UDC 620.179.18

THE USE OF ARTIFICIAL NEURAL NETWORK MODELS IN THE ACOUSTIC DIAGNOSTICS OF MULTI-SHAFT GEAR DRIVES

A. N. Parfievich[1], V. A. Sokol[2], M. V. Neroda[3]

[1] Master of Technical Sciences, Senior Lecturer of the Department of Mechanical Engineering and Operation of Vehicles, Brest State Technical University, Brest, Belarus, e-mail: parfievichand@gmail.com
[2] Master of Technical Sciences, Senior Lecturer of the Department of Mechanical Engineering and Operation of Vehicles, Brest State Technical University, Brest, Belarus, e-mail: sokolva@mail.ru
[3] The First Vice Rector, Ph.D in Engineering, Associate Professor, Brest State Technical University, Brest, Belarus, e-mail: nerodamv@mail.ru

Abstract

The article considers the possibility of diagnosing a multi-shaft gear mechanical system based on the analysis of an acoustic signal using artificial neural network models on the example of the speed box of the SN-501 lathe. A sufficiently high efficiency and accuracy of detecting a local defect of the gear wheel in conditions of high acoustic activity of all components of the drive when monitoring its condition is shown.

Keywords: gear wheel, local defect, artificial neural network model, diagnostics, acoustic signal, multi-shaft gear drive.

ИСПОЛЬЗОВАНИЕ ИСКУССТВЕННЫХ НЕЙРОСЕТЕВЫХ МОДЕЛЕЙ ПРИ АКУСТИЧЕСКОЙ ДИАГНОСТИКЕ МНОГОВАЛЬНЫХ ЗУБЧАТЫХ ПРИВОДОВ

А. Н. Парфиевич, В. А. Сокол, М. В. Нерода

Реферат

В статье рассмотрена возможность диагностики многовальной зубчатой механической системы на основе анализа акустического сигнала с применением искусственных нейросетевых моделей на примере коробки скоростей токарного станка SN-501. Показана достаточно высокая эффективность и точность выявления локального дефекта зубчатого колеса в условиях высокой акустической активности всех составляющих привода при проведении мониторинга его состояния.

Ключевые слова: колесо зубчатое, локальный дефект, искусственная нейросетевая модель, диагностика, акустический сигнал.

Introduction

Currently, diagnostic specialists who study various kinds of mechanisms on the basis gear wheels are faced with a difficult task associated with the formalization of the monitoring procedure, but at the same time it is important not to lose in the process of simplification that amount of information which carries information about changes in the diagnosed object. To achieve this goal, they are increasingly resorting to the joint use of the known methods of representing oscillatory processes accompanying the operation of the device, and modern mathematical means.

One of the most widespread methods for representing a oscillation signal is a spectral analysis, the mathematical basis of which has been sufficiently well studied and implemented practically on all modern control and diagnostic tools. To diagnose periodic oscillatory processes using amplitude-frequency analysis, the Fourier transformation procedure is most often used. This method of representing an acoustic signal makes it possible to evaluate its composition and the amplitude of the characteristic frequencies generated by each element of the mechanical drive, as well as to track their changes determined by the change in the state of cog wheels.

Object and subject of research

As an object of research, a complex mechanical system was chosen − a gearbox of the drive of the main movement of a SN-501 lathe model. When the drive is operating, both the gearings of the kinematic chain of rotation transmission to the output shaft and its other elements that do not affect the rotation of the spindle (guitar drives of replaceable wheels, reverse, brake mechanism and parasitic gear wheels), but influencing the formation of the final acoustic signal of the drive are in motion. This leads to the appearance on the spectrum of a large number of additional components, which complicate the identification and analysis of harmonics at the frequencies of interest.

As a source of information was used an acoustic signal generated by a VIK-MA hardware-software complex on the basis of data obtained from a measuring microphone with an M101 capsule, installed at a distance of 300 mm from the body of the gearbox in the horizontal plane [1]. The measurement of acoustic signals was carried out at the input shaft rotation frequencies which correspond to the operational ones both under load and without it.

The simultaneous use of angular displacement transformers on the input and output shafts of the drive made it possible to determine with high accuracy the rotational frequences of the input and output shafts, as well as the frequencies of the characteristic components on the spectrum of the analyzed signal.

On Z = 43 gear of shaft II, which is included in the studied kinematic chain of the gearbox, an operational local defect of the working part of the tooth of various sizes was simulated (25 %, 50 %, 75 %) of the length at the top of the tooth and without a tooth (Fig. 1). The measurements were carried out for each condition of the tooth multiple times to accumulate the required amount of data for statistical processing. The results obtained while using serial wheels are taken as reference.

