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Application of Neural Networks in the Tests of Hand Grenade Fuses

DARIUSZ AMPUŁA

Military Institute of Armament Technology,
7 Wyszyński Str., 05-220 Zielonka, Poland, ampulad@witu.mil.pl

Abstract. The neural networks, which find currently use in the unusually wide range of problems, in such fields as: finance, medicine, geology or physics, were characterized in the article. It was accent, that neural networks are very sophisticated technique of modelling, able to map extremely complex functions. It was noticed particularly, that neural networks had a non-linear character, what very essentially improve the possibilities of their applications.
Some previous applications of neural networks were introduced, both in the area of domestic and foreign, including also military applications.
The fuse of UZRGM type (Universal Modernized Fuse of Hand Grenades) was characterized, describing his building and way of action, special attention-getting on the tested features during laboratory diagnostic tests.
Necessary technical parameters for the first and the second laboratory diagnostic tests, whose purpose was to build two independent neural networks, on the basis of existing test results and undertaken post-diagnostic decisions were designed. A few artificial neural networks were made and finally the best two independent neural networks were chosen. The main parameters of the chosen active neural networks were introduced in the pictures.
Concise information, relating to the built artificial neural networks, for the first and the second laboratory diagnostic tests of the fuses of UZRGM type, was presented in the end of the article. In the summary, clearly distinguished are advantages of the applications of the proposed evaluation method, which significantly shortens an evaluation process of new empirical test results and causes complex automatization of an evaluation process of the tested fuses.
Keywords: artificial intelligence, neural networks, activation function, hidden neurons, fuse
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1. Introduction

The artificial intelligence, applied in practice, in form of artificial neural networks turned out to be a comfortable tool, useful for realization of many different practical tasks. In reality, neural networks are applied in the unusually wide range of fields as finance, medicine, engineering, geology or physics. There can be more usages of this method because neural networks can be applied everywhere where there appear the problems related to the processing and analysis of the obtained empirical data, with their prediction, classification or control.

For many years [1], a generally applied technique of mathematical description of different objects and processes was the linear modelling. Such proceeding is applied prosperously also at present, bringing favourable results, mainly in consideration of the well known strategy of the optimization applied at the building models of this type. However, everywhere where there are no bases to the linear approximation of appearing phenomena and processes, linear models did not come true, leading sometimes to formulation of unjust opinions about the total lack of the possibility of mathematical description of these or other systems. In such cases, during solving these difficult and troublesome issues, invoke to the models created with the use of neural networks (models which can map non-linear dependences) can be the fastest and the most comfortable solution of the given problem.

A very important feature of artificial neural networks is the fact that networks do not use the relationship causally — consecutive of the analysed research problems. To design the artificial neural network, we should introduce many of the necessary data, for the purpose of building the best network resolvent of the considered research problem. Such a problem could be for example: elaboration of the postdiagnostic decisions of the tested fuses, e.g., of UZRGM type on the basis of the obtained empirical data. In another words — the definition of postdiagnostic decision, which will determine the correct prediction term on the tested fuses in which the term checked fuses of UZRGM type should be safe in the use and reliable in the working.

The advantages of neural networks, in compliance with [1], do not limit free and easy creation of non-linear models (without necessity of independent formulating complicated hypotheses by the user). The networks enable also the control over a complex problem of the multidimensionality, which for application of other methods significantly makes difficult attempts of modelling non-linear functions with the large number of independent variables (so-called vectorial functions).

The teaching algorithms are the bases of neural networks functioning, enabling selection of network parameters according to the solved problem. The teaching algorithms undoubtedly constitute one of the most essential and the most interesting issues in the field of artificial neural networks.

Furthermore, in compliance with [2], artificial neural networks were also used for prediction of determined phenomena and events, i.e., they that have the ability of prognosing output data (future events) on the basis of the taught input data that are of course correlated with suitable to them the output data. This is the feature, which can be prosperously used in the diagnostic tests of elements of ammunition, that is the attempt of elaboration of such evaluation model based on the obtained empirical results of the checked tested fuses of UZRGM type was also undertaken in the article.

