ARCHIVES OF ACOUSTICS
31, 4, 521–528 (2006)

AN APPLICATION OF ACOUSTIC MEASUREMENTS TO QUALITY CONTROL OF LOW POWER ELECTRICAL MOTORS

M. GIBIEC

AGH University of Science and Technology
Department of Robotics and Mechatronics
Al. Mickiewicza 30, 30-059 Kraków, Poland
e-mail: mgi@uci.agh.edu.pl

(*received April 30, 2005; accepted October 25, 2005*)

In this article, an example of the application of acoustic measurements to condition assessment of electric machines is presented. Quality control of new components is considered in this case study. The first symptoms of unserviceability are disclose in the acoustic domain and then, in later exploitation, they develop into a form that is detectable during vibration measurements. The assessment is based on acoustical wave spectrum normalized with respect to rotational speed. An adequately prepared neural network of the Kohonen's type was used as assessing tool. Its performance was compared to results of the minimum distance method based on averaged spectrum patterns.

Key words: machine state assessment, acoustic signals, neural networks.

1. Introduction

Acoustical signals are less often used in diagnostics than vibration signals. This stems from the fact that they are more sensitive to external disturbances. However, their information capacity is comparable to that of vibration signals or even larger.

The easiness of energy transfer paths identification and elimination of undesirable external influences are considered to be the main advantage of vibration measurements. However in some applications it is not possible to place a sensor in the source of vibrations. Also in the case of standard components quality control, time required for the sensor assembly and disassembly seems to be too expensive. Due to the lack of above inconveniences, measurements of acoustical waves generated by machines seem to be a promising solution.

The realization of this solution is difficult, but the development of signal processing and analyzing methods makes it possible. Modeling of a real acoustical field (complex restricting surface shapes, unknown sound absorption ratios and propagation conditions) is particularly complicated when obtaining of a real time model is required [5]. Therefore the application of artificial intelligence methods – neural networks is proposed by the authors. These methods can be used even when the model structure remains unknown. It is important that these methods are able to approximate arbitrary nonlinear functions [1].

In this article, an example of the application of the proposed methods to the electric condition assessment of machines on the basis of acoustical signals analysis is presented. The case study considered a new components quality control. In such a case, the first symptoms of unserviceability disclose in the acoustical domain and then, in the later exploitation, they develop into a form detectable during vibration measurements. Therefore the authors concentrated on acoustical signals as carriers of the machine state information. Due to the structural (commutator) and functional (flow of sucked air) properties, the machines of interest generate acoustical signals in a broad frequency band, which additionally complicates the classification process.

2. Experiment description

During the experiment, digital measurements were carried out and the acoustical pressure accompanying the work of AC low power commutator electrical motors was recorded. For the sake of the motors utilitarian function, they are equipped with an integrated centrifugal fan that can be treated as an additional aerodynamical noise source with a continuous spectrum. The motors belonged to the same production series and were classified as faulty with a specified basic defect (vibrations caused by rotor, rotor clearance, faulty bearing, increased loudness). The measurements were carried out in an anechoic chamber of the Department Mechanics and Mechatronics at AGH, which allowed to eliminate the influence of external disturbances, reflections and resonances of the research room. Apart from the noise characteristics, the rectangular characteristic of the rotational frequency of the tested motor was also registered. The characteristic of the rotational frequency can be used for the purpose of the acoustical spectrum scaling and spectral synchronous analysis. Two series of tests were realized, one for a free and another one for a loaded run (flow chocking at the suction side). Since during the preliminary, auditory tests a distinct relationship between spectrum and the rotational velocity of same motors was stated, the registration was started after 30 seconds of run for stationary rotational velocities.

The research was carried out in the measurement stand shown in Fig. 1.

