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Investigation of the Effectiveness of the Method for Recognizing Pre-Emergency Situations at Mining Facilities

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Abstract. In previous reports, an analysis of the basic mathematical methods used to solve the pattern recognition problem was carried out. The inappropriateness of applying the Bayesian classification and cluster analysis to solve the problem of recognizing pre-emergency situations in the process of drilling a well is shown. As a mathematical apparatus for solving the problem of determining the current state of an object of research by a given set of features, a pattern recognition method based on an artificial neural network is selected. In this paper, an analysis is made of existing approaches to improving the quality of education aimed at improving the efficiency of its functioning. The results obtained in this paper will improve the quality of work of the previously developed modified algorithm for training the pre-emergency classifier based on the back propagation method, which differs from the classical one by the procedure for finding the global minimum of the error function, and its software implementation has been implemented. The work is an integral part of previously published developments presented in the materials of articles in 2-nd, 3-rd and 4-th International innovative mining symposiums (2017-2019).

1 Introduction

The previously proposed general structure of the neural network classifier for pre-emergency situations has shown the possibility and feasibility of solving the recognition problem for each pre-emergency situation separately, which requires justification of the decomposition of the task of constructing a neural network classifier.

In this connection, in this work, a substantiation of the developed structure of the neural network classifier is proposed, consisting of one hidden layer with the number of neurons equal to the number of classifier inputs.

The obtained results confirm the previously stated generalized method for recognizing emergency situations in the process of industrial drilling of coal wells.

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2 Method used

Investigation of the influence of algorithm parameters on the accuracy of recognition of pre-emergency situations

To train the neural network classifier of the drilling condition, the back propagation algorithm was used, modified to find the global minimum of the optimization criterion [1, 3, 5, 6, 7, 12, 13, 15]. The developed algorithm was investigated on real data. The accuracy of recognition of pre-emergency situations and the number of iterations necessary for the learning algorithm to converge, i.e. neural network link weights stabilized.

As the parameters of the learning algorithm were used [2, 4, 16, 17, 18, 20, 21]:

- *K* - the number of repetitions of the search procedure from various starting points of the minimum value of the neural network learning error;
- *Rmax* - the maximum radius of the search for the global minimum of learning errors.

The results of the study of the dependence of recognition accuracy and the number of iterations required to complete the training on the value of *K* for the pre-emergency situation of "Gas and Oil Water Manifestations" are given in Table 1. Based on the results obtained, it can be concluded that when the value of *K* is more than three, the recognition accuracy increases insignificantly, while the number of iterations of learning continues to increase in proportion to the value of *K*.

Table 1. The dependence of the recognition accuracy and the number of learning iterations on the value of K.

Value of *K*	Recognition accuracy	Number of iterations
1	0.93	25
2	0.95	54
3	0.96	78
5	0.961	211
10	0.963	501
15	0.967	743

The results of the study of the dependence of recognition accuracy and the number of iterations required to complete the training on the *Rmax* value are shown in Table 2.

Based on the results obtained, it can be concluded that the number of learning iterations is less dependent on the *Rmax* value than on *K*, at the same time training accuracy increases with increasing *Rmax*, which is explained by a non-smooth response surface, i.e. the presence of several extremes in the study area for most pre-emergency situations. Therefore, it seems appropriate to use the maximum possible value of *Rmax* (of the order of two), while the value of *K* may not exceed three.

Table 2. Dependence of recognition accuracy and the number of learning iterations on the value of *Rmax.*

Value of *Rmax*	Accuracy	Number of iterations
0.1	0.73	78
0.2	0.83	90
0.3	0.831	95
0.5	0.83	90
1	0.963	104
2	0.967	110

Table 3. The dependence of the recognition accuracy and the number of learning iterations on the value of *K*.

Value of *K*	Accuracy	Number of iterations
1	0.91	24
2	0.948	56
3	0.962	82
5	0.967	222
10	0.969	500
15	0.976	747

Table 4. The dependence of recognition accuracy and the number of iterations of learning on the value of *Rmax*.

