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PREDICTION OF THE FUTURE DEVELOPMENT OF CONSTRUCTION COMPANIES BY MEANS OF ARTIFICIAL NEURAL NETWORKS ON THE BASIS OF DATA FROM THE CZECH REPUBLIC

Abstract. *The construction sector is one of the main pillars of an advanced economy. It is the first sector to indicate potential national economic problems. In a similar way it is the first sector to show signs of recovery when an economy is coming out of recession or crisis.*

The aim of this article is to apply a neural network to be able to predict potential financial problems in construction companies in the Czech Republic.

Data on all construction companies in the Czech Republic over the period 2003-2013 were used for the modelling of the neural network. The data file contained 67,000 records. These records included both financial statements and non-accounting data (e.g. data on company employees).

The following networks were used for modelling the neural network: a linear network, a probabilistic neural network (PNN), a generalised regression neural network (GRNN), a radial basis function network (RBF), a three-layer perceptron network (TLP) and a four-layer perceptron network (FLP).

The analysis resulted in a concrete model of an artificial neural network. The neural network is able to determine with more than ninety per cent accuracy whether a company is able to overcome potential financial problems, within how many years a company might go bankrupt, or whether a company might go bankrupt within one calendar year. The text also includes the basic statistical characteristics of the examined sample and the achieved results (sensitivity analysis, confusion matrix, etc.).

The model can be exploited in practice by construction company managers, investors looking for a suitable company for capital investment, competitors, etc.

Keywords: *construction company, financial problems, prediction, artificial neural network, model.*

Introduction

Traditional methods supporting financial decision making include «consumer credit scorecards» (Mester, 1997, Reichert at al., 1983, Rosenberg and Gleit, 1994, [8]) and discrimination models for the assessment of a company´s financial health (Altman at al., 1995, Reichert at al., 1983, [1]). Both are basically linear models with multiple variables. A neural network is a flexible non-parametric modelling tool for designing a prediction model based on logical links (formulae) between historic data. Schemes in historic data may often exist in both spatial and time planes. A conventional MLP NN (Multiparametric Neuron Network) focused on the retrospective revelation of error algorithms is arranged in such a way as to define constant schemes that do not vary with time.

Neural structures have recently come to the fore as the preferred method for predicting the collapse of a society (Kumar and Ravi, 2007, [5]). The work by Odom a Sharda (1990, [9]) was one of the first studies to apply neural networks to the issue of bankruptcy prediction. Odom and Sharda used Altman's relative financial indices as inputs for neural networks to which they subsequently applied their methods. These methods included MDA to compare a certain number of US companies, both solvent and insolvent, whereby the data used for bankrupt companies came from their last financial statements prior to declaring bankruptcy. They took into account 128 companies and performed several trials. During these trials the proportion of declining and prospering companies in the examined sample where changed. The method of artificial neural networks achieved a Type I classification accuracy within the range 77.8% – 81.5% (depending on the examined sample) and Type II accuracy within the range 78.6 – 85.7%. The corresponding results for MDA for Type I accuracy were within the range 59.3% – 70.4% and for the Type II accuracy 78.6% – 85.7%.

