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Hybrid Scheme for Wind Turbine Condition Monitoring Based on Instantaneous Angular Speed and Pattern Recognition

Ilyes Khelf, Jose L. Gomez, Adeline Bourdon,
Hugo Andre and Didier Remond

Abstract Wind turbines are designed to operate under varying conditions of speed and load. These rough operational conditions undermine conventional monitoring techniques and lead to unexpected failures of mechanical components. This work comes within the framework of wind turbine on-line condition monitoring. For this purpose, a particular attention was given to Instantaneous Angular Speed (IAS) emerging as a viable alternative to vibration analysis, especially in non stationary conditions. In this work, IAS signals were recorded from extensive measurement campaigns on different operating wind turbines. Suitable processing techniques have been specifically developed and allowed to analyze signals in healthy condition and in the presence of different bearing faults. Based on the latter, a huge number of expected relevant indicators was extracted. Different configurations of features transformation, selection and classification tools were tested. An optimized hybrid scheme has been designed. This approach allowed an optimal exploitation of IAS information and the construction of an effective tool for wind turbine condition monitoring.

Keywords Condition monitoring · Instantaneous angular speed · Wind turbine · Feature selection · Pattern recognition

1 Introduction

Nowadays, wind is considered as one of the most attractive alternative energy solutions. Wind turbine energy production market is getting bigger and optimal use of available resources becomes important. To get the most of wind energy sources, intensive attention of turbine component operation condition should be taken [1].

I. Khelf (✉) · J.L. Gomez · A. Bourdon · D. Remond
CNRS UMR5259, INSA-Lyon, LaMCoS, Univ Lyon, 69621 Lyon, France
e-mail: ilyes.khelf@insa-lyon.fr

I. Khelf · J.L. Gomez · H. Andre
MAIA EOLIS, Tour de Lille, Boulevard de Turin, 59000 Lille, France

Wind turbines belong to a specific category of rotating machines. They operate in non-stationary conditions undermining conventional monitoring techniques [2].

In recent years, Instantaneous Angular Speed (IAS) emerged as an alternative condition monitoring tool, tailored to machines operation monitoring in non-stationary conditions. This technique has proven effective where promising results and developments were seen and discussed in previously published papers [3–7].

The extraction of relevant information from IAS Signal is a critical aspect of an efficient condition monitoring. This information may be represented in a set of indicators extracted from the signals [8]. Mainly, two approaches are seen in literature to optimize the construction of indicator sets. The former, based on the selection of a number of indicators from the entire set [9]. The second is about the transformation of indicators from one space to another [10, 11].

For the evaluation of indicators sets relevance, pattern recognition tools could be used as objective assessors. In fact, the classifier accuracy depends greatly on the quality of indicators composing their input vector, and their ability to distinguish the different operating conditions.

In this paper, a hybrid scheme for condition monitoring of operating wind turbines is introduced. Firstly, descriptions of the performed experiments and the exploited data sources are presented. Then, an attention was taken on indicators construction and processing techniques, within these techniques, standardization and Principal Component Analysis (PCA) were used for the indicator transformation, while Genetic Algorithms (GA) and selection filters have been tested for the indicator selection. Radial Basis Function neural networks (RBF) were subsequently built and the classification results used to assess the relevance of the constructed indicators sets.

2 Materials and Methods

2.1 Experimental Procedure

A judicious instrumentation allowed MAIA EOLIS to collect information on their wind turbine condition over long periods. In this paper data collected on two different machines is used. Both machines have the same transmission kinematic shaft line. The wind turbine set up is presented in Fig. 1. Two encoders were installed on the wind turbine drive train (three stages gear box), mounted on the High Speed Shaft (HSS) and on the Low Speed Shaft (LSS). In this paper only the HSS signals are studied.

Mainly, two different bearing defects were observed (Bearing A: Spalling in the inner and the outer rings and Bearing B: Spalling in the outer ring, Fig. 1), one on each machine. The two defective bearings are both installed on the HSS, on different locations.

