Health Monitoring Approach of Bearing : Application of Adaptive Neuro Fuzzy Inference System (ANFIS) for RUL-estimation and Autogram Analysis for Fault-localization

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***Abstract*—Bearings usually operate under harsh conditions which result in a dynamic behavior generating non-stationary vibration signals and overwhelmed by noise. Therefore, bearing fault diagnosis and prognosis become difficult since the purpose is to extract robust features able to detect the appearance of faults, monitoring the degradation of health state and to predict the remaining useful life (RUL) of bearing. The aim of this paper, is to propose a method for bearing faults feature-extraction using adaptive neuro fuzzy inference system (ANFIS) and autogram analysis. First, times domain features are applied for the raw vibration signal. Then, the selected features are computed to will be analyzed as one of the characteristics that describes the degradation of state system. After that, the curve fitting (smoothing) is applied to normalize the amplitude of the irregular values relatively to others feature values. The calculated value of acquired signal cannot be smoothed or calculated three or more times, hence ANFIS intervenes for modeling the transfer from an indeterminate input to a more relevant value for monitoring the fault evolution. Then, the output of ANFIS estimates the days of acquisition and predict the RUL of bearing. Finally, the autogram analysis is used to identify the degraded element in the bearing.**

***Index Terms*—Time domain features (TDFs),Features extraction, Prognostic and health management (PHM), Adaptive neuro fuzzy inference system (ANFIS), Autogram analysis.**

I. Introduction

Prognostic and health management (PHM) is one of the research challenges of the last decades, the main objective of the prognosis is to provide information and making good decisions which is based on estimation of Remaining useful life (RUL) [1] . Contrary to the diagnosis, the prognosis is introduced to estimate the future state of the monitored component [2], [3]. This type of research allows us to avoid un-programmed failures and to predict the time of machine availability . For this purpose it is necessary to accurately estimate the RUL prediction . This challenge requires reliable approaches when designing prediction models. In the literature ,it appears that the prediction methods generally differ by the type of application , while the used tools depend mainly on the nature of the data and the available knowledge .

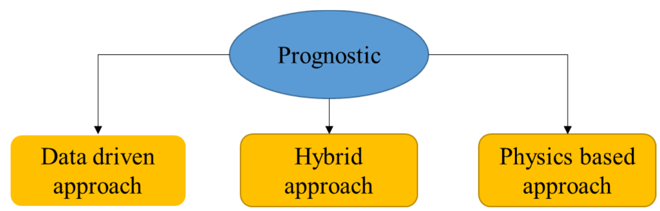

Fig. 1. Prognostic approaches.

Also, these methods and tools can be grouped in a limited number of approaches. The following classification tends to gain consensus within the PHM community (Fig. 1).

Data-driven approaches are based on statistical features and machine learning techniques [4] such as:Artificial Neural Network (ANN) [5]–[7],Fuzzy logic System (FLS) [8], [9], Adaptive Neuro Fuzzy Inference System (ANFIS) [10], [11].It does not require a physical model of the system: these techniques are very successful in fault detection, classification and RUL estimation [12]. Physics based approach relies extensively on physical knowledge of the system, which requires the implementation of mathematical models describing the physics of the component in order to assess its current and future health. The performance of this type of model depends on the ability to describe the physical model to accurately represent failure and degradation phenomena [13], [14]. Cubillo details more this part [15]. Hybrid approach combines different types of models, where this approach integrates physical model and data-based methods, to obtain a more robust health assessment . A hybrid prognostic method implemented a physical model and a data-driven approach. When a physical model can be established, a data-oriented approach is used to estimate and predict the un-observable parameters of the model. In such cases, the data-oriented tool is generally used to estimate and predict unexplained the un-modelled phenomena [16].

