FORMATION OF COMPLEX COMPANY EVALUATION METHOD THROUGH NEURAL NETWORKS BASED ON THE EXAMPLE OF CONSTRUCTION COMPANIES´ COLLECTION

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Abstract: The main goal of this contribution is to create a model through the use of neural networks, which will be able to predict the company´s ability to survive a prospective financial crisis. Artificial neural networks are able to conduct non-linear statistical modelling and offer a completely suitable alternative to individual financial indicators within complex methods of evaluation. The contribution examines the basic data on companies coming from the Albertina database. The collection includes both financial and non-financial indicators of all construction companies in the Czech Republic within the period of 2008 to 2014. The object is to find an artificial neural network, which can classify each company based on the input data. Three neural networks are given and described, proving positive results. The best results are achieved by MLP 15:15-54-66-4:1. Through this network the Czech construction companies´ ability to survive a possible distress is consequently evaluated.

Keywords: complex company evaluation, artificial neural networks, construction company, company bankruptcy, financial and non-financial indicators, predictive model

1 Introduction

In all companies, the meaning of enterprise evaluation keeps growing within today´s constantly changing economic environment (Fotr and Kislingerova, 2009). Enterprise evaluatio n is the basic element for understanding the sources of company competition and at the same time, it is a source for company´s strategy implementation support. It is obvious that the knowledge of a company´s financial position is necessary. Reverse information is able to discover areas in which the enterprise was successful and how or where it has fulfilled the expectations and its aims. They may also point to situations not expected or managed by the enterprise and to situations, which may occur in the closest future (Vochozka et al., 2017). According to Wang, Stockton and Baguley (2010), success of the enterprise is even directly dependent on an exact prediction of future development.

The process of a complex enterprise evaluation represents an objective, just and exact evaluation of enterprise function using mathematical statistics and operative research principles (Zhang and Zhong, 2015, p. 178). A correct enterprise evaluation may be ensured only by relevant methods. The last fifty years have brought a varied consideration range of approaches, methods, and tools of its measurements (Wagner, 2011, p. 776). According to Vlachy (2009, p. 147) traditional methods of financial analysis are insufficient. For instance, ratio analysis, using balance sheet and profit and loss statement data is still a widely used method, which may thus easily interpret the enterprise´s financial situation (Savvidis and Ginoglou, 2013). But not even this enterprise evaluation based on the analysis of financial data is sufficient (Smeureanu et al., 2011). Modern enterprises produce huge amounts of data, and traditional analytical tools and methods are no longer able to process such amounts of information collectively (Yan, Wang and Liu, 2012, p. 275). Enterprise evaluation should use both financial and non-financial indicators. (Hsiang et al. 2013). The truth is that information nowadays may represent relatively precious company wealth. A huge amount of data may also fundamentally influence complex enterprise evaluation (Machek and Hnilica, 2012). The ability to analyse and use massive amounts of information still keeps lagging behind the ability to collect and keep them (Wang, Rees and Liao, 2002).

Complex enterprise evaluation methods are a specific group of tools used for suitable enterprise evaluation – mainly multidimensional models working with several criteria assigned specific weight (importance). The enterprise´s situation is then collectively expressed by one number, which evaluates the level of the enterprise´s financial health (Vochozka, 2010, p. 675). Artificial neural networks are able to carry out non-linear statistical modelling in these models, and thus provide a suitable alternative for simple financial indicators including a frequently-used logistical regression or discrimination analysis (García, Giménez and Guijarro, 2013). These collective indexes serve according to Vochozka (2010) mainly investors and owners of the enterprise to determine the performance of the given enterprise from the perspective of value creation, or serve creditors in predicting whether the enterprise is not reaching bankruptcy in the nearest future.