Value of *Rmax*	Accuracy	Number of iterations
0.1	0.74	80
0.2	0.85	93
0.3	0.847	98
0.5	0.845	100
1	0.966	111
2	0.969	121

Table 5. The dependence of recognition accuracy and the number of learning iterations on the value of *K*.

Value of *K*	Accuracy	Number of iterations
1	0.92	26
2	0.951	57
3	0.961	85
5	0.971	231
10	0.98	505
15	0.99	745

Table 6. Dependence of recognition accuracy and the number of iterations of training on the value of *Rmax*.

Value of *Rmax*	Accuracy	Number of iterations
0,1	0.75	79
0,2	0.86	92
0,3	0.867	96
0,5	0.861	99
1	0.973	108
2	0.987	115

The following graphs show the results of studies for four pre-emergency situations.

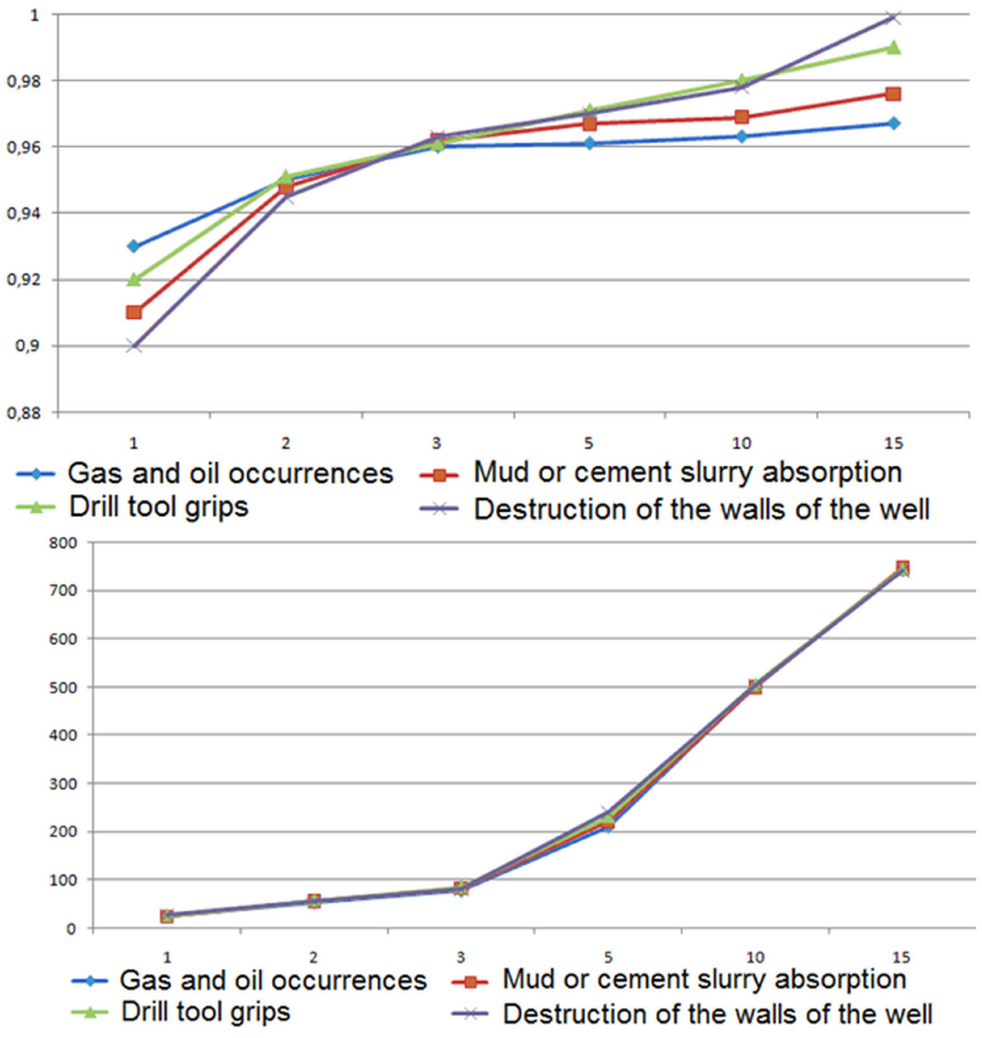

Fig. 1. Graphs showing the accuracy of recognition and the number of iterations of learning on the value of *K*.

