ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ В ЕКОНОМІЦІ

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EVALUATION OF SOLVENCY OF POTENTIAL CUSTOMERS OF A COMPANY

Abstract. *The manufacturing 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 manufacturing companies in the Czech Republic.

Data on all manufacturing 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 manufacturing company managers, investors looking for a suitable company for capital investment, competitors, etc.

Key words: *manufacturing company, financial problems, prediction, artificial neural network, model.*

Introduction

Vomocil, Hajek and Olej [13] present that solvency in general means the ability of an entity to duly fulfil its obligations. Evaluation of creditworthiness of customers by business partners or banks is based on solvency, while high solvency indicates a low credit risk and low solvency indicates a high credit risk. An analysis of customer solvency is a necessary condition for healthy business relation according to [3]. According to [10] evaluation of solvency of potential customers belongs among strategic decisions of a company management, where the so called credit management, whose aim is to evaluate objectively the solvency of customers with selection of the procedure to be applied to the seller, decides on a deal. Classification of customers according to their solvency and importance for the company is used for this purpose, while evaluation of solvency represents a process of their multidimensional classification [10].

A solvent customer can only operate healthily if it perfectly manages not only the business, but particularly the finance aspect of its business activity [15].

A thorough investigation into potential customer's solvency is particularly used in the bank sector in provision of loans. Mansouri and Dastoori [7] claim that a credit risk is one of the biggest challenges banks and similar institutions face in all economic systems. Solvent and insolvent customers thus have to be classified. A company should be able to identify customers that represent a potential risk. According to [10] this is mainly the payment risk, which might be the risk of inability to pay, unwillingness to pay and the risk of payment delay. Unless customers are solvent and not able to pay their debts, this might even lead to serious threat to company health [7]. It is not easy to find the balance between the ability to pay own bills, funding the operation capital and having satisfied solvent customers. Solvency of customers differs in the individual countries and sectors, while it depends not only on financial abilities of customers, but also on local habits [3].

Availability of trade credits is a factor that particularly determines the existence of small and medium sized companies according to [15]. Trade credit is a crucial element of company credit policy [4]. It is necessary to introduce a suitable system of evaluation of client's solvency as selection of suitable business partners is the key aspect of company success [15].

A so called Customer Profitability Analysis – CPA, which operates on the base of historic data, particularly on the short-term base is often used for evaluation of buyers' solvency [4]. However numerous methods of assessment of customer's solvency exist. Bank information, solvency models (Kralicek Quicktest, Solvency Index etc.), bankruptcy models (Altman Model, Index IN05 etc.), combined models (Balanced Scorecards) or a financial analysis are among those most frequently used.

The Kralicek Quicktest is always based on one representative of each of the four basic spheres of financial analysis (finance, liquidation, profitability and return), while the selection of these indicators is based on their economic significance. Marks are always assigned to the indicators and their sum gives the overall evaluation of the company [6].

The Solvency Index is based on multivariate discriminant analysis, it is mainly used in Central European Countries and consists of six financial ratios.

The Altman Model [1] belongs among the best known general indices of evaluation of a company business situation according to [11], while several modifications have been created through the years (a variant for public limited companies, a variant for private limited companies, a variant for non-manufacturing companies or a variant for Czech companies). The discriminant analysis, which reveals coefficients in a linear combination of the individual financial ratios is applied to the calculation.

Index IN05, suitable for a less liquid capital market belongs to a series of variants (IN95, IN99, IN01, IN05) designed by the Neumaiers [11]. They also contain indicators of activity, return, indebtedness and liquidity [9].

The Balanced Scorecard method focuses on the strategic approach to performance, including value processes. It consists of individual sections, which are assigned to four perspectives (finance, customer, learning and growth and internal processes), while fulfilment of one goal leads to fulfilment of the next one (causal relation). These perspectives contain strategic goals, which then contain the key indicators of performance [5].

According to [10] the cluster analysis is the most suitable applicable method. Its aim is to classify a given number of objects into several relatively homogenous clusters on the base of the requirement that the objects inside a cluster are as similar as possible and the objects belonging to different clusters are as different as possible. Modelling assisted by rating is the most frequently used solvency modelling method according to [13]. Rating is an independent evaluation based on quantitative and qualitative parameters and its goal is to reveal how a given entity is able and willing to fulfil its obligations in time.