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In recent years, much effort has been devoted to the development of regression-based methods for predecting the RUL of rotating machines. Li et al [17] have improved the performance of the classical exponential regression model and have applied the improved regression model to vibration data collected from the bearings to RUL prediction. Sutrisno and his collaborators [18] studied the accuracy of predicted RUL using three different techniques ; They compared the Bayesian Monte Carlo method with the moving average of spectral Kurtosis, support vector regression (SVR) and an algorithm for detecting anomalies as a function of their performance in estimating the RUL of a ball bearing. Loukopoulos et al [19] investigated the performance of different machine learning methods: linear,polynomial and K-Nearest Neighbors regression. The obtained results show that methods based on the weighted mean predicted RUL of each individual method offers greater predictive accuracy.

In this paper, we present a method to estimate the RUL of bearing using Adaptive Neuro Fuzzy Inference System (ANFIS) for modelling the undetermined feature inputs and the Autogram analysis for detecting the degraded element in bearing (Fault-localization). The monitoring is based on data acquisition using sensors and the calculated value from the sensors must be processed to detect faults or predict the health state of bearing. The aim of this study is to know how to switch from a calculated value from a vibration signal to more interesting information for fault detection and prediction .

II. Time Domain Features (TDFs)

Many researchers have focused on extracting features from vibration signal where the vibration analysis is the most useful technique of data acquisition because vibration signals carry the relevant dynamic information of the rotating machines [20]. Time Domain Characteristics (TDF) are calculated from the raw signals if the collected data from sensors are not largely affected by noise,however, if the signal is affected it must first proceed through the filtering step. We present some of the most commonly used health indicators (HI) for monitoring the rotated systems based on vibration signal: kurtosis(X_{kur}), root mean square (X_{rms}), standard deviation (X_{std}), variance (X_{var}), entropy (X_{ent}),etc. It has been demonstrated that these features are sensitive to one or more faults and contribute in describing the state of machine [21].

$$X_{std} = \left(\frac{1}{N} \sum_{i=1}^{N} (x_i - X_{mean}) \right)^{\frac{1}{2}} \tag{1}$$

$$X_{kur} = \frac{1}{X_{rms}^4} \sum_{i=1}^{N} (x_i - X_{mean})^4 \tag{2}$$

where, i is the sample of signal x, N:is the length of x, X_{mean}: mean of x and X_{rms}: RMS of x.

III. Techniques of Signal processing

Frequency domain methods offer the possibility of isolating specific frequency components related to specific machine component faults. The limitations of these conventional methods appear when analyzing the non-stationary vibrations signals generated by faults having low energy and overwhelmed by a large amount of noise. To deal with these problems, time-frequency (TF) analysis techniques have been developed. Empirical Mode Decomposition (EMD) [22], Empirical Wavelet Transform (EWT) [23] etc. In the last decade, the wavelet transform has drawn a lot attention and it could overcome the classical TF tools. It has many application in rotating machines diagnosis such the work of YAN Ruqiang et al [24]. The high-frequency band is not divided when the modulation of the information of a machine fault exists. Thus, the wavelet packet transform (WPT) is proposed. It provides a complete level by level TF decomposition of signal. It may not only supply richer information but also supply more promise frequency localization information. Nevertheless, the WT or even WPT cannot give an effective information due to the lack of adaptability [25], [26]. The Kurtogram analysis is powerful tool in bearing fault detection [27] by determining the most impulsive frequency-band. The FK has the ability to detect fault frequencies from the non-stationary signal and in strong gaussian noise. Many researchers observed that FK is less successful in non-gaussian noise (low Signal to Noise Ratio (SNR)) and they are investigated to develop the FK to overcom difficulties of detection in this several condition .The improved FK called Autogram analysis which is developed by Moshrefzadeh al [28] confirms the advantages of analysis in bearing and also in gears systems [28], [29].

IV. Mathematical background

A. Autogram analysis

The Autogram is an improved method of Fast Kurtogram (FK), where the FK is effective tool and especially in detecting faults of bearings by determining the impulsive frequency band. FK can detect and localize fault from non-stationary signal and even strong gaussian noise, but its effectiveness is limited in cases where the signal is affected by non-Gaussian noise. To overcome the limitations of FK, a new technique based on Auto-correlation (AC) is introduced ti find suitable band-pass for demodulation where the corresponding procedure are described as follows:

(i) the original signal is divided in different frequency bands using Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) which eliminates the down-sampling part in Discrete Wavelet Packet Transform (DWPT) [21] [30].

