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ASPECTS OF ASSESSMENT OF ECOLOGICAL IMPACT OF AN ASH-SLUDGE COLLECTOR OF PAVLODAR ALUMINUM PLANT (KAZAKHSTAN)

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Abstract: On the base of samples taken from ash-sludge collector of Pavlodar Aluminum Plant we have created neural network for making forecasts of concentration distributions of different elements compounding production waste of the plant. For every analyzed element separate neural network was created. Levenberg-Marquardt algorithm was chosen for training. Architecture of neural network includes 5 layers, where one layer is input, one – output and three between them are hidden layers. Neural network demonstrates high accuracy on all of three samples of data obtained by means of partitioning of samples taken from different locations of the lake. Much higher concentration in every location is observed for Silicon (Si), Calcium (Ca), Cuprum (Cu) and Ferrum (Fe). The less concentrations were obtained for Manganese (Mn), Vanadium (V), Titanium (Ti), Scandium (Sc), Gallium (Ga). Accuracy of neural network calculations depends on setting parameters such as number of layers, training algorithm.

Introduction

Artificial neural networks are ones of the most used instruments in the area of machine learning. Neural networks are the systems like our brain, they are destined to model educational process due to determined training procedure. Although neural networks (also known as “perceptron”) exist from the 1940s, they become an important part of researches in the area of artificial intellect only in the last several decades. That is related with development of new method of training of neural networks called as “backpropagation”. Another important occurrence was appearance of levels deep neural networks, where different layers of multilayer network extract various functions until they will not be able to find out what they are looking for.The main task of analytic using neural networks for solving some problems is to create the most effective architecture of neural network, i.e. make right choose of type of neural network, algorithm of its training, number of neurons and types of relations between them. That work does not have formalized procedures, it requires deep understanding of various types of architectures of neural networks and includes large amount of research and analytical work and can take quite a bit of time (Gurney 1997).

Materials and methods

On the base of samples taken from ash-sludge collector of Aluminum plant we have created neural network for making forecasts of concentration distributions of different elements compounding production waste of the plant. On the stage of training we used coordinates of the places, when we have taken samples for analyses, as input data for neural network. As well on the training stage we directly set the result, which we are expecting to obtain for current pair of coordinates, for every pair of coordinates from input data. After that, on the base of neural network training algorithm and empirical calculations weight numbers are formed and relevant functions of transitions for every layer of neural network are selected (Chow et al. 2007). This stage is the most complicated because behavior of the network depends on settings data and every change in diapason of input data must be adequately processed by network, and consequently the network must give determined forecasted result.

We used various settings data at creation of distribution map for every element. It is related to the fact that diapason of concentrations of different elements is different, that, consecutively influence weight numbers of different layers, as well activation functions can be different.

For neural network for forecasts of element concentration on input two coordinates are given on input. Hidden layers of neural network consist of determined fixed number n of neurons, which are grouped with neurons in input and output layers through a matrix of weight numbers. Further, we calculate activation functions for every neuron of hidden layers. Neurons of hidden layer in turn grouped with neurons of output layer through the matrix of weight numbers with dimension nx1 (because we have only one neuron of output layer) (Croall and Mason 1992, Fine 1999). After that, based on calculation of activation function on output layer we obtain real number representing approximated value of concentration of given element in coordinates, given in input layer of neural network.

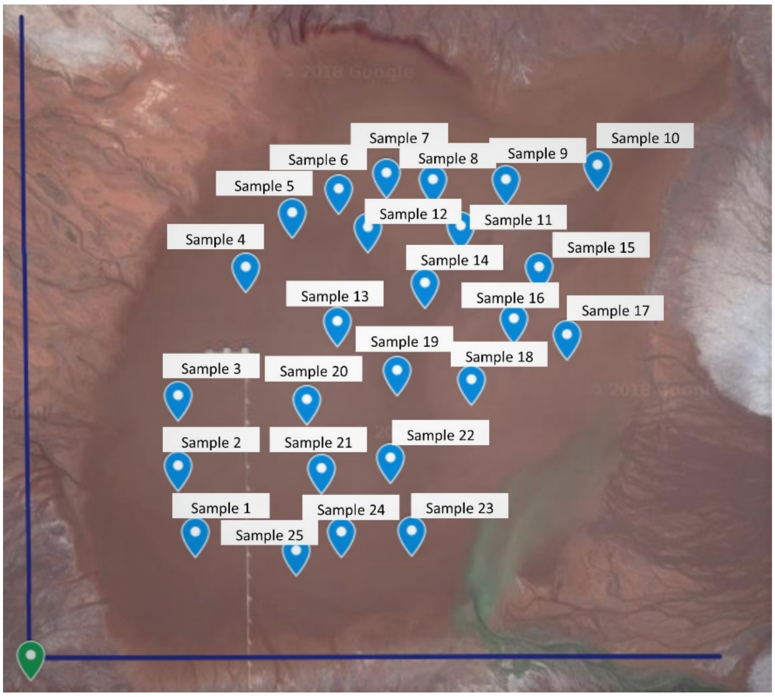

Figure 1. The sampling map
1. ábra A mintavételek helyszíneinek térképe

Waste sampling for quality and quantity elemental analysis of soils from waste dump of Aluminum plant was carried out according to “GOST 17.4.4.02-84. Soils. Methods of selection and preparation of samples for chemical, biological and helminthological analysis”, “GOST 17.4.3.01-83. Soil. General requirements for sampling”, “GOST 5180-84. Soils. Methods of laboratory determination of physical characteristics”.