To keep pace with competitors companies must keep their customers satisfied, which depends mainly on an analysis and evaluation of their solvency. Analyse information [4] on customers (the information which cannot be handled by mathematical models and optimization techniques) by means of artificial neural networks.

The approach to evaluation of customer's solvency has been changing a lot recently with the growth of the progress in the IT sphere. The classical statistics, expert systems or artificial intelligence are some of the methods used for evaluation of solvency according to [2]. These systems have an advantage in the possibility to evaluate the financial health of a customer from more points of view with regard to interaction between the individual parameters. Neural networks are one of the calculation models utilized in artificial intelligence, and they are based on the example of biologic structures [8]. They are utilized for distributed parallel data processing. Neutrons, which have an arbitrary number of inputs but just one output are interconnected in a network, exchange signals between each other, which they transform by means of transmission functions according to [12]. It is hard to understand neural networks and to interpret them, they might moreover suffer from overlearning [8]. Artificial neural networks undoubtedly represent a contribution in the sense of objectivity and effectiveness of decision making on solvency, while they also reduce the risk of the unfavourable influence of the human factor on decision making [2]. Financial health of customers also depends on numerous parameters that might change quickly. This is why it is also necessary to evaluate the level of adaptability of artificial neural networks to new conditions, which is in fact also excellent [4].

E.g. [14] deal with evaluation of solvency of energetic customers. They use learning vector quantisation of a neural network to create an analytic credit model.

Vomocil, Hajek and Olej [13] deal with modelling of solvency of communities by means of neural networks, which partially differs from modelling of solvency of customers. The final model is based on a forward-propagation neural network with several variants, which are verified, and their quality is evaluated according to the criterion of mean square deviation of the data in the tested set. The best results are achieved by the variants with the Quick Propagation learning function [13].

The aim of this article is to utilize neural networks for creation of a model for determination of solvency of customers of a manufacturing company.

1. Material and methodology

The data file was created on the base of a randomly selected sample of 110 manufacturing companies. Specializations of the companies was not important for the selection. However it was necessary to choose companies with longer than 20-year history, which means somehow established companies. The data relates to 2014.

As mentioned above the group contains information on 110 companies, namely:

– company name;

– place of business;

– the complete financial statement data for the examined year;

– selected financial ratios (return on assets, return on equity, return on capital employed, 1-3 level liquidity, debt etc.).

MS Excel was used for the preparation of the data file. The data for each company was always presented on one line. The file thus contains (apart from the heading) 110 lines and 167 characteristics in each line. It was imported into Statistica software by DELL. The data was subsequently processed by an intelligent problem solver, actually this was a classification problem processed by means of artificial intelligence (artificial neural networks).

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 two groups:

1. solvent company,
2. insolvent company.

First we determined the characteristics of the individual companies. We had to define the output category quantity. In this case it was obviously the value presented in the column "final status" of the MS Excel sheet. A solvent company shows a positive difference between the working capital, trade liabilities and has no overdue debts. Unless these conditions are met we talk about an insolvent company. Such a company is considered to some extent risky to trade with, i.e. required a higher guarantee for unpaid debts (cash payment in advance, insurance, a letter of credit etc.). The other quantities are input ones and are continuous except for the place of business. The place of business is an input – categorical quantity.

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 21 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.

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

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]

	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error
1	Linear 1:1-1:1	0.627907	0.714286	0.619048	0.481156	0.886400
2	Linear 2:2-1:1	0.674419	0.476190	0.428571	0.477751	0.883533
3	PNN 1:1-43-2-2:1	0.558140	0.666667	0.571429	0.513807	0.538365
4	PNN 2:2-43-2-2:1	0.604651	0.666667	0.476190	0.535191	0.530754
5	RBF 45:45-8-1:1	0.906977	0.857143	0.904762	0.287553	0.399138
6	RBF 45:45-12-1:1	0.953488	0.809524	0.904762	0.244266	0.361051
7	RBF 45:45-15-1:1	0.930233	0.857143	0.857143	0.215383	0.330831
8	MLP 91:91-99-59-1:1	0.953488	0.904762	0.904762	0.000000	0.100207
9	MLP 99:99-41-1:1	1.000000	0.904762	0.761905	0.001118	0.062911
10	MLP 99:99-55-1:1	0.953488	0.857143	0.952381	0.000256	0.012762

