Bearing Health monitoring based on Hilbert-Huang Transform, Support Vector Machine and Regression

A. Soualhi, K. Medjaher, and N. Zerhouni

***Abstract*— the detection, diagnostic and prognostic of bearing degradation play a key role in increasing the reliability and safety of electrical machines especially in key industrial sectors. This paper presents a new approach which combines the Hilbert-Huang transform, the support vector machine and the support vector regression for the monitoring of ball bearings. The proposed approach uses the Hilbert-Huang transform to extract new heath indicators from stationary/non-stationary vibration signals able to tack the degradation of the critical components of bearings. The degradation states are detected by a supervised classification technique called support vector machine and the fault diagnostic is given by analyzing the extracted health indicators. The estimation of the remaining useful life is obtained by a one-step time series prediction based on support vector regression. A set of experimental data collected from degraded bearings is used to validate the proposed approach. Experimental results show that the use of the Hilbert-Huang transform, the support vector machine and the support vector regression is a suitable strategy to improve the detection, diagnostic and prognostic of bearing degradation.**

***Index Terms*— Fault detection, Fault diagnosis, Prognostic, Feature extraction, Pattern recognition, Time-frequency analysis, Vibration analysis, Times series prediction.**

I. Introduction

ELECTRICAL actuators based on rotating machine are widely used in industrial applications because of their low cost, high performance and robustness. However, different types of failures may occur during the life of the machine. In order to identify them, the Electric Power Research Institute (EPRI) and the Motor Reliability Working Group of the IEEE-IAS surveyed respectively 6312 and 1141 induction motors [1],[2]. They identified as potential failures those of bearings, inter-turn short circuits in stator windings, broken rotor bars and end ring faults. Bearing failures are responsible for approximately 42% of the identified faults, inter-turn short circuits in stator windings represent approximately 31% and broken rotor bars and end ring faults represent around 9%. From these results, it is obvious that the great part of failures in these machines is due to defects in bearings. Bearing faults have many causes such as lubricant contamination, excessive load [3] or the flow of leakage currents induced by Pulse Width Modulation (PWM) inverters [4], [5]. Therefore, the best idea to tackle these problems is to adopt a new data-driven Prognostic and Health Management (PHM) approach to improve the health monitoring of bearings [6]-[8]. The data-driven approach is not the only way to do this, there exist two other approaches, namely: model-based and hybrid approaches [9]-[14]. The first approach uses mathematical models to represent bearing dynamic behaviour and degradation phenomena. This approach is applicable when accurate mathematical model could be developed from bearing failure or degradation modes. However, the bearing is a complex system and the degradation mechanisms are generally stochastic, so difficult to represent by mathematical models. Consequently, the applicability of this approach may be difficult. The second approach is based on the combination of both data-driven and model-based approaches. Regarding bearings and knowing the difficulty to analytically model their degradations, the data-driven approach seems to be the tradeoff to perform reliable fault detection, diagnostic and prognostic. The data-driven approach uses measured data (i.e. vibration and acoustic signals, temperature, pressure, oil debris, currents, voltages, etc.) extracted from sensors as source for getting a better understanding of bearing degradation phenomena [15]-[18]. The advantage of the data-driven approach is that the user does not need to have any hypotheses about the underlying physical model.

In this paper, the proposed approach passes through three steps.

- The first step consists of improving the detection and diagnostic of bearing degradation by introducing new health indicators able to detect and diagnose the critical components of bearings (inner race, outer race, balls). These indicators are extracted from vibration data by using a signal processing method called Hilbert-Huang transform (HHT) [19], [20]. There exist in the literature three signal processing methods: the temporal analysis, the frequency analysis and the time-frequency analysis. The temporal analysis is historically the oldest method. The assumption behind this method is that any fault occurrence can be monitored through statistical health indicators like Root Mean Square (RMS), peak to peak value and Kurtosis. However, these indicators, even if they are well suited for online monitoring, do not identify the defect responsible of the degradation. Moreover, the temporal indicators often generate “false alarms” when the signals are not Gaussian. The frequency analysis provides a frequency spectrum for each time sample, performing the derivation of the characteristic frequencies of bearing faults. However, the effectiveness of frequency analysis, in the case of ball bearings, strongly depends on the operating conditions: stationary or non-stationary. In fact, a recorded vibration signal is the result of a mixture of different sources corresponding to the external environment as well as non-stationary signals induced by internal components of the ball bearing. There exist in literature several time-frequency analysis techniques applied to the monitoring of bearings: the short-time Fourier transform (STFT) [21], the Wigner-Ville distribution (WVD) [22] and wavelet analysis (WA) [23]. However, in the STFT, the resolutions in time and frequency are always constant and the WVD can lead to the appearance of cross terms, which in turn lead to misinterpretation of the signal. The efficiency of the wavelet analysis strongly depends on the quality of the analyzed signal. In the case of ball bearings, a chipping causes shocks and a resonance of the bearing. This phenomenon occurs at high frequencies by peaks which increase progressively as the bearing deteriorates. This causes choking low frequencies and prevents early detection of faults. In this case, the idea is to separate the contribution of different vibration sources by the Hilbert-Huang Transform. Recent research works using the HHT are reported in the literature. We cite for example the works published in [24] and [25]. In [24], the authors use the ensemble empirical mode decomposition (EEMD) and the HHT for bearing fault diagnosis. The EEMD extracts from the original vibration signal a new signal composed of a set of selected intrinsic mode functions (IMFs) by estimating the instantaneous amplitude and instantaneous frequency at any time instant. Therefore, the bearing fault can be recognized by using the Hilbert-Huang transform spectrum. In [25], the authors use the HHT and the EEMD to calculate the amplitude modulation of different IMFs. This allows extracting health indicators from the information contained on the IMFs. Like [24], [25], the feature extraction method we propose decomposes each vibration signal into a set of IMFs. Each IMF is located in a specific frequency band. The difference between the proposed method and those cited in the investigated papers is in the extraction of the health indicators. This extraction is done by calculating the Hilbert spectral density of the characteristic frequencies of bearing faults at any time instant in each IMF and choosing the one(s) which maximize this spectral quantity. The selected IMFs allow extracting health indicators by calculation the Hilbert marginal spectrum. These indicators are thus able to identify the degraded component and estimate the level of the degradation.

- The second step consists of how to use the extracted health indicators for fault detection and diagnostic. There exist two methods to estimate the degradation of bearings. The first one combines all the health indicators of bearings into one indicator. This is obtained by using well-established techniques for linear/nonlinear dimensionality (feature) reduction such as the principal component analysis and ISOMAP [26]. However, a feature reduction implies a loss of information which can affect the monitoring of bearings. This is not a drawback but a condition to obtain one health indicator of degradation. The second method proposes to combine the health indicators in order to construct a representation space. This space allows identifying sub-spaces called "classes" which regroup similar measures representing the different states of bearing degradation [27], [28]. The Pattern Recognition (PR) is a well-known technique to classify new measures in these classes. This classification is obtained by using supervised classification techniques. There exist in literature several techniques for the supervised classification, i.e. the Bayesian statistics, Kernel estimators, K-nearest neighbors and Random forests [29]-[31]. But, the more sophisticated are Artificial Neural Networks and the Support Vector Machine (SVM) [32], [33]. While ANNs are an ultimate "black box" system following a heuristic development with extensive experimentation proceeding theory, the development of SVMs involved sound theory first, then implementation and experiments. SVMs are a new promising non-linear, non-parametric classification technique, which already showed good results in the medical diagnostics, optical character recognition, electric load forecasting and other fields.

