Influence of geological information density on the training quality of neural networks as forecast models

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Abstract

The spatial information for the values of basic geological parameter (copper grade) from the different exploration and exploitation stages of porphyry copper deposit has been used in the investigation. Neural networks have been trained with different density of training data for some production levels. The train and test errors of forecast model – neural network have been analyzed. Their values can be used for training information density evaluation with the purpose of risk reduction in geological parameter prognostication. The obtained results give us possibilities of train data optimal density determination.

Keywords: *ore deposit, exploration, density of exploration data, neural networks, prognosis*

1 Neural networks as a modeling instrument

Recently neural networks as a product of artificial intelligence are used increasingly to solve various application problems such as pattern recognition, classification and clustering, forecasting etc. They find application in various fields of investigation. Geology exploration and mining are characterized by highly nonlinear structures and probabilistic nature, which makes difficult their formalized description. For this reason, neural networks are suitable for analysis of geological data, for models building, which correctly support the engineering problems solutions.
Different types of neural networks and ways of training depending on the solved problems with their help have been developed. In (Topalov and Hristov, 2007) and (Topalov and Hristov, 2008) multilayer perceptron has been shown as suitable neural network for prediction of geologic parameter and study its changeability. The module Neural Networks from STATISTICA 7 of StatSoft Inc. in particular sub-module Intelligent Problem Solver

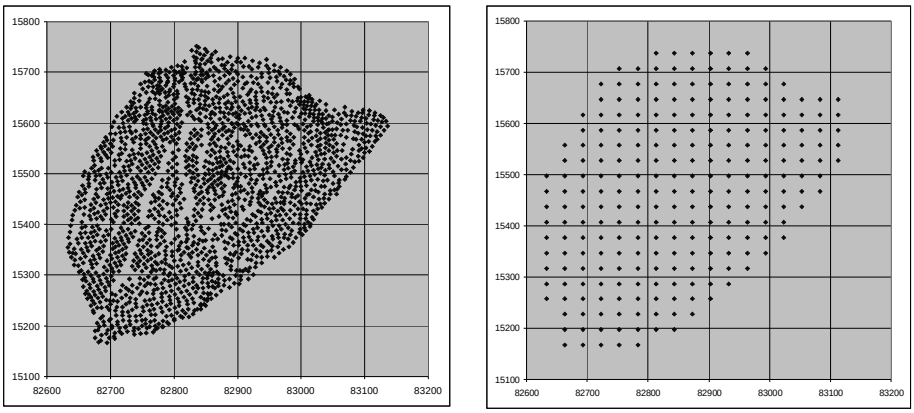
(IPS), was used in this study. IPS allows training and evaluation of different types of neural network architectures, with different parameters. It trains and tests many different neural networks by same training and testing data simultaneously and then ranks them according to their quality. This facilitates discovering of the appropriate class of models and some of their parameters.

2 Object of Investigation

The porphyry copper deposit "Elatzite" is situated in Etropole's part of Balkan mountain. It was discovered in 1952 (Milev et al., 2007). Its detailed exploration have been performed by boreholes and drive prospect workings during the period of years 1952 – 1968. The exploration grid has different density – from 100×100 m, at intervals of 50×100 m till to 71×71 m (152 drill holes and 4115 m drive prospect workings).
The ore body of the deposit is an ore stock and has not well-defined contacts. The central part of the deposit is most strongly mineralized which decrease to the periphery up to barren rocks. The horizontal sections of the irregular ore body shape are elliptical with next size 1400×850 m. The vertical size of mineralization is nearly 870 m. In the ore are fixed 61 minerals generally. 48 of them are ore minerals and the others are non-metallic minerals. The main ore minerals are chalcopyrite, pyrite, bornite and molybdenite.
The main useful component – copper grade has been studied sufficiently in details. Its distribution has been revealed by detailed exploration and exploitational exploration samples, especially by purposeful mineralogical and statistical investigations for the regularities clarifying from research team led by July Todorov (Milev et al., 2007).
Now, during the mining process exploitational exploration is realized by systematic blast hole sampling. The samples are located in grid approximately 14×14 m. Mining method is opencast mining. Most of the extracting levels are already worked-out. All the information about copper grade from these levels is available.