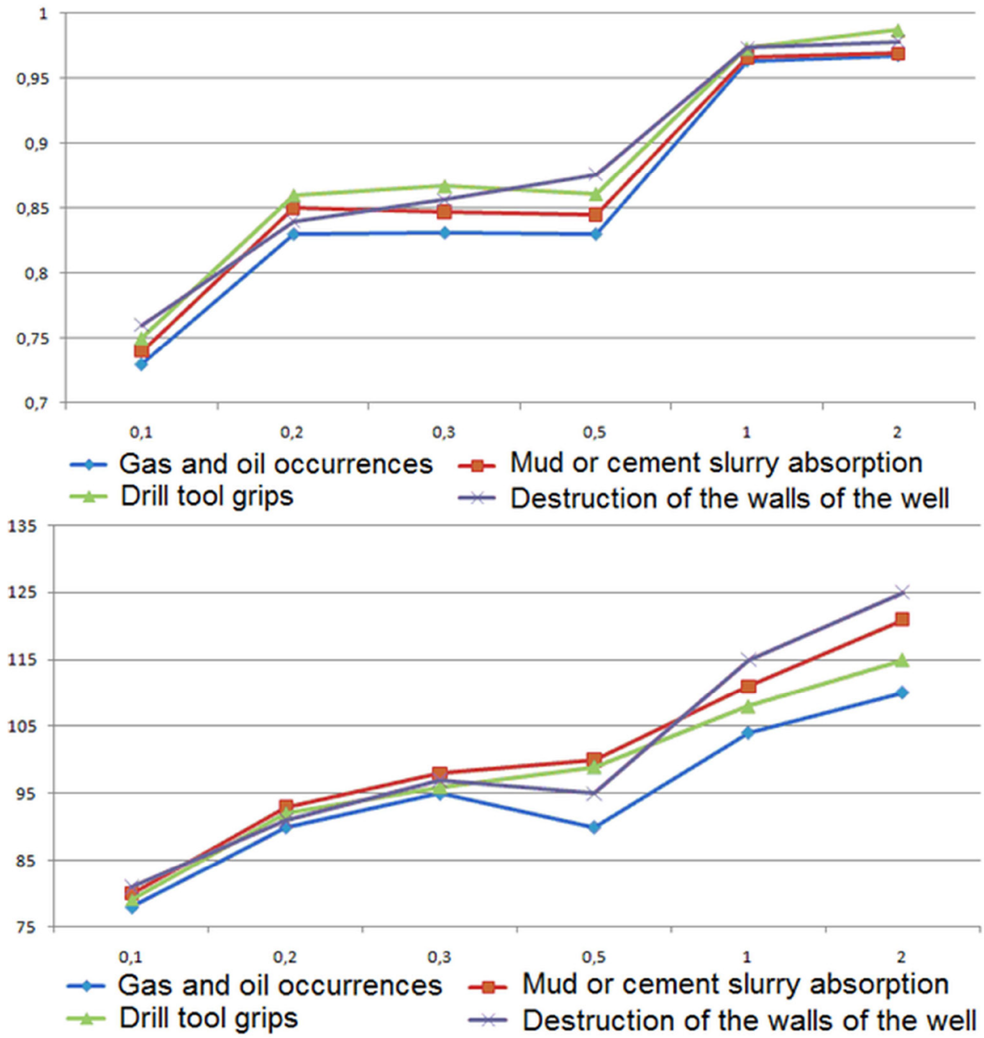

Fig. 2. Graphs of the dependence of recognition accuracy and the number of training iterations on the value of *Rmax*.

The results of the study of the dependence of recognition accuracy and the number of iterations required to complete the training on the values of *K* and *Rmax* for four different pre-emergency situations are shown in Figures 1-2.

On the basis of the obtained data, we can conclude that the nature of the dependencies for all four studied situations practically coincides, which allows us to extend Conclusions made for the pre-emergency situation of "Oil and gas-water occurrence" [8, 9, 10, 20] for the entire class of pre-emergency situations considered.

