).
- The proposed method is dedicated to one critical component at time.
- The sensors used for data acquisition are not faulty.
- No maintenance intervention during the process.
- The degradation of the components develops due to incipient faults.

I.7 Scope and Limitations

This study covers the application of machine learning algorithms performed on multiple types of bearings to estimate the RUL based on health and trend indicators. The thesis limitations relate to applying the machine learning algorithms in the prognostic module. The development of other PHM layers, such as the diagnostics and the aid decision, are beyond this study's scope. The Figure 5. Illustrates the layers to be handled in this research in red color.

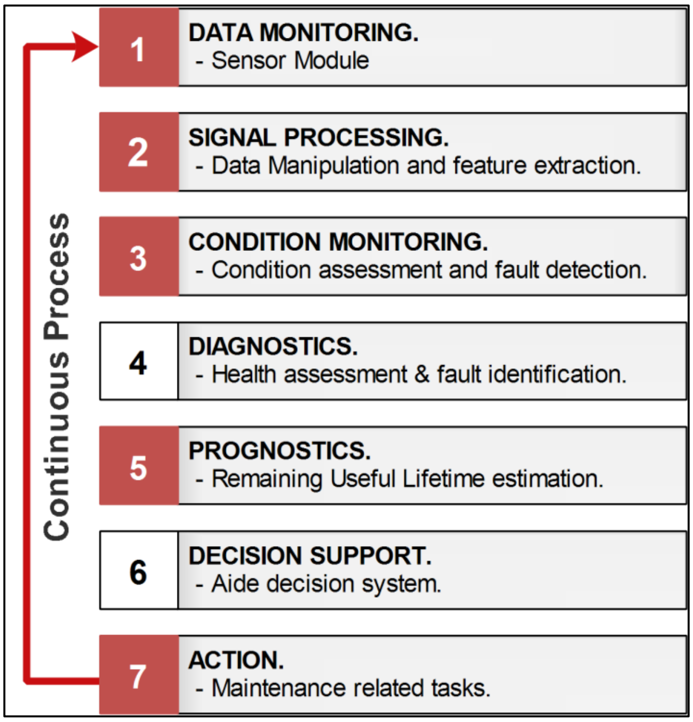


Figure 5: Prognostics and health monitoring layers in the scope of our research

I.8 Thesis outlines

The current thesis is subdivided into five chapters organized as follows:

Chapter 1 presents an introduction to industrial maintenance generally and the PHM, especially a brief description of the motivation, objectives, and contribution of this case study.

Chapter 2 gives an overview of state-of-the-art research in this field: the details of the features extraction techniques and the applied algorithms for constructing health and trend indicators.

Chapter 3 is dedicated to the data acquisition and the feature engineering used for the health indicator construction going through the details of different feature domains and algorithms.

Chapter 4 focuses on RUL estimation based on the condition indicator. It also covers fault and failure detection and the multiple methods used to build the trend indicator.

Chapter 5 discusses the results of applying the previous methods on multiple benchmark-bearing databases.

Lastly, a general conclusion is provided with the main results and perspectives on future works

Chapter II:

Literature Review of PHM

Quote:

“Whoever takes a path upon which to obtain knowledge, Allah makes the path to Paradise easy for him.”

Mohammed Messenger of Allah (ﷺ) - Jami` at-Tirmidhi 2646

II. Literature Review of PHM

Over the past decade, numerous efforts have been placed into the development of prognostic algorithms as well as the design of PHM systems. However, it has been observed that many industries have researched and developed related technologies in different applications. Considering the increasing research on the PHM systems, many standards are proposed, such as the ISO 17359:2018 (International Organization of Standardization), MIMOSA (Machinery Information Management Open Standards Alliance), and SAE (Society of Automotive Engineers) standards… (Zhou et al., 2013).

II.1 Introduction

Prognostics and Health Management (PHM) is an emerging field that aims to predict the Remaining Useful Life (RUL) of a system or component based on its health condition. This technology plays a crucial role in many industries, such as aerospace, automotive, and manufacturing, where system failures can lead to catastrophic consequences. Over the years, researchers and engineers have developed various techniques and algorithms to estimate RUL accurately. These techniques include model-based approaches, data-driven approaches, and hybrid approaches that combine both. With the advances in sensing, data storage, and processing capabilities, PHM systems have become more sophisticated and accurate, leading to improved system reliability, reduced maintenance costs, and increased safety. In this state of the art, we will discuss the latest developments in PHM and RUL estimation, including current challenges and future directions.

II.2 PHM approaches.

Many PHM algorithms have been developed to satisfy different application requirements. Efforts to review these algorithms and summarize their pros and cons can be found in (Lee et al., 2014; Niu, 2017). There are three different approaches: the physical approach, the knowledge-based (experience-based) approach, and the data-driven approach, as proposed by (Vachtsevanos et al., 2007). Figure 6 illustrates the PHM approaches and their selection condition.

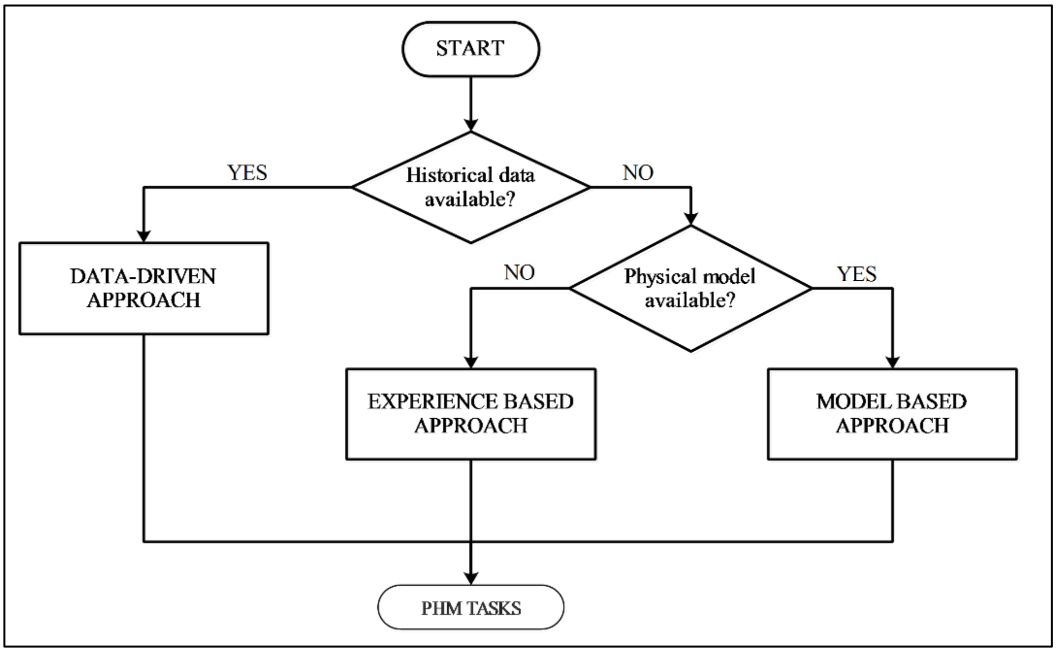


Figure 6: PHM Approaches

Data-driven methods aim at transforming the raw monitoring data into relevant information of the system, including the degradation, which offers good diagnostic accuracy, especially when the operating context is variable or in the case of new systems because of a lack of experts. However, the results are less precise than those provided by model-based methods (Tobon-Mejia et al., 2010). But it is important to note that getting the mathematical representation of a component and its faults is so challenging and nearly impossible taking in count the real-life environment variables.

II.3 PHM Signal preprocessing

Since the condition monitoring process is based mainly on the extracted features from the preprocessing layer. This session explores the different feature extraction and reduction techniques.

II.3.1 Feature extraction techniques

Different features can be extracted from raw signals to transform the raw input data into a reduced informative representation. These features can be derived from the time domain, frequency domain, or joint time-frequency domain (Mosallam et al., 2013).

II.3.1.1 Time-domain Analysis

Analyzing the vibration signals directly in the time domain is one of the simplest and fastest detections and diagnosis approaches. Various time-domain statistical parameters have been used as trend parameters to detect the presence of incipient bearing damage. The most commonly used ones are the peak, RMS, crest factor, and kurtosis (Galar et al., 2012; Y. Wang et al., 2016).

These parameters have more significant values for a damaged bearing than a normal one. Many researchers focused mainly on the application of the time-domain features in fault detection and diagnostics tasks, combined with machine learning algorithms such as the Support Vector Machine (SVM) (Fuqing, 2011; Galar et al., 2012; He & Yang, 2012), Neural Network (NN) (Boukhobza et al., 2013; Guo et al., 2017), and Genetic Algorithm (GA) (Ettefagh et al., 2014). The results confirmed that the statistical method could identify different defects in the bearing but with less overall accuracy. The results revealed that the kurtosis and the crest factor are the more adequate features for fault detection (Ocak, 2004).

II.3.1.2 Frequency Domain Analysis

The key in determining the bearing condition is the spectral content rather than the vibration amplitude. Therefore, this approach explores the Fast Fourier transform (FFT) of the vibration signal instead of analyzing vibration directly in the time domain. This approach requires that bearing defect frequencies should be known. As faults start to develop in one of the bearing components, the vibration spectrum peaks at the bearing defect frequency and its harmonies are associated with the faulty bearing element. Around each peak, there are also sidebands.

The spacing of the sidebands depends on the periodic properties of the loading and the transmission path; as the severity of the damage increases, the corresponding amplitudes of the peaks in the power spectrum increase. When the Signal-to-Noise Ratio (SNR) is low, and the vibration spectrum has a large number of frequency components due to the system's complexity, it becomes almost impossible to distinguish the fault-imposed peaks from the unwanted components. This is the most challenging problem associated with the FFT-based fault detection approach.

The frequency features with their importance were not used alone in the PHM task and were always joined with other domain features. Citing some primary research in this field using the frequency features, such as the use of Artificial Neural Networks (ANN) by (Boukhobza et al., 2013) and other machine learning methods (Priya et al., 2014; Shakya et al., 2013).

II.3.1.3 Time-Frequency Domain Analysis

The FFT of a signal provides information about the frequency characteristics of the signal. Thus, frequency analysis-based techniques discard time-domain information and only use frequency-domain information. The main advantage of time-frequency domain techniques is the use of both time and frequency domain information allowing for the investigation of the transient features. Several time-frequency domain techniques have been proposed, including Short Time-Frequency Transform (Antoni, 2006; Obuchowski et al., 2014), the Hilbert–Huang transform (Soualhi et al., 2015; Y. S. Wang et al., 2014), the Wavelet Transform (N. Li et al., 2012; Yan et al., 2014), and the empirical mode decomposition (Ben Ali et al., 2015; Lv et al., 2016; Mosallam et al., 2014b). Such methods require relatively more time and computational power than the previous methods.

II.3.2 Dimensionality reduction

Multivariate statistical techniques are powerful tools for compressing information and revealing essential phenomena in feature space. One typical method is principal component analysis (PCA) which is extensively reported in the literature (Harmouche et al., 2015; Z. Wang et al., 2012). Besides the PCA, the correlation analysis is also used to reduce the extracted features citing the work of (Guo et al., 2017; Lv et al., 2016; Qian et al., 2017). Recently, manifold learning (Gan et al., 2015; J. Wang et al., 2013) and isometric feature mapping (Benkedjouh et al., 2013) are also employed in bearing fault diagnosis. Consider the survey of (Liu et al., 2014) for more dimensionality reduction techniques.

II.4 Condition assessments

In condition assessment and fault diagnosis, the health indicator (HI) is the parameter to be monitored. It provides information about the health state of the system. In the literature review, there is no standard health indicator for bearings. Every researcher develops a valuable health indicator according to the available components and working conditions.

Where (Sassi et al., 2006) introduced two new parameters, TALAF, which describes the damage's evolution over time, and THIKAT represents the degree of confidence relative to the use of defective bearing and confirms the TALAF early diagnosis. The health indicator created by (Guo et al., 2017) is based on the related-similarity features combined with the Recurrent Neural Network.

In contrast,(P. Wang et al., 2012) proposed two health indicators, PHI and VHI, for physical and virtual health indicators, respectively. The PHI uses a dominant physical signal as a direct health metric, and the VHI uses a normalized health index as a combination of multiple physical signals. The Rayleigh distribution is used in HI construction in the work of (Bechhoefer & Schlanbusch, 2015); then, the RUL is calculated by applying Paris's law and estimated using the Kalman filter. The Self-Organizing Map (MAP) is also used as a health indicator in the work of (R. Li et al., 2012; Qiu et al., 2003).

It is essential to mention that the prognosis analysis based on intelligent health indicators performs better than directly exploiting raw signals (Atamuradov et al., 2017).

II.5 Prognostic (RUL estimation)

Prognostic capabilities are designed to provide maintenance personnel with insight into the future health of a monitored system. Since prognostic is associated with predicting the future, it inherently involves a degree of uncertainty. Indeed, the prognostic task is considered significantly more complex than the diagnostic since the evolution of equipment fault conditions is subject to stochastic processes.

The bearings failure is the highest cause of failures in rotary machines. A bearing can cause damage, often more than a thousand times its price, and the bearing cost is negligible for some cases like wind turbine generators and trains. To prevent such damage, many researchers focus on bearing prognostics and health assessment. Citing in this research field, the work of (Medjaher, Tobon-Mejia, et al., 2012), where the Mixture of Gaussians -Hidden Markov Model (MoG- HMM) is used for data-driven prognostic.

Hereafter, the principal component analysis is used by (Djeziri et al., 2018; Mosallam et al., 2015) as a data-driven method for residual space projection. Then, the remaining useful lifetime is calculated using a kinematic approach based on calculating the Euclidean distance from the normal operation to the faulty operation's clusters.

In addition, the work done by (Gonzalez et al., 2017) considers the uncertainties of the prognostic process based on the local analysis of the failure modes prognostics. Then, the Basic Belief Assignments (BBAS) method is used on several failures. Moreover, the author calculates the uncertainties from Mean Time to Failures (MTTF) and Mean Time Between Failures (MTBF). More details in surveys about methods used in prognostics are cited here (Atamuradov et al., 2017; Jing & Li, 2016). It is important to clarify that these researches are applied to the critical components and not the overall system. Nevertheless, there are other studies about the prognostic of complete system, where the model is known with accuracy (Atamuradov et al., 2017; Gonzalez et al., 2017).

One of the data-driven approaches in prognostic relies upon projection methods, which project the current level of degradation into the future. This task is essentially a time-series prediction problem, and it has been addressed by a variety of approaches, including autoregressive models (Qian et al., 2017) and exponential smoothing techniques (Liu et al., 2014; Niu, 2017). Many regression methods were applied in this context. Consider reviewing these researches for further details (Datong Liu et al., 2012; Soualhi et al., 2015).

The bearing prognostic problem is viewed as a pattern identification problem. Feature extraction techniques are used to extract features from vibration signals. These features are used for training neural networks, which are then used to match the future condition of the bearing. One of the most common data-driven techniques applied to prognostic problems is artificial neural networks (ANNs) (Boukhobza et al., 2013; Bouzidi et al., 2011; McCormick & Nandi, 1997; Patel et al., 2013; C. Xu et al., 2010; Yoon et al., 2011). They have been applied in several different ways for prognostics. Besides the ANNs, deep learning has been used (Guo et al., 2017; Gurvich et al., 2016; Lu et al., 2015; Sohaib et al., 2017), the Gaussian Process Regression (GPR)(Maran Beena & Pani, 2021; Wågberg et al., 2016), and the Hidden Markovian model (HMM) was discussed by (Tobon-Mejia et al., 2012). In order to explore the application of other machine learning in the bearings PHM field, we can refer to (B. Huang et al., 2017; Lee et al., 2014; Yoon et al., 2011)

More recent works are conducted in these couple of years, the work of (H. Xu & Ma, 2021) describes the use of the wavelet for feature extraction along with Attention-based LSTM (Long Short-Term Memory) and Random Forest (RF) to predict time series trends. And (Daniyan et al., 2020) dealt with the use of the envelope spectrum and kurtosis analysis for the detection of the bearing's inner and outer race fault for fault detection and the Least Square Method for a prognostic model. The used method for prognostics in our case of study was also the object of (Maran Beena & Pani, 2021) works along with other methods such as the ensemble of deep- autoencoder (DAE) and locally linear embedding (LLE), jointly referred to as the ‘‘DAE-LLE ensemble’’ detailed in (Bilendo et al., 2021). Another area of research is the development of more advanced machine learning algorithms that can analyze large and complex data sets. For example, the work of (C. Yang et al., 2021) where they used the generalized regression neural network (GRNN) to predict the health indictor by combining improved independent component analysis and the gray regression model. Another usage of the GRNN can be discussed in the work of (Tan, 2019), who studied the effect of the monotonicity, the trendability, the identifiability and the robustness of the statistical indicators on the ability of a fault feature to track and monitor the fault evolution process.

To fasten the RUL estimation, (Barbieri et al., 2021) adjust the parameters of the learning phase before using it in the prediction phase to reconstruct the Probability Density Function (PDF) of the current state.

The results of the previous researched demonstrate the quality of prognostics depends mainly on the feature extracted(Zhao et al., 2021).

II.6 Challenges

In the field of PHM, several challenges arise when trying to accurately predict the remaining useful life (RUL) of a system. One of the primary challenges is the lack of sufficient data, particularly run-to-failure data sets, which are necessary for training accurate models. Additionally, data from different sources and modalities must be integrated, which can lead to data quality issues and increased complexity. Choosing appropriate features that can capture the degradation process is another difficult task, and selecting the appropriate model and its parameters is equally important for achieving accurate RUL predictions.

This challenge is especially critical for systems where failures can have severe consequences, such as in aerospace and defense applications. Due to the scarcity of failure data and the difficulty of reproducing the scenarios that lead to failure, accurately predicting RUL remains a challenging and ongoing research topic in the field of PHM.

II.7 Conclusion

The following Table 2 englobes the relevant research from the literature review categorized according to the PHM layers:

Table 2: Prognostics literature review

PHM layer	Methods	References	Observation
Data Acquisition (Data domain)	**Data-Driven**	(Sassi et al., 2006 ; Sugumaran & Ramachandran, 2011).	• Most used approach. • Request historical data only.
	Model-Based	(SIMATRANG, 2015; Sohaib et al., 2017)	• Request a complete understanding of the asset. • Request a Mathematical model of components and failures.
	Experience Based	(Butler, 2012; Kamsu-Foguem & Mathieu, 2014)	• Based on expert feedback. • Not used in prognostics.
Signal Processing (Data Manipulation)	**Time Domain Extraction**	(Galar et al., 2012; He & Yang, 2012; Y. Wang et al., 2016)	• Adequate for fault detection. • Can be optimized. • Not accurate in diagnostics.
	Frequency Domain Extraction	(Patel et al., 2013; Priya et al., 2014)	• Adequate and accurate diagnostics and fault isolation. • Not accurate in fault detection and prognostics.
	Time-Frequency Domain Extraction	(Ben Ali et al., 2015 ; Lv et al., 2016 ; Mosallam et al., 2014b)	• Adequate for prognostics. • Request more time and computational power.

			• Complicated compared to the time and frequency domains.
Condition Monitoring (Fault detection)	**Self-Organizing Map**	(R. Li et al., 2012; Ren et al., 2011)	• Projecting high-dimensional data into a low-dimensional space • Preserve the neighborhood structure
	Statistical Feature Fusion	(McBain & Timusk, 2014; Qian et al., 2017)	• Combine extracted features based on a numerical experiment. • Adequate for a targeted situation.
	Principal Component Analysis	(Harmouche et al., 2015; Z. Wang et al., 2012)	• The most used method in data compression • Maximize the projected variance
Prognostics (RUL estimation)	**Gaussian Process Regression**	(Mosallam et al., 2014a)	• One of the most critical regression approaches • A nonparametric model with uncertainty predictions
	Hidden Markovian Model	(Medjaher, Tobon-Mejia, et al., 2012 ; Tobon-Mejia et al., 2012)	• Generally combined with a mixture of Gaussians. • Used to represent several failure modes.
	Deep learning-based Neural Networks	(Guo et al., 2017; Gurvich et al., 2016)	• Allow for more informative feature extraction. • Request considerable data to be trained.