2. Practical application of neural network

Many uses of artificial intelligence in form of neural networks, according to [2], are, e.g., military systems of autoprobing target from great distance for „intelligent" rockets and torpedoes (Automatic Target Recognition), basing on the picture of radar and picture from a camera. One of such systems, used in USA, based just on the basis of neural networks is in a position to classify the object to one of four groups (planes, ground vehicle, helicopters, groups of people and disturbances) with probability of above 90%.

The neural networks were applied in the army, in compliance with [4], to the HUM system (Hearth Usage and Monitoring). This is the monitoring system of damages removal in the driving system of helicopters. A task of the system is to control the state of the chosen parameters (the control system, driving system, the rotor and the oil system) in the real time. A fundamental undertaking, being realized in the context of the control, is failure sensing arising as a result of the machine fatigue in driving transmissions. To implement the subsystem of analysis of the data, obtained from the sensors arranged at essential points of helicopter, just neural networks was used.

Except military uses, neural networks are applied of course in the civil area, e.g., to generate strategic decision (investment) on the Stock Exchange or to support granting decisions.

However, neural networks are mainly applied in medicine [1]. The elaborated models can, among other, efficiently classify blood corpuscles or can analyse superficial factors appearing in only one of blood corpuscles, e.g., in lymphocytes of T type. They are used also for classification of more complex biomedical problems, e.g., can classify reactions of patients on different forms of treatment, showing simultaneously that good model of neural networks can both, classify reactions of patients on different medicines, but also can help to predict these reactions.

The neural networks can be also very useful in the data analysis of coming from modern physical examination, which is the magnetic resonance. Series of results from this examination, subjected to analyses and grouping with the use of neural networks, allowed to significantly better and more exactly evaluate the results of this expensive examination, allowing outright semi-automatic formulating diagnosis of the chosen patients.

However, there exist the areas, according to [3], in which application of artificial neural networks is impossible or is illegitimate. Firstly, neural networks do not apply to resolve the tasks, which have exact algorithm of solution, and also everywhere there, where high accuracy of mathematical result is required. Secondly, by means of artificial neural networks will not be obtained good results in the tasks requiring multistage reasoning. Thirdly, neural networks do not find the use in tasks which require "the manipulation" on symbols.

Analysing the possibilities and properties of neural networks, the attempt was made in application of neural networks to the analysis of the obtained empirical data of the tested elements of ammunition. The focus has been on the evaluation module and on the attempt to replace it by the determined designed artificial neural network. The purpose of this article will be to define the input and output parameters and a proper choice of a proceeding method that is a definition of the best structure of an artificial neural network, which with the highest probability will work post-diagnostic decisions of the tested fuses of UZRGM type on the basis of an existing evaluation module, which was determined in the test methodology [7].

Summing up, the main purpose of the presented in this article of the author's tests was shortening the evaluation time of new empirical test results and introduction of fully automatic evaluation process of the tested hand grenade fuses of UZRGM type.

3. Building of neural network for fuses of UZRGM type

The designed artificial neural network for the first laboratory diagnostic tests prepared test results of the UZRGM fuses [9, 10]. These fuses are applied in hand grenade types F-1, RG-42, RGO-88, RGZ-89, and CGR-42A. So-called scientific--research examinations, which are not authoritative to the remaining tests have been eliminated. The diagnostic tests, carried out for the Department of Internal Matters, were not analysed, too. Simply, only these tests were taken, in which a kind of a test determined in test methodology [7] has the value one for the test samples stored in the magazine of the Polish Army. It means that only the tested sets of fuses, stored in the subset of the storage determined as "K" could be considered. By accepting all these restrictions, a homogeneous set of the data results was created, which can be analysed by artificial neural networks.

The fuse of UZRGM type is a time fuse, which in its construction has some delay in action (delay time of fuse action). It consists, according to [8], of three fundamental parts: the striking device, protecting mechanism, and incendiary device. The delay of this fuse differ from 3.2 seconds to 4 seconds and it is basic checked parameter during a laboratory diagnostic test. The next tested element is the spring, which constructively is applied inside the fuse. Also correct action of a primer cap and a detonating cap, action of a fire chain were controlled as well as corrosion of individual parts and groups of the fuse and condition of protection of the fuse and correct action of firing pin of fuse were checked.