- The third step consists of estimating the Remaining Useful life (RUL) of bearings by using time-series prediction. A time series is a sequence of observations acquired at successive time intervals. So, the typical approach to estimate the RUL is to learn this time series in order to forecast its evolution in the future. This is done by a forecasting model called Support Vector Regression (SVR). SVR is a version of the SVM for regression proposed by Vapnik, Steven Golowich, and Alex Smola [34]. It has been applied successfully to a wide range of prediction problems especially in rotating machinery [35].

In this paper, we focus on the detection, diagnostic and prognostic of bearing degradation by applying the Hilbert-Huang transform, the support vector machine and support vector regression. The aim is first to evaluate the effectiveness of HHT to extract sensitive health indictors, second to evaluate the effectiveness of the SVM for the estimation of bearing degradation and third to evaluate the effectiveness of the SVR for the estimation of the remaining useful life of bearings. For this purpose, the paper is structured as follows: a description of the proposed approach is given in section II. This section is divided into three parts. The first part, called feature extraction, is dedicated to the extraction of three health indicators. Each of these indictors is sensitive to the failure and degradation of the bearing's critical component. The second part, called detection and diagnostic, consists of detecting the different states of bearing's degradation by SVM. The diagnostic process uses the extracted health indicators to identify the component responsible of this degradation. The third part of this section is dedicated to the prognostic process. In this part, we use the SVR as a prediction tool in order to estimate the remaining useful life of the bearing. In section III, we investigate the described approach on experimental bearing degradation data taken from the PRONOSTIA platform [36]. Finally, conclusions and future works are given in section IV.

II. Health Monitoring and Prognostic Approach

As has been described in section I, the proposed approach is decomposed into three parts (see fig. 1).

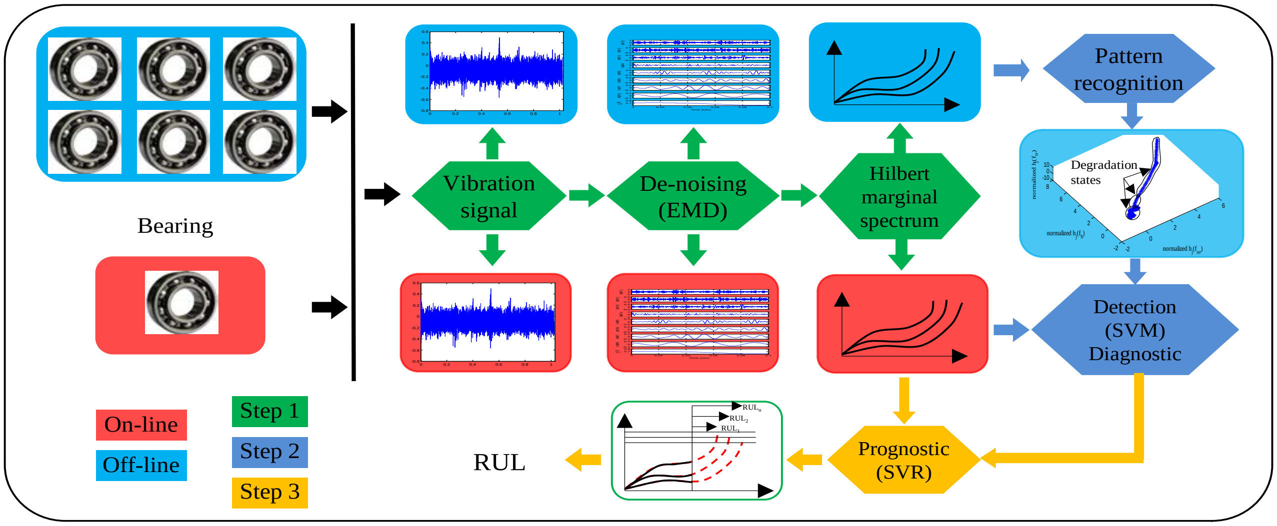


Fig.1. An integral architecture for bearing fault detection, diagnostic and prognostic.

A. *Feature extraction*

The first part consists of extracting health indicators able to detect the appearance of degradations and track their time evolution (prognostic). These indicators are extracted from the analysis of vibration signals by using the Hilbert-Huang transform. There exist numerous types of signals which could be used to extract health indicators able to enhance failure detection and tracking bearing degradation. We can use acoustic signals, temperature, torque signals, electrical signals and vibration signals. But, the most promising is the vibration signal. Vibrations emitted by a bearing could contain useful information related to its critical components. This information is analyzed through appropriate signal processing methods. Indeed, the operation of bearings usually results in a dynamic behavior that generates stationary/non-stationary vibration signals mixed with an amount of background noise. This makes the use of temporal and frequency analysis insufficient in the case of non-stationary vibration signals. This drawback can be resolved by using a time-frequency analysis and the most promising technique is the Hilbert-Huang Transform [37]. This analysis removes noised signals that are not related to the failure of ball bearings and therefore allows extracting health indicators that maximize the chances of early detection of incipient faults.

The Hilbert Huang transform is a new emerging technique of time-frequency signal processing designed to analyze non-stationary signals. It has been used in many applications, particularly in fault detection and diagnostic [38]. This technique decomposes a vibration signal $x(t)$ into several intrinsic modal functions (IMFs) representing the average trend of the signal. These IMFs, obtained thanks to the empirical mode decomposition (EMD) [39], represent the input signal in specific frequency bands. Figures 2 and 3 show how the first intrinsic modal function is extracted. The purple line, designated by m_{10}, represents the mean value of the upper and lower envelope of the vibration signal $x(t)$. The difference between the signal $x(t)$ and m_{10} provides a first component denoted h_{10}.

$$x(t) - m_{10}(t) = h_{10}(t) \quad (1)$$

h_{10} is considered as an IMF if it satisfies the following constraints:

- In the whole data set of $x(t)$, the number of extrema and the number of zero-crossings must either equal or differ at most by one;
- At each instant t, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is near to zero.

If h_{10} is not an IMF, then it will be considered as the original signal and a new mean value defined by its upper and lower envelope is calculated. The second IMF denoted h_{11} is obtained by the following formula:

$$h_{11}(t) = h_{10}(t) - m_{10}(t) \quad (2)$$

This process is called a sifting process and it is repeated successively until time k on h_{ik} until the middle line between the upper and lower envelope is close to zero at each point.

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1(k-1)}(t) \quad (3)$$

where $m_{1(k-1)}$ is the mean of the upper and lower envelope of $h_{1(k-1)}$ and k is the number of the iteration.

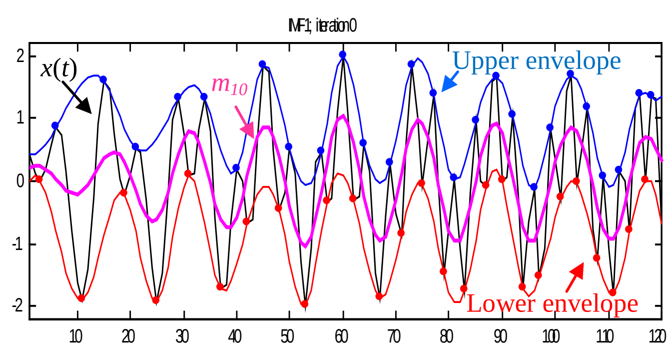


Fig.2. Sifting process: original signal $x(t)$ with the upper envelop (blue line) and lower (red line) and the resultant mean line m_{10} (purple line).

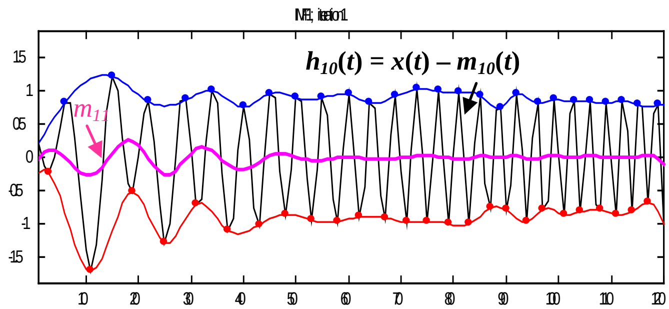


Fig.3. First component of the signal $x(t)$.