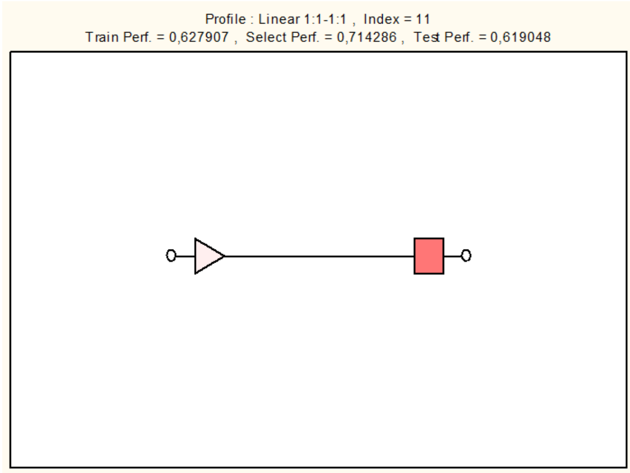
	Profile	Test Error	Training/ Members	Inputs	Hid (1)	Hid (2)
1	Linear 1:1-1:1	0.53625	PI	1	0	0
2	Linear 2:2-1:1	0.53456	PI	2	0	0
3	PNN 1:1-43-2-2:1	0.51521		1	43	2
4	PNN 2:2-43-2-2:1	0.51369		2	43	2
5	RBF 45:45-8-1:1	0.35694	KM, KN, PI	45	8	0
6	RBF 45:45-12-1:1	0.33981	KM, KN ,PI	45	12	0
7	RBF 45:45-15-1:1	0.35566	KM, KN, PI	45	15	0
8	MLP 91:91-99-59-1:1	10.31337	BP100, CG20, CG1b	91	99	59
9	MLP 99:99-41-1:1	4.70291	BP100, CG20, CG58b	99	41	0
10	MLP 99:99-55-1:1	7.14166	BP100, CG20, CG0b	99	55	0

Source: Authors

Particularly linear neural networks were retained among the ten best networks, then probabilistic neural networks, radial basic function neural networks, multiple perceptron networks with two hidden layers and a multiple perceptron network with four layers.

Figure 1 shows a schematic illustration of a linear neural network Linear 1:1-1:1.

[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.

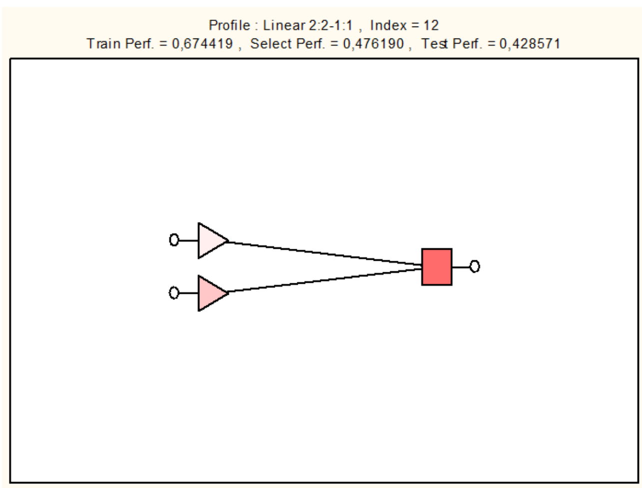


Source: Authors

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

The first layer (from the left) represents the input to the model. The triangle represents an input for the model, namely a continuous quantity. The model does not have high success rate, it oscillates depending on the set (the training set, the validation set and the data test set) from nearly 62% to nearly 71.5%. The model is nevertheless interesting because of the fact that it is only based on a single quantity that may be simply identified in the practice, even by a layperson – we namely derive the correct result from the value of the tangible assets. These are assets with the time of use longer than one year (buildings, land, machines, groups of movable things etc.). The model is particularly suitable for quick identification of seller's solvency and for determination of the condition for further transactions between a supplier and a customer.

Figure 2 shows a graphic illustration of a linear neural network in the Linear 2:2-1:1 configuration.