The location of the test site was plotted on the map. On the Figure 1 lake, where industrial waste of Aluminum plant is collected, is shown. Points marked on the lake represent locations of sampling for elemental analysis (Figure 1). Corresponding point coordinates are calculated relatively point (0.0) showed on the map on crossing of two perpendicular line segments representing two orthogonal axes: x and y. The lake has approximate width (axis x) of 760 m and length (axis y) equal to 737 m.

The location of sampling points depends on the configuration of the field. On a narrow, elongated segment, they can be placed along (in the middle) the field. On a wide, near-square field, the optimal arrangement of the sampling points is chess. On very large areas sampling is carried out on one or two diagonals (Mineev 2001). Since the investigated ash-sludge collector has a shape close to the oval, the concentric arrangement of the points was chosen.

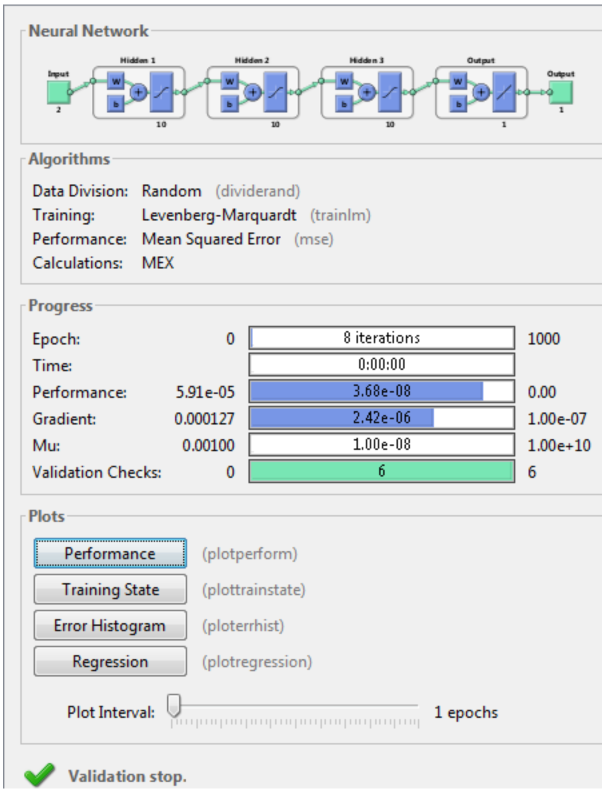

Figure 2. Architecture and setting parameters of neural network for iodine (I)
2. ábra A jódhálózat neurális hálózatának architektúrája és paraméterei (I)

For every analyzed element separate neural network was created. In every network for all elements architecture was generalized, but input data in training set were different.

Levenberg-Marquardt algorithm was chosen for training. This algorithm usually requires more memory space, but less time for execution. Training automatically stopped when the result is no longer improving as evidenced by an increase in mean square deviation of the sample. It is a modification of the method of gradient descent and the method of confidence intervals.

Results and discussion

Pavlodar is placed in North-Eastern Kazakhstan. In physical-geographical terms, Pavlodar is located on the West Siberian Plain. Pavlodar has an area of 400 km^2. Altitude of the center of Pavlodar is of 123±1 m. Type of climate in Pavlodar is abruptly continental.

Pavlodar is one of the biggest industrial hub of Kazakhstan. It has more than 2000 industrial enterprises including gigantic plants like oil refining factory, aluminum plant, electrolysis plant, pipe rolling plant, GRES (a condenser type electricity-only thermal power station), TEC (combined heat and power plants). According to statistics of the region government the volume of emissions of Pavlodar industrial enterprises is about 600 000 ton per year. It is approximately a quarter of emissions volume in the whole country.

On the figure 3 territory of Pavlodar with adjoined industrial objects – ash-sludge collectors of Pavlodar aluminum plant have shown. The territory of Pavlodar is contoured by red. The territory of studied ash-sludge collector is contoured by orange.

Figure 3. Map of Pavlodar with adjoined industrial objects ash-sludge storages of Pavlodar aluminum plant (the territory surrounded by orange color is the object under study)

3. ábra Pavlodar térképe a szomszédos ipari objektumokkal és a kapcsolódó Pavlodari Alumíniumgyár hamu- és salakiszap tárolóival (a narancssárga színnel körbevéve a vizsgálati terület)

Pavlodar aluminum plant is one of the biggest industrial enterprises of the region. It produces 1.4–1.5 million ton of alumina per year. Pavlodar aluminum plant belongs to "Kazakhstan's Aluminium" corporation. In the BROOK HUNT ratings "Kazakhstan's Aluminium" corporation is placed on 10th position among the World alumina producers with estimated alumina production capacity of 1.5 million ton. In CIS countries "Kazakhstan's Aluminium" corporation is placed on 1st position by sold capacity.