The issue of artificial neural networks related to enterprise evaluation belongs among rather young subjects. Their development and especially wide application expansion is being observed since 1980´s (Du Jardin, 2010). Nowadays, still new types of networks keep appearing, as well as massive development of information technologies and computing technologies for their implementation (Synek, Hoffmann and Mackenzie, 2013). Neural networks belong, together with fuzzy sets, expert systems, gnostic theory in uncertain data or genetic algorithms, etc., among non-static higher methods of financial analysis (Vochozka et al., 2016). Most simple indicators, but also mathematical-statistical or non-statistical methods prove shortcomings that implement a certain level of inaccuracy into the result. They often do not take into account specific differences – for instance, the level of inflation or tax policy. They also have difficulties capturing causes of problems and are not able to work with intangible assets, know-how for instance (Kuzey, Uyar and Delen, 2014). Modern methods try to get rid of these shortcomings. So-called higher methods of financial analysis demand high-quality software equipment and knowledge of mathematical statistics. Data availability and ability to provide the model with information wanted are also necessary. Neural networks require a certain set of data to refine the network outcome, that is why they are not able to evaluate enterprise performance correctly without model data (Amusan et al., 2013). Savvidis and Ginoglou (2013) state that the performance of artificial neural networks and of complete company evaluation depends mainly on data. If there is enough data it is possible to claim that artificial neural network is the correct choice for enterprise evaluation (Ghodsi, Zakerinia and Jokar, 2011).

The main advantage predicting artificial neural networks for application in economy is, according to Vesely (2011) the ability to work with non-linear data, too. In complex enterprise evaluation, there are countless non-linear relations or structures (Ciobanu and Vasilescu, 2013). A non-linear enterprise evaluation model assembled on the basis of neural networks may stimulate economic phenomena better, and its results are objective, relatively exact and have a practical referential value (Zhang and Zhong, 2015, p. 178). This advantage of artificial neural networks is confirmed also by Wu et al. (2011) claiming that networks are able to learn, and having learned, they are able to capture the hidden, and even strongly non-linear dependencies. They use distributed parallel processing of information and reach high speed processing of large data volumes. According to Mostafa (2009), artificial neural network models have a great potential in classifying the relative enterprise performance thanks to their robustness and algorithm modelling flexibility.

A model based on artificial neural networks, evaluating enterprise performance may be set in many ways. Input data is often represented by significant items which are usually a part of a balance sheet or profit and loss statement. Shi, Bian and Zhang (2010) for instance, classify the value of total enterprise assets, the amount of workers, main enterprise costs, net fixed assets, net profit, main enterprise income, total asset turnover indicator and income per share among input information. Zhang and Zhong (2015) use up to 20 enterprise financial indicators for the purposes of education and testing of back propagation type neural network samples. They include, for instance, net income per share, main enterprise costs, total costs of annual wages, main entrepreneurship income, net profit after tax, return on total assets, or profitability on equity (Zhang and Zhong, 2015, p. 179). The output is represented by a value copying the course of economic indicator by which the network was determined – a whole range of economic indicators may be used, while the most suitable are difficult to be set and complex or testifying (Galushkin, 2012). Different types of artificial neural networks may create the network architecture – according to what the neuron transmission function is, how neurons are interconnected mutually, how many input neurons, hidden layers there are, etc. (García, Giménez and Guijarro, 2013). Similarly, the amount of layers depends on the given model´s author´s consideration. If there are not so many in the neural networks, they learn quicker. If there are bigger numbers of layers, they are able to generalize better (Elsawy, Hosny and Razek, 2011).

The disadvantage is that we never know how the network makes its decisions, and why it has decided the way. It is thus impossible to know the inner structure of this system. That is why neural networks are also termed as ´black boxes´ (Tzeng and Ma, 2005). The networks are very comfortable and practical, but the way they evaluate the enterprise exactly, is not always very clear (Shi, Bian and Zhang, 2010, p. 640). We also always operate with the probability that the response will be, in certain percentage, wrong. This fact considerably limits its use in areas with one-hundred-percent-flawlessness (Slavici, Mnerie and Kosutic, 2012). While evaluating an enterprise, networks are also sensitive to organization and preparation of data, but also to the whole configuration. To apply them, a high computing power is needed, and their processing takes a long time (Kim, An and Kang, 2004).

Advantages in using artificial neural networks during a complex enterprise evaluation are the following (Ciobanu and Vasilescu, 2013):

- Simple implementation,
- Possibility of parallel processing,
- Learning and generalization ability,
- Adaptation ability,
- Distributed representation and calculation.

Nevertheless, there is a range of disadvantages while using artificial neural networks while evaluating an enterprise in a complex manner (Knez-Riedl and Mulej, 2014):

They work with a so-called ´black-box approach´ - their inner functionality is not directly known,
At the training stage they are computing-power consuming,
Their processing often takes a long time,
Networks are unable to solve other, similar problems other than those they are trained to solve,
Networks are an approximation of the required solution – it is necessary to always count on certain error rate,
Networks are prone to be over-trained.

