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COMPARATIVE ANALYSIS USING NEURAL NETWORKS PROGRAMMING ON JAVA FOR OF SIGNAL RECOGNITION

Abstract. The results of the study of a multilayer persertron and a radial basic neural network for signal recognition are presented. Neural networks are implemented in Java in the environment NetBeans. The optimal number of neurons in the hidden layer is selected for building an effec tive architecture of the neural network. Experiments were performed to analyze MSE values, Eu clidean distance and accuracy.

Keywords: composite materials, neural networks, multilayer perceptron with *back propagation training, radial basic neural network, defect, function of activity.*

Introduction. At conducting non-destructive control of composite materials it follows to take difficult relief of surface into account them. The manufacturing techniques of fibrous composites, usually, do not provide for mechanical processing. The surface scanning process is complicated by various types of noise [1, 2].

When analyzing signals, we obtain information on the presence and size of defects. For the decision of such tasks neural networks are used, what actively develop lately, own universal and adaptive properties and provide high efficiency of recognition [1, 2].

In the article is a using programming language Java for neural network creating. Java is the most widely used programming language. It allows you to develop projects on one computer and run them on many different machines supporting the java environment. In addition, when artificial intelligence processing is part of an enterprise application, no other language can compete with Java [3, 5÷ 7].

Problem definition. The purpose of this work is to conduct a comparative analysis when creating a multilayer perceptron and a radial-basic neural network in the JAVA language for recognizing electromagnetic signals.

Main part. Each artificial neural network is a set of simple elements - neurons that are connected in some way. The particular form of executable network data conversion due not only characteristics of neurons that make up its structure but also its architectural features such as topology interneuron links directions and methods of information transfer between neurons and learning tools[3, 4].

Multilayer neural networks of direct distribution are nonlinear systems that enable better qualified than conventional statistical methods. Multilayer perceptron (MLP) has a plurality of input nodes that provide the input layer with one or more hidden layers of neurons and output layers. Each neuron of MLP which learns based on back propagation algorithm has nonlinear smooth activation function often use nonlinear logistic sigmoid function type or hyperbolic tangent [3, 4].

The construction of a radial-basis function (REF) network involves three layers with entirely different roles. The input layer is made up of source nodes that connect the network to its environment. The second hidden layer applies a nonlinear transformation from the input space to the hidden space. The output layer is linear, supplying the response of the network to the activation pattern (signal) applied to the input layer.

Radial-basis function (RBF) networks and multilayer perceptrons are examples of nonlinear layered feedforward networks. They are both universal approximators. It is therefore not surprising to find that there always exists an RBF network capable of accurately mimicking a specified MLP, or vice versa. However, these two networks differ from each other in several important respects [4].

1. An RBF network has a single hidden layer, whereas an MLP may have one or more hidden layers.

2. Typically the computation nodes of an MLP, located in a hidden or an output layer, share a common neuronal model. On the other hand, the computation nodes in the hidden layer of an RBF network are quite different and serve a different purpose from those in the output layer of the network.

3. The hidden layer of an RBF network is nonlinear, whereas the output layer is linear. However, the hidden and output layers of an MLP used as a pattern classifier are usually all nonlinear.

4. The argument of the activation function of each hidden unit in an RBF network computes the Euclidean norm (distance) between the input vector and the center of that unit. Meanwhile, the activation function of each hidden unit in an MLP computes the inner product of the input vector and the synaptic weight vector of that unit.

5. MLPs construct global approximations to nonlinear input-output mapping. On the other hand, RBF networks using exponentially decaying localized nonlineari-

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ties (e.g., Gaussian functions) construct local approximations to nonlinear input-output mappings [4].

When scanning composite materials using an eddy current transformer, there is a smooth change in the waveform from unimodal with a maximum amplitude (defects exceed the control zone) to bimodal with the highest dips. Such changes are modeled using the expression [1]:

$$y(x) = \exp(-1{,}5x^2) - k \cdot \exp(-3x^2) \tag{1}$$

In article [2] a multilayer perceptron(MLP) with a back-propagation algorithm was used for signal recognition. Researches were conducted to determine the best network parameters, such as: activation functions of input and hidden neurons and determining the number of neurons in the hidden layer. Hyperbolic tangential activation function (Hypertan) and logistic sigmoidal activation function (Siglog) were used in experiments.