The motors under test were fixed in a specially shaped bearing made of a vibration-damping material. The bearing admitted also the sucked air. The measurement microphone G.R.A.S. with a pre-amplifier 6 AK was placed at a tripod in 0.5 [m] distance above the tested motor at the commutator side. The rotational velocity was measured using a digital optical waveguide switch E3X-DA-N (OMRON), which cooperated with an element fixed to the tested motor axis that reflected the light stream. A two-channelled DF-1 TEAC analyzer was used for the data registration. This analyzer cooperated with

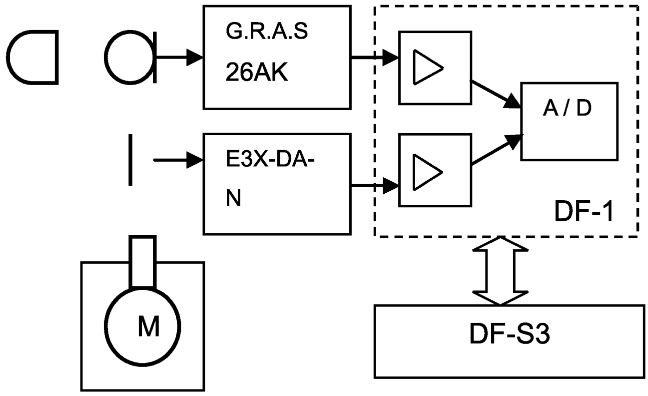

Fig. 1. Scheme of the measurement stand.

the DF-S3 TEAC software run at the PC computer that served as a superior control system registering the data flow [4].

During the experiment, the averaged signal power spectra were also registered for the purposes of preliminary assessment of the considered process. These spectra are complex: on the background of the continuous spectrum of a relatively high level, a certain number of harmonic components of the distribution characteristic for individual defects can be noticed.

3. Analysis of the data obtained

The acoustical pressure time series for all the tested machines are similar. The characteristic estimates have also similar values. Therefore it was decided to carry out the further data analysis in the frequency domain. In the spectral analysis, a window of size equal to the number of samples registered during 1 second was assumed. An example of the spectrum is shown in Fig. 2.

It was stated during the analysis that the tested machines have different working speeds. In order to create objective circumstances of the analysis, a spectrum normalisation was performed making use of the measured rotational velocities. It is also possible to determine the basic harmonic on the basis of the spectrum plot. The normalised spectrum contained components for multiples of a basic harmonic with the precision 1/100 of its value. An example of the spectra is presented in Fig. 3.

The spectra obtained are of big sizes – 16 385 elements, which complicates the creating symptom – state relations on the basis of the classical classification methods. Even in the case of specified spectral standards for certain machine defects, a currently analysed spectrum can be classified incorrectly. Such a situation results from the fact that a given spectrum differs from other standards only in a few points; in the case of such a long tested vector, the differences can be insignificant. Therefore a non-distant method of finding similarities between the tested spectra was proposed.

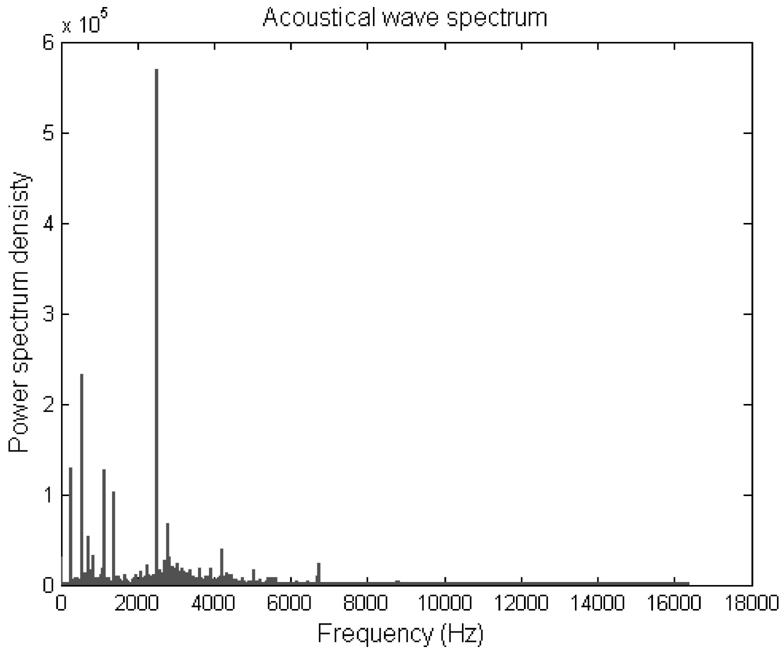

Fig. 2. Acoustical wave spectrum.

