APPLICATION OF NEURAL NETWORK TECHNOLOGIES FOR DIAGNOSTICS OF THE TECHNICAL STATE OF POWER PLANT TURBO GENERATORS BASED ON SPECTROGRAMS OF THE VIBRATION MEASUREMENTS

Vladimir Arbuzov[1], Valery Ivchenko[1], Ekaterina Matiukhina[1], Sergey Pavelyev[1] and Andrey Ostroukh[2]
[1]Moscow Technological University (MIREA), Moscow, Russian Federation
[2]Moscow Automobile and Road State Technical University (MADI), Moscow, Russian Federation
E-Mail: ostroukh@mail.ru

ABSTRACT

This article discusses the use of neural network technology in diagnosing problems of the technical state of turbo generators for power stations spectrograms vibration measurements. Two tasks were solved: filtering noise in the measurement data using a linear neural network and diagnosing (classification) the technical state of turbo generators based on the analysis of spectrograms of vibration measurements using a perceptron type neural network.

Keywords: safety, intelligent technologies, monitoring, vibration analysis, spectrograms, neural networks, neural network classifier, turbo generators, steam and gas turbines, thermal power plant.

1. INTRODUCTION

At present a large number of steam and gas turbine units are in operation in Russia [1, 2]. Basically these are turbogenerators of steam power equipment for various power schemes as well as turbogenerators of combined-cycle power units. In modern conditions turbo generators often operate at the limiting modes, and their operation requires a special attitude to control the operating modes and diagnose the technical condition of the machine. Turbine generators are of large longitudinal size, considerable complexity of construction, and the defect has been arisen in one of the structural elements causing the increased vibration level of a direct impact on the other elements of turbogenerators associated with. In connection with it, recently a special interest is comprised in the creation of monitoring and vibration diagnostics systems that not only provide for the detection of increased vibration of the machine, but also based on the results of the analysis of vibration measurement data allowing to identify the causes of such vibroactivity, as well as to formulate technical solutions and recommendations on its elimination.

The monitoring of the technical condition of the turbine unit means observing the process of changing its operability in order to alert personnel about the achievement of the limit state which makes it possible to transfer most failures from the category of sudden personnel to the gradual category due to early detection and timely warning [3 - 6]. Monitoring of machines with the help of such systems is carried out in real time and is necessary for continuous observing the vibration state of the machine, in particular for the level of vibration of its main nodes and elements [19, 20]. Diagnostics of defects is fulfilled on the basis of pre-formed experimental databases and generalized knowledge bases that match the increased level of vibroactivity with the causes that drive it. Various defects of the active parts of the turbogenerators arising during operation require an emergency stop of the generator, which is an extremely undesirable event for the plant. To prevent these events, it is advisable to use a monitoring system for the technical condition of the turbogenerators, which can perform early diagnostics of these violations. Artificial neural networks can serve as an effective tool for solving the problem of early diagnosis (classification) of technical condition of turbo-generators.

2. THE TASK OF NOISE FILTERING

First, we are to consider the problem of the application of artificial neural networks for solving the low-frequency filtering problem. Simulation of the operation of neural networks was carried out in the environment of the mathematical software SciLab [7].

We are to investigate the applicability for this purpose of a single-layer dynamic neural network with input delay lines containing one neuron obtaining a linear activation function (Figure-1). It should be noted that the neural network and the non-recursive digital filter are described by the same equation [8]. The only difference is in the methods of finding the coefficients of the digital filter equation - the weights of the neural network.

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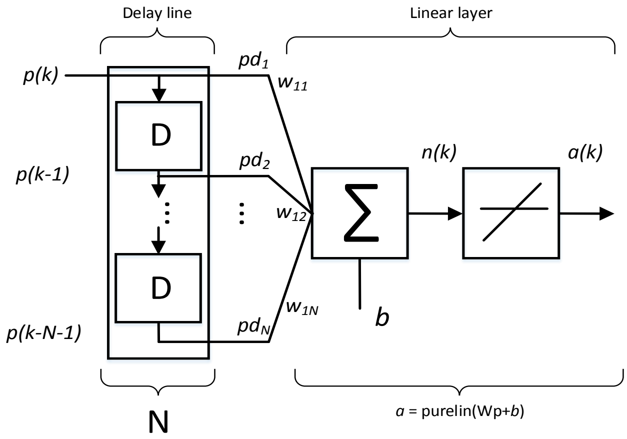

Figure-1. Low-pass filter based on an artificial neural network.

