

RESEARCH OF NEURAL NETWORKS FOR IDENTIFICATION SIGNALS EDDY CURRENT FLAW DETECTION

Abstract. The optimal type of neural network, its training options and settings to identify defects signal in Eddy current method of defectoscopy of composites materials was determined by using computer modeling.

Keywords: neural networks, Eddy current defectoscopy, composite materials.

Introduction. The main challenge in the search for defects continuity composites materials using Eddy current method is the identification of defect signal with background hindering factors caused by surface features composite materials (noise) and specifics of research [1].

The form of the classic modulation signal received from Eddy current transducer when his path crosses scanning surface crack with length considerably maine st Eddy current transducer diameter, is shown in Figure 1, and as compared to the artificially created noise with commensurate amplitude - Fig. 2.

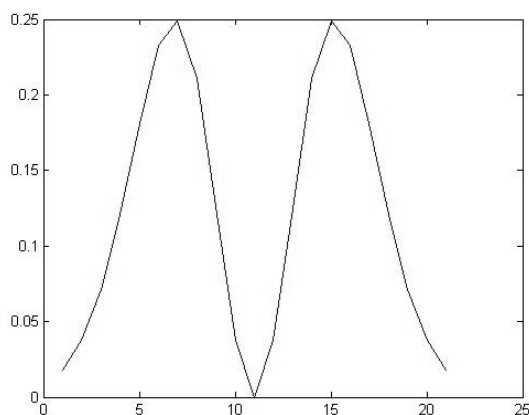


Fig.1. Modulation signal while passing Eddy current transducer of point defects

For the defect signal identification with backgrounds noise caused by difficult terrain surface composite material with reinforcing fibers carbon, the capabilities of neural networks (NN) are research promising [2].

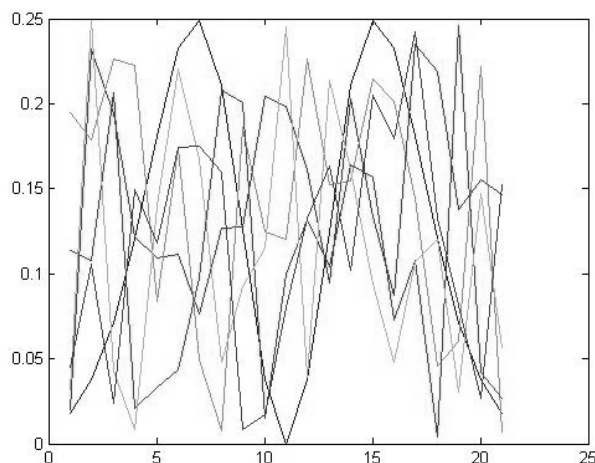


Fig.2 Defect signal and sampling the noise with commensurate amplitude

Statement of the problem. The aim is analyze the possibility of use NN for identification of signal defect which has been additive mixed with white Gaussian noise and determine the optimal type NN to conduct such research.

Main section. To solve this problem, computer mathematical package Octave (freeware analogue package Matlab) was used. The computer program was developed in this package, program algorithm is presented in Figure 4. This program operated with next input data:

- Unidimensional matrix (one column) of 21 rows (Figure 3), which values correspond to serial defect signal samples shown in Figure 1 (distance between samples along the horizontal axis is 0.2 mm in scanning trajectory);
- Given the number of matrices that contain sample noise of varying intensity corresponding scanning surface defect-free composite;
- Multilayer neural networks containing 2 layers of neurons with the number of input signals 21 (for submission sequentially for each entry a value of matrix signals) and 1 output signal (with a value of "1" - corresponding to the defect presence and "0" - defect absence).