Chapter III:

Health Indicator Based Condition Assessment

Quote:

Verily, the angels lower their wings for the seeker of knowledge. The inhabitants of the heavens and earth, even the fish in the depths of the water, seek forgiveness for the scholar.

Mohammed Messenger of Allah (ﷺ) - Sunan Abī Dāwūd 3641

III. Health Indicator (Based Condition Assessment)

The condition assessment method aims to develop a health indicator from the extracted data of the monitored asset (e.g., bearings in our case study). The health indicator is built using extracted features from multiple domains, which makes the feature extraction and feature reduction crucial phases in the condition assessment process. Thus, this chapter details feature extraction, dimensionality reduction, and health indicator construction.

III.1 Introduction

A health indicator should be able to detect any malfunction and reveal its sensitivity. The first term reflects the ability of an indicator to detect the onset of a malfunction before or at the beginning of physical alterations. On the other hand, the second term describes the importance of the indicator evolution in the presence of a defect revealed concerning its previous value. In contrast, fault identification and isolation are subject to the diagnostic layer, which is beyond the scope of this thesis.

Feature extraction seeks a transformation of the original variables to a smaller set. The original variables in our case study are obtained from the vibration monitoring of bearings, and vibration monitoring is carried out using time-domain, frequency-domain, or time-frequency analysis.

III.2 Data acquisition

Data acquisition is collecting and storing data from targeted engineering assets for condition monitoring, diagnostics, and prognostics. This process is an essential step in the PHM implementation and can affect the quality of the final decisions (Niu, 2017). Therefore, the decision of the data acquisition technique influences the workflow steps. During data acquisition, the choice of sampling frequency is crucial. Theoretically, to avoid any loss of information between the sensor's output and the acquisition card's input, the sampling frequency must be greater or equal to twice the maximum frequency of the signal to be sampled (Shannon’s condition). With the rapid development of computers and advanced sensor technologies, data acquisition facilities and technologies have become more powerful and less expensive, making data acquisition for PHM implementation more affordable and feasible.

III.3 Data Manipulation

Data manipulation lays a solid cornerstone for building reliable data-driven models. It aims at converting raw sensor data into usable information. In practice, raw sensor signals are usually very complex, and information about the degradation process of the monitored component is not always available. Generally, data manipulation methods can be divided into three main tasks: pre-processing, feature extraction, and feature reduction.
The extracted features should be sensitive to machine faults and, at the same time, robust to background noise. Another important consideration in data manipulation is that the computation complexity for extracting features should be low to be suitable for real-time implementation.

III.3.1 Data preprocessing

The acquired data are checked in order to detect possible errors or missing data. Indeed, sometimes certain parts of data matrices are replaced by a zero value or are entirely avoided. In such cases, the preprocessing substitutes missing symbols or data with other numerical values (averages in a window of previous data). Note that gathered data can undergo additional preprocessing, such as filtering to remove noise or resampling to reduce their size. Signal preprocessing is necessary to remove or reduce noise from a raw signal and extract compact information as features representing the signal's dynamics.
This process is applied in high voltages, noisy environments, and high signals to transform the sensor data into suitable forms for later processing. This way, signal preprocessing can maximize a system's accuracy and guarantee the constitutive device's safety. Signal preprocessing can include the following processes, amplification, attenuation, filtering, handling missing data, and validation. Data can then be displayed, analyzed, or processed with algorithms developed explicitly for PHM applications.

III.3.2 Feature Extraction

The feature extraction stage within a PHM system is designed to generate a vector of data features, which can infer the current fault status of a monitored asset and its future projection. The goal of feature extraction is to transform raw signals into other coherent and relevant signals. Besides, these extracted features depend on their further use; for example, failure detection features can differ from those used in prognosis analysis.

Other benefits of the feature extraction process are discussed by Zhu & Trevor (Zhu, 2001). This process is carried out using at least one of the three methods: time-domain analysis, Frequency domain analysis, and time-frequency analysis.

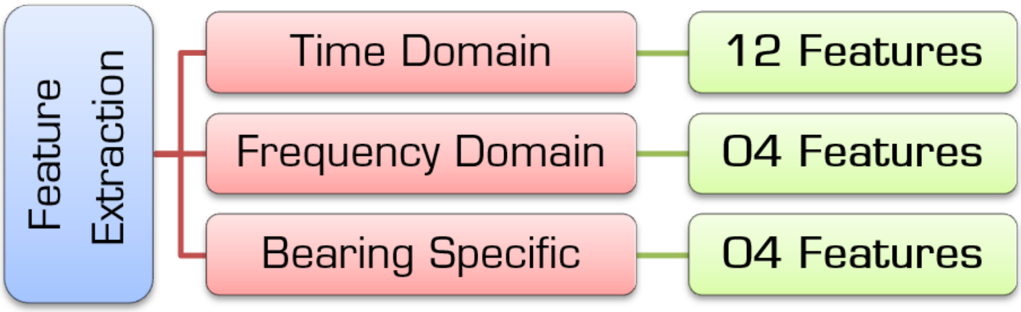


Figure 7 : Features Extraction

III.3.2.1 Time-domain descriptors

The time-domain features are recommended because standard and defective signals differ in their statistical characteristics in the time domain, where the calculation is simple and low complexity (Galar et al., 2012). In addition, they are calculated from vibration signals directly without any frequency calculations, reducing computation time and making them easily adaptable in the industry because of the simplicity of their application (Boukhobza et al., 2013).

The extracted features focus on calculations of the statistical parameters of the signal. They are used to perform fault detection analysis. However, their direct use in prognostic can lead to unsatisfactory results. Time-domain methods are directly based on the time waveform such as mean, peak, standard deviation, root amplitude, root mean square (RMS), skewness, kurtosis, Hyper-kurtosis, Shape factor, Crest factor, Impulse factor, and Clearance factor, where the description and the formulation are listed in Table 3 (Chalouli et al., 2017).

Table 3: Time-domain features

N°	Feature	Symbol	Equation	
1	Mean	$\bar{x}$	$\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert$	eq. (5)
2	Root mean square	x_{rms}	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$	eq. (6)
3	Peak	x_{peak}	$max(\lvert x_i\rvert)$	eq. (7)
4	Root amplitude	x_{ram}	$\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x_i\rvert}\right)^2$	eq. (8)
5	Standard deviation	x_{std}	$\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2}$	eq. (9)
6	Skewness	x_{skew}	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^3}{(n-1).x_{std}{}^3}$	eq. (10)
7	Kurtosis	x_{kur}	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{(n-1).x_{std}{}^4}$	eq. (11)
8	Hyper Kurtosis	X_{hku}	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^6}{(n-1).x_{std}{}^6}$	eq. (12)
9	Shape factor	x_{shf}	$\frac{x_{rms}}{\bar{x}}$	eq. (13)
10	Crest factor	x_{crf}	$\frac{x_{peak}}{x_{rms}}$	eq. (14)
11	Impulse factor	x_{imf}	$\frac{x_{peak}}{\bar{x}}$	eq. (15)
12	Clearance factor	x_{clf}	$\frac{x_{peak}}{x_{ram}}$	eq. (16)

The use of time-domain features directly has many shortcomings. Noting initially, when a defect appears, the tiny shocks increase the peak level considerably but have less influence on the RMS. The RMS level may become significantly high in bearings with multiple or spreading defects, reducing the Crest factor. (Sassi et al., 2006).

III.3.2.2 Frequency domain descriptors

However, even if they are well suited for online monitoring, time-domain indicators do not identify the defect responsible for the degradation (Sassi et al., 2006). The Fast Fourier transformation (FFT) is the common method to migrate from the time domain to the frequency domain. The frequency domain is more suitable for diagnostics because it provides specific information about faults and failures. Now that the data are represented in frequency space, we extract the following features: the Max Amplitude, Frequency Center, RMS Frequency, and Root Variance Frequency; more details about the formulation are given in (Boldt et al., 2013).

III.3.2.3 Bearing Specific descriptors

The particularity of these features is to be used only for the bearings. In this case, four critical frequencies are recommended for monitoring: the ball pass outer race (BPFO), ball pass inner race (BPFI), ball spin frequency (BSF), and fundamental train frequency (FTF). These frequencies are extracted continuously during the run–to–failure process, where the formulation and description can be consulted at (Miao et al., 2011). Signals with time-varying frequency content cannot be treated with the traditional Fourier Transform because this method averages the time-varying signal and loses the non-stationary characteristics, which may be necessary.

III.3.2.4 Effect of Features

Among the three techniques, time-domain indicators are the simplest and easy to implement (P et al., 2014). They are independent of the rotational speed even when there is no load (Batista et al., 2013). While the frequency-domain indicators give specific information about the bearing failure but not the time of occurrence, which is useless from the prognostic point of view. Time-frequency techniques map the one-dimensional signal to a two-dimensional in the function of time and frequency. Thus, these techniques present a valid tool for analyzing a non-stationary signal. However, each of these techniques has some drawbacks. It also seems that eliminating one of these shortcomings leads to the loss of advantage in another aspect of the analysis. All three techniques have been described in detail in (Patidar & Soni, 2013) and compared in (Boudiaf et al., 2016).

III.3.3 Dimensionality reduction

Given the unawareness of degradation phenomena, extracting more characteristics than necessary is not so rare, making their representation and visualization difficult. Bearing that some features are similar to others and knowing that calculation time and cost are directly proportional to the number of treated features make feature reduction an important step. To circumvent this situation, we can consider two strategies, as illustrated in Figure 8:

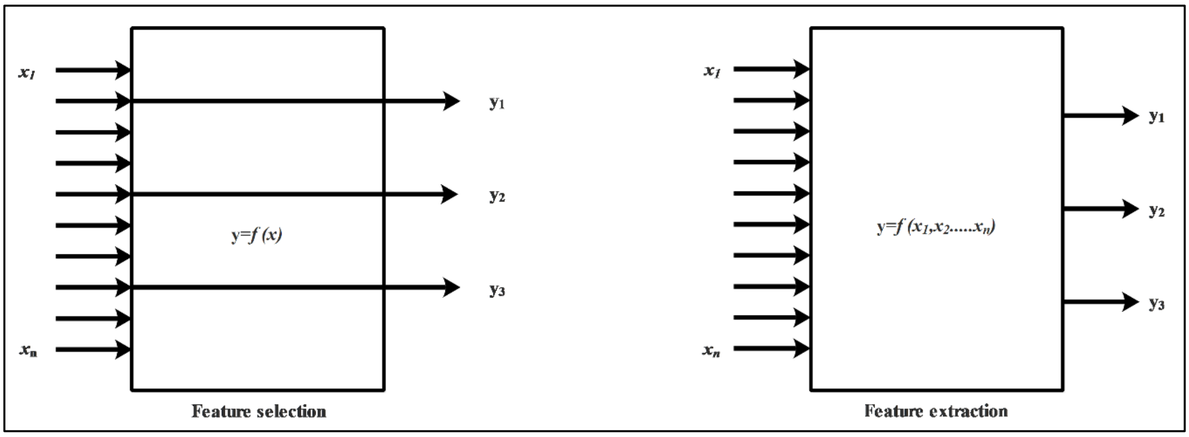


Figure 8: Dimensionality reduction techniques

In our case study, the feature selection based on the cross-correlation filter is used as a dimensionality reduction method. In contrast, the feature reduction based on the SOM or the PCA is used for the health indicator construction.

III.3.3.1 Cross-Correlation Filter

A cross-correlation filter is applied to reduce the non-informative features, selecting only the informative for the fault detection task at the end of the process. Where the coefficient of correlation between two features is calculated by equation (17):

$$CC(A,B) = \frac{CV(A,B)}{\sqrt{CV(A,A)*CV(B,B)}} \qquad \text{eq. (17)}$$

$$CV(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}(A_i - \mu_A) * (B_i - \mu_B) \qquad \text{eq. (18)}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} A_i \qquad \text{eq. (19)}$$

The advantages of this method against others, such as Principal Component Analysis (PCA), can be resumed in two main points.

The non-alteration of the feature's nature, where the results are a reduced number of features saving the characteristic of each feature, while the results of PCA, for example, give a new representation of input data in other spaces. The direct selection of non-redundant features represents the second point after the features are reduced, which does not require other calculations compared to the PCA method, where the analysis must be done every time, the features have to be reduced. This advantage is well illustrated when the relevant features process is invoked more than once.

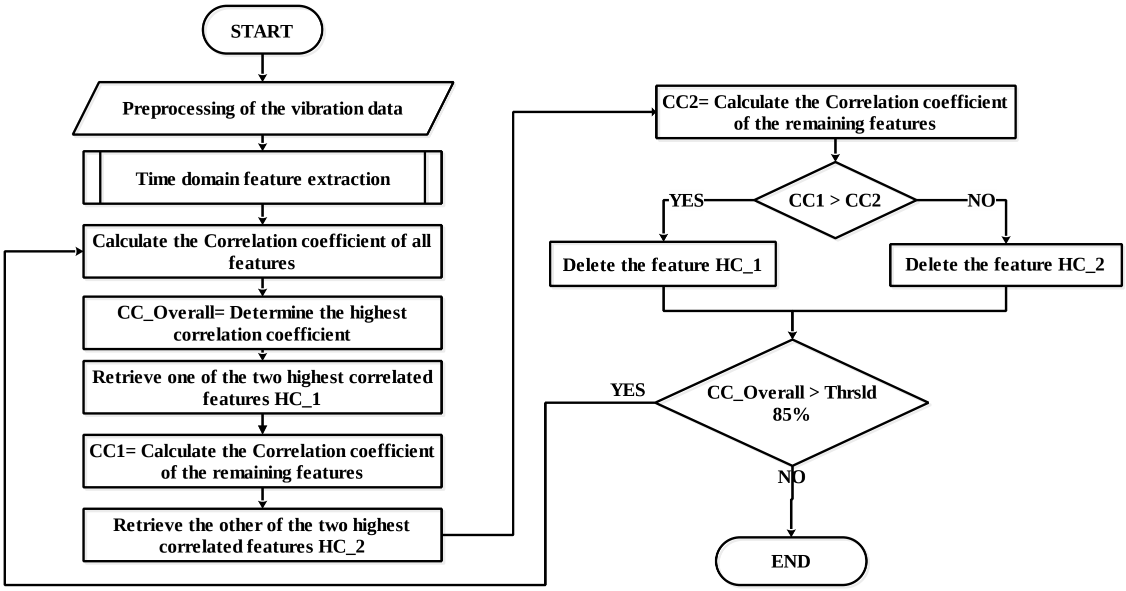


Figure 9: Cross-correlation filter algorithm

A Correlation-based feature selection is applied for the redundant features isolation phase to determine the similar features before eliminating one of each two highly correlated features according to the algorithm described in Figure 9. Once the two features with the highest correlation value are selected, the correlation coefficient is calculated using one of these two with the rest of the features. The feature giving the highest correlation coefficient should be removed, and the whole process is repeated until the overall coefficient reaches a predefined threshold (Th). The remaining features are inputs for the next relevant feature selection phase. More details about the cross-correlation filer are available in (McBain & Timusk, 2014)

III.3.3.2 K-Means clustering

K-means is one of the industry's most popular clustering algorithms (Medjaher, Tobon-Mejia, et al., 2012). It is calculated using Lloyd's algorithm, which begins with k arbitrary centers chosen randomly among the data points. Once done, each point is assigned to the nearest center. Then, it calculates each center as the center of all its assigned data points. Finally, the whole process except the random choice is repeated until the process stabilizes.

The speed and simplicity of the k-means method make it appealing(Benkedjouh et al., 2013). The initial point for the k-means clustering should be appropriately chosen to overcome the problems associated with local optima (Hong & Zhou, 2012). It is used in our case to evaluate the optimality criterion –the best distinction between the bearing's different health states – for all possible combinations of "d" variables selected from "F" features and select the combination for which this criterion is a maximum. The difficulty arises because the number of possible subsets is:

$$N_{feat} = \frac{F!}{(F-d)!\,d!} \qquad \text{eq. (20)}$$

Which can be very large even for moderate values. In our case, selecting the best ten features out of 20 means that 184 756 feature sets must be evaluated.

Therefore, according to the literature review, we applied the optimization only to the time-domain features (12 features), which only two features can be represented (Ocak, 2004).

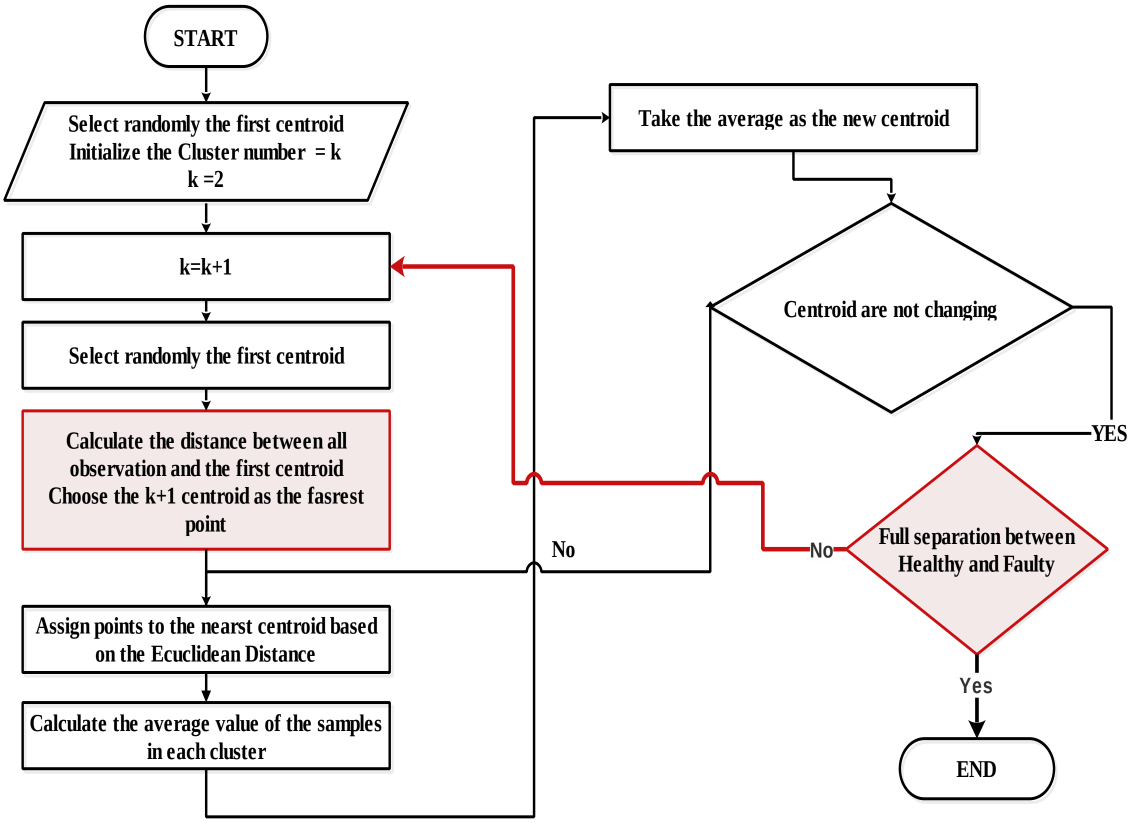


Figure 10 : K-Means ++ flowchart

III.4 Health Indicator Construction

Health indicators are signals constructed either from raw data or from extracted features. In both cases, their construction usually requires several processing steps (data fusion, filtering, and extraction of residuals), intending to obtain an indicator with enough information to reveal the component's health status. Previous research has shown that no feature is suitable for all defect types at all degradation stages. Thus, the reliable performance of the fault detection method should take advantage of mutual information from multiple features (Hai Qui & Lee, 2004). In this case, future fusion is key to getting a robust health indicator detecting several defect types at different stages. The health indicator goodness is represented by the earlier detection of the component degradation going from a healthy state to a faulty condition. We studied several methods to extract adequate health indicators for that purpose.

