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GEARBOX FAULTS IDENTIFICATION USING VIBRATION SIGNAL ANALYSIS AND ARTIFICIAL INTELLIGENCE METHODS

IDENTYFIKACJA USZKODZEŃ SKRZYNI BIEGÓW ZA POMOCĄ ANALIZY SYGNAŁU DRGAŃ ORAZ METOD SZTUCZNEJ INTELIGENCJI

The paper addresses the implementation of feature based artificial neural networks and vibration analysis for the purpose of automated gearbox faults identification. Experimental work has been conducted on a specially designed test rig and the obtained results are validated on a belt conveyor gearbox from a mine strip bucket wheel excavator SRs 1300. Frequency and time domain vibration features are used as inputs to fault classifiers. A complete set of proposed vibration features are used as inputs for self-organized feature maps and based on the results a reduced set of vibration features are used as inputs for supervised artificial neural networks. Two typical gear failures were tested: worn gears and missing teeth. The achieved results show that proposed set of vibration features enables reliable identification of developing faults in power transmission systems with toothed gears.

Keywords*: gearbox vibration, gear fault, artificial neural network, self-organized feature map.*

Artykuł omawia zastosowanie sztucznych sieci neuronowych opartych na cechach oraz analizy drgań do celów automatycznej identyfikacji uszkodzeń skrzyni biegów. Prace eksperymentalne przeprowadzono na specjalnie zaprojektowanym stanowisku badawczym, a uzyskane wyniki zweryfikowano na przykładzie przekładni przenośnika taśmowego koparki wielonaczyniowej SRs 1300 wykorzystywanej w kopalni odkrywkowej. Cechy drgań w dziedzinie czasu i częstotliwości są wykorzystywane jako wejścia klasyfikatorów uszkodzeń. Kompletny zbiór proponowanych cech drgań wykorzystano jako wejścia samoorganizujących się map cech, a na podstawie wyników opracowano zredukowany zbiór cech drgań, które wykorzystano jako wejścia do nadzorowanych sztucznych sieci neuronowych. Zbadano dwa typowe uszkodzenia przekładni : zużycie przekładni oraz brakujące zęby przekładni. Uzyskane wyniki wskazują, że proponowany zbiór cech drgań umożliwia niezawodną identyfikację rozwijających się uszkodzeń w układach przenoszenia napędu z kołami zębatymi.

Słowa kluczowe*: drgania skrzyni biegów, uszkodzenie skrzyni biegów, sztuczna sieć neuronowa, samoorganizująca się mapa cech.*

1. Introduction

Rotating machines are the most common type of machines found in different industry fields and they have to work with high performances. An unscheduled stop due to the machine's failure leads to high maintenance and production costs risks. High costs are initiated through the production stops, losses, and urgent procurements of spare parts. High risks are associated with the possibilities of workers' injuries and secondary damages of neighboring machines. To avoid such a scenario, several maintenance strategies have been developed, from the breakdown maintenance to condition based and proactive maintenance. The implementation of condition-based maintenance implies monitoring of machine operating condition based on the physical parameter that is sensitive to machine degradation. Among many possible parameters, mechanical vibration acquired at the bearing's housing is one of the best parameter for early detection of a developing fault inside a machine. Methods of vibration signal analysis enable the extraction of type and severity of a fault. Despite the fact that the information on type and severity of a fault is contained in the vibration signal, due to the:

a. existence of multiple faults on a machine,
b. dependence of vibration signal content on operating conditions,
c. existence of vibration components from neighboring machines,

derivation of incorrect vibrodiagnostical conclusions and wrong estimation of machine criticality in the plant, is a very common situation. To avoid this, there are two approaches:

a. engagement of highly skilled and trained vibration analysts or
b. application of artificial intelligence (AI) methods for reliable extraction of an existing fault.

Engagement of certified vibration analysts can be a problematic issue due to the following reasons: there are not many of them, in many cases they don't have a substitution when absent and they are often engaged in other maintenance tasks so they cannot be fully focused on the analysis of acquired data from the machine. In such an environment, implementation of AI methods through previously developed and validated fault identification algorithm has a huge potential.