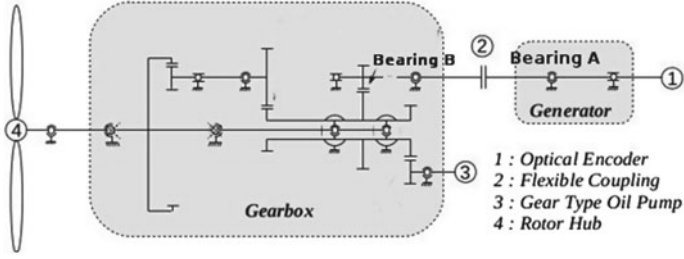


Fig. 1 Wind Turbine Set-up

In this work, we seek for the construction of specific monitoring tools for each element of the machine. Therefore, for monitoring bearing (A), we have considered: signals from the faulted bearing (A), signals from a healthy machine, and, to enhance the robustness of the tool, a set of signals presenting other defects affecting the machine.

2.2 IAS Signal

The Elapse time method is used in this work for the processing of encoder signals and the construction of IAS [2]. The rotating speed ω_i is estimated for each rising edge of the encoder signal i by counting the pulses delivered by a high frequency clock, respecting Eq. 1

$$\omega_i = \frac{60}{R} \cdot \frac{f_c}{N + \epsilon} \quad (1)$$

where R denotes the resolution of the encoder; f_c the counter frequency; N is the entire number of pulses delivered by the High frequency clock between two rising edges of the encoder; ϵ an uncertainty term that globally includes the geometrical, electrical and quantification measurement errors.

An apodization window is then applied to the IAS signal to prevent from the broadband effect induced by the macroscopic trend of the angular speed [6]. An adapted Fourier Transform can also be applied to the construction of an Angular Frequency Spectrum in order to emphasize cyclic periodicities. Figure 2 shows in (a) an extracted IAS signal, and in (b) two Angular Frequency Spectra, one with (red) and one without (blue) the presence of bearing defects, focused around the characteristic frequency (Bearing BPFO: Ball Pass Frequency Outer (Outer ring)).

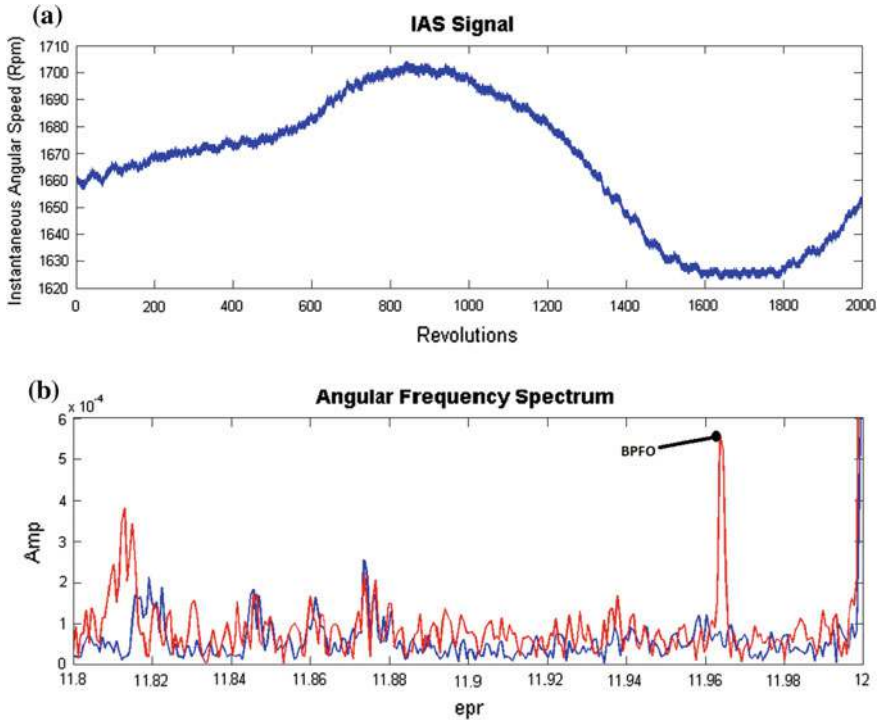


Fig. 2 a IAS Signal b IAS Spectra

3 Construction of the Databases

In this work, the monitoring process is only focused on the bearing A (see Fig. 1) installed on the first Wind Turbine (WT1), the bearing B defect condition is considered as the third condition.

3.1 Indicators Extraction

As the monitoring process presented in this work focuses only on a bearing (A) defect, specific indicators were extracted from IAS signals and order spectra at characteristic angular frequencies. Globally four kinds of indicators were extracted:

- **Defect Frequencies Amplitude level:** The amplitude level at the characteristic frequencies.
- **Band RMS:** the Root Mean Square of energetic frequency bands.
- **Ratio:** Different ratios(amplitude/amplitude and amplitude/band).
- **Scalar:** Scalar indicators extracted from the raw signal.