Figure 1 – Experimental Z = 43 gear with operational local tooth defect

doi.org/10.36773/1818-1112-2021-126-3-72-75

The spectral characteristics of an acoustic signal obtained during the experiment indicate that each of the drive elements makes its own contribution to its formation. But with a large number of sources of acoustic activity, a highly qualified diagnostician is needed to identify the characteristics of each element of the object and then make the appropriate diagnosis, therefore, spectral analysis has limitations in diagnosing complex mechanical systems on the basis of gear wheels and requires formalization and automation of processing of incoming data for analysis.

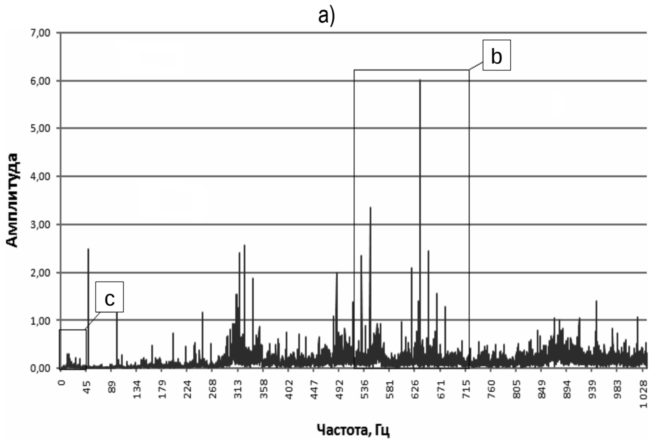
Analyzing the obtained spectra of acoustic activity of the investigated object, one can point out the problem of its excessive saturation with various components from the drive operating elements, but at the same time, a decrease in the spectrum resolution can lead to the loss of data that can carry diagnostic information.

As is known from a number of literary sources [2, 3, etc.], the following number of frequency components have the greatest diagnostic value, the change in the amplitudes of which carries significant information about the state of the investigated element of the object:

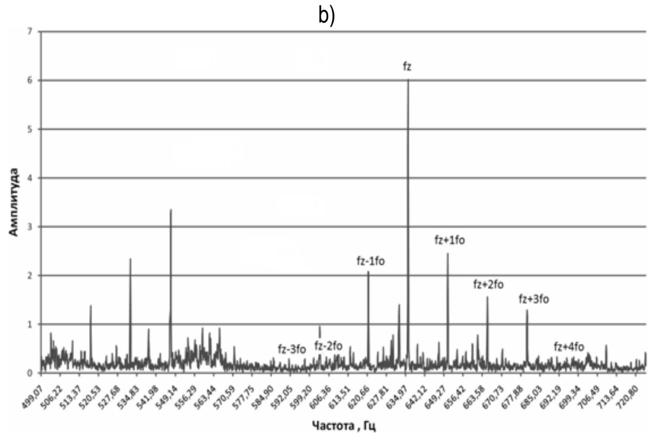
- in the low-frequency area – reverse f_o and multiple components of the all gear wheels of the kinematic chain;
- in the area of tooth connection – toothed f_z, multiple components of the gear wheels, as well as other frequency components at the combined frequencies $l \cdot f_z \pm n \cdot f_o$, arising from various kinds of signal modulations (l, n = 1; 1,5; 2, etc.).

Taking into account a very large number of characteristic frequency components to be analyzed for each gear wheel, determining their characteristics ‘manually’ is a very painstaking process. For its automation in the software part of the complex, a new function ‘Harmonics analysis’ has been developed and implemented, which allows to automatically obtain the values of the frequencies and amplitudes of the circulating and cogging spectrum components, their multiple harmonics, as well as the combined components formed during operation of each gear wheel and forming a set of the most informative frequency components when detecting defects and errors of gear wheels (Fig. 2).