There are several methods of AI, which can be used for automatic fault identification of rotating machine: artificial neural networks (ANN), fuzzy logic, expert systems and hybrid intelligence systems. The most applied are ANN [22, 1]. One of the reasons for that is due to their ability to learn i.e. to adopt novelties. This adaptability of ANN results in a possibility for detection of an existence of a new condition (fault) based on the existing data [21, 9]. In addition, ANN are efficient in modeling of complex nonlinear phenomena that are present in several types of rotating machinery faults.

A review of existing literature [10, 6, 20] shows that several types of ANN are successfully implemented in automatic fault identification: back propagation feed forward network (BPFF), multiple layer perceptron network (MLP), back propagation multiple layer perceptron (BPMLP), radial basis function network (RBF), self-organized feature map (SOFM) and principal component's analysis (PCA). An excellent review of different types of ANN and training algorithms implementation for different types of rotating machinery can be found in [17]. From the data presented, the increasing trend of implementation of MLP with back propagation training algorithm, with the number of neurons in hidden layers taken as a variable, is evident.

A successful implementation of BPMLP and SOFM for the identification of gearbox faults can be found in [2, 3, 8, 12, 14, 16, 19, 7]. The authors used different scalar features obtained from vibration data as inputs for neuron classifiers.

In this paper, the authors used vibration scalar features obtained in both, frequency and time domains. Definition of vibration features is done based on an assumption that these parameters are sensitive to gearbox failures tested in this paper: worn gears and missing teeth.

2. Vibration analysis techniques for gearbox failures identification

The main origin of vibrations in gearboxes is a tooth meshing which is transient by its nature. According to [15] there are several components of gear vibrations: components at the gear mesh frequencies (GM) due to the tooth profile deviation from an ideal profile, components of amplitude modulation due to the gearbox load variation, components of the frequency modulation due to the uneven space between individual teeth and transients due to the surface irregularities on the tooth surface. Along with these components from the gears, the vibration signal acquired from the gearbox housing can contain components due to the existing unbalance, misalignment, defective bearings, bent and cracked shafts, looseness etc. Gearbox GM components are calculated for every transmission stage as:

$$GM = T_{in} * f_{in} = T_{out} * f_{out} \quad (1)$$

where T_{in} and T_{out} are number of teeth on input and output gear, respectively, while f_{in} and f_{out} are rotating frequencies of the input and output shaft, respectively.

The most exploited vibration signal analysis techniques for gearbox defect identification are: time domain techniques, frequency domain techniques, cepstrum analysis and time –frequency techniques.

Time domain techniques are focused on extracting the statistical indices of time wave in order to quantify the transient phenomena that originates from the defective gear. Time domain techniques for gearbox diagnostics can be performed on several types of time waveform: raw time waveform, time waveform obtained through synchronized time averaging technique (TSA), residual time waveform, differential time waveform and band pass filtered time waveform. Residual time waveform is obtained from TSA waveform by removal of harmonic families of shaft speed and gear mesh components, while the band pass filtered time waveform is a result of a band pass filtering of TSA time waveform around a gear mesh component and its modulation sidebands. Differential signal is obtained by removal of sidebands from a residual signal. Scalar features that can be extracted on these time waveforms are classic features from higher order statistics, such as root mean square (RMS), peak values (P), standard deviation (StDev), kurtosis parameter (Kurt), skewness (Sk) and also special features developed for gearbox monitoring [18].

Frequency domain techniques refer mainly to the representation of the time signal in frequency domain using the algorithm of Fast Fourier transformation (FFT). The main advantage in using cepstrum analysis is the ability to detect periodicity in frequency domain i.e. repeated patterns in a spectrum, which is common in cases with defective gears. Time - frequency methods founded their role in gearbox diagnostics since, due to the presence of transients generated by the gear mesh activity, the signal is non-stationary. As a result, time-frequency methods provide a simultaneous view in both domains (time and frequency). The main time-frequency methods used are short time Fourier transformation (STFT), Wigner-Ville distribution (WVD) and Wavelet analysis (WA).