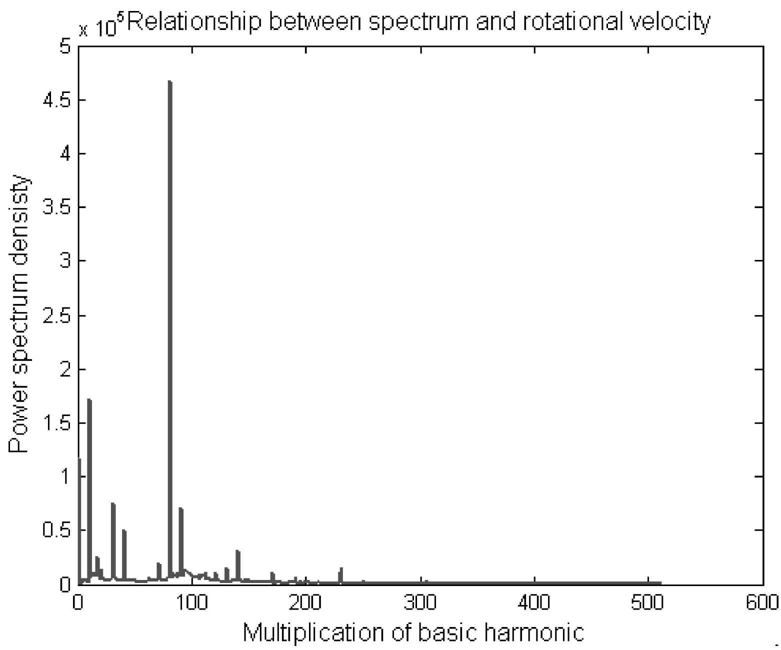

Fig. 3. Relationship between the spectrum and rotational velocity.

Since the state of the machine for which the acoustical pressure was measured is known, supervised neural networks can be applied. Those networks have the ability of mapping approximating by the use of provided examples. In such a case, a set of example spectrum – machine state pairs is accessible. The gradient methods used in the learning processes of such neural networks require large memory resources depending on the size of the input vector and the number of examples. In discussed case, this size exceeds the computer capacity. Therefore a reduction of the input vector size is necessary.

Unsupervised neural networks can also be used. Such networks are able to process vast amounts of input data. They can be used only when it is possible to normalize the input vector and specify the predicted number of data groups that can be distinguished. In consequence, 1 is returned at the output of one neuron and 0s at the outputs of the remaining neurons [3]. On the basis of the network response for the examples described above, it is identified for which neurons value 1 signifies a given machine state [2]. Taking into consideration the above assumptions, neural networks with 7 neurons (for 4 defected and normal states) were trained. Even though the learning process was carried out repeatedly, the obtained neural network was capable of recognizing 2 states only: free and loaded machine runs. This shows that in the spectrum there appear more elements characteristic for work conditions than for defects. For the purposes of the further analysis only measurements for a free run were considered.

The learning set containing 60 elements for the machine maximum velocity and 15 test elements was created. As the result of the learning process, a neural network with 10 neurons working properly was obtained. The number of neurons was gradually reduced in the repeated learning processes. At last a neural network with 5 neurons was obtained. This neural network generates correct responses for a learning set as well as for a testing set.

4. Results

During the learning process, weights of individual neurons form an input vector standard characteristic of a given machine state. In Fig. 4, there are presented standards identified by a neural network. For the purposes of comparison, in the next figure averaged spectra for different machine states are shown.

A comparison of the figures presented above shows that in this case the classification task is not trivial, because the obtained spectrum standards are different. Both the spectrum standards were used for the state assessment and components testing. As the result of neural network testing, a number of active neurons was obtained. For an averaged spectrum standard the number of standards which is closest to the tested spectrum vector was identified.

