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The Use of Artificial Neural Network for the Improvement of Quality of Steelworks Products

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Abstract: *this contribution deals with the application of artificial neural networks in metallurgy. There were problems with the forging ingots made of carbon steelbrand grade in accordance with ČSN 11523 standard in the Czech Republic. The problems occurred randomly and independenty from the technological procedure. The creation of the new artificial neural networks is based on the data provided by the steelworks company. The data were based on carbon steelbrand grade in accordance with ČSN 11523 standard in the Czech Republic.*

The new artificial neural network have been created by the computer programme STATISTICA – Neural Network. The artificial neural networks with the best results have been used to create the response graphs. These response graphs represent the influence of the first element on the system. The results of this project indicate that the use of artificial neural networks for predicting defects of ingots in steelworks is very perspective.The problem was solved together with further applications of artificial intelligence in the framework of the grant project GAČR 106/05/2596.

Keywords: *artificial neural network, sensitivity analysis, response graph, forging ingots*

1 Introduction

Ingots production of bigger sizes, which is determined above all for forges, represents still inconsiderable part of metallurgical production. Just a considerable weight of ingots leads to an effort to increase the rate of quality production. At some types of ingots the technological deviations exhibit by defects that result in creation of cracks at once at the beginning of the first forging operation. Prompt prediction of such defects would enable a fast intervention to the proceeding process with aim to reduce costs for the defects reparation. On the basis of the statistical treatment of operational data there was proven, that the defects were not caused by exceeding of any measured parameter in the production. However, they are caused by an unsuitable combination of more parameters.

For a draft of measures for an improvement of the steelworks production quality neural networks can be successfully applied in such case, because they are especially suitable for an approximation of relations between various sensor-based data, particularly between unstructured data with a high degree of nonlinearity and a big scale of uncertainty.

2 Neural network Design and optimization

Neural networks use a distributed parallel processing of the information during practicing the calculations, it means that information recording, processing and transferring are carried out by means of the whole neural network then by means of particular memory places. Learning is a basic and essential feature of neural networks. Knowledge is recorded especially through strength of linkages between particular neurons. Linkages between neurons leading to "correct answer" are strengthened and linkages leading to "wrong answer" are weakened by means of repeated exposure of examples describing the problem area. A complex of submitted examples creates so called training set.

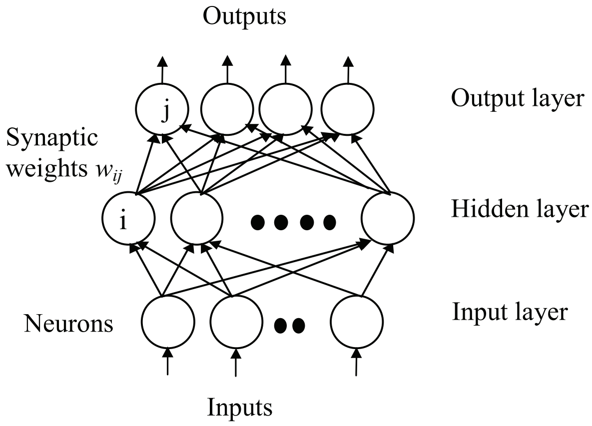

Figure 1. Topology of multilayer feedforward neural network

A capability to learn from examples and ability to describe well also non-linear dependences is a big advantage of neural networks. A disadvantage is the fact, that a size of error, which is strongly dependent on network parameters and on a training set data quality, cannot be generally estimated in advance. The design of a structure and parameters of the neural network is always connected with some experiences. The experience, intuition and experiments are also important for the optimization of the neural network. Neural networks, which are universal function approximators, consequently especially Backpropagation type networks utilizing for their learning (adaptation) Backpropagation algorithm, are suitable essentially for all types of predictions. This algorithm is suitable for multilayer feedforward networks learning, which are created minimally by three layers of neurons: input, output and at least one inner (hidden) layer (Fig. 1). Between two adjoining layers there is always so called total connection of neurons, thus each neuron of the lower layer is connected to all neurons of the higher layer. Learning in the neural network is realized by setting the values of synaptic weights between neurons, biases or inclines of activation functions of neurons. The adaptation at networks with Backpropagation algorithm calls „supervised learning“, when the neural network learns by a comparison of the actual and the required output. The algorithm tries to accomplish a minimal difference between required value and value on the network output by a gradual setting of synaptic weights.