3. Experimental set up and results

The test rig, designed for the purpose of dataset collection, is shown on the Figure 1. The test rig consists of a 0.37kW variable frequency drive connected over the universal joint shaft to the single stage gearbox with spur gears. In reality and especially in mining industry, gearboxes often operate under the conditions of unsteady load and speed. As a result, their behavior and acquired vibration signals are very dependent on the current operating regime [4, 5, 23, 24]. For the purpose of load detection and control, the output shaft is connected to the friction brake. The resulting torque is measured through the bending force registered with a platform type load cell. For the purpose of load control, the stranded wire is connected to the friction pads and over the pulley; the other end is loaded by the mounted weight. This assures a constant torque for different level of brake pads wornness.

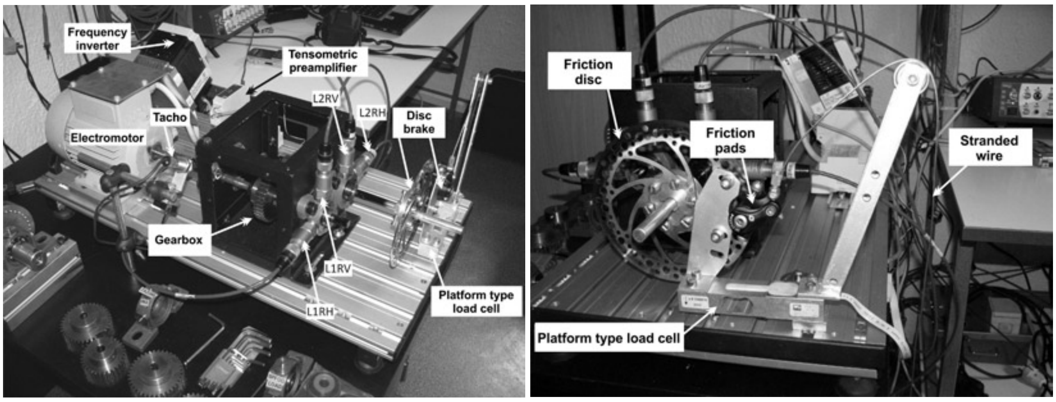

Fig. 1. Test rig used for vibration acquisition on faulty gearbox

Gearbox vibrations are measured in radial directions, using an industrial type IEPE accelerometers mounted at the roller element bearing housings using mounting studs. Input shaft speed is measured using a non-contacting laser sensor and a reflective mark. Also equivalent noise levels with A weighting were measured using an IEPE based microphone. Three sets of gears were tested: gears in a new condition, worn gears and gears with two missing teeth on the input gear, labeled as "OKOK", "PZOK" and "NZOK", respectively. All the tests were performed at the 22Hz of input speed; the input gear has 37 teeth so the five harmonics of GM frequencies are 814 Hz, 1628 Hz, 2442 Hz and 4070 Hz, respectively.

Vibration, force and tacho signals were acquired simultaneously using a multichannel vibration analyzers NetdB and MVX and dbFA and XPR software from 01db-Metravib.

Vibration acquisition included the measurement of[1]: raw time waveforms, narrow band FFT in different frequency ranges with 3200 lines of resolution (2 Hz–2 kHz, 2 Hz–5 kHz, 2 Hz–20 kHz), envelope spectra, time waveform obtained by TSA technique with 100 averages, Cepstrum and autocorrelation functions of the raw and TSA time waveforms. Based on these measurements 58 scalar features were extracted: RMS values of vibration velocity, RMS values of acceleration in several frequency bands (10 Hz – 20 kHz, 2 Hz – 300 Hz, 2 Hz – 2 kHz, 1 kHz – 2 kHz, 2 kHz – 6 kHz, 6 kHz – 10 kHz, 10 kHz – 20 kHz), 01dB bearing defect factor[2], Kurtosis values obtained from raw, band pass filtered (700 Hz – 1400 Hz) and TSA time waveforms, peak to peak values obtained from raw and TSA time waveforms, amplitudes of first five harmonics of GM, overall accelerations obtained from narrow bands around first five harmonics of GM (with bandwidth equals to five sidebands from each side of the central frequency – GM as shown on Figure 2.), amplitude extractions for first four harmonics of the roller elements bearing defect frequencies obtained from FFT and envelope spectra and equivalent A weighted noise levels.