3 Optimum density of neural network training data determination

The study is focused on six fully or partially operating extracting levels for which basic geological parameter data are available - the copper grade from all stages of the deposit exploration. The high density of the available information allows to be determined by diluting such data quantity that provides reliable neural network training, and effective forecasting.
Dilution is realized by defining regular grid nodes by analogy with the detailed exploration. Different variants on a regular network with different distances between nodes were formed. The data from the exploitation stage of sampling (Figure 1a) are not organized in regular grid by technological reasons. This requires a special approach for the geological parameter determination in the nodes of a regular grid (Figure 1b). The exploitation sampling information falling within a circle with certain radius around each node of regular grid was used. Those samples within the circle have different impacts on the geological parameter value in the grid node. Weighted average is used, as a rule the weight of each sample depends on the distance to the knot. The Visual Basic for Application of MS Excel program was created for the purpose. It can calculate the nodes value from exploitation samples for the chosen extracting level by specified circle radius and grid lag. The program allows to the user to enter the radius and lag value.



a) exploitation sampling – 1954 samples

b) regular grid nodes (243)
grid lag is equal to 30 m

Figure 1. Extracting level 1015 – samples situation

The number of variants of that dilution is deliberately increased as the lag of regular grid varies from 10 up to 70 meters with step of 10 meters and the radius is chosen to be equal to the specified lag. The data from the detailed exploration stage (DES) are included as an individual variant. Thus, this produces a different number of nodes in different variants (Table 1). Figure 2 illustrates the number grid nodes change depending on the assumed regular grid lag. The determined geological parameter values in these grid nodes are used for neural networks training.

Table 1. Regular grid node numbers by extract levels

Lag	10	20	**30**	40	50	60	70	DES
Level 1015	1878	512	**243**	147	100	70	58	140
Level 1000	1705	466	**219**	134	88	66	48	136
Level 985	1341	371	**178**	107	72	58	41	135
Level 970	1193	332	**158**	97	70	48	37	134
Level 955	824	229	**116**	72	46	37	28	135
Level 940	482	142	**72**	44	29	22	18	131
Average	1237	342	**164**	100	68	50	38	135

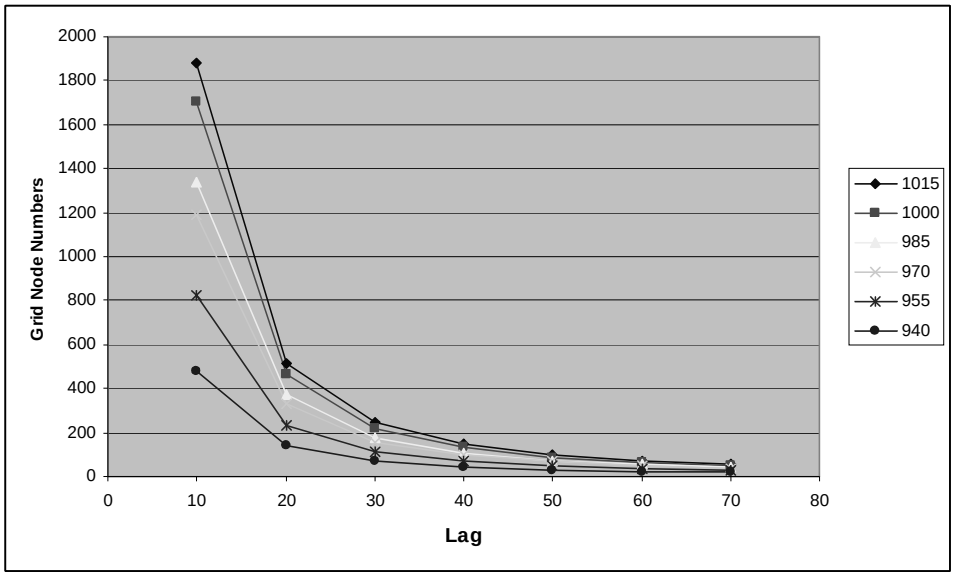
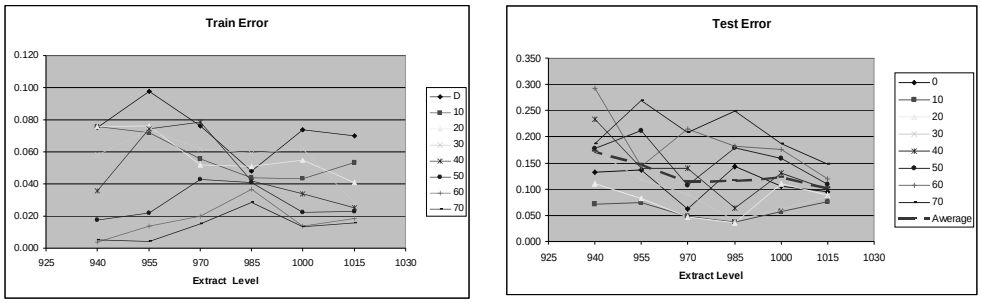