A neural network was synthesized with a number of delay elements equal to 20. As a training set of input signals, one discrete sequence of length N = 500 was used, comprising a useful signal - pseudo-white noise in a limited frequency range from the meaning of 0 to 100 hertz, on which a high-frequency interference was additively imposed. The useful signal was obtained by means of a Fourier series whose coefficients were chosen randomly in accordance with the normal distribution law.

Figure-2 shows two curves - a useful signal and a useful signal distorted by high-frequency interference.

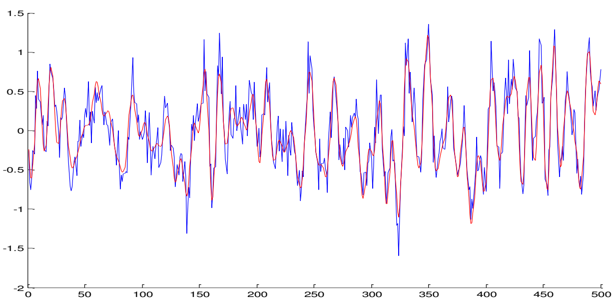

Figure-2. Example of a useful signal and a useful signal distorted by high-frequency interference.

Further, the neural network was trained, and a useful signal and a high-frequency noise were applied to the input of the network. As a reference signal, a useful signal was taken. The quality of the network was tested by feeding a polynomial signal distorted by high-frequency noise to the input of the network. Figure-3 shows a useful polynomial and noisy signals.

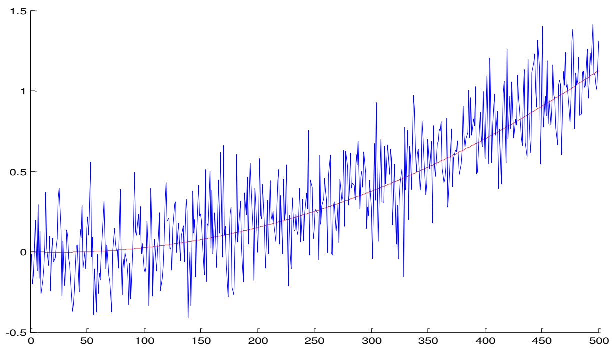

Figure-3. Useful and noisy signals used in testing the digital filter.

Figure-4 shows the results of a digital filter implemented using a neural network. This figure shows two curves:

- distorted useful signal arriving at the input of the network;
- signal at its output.

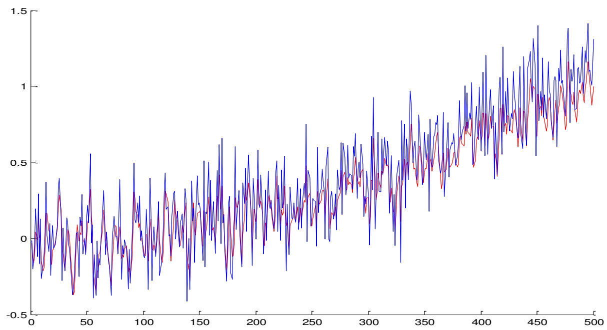

Figure-4. The output of digital filter.

To evaluate the quality of the filter, an error was calculated in accordance with expression

$$e = \frac{\sum_{n=1}^{N}(x(nT) - z(nT))^2}{\sum_{n=1}^{N} x^2(nT)}. \quad (1)$$

It should be noted that if the error at the filter input was 17.2%, then at its output the error decreased to 7.5%.

Simulation of the network was also carried out in the environment of the "MVTU" package [9]. A sinusoidal signal was injected into the input of the network. The output signal of the network is shown in Figure-5.