III.4.1 HI-Based Self-Organizing Map

The self-organizing map (SOM) is a type of artificial neural network that is often used for data visualization and pattern recognition. Recently, researchers have explored the use of SOMs as a health indicator in the field of prognostics and health monitoring (PHM). SOMs can be used to visualize and analyze sensor data from equipment, enabling maintenance teams to identify patterns and anomalies in equipment behavior.

SOMs can be particularly useful for identifying complex patterns in large and complex data sets. For example, SOMs can be used to identify clusters of data points that represent different operating conditions or failure modes. Previous research has shown that no feature is suitable for all defect types at all degradation stages. For example, Kurtosis is ideal for detecting incipient defects, whereas the RMS value indicates severe defects.

III.4.1.1 SOM Principals

The SOM is an appropriate tool for this task with its unique capability of projecting high-dimensional data into a low-dimensional space while preserving their inherent topographic relationships (Hai Qui & Lee, 2004). The SOM is a neural network concept developed by Kohonen in 1990 (Kohonen, 1990). It provides a non-linear, ordered, smooth mapping of high-dimensional input data manifolds onto the elements of regular, low-dimensional.

During the training process, the neurons compete with each other to become the best matching unit (BMU) for a given input vector. The BMU is the neuron in the SOM that is most similar to the input vector, based on a similarity measure such as the Euclidean distance.

When a new input vector is presented to the SOM, the BMU is identified by computing the distances between the input vector and each neuron in the SOM. The neuron with the smallest distance to the input vector is selected as the BMU as described by equation 21.

$$BMU_i = arg_i\, min\,\{\|X_i - W_i\|^2\} \quad \text{eq. (21)}$$

Where:

X_i are the input vector's values

W_i are the Neuron wights

arg_i min operator is used to find the index of the neuron with the smallest Euclidean distance. This means that the BMU is the neuron whose weight vector is closest to the input vector x.

Thus, the BMU is the neuron whose weight vector is closest to the input vector, and it is found by calculating the Euclidean distance between each neuron's weight vector and the input vector, and then selecting the neuron with the smallest distance. Once the BMU is identified, the SOM algorithm updates the weights of the BMU and its neighboring neurons in the SOM grid, according to a learning rate and a neighborhood function. This process is known as the SOM learning rule.

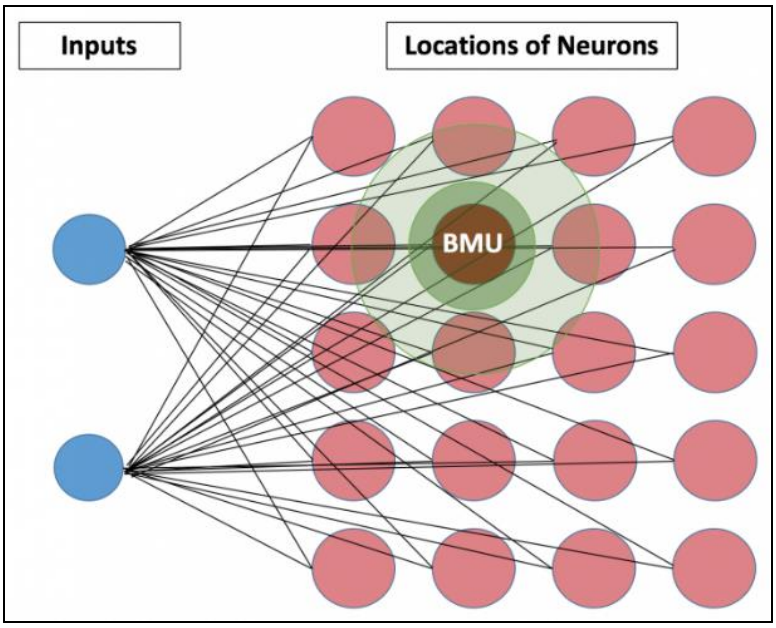


Figure 11 : SOM MAP

Generally, the SOM algorithm uses the following equation for weight adaptation.

$$W(t+1) = W(t) + \theta(t) * L(t) * (X_i(t) - W(t)) \quad \text{eq. (22)}$$

Where:

t: is the time-step.

W(t) is the weight vector of the neuron at time t.

W(t+1) is the updated weight vector of the neuron at time t+1.

θ(t) is the learning rate at time t, which controls the magnitude of the weight update.

L(t) is the neighborhood function at time t, which determines the extent of influence that neighboring neurons have on the weight update.

$X_i(t)$ is the input vector at time t.

The learning rate, the neighborhood function, and the difference between the input vector $X_i(t)$ and the current weight vector W(t) are three terms that must be multiplied together to create the updated weight vector at time t+1.

The learning rate, which normally ranges from 0 to 1, controls the size of the weight update. Larger weight updates and quicker convergence are produced by higher learning rates, although instability and oscillation are also possible side effects. A smaller weight update and slower convergence are produced by a lower learning rate, but the system is more stable.

The degree to which nearby neurons affect the weight update is determined by the neighborhood function L(t). Usually described as a Gaussian function, it is a decreasing function of separation from the Best Matching Unit. The neighborhood function makes sure that neighboring neurons in the SOM grid are updated as well, allowing the map to self-organize and maintain the input space's structure.

Overall, the equation explains how the SOM algorithm updates a neuron's weight vector over time based on the input data and the connections between nearby neurons. More information about the Learning rate calculation can be found here (Cho et al., 2004).

The tool used for dimensionality reduction in our case study, the vector quantization. Which is considered as a way of reducing the dimensionality of the input data while preserving the essential characteristics of the data. The squared distance between an observed data X_i and its corresponding centroid (Best matching unit BMU) is the quantization error (Bodt et al., 2002).

In our case study, the relevant features selected for fault features extraction are trained using the SOM toolbox described by (Vesanto et al., 1999) in two steps: First, applying training with a large neighborhood radius and learning rate, followed by fine-tuning. After training, the next step is calculating the mean quantization, which produces the average distance between each data vector and its best matching unit.

The Figure 12 represents the flowchart of the SOM algorithm implemented in our case study Where the Batch algorithm is applied twice. The first as a rough training and the second as a fine tuning.

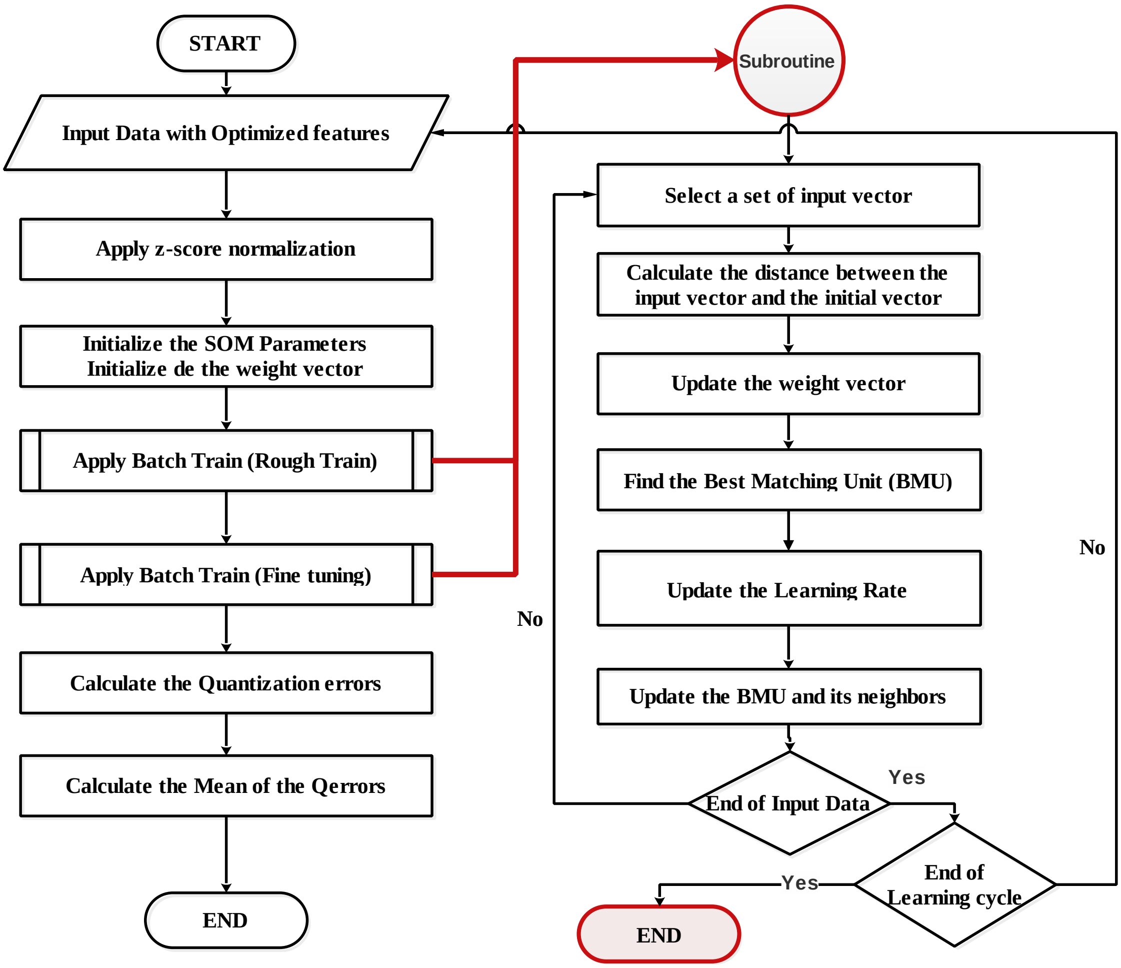


Figure 12 : Self-Organizing Map flowchart

III.4.1.2 Mean Quantization Error

The mean quantization error (MQE) is a measure of this quantization error. It is defined as the average distance between each input vector and its BMU (Best Matching Unit) in the map. A lower MQE indicates that the SOM has learned to represent the input space more accurately. The MQE can be calculated as:

$$Q_{error} = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} \sum \|X_i - B_i\|$$

Where:

N: Number of sample vectors x in the input data.

Xi: Data-vector

Bi: Best matching prototype of the corresponding Xi (equation 21)

Some key factors that affect the MQE are:

- SOM size - A larger SOM with more neurons will typically have a lower MQE, as it can represent the input space with higher resolution.

- Training iteration - The MQE will decrease over training iterations as the SOM learns to better quantize the input space.

- Input distribution - A more uniform input distribution will generally lead to a lower MQE compared to a clustered distribution. Clustered data is harder for the SOM to quantize accurately.

- Learning rate - A lower learning rate will often result in a lower MQE, as the SOM is able to make finer adjustments to neuron weights during learning.

- Neighborhood function - A decreasing neighborhood size usually results in a lower MQE compared to a fixed neighborhood size. This is because neurons become specialized to represent specific regions of the input space.

So, in summary, the MQE measures how accurately the SOM can represent the input data, with a lower MQE indicating a more accurate quantization of the input space.

MQE is a continuous value that can be used to monitor the health of the bearing over time. As the bearing degrades, the MQE value will increase, allowing for early fault detection.

Figure 13 demonstrates the MQE flowchart which is used in our case as the health indicator allowing an early fault detection.

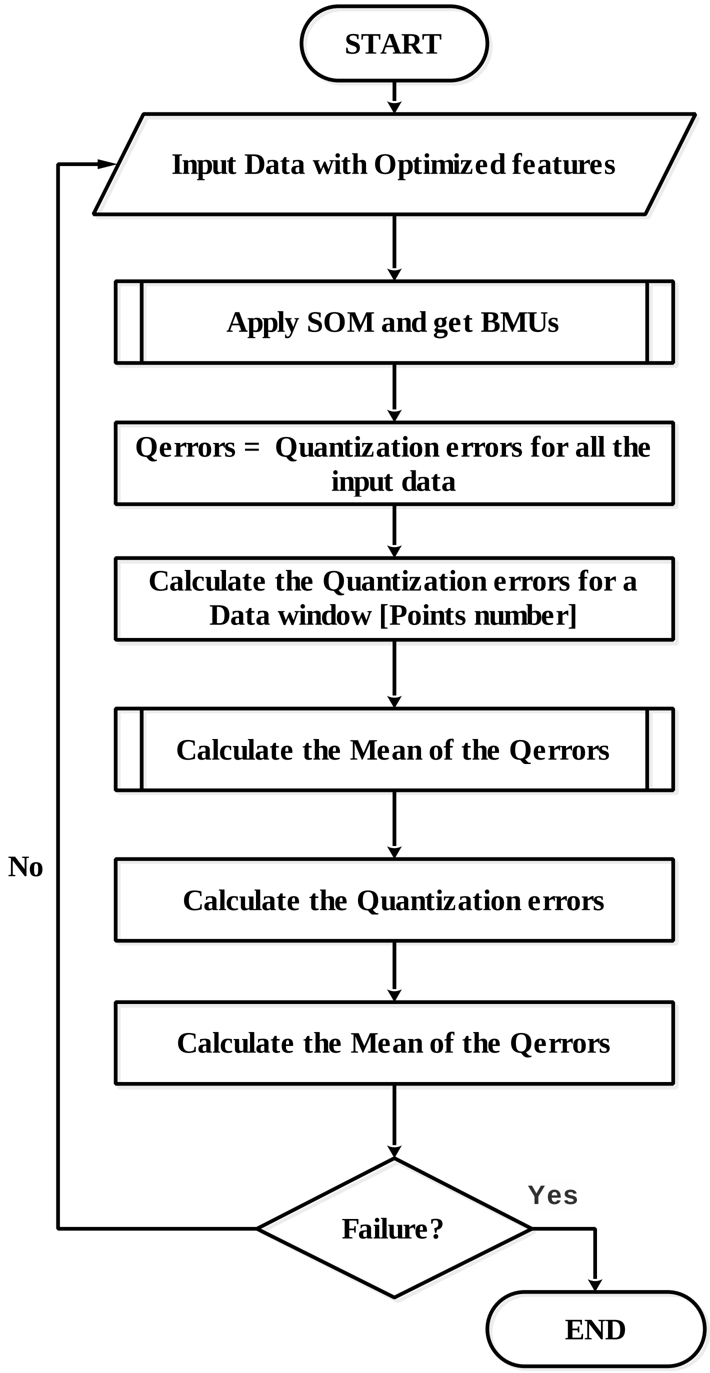


Figure 13: Mean Quantization Error

III.4.2 HI-Based Principal Component Analysis

PCA is a technique that can be used to simplify a dataset. More formally, it is defined as a linear transformation that chooses a new coordinate system for the data set such that the most significant variance by any projection of the dataset comes to lie on the first axis, which is called the first principal component (PC), the second most significant variance on the second axis. The matrix after the transformation has a diagonal covariance matrix, which means new matrix column vectors are not correlated with each other. This makes it easy to eliminate the influence of noise or redundant variables on the determinant variables. Figure 14 gives one graphical example of PCA. (Jiang, 2012)

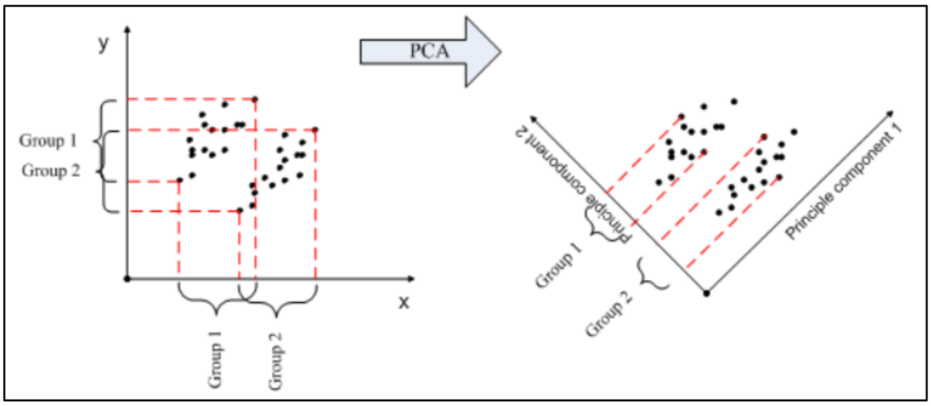


Figure 14: Graphical example of PCA

The dataset in Figure 14 consists of two groups of data. The left graph shows a scatter plot of the data. It is hard to identify the two groups using either the x variable or the y variable since x and y are correlated, and their duplicated information weakens their ability to classify the data by themselves. The right graph shows the result after PCA transformation. Data has been projected to a new coordinate system with PC1 and PC2. PC1 and PC2 are entirely uncorrelated, and the two groups can be easily identified by setting a dividing threshold for PC2.

PCA converts feature vectors into a lower-dimensional random variable with independently distributed components; by finding the eigenvalues and eigenvectors of the covariance matrix to represent the statistical significance and directions of principal components, respectively. More details about PCA are discussed in (Abdi & Williams, 2010; Ardakani et al., 2012; Baraldi et al., 2010; Han et al., 2010; He & Yang, 2012). The first component and Hotelling's T-squared values are used in our case study.

III.4.2.1 First Component

The objective of PCA is to find unit-length linear combinations of the variables with the most significant variance. The first principal component represents the line that minimizes the total sum of squared perpendicular distances from the points to the line.

It represents the maximum variance direction in the data, where each point may be projected onto this line to get a coordinate value along the principal component line.

III.4.2.2 Hotelling's T-Squared

In 1931, Harold Hotelling proposed a multivariate generalization of the student t-distribution. Hotelling's T-squared distribution is essential in statistics because it arises as a set of statistical distributions. In particular, the distribution arises in multivariate statistics in undertaking tests of the differences between the (multivariate) means of different observations. (Onwuka, 2012).

III.5 Conclusion

In conclusion, it is essential to clarify the difference between the feature extraction, reduction, and selection discussed in this chapter:

- **Feature Extraction:**
  This step determines the signal descriptors according to a specific domain (time, frequency, and time-frequency). Features from multiple domains are used in our case study.

- **Feature Selection:**
  A large dataset of features requires more time and cost for computation, which is a problem to avoid. The cross-correlation filter is applied in our algorithms.

- **Feature Reduction:**
  Once the redundant features are ignored, we select only the relevant features at the end of the process. The SOM and PCA are applied to reduce the feature dimensionality.

Chapter IV:

Trend Indicator Based RUL Estimation

Quote:

“˹O Prophet,˺ “Are those who know equal to those who do not know?” None will be mindful ˹of this˺ except people of reason.”

Az-Zumar 39:09 – QURAN

IV. Trend Indicator (Based RUL Estimation)

In recent years, prognostics got many definitions citing the Standard (ISO 13381-1: 2015), which defines prognostics as “an estimation of time to failure and risk for one or more existing and future failure modes.” The main aim of prognostics analysis is to provide the needed information to make the right decision regarding the machine's condition.

IV.1 Introduction

One of the most significant pieces of information the prognostic can deliver is the RUL estimation. The RUL can be defined as the time to failure of a component or a system according to the state's current health and the component performance history. The RUL estimation is the process of estimating the remaining time left for an asset before failure. The industry uses it to manage risks that result from unexpected equipment failure. So far, the process is based on historical observations of the machine.

IV.2 Prognostics Based Data-Driven

Recently, various techniques have been applied to predict the RUL of monitored systems, which is reflected in the diverse range of applications. Data-driven models are based on statistical and learning techniques. In this thesis, the learning approach involves developing software that optimizes a performance criterion based on historical data. With the growing number of sensors in a real-world system, the possibility of detecting the machine's behavior and the current state increased. Therefore, most approaches in recent literature on failure type detection and predictive maintenance rely upon data-driven techniques. These models are more generic than physical and knowledge-based models. There are three different learning techniques, as described in the following Figure 15 (Patrick Jahnke, 2015).

