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Application of genetic algorithms in the task of choosing inputs for probabilistic neural network classifier of faults of gear-tooth

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ABSTRACT

In this article are presented results of trials of building an application based on probabilistic neural network, used to diagnose damages to the gear wheel teeth in the form of cracks at the base of the tooth. To determine the proper network learning process is necessary to get from the tested object numerous set of input data. Conducted researches are based on data obtained from the identified model of gear working in the drive system, which made it possible to acquire the necessary amount of data. In experiments was tested the usefulness of different sets of descriptors of teeth damages, constructed on the basis of vibratory signals, processed using the Wigner-Ville transform. Often the problem, which makes the proper learning of the neural classifiers impossible is the size of the network structure. Therefore, in further studies was examined the usefulness of genetic algorithms which task is selecting an input data for the artificial neural networks of PNN type.

Keywords: gearbox, diagnostics, neural networks, Wigner-Ville transform, genetic algorithm

1. Introduction

Gears are used in a number of construction solutions of the drive systems. In many national and international centers are being conducted researches to develop methods of diagnosing gears. Particularly it appears desirable to create tools detecting failures in a non-invasive way still in the early stages of their development [9, 11, 20].

In recent years it can be noticed a huge interest in diagnostics using vibroacoustic method. In literature it can be found whole range of methods of signal processing and analysis in both time and frequency domains, and in both areas at the same time [1-6, 9, 11, 19, 20].

Another new tool, of which examples of use to diagnose the condition of objects can be increasingly found in the literature, are artificial neural networks. They belong to artificial intelligence methods that properly designed and taught enable finding in vibration signal failure symptoms impossible to capture by man (diagnostician) bare eyes. These methods allow to model arbitrary non-linearity, and are characterized by a resistance to interference and ability to the knowledge generalization [9, 13, 15-17].

2. Procedure for construction of patterns classes gear wheel teeth damage

Proper selection and preparation of reference data, which are used for learning process for classifiers based on artificial intelligence methods, determines the correct operation of the final diagnostic system [1, 3, 11, 13, 15-17, 19].

Because the set of patterns must contain a large number of learning examples it is assumed that there is no possibility of obtaining in researches at the real object sufficient number of data. In order to obtain the necessary for further studies learning sequence, it was decided to take advantage of the dynamic model of the working gear in the drive system. The model was developed at the Department of Transport at Silesian University of Technology. Implemented in Matlab-Simulink environment, takes into account the characteristics of the electric drive motor, single-stage gear, clutches and working machine. Description of the phenomena occurring in interpenetration is consistent with the model of Müller.

In the simulation model the tooth damage was adapted in the form of cracks in the alloy as the percentage change in rigidity of the interpenetration in relation to the intact gear. Because in the literature it was not found accurate data about the impact of the initiation and development of the slot at the base of the tooth at the change of the interpenetration rigidity, it was determined following five classes of damage degree in terms of reduced rigidity relative to the interpenetration of undamaged gear by the value of:

- 0-9% - Class 1,
- 20-39% - Class 2,
- 40-9% - Class 3,
- 60-9% - Class 4,
- 80-100% - Class 5.

The need to obtain sufficient and covering all classified patterns gear wheel teeth damage to systems based on artificial intelligence methods, forced to repeat the process model simulation gear. Because learning data should cover the widest group of cases for each class, it was determined the simulation for every one percent of change in rigidity in the range of 0 to 100% relative to the undamaged gear for damage in the form of cracks in the alloy of the tooth. Additionally, in order to increase the representativeness of learning sequence, simulation was repeated for the following parameters:

1. The first series:
   - "cyclic error" for the pinion: 0 mm/pitch length (normal state),
   - "cyclic error" for the wheel: 0 mm/pitch length (normal state),
   - "random errors" - maximum pinion runtime error: 0 mm (nominal state),
   - "random errors" - maximum wheel runtime error: 0 mm (nominal state),
2. The second series:
   - "cyclic error" for the pinion: -7 mm/pitch length,
   - "cyclic error" for the wheel: 5 mm/pitch length,
   - "random errors" - maximum pinion runtime error: ±4,5 mm,
   - "random errors" - maximum wheel runtime error: ±4,5 mm,
3. The third series:
   - "cyclic error" for the pinion: -14 mm/pitch length,
   - "cyclic error" for the wheel: 10 mm/pitch length,
   - "random errors" - maximum pinion runtime error: ±9 mm,
   - "random errors" - maximum wheel runtime error: ±9 mm.

In the first series it was simulated the operation of the faultless gear. In second and third series were founded the gear operation with increased cyclic and random errors. To increase and diversify the number of patterns the second and third series were performed five times, at different values of random errors. Received 1111 simulations represented the basis to reach the patterns of degree classes of cracks at the base of the tooth.

Due to the time-consuming process of obtaining a classes pattern accepted to the analysis data from the model of the gear at operating the wheel shaft rotational speed n = 1800 rpm and a load of 2.58 MPa.