Figure 2. Regular grid node numbers by extract levels

Different types of neural networks – multilayer perceptrons have been trained by IPS for each regular grid node variant. They have been tested on all available exploitation sampling data from the corresponding extract level. The best network from the IPS ranked networks was chosen by lowest test error criterion. These are four layers perceptrons with two hidden layers. The input layer has two nodes - the sample (node) coordinates, output layer has one node - the sample copper grade value. The results in our earlier studies show that the small number of nodes in each inner layer does not provide better accuracy due to model globalization. On the other hand a very large number of nodes lead to network re-training and testing error increasing. In this study the number of nodes in the inner layers has been limited between 6 and 9. Table 2 presents the test errors of all the best-trained neural networks for six extract levels for all versions of dilution.

Table 2. Test errors of the best trained neural networks

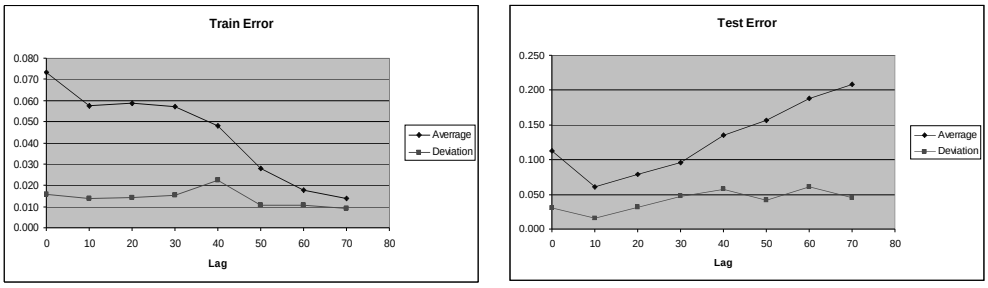
Lag	10	20	**30**	40	50	60	70	DES
Level 1015	0.076	0.088	**0.086**	0.100	0.109	0.120	0.148	0.095
Level 1000	0.058	0.110	**0.062**	0.131	0.158	0.176	0.187	0.106
Level 985	0.037	0.036	**0.041**	0.064	0.178	0.182	0.249	0.144
Level 970	0.049	0.047	**0.090**	0.139	0.107	0.215	0.208	0.063
Level 955	0.074	0.082	**0.119**	0.140	0.212	0.142	0.270	0.137
Level 940	0.071	0.110	**0.174**	0.234	0.178	0.292	0.186	0.132
Average	0.061	0.079	**0.095**	0.135	0.157	0.188	0.208	0.113



a) b)

Figure 3 Train and test errors of the best neural networks by extract levels

Figure 3 shows the errors in the training and testing of the best networks for different extract levels. There can not be seen clear regularity. May be noted that when training on data with less density, neural networks achieve a small train error, but while testing them – these networks provide bigger errors. For purposes of the forecasting, test errors are determinative for prediction accuracy because they are set on the maximum density of information - data from exploitation exploration. Figure 3b shows the test error average by extract levels (dash line). These average errors are closest to errors in testing at a density of 30 and 40 m (highest values of correlation coefficient - 0.84), but errors in density 30 m are almost everywhere smaller than average. On the other side of Table 1 and Figure 1 show that the number of nodes of regular grid with lag up to 30m is relatively small, while for networks with higher nodes density their number sharply increase - repeatedly.



a) b)

Figure 4. Train and test error behavior in case of different training data density

Figure 4 shows graphs of error average and their variance from all extract levels in the training and testing process according to the regular grid lags (the density of training data). The error values of the initial point 0 in the graphs are those of trained neural networks with training data from detailed exploration. These graphs confirm that neural networks are trained with smaller error in reducing the density of data (Figure 4a), but they give greater error in testing (Figure 4b). It can be seen from the two graphs that the errors variance is comparatively invariable, i.e. does not depend on the density of training data. This can be considered as a symptom of some stability achieved in the quality of training of neural networks in different extract levels regardless of the lag value.