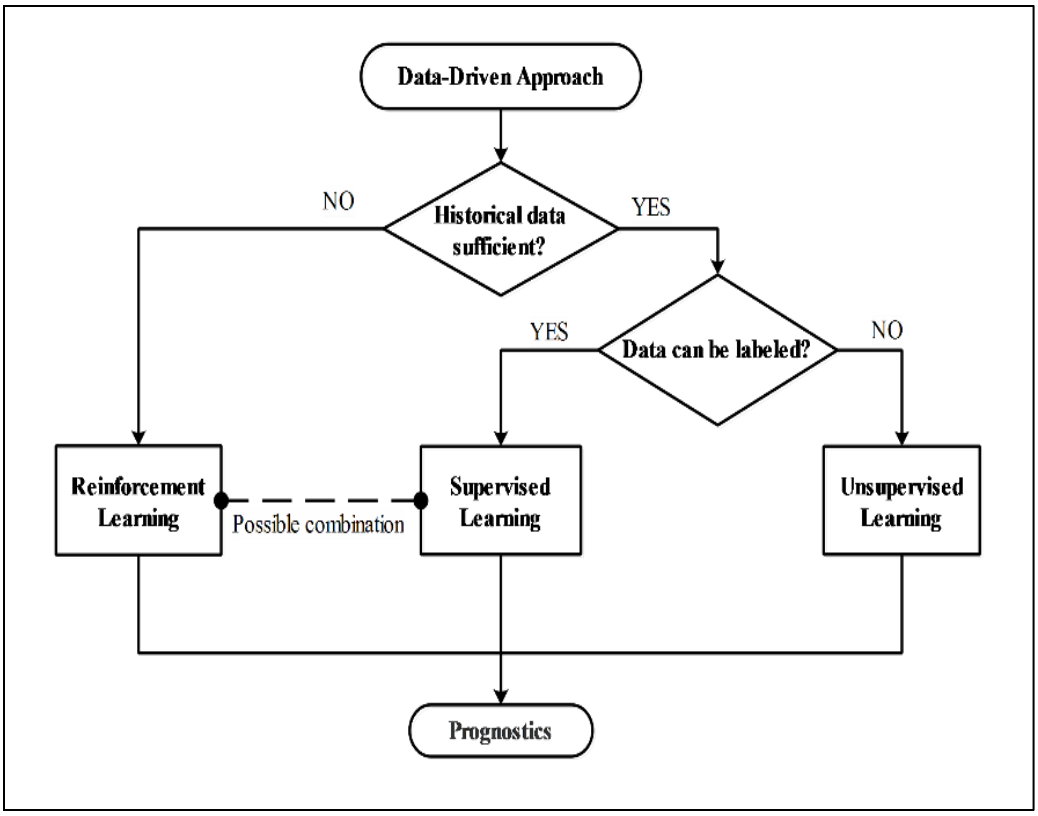


Figure 15: Data-Driven techniques

IV.3 Remaining Useful Life Identification

The aim of prognostics is "the estimation of the Time to Failure and the risk of existence or later appearance of one or more failure modes." Medjaher, Tobon-Mejia, et al., 2012); to provide information that helps in making correct decisions. Therefore, the RUL can be defined as the time between the fault time and the failure time (Okoh et al., 2014; Qian et al., 2017; Tobon-Mejia et al., 2012). Thus, it is crucial to define suitable fault and failure thresholds for accurate prognostic.

IV.4 Trend Indicator

The life prediction model's key is finding a prognostic feature that generates a health indicator and then extrapolates it to a certain predefined critical failure threshold. To make an autonomous routine to effectively select the good features, a set of metrics to characterize the suitability of prognostic features has been proposed (Jin, 2016).

The following parameters can evaluate the Prognostic ability:

- **Separability**:
  The general idea is to rank the features by their ability to distinguish the difference between the two classes: healthy and faulty, which means that the data are far apart between different classes and close to each other for the same class. For prognostics, the critical point is the continuity of the separation between time segments instead of separability between two clusters as in diagnostics. The prognostics separability measures the ability of feature separation between the continuous-time segments over the asset's entire life.
- **Monotonicity**:
  It is a function that is either entirely nonincreasing or nondecreasing. A function is monotonic if its first derivative (which need not be continuous) does not change the sign.

These two parameters are the key indicators to measure the effectiveness of a feature representing the failure progression. More details about the prognostic criteria are discussed in (Boukra & Lebaroud, 2014; Guo et al., 2017; Jin, 2016; Mosallam et al., 2014a). We are interested in the trend indicator construction using regression methods in our case study.

IV.4.1Based on linear regression

The name “LOWESS” is derived from “LOcally WEighted Scatterplot Smooth,” as the method uses locally weighted linear regression to smooth data based on linear polynomial fitting. The smoothing process is considered local because, like the moving average method, each smoothed value is determined by neighboring data points defined within the span. It is a popular tool used in regression analysis that creates a smooth line through time or scatters plots helping to see the relationship between variables and foresee trends. The robust function is not integrated into this case study since the outliers are essential to consider.

LOWESS is a non-parametric strategy for fitting a smooth curve to data points. Because some distribution is assumed in advance, a parametric fitting can lead to fitting a smooth curve that misrepresents the data. In those cases, non-parametric smoothers are a better choice.

The local polynomials that fit each subset of the data are usually of the first or second degree. High-degree polynomials would tend to over-fit the data in each subset. They are also numerically unstable and make accurate computations difficult.

IV.4.2Based on Empirical Mode Decomposition

Huang originally proposed the empirical mode decomposition (EMD) in 1998, and it has attracted attention due to its ability to self-adaptive decomposition of non-stationary signals. The EMD is based on the Intrinsic Mode Functions (IMFs), which decompose the health indicator into time signals with different frequencies. Each IMF must satisfy the following definition:

- The IMFs have the same number of extrema and zero-crossings.
- Among all the values of the signal *x(t)*, the number of extrema and that of zero-crossings must be equal or differ at most by one.
- At each instant t, the average value of the envelope defined by the local maximum and the envelope defined by the local minimum is close to zero

More explanations about the EMD implementation are provided by (J. Huang et al., 2011; Junsheng et al., 2006), and (Gouriveau et al., 2016).

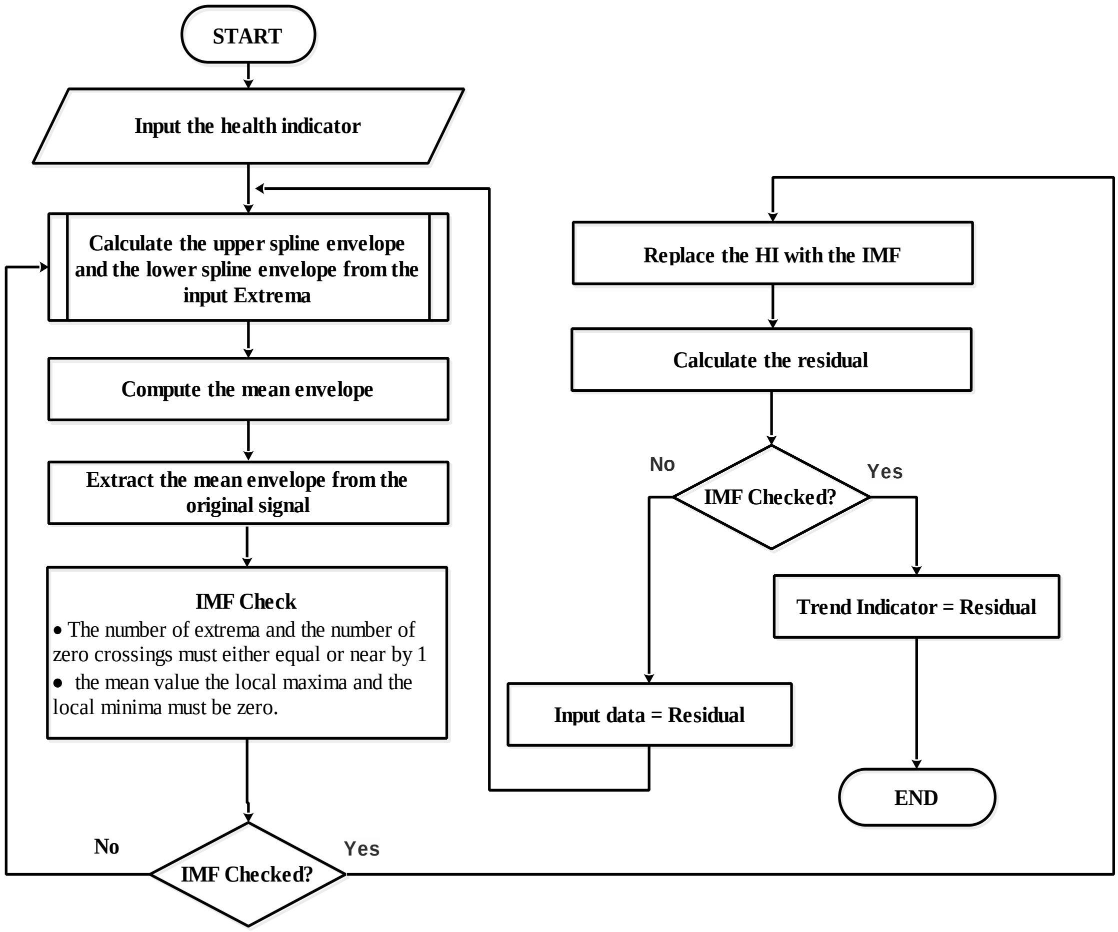


Figure 16 : EMD Flowchart

IV.5 RUL Estimation

Estimating a system's RUL, which involves estimating when a component will stop working, is a crucial step in PHM. In order to prevent unplanned downtime and lower maintenance costs, proactive maintenance requires an accurate RUL estimate. we will focus on the use of GPR for RUL estimation, with a particular emphasis on the calculation of confidence intervals to provide a more robust estimate of RUL.

For RUL estimation, where the underlying physics may be complex and nonlinear, GPR offers a probabilistic framework for regression analysis that can handle nonlinear and nonstationary data. Another crucial element of RUL estimation is the use of confidence intervals, which offer a level of assurance about the projected RUL.

IV.5.1Gaussian Process Regression

Only after degradation is detected can a machine's remaining useful life (RUL) be predicted. RUL is the remaining time until the machine can no longer serve its intended function. RUL is generally predicted by extrapolating the health metric to the defined end-of-life (EOL) threshold. Setting an appropriate threshold is not simple but can be set using statistical limits or more accurately based on previous experiences.

One method for RUL prediction is to use time series models, such as regression techniques, to predict future health. Another way to use the similarity-based approach that predicts the RUL is by comparing the current degradation trend with historical run-to-failure trends and using an aggregate of similar historical trends to make a prediction (Gouriveau et al., 2016; MOSALLAM, 2014). We are interested in our case study by the regression approach where the Gaussian process regression (GPR) method is applied.

The Gaussian process regression is a flexible, powerful, and probabilistic approach to dealing with a nonlinear regression; it provides a variance around its mean predictions to describe the associated uncertainty. In GPR, the model-training inputs are generated from degradation data in the run-to-failure experiments. Then the dynamic model is applied to predict the bearing health state for the next period(MOSALLAM, 2014). More technical formulation is detailed in (Lei et al., 2018; MOSALLAM, 2014; Mosallam et al., 2014a; Wågberg et al., 2016), while the advantages and drawbacks of this method are discussed in (Kan et al., 2015; Lei et al., 2018).

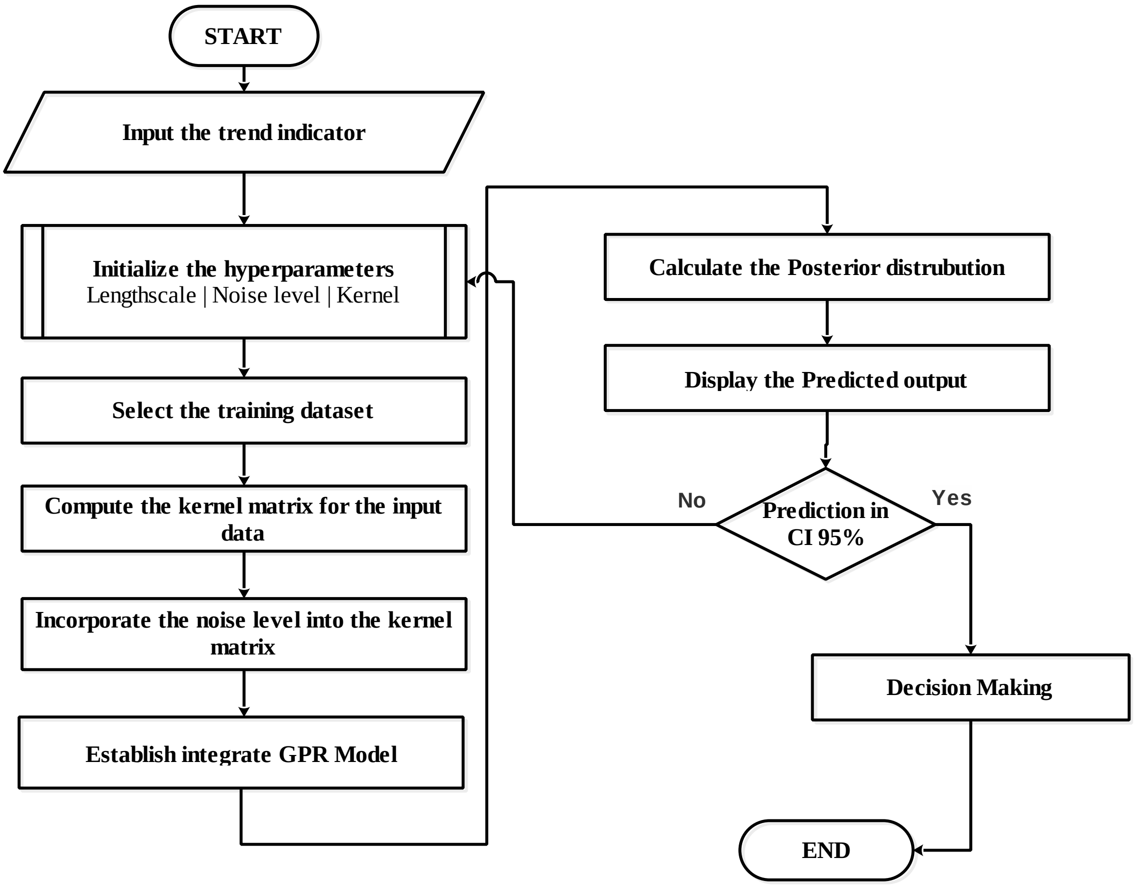


Figure 17 : GPR Flowchart

IV.5.1.1 GPR Parameters

Gaussian Process Regression (GPR) is a powerful machine learning technique that is increasingly being used in the field PHM to predict the RUL of components and systems. GPR is a non-parametric Bayesian approach that can capture complex relationships between inputs and outputs, making it well-suited for PHM applications where there may be limited data or complex failure mechanisms.

There are several parameters that need to be selected when using GPR for PHM, including the kernel function, hyperparameters, and noise level. The kernel function determines the shape of the covariance matrix between input data points and plays a crucial role in GPR's ability to capture underlying patterns and trends. The choice of kernel function depends on the nature of the data and the problem being solved.

Hyperparameters are another important parameter that needs to be selected when using GPR. These are parameters that define the behavior of the kernel function, such as the length scale or noise level. Proper selection of hyperparameters can lead to more accurate RUL predictions.

IV.5.1.1.1 GPR Kernel

In Gaussian Process Regression, the kernel function is essential because it establishes the correlation between the input variables and serves as the foundation for creating predictions. The underlying data and the current problem determine which kernel function should be used. The squared exponential kernel, usually referred to as the radial basis function kernel, is the most frequently used kernel function in GPR. Because it is infinitely differentiable and offers a smooth and adaptable function that may identify intricate patterns in the data, the squared exponential kernel is well-liked. Given sufficient data, it can approximate any function with arbitrary precision, earning it the nickname "universal kernel." Another advantage of the squared exponential kernel is that it can handle input variables with different units and scales, which is common in PHM applications. The squared exponential kernel is defined as:

$$k\left(X_i, X_j|\theta\right) = \sigma_f^2 . e^{\left(-\frac{1}{2} . \frac{\left(x_i - x_j\right)^T \left(x_i - x_j\right)}{\sigma_l^2}\right)} \quad \text{eq. (23)}$$

Where:

σ_l is the characteristic length scale,

σ_f is the signal standard deviation,

σ_n^2 is the signal variance.

IV.5.1.1.2 Length scale

The length scale is a hyperparameter in GPR that determines the degree of correlation between input variables and controls the smoothness and flexibility of the function. It is typically optimized on a training set to achieve good generalization to new data, and can be thought of as the characteristic length over which the variables influence each other. A small length scale results in a wiggly function closely fitting the training data, while a large length scale results in a smoother function interpolating the data less closely. The length scale equation is defined as:

$k(X_i, X_j) = e^{\left(\frac{1}{2} \cdot \frac{\|(X_i, X_j)\|^2}{L^2}\right)}$ eq. (24)

Where:

$\|(X_i, X_j)\|^2$ is the squared Euclidean distance,

L is the correlation coefficient

IV.5.1.1.3 Noise level

The noise level is a hyperparameter in GPR that accounts for the inherent noise in the data. It represents the variance of the Gaussian distribution that is added to the diagonal of the kernel matrix to ensure numerical stability and prevent overfitting. In other words, it controls the amount of noise that is allowed in the data and helps the GPR model to generalize to new data by smoothing out the predictions. The noise level is defined as:

$y = f(x) + \aleph\,(0, \sigma_n^2)$ eq. (25)

Where:

f(x) is the underlying Gaussian Process,

$\aleph\,(0, \sigma_n^2)$ is the Gaussian noise with zero mean

σ_n^2 is the signal variance.

IV.5.2Confidence Interval

Confidence Interval (CI) measures the range of predictions among the different instances at the same time index, taking into account uncertainties in the input signals to the learned models(F. Yang et al., 2016). Knowing the probabilistic density allows specifying an interval on the output into which 95% of the observations are likely to fall. Therefore, the width of this interval measures how certain we are about the prediction made by this classifier. The confidence interval (CI) metric is defined as an interval that contains a specified percentage of the predicted RULs at a time index

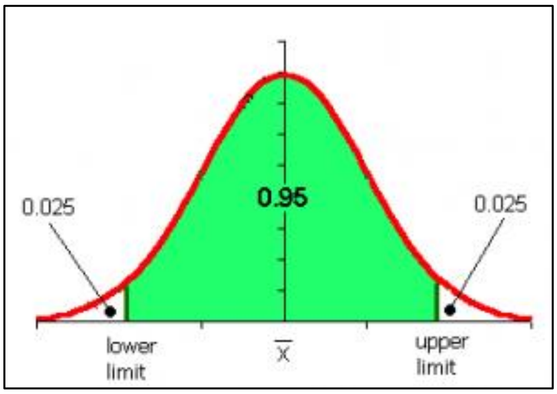


Figure 18: Confidence Interval

$$\varepsilon = \Pr\left(R_t - \frac{(1-\varepsilon)}{2} \leq R_t^i \leq R_t + \frac{(1-\varepsilon)}{2}\right) \quad \text{eq. (26)}$$

Where:

Pr is the probability density function. | R_t^i is the predicted RUL of the instance *i* at *t*.

ε is the pre-specified percentage, which is generally selected as 95%.

IV.6 Conclusion

Among the used methods for trend indicator construction, the residual of the EMD provides the best results. In contrast, the GPR is an adequate regression tool in our case study. Hereafter, the estimation process gets the prior probability distribution and the current observations as input.

Chapter V:

Results and Discussion

Quote:

“My Lord! Increase me in knowledge. - وَقُل رَّبِّ زِدْنِي عِلْمًا ”

TAHA 20:114 - QURAN

V. Results and Discussion

In this chapter, we discuss the results of our proposed methods related to predicting the remaining useful life of bearing.

V.1 Introduction

The Results and Discussion chapter is one of the most critical sections of this thesis. It represents the statistical analyses, and comparisons with existing techniques. The results are interpreted, discussed, and evaluated in the context of the research questions and objectives, providing insights into the effectiveness and limitations of the proposed method.

