

The possibility of artificial neural network application in prototyping in instrument making industry

Galina A. Ovseenko¹, Rustem S. Kashaev², Irina A. Koshkina³

^{1,2} Kazan State Power Engineering University
^{1,2} Kazan, Russian Federation

³ Kazan Federal University - Naberezhnye Chelny Institute
³ Naberezhnye Chelny, Russian Federation

¹galinka.ovseenko@mail.ru, ²kashaev2007@yandex.ru,
³irene_2000@mail.ru

Valera V. Kosulin⁴, Gulia A. Khamatgaleeva⁵, Ruslan A. Ulengov⁶

⁴ Kazan State Power Engineering University

⁵ Kazan Cooperative Institute (branch) of the Russian University of Cooperation

⁶ Kazan Federal University

^{4,5,6} Kazan, Russian Federation

⁴valerakosulin@rambler.ru, ⁵khamatgaleeva@mail.ru,
⁶Ruslan.Ulengov@kpfu.ru

Abstract— The article explores the direction of using artificial neural networks to solve problems of classification of defects in the details of the instrument-making industry on the example of cellular panels. An algorithm for constructing and operating principle of a defect classification system based on a multilayer perceptron is described. Studies of the developed system are presented, in the classification of which experimental data obtained during the control of samples of cellular panels by the low-speed impact method were used. The developed neural network made it possible to perform nonlinear separation and classification of objects according to a set of diagnostic features, to identify a complex relationship between the degree of damage to the control object and the values of informative parameters. The disadvantages of the system in training a neural network are shown, which can be attributed to the need to train a multilayer perceptron to the existence of a training sample containing information about possible defects.

Keywords— neural network, honeycomb panels, defect classification system

I. INTRODUCTION

A new applied field of mathematics specializing in artificial neural networks (ANN) has been rapidly developing in recent decades. The relevance of research in this direction is confirmed by a variety of applications of ANN. The transfer functions of all neurons in the artificial neural network are fixed. Weights of an artificial neural networks are its parameters and can change. The work of an artificial neural network consists of converting an input vector into an output vector. This transformation is set by the weights of the neural network.

The neural network is trained by changing the weight. When teaching without a teacher, the training set consists only of input vectors. The training algorithm adjusts the weights of the network so that consistent output vectors are obtained, that is, that the presentation of sufficiently close input vectors gives the same outputs. The learning process, therefore, highlights the statistical properties of the training set and group's similar vectors into classes. Presenting an input vector from this class will give a certain output vector, but before training, it is impossible to predict which output this class of input vectors would produce. This means that the outputs of such a network should be transformed into some understandable form due to the learning process.

The relevance of the research is in the neural networks application prospects for non-destructive testing and

classification of defects. These are automation of pattern recognition processes, adaptive control, approximation, forecasting, creation of expert systems, and many other applications [1-3].

The problem of image resolution enhancement, known as Super Resolution, is the main topic of study in the field of computer vision [4]. Super-Resolution is a method of restoring a high-resolution image from one or more low-resolution images of the same scene with the restoration of details. With the increase in computing power and the development of neural networks, the Super-Resolution problem was solved using neural networks, and they show good results on average for random images. The wide range of tasks solved by ANNs does not currently allow creating universal powerful networks, forcing the development of specialized ANNs, functioning according to different algorithms. ANN models can be of software and hardware design. In the future, we will consider the programmatic use of neural networks. The most appropriate is the use of artificial neural networks in the tasks of technological preparation of instrument manufacturing in order to predict and simulate parameters, classification, grouping and pattern recognition, etc. [5-11].

The neural network approach is successfully used for linear and complex nonlinear dependencies and is especially effective in exploratory data analysis when it is necessary to find out whether there are dependencies between these variables.

II. CLASSIFICATION OF A NEURAL NETWORK

To build a neural network classifier of defects in various details of the instrument industry, the neural network «Multilayer perceptron» was selected [1].

As is known that with three or more layers in a Perceptron, the solution area can consist of non-contiguous area bounded by a hyperplane. Multilayer Perceptrons make it possible to build complex separating surfaces and therefore have wide application for solving classification problems.

