WIND TURBINES' ROLLING ELEMENT BEARINGS FAULT DETECTION ENHANCEMENT USING MINIMUM ENTROPY DECONVOLUTION

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Summary

Minimum Entropy Deconvolution (MED) has been recently introduced to the machine condition monitoring field to enhance fault detection in rolling element bearings and gears. MED proved to be an excellent aid to the extraction of these impulses and diagnosing their origin, i.e. the defective component of the bearing. In this paper, MED was applied for fault detection and diagnosis in rolling element bearings in wind turbines.

MED parameter selection as well as its combination with pre-whitening is discussed. Two main cases are presented to illustrate the benefits of the MED technique. The first was taken from a fan bladed test rig. The second case was taken from a wind turbine with an inner race fault. The usage of the MED technique has shown a strong enhancement for both fault detection and diagnosis. The paper contributes to the knowledge of fault detection of rolling elements bearings through providing an insight into the usage of MED in rolling element bearings diagnostic by providing a guide for the user to select optimum parameters for the MED filter and illustrating these on new interesting cases both from a lab environment and an actual case.

Keywords: rolling bearing, fault detection, Minimum Entropy Deconvolution (MED), wind turbine.

POPRAWA WYKRYWANIA USZKODZEŃ ŁOŻYSK TOCZNYCH W TURBINACH WIATROWYCH PRZY UŻYCIU METODY MINIMUM ENTROPY DECONVOLUTION

Streszczenie

Metoda Minimum Etropy Deconvolution (MED) została niedawno wprowadzona do diagnostyki w celu poprawy wykrywania uszkodzeń łożysk tocznych i przekładni. MED okazała się bardzo pomocna w ekstrakcji impulsów pochodzących od tych uszkodzeń i określania miejsca ich pochodzenia (np. uszkodzonego elementu łożyska). W niniejszym artykule MED zastosowano do wykrywania uszkodzeń łożysk tocznych w turbinach wiatrowych.

W artykule opisano zagadnienie selekcji parametrów metody MED oraz metody „wybielania sygnału" (ang. pre-whitening). Korzyści płynące z zastosowania metody przedstawiono na dwóch przypadkach. Pierwszym jest stanowisko laboratoryjne, a drugim – turbina wiatrowa z uszkodzoną bieżnią wewnętrzną łożyska generatora. Zastosowanie metody MED pozwoliło na znaczącą poprawę zarówno wykrycia, jak i lokalizacji uszkodzenia. Najistotniejszymi częściami niniejszego artykułu są: opis metody MED, wskazówki dotyczące optymalnego dostrojenia metody oraz interesujące przypadki zarówno laboratoryjne, jak i rzeczywiste.

Słowa kluczowe: łożysko toczne, wykrywanie uszkodzeń, Minimum Entropy Deconvolution (MED), turbina wiatrowa.

1. INTRODUCTION

Rolling element bearings (REBs) are components, which transfer the load through elements in rolling contact. The REB consists of: inner race, outer race, balls (or in general, rolling elements) and a cage, which holds the rolling elements in a given relative position. Rolling element bearings are key components in modern machinery. Detection of their faults is very important, as it prevents any further deterioration to other components which may lead to catastrophic failure. One of the most important and more and more popular machines using REBs are wind turbines.

Figure 1 shows the gearbox and the main bearing of a 1.5 MW turbine. The typical wind turbine drivetrain consists of a main shaft, planetary gearbox, two stage parallel gearbox and a generator. Depending on the location in a wind turbine drivetrain, the replacement of a bearing can cost between 2500 to 32000 EUR, while the replacement of a gearbox may cost anything between 75000 to 240000 EUR [1]. These operations depend very much on the accessibility to the wind turbine, which in turn depends on weather conditions, especially wind speed. This aspect is even more important for the offshore wind parks. Bearing spalls, subject to the machine speed and load, usually propagate slowly, thus giving the analyst enough time for monitoring and maintenance scheduling before any catastrophic failure. Therefore, a huge body of research in the area of bearing diagnostics concentrated on the early detection of the bearing faults to enable providing enough lead time for maintenance purposes [2]. The knowledge about the technical status of the REB and its fault development and propagation are being employed to develop a reliable prediction of the remaining useful life of the rolling elements bearings in what is known as bearing prognostics [3], which is becoming an important aspect of the new trend in monitoring the health of rotating machines. Cempel proposed a set of methods for machinery components lifetime prediction and calculation of limit values [4].