The EMD decomposes the signal $x(t)$ into a set of IMFs. The first IMF is the decomposition of the signal's component with the shortest period (high frequency). The components of long periods (low frequencies) are then decomposed by order in the next IMFs. The frequency band contained in each IMF is different from a component to another according to the signal $x(t)$. Its identification involves extracting the Hilbert marginal spectrum $h_i(f)$ of the frequency from the instantaneous amplitude $a_i(t)$ and the instantaneous frequency $f_i(t)$ of the i^{th} IMF, with $i = 1, \ldots, n$ and, n is the number of IMFS.

In the following, each IMF_i will be denoted $c_i(t)$. The analytic form of an IMF, denoted $c_i^A(t)$, is defined as:

$$c_i^A(t) = c_i(t) + jc_i^H(t) = a_i(t)e^{j\theta_i(t)} \tag{4}$$

where $c_i^H(t)$ is the Hilbert transformation of $c_i(t)$, that is:

$$c_i^H(t) = \frac{1}{\pi} P \int \frac{c_i(s)}{t-s} ds \tag{5}$$

where P is the Cauchy principal value.

The polar coordinate from the analytical IMF $c_i(t)$ allows obtaining the instantaneous amplitude $a_i(t)$ and phase $\theta_i(t)$. They are given as follows:

$$\begin{cases} a_i(t) = \sqrt{c_i^2 + c_i^{H2}} \\ \theta_i(t) = \tan^{-1}\left(\dfrac{c_i^H}{c_i}\right) \end{cases} \tag{6}$$

From the instantaneous phase $\theta_i(t)$, the instantaneous frequency $f_i(t)$ can be obtained by using the following formula:

$$f_i(t) = \frac{1}{2\pi}\frac{d\theta_i(t)}{dt} \tag{7}$$

The Hilbert marginal spectrum can be estimated as follows:

$$h_i(f) = \int h_i(f,t)\,dt = \int a_i^2(f_i,t)\,dt \tag{8}$$

where $h_i(f, t)$ represents the Hilbert spectral density obtained from the i^{th} IMF of the signal $x(t)$ and $a_i(f_i,t)$ combines the amplitude $a_i(t)$ and the instantaneous frequency $f_i(t)$ of the signal together.

Once the frequency bands are identified, it is possible to select the IMFs according to the characteristic frequencies of bearing faults by using the following formula:

$$c_i(t) \rightarrow \max_{1\le i\le n}\left[h_i(f_{or}, f_{ir}, f_b)\right] \tag{9}$$

with f_{ir} the inner race frequency, f_{or} the outer race frequency and, f_b the ball frequency. These frequencies depend on the rotation speed and the geometry of the bearing. They are given as follows:

- Inner race frequency (f_{ir}):

$$f_{ir} = \frac{n_b}{2} \cdot f_r \cdot \left[1 + \frac{DB}{DP} \cdot \cos\psi\right] \tag{10}$$

- Outer race frequency (f_{or}):

$$f_{or} = \frac{n_b}{2} \cdot f_r \cdot \left[1 - \frac{DB}{DP} \cdot \cos\psi\right] \tag{11}$$

- Ball frequency (f_b)

$$f_b = \frac{DP}{DB} \cdot f_r \cdot \left[1 - \frac{DB^2}{DP^2} \cdot \cos^2\psi\right] \tag{12}$$

where f_r is the rotation frequency, Ψ the contact angle, n_b the number of balls, DB the ball diameter and DP the pitch diameter of the bearing.

The selected IMFs allow extracting three indicators: $h_i\,(f_{or})$, $h_i\,(f_{ir})$ and $h_i\,(f_b)$. These indicators will then be used for the detection, diagnostic and prognostic of bearing degradation. The flowchart given in fig. 4 summarizes the steps for an automatic extraction of the Hilbert marginal spectrum related to the three characteristic frequencies f_{or}, f_{ir} and f_b.

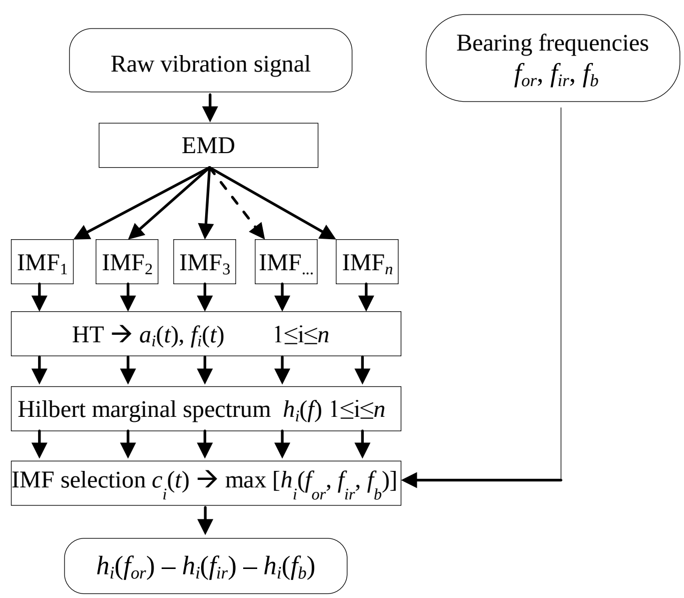


Fig.4. The health indicators extraction process.

B. *Detection and diagnostic of bearing degradation*

The detection of bearing degradation by pattern recognition consists of combining bearing health indicators of each critical component in order to assess the degradation state. Note that in the case of ball bearings, it is difficult to assess its degradation state by monitoring each health indicator separately (see fig. 5). The combination of health indicators of degradation allows building a representation space. From this space, it is possible to visualize the evolution of bearing degradation at each time step.

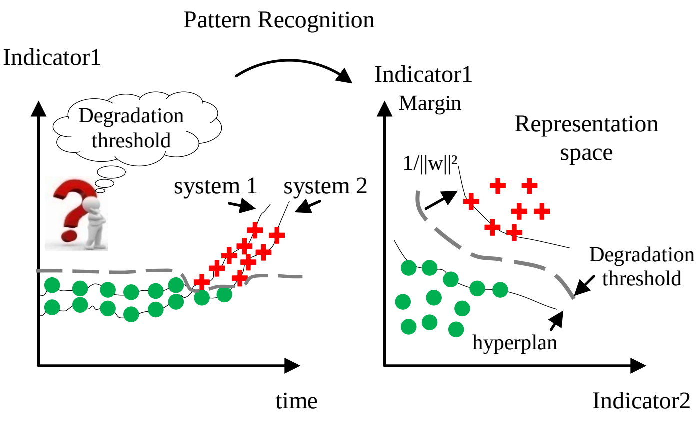


Fig.5. Time representation Vs pattern representation for fault detection.

As shown in fig. 5, the time is not used as an axis of the representation space. This does not reduce its efficiency to assess bearing degradation; on the contrary, it allows better distinguishing similar observations which are represented by various classes of different shapes. In the case of monitoring, these classes represent the states of bearing degradation.

The detection of bearing degradation can be interpreted as a pattern recognition problem. The goal is to classify an observation denoted $x = [h_j\,(f_{or})\; h_j\,(f_{ir})\; h_j\,(f_b)]$ acquired at time instant t in one of the classes which represent the degradation state of the bearing (Ω_1, Ω_2, ..., Ω_M). The M-classes regroup historical observations collected from bearings with the same characteristics and the same operating conditions of the bearing being tested. These classes are trained by the SVM technique. Since this is a supervised classification problem, the SVM uses the historical observations as a set of training data to build a classifier $f(x)$.