The rate of inaccuracy between predicated value of neural network output and actual value of object output represents a prediction error. In technical applications the error is mainly represented by following relations [Myllykoski, P. 1996, Larkiola, J. 1996, Nylander, J. 1996]:

- relation for RMS error calculation (Root Mean Squared) – it does not compensate used units

$$RMS = \sqrt{\frac{\sum_{i=0}^{i=n-1} (y_i - o_i)^2}{n-1}} \qquad (1)$$

- relation for REL_RMS relative error calculation – it compensates used units

$$REL\_RMS = \sqrt{\frac{\sum_{i=0}^{i=n-1} (y_i - o_i)^2}{\sum_{i=0}^{i=n-1} (y_i)^2}} \qquad (2)$$

where:

- n - number of patterns of training or test set
- y_i - predicted values of neural network output
- o_i - actual values of object output

3 Prediction of defects of forging ingots

Technological data, which were gained from records acquired on several furnace aggregates and devices of secondary metallurgy in the steelworks, were used for design of artificial neural network model for prediction of defects of forging ingots. This database includes also information on further manipulation with already cast ingots up to the phase of dispatch to the forge operation. Data on content of some elements at charge smelting, which influence melt time, exert in increased oxidation potential, report on some accompanying elements from charge raw materials etc., were included to the database. Further the database contains data on stripping, on ingots dispatch to forge, on workers on shifts and on aggregates, which executed particular heats. These data can influence above-mentioned quality problem according to operational experiences. An example of used technological data for selected ingots and heats is presented in Table 1.

The whole database contained in total 242 heats, from which 32 heats showed quality problems. Database was statistically preprocessed and modified thus that it was created by 18 basic types of ingots, whereas 4 types of them showed increased number of defects [Jančíková, Z. 1996, Jančíková, Z., Heger, M. 1996]:

Table 1. Example of used technological data for selected ingots and heats

heat	58894	58895	58895	58895	58902	58902	58904
ingot type	IT 1	IT 2	IT 3	IT 3	IT 4	IT 4	IT 1
mister	M 1	M 1	M 1	M 1	M 1	M 1	M 1
furnaceman	F 1	F 1	F 1	F 1	F 1	F 1	F 1
furnacem.LF	F LF 1	F LF 1	F LF 1	F LF 1	F LF 1	F LF 1	F LF 2
T after LF	1677	1660	1660	1660	1666	1666	1660
T before VD	1664	1648	1648	1648	1655	1655	1658
T after VD	1574	1577	1577	1577	1580	1580	1564
T likv	1518,8	1514,3	1514,3	1514,3	1515,7	1515,7	1514,4
T strip	695	715	715	715	695	730	710
T desp	670	685	685	685	665	690	695
CaO-St	57,6	59,88	59,88	59,88	59,99	59,99	58,01
SiO2-St	9,92	6,6	6,6	6,6	7,09	7,09	12,31
Al2O3-St	24,3	28,04	28,04	28,04	23,68	23,68	21,92
Sumox	1,08	0,91	0,91	0,91	0,89	0,89	1,01
S-St	0,513	0,673	0,673	0,673	0,404	0,404	0,509
Si	11	32	32	32	28	28	9
P	8	8	8	8	11	11	9
S	2	2	2	2	3	3	1
Cu+Sn	95,36	87,6	87,6	87,6	71,08	71,08	89,6
Al	7	30	30	30	30	30	12
N_2	5	6	6	6	7	7	5
H_2	0,6	0,6	0,6	0,6	0,7	0,7	0,7
a(o)	5,5	2,7	2,7	2,7	3,8	3,8	5,4
Al - decline	16	26	26	26	17	17	13
opt. basic.	0,7843	0,7949	0,7949	0,7949	0,8028	0,8028	0,7796
mannesman	0,2389	0,3236	0,3236	0,3236	0,3573	0,3573	0,2150
(s)/[s]	256,500	336,500	336,500	336,500	134,667	134,667	509,000
sulfid.ka.	0,0120	0,0176	0,0176	0,0176	0,0238	0,0238	0,0090
CaO/Al_2O_3	2,3704	2,1355	2,1355	2,1355	2,5334	2,5334	2,6464
quality	NO	YES	YES	YES	NO	NO	YES