As a result of work of all technological hubs of alumina production there are emissions in atmosphere: suspended solids (dust of bauxite, limestone, coal, alumina), alkali vapor and gases: sulfurous anhydride, oxides of nitrogen and carbon. According to the Department of Environmental Protection, 46 kinds of pollutants get in atmosphere from acting production of the plant. To catch harmful emissions, all technological equipment of alumina production is equipped with gas cleaning devices.

The enterprise has three storages of waste: sludge collector consisting of two parts, ash dump of TEC and departmental landfill of industrial and domestic waste. Sludge is characterized by calcium-silicate content and significant amount of Fe_2O_3 (27–32%).

Dicalcium silicate contained in the sludge in significant amounts has great specific surface of particles and shows binding properties. It points on the opportunities of using the sludge as a separate binder or as a component of building binders. “Kazakhstan’s Aluminium” corporation has developed technology of ceramic and clinker brick production, practical possibility of silicate brick production using sludge of alumina production and ash-slag waste of TEC has been shown.

In dumps of Pavlodar alumina plant it was accumulated about 60 million ton of sludge as of December 2000. Annual sludge production volume is 100–120 thousands ton. In order to organize waste free production or to lower amount of waste accumulated in dumps we can use them as secondary raw materials for producing new products like building mixtures or catalysts in some cases. Thus, we can consider dumps as a secondary source of raw materials. For estimation of capacity of the sources, we should know quality and quantity content of these dumps. However, the main difficulty of the task is that distribution of elements in the dump is not uniform. The study of that nonuniformity can be done by two ways. The first method is to get many samples. The more samples you will investigate, the more accurate results about elemental distribution you will get. However, it is very expensive way and it demands a long time. Another way is to get a specified number of samples, perform elemental analysis and put obtained data in a computer model in order to machine predict the distribution character or trends. When we use computers for prediction, accuracy of results will depend on correctness of used mathematic model. Often in present days for analogous calculations, they use computer models named as neural networks or neuronets.

As can be seen from Figure 4 architecture of neural network includes 5 layers, where one layer is input, one – output and three between them are hidden layers.