(ii) Application of squared envelope on the resulting nodes from MODWPT , the aim of this part is to better visualize the amplitude modulation in the nodes.

(iii) Integrate the advantage of auto-covariance periodicity function that can charactirizes the second order of vibration signal cyclo-stationarity . The AC is calculated from the squared envelope.A modified version of the kurtosis is proposed to quantify the impulsivity of the AC for each nodes [28].

(iv) Calculate the kurtosis of the resulting AC and select band-pass that contains the highest kurtosis value of nodes.
(v) Compute the fourier transform to extract fault characteristics from squared envelope .

B. Adaptive neuro inference system (ANFIS)

The ANFIS system is combined between the artificial neural network (ANN) and fuzzy logic system (FLS), it takes the advantages of these two techniques to have a good decision of input or data set, this decision is automatic and hybrid to determine the situation or severity or location of a defect in rotating machines as in fault diagnosis, we hope that this decision will be approximate to the human decision. ANFIS system is integrated in Takagi Segueno model fuzzy logic where the gradient descent and the least squares method are used determine the consequent parameters. ANFIS has an architecture of five layers which contains nodes. To better understand the functionality of this system we give this example of two inputs and one output.

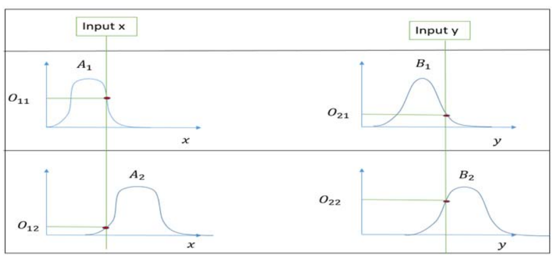

Fig. 2. degree membership of inputs

$$\begin{cases} O_{1i} = \mu_{Ai}(x) & i = 1,2 \\ O_{2i} = \mu_{Bi}(x) & i = 1,2 \end{cases} \tag{3}$$

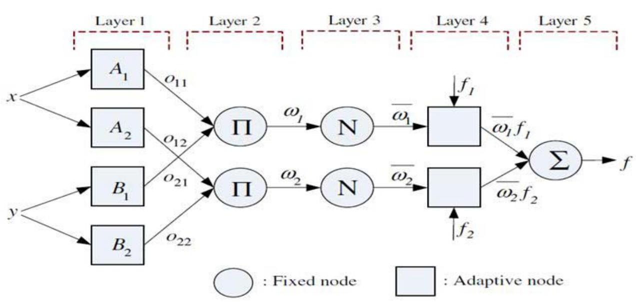

Fig. 3. ANFIS architecture.

- Layer1: the input layer contains nodes which generate membership grade of inputs, these nodes are adaptive.

- Layer2: this fixed nodes will multiplies the two grades of membership (A,B) of the two inputs.

$$\mu_{Ai}(x) * \mu_{Bi}(y) \quad , \quad i = 1,2 \tag{4}$$

- Layer3: layer will normalize the strength of a rule which are the consequent of the second layer.
- Layer4: this layer is linear, the input of his adaptive nodes are multiplied by which is a first order polynomial with the parameters$(p_i, q_i, r_i$, so the output of this layer is given by:

$$\overline{w_i} * f_i = \overline{w_i} * (p_i x + q_i y + r_i) \tag{5}$$

- Layer5: the last layer performs the summation of incoming signals (inputs of layer or the outputs of recent layer) , where the output is given as follows:

$$f = \sum \overline{w_i} * f_i \quad = \frac{\sum_i \overline{w_i} * f_i}{\sum_i w_i} \qquad for \quad i = 1,2 \tag{6}$$

V. Experimental result and discussion

A. Experiment data acquisition

Vibration data was collected using the Green Power Monitoring System from a high-speed shaft bearing mounted inside a 2 MW wind turbine. The vibration measurement was collected from 50 consecutive days using accelerometers which are positioned radially on the bearing support ring [31].The speed of input shaft bearing was 1800 rpm which is equal to 30 hz where the sampled frequency is 97656 Hz for 6 s .