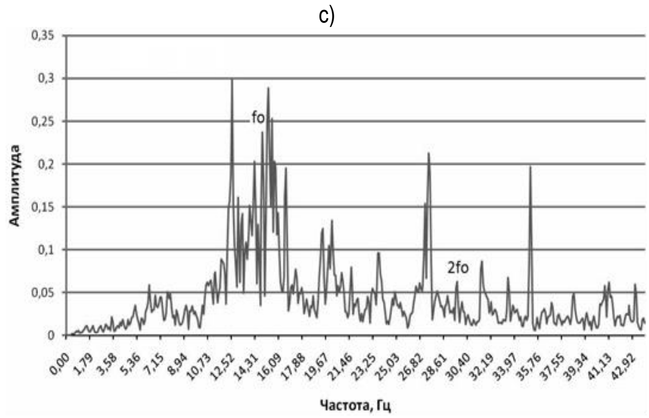
a)



b)



c)



d)

i	Amplitudes of harmonics							
	reverse frequency f_{oi}	cog frequency f_{zi}	combined frequencies $f_{zi} + f_{oi}$					
			j=-3	j=-2	j=-1	j=1	j=2	j=3
1	0,237	6,018	0,2877	0,2203	2,0718	2,2243	1,5597	1,1467
2	0,0632	1,473	1,1489	0,9026	0,3780	2,037	0,2023	0,1939
3	0,0205	0,355	0,3953	0,1080	0,3725	0,1903	0,1491	0,1451
4	0,0405	0,073	0,0465	0,0588	0,0535	0,0524	0,0304	0,0312
5	0,0290	0,022	0,0814	0,0513	0,0295	0,0251	0,0349	0,0369

a) a fragment of the spectrum of the acoustic signal of the object under study; b); a fragment of the spectrum of the acoustic signal in the frequency range (f_z – 5f_o) – (f_z + 5f_o) of the gear under study; c) a fragment of the spectrum of the acoustic signal in the area of the reverse frequencies of the gear under investigation; d) experimental data obtained using the «Harmonic Analysis» complex function for the gear under study

Figure 2 – The spectrum of an acoustic signal of the multi-shaft gear drive and the result of its processing by the software of the VIKMA complex

The developed technique for automatic spectral characteristics processing makes it possible to simplify the procedure for analyzing the parameters of acoustic noise. This gives a possibility to narrow the set of analyzed data for making a diagnosis and to take steps to formalize the diagnostic procedure through the use of powerful modern mathematical means, by way of proposing the use of the capabilities of artificial neural networks.

Neural network diagnostic method

The obtained volume of experimental data on the acoustic activities of the drive was divided into 5 classes, depending on the condition of the tooth (Table 1) and used to solve the classification problem. As a training excerpts, 25 samples of each of the analyzed states were formed, 5 of which were provided to the network for testing.

The description of each sample was carried out by the amplitudes of the acoustic signal harmonics obtained from the high-resolution spectra by the software of the complex using the «Harmonics analysis» function. For each toothed wheel, the amplitudes of at least 5 harmonics of the reverse f_o and the tooth f_z frequency and 10 amplitudes of the modulated side bands $f_z - if_o$, i = -5…5 were taken as such.

Table 1 – Classification of the state of the experimental Z = 43 gear.

Class Number	Tooth condition
1	No defects
2	25% of the tooth surface is damaged
3	50% of the tooth surface is damaged
4	75% of the tooth surface is damaged
5	Chipped tooth

A multilayer neural network with one hidden layer consisting of Kohonen neurons [4], the structure of which is shown in Figure 3, was chosen as a classifier.

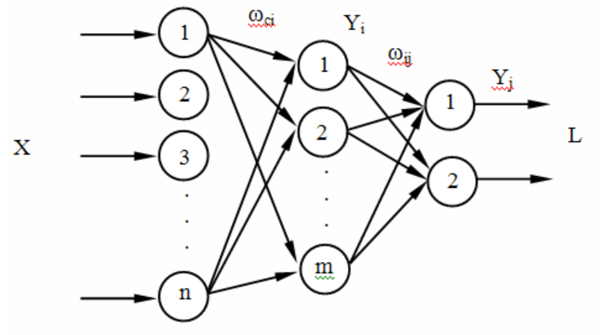


Figure 3 – The structure of a neural network classifier on the basis of Kohonen neurons.

The choice of the given structure of an artificial neural network is determined by the limited set of analyzed data. Thus, when using a multilayer perceptron as a classifier, the following size of the training excerpt is necessary [5]:

$$L \approx \frac{V}{\varepsilon} \tag{1}$$

where ε – the permissible classification accuracy;

V – the total number of adjustable parameters (weight coefficients and threshold values) is calculated by the formula:

$$V = m \cdot (n + 3) + k \tag{2}$$

where m – the number of neurons in the hidden layer;

n – the number of neurons in the distribution (input) layer;

k – the number of neurons in the output layer.

Let's assume, n = 60, m = 30, k = 5 and ε = 0.1. Then $L \approx$ 18950.

A similar result can be obtained for multi-recurrent neural networks [6], as well as for deep learning neural networks [7].