The network learning process includes setting values weights and bias of network to optimize network performance. Setting performance for networks with direct propagation is determined by the mean squared function (mse) between the outputs of the network (a) and targeted outputs (t) and defined by the formula [2, 3]:

$$\mathrm{mse}(a, t) = \frac{1}{N} \sum_{i=1}^{N} (t_i - a_i)^2 \tag{2}$$

Parameters MSE (2) and accuracy was used for evaluate the neural network. The parameter accuracy is formed on the basis of the real and estimated data provided by the neural network.

After training and testing neural network the network object can be used to calculate the answer for any input value.

The graph (Figure 1) shows a comparison between the real (black line) and the estimated (green line) signal values for multilayer perceptron.

The neural network works well and the accuracy value varies between 80% and 97%.

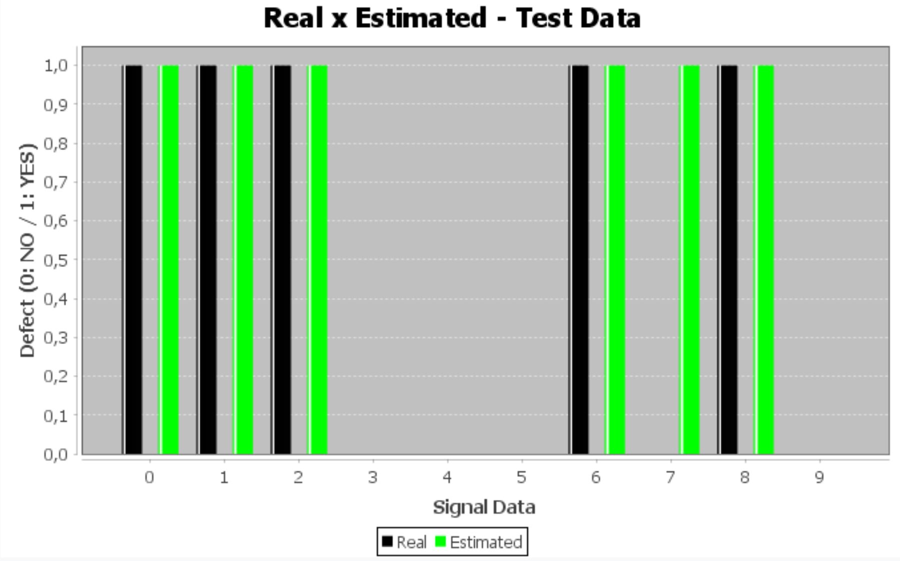

Figure 1 – Graph showing comparison between real (black line) and estimated (green line) by neural network (MPL)

For comparison we will use radial basis neural networks. The learning quality criterion for a radial-basic network is the Euclidean distance between the vectors x_{ik} and x_{jk} , which defined by:

$$d(x_i, x_j) = \left[\sum_{k=1}^{N}(x_{ik} - x_{jk})^2\right]^{1/2} \qquad (3)$$

where x_{ik} and x_{jk} are the k-th elements of the input vectors X_i and X_j, respectively. Correspondingly, the similarity between the inputs represented by the vectors x_{ik} and x_{jk} is defined as the reciprocal of the Euclidean distance $d(x_{ik}, x_{jk})$. The closer the individual elements of the input vectors x_{ik} and x_{jk} are to each other, the smaller the Euclidean distance $d(x_{ik}, x_{jk})$ will be, and therefore the greater the similarity between the vectors x_{ik} and x_{jk} will be.

There is a large class of radial-basis functions; it includes the following functions that are of particular interest in the study of RBF networks:

- Multiquadrics: $f(x) = (1 + x\hat{}2)^{1/2}$; (4)
- Inverse multiquadrics: $f(x) = 1/(1 + x^2)^{1/2}$; (5)
- Gaussian function: $(x) = \exp(-x^2)$. (6)

Studies were carried out - various activation functions (4) ÷ (6) were used and the number of neurons in the hidden layer was changed. The output for all cases used a linear function. Euclidean distance was used to test the quality of training.

Initially, the experiments were carried out on ideal signals without noise. The results of sets for unimodal (Table 1) are shown below.

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Table 1

Research of unimodal signals without noise

Number of neuron in hidden layer	Activation function	Euclidean distance
6	GAUSS	0.00872626318992018
6	SQUARE	0.08726263189920182
6	INSQUARE	0.1429747138353948
9	GAUSS	0.00998969534147190
9	SQUARE	0.08526263187720182
9	INSQUARE	0.009995887400215548
13	GAUSS	0.001951243722342713
13	SQUARE	0.08756263184420182
13	INSQUARE	0.21417024639925641

The study of the neural network at Euclidean distance showed that the use of the Gaussian function in the hidden layer is more efficient for solving such problems. Graphs signal recognition (Fig. 2) based on the Gaussian function in the hidden layer and linear at the output in the unimodal signal are given below.