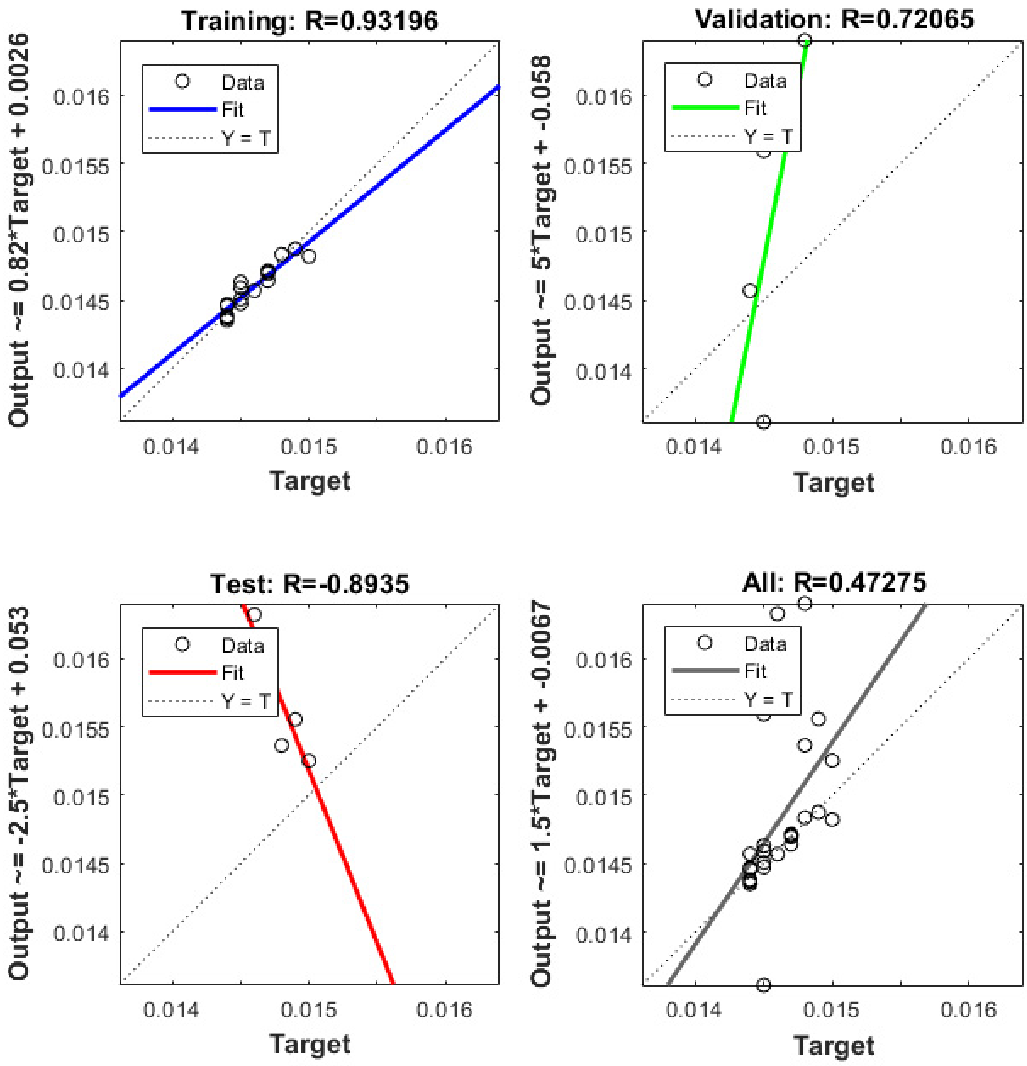

Figure 4. Matching of points in training, validation and test samples with values in points obtained using neural network

4. ábra A pontok összevetése a gyakorlatban, az érvényesítésben és a tesztmintákban a neurális hálózaton kapott pontokban megadott értékekkel

As shown on Figure 4 neural network demonstrates high accuracy on all of three samples of data obtained by means of partitioning of samples taken from different locations of the lake.

Tables 1 to 6 show data about distribution of Cr, Cu, Fe, Ga, Mn, V, obtained using developed neural network. The distribution is represented using concentration of element and relevant coordinates. Figures 5 to 10 show electronic maps of distribution of Cr, Cu, Fe, Ga, Mn, V, obtained using developed neural network. The more concentration of element in specified point, the more red color it has on the map and vice versa. The distribution of values in the Figure 5 obtained by neural network, given the sample points shown in the Table 1, attains a good fit on the sample points, which can be seen from Figure 4. Figure 4 shows how strongly predicted values correlate with the data in the training, validation and test datasets. Neural network model, however, might require more data points to attain even better prediction accuracy.

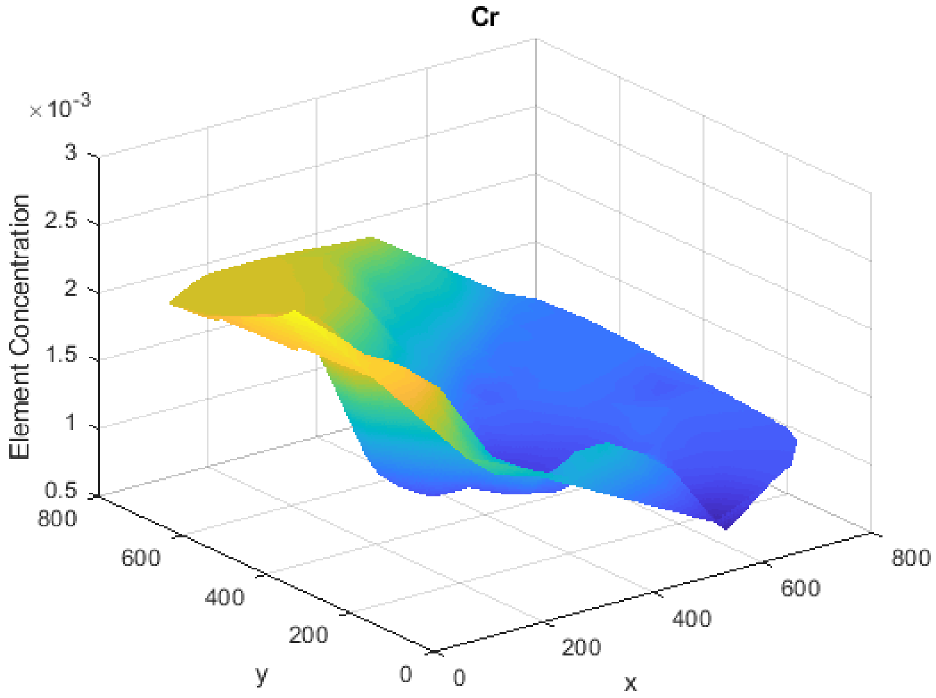

Figure 5. Concentration distribution of chrome (Cr)
5. ábra A króm (Cr) koncentráció eloszlása

Table 1. Sample of chrome (Cr) concentrations in various points
1. táblázat Példák a króm (Cr) koncentrációra különböző pontokban

x	y	Element concentration
181	125	0.0021
177	197	0.0022
176	275	0.0024
246	428	0.0024
296	488	0.0017
337	515	0.0017
388	535	0.0027
443	526	0.0026
522	525	0.0015
619	542	0.0023
473	475	0.0021
366	475	0.0015
335	368	0.0018
432	412	0.0021
560	428	0.0021
528	373	0.0015
591	354	0.0021
485	304	0.0027
403	314	0.0017
301	284	0.0020
319	206	0.0026
390	219	0.0023
419	140	0.0021
340	137	0.0015
290	117	0.0019