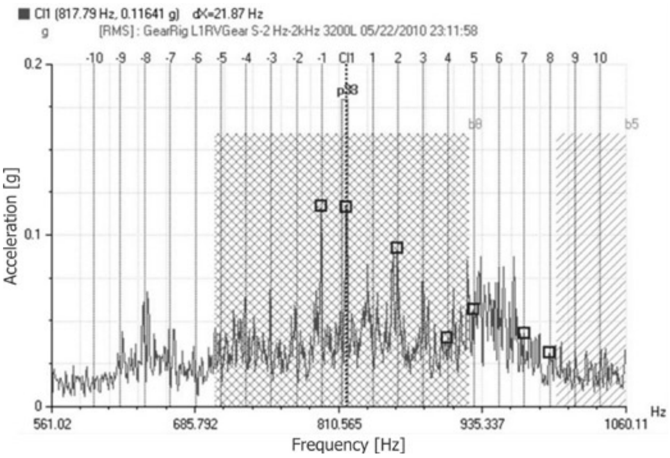

Fig. 2. 1xGM extraction and width for overall energy calculation in the frequency band

SOFM [11] is an excellent tool for the visualization of high dimensional data. In this paper, the idea of using SOFM is the selection of most suitable input features for ANN, since the success of ANN pattern recognition is highly dependent on the choice of input features. SOFM consists of neurons organized in a low dimensional grid where each neuron has a dimension that equals to the number of the input features. The map topology is dictated through neighboring relations between the adjacent neurons. During the SOFM training, the weight vectors move across the data, the map gets organized and, in result, the neighboring neurons have similar weight vectors. SOFM testing was performed in SOM toolbox for Matlab environment [25]. The quality of clustering is analyzed using distance matrix, which visualizes the distances between adjacent neurons on the map: low values indicate clusters while higher values indicate the borders between existing clusters. On the other hand, component planes for each input feature show the values of that feature for each unit on the map. This makes them convenient for analyzing the influence of each input feature on the clustering.

For every gear pair tested, 100 measurements were acquired with 10 minutes of delay between them. This resulted in the matrix of input features with 300 rows. Input matrix with 58 scalar features was labeled and introduced to SOFM algorithm. As a results, a SOFM with quantization error 1.8512, shown on figure 3, is generated. The quantization error is a measure of map resolution and is defined as an average distance between each data vector and its best matching unit. Figure 4 shows the map topology with the projections of input vectors and color coded labels (OKOK-red, NZOK-green, PZOK-blue).