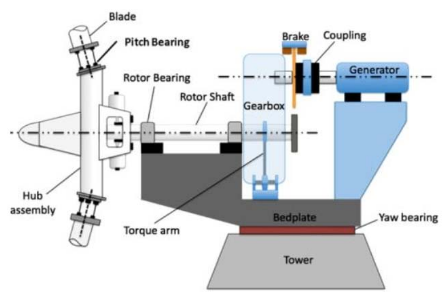

Fig. 4. Experimental test-bed.

B. The proposed approach

In this section,we present the procedure of the proposed a method for RUL estimation based on feature extraction using adaptive neuro fuzzy inference system (ANFIS) and fault identification using autogram analysis.The collected signals are grouped in order to visualize the amplitude variation(Amplitude modulation) caused by the fault evolution in bearing (Fig.7).

In the first step, time domain features(TDFs) are applied to extract reliable characteristics that can monitoring the evolution of fault in ball bearing which are acquired during 50 days of acquisition. Figure 8 presents the evolution of scalar indicators: Standard deviation(std), peaktopeak (P2P), Entropy log energy(En-log-en) and kurtosis (KUR) .The degradation of state is observed from these indicators; especially in KUR, stability is observed in the first 26 days, but after these days

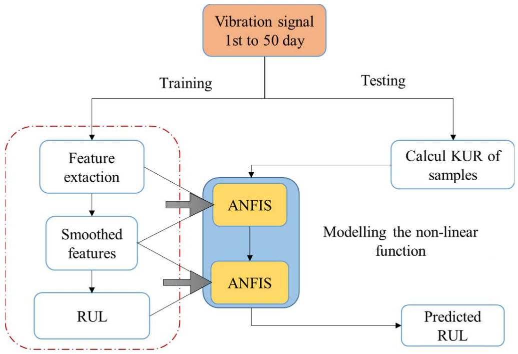

Fig. 5. Proposed approach.

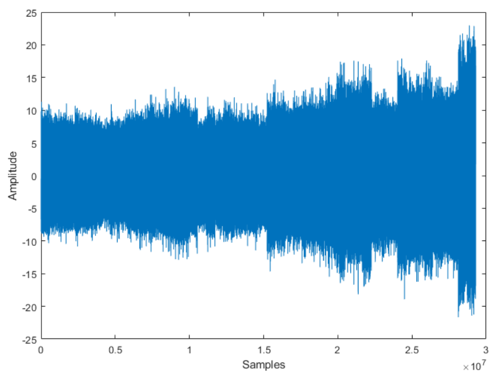

Fig. 6. Acquired vibration signals of 50 days .

it is unstable, which makes difficult to assess the fault bearing degradation .

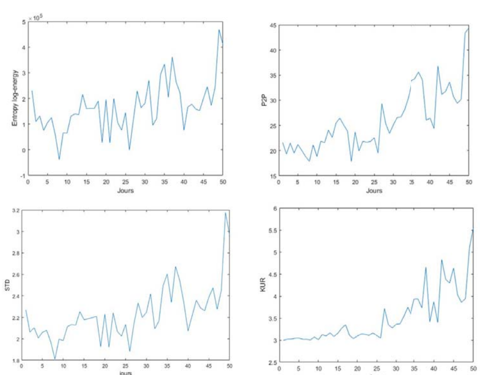

Fig. 7. Evolution of TDFs.