Foreign sources offer an overview of various neural network types, including MLP NN (Multiparametric Neuron Networks), probability neural networks (PNN), auto-associative neural networks (AANN), self-organizing maps (SOM), learning vector quantization (LVQ) and cascade correlation (Cancor). A lot of these studies focused on comparing neural networks with classic statistical techniques like factor analysis, logit analysis and various forms of discrimination analyses. A lot of these cases show that neural networks provide a more accurate prediction of bankruptcy than parametric statistical approaches. However, the results are also often diverse. Tam and Kiang (1992, [13]) compared different types of models when the application of neural networks to bankruptcy examination first began. They studied MDA, LA, K-nearest neighbour (KNN), decision tree classification algorithm (ID3), single-layer neural networks and multi-layer neural networks. The used neural networks were the standard of back-propagation (BPNN). The multi-layer neural network was the most suitable for the prediction of bankruptcy based on relative financial indices one year prior to bankruptcy. In comparison, logit-analysis achieved better results for the two-year period prior to bankruptcy. When Salchenberger, Cinar and Lash (1992, [12]) analysed bankruptcies of thrifts, they found that BPNN substantially outclassed logit analysis. For example, an 18-month prediction LA achieved a classification accuracy of 83.3% – 85.4% (depending on some threshold values), while NN reached 91.7%. Coats and Fant (1993, [4]) found when they compared BPNN and MDA that BPNN was better in general, although it had larger variances in the classification of the results depending on the time period used. Altman et al. (1995) compared the BPNN and MDA methods in the field of failure prediction on 1,000 Italian companies. According to their conclusions MDA showed slightly better results than BPNN in its predictions for the one-year period. Boritz, Kennedy and Albuquerque (1995, [3]) compared numerous techniques, including various BPNN, LA and MDA procedures. The comparison results were inconclusive. In a lot of studies BPNN showed better prediction ability of company failure than MDA and the other aforementioned techniques. It is for this reason that new hybrid techniques and genetic algorithms have recently come to the fore. Lee et al. (1996, [6]) tested combinations of models like MDA, ID3, SOM and BPNN. They compared the predictive abilities on Korean companies and drew the conclusion that SOM together with neural networks achieved the best results. Zhang et al. (1999, [14]) used a fivefold scheme of mutual validity control on a group of manufacturing companies and compared BPNN with LA for bankruptcy prediction. BPNN was again substantially better than LA. McKee and Greenstein (2000, [6]) developed an approach based on decision trees. They tested this approach on a sample of American companies based on data a year prior to bankruptcy. Their method achieved better results than MDA and BPNN for Type II classification errors but worse results for Type I classification errors. Atiya (2001, [2]) developed new indices obtained from the securities market. The application of these indices together with traditional relative financial indices brought substantial improvements in the accuracy of bankruptcy predictions. The predictions were based on financial data three years prior to bankruptcy.

The aim of this article is to exploit neural networks for the prediction of potential financial problems in construction companies in the Czech Republic.

1. Material and Methodology

The information on companies given below comes from the Albertina database. The data covers all the construction companies which operated on the Czech market between the years 2003-2013 and which fall under the CZ-NACE classification under Section F. The following activities are included – construction of buildings, civil engineering and specialized construction activities.

The file contains a total of 67,492 rows of data in columns labelled:

– company name (15,189 companies);
– region;
– list of annual financial statements between 2003-2013;
– list of additional data.

MS Excel was used for the preparation of the data file. The data (financial as well as non-financial) for each company for each year was always presented on one line. The file containing the 67,492 records of construction companies for individual years, including 100 characteristics on each company, was imported into Statistica software by DELL. The data was subsequently processed by an intelligent problem solver.

An artificial neural structure was sought that would be able to classify each company on the basis of the input data into one of the following groups:

– solvent company;
– company that will go bankrupt in the current year;
– company that will go bankrupt in 2 years;
– company that will go bankrupt in the future.

First we determined the characteristics of the individual companies. We had to define the output category quantity. These were defined on the basis of the values presented in the column «final status» in the excel sheet. The category output quantities are «Financial Statement Extent», «Financial Statement Structure» and the «Auditor’s Statement». All the items shown from the financial statements are continuous quantities.

Once this exercise was completed, 1,000 artificial neural structures[1] were generated, of which the 10 most suitable were retained. For the model, linear neural networks, probabilistic neural networks, radial basis function neural networks, three-layer perceptron networks and four-layer perceptron networks, were utilised. For the radial basis function neural network we used 1 up to 15,998 hidden neurons. The 2nd layer of the three-layer perceptron network contained 1 up to 100 hidden neurons. The 2nd and the 3rd layers of the four-layer perceptron network both contained 1 up to 100 hidden neurons.

2. Results – Production Function

1,000 artificial neural networks were generated on the basis of the set parameters. 10 artificial neural networks showing the best characteristics were retained for further assessment and subsequent processing. The results of the analysis are given in Table 1.