Only a few authors dedicate their work to applying neural networks in order to evaluate an enterprise in a complex manner. The reasons are probably reasonably significant disadvantages of artificial neural networks, and the existence of many complex, and often simpler models for enterprise evaluation. Zhang and Zhong (2015) have suggested a model based on artificial neural networks, which has a high prediction accuracy and its results are objective and exact. A similar model is presented by Makeeva and Bakurova (2012). The background for its creation is profitability, liquidity, indebtedness and return indicators. Al-Shayea and El-Refae (2012) have created a model for insolvency prediction based on less used types of neural networks – GMDH[1], Counter Propagation and fuzzy ARTMAP[2] networks. The most influencing factors when evaluating, are, according to them, net profit, total equity, costs on sale, sales, cash flow, and credits. Net profit, annual volume of work and work capital are the main indicators of financial performance of any building company (Mohamad et al., 2014). It was Mohamad et al. (2014) who have developed a hybrid model (an artificial neural network technique + genetic algorithm) with the aim to predict, based on the previously published data on financial statements, the amount of the three main given indicators of building companies´ financial performance. Complex enterprise evaluation methods created via artificial neural networks are often used by banks when considering credit requests – credit risk evaluation in a given enterprise (Mansouri and Dastoori, 2013). A complex enterprise evaluation´s aim in this case is to minimize credit risk and improve decision-making process while establishing business relationships in economic, legal and social sphere (Yongli et al., 2013). A model based on GRNN[3] neural network, designed by Zhu et al. (2015) may serve as an example. It may evaluate credit risk efficiently.

Complex enterprise evaluation methods are nowadays created by modern analytical models using computers and sophisticated mathematical models (Gholizadeh et al., 2011). Neural network imperfections, however, point to the fact that this technology still undergoes the process of development and improvement. Even so, they may be used as a complex enterprise evaluation indicator, while complemented and combined with other models very often. Many authors have proven that complementation by other models improves the calculation, and raises the efficiency and accuracy of the result (Ciobanu and Vasilescu, 2013, p. 448). The obtained model outputs may be further compared to the other enterprises´ results or to the results of best enterprises working in the same branch (Rosillon and Alejandra, 2009).
The aim of this contribution is to create a model, using neural networks, which will be able to predict the enterprise´s ability to survive possible financial distress.

2 Data and Methods

Basic data about enterprises, which is going to be analysed and examined comes from the Albertina database. These are enterprises classified among building enterprises by the Czech Statistical Office. These enterprises fall among the classification F-section in CZ-NACE (economic activity classification). The resulting file includes exactly 65 536 data lines. Each line consists of a hundred characteristics. Specifically, they are financial parameters and non-financial indicators.

Financial parameters include all data from financial statements i. e. balance sheets, profit and loss statements, cash flow statements. Further, earnings before interest and tax (EBIT) is included. Non-financial indicators include enterprise identification (name and identification number), enterprise business district, number of employees and the enterprise auditor´s statement.

It is common to start the paper with input data analysis from the perspective of their objective interpretation. Data analysis has been carried out, but only on the level of variable classification, not from the perspective of ´economic fundaments´. In case some available data is excluded already at the stage of data file preparation, we could reach a situation of excluding a variable, which, although refused by current economic theory, may significantly influence the result. Thus, we are facing a dilemma whether to include a greater amount of variables (some even against the sense of current knowledge) and obtain a result, which may be economically difficult to interpret, or whether the amount of variables should be decreased to values possible to be relatively easy interpreted today. I have chosen the first option. The economic environment has changed so much as we can not describe it using the same variables as we had done several decades ago.

To prepare a data file MS Excel will be utilized. The data file will be imported into the DELL Statistica software in version No 12 and version No 7 (result visualization). Subsequently it will

[1]Group Method of Data Handling – Networks with inductive modelling.
[2]Adaptive Resonance Theory MAP – neural network hybrid architecture.
[3]Generalized Regression Neural Network.

be processed via ´Automated neural networks´ tool. The result, if its validity is improved (it will prove a higher level of accuracy), it will be subsequently varied on the level of vector weights among neurons.

We are looking for an artificial neural structure, which will be able to classify each enterprise, based on the input data, into one of four groups:

The enterprise is not going bankrupt (a creditworthy enterprise),
Bankruptcy in the given year,
Bankruptcy in two years,
Bankruptcy in the future (in a period longer than two years).