Source: Authors

Figure 2 – Graph of artificial neural network (Linear 2:2-1:1)

In this case the network did not reach the optimum values either. The prediction or classification power oscillates across the sets of the group within nearly 43% and nearly 67.5%. This model is characterized by high simplicity as well. An evaluator is able to determine the resulting state on the base of two quantities. Like in the first case these are the tangible assets. The material and energy consumption is an additional indicator. The second indicator is very useful – it presumes the level of company performance. Unfortunately it has caused lower accuracy of the model. And as the model has not reached the prediction power higher than 50%, it is useless in the practice (although it might be useful in the theory).

Figure 3 shows a graphic illustration of a probabilistic neural network PNN 1:1-43-2-2:1.

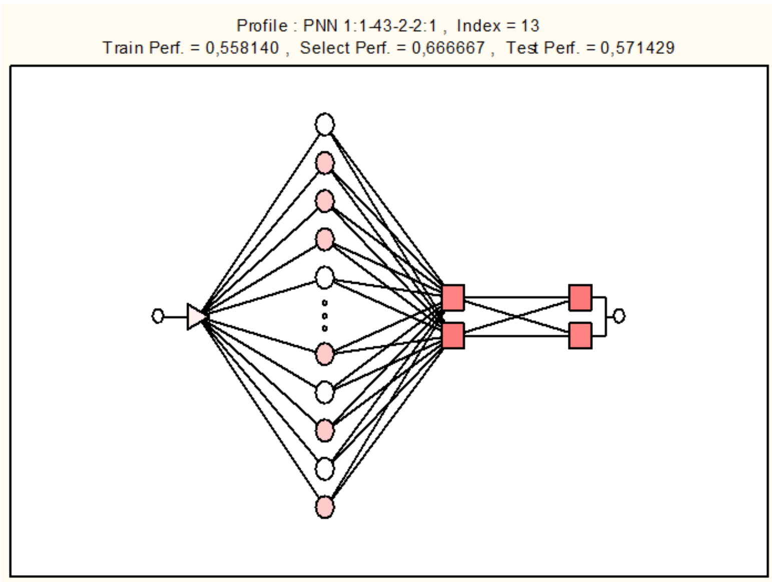


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Figure 3 – Graph of artificial neural network (PNN 1:1-43-2-2:1)

In the instance of the described probabilistic neural network the probability of prediction oscillates from nearly 56% to more than 66%. The model is thus more successful than the second linear network. Although there is one input indicator, it does not use the same linear models as tangible assets. On the other hand it avoids the use of financial ratios and uses the number of employees as the basic indicator. It is applicable in the practice for its simplicity. The prediction power is also higher than 50%. The application of this network is however less beneficial than that of the first linear network.

Figure 4 shows a graphic illustration of a probabilistic neural network PNN 2:2-43-2-2:1.