All the tested properties (features) of UZRGM fuses, according to [7], were divided into four classes of the importance (inconsistencies): A, B, C, and E. Depending on the quantity of the detected inconsistencies, in individual classes of the importance, during laboratory test, the postdiagnostic decision, determined in compliance with the evaluation module, was received.

The results of all these tested features of the given fuse, constituted, in our case, the entrance parameters (input signals) of a neural network. These parameters were delivered to the network in the record form as a numerical mark, i.e., if during the diagnostic test found no inconsistencies of the given class, then the value zero was delivered. However, if the test detected inconsistencies, then the specific quantity of these inconsistencies was given. The proposed neural network will consist only of one hidden layer. The exit parameters, for this built network, determine post-diagnostic decision according to the record of test methodology [7]. In compliance with obligatory evaluation module in this methodology, as a result of the carried out first laboratory tests, six different postdiagnostic decisions can be undertaken.

The proposed scheme of the designed neural network ought to adapt requirements of the formal built neural networks. Input signals, which will be stimulation of neurons in a hidden layer, will be transformed by the established function of neuron activation. The value, calculated through this function, will be finally an exit value that is the exit signal of these neurons' layer. It is worth remembering that, behaviour of neuron will be strongly dependent on the kind of the used activation function. At the beginning of the being built network, a logistic function as the activation function of the hidden layer was accepted. Then, this function was changed, accepting tanh function, exponential function, and linear function during neural network designing.

The joining way of neurons was the next problem, which should have been determined at the neural networks. Input, hidden, and exit neurons must be mutually connected with themselves what places before the creator of a network problem of the choice of its structure. Simple networks have one-way structure (so-called *feedforward*), the signal passes only in one direction, from input, across following hidden neurons, achieving finally the exit neurons.

During building our neural networks so, one-way neural networks, as the most fitting for the considered research problem were proposed. The connections of neurons type every with everyone were also applied, between individual layers of building model of network. In our projected neural network, in hidden layer connection of these many neurons, permitted us to create the network, which is called multilayer perceptron (MLP).

During designing the neural network, the following problem was the definition of quantity of neurons in the hidden layer. In most cases, this quantity determines the method of test and mistakes, carrying out simulation attempts, e.g., by the specialist programme. We can also calculate its analytically by using the determined final formulas, however, these calculations are only preliminary and exact assessment of this quantity requires a few tests and verifications of the proposed determined quantities.

In the case of our designed neural network for the fuses of UZRGM type, for the first laboratory diagnostic tests, seven input signals were accepted, which were the amounts of information obtained after the carried out diagnostic tests. These are the following input information (predictors):

— total quantity of inconsistent fuses (N) ;
— number of inconsistences in importance class A (LA);
— number of inconsistences in importance class B (LB);
— number of inconsistent fuses in importance class B (NB);
— number of inconsistences in importance class C (LC);
— number of inconsistent fuses in importance class C (NC);
— number of inconsistences in importance class E (LE).

After the conducted analysis of the previous test results, the LA predictor has not been classified to the being built neural network for the first diagnostic tests, because this predictor showed no statistical variability. The rest of the predictors were essential statistically.

During building neural networks, the next important step was to define a value of weight coefficients (synaptic weights) for individual input signals. These values were randomly established by the software [11], which for the subsequent calculations and analyses, has itself introduced a specific value of weight and next corrected this value in order to obtain the highest probabilities of the counted values of quality.

In our designed model of the network, we have to deal with classifying character of networks, in consideration of the fact that we can receive one from several possible diagnostic decisions. 800 neural networks have been built for each of different quantity of neurons of a hidden layer. It was initiated with the least possible quantity of these neurons, namely with three hidden neurons and was finished with twelve hidden neurons. The changing parameters of the built networks were observed and it was stated that further enlargement of quantity of the hidden neurons in the hidden layer had brought noting essential, because the obtained parameters of neural networks were more and more worse. For every built 200 networks, for the specific activation function of the hidden layer, one of the best network has been chosen, the parameters of which were recorded for the further comparative analysis. While designing neural networks, to every quantity of the hidden neurons, four kinds of the higher mentioned activation functions for the hidden layer were applied. Several thousand neural networks were built, which were exactly analysed and the best one was chosen, which has the best indicators of the work. As the activation function of the exit layer, a function of softmax type was applied.