For the selected structure of the neural network classifier, there are no strict requirements for the dimension of the training excerpt. It is sufficient that the size of the training excerpt is as follows:

$$L \geq 2 \cdot m \tag{3}$$

The first layer of neural elements is designed to distribute input signals to the Kohonen hidden layer neurons. The dimension of the input layer (the number of neurons in the input layer) is determined by the dimension of the analyzed data. In our case, data with a dimension of 60 are used, therefore, the number of neurons in the distribution layer is n = 60. The input signals are parameters formed on the basis of the function of the hardware-software 'Harmonics Analysis' complex (Fig. 2, r).

The second, the artificial neural network hidden layer consists of Kohonen neurons. The Kohonen layer plays a key role in the classification of data and performs the clustering of the input image space, as a result of which clusters of different images are formed, each of which corresponds to its own neural element. The optimal number of neurons in the hidden layer of Kohonen is determined experimentally, and may differ from the type of tasks, data structure, etc. In the given case, the experiments showed good results, with the number of neurons in the hidden layer equal to m = 30.

To train the Kohonen layer, a competitive teaching method is used [4, 5]. The essence of this learning method is that in the teaching process there is competition between neural elements, as a result of which a winning neural element is determined, which characterizes the class of analyzed data. To determine the winner neuron, the Euclidean distance between the input and weight vectors is used, which is defined as:

$$D_i = \left|X - \omega_i\right| = \sqrt{(X_1-\omega_{1i})^2 + (X_2-\omega_{2i})^2 + \ldots + (X_c-\omega_{ci})^2}, \tag{4}$$

where ωci – the weight coefficient between the c-m neuron of the distribution layer and the i-m neuron of the Kohonen layer;

$X = [X1, X2 \ldots Xn]$ - input image.

During the teaching process, synaptic connections for the winner neuron are strengthened, but for the rest of the neurons they are not change. Thus, after training the artificial neural network, when the input image is submitted, the activity of the winning neuron is taken equal to one, and the remaining neurons are 'reset' to zero [4-6]. This teaching rule is known under the name "the winner-takes-it-all" [4, 5].

The third layer consists of five linear neural elements and realizes the representation of the clusters, formed by the Kohonen layer, into 5 classes, respectively. The activity of the output neuron, when its value is equal to one, characterizes this or that class. In this case, all other output neurons have an activity equal to zero.

The neural network training algorithm can be represented as the following sequence of steps:

1. Random initialization of the weight coefficients ωci of the neurons of the Yi layer.
2. Distribution of the input image from the training excerpt to the neural network and the calculation of the following parameters:

a) the Euclidean distance between the input image and the weight vectors of the neural elements of the Yi layer is determined:

$$D_i = \left|X - \omega_i\right| = \sqrt{(X_1-\omega_{1i})^2 + (X_2-\omega_{2i})^2 + (X_n-\omega_{ni})^2}, \tag{5}$$

where $i = \overline{1,m}$.

b) neural element winner with number k:

$$D_k = \min_j D_j. \tag{6}$$

c) the output value of the winner neuron is set to '1', and the output of the remaining neural elements is set to '0':

$$Y_i = \begin{cases} 1, i = k \\ 0, \textit{иначе} \end{cases} \tag{7}$$

d) the weighting coefficients of the winner neuron are modified in accordance with the following expression:

$$\omega_{ck}(t+1) = \omega_{ck}(t) + \gamma\,(X_c - \omega_{ck}(t)), \tag{8}$$

e) if the winner neuron is the neuron corresponding to the presented image (so, when the number of neurons in the Yi layer is equal to 5, when the image corresponding to the whole gear wheel is fed to the input of the network, the winner neuron must be with index 1; when feeding the image corresponding to 25% damage, the winner neuron should be indexed 2, etc). Otherwise:

$$\omega_{ck}(t+1) = \omega_{ck}(t) - \gamma\,(X_c - \omega_{ck}(t)). \tag{9}$$

The process is repeated starting with item 2 for all input images.

3. Training is performed to the desired degree of agreement between the input and weight vectors.

The value of discernment reliability in the course of training the neural network was 93.3%, the mistakenly recognized images corresponded to neighboring classes.

Neural network testing

At the initial stage, the z = 24 gears of shaft III and z = 27 of shaft IV of the SN-501 lathe gearbox in a technically correct state were used as test objects. The accuracy of the diagnosis with the trained neural network was 100%.

To check the adequacy of the proposed method of acoustic diagnostics, in addition to the gearbox of the SN-501 lathe main movements drive as a base object, the elements of such gear drives as a PM-250 model horizontal reducer with cylindrical spur wheels and a gearbox of a model 2K52 radial boring mill were tested.