Suppose we have a training data set $(x_i, \Omega_i)_{\,i\in\{1,2,\ldots,l\}}$, $x_i \in \mathbb{R}^3$, $\Omega_i \in \{-1,+1\}$.

The SVM is defined by a classifier $f(x)$ of the form:

$$f(x) = sign\left[\sum_{i=1}^{l} \alpha_i \Omega_i\, K(x_i,x)+b\right] \tag{13}$$

where Ω_i is either 1 or −1, indicating the class to which the observation x belongs, l is the number of elements in the training set, α_i are Lagrange multipliers and b is a real constant. $K(.,.)$ is a kernel function.

The expression of $f(x)$ is interpreted as a non-linear hyperplane of the form:

$$\begin{cases} w^T \cdot \Phi(x)+b \geq 1 \\ w^T \cdot \Phi(x)+b \leq -1 \end{cases} \tag{14}$$

which is equivalent to:

$$\Omega_i\left[w^T \cdot \Phi(x)+b\right] \geq 1, \quad \begin{matrix} \Omega_i \in \{-1,+1\} \\ i \in \{1,2,\ldots,l\} \end{matrix} \tag{15}$$

where w is the normal vector (margin) to the hyperplane given by (23). Φ: $x \rightarrow \Phi(x)$ is a non-linear function which projects the observation x into a higher dimensional space. Dot products with w for classification can be computed by the kernel trick:

$$w^T.\Phi(x) = \sum_{i=1}^{l} \alpha_i \Omega_i\, \Phi(x_i)\cdot\Phi(x) \tag{16}$$

The kernel is related to the transform $\Phi(x_i)$ by:

$$K(x_i, x) = \Phi(x_i)\cdot\Phi(x) \tag{17}$$

where $K(x_i, x)$ can be of the form, polynomial of degree d: $K(x_i, x) = (x_i^T.x + 1)^d$, radial basis function (RBF): $K(x_i, x) = \exp\{-\|x\text{-}x_i\|^2/\sigma^2\}$ and hyperbolic tangent: $K(x_i, x) = \tanh(\beta x_i\,.\,x + c)$, for some (not every) $\beta>0$ and $c<0$.

Finally, the classifier $f(x)$ is equivalent to:

$$f(x) = sign\left[w^T.\Phi(x)+b\right] \tag{18}$$

From (19), the parameters that define the separating hyperplane and hence the Support Vector Machine are w and b. The aim is then to find these parameters (w and b) which separate the degradation states with maximal margin. This can be achieved by minimizing $\|w\|^2$ which leads to the following quadratic optimization problem:

$$\min \frac{1}{2}\|w\|^2 \tag{19}$$

In the case of non-complete separable observations, one can introduce slack variables ξ_i which measure the degree of misclassification of the observation x. The quadratic optimization problem becomes:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} \xi_i \tag{20}$$

where C is a parameter which controls the trade-off between the slack variable ξ_i and the margin w.

Reformulating (21) as a Lagrangian (Lp), the aim is to find the parameters w and b which minimize (22) and also the positive Lagrange multipliers α_i which maximize (22) (while keeping $\alpha_i \geq 0$, $\forall\, i$). This can be done by differentiating Lp with respect to w and b and setting the derivatives to zero:

$$Lp = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\xi_i - \sum_{i=1}^{l}\alpha_i\left[\Omega_i[w^T\cdot\Phi(x_i)+b]-1+\xi_i\right] - \sum_{i=1}^{l}\mu_i\xi_i \tag{21}$$

$$\frac{\partial Lp}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^{l}\alpha_i\Omega_i\Phi(x_i) \tag{22}$$

$$\frac{\partial Lp}{\partial b} = 0 \Rightarrow \sum_{i=1}^{l}\alpha_i\Omega_i = 0 \tag{23}$$

$$\frac{\partial Lp}{\partial \xi_i} = 0 \Rightarrow C = \alpha_i + \mu_i \quad (24)$$

where the μ_i are the Lagrange multipliers introduced to strengthen the positivity of ξ_i.

Substituting (23) and (24) into (22) gives a new formulation which, being dependent on α, one needs to maximize L_D:

$$\begin{aligned} L_D &= \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j \Omega_i \Omega_j K(x_i, x_j) \\ &= \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i H_{ij} \alpha_j = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha^T H \alpha \end{aligned} \quad (25)$$

$$\text{s.t} \quad 0 \le \alpha_i < C \ \forall i \quad \text{and} \quad \sum_{i=1}^{l} \alpha_i \Omega_i = 0$$

$$H_{ij} = \Omega_i \Omega_j K(x_i, x_j)$$

This is a convex quadratic optimization problem, where the objective is to find α so that (26) is maximized. The QP (Quadratic Programming) solver is used to obtain α and get w from (23). What remains is to calculate b.

Any observation satisfying (24) which is a Support Vector x_s will have the form:

$$\Omega_S \left[w^T \Phi(x_S) + b \right] = 1$$

Substituting in (23):

$$\Omega_S \left[\sum_{m \in S} \alpha_m \Omega_m \Phi(x_m) \cdot \Phi(x_S) + b \right] = 1$$

where s denotes the set of indices of the Support Vectors. It is determined by finding the indices i where $\alpha_i > 0$. Multiplying by Ω_s and then using Ω_s^2 we obtain:

$$b = \Omega_S - \sum_{m \in S} \alpha_m \Omega_m \Phi(x_m) \cdot \Phi(x_S) \quad (26)$$

We now have the parameters w and b that define the classifier given by (19).

C. *Prognostic*

Estimating the remaining useful life of a bearing consists in predicting the trend (evolution) of its degradation indicators through the time via a time series prediction technique where the principle is illustrated in fig. 6.

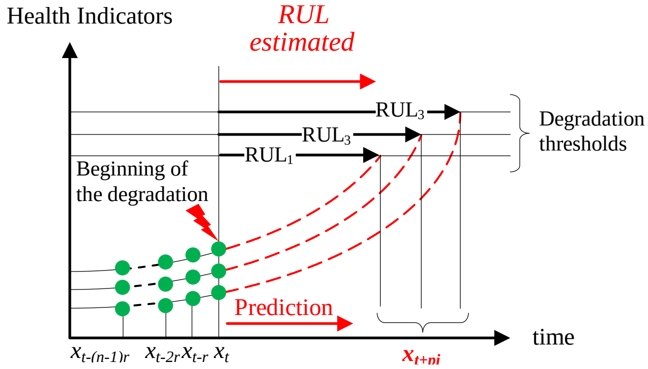


Fig.6. RUL estimation by times series prediction.

The difference between the time instant t, where an early degradation is detected, and time (t + RUL), where the bearing is considered as defective, allows estimating the RUL before the real degradation occurrence.

The time series prediction is formulated as follows: consider a health indicator measured up to time t, and a time series of observation $X_t = \{x_t, x_{t-r}, x_{t-2r}, x_{t-3r} \ldots x_{t-(n-1)r}\}$ extracted from this indicator, where r is the interval of the measure and (n-1) defines the length of the series. We need to know the value of the health indicator (x_{t+p}) at time (t+p), where p is the horizon of prediction. (x_{t+p}) is obtained following three steps:

- The first step consists of defining how to get x_{t+p}. This can be obtained directly from the time series $X_t = \{x_t, x_{t-r}, x_{t-2r}, x_{t-3r} \ldots x_{t-(n-1)r}\}$, this technique requires to get a prediction model for each horizon (p). Or indirectly from the previous predictions. The first prediction is inserted in the time series, then the second and so on. For this technique, a single prediction model is required. However, the results are sensitive to the inputs of the time series, because these inputs are estimated ones and not real measures. In our case, the first technique is chosen, which is based on the one step ahead prediction. It is formulated as follows:

$$\hat{x}_{t+p} = f\left(x_t, x_{t-r}, x_{t-2r}, x_{t-3r}, \ldots, x_{t-(n-1)r}\right) = f(X_t) \quad (27)$$

where $f(X_t)$ represents the prediction model of the time series X_t.