Every neural network, to function correctly, must come the arduous way of learning process of network, which is interdeterministic process. There are many methods of network learning, but in our case, the most often applied method of backward propagation of errors (backpropagation) is accepted. Moreover, according to [6], the speed learning of neural network (velocity of convergence of an optimized function) depends not only on the choice of a learning algorithm of network, but also on quality of learning data.

The first activity, in the process of the network learning, was preparation of two sequences of data: the learning sequence and testing sequence. 70% of the possessed test results have been generated to learning sequence for simulation of the designed neural network. Because of large quantity of empirical data, the simulation process of operation of the built networks proceeds quite long. In the designed neural networks, this large quantity of learning attempts was an advantage, because thanks to this, there exists high probability that the built neural network will be correctly designed.

After processing the entire learning sequence (called the epoch), the error for so determined epoch is counted. The calculation of this error for a single epoch and the entire building cycle of the network was repeated to the moment, till this error will not descend below the adopted, by a creator of network, the determined permitted level.

Having so learnt the designed neural network, it was checked by means of a testing sequence. This sequence served for realization of independent control of the progresses in the learning algorithm. 15% of the possessed test results were chosen to the testing sequence. This sequence had the same features what the learning sequence and these data were not earlier used in the learning process. The testing sequence has been processed, however, the difference was that in this process the errors had not been bearing backwards and only the quantity of correct answers was registered and on this basis the decision was made, whether the built network met our requirements — that is how it was taught.

The last thing, which was performed in the designed artificial neural network, was validation of the built network that is [5] testing the network on the ability of generalization on the validation set. The validation sequence took also 15% of the possessed test results. These results were not earlier introduced to this designed neural network, either in the learning sequence, nor in the testing sequence.

4. Results of building neural network for the first tests

As earlier mentioned, our built artificial neural network began from the foundation that this network will be one way network of MLP type. All neurons in the network will be connected with themselves on the basis on one to each other. At the beginning, sigmoidal function as activation function for hidden layer was accepted. The designated sets: learning, testing, and validation in the proportions of 70%, 15%, and 15%, respectively. It was also assumed that we would design the neural networks on the basis of four kinds of the activation function of the hidden layer and 200 networks for every analysed activation function were built.

As a result of the built and chosen, to the analysis, artificial neural networks, for the tested fuses of UZRGM type, for the first laboratory tests, different parameters of designed neural networks were received. The exact analysis parameters of the designed neural networks caused the choice of one neural network for these first tests form MLP 6–3–6, Id network 136 which main parameters were presented in Fig. 1 in recapitulation.

The basic parameter, which was considered during the choice of active neural network was the obtained value of testing quality for the given network. The higher was this quality, the more reliable work would perform the built artificial neural network. This parameter determines the accuracy of the built artificial neural network. The next very important determinant choice of the built neural network was its topology.

During building our neural network, a learning algorithm of BFGS type was applied. We received the value of 72 epochs, at which the highest accuracy of the built neural network was achieved. During designing our neural network, the error function

Summary of active networks (UZRGM RB=1)

Id network	Name of network	Quality (learning)	Quality (testing)	Quality (validation)	Algorithm of learning	Error function	Activation (hidden)	Activation (exit)
136	MLP 6-3-6	94,60606	95,46742	94,90085	BFGS 72	Entropy	Tanh	Softmax

Fig. 1. Summary of chosen active neural networks for first diagnostic tests

was used in form of mutual entropy and the tanh activation function of the hidden layer and also the activation function of the exit layer of softmax type were applied.

In the learning process, in the following iterative steps, the designed network worked out randomly values of synaptic weights, which were changed in the building process connections in the following new neural networks, in connection with occurrence of so-called learning errors. The fragment of final values of these weights, for our chosen active neural network form 136.MLP 6–3–6, was presented in Fig. 2.

The graph of learning for the chosen active neural neuron was shown in next Fig. 3, in which we can notice the 72nd epoch at which the network finally learnt to find correct exit signals. The truth from this figure it is noticeable that already at the 40th epoch, our neural network was almost taught, but apparently not all parameters were yet legitimate, therefore only the 72nd epoch turned out to be correct.

Figure 4 shows us the calculated values of sensibility indicators in the learning process for our predictors introduced to the network. The order of their presentation is not of course random, because they are sorted according to the importance for our chosen active neural network.