On the z = 40 gear wheel of the PM-250 horizontal reduction gear with spur wheels, similar local defects in the form of tooth damage were simulated, as in the lathe gearbox (25 %, 50 % and 75 % of the tooth length, and no tooth).

When diagnosing the gearbox of the 2K52 radial boring mill, the object of the research was a technically serviceable z = 42 gear wheel of the kinematic chain. At the stage of data collection, various situations were simulated: operation of the gearbox at idle stroke and work under load (in the course of using the lathe during mechanical processing).

The results of using a neural network to detect gears with damaged teeth are shown in Table 2.

doi.org/10.36773/1818-1112-2021-126-3-72-75

Table 2 – Reliability of detecting tooth damage of multi-shaft drives by acoustic data using an artificial neural network

Classes of diagnosed parameters of a cogwheel	Accuracy of diagnosis, %				
	Whole tooth	25% of tooth length	50% of tooth length	75% of tooth length	No tooth
Serviceable gears z = 24 and z = 27 of the SN-501 lathe gear box					
Whole tooth	100%	-	-	-	-
25% of tooth width	-	-	-	-	-
50% of tooth width	-	-	-	-	-
75% of tooth width	-	-	-	-	-
No tooth	-	-	-	-	-
Gear wheel Z = 40 of the PM-250 reducer with a whole chipped tooth					
Whole tooth	-	-	-	-	-
25% of tooth width	-	-	-	-	-
50%of tooth width	-	-	-	-	-
75% of tooth width	-	-	-	13,3%	-
No tooth	-	-	-	-	86,7%
Gear wheel Z = 40 of the PM-250 reducer with 75% damage of the tooth length					
Whole tooth	-	-	-	-	-
25% of tooth width	-	-	-	-	-
50% of tooth width	-	-	3,3%	-	-
75% of tooth width	-	-	-	96,7%	-
No tooth	-	-	-	-	-
Gear wheel Z = 40 of the PM-250 reducer with 50% damage of the tooth length					
Whole tooth	-	-	-	-	-
25% of tooth width	-	-	-	-	-
50% of tooth width	-	-	100%	-	-
75% of tooth width	-	-	-	-	-
No tooth	-	-	-	-	-
Gear wheel Z = 40 of the PM-250 reducer with 25% damage of the tooth length					
Whole tooth	13,3%	-	-	-	-
25% of tooth width	-	83,3%	-	-	-
50% of tooth width	-	-	3,3%	-	-
75% of tooth width	-	-	-	-	-
No tooth	-	-	-	-	-
Serviceable gear wheel Z = 40 of the PM-250 reducer					
Whole tooth	100%	-	-	-	-
25% of tooth width	-	-	-	-	-
50% of tooth width	-	-	-	-	-
75% of tooth width	-	-	-	-	-
No tooth	-	-	-	-	-
Serviceable gear z = 42 of the radial 2K52 boring mill gearbox					
Whole tooth	100%	-	-	-	-
25% of tooth width	-	-	-	-	-
50% of tooth width	-	-	-	-	-
75% of tooth width	-	-	-	-	-
No tooth	-	-	-	-	-

The accuracy of the diagnosis of an artificial neural network trained on one object when using it on other gear drives was no less than 83%, since the diagnostic features describing the classes of the state of gear wheels for similar objects are identical. Moreover, in all cases, the erroneous results corresponded to the neighboring class of tooth condition, and the wheels with undamaged teeth were assessed without error as serviceable. It is obvious that the selected set of acoustic signal parameters for describing the state of damaged wheels is sufficient for adequate operation of the neural network analyzer.

Conclusion

Thus, the method for diagnosing elements of multi-shaft in-line gear drives developed in the course of experimental studies using neural network models has shown a fairly high efficiency and accuracy. The proposed structure of a neural network immune detector for the classification of the proposed states of the gear tooth is characterized by a small volume of the training excerpt and is distinguished by a high level of clustering accuracy in the analysis of the acoustic signal, which is the 'product' of the activities of all elements of the kinematic chain of the SN-501 lathe gearbox. This approach in the study of multi-shaft gear drives is supposed to minimize human participation directly in the diagnosis procedure, which, in turn, is intended to increase its objectivity. Despite the fact that this method requires additional actions that are not directly related to the diagnostic process (training the network on theoretically and practically grounded diagnostic features, determining the data preparation technology), the prepared artificial neural network can further be used to make a diagnosis on other similar objects that have a similar nature of the formation of the analyzed signal.

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Accepted 26.10.2021