This model of an artificial neural network is easily implemented using modern software and hardware. So, with the help of a multilayer Perceptron it is possible to solve problems of any complexity. To build a system for classifying defects in cellular panels, a three-layer Perceptron with different numbers of neurons in the hidden layers and in the source layer was implemented. The neurons of each layer are connected to the neurons of the previous and subsequent layers

according to the «each to each» principle. The number of neurons in the output layer depends on the number of classes, and the number of neurons is selected based on the complexity of hyperplanes surfaces that separate diagnostic features describing areas with different degrees of defectiveness in the hidden layers. Each layer performs a nonlinear transformation from a linear combination of output signals of the previous layer.

Approximation is achieved by alternately calculating linear combinations and nonlinear transformations of an arbitrary multidimensional function with an appropriate choice of network parameters. Hundreds of software products have been created with different possibilities, different scope of application and accordingly - the cost of the license.

1) The Neural package Neural 10, which is developed by Southern Scientific CC, South Africa, has rather limited capabilities, implements only one neural network paradigm - a two-layer neural network of direct propagation.

2) NeuroPro package, has the ability to set the number of up to 10 layers and the number of neurons in a layer - up to 100. But neurons can only be with a non-linear sigmoidal activation function, the steepness of which can be set for each layer separately, it is possible to set the training accuracy. For training we can use one of the following methods: gradient descent, modified ParTan method, conjugate gradient method.

3) Only one type of neural network is realized in the package QwikNet 32 - a multilayer network of forward propagation with the number of hidden layers (up to 5) and the possibility to choose one of 6 algorithms of training (modification of the method of backward propagation).

4) The program shell NeuralPlaner allows to model neural networks of different configuration. It implements the work in a local network.

5) The package BrainMaker is intended for modeling of multilayer neural networks with the back propagation learning algorithm. The package is focused on a wide range of tasks - from solving prediction problems, to pattern recognition systems. The program processes the input data of a neural network, outputs its training statistics and runs. The program has a large number of control functions to optimize the learning process.

6) Statistica Neural Network software is a universal neural network analysis package created by StatSoft. Many types of neural networks are implemented in the package, it is possible to create complex combinations from networks of various architectures.

7) MatLab software package contains a lot of possibilities, concerning the creation and usage of artificial neural network algorithms. These are Neural Network Toolbox and Simulink packages, working with the help of MatLab package internal data description speech. The package allows you to solve a wide variety of problems and build complex systems.

8) Neuro Solutions package is a Neuro Dimension Neuro Solutions image-based package provides the most powerful and flexible environment for building artificial neural networks. The intuitiveness of the package has advantages over other software products, its interface makes it fast and easy to build and teach a neural network to solve any complex problem. The package has a powerful graphical, user-friendly, interface.

III. PROBLEM FORMULATION

Automatic control objects, control and automation tools are dynamic parts of closed automatic control systems. Transients in such systems are determined by the dynamic properties of their components. The process of determining a mathematical model of an object that reflects the basic dynamic properties of elements or the entire system as a whole is called the identification of an object by its mathematical model or, more simply, the identification of an object. When identifying by experimental analysis methods, a mathematical model of a stable object is usually found by measuring its input and output values.

In dynamic systems, the object to be recognized depends on the instantaneous values of the training pairs, which are a function of time. If we take x as the state vector $x \in R_n$, u as the input vector $u \in R_N$, and y as the output vector $y \in R_M$, then the general description of a nonlinear system functioning in discrete time can be represented as

$$x(k+1)=f[x(k),u(k)] \quad (1)$$

$$y(k)=F[x(k)] \quad (2)$$

where $x(k)$, $u(k)$, $y(k)$ denote the vectors of the instantaneous values of the corresponding variables, f и F signs of vector statistical nonlinear functions, $f \in R_n, F \in R_M$.