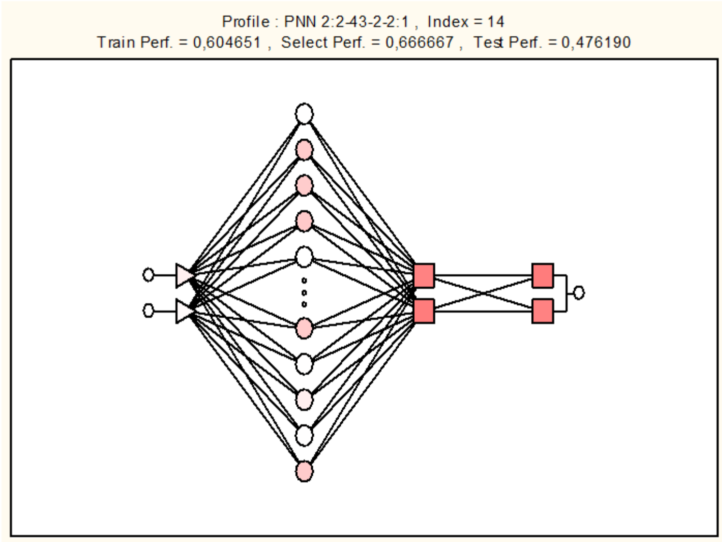

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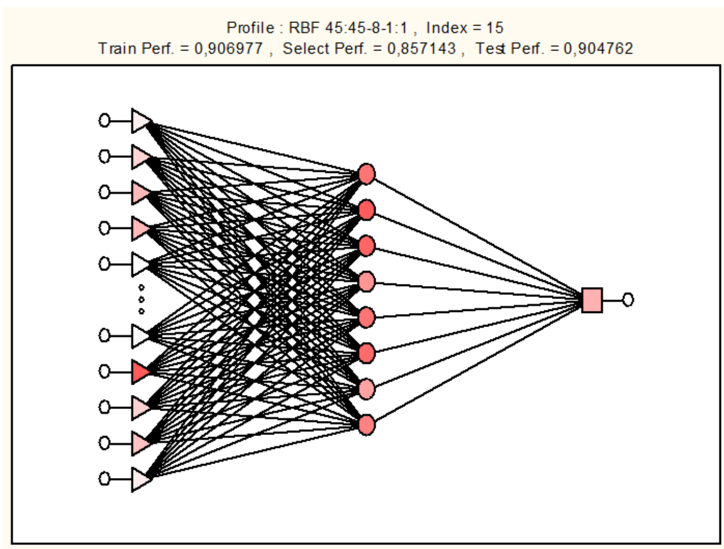
Figure 4 – Graph of artificial neural network (PNN 2:2-43-2-2:1)

In the instance of the second probabilistic neural network the classification accuracy is set across the sets of data from more than 47.5% to more than 66%. With regard to the fact that the value is lower than 50% for one set, the file cannot be used in practice. There is an interesting point that the model utilizes two inputs, namely the number of employees and the type of company according to the financial statement. The economic interpretation of the results is thus not fully logical either.

Figure 5 shows a graphic illustration of a radial basis function neural network RBF 45:45 -8 -1:1.



Source: Authors

Figure 5 – Graph of artificial neural network (RBF 45:45 -8 -1:1)

In the instance of this radial basis function neural network the classification power oscillates at the level from 85.7% to 90.7%. The prediction accuracy is thus very high. The networks uses 45 continuous quantities as the input values. These are various data on employees, all the financial statement components as well as selected financial ratios, namely from the number of employees via current assets up to the proportion of bank loans in the total liabilities. We admit that a large volume of data is necessary here. On the other hand it is a remarkable quality proportion from the point of view of prediction. 85.7% represents relatively reliable classification of a company and the whole model is thus applicable in the practice (even despite the number of input data).

Figure 6 also shows a graphic illustration of a radial basis function neural network RBF 45:45-12-1:1.

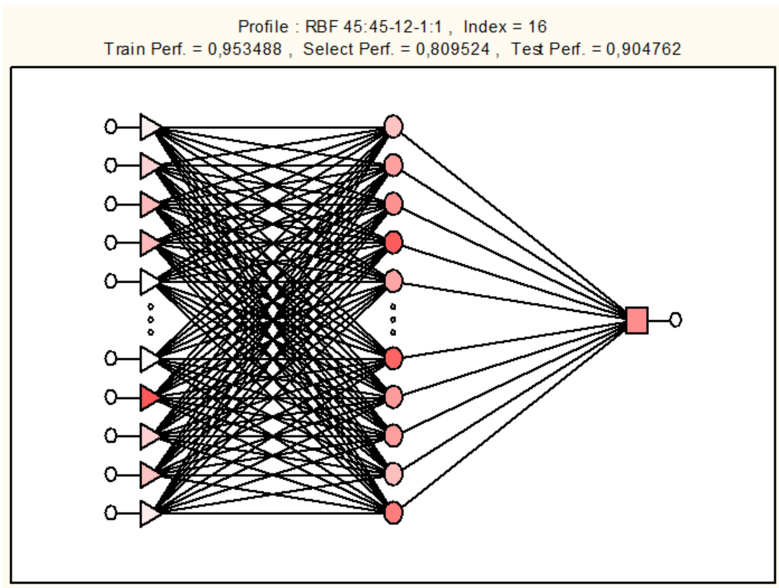


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Figure 6 – Graph of artificial neural network (RBF 45:45-12-1:1)

In the instance of the second neural network the probability of correct classification of a company is also relatively high. It oscillates from 80.9% up to 95.3%. Although it is lower, the model is still applicable in the practice. This network is also characterized by high demand for input quantities. It also needs 45. The input data is identical to that of the network No. 15. We may then see the difference between the two networks in the number of hidden neurons only.