As has been shown by many authors [e.g. 5, 6], the envelope spectrum is a very efficient diagnostic tool for REB faults, as the information about the fault is extracted from the spacing between impulses and not by the excited frequencies. The process of obtaining the envelope spectrum is often referred to as the signal demodulation. There are several methods to properly select the frequency band to perform the demodulation. An informative source for rolling element bearing diagnostics can be recalled in [2].

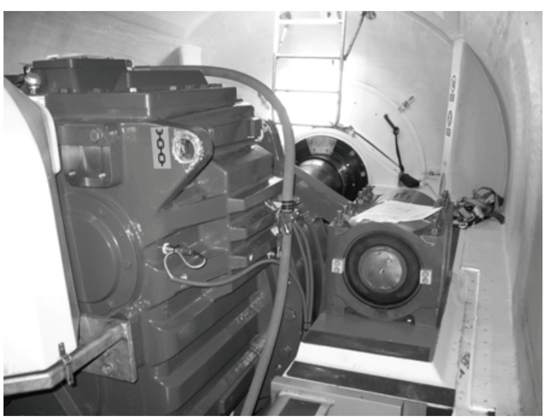

Fig. 1. The view of the 1.5 MW wind turbine gearbox (front) and the main bearing (behind).

To illustrate the content of a measured vibration signal with a defective rolling element bearing, a simple model of the generation process is presented in figure 2. The symbol "***h**" represents the convolution of the combined vibration signal (deterministic signals, bearing defective signal and noise) with the transfer path between the vibration source and the sensor location. In reality, the mechanism is far more complex, as it involves a number of vibration sources which may be added or convolved in rather different forms.

For a clear diagnosis of the bearing fault a number of techniques have bee proposed to separate deterministic components from bearing component. techniques such as discrete random separation (DRS) [7, 8], self adaptive noise cancellation (SANC) [6] and time synchronous averaging (TSA) [9], which benefits from the slippage phenomena has been proposed with good results. This technique was applied to wind turbines diagnostics by Barszcz [10]. A number of papers proposed methods to improve the signal to noise ratio of the REB fault component, by selecting a frequency range in which the energy of the signal components is relatively stronger. Different criteria for so called optimum frequency band (OFB) were proposed. A very successful approach (*kurtogram*), based on maximizing the kurtosis of the band filtered signal was proposed by Antoni and Randall [11]. Recently, Barszcz and Jabłoński [12] proposed the criterion of kurtosis of the envelope spectrum (*protrugram*), which is more robust to random impulsive impacts.

Another problem with detection of small impulses induced by REB faults is the transfer path between the faulty component (e.g. inner race) and the vibration sensor. Impacts, which are initially sharp after travelling the distance between the bearing and the sensor may be very distorted. The method was originally proposed by Sawalhi et al [13] with the application to a test rig. This paper provides a means for removing the effect of the transfer path ***h** through inverse filtration. The aim is to design an inverse filter to remove/minimize the effect of the transfer path filter. The base to optimize this filter is to minimize the entropy of the signal, or in other words to maximize the impulsiveness (kurtosis) of the signal. This filter will then be used to deconvolve (as opposed to convolve) the signal, thus recovering the defective bearing fault signal (impulses) in a rather clear way. The filter used to do so is refereed to as minimum entropy deconvolution (MED).