Table 1 – Models of artificial neural networks showing the best characteristics[2]

Index	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error
1	MLP 1:4-33-61-4:1	0.943588	0.945240	0.944865	1.430218	1.541917
2	MLP 2:7-88-63-4:1	0.038504	0.037695	0.038320	1.002620	1.040046
3	MLP 15:15-54-66-4:1	0.943182	0.945052	0.944427	0.586112	0.591007
4	Linear 84:86-4:1	0.944432	0.945490	0.944865	0.160929	0.163963
5	Linear 90:98-4:1	0.944307	0.945490	0.944615	0.160849	0.162028
6	PNN 88:93-31997-4:1	0.944245	0.946052	0.945427	0.162359	0.160338
7	PNN 87:92-31997-4:1	0.944245	0.946052	0.945427	0.162360	0.160335
8	RBF 61:69-328-4:1	0.943870	0.945490	0.944802	0.159620	0.158623
9	RBF 61:69-359-4:1	0.943713	0.945115	0.944802	0.159637	0.158612
10	RBF 61:69-360-4:1	0.943870	0.945427	0.945052	0.159324	0.158588

Index	Test Error	Training/Members	Inputs	Hidden(1)	Hidden(2)
1	1.453480	BP100,CG20,CG0b	1	33	61
2	1.014261	BP100,CG20,CG0b	2	88	63
3	0.583500	BP100,CG20,CG0b	15	54	66
4	0.160875	PI	84	0	0
5	0.160743	PI	90	0	0
6	0.160657		88	31,997	0
7	0.160657		87	31,997	0
8	0.159088	SS,KN,PI	61	328	0

[1]Unless the improvement in the individual trained networks is significant the training of neural networks can be shortened.

[2]A linear neural network is indicated as Linear, probabilistic neural network as PNN, generalized regression neural network as GRNN, radial basis network as RBF and multi-layer perceptron network as MLP.

Continued (Table 1)

Index	Test Error	Training/Members	Inputs	Hidden(1)	Hidden(2)
9	0.159930	SS,KN,PI	61	359	0
10	0.159093	SS,KN,PI	61	360	0

Multiple perceptron networks with two hidden layers were retained among the ten best networks, see lines 1 – 3 of the table. Two linear neural networks, two probabilistic neural networks and three radial basis function neural networks then follow.

Figure No. 1 shows a schematic illustration of a multiple perceptron network with two hidden layers, namely MLP 1:4-33-61-4:1.

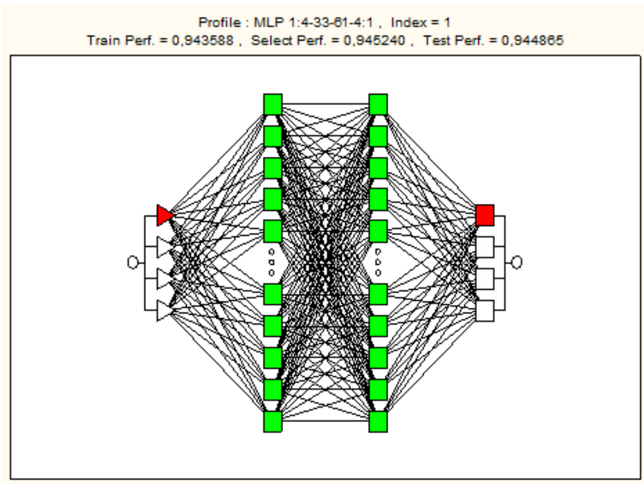

Figure 1 – Graph of artificial neural network (MLP 1:4-33-61-4:1)

The first layer (from the left), in the form of triangles, represent the inputs for the models, namely continuous and category qualities. White indicates a positive quantitative value, whereas red a negative one. Two hidden layers follow. The resulting classification is finally defined by the output layer, whereby a company is allocated to one of the four groups identified in Section 1 of this article. The percentage success rate of the training, validation and verification sample should in general be almost the same in order to be able to say that the network is of a good quality and has the characteristics required to apply it in practice. For the network represented above the values for all three samples were above the 94% level.

Figure 2 shows a graphic illustration of a multi-layer perceptron network MLP 2:7-88-63-4:1.