3 Results and Discussion

Definition of the impact of learning speed for selected pre-emergency situations. Let us consider the influence of the learning rate of the error back propagation algorithm on the number of iterations of this algorithm and on the number of necessary machine operations, on which the training time directly depends.

Table 7. The dependence of the number of iterations on the learning speed for different numbers of hidden layer neurons with a recognition accuracy of 0.9 in a single-layer architecture.

Learning speed	Number of Hidden Layer Neurons / Single Layer Neural Network							
	1	2	3	4	5	10	25	100
0.1	3000	2100	1350	650	648	649	648	647
0.2	2860	2050	1320	600	589	699	599	598
0.3	2710	1940	1260	560	550	555	554	553
0.4	2630	1880	1110	520	517	518	518	517
0.5	2500	1720	1090	490	484	484	583	581
0.6	2440	1590	1000	470	465	464	463	461
0.7	2280	1460	900	430	421	420	419	418
0.8	2110	1280	840	380	380	375	374	373
0.9	2000	1200	780	360	357	356	355	354

Table 8. The dependence of the number of iterations on the learning speed for different numbers of neurons of the hidden layer with a recognition accuracy of 0.9 in a two-layer architecture.

Learning speed	Hidden Layer Number of Neurons - Bilayer Neural Network							
	1	2	3	4	5	10	25	100
0.1	2400	1680	1080	520	518.4	519.2	518.4	517.6
0.2	2288	1640	1056	480	471.2	559.2	479.2	478.4
0.3	2168	1552	1008	448	440	444	443.2	442.4
0.4	2104	1504	888	416	413.6	414.4	414.4	413.6
0.5	2000	1376	872	392	387.2	387.2	466.4	464.8
0.6	1952	1272	800	376	372	371.2	370.4	368.8
0.7	1824	1168	720	344	336.8	336	335.2	334.4
0.8	1688	1024	672	304	304	300	299.2	298.4
0.9	1600	960	624	288	285.6	284.8	284	283.2

From the above tabular data it follows that the number of iterations of the learning algorithm decreases with an increase in the number of neurons in the hidden layer of the neural network. However, this does not allow one to directly assess the change in training time, since the number of necessary machine operations increases in proportion to the number of neurons. Therefore, it is necessary to compare the nature of the change in the number of operations, the graphs of which are presented in Figure 3.

Table 9. The dependence of the number of machine operations on the learning speed for different numbers of hidden layer neurons with a recognition accuracy of 0.9 in a single-layer architecture.

Learning speed	**Number of Hidden Layer Neurons / Single Layer Neural Network**							
	1	**2**	**3**	**4**	**5**	**10**	**25**	**100**
0.1	3000	4200	4050	2600	3240	6490	16200	64700
0.2	2860	4100	3960	2400	2945	6990	14975	59800
0.3	2710	3880	3780	2240	2750	5550	13850	55300
0.4	2630	3760	3330	2080	2585	5180	12950	51700
0.5	2500	3440	3270	1960	2420	4840	14575	58100
0.6	2440	3180	3000	1880	2325	4640	11575	46100
0.7	2280	2920	2700	1720	2105	4200	10475	41800
0.8	2110	2560	2520	1520	1900	3750	9350	37300
0.9	2000	2400	2340	1440	1785	3560	8875	35400

Table 10. The dependence of the number of machine operations on the learning speed for different numbers of hidden layer neurons with a recognition accuracy of 0.9 in a two-layer architecture.

Learning speed	Number of Hidden Layer Neurons / Single Layer Neural Network							
	1	2	3	4	5	10	25	100
0.1	2400	3360	3240	2080	2592	5192	12960	51760
0.2	2288	3280	3168	1920	2356	5592	11980	47840
0.3	2168	3104	3024	1792	2200	4440	11080	44240
0.4	2104	3008	2664	1664	2068	4144	10360	41360
0.5	2000	2752	2616	1568	1936	3872	11660	46480
0.6	1952	2544	2400	1504	1860	3712	9260	36880
0.7	1824	2336	2160	1376	1684	3360	8380	33440
0.8	1688	2048	2016	1216	1520	3000	7480	29840
0.9	1600	1920	1872	1152	1428	2848	7100	28320

