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NEURAL NETWORK ANALYSIS OF VIBRATION SIGNALS IN THE DIAGNOSTICS OF PIPELINES

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ABSTRACT

The article is devoted to the improvement of heat network calculation and diagnostics methods. Currently used instruments have many shortcomings for the diagnosis of pipelines, including low reliability of defect detection and subjective decision-making. The authors created an experimental stand, which allows to conduct the diagnostics of pipelines by a vibration-acoustic method. They studied steel pipes filled with water, the surface of which 50x50 mm defect and the depth of thinning of 2 mm, 3 mm, and 5 mm. Using the vibration-acoustic sensors fixed on an outer surface, the vibration signals generated by the water flow in the pipe were obtained. In order to process the large volumes of data obtained as the result of experiments, it is proposed to use artificial neural networks. Among all considered types of neural networks, the authors prefer Kohonen's networks due to the best effectiveness of a defect determination. The program for an acoustic signal processing and analyzing through a neural network was implemented in LabView 8.5 work environment. Depending on the accuracy of a problem being solved, and the details of a training sample, the program is able to produce the results of sample classification of samples for a defect-free and defective pipes of different depth of damage. The results of the classification by Kohonen's trained neural network show good abilities for the analysis of unknown samples and a high degree of their recognition reliability.

Keywords: diagnosis, corrosion, defect, pipelines, acoustic signal, neural network.

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1 INTRODUCTION

Heat and water supply pipelines are more susceptible to corrosion and cracking processes, since they do not contain electric-chemical protection and are not subjected to flaw detection during construction and operation. Thus, nowadays many settlements of Russia have outdated public utility network pipelines at 70-80 percent, the networks have many leaks. The successful solution of specific fuel consumption reduction task in the production and the consumption of energy resources is heat supply reliability increase, as well as heat loss reduction during the transportation of a heat carrier is associated with the improvement of calculation and diagnosing methods for heat networks based on the search for optimal solutions and a systematic approach. A great variety of the methods and the means of leak testing was developed, but from the ecological and economic point of view, it is more appropriate to prevent the occurrence of leaks in pipelines, and not to state the fact of their occurrence. There is a large number of flaw detectors for this, differing by a principle of operation and the way of a signal processing. Acoustic flaw detectors are the most reliable ones. However, they also have a number of shortcomings: difficulties concerning defect type and size determination, difficulties arise with the detection of local defects, less than 20 cm in diameter, an incorrect classification of a group of defects of the same size localized within 10 meters [1-5,16].

2 METHODS

All of the abovementioned deficiencies in the diagnosis of pipelines, as well as the difficulty of defect identification, a large volume of data sets for post-processing, a large percentage of erroneous classification for defective pipeline sections pose the task of a diagnostic complex development using advanced signal processing algorithms [6-8].

They studied the sections of steel pipes with the conditional diameter of 159 mm, the length of 1 m and the wall thickness of 4.5 mm using the test stand the scheme of which is shown on Fig. 1.

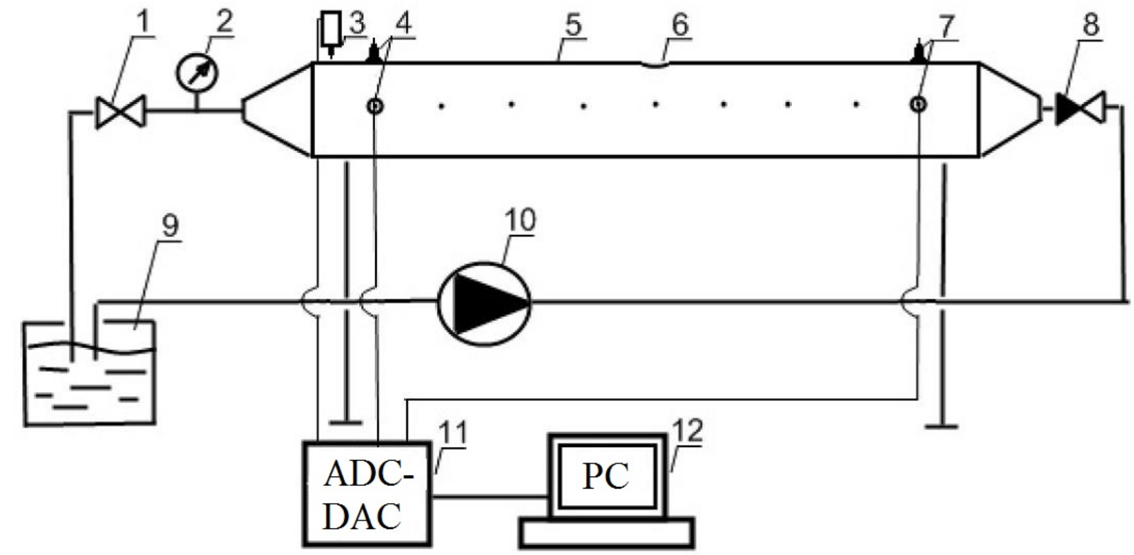

Fig.1. Experimental stand for the study of pipelines: 1 - valve; 2 - manometer; 3 - drummer; 4, 7 - piezosensors; 5- pipeline; 6 - defect; 8 - return valve; 9 - tank; 10 - pump; 11 - ADC-DAC; 12 - personal computer