In researches as the base signal, which is subjected to feature extraction, assumed the speed of transverse vibration of wheel shaft.

Collected vibratory signals from the model was treated by five filters:

- a lowpass between 6 kHz,
- a lowpass range of 12 kHz,
- to obtain the residual signals,
- to obtain difference signals,
- a bandpass of 0.5 - 1.5 interpenetration frequency.

Residual signals were obtained by removing from the spectrum the frequency bands containing rotating components of wheel shafts and their harmonics, and frequency components of interpenetration and its harmonics. The differential signal was obtained as the residual signal, but the removed bands around interpenetration frequency and their harmonics are wider and included sidebands related to the rotation frequencies of the gear.

Received vibratory signals were used to build the patterns of damage to the gear wheel teeth. To this end, from the filtered signals were created the time-frequency schedules using the Wigner-Ville transform (WVD).

WVD transform is one of the methods that allow the simultaneous analysis of the frequency and time domains. It is used to temporarily alternating signals in terms of amplitude and frequency, as so non-stationary signals. It is defined as follows:

$$WVD(t,f) = \int_{-\infty}^{+\infty} w(\tau)\cdot x\left(t+\frac{\tau}{2}\right)\cdot x^{*}\left(t-\frac{\tau}{2}\right)\cdot e^{-j2\pi f\tau}d\tau \qquad (1)$$

where:
$x^*(t)$ – shifted in the time domain window function,
$w(t)$ – symmetric weighting function.

For a description about the nature of the WVD distribution changes depending on the degree of damage to the teeth of wheels adopted a two-step procedure.

In step I for subsequent frequency the statistical measures were determined. Here were verified the usefulness of 34 estimates, which are widely described in the literature (coefficients of variation, peak, play, shape, impulsity and asymmetry, quadrantal and average deviation, arithmetic average, geometric and harmonic, quartiles, dyscriminants dimensionless, central moments, cumulants, energy of the signal, RMS and peak, maximum and minimum variance, positional coefficient of variation). Such procedure was to describe the nature of changes in the time domain for subsequent frequency designated in accordance with a predetermined sampling frequency.

In step II, ranges were isolated from so obtained frequency characteristics:

- the range to the value of the rotational frequency ,
- another interpenetration frequency ,
- the frequency ranges ,
- the frequency ranges.

The frequency ranges and ranges were divided into nine, six and three sub-ranges, giving respectively sub-ranges lengths Hz, Hz and Hz. The purpose of the division into sub-ranges of the three options was to examine the effect of the size of their volume on the outcome of the classification.

In each separate part of so obtained spectra the nature of the distribution of variability was described using 34 measures. The vector consisting of a predetermined measure of each component of the spectrum, was the input data for the neural classifier. The entire procedure of the construction of patterns classes of damage were repeated for the vibration signals obtained using successive filters. As a result of conducted calculation were built 17340 sets of patterns classes of the damage degree the gear wheel teeth. Each of the set had a dimension $m \times n$, where m was the number of cases, and n – the number of network inputs. The number of cases was the number of carried simulations, equal to 1111. Depending on way of the construction of patterns the number of network inputs was equal to 192, 144 or 96.

Each set of patterns were divided into parts - used in the learning process (556 cases) and testing (555 cases). Number of patterns sets was too large to check activities of neural networks learned with their help, that is why it was decided to choose the best variants of set of patterns for used another five filters and three ways of sharing the sub-ranges. Experiment of selection of the best patterns sets were divided into three stages. The selection criterion was the value of network testing error. In the first stage, the measure describing the changes of WVN characteristics in time, for the next frequencies were assumed the effective value. As a result of the stage conducted were determined the best measures describing the change course in the frequency domain for methods of patterns construction using another filters and division the selected frequency bands at 9, 6 and 3 sub-ranges.

In the second stage of tests for the preselected measures describing waves in frequency domain was checked the usefulness of 34 measures for describing the changes of WVN characteristic for in time domain. The second stage was therefore the verification of the accepted assumption in the earlier stage, which concerned the election of the effective value as a measure describing the characteristics in the time domain. At this stage of experiment was conducted also research using in the build process of patterns five filters and three ways of division the selected frequency bands on sub-ranges. In the third stage of the experiment from the best results of the 1st and 2nd stage were selected the best variants of used measures to describe the changes in time domain and frequency of characteristics which were reached by WVD analysis. The selection was made for different variants of classifiers learned on patterns which were built by using five filters and by division to 3, 6 and 9 sub-ranges.

For each variant of construction of patterns classes gear wheel teeth damage were matched the value of the g factor for PNN network. This represents the radial deviation of the Gaussian functions and is a measure of the spread of neurons in the hidden layer [13, 15-17]. Too low value causes the loss of the property to knowledge generalization by the network, and too high prevents the proper description of the details. The g factor is being chosen experimentally. In the research were examined the operation of the PNN network for 86 different values of this factor.