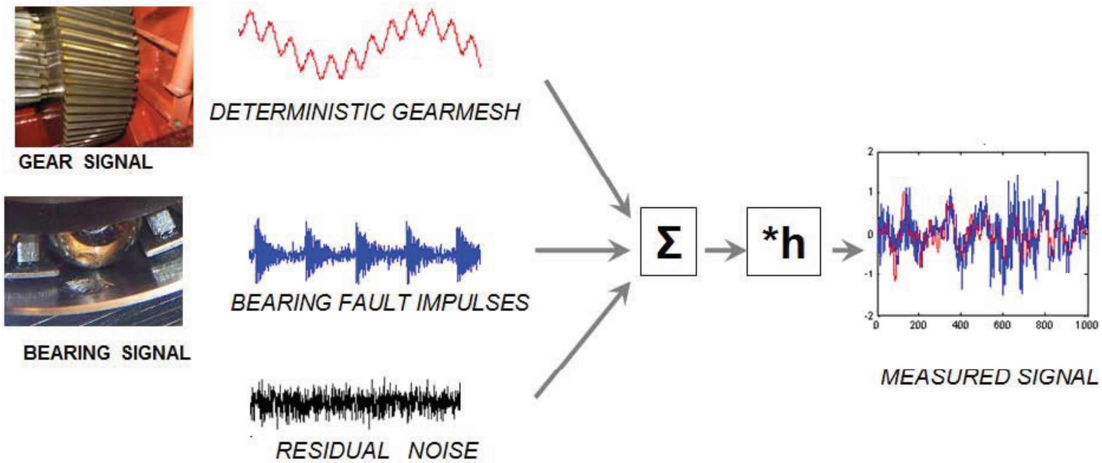

Fig. 2. Model of the generation of the vibration signal from a machine with gears and bearings.

2. MINIMUM ENTROPY DECONVOLUTION TECHNIQUE

The Minimum Entropy Deconvolution technique (MED) is a type of system identification method that was originally proposed by Wiggins [14]. Its main original use was to aid the extraction of reflectivity information in seismic data in order to identify and locate layers of subterranean minerals. MED has shown its effectiveness in deconvolving the impulse excitations from a mixture of response signals [15, 16]. In the machine condition monitoring field, it was used initially by Endo and Randall [17] to enhance the impulses arising from spalls and cracks in gears. It was then adopted by Sawalhi et al. [13] to enhance the detection of spalls in rolling element bearings in high speed machines.

Figure 3 illustrates the deconvolution process involved in the MED filtering when used to enhance the detection of bearing faults. In order to gain the full benefit from using the MED technique for rolling element bearings, it is recommended that the signal is first order tracked. After the order tracking the synchronously averaged part (deterministic component) should be removed. Another recommended pre-processing step is to pre-whiten [13] the residual signal (i.e. total signal minus the synchronous average part). Pre-whitening can be achieved by using an autoregressive model (AR) [18]. As the main aim is to have a relatively flat spectrum, there is not usually a great emphasis on the selection of the order of the AR process.

The proposed algorithm has been implemented in this study by using the Objective Function Method (OFM) given in [19]. This method is an iterative optimization process, which is designed to maximize the kurtosis of the MED output (thus minimizing the entropy). The OFM achieves this by changing the values of the coefficients in the MED filter. The optimization process finishes when the values of the coefficients converge within the specified tolerance.