V.2 Prognostics workflow

Our proposed method aims to estimate the remaining useful life for multiple kinds of bearing under different conditions; starting by extracting twenty features, twelve time-domain features, four domain-specific features, and four frequency-domain features from the vibration input signals. Hereafter, a cross-correlation filter is applied to select the relevant features automatically. The Self-Organizing Map is used to build a more coherent health indicator offering representation. Then, the empirical mode decomposition is applied, where the residual is considered the Trend Indicator (TI). Finally, to predict the RUL, many algorithms were used for the trend indicator, but the GPR provides the best result overall for the datasets.

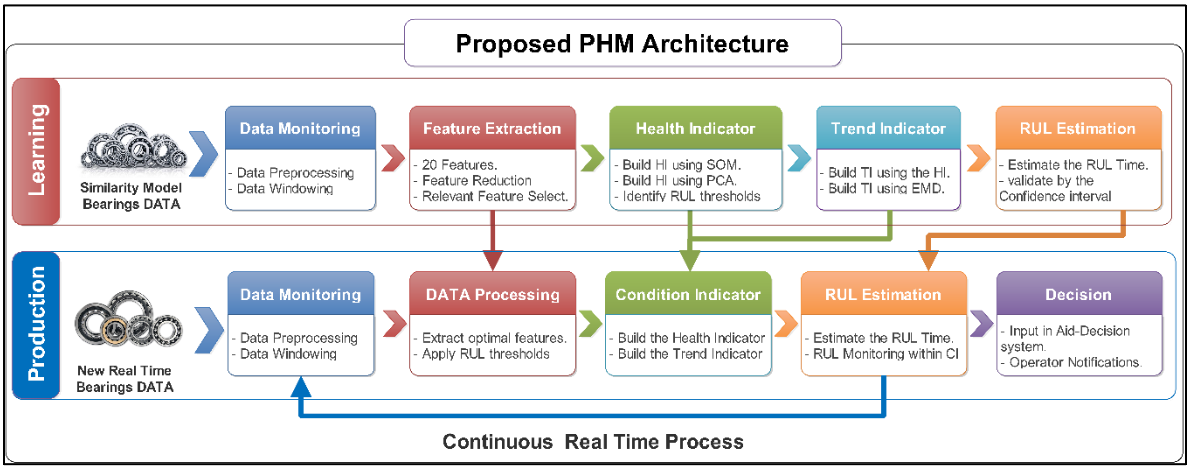


Figure 19: The proposed method for prognostics

The process can be divided into two main parts: Learning and Production.

V.2.1 Learning mode

The learning is based on extracting multiple domain descriptors from the raw vibration signal. Once the features are extracted, the cross-correlation filter is used to eliminate the redundant and irrelevant features. Since more than half of the features are time domain, an unsupervised machine-learning algorithm is requested to determine only features carrying relevant information. In this case, the Euclidean square distance of K-Means determines the optimal features.

Hereafter, the health indicator is built for monitoring the health state of the bearing using a self-organizing map or principal component analysis as dimension reduction approaches. The method's simplicity and ease of implementation make it suitable for real-time industrial applications.

An idle health indicator has a monotonic curve, but such a curve is almost impossible to get in real life. Thus, a smoothing of the results is required to make the results more exploitable without altering the significance of the health indicator. Then, fault and failure thresholds are set. The RUL is calculated for all the bearings in multiple datasets and compared to the known RUL to find a formula that can be applied on all the bearings with a minimal error marge. Finally, the formula with the lowest error rate is maintained. The organigram in Figure 21 illustrates the production process.

V.2.2 Production mode

In contrast to the learning mode, which is based on well-known bearings for learning, the production mode is applied to new bearings. The acquisition process remains the same as in the learning mode, and the feature extraction this time is faster and more accurate since the adequate features to be extracted are already known from the learning phase. Moreover, the trend indicator is built using the residual of the EMD method applied to the health indicator. Hereafter, the results are used in GPR to predict the future state of the bearings, and a confidence interval is set to judge the rightness of the results before implementing the results into an aid-decision system. The following organigram illustrates the production mode process.

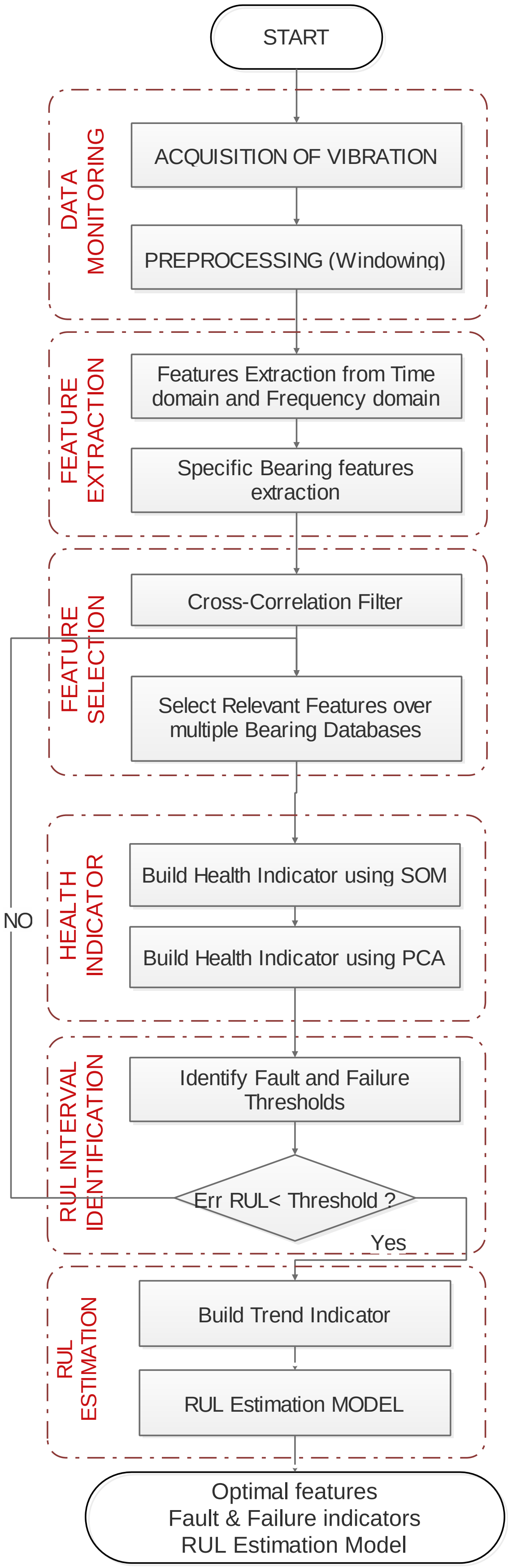


Figure 20: Flowchart of the learning phase

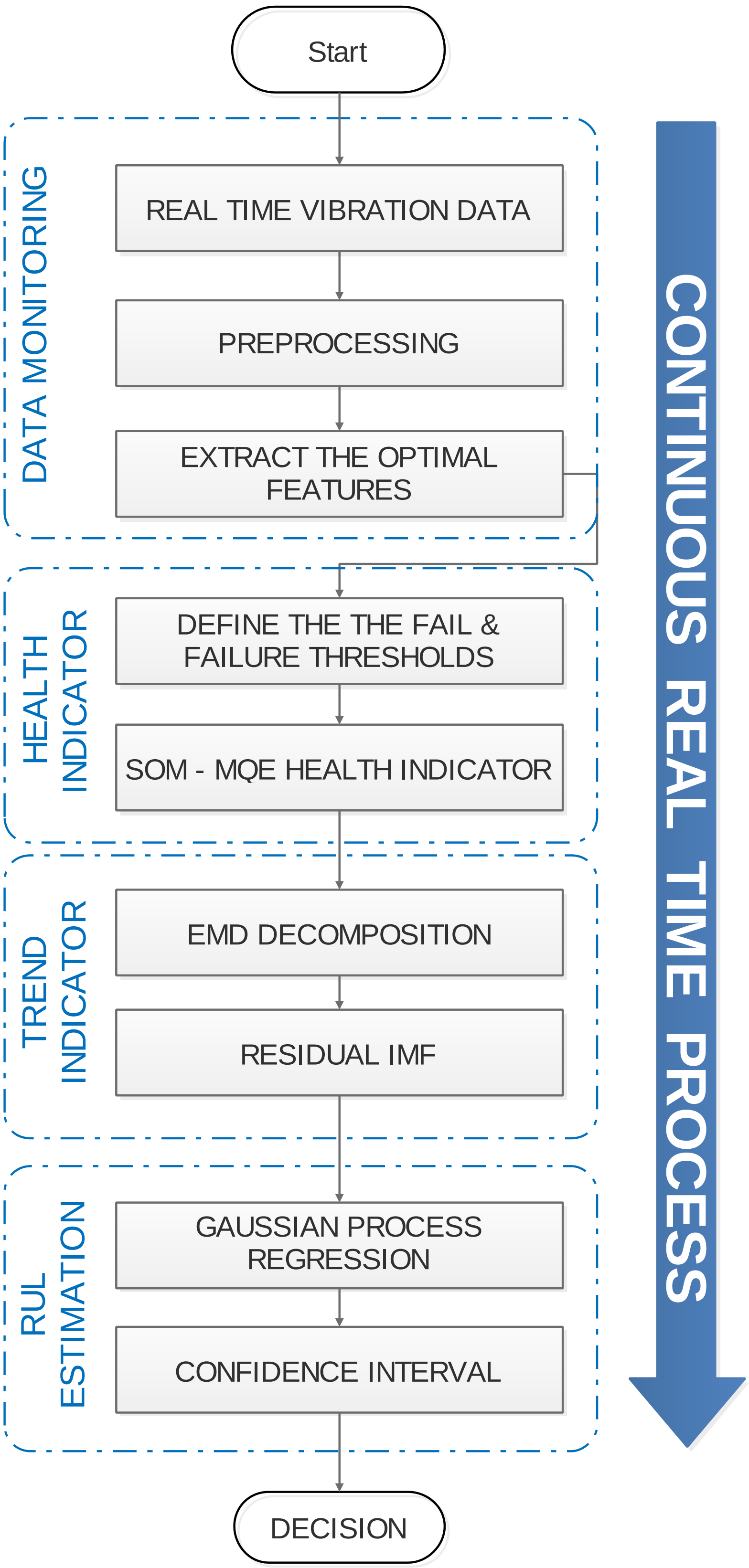


Figure 21: Flowchart of the production phase

V.3 Benchmark Datasets

To validate our research, three international benchmark databases are used. Table 4 resumes the principal information of each database.

Table 4: Benchmark-bearing datasets

<table>
<tr><th>Databases /
Type</th><th>Bearing type</th><th>Speed [RPM]</th><th>Radial load</th><th>Samples per sec</th><th>Bearing Quantity</th><th>Fault types</th></tr>
<tr><td>IMS Center
/
Run-to-Failure</td><td>Rexnord ZA-2115 double row</td><td>2000</td><td>26689 N</td><td>20 000</td><td>12
(4 Known failures)</td><td>Inner Race
Outer Race
Roller Element</td></tr>
<tr><td rowspan="3">IEEE PHM’12 Data Challenge FEMTO-ST
/
Run-to-Failure</td><td rowspan="3">Rotating deep groove ball bearings</td><td>1800</td><td>4000 N</td><td rowspan="3">2 560 each 10s</td><td rowspan="3">17
(6 Known failures)</td><td rowspan="3">Undefined type</td></tr>
<tr><td>1650</td><td>4200 N</td></tr>
<tr><td>1500</td><td>5000 N</td></tr>
<tr><td rowspan="6">Case Western Reverse University
-CWRU-
/
Classification</td><td rowspan="6">6205-2RS JEM SKF, normal deep groove ball bearing</td><td>1797</td><td>0 N</td><td rowspan="3">12 000</td><td rowspan="6">57

(54 Faulty
/
3 Healthy)</td><td rowspan="6">Inner Race:
7mm – 14mm – 21mm
Outer Race:
7mm – 14mm – 21mm
Ball:
7mm – 14mm – 21mm</td></tr>
<tr><td>1750</td><td>1 471 N</td></tr>
<tr><td>1730</td><td>2 206 N</td></tr>
<tr><td>1797</td><td>0 N</td><td rowspan="3">48 000</td></tr>
<tr><td>1750</td><td>1 471 N</td></tr>
<tr><td>1730</td><td>2 206 N</td></tr>
</table>

V.4 Data Acquisition

In this case study, we are interested in the prognostic based on the vibration data. For accurate results, the data cannot be used directly in the prognostic process and requests some conditioning before being exploited, such as the windowing process where a rectangle window is used to divide the continuous vibration signal into small windows. The windows length is specified in the following Table 5:

Table 5: Benchmark Databases windows

Databases	Database type	Windows [second]	Number of points
IMS	Run to failure	1.024	20480
PHM'2012	Run to failure	1.000	2560
CWRU (12K)	Classification	0.050	600
CWRU (48K)	Classification	0.050	2400

V.5 Feature Extraction

The feature extraction process is considered as one of the most critical phases in both diagnostics and prognostics—a reliable prognostic consists of the best choice of the used features. To get the possible information from the input signal, we extracted the most used features in bearing.

From the figure below (Figure 22), we note that several features mostly have the same shape, and it is irrelevant to treat the same data more than once. Therefore, and for optimization purposes, two phases are needed:

- **Learning mode:** where all the potential features are extracted from more than one domain, citing: 12 features from the time domain, 04 features from the frequency domain, and 04 specific bearing features from the time and frequency domain.
- **Production mode:** only the optimal selected features are extracted, considerably reducing computational power and time. The feature selection criteria are discussed in the next chapter.

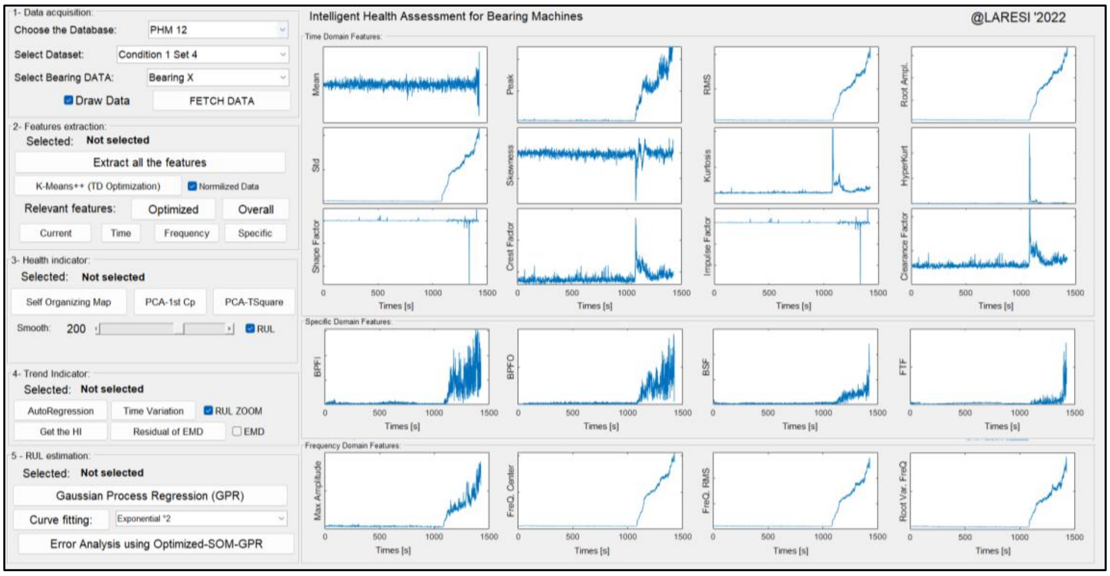


Figure 22: Data extraction from PHM datasets.

V.6 Feature Selection

Before tackling the feature selection, feature reduction is required in this phase. Therefore, the cross-correlation filter is applied to eliminate the redundant –irrelevant– features. Where the two features with the highest correlation value are selected. The correlation coefficient is calculated using one of these two with the rest of the features. The feature giving the highest correlation coefficient is removed, and the whole process is repeated until the overall coefficient reaches a threshold of 0.8, according to the algorithm described in equation 17.

The overall results show that seven dominant features remain from the twelve time-domain features: Mean, Peak, RMS, Skewness, Kurtosis, Shape Factor, and Max Amplitude. In addition to the frequency domain and specific domain features. Figure 23 shows the relevance of the time-domain features and their correlation.

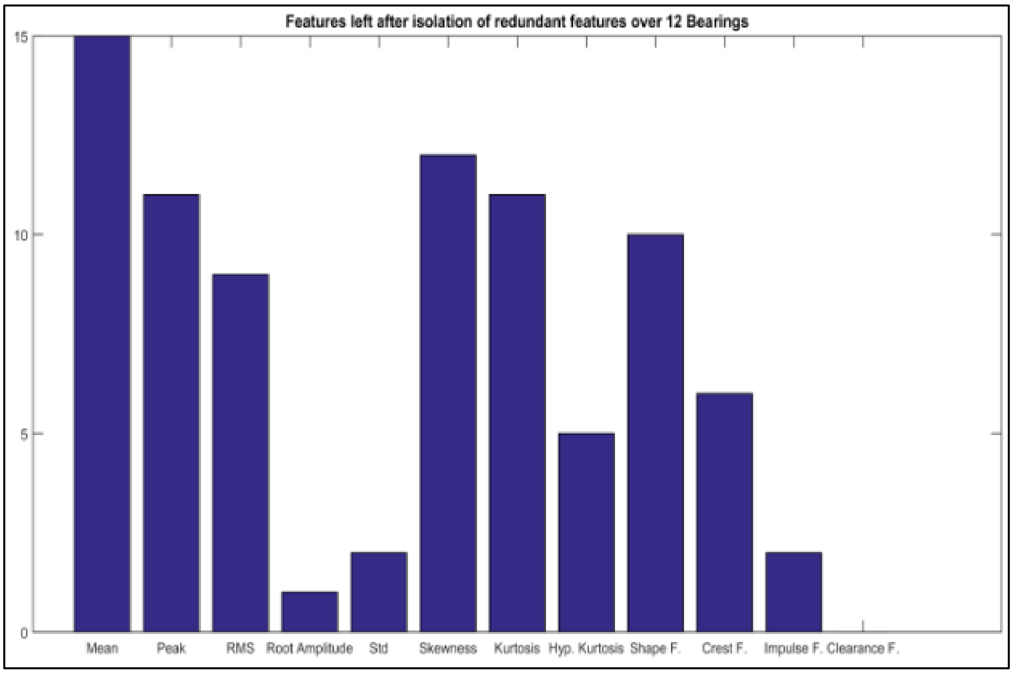


Figure 23: Dominant time-domain features for bearing

The red graphs in Figure 24 represent the dominant features, while those in blue refer to the redundant features.

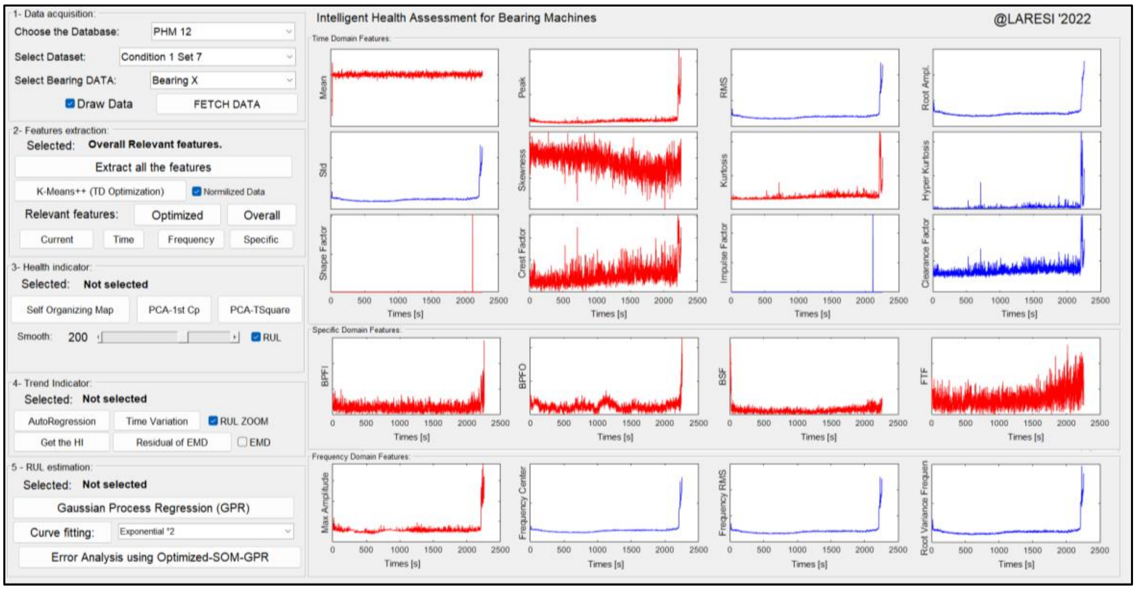


Figure 24: Selected non-redundant features for bearing applied to the PHM database

To extract the optimal time-domain features and to confirm that the chosen features are adequate for fault and failure detection; we used the CWRU classification database. Where the K-Means is used to determine the characteristics given the further square

Euclidian distance between healthy and faulty bearing, this process was applied only to the time domain since they represent more than half the selected features.