$$\|y^*-y\| \leq e \quad (3)$$

Among the many possible approaches to the implementation of such a nonlinear system, we choose a method based on the use of a neural sigmoidal network, in general, a multilayer one. If we restrict ourselves to one input and output, and also imagine the excitation vectors u and the response of the object y consisting of delay elements, that is $u(k) = [u(k), u(k-1), \dots, u(k-p)]^T$, $y(k) = [y(k), y(k-1), \dots, y(k-q)]^T$, then the general description of a nonlinear dynamic model can be expressed without a state vector x in the form

$$y^*(k+1)=fun(y(k), u(k)) \quad (4)$$

In this equation, $y(k+1)$ denotes the response of a nonlinear object at time $k+1$, and $y^*(k+1)$ is the response of the neural model of this object at the same time. The difference signal $e(k+1) = y(k+1) - y^*(k+1)$ controls the process of adapting the model parameters. A number of delay elements at the system input form a delay line with branches. Identification can be carried out using programming languages or using specialized packages that allow you to work with neural networks (NeuroSolution, MatLab).

Thus, the problem of identifying an object is reduced to constructing such a parametric model of it that the responses of the object $y(k)$ and models $y^*(k)$ for the same excitation, $u(k)$ coincided within the permissible error. Taking into account the analysis carried out, we believe that to solve various technological problems it is advisable to use the MatLab package and the NeuroSolutions system. Unfortunately, neural networks are practically not used in instrumentation in the prototyping, when analyzing 3D models and improving the transformation of their shape into control commands for CNC equipment (3D printers). Therefore, it is proposed to create a system that analyzes a 3D model and breaks it down into structural units (for a part of the «shaft» type its degrees will be conditional units) on the basis of the

artificial neural network methodology. Later the system performs calculations of the model for strength and offers to change its structure and percentage of filling for the problem places of the part.

The development of the software for the classification system of the state of control objects was carried out in the NI LabVIEW 2009 software package. Using this programming environment allowed to develop a multifunctional control system for composite materials. A large set of built-in mathematical transformations, easy to connect external components, a set of tools to create a graphical user interface allowed you to quickly get a multifunctional software product. Availability of the C / C ++ programming language interpreter, high level of integration with MatLAB mathematical programming language, the possibility to work with dynamic dll libraries allowed to use the existing program modules and blocks with maximum efficiency, while excluding the labor-intensive process of their translation into a single language platform.

The algorithm of the system is made on the example of the manufacture of the «shaft» part and consists of the following stages:

1. transferring the 3D model of the shaft to the input of the neural network;
2. partitioning the part into component parts (stages) that make up the «shaft»;
3. calculation of weak points and stiffnesses at standard parameters;
4. changing the grid type and percentage of filling for weak spots or one of the component parts of the part;
5. Calculation of weak points and stiffnesses after making changes to the internal structure;
6. checking the condition - the stiffness of the part on the whole length must be the same, if this condition is fulfilled or the parameters are close to fulfilling the condition, then proceed to the next step, otherwise return to step 4,
7. Forming G code for the 3D printer;
8. comparing the previous form of the part with the current one. If no changes in the form are found, we proceed to the next step, otherwise we display an error and return to step 2;
9. saving the obtained results.

IV. RESULTS

To study the developed classification system, we used the experimental data, obtained during the control of samples of honeycomb panels by the method of low-speed impact [3].

The low-speed impact method is based on measuring the parameters of impact on the controlled object. The impact force pulse, which is characterized by the amplitude, duration and shape appears on the controlled object. The sample that was examined had five characteristic zones - without defect and four zones with different degrees of damage. The developed system was tested using two diagnostic features: amplitude and duration of the information signal pulse obtained by the low-speed impact method. Changing the indicated parameters makes it possible to determine the presence of a cellular panel defect and to classify its type according to the degree of damage.

Thus, the use of other parameters in solving these problems is optional, which simplifies the architecture of the developed neural network, increases the speed of the system and reduces the hardware costs. Several multilayer Perseptron architectures with different numbers of neurons on the first and second hidden layers were experimentally investigated. The control veracity of multilayer Perseptron for the classification of defective sections of different types ranges from 96 to 98%, the veracity of defect-free section detection is 100%. So this type of neural network can accurately identify whether the object of control is suitable for further operation or not. Also it should be noted that the veracity of non-destructive testing results using multilayer Perseptron with more than 60 neurons in the hidden layers does not significant increase the veracity index, but significant reduces the system performance and increases the need for additional computer resources, so their use to solve the tasks is not expedient. Fig. Figure 3 - 5 shows the distribution of diagnostic features in the plane of pulse oscillation amplitude from defective and non-defective areas of the cellular panel sample under study. The letter «a» denotes the selected area of diagnostic features, typical for a particular class, the letter «b» - the area of diagnostic features not related to this class (typical for other classes). Fig. 1-5 shows the distribution of diagnostic attributes in the amplitude-length pulse plane from defective and non-defective areas of the cellular panel sample under study.