The testing set consists of 20 components – 4 for each machine state. The performance of the neural network is correct for all the 20 tested components, the averaged spectrum method generates sometimes false assessments – 15 correct assessments for 20

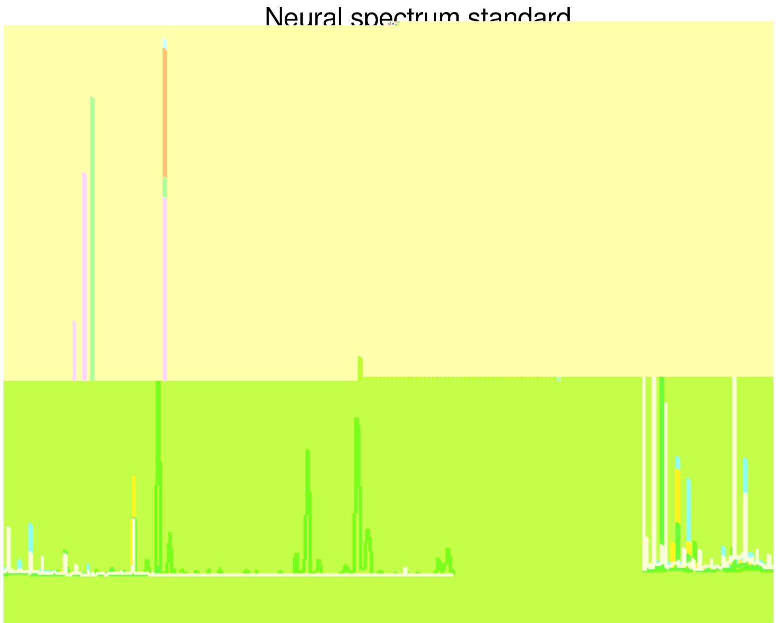

Fig. 4. Neural spectrum standard.

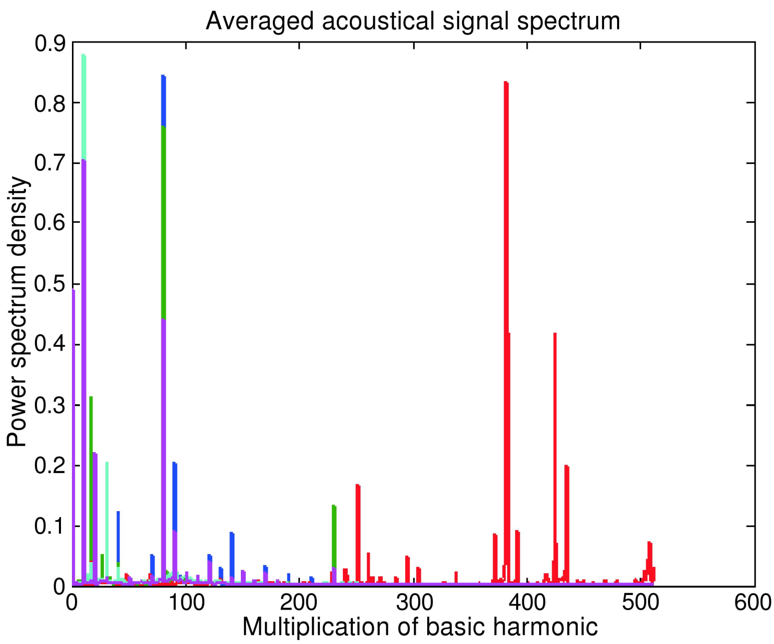

Fig. 5. Averaged acoustical signal spectrum.

tested components. The results are shown in Table 1. False assessments of the machine state are marked in bold.

Table 1.

	Assessment of machine state
Correct	1 4 5 3 2 1 4 5 3 2 1 4 5 3 2 1 4 5 3 2
Neural network	1 4 5 3 2 1 4 5 3 2 1 4 5 3 2 1 4 5 3 2
Averaged spectrum	1 4 **3** **4** 2 1 4 5 **4** 2 1 4 5 **4** 2 1 4 5 **4** 2

The spectrum normalization with respect to the rotational speed should enable a correct machine state assessment also in case of components working with speeds differing from the nominal ones. So the methods presented above were tested with a speed equal to 75% of the nominal speed. The same set of components as above one was used for testing. The neural network gives correct assessments for 15 tested components, the averaged spectrum method generates correct assessments 9 times for 20 the tested components. The results are shown in Table 2. False assessments of the machine states are marked in bold.