Most research uses the smoothing function to stabilize health indicators (HI) and to normalize unregulated values in the set of vector points .So to enhance and to construct more reliable features ,the extracted characteristics are smoothed by the given equation :

$$\begin{cases} \mathrm{Y(1) = y(1)} \\ \mathrm{Y(2) = (y(1) + y(2) + y(3))/3} \\ \mathrm{Y(n) = {}^{y(n-i)+...+y(n)+...+y(n+i)}/_{L}} \end{cases} \tag{7}$$

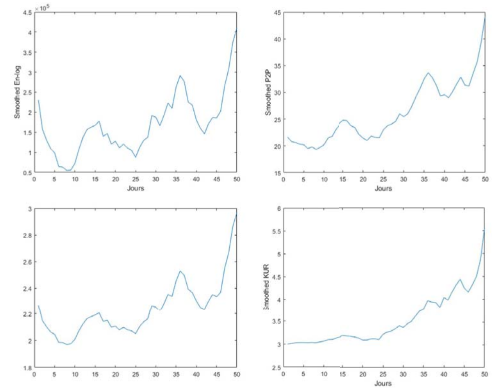

Fig. 8. Evolution of Smoothed-TDFs.

where Y is the smoothed value,y is kurtosis value, L is the total number of series-value and i is the iteration number it's defined in [1 to L].

Figure 8 shows the evolution of the smoothed characteristics where the smoothed kurtosis indicator (Sm-KUR) presents an appreciable input vector where degradation is really observed. Thus, the smoothed KUR characteristic describes the health state of bearing and the RUL is estimated according to the selected indicator.

In this study, the measured Kurtosis value from vibration signal cannot be smoothed and we have no information on the passage from a point to a smoothed value. This is why ANFIS was introduced to give a more accurate model, especially in areas of fluctuation that can cause incorrect results. The first model presents a learning system for the transfer of the normal kurtosis value to a smoothed value and the second ANFIS converts the smoothed-kur to the estimated RUL.

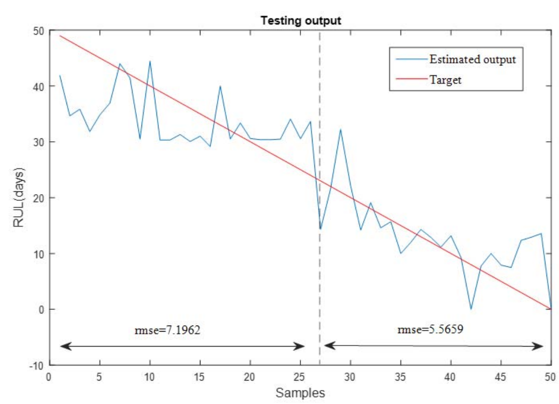

Fig. 9. Predicted RUL on tested data.

Figure 9 shows the results of the RUL estimation of each tested samples over 50 days. The training system is learned by ANFIS using the proposed method and the output is the result tested samples.The result of proposed approach is compared to other techniques by calculating the root mean squared error (RMSE) of output as it is presented in Eq.8:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}} \times \mathrm{abs}\left((\mathrm{predictedRUL} - \mathrm{Target})\right)} \qquad (8)$$

According to the presented results in the Table.1 , it can be concluded that the proposed approach provides a more accurate RUL estimation and confirms its effectiveness in predicting the life time of ball bearings.

TABLE I
FORMULA OF EXPECTED BEARING FAULTS FREQUENCIES.

Methods	RMSE
Proposed approach	6.4652
Polynomial regression	29.94.2
K.Abid [32]	16.484
sk-mean exp model [32]	22.214

C. degraded element in bearing using Autogram analysis

This part identify the degraded component in bearing using Autogram analysis, a comparison with FK analysis is introduced to validate the effectiveness of the proposed method. First, we present the result of FK of 15,30 and 45th day of acquisition. The resulting frequencies are referred to the fault frequencies given in the Table 2.

TABLE II
FORMULA OF EXPECTED BEARING FAULTS FREQUENCIES.