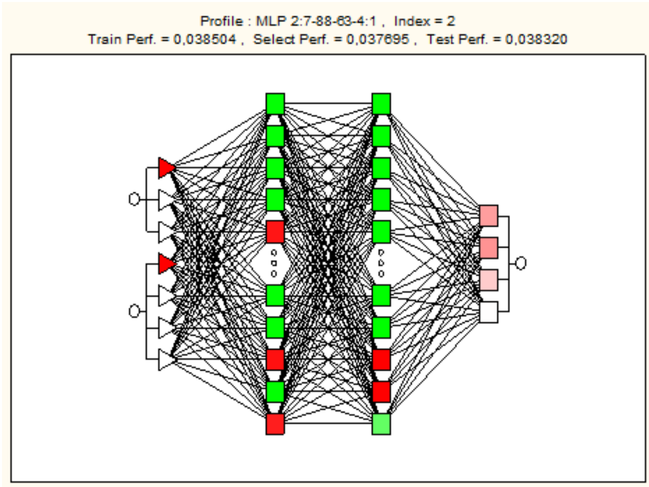

Figure 2 – Graph of artificial neural network (MLP 2:7-88-63-4:1)

The values of all the parts of this network achieve a level of approximately 4%. This means that the network is of poor quality and not applicable in practice.

Figure 3 shows a graphic illustration of a multi-layer perceptron network MLP 15:15-54-66-4:1.

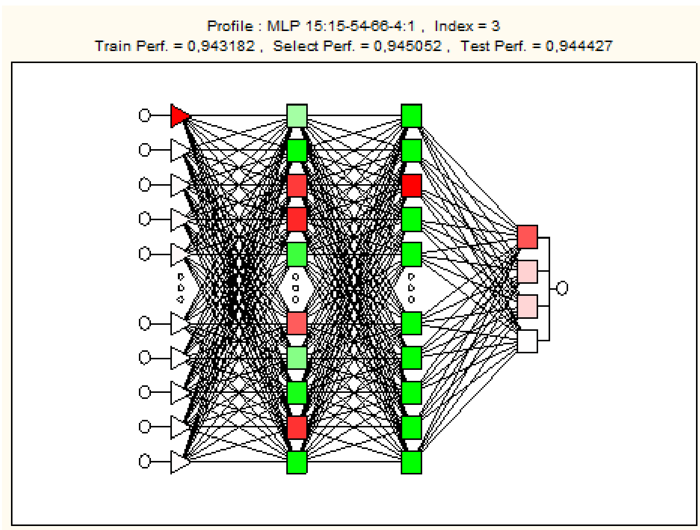

Figure 3 – Graph of artificial neural network (MLP 15:15-54-66-4:1)

In the network represented above the values of the training, validation and verification data oscillate above the 94% level.

Figure 4 shows a graphic illustration of a linear neural network Linear 84:86 - 4:1.

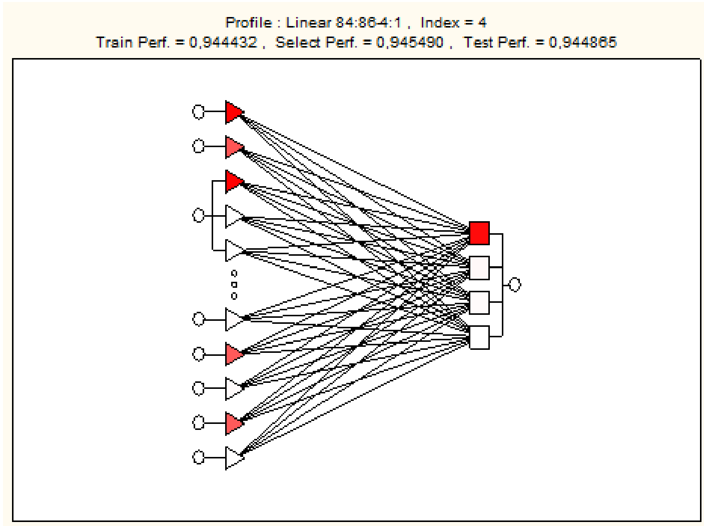

Figure 4 – Graph of artificial neural network (Linear 84:86-4:1)

In this case the network has two types of neurons - input and output layers. There is no hidden layer. In the case of the linear network represented above the values of the training, validation and verification data oscillate above the 94% level.

Figure 5 shows a graphic illustration of a linear neural network Linear 90:98 - 4:1.