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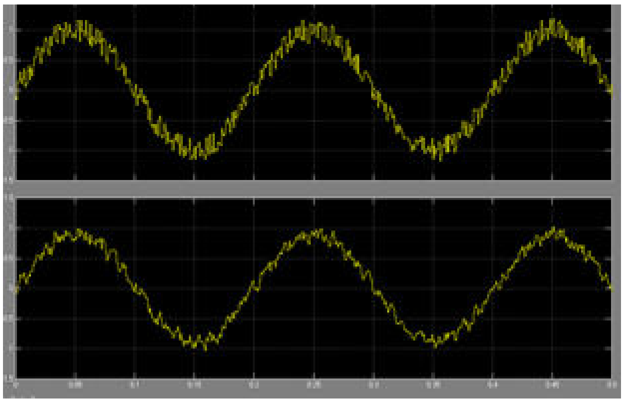

Figure-5. Simulated signal before and after filtering.

It can be seen from the figure that the filter reproduces the useful component of the input signal well, while the noise component of the output signal at the output of the filter has decreased. Calculations have shown that the error has decreased 2.65 times.

3. THE TASK OF TECHNICAL CONDITION DIAGNOSTICS

The digital sequences of vibrating signals were obtained experimentally from a steam turbo generator in a fault-free and three faulty state. For each of these sequences a discrete Fourier transform was applied, as a result of which spectrograms (values of the spectral coefficients at certain frequencies) were obtained and according to which the technical state of the turbine set was classified [10 - 15].

Figures 6, 7, 8 show the spectrograms that are typical of the steam turbo-generator with various defects.

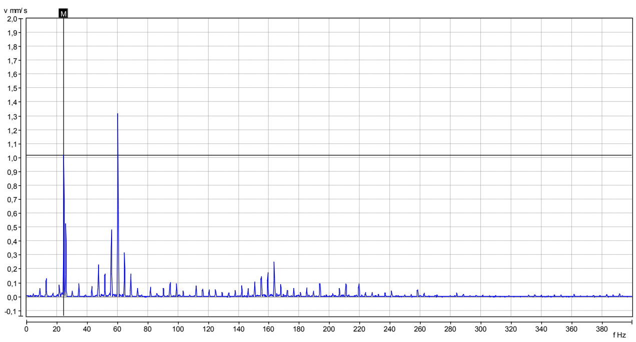

Figure-6. Rotor beating.

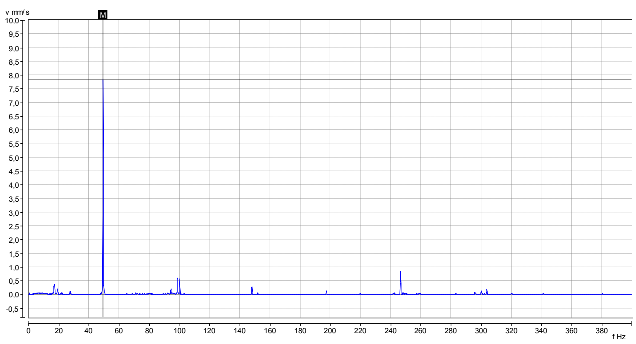

Figure-7. Rotor imbalance.

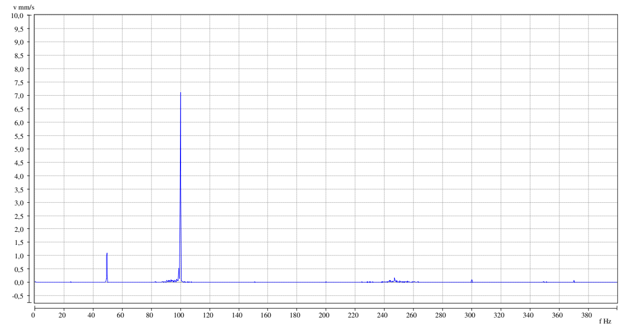

Figure-8. Alignment

It should be noted that for the spectral components of the serviceable turbogenerators amplitude should not exceed unity over the entire frequency range.

