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APPLYING OF NEURAL NETWORKS FOR TESTING OF TRACERS WITH USING OF EMPIRICAL DATA

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ABSTRACT

An attempt of designing artificial neural networks for empirical laboratory test results tracers No. 5, No. 7 and No. 8 was introduced in the article. These tracers are applied in cartridges with calibres from 37 mm to 122 mm which are still used and stored both in the marine climate and land. The results of laboratory tests of tracers in the field of over 40 years of tests have been analysed. They have been properly prepared in accordance with the requirements that are necessary to design of neural networks. Only the evaluation module of these tracers was evaluated, because this element of tests, fulfilled the necessary assumptions needed to build artificial neural networks. Several hundred artificial neural networks have been built for each type of analysed tracers. After an in-depth analysis of received results, it was chosen one the best neural network, the main parameters of which were described and discussed in the article. Received results of working built of neural networks were compared with previously functioning manual evaluation module of these tracers. On the basis conducted analyses, proposed the modification of functioning test methodology by replacing the previous manual evaluation modules through elaborated automatic models of artificial neural networks. Artificial neural networks have a very important feature, namely they are used in the prediction of specific output data. This feature successfully used in diagnostic tests of other elements of ammunition.

Keywords:

neural networks, tracer, laboratory tests, importance classes, evaluation module, hidden layer, neuron.

Research article

INTRODUCTION

Neural networks according to [2] have been experiencing periods of ups and downs since their birth in the 1940s. From the initial fascination with their abilities, through a significant drop in interest, even forgetfulness after Minski's book, to the renaissance in the eighties and nineties, which continues to this day.

Neural networks is a modern statistical tool intended for researchers who have an empirical database, collected best over dozens of years of diagnostic tests. These data can concern any technical object tested according to strictly determined test procedures, which should be recorded, for example in the test methodology. Thanks to this knowledge, it is possible to develop artificial neural networks for those technical objects that will automatically generate specific output signals based on the input signals (predictors) entered into these networks. The necessary condition for introducing a given predictor into the data network is the statistical significance of this predictor.

Available literature on the subject indicates that a number of artificial neural networks have already been developed, in various fields of knowledge, which significantly accelerate the evaluation process tested e.g. technical objects. Networks of this type are used in various fields such as, for example, support of investment decisions [2], process modeling e.g. the vacuum nitriding of tool steels [10], flight research planning [9], prediction of results surgery of accessory sinuses [8] or in military applications in automatic target recognition systems from a distance for 'intelligent' missiles and torpedoes fired from ships and to identify submarines based on the analysis of noise caused by their propeller motors [3]. In all these areas of knowledge, the use of artificial neural networks provides a faster process of working out certain final decisions, the type of which depends only on the considered research problem.

The purpose of this article was to attempt to design and build artificial neural networks for each type of tracer analysed in this article and used in cartridges stored in marine and land climate. The analysis of available national literature on the subject of neural networks indicates the possibility of developing such models of artificial neural networks for the analysed tracers.

THE WAY OF BUILD OF NEURAL NETWORKS

Tracers [1] are the elements of ammunition, whose task is to produce a light streak on the flight path of projectiles intended to destroy the uncovered fixed targets, and above all the moving ones. The streak of light behind the projectile allows the shooter to observe the flight path and quickly make corrections in case the projectile deflect from the required direction. Pointing the trajectory of the projectiles is widely used in shooting tanks, combat vehicles, ships and aircraft. Light streaks contain chemical compounds that should be tested in the laboratory. The essential requirement that the tracer should respond to is the good visibility of the flame during the day and at night.

In the projectiles, the tracer is a separate element mounted directly to the bottom of the projectile and is scratched or screwed. It can also be placed in a special screw, which is screwed into the bottom of the projectile.

To the designed artificial neural networks, the results of diagnostic tests were prepared for the first laboratory tests of tracers No. 5, No. 7 and No. 8 [4, 6]. The tracers of these types have the most accumulated previous results in the first laboratory diagnostic test. Test samples of tracers No. 5 and No. 8 were also collected from ammunitions, the central logistic authority of which was the Navy.

All three types of tracers analysed in the article are tracers [1], which in their construction have incendiary mass, fundamental mass and the cover of the tracer. The tracer lights up in the barrel while shooting from the flame of the propellant charge of the cartridge.

Laboratory tests of tracers [5] include: checking surface, marking humidity, marking activity of metal, tests of shaking, definition ability of inflammation and burning time of tracer and marking of fragility. Usually, to tests of shaking intended these tracers which not have external defects.

From the databases owned in the article of the types of tracers, eliminated the test results of the so-called analytically — scientific inquiries whose scope of test differs from other standard diagnostic tests for these tracers. The results of diagnostic tests carried out for other ministries rather than the national defense ministry were also not analysed. In accordance with the test methodology [5] analysed the test results for which the type of test was worth one (RB = 1) and tested samples of tracers were stored in storage subsets defined in the test methodology as ‘K’ and ‘M’. The ‘M’ storage subset means ammunition stored in marine climate for the needs of the Navy forces, the subset of ‘K’ is a land climate. All these restrictions of the prepared sets of data results were carried out, aimed at creating homogeneous sets of test results that could be analysed during the building of artificial neural networks for tracers.