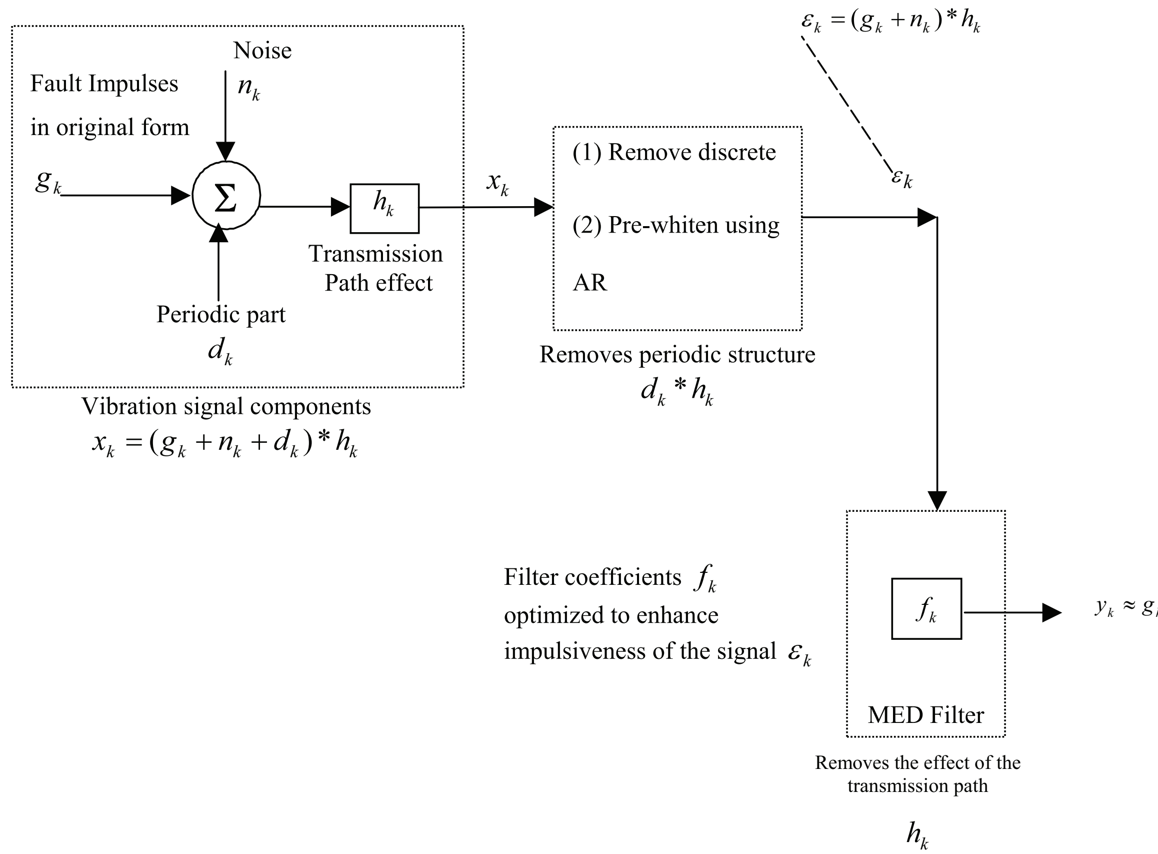

Fig. 3. The proposed inverse filtering (deconvolution) process to enhance the detection of bearing faults using the MED technique

3. CASE STUDY ON A WIND TURBINE REB

MED has been attempted on a signal taken from a wind turbine with extended inner race spalls. The turbine was of the GE 1.5sl type from one of German wind parks. This is a 1500 kW turbine with the doubly fed generator and pitch control [20]. The turbine has had a bearing fault on the generator shaft in its inner race as seen in figure 4.

The raw acceleration time domain signal, the results of the different processing stages, and their corresponding envelope spectra and selection criteria are shown in figures 5 and 6 and 7 respectively.