ID of weight	Weights of network (UZRGM RB=1) Connections 136.MLP 6-3-6	Values of weights
1	LB --> hidden neuron 1	2,7859
2	NB --> hidden neuron 1	19,5209
3	N --> hidden neuron 1	-61,6464
4	NC --> hidden neuron 1	-69,9645
5	LC --> hidden neuron 1	-51,7593
6	LE --> hidden neuron 1	-40,2541
7	LB --> hidden neuron 2	-2,3153
8	NB --> hidden neuron 2	3,7525
9	N --> hidden neuron 2	-13,1033
10	NC --> hidden neuron 2	-21,9800
11	LC --> hidden neuron 2	23,6593
12	LE --> hidden neuron 2	-23,0524
13	LB --> hidden neuron 3	-0,5206
14	NB --> hidden neuron 3	1,1100
15	N --> hidden neuron 3	-3,5902
16	NC --> hidden neuron 3	-3,3703
17	LC --> hidden neuron 3	3,6499
18	LE --> hidden neuron 3	-88,7441
19	dislocation input --> hidden neuron 1	0,2999
20	dislocation input --> hidden neuron 2	1,0306
21	dislocation input --> hidden neuron 3	0,8122

Fig. 2. Fragment of designed values of weights for the first diagnostic tests

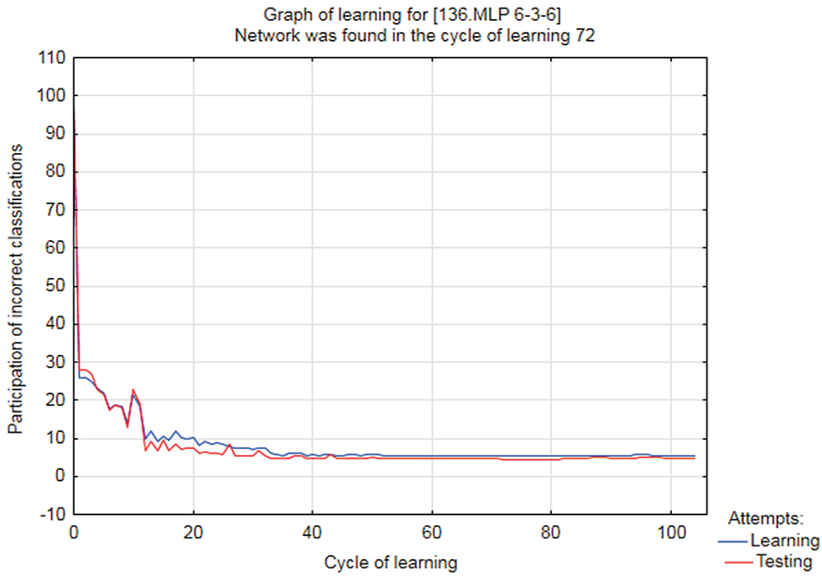

Fig. 3. Graph of learning for the chosen neural network for the first tests

For building artificial neural network of MLP 6–3–6 form, also prediction of all previously undertaken postdiagnostic decisions were taken for the learning attempt. The fragment of the prediction sheet, for individual postdiagnostic decisions, presents Fig. 5. In this figure, there are visible, marked in red colour — the postdiagnostic decisions B5 and W, which according to our designed neural network should be undertaken. The earlier undertaken decisions B3 and PS can be also seen in the cards of the tests.

Network	Analysis of sensitivity (UZRGM RB=1) Attempts: Learning LE	N	NC	LC	NB	LB
136.MLP 6-3-6	140,1231	49,41957	38,53482	32,67206	2,451333	1,010082

Fig. 4. Table indicators analysis of sensitivity for the first diagnostic tests

Thanks to obtainment of this information, we can make verification of all undertaken previous postdiagnostic decisions and we can check legitimacy of the other undertaken decisions. The cases, lacking in this set, have been qualified to the testing set or to the validation set.