The simulation started with twelve features, and seven were eliminated at the isolation of redundant features process using the cross-correlation filter. At the same time, the remaining was normalized for the relevant features selection task. Hereafter, the two features with the best representation (density distribution) and the highest distance are the relevant fault features in the time domain. Table 7 shows the squared Euclidean distance between the health centroid and the fault one for the dominant features.

Table 6: Comparison of original and normalized data for kurtosis and Crest factor.

Kurtosis-Crest Factor			
Health /Inner R_12	(Norm-Org)007	(Norm-Org)014	(Norm-Org)021
RPM 1797	0-0	0-0	0-0
RPM 1750	0-1	0-0	0-0
RPM 1730	0-2	0-2	0-1
Health /Outer R_12			
RPM 1797	0-0	0-12	0-0
RPM 1750	0-0	0-85	0-0
RPM 1730	0-0	0-94	0-1
Health /Ball_12			
RPM 1797	0-12	0-75	0-12
RPM 1750	0-89	0-58	0-36
RPM 1730	0-79	0-67	0-111
	Normalized error:		**0**
	Original errors:		**737**

Table 7: Squared Euclidean distance between health and fault states of time-domain features

Features	RMS - Skewness	RMS - Kurtosis	RMS- Crest F.	Peak- Kurtosis	Skewness- Crest F.	Skewness- Kurtosis	Kurtosis- Crest F.
Squared Euclidean distance	0.1605	0.1642	0.1648	0.1646	0.1647	0.1641	**0.1682**

The kurtosis and crest factor gives the most considerable distance. Thus, they are considered relevant features and can be described as:

- **Kurtosis:** Defined as the fourth normalized moment and described as the ratio of the fourth moment to the variance. It measures peakedness and its degree of distribution compared to a normal distribution. A high value of kurtosis means a long tail of the distribution.
- **Crest factor:** Defined as the ratio of the peak value over the RMS value. It gives an idea about any impacts present in the signal, which detects acceleration bursts even if the signal RMS has not changed.

Many researchers confirm that Kurtosis and Crest factor are the more suitable features for fault diagnosis. These features are non-dimensional magnitudes, so they are immune from weaknesses in the data process due to the quality of the sensors or the location where they are mounted(Öztürk et al., 2015).

Table 8. Relevant Features are classified by the measure of separability.

	Occurrence	Occurrence %
Kurtosis – Crest Factor	**14**	**52%**
Shape Factor– Crest Factor	11	41%
Mean-Skewness	02	7%
TOTAL	**27**	**100%**

Table 8 shows the results applied to nine cases of classification between “healthy bearing and Inner race fault”, “healthy bearing and Outer race fault” and “healthy bearing and Ball bearing fault”, from the CWRU database. The 27 cases show that the two features providing the farther distance intra-class are Kurtosis and Crest fact.

Moreover, the frequency and specific domain features are added after optimizing the time-domain features. From the results, it can be deduced that even for the same kind of bearing, there is a slight difference in the number of dominant features because of the measurements and manufacturing conditions. In our case study, the seven optimal overall features are:

Time domain: Kurtosis – Crest Factor,

Specific domain: BPFI – BPFO – BSF,

Frequency domain: Frequency Max amplitude, and Root Variance Frequency.

In the scope of the study of the features, several combinations of features are taken:

- **Optimized selection [07]:** Kurtosis – Crest Factor – BPFI – BPFO – BSF – Max Frequency Amplitude.
- **Overall selection [11]:** Mean – Peak – Skewness – Kurtosis – Crest factor – Shape factor – BPFI – BPFO – BSF – FTF – Max frequency amplitude.
- **Time-only selection [02]:** Kurtosis – Crest Factor.
- **Frequency only selection [04]:** Max frequency amplitude – Frequency center – Frequency RMS – Root variance frequency.
- **Specific only selection [04]:** BPFI – BPFO – BSF – FTF.

The results show that using a single domain gives unsatisfactory results. On the other hand, using all the features takes relatively more time and computational power with less accurate results than optimizing features.

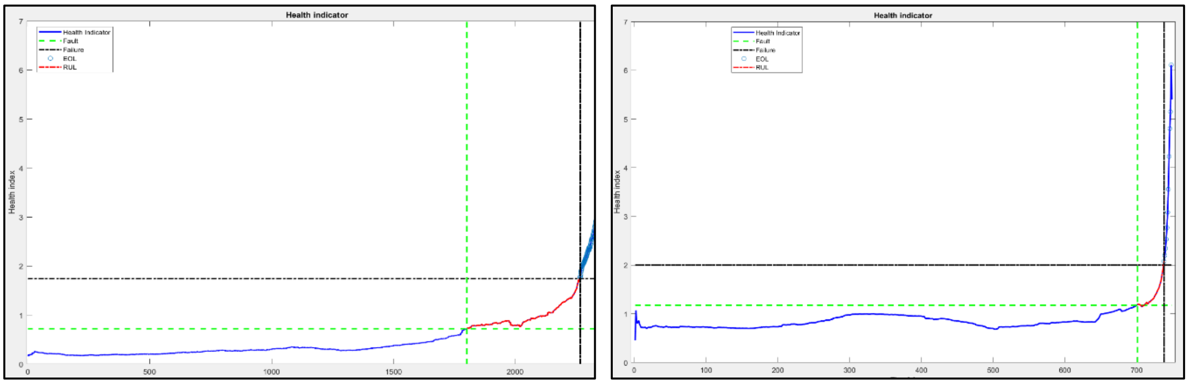
V.7 Health Indicator Construction

The health indicator construction aims to identify fault and failure and comprehensively represent the bearing health state. The health indicator can also be considered a feature reduction technique since it reduces the selected optimal features to one feature with a two-dimensional projection.

The health indicator is considered reliable if the level of failure is always higher than the level of fault. Moreover, once the fault level is reached, it cannot step back to a healthy level. Therefore, several HIs are experimented in order to get more accuracy from one hand. On the other hand, getting a generic formula to be applied to multiple types of bearings in various working conditions. In addition, the smoothing process is applied at the end of the health indicator construction to get a coherent curve representing the bearing health states. Where smoothing is removing the unnecessary oscillations associated with the raw signal by modifying its data points. So, points with higher values than neighboring points are reduced, and points with lower values are increased. The resulting signal is smoother with reduced noise levels and outliers. A moving average filter is used to smooth our health indicator with an experimental span taken at 200.

V.7.1 Self-Organizing Map (SOM)

The application of the SOM provides overall accepted results. Figure 25 demonstrates the results of the PHM'2012 database.



Condition 1 Set 3 Condition 2 Set 4

Figure 25: Health Indicator using the SOM method

This method provides good results on both benchmarked databases and offers a coherent representation of the bearing health states.

V.7.2 1st component of Principal Component Analysis

The results obtained from the PCA are not suitable for all the cases of bearing that we have. Figure 26 illustrates different results given by the first component of PCA.

PHM'12 - Condition 1 Set 3 IMS - Set 1 Bearing 4

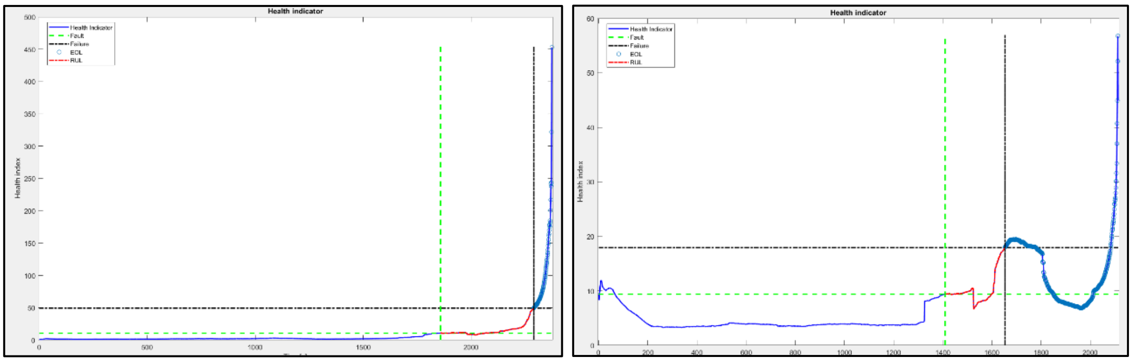
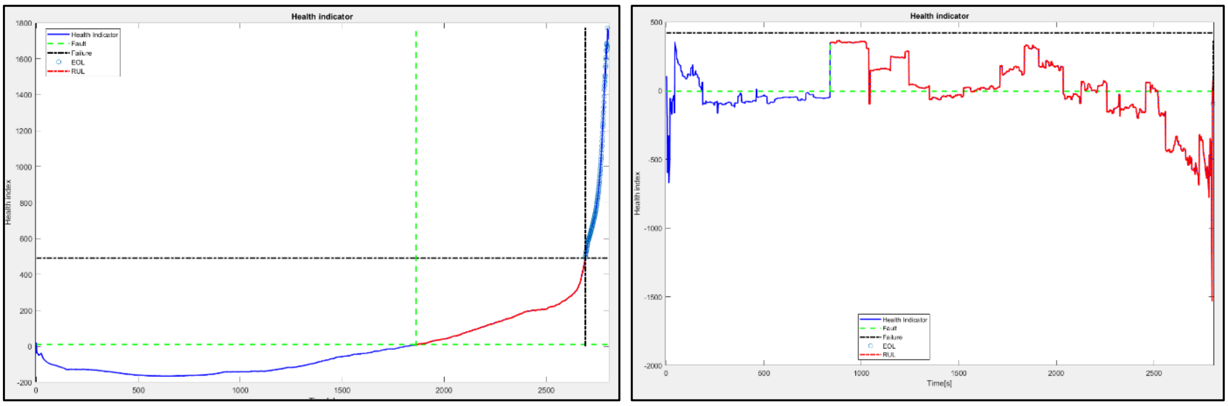


Figure 26: Health Indicator using the first component of the PCA method

The curve obtained from the PHM database, as illustrated on the left of Figure 26, is reliable and suitable for fault detection tasks, while the right curve from the IMS database presents a wrong indicator since the level of the health state reaches the failure edge and return to the healthy area before reaching the failure level once more. Therefore, the PCA using the first component is not considered a reliable health indicator in this case.

V.7.3 T-square of Principal Component Analysis.

To explore this field more, we studied another parameter extracted from the PCA: Hotelling's T-Square. Figure 27 shows the results of the T-square when applied to the first set of the first condition of the PHM'2012 database. The HI on the left is built using the optimized features (07 features: Kurtosis – Crest Factor – BPFI – BPFO – BSF – Max Frequency Amplitude). While the suitable HI on the right is built using (Mean – Peak – Skewness – Kurtosis – Hyper kurtosis – Crest factor – Shape factor – BPFI – BPFO – BSF – FTF). Even if five features are common between the two configurations, the results are very different for the HI.



Optimized Features | Current Features

Figure 27: PHM' 2012 Condition 1 Set 1 HI using the T-Square of PCA method

V.8 Remaining Useful Life Identification.

Once the HI is constructed, the decision is made according to the position of the health indicator to the fault threshold (Green) given by equation (27) and failure threshold (Black) given by equation (28), as illustrated in Figure 28.

$$\text{Fault} = \frac{\frac{1}{n}\sum_{i=1}^{n}(Hi_i)}{\sqrt{2}} \qquad \text{eq. (27)}$$

$$\text{Failure} = 2 \times \sqrt{\frac{1}{n}\sum_{i=1}^{n} {Hi_i}^2} \qquad \text{eq. (28)}$$

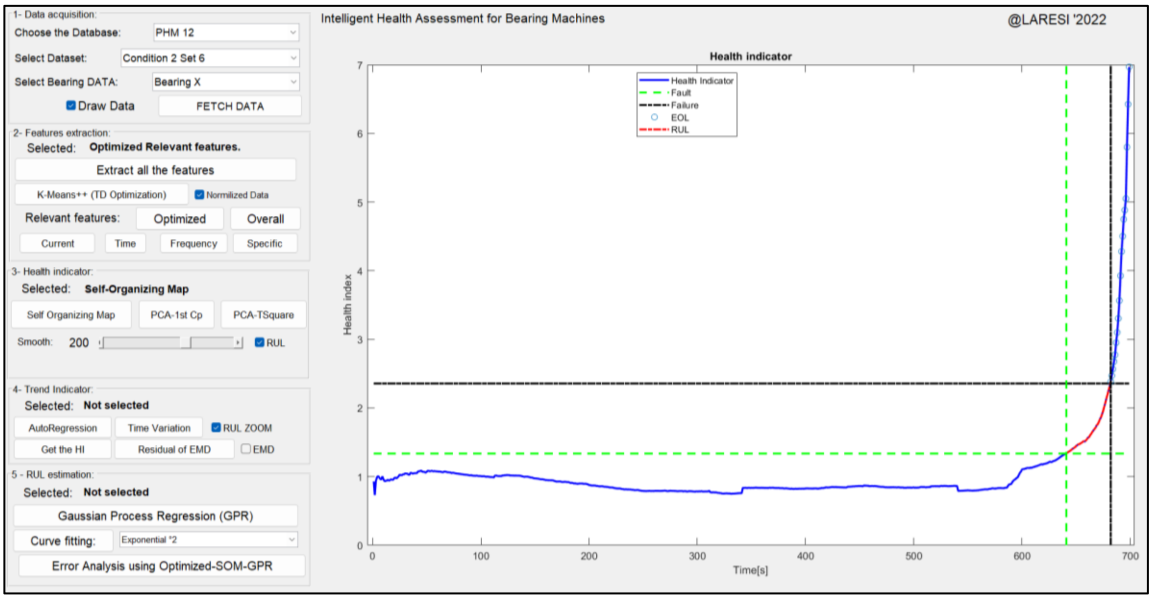


Figure 28: Health Indicator with fault and failure identification

The prognostic is based on the prediction of the RUL, which means detecting the fault and estimating the failure. Thus, wrong identification of the fault or the failure compromises the process.

Table 9 is extracted using the empiric threshold calculated according to equations 27 and 28 for the fault and the failure, respectively.

Table 9: HI Comparison

Bearing	ACTUAL RUL (s)	SOM (s)	1st Component - PCA (s)	T-Square - PCA (s)	Error % SOM	Error % 1st - PCA	Error % TS - PCA
Bearing1_3	5730	4820	4320	5760	**15.88**	24.61	-0.52
Bearing1_4	2900	2570	2910	2330	**11.38**	-0.34	19.66
Bearing1_5	1610	670	640	4380	**58.39**	60.25	-172.05
Bearing1_6	1460	4110	8490	8580	**-181.51**	-481.51	-487.67
Bearing1_7	7570	680	640	640	**91.02**	91.55	91.55
Bearing2_3	7530	650	670	720	**91.37**	91.10	90.44
Bearing2_4	1390	170	670	720	**87.77**	51.80	48.20
Bearing2_5	3090	570	660	0	**81.55**	78.64	100.00
Bearing2_6	1290	370	670	780	**71.32**	48.06	39.53
Bearing2_7	580	280	330	360	**51.72**	43.10	37.93
Bearing3_3	820	410	590	850	**50.00**	28.05	-3.66
				TOTAL	**38.99**	**3.21**	**-21.51**

The mean error is minimal using the first component of PCA against SOM. But, after considering the error range as illustrated in Table 10, we deduce that the SOM's error range is less than half of the error range of the two HI extracted from the PCA method, as shown in Table 10.

Table 10: HI Error Analysis

/	Error % SOM	Error % 1st - PCA	Error % TS - PCA
Min Err	-181.50685	-481.5068	-487.67123
Max Err	91.3678619	91.545575	100.00000
Mean Err Range	**272.874711**	**573.05242**	**587.671233**

Our results are compared to the work of (Guo et al., 2017), illustrated in Table 11.

Table 11: Comparing the HI with different methods

Testing	ACTUAL RUL (s)	Current (s)	Predict (s)	SOM-HI Error%
Bearing1_3	5730	18010	3250	-31.76
Bearing1_4	2900	11380	1100	62.76
Bearing1_5	1610	23010	1980	-136.03
Bearing1_6	1460	23010	1150	-32.88
Bearing1_7	7570	15010	6220	-11.09
Bearing2_3	7530	12010	4680	44.22
Bearing2_4	1390	6110	1660	-55.40
Bearing2_5	3090	20010	1410	68.61
Bearing2_6	1290	5710	1470	-51.94
Bearing2_7	580	1710	900	-68.97
Bearing3_3	820	3510	790	-21.96
			TOTAL	**53.24**

Our results are **14.25%** better than those provided by the same SOM algorithm. The featured effect can be clearly shown when getting different results using the same algorithm. In addition, these results are obtained from one database only while our algorithms are trained with three databases and designed for generic use.

V.9 Trend Indicator Construction

The prognostic is based on the evolution of the health indicator over time. However, the health indicator can distinguish the health states perfectly in time (t) but cannot provide reliable information in (t+1) (Agarwal et al., 2015). Therefore, a trend indicator is built to provide class separability over time. Several methods were used to select an adequate indicator.

V.9.1 Autoregression

The trend indicator's shape based on the autoregression method is not monotonic, as demonstrated in Figure 29. Therefore, the estimation of the RUL based on this trend indicator is unreliable with a significant estimation error.

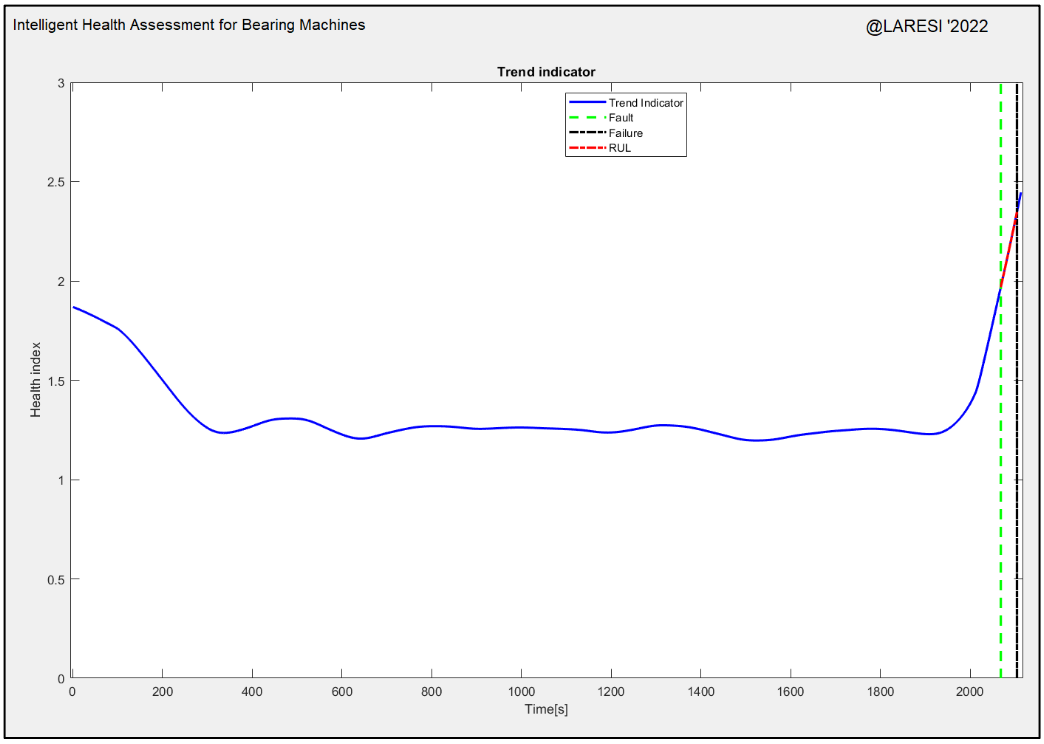


Figure 29: Trend Indicator using an Autoregression method

V.9.2 Time Variation

Besides the autoregression, the time variation method is used where the signal represents the health indicator evolution over time, as illustrated in Figure 30. Statistically, this method is another representation of the health indicator, which is not designed for prognostic tasks. This trend indicator cannot be used for RUL estimation because of the bad results provided.