Fig. 4. Spalled inner race of a wind turbine

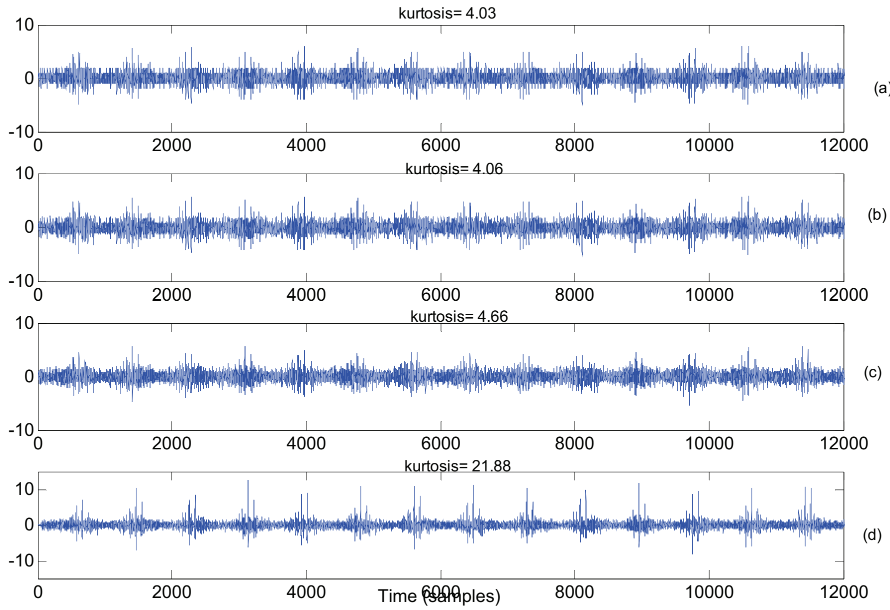

Fig. 5. vibration signals (acceleration) for the extended inner race fault (a) raw measured signal (b) After the removal of synchronous average (c) signal b Pre-whitened (d) signal c after using the MED

As can bee seen from figure 5, the application of the MED has significantly increased the kurtosis of the vibration signal. While the kurtosis of the raw signal was just 4.03, it reached 21.88 after application of the obtained inverse filter. These results can be also clearly observed in figure 6, which presents the envelope spectra of signals from the figure 5. In the envelope spectra it is observed that MED not only causes the increased clarity of the BPFI harmonics, but also discloses the presence of strong modulation by the rotational speed of the shaft. The harmonic spacing in figure 6 equals 283.87 Hz, which was found equal to the repetition period of the BPFI (ball pass frequency inner ring). The sidebands were spaced at 30.11 Hz, which is the rotational speed of the generator shaft during the measurement session.

Finally the dependency between AR and MED algorithms parameters were plotted (see figure 7). The trend observed earlier in the experimental research can be clearly seen here. A low AR order model has been used (AR (1)) and a filter length of 4096 was used (although 1024 or 2048 would also give enough good results).

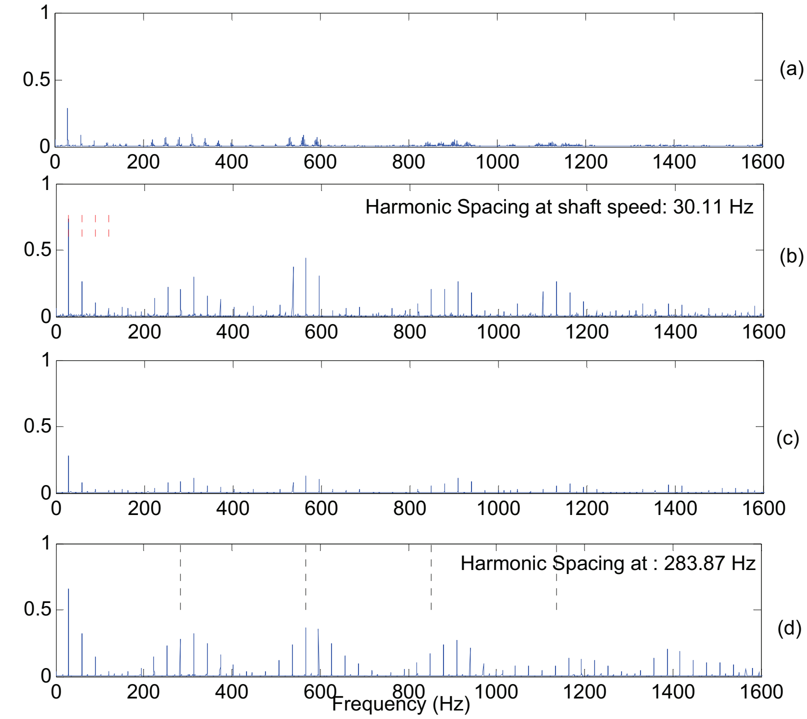

Fig. 6. Envelope spectra (band pass from 1000 to 10000 Hz): (a) raw (b) residual after subtracting the synchronous average (c) signal b pre-whitened (d) the MED result