- The second step consists of choosing the prediction model. After the realization of SVM, the SVR, which has the same principles as the SVM for classification with only few minor modifications, is employed.

Contrary to the SVM where the output is a class membership, the output $f(X_t)$ of the SVR is a real number of the form:

$$f(X_t) = \Omega = w^T . \Phi(X_t) + b \quad (28)$$

The first modification on the SVR is that a margin of tolerance ε is set to tolerate the deviation of the regression from the real values. Referring to fig.7, the region bounded by $f(X_t)\pm$ is called ε-insensitive tube.

Another modification to the SVM is that the observations which are outside the tube are given one of two slack variable penalties depending on whether they lie above (ξ_i^+) or below (ξ_i^-) the tube (where $\xi_i^+ \ge 0$, $\xi_i^- \ge 0 \ \forall i$).

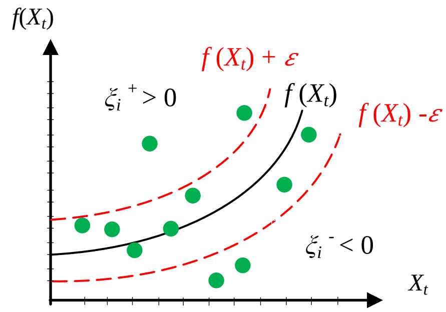


Fig.7. Regression with ε-insensitive tube.

From (29), the parameters that define the prediction model and hence the Support Vector Regression are w and b. The principle of the SVR is similar to the SVM. Given a training time series $x_i = \{x_t, x_{t-r}, x_{t-2r}, x_{t-3r} \ldots x_{t-(n-1)r}\}_{\ i \in \{1,2,\ldots,n-1\}}$, the aim is to find the parameters w and b by reformulating (30) as a Lagrangian.

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n-1}\left(\xi_i^+ + \xi_i^-\right) \qquad (29)$$

Using the method of Lagrange multipliers, one can obtain the dual formulation which is expressed in terms of variables α_i^+ and α_i^-:

$$\begin{aligned} L_D = {} & \sum_{i=1}^{n-1}(\alpha_i^+ - \alpha_i^-)\Omega_i - \varepsilon\sum_{i=1}^{n-1}(\alpha_i^+ - \alpha_i^-) \\ & -\frac{1}{2}\sum_{i,j}(\alpha_i^+ - \alpha_i^-)(\alpha_j^+ - \alpha_j^-)K(x_i, x_j) \end{aligned} \qquad (30)$$

α_i^+ and α_i^- are obtained by applying a QP solver on (31) which is subject to the constraints:

$$0 \le \alpha_i^+ < C, 0 \le \alpha_i^- < C \quad \text{and} \quad \sum_{i=1}^{n-1}(\alpha_i^+ - \alpha_i^-) = 0 \ \forall i$$

The parameters w and b are obtained from the following equations:

$$w = \sum_{i=1}^{n-1}(\alpha_i^+ - \alpha_i^-)\Phi(x_i) \qquad (31)$$

$$b = \Omega_s - \varepsilon - \sum_{m \in S}(\alpha_m^+ - \alpha_m^-)\Phi(x_m)\cdot\Phi(x_s) \qquad (32)$$

where s denotes the set of indices of the Support Vectors. The parameters w and b define the SVR function given by (29).

- The third step consists of defining a strategy of prediction. In the case of bearings, we have three health indicators. So, the idea is to predict separately the trend of each health indicator in order to obtain three estimations: x_{t+p1}, x_{t+p2}, x_{t+p2}. Each of x_{t+pi} represents a measure for which the studied bearing is considered as degraded. In other word, x_{t+pi} represent degraded thresholds. These thresholds are obtained from historical degradations of same type of bearings with the same characteristics and the same operating condition. Finally, x_{t+pi} allows estimating three RULs, the final RUL is taken as the smallest one (see fig. 6).

$$RUL_{estimated} \leftarrow \min\left(RUL_1, RUL_2, RUL_3\right) \qquad (33)$$

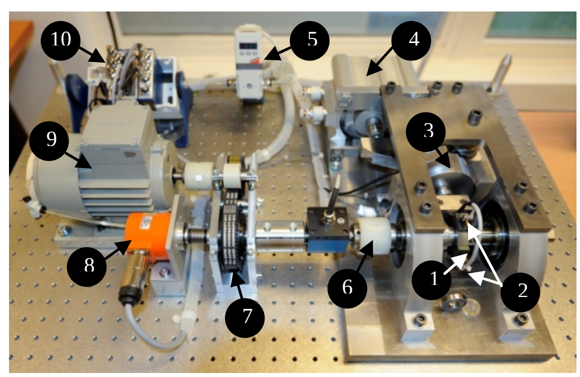
III. Experimental Validation

A. *Description of the experimental setup*

The experimental validation is done on an accelerated ageing platform named "PRONOSTIA" (see fig.8). This platform is built especially to observe the natural degradation of ball bearings. In fact, there exist different techniques to simulate the degradation of ball bearings. This degradation can be created by introducing some impurities into the lubricant or drilling or scratching the surface of the balls. But, these artificial degradations do not reflect the natural degradation of bearings. The aim of the platform "PRONOSTIA" is to provide realistic information which characterizes the natural degradation of bearings throughout their useful life. This platform is composed of two high frequency accelerometers of type 3035B DYTRAN placed horizontally and vertically on each bearing to pick up the horizontal and vertical vibration signals. A synchronous motor, a shaft, a speed controller and an assembly of two pulleys are used to vary the speed of the tested bearings. In our experimentation, the speed is kept constant at 1800 rpm. A proportional pneumatic jack is used to apply a radial force of 4200 N to the shaft and the tested bearing. The collected vibration signals are composed of 2560 samples recorded every 10 seconds with a sampling frequency equal to 25.6 kHz. These vibration signals are available at the following address: [http://www.femto-st.fr/en/Research-departments/AS2M/Research-groups/PHM/IEEE-PHM-2012-Data-challenge.php].

Three bearings (1, 2 and 3) of type NSK 6804RS are used to validate the proposed approach. The characteristics of these bearings are detailed in table I.

The vibration signals extracted from these bearings are used to evaluate the performance of our approach for the detection, diagnostic and prognostic of bearing degradation. For this purpose, we suppose the availability of the historical degradation of another bearing numbered 4 with the same characteristics and the same constraints of the three tested bearings. This dataset will be used to detect the degradation states and identify the parameters of SVM and SVR.



1- Test bearing **2-**Accelerometers **3-**Force sensor
4- Pneumatic jack **5-**Pneumatic regulator **6-**Coupling
7- Pulleys **8-** Speed recorder **9-**AC motor
10- Acquisition system

Fig.8. Ageing platform "PRONOSTIA".

Table I. Characteristics of the studied bearings

Diameter of rolling elements (mm)	3.5
Number of rolling element	13
Diameter of the outer race (mm)	29.1
Diameter of the inner race (mm)	22.1
Bearing mean diameter (mm)	25.6

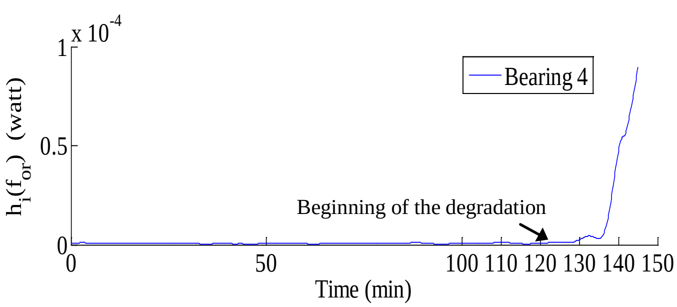
B. *Feature extraction*

The feature extraction technique described in sub-section II-A is applied to extract the health indicators $h_i(f_{or})$ – $h_i(f_{ir})$ – $h_i(f_b)$ from the vibration signals of the tested bearings. The operating conditions (speed and radial force) applied to the bearings and their dimensions allow calculating the three characteristic frequencies corresponding to the three faults.