T after LF – temperature after treatment in pot furnace, Furnacem. LF –operator of pot furnace, T likv – liquid temperature, T strip – stripping temperature, T desp – dispatching temperature, Opt.bazic. – optic basicity, Sulfid.ka. – sulfide capacity, Mannesman – Mannesman coefficient, CaO – calcium oxide in slag, Al_2O_3-St – aluminum oxide in slag, SiO_2-St – silicon dioxide in slag, S-St – sulfur in slag, P – phosphorus, S – sulfur, H_2 – hydrogen , N_2 – nitrogen, Cu + Sn – copper + tin, Al – aluminum, a(o) – oxygen activity, Si – silicon, (s)/[s] – distributive coefficient of sulfur, CaO/Al_2O_3 – calcium oxide / aluminum oxide

On the basis of analysis of acquired data 12 artificial neural networks were designed and verified. Neural networks were created in STATISTICA – Neural Networks software. This system enables among others creation of a group of different neural networks, the choice of the most suitable one with the best performance; it contains useful investigatory and analytical techniques enabling a choice of suitable input values for analysis of investigated data (algorithms for choice of inputs properties). It further enables to acquire summary description statistics, to execute a sensitivity analysis and to create response graphs.

A window with parameters of created neural networks in system STATISTICA - Neural Networks is illustrated on Figure 2.