Laboratory diagnostic tests of each of these three types of tracers involve the test of their properties (features), which according to the test methodology [5] have been divided into three importance classes (inconsistencies): A, B and C. Depending on the number of detected inconsistencies in individual importance classes during laboratory tests, a post-diagnostic decision determined in accordance with the evaluation module. Tracers stored in cartridges in marine and land climate were tested according to the same test procedures. Marine climate, which is characterized by high humidity and frequent rainfall, cannot adversely affect the combat properties of the cartridges stored in it containing the tested tracers.

In building models of artificial neural networks, only the evaluation modules of these tracers were analysed and it was assumed that all tested features of a given type of tracer constituted in our cases input signals (so-called predictors) of designed neural networks. These predictors were delivered to the built networks in the form of a record as a numerical mark, i.e. if during the diagnostic test there were no inconsistencies of the given importance class, then the zero value was provided. However, in the case when inconsistencies were detected during the tests, then a specific number of these inconsistencies was given in a given importance class. Built neural networks for all types of tracers, consisted of only one hidden layer. The output parameters for these designed neural networks were post-diagnostic decisions obtained after laboratory tests. The number of these specific output parameters depends on the possible type of post-diagnosis decision that have been specified in the evaluation module.

Established predictors will therefore be in our neural networks to stimulate neurons in hidden layers, where they will be transformed by specific neuron activation functions. The values calculated by these functions will ultimately be the output values, i.e. the output parameters of these neural layers. Thus, acceptance of all hidden neurons was very strongly dependent on the type of activation function used. In all artificial neural networks being built, four types of hidden layer activation functions were accepted: logistic function, exponential function, hyperbolic tangent function and linear function.

An important element in the design of neural networks is also the acceptance of the activation function for the output layer. In our case, a softmax function was accepted for all artificial neural networks being built, which was forced by the use of the BFGS learning algorithm during building of the neural network.

Another issue that should be determined when designing these neural networks was the way neurons connect to each other. After the structural analysis of the considered tracers, proposed one-way neural networks of the so-called feedforward, because this type of network was found to be the most suitable for the technical object in question. There were used connections between peer-to-peer neurons between the different layers of neural network models built, which allowed to create a network called multilayer perceptron (MLP).

The next problem during designing artificial neural networks was to determine the amount of neurons hidden in the hidden layers. These quantities, determined by trial and error, can sometimes take months but thanks to modern computer software [7] simulations can be carried out and determined much faster, however, this method can be used for searching for the most appropriate neural network for weeks, because different sizes of these hidden neurons should be considered and thus several hundred artificial neural networks should be built.

The next step during the building of artificial neural networks was to determine the values of weight coefficients (synaptic weights) for individual predictors. Thanks to the software [7], these values were randomly determined by this software, which, as the calculations and analyses were carried out, introduced the specific weight value itself and corrected it to obtain the highest probabilities of the calculated values of the quality indicators. The values of these weights are one of the main determinants of the neural networks being built.

During designing artificial neural networks, each network built had to go through the tedious path of the network learning process, which is known as an inter-deterministic process. There are many learning methods, but in our case the most commonly used method of backward propagation of errors (back-propagation) is accepted.

By building all these artificial neural networks, two data sequences were first created: a learning sequence and a training sequence. For the simulation of the designed neural networks, 70% of the test results were generated to the learning sequence. After processing the entire learning sequence (called the epoch), an epoch error was calculated and the entire cycle of building of a given network was repeated until the error has fallen below that the network creator of the given permissible level was accepted.

Taught networks were checked using a training sequence to which 15% of the test results were selected, but these data were not used before in the network learning process. This sequence was used to conduct independent control of the progress of the accepted learning algorithm.

The last thing that was done in the designed artificial neural networks, was the validation of built neural networks, that is, the network's test on the ability to generalize on a specific validation set. 15% of the test results were also generated to the validation sequence, which were also not introduced in the training sequences or learning sequence before. So validation of designed neural networks was another test of the correct functioning of built artificial neural networks.

TRACERS NUMBER 5

The building of an artificial neural network for tracers No. 5 for the first diagnostic tests began with the assumption that this network will be one-way network type MLP. All neurons in the network will be connected on a peer-to-peer basis. Initially, the sigmoid function was assumed as a function of the hidden layer activation and three neurons hidden in this layer were assumed. In order to find the best neural network, the next neurons were introduced to the hidden layer, ending with the value of 15 hidden neurons. Further introduction of more of these neurons, caused deterioration of the parameters of the neural networks being built. Learning, training and validation sets were determined in the proportions specified above. 200 networks were built for each of the hidden layer activation functions analysed and 200 neural networks for each number of hidden neurons used in the neural networks being built. As the output signals, two types of post-diagnostic decisions were accepted in accordance with the previous laboratory tests results.