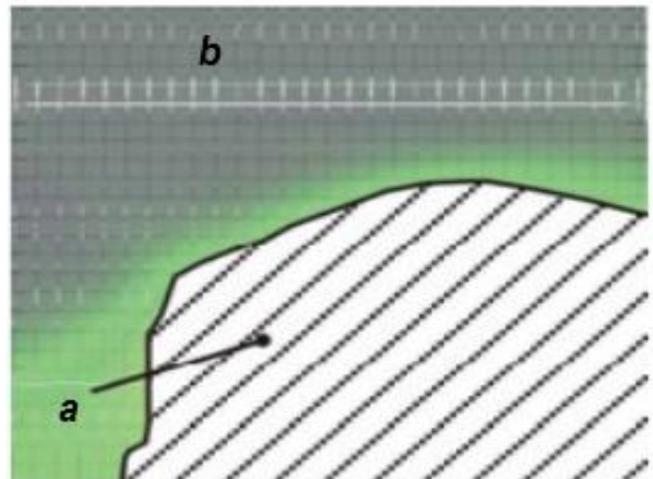


Fig. 1. Distribution of diagnostic features characteristic of the defect-free area.

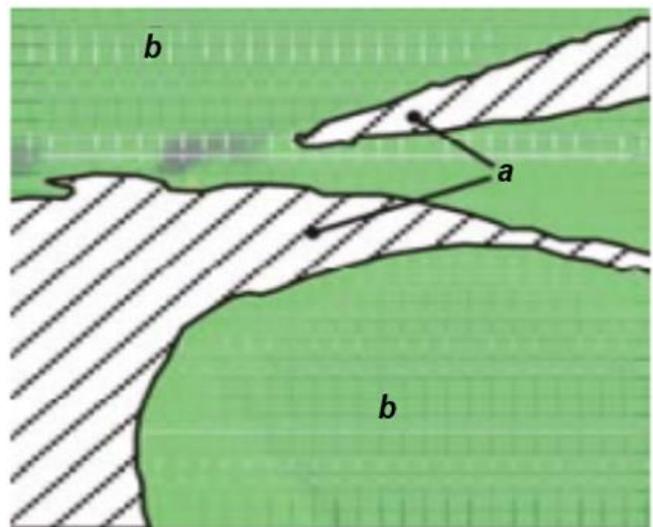


Fig. 2. Distribution of diagnostic signs, typical for the defective section of type 1.

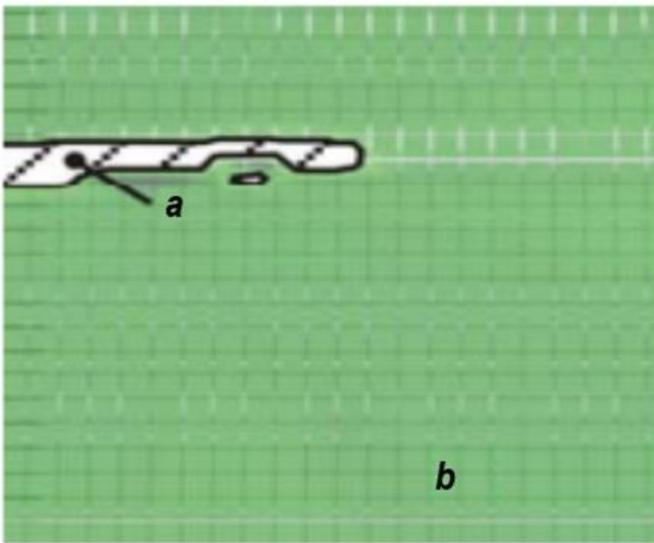


Fig. 3. Distribution of diagnostic features characteristic of the defective section of type 2.