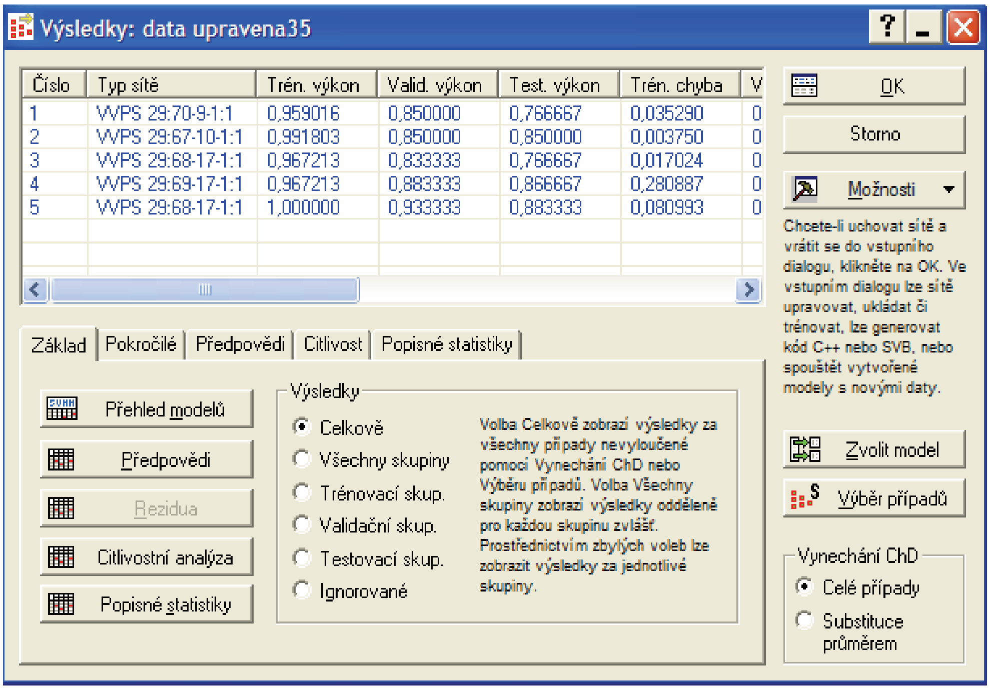

Figure 2. Window with results of created neural networks

The first neural networks (NS1 – NS4) were created for those 4 types of ingots, which showed the most defects, namely for each type of ingot separately. The fifth neural network (NS5) was created for a set of all these 4 types of ingots together. A set of all 18 types of ingots was treated in the sixth neural network (NS6). Inputs of last 2 neural networks (NS5 – NS6) were reduced thus that they did not contain inputs „casting velocity“ and „casting time“. A function of software STATISTICA – Neural Networks, which enabled to choose a sub group of independent input variables and thus to reduce their number, was used at creation of these networks. Further 6 neural networks (NS7 – NS12) were created from the same databases as previous networks with the difference that the function for a choice of a sub group of independent inputs was not used and also input variables, which contained a human factor (master, furnace man, operator of pot furnace) were eliminated. The human factor elimination was initialized thereby that statistical analysis of an influence of the particular human factors did not show statistically considerable difference between particular cases, but also thereby that human factor would show in other measured technological values. The last 2 networks (NS11 a NS12) also did not contain input values „casting velocity“ and „casting time“.

For each of the created networks a sensitivity analysis, which shows to what measure particular input variables influence the output variable (ingot defect), was executed. For each network a table expressing an order of significance of particular input variables, was created.