First, we will establish the properties of individual characteristics of the enterprise. It is necessary to define the output categorical quantity. In this case, it is obvious that this will be a value within a column in the MS Excel notebook marked as ´resulting situation´. At the same time, we need to know the results for at least the periods of 2008 to 2014. Further, we will establish the categorical input quantities. In case of neural structures, categorical quantities are transferred into a binary code, i.e. into the form of ´YES´ (1) or ´NO´ (0). In case of, for instance, placing the enterprise within a given region, we are counting on 14 regions. The code will state that the enterprise does not reside in thirteen regions, and it does reside in the fourteenth region – the numeric code thus contains 14 numerals (0 or 1). These are non-financial indicators (e.g. the place of the enterprise residence, the region respectively). All the stated items of financial statements and numbers of employees will belong among continuous quantities.

Subsequently, the file will be randomly divided (sampled) into three groups of enterprises – i.e. a training file (neural networks are trained on this one to reach the best results possible), a testing file (this file tests the success of trained artificial neural structures classification), and a validational file (used for the second validation of the result obtained). The data will be divided in the following ratio among the training, testing and validational file: 70:15:15. The choice will be random. Thus, the ratio of individual enterprise groups is not preserved (the enterprise is not going bankrupt, bankruptcy in two years, bankruptcy in the future) in individual data files. If we keep the ratio, we might distort the result. Equally, the sub-sampling[4] will be done randomly. A maximum of two sub-samples will be created. The seed (for a random number choice) for sub-sampling will be stated at a value of 10.

Subsequently, 10,000 random artificial neural structures[5] will be generated, out of which, ten of the best results will be preserved. To create the model, we will use multiple perceptron networks (MLP) and linear neural networks, probabilistic neural networks (PNN), generalized regression neural networks (GRNN), radial basic-function neural networks (RBF), three-layer perceptron networks (TLP), and four-layer perceptron networks (FLP).

In case of radial basic-function neural networks, we will use 1 up to 40 hidden neurons. The second layer of the three-layer perceptron network will contain 1 to 10 hidden neurons. The second and third layer of the four-layer perceptron network will contain always 1 to 10 hidden neurons. Perceptron networks will classify individual enterprises based on cross entropy. That works with multinomial division of frequency (unlike e.g. smallest squares sum, which presumes a normal division of frequency). The analysis thus can be stopped, if the value of cross entropy draws near the value of 0 and if it does not improve any longer. The threshold of classification is assigned based on the highest trust. Hidden layers as well as output neurons of identical functions will be utilized as activation functions for neurons, and they are presented in Table No. 1.

[4]By sub-sampling, in this case, clustering of data lines is meant to be based on reported similar characteristics.
[5]If the improvement of individual trained networks is not significant, training of neural networks can be shortened.

Table 1: Activation Functions in Neurons´ Hidden and Output Layers

Function	Definition	Extension
Identical	x	(-∞, +∞)
Logistical	$\frac{1}{1+e^{-x}}$	(0, +1)
Hyperbolic	$\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$	(-1, +1)
Exponential	e^{-x}	(0, +∞)
Sinus	$\sin x$	[0, +1]

Source: Author

Weight decomposition will be carried out with a one-hundredth accuracy for both hidden and output layers[6]. Initialization will not be used.

The result of the calculation will be:
An overview of the best 10 generated and preserved networks (including a complete result description in an xml file) from the previously generated 10,000. Confusion matrices via which we will determine classification (prediction) success of a possible enterprise bankruptcy, respectively the correctness and incorrectness of estimates in individual cases.

Sensitivity analysis, which will confirm in every generated neural network which input quantities are necessary for the given neural structure, and the weight of the specific input quantity included. The scheme of preserved neural structures.

3 Results

The overview of individual generated and preserved networks is the object of Table No. 2[7] (Inserted in Attachment number 1).