Type of fault	faults frequencies
Inner-race fault (IR)	$9.47.f_r$
Outer-race (OR)	$6.72.f_r$
Rolling-element (B)	$1.435.f_r$
Cage fault (CG)	$0.42.f_r$

The results of Kurtogram and Autogram are described in Table 3 . Kmax of the three days in FK didn't indicate the presence of fault , but on the other side, the autogram has an acceptable and logical indication when its Kmax value progresses. Figure 10 and Figure 11 show the spectrum of the resulting band-pass (selected band) using kurtogram and Autogram analysis respectively ; where the kurtogram failed to extract fault frequency, however the Autogram detects the appearance of new frequencies in the 30 and 45 days which really means that these frequencies correspond to fault frequency of degraded element in bearing (Fir= 283.8 hz) and to rotation frequency (Fr= 30 hz).Based on the spectrum analysis, the autogram gives satisfactory results by detecting the degraded element in the bearing.

TABLE III
FORMULA OF EXPECTED BEARING FAULTS FREQUENCIES.

Day of acquisition	Parameters	FK	Autogram
15^{th}	Level	1	7
	$\mathrm{B}_w(hz)$	24414	381.4688
	$\mathrm{f}_c(hz)$	12207	1716.6094
	K_{max}	0.1	2.1
30^{th}	Level	6	5
	$\mathrm{B}_w(hz)$	762.9375	1525.875
	$\mathrm{f}_{c(hz)}$	11825.5313	12969.9375
	K_{max}	0.1	3.8
45^{th}	Level	7	4
	$\mathrm{B}_w(hz)$	381.4688	3051.75
	$\mathrm{f}_c(hz)$	11253.328	1068.125
	K_{max}	0.2	9.3

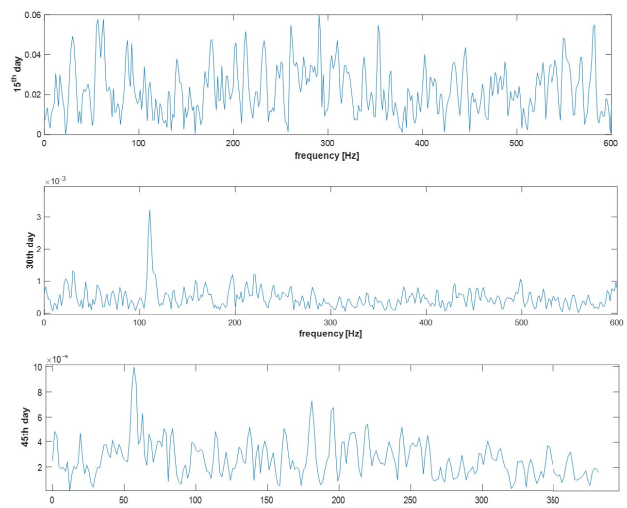

Fig. 10. Spectrum of resulting band with FK .

VI. CONCLUSION

This paper presents a data-based prognostic method using vibration signal acquired from a wind turbine gearbox. The approach addresses to bearing prognosis by predicting the RUL of high speed shaft bearing, that is based on feature extraction (kurtosis indicator). ANFIS is used to model the non-linear degradation function and to predict the life of the rotating components. the analysis is structured in two parts: the first one is based on feature extraction for fault health assessment and the second using autogram technique for fault

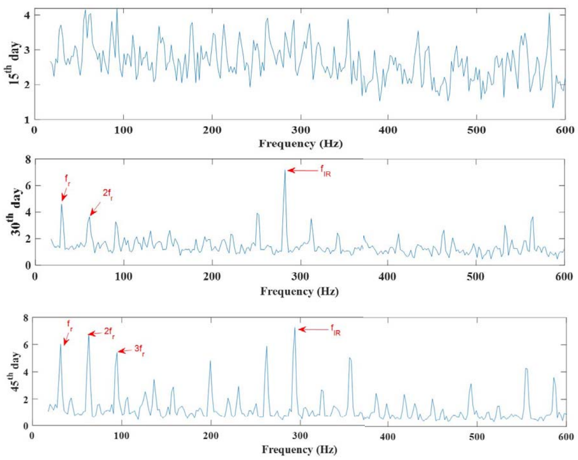

Fig. 11. Spectrum of resulting band with Autogram.

identification and localization.The obtained experiment results show the the efficiency of proposed approach. In the coming challenges, it is hoped to introduce the autogram analysis as a diagnostic and prognostic tool to improve the adaptation of the approach to problems that will be encountered in future research.