Besides raw indicators extraction, two indicator transformation procedures were done:

- Standardization procedure according to rotational speed, which allows moderating the effects of speed and load variation on indicators amplitudes [5].
- Principal Components Analysis creates uncorrelated indicators in a low dimensional representation [10].

3.2 Indicator Selection

Indicator selection allows finding from a complete set of indicators those that are most relevant and that can separate the best operating conditions.

Indicator selection can be undertaken in two approaches (Filter and Wrapper), according to their dependence or independence on the desired application. In the filter approach, we seek an individual evaluation of indicators based on some relevance measures. By contrast Wrapper approach seek a global evaluation of indicator sets based on classifier accuracy [9, 12].

3.2.1 ReliefF Filter

ReliefF seeks an estimation of indicator quality based on the distance between nearest neighbors. For this purpose, given a randomly selected example A from a data set S with k indicators, ReliefF searches the data set to its nearest neighbors: one of the same class, called the nearest hit H , and others from different classes, called the nearest miss M . It updates the quality estimation $W[IN_i]$ for all indicators IN based on the values of difference function $Diff()$ to X , H and M , on m iterations.

$$Diff(A, I_1, I_2) = \frac{|value(A, I_1) - value(A, I_2)|}{min(A) - max(A)} \quad (2)$$

and for $P(c)$ the prior probability of the class and $1 - P(class(r))$ represents the sum of probabilities for the misses classes we have: $W[IN_i] = W[IN_i] - \sum_{j=1}^k Diff(A, R_i, H_j)/(m.k)$

$$+ \sum_{C \neq cl(R_i)} \left[\frac{P(C)}{1 - P(class(R_i))} \sum_{j=1}^k Diff(A, R_i, M_j(C)) \right] / (m.k) \quad (3)$$

3.2.2 Information Gain

The information gain criterion measures the difference between two probability distributions. It was intensively adopted for feature selection in decision tree construction [9]. After selection, we keep only indicators with maximal information gain.

3.2.3 Chi-2

The Chi-2 statistic quantifies the dependence between an indicator IN and a class cl by measuring their chi-squared statistics with respect to the classes. For the case of numeric indicators, it proceeds by a discretization of each indicator on a number of iterations. On each one, the discretized intervals are merged according to the values of the obtained χ^2 (Eq. 4). Indicators with the greatest number of intervals have the highest rank.

$$\chi^2 = \sum_{i=1}^2 \sum_{j=1}^k \frac{(A_{ij} - E_{ij})^2}{E_{ij}} \quad (4)$$

where k is the number of classes, A_{ij} the number of examples in the i th interval, j th class; and E_{ij} the expected frequency of A_{ij} .

3.2.4 Genetic Algorithm

Belonging to the evolutionary algorithms class, Genetic algorithms (GA) are derived from genetics and natural evolutionary mechanisms. These algorithms are particularly suitable for the combinatorial problems optimization “NP-Hard problems”. Those latters require a computing time growing exponentially with the problem complexity [12].

GA are based on the natural evolution and selection, and survival of the fittest ideas. The genetic algorithm represents a solution to the problem as a chromosome. It then creates a population of possible solutions and applies genetic operators such as mutation and crossover to find the fittest solution. In this work the GA seeks the selection of input vector (composed of relevant indicators) allowing the best classification performances and pursues the following steps:

First population generation In this step is proposed a generation of the first chromosome population. In each chromosome, a set of indicators is constructed randomly. The population is composed of 100 chromosomes

Evaluation The performance of each input vector is based on RBF classification accuracy on a fixed validation set.

Selection The steady-state selection is used. In every generation, few chromosomes are selected (the 50 fittest ones) to create children. Subsequently, the worst chromosomes are removed and replaced randomly with newly created ones.

Evolution Operators: Crossover it applies on two different chromosomes. As a result, it produces new chromosomes formed from genes of both parents for the next generation. In this work, a cross at a random point strategy was applied.

Mutation it applies to an individual by modifying one or more genes, chosen randomly from the population. The percentage of mutation is set to 1%.

Stopping Criterion The algorithm stops at one of the following criteria:

- Maximum number of iterations = 200.
- 50% of the population of chromosomes is similar to the first gene.