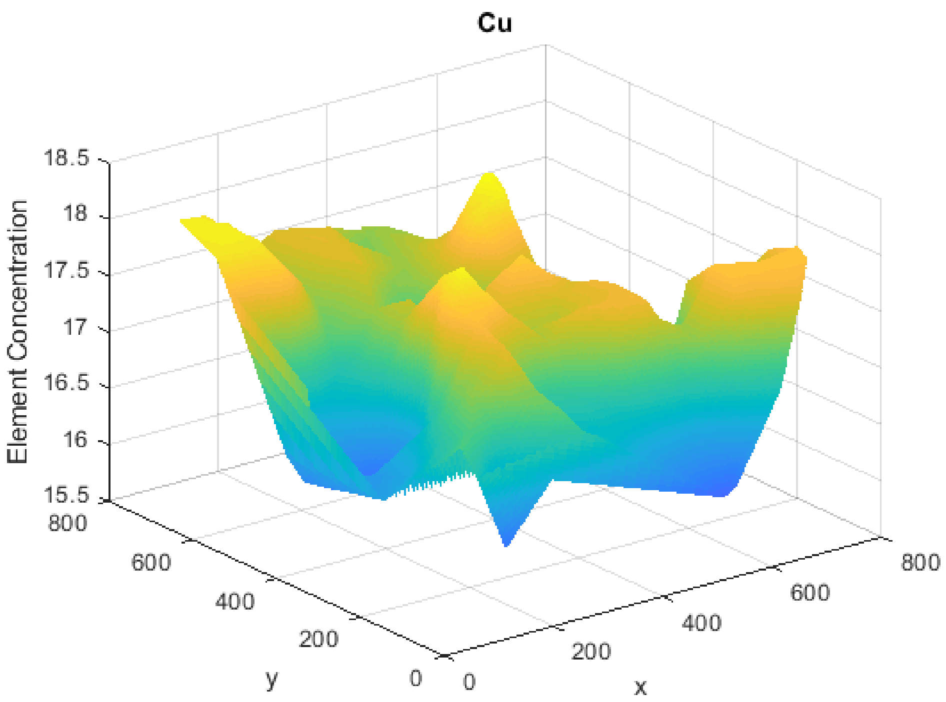

Figure 6. Distribution of copper (Cu) concentrations
6. ábra A réz (Cu) koncentrációjának eloszlása

Table 2. Sample of copper (Cu) concentrations in various points
2. táblázat Példák a réz (Cu) koncentrációra különböző pontokban

x	y	Element concentration
181	125	16.3538
177	197	15.6715
176	275	18.5271
246	428	15.7020
296	488	17.1586
337	515	15.5866
388	535	16.0002
443	526	15.7335
522	525	15.8036
619	542	15.8093
473	475	15.2725
366	475	18.6135
335	368	17.8386
432	412	17.8729
560	428	15.7356
528	373	18.6523
591	354	17.2628
485	304	15.2509
403	314	17.6275
301	284	17.2323
319	206	18.5990
390	219	17.9560
419	140	16.7376
340	137	17.8051
290	117	16.7051

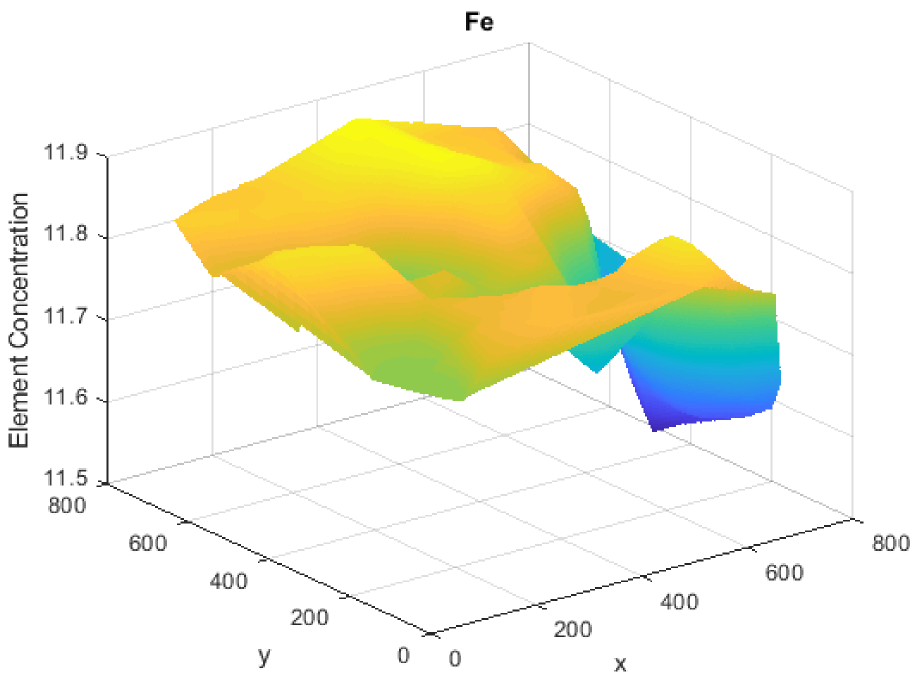

Figure 7. Distribution of iron (Fe) concentrations
7. ábra A vas (Fe) koncentrációjának eloszlása