Figure 7 shows a graphic illustration of a third radial basis function neural network RBF 45:45-15-1:1.

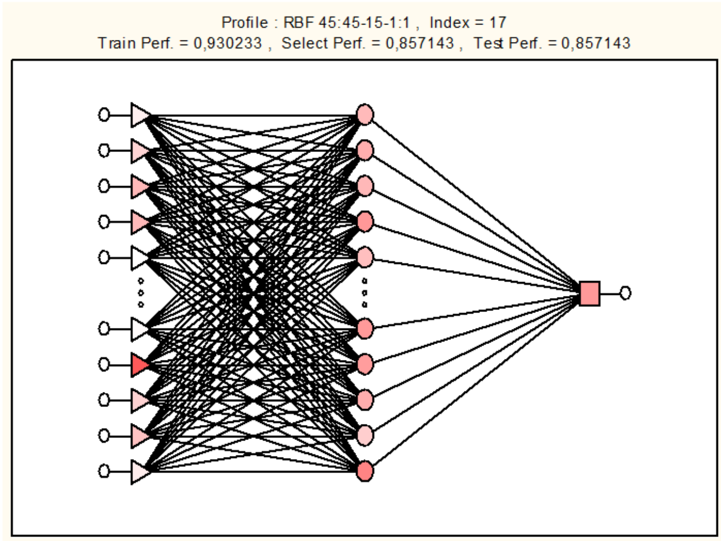

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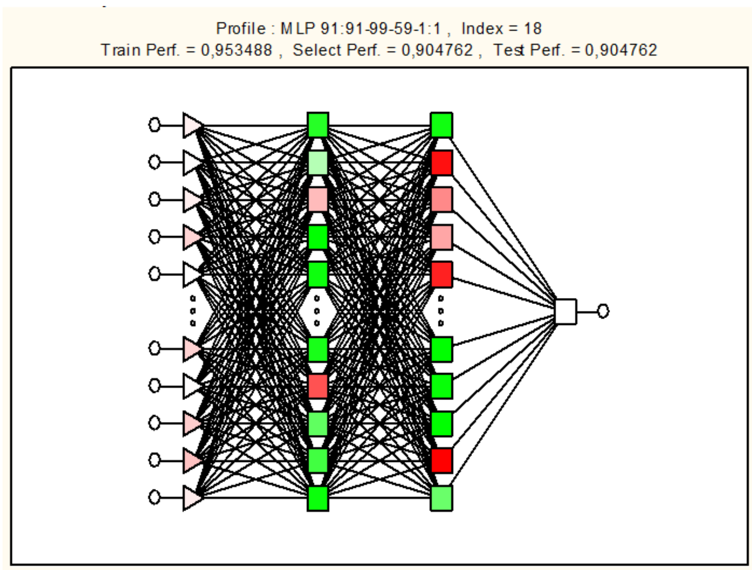
Figure 7 – Graph of artificial neural network (RBF 45:45-15-1:1)

The third RBF offers reliability at the level from 85.7% to 83%. This means that it is characterized by the highest success in company solvency prediction. This RBF also works with 45 input data identical with those of the previous two networks. However it utilizes 15 neutrons in the hidden layer. This model is the most successful one so far, and moreover, despite the need of significant volume of data it is applicable in the practice.

Figure 8 shows a graphic illustration of a multi-layer perceptron network with two hidden layers MLP 91:91-99-59-1:1.



Source: Authors

Figure 8 – Graph of artificial neural network (MLP 91:91-99-59-1:1)

The four-layer perceptron network MLP 91:91-99-59-1:1 shows the success rate in classification of solvent and insolvent companies at the level from 90.5% to 95.3%. It is thus the most suitable model so far. Unfortunately it utilizes 91 various company data as input values. It uses 99 neutrons in the first hidden layer and 59 in the second one. The prediction power is however very high, more than 90%. Thanks to this fact the neural network is applicable in the practice.