Case name	Sheet of prediction for DEC (UZRGM RB=1) Attempts: Learning DEC Dependent variable	DEC - Exit 136. MLP 6-3-6
842	B5	B5
843	B5	B5
845	B5	B5
846	B5	B5
848	B5	B5
849	BP	BP
850	B5	B5
851	B5	B5
852	B5	B5
853	B3	B5
854	B5	B5
856	B5	B5
858	B5	B5
860	PS	W
861	B5	B5
862	B5	B5
863	B5	B5
864	B5	B5
865	B5	B5
867	B5	B5
868	B5	B5
870	B5	B5

Fig. 5. Fragment of a sheet of predicted decisions for the first diagnostic tests

5. Results of building neural network for the second tests

In the case of building an artificial neural network, for the second laboratory diagnostic tests of the fuses of UZRGM type, the same foundations as for the first tests, were accepted, i.e., it was assumed that it will be one way network of MLP type. The base of test results was prepared according to the same key as in the case of the first laboratory diagnostic tests. All neurons were connected with themselves on the basis of one to each other. During the designing process, at the beginning, three neurons were assumed in the hidden layer and then, their number was increased in the next networks. Also the sets: learning, testing, and validation were designated in the same proportions as for the first diagnostic tests. We would apply four kinds of the activation function of the hidden layer, i.e., the logistic function, tanh, exponential, and linear one. Also 200 networks were built for every analysed activation function. The activation function for the exit layer was also the softmax function. As input signals, of course the same predictors as in the case of the first diagnostic tests were used, however, with the difference, that the predictor LA was here essential statistically.

According to the test methodology [7], but specifically in compliance with the obligatory evaluation module in this methodology, as a result of the conducted second laboratory tests we can undertake five different postdiagnostic decisions. These decisions were accepted as the exit signals in the built artificial neural network.

As a result we received different values of parameters of the built networks designed and chosen to analysis of neural networks for the tested fuses of UZRGM type, for the second laboratory diagnostic tests. The determinants during the choice of this one active network, i.e., these which have been chosen were the same parameters as in the first diagnostic tests. The exact analysis of the designed neural networks caused the choice of active neural network of MLP 7–3–5 form, Id network 25 which main parameters was presented in Fig. 6 in recapitulation.

Summary of active networks (UZRGM RB=2)

Id network	**Name of network**	Quality (learning)	Quality (testing)	Quality (validation)	Algorithm of learning	Error function	Activation (hidden)	Activation (exit)
25	MLP 7-3-5	82.24299	90.90909	90.90909	BFGS 16	Entropy	Linear	Softmax

Fig. 6. Summary of the chosen active neural networks for the second diagnostic tests

In the designed neural network, mutual entropy was applied as an error function, activation function for a hidden layer was linear function, however, for the exit layer a softmax function.

Figure 7 shows us the calculated values of sensibility indicators in the learning process for our introduced predictors, during neural network building. The order of their presentation shows us their importance for building our active neural network.

Network	Analysis of sensitivity (UZRGM RB=2) Attempts: Learning LE	LC	NC	N	NB	LB	LA
25.MLP 7-3-5	1.606514	1.526726	1.450980	1.348075	1.020328	1.016957	0.999999

Fig. 7. Table of indicators analysis of sensitivity for the second diagnostic tests

In the learning process, our neural network worked out the values of weights' coefficients, which fragments of final values for our neural network marked as 25. MLP 7–3–5 were presented in Fig. 8.

ID of weight	Weights of network (UZRGM RB=2) Connections 25.MLP 7-3-5	Values of weights
22	dislocation input --> hidden neuron 1	-0.61541
23	dislocation input --> hidden neuron 2	-2.64634
24	dislocation input --> hidden neuron 3	-0.72105
25	hidden neuron 1 --> DEC(B3)	1.50130
26	hidden neuron 2 --> DEC(B3)	0.39708
27	hidden neuron 3 --> DEC(B3)	-3.05053
28	hidden neuron 1 --> DEC(B5)	4.26949
29	hidden neuron 2 --> DEC(B5)	-2.18213
30	hidden neuron 3 --> DEC(B5)	-1.64241
31	hidden neuron 1 --> DEC(PS)	-2.98448
32	hidden neuron 2 --> DEC(PS)	-1.28023
33	hidden neuron 3 --> DEC(PS)	2.66258
34	hidden neuron 1 --> DEC(W)	-2.12356
35	hidden neuron 2 --> DEC(W)	1.23410
36	hidden neuron 3 --> DEC(W)	1.67755
37	hidden neuron 1 --> DEC(Z)	-0.77837
38	hidden neuron 2 --> DEC(Z)	1.72554
39	hidden neuron 3 --> DEC(Z)	0.03936
40	dislocation hidden --> DEC(B3)	3.53210
41	dislocation hidden --> DEC(B5)	0.71861
42	dislocation hidden --> DEC(PS)	-5.93055
43	dislocation hidden --> DEC(W)	-0.68187
44	dislocation hidden --> DEC(Z)	2.38808