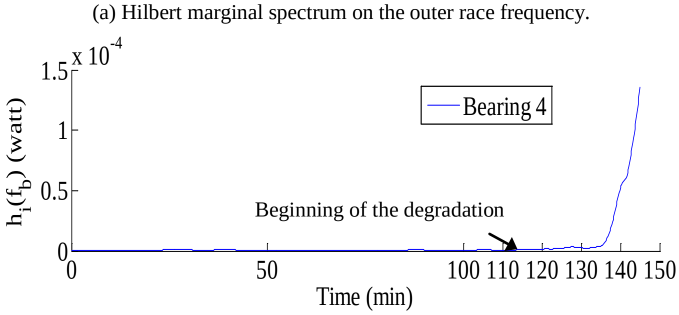
- Inner race frequency (f_{ir}): 221 Hz
- Outer race frequency (f_{or}): 168Hz
- Frequency of the ball (f_b): 215.48 Hz

These features are extracted from accelerometers installed on the horizontal axis which provide better results for tracking the bearing degradation than the accelerometers installed on the vertical axis.

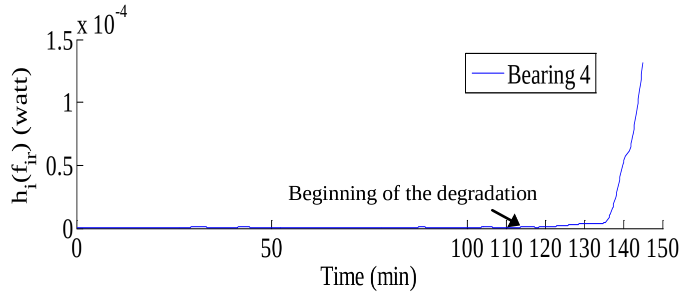
Figures 9(a), (b), (c) and (d) show respectively the evolution of the health indicators: Hilbert spectral density of the outer race, inner race, ball frequencies versus time of the bearing number 4. In addition to these health indicators, the root mean square (RMS) is added to show the difference between the time and time-frequency analysis. Note that the bearing numbered 4 is operated at 1800 rpm with a radial force equal to 4200 N for about 145 minutes of test. The test is stopped when the amplitude of the vibration signal exceeds 20 mm/s^2. After 114 minutes of test, the first sign of ageing was noticed in the ball. After 116 minutes of test, the second signs of degradation were noticed in the ball and the inner race. After 122 minutes of test, the third signs of degradation were noticed in the ball, the inner race and the outer race. For the RMS, the first sign of degradation appears only after 138 minutes of test. After that, the value of the RMS and the other heath indicators continued to rise as the degradation increases. These results show the effectiveness of the proposed technique to extract health indicators able to monitor separately the critical components of the ball bearings.



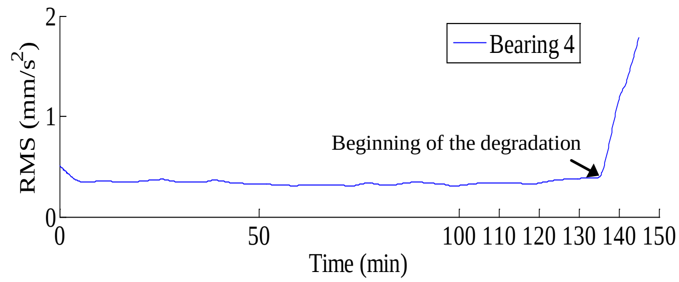
(a) Hilbert marginal spectrum on the outer race frequency.



(b) Hilbert marginal spectrum on the ball frequency.



(c) Hilbert marginal spectrum on the inner race frequency.



(d) Root Mean square

Fig.9. Evolution of the health indicators according to the degradation of bearing (4).

C. *Detection and diagnostic of bearing degradation*

As presented in the sub-section II-B, the detection of the degradation states is obtained by combining the health indicators $h_i(f_{or})$ – $h_i(f_{ir})$ – $h_i(f_b)$. This combination allows constructing a representation space from which is possible to identify all the degradation states (classes) of a bearing. Note that for the extracted health indicators, several observations disturbed by noise can appear. Thus, a class which regroups similar observations of the same degradation state will not be represented by a single data point but represented by an area of data points. If the health indicators are well extracted, each state of degradation can be represented by a constrained class in the representation space as shown in fig. 10.

From fig. 10, it is possible to define three degradation states represented by three classes (Ω_1, Ω_2, Ω_3). The first class (Ω_1) includes a set of observations belonging to the bearing number 4. The class (Ω_1) represents a bearing degradation ranging from 0% to 23%. This percentage is obtained by averaging the degradation percentage of each health indicator corresponding to the class (Ω_1). The last class (Ω_3) includes another set of observations belonging to the bearing number 4. The class (Ω_3) represents a bearing degradation ranging from 38% to 100%. This class represents a bearing in a bad state of degradation. In addition to (Ω_1) and (Ω_3), it is possible to distinguish an intermediate class denoted (Ω_2). This class includes a set of observations ranging from 24% to 37% of the degradation. Thus, this class represents a bearing in a medium degradation state.

The obtained classes (Ω_1, Ω_2, Ω_3) represent respectively a bearing in a: good state, medium state and degraded state. Each class has a geometric area in the representation space. Given an observation performed in a new bearing, the detection process consists of affecting this observation to one of the obtained classes according to equation (19). The identification of the class membership allows detecting the current degradation state of the tested bearing. The diagnostic

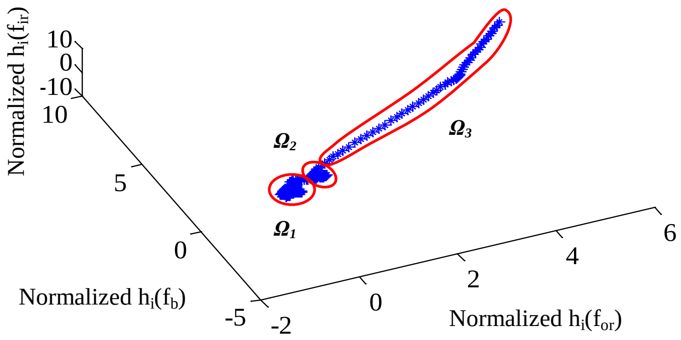


Fig.10. Degradation states of bearing number 4.

process consists of identifying the component(s) (inner race, outer race, balls) responsible of this degradation by analyzing each health indicator separately.

The SVM uses each class as training data to learn its parameters. Finally, we obtain three SVMs defined by three hyper-plans able to separate each class. The kernel function used in this experiment is a polynomial of degree 3.

Once the SVMs are constructed, they are used to detect the degradation states of bearings (1, 2 and 3). This is shown in fig. 11. It is also possible to identify the components responsible of the degradation. If we take for example the bearing (2), the appearance of the medium degradation is detected after 401 minutes of test. Based on the three health indicators, we can conclude that the medium degradation of bearing (2) is due to a degradation of: 28% in the outer race, 26% in the inner race and 26 % in ball.