Figure 9 shows a multi-layer perceptron network with one hidden layer MLP 99:99-41-1:1.

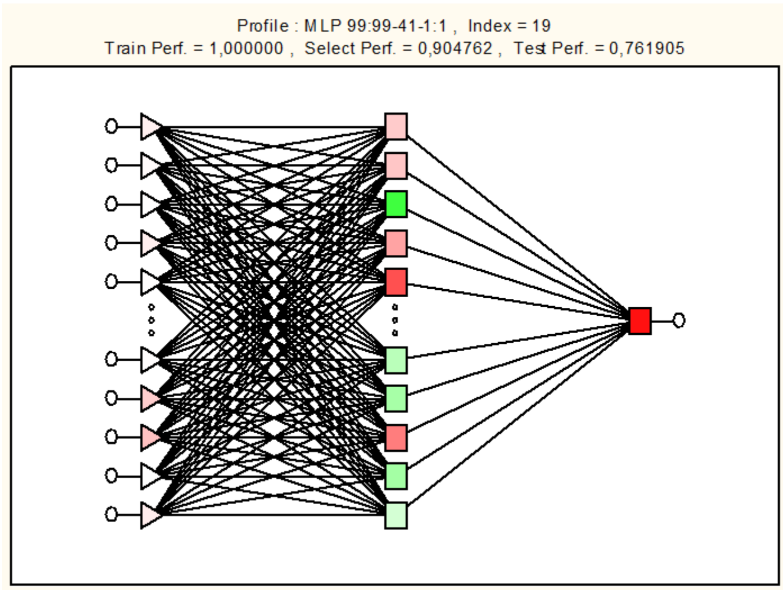


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Figure 9 – Graph of artificial neural network (MLP 99:99-41-1:1)

The three-layer perceptron network MLP 99:99-41-1:1 shows prediction capability from 76% to 100%. Unfortunately the difference between the individual data sets in terms of prediction power is too big, nearly 24%. This handicaps the practical applicability of the whole network. It moreover needs 99 input data items.

Figure 10 also represents a three-layer perceptron network, namely MLP 99:99-55-1:1.

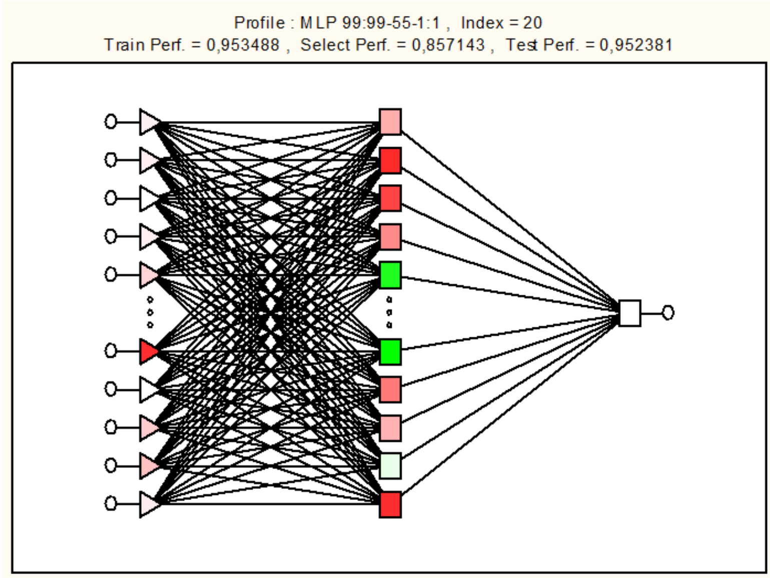

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Figure 10 – Graph of artificial neural network (MLP 99:99-55-1:1)

The second perceptron network utilizes 99 input data items for the calculation as well. However its success rate is remarkably better than in the previous case. Its prediction ability oscillates from 85.7% to 95.2%. This means that this network is applicable in the practice as well.

Only on the base of the graphic representation of the individual networks and their basic characteristics we can say that the multi-layer perceptron network with two hidden layers MLP 91:91-99-59-1:1 seems the best – throughout three data sets (a training one, a validation one and a testing one).

To be able to confirm the results derived from the schemes of the individual networks and the prediction power as the most important characteristic we will use the ROC Curve (Receiver Operating Characteristic). The curve is shown in figure 10.