Fig. 8. Fragment of the designed values of weights for the second diagnostic tests

Figure 9 shows the learning graph for our chosen neural network, on which one can notice the 16th epoch, at which the being built network learnt to find correct output signals, that is, correct postdiagnostic decisions for the tested fuses of UZRGM type for the second laboratory diagnostic tests.

The designed and built artificial neural network of MLP 7–3–5 form, prediction of all previous undertaken decisions for learning attempt was made. The fragment of the prediction sheet presents Fig. 10. There are noticeable, marked in red colour, postdiagnostic decisions of B3 type which according to the designed neural network should be undertaken, but in reality other Z-type decisions were taken.

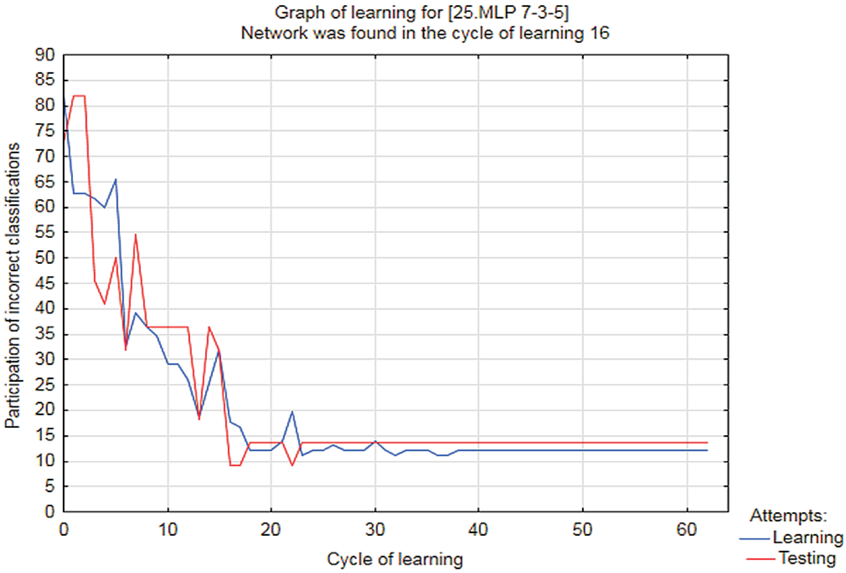

Fig. 9. Graph of learning for the chosen neural network for the second tests

Case name	Sheet of prediction for DEC (UZRGM RB=2) Attempts: Learning DEC Dependent variable	DEC - Exit 25. MLP 7-3-5
93	B5	B5
94	B5	B5
95	W	W
96	W	W
97	W	W
98	W	W
100	W	W
101	W	W
102	Z	B3
103	B5	B5
105	B5	B5
108	B3	B3
111	B5	B5
113	W	W
114	W	W
116	W	W
117	B5	B5
118	B5	B5
119	B5	B5
120	W	W
121	W	W
122	W	W
123	W	W
125	Z	B3
126	B3	B3

Fig. 10. Fragment of a sheet of predicted decisions for the second diagnostic tests

So, we can make verification of these postdiagnostic decisions and check why in the evaluation process somewhat other decisions were taken. The cases, lacking in this learning set, were qualified by the programme to the testing set or to the validation set.

6. Conclusions

An attempt of designing two artificial neural networks for the first and the second laboratory diagnostic tests of the fuses of UZRGM type was undertaken in this work. There were determined necessary parameters for creation of the correct structures of these networks, which finally conclude to the choice of neural networks about relatively high qualitative indicators. This was possible thanks to having at its disposal suitably large test base which concentrates the previous test results of fuses of UZRGM type. Thanks to the software [11], simulation of the designed neural networks was performed and consequently it was proved that there exists the possibility of elaboration of evaluation modules for the fuses of UZRGM type basing on this type of networks.