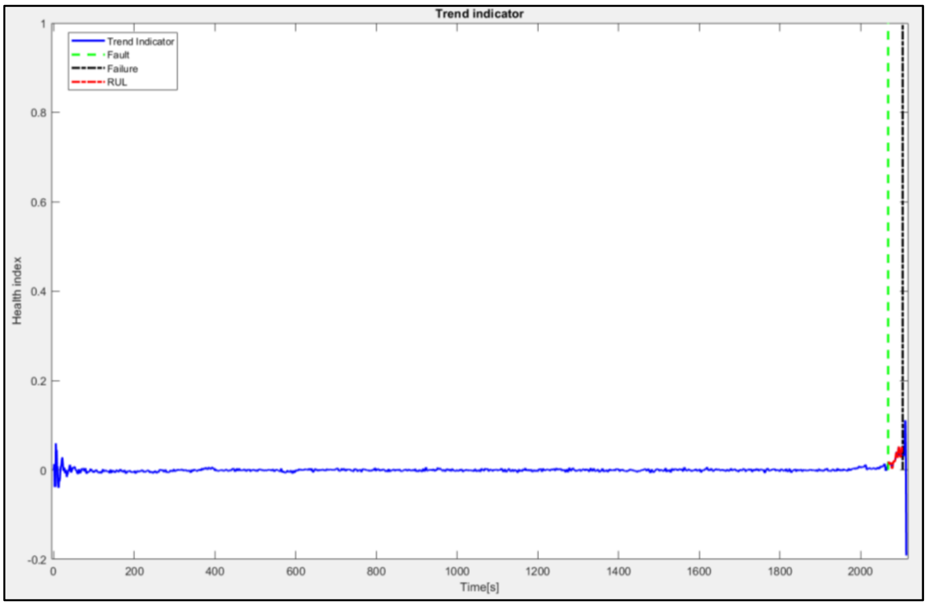


Figure 30: Trend Indicator using the time variation method

V.9.3 Empirical Mode Decomposition

A trend indicator is considered reliable and reprehensive if it is monotonic. The EMD is applied to the health indicator to get a monotonic signal, as illustrated in Figure 31. The residual of EMD constitutes the best trend indicator among all the methods tested earlier.

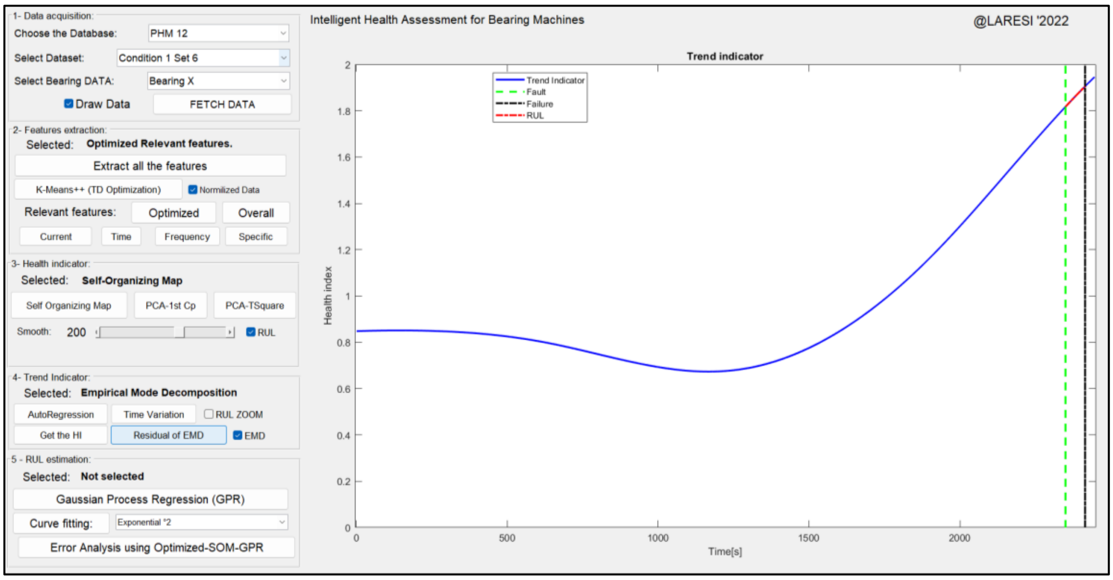


Figure 31: Trend Indicator using EMD Method

Moreover, studying the EMD residual of multiple databases shows that every fault has a specific pattern. Plotting the trend indicator of a healthy bearing and a faulty one clearly shows the difference in shape, which is also used for diagnostics and failure identification. Figure 32 illustrates the difference between three types of failure.

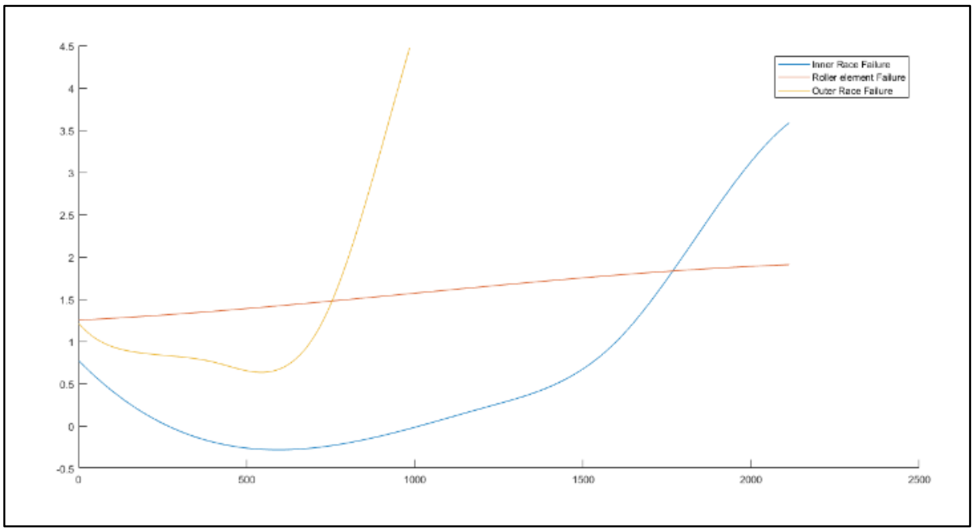


Figure 32: Three trend indicators of failures

V.10 Remaining Useful Life Estimation.

The trend indicator is selected by applying several methods to known RUL. The RUL estimation is based on the extrapolation or the prediction of t+1 of the trend indicator once it reaches the fault point. The Gaussian process regression (GPR) and multiple curve fitting algorithms are used for that.

V.10.1 Gaussian Process Regression

Figure 33 demonstrates the results of the RUL estimation applied to the PHM'2012 database and the IMS database, respectively. The regression is based on the trend indicator learned from the beginning of the acquisition to the fault point. The RUL estimation using the GPR applied on the trend indicators based on the SOM, and the EMD residual provides accepted results over all the tests.

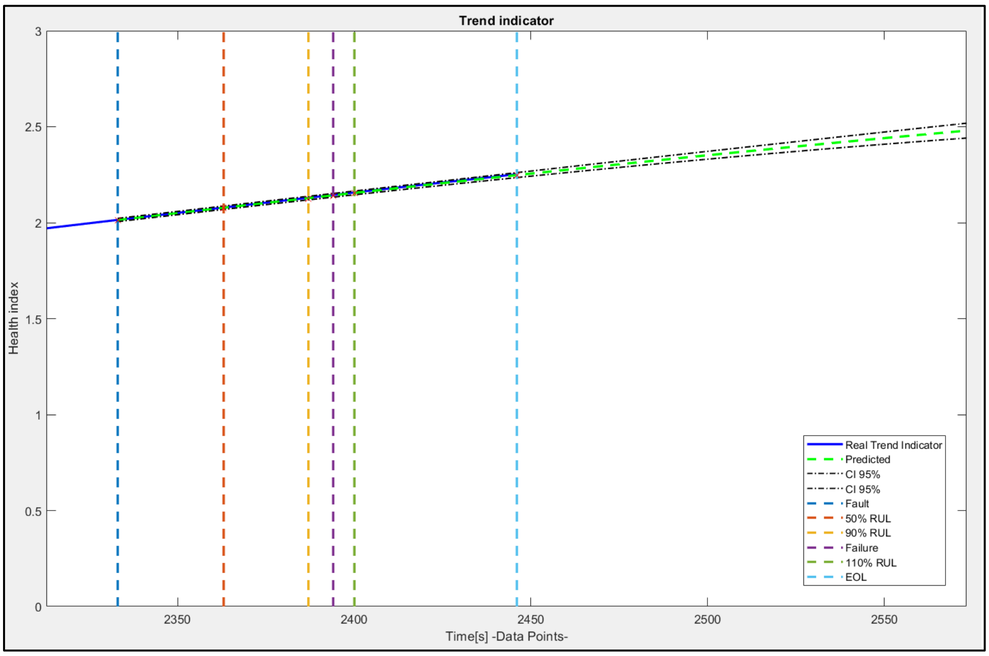


Figure 33: RUL estimation using GPR based on EMD trend indicator

Different trend indicators based on the autoregression method and the time variation were generated for comparison to investigate the RUL estimation and the effectiveness of the GPR. The results show that the trend indicator selection has a significant role in a reliable and accepted RUL estimation. Figure 34 illustrates an imperfect RUL estimation applied to the autoregression trend indicator based on the PCA 1st component health indicator.

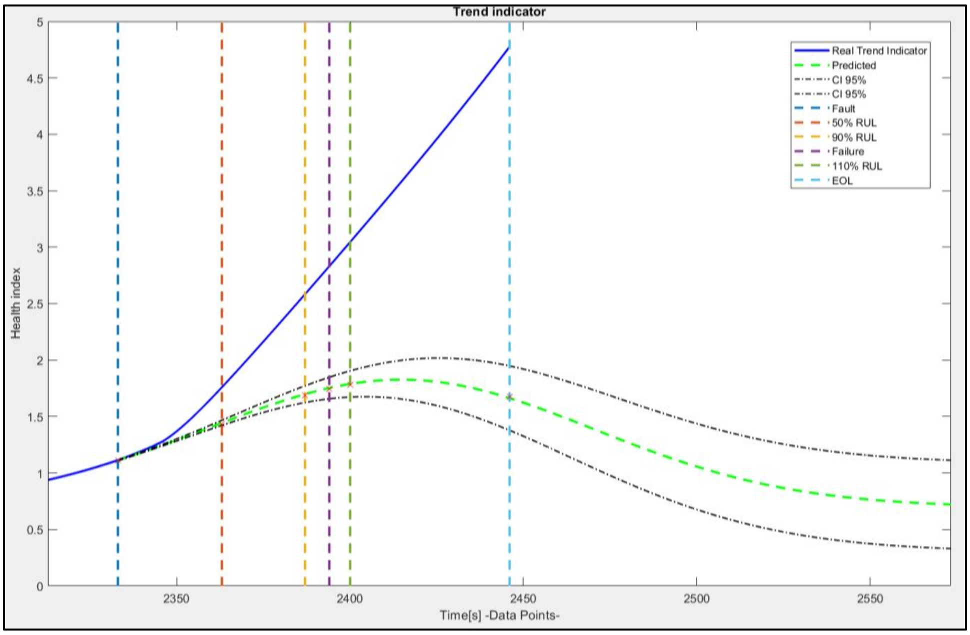


Figure 34: RUL estimation using GPR based on Auto regression trend indicator

Thus, the correct estimation relies not only on a suitable extrapolation method but on the whole process of prognostics, starting from the feature extraction to the RUL estimation. Figure 35 represents how the HI choice affects the final decision, while

Figure 36 represents the importance of the TI choice for reliable estimation.

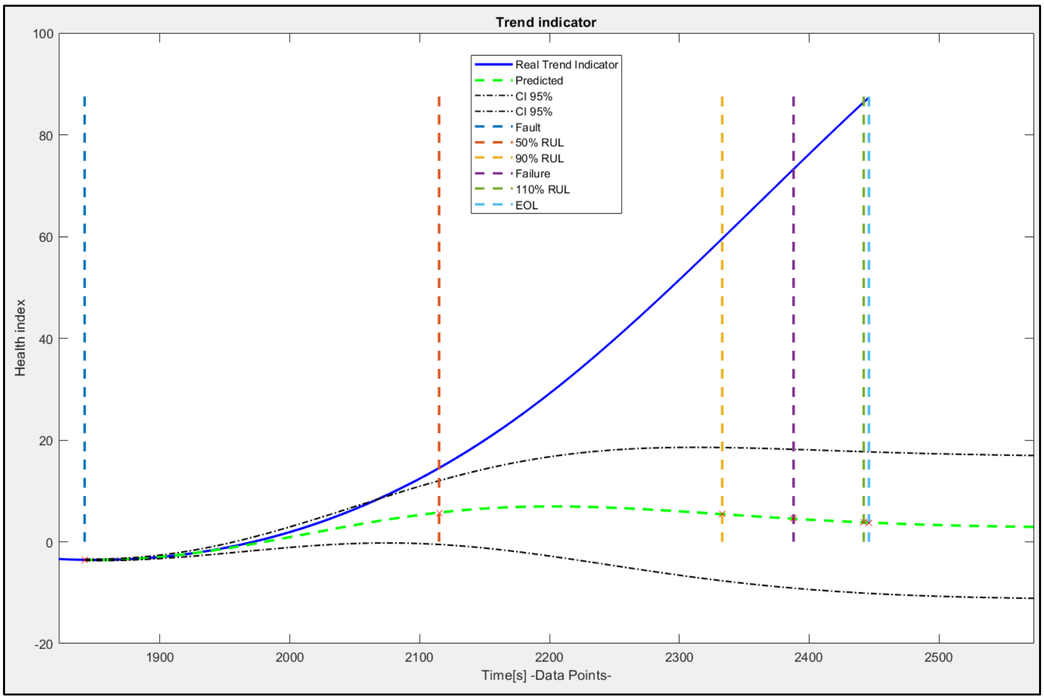


Figure 35: RUL estimation using GPR based on PCA HI

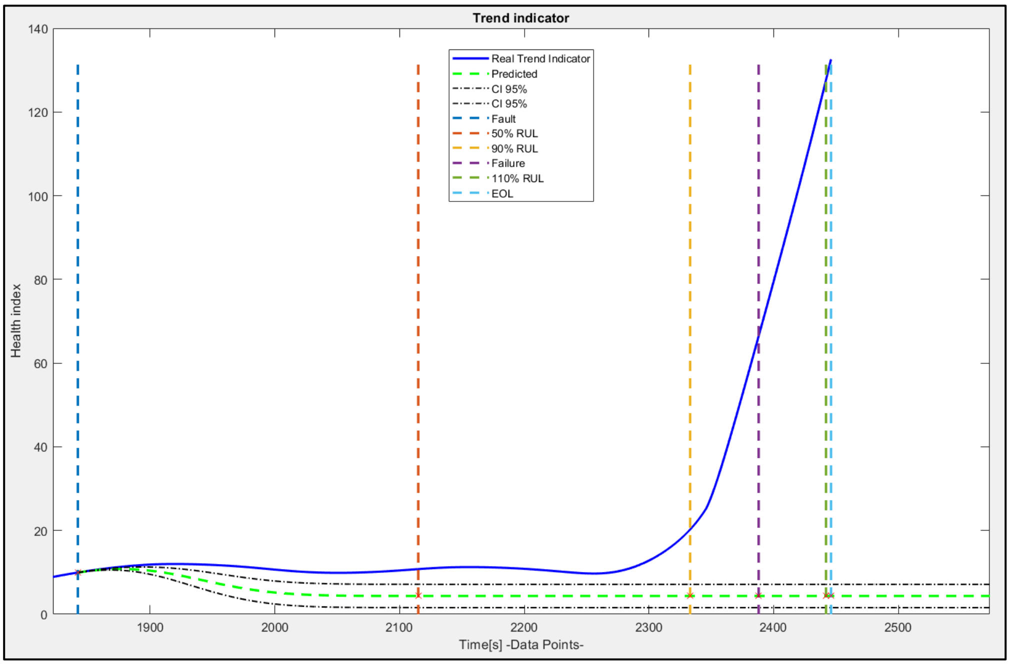


Figure 36: RUL estimation using GPR based on Auto regression TI

V.10.2 Curve fitting

Besides the GPR, several curve fittings were applied for the RUL estimation task, citing model names and equations:

- Exponential

$$E2 = a.e^{(b*x)} + c.e^{(d*x)} \quad \text{eq. (29)}$$

- Polynomial

$$P3 = P_1.x^3 + P_2.x^2 + P_3.x^1 + P_4 \quad \text{eq. (30)}$$

$$P8 = P_1.x^8 + P_2.x^7 + \cdots + P_9 \quad \text{eq. (31)}$$

- Fourier

$$F3 = \mathrm{a}_0 + \mathrm{a}_1.\cos(x.p) + \mathrm{b}_1.\sin(x.p) + \cdots + \mathrm{a}_3.\cos(3.x.p) + \mathrm{b}_3.\sin(3.x.p) \quad \text{eq. (32)}$$

$$F8 = \mathrm{a}_0 + \mathrm{a}_1.\cos(x.p) + \mathrm{b}_1.\sin(x.p) + \cdots + \mathrm{a}_8.\cos(8.x.p) + \mathrm{b}_8.\sin(8.x.p) \quad \text{eq. (33)}$$

Where $p = \frac{2.\pi}{(max(x_{data}) - min\,(x_{data}))}$

- Gaussian

$$G2 = a_1.e^{\left(-\frac{(x-b_1)}{c_1}\right)^2} + a_2.e^{\left(-\frac{(x-b_2)}{c_2}\right)^2} \quad \text{eq. (34)}$$

$$G8 = a_1.e^{\left(-\frac{(x-b_1)}{c_1}\right)^2} + \cdots + a_8.e^{\left(-\frac{(x-b_8)}{c_8}\right)^2} \quad \text{eq. (35)}$$

- Power

$$Pow2 = a.x^b + c \quad \text{eq. (36)}$$

The results obtained from these models can fit for one case only over all the databases where the second-order exponential provides bad results for the case “Condition 2 Set 6,” and the “Condition 1 Set 1,” as illustrated in Figure 37.

Figure 38 demonstrates another concept with the polynomial model, where it fits perfectly for the case “Condition 1 Set 3” and badly for the case “Condition 1 Set 7” even if it is under the same condition.