REFERENCES

[1] Racha Khelif, Simon Malinowski, Brigitte Chebel-Morello, and Noureddine Zerhouni. Rul prediction based on a new similarity-instance based approach. In *2014 IEEE 23rd International Symposium on Industrial Electronics (ISIE)*, pages 2463–2468. IEEE, 2014.

[2] ISO. Condition monitoring and diagnostics of machines prognostics part1: General guidelines, 2004.

[3] Y Li, TR Kurfess, and SY Liang. Stochastic prognostics for rolling element bearings. *Mechanical Systems and Signal Processing*, 14(5):747–762, 2000.

[4] Faris Elasha, Suliman Shanbr, Xiaochuan Li, and David Mba. Prognosis of a wind turbine gearbox bearing using supervised machine learning. *Sensors*, 19(14):3092, 2019.

[5] Adel Afia, Chemseddine Rahmoune, Djamel Benazzouz, Boualem Merainani, and Semcheddine Fedala. New gear fault diagnosis method based on modwpt and neural network for feature extraction and classification. *Journal of Testing and Evaluation*, 49(2), 2019.

[6] Mohamed Zair, Chemseddine Rahmoune, and Djamel Benazzouz. Multi-fault diagnosis of rolling bearing using fuzzy entropy of empirical mode decomposition, principal component analysis, and som neural network. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 233(9):3317–3328, 2019.

[7] Boualem Merainani, Chemseddine Rahmoune, Djamel Benazzouz, and Belkacem Ould-Bouamama. A novel gearbox fault feature extraction and classification using hilbert empirical wavelet transform, singular value decomposition, and som neural network. *Journal of Vibration and Control*, 24(12):2512–2531, 2018.

[8] Fawzi Gougam, Chemseddine Rahmoune, Djamel Benazzouz, and Boualem Merainani. Bearing fault diagnosis based on feature extraction of empirical wavelet transform (ewt) and fuzzy logic system (fls) under variable operating conditions. *Journal of Vibroengineering*, 21(6):1636–1650, 2019.

[9] Lotfi A Zadeh. Fuzzy logic. *Computer*, 21(4):83–93, 1988.

[10] J-SR Jang. Anfis: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, 23(3):665–685, 1993.

[11] Victor H Quej, Javier Almorox, Javier A Arnaldo, and Laurel Saito. Anfis, svm and ann soft-computing techniques to estimate daily global solar radiation in a warm sub-humid environment. *Journal of Atmospheric and Solar-Terrestrial Physics*, 155:62–70, 2017.

[12] Kamal Medjaher, Diego Alejandro Tobon-Mejia, and Noureddine Zerhouni. Remaining useful life estimation of critical components with application to bearings. *IEEE Transactions on Reliability*, 61(2):292–302, 2012.

[13] Charles H Oppenheimer and Kenneth A Loparo. Physically based diagnosis and prognosis of cracked rotor shafts. In *Component and Systems Diagnostics, Prognostics, and Health Management II*, volume 4733, pages 122–132. International Society for Optics and Photonics, 2002.

[14] Bhaskar Saha and Kai Goebel. Model adaptation for prognostics in a particle filtering framework. *International Journal of Prognostics and Health Management*, 2:61, 2011.

[15] Adrian Cubillo, Suresh Perinpanayagam, and Manuel Esperon-Miguez. A review of physics-based models in prognostics: Application to gears and bearings of rotating machinery. *Advances in Mechanical Engineering*, 8(8):1687814016664660, 2016.

[16] Shen Yin and Xiangping Zhu. Intelligent particle filter and its application to fault detection of nonlinear system. *IEEE Transactions on Industrial Electronics*, 62(6):3852–3861, 2015.