BP value in the table indicates using the Back Propagation algorithm. It is one of the so-far mostly used algorithms, which has been published independently by several authors: Rumelhart, Hinton and Williams (1986), Werbos (1974) and Parker (1985). Its advantage is that it requires less memory than most of other algorithms, and it usually reaches an acceptable amount of error quite fast. Moreover, it is useful for most neural networks. The abbreviation ´CG´ represents the Conjugate gradient descent algorithm (Bishop, 1995; Shepherd, 1997). It is an advanced method of training of a multilayer perceptron network. Usually, it proves significantly better results than Back propagation. Equally, it can be used to solve the same tasks as Back propagation. Its use is recommended for any networks with a greater amount of weights, and a multiple outcome. PI, i.e. Pseudo-Inverse Algorithm represents the optimization technique via the method of smallest squares (Kahan, 1965). SS represents a (sub) sample, i.e. sub-sampling. KN represents nearest neighbor deviation assignment. It is an algorithm assigning radial unit deviations via RMS (an efficient value) distance from K units closest towards each unit in the form of standard deviation. Each unit thus has its own, independently calculated deviation based on the density of points clustered near each other.

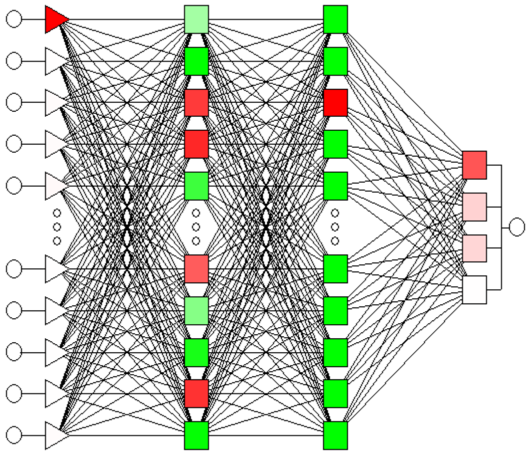
The most valuable network is the one, which proves the highest reliability values for the training, testing and evaluating data file. At the same time, ideally an identical or at least similar value is required in all three sets. In case of obtained results, it may be observed that this condition has been met in nine out of ten preserved networks. The only exception is Network No. 2, MLP 2:7-88-63-4:1, proving minimal values. At the same time, we are looking for a network, which proves minimal error, again relatively identical for all, training, testing and verifying data

[6]Weight decomposition is determined based on iteration in the software. Iteration accuracy of each weight was determined to be equal to 0.01 for the analysis´ purpose.
[7]It is suitable to add that results may slightly differ for repeatedly carried-out analyses. This is given by the fact that neural network algorithm uses slightly different generators meant for variable initiation weights. This helps reach a slightly different local minimum in a function. The result is not significantly influenced by this fact.

sets. In our case the lowest error is optically proved by the RBF networks. All reach a value lower than 0.16. Optically we will be looking for a result in the form of one of RBF networks.

Nonetheless, to be able to determine whether this or other neural network is useful in practice, i.e. whether its results are economically reliably interpretable, and whether they prove acceptable accuracy, a confusing matrix has to be set. In fact, it is a confusion matrix made of several partial matrices. It is a 10x4 matrix (10 neural structures, 4 possible results) always for three data sets (training, testing and validation). It is necessary for us to find one, which will be able to predict all assumed results, i.e. the enterprise is not going bankrupt, it will go bankrupt in the given year, it will go bankrupt in two years, and it will go bankrupt in the future. Moreover, it is important for the neural structure not to be mistaken in its predictions. Relatively interesting results are presented by neural networks No. 3, 4, and 5 (i.e. MLP 15:15-54-66-4:1, Linear 84:86-4:1 a Linear 90:98-4:1). Network No. 3 is a multiple perceptron network with two hidden layers. It works with 15 input variables, which are processed by 54 neurons in the first hidden layer, and 66 neurons in the second hidden layer. The output layer is represented by four neurons (i.e. four possible results) out of which the only option is being opted for. With regard to the fact that we are using 15 input variables, and at the same time the network contains 15 neurons in the input layer, the network uses only continuous quantities input
variables. The network model is the object of Figure No. 1.

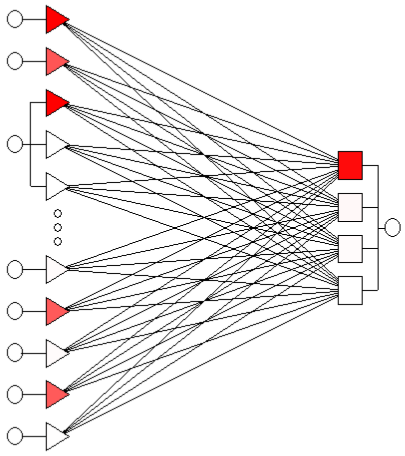
Figure 1: MLP 15:15-54-66-4:1 neural network model



Source: Author

The obtained linear networks work with both continuous and discrete quantities. The first one, Linear 84:86-4:1 assumes 84 input variables. The network model is the object of Figure No. 2.