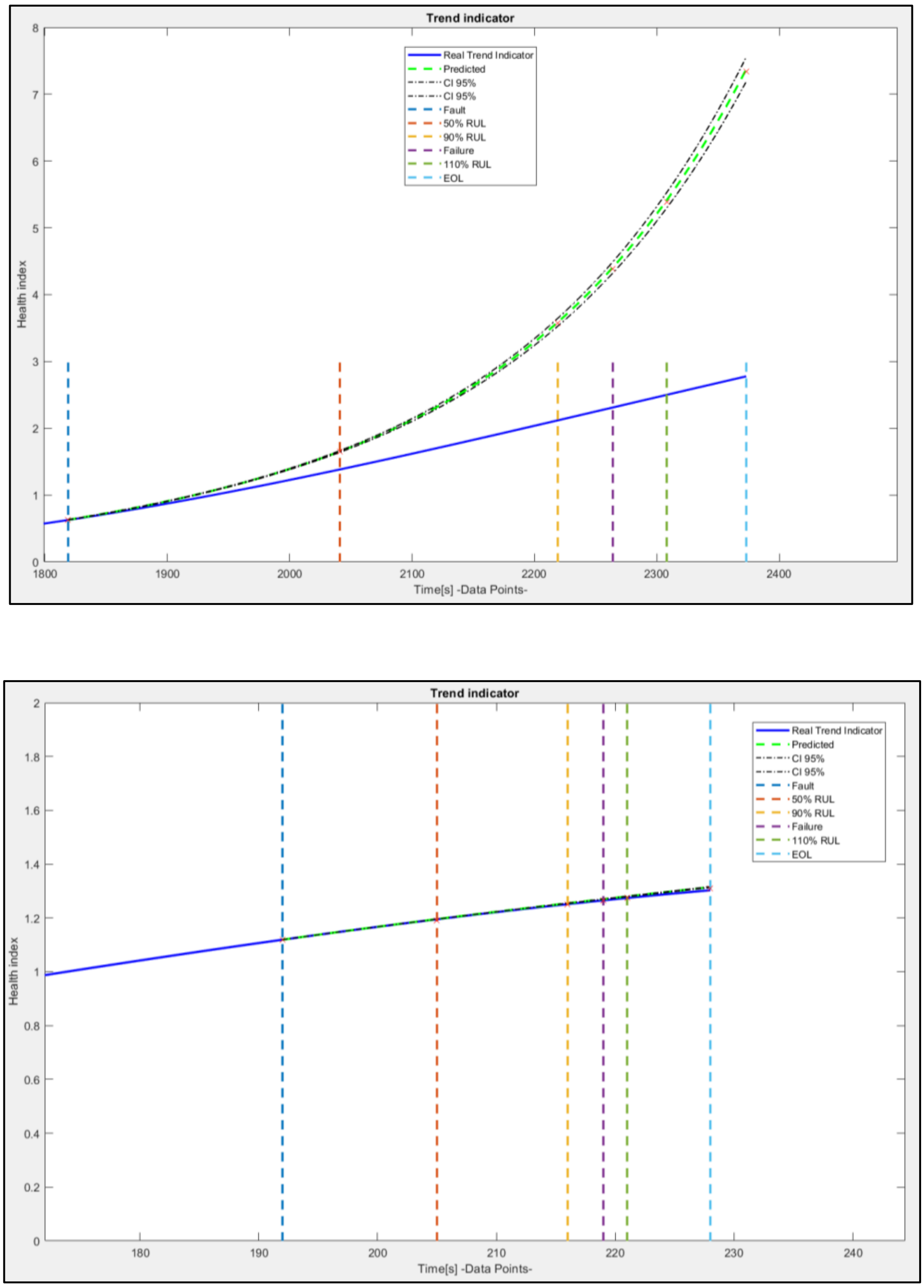


Figure 37: RUL estimation using exponential curve fitting

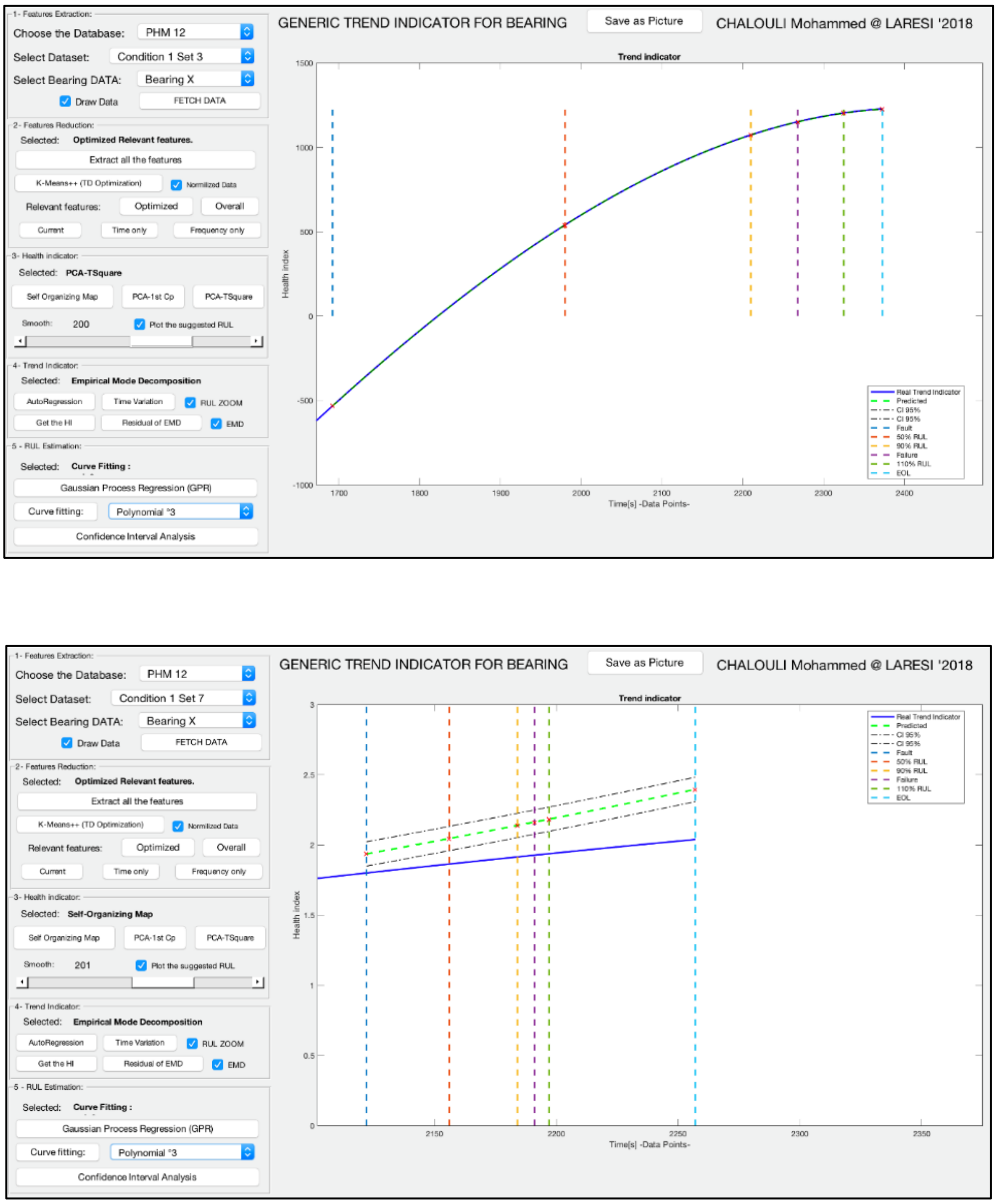


Figure 38: RUL estimation using polynomial curve fitting

V.10.3 Confidence Interval Analysis

Using the GPR for RUL estimation provides a good result where the real RUL is almost in the 95% marge of the predicted real RUL. Figure 39 presents the accurate estimation over the PHM'2012 database, whereas Figure 40 presents a slight deviation of the predicted RUL. This deviation is due to the generic formula since each bearing's kind and each fault type have a specific signature. Thus, finding a formula that works for all bearings is tricky, and some tolerance is required in this study case.

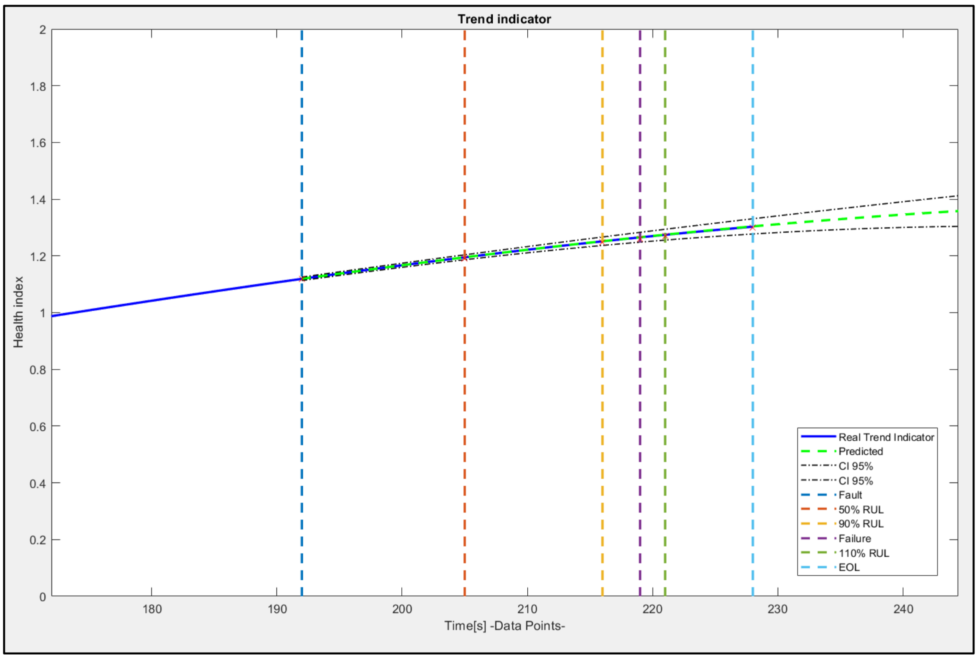


Figure 39: Confidence interval for RUL estimation using GPR

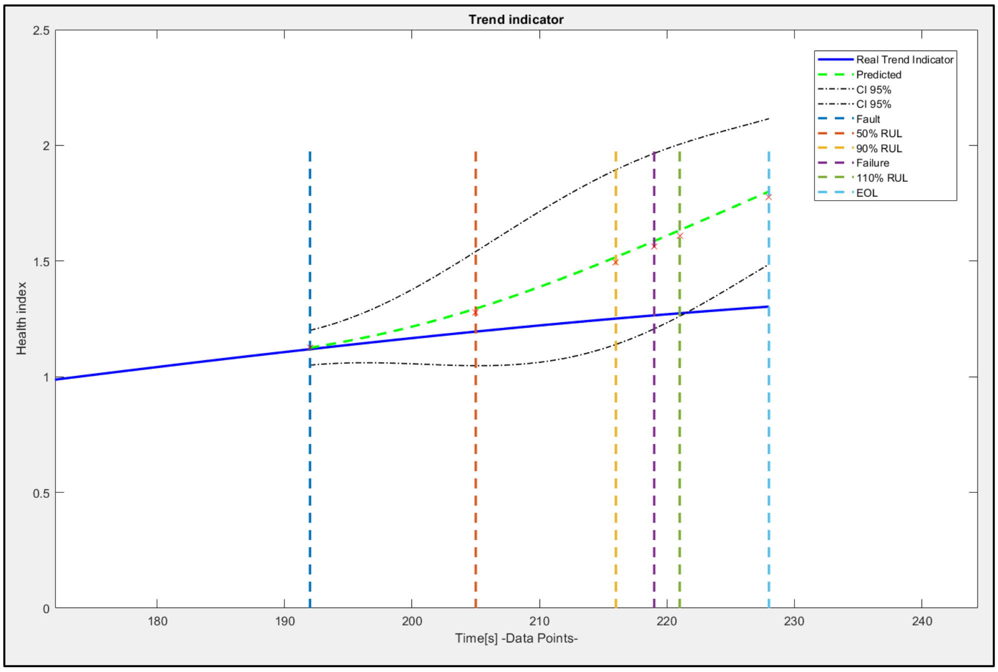


Figure 40: Confidence interval for RUL estimation using Gaussian curve fitting

To study the effectiveness of the generic algorithm, we apply the RUL estimation on all the bearings over the two datasets, and we calculate the error between the estimated RUL and the real one. The results are presented in Figure 41 and Table 12.

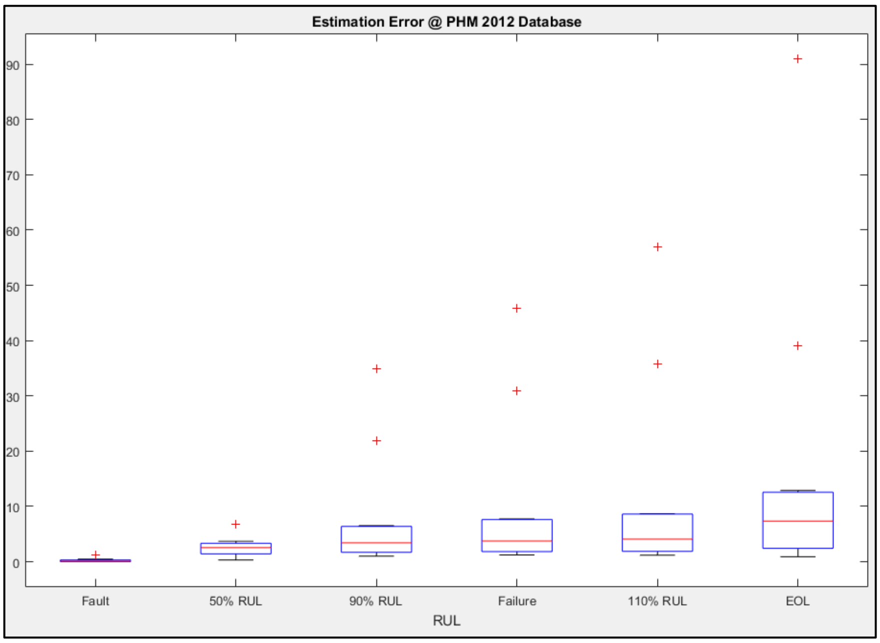


Figure 41: Error analysis for RUL estimation using GPR.

Table 12: Error analysis for RUL estimation in %

Bearing	Fault	50% RUL	90% RUL	Failure	110% RUL	EOL
Bearing1_3	0.023	0.321	1.009	1.330	1.697	2.248
Bearing1_4	0.017	6.776	34.957	45.788	57.027	91.035
Bearing1_5	0.461	2.245	3.414	3.753	4.091	7.352
Bearing1_6	0.010	3.222	21.886	30.912	35.849	38.993
Bearing1_7	0.343	1.680	2.331	2.571	2.743	5.348
Bearing2_3	0.093	1.296	1.666	1.814	1.944	2.907
Bearing2_4	1.157	2.546	1.852	1.852	1.852	1.157
Bearing2_5	0.122	1.345	1.264	1.223	1.182	0.897
Bearing2_6	0.188	3.347	5.604	6.469	7.202	10.831
Bearing2_7	0.019	3.710	6.520	7.747	8.696	12.905
Bearing3_3	0.097	3.267	5.978	7.236	8.398	11.592
MEAN	**0.230**	**2.705**	**7.862**	**10.063**	**11.880**	**16.842**

We deduce from the result that the RUL error tends to have larger values with every step after the Fault point. Moreover, it is essential to clarify that the error in Table 12 represents only the errors in the GPR estimation and not in the overall process.

V.11 Conclusion

This chapter discussed the results obtained over several years of tests and analyses dedicated to studying bearings, their fault features, condition monitoring, and prognostics. The lack of labeled data in this field constitutes a challenge. Moreover, developing a generic solution that provides accepted results over other multiple kinds of bearings running under different conditions is another problem we have to deal with to establish this work.

The results show the sensibility of the prognostics process and the effect of the features on the result. Combining the Optimized features, the SOM, the EMD, and the GPR provided accepted results for the bearing prognostics.

General Conclusion & Perspectives

This thesis investigated prognostics as one of the PHM pillars and its application to bearing machines. For that purpose, multiple machine learning algorithms were discussed under the data-driven approach. The work presented in this thesis demonstrates the usefulness of the trend indicator in prognostic and focuses on the methodology applied from feature extraction to RUL estimation. Three methods (PHM layers) were discussed:

- *Data acquisition and manipulation*

Where the cross-domain descriptors are extracted from vibration signals followed by feature selection, the results indicate that the optimized combination (Kurtosis – Crest Factor – BPFI – BPFO – BSF – Max Frequency Amplitude) is the most adequate and sensitive to the bearings fault variation. It is important to note that the feature selection process is done only once in the learning phase.

- *Condition Monitoring*

Focusing on health indicator construction, fault detection, and failure identification. The results indicate that the SOM using the Batch algorithm is more suitable as a health indicator than other methods such as the PCA. For more precision, the mean quantization error extracted from the SOM was taken as the HI because of its pseudo-monotonic shape provided over the different bearing databases and its sensitivity to the degradation of the bearings. Hereafter, the HI is used to determine the fault and failure thresholds, which highly influence the RUL estimation results. For that purpose, we developed new dynamic thresholds for fault and failure, and the results show their effectiveness.

- *Prognostics*

The last phase consists of the trend indicator construction and the RUL estimation. The EMD residual demonstrates its effectiveness as the TI, and the GPR provided the best results for the RUL estimation. An accurate prognostic depends on the trend indicator and the GPR as a regression technique. Where the trend indicator determines how precisely the health indicator evolves, and the GPR determines how accurately the TI can be projected in the future.

This thesis illustrates the challenge of finding generic parameters that can be applied over different bearings under different conditions.

Future Work:

Although numerous headways have been accomplished within the field of prognostics, several research areas still have to be explored. As perspectives and guidelines for researchers in this field, some investigations are preferable, such as:

- Integration of the transfer learning to transfer the acquired knowledge from one type of bearing to another or even to new components.

- Application of the current HI on different new types of bearing to validate the generic aspect of the bearing HI since there is currently no well-known generic HI for bearings.

- Application of the same algorithm on the same data type but acquired from different emplacements of the machine to get the best possible place for fault-bearing detection and prognostics.

- Discover other features from multiple domains and study their effects and their effectiveness.

- In this thesis, we applied the common GPR for RUL estimation. In future work, we look to develop a new regression tool based on the GPR to meet the particular requirement of the bearing prognostics.

- Using a single indicator that merges both quality of the HI (Class separability) and the TI (Overtime separability) is an interesting research field that requests more attention.

Publication

Chalouli, M., Berrached, N. Eddine, & Denai, M. (2017). Intelligent Health Monitoring of Machine Bearings Based on Feature Extraction. *Journal of Failure Analysis and Prevention*, *17*(5), 1053–1066. https://doi.org/10.1007/s11668-017-0343-y

Communication

Chalouli, M., Berrached, N. Eddine, & Denai, M. (2018). Modular Platform of e-Maintenance with Intelligent Diagnosis : Application on Solar Platform. *Artificial Intelligence in Renewable Energetic Systems*, *35*(1), 262–269. https://doi.org/https://doi.org/10.1007/978-3-319-73192-6_27

Abbreviation List

AI	Artificial Intelligence
BBAS	Basic Belief Assignments
Bd	Ball diameter
BMU	Best matching unit
BPF	Ball Pass Frequency
BPFI	Ball Pass Frequency Inner race
BPFO	Ball Pass Frequency Outer race
BS	Ball Spin
CBM	Case Based Maintenance
DAE	Deep Auto Encoder
EMD	Empirical Model Decomposition
FTF	Fundamental Train Frequency
GA	Genetic Algorithm
GPR	Gaussian Process Regression
GRNN	generalized regression neural network
HI	Health Indicator
IR	Inner Race frequency
LLE	locally linear embedding
LOWESS	Locally Weighted Scatterplot Smooth
LSTM	Long Short-Term Memory
MIMOSA	Machinery Information Management Open Standards Alliance
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failures
NN	Neural Network
OR	Outer Race frequency
OSA	Open system architecture

PC	principal component
PCA	Principal Component Analysis
Pd	Pitch diameter
PDF	Probability Density Function
PdM	Predictive maintenance
PHI	Physical health indicators
PHM	prognostics & health monitoring
RF	Random Forest
RNN	recurrent neural network
RUL	Remaining Useful Lifetime
SAE	Society of Automotive Engineers
SNR	Signal-to-Noise Ratio
SOM	Self-Organizing Map
TI	Trend Indicator
VHI	virtual health indicators

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