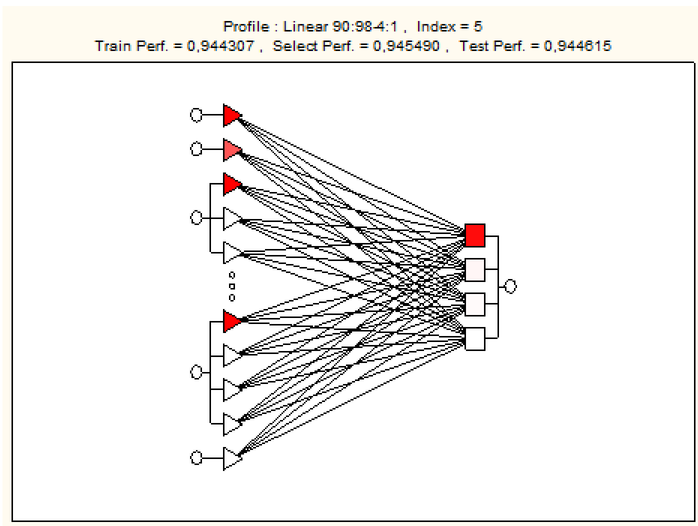

Figure 5 – Graph of artificial neural network (Linear 90:98-4:1)

In the case of the linear network represented above the values of the training, validation and verification data oscillate above the 94% level.

Figure 6 shows a graphic illustration of a probabilistic neural network PNN 88:93-31997-4:1.

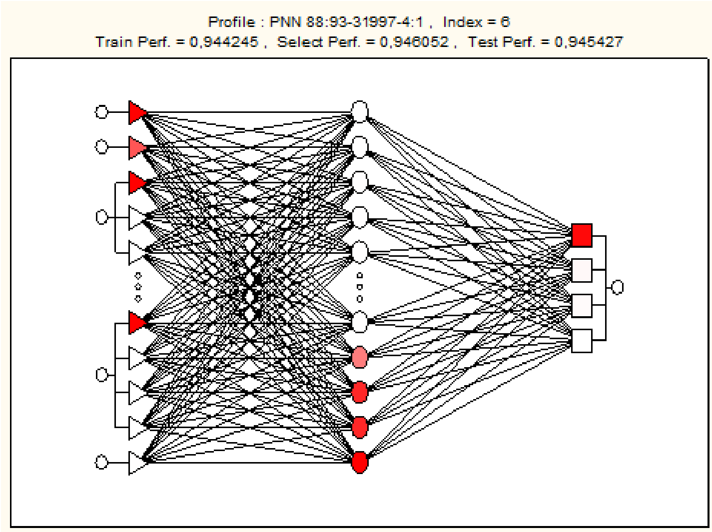

Figure 6 – Graph of artificial neural network (PNN 88:93-31997-4:1)

A probabilistic neural network works with one hidden layer of neurons. According to the calculations the central layer of the neural network represented above hides 31,997 neurons. In this case the values of the training, validation and verification data oscillate above the 94% level.

Figure 7 shows a graphic illustration of a probabilistic neural network PNN 87:92-31997-4:1.

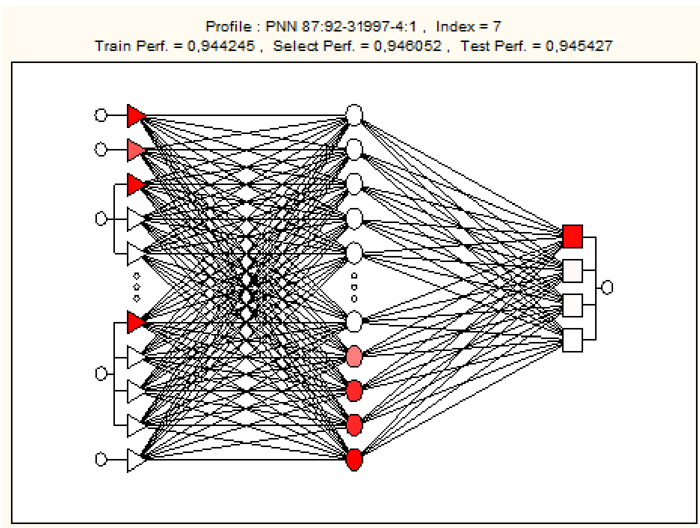

Figure 7 – Graph of artificial neural network (PNN 87:92-31997-4:1)

In the case of the probabilistic network represented above the values of the training, validation and verification data oscillate above the 94% level.