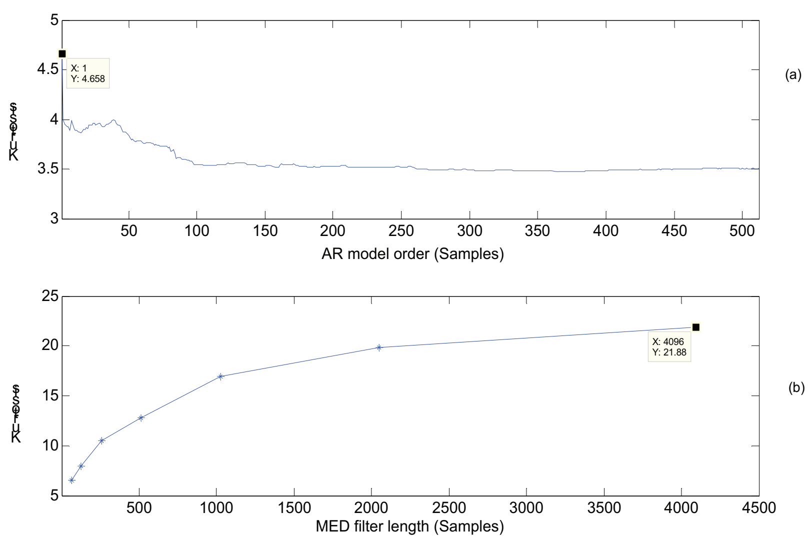

Fig. 7. Wind turbine data: AR and MED parameter selection (a) AR model order selection based on maximizing the kurtosis (B) MED filter length selection based on the kurtosis of the filtered signal

4. SUMMARY AND CONCLUSIONS

This paper presents further development of the minimum entropy deconvolution (MED) method to aid extracting faults in rolling element bearings. The MED technique was applied to signals with defective bearings taken from an experimental test rig and a wind turbine. The synchronously averaged signal (containing deterministic components) was subtracted from the total signal to get a residual signal, which contains fault impulses. The residual signal was then pre-whitend to further aid the enhancement of the impulses by minimizing the variation between adjacent frequencies. The MED was then applied with the aim of removing the effect of the transfer path (deconvolution) and enhances the clarity of the impulses and then the detection and diagnoses of the bearing fault. It is shown that MED significantly increase the peakedness of the vibration signals and the clarity of the impulses. This has been illustrated in both the time domain signals and further observed on the envelope spectra. In particular, the modulations at the shaft speed in the case of inner race faults were dramatically enhanced and observed with the introduction of the MED technique. The selection of the filter length for the MED and the model order for pre-whitening are based on maximizing the kurtosis of the signal, which in effect means more clarity in the impulses and a better detection and analyses of the fault. It is observed that for pre-whitening purposes a low model order is usually required to achieve a high kurtosis. For the MED filter, it is observed that the longer the filter the highest the kurtosis value (associated with a long tail). The variation between the kurtosis values above a filter length of 1024 samples is not dramatic, but the computational burden is. So a filter length between 1024 and 4096 samples would be suitable. Filters with length above 4096 samples will slightly increase the kurtosis, but will require a huge memory.

5. ACKNOWLEDGMENTS

The authors would like to express their gratitude to the company SeaCom GmbH (Herne, Germany) for access to the wind turbine data.