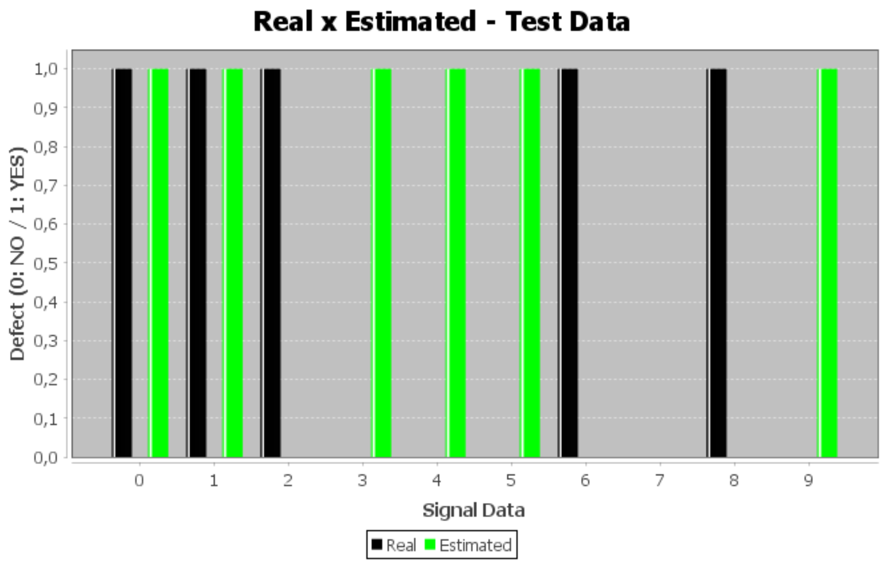

Figure 2 – Graph showing comparison between real (black line) and estimated (green line) by radial-basis neural networks

To understand the effectiveness of the neural network in recognizing signals with noise, it is necessary to conduct testing, during which the neural network will learn from signals with a fixed noise level, and testing for different noise levels (Table 2).

Testing will be performed from 0 with a noise step of 0.05. The maximum noise we can reach is 0.3.

Table 2

Recognition of signals with different noise levels

Noise levels	Euclidean distance
0.05	0.009925824698545417
0.1	0.009991145568174346
0.15	0.05113776373180032
0.2	0.06806558483945598
0.25	0.07761553684062489
0.3	0.08647269230634994

Testing was performed as follows: Noise with an average value of 0 and a standard deviation from 0 to 0.2 in increments of 0.05 was added to the input vectors. For each noise level we calculated and constructed histograms the expected class along with the classification estimated by the neural network

Conclusions. Recognition tasks belong to one of the most frequently used types of supervised tasks in the fields of machine learning/data mining, and neural networks proved to be very appropriate for application to such problems.

Training network on different sets of signals with noise allowed to teach her to work with distorted information, which is typical when conducted non-destructive testing in real conditions.

After conducting a comparative analysis between a multilayer perceptron and a radial basis neural network, it can be concluded that a multilayer perceptron is better suited for recognizing electromagnetic signals.

The root mean square error is two orders of magnitude lower than for the radial-base neural network. Multilayer perceptron shows an accuracy of 85-97%.

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Порівняльний аналіз при використанні нейронних мереж запрограмованих на мові Java для розпізнавання сигналів

Задача визначення дефектності виробів і ухвалення рішення щодо їх придатності пов'язана з інтенсивним використанням людського інтелекту й кваліфікованої праці. Високу ефективність для вирішення цієї задачі продемонстрували штучні нейронні мережі, використання яких при проведені неруйнівного контролю композитних матеріалів дуже актуальне.

В запропонованій статті проводиться порівняльний аналіз використання багатошарового персептрона та радіально базисної нейронної мережі для розпізнавання форми електромагнітного сигналу. Форма сигналу надає інформацію щодо довжини та розташування дефектів у композиційних матеріалах.

Нейронні мережі створювались засобами мови Java. Для створення оптимальної архітектури мережі проводились експерименти з кількістю нейронів у прихованому шарі та змінювались функції активації.

Багатошаровий персептрон показав кращі результати для розпізнавання сигналів. Середньоквадратична помилка на два порядки нижча, ніж для радіально базисній нейронній мережі. Багатошаровий персептрон показує точність 85 97%.

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