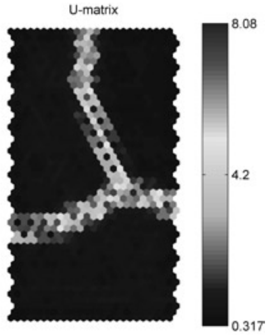

Fig. 3. Distance matrix for SOFM with 58 input features

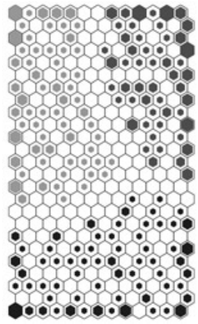

Fig. 4. SOFM topology with color coded labels

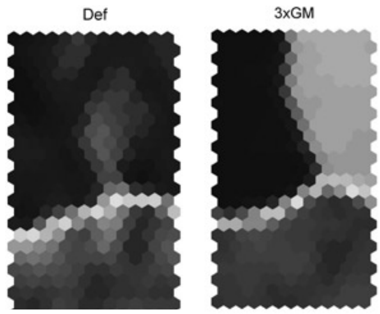

Fig. 5. Component planes for bearing defect factor and 3rd GM harmonic

Figure 5 shows component planes for bearing defect factor and the third harmonic of the GM. It is evident that the GM harmonic amplitude is a much better choice. Therefore, based on the analysis of the component planes, a reduction of the number of the input features is done. As a result from a total of 58 input features, 24 were chosen: overal acceleration in the mentioned frequency bands, Kurtosis parameters of the raw and TSA time waveforms and their autocorrelations, peak to peak values of the raw and TSA timewaveforms, A weighted noise levels, amplitudes of the GM harmonics and overall accelerations from narrow bands around the GM components. As a results of the SOFM training with the dataset that consists 24 input features a SOFM with much smaller quatization error (0.9031) is generated – Figure 6.

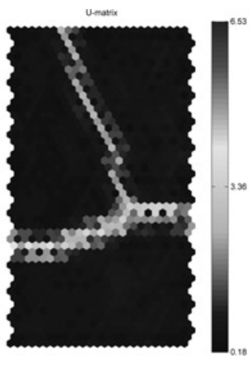

Fig. 6. Distance matrix for SOFM with 24 input features

MLP ANN utilized in this research had a classification task – to detect an exact gearbox defect type. Several architectures of MLP ANN were tested by the means of choosing the optimal network architecture from the point of the number of neurons in the hidden layer,

1 Definition of measurement parameters and frequency ranges was guided by additional tests, performed, but not presented in this paper – analysis of combination of gear and roller element bearing faults and development of automatic alghoritms for multiple faults identification.

2 Linear combination of peak and RMS values of acceleration.

type of activation functions and type of the learning algorithm. For building, testing and training, Statistica Automatic Neural Networks package has been used. 210 input vectors (70% of the dataset) were used for training while 45 input vectors were used for cross verification and testing. The software automatically determined network complexity. 20 networks were tested. The best network with 12 neurons in hidden layer (MLP 24-12-3) and with excellent classification – 100% for each output case.

4. Case study

SOFM and ANN for automatic identification of rotating machinery faults was implemented on the mine strip bucket wheel excavator SRs 1300 [23, 24], where an online system for the excavator surveillance based on strain, stress and vibration measurement has been installed [13]. After the monitoring system was installed, several faults on the excavator were identified (roller element bearings faults on the input stage of the bucket wheel drive gearbox, roller element bearings fault on the motor of the first belt conveyor drive, gear failure at the third transmission stage of the first belt conveyor gearbox etc.). As a case study to be presented in this paper, a pinion failure of the belt conveyor gearbox is chosen. A belt drive is driven through a 450 kW motor working at 955 RPM. A three stage gearbox (shown on Figure 7) is connected to the drive through rigid coupling. The numbers of teeth on gears and GM components in the term of orders of the input frequency are shown on table 1.

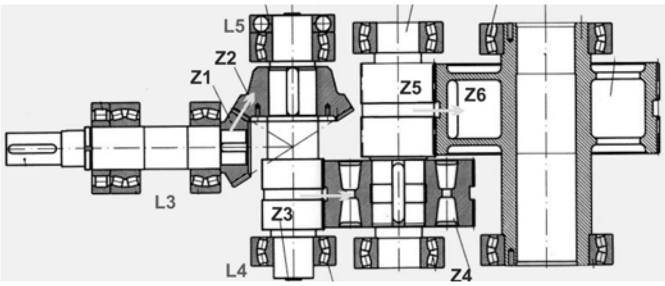

Fig. 7. Belt drive gearbox scheme with the locations of accelerometers (L3, L4, L5)

Table 1. Number of teeth and GM frequencies for the analyzed gearbox

Number of teeth		Transmission ratio	GM [order]
z1	29	0.63043	29
z2	46		
z3	57	0.40141	35.93478261
z4	142		
z5	47	0.31973	11.89390692
z6	147		

Nearly two years after monitoring system installation and data collection, maintenance engineers reported a sudden increase in accelerations coming from the sensors mounted on the gearbox. Analysis of the frequency spectra revealed that the increase in overall accelerations originates from the occurrence of GM of the third transmission stage (Figure 8). Also sidebands from the pinion's drive are visible. Unfortunately, the initial measurement setup did not include accelerometers mounted at the bearings of the third transmission stage. Therefore, measurements from location L5, as the closest to the third stage, were chosen for the analysis.