Now consider the actual solution of the problem of diagnostics (classification) using a perceptron type neural network. The initial information for the synthesis of the neural network was the spectrograms of the vibrational measurements of serviceable and faulty turbogenerators. To simplify the problem and make it more clear the entire spectral range of each spectrogram was divided into three sections. The first section included frequencies from meaning of 0 to 40 Hz, the second section - from 40 to 80 Hz, the third - over 80 Hz. At each of the sections examined the maximum values of the amplitudes were chosen. Thus, each technical state of a turbo-generator of the 4s available can be characterized by a 3-dimensional vector of spectral coefficients.

The perceptron consists of many elements, which are a single network of a certain configuration [16]. The simplest scheme of a perceptron having one layer consisting of one neuron is to represent in the following form (Figure-9).

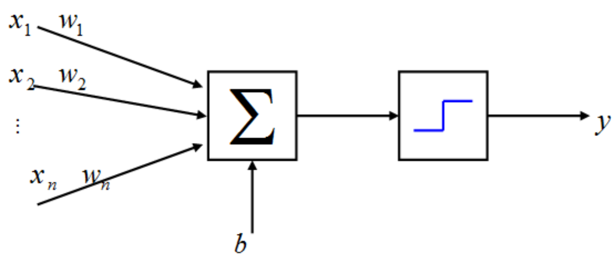

Figure-9. The scheme of the simplest perceptron.

In the figure, X is the vector of input signals, each element of which goes to the adder with weights, b - displacement. The signal of the output of the adder is:

$$S = W' \cdot x + b, \tag{2}$$

where W' is the transposed vector of weights.

Then:

$$S = w_1 \cdot x_1 + w_2 \cdot x_2 + ... + w_n \cdot x_n + b. \tag{3}$$

Then the signal goes to the input of the element with the activation function shown in Figure-10.

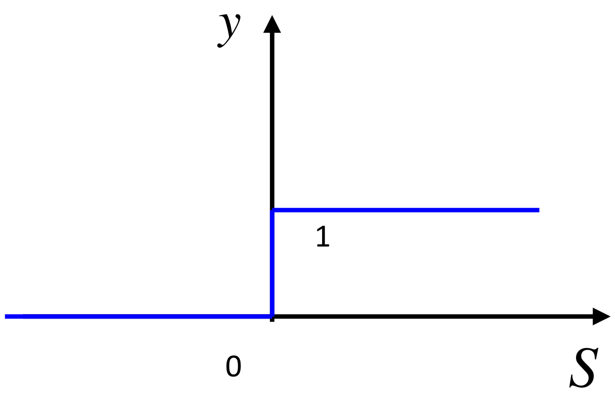

Figure-10. Perceptron neuron activation function.

The signal y at the output of the perceptron can take only two values 0 and 1.

$$y = \begin{cases} 1, & if \quad S \geq 0; \\ 0, & if \quad S < 0. \end{cases} \tag{4}$$

Activation function of this type makes it possible perceptron to classify input vectors dividing the space into two inputs area.

Consider the case of two-dimensional input signals:

$$X = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \tag{5}$$

Assuming $w_1 = 2$, $w_2 = -1$ and $b = 0.5$, we are to find a boundary that provide dividing the input vectors into two classes (Figure-11).

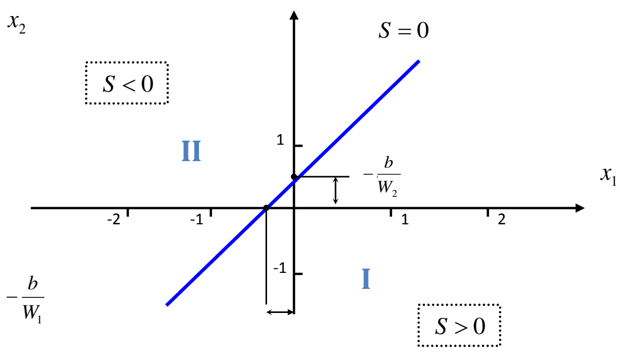

Figure-11. Example of the space of two-dimensional input signals.