The designed artificial neural network for the first laboratory tests of MLP 6–3–6 form, after the made learning process, by software [11] help, very correctly worked out answers, that is the determined correct postdiagnostic decision. In connection with this fact, the prediction of new postdiagnostic decisions on the new, given predictors' values was made. The network correctly took the postdiagnostic decision with a very high level of probability.

The same was made for the second laboratory diagnostic tests, the built network of MLP 7–3–5 form has been chosen. Here, also high level of correctness of the undertaken postdiagnostic decisions was obtained for the new tested lots of fuses of UZRGM type.

Summing up, thanks to designing two artificial neural networks for the tested fuses of UZRGM type, for the first and the second laboratory diagnostic tests, we can currently make evaluation of new test results of this type of fuses by means of the built artificial neural networks. Two new evaluation modules were elaborated. They are based on a modern tool which can be applied in research, thus reducing the possibility of making the evaluations errors and significantly accelerating the evaluation process for the tested fuses of UZRGM type because this process can proceed fully automatically, on the condition of direct initiation of all current test results to the earlier prepared computer data bases.

In the result of the designing the above neural networks, also other statistics of data were received, e.g., calculated matrices and necessary graphs. All these additional data of neural networks, that are not shown in this article, determine detailed parameters of the built networks. This article presents only these most important data, which generally characterize the chosen active artificial neural network for the specific laboratory diagnostic tests.

The old evaluation method is based on the manual evaluation process, executed by the authorized person, designated to this works. In this method, subjective evaluation errors made by evaluating persons can appear. Furthermore, the time of execution of the given evaluation depends on the time which can be invested by this person. Sometimes, it can be even a week, because of other equally made important works executed by this evaluating person.

The elaborated new evaluation method is, in all these aspects, better, because the evaluation executes automatically, directly after introduction of empirical data to the memory of a computer. This method enrolls into the area of military engineering and, exactly specifying, into the area of engineering reliability of technical objects and such special technical objects are just hand grenade fuses.

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Dariusz Ampuła https://orcid.org/0000-0002-9036-9498

LITERATURE

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D. AMPUŁA

Zastosowanie sieci neuronowych w badaniach zapalników do granatów ręcznych

Streszczenie. W artykule scharakteryzowano sieci neuronowe, które znajdują obecnie zastosowanie w niezwykle wielu problemach, w takich dziedzinach jak: finanse, medycyna, geologia czy fizyka. Podkreślono, że sieci neuronowe są bardzo wyrafinowaną techniką modelowania, zdolną do odwzorowania nadzwyczaj złożonych funkcji. W szczególności zauważono, że sieci te mają charakter nieliniowy, co bardzo istotnie wzbogaca możliwości ich zastosowania.
Przedstawiono niektóre dotychczasowe zastosowania sieci neuronowych, zarówno w obszarze krajowym, jak i zagranicznym, włączając w to także zastosowania wojskowe.
Scharakteryzowano zapalnik typu UZRGM, opisując jego budowę oraz sposób działania, zwrócono szczególną uwagę na badane cechy podczas laboratoryjnych badań diagnostycznych. Zaprojektowano niezbędne parametry techniczne dla pierwszych i drugich laboratoryjnych badań diagnostycznych, których celem była budowa dwóch niezależnych sieci neuronowych na podstawie istniejących wyników badań oraz podjętych decyzji podiagnostycznych. Zbudowano wiele sztucznych sieci neuronowych, których wynikiem były zaprojektowane i wybrane jako najlepsze dwie niezależne sieci neuronowe. Na rysunkach przedstawiono główne parametry wybranych aktywnych sieci neuronowych.
Na końcu artykułu znajdują się zwięzłe informacje dotyczące zbudowanych sztucznych sieci neuronowych dla pierwszych i drugich laboratoryjnych badań diagnostycznych zapalników typu UZRGM. W podsumowaniu jasno wyróżniono zalety stosowania zaproponowanej metody oceny, która znacząco skraca proces oceny nowych empirycznych wyników badań oraz powoduje pełną automatyzację procesu oceny badanych zapalników.
Słowa kluczowe: sztuczna inteligencja, sieci neuronowe, funkcja aktywacji, neurony ukryte, zapalnik
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