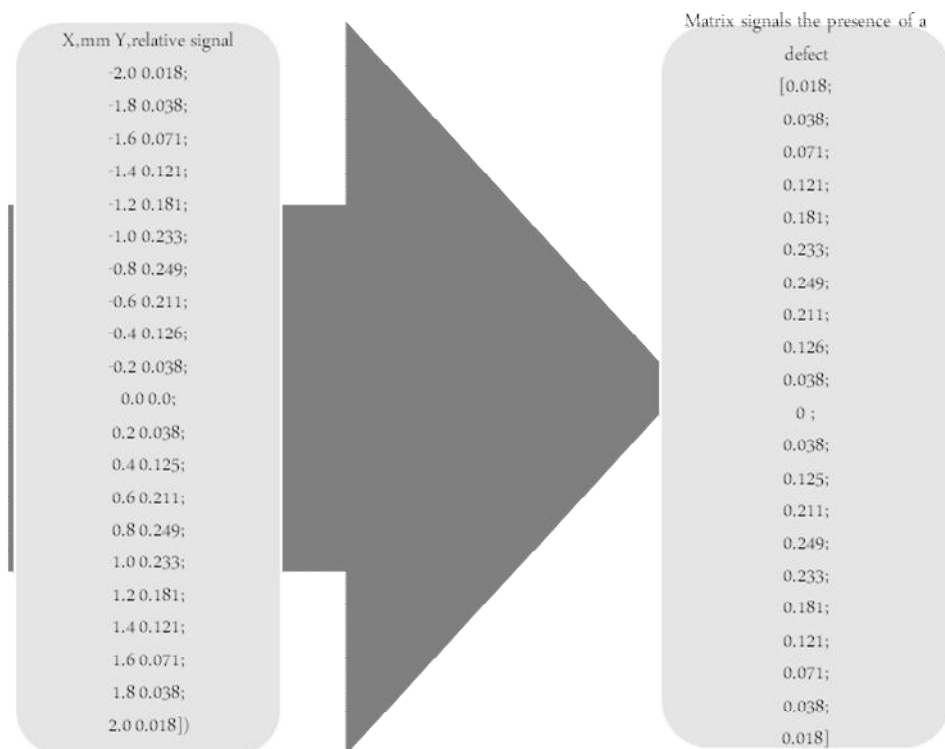


Figure 3. Formation the matrix of signal countdown defect

In the research as promising types of NN in terms of compliance tasks Eddy current flaw detection method for types of solvable problems using NN [3,4,5], addressed the following multi-layers NN:

- feedforward neural network with backpropagation;
- time delay feedforward neural network with backpropagation;
- Hopfield recurrent neural network with dynamic feedback;
- neural network with Kohonen self-organizing feature map;
- probabilistic neural network;
- radial basic function neural network;

As activation function NN were used:

- hyperbolic tangent function;

for linear NN and in the output layer of multi-layer networks:

- linear activation function;

for radial basic function neural network:

- Gaussian radial basis function;

for self-organizing NN:

- rivals function activation;

As learning algorithms have been used to study prospective informal relationships, the following algorithms:

- gradient descent algorithm of choice parameter speed settings;
- Quasi-Newton Levenberg–Marquardt algorithm;
- Quasi-Newton Levenberg-Marquardt algorithm using Bayesian regularization;
- a modified Fletcher-Reeves method conjugate gradient formula for backpropagation Neural Network;
- a modified Polak and Ribere method conjugate gradient formula for backpropagation Neural Network;
- combination of conjugate gradient and Quasi-Newton methods in the modification Moller.

As a function parameters settings NN weights to calculate the increases and shifts in teaching were used corresponding selected types of neural following functions:

- Widrow-Hoff weight/bias learning function;
- function parameters settings by gradient descent;
- function parameters settings by gradient descent with disturbance;
- function parameters setting weights Learning Vector Quantization NN according LVQ 1 weight learning function;
- function parameters setting weights by Kohonen self-organizing maps.

As a criterion of quality study were used standard valuation methods to minimize errors NN - the difference between the desired and actual output signal NN. In order to generate teaching samples were used white noise Gaussian distribution of amplitude noise restriction level to the maximum amplitude of the signal defect (A_{def}) [6]. NN study was conducted on a given type using the specified parameters, the ideal signal defect, the ideal signal defect of enclosing the maximum noise level of the ideal signal by adding to it half the maximum noise level and so on.