Table 3. Sample of iron (Fe) concentrations in various points
3. táblázat Példák a vas (Fe) koncentrációra különböző pontokban

x	y	Element concentration
181	125	11.4449
177	197	11.4071
176	275	11.4192
246	428	11.4197
296	488	11.4038
337	515	11.4236
388	535	11.3224
443	526	11.4940
522	525	11.4090
619	542	11.4852
473	475	11.4106
366	475	11.5420
335	368	11.4947
432	412	11.5258
560	428	11.3429
528	373	11.3935
591	354	11.3718
485	304	11.3742
403	314	11.4081
301	284	11.5348
319	206	11.4549
390	219	11.4690
419	140	11.3700
340	137	11.4154
290	117	11.4553

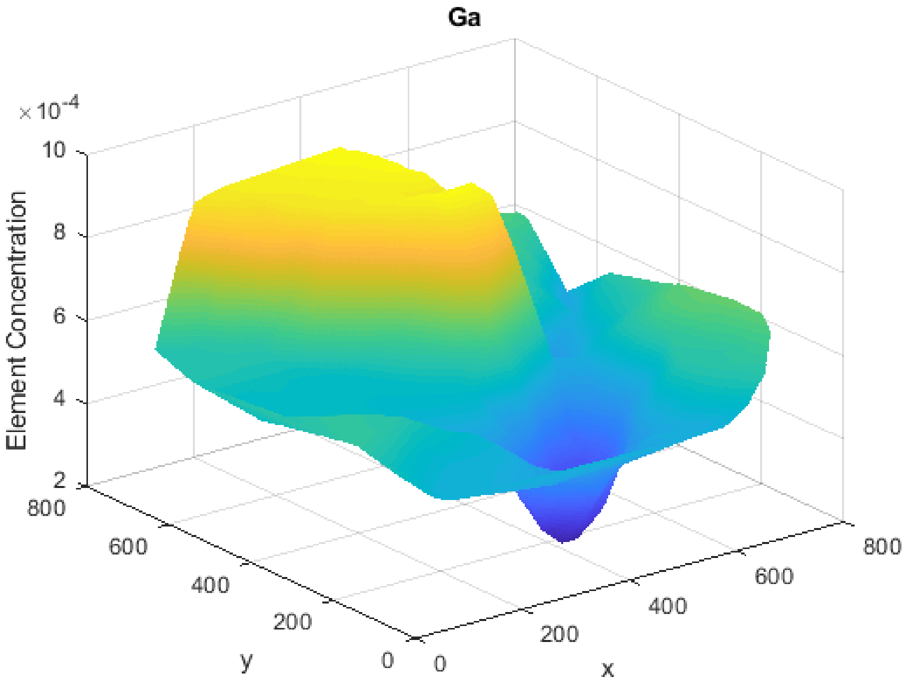

Figure 8. Distribution of Gallium (Ga) concentrations
8. ábra A gallium (Ga) koncentrációjának eloszlása

Table 4. Sample of Gallium (Ga) concentrations in various points
4. táblázat Példák a gallium (Ga) koncentrációra különböző pontokban

x	y	Element concentration
181	125	0.0006
177	197	0.0009
176	275	0.0007
246	428	0.0008
296	488	0.0009
337	515	0.0009
388	535	0.0009
443	526	0.0009
522	525	0.0010
619	542	0.0008
473	475	0.0009
366	475	0.0007
335	368	0.0010
432	412	0.0009
560	428	0.0008
528	373	0.0009
591	354	0.0008
485	304	0.0008
403	314	0.0008
301	284	0.0009
319	206	0.0006
390	219	0.0007
419	140	0.0006
340	137	0.0009
290	117	0.0010