6. REFERENCES

[1] Gajetzki, M. (2006): *SeaCom – Digital Measurement and Communication Systems*, SeaCom, Herne.
[2] Randall R. B., Antoni J. (2011). *Rolling element bearing diagnostics--A tutorial*, Mechanical Systems and Signal Processing, 25: 485-520
[3] Heng A., Zhang S., Tan A. C. C., Mathew J. (2009): *Rotating machinery prognostics: State of the art, challenges and opportunities*, Mechanical Systems and Signal Processing, 23: 724 – 739
[4] Cempel C. (2008). *Decomposition of symptom observation matrix and grey forecasting in vibration condition monitoring of machines*. International Journal of Applied Mathematics and Computer Science, 18: 569 – 579
[5] Klein, U. (2003): *Schwingungsdiagnostische Beurteilung von Maschinen und Anlagen (Vibrodiagnostic assessment of machines and devices)* [in German], Stahleisen Verlag, Duesseldorf 2003.
[6] Ho, D., Randall, R.B. (2000): *Optimisation of bearing diagnostic techniques using simulated and actual bearing fault signals*, Mechanical Systems and Signal Processing 14: 763–788.
[7] Antoni, J., Randall, R.B. (2004): *Unsupervised noise cancellation for vibration signals: Part I- evaluation of adaptive algorithms*. Mechanical Systems and Signal Processing, 18: 89–10.
[8] Antoni, J., Randall, R.B. (2004): *Unsupervised noise cancellation for vibration signals: Part II- a novel frequency domain algorithm*. Mechanical Systems and Signal Processing, 18: 103–117.
[9] Braun S. (2010): *The synchronous (time domain) average revisited*, The 24th International Conference on Noise and Vibration engineering (ISMA2010), Leuven (Belgium), 20 to 22 September 2010.
[10] Barszcz, T. (2009): *Decomposition of vibration signals into deterministic and nondeterministic components and its capabilities for fault detection and identification*. International Journal of Applied Mathematics and Computer Science, 19: 327-335
[11] Antoni, J., Randall, R.B. (2006): *The spectral kurtosis: application to the vibratory surveillance and diagnostics of rotating machines.* Mechanical Systems and Signal Processing, 20: 308-331.
[12] Barszcz, T., Jabłoński, A. (2011): *A novel method for the optimal band selection for vibration signal demodulation and comparison with the Kurtogram*. Mechanical Systems and Signal Processing, 20: 308-331.
[13] Sawalhi, N., Randall, R.B., Endo, H. (2007): *The enhancement of fault detection and diagnosis in rolling element bearings using minimum entropy deconvolution combined with spectral kurtosis*, Mechanical Systems and Signal Processing, 21: 2616-2633.
[14] Wiggins, R. A. (1978): *Minimum entropy deconvolution*. Geoexploration, 16: 21-35.
[15] Nandi, A. K., Mampel, D., Roscher, B. (1997): *Blind deconvolution of ultrasonic signals in non-destructive testing applications*. IEEE Trans of Signal Processing, 45: 1382-1390.
[16] Boumahdi, M., Lacoume, J. (1995): *Blind identification using the Kurtosis: Results of field data processing*. IEEE Trans of Signal Processing, 0-7803-2431-5/95, pp. 1960-1983.
[17] Endo, H., Randall, R.B. (2007): *Application of a minimum entropy deconvolution filter to enhance Autoregressive model based gear tooth fault detection technique*. Mechanical Systems and Signal Processing, 21: 906-919.
[18] Wang, W., Wong, A. K. (2002): *Autoregressive model-based gear fault diagnosis*. Transaction of ASME, Journal of Vibration and Acoustics, 124: 172- 179.
[19] Lee J. Y., Nandi A. K. (1999): *Extraction of impacting signals using blind de-convolution*. Journal of Sound and Vibration 232: 945 – 962
[20] Hau, E. (2006): *Wind Turbines. Fundamentals, Technologies*, Applications, Economics. 2nd Edition, Springer Verlag, Berlin Heisenberg.