The stand for the study of pipelines works in the following way. The pump 10 is turned on, thus the liquid begins to circulate through the pipeline 5. According to the readings of pressure gauge 2, valve 1 sets the required pressure of the liquid. Using the valve 1, the liquid pressure in the pipeline 5 can be varied from 0 to 0.4 MPa. When the fluid current (dynamic pressure) makes its impact by the pipeline defect experiences the oscillations of the acoustic frequency range, i.e. the movement of the liquid in the pipeline under study 5 excites acoustic pulses that are captured by the piezoelectric sensor 4 and 7. During the experiments, the sensor was moved with the interval of 0.15 m along the entire length of the section under study along 9 points on the pipeline. The sensor was moved to obtain the information on pipe sections, and to avoid possible errors caused by: 1) a loose fitting of the sensor to the pipes due to the roughness of the pipes; 2) the appearance of local zones of flow turbulence. Then the signals are processed in the unit 11 by an analog-to-digital converter and recorded using a specially created software package on a personal computer 12 [9,11,13,14].

During the experiments, the vibration spectra of a defect-free pipeline were obtained, as well as the spectra of pipelines with the defects of 50x50 mm and the depth of thinning of 2 mm, 3 mm, 5 mm.

The interpretation of vibration signals obtained after pipeline research is a complex and a time-consuming task. The presence of a large amount of data of pipeline amplitude-frequency characteristics is necessary to ensure a high level of the study reliability, however, this makes it difficult to extract the necessary signals indicative of the current state of a pipeline. The use of artificial neural networks, in contrast to the classical methods of result processing, allows us to take into account not only simple linear laws, but, first of all, a complex nonlinear character of feedbacks in the data.

There are several types of neural networks: a single-layer perceptron, a neural network of a backward propagation, Hopfield's network, Kohonen's network, etc. However, one can not think of one single universal artificial neural network that would be suitable for different types of tasks.

In order to conduct comparative analysis and select the best network, different types of networks were tested on the same training set. The networks were evaluated according to the same criteria - the maximum percentage according to the number of coincidences of the winning neurons with the correct answer. In order to check all networks, the same sampling of values was presented, with 1000 values of waveforms. Among all neural networks we have considered, Kohonen's networks were preferred in the processing of experimental data due to the better effectiveness of a defect determination.

A specialized Neurotracer program was developed in the LabView 8.5 working environment. It implements the method for the technical condition of pipeline monitoring in order to analyze the acoustic signals by Kohonen's network. The result of the program is the output of information about the probability of a defect in the controlled section of a pipeline and its size on a monitor screen.

Depending on the accuracy of the problem being solved, and the details of a training sample, the program is able to produce the results of value classification more accurately, where the differences concerning the magnitude of a defect make several millimeters. This program performed a detailed classification of samples concerning defect-free and defective pipes, with the same defect spread over the surface of 50x50 mm, and with different depth of lesion: 2 mm, 3 mm, 5 mm [10,12,15].

In order teach a neural network to classify pipelines by the presence of specific types of defects properly, a correct training sample shall be determined. The networks were presented with detailed samples of amplitude-frequency characteristic values for the pipelines at 9 points of different defectiveness: the sample for a defect-free pipeline, the sample for the pipe with the defect of 50x50 mm and the depth of 2 mm, the sample for the pipe with the defect of 50x50 mm and the depth of 3 mm, the sample for the pipeline with the defect 50x50 mm and the depth of 5 mm. Each sample was specified by nine columns of values for each point on the pipeline. Each point has 1000 values of waveforms. All signals with the amplitude of less than 0.01 were assumed to be zero. The threshold value of the signal 0.01 is taken in connection with the existing error of the measuring system, since it is not advisable to consider the signals below this threshold. Table 1 shows the training sample of values for a defect-free pipeline as an example.