Table 2.

	Assessment of machine state
Correct	1 4 5 3 2 1 4 5 3 2 1 4 5 3 2 1 4 5 3 2
Neural network	1 4 **2** 3 2 1 4 5 3 **5** 1 4 **2** 3 **1** 1 4 5 3 **5**
Averaged spectrum	1 4 5 **1** **1** 1 4 **2** **4** **1** 1 **3** **2** **4** **1** 1 4 5 **1** **1**

The application of the averaged spectrum generates false state assessments. The neural network assesses correctly components of types 1, 3 and 4. It results from the neural network ability of generalization achieved in the learning process. One can also state that these types of components are easier to distinguish. Components of type 2 and 5 are assessed wrongly. The neural network performance can be improved by adding examples of the spectrum characteristic for components working with different speeds to the learning set. The next test concerned the quality assessment of components under the payload. Since in this case the spectrum of the measured acoustic signal is much different from those in the previous case, both methods gave false results.

5. Conclusions

In this article, an example of the condition assessment of electric machines is presented. The case study concerned new components of quality control. The acoustical wave spectrum is the basis of the assessment. Due to various parameters of the assessed machines, the spectra have to be normalized with respect to rotational speed. The large size of the spectrum amplitude vector makes the application of distance methods and supervised neural networks difficult. The adequately prepared neural network of Kohonen's type (unsupervised) correctly assesses the quality of new components on the production line. The assessment is made on the basis of the acoustical wave spectrum generated by the tested component without the payload working with a nominal speed. The neural network obtained works correctly for three out of five cases, for components working with speeds different from the nominal ones. In the case of components under payload, the neural network generates wrong assessments. It may result from the fact that the structure of analyzed spectrum differs from the spectrum obtained in the payload free mode. The results generated by the neural network described above proved to be better than those of the minimum distance method basing on the averaged spectrum standards.

References

[1] GIBIEC M., *Soft computing tools for machine diagnosing*, Journal of Theoretical and Applied Mechanics, **42**, 3, 483–501, 2004.

[2] GIBIEC M., DOSKOWSKI G., UHL T., *Kohonen neural networks utilisation to aid diagnostic process*, AI-METH, Gliwice 2002.

[3] KOHONEN T., *The self-organizing map*, Springer, Berlin Heidelberg 1995.

[4] TEAC DF-S3 user's manual. Teac Corp., Tokyo 2003

[5] ŻYSZKOWSKI Z., *Acoustic Measurement* [in Polish], WNT, Warszawa 1987.

[6] DUCH W., KORBICZ J., RUTKOWSKI L., TADEUSIEWICZ R., *Biocybernetyka i inżynieria biomedyczna 2000. Tom 6: Sieci neuronowe*, Akademicka Oficyna Wydawnicza EXIT, Warszawa 2000.

[7] IKONOMOPOULOS A., UHRIG R. E., TSOUKALAS T. H., *Use of neural networks to monitor power plants components*, Proc. of the 54th American Power Conference, Chicago, IL, April 1, 1992.

[8] KORBICZ J., UCIŃSKI A., OBUCHOWICZ D., *Sztuczne sieci neuronowe podstawy i zastosowania*, Akademicka Oficyna Wydawnicza, Warszawa 1994.

[9] MORZYŃSKI L., MAKAREWICZ G., *System aktywnej redukcji hałasu z zastosowaniem sztucznych sieci neuronowych*, Materiały V Szkoły Metody Aktywne Redukcji Drgań i Hałasu, pp. 219–224, 2001.

[10] SORSA T., KOIVO H. N., KOIVISTO H., *Neural networks in process fault diagnosis*, IEEE Trans. Systems, Man and Cybernetics, v. SMC-21, 4, 1991.

[11] TADEUSIEWICZ R., *Sieci neuronowe*, Akademicka Oficyna Wydawnicza, Warszawa 1993.