The boundary equation has the form:

$$w_1 \cdot x_1 + w_2 \cdot x_2 + b = 0 \tag{6}$$

Or

$$2 \cdot x_1 - x_2 + 0{,}5 = 0 \tag{7}$$

The straight line *S* divides the plane of the input signals into two half-planes I and II, where, respectively $S > 0$ and $S < 0$.

If the input vectors are arranged in the half plane x_1, then the signals at the output of the perceptron will be equal to 0.

For input vectors located in the half-II output signals at the output of the perceptron is equal to 1.

If the offset $b = 0$, then the border passes through the origin. In general, the perceptron provide to classify the input signals belonging to the n-dimensional space (hyperspace) over a number of classes.

Consider a perceptron model in which it has a single layer consisting of m neurons, the input of each of which is fed an n-dimensional vector of input signals x. The vector signal at the outputs of the adders is:

$$S = W \cdot x + B, \tag{8}$$

where *W* is the matrix of weights, *B* is the displacement vector.

The perceptron allows us to divide the n-dimensional hyperspace of the input signals by hyperplanes into at most regions, where m is the number of perceptron outputs.

To solve the problem of recognition (classification) of the technical state of a steam turbo generator a single-layer neural network with two neurons was synthesized. To train the network at its entrance three vectors were assigned, all of them are belonging to one of the four technical conditions of the turbo-aggregate. A two-digit binary number has been assigned to each technical state. For example, the working state corresponded to number of 01, faults of the self-oscillation type in the bearing - 10, etc. With the help of such two-digit binary numbers, the target vector was formed.

Perceptron has been trained. The training vectors and dividing planes are shown in Figure-12.

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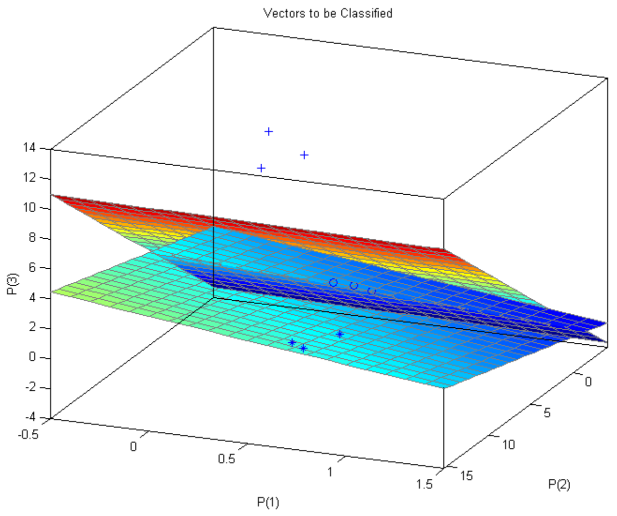

Figure-12. Training vectors and separating plane formed.

To optimize the structure of the neural network that used to solve the classification problem various combinations of network parameters were considered - the number of neurons in the hidden layer, the number of layers and the type of neuron activation functions.

To estimate the number of neurons in a hidden layer one can use the empirical formula for determining the synaptic weights in a multilayer network [17]:

$$\frac{mN}{1+\log_2 N} \le L_w \le m(\frac{N}{m}+1)(n+m+1)+m, \quad (9)$$

where

n - dimension of input signal;

m - dimension (meaning) of output signal;

N - a number of elements in the training sample.

Having estimated the necessary number of weights, they calculate the number of neurons in the hidden layer. For a network with one hidden layer the number of neurons is [18]:

$$L = \frac{L_w}{n+m}. \quad (10)$$

Several activation functions of neurons have been tested for multilayer neural network:

1) $f_{Ai}^{(k)} = e^{-\frac{S_i^{(k)2}}{2}}$;

2) $f_{Ai}^{(k)} = \frac{1}{1+e^{-S_i^{(k)}}}$;

3) $f_{Ai}^{(k)} = \frac{e^{S_i^{(k)}} - e^{-S_i^{(k)}}}{e^{S_i^{(k)}} + e^{-S_i^{(k)}}}$;

4) $f_{Ai}^{(k)} = \frac{th\left(S_i^{(k)}\right)+1}{2}$

5) $f_{Ai}^{(k)} = \ln\left(S_i^{(k)} + \sqrt{S_i^{(k)}+1}\right)$.