The ROC Curve examines the sensitivity and specificity of the individual selected neural networks. We ideally seek for a point approximating the point [0,1]. Figure 10 demonstrates the course of 30 curves, i.e. 10 neural networks, each with three data sets.

An ideal network would offer the result in the form of three 1s. If we examine the curves and the keys to these curves, we choose the most successful networks among numbers 18, 19 and 20. Two of their data sets always give 1 as the result. We thus determine the most successful network according to the highest value of the third set. This is 0.963 of network No. 18.

We can then say that we have found and confirmed the most successful model for prediction of solvency and possible risk of potential clients of a manufacturing company. It is the four-layer perceptron network MLP 91:91-99-59-1:1, which defines the required result with at least 90 per cent accuracy.

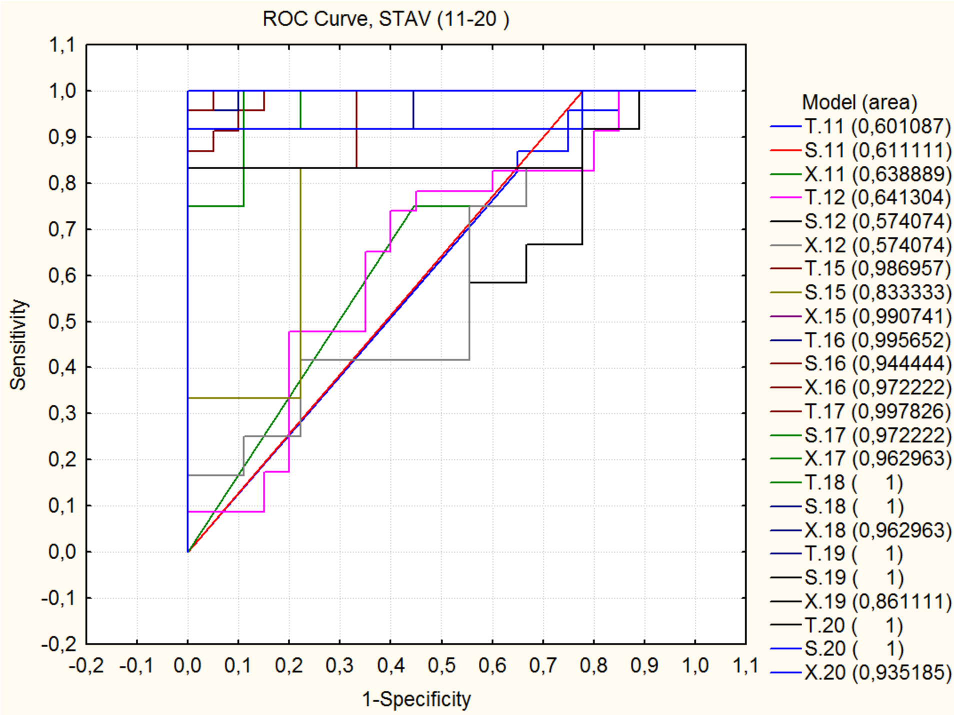

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Figure 11 – Receiver Operating Characteristic Curve

Conclusion

The aim of the article was to utilize neural networks for creation of a model for determination of solvency of potential customers of a manufacturing company.

On the base of obtained data on a group of 110 manufacturing companies 1,000 artificial neural networks were generated. Ten of these networks, which showed the best results, were retained for further processing. After an analyses of the individual networks and upon application of the ROC Curve a four-layer perceptron neural network with two hidden layers MLP 91:91-99-59-1:1 was determined as the best one.

The obtained neural network predicts solvency or possible risk of a company (potential customer of a manufacturing company) with the probability higher than 90%. Such a prediction power predetermines the model to practical application. The other networks are not so far as successful in company classification as the one. The fact that the network needs 91 company characteristics to provide the required result is a negative side of the model. If we wanted to use a neural network for some kind of a quick test only the linear network Linear 1:1-1:1 would be suitable, as it identifies the result with relatively high rate of reliability upon a single variable – the tangible assets.

We should note that the model becomes applicable in the practice thanks to its properties. It may be utilized by the company itself or by the customers of the company or other entities.

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