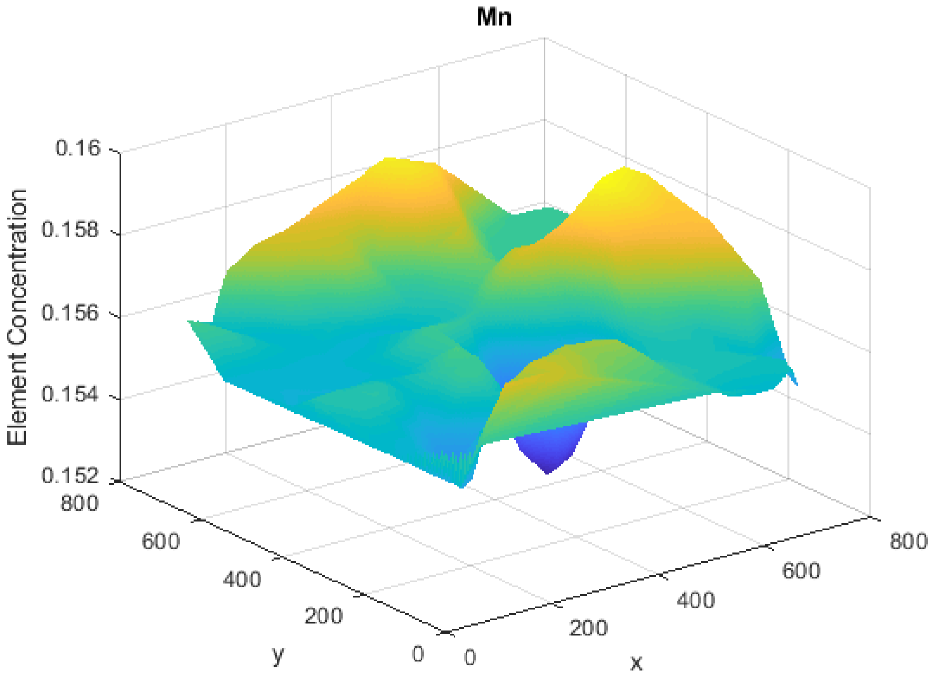

Figure 9. Distribution of manganese (Mn) concentrations
9. ábra A mangán (Mn) koncentrációjának eloszlása

Table 5. Sample of manganese (Mn) concentrations in various points
5. táblázat Példák a mangán (Mn) koncentrációra különböző pontokban

x	y	Element concentration
181	125	0.1560
177	197	0.1562
176	275	0.1569
246	428	0.1567
296	488	0.1577
337	515	0.1583
388	535	0.1562
443	526	0.1595
522	525	0.1562
619	542	0.1563
473	475	0.1593
366	475	0.1562
335	368	0.1596
432	412	0.1591
560	428	0.1580
528	373	0.1575
591	354	0.1561
485	304	0.1596
403	314	0.1594
301	284	0.1552
319	206	0.1563
390	219	0.1578
419	140	0.1567
340	137	0.1572
290	117	0.1556

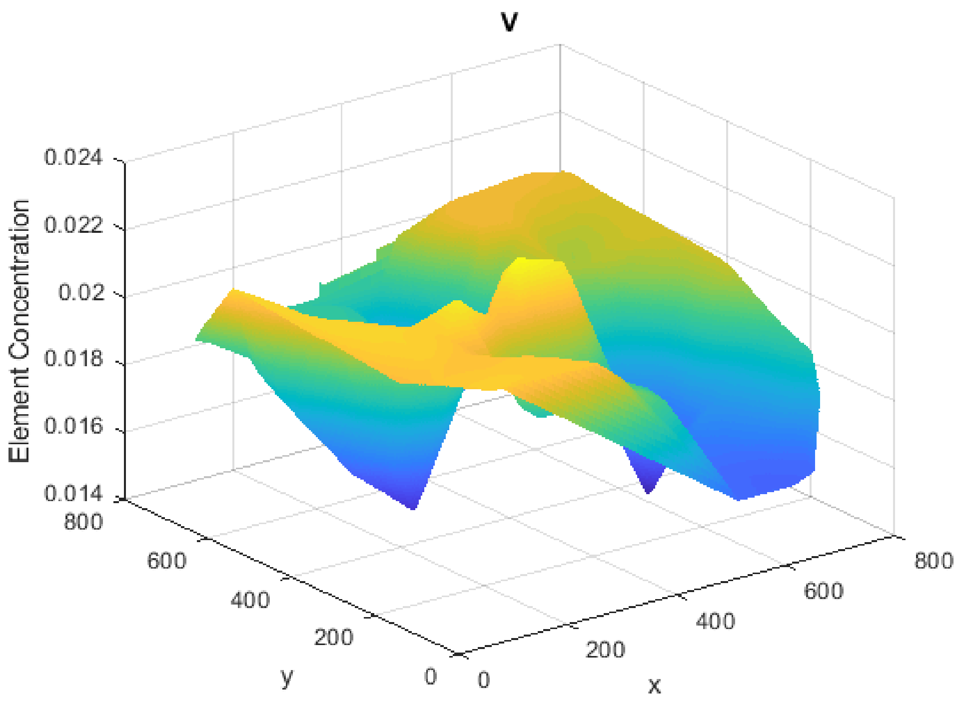

Figure 10. Distribution of vanadium (V) concentrations
10. ábra A vanádium (V) koncentrációjának eloszlása

Table 6. Sample of vanadium (V) concentrations in various points
6. táblázat Példák a vanádium (V) koncentrációra különböző pontokban

x	y	Element concentration
181	125	0.0003
177	197	0.0002
176	275	0.0002
246	428	0.0002
296	488	0.0003
337	515	0.0003
388	535	0.0002
443	526	0.0002
522	525	0.0002
619	542	0.0003
473	475	0.0002
366	475	0.0003
335	368	0.0002
432	412	0.0003
560	428	0.0003
528	373	0.0002
591	354	0.0002
485	304	0.0003
403	314	0.0003
301	284	0.0002
319	206	0.0003
390	219	0.0002
419	140	0.0003
340	137	0.0002
290	117	0.0002