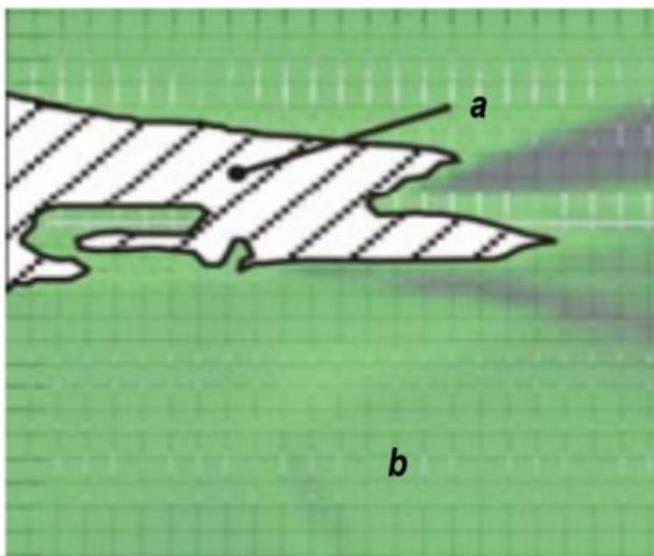


Fig. 4. Distribution of diagnostic features characteristic of the defective section of type 3.

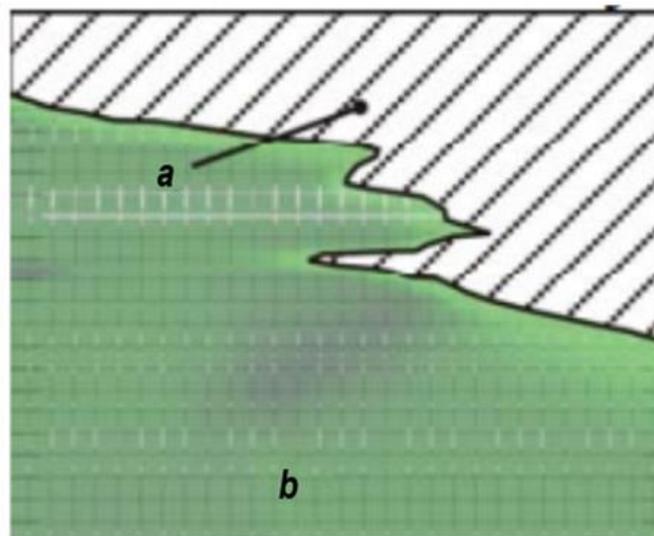


Fig. 5. Distribution of diagnostic signs, typical for the defective section of type 4.

Figure 1-5 clearly shows that the multilayer Perseptron performed a nonlinear classification and distinguished areas with a complex structure (nonlinear boundaries).

The developed neural network allows to carry out the nonlinear separation and classification of objects according to the set of diagnostic attributes, to allocate a complex relation between the degree of damage of control object and the values of informative parameters. During the training the neural network can automatically change its own parameters, achieving the highest control veracity. The disadvantages of the system include the necessity to train a multilayer Perseptron the existence of a training sample containing information about possible defects. Entering information about a new type of defect is accompanied by a complete retraining of the network. This drawback can be solved by using hybrid neural networks, or a combination of multilayer Perseptron and other networks, which learn without a teacher and have the ability to change their parameters in the process of work and to adapt to changes of input data. The classification system based on the multilayer Perseptron has a high control veracity.

V. CONCLUSION

The obtained results showed the prospects of neural networks application in nondestructive testing and defect classification. The use of artificial neural networks, solving the problem of changing the internal structure of 3D-model parts during their design, will improve the quality of the obtained parts by ensuring the necessary rigidity at minimum consumption of machining material. As a result of the work performed, a system of classification of the technical condition of cellular panels was developed, which allows you to determine the defective areas of the control object and conduct their classification by the degree of damage. The application of artificial neural networks apparatus for processing the experimental data obtained makes it possible to automate this process and the decision-making process based on the results of nondestructive testing.

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