Summary of active networks (No.5 RB=1)								
Id network	Name of network	Quality (learning)	Quality (testing)	Quality (validation)	Algorithm of learning	Error function	Activation (hidden)	Activation (exit)
113	MLP 2-3-2	97,89474	100,0000	100,0000	BFGS 0	Entropy	Tanh	Softmax

Fig. 1. Summary of the selected neural networks for tracers No. 5

As a result of built artificial neural networks for tracers No. 5 for the first laboratory diagnostic tests, various parameters of designed neural networks were obtained. A exact analysis of these parameters of the designed neural networks caused the selection of one best neural network for the first diagnostic tests form MLP 2-3-2, network Id 113 whose main parameters are presented in fig. 1 in the summary.

The basic parameter that was taken into account during choosing the best neural network was the value of testing quality for a given network, the higher it was, the neural network built more reliably performed its assigned task. This parameter determines the accuracy of built artificial neural network. Another very important factor in choosing a given neural network was its topology. Due to the fact that during designing several neural networks with the same topology and the same value of testing quality were created, during the selection of this best designed artificial neural network of course, further parameters of the constructed neural network were taken into account, which clearly indicated the superiority of this network in comparison to other neural networks. Standard deviation values for introduced predictors were analysed and this value in this case determined the selection of the best artificial neural network.

During building of this neural network, a BFGS type learning algorithm was used, which forced the use of the softmax output layer activation function. We have received the value of the zero epoch at which this value has already been achieved, presented in the summary of the test quality value. Achieved value of this quality is the highest possible because it is 100 percent. While designing this neural network, the error function of the form of mutual entropy and tangent function of hyperbolic activation of the hidden layer were used.

	Weights of network (No5 RB=1)	
ID of weight	Connections 113.MLP 2-3-2	**Values of weights 113.MLP 2-3-2**
1	LB --> hidden neuron 1	0,22760
2	LC --> hidden neuron 1	0,02205
3	LB --> hidden neuron 2	2,38779
4	LC --> hidden neuron 2	0,03213
5	LB --> hidden neuron 3	1,84956
6	LC --> hidden neuron 3	-1,27284
7	dislocation input --> hidden neuron 1	-0,96686
8	dislocation input --> hidden neuron 2	0,72970
9	dislocation input --> hidden neuron 3	-0,85979
10	hidden neuron 1 --> DEC(B3)	-0,21350
11	hidden neuron 2 --> DEC(B3)	0,54028
12	hidden neuron 3 --> DEC(B3)	1,79189
13	hidden neuron 1 --> DEC(B5)	0,30205
14	hidden neuron 2 --> DEC(B5)	-0,56018
15	hidden neuron 3 --> DEC(B5)	-1,81457
16	dislocation hidden --> DEC(B3)	-1,42862
17	dislocation hidden --> DEC(B5)	1,44074

Fig. 2. Fragment of weights values for tracers No. 5

In the learning process in the next iterative steps, the designed network randomly developed a series of values of synaptic weights, which were changed in the process of building connections in subsequent new neural networks, in connection with the occurrence of so-called learning errors. A fragment of the final values of these weighting coefficients for our 113.MLP 2-3-2 neural network are shown in fig. 2.

Fig. 3 shows a table with calculated values of sensitivity indicators in the learning process for the predictors introduced into the network. The order of their display is not accidental, of course, because they are sorted according to their importance for the selected artificial neural network, from the least important to the most important. The LA predictor was not included in our neural network due to the fact that it is not statistically significant. Such predictors do not contribute anything to statistical analysis and are not considered.

Network	Analysis of sensitivity (No5 RB=1) Attempts: Learning LB	LC
113.MLP 2-3-2	1,733748	1,017368

Fig. 3. Table of sensitivity indicators for tracers No. 5

Fig. 4 shows the learning graph of network for our selected neural network. In this graph, you can see a zero epoch at which the network finally learned to correctly find the values of the output signals. This is the best possible result when the network is able to function properly in the zero epoch.