Figure 8 shows a graphic illustration of a radial basis function neural network RBF 61:69-328-4:1.

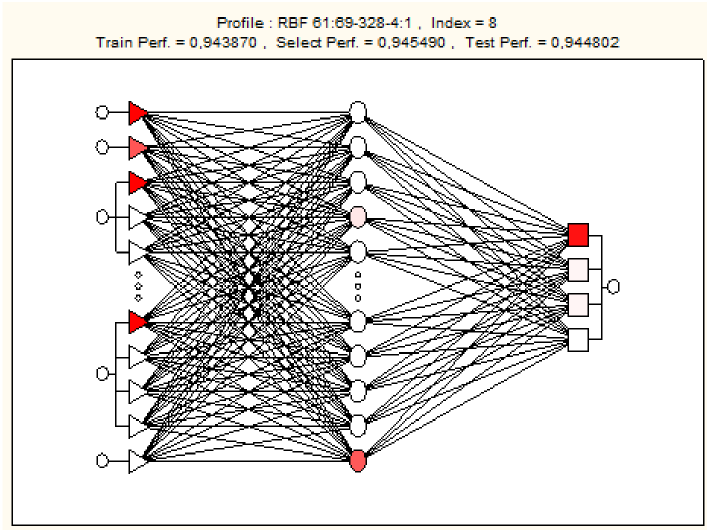

Figure 8 – Graph of artificial neural network (RBF 61:69-328-4:1)

A radial basis function neural network works with one hidden layer of neurons. According to calculations the central layer of the neural network represented above hides 328 neurons. In this case the values of the training, validation and verification data oscillate above the 94% level.

Figure 9 shows a graphic illustration of a radial basis function neural network RBF 61:69-359-4:1.

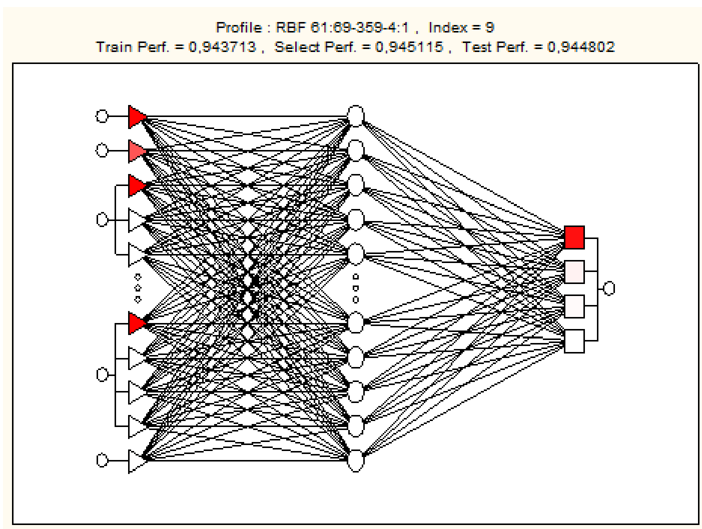

Figure 9 – Graph of artificial neural network (RBF 61:69-359-4:1)

In the case of the neural network represented above the values of the training, validation and verification data oscillate above the 94% level.

Figure 10 shows a graphic illustration of a neural network of radial basis function RBF 61:69-360-4:1.

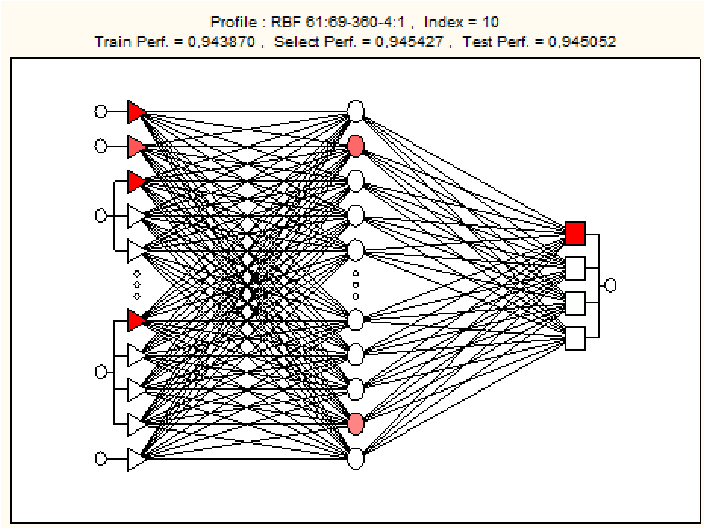

Figure 10 – Graph of artificial neural network (RBF 61:69-360-4:1)

In the case of the radial basis function neural network represented above the values of the training, validation and verification data oscillate above the 94% level.