After the gearbox overhaul, the origin of high GM activity was found – missing teeth on the pinion gear at the third transmission stage. Initial measurement setup defined for this machine included

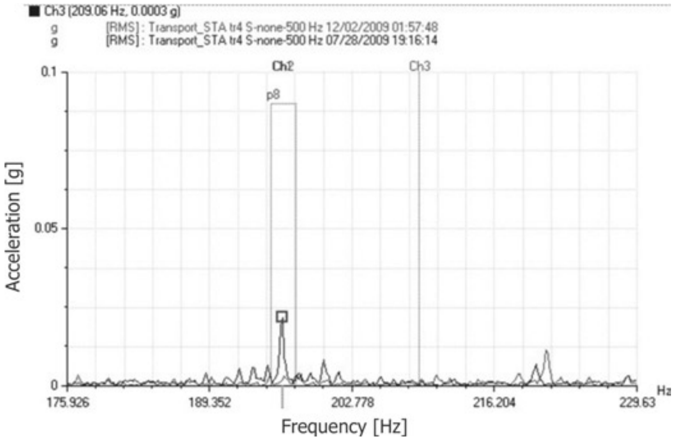

Fig. 8. Comparison of frequency spectra from the measurement point L5

amplitudes from first three harmonics of GM frequencies, overall accelerations in bands around GM and their difference calculated at each GM harmonic. Therefore, these values (for the GM on the third stage) were chosen as input features for SOFM and ANN. The occurrence of a fault was identified on trend plots of the mentioned features so it was easy to assign labels to the input dataset, which was consisted of 1011 individual records. Input matrix was introduced to the SOFM algorithm and a SOFM with quantization error 0.7273 was generated (Figures 9 and 10). As it can be seen from the figures the classification of the map neurons in two distinct clusters are more than satisfactory.

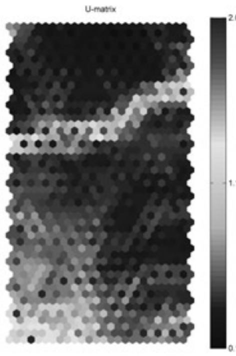

Figure 9. Distance matrix for SOFM with 9 input features

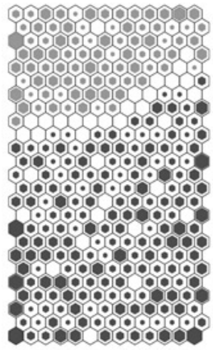

Figure 10. SOFM topology with color coded labels (green-OK, red-NOK)

Result of the unlabeled dataset introduction to ANN algorithm resulted in the ANN with excellent classification – 100% for each case. As in previous cases 70%, 15% and 15% of the total dataset was used for training, cross verification and testing of the ANN. The wining network had 4 neurons in the hidden layer (MLP 9-4-2).

5. Conclusion

Vibration analysis is a proven method for achieving a high reliability of rotating machinery. However, for complex machines, such as gearboxes, evaluation of machine condition based on vibration measurements could be a hard task and implementation of AI can help. In this paper, we demonstrated the use of SOFM and ANN for automatic identification of missing and worn teeth in gearboxes that work under steady loads. It is shown that SOFM can be used for preprocessing phase where a reduced set of vibration features should be defined as inputs in ANN algorithm. Excellent classification of existing faults was obtained by the use of ANN. Results indicated that overall acceleration values defined in frequency bands that cover GM components and amplitudes of GM are satisfactory features that can be used for automatic identification of gear faults.

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