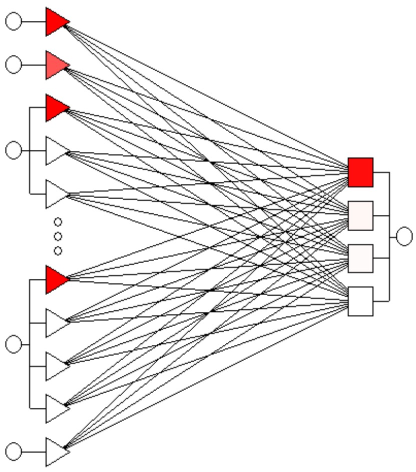
Figure 2: Linear 84:86-4:2 neural network model



Source: Author

The second linear neural network called ´Linear 90:98-4:1 works with 90 input quantities. The neural network model is captured in Figure No. 3.

Figure 3: Linear 90:98-4:1 neural network model



Source: Author

Figures No. 1-3 are best able to interpret the network structure. The figure always shows clearly which input variable is meant (categorical, continuous), and the neuron function (signal amplification and weakening). Also, it is clear in what manner the signal is further modified. Unfortunately, detailed modification is unclear (the input variable in hidden neuron functions and in output layer neurons). Finally, even the output of the neural function is noticeable. The description of individual model components in weight decomposition is available in the xml form at the following link http://www.vstecb.cz/data/1487593732162SANN_PMML_Code_rozcleneni-souboru-214-podniku-do-5-skupin.rar (the length of each of them significantly exceeds the size of this contribution itself that is why they are not included standardly in the contribution appendix).

The implemented sensitivity analysis evaluates the meaning of individual input variables for preserved neural networks. However, the range of this contribution does not allow interpreting the complete executed analysis. Nevertheless, even so we are able to identify the most significant variables to determine the prediction model. They are the following:

- The year of establishing the company,
- Business contact receivables,
- Short-term financial property in thousands CZK,
- Other current assets,
- Other short-term obligations,
- Revenues for sale of goods in thousands CZK,
- Return interest in thousands CZK.

At the same time, it is suitable to submit the result to the modification of vector weights between individual vectors. The aim is an increase in the efficiency of the obtained model. With regard to the amount of variables, this is rather an attempt. In this case, a significant increase in classification (prediction) accuracy has not occurred, not in one of the three most suitable neural structures (MLP 15:15-54-66-4:1, Linear 84:86-4:1, and Linear 90:98-4:1).

4 Conclusion

When processing this paper, three neural structures were determined and described, showing similar positive results (MLP 15:15-54-66-4:1, Linear 84:86-4:1 a Linear 90:98-4:1), respectively the best results from the 10 preserved neural structures. Based on the reached reliability values, it is impossible to unambiguously determine the one neural structure with the best parameters. If we focus on the calculated error, preferring both linear networks, while, during a detailed testing the Linear 90:98-4:1 network will be preferred. On the other hand, the other tool, confusing matrix, pretends a completely different result. All four situations, i.e. that the enterprise is not going bankrupt, it is going bankrupt in two years and i tis going bankrupt in the future, are best predicted by the multilayer perceptron MLP 15:15-54-66-4:1 network.

With regard to the usability of the model and minimal deviations from the other two models which were being taken into account we may judge that the best results are shown by the MLP 15:15-54-66-4:1. Thanks to its parameters, we may claim that the result is applicable in practice. Via MLP 15:15-54-66-4:1 we will judge the ability of a building enterprise in the CZ to survive possible financial distress.

A comparison of the obtained model to already renowned and used bankruptcy models (such as Altman indexes, the Neumaier IN indexes, and Taffler index) occurs. A range of expert papers has dealt with their predictive value, such as Vochozka (2010). Generally, it may be concluded that they show the following shortcomings (Vochozka, 2010):

- Assumption of bipolar dependent variables,
- Data choice method in model enterprises,
- Assumption of data stationarity and instability,
- Choice of independent variables,
- The use of annual financial statements,
- Time dimension.