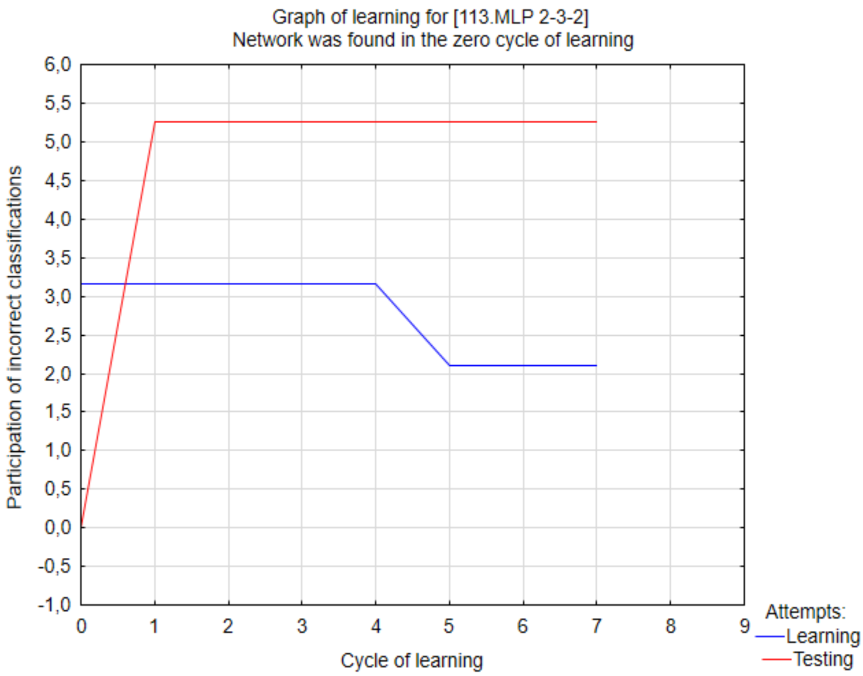

Fig. 4. Learning graph for selected network for tracers No. 5

For our designed artificial neural network form MLP 2-3-2, we also predicted all previous undertaken for the learning sample post-diagnostic decision were also made. The fragment of the prediction sheet for individual post-diagnostic decisions is shown in fig. 5. In this figure, the B5 post-diagnostic decision is shown in red colour, which according to the designed network should be taken and in reality the B3 decision was undertaken in the test card. As you can see, there are some differences between the predictions of our built artificial neural network and the decisions undertaken by the evaluating person of the test results. Both decisions B3 and B5 are positive, they differ only in a prediction period of three or five years.

The case of tracers No. 5 is slightly different from the other two types of tracers, i.e. No. 7 and No. 8. The difference lies in the fact that in the case of tracers No. 5 we have only two output signals which could give us the opportunity to apply other types of analysis to design neural networks. The quality variable obtained as output signals, unfortunately, limits our analysis to the type of classification. Therefore, it is not possible to apply other statistical analyses during building artificial neural networks for this type of tracers.

	Sheet of prediction for DEC (No5 RB=1) Attempts: Learning			
Case name	DEC Dependent variable	DEC - Exit 113. MLP 2-3-2	DEC - Validity 113. MLP 2-3-2	**DEC - Levels of activations 113. MLP 2-3-2**
40	B5	B5	Correct	0,986735
41	B5	B5	Correct	0,986735
42	B5	B5	Correct	0,986735
44	B5	B5	Correct	0,986735
45	B5	B5	Correct	0,986735
46	B5	B5	Correct	0,986735
47	B3	B3	Correct	0,782785
48	B5	B5	Correct	0,986735
49	B5	B5	Correct	0,986735
50	B5	B5	Correct	0,986735
51	B5	B5	Correct	0,986735
52	B5	B5	Correct	0,986735
54	B5	B5	Correct	0,935572
56	B5	B5	Correct	0,986735
57	B5	B5	Correct	0,847268
59	B5	B5	Correct	0,678596
60	B3	B5	Incorrect	0,986735
61	B5	B5	Correct	0,986735
62	B5	B5	Correct	0,986735
63	B5	B5	Correct	0,986735

Fig. 5. Fragment of the decision prediction sheet for tracers No. 5

TRACERS NUMBER 7

In the case of building of an artificial neural network for the first laboratory diagnostic tests of the No. 7 tracers, the same assumptions were accepted as for tracers No. 5, i.e. it was assumed, that it would be a MLP type one-way network. The database of test results was prepared according to the same key as in the case of tracers No. 5. Design was also started from three neurons in the hidden layer and increased as the building of the next networks. The use of the same four types of hidden layer activation functions and the function of activating the softmax output layer was also assumed. Also, 200 networks were built for each of the hidden layer activation functions analysed and 200 neural networks for each number of hidden neurons used. As input signals, the same predictors were used as in the case of tracers No. 5. All predictors in this case were statistically significant. As the output signals, four types of post-diagnostic decisions were accepted in accordance with the previous laboratory tests results.

Summary of active networks (No.7 RB=1)

Id network	Name of network	Quality (learning)	Quality (testing)	Quality (validation)	Algorithm of learning	Error function	Activation (hidden)	Activation (exit)
12	MLP 3-3-4	85,49618	82,14286	89,28571	BFGS 5	Entropy	Exponential	Softmax

Fig. 6. Summary of the selected neural networks for tracers No. 7

As a result, designed and built according to the above findings of artificial neural networks for tracers No. 7 for the first laboratory diagnostic tests, a number of networks with different parameter values characterizing these neural networks were obtained. The exact analysis of the designed neural networks caused the selection of neural network MLP 3-3-4, network Id 12 whose main parameters were shown in the summary in fig. 6.

We should pay attention to the fact, that quality test for our neural network is 82,14 percent what is not a bad result. Built neural network will be of course fulfil placed tasks to work.

In the designed neural network, as the error function, also mutual entropy was assumed, the function of activation for the hidden layer is the exponential function however, for the output layer the softmax function, which resulted from the use of the BFGS type learning algorithm.

In the learning process, the neural network developed a number of values of synaptic weights, a fragment of the final sizes for our selected neural network designated as 12.MLP 3-3-4 are shown in fig. 7.