After learning NN conducted the following studies on its use:

- generated noise sample with an amplitude that consistently increased 1% from 0% to 100% of A_{def} attached to the defect signal values;
- generated signals about the presence and absence of the defect signal fed to the inputs NN correctness and checked identification signal defect and correct identification no defect;
- of the number of cases received by the correct identification of the defect signal and no signal identifying the defect of noise added to the signal used to determine the optimal NN and its parameters.

To automate research a computer program has been developed (Figure 4), which created NN, train them and consistently analyze the percentage of correct identification signal when changing the type and settings NN.

Most suitable for identifying the defect signal was a feedforward NN with backpropagation. The test results are shown in Figure 5 and Table 1.

On fig.5 with additional graphics points by chart symbol "*" is shown graph of studies feedforward NN with backpropagation, hyperbolic tangential function activation, Quasi-Newton Levenberg–Marquardt algorithm, the method of gradient descent with disturbance and a combined criterion of quality training (which showed the best results when modeling) against the background of graphs NN with other parameters.

The reliability of the identification signal is higher, the more it differs from the threshold of 50% of correct identification, so a graph in Figure 5 it is clear that the reliability of acceptable identification is achieved only when the noise level to 30%.

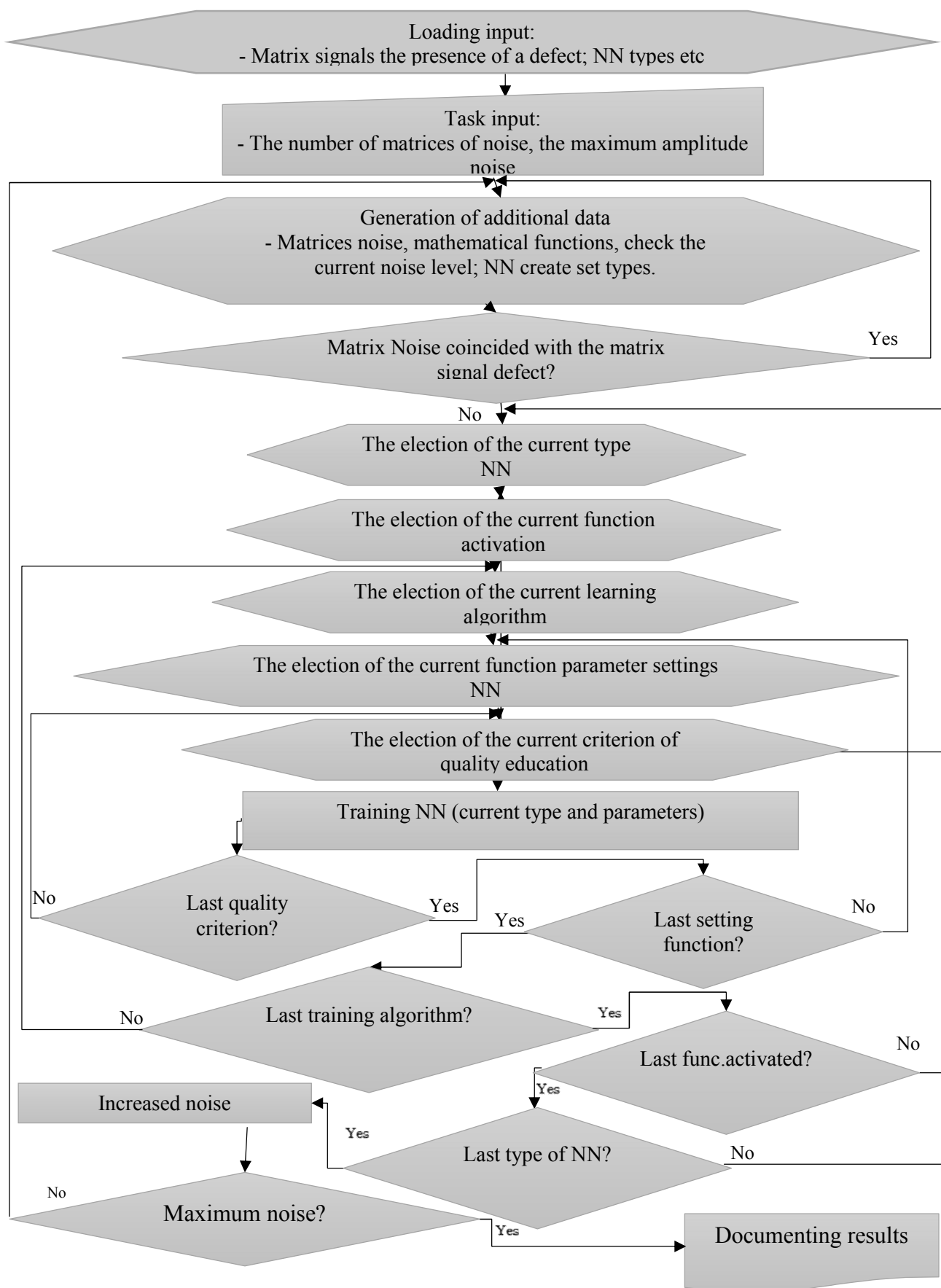


Fig. 4. The algorithm of the program

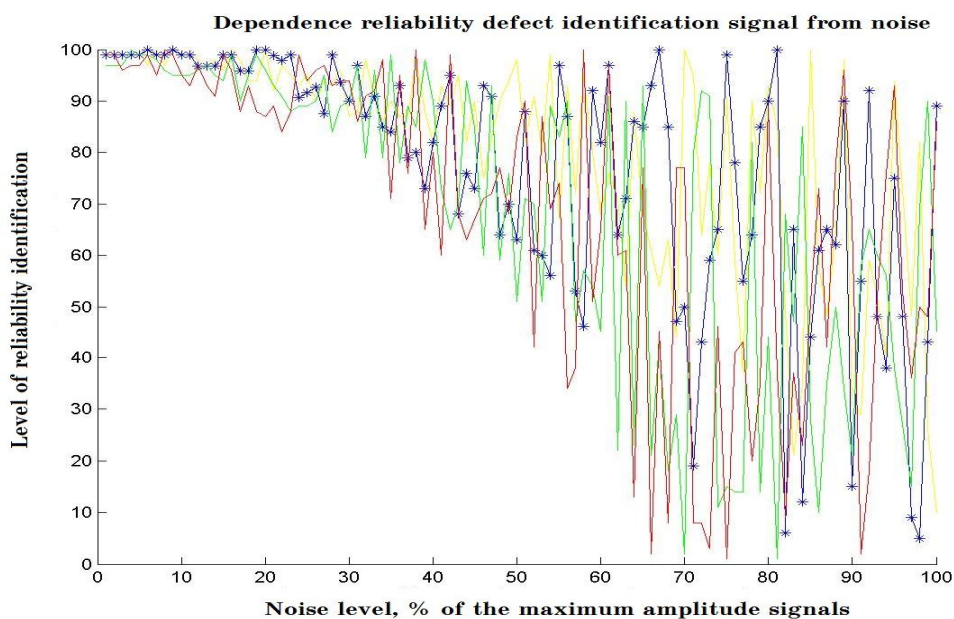


Figure 5. Dependence reliability defect identification signal from noise

Table 1. The dependence reliability defect identification signal NN feedforward with backpropagation depending from the used NN settings.

N N type	Activ ation func tion	Learning algorithm	Settings options	Criterion of quality training	% Error in the definition of noise			
					0	10	20	30
NN feedforward with backpropagation	hyperbolic tangential function activation	Quasi-Newton Levenberg-Marquardt algorithm	method of gradient descent with disturbance	combined criterion of quality training	0	2	4	13
				mean square error	0	3	13	33
			method of gradient descent	combined criterion of quality training	0	4	12	17
				mean square error	0	7	24	27
		Quasi-Newton Levenberg-Marquardt algorithm using Bayesian regularization	method of gradient descent with disturbance	combined criterion of quality training	0	1	18	16
				mean square error	0	1	21	28
	Linear activation function	Quasi-Newton Levenberg- Marquardt algorithm	method of gradient descent with disturbance	combined criterion of quality training	0	12	16	31
				mean square error	0	7	12	30
			method of gradient descent	combined criterion of quality training	0	8	21	28
				mean square error	0	5	23	31

Conclusions.