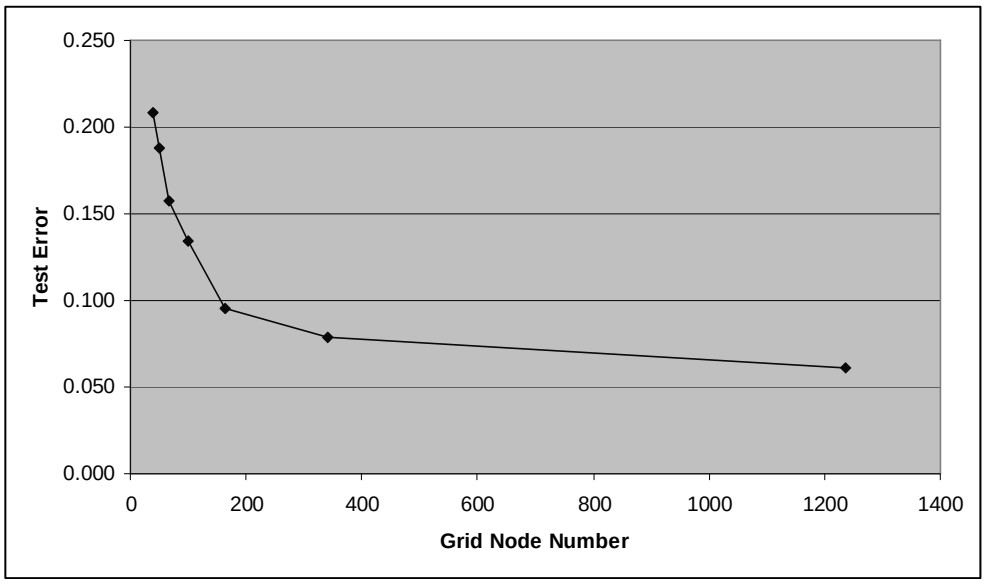


Figure 5. The relationship between the average test errors and the average number of regular grid nodes

It is necessary to find the optimum value of the ratio between test error and train sample number (their density. Figure 5 shows the relationship between the average test errors (last row of Table 2) and the average number of regular grid nodes (the last row of Table 1). It can be seen that the test error increases sharply at low density of training data. Breaking point on the graph corresponds to the density of training data from 30 x 30 m. This confirms the comments of Figure 3b.

4 Conclusions

Some results from previous investigations (Hristov and Topalov, 2009), (Topalov and Hristov, 2007) and (Topalov and Hristov, 2008) demonstrate convincingly the ability to detect geological parameter - copper grade changeability and its prediction using neural networks. As we know the number, uniformity and density of training data significantly affect the quality of training. On the other hand provide a very large number of samples are associated with significant costs. It is therefore necessary to find the optimal ratio between the number of training data (samples) and quality of training of the network, i.e. forecast quality. That is the reason to use in the investigation all available information about the basic geological parameter provided at all exploration stages of the ore deposit. Present studies have focused on six consecutive full and/or partially mined levels. The following results were achieved:

1. The Visual Basic for Application of MS Excel program has been developed, which extract from spatial sampling data the values of geological parameter in regular grid with different density, which can be user defined.
2. By this program have been formed 42 regular networks - 7 of every level

3. Many neural networks have been trained on these regularly arranged data and the best one has been selected by minimal test error criterion of exploitation data sampling.
4. The optimal density of training data - 30 x 30 m is determined on the basis of achieved results.

The obtained results allow increasing the training quality of neural network with not so many data and can be used for prediction at non mined areas and deeper extract levels. There is no need to crowd together sampling adopted in the case of a grid of 14 x 14 m.

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