ID of weight	Weights of network (No7 RB=1) Connections 12.MLP 3-3-4	Values of weights 12.MLP 3-3-4
9	LC --> hidden neuron 3	-0,94523
10	dislocation input --> hidden neuron 1	0,39811
11	dislocation input --> hidden neuron 2	0,31458
12	dislocation input --> hidden neuron 3	0,11779
13	hidden neuron 1 --> DEC(B3)	-0,02161
14	hidden neuron 2 --> DEC(B3)	-0,02832
15	hidden neuron 3 --> DEC(B3)	0,12946
16	hidden neuron 1 --> DEC(B5)	0,98539
17	hidden neuron 2 --> DEC(B5)	1,70153
18	hidden neuron 3 --> DEC(B5)	0,69959
19	hidden neuron 1 --> DEC(BS)	-0,68624
20	hidden neuron 2 --> DEC(BS)	-1,37313
21	hidden neuron 3 --> DEC(BS)	-0,71614
22	hidden neuron 1 --> DEC(Z)	-0,19320
23	hidden neuron 2 --> DEC(Z)	-0,27779
24	hidden neuron 3 --> DEC(Z)	-0,01243
25	dislocation hidden --> DEC(B3)	0,10826
26	dislocation hidden --> DEC(B5)	-0,57579
27	dislocation hidden --> DEC(BS)	0,34730
28	dislocation hidden --> DEC(Z)	0,19288

Fig. 7. Fragment of weights values for tracers No. 7

Fig. 8 shows the calculated values of sensitivity indicators in the learning process for the introduced predictors during the building of the artificial neural network. The order of their presentation indicates their importance in this process for our artificial neural network built.

Network	Analysis of sensitivity (No7 RB=1) Attempts: Learning LB	LC	LA
12.MLP 3-3-4	1,533651	0,998377	0,998293

Fig. 8. Table of sensitivity indicators for tracers No. 7

The learning graph created as a result of learning the neural network (fig. 9) shows that in the 5th epoch the network learned to find the correct output signals, i.e. correct post-diagnostic decisions for the tested tracers No. 7 for the first laboratory diagnostic tests.

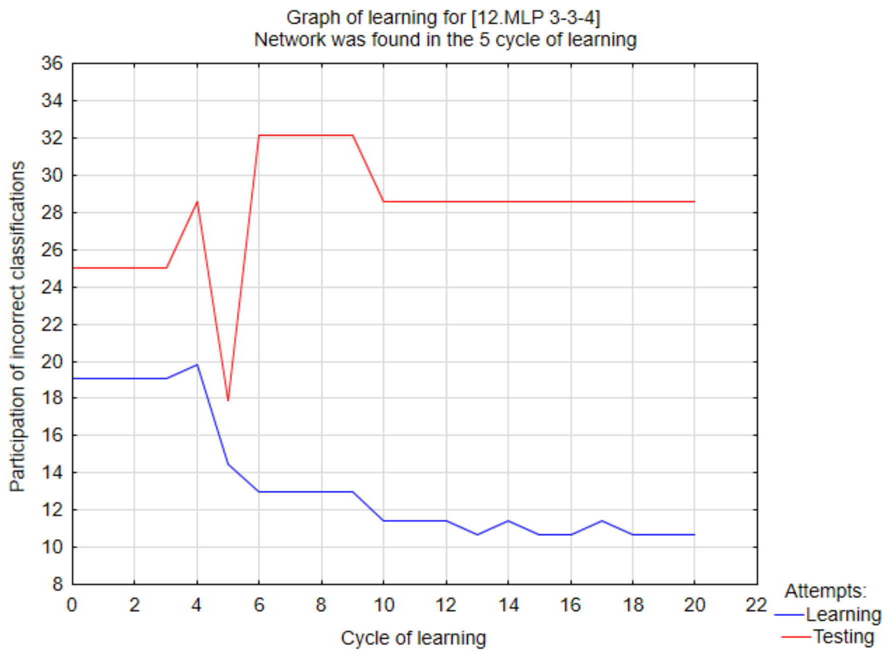

Fig. 9. The learning graph for selected network for tracers No. 7

Case name	Sheet of prediction for DEC (No7 RB=1) Attempts: Learning DEC **Dependent variable**	DEC - Exit 12. MLP 3-3-4	DEC - Validity 12. MLP 3-3-4	DEC - Levels of activations 12. MLP 3-3-4
140	B5	B5	Correct	0,967538
141	Z	B5	Incorrect	0,967538
142	B5	B5	Correct	0,967538
143	B5	B5	Correct	0,967538
145	B5	B5	Correct	0,967538
146	B5	B5	Correct	0,967538
147	B5	B5	Correct	0,967538
148	B5	B5	Correct	0,967538
149	B5	B5	Correct	0,967538
152	B3	B5	Incorrect	0,967538
153	B5	B5	Correct	0,967538
154	B5	B5	Correct	0,967538
156	B5	B5	Correct	0,967538
157	Z	B5	Incorrect	0,967538
158	B5	B5	Correct	0,967538
159	B5	B5	Correct	0,967538
160	B5	B5	Correct	0,967538
162	Z	B5	Incorrect	0,967538
163	B5	B5	Correct	0,967538
166	B5	B5	Correct	0,967538