The results of modeling demonstrate the feasibility of using neural networks to identify surface cracks modulation signal obtained by scanning the surface of Eddy current transducer products from composite materials on a background of intense noise, due to the influence of surface roughness.

According to the research was determined the optimal network type and its parameters. It is feedforward NN with backpropagation, hyperbolic tangential function activation, Quasi-Newton Levenberg–Marquardt algorithm, the method of gradient descent with disturbance and a combined criterion of quality training.

Acceptable, with a practical standpoint, the reliability of the identification of the defect obtained at noise levels up to 30% of the signal amplitude defect.

REFERENCES

1. Хандецкий В.С., Герасимов В.В. Спектральная идентификация сигналов в дефектоскопии композитов с использованием теории статистических испытаний / Вісник ДНУ: Фізика. Радіоелектроніка. -Дніпропетровськ: - 2003. №10 – С.128-132.
2. Хандецкий В.С., Антонюк И.Н. Использование искусственных нейронных сетей для идентификации модуляционных импульсов дефектов / Дефектоскопия: РАН: Екатеринбург: - 2001. №4 – С.49-57.
3. Ф. Уоссермен. Нейрокомпьютерная техника: Теория и практика. Пер.с англ./ Ф. Уоссермен-М.«Мир».1992
4. И. В. Заенцев. Нейронные сети: основные модели. Воронеж. 1999
5. Хайкин Саймон. Нейронные сети: полный курс, 2-е издание: Пер.с англ./ Хайкин Саймон-М.«Вильямс».2006.
6. Герасимов В.В. Спектральна ідентифікація модуляційних імпульсів різних амплітуд в дефектоскопії композитних матеріалів. / Системні технології. Регіональний міжвузівський збірник наукових праць. Дніпропетровськ, 2014. № 1(90) – С.69-74.

Реферат

Розглянуто питання визначення оптимального типу нейронної мережі та її параметрів для ідентифікації модуляційного сигналу поверхневої тріщини при дефектоскопії композитних матеріалів зі значною шорсткістю поверхні.

Найкращі результати при моделюванні показала мережа прямої передачі із зворотнім напрямком поширення помилки, гіперболічною тангенціальною функцією активації, квазіньютонівим алгоритмом навчання Левенберга – Марквардта та настройкою параметрів методом градієнтного спуску із збурюванням.

Прийнятна, з практичної точки зору, достовірність ідентифікації дефекту отримується при рівні шуму до 30% від рівня амплітуди сигналу дефекту.

Реферат

Рассмотрены вопросы определения оптимального типа нейронной сети и ее параметров для идентификации модуляционного сигнала поверхностной трещины при дефектоскопии композитных материалов со значительной шероховатостью поверхности.

Наилучшие результаты при моделировании показала сеть прямой передачи с обратным направлением распространения ошибки, гиперболической тангенциальной функцией активации, квазиньютоновым алгоритмом обучения Левенберга-Марквардта и настройкой параметров методом градиентного спуска с возмущением.

Приемлемая, с практической точки зрения, достоверность идентификации дефекта получается при уровне шума до 30% от уровня амплитуды сигнала дефекта.

Abstract

The problems of determining the optimal type of neural network and its parameters for identification of the modulation signal at the surface crack inspection of composite materials with a large surface roughness were considered.

The best results in the simulation showed by feedforward NN with backpropagation, hyperbolic tangential function activation, Quasi-Newton Levenberg–Marquardt algorithm, the method of gradient descent with disturbance.

Acceptable, from a practical point of view, the reliability of the identification defect that is obtained when the noise level up to 30% of the level of the defect signal amplitude.

Autor: Starodubtsev Oleksii, assistant department computers DNU, 067-5601773, alexeystar75@gmail.com