Conclusions

As can be seen from the above data used model is appropriate for prediction of elements distribution on the industrial site of studied landscape. Here we have shown calculated distributions of elements Cr, Cu, Fe, Ga, Mn, V. Used model of neural network has shown that distribution of Cr is characterized by concentration of the metal compositions on the Northwestern part of the collector with maximal concentration about 0.0027%. However, that nonuniformity of distribution is not significant because of very low concentration of the element even in maximal points. The same we can say about Mn, it has two maximal concentration points on the North and Southwest parts of the dump, but the concentrations are too low.

The most uniform distribution was obtained for Fe. This element presents in the content in every calculated point at concentration of about 11.5%. Also good distribution was obtained for Cu, but content changed from 15% to 18% with different dependences. Elements V and Ga were found in traces amounts.

Thus, we can say, that more important elements from concentration point of view are Fe and Cu. They present in the waste content preferable in oxide forms. Usually oxides of iron are not considered as toxic compounds. However, iron oxide in large volumes can lead to serious consequences for the environment. The flooding of iron mines into ponds, rivers and lakes can result in huge amounts of iron, which can lead to fish poisoning and environmental pollution. Iron molecules react with oxygen, resulting in the formation of a solid iron oxide of yellow color, which falls on the bottom of water bodies and pollutes them. Yellow iron oxide smothers aquatic life and fauna, killing fish and underwater plants. Iron oxide can cause breathing problems and aggravate asthma, allergies and sinusitis.

One of the causes of toxicity of Cu is that it belongs to elements intensively accumulating in plants. Because of that, plants have intoxication symptoms appeared: leaf chlorosis, poor development of the root system, tissue damage occurs, changes in the permeability of cell membranes and inhibition of photosynthetic processes, seed germination slows down. Copper belongs to group of elements necessary for live organisms. At the same time, excess of copper has a harmful effect on the body warm-blooded. Copper refers to a group of highly toxic metals that can cause acute poisoning of humans and animals, and have a wide range of toxic effects with a variety of clinical manifestations.

The obtained results point out that development of ways to utilization of the waste from studied dump of Pavlodar aluminum plant is should be continued. Solving of the problem is of very high importance for Pavlodar region.

Acknowledgments

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References cited

Chow W.S., Tommy W.S., Chow S-Y.C. 2007: Neural Networks and Computing: Learning Algorithms and Applications. Imperial College Press: London, Great Britain, 322 p.

Croall I.F., Mason J.P. 1992: Industrial applications of neural networks: project ANNIE handbook. Springer-Verlag: Berlin, Heidelberg, Germany, 297 p.

Fine T.L. 1999: Feedforward Neural Network Methodology. Springer-Verlag: New York, USA, 340 p.

GOST 17.4.4.02-84. Soils. Methods of selection and preparation of samples for chemical, biological and helminthological analysis. (in Russian)

GOST 17.4.3.01-83. Soil. General requirements for sampling. (in Russian)

GOST 5180-84. Soils. Methods of laboratory determination of physical characteristics. (in Russian)

Gurney K. 1997: Introduction to Neural Networks. Taylor & Francis Group: New York, USA, 148 p.

Mineev V.G. 2001: Practical work on agrochemistry. Publishing house of Moscow university: Moscow, Russia, 689 p. (in Russian)

SZEMPONTOK A KAZAKHSZTÁNI PAVLODARI ALUMINIUMGYÁR HAMU-ISZAP GYŰJTŐJE KÖRNYEZETI HATASAINAK ÉRTEKELÉSÉHEZ

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Kulcsszavak: idegpálya hálózat, hulladék, hamu-iszap gyűjtő, összetevő elemzés, Levenberg-Marquardt algoritmus

Összefoglalás: A Pavlodari Alumíniumgyár hamu-iszap gyűjtőjéből szerzett minták alapján elkészítettünk egy idegpálya hálózati modellt, amely segítségével előre jelezhető a termelés során keletkező hulladék anyagok koncentrációja és mennyisége. Minden egyes elem külön idegpálya modellen van reprezentálva. A modellt a Levenberg-Marquardt algoritmus vezérli. Az idegpálya 5 szintből áll, az első a bemenet, az ötödik a kimenet, köztük pedig 3 rejtett szint található. Az idegpálya modell nagy pontossággal elemzi a tó különböző részeiről beszerzett mintákat, Az elemzés kimutatja, hogy nevezett helyeken nagy fokú a szilicium (Si), kalcium (Ca), réz (Cu, és vas (Fe) koncentráció, ugyanakkor a mangán (Mn), vanádium (V), titán (Ti), szkandium (Sc) és gallium (Ga) kisebb mennyiségben van jelen. Az idegpálya modell pontosságát meghatározó tényezők között említendő a rétegek, vagy szintek száma, illetve az irányító algoritmus.