3.3 Radial Basis Function Neural Network

In this work Radial Basis Function Network (RBF) is utilized as a classification tool. RBF network is a feed forward neural network type with three layers: one input layer, one hidden layer “RBF layer” and one output layer. Each layer is fully connected to the next. Each neuron in the hidden layer is described by a Gaussian law centered on a point of the input space. For a given input x , the output of the neuron in the hidden layer is the amplitude of the Gaussian at that point.

The output of the network is a linear combination of the outputs of neurons in the hidden layer adjusted by the weight of their respective connections. The response depends on the distance function between the input vector x , the vector prototype (center) and the size of the influence field [10].

4 Results and Discussion

In this work, we seek the optimal use of IAS information for wind turbine condition monitoring. In this way, a hybrid scheme (Fig. 3) was designed combining indicators transformation, selection and classification tools.

- Firstly, a stratified extraction of signals was done in order to get the same ratio of signals (100) in each class (Healthy condition; Bearing A defect and other defects).
- Then, an indicator extraction was performed on IAS signal and spectra, where 76 raw indicators (RI) were extracted from each signal.
- A Parametric Standardization Process was applied, then on the raw indicators, creating a new set composed of 76 standardized indicators (SI).
- Principal Component Analysis was applied and 30 Principal Components (PC) were added to the database.
- All extracted and transformed indicators were then mixed in one database (MI).
- Classification experiment was done based on MI in order to asses indicator transformation procedures
- Indicator selection procedure was applied on MI, where different approaches were tested in order to pull out only relevant indicators from the whole set.

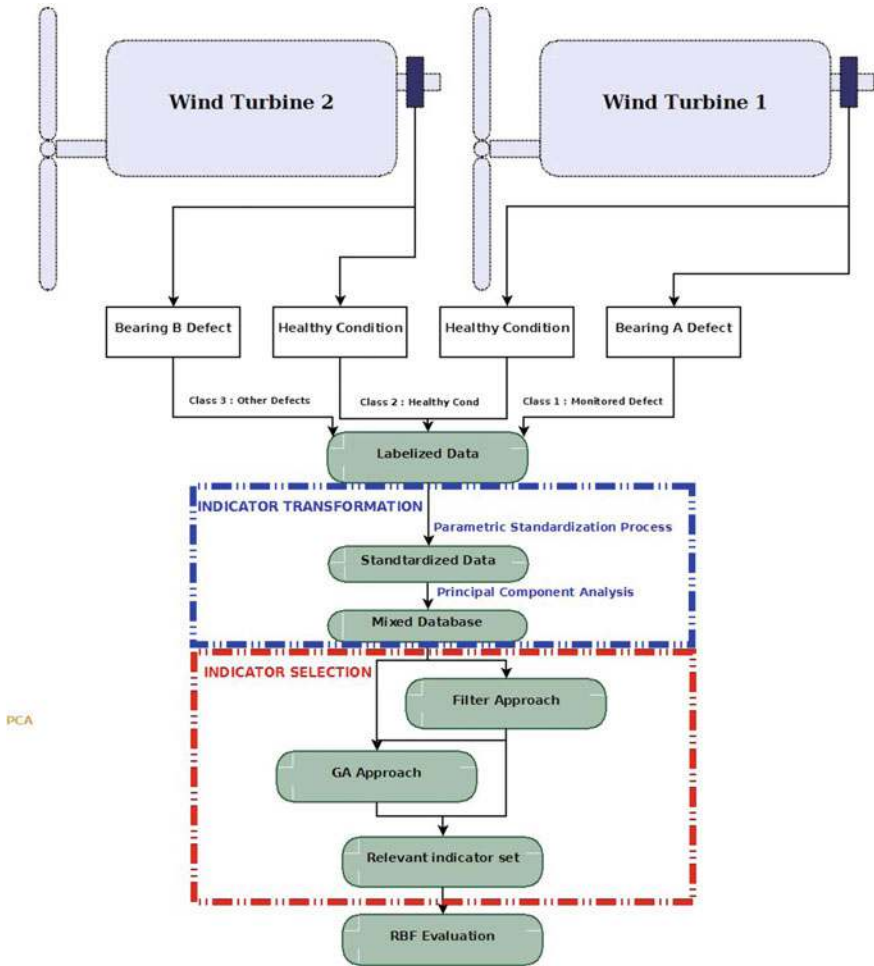


Fig. 3 Hybrid Scheme for wind turbine condition monitoring

- Firstly, one stage selection based on each of Genetic Algorithms and selection filters (Chi2; GI and ReliefF) approaches.
- Then, a two stages approach was constructed, where the first stage is based on filter approach in order to get a reduced set of relevant indicators followed by a GA seeking the best combination.
- The effectiveness of each scheme was evaluated based on RBF classification accuracy (66% of the data used for training and 33% for test). The obtained results are resumed in the Table 1.