The quality of training graphs for a two-layer neural network with different types of activation functions (1-5) are shown in Figure-13.

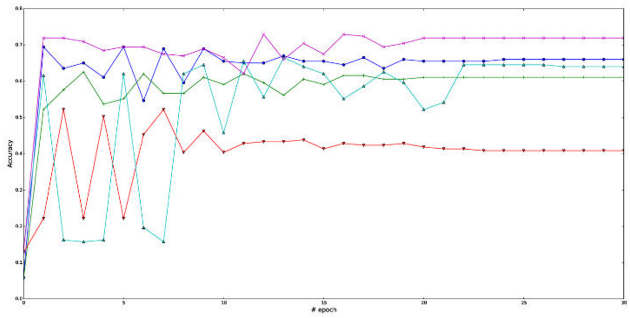

Figure-13. The average relative error whilst using different activation functions in the neural network.

The next step was to test the accuracy of the classification based on the number of layers of the neural network using the activation the function providing the highest quality of training (Figure-14).

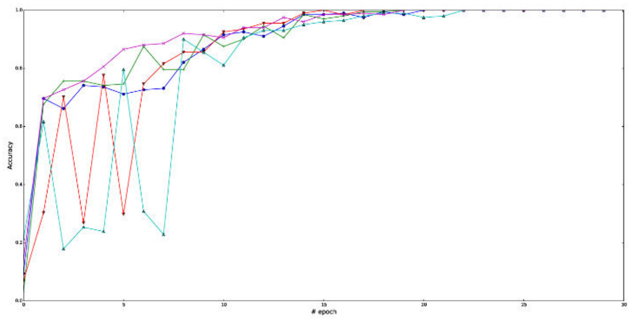

Figure-14. The average relative error whilst using different numbers of layers in a neural network.

Based on the simulation results the three-layer neural network of the perceptron type was the most suitable for solving the problem of classification of faults of turbogenerators. The training of networks with larger number of layers did not give a significant advantage in the accuracy of the classification. As a method of training, the method of back propagation of the error was used, and which in its standard implementation allows training of neural networks with two and three deep layers to solve the problem of spectrogram analysis, but it has a slow convergence. Therefore, modifications were applied: the random change in weights during training; the increase in the initial values of the weight coefficients; the values of the inputs and outputs of the sample were scaled to the interval [0...1] which also increased the accuracy of the classification. Preliminary training of a single-layer perceptron and the use of its weight coefficients as a first layer for a two-layer and three-layer networks were carried out. Such methods allowed obtaining high reliability of classification - more than 0.9.

Thus, with the help of a perceptron the problem of classification - the determination of the technical state of a steam turbo generator according to spectrograms of vibration measurements - was solved.

4. CONCLUSIONS

The possibility of efficient solution of noise filtering problems in measurement data and diagnostics (classification) of technical condition of turbogenerators is shown on the basis of analysis of spectrograms of vibration measurements with the help of artificial neural networks.

Thus artificial neural networks can be used to construct vibration monitoring systems for turbo-generators of thermal power plants that solve the problems of classification of turbine units on the basis of analysis of spectrograms of vibration measurements carried out by sensors located on aggregates.

The use of artificial neural networks will facilitate early detection of pre-emergency signs in comparison with standard threshold monitoring methods which are to allow timely notification of personnel about their appearance, as well as the type of possible malfunctions.

The further development of the proposed approach is the use of two neural networks as part of the monitoring system: the first network determines the presence of defects in the measuring channel (rotor imbalances, weakening of the support nodes, damage to the babbit of the inserts, increased rotor- bearing clearance, and etc.), and if such defect is detected, the second network is launched and can issue an opinion on the status of the monitoring object: "Norm", "Norm with significant deviations", "Aggravated state", "Pre-crash state", "Accident".

5. ACKNOWLEDGEMENTS

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