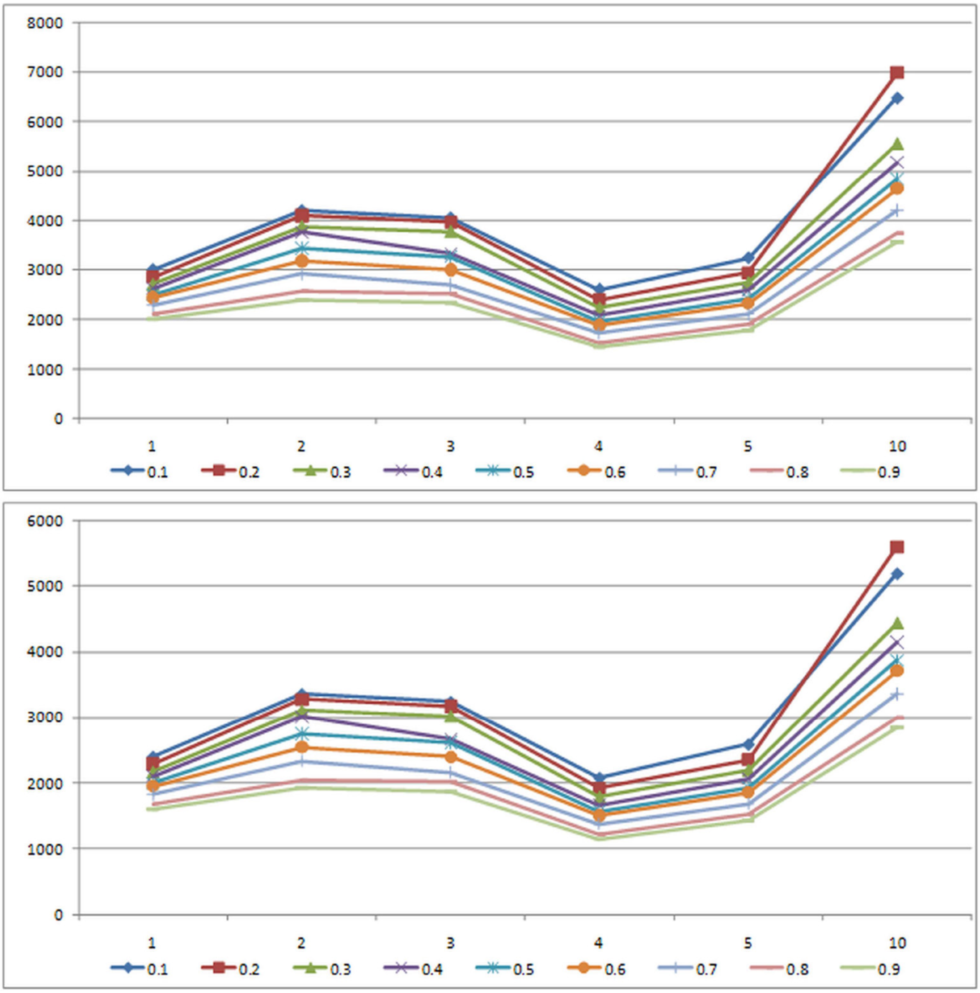

Fig. 3. Graphs of the number of learning iterations from different values of learning speeds for NS with different layers and different numbers of hidden layer neurons with the same recognition probability = 0.9.

From these graphs, we can conclude that the minimum number of operations (and, consequently, the training time) is achieved when the number of neurons in the hidden layer coincides with the number of classifier inputs. An increase in the learning rate also leads to a decrease in the number of operations; therefore, it is advisable to use a speed value close to unity. The study of the influence of the classifier structure on recognition results is described in detail in [21].

4 Conclusions

From the results obtained, it can be concluded that for all four types of pre-emergency situations considered, the average recognition accuracy of the specialized classifier turned out to be higher than the universal accuracy, and the number of iterations of the learning algorithm is less than that of the universal one. This allows us to state that in all the cases considered, the use of a specialized classifier is more appropriate.

To solve the problem of recognition of emergency situations it is necessary to have the appropriate information base. As such a basis, the work used real data from the drilling process of the Mokhovsky coal mine, Kemerovo region.

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