In case of individual variables, it is clear that their absolute size is in question. Nevertheless, we must understand the result not as individual variables, but as a file of variables within which the individual variables interact. To make it clearer, we are only indicating the most significant variables. But also among them there are quantities characterizing the enterprise size – e.g. ´revenues for sales of goods in thousands CZK´. Less significant variables, such as numbers of employees or total assets are not mentioned.

Suggested Solution: the neural structure shows some shortcomings, as well as models constructed via multiple discrimination analysis do. Some are eliminated, specifically the assumption of bipolar dependent variables (the model works with four values), the choice of independent variables (the model has allowed using all available variables – it was not necessary to eliminate some), and the time dimension (the enterprise´s neural networks, respectively recording lines do classify. Thus, it is possible to work with the history of individual enterprises).

Regarding the specific comparison, we may refer to Vochozka (2010), Delina and Packova (2013), Kubenka and Slavicek (2014) or Mertlova (2015). The suggested neural structure shows significantly better values of prediction, 15-20% higher accuracy on the average.
Interesting results have been brought by sensitivity analysis. Based on their results we may arrive to these partial conclusions:
The year of the enterprise´s establishment tells us that an enterprise with a longer history has gained greater experience, and thus will be probably able to survive possible financial distress.

An enterprise, which generates greater business-contact receivables will, with a greater c, be able to survive possible financial distress. This claim is relatively courageous, as we are unable to analyse claim structure out of financial statements. They may be expired claims, or even impregnable claims. Business-contact claims may be a false positive indicator.
A higher value of short-term financial property expressed in thousands CZK indicates the enterprise´s ability to survive probable financial distress.

An enterprise that creates other higher current assets will probably survive possible financial distress.
A higher value of short-term obligations means a higher ability of the enterprise to survive possible financial distress. Optically, it may seem to be a false positive indicator. But, if we look at the result through money supply creation, the indicator makes sense. The enterprise, thanks to a longer due date of its obligations, accumulates short-term financial property. The indicator thus complements point No. 3 more than appropriately.

Higher revenues for sale of goods in thousands CZK create an assumption that the enterprise will probably survive possible financial distress. It is interesting that the overview also includes sale revenues in the building industry section. It might be assumed revenues for own products and services will be calculated with a greater probability. Nevertheless, the indicator is certainly not false positive.

A higher value of return interest in thousands CZK means a higher ability of the enterprise to survive possible financial distress. Even in this case it may be a matter of a rather negligible item in profit and loss statement within a building enterprise. But, the value again is certainly not false positive.

The determined aim to create, via neural networks, a model, which will be able to predict a building-enterprise´s ability to survive possible financial distress, has been fulfilled.

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Primary Paper Section: A

Secondary Paper Section: AE, AH

Attachment number 1.

Table 1: An Overview of Preserved neural networks

	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Training/Members	Inputs	Hidden (1)	Hidden (2)
1	MLP 1:4-33-61-4:1	0.94359	0.94524	0.94487	1.43022	1.54192	1.45348	BP10, CG20, CG0b	1	33	61
2	MLP 2:7-88-63-4:1	0.03850	0.03760	0.03832	1.02620	1.04046	1.01426	BP10, CG20, CG0b	2	88	63
3	MLP 15:15-54-66-4:1	0.94318	0.94505	0.94443	0.58611	0.59107	0.5835	BP10, CG20, CG0b	15	54	66
4	Linear 84:86-4:1	0.94443	0.94549	0.94487	0.16093	0.16396	0.16088	PI	84	0	0
5	Linear 90:98-4:1	0.94431	0.94549	0.94462	0.16085	0.16203	0.16074	PI	90	0	0
6	PNN 88:93-31997-4:1	0.94425	0.94605	0.94543	0.16236	0.16034	0.16066		88	31997	0
7	PNN 87:92-31997-4:1	0.94425	0.94605	0.94543	0.16237	0.16034	0.16066		87	31997	0
8	RBF 61:69-328-4:1	0.94387	0.94549	0.94480	0.15962	0.15862	0.15909	SS,KN,PI	61	328	0
9	RBF 61:69-359-4:1	0.94371	0.94512	0.94480	0.15964	0.15861	0.15993	SS,KN,PI	61	359	0
10	RBF 61:69-360-4:1	0.94387	0.94543	0.94505	0.15932	0.15859	0.15909	SS,KN,PI	61	360	0

Source: Author