Table 1. Learning sample of values for a defect-free pipeline

Mode №	Numbers of points on a defect free pipeline								
	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0,04348	0	0	0
50	0	0	0,00775	0	0	0	0	0,01818	0
100	0,0031	0	0,0155	0	0	0,02174	0	0	0
150	0,0155	0	0,00775	0,10638	0,00287	0,01087	0,0111	0,01818	0,0196
200	0,3707	0,0181	0,21705	0,26596	0,16954	0,41304	1	0,03636	0
250	0	0,0272	0,0155	0,01064	0	0,01087	0,0222	0	1
300	0	0	0	0,01064	0,00287	0,01087	0,0222	0	0
350	0	0	0	0,02128	0	0	0	0	0,0065
400	0	0	0	0	0	0	0	0	0
450	0	0	0	0	0	0	0	0	0,0065
500	0	0	0	0	0	0	0	0	0
550	0	0	0	0	0	0	0	0	0
600	0	0	0	0	0	0	0	0	0
650	0	0	0	0	0	0	0	0	0

700	0	0	0	0	0	0	0	0	0,0065
750	0	0	0	0	0	0	0	0	0,0065
800	0	0	0	0	0	0	0	0	0
850	0	0	0	0	0	0,01087	0	0	0
900	0	0	0	0	0	0	0	0	0
950	0	0	0	0	0	0	0	0	0
1000	0	0	0,00775	0	0	0	0	0	0

In order to implement the clustering and the visual illustration of classification results by a network of samples, it needs to specify the boundary conditions for each type of defect. Table 2 shows the conditions for the occurrence of defects, where "net" means the absence of a defect and "da" means the presence of a defect. The averaged values for each type of defect are taken: v1 - for a defect-free pipeline, v12 - for a pipeline with the defect of 50x50 mm and the depth of thinning of 2 mm, v26 - for a pipeline with the defect of 50x50 mm and the depth of thinning of 3 mm, v30 - for a pipeline with the defect of 50x50 mm and the depth of thinning of 5 mm, with a signal value of 0.01 at least.

Table 2. Categorical input variables, characterized by belonging to classes

Mode №	Categorical input variables			
	Bezdef	Defect 2 mm	Defect 3 mm	Defect 5 mm
1	2	3	4	5
1	net	net	net	net
2	net	net	net	net
3	net	net	net	net
4	net	net	net	net
5	net	net	net	net
6	net	net	da	net
7	net	net	da	net
8	net	net	da	net
9	net	net	net	net
10	net	net	net	net

50	net	net	net	net
100	net	da	da	da
150	da	da	da	da
200	da	net	da	da
250	net	da	da	net
300	net	net	da	da
350	net	net	da	net
400	net	net	net	net
450	net	net	net	net
500	net	net	net	net
550	net	net	net	net
600	net	net	net	net
650	net	net	net	net
700	net	net	net	net
750	net	net	net	net
800	net	net	net	net
850	net	net	net	net
900	net	net	net	net
950	net	net	net	net
1000	net	da	net	net

Each type of defects has an individual index: for a defect-free one - "1", for a pipe with the defect of 50x50 mm and the depth of 2 mm - "2", for a pipe with the defect of 50x50 mm and the depth of 3 mm - "3", for a pipe with the defect of 50x50 mm and the depth of 5 mm - "5", the absence of belonging to any class - "0" (Table 3).

Table 3. Weighing of categorical output variable indices

Result	Formula	Index
Bezdef	(1)=(v1>=0,01)	1
Defect 2 mm	(2)=(v12>=0,01)	2
Defect 3 mm	(3)=(v26>=0,01)	3
Defect 5 mm	(5)=(v30>=0,01)	5

The network operates according to the following principle: "the winner takes everything". In accordance with Table 2 "da" characterizes the presence of a defective signal and a corresponding index, "net" characterizes the absence (Table 4).

Table 4. Indices of categorical input variable classification

Mode №	Identifiers of categorical input variables			
	Bezdef	Defect 2 mm	Defect 3 mm	Defect 5 mm
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	3	0
7	0	0	3	0
8	0	0	3	0
9	0	0	0	0
10	0	0	0	0
50	0	0	0	0
100	0	2	3	5
150	1	2	3	5
200	1	0	3	5
250	0	2	3	0
300	0	0	3	5
350	0	0	3	0
400	0	0	0	0
450	0	0	0	0
500	0	0	0	0
550	0	0	0	0
600	0	0	0	0
650	0	0	0	0
700	0	0	0	0

750	0	0	0	0
800	0	0	0	0
850	0	0	0	0
900	0	0	0	0
950	0	0	0	0
1000	0	2	0	0

3 RESULTS

If the network is trained properly trained, then it is capable to classify new and unknown samples. In order to test this possibility, the fragments of a control sample of values that are not included in the training sample of four samples of pipelines of different states were introduced into the program: 1) defect-free; 2) with the defect of 50x50 mm and the depth of 2 mm; 3) with the defect of 50x50 mm and the depth of 3 mm; 4) with the defect of 50x50 mm and the depth of 5 mm.