Nevertheless, it was not possible to determine anything substantive from the graphic illustration. The confusion matrix (see Table 2) that was subsequently drawn up helped to clarify the situation.

The table describes the success rate and consequently the predictions of the individually generated artificial neural networks. The confusion matrix calculates the absolute value of the correctly classified quantities. This enabled the identification of the network with the highest success rate in predicting the future development of the companies in the examined sample.

The neural networks 1, 2, 6 and 7 showed relatively good results in predicting solvent companies, however the results were very poor when it came to identifying the potential bankruptcy of a company. The other networks were also able to predict solvency (with slightly lower levels of accuracy). However, of these other networks some were better in predicting the potential bankruptcy of a company in the current business year, within two years, or further into the future.

The results are therefore not definitive. However, if the networks are compared on the basis of their prediction success rate for the individual classified groups, neural network 5 is the best and the most applicable in practice. It is a linear neural network Linear 90:98-4:1. It is of interest that 90 input data entered the calculation. Compared to the other generated networks this is the highest number of inputs.

This means that a possible sensitivity analysis should determine the result sensitivity accurate to ninety inputs (of various weights). It is also of interest that for example the first two perceptron networks worked with only two inputs. In the end they were able to accurately define solvent companies. However, the low number of inputs meant they were unable to predict the future potential bankruptcy of a company. The third function, which took 15 inputs into account provided better results. Once again, the results were not optimal and it is therefore not applicable in practice.

Table 2 – Confusion matrix (neural networks 1 – 10)

	T.Solvent company	T.Bankr. in current year	T.Bankr. in the future	T.Bankr. in two years	T.Bankr. next year	S.Solvent company	S.Bankr. in current year	S.Bankr. in the future	S.Bankr. in two years	S.Bankr. next year
1	2	3	4	5	6	7	8	9	10	11
Solvent company.1	30192	1232	569	0	4	15121	603	270	3	0
Bankr. in current year.1	0	0	0	0	0	0	0	0	0	0
Bankr. in the future.1	0	0	0	0	0	0	0	0	0	0
Bankr. in two years.1	0	0	0	0	0	0	0	0	0	0
Solvent company.2	30192	1232	569	0	4	15121	603	270	3	0
Bankr. in current year.2	0	0	0	0	0	0	0	0	0	0
Bankr. in the future.2	0	0	0	0	0	0	0	0	0	0
Bankr. in two years.2	0	0	0	0	0	0	0	0	0	0
Solvent company.3	30177	1229	569	0	4	15118	598	270	3	0
Bankr. in current year.3	1	2	0	0	0	1	0	0	0	0
Bankr. in the future.3	14	1	0	0	0	2	5	0	0	0
Bankr. in two years.3	0	0	0	0	0	0	0	0	0	0
Solvent company.4	30182	1198	566	0	4	15110	588	269	3	0
Bankr. in current year.4	10	34	0	0	0	11	15	1	0	0
Bankr. in the future.4	0	0	3	0	0	0	0	0	0	0
Bankr. in two years.4	0	0	0	0	0	0	0	0	0	0
Solvent company.5	30176	1196	564	0	4	15109	587	268	3	0
Bankr. in current year.5	16	36	2	0	0	12	16	2	0	0
Bankr. in the future.5	0	0	3	0	0	0	0	0	0	0
Bankr. in two years.5	0	0	0	0	0	0	0	0	0	0
Solvent company.6	30192	1213	567	0	4	15120	589	270	3	0
Bankr. in current year.6	0	19	0	0	0	0	14	0	0	0

Continued (Table 2)