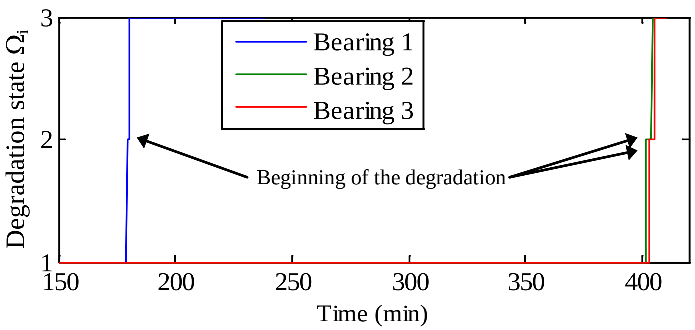


Fig.11. Fault detection of bearings degradation.

D. *Prognostic*

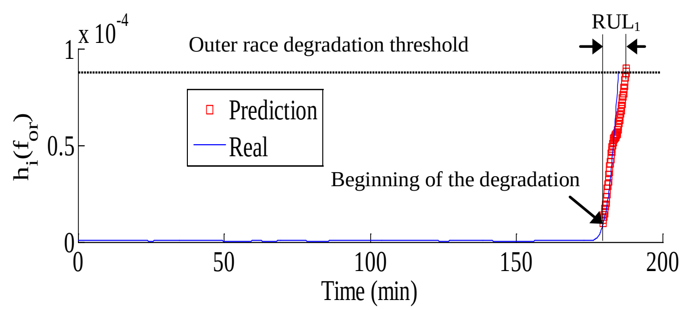
The prognostic process consists of estimating the remaining useful life of the studied bearing by predicting the trend of each health indicator. Like the SVM, three SVRs are constructed. The kernel function used in the prediction case is a radial basis function (RBF). The interval of measures (r) is fixed at 6 minutes. The length of the series (n-1) is equal to 4 and the horizon of prediction (p) is a variable ranging from [1 to k]*T_s where k is an integer, T_s is a prediction step equal to 10 seconds and k*T_s is the moment where the bearing is considered as degraded. The thresholds for which the bearing is considered as degraded are extracted from the class (Ω_3). The first RUL_1 is obtained for a degradation threshold equal to 8.9×10^{-5} watt for the outer race. RUL_2 is obtained for a degradation threshold equal to 1.35×10^{-4} watt for the ball. RUL_3 is obtained for a degradation threshold equal to 1.31×10^{-4} watt for the inner race. For the test bearings (1, 2 and 3), the RUL of each health indicator and the error of prediction (E_r%) are calculated.

The error of prediction is given by the following formula:

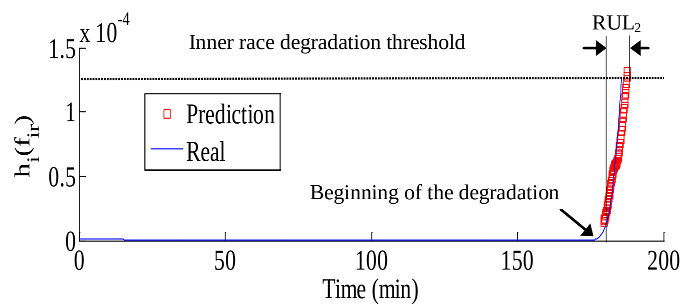
$$E_r(\%) = 100 \times \left| \frac{t_{failure} - \hat{t}_{failure}}{t_{failure}} \right| \quad (34)$$

where $t_{failure}$ and $\hat{t}_{failure}$ are respectively the real and the estimated time to failure for the tested bearing.

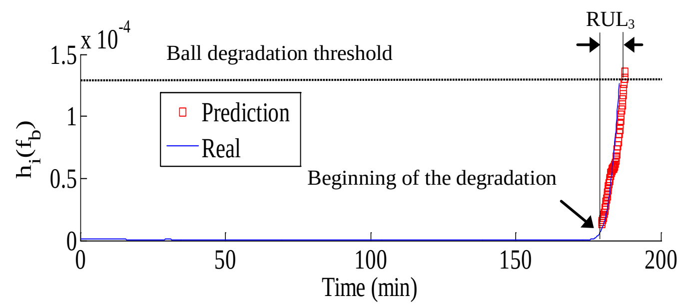
The validation of the prediction results are shown in table II. Figure 12 shows experimental results about the estimation of the RULs of bearing (1) corresponding to the three health indicators $h_i(f_{or}) - h_i(f_{ir}) - h_i(f_b)$. The prediction begins when the acquired measure is classed in the medium state of degradation by using the SVM.



(a) Time series prediction of the outer race health indicator.



(b) Time series prediction of the inner race health indicator.



(c) Time series prediction of the ball health indicator.

Fig.12. RUL estimation by times series prediction of bearing (1).

Table II. Prediction results

	Bearing 1	Bearing 2	Bearing 3
RUL_1 (min)	6.8	2	1.5
RUL_2 (min)	7.3	4.3	1.2
RUL_3 (min)	7.1	3.8	1.2
RUL estimated (min)	6.8	2	1.2
E_r(%)	0.6	1.1	1.25

IV. Conclusion

A new approach for the detection, diagnostic and prognostic of the degradation in ball bearings has been proposed in this paper. This approach has been described as well its implementation in a real case of bearing degradation.

For stationary/non-stationary vibration signals, the Hilbert-Huang transform showed that it is possible to extract relevant health indicators able to track the degradation of bearings. One difficulty of the Hilbert Huang Transform is that the number of IMFs can differ from one signal to another. This problem is called mode mixing problem and makes the feature extraction difficult because the feature cannot be fixed in one IMF index.

The extracted features have been successfully implemented in the detection and diagnostic process thanks to the SVM. Also, these features have been successfully implemented in the prognostic process thanks to the SVR combined with the one-step time series prediction. However, the implementation of the proposed approach depends on the availability of historical data about the degradation of the bearings. These data are required to train the SVM and the SVR. This assumption limits the applicability of this approach in cases where historical data are difficult to obtain.

The application of the proposed approach can be extended to other types of components, such as gearboxes and wind turbines as they can be subject to similar degradations and can be monitored by similar types of features.

Acknowledgement

This work is supported by the MainPreSI project realized within the framework of the European Territorial Cooperation program INTERREG IV. A France – Switzerland, financed by the European Regional Development Fund.

References

[1] P. F. Albrecht, J. C. Appiarius, and D. K. Sharma, "Assessment of the reliability of motors in utility applications-Updated," *IEEE Transactions on Energy Conversion.*, vol. 1, pp. 39-46, 1986.

[2] I. C. Report, "Report of large motor reliability survey of industrial and commercial installation, Part I and Part II," *IEEE Transactions on Industry Applications.*, vol. 21, pp. 853-872, 1985.

[3] R. A. Guyer, *Rolling Bearings Handbook and Troubleshooting Guide*, Chilton Book Compagny, Radnor, Pennsylvania, 1996.

[4] D. F. Busse, J. M. Erdman, R. J. Kerkman, D. W. Schlegel, G. L. Skibinski, "The effects of PWM voltage source inverters on the mechanical performance of rolling bearings," *IEEE Trans. on Industry Applications*, vol. 33, no. 2, pp. 567–576, Mar-Apr. 1997.

[5] J. R. Stack, T. G. Habetler, R. G. Harley, "Experimentally Generating Faults in Rolling Element Bearings Via Shaft Current," *IEEE Trans. on Industry Applications.*, vol. 41, no. 1, pp. 25–29, Jan-Feb. 2005.

[6] C. Chaochao, Z. Bin, G. Vachtsevanos, "Prediction of Machine Health Condition Using Neuro-Fuzzy and Bayesian Algorithms," *Instrumentation and Measurement, IEEE Transactions on*, vol.61, no.2, pp.297–306, Feb. 2012.

[7] Jie Liu, Wang. W, Golnaraghi. F, "An Enhanced Diagnostic Scheme for Bearing Condition Monitoring," *Instrumentation and Measurement, IEEE Transactions on*, vol.59, no.2, pp.309–321, Feb. 2010.