Fig. 10. Fragment of the decision prediction sheet for tracers No. 7

Also, for the designed artificial neural network, a prediction of all previous undertaken for the learning sample post-diagnostic decisions was made. A fragment of the sheet of predictions is shown in fig. 10. It shows the red-marked decisions B5, which according to the built neural network should be taken, instead of other decisions undertaken by the person assessing these test results. Due to the lower value of quality test obtained during the building of this neural network, the amount of certain decisions obtained (visible in red) requires to check and verify them by analysts. Decisions B5 and B3 are positive decisions, differ only in the length of the prediction period, while the decision Z orders to use the given tested lot of tracers first, that is, given lot is reliable in working and safe in use, but it should be used as soon as possible.

TRACERS NUMBER 8

During designing artificial neural networks for tracers No. 8 for the first laboratory diagnostic tests, the same assumptions were accepted as for the previous tracers. The database of test results was prepared according to the same requirements to create a homogeneous set of these data results. It was assumed that the network will be built as a MLP one-way network. At the beginning, three neurons were assumed in the hidden layer during simulation and this number of neurons was increased to 15 hidden neurons, because further increase of this amount caused worse and worse results of the quality indicators of the designed neural networks. Four types of hidden layer activation functions were used, i.e. linear, logarithmic, exponential and hyperbolic functions. As a function of the output layer, the softmax function was assumed. Also 200 different networks were built for each of the hidden layer activation functions being analysed. The same types of predictors were used as in the case of tracers No. 5 and No. 7. Four different possible post-diagnostic decisions were accepted as output signals in accordance with the previous laboratory results.

As a result of designed and built artificial neural networks for tracers No. 8 for the first laboratory diagnostic tests, several hundred networks with different values of parameters characterizing these neural networks were obtained. The exact analysis of the designed neural networks has led to the selection of the neural network: MLP 3-3-4, network Id 66 whose main parameters are presented in the summary in fig. 11. As you can see in this case, the same network topology was chosen as in the case of tracers No. 7.

Summary of active networks (No.8 RB=1)								
Id network	Name of network	Quality (learning)	Quality (testing)	Quality (validation)	Algorithm of learning	Error function	Activation (hidden)	Activation (exit)
66	MLP 3-3-4	86,61710	89,47368	80,70175	BFGS 60	Entropy	Tanh	Softmax

Fig. 11. Summary of selected neural networks for tracers No. 8

The quality of testing was determined at 89.47%, which is a good result obtained for the built neural network. As the error function, mutual entropy was assumed, the function of activating the hidden layer for the selected neural network is the hyperbolic tangent function however, for the output layer the softmax function, which in turn was forced by the BFGS learning algorithm.

The network learning process led to the determination of individual synaptic weights, a fragment of the final sizes for our selected neural network designated as 66.MLP 3-3-4 is shown in fig. 12.

ID of weight	Weights of network (No8 RB=1) **Connections 66.MLP 3-3-4**	Values of weights 66.MLP 3-3-4
1	LA --> hidden neuron 1	9,7013
2	LB --> hidden neuron 1	3,9120
3	LC --> hidden neuron 1	10,3917
4	LA --> hidden neuron 2	-4,8198
5	LB --> hidden neuron 2	-8,6814
6	LC --> ukryty neuron 2	-22,4511
7	LA --> hidden neuron 3	0,7389
8	LB --> hidden neuron 3	-1,6852
9	LC --> hidden neuron 3	-3,4732
10	dislocation input --> hidden neuron 1	-1,7584
11	dislocation input --> hidden neuron 2	2,7022
12	dislocation input --> hidden neuron 3	0,1892
13	hidden neuron 1 --> DEC(B3)	-4,2365
14	hidden neuron 2 --> DEC(B3)	0,9051
15	hidden neuron 3 --> DEC(B3)	-6,6984
16	hidden neuron 1 --> DEC(B5)	3,3216
17	hidden neuron 2 --> DEC(B5)	1,1988
18	hidden neuron 3 --> DEC(B5)	6,1444
19	hidden neuron 1 --> DEC(BS)	5,7148
20	hidden neuron 2 --> DEC(BS)	3,0920

Fig. 12. Fragment of the weights values for tracers No. 8

During the network learning process, create so-called a learning graph showing the number of epochs after which the building neural network begins to correctly detect the output signals, in our case it begins to determine the correct post-diagnostic decisions. In this case, the correct process began only from the 60 epoch. The learning graph for this neural network is shown in fig. 13.