Each of the samples is a cluster. Thus, there are 4 clusters for classification. The belonging of a control sample to some cluster is determined by the frequencies of its winning when the values in a same mode coincide with a training sample. The process of a control sample classification was carried out in four epochs. An epoch is one iteration in the learning process, including the presentation of all the examples from a training set and the check of training quality using a control set. As an example Table 5 shows the classification results according to a control sample of 50x50 mm defect and the depth of 2 mm. The table illustrates the winning frequencies within a given control sample according to nine points for each of four samples.

Table 5. Classification results according to the control sample of 50x50 mm defect and the depth of 2 mm

Frequencies of winnings during the processing of sampling signals with the defect of 50x50 mm and the depth of 2 mm										
Defect free pipe	Epoch numbers	Number of points on a defect-free pipe								
		1	2	3	4	5	6	7	8	9
	1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	3	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	4	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
50x50 mm and the depth of 2 mm	Epoch numbers	Number of points on the pipe with the defect of 50x50 mm and the depth of 2 mm								
		1	2	3	4	5	6	7	8	9
	1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	752,000	0,00
	2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,000	0,00
	3	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,000	0,00
	4	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,000	0,00
50x50 mm and the depth of 3 mm	Epoch numbers	Number of points on the pipe with the defect of 50x50 mm and the depth of 3 mm								
		1	2	3	4	5	6	7	8	9
	1	0,00	0,000	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	2	0,00	247,000	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	3	0,00	0,000	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	4	0,00	0,000	0,00	0,00	0,00	0,00	0,00	0,00	0,00
50x50 mm and the depth of 5 mm	Epoch numbers	Number of points on the pipe with the defect of 50x50 mm and the depth of 5 mm								
		1	2	3	4	5	6	7	8	9
	1	0,00	0,00	0,00	0,00	1,000	0,00	0,00	0,00	0,00
	2	0,00	0,00	0,00	0,00	0,000	0,00	0,00	0,00	0,00
	3	0,00	0,00	0,00	0,00	0,000	0,00	0,00	0,00	0,00
	4	0,00	0,00	0,00	0,00	0,000	0,00	0,00	0,00	0,00

4 DISCUSSION

The following is observed from the classification results shown in Table 5: the frequency of the winnings makes 752 at the 1st epoch of the 8th point of the pipeline with the defect of 50x50 mm and the depth of 2 mm, 247 at the 2nd epoch of the pipeline 2nd point with the defect of 50x50 mm and the depth of 3 mm, 1 in the 1st epoch of the 5th point of the pipeline with the defect of 50x50 mm and the depth of 5 mm. The winning frequencies are zero ones for the rest samples.

1) Similar results were obtained for the remaining fragments of the control sample:

2) Concerning the control sample of a defect-free pipeline, the winning frequency makes 800 at the 2nd epoch for the 2nd point of a defect-free pipeline, 115 on the 4th epoch for the 2nd point of a defect-free pipeline, and 82 on the 2nd epoch for the 5th point of a defect-free pipeline. For the rest samples the winning frequencies are zero ones.

3) according to the control sample of the pipeline with the defect of 50x50 mm and the depth of 3 mm, the winning frequency makes 74 at the 1st epoch of the the pipeline 7th point with the defect of 50x50 mm and the depth of 3 mm, 312 on the 2nd epoch of the 8th point of the pipeline with the defect of 50x50 mm and the depth of 3 mm, 606 on the 4th epoch of the 9th point of the pipeline with the defect of 50x50 mm and the depth of 3 mm, 1 on the 3rd epoch of the pipeline 5th point with the defect of 50x50 mm and the depth of 5 mm. For the rest of the samples, the winning frequencies are zero ones.

According to the control sample of the pipeline with the defect of 50x50 mm and the depth of 5 mm, the frequency of the winnings makes 16 at the 1st epoch of the pipeline 3rd point with the defect of 50x50 mm and the depth of 5 mm, 171 at the 4th epoch of the pipeline 4th point with the defect of 50x50 mm and the depth of 5 mm, 702 on the 2nd epoch of the pipeline 6th point with the defect of 50x50 mm and the depth of 5 mm, 110 at the 2nd epoch of the pipeline 9th point with the defect of 50x50 mm and the depth of 5 mm, one on the 2nd epoch of the pipeline 4th point with the defect of 50x50 mm and the depth of 3 mm. For the remaining samples, the winning frequencies are zero ones [16].

5 CONCLUSIONS

The created Kohonen's neural network presented the following correctness percentage for the classification of control samples and the processing of received signal data array:

- Defect-free sampling - 100%
- The sampling of the pipeline with the defect of 50x50 mm and the depth of 2 mm - 67%
- The sampling of the pipeline with the defect of 50x50 mm and the depth of 3 mm - 99%

• The sampling of the pipeline with the defect of 50x50 mm and the depth of 5 mm - 99%.

6 . SUMMARY

The results of the classification by Kohonen's trained neural network show good ability for the analysis of unknown samples and a high degree of their recognition reliability.

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