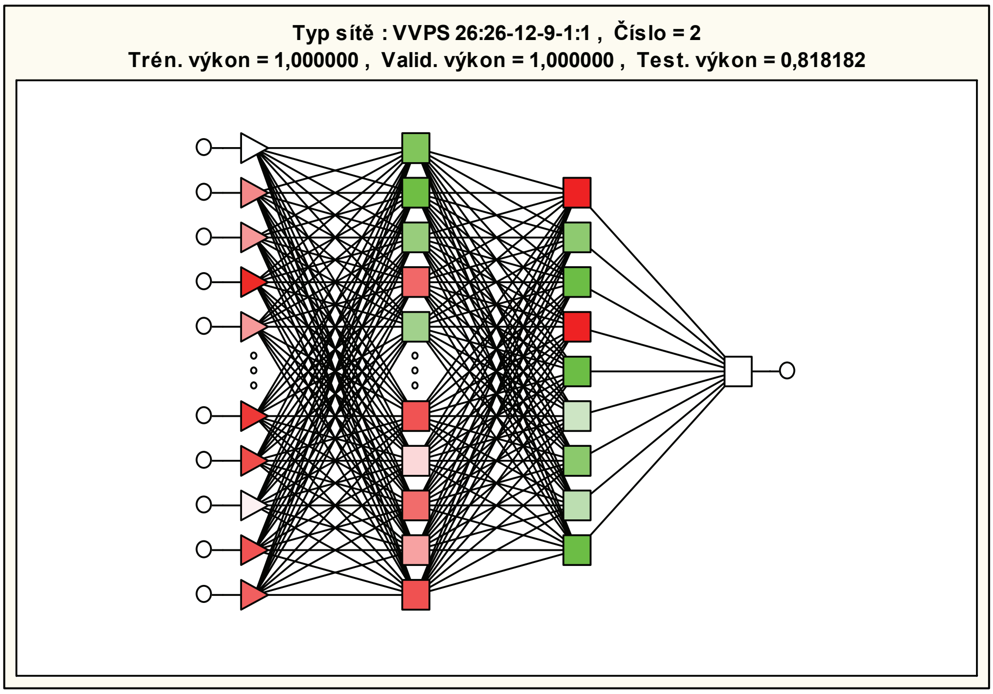

Figure 3. Structure of artificial neural network NS11 with 26-12-9-1 topology

Networks NS11 a NS12 appeared to be the most suitable for a practical application. These networks showed very good learning results, when a prediction of defect moved above 95 percent at utilization of 50 percent of input data for accuracy testing at NS11 network and 30 percent NS12 network. The response graphs were created at these networks. These graphs express an influence of the chosen parameter to a given system. An example of the response graph of NS11 neural network, which expresses an influence of distributive coefficient of sulfur to the ingot defect creation, is illustrated on Fig. 4. From the graph results, that with increasing amount of distributive coefficient of sulfur a probability of the ingot defect creation decreases. Since the particular input parameters can mutually interact and the result is dependent on a combination of more input parameters, it would be apparently more suitable to use for determination of output dependence on the particular inputs for example approaches of cluster analysis methods, which would enable to choose a specific input combinations and to observe dependence of the output value on the combination of these inputs [Jančíková, Z. 1996, Jančíková, Z., Heger, M. 1996]:

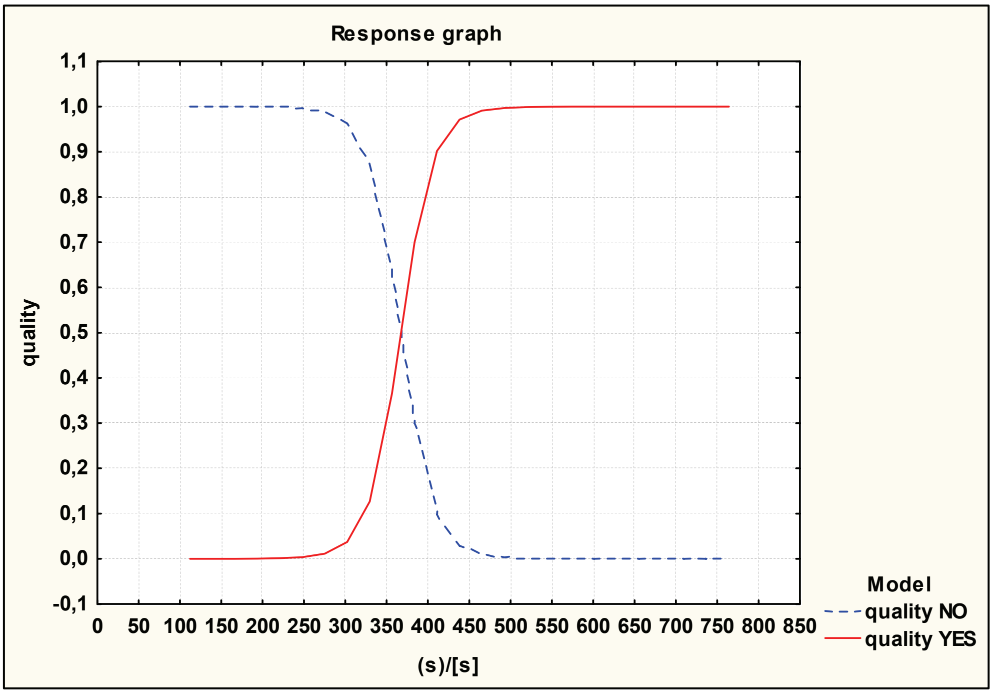

Figure 4. Response graph of NS11 neural network for (s)/[s]

4 Conclusion

It was created a model of neural network for prediction of defects of forging ingots in steelworks. Technological data, which were gained from records acquired on several furnace aggregates and devices of secondary metallurgy in the steel works, were used for a design of the neural network. Twelve models of artificial neural networks were designed. For each of the created networks was executed sensitivity analysis. The sensitivity analysis shows how significantly each input value influences the given system. Two neural networks, which showed very good results of learning, were chosen for practical application. In some cases practically hundred-per-cent accordance of actual and predicted results on testing set occurred in the course of verification of the generalization ability. It was verified that usage of artificial neural networks for prediction of defects of forging ingots is very perspective. The problem was solved together with further applications of artificial intelligence in the framework of the grant project GAČR 106/05/2596.

5 References

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