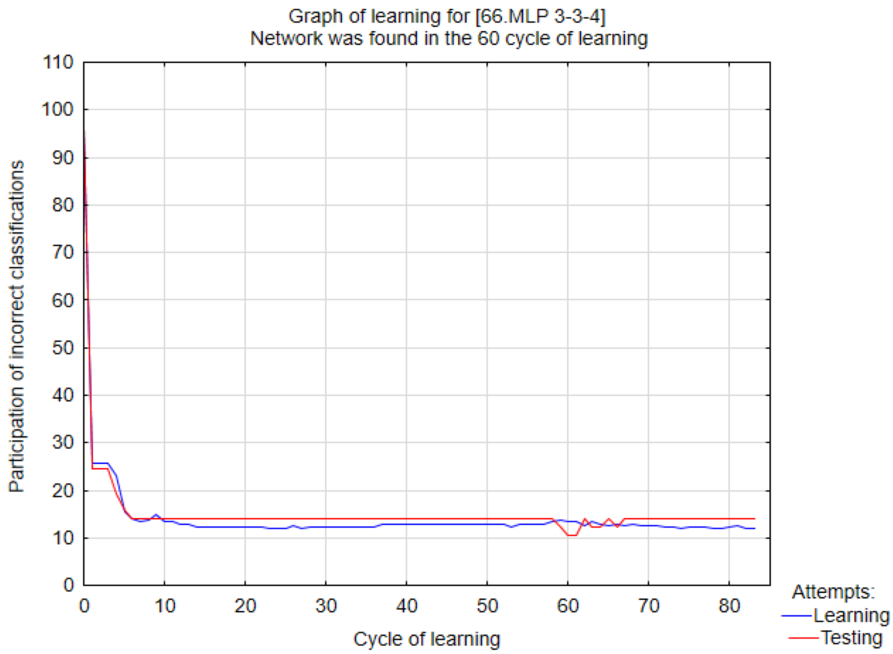

Fig. 13. The learning graph for selected network for tracers No.8

Network	Analysis of sensitivity (No8 RB=1) Attempts: Learning LB	LC	LA
66.MLP 3-3-4	1,725928	1,375875	1,019827

Fig. 14. Table of sensitivity indicators for tracers No. 8

Fig. 14 shows the calculated values of sensitivity indicators in the network learning process for the introduced predictors values during building of the artificial neural network. An important information is the order in which they are presented, from the least relevant to the most important.

The prediction of post-diagnostic decisions taken for all elements of the learning test was also made. A fragment of this prediction sheet is shown in fig. 15, which shows three highlighted red B5 decisions, which should be taken according to the built artificial neural network, instead of other decisions (B3 and Z) undertaken by the person assessing the test results.

Case name	Sheet of prediction for DEC (No8 RB=1) Attempts: Learning DEC Dependent variable	DEC - Exit 66. MLP 3-3-4	**DEC - Validity 66. MLP 3-3-4**	DEC - Levels of activations 66. MLP 3-3-4
330	B5	B5	Correct	0,902717
331	B5	B5	Correct	0,902717
332	B5	B5	Correct	0,902717
334	B5	B5	Correct	0,902717
336	B5	B5	Correct	0,902717
337	B5	B5	Correct	0,902717
338	B5	B5	Correct	0,902717
339	B5	B5	Correct	0,902717
341	B5	B5	Correct	0,902717
342	B5	B5	Correct	0,902717
343	B5	B5	Correct	0,902717
344	B5	B5	Correct	0,902717
345	B5	B5	Correct	0,902717
348	B5	B5	Correct	0,902717
349	B5	B5	Correct	0,902717
350	Z	B5	Incorrect	0,902717
351	Z	B5	Incorrect	0,902717
352	B5	B5	Correct	0,902717
353	B3	B5	Incorrect	0,902717
354	B5	B5	Correct	0,902717

Fig. 15. Fragment of the decision prediction sheet for tracers No. 8

CONCLUSIONS

The article attempts to design and build models of artificial neural networks for three types of tracers, which were stored in cartridges stored in a land climate and in a marine climate. The aim set at the beginning of the article has been fully achieved. The necessary parameters were determined to build the correct structures of neural networks, which in the final result led to the built of neural networks with fairly high values of quality indicators. Thanks to modern specialized computer software [7] simulation of designed neural networks was carried out, with different structures of these networks and one of the best neural network was selected for several types of tracers analysed in this article.

Designed artificial neural network for the first laboratory tests for tracers No. 5 form MLP 2-3-2 is characterized by the best network parameters and has a test quality value at the highest level of 100.00%. Similarly, the neural network MLP 3-3-4 designed for the first diagnostic tests for tracers No. 7 is also characterized by the best network parameters, however, in this case the test quality level was achieved of 82.14%. The last built network was the neural network of the same form as before, i.e. MLP 3-3-4 for the first diagnostic tests for tracers No. 8, which reached the level of test quality 89.47%.

Built neural networks and their topology indicate that these networks do not require a large number of hidden neurons in hidden layers for functioning at a high quality level. In all three cases, only 3 of them are needed. In this article, due to formal restrictions on the size of the article, no other data statistics have been demonstrated that explicitly define and characterize built artificial neural networks.

The article also includes an in-depth analysis of the results obtained from the built artificial neural networks for the analysed tracers with the manual evaluation module that has been working until now. The inconsistencies found in the results were re-analysed and led to the conclusion that the evaluation person made a mistake, due to the fact that the post-diagnostic decision included in the test card differed from the form of the evaluation table. Thus, elimination of the human element from the system may affect only correct, in line with the assessment module, post-diagnostic decisions.