3. Results of experiment

On the basis of three-stages tests was established the type of estimates used in patterns building process of classes of damages (Table 1) for which the neural classifiers showed the highest compliance with the pattern.

Table 1. Selected estimates used in the patterns building process of the teeth damage [own study]

	The number of sub-bands	No. of the filter	Name of the measure describing the nature of changes in:	
			the time domain	the frequency domain
1	9	1	positional coefficient of variation	positional coefficient of variation
2		2	effective value	aspect ratio
3		3	quartile 3	aspect ratio
4		4	average deviation	root mean square
5		5	quartile deviation	quartile 3
6	6	1	quartile 3	median
7		2	average deviation	quartile 1
8		3	discriminant X4	harmonic mean
9		4	effective value	quartile deviation
10		5	effective value	harmonic mean
11	3	1	effective value	the signal energy
12		2	effective value	clearance rate
13		3	the arithmetic mean	quartile deviation
14		4	peak to peak	quartile 3
15		5	quartile 3	geometric mean

Because the aim of the research was to develop the neural classifier characterized by the least error in the diagnosis process of damage to the teeth of the gear wheel, consequently an additional trials were made to make the selection of input data, using for this purpose genetic algorithms. For this purpose, inputs of the network were encoded as a string of zeros and ones, where “1” meant that the selected input should stay, and “0” does not. Obtained in this way chromosome chains were subjected to crossover and mutation operations. Selection of the fittest individuals, that is, a set of inputs, were made using the method of the roulette wheel. In researches was assumed that outcome of this proceeding will be obtained for each variant of the process of building a set of patterns of the lower value of testing error.

As a result of experiments with the use of genetic algorithms to the selection of inputs of the PNN neural networks, were achieved the networks architectures with significantly lower complexity. The number of inputs of neural classifiers before and after the process for their selection are presented in Table 2.

Table 2. Number of inputs PNN network before and after the application of genetic algorithms for selecting inputs classifier of teeth damage [own study]

	The number of sub-bands	No. of the filter	Number of inputs PNN classifier	
			before using genetic algorithms	after using genetic algorithms
1	9	1	192	126
2		2	192	153
3		3	192	31
4		4	192	77
5		5	192	38
6	6	1	144	87
7		2	144	106
8		3	144	50
9		4	144	63
10		5	144	36
11	3	1	96	30
12		2	96	52
13		3	96	22
14		4	96	25
15		5	96	28

The lowest obtained error levels of testing for neural network of PNN type with inputs chosen by using genetic algorithms are shown in Figure 1.

Results obtained in experiments shows, that it is possible to create PNN neural classifier for diagnosing the degree of cracks at the base of the gear wheel teeth.

Conducted experiments were based on the vibration signals obtained from the dynamic model of the gear. The next step that must be carried out is the examination whether the proposed method of construction of neural classifiers will be equally useful for vibration signals coming from the actual gear.

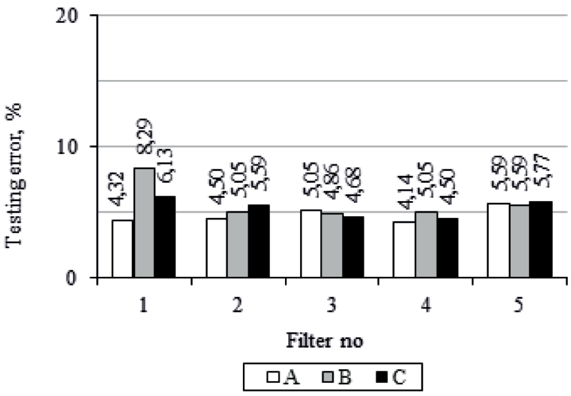

Fig. 1. The best results for the PNN type neural classifiers, A - the number of sub-ranges = 9, B - the number of sub-ranges = 6, C - the number of sub-ranges = 3 [own study]

4. Conclusion

To increase the efficiency and reliability of drive systems in the process of theirs operation are used a variety of methods and techniques to detect damage. Especially desirable are methods of detecting early stages of the damage. Undetected in time may become the cause of damages occurrence threatening human health and life.

Today, worldwide, are conducted numerous studies, which aim is to increase the reliability of technical objects, which in turn will increase the safety of people [1-12, 14, 18-20].

In recent times, to monitor the technical condition of propulsion components are increasingly used expert systems based on artificial intelligence elements [1, 3, 11, 13, 15-17, 19]. Well structured system can automatically recognize occurring of the damage. One of the methods of artificial intelligence are probabilistic neural networks. The main problem in the construction of such systems is to define a set of input data and to gain properly numerous ensemble of the learning data. The way out of the situation may be the usage of the simulation models, appropriately processed vibroacoustic signals and methods enabling to reduce the size of patterns, ie. genetic algorithms. Conducted research has indicated this possibility.

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