1	2	3	4	5	6	7	8	9	10	11
Bankr. in the future.6	0	0	2	0	0	1	0	0	0	0
Bankr. in two years.6	0	0	0	0	0	0	0	0	0	0
Solvent company.7	30192	1213	567	0	4	15120	589	270	3	0
Bankr. in current year.7	0	19	0	0	0	0	14	0	0	0
Bankr. in the future.7	0	0	2	0	0	1	0	0	0	0
Bankr. in two years.7	0	0	0	0	0	0	0	0	0	0
Solvent company.8	30190	1222	568	0	4	15120	598	270	3	0
Bankr. in current year.8	2	10	0	0	0	1	5	0	0	0
Bankr. in the future.8	0	0	1	0	0	0	0	0	0	0
Bankr. in two years.8	0	0	0	0	0	0	0	0	0	0
Solvent company.9	30190	1227	568	0	4	15118	602	270	3	0
Bankr. in current year.9	2	5	0	0	0	3	1	0	0	0
Bankr. in the future.9	0	0	1	0	0	0	0	0	0	0
Bankr. in two years.9	0	0	0	0	0	0	0	0	0	0
Solvent company.10	30181	1212	569	0	4	15115	594	270	3	0
Bankr. in current year.10	11	20	0	0	0	6	9	0	0	0
Bankr. in the future.10	0	0	0	0	0	0	0	0	0	0
Bankr. in two years.10	0	0	0	0	0	0	0	0	0	0

	X.Solvent company	X.Bankr. in current year	X.Bankr. in the future	X.Bankr. in two years	X.Bankr. next year	I.Solvent company	I.Bankr. in current year	I.Bankr. in the future	I.Bankr. in two years	I.Bankr. next year
1	2	3	4	5	6	7	8	9	10	11
Solvent company.1	15115	613	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.1	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.1	0	0	0	0	0	0	0	0	0.00	0.00

Continued (Table 2)

1	2	3	4	5	6	7	8	9	10	11
Bankr. in two years.1	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.2	15115	613	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.2	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.2	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.2	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.3	15107	611	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.3	2	1	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.3	6	1	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.3	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.4	15101	599	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.4	14	14	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.4	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.4	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.5	15099	600	262	1	5	0	0	0	0.00	0.00
Bankr. in current year.5	16	12	1	0	0	0	0	0	0.00	0.00
Bankr. in the future.5	0	1	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.5	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.6	15115	604	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.6	0	9	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.6	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.6	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.7	15115	604	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.7	0	9	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.7	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.7	0	0	0	0	0	0	0	0	0.00	0.00

Continued (Table 2)

1	2	3	4	5	6	7	8	9	10	11
Solvent company.8	15113	612	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.8	2	1	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.8	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.8	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.9	15111	610	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.9	4	3	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.9	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.9	0	0	0	0	0	0	0	0	0.00	0.00
Solvent company.10	15109	604	263	1	5	0	0	0	0.00	0.00
Bankr. in current year.10	6	9	0	0	0	0	0	0	0.00	0.00
Bankr. in the future.10	0	0	0	0	0	0	0	0	0.00	0.00
Bankr. in two years.10	0	0	0	0	0	0	0	0	0.00	0.00

Conclusion

The aim of this article was to apply neural networks to predict potential financial problems in construction companies in the Czech Republic.

1000 artificial neural networks were generated on the basis of data obtained on construction companies for the period 2003 – 2013. Ten of these neural networks were retained for further processing. Analysis of the results of a confusion matrix determined that neural network 5 was the most successful. It provided the optimal ratio of prediction success rate for all the possible results, namely «solvent company», «bankruptcy in the current year», «bankruptcy in the future» and «bankruptcy in two years». It is a linear neural network Linear 90:98-4:1. The artificial neural network is able to predict the future development of a construction company in the Czech Republic with a success rate higher than 94%. Eight other artificial neural networks achieved similar results, however they were not able to predict the potential bankruptcy of a company. It is for this reason that it was more suitable to select an artificial neural network that made slightly worse predictions with regards to solvent companies but which was able to more accurately predict (in tens of percent) potential bankruptcy.

The model is applicable in practice due to its characteristics. It can be utilised by construction companies, financial analysts, banks, competitors or potential investors alike.

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