[8] E.C.C. Lau, H. W. Ngan, "Detection of Motor Bearing Outer Raceway Defect by Wavelet Packet Transformed Motor Current Signature Analysis," *Instrumentation and Measurement, IEEE Transactions on.*, vol.59, no.10, pp.2683–2690, Oct. 2010.

[9] J. Luo, K. Pattipati, L. Qiao, and S. Chigusa, "Model-based prognostic techniques applied to a suspension system," *IEEE Trans. Systems, Man and Cybernetics*, Part A: Systems and Humans., vol. 38, no. 5, pp. 1156–1168, Sept. 2008.

[10] N. Tandon and A. Choudhury "An analytical model for the prediction of the vibration response of rolling element bearings due to a localized defect," *J. Sound Vib.*, vol. 205, no. 3, pp.275–292, 1997.

[11] M. Blodt, P. Granjon, B. Raison, G. Rostaing, "Models for Bearing Damage Detection in Induction Motors Using Stator Current Monitoring," *Industrial Electronics, IEEE Transactions on*., vol.55, no.4, pp.1813–1822, April. 2008.

[12] Qingbo He; Yongbin Liu; Qian Long; Jun Wang, "Time-Frequency Manifold as a Signature for Machine Health Diagnosis," *Instrumentation and Measurement, IEEE Transactions on*., vol.61, no.5, pp.1218–1230, May. 2012.

[13] Szczesny, R.; Kurzynski, P.; Piqueb, H.; Hwan, K, "Knowledge-base system approach to power electronic systems fault diagnosis," *Industrial Electronics, ISIE '96., Proceedings of the IEEE International Symposium on*, Jun.1996, vol.2, pp.1005–1010.

[14] A. C. Renfrew and J. X. Tian, "The use of a knowledge based system in power electronic circuit fault diagnosis," *EPE '93 Conf. Brighton 1993*.

[15] F. Immovilli, M. Cocconcelli, A. Bellini, and R. Rubini, "Detection of generalized-roughness bearing fault by spectral-kurtosis energy of vibration or current signals, " *IEEE Trans. Ind. Electron*., vol. 56, no. 11, pp. 4710–4717, Nov. 2009.

[16] B. Zhang, C. Sconyers, C. Byington, R. Patrick, M. Orchard, and G. Vachtsevanos, "A probabilistic fault detection approach: Application to bearing fault detection, " *IEEE Trans. Ind. Electron*., vol. 58, no. 5, pp. 2011–2018, May. 2011.

[17] T. Benkedjouh, K. Medjaher, N. Zerhouni, S. Rechak, "Fault prognostic of bearings by using support vector data description," in *Proc. IEEE-PHM*, 2012, pp.1–7.

[18] K. Medjaher, D.A. Tobon-Mejia, N. Zerhouni, "Remaining Useful Life Estimation of Critical Components With Application to Bearings," *Reliability*, *IEEE Transactions on*., vol.61, no.2, pp.292–302, June. 2012.

[19] N.E. Huang, Z. Shen, S. Long, M.C. Wu, H.H. Shih, Q. Zheng, N.C. Yen, C.C. Tung, H.H. Liu, "The Empirical Mode Decomposition and Hilbert Spectrum for nonlinear and non-stationary time series analysis, " in *Proc*. R. Soc. London A, 1998, pp.903–995.

[20] N.E. Huang, Z. Shen, S. Long, "A new view of nonlinear water waves: The Hilbert Spectrum," *Annual Review of Fluid Mechanics.*, vol.61, 1999, pp.417–457.

[21] S.Gade, and H.Herlufsen, *Digital Filter Techniques vs. FFT Technique for Damping Measurements*, Brüel & Kjær Technical Review No.1. 1994.

[22] J. Ville, *Theory et Application de la Notion de Signal Analytique*, Cables et Transmissions, 20 A, 1984.

[23] D.E. Newland, "Wavelet Analysis of Vibration Part 1: Theory, " *ASME Journal of Vibration and Acoustics*, Oct. 1994.

[24] H. Li, Y. Wang, Y. Ma, "Ensemble empirical mode decomposition and Hilbert-Huang transform applied to bearing fault diagnosis," *Image and Signal Processing (CISP), 3rd International Congress on* , vol.7, pp.3413-3417, Oct. 2010.

[25] T-Y. Wu, C-C. Wang, Y-L. Chung, "The bearing fault diagnosis of rotating machinery by using Hilbert-Huang transform," *Electric Information and Control Engineering (ICEICE), International Conference on*, pp.6238-6241, April. 2011.

[26] Benkedjouh. T, Medjaher. K, Zerhouni. N, Rechak. S, "Remaining useful life estimation based on nonlinear feature reduction and support vector regression," *Engineering Applications of Artificial Intelligence.*, Vol.26, no.7, pp.1751–1760, August. 2013.

[27] A. Soualhi, H. Razik, G. Clerc, D.D. Doan, "Prognosis of Bearing Failures Using Hidden Markov Models and the Adaptive Neuro-Fuzzy Inference System," *IEEE Transactions on Industrial Electronics.*, vol.61, no.6, pp.2864–2874, June 2014.

[28] A. Soualhi, G. Clerc, H. Razik, "Detection and Diagnosis of Faults in Induction Motor Using an Improved Artificial Ant Clustering Technique," *IEEE Transactions on Industrial Electronics.*, vol.60, no.9, pp.4053–4062, Sept. 2013.

[29] G. Cao, X.K. Ge, and L.Q. Yang, "Locally weighted naive bayes classification algorithm based on K-nearest neighbour," *Computer Applications and Software.*, vol. 28, pp.267–268, Sep. 2011.

[30] J.L. Tan, and J.H. Wu, "Classification algorithm of rule based on decision-tree," *Computer Engineering and Design.*, vol. 31, pp.1017–1019, 2010.

[31] Y.D. Liu, and H.M. Niu, "KNN Classification Algorithm Based on k-Nearest Neighbor Graph for Small Sample," *Computer Engineering.*, vol. 37, pp.198–200, May. 2011.

[32] A. Sperduti, A. Starita, "Supervised neural networks for the classification of structures," *Neural Networks, IEEE Transactions on*., vol.8, no.3, pp.714–735, May. 1997.
[33] V. Vapnik, *The Nature of Statistical Learning Theory*. Springer-Verlag, New York, 1995.
[34] V. Vapnik, S. Golowich, and A. Smola, "Support vector method for function approximation, regression estimation, and signal processing," *Advances in Neural Information Processing Systems.*, Vol.9, pp.281–287, 1996.
[35] L.Yanfeng, Y. Haibin, "Three-phase Induction Motor Operation Trend Prediction Using Support Vector Regression for Condition-based Maintenance," *Intelligent Control and Automation*, WCICA., 2006, pp.7878–7881.
[36] P. Nectoux, R. Gouriveau, K. Medjaher, E. Ramasso, B.C. Morello, N. Zerhouni, C. Varnier, " PRONOSTIA : An experimental platform for bearings accelerated degradation tests, " *in IEEE International Conference on Prognostics and Health Management*, PHM'12., Denver, Colorado, 2012.
[37] R. Yan, and R. X. Gao, "Hilbert–Huang transform-based vibration signal analysis for machine health monitoring," *IEEE Trans on Instrum. Meas*., vol. 55, no. 6, pp.2320–2329, 2006.
[38] L.Hui, Z.Yuping, and Z. Haiqi, "Wear Detection in Gear System Using Hilbert-Huang Transform," *Journal of Mechanical Science and Technology*., Vol.20, no.11, pp.1781–1789, 2006.
[39] A.-O. Boudraa and J.-C. Cexus "EMD-based signal filtering", *IEEE Trans on Instrum. Meas*., vol. 56, no. 6, pp.2196–2202, 2007.