Summing up, thanks to the designed and built of artificial neural networks for the first diagnostic tests for tracers No. 5, No. 7 and No. 8, it is now possible to carry out the process of evaluating new obtained test results of these types of tracers using these neural networks. Introduced new values of predictors to the built-up neural networks, cause their immediate analysis and automatically determine the prediction in the form of the right post-diagnostic decision, of course, at a high level of probability of making this decision. Replacing the previous 'manual' evaluation modules [5] by designed artificial neural networks for particular types of tracers seems to be an indispensable necessity at present. However, distrust of potential future users of these networks in relation to a new and unusual tool may result the lack of acceptance of their implementation for real use. It is a barrier that should be overcome by the exploiters of this modern designed tool.

The models of artificial neural networks presented in the article for the analysed tracers can be easily made available in the form of easy-to-use programs to be installed on any computer (terminal), which must work with the main software [7] located on the plant server. Therefore, it will be possible to automatically predict the post-diagnostic decision directly on the test stand.

REFERENCES

[1] *Amunicja wojsk lądowych*, collective work, Publ. Ministerstwo Obrony Narodowej, Warszawa 1985 [*The ammunition of ground forces* — available in Polish].

[2] Domaradzki R., *Zastosowanie sieci neuronowych do generowania strategii decyzyjnych (inwestycyjnych)*, PhD thesis, Publ. Akademia Górniczo-Hutnicza, Kraków 2007 [*Application of neural networks to generating of strategies decision's (investment)* — available in Polish].

[3] Helt P., Parol M., Piotrowski P., *Metody sztucznej inteligencji*, Publ. Oficyna Wydawnicza Politechniki Warszawskiej, Warszawa 2012 [*Methods of the artificial intelligence* — available in Polish].

[4] *Karty z badań laboratoryjnych smugaczy nr 5, nr 7 i nr 8*, Archives WITU, 1969–2010 [*Cards from laboratory tests of tracers No. 5, No. 7 and No. 8* — available in Polish].

[5] *Metodyka badań diagnostycznych amunicji*, collective work, Archives WITU, Index N-5001b, 1985 [*The methodology of diagnostic tests of ammunition* — available in Polish].

[6] *Sprawozdania z badań środków bojowych*, Archives WITU [*Reports from tests of ammunition* — available in Polish].

[7] *Statistics 13.3 PL*, StatSoft Polska, 2018.

[8] Szaleniec J., Jak uniknąć pułapek przy budowaniu sieci neuronowych? Przewidywanie wyników operacji zatok przynosowych, StatSoft Polska, 2015, pp. 59–80 [*How to avoid traps at building neural networks? Forecasting of results surgery of accessory sinuses* — available in Polish].

[9] Wołowiec-Korecka E., *Zastosowanie sztucznych sieci neuronowych do modelowania procesów azotowania próżniowego stali narzędziowych*, StatSoft Polska, 2016, pp. 21–36 [*Application of artificial neural networks to modelling processes of vacuum nitriding of tools steel* — available in Polish].

[10] Zieja M., Wójcik J., *Artificial neural networks as applied to aircraft flight test planning / Wykorzystanie sztucznych sieci neuronowych w planowaniu badań w locie*, 'Journal of KONBiN', 2012, Vol. 21, No. 1, pp. 149–162.

ZASTOSOWANIE SIECI NEURONOWYCH DO BADAŃ SMUGACZY Z WYKORZYSTANIEM DANYCH EMPIRYCZNYCH

STRESZCZENIE

W artykule przedstawiono próbę zaprojektowania sztucznych sieci neuronowych dla empirycznych wyników badań laboratoryjnych smugaczy nr 5, nr 7 i nr 8. Smugacze te stosowane są w nabojach o kalibrach od 37 mm do 122 mm, które są ciągle użytkowane i magazynowane zarówno w klimacie morskim, jak i lądowym. Analizie poddano wyniki badań laboratoryjnych smugaczy, które otrzymywano przez ponad czterdzieści lat. Zostały one odpowiednio przygotowane, zgodnie z wymogami projektowania sieci neuronowych. Ocenie poddano moduł ocenowy smugaczy, ponieważ ten element badań spełniał niezbędne założenia potrzebne do zbudowania sztucznych sieci neuronowych. Zbudowano kilkaset sztucznych sieci neuronowych dla każdego rodzaju analizowanego smugacza. Po analizie otrzymanych wyników wybrano po jednej najlepszej sieci neuronowej. Ich główne parametry zostały opisane. Wyniki działania zbudowanych sieci neuronowych zostały porównane z funkcjonującym dotychczas manualnym modułem ocenowym smugaczy. Na podstawie analiz zaproponowano modyfikację funkcjonującej metodyki badawczej poprzez zastąpienie ręcznych modułów ocenowych opracowanymi automatycznymi modelami sztucznych sieci neuronowych.

Słowa kluczowe:

sieci neuronowe, smugacz, badania laboratoryjne, klasy ważności, moduł ocenowy, warstwa ukryta, neuron.

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