Table 1 Performances evaluation

		Indicators number	Accuracy (%)
Raw indicators		76	83
Indicator transformation		182	93
One stage	GA	91	94
Indicator selection	Chi-2	17	94
	GI	17	94
	ReliefF	32	94
Multi stage	Chi-2	11	95
Indicator selection	GI	12	95
	ReliefF	14	97

Indicator transformation improved the classifier accuracy from 83% on Raw Indicators Dataset to 93% on the mixed database. However, the dimension of input vector became huge (183 Indicators).

One stage Indicator selection improved slightly the latter accuracy, where GA and Filter based approaches gave the same results (94%). Nevertheless, GI and CHI2 used only 17 indicators to reach it where ReliefF used 32 indicators and GA based used 91 indicators.

The main problem using the GA approach is the high risk to quickly converge on a local optimum (which seems to be the case in this application). On the other hand, filter approaches don't consider redundancy between indicators, which is considered as a disturbing phenomenon on classifier performances.

The Multi-Stage Scheme improved more significantly performances in terms of Accuracy and indicators number. The best results were obtained using the combination ReliefF filter-GA, where 97% accuracy was reached using only 14 indicators. GA approach was more effective dealing with reduced datasets, where the risk of falling on local optimum is lower. Also, the use of a filter approach as preprocessing technique guarantee to have only relevant indicators on the reduced set.

The projection of three indicators among the selected ones can be seen in Fig. 4 and demonstrate their effectiveness to separate the different classes.

A closer look at the input vector composition can be seen in Fig. 5, where a repartition of the indicators composing it is drawn according to their originating databases. Half of the indicators are Standardized ones (proving the effectiveness of the standardization giving more relevant indicators). Only one Principal Component was pulled out on the selected input vector. The construction of each Principal Component requires the computation of the whole set of indicators which seems incompatible with such an industrial application. The low number of retained PCs does not encourage to proceed in this way.

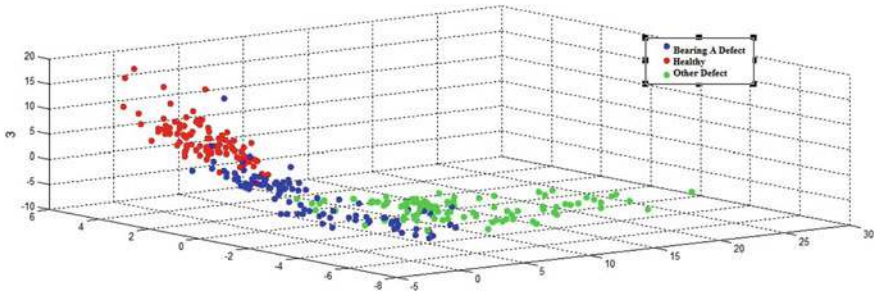
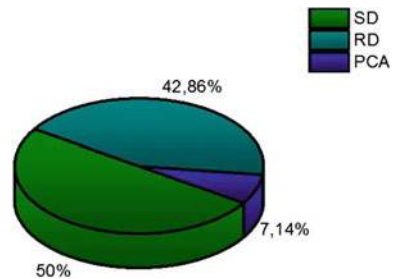


Fig. 4 Selected indicators representation

Fig. 5 Selected input vector composition



5 Conclusion

In this work, wind turbine condition monitoring issue was tackled, where IAS signals were proposed as an alternative information source to conventional analysis. Specifically developed processing techniques were applied to IAS raw signal and allowed the monitoring of two industrial wind turbines during healthy and defective periods. From each measured IAS signal, a huge number of representative indicators can be extracted. To get the most from the available information, numerous indicator transformation and selection approaches were experimented, and hybrid Scheme based on a multi stage indicator selection designed.

The proposed scheme based on the combination ReliefF selection Filter and Genetic algorithm avoids falling into local optimum and indicator redundancy problems and allow us to get the most relevant indicators and the highest classification accuracy. Furthermore, the proposed approach gave an objective assessment of transformation procedures where standardization process demonstrated its effectiveness. In this paper, only IAS information was used. In future works, a closer look to other information sources will be taken, where indicator selection presents an attractive solution to information fusion.

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