[17] Naipeng Li, Yaguo Lei, Jing Lin, and Steven X Ding. An improved exponential model for predicting remaining useful life of rolling element bearings. *IEEE Transactions on Industrial Electronics*, 62(12):7762–7773, 2015.

[18] Edwin Sutrisno, Hyunseok Oh, Arvind Sai Sarathi Vasan, and Michael Pecht. Estimation of remaining useful life of ball bearings using data driven methodologies. In *2012 IEEE Conference on Prognostics and Health Management*, pages 1–7. IEEE, 2012.

[19] Panagiotis Loukopoulos, George Zolkiewski, Ian Bennett, Suresh Sampath, Pericles Pilidis, X Li, and David Mba. Abrupt fault remaining useful life estimation using measurements from a reciprocating compressor valve failure. *Mechanical Systems and Signal Processing*, 121:359–372, 2019.

[20] Sadok Sassi, Bechir Badri, and Marc Thomas. Talaf and thikat as innovative time domain indicators for tracking ball bearings. In *Proceedings of the 24nd Seminar on machinery vibration, Canadian Machinery Vibration Association, éditeur M. Thomas, Montréal, Canada*, pages 404–419, 2006.

[21] B Samanta and KR Al-Balushi. Artificial neural network based fault diagnostics of rolling element bearings using time-domain features. *Mechanical systems and signal processing*, 17(2):317–328, 2003.

[22] Hafida Mahgoun, Fakher Chaari, Ahmed Felkaoui, and Mohamed Haddar. L-kurtosis and improved complete ensemble emd in early fault detection under variable load and speed. In *International Conference on Acoustics and Vibration*, pages 3–15. Springer, 2018.

[23] Shishir Maheshwari, Ram Bilas Pachori, and U Rajendra Acharya. Automated diagnosis of glaucoma using empirical wavelet transform and correntropy features extracted from fundus images. *IEEE journal of biomedical and health informatics*, 21(3):803–813, 2016.

[24] Ruqiang Yan, Robert X Gao, and Xuefeng Chen. Wavelets for fault diagnosis of rotary machines: A review with applications. *Signal processing*, 96:1–15, 2014.

[25] Szi-Wen Chen and Yuan-Ho Chen. Hardware design and implementation of a wavelet de-noising procedure for medical signal preprocessing. *Sensors*, 15(10):26396–26414, 2015.

[26] Jian-Hua Zhong, Pak Kin Wong, and Zhi-Xin Yang. Simultaneous-fault diagnosis of gearboxes using probabilistic committee machine. *Sensors*, 16(2):185, 2016.

[27] Chemseddine Rahmoune and Djamel Benazzouz. Monitoring gear fault by using motor current signature analysis and fast kurtogram method. *International Review of Electrical Engineering (IREE)*, 8(2):616–625, 2013.

[28] Ali Moshrefzadeh and Alessandro Fasana. The autogram: An effective approach for selecting the optimal demodulation band in rolling element bearings diagnosis. *Mechanical Systems and Signal Processing*, 105:294–318, 2018.

[29] Adel Afia, Chemseddine Rahmoune, and Djamel Benazzouz. Gear fault diagnosis using autogram analysis. *Advances in Mechanical Engineering*, 10(12):1687814018812534, 2018.

[30] Denis Keuton Alves, Flavio B Costa, Ricardo Lúcio de Araujo Ribeiro, Cecilio Martins de Sousa Neto, and Thiago de Oliveira Alves Rocha.

Real-time power measurement using the maximal overlap discrete wavelet-packet transform. *IEEE Transactions on Industrial Electronics*, 64(4):3177–3187, 2016.
[31] Eric Bechhoefer, Brandon Van Hecke, and David He. Processing for improved spectral analysis. In *Annual conference of the prognostics and health management society*, pages 14–17, 2013.
[32] Koceila Abid, Moamar Sayed-Mouchaweh, and Laurence Cornez. Adaptive data-driven approach for fault prognostics based